Numba Documentation

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Anaconda

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FOR ALL USERS

This is the Numba documentation. Unless you are already acquainted with Numba, we suggest you start with the *User manual*.

CHAPTER

ONE

USER MANUAL

1.1 A ~5 minute guide to Numba

Numba is a just-in-time compiler for Python that works best on code that uses NumPy arrays and functions, and loops. The most common way to use Numba is through its collection of decorators that can be applied to your functions to instruct Numba to compile them. When a call is made to a Numba-decorated function it is compiled to machine code "just-in-time" for execution and all or part of your code can subsequently run at native machine code speed!

Out of the box Numba works with the following:

- OS: Windows (64 bit), OSX, Linux (64 bit). Unofficial support on *BSD.
- Architecture: x86, x86_64, ppc64le, armv8l (aarch64), M1/Arm64.
- GPUs: Nvidia CUDA.
- CPython
- NumPy 1.24 - 1.26

1.1.1 How do I get it?

Numba is available as a conda package for the Anaconda Python distribution:

```
$ conda install numba
```

Numba also has wheels available:

```
$ pip install numba
```

Numba can also be *compiled from source*, although we do not recommend it for first-time Numba users.

Numba is often used as a core package so its dependencies are kept to an absolute minimum, however, extra packages can be installed as follows to provide additional functionality:

- `scipy` - enables support for compiling `numpy.linalg` functions.
- `colorama` - enables support for color highlighting in backtraces/error messages.
- `pyyaml` - enables configuration of Numba via a YAML config file.
- `intel-cmplr-lib-rt` - allows the use of the Intel SVML (high performance short vector math library, x86_64 only). Installation instructions are in the *performance tips*.

1.1.2 Will Numba work for my code?

This depends on what your code looks like, if your code is numerically orientated (does a lot of math), uses NumPy a lot and/or has a lot of loops, then Numba is often a good choice. In these examples we'll apply the most fundamental of Numba's JIT decorators, `@jit`, to try and speed up some functions to demonstrate what works well and what does not.

Numba works well on code that looks like this:

```
from numba import jit
import numpy as np

x = np.arange(100).reshape(10, 10)

@jit
def go_fast(a): # Function is compiled to machine code when called the first time
    trace = 0.0
    for i in range(a.shape[0]):   # Numba likes loops
        trace += np.tanh(a[i, i]) # Numba likes NumPy functions
    return a + trace              # Numba likes NumPy broadcasting

print(go_fast(x))
```

It won't work very well, if at all, on code that looks like this:

```
from numba import jit
import pandas as pd

x = {'a': [1, 2, 3], 'b': [20, 30, 40]}

@jit(forceobj=True, looplift=True) # Need to use object mode, try and compile loops!
def use_pandas(a): # Function will not benefit from Numba jit
    df = pd.DataFrame.from_dict(a) # Numba doesn't know about pd.DataFrame
    df += 1                        # Numba doesn't understand what this is
    return df.cov()                # or this!

print(use_pandas(x))
```

Note that Pandas is not understood by Numba and as a result Numba would simply run this code via the interpreter but with the added cost of the Numba internal overheads!

1.1.3 What is `object mode`?

The Numba `@jit` decorator fundamentally operates in two compilation modes, `nopython` mode and `object` mode. In the `go_fast` example above, the `@jit` decorator defaults to operating in `nopython` mode. The behaviour of the `nopython` compilation mode is to essentially compile the decorated function so that it will run entirely without the involvement of the Python interpreter. This is the recommended and best-practice way to use the Numba `jit` decorator as it leads to the best performance.

Should the compilation in `nopython` mode fail, Numba can compile using `object mode`. This achieved through using the `forceobj=True` key word argument to the `@jit` decorator (as seen in the `use_pandas` example above). In this mode Numba will compile the function with the assumption that everything is a Python object and essentially run the code in the interpreter. Specifying `looplift=True` might gain some performance over pure `object mode` as Numba will try and compile loops into functions that run in machine code, and it will run the rest of the code in the interpreter. For best performance avoid using `object mode` mode in general!

1.1.4 How to measure the performance of Numba?

First, recall that Numba has to compile your function for the argument types given before it executes the machine code version of your function. This takes time. However, once the compilation has taken place Numba caches the machine code version of your function for the particular types of arguments presented. If it is called again with the same types, it can reuse the cached version instead of having to compile again.

A really common mistake when measuring performance is to not account for the above behaviour and to time code once with a simple timer that includes the time taken to compile your function in the execution time.

For example:

```
from numba import jit
import numpy as np
import time

x = np.arange(100).reshape(10, 10)

@jit(nopython=True)
def go_fast(a): # Function is compiled and runs in machine code
    trace = 0.0
    for i in range(a.shape[0]):
        trace += np.tanh(a[i, i])
    return a + trace

# DO NOT REPORT THIS... COMPILATION TIME IS INCLUDED IN THE EXECUTION TIME!
start = time.perf_counter()
go_fast(x)
end = time.perf_counter()
print("Elapsed (with compilation) = {}s".format((end - start)))

# NOW THE FUNCTION IS COMPILED, RE-TIME IT EXECUTING FROM CACHE
start = time.perf_counter()
go_fast(x)
end = time.perf_counter()
print("Elapsed (after compilation) = {}s".format((end - start)))
```

This, for example prints:

```
Elapsed (with compilation) = 0.33030009269714355s
Elapsed (after compilation) = 6.67572021484375e-06s
```

A good way to measure the impact Numba JIT has on your code is to time execution using the timeit module functions; these measure multiple iterations of execution and, as a result, can be made to accommodate for the compilation time in the first execution.

As a side note, if compilation time is an issue, Numba JIT supports *on-disk caching* of compiled functions and also has an *Ahead-Of-Time* compilation mode.

1.1.5 How fast is it?

Assuming Numba can operate in `nopython` mode, or at least compile some loops, it will target compilation to your specific CPU. Speed up varies depending on application but can be one to two orders of magnitude. Numba has a *performance guide* that covers common options for gaining extra performance.

1.1.6 How does Numba work?

Numba reads the Python bytecode for a decorated function and combines this with information about the types of the input arguments to the function. It analyzes and optimizes your code, and finally uses the LLVM compiler library to generate a machine code version of your function, tailored to your CPU capabilities. This compiled version is then used every time your function is called.

1.1.7 Other things of interest:

Numba has quite a few decorators, we've seen `@jit`, but there's also:

- `@njit` - this is an alias for `@jit(nopython=True)` as it is so commonly used!
- `@vectorize` - produces NumPy `ufunc` s (with all the `ufunc` methods supported). *Docs are here*.
- `@guvectorize` - produces NumPy generalized `ufunc` s. *Docs are here*.
- `@stencil` - declare a function as a kernel for a stencil like operation. *Docs are here*.
- `@jitclass` - for jit aware classes. *Docs are here*.
- `@cfunc` - declare a function for use as a native call back (to be called from C/C++ etc). *Docs are here*.
- `@overload` - register your own implementation of a function for use in nopython mode, e.g. `@overload(scipy.special.j0)`. *Docs are here*.

Extra options available in some decorators:

- `parallel = True` - *enable* the *automatic parallelization* of the function.
- `fastmath = True` - enable *fast-math* behaviour for the function.

ctypes/cffi/cython interoperability:

- `cffi` - The calling of *CFFI* functions is supported in `nopython` mode.
- `ctypes` - The calling of *ctypes* wrapped functions is supported in `nopython` mode.
- Cython exported functions *are callable*.

GPU targets:

Numba can target Nvidia CUDA GPUs. You can write a kernel in pure Python and have Numba handle the computation and data movement (or do this explicitly). Click for Numba documentation on *CUDA*.

1.2 Overview

Numba is a compiler for Python array and numerical functions that gives you the power to speed up your applications with high performance functions written directly in Python.

Numba generates optimized machine code from pure Python code using the LLVM compiler infrastructure. With a few simple annotations, array-oriented and math-heavy Python code can be just-in-time optimized to performance similar as C, C++ and Fortran, without having to switch languages or Python interpreters.

Numba's main features are:

- *on-the-fly code generation* (at import time or runtime, at the user's preference)
- native code generation for the CPU (default) and *GPU hardware*
- integration with the Python scientific software stack (thanks to Numpy)

Here is how a Numba-optimized function, taking a Numpy array as argument, might look like:

```
@numba.jit
def sum2d(arr):
    M, N = arr.shape
    result = 0.0
    for i in range(M):
        for j in range(N):
            result += arr[i,j]
    return result
```

1.3 Installation

1.3.1 Compatibility

For software compatibility, please see the section on *version support information* for details.

Our supported platforms are:

- Linux x86_64
- Windows 10 and later (64-bit)
- OS X 10.9 and later (64-bit and unofficial support on M1/Arm64)
- NVIDIA GPUs of compute capability 5.0 and later
  - Compute capabilities 3.5 and 3.7 are supported, but deprecated.
- ARMv8 (64-bit little-endian, such as the NVIDIA Jetson)
- Linux ppcle64, e.g. POWER8, POWER9 (unofficially supported)
- BSD (unofficial support only)

Automatic parallelization with @jit is only available on 64-bit platforms.

1.3.2 Installing using conda on x86/x86_64/POWER Platforms

The easiest way to install Numba and get updates is by using `conda`, a cross-platform package manager and software distribution maintained by Anaconda, Inc. You can either use Anaconda to get the full stack in one download, or Miniconda which will install the minimum packages required for a conda environment.

Once you have conda installed, just type:

```
$ conda install numba
```

or:

```
$ conda update numba
```

Note that Numba, like Anaconda, only supports PPC in 64-bit little-endian mode.

To enable CUDA GPU support for Numba, install the latest graphics drivers from NVIDIA for your platform. (Note that the open source Nouveau drivers shipped by default with many Linux distributions do not support CUDA.) Then install the CUDA Toolkit package.

For CUDA 12, `cuda-nvcc` and `cuda-nvrtc` are required:

```
$ conda install -c conda-forge cuda-nvcc cuda-nvrtc "cuda-version>=12.0"
```

For CUDA 11, `cudatoolkit` is required:

```
$ conda install -c conda-forge cudatoolkit "cuda-version>=11.2,<12.0"
```

You do not need to install the CUDA SDK from NVIDIA.

1.3.3 Installing using pip on x86/x86_64 Platforms

Binary wheels for Windows, Mac, and Linux are also available from PyPI. You can install Numba using `pip`:

```
$ pip install numba
```

This will download all of the needed dependencies as well. You do not need to have LLVM installed to use Numba (in fact, Numba will ignore all LLVM versions installed on the system) as the required components are bundled into the llvmlite wheel.

To use CUDA with Numba installed by `pip`, you need to install the CUDA SDK from NVIDIA. Please refer to *Setting CUDA Installation Path* for details. Numba can also detect CUDA libraries installed system-wide on Linux.

1.3.4 Installing on Linux ARMv8 (AArch64) Platforms

We build and test conda packages on the NVIDIA Jetson TX2, but they are likely to work for other AArch64 platforms. (Note that while the CPUs in the Raspberry Pi 3, 4, and Zero 2 W are 64-bit, Raspberry Pi OS may be running in 32-bit mode depending on the OS image in use).

Conda-forge support for AArch64 is still quite experimental and packages are limited, but it does work enough for Numba to build and pass tests. To set up the environment:

- Install miniforge. This will create a minimal conda environment.
- Then you can install Numba from the `numba` channel:

```
$ conda install -c numba numba
```

On CUDA-enabled systems, like the Jetson, the CUDA toolkit should be automatically detected in the environment.

1.3.5 Installing from source

Installing Numba from source is fairly straightforward (similar to other Python packages), but installing llvmlite can be quite challenging due to the need for a special LLVM build. If you are building from source for the purposes of Numba development, see *Build environment* for details on how to create a Numba development environment with conda.

If you are building Numba from source for other reasons, first follow the llvmlite installation guide. Once that is completed, you can download the latest Numba source code from Github:

```
$ git clone https://github.com/numba/numba.git
```

Source archives of the latest release can also be found on PyPI. In addition to `llvmlite`, you will also need:

- A C compiler compatible with your Python installation. If you are using Anaconda, you can use the following conda packages:
  - Linux `x86_64`: `gcc_linux-64` and `gxx_linux-64`
  - Linux `POWER`: `gcc_linux-ppc64le` and `gxx_linux-ppc64le`
  - Linux `ARM`: no conda packages, use the system compiler
  - Mac OSX: `clang_osx-64` and `clangxx_osx-64` or the system compiler at `/usr/bin/clang` (Mojave onwards)
  - Mac OSX (M1): `clang_osx-arm64` and `clangxx_osx-arm64`
  - Windows: a version of Visual Studio appropriate for the Python version in use
- NumPy

Then you can build and install Numba from the top level of the source tree:

```
$ python setup.py install
```

If you wish to run the test suite, see the instructions in the *developer documentation*.

Build time environment variables and configuration of optional components

Below are environment variables that are applicable to altering how Numba would otherwise build by default along with information on configuration options.

`NUMBA_DISABLE_OPENMP (default: not set)`

To disable compilation of the OpenMP threading backend set this environment variable to a non-empty string when building. If not set (default):

- For Linux and Windows it is necessary to provide OpenMP C headers and runtime libraries compatible with the compiler tool chain mentioned above, and for these to be accessible to the compiler via standard flags.
- For OSX the conda package `llvm-openmp` provides suitable C headers and libraries. If the compilation requirements are not met the OpenMP threading backend will not be compiled.

`NUMBA_DISABLE_TBB (default: not set)`

To disable the compilation of the TBB threading backend set this environment variable to a non-empty string when building. If not set (default) the TBB C headers and libraries must be available at compile time. If building with `conda build` this requirement can be met by installing the `tbb-devel` package. If not building with `conda build` the requirement can be met via a system installation of TBB or through the use of the `TBBROOT` environment variable to provide the location of the TBB installation. For more information about setting `TBBROOT` see the Intel documentation.

1.3.6 Dependency List

Numba has numerous required and optional dependencies which additionally may vary with target operating system and hardware. The following lists them all (as of July 2020).

- Required build time:
  - `setuptools`
  - `numpy`
  - `llvmlite`
  - Compiler toolchain mentioned above
- Required run time:
  - `numpy`
  - `llvmlite`
- Optional build time:

  See *Build time environment variables and configuration of optional components* for more details about additional options for the configuration and specification of these optional components.
  - `llvm-openmp` (OSX) - provides headers for compiling OpenMP support into Numba's threading backend
  - `tbb-devel` - provides TBB headers/libraries for compiling TBB support into Numba's threading backend (version >= 2021.6 required).
- Optional runtime are:
  - `scipy` - provides cython bindings used in Numba's `np.linalg.*` support
  - `tbb` - provides the TBB runtime libraries used by Numba's TBB threading backend (version >= 2021 required).
  - `jinja2` - for "pretty" type annotation output (HTML) via the `numba` CLI
  - `cffi` - permits use of CFFI bindings in Numba compiled functions
  - `llvm-openmp` - (OSX) provides OpenMP library support for Numba's OpenMP threading backend.
  - `intel-openmp` - (OSX) provides an alternative OpenMP library for use with Numba's OpenMP threading backend.
  - `ipython` - if in use, caching will use IPython's cache directories/caching still works
  - `pyyaml` - permits the use of a `.numba_config.yaml` file for storing per project configuration options
  - `colorama` - makes error message highlighting work
  - `intel-cmplr-lib-rt` - allows Numba to use Intel SVML for extra performance
  - `pygments` - for "pretty" type annotation

  - `gdb` as an executable on the `$PATH` - if you would like to use the gdb support
  - `setuptools` - permits the use of `pycc` for Ahead-of-Time (AOT) compilation
  - Compiler toolchain mentioned above, if you would like to use `pycc` for Ahead-of-Time (AOT) compilation
  - `r2pipe` - required for assembly CFG inspection.
  - `radare2` as an executable on the `$PATH` - required for assembly CFG inspection. See here for information on obtaining and installing.
  - `graphviz` - for some CFG inspection functionality.
  - `typeguard` - used by `runtests.py` for *runtime type-checking*.
  - `cuda-python` - The NVIDIA CUDA Python bindings. See *CUDA Bindings*. Numba requires Version 11.6 or greater.
  - `cubinlinker` and `ptxcompiler` to support *CUDA Minor Version Compatibility*.
- To build the documentation:
  - `sphinx`
  - `pygments`
  - `sphinx_rtd_theme`
  - `numpydoc`
  - `make` as an executable on the `$PATH`

1.3.7 Version support information

This is the canonical reference for information concerning which versions of Numba's dependencies were tested and known to work against a given version of Numba. Other versions of the dependencies (especially NumPy) may work reasonably well but were not tested. The use of `x` in a version number indicates all patch levels supported. The use of `?` as a version is due to missing information.

Numba	Release date	Python	NumPy	llvmlite	LLVM	TBB
0.61.0	2025-01-16	3.10.x <= version < 3.14	1.24 <= version < 1.27 ; 2.0 <= version < 2.2 ;	0.44.x	15.x	2021.6 <= version
0.60.0	2024-06-13	3.9.x <= version < 3.13	1.22 <= version < 1.27 ; version == 2.0 †	0.43.x	14.x	2021.6 <= version
0.59.1	2024-03-18	3.9.x <= version < 3.13	1.22 <= version < 1.27	0.42.x	14.x	2021.6 <= version
0.59.0	2024-01-31	3.9.x <= version < 3.13	1.22 <= version < 1.27	0.42.x	14.x	2021.6 <= version
0.58.1	2023-10-17	3.8.x <= version < 3.12	1.22 <= version < 1.27 .	0.41.x	14.x	2021.6 <= version
0.58.0	2023-09-20	3.8.x <= version < 3.12	1.22 <= version < 1.26	0.41.x	14.x	2021.6 <= version
0.57.1	2023-06-21	3.8.x <= version < 3.12	1.21 <= version < 1.25	0.40.x	14.x	2021.6 <= version
0.57.0	2023-05-01	3.8.x <= version < 3.12	1.21 <= version < 1.25	0.40.x	14.x	2021.6 <= version
0.56.4	2022-11-03	3.7.x <= version < 3.11	1.18 <= version < 1.24	0.39.x	11.x	2021.x
0.56.3	2022-10-13	3.7.x <= version < 3.11	1.18 <= version < 1.24	0.39.x	11.x	2021.x
0.56.2	2022-09-01	3.7.x <= version < 3.11	1.18 <= version < 1.24	0.39.x	11.x	2021.x
0.56.1	NO RELEASE					
0.56.0	2022-07-25	3.7.x <= version < 3.11	1.18 <= version < 1.23	0.39.x	11.x	2021.x
0.55.2	2022-05-25	3.7.x <= version < 3.11	1.18 <= version < 1.23	0.38.x	11.x	2021.x
0.55.{0,1}	2022-01-13	3.7.x <= version < 3.11	1.18 <= version < 1.22	0.38.x	11.x	2021.x
0.54.x	2021-08-19	3.6.x <= version < 3.10	1.17 <= version < 1.21	0.37.x	11.x	2021.x
0.53.x	2021-03-11	3.6.x <= version < 3.10	1.15 <= version < 1.21	0.36.x	11.x	2019.5 <= version < 2021.4
0.52.x	2020-11-30	3.6.x <= version < 3.9	1.15 <= version < 1.20	0.35.x	10.x (9.x for aarch64)	2019.5 <= version < 2020.3
0.51.x	2020-08-12	3.6.x <= version < 3.9	1.15 <= version < 1.19	0.34.x	10.x (9.x for aarch64)	2019.5 <= version < 2020.0
0.50.x	2020-06-10	3.6.x <= version < 3.9	1.15 <= version < 1.19	0.33.x	9.x	2019.5 <= version < 2020.0
0.49.x	2020-04-16	3.6.x <= version < 3.9	1.15 <= version < 1.18	0.31.x <= version < 0.33.x	9.x	2019.5 <= version < 2020.0
0.48.x	2020-01-27	3.6.x <= version < 3.9	1.15 <= version < 1.18	0.31.x	8.x (7.x for ppc64le)	2018.0.5 <= version < ?
0.47.x	2020-01-02	3.5.x <= version < 3.9; version == 2.7.x	1.15 <= version < 1.18	0.30.x	8.x (7.x for ppc64le)	2018.0.5 <= version < ?

- †: binary compatibility only

1.3.8 Checking your installation

You should be able to import Numba from the Python prompt:

```
$ python
Python 3.10.2 | packaged by conda-forge | (main, Jan 14 2022, 08:02:09) [GCC 9.4.0] on␣
↪linux
Type "help", "copyright", "credits" or "license" for more information.
>>> import numba
>>> numba.__version__
'0.55.1'
```

You can also try executing the `numba --sysinfo` (or `numba -s` for short) command to report information about your system capabilities. See *Command line interface* for further information.

```
$ numba -s
System info:
--------------------------------------------------------------------------------
__Time Stamp__
Report started (local time)                 : 2022-01-18 10:35:08.981319

__Hardware Information__
Machine                                     : x86_64
CPU Name                                    : skylake-avx512
CPU Count                                   : 12
CPU Features                                :
64bit adx aes avx avx2 avx512bw avx512cd avx512dq avx512f avx512vl bmi bmi2
clflushopt clwb cmov cx16 cx8 f16c fma fsgsbase fxsr invpcid lzcnt mmx
movbe pclmul pku popcnt prfchw rdrnd rdseed rtm sahf sse sse2 sse3 sse4.1
sse4.2 ssse3 xsave xsavec xsaveopt xsaves

__OS Information__
Platform Name                               : Linux-5.4.0-94-generic-x86_64-with-
↪glibc2.31
Platform Release                            : 5.4.0-94-generic
OS Name                                     : Linux
OS Version                                  : #106-Ubuntu SMP Thu Jan 6 23:58:14 UTC␣
↪2022

__Python Information__
Python Compiler                             : GCC 9.4.0
Python Implementation                       : CPython
Python Version                              : 3.10.2
Python Locale                               : en_GB.UTF-8

__LLVM information__
LLVM Version                                : 11.1.0

__CUDA Information__
Found 1 CUDA devices
id 0      b'Quadro RTX 8000'                              [SUPPORTED]
```

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```
                      Compute Capability: 7.5
                           PCI Device ID: 0
                              PCI Bus ID: 21
                                    UUID: GPU-e6489c45-5b68-3b03-bab7-0e7c8e809643
                                Watchdog: Enabled
             FP32/FP64 Performance Ratio: 32
```

(output truncated due to length)

1.4 Compiling Python code with `@jit`

Numba provides several utilities for code generation, but its central feature is the *numba.jit()* decorator. Using this decorator, you can mark a function for optimization by Numba's JIT compiler. Various invocation modes trigger differing compilation options and behaviours.

1.4.1 Basic usage

Lazy compilation

The recommended way to use the `@jit` decorator is to let Numba decide when and how to optimize:

```
from numba import jit

@jit
def f(x, y):
    # A somewhat trivial example
    return x + y
```

In this mode, compilation will be deferred until the first function execution. Numba will infer the argument types at call time, and generate optimized code based on this information. Numba will also be able to compile separate specializations depending on the input types. For example, calling the `f()` function above with integer or complex numbers will generate different code paths:

```
>>> f(1, 2)
3
>>> f(1j, 2)
(2+1j)
```

Eager compilation

You can also tell Numba the function signature you are expecting. The function `f()` would now look like:

```
from numba import jit, int32

@jit(int32(int32, int32))
def f(x, y):
    # A somewhat trivial example
    return x + y
```

`int32(int32, int32)` is the function's signature. In this case, the corresponding specialization will be compiled by the `@jit` decorator, and no other specialization will be allowed. This is useful if you want fine-grained control over types chosen by the compiler (for example, to use single-precision floats).

If you omit the return type, e.g. by writing `(int32, int32)` instead of `int32(int32, int32)`, Numba will try to infer it for you. Function signatures can also be strings, and you can pass several of them as a list; see the *numba.jit()* documentation for more details.

Of course, the compiled function gives the expected results:

```
>>> f(1,2)
3
```

and if we specified `int32` as return type, the higher-order bits get discarded:

```
>>> f(2**31, 2**31 + 1)
1
```

1.4.2 Calling and inlining other functions

Numba-compiled functions can call other compiled functions. The function calls may even be inlined in the native code, depending on optimizer heuristics. For example:

```
@jit
def square(x):
    return x ** 2

@jit
def hypot(x, y):
    return math.sqrt(square(x) + square(y))
```

The `@jit` decorator *must* be added to any such library function, otherwise Numba may generate much slower code.

1.4.3 Signature specifications

Explicit `@jit` signatures can use a number of types. Here are some common ones:

- `void` is the return type of functions returning nothing (which actually return `None` when called from Python)
- `intp` and `uintp` are pointer-sized integers (signed and unsigned, respectively)
- `intc` and `uintc` are equivalent to C `int` and `unsigned int` integer types
- `int8`, `uint8`, `int16`, `uint16`, `int32`, `uint32`, `int64`, `uint64` are fixed-width integers of the corresponding bit width (signed and unsigned)
- `float32` and `float64` are single- and double-precision floating-point numbers, respectively
- `complex64` and `complex128` are single- and double-precision complex numbers, respectively
- array types can be specified by indexing any numeric type, e.g. `float32[:]` for a one-dimensional single-precision array or `int8[:,:]` for a two-dimensional array of 8-bit integers.

1.4.4 Compilation options

A number of keyword-only arguments can be passed to the `@jit` decorator.

nopython

Numba has two compilation modes: *nopython mode* and *object mode*. *Nopython mode* is the default and it produces much faster code, but has limitations.

```
@jit  # same as @jit(nopython=True) or @njit since Numba 0.59
def f(x, y):
    return x + y
```

See also:

Troubleshooting and tips

nogil

Whenever Numba optimizes Python code to native code that only works on native types and variables (rather than Python objects), it is not necessary anymore to hold Python's global interpreter lock (GIL). Numba will release the GIL when entering such a compiled function if you passed `nogil=True`.

```
@jit(nogil=True)
def f(x, y):
    return x + y
```

Code running with the GIL released runs concurrently with other threads executing Python or Numba code (either the same compiled function, or another one), allowing you to take advantage of multi-core systems. This will not be possible if the function is compiled in *object mode*.

When using `nogil=True`, you'll have to be wary of the usual pitfalls of multi-threaded programming (consistency, synchronization, race conditions, etc.).

cache

To avoid compilation times each time you invoke a Python program, you can instruct Numba to write the result of function compilation into a file-based cache. This is done by passing `cache=True`:

```
@jit(cache=True)
def f(x, y):
    return x + y
```

Note: Caching of compiled functions has several known limitations:

- The caching of compiled functions is not performed on a function-by-function basis. The cached function is the the main jit function, and all secondary functions (those called by the main function) are incorporated in the cache of the main function.
- Cache invalidation fails to recognize changes in functions defined in a different file. This means that when a main jit function calls functions that were imported from a different module, a change in those other modules will not be detected and the cache will not be updated. This carries the risk that "old" function code might be used in the calculations.

- Global variables are treated as constants. The cache will remember the value of the global variable at compilation time. On cache load, the cached function will not rebind to the new value of the global variable.

---

parallel

Enables automatic parallelization (and related optimizations) for those operations in the function known to have parallel semantics. For a list of supported operations, see *Automatic parallelization with @jit*. This feature is enabled by passing `parallel=True` and must be used in conjunction with `nopython=True`:

```
@jit(nopython=True, parallel=True)
def f(x, y):
    return x + y
```

See also:

Automatic parallelization with @jit

1.5 Creating NumPy universal functions

There are two types of universal functions:

- Those which operate on scalars, these are "universal functions" or *ufuncs* (see `@vectorize` below).
- Those which operate on higher dimensional arrays and scalars, these are "generalized universal functions" or *gufuncs* (`@guvectorize` below).

1.5.1 The `@vectorize` decorator

Numba's vectorize allows Python functions taking scalar input arguments to be used as NumPy ufuncs. Creating a traditional NumPy ufunc is not the most straightforward process and involves writing some C code. Numba makes this easy. Using the *vectorize()* decorator, Numba can compile a pure Python function into a ufunc that operates over NumPy arrays as fast as traditional ufuncs written in C.

Using *vectorize()*, you write your function as operating over input scalars, rather than arrays. Numba will generate the surrounding loop (or *kernel*) allowing efficient iteration over the actual inputs.

The *vectorize()* decorator has two modes of operation:

- Eager, or decoration-time, compilation: If you pass one or more type signatures to the decorator, you will be building a NumPy universal function (ufunc). The rest of this subsection describes building ufuncs using decoration-time compilation.
- Lazy, or call-time, compilation: When not given any signatures, the decorator will give you a Numba dynamic universal function (*DUFunc*) that dynamically compiles a new kernel when called with a previously unsupported input type. A later subsection, "*Dynamic universal functions*", describes this mode in more depth.

As described above, if you pass a list of signatures to the *vectorize()* decorator, your function will be compiled into a NumPy ufunc. In the basic case, only one signature will be passed:

Listing 1: from `test_vectorize_one_signature` of `numba/tests/doc_examples/test_examples.py`

```
from numba import vectorize, float64

@vectorize([float64(float64, float64)])
def f(x, y):
    return x + y
```

If you pass several signatures, beware that you have to pass most specific signatures before least specific ones (e.g., single-precision floats before double-precision floats), otherwise type-based dispatching will not work as expected:

Listing 2: from `test_vectorize_multiple_signatures` of `numba/tests/doc_examples/test_examples.py`

```
from numba import vectorize, int32, int64, float32, float64
import numpy as np

@vectorize([int32(int32, int32),
            int64(int64, int64),
            float32(float32, float32),
            float64(float64, float64)])
def f(x, y):
    return x + y
```

The function will work as expected over the specified array types:

Listing 3: from `test_vectorize_multiple_signatures` of `numba/tests/doc_examples/test_examples.py`

```
a = np.arange(6)
result = f(a, a)
# result == array([ 0,  2,  4,  6,  8, 10])
```

Listing 4: from `test_vectorize_multiple_signatures` of `numba/tests/doc_examples/test_examples.py`

```
a = np.linspace(0, 1, 6)
result = f(a, a)
# Now, result == array([0. , 0.4, 0.8, 1.2, 1.6, 2. ])
```

but it will fail working on other types:

```
>>> a = np.linspace(0, 1+1j, 6)
>>> f(a, a)
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: ufunc 'ufunc' not supported for the input types, and the inputs could not be␣
↪safely coerced to any supported types according to the casting rule ''safe''
```

You might ask yourself, "why would I go through this instead of compiling a simple iteration loop using the *@jit* decorator?". The answer is that NumPy ufuncs automatically get other features such as reduction, accumulation or broadcasting. Using the example above:

Listing 5: from `test_vectorize_multiple_signatures` of `numba/tests/doc_examples/test_examples.py`

```
a = np.arange(12).reshape(3, 4)
# a == array([[ 0,  1,  2,  3],
#             [ 4,  5,  6,  7],
#             [ 8,  9, 10, 11]])

result1 = f.reduce(a, axis=0)
# result1 == array([12, 15, 18, 21])

result2 = f.reduce(a, axis=1)
# result2 == array([ 6, 22, 38])

result3 = f.accumulate(a)
# result3 == array([[ 0,  1,  2,  3],
#                   [ 4,  6,  8, 10],
#                   [12, 15, 18, 21]])

result4 = f.accumulate(a, axis=1)
# result3 == array([[ 0,  1,  3,  6],
#                   [ 4,  9, 15, 22],
#                   [ 8, 17, 27, 38]])
```

See also:

Standard features of ufuncs (NumPy documentation).

Note: Only the broadcasting and reduce features of ufuncs are supported in compiled code.

The *`vectorize()`* decorator supports multiple ufunc targets:

Target	Description
cpu	Single-threaded CPU
parallel	Multi-core CPU
cuda	CUDA GPU **Note:** This creates an *ufunc-like* object. See documentation for CUDA ufunc for detail.

A general guideline is to choose different targets for different data sizes and algorithms. The "cpu" target works well for small data sizes (approx. less than 1KB) and low compute intensity algorithms. It has the least amount of overhead. The "parallel" target works well for medium data sizes (approx. less than 1MB). Threading adds a small delay. The "cuda" target works well for big data sizes (approx. greater than 1MB) and high compute intensity algorithms. Transferring memory to and from the GPU adds significant overhead.

Starting in Numba 0.59, the `cpu` target supports the following attributes and methods in compiled code:

- `ufunc.nin`

- `ufunc.nout`
- `ufunc.nargs`
- `ufunc.identity`
- `ufunc.signature`
- `ufunc.reduce()` (only the first 5 arguments - experimental feature)

1.5.2 The `@guvectorize` decorator

While *`vectorize()`* allows you to write ufuncs that work on one element at a time, the *`guvectorize()`* decorator takes the concept one step further and allows you to write ufuncs that will work on an arbitrary number of elements of input arrays, and take and return arrays of differing dimensions. The typical example is a running median or a convolution filter.

Contrary to *`vectorize()`* functions, *`guvectorize()`* functions don't return their result value: they take it as an array argument, which must be filled in by the function. This is because the array is actually allocated by NumPy's dispatch mechanism, which calls into the Numba-generated code.

Similar to *`vectorize()`* decorator, *`guvectorize()`* also has two modes of operation: Eager, or decoration-time compilation and lazy, or call-time compilation.

Here is a very simple example:

Listing 6: from `test_guvectorize` of `numba/tests/doc_examples/test_examples.py`

```
from numba import guvectorize, int64
import numpy as np

@guvectorize([(int64[:], int64, int64[:])], '(n),()->(n)')
def g(x, y, res):
    for i in range(x.shape[0]):
        res[i] = x[i] + y
```

The underlying Python function simply adds a given scalar (`y`) to all elements of a 1-dimension array. What's more interesting is the declaration. There are two things there:

- the declaration of input and output *layouts*, in symbolic form: `(n),()->(n)` tells NumPy that the function takes a *n*-element one-dimension array, a scalar (symbolically denoted by the empty tuple `()`) and returns a *n*-element one-dimension array;
- the list of supported concrete *signatures* as per `@vectorize`; here, as in the above example, we demonstrate `int64` arrays.

Note: 1D array type can also receive scalar arguments (those with shape `()`). In the above example, the second argument also could be declared as `int64[:]`. In that case, the value must be read by `y[0]`.

We can now check what the compiled ufunc does, over a simple example:

Listing 7: from test_guvectorize of numba/tests/doc_examples/test_examples.py

```
a = np.arange(5)
result = g(a, 2)
# result == array([2, 3, 4, 5, 6])
```

The nice thing is that NumPy will automatically dispatch over more complicated inputs, depending on their shapes:

Listing 8: from test_guvectorize of numba/tests/doc_examples/test_examples.py

```
a = np.arange(6).reshape(2, 3)
# a == array([[0, 1, 2],
#             [3, 4, 5]])

result1 = g(a, 10)
# result1 == array([[10, 11, 12],
#                   [13, 14, 15]])

result2 = g(a, np.array([10, 20]))
g(a, np.array([10, 20]))
# result2 == array([[10, 11, 12],
#                   [23, 24, 25]])
```

Note: Both *vectorize()* and *guvectorize()* support passing nopython=True *as in the @jit decorator*. Use it to ensure the generated code does not fallback to *object mode*.

Scalar return values

Now suppose we want to return a scalar value from *guvectorize()*. To do this, we need to:

- in the signatures, declare the scalar return with [:] like a 1-dimensional array (eg. int64[:]),
- in the layout, declare it as (),
- in the implementation, write to the first element (e.g. res[0] = acc).

The following example function computes the sum of the 1-dimensional array (x) plus the scalar (y) and returns it as a scalar:

Listing 9: from test_guvectorize_scalar_return of numba/tests/doc_examples/test_examples.py

```
from numba import guvectorize, int64
import numpy as np

@guvectorize([(int64[:], int64, int64[:])], '(n),()->()')
def g(x, y, res):
    acc = 0
    for i in range(x.shape[0]):
        acc += x[i] + y
    res[0] = acc
```

Now if we apply the wrapped function over the array, we get a scalar value as the output:

Listing 10: from `test_guvectorize_scalar_return` of `numba/tests/doc_examples/test_examples.py`

```
a = np.arange(5)
result = g(a, 2)
# At this point, result == 20.
```

Overwriting input values

In most cases, writing to inputs may also appear to work - however, this behaviour cannot be relied on. Consider the following example function:

Listing 11: from `test_guvectorize_overwrite` of `numba/tests/doc_examples/test_examples.py`

```
from numba import guvectorize, float64
import numpy as np

@guvectorize([(float64[:], float64[:])], '()->()')
def init_values(invals, outvals):
    invals[0] = 6.5
    outvals[0] = 4.2
```

Calling the *init_values* function with an array of *float64* type results in visible changes to the input:

Listing 12: from `test_guvectorize_overwrite` of `numba/tests/doc_examples/test_examples.py`

```
invals = np.zeros(shape=(3, 3), dtype=np.float64)
# invals == array([[6.5, 6.5, 6.5],
#                  [6.5, 6.5, 6.5],
#                  [6.5, 6.5, 6.5]])

outvals = init_values(invals)
# outvals == array([[4.2, 4.2, 4.2],
#                   [4.2, 4.2, 4.2],
#                   [4.2, 4.2, 4.2]])
```

This works because NumPy can pass the input data directly into the *init_values* function as the data *dtype* matches that of the declared argument. However, it may also create and pass in a temporary array, in which case changes to the input are lost. For example, this can occur when casting is required. To demonstrate, we can use an array of *float32* with the *init_values* function:

Listing 13: from `test_guvectorize_overwrite` of `numba/tests/doc_examples/test_examples.py`

```
invals = np.zeros(shape=(3, 3), dtype=np.float32)
# invals == array([[0., 0., 0.],
#                  [0., 0., 0.],
#                  [0., 0., 0.]], dtype=float32)
outvals = init_values(invals)
# outvals == array([[4.2, 4.2, 4.2],
```

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```
#                   [4.2, 4.2, 4.2],
#                   [4.2, 4.2, 4.2]])
print(invals)
# invals == array([[0., 0., 0.],
#                  [0., 0., 0.],
#                  [0., 0., 0.]], dtype=float32)
```

In this case, there is no change to the *invals* array because the temporary casted array was mutated instead.

To solve this problem, one needs to tell the GUFunc engine that the `invals` argument is writable. This can be achieved by passing `writable_args=('invals',)` (specifying by name), or `writable_args=(0,)` (specifying by position) to `@guvectorize`. Now, the code above works as expected:

Listing 14: from `test_guvectorize_overwrite` of `numba/tests/doc_examples/test_examples.py`

```
@guvectorize(
    [(float64[:], float64[:])],
    '()->()',
    writable_args=('invals',)
)
def init_values(invals, outvals):
    invals[0] = 6.5
    outvals[0] = 4.2

invals = np.zeros(shape=(3, 3), dtype=np.float32)
# invals == array([[0., 0., 0.],
#                  [0., 0., 0.],
#                  [0., 0., 0.]], dtype=float32)
outvals = init_values(invals)
# outvals == array([[4.2, 4.2, 4.2],
#                   [4.2, 4.2, 4.2],
#                   [4.2, 4.2, 4.2]])
print(invals)
# invals == array([[6.5, 6.5, 6.5],
#                  [6.5, 6.5, 6.5],
#                  [6.5, 6.5, 6.5]], dtype=float32)
```

1.5.3 Dynamic universal functions

As described above, if you do not pass any signatures to the *vectorize()* decorator, your Python function will be used to build a dynamic universal function, or *DUFunc*. For example:

Listing 15: from `test_vectorize_dynamic` of `numba/tests/doc_examples/test_examples.py`

```
from numba import vectorize

@vectorize
def f(x, y):
    return x * y
```

The resulting `f()` is a *DUFunc* instance that starts with no supported input types. As you make calls to `f()`, Numba

generates new kernels whenever you pass a previously unsupported input type. Given the example above, the following set of interpreter interactions illustrate how dynamic compilation works:

```
>>> f
<numba._DUFunc 'f'>
>>> f.ufunc
<ufunc 'f'>
>>> f.ufunc.types
[]
```

The example above shows that *DUFunc* instances are not ufuncs. Rather than subclass ufunc's, *DUFunc* instances work by keeping a *ufunc* member, and then delegating ufunc property reads and method calls to this member (also known as type aggregation). When we look at the initial types supported by the ufunc, we can verify there are none.

Let's try to make a call to `f()`:

Listing 16: from `test_vectorize_dynamic` of `numba/tests/doc_examples/test_examples.py`

```
result = f(3,4)
# result == 12

print(f.types)
# ['ll->l']
```

If this was a normal NumPy ufunc, we would have seen an exception complaining that the ufunc couldn't handle the input types. When we call `f()` with integer arguments, not only do we receive an answer, but we can verify that Numba created a loop supporting C `long` integers.

We can add additional loops by calling `f()` with different inputs:

Listing 17: from `test_vectorize_dynamic` of `numba/tests/doc_examples/test_examples.py`

```
result = f(1.,2.)
# result == 2.0

print(f.types)
# ['ll->l', 'dd->d']
```

We can now verify that Numba added a second loop for dealing with floating-point inputs, `"dd->d"`.

If we mix input types to `f()`, we can verify that NumPy ufunc casting rules are still in effect:

Listing 18: from `test_vectorize_dynamic` of `numba/tests/doc_examples/test_examples.py`

```
result = f(1,2.)
# result == 2.0

print(f.types)
# ['ll->l', 'dd->d']
```

This example demonstrates that calling `f()` with mixed types caused NumPy to select the floating-point loop, and cast the integer argument to a floating-point value. Thus, Numba did not create a special `"dl->d"` kernel.

This *DUFunc* behavior leads us to a point similar to the warning given above in "*The @vectorize decorator*" subsec-

tion, but instead of signature declaration order in the decorator, call order matters. If we had passed in floating-point arguments first, any calls with integer arguments would be cast to double-precision floating-point values. For example:

Listing 19: from `test_vectorize_dynamic` of `numba/tests/doc_examples/test_examples.py`

```
@vectorize
def g(a, b):
    return a / b

print(g(2.,3.))
# 0.6666666666666663

print(g(2,3))
# 0.6666666666666663

print(g.types)
# ['dd->d']
```

If you require precise support for various type signatures, you should specify them in the *vectorize()* decorator, and not rely on dynamic compilation.

1.5.4 Dynamic generalized universal functions

Similar to a dynamic universal function, if you do not specify any types to the *guvectorize()* decorator, your Python function will be used to build a dynamic generalized universal function, or GUFunc. For example:

Listing 20: from `test_guvectorize_dynamic` of `numba/tests/doc_examples/test_examples.py`

```
from numba import guvectorize
import numpy as np

@guvectorize('(n),()->(n)')
def g(x, y, res):
    for i in range(x.shape[0]):
        res[i] = x[i] + y
```

We can verify the resulting function `g()` is a GUFunc instance that starts with no supported input types. For instance:

```
>>> g
<numba._GUFunc 'g'>
>>> g.ufunc
<ufunc 'g'>
>>> g.ufunc.types
[]
```

Similar to a *DUFunc*, as one make calls to `g()`, numba generates new kernels for previously unsupported input types. The following set of interpreter interactions will illustrate how dynamic compilation works for a GUFunc:

Listing 21: from test_guvectorize_dynamic of numba/tests/doc_examples/test_examples.py

```
x = np.arange(5, dtype=np.int64)
y = 10
res = np.zeros_like(x)
g(x, y, res)
# res == array([10, 11, 12, 13, 14])
print(g.types)
# ['ll->l']
```

If this was a normal `guvectorize()` function, we would have seen an exception complaining that the ufunc could not handle the given input types. When we call `g()` with the input arguments, numba creates a new loop for the input types.

We can add additional loops by calling `g()` with new arguments:

Listing 22: from test_guvectorize_dynamic of numba/tests/doc_examples/test_examples.py

```
x = np.arange(5, dtype=np.double)
y = 2.2
res = np.zeros_like(x)
g(x, y, res)
# res == array([2.2, 3.2, 4.2, 5.2, 6.2])
```

We can now verify that Numba added a second loop for dealing with floating-point inputs, `"dd->d"`.

Listing 23: from test_guvectorize_dynamic of numba/tests/doc_examples/test_examples.py

```
print(g.types) # shorthand for g.ufunc.types
# ['ll->l', 'dd->d']
```

One can also verify that NumPy ufunc casting rules are working as expected:

Listing 24: from test_guvectorize_dynamic of numba/tests/doc_examples/test_examples.py

```
x = np.arange(5, dtype=np.int64)
y = 2
res = np.zeros_like(x)
g(x, y, res)
print(res)
# res == array([2, 3, 4, 5, 6])
```

If you need precise support for various type signatures, you should not rely on dynamic compilation and instead, specify the types them as first argument in the *`guvectorize()`* decorator.

`@guvectorize` functions can also be called from jitted ones. For instance:

Listing 25: from test_guvectorize_jit of numba/tests/doc_examples/test_examples.py

```
import numpy as np

```

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```
from numba import jit, guvectorize

@guvectorize('(n)->(n)')
def copy(x, res):
    for i in range(x.shape[0]):
        res[i] = x[i]

@jit(nopython=True)
def jit_fn(x, res):
    copy(x, res)
```

Warning: Broadcasting is not supported yet. Calling a guvectorize function in a scenario where broadcasting is needed may result in incorrect behavior. Numba will attempt to detect those cases and raise an exception.

Listing 26: from `test_guvectorize_jit` of `numba/tests/doc_examples/test_examples.py`

```
import numpy as np
from numba import jit, guvectorize

@guvectorize('(n)->(n)')
def copy(x, res):
    for i in range(x.shape[0]):
        res[i] = x[i]

@jit(nopython=True)
def jit_fn(x, res):
    copy(x, res)

x = np.ones((1, 5))
res = np.empty((5,))
with self.assertRaises(ValueError) as raises:
    jit_fn(x, res)
```

1.6 Compiling Python classes with `@jitclass`

Note: This is a early version of jitclass support. Not all compiling features are exposed or implemented, yet.

Numba supports code generation for classes via the *numba.experimental.jitclass()* decorator. A class can be marked for optimization using this decorator along with a specification of the types of each field. We call the resulting class object a *jitclass*. All methods of a jitclass are compiled into nopython functions. The data of a jitclass instance is allocated on the heap as a C-compatible structure so that any compiled functions can have direct access to the underlying data, bypassing the interpreter.

1.6.1 Basic usage

Here's an example of a jitclass:

```
import numpy as np
from numba import int32, float32    # import the types
from numba.experimental import jitclass

spec = [
    ('value', int32),               # a simple scalar field
    ('array', float32[:]),          # an array field
]

@jitclass(spec)
class Bag(object):
    def __init__(self, value):
        self.value = value
        self.array = np.zeros(value, dtype=np.float32)

    @property
    def size(self):
        return self.array.size

    def increment(self, val):
        for i in range(self.size):
            self.array[i] += val
        return self.array

    @staticmethod
    def add(x, y):
        return x + y

n = 21
mybag = Bag(n)
```

In the above example, a `spec` is provided as a list of 2-tuples. The tuples contain the name of the field and the Numba type of the field. Alternatively, user can use a dictionary (an `OrderedDict` preferably for stable field ordering), which maps field names to types.

The definition of the class requires at least a `__init__` method for initializing each defined fields. Uninitialized fields contains garbage data. Methods and properties (getters and setters only) can be defined. They will be automatically compiled.

1.6.2 Inferred class member types from type annotations with `as_numba_type`

Fields of a `jitclass` can also be inferred from Python type annotations.

```
from typing import List
from numba.experimental import jitclass
from numba.typed import List as NumbaList

@jitclass
class Counter:
```

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```
    value: int

    def __init__(self):
        self.value = 0

    def get(self) -> int:
        ret = self.value
        self.value += 1
        return ret

@jitclass
class ListLoopIterator:
    counter: Counter
    items: List[float]

    def __init__(self, items: List[float]):
        self.items = items
        self.counter = Counter()

    def get(self) -> float:
        idx = self.counter.get() % len(self.items)
        return self.items[idx]

items = NumbaList([3.14, 2.718, 0.123, -4.])
loop_itr = ListLoopIterator(items)
```

Any type annotations on the class will be used to extend the spec if that field is not already present. The Numba type corresponding to the given Python type is inferred using `as_numba_type`. For example, if we have the class

```
@jitclass([("w", int32), ("y", float64[:])])
class Foo:
    w: int
    x: float
    y: np.ndarray
    z: SomeOtherType

    def __init__(self, w: int, x: float, y: np.ndarray, z: SomeOtherType):
        ...
```

then the full spec used for `Foo` will be:

- `"w"`: `int32` (specified in the `spec`)
- `"x"`: `float64` (added from type annotation)
- `"y"`: `array(float64, 1d, A)` (specified in the `spec`)
- `"z"`: `numba.as_numba_type(SomeOtherType)` (added from type annotation)

Here `SomeOtherType` could be any supported Python type (e.g. `bool`, `typing.Dict[int, typing.Tuple[float, float]]`, or another `jitclass`).

Note that only type annotations on the class will be used to infer spec elements. Method type annotations (e.g. those of `__init__` above) are ignored.

Numba requires knowing the dtype and rank of NumPy arrays, which cannot currently be expressed with type annota-

tions. Because of this, NumPy arrays need to be included in the `spec` explicitly.

1.6.3 Specifying `numba.typed` containers as class members explicitly

The following patterns demonstrate how to specify a `numba.typed.Dict` or `numba.typed.List` explicitly as part of the `spec` passed to `jitclass`.

First, using explicit Numba types and explicit construction.

```
from numba import types, typed
from numba.experimental import jitclass

# key and value types
kv_ty = (types.int64, types.unicode_type)

# A container class with:
# * member 'd' holding a typed dictionary of int64 -> unicode string (kv_ty)
# * member 'l' holding a typed list of float64
@jitclass([('d', types.DictType(*kv_ty)),
           ('l', types.ListType(types.float64))])
class ContainerHolder(object):
    def __init__(self):
        # initialize the containers
        self.d = typed.Dict.empty(*kv_ty)
        self.l = typed.List.empty_list(types.float64)

container = ContainerHolder()
container.d[1] = "apple"
container.d[2] = "orange"
container.l.append(123.)
container.l.append(456.)
print(container.d) # {1: apple, 2: orange}
print(container.l) # [123.0, 456.0]
```

Another useful pattern is to use the `numba.typed` container attribute `_numba_type_` to find the type of a container, this can be accessed directly from an instance of the container in the Python interpreter. The same information can be obtained by calling *`numba.typeof()`* on the instance. For example:

```
from numba import typed, typeof
from numba.experimental import jitclass

d = typed.Dict()
d[1] = "apple"
d[2] = "orange"
l = typed.List()
l.append(123.)
l.append(456.)


@jitclass([('d', typeof(d)), ('l', typeof(l))])
class ContainerInstHolder(object):
    def __init__(self, dict_inst, list_inst):
        self.d = dict_inst
```

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```
        self.l = list_inst

container = ContainerInstHolder(d, l)
print(container.d) # {1: apple, 2: orange}
print(container.l) # [123.0, 456.0]
```

It is worth noting that the instance of the container in a `jitclass` must be initialized before use, for example, this will cause an invalid memory access as `self.d` is written to without `d` being initialized as a `type.Dict` instance of the type specified.

```
from numba import types
from numba.experimental import jitclass

dict_ty = types.DictType(types.int64, types.unicode_type)

@jitclass([('d', dict_ty)])
class NotInitialisingContainer(object):
    def __init__(self):
        self.d[10] = "apple" # this is invalid, `d` is not initialized

NotInitialisingContainer() # segmentation fault/memory access violation
```

1.6.4 Support operations

The following operations of jitclasses work in both the interpreter and Numba compiled functions:

- calling the jitclass class object to construct a new instance (e.g. `mybag = Bag(123)`);
- read/write access to attributes and properties (e.g. `mybag.value`);
- calling methods (e.g. `mybag.increment(3)`);
- calling static methods as instance attributes (e.g. `mybag.add(1, 1)`);
- calling static methods as class attributes (e.g. `Bag.add(1, 2)`);
- using select dunder methods (e.g. `__add__` with `mybag + otherbag`);

Using jitclasses in Numba compiled function is more efficient. Short methods can be inlined (at the discretion of LLVM inliner). Attributes access are simply reading from a C structure. Using jitclasses from the interpreter has the same overhead of calling any Numba compiled function from the interpreter. Arguments and return values must be unboxed or boxed between Python objects and native representation. Values encapsulated by a jitclass does not get boxed into Python object when the jitclass instance is handed to the interpreter. It is during attribute access to the field values that they are boxed. Calling static methods as class attributes is only supported outside of the class definition (i.e. code cannot call `Bag.add()` from within another method of `Bag`).

Supported dunder methods

The following dunder methods may be defined for jitclasses:

- `__abs__`
- `__bool__`
- `__complex__`
- `__contains__`
- `__float__`
- `__getitem__`
- `__hash__`
- `__index__`
- `__int__`
- `__len__`
- `__setitem__`
- `__str__`
- `__eq__`
- `__ne__`
- `__ge__`
- `__gt__`
- `__le__`
- `__lt__`
- `__add__`
- `__floordiv__`
- `__lshift__`
- `__matmul__`
- `__mod__`
- `__mul__`
- `__neg__`
- `__pos__`
- `__pow__`
- `__rshift__`
- `__sub__`
- `__truediv__`
- `__and__`
- `__or__`
- `__xor__`
- `__iadd__`

- `__ifloordiv__`
- `__ilshift__`
- `__imatmul__`
- `__imod__`
- `__imul__`
- `__ipow__`
- `__irshift__`
- `__isub__`
- `__itruediv__`
- `__iand__`
- `__ior__`
- `__ixor__`
- `__radd__`
- `__rfloordiv__`
- `__rlshift__`
- `__rmatmul__`
- `__rmod__`
- `__rmul__`
- `__rpow__`
- `__rrshift__`
- `__rsub__`
- `__rtruediv__`
- `__rand__`
- `__ror__`
- `__rxor__`

Refer to the Python Data Model documentation for descriptions of these methods.

1.6.5 Limitations

- A jitclass class object is treated as a function (the constructor) inside a Numba compiled function.
- `isinstance()` only works in the interpreter.
- Manipulating jitclass instances in the interpreter is not optimized, yet.
- Support for jitclasses are available on CPU only. (Note: Support for GPU devices is planned for a future release.)

1.6.6 The decorator: `@jitclass`

numba.experimental.**jitclass**(*cls_or_spec=None*, *spec=None*)

A function for creating a jitclass. Can be used as a decorator or function.

Different use cases will cause different arguments to be set.

If specified, `spec` gives the types of class fields. It must be a dictionary or sequence. With a dictionary, use collections.OrderedDict for stable ordering. With a sequence, it must contain 2-tuples of (fieldname, fieldtype).

Any class annotations for field names not listed in spec will be added. For class annotation *x: T* we will append `("x", as_numba_type(T))` to the spec if `x` is not already a key in spec.

Returns

If used as a decorator, returns a callable that takes a class object and returns a compiled version.
If used as a function, returns the compiled class (an instance of `JitClassType`).

Examples

1) `cls_or_spec = None`, `spec = None`

```
>>> @jitclass()
... class Foo:
...     ...
```

2) `cls_or_spec = None`, `spec = spec`

```
>>> @jitclass(spec=spec)
... class Foo:
...     ...
```

3) `cls_or_spec = Foo`, `spec = None`

```
>>> @jitclass
... class Foo:
...     ...
```

4) `cls_or_spec = spec`, `spec = None` In this case we update `cls_or_spec, spec = None, cls_or_spec`.

```
>>> @jitclass(spec)
... class Foo:
...     ...
```

5) `cls_or_spec = Foo`, `spec = spec`

```
>>> JitFoo = jitclass(Foo, spec)
```

1.7 Creating C callbacks with @cfunc

Interfacing with some native libraries (for example written in C or C++) can necessitate writing native callbacks to provide business logic to the library. The *numba.cfunc()* decorator creates a compiled function callable from foreign C code, using the signature of your choice.

1.7.1 Basic usage

The @cfunc decorator has a similar usage to @jit, but with an important difference: passing a single signature is mandatory. It determines the visible signature of the C callback:

```
from numba import cfunc

@cfunc("float64(float64, float64)")
def add(x, y):
    return x + y
```

The C function object exposes the address of the compiled C callback as the *address* attribute, so that you can pass it to any foreign C or C++ library. It also exposes a ctypes callback object pointing to that callback; that object is also callable from Python, making it easy to check the compiled code:

```
@cfunc("float64(float64, float64)")
def add(x, y):
    return x + y

print(add.ctypes(4.0, 5.0))  # prints "9.0"
```

1.7.2 Example

In this example, we are going to be using the scipy.integrate.quad function. That function accepts either a regular Python callback or a C callback wrapped in a ctypes callback object.

Let's define a pure Python integrand and compile it as a C callback:

```
>>> import numpy as np
>>> from numba import cfunc
>>> def integrand(t):
        return np.exp(-t) / t**2
   ...:
>>> nb_integrand = cfunc("float64(float64)")(integrand)
```

We can pass the nb_integrand object's ctypes callback to scipy.integrate.quad and check that the results are the same as with the pure Python function:

```
>>> import scipy.integrate as si
>>> def do_integrate(func):
        """
        Integrate the given function from 1.0 to +inf.
        """
        return si.quad(func, 1, np.inf)
   ...:
>>> do_integrate(integrand)
```

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```
(0.14849550677592208, 3.8736750296130505e-10)
>>> do_integrate(nb_integrand.ctypes)
(0.14849550677592208, 3.8736750296130505e-10)
```

Using the compiled callback, the integration function does not invoke the Python interpreter each time it evaluates the integrand. In our case, the integration is made 18 times faster:

```
>>> %timeit do_integrate(integrand)
1000 loops, best of 3: 242 µs per loop
>>> %timeit do_integrate(nb_integrand.ctypes)
100000 loops, best of 3: 13.5 µs per loop
```

1.7.3 Dealing with pointers and array memory

A less trivial use case of C callbacks involves doing operation on some array of data passed by the caller. As C doesn't have a high-level abstraction similar to Numpy arrays, the C callback's signature will pass low-level pointer and size arguments. Nevertheless, the Python code for the callback will expect to exploit the power and expressiveness of Numpy arrays.

In the following example, the C callback is expected to operate on 2-d arrays, with the signature `void(double *input, double *output, int m, int n)`. You can implement such a callback thusly:

```
from numba import cfunc, types, carray

c_sig = types.void(types.CPointer(types.double),
                   types.CPointer(types.double),
                   types.intc, types.intc)

@cfunc(c_sig)
def my_callback(in_, out, m, n):
    in_array = carray(in_, (m, n))
    out_array = carray(out, (m, n))
    for i in range(m):
        for j in range(n):
            out_array[i, j] = 2 * in_array[i, j]
```

The *numba.carray()* function takes as input a data pointer and a shape and returns an array view of the given shape over that data. The data is assumed to be laid out in C order. If the data is laid out in Fortran order, *numba.farray()* should be used instead.

1.7.4 Handling C structures

With CFFI

For applications that have a lot of state, it is useful to pass data in C structures. To simplify the interoperability with C code, numba can convert a `cffi` type into a numba `Record` type using `numba.core.typing.cffi_utils.map_type`:

```
from numba.core.typing import cffi_utils

nbtype = cffi_utils.map_type(cffi_type, use_record_dtype=True)
```

Note: **use_record_dtype=True** is needed otherwise pointers to C structures are returned as void pointers.

Note: From v0.49 the `numba.cffi_support` module has been phased out in favour of `numba.core.typing.cffi_utils`

For example:

```
from cffi import FFI

src = """

/* Define the C struct */
typedef struct my_struct {
   int    i1;
   float  f2;
   double d3;
   float  af4[7]; // arrays are supported
} my_struct;

/* Define a callback function */
typedef double (*my_func)(my_struct*, size_t);
"""

ffi = FFI()
ffi.cdef(src)

# Get the function signature from *my_func*
sig = cffi_utils.map_type(ffi.typeof('my_func'), use_record_dtype=True)

# Make the cfunc
from numba import cfunc, carray

@cfunc(sig)
def foo(ptr, n):
   base = carray(ptr, n)  # view pointer as an array of my_struct
   tmp = 0
   for i in range(n):
      tmp += base[i].i1 * base[i].f2 / base[i].d3
      tmp += base[i].af4.sum()  # nested arrays are like normal NumPy arrays
   return tmp
```

With `numba.types.Record.make_c_struct`

The `numba.types.Record` type can be created manually to follow a C-structure's layout. To do that, use `Record.make_c_struct`, for example:

```
my_struct = types.Record.make_c_struct([
   # Provides a sequence of 2-tuples i.e. (name:str, type:Type)
   ('i1', types.int32),
   ('f2', types.float32),
   ('d3', types.float64),
   ('af4', types.NestedArray(dtype=types.float32, shape=(7,))),
])
```

Due to ABI limitations, structures should be passed as pointers using `types.CPointer(my_struct)` as the argument type. Inside the `cfunc` body, the `my_struct*` can be accessed with `carray`.

Full example

See full example in `examples/notebooks/Accessing C Struct Data.ipynb`.

1.7.5 Signature specification

The explicit `@cfunc` signature can use any *Numba types*, but only a subset of them make sense for a C callback. You should generally limit yourself to scalar types (such as `int8` or `float64`) ,pointers to them (for example `types.CPointer(types.int8)`), or pointers to `Record` type.

1.7.6 Compilation options

A number of keyword-only arguments can be passed to the `@cfunc` decorator: `nopython` and `cache`. Their meaning is similar to those in the `@jit` decorator.

1.7.7 Calling C code from Numba

It is also possible to call C code from Numba `@jit` functions. In this example, we are going to be compiling a simple function `sum` that adds two integers and calling it within Numba `@jit` code.

Note: The example below was tested on Linux and will likely work on Unix-like operating systems.

```
#include <stdint.h>

int64_t sum(int64_t a, int64_t b){
   return a + b;
}
```

Compile the code with `gcc lib.c -fPIC -shared -o shared_library.so` to generate a shared library.

```
from numba import njit
from numba.core import types, typing
from llvmlite import binding
```

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```
import os

# load the library into LLVM
path = os.path.abspath('./shared_library.so')
binding.load_library_permanently(path)

# Adds typing information
c_func_name = 'sum'
return_type = types.int64
argty = types.int64
c_sig = typing.signature(return_type, argty, argty)
c_func = types.ExternalFunction(c_func_name, c_sig)

@njit
def example(x, y):
   return c_func(x, y)

print(example(3, 4)) # 7
```

It is also possible to use `ctypes` as well to call C functions. The advantage of using `ctypes` is that it is invariant to the usage of JIT decorators.

```
from numba import njit
import ctypes
DSO = ctypes.CDLL('./shared_library.so')

# Add typing information
c_func = DSO.sum
c_func.restype = ctypes.c_int
c_func.argtypes = [ctypes.c_int, ctypes.c_int]

@njit
def example(x, y):
   return c_func(x, y)

print(example(3, 4)) # 7
print(example.py_func(3, 4)) # 7
```

1.8 Compiling code ahead of time

While Numba's main use case is *Just-in-Time compilation*, it also provides a facility for *Ahead-of-Time compilation* (AOT).

Note: To use this feature the `setuptools` package is required at compilation time, but it is not a runtime dependency of the extension module produced.

Note: This module is pending deprecation. Please see *Deprecation of the numba.pycc module* for more information.

1.8.1 Overview

Benefits

1. AOT compilation produces a compiled extension module which does not depend on Numba: you can distribute the module on machines which do not have Numba installed (but NumPy is required).
2. There is no compilation overhead at runtime (but see the `@jit` *cache* option), nor any overhead of importing Numba.

See also:

Compiled extension modules are discussed in the Python packaging user guide.

Limitations

1. AOT compilation only allows for regular functions, not *ufuncs*.
2. You have to specify function signatures explicitly.
3. Each exported function can have only one signature (but you can export several different signatures under different names).
4. Exported functions do not check the types of the arguments that are passed to them; the caller is expected to provide arguments of the correct type.
5. AOT compilation produces generic code for your CPU's architectural family (for example "x86-64"), while JIT compilation produces code optimized for your particular CPU model.

1.8.2 Usage

Standalone example

```
from numba.pycc import CC

cc = CC('my_module')
# Uncomment the following line to print out the compilation steps
#cc.verbose = True

@cc.export('multf', 'f8(f8, f8)')
@cc.export('multi', 'i4(i4, i4)')
def mult(a, b):
    return a * b

@cc.export('square', 'f8(f8)')
def square(a):
    return a ** 2

if __name__ == "__main__":
    cc.compile()
```

If you run this Python script, it will generate an extension module named `my_module`. Depending on your platform, the actual filename may be `my_module.so`, `my_module.pyd`, `my_module.cpython-34m.so`, etc.

The generated module has three functions: `multf`, `multi` and `square`. `multi` operates on 32-bit integers (`i4`), while `multf` and `square` operate on double-precision floats (`f8`):

```
>>> import my_module
>>> my_module.multi(3, 4)
12
>>> my_module.square(1.414)
1.9993959999999997
```

Distutils integration

You can also integrate the compilation step for your extension modules in your `setup.py` script, using distutils or setuptools:

```
from distutils.core import setup

from source_module import cc

setup(...,
      ext_modules=[cc.distutils_extension()])
```

The `source_module` above is the module defining the `cc` object. Extensions compiled like this will be automatically included in the build files for your Python project, so you can distribute them inside binary packages such as wheels or Conda packages. Note that in the case of using conda, the compilers used for AOT need to be those that are available in the Anaconda distribution.

Signature syntax

The syntax for exported signatures is the same as in the `@jit` decorator. You can read more about it in the *types* reference.

Here is an example of exporting an implementation of the second-order centered difference on a 1d array:

```
@cc.export('centdiff_1d', 'f8[:](f8[:], f8)')
def centdiff_1d(u, dx):
    D = np.empty_like(u)
    D[0] = 0
    D[-1] = 0
    for i in range(1, len(D) - 1):
        D[i] = (u[i+1] - 2 * u[i] + u[i-1]) / dx**2
    return D
```

You can also omit the return type, which will then be inferred by Numba:

```
@cc.export('centdiff_1d', '(f8[:], f8)')
def centdiff_1d(u, dx):
    # Same code as above
    ...
```

1.9 Automatic parallelization with `@jit`

Setting the *parallel* option for `jit()` enables a Numba transformation pass that attempts to automatically parallelize and perform other optimizations on (part of) a function. At the moment, this feature only works on CPUs.

Some operations inside a user defined function, e.g. adding a scalar value to an array, are known to have parallel semantics. A user program may contain many such operations and while each operation could be parallelized individually, such an approach often has lackluster performance due to poor cache behavior. Instead, with auto-parallelization, Numba attempts to identify such operations in a user program, and fuse adjacent ones together, to form one or more kernels that are automatically run in parallel. The process is fully automated without modifications to the user program, which is in contrast to Numba's `vectorize()` or `guvectorize()` mechanism, where manual effort is required to create parallel kernels.

1.9.1 Supported Operations

In this section, we give a list of all the array operations that have parallel semantics and for which we attempt to parallelize.

1. All numba array operations that are supported by *Case study: Array Expressions*, which include common arithmetic functions between Numpy arrays, and between arrays and scalars, as well as Numpy ufuncs. They are often called *element-wise* or *point-wise* array operations:
   - unary operators: `+ - ~`
   - binary operators: `+ - * / /? % | >> ^ << & ** //`
   - comparison operators: `== != < <= > >=`
   - *Numpy ufuncs* that are supported in *nopython mode*.
   - User defined `DUFunc` through `vectorize()`.
2. Numpy reduction functions `sum`, `prod`, `min`, `max`, `argmin`, and `argmax`. Also, array math functions `mean`, `var`, and `std`.
3. Numpy array creation functions `zeros`, `ones`, `arange`, `linspace`, and several random functions (rand, randn, ranf, random_sample, sample, random, standard_normal, chisquare, weibull, power, geometric, exponential, poisson, rayleigh, normal, uniform, beta, binomial, f, gamma, lognormal, laplace, randint, triangular).
4. Numpy `dot` function between a matrix and a vector, or two vectors. In all other cases, Numba's default implementation is used.
5. Multi-dimensional arrays are also supported for the above operations when operands have matching dimension and size. The full semantics of Numpy broadcast between arrays with mixed dimensionality or size is not supported, nor is the reduction across a selected dimension.
6. Array assignment in which the target is an array selection using a slice or a boolean array, and the value being assigned is either a scalar or another selection where the slice range or bitarray are inferred to be compatible.
7. The `reduce` operator of `functools` is supported for specifying parallel reductions on 1D Numpy arrays but the initial value argument is mandatory.

1.9.2 Explicit Parallel Loops

Another feature of the code transformation pass (when `parallel=True`) is support for explicit parallel loops. One can use Numba's `prange` instead of `range` to specify that a loop can be parallelized. The user is required to make sure that the loop does not have cross iteration dependencies except for supported reductions.

A reduction is inferred automatically if a variable is updated by a supported binary function/operator using its previous value in the loop body. The following functions/operators are supported: +=, +, -=, -, *=, *, /=, /, `max()`, `min()`. The initial value of the reduction is inferred automatically for the supported operators (i.e., not the `max` and `min` functions). Note that the //= operator is not supported because in the general case the result depends on the order in which the divisors are applied. However, if all divisors are integers then the programmer may be able to rewrite the //= reduction as a *= reduction followed by a single floor division after the parallel region where the divisor is the accumulated product. For the `max` and `min` functions, the reduction variable should hold the identity value right before entering the `prange` loop. Reductions in this manner are supported for scalars and for arrays of arbitrary dimensions.

The example below demonstrates a parallel loop with a reduction (`A` is a one-dimensional Numpy array):

```
from numba import njit, prange

@njit(parallel=True)
def prange_test(A):
    s = 0
    # Without "parallel=True" in the jit-decorator
    # the prange statement is equivalent to range
    for i in prange(A.shape[0]):
        s += A[i]
    return s
```

The following example demonstrates a product reduction on a two-dimensional array:

```
from numba import njit, prange
import numpy as np

@njit(parallel=True)
def two_d_array_reduction_prod(n):
    shp = (13, 17)
    result1 = 2 * np.ones(shp, np.int_)
    tmp = 2 * np.ones_like(result1)

    for i in prange(n):
        result1 *= tmp

    return result1
```

Note: When using Python's `range` to induce a loop, Numba types the induction variable as a signed integer. This is also the case for Numba's `prange` when `parallel=False`. However, for `parallel=True`, if the range is identifiable as strictly positive, the type of the induction variable will be `uint64`. The impact of a `uint64` induction variable is often most noticeable when undertaking operations involving it and a signed integer. Under Numba's type coercion rules, such a case will commonly result in the operation producing a floating point result type.

Note: Only prange loops with a single entry block and single exit block can be converted such that they will be run in parallel. Exceptional control flow, such as an assertion, in the loop can generate multiple exit blocks and cause the loop

not to be run in parallel. If this is the case, Numba will issue a warning indicating which loop could not be parallelized.

Care should be taken, however, when reducing into slices or elements of an array if the elements specified by the slice or index are written to simultaneously by multiple parallel threads. The compiler may not detect such cases and then a race condition would occur.

The following example demonstrates such a case where a race condition in the execution of the parallel for-loop results in an incorrect return value:

```
from numba import njit, prange
import numpy as np

@njit(parallel=True)
def prange_wrong_result(x):
    n = x.shape[0]
    y = np.zeros(4)
    for i in prange(n):
        # accumulating into the same element of `y` from different
        # parallel iterations of the loop results in a race condition
        y[:] += x[i]

    return y
```

as does the following example where the accumulating element is explicitly specified:

```
from numba import njit, prange
import numpy as np

@njit(parallel=True)
def prange_wrong_result(x):
    n = x.shape[0]
    y = np.zeros(4)
    for i in prange(n):
        # accumulating into the same element of `y` from different
        # parallel iterations of the loop results in a race condition
        y[i % 4] += x[i]

    return y
```

whereas performing a whole array reduction is fine:

```
from numba import njit, prange
import numpy as np

@njit(parallel=True)
def prange_ok_result_whole_arr(x):
    n = x.shape[0]
    y = np.zeros(4)
    for i in prange(n):
        y += x[i]
    return y
```

as is creating a slice reference outside of the parallel reduction loop:

```
from numba import njit, prange
import numpy as np

@njit(parallel=True)
def prange_ok_result_outer_slice(x):
    n = x.shape[0]
    y = np.zeros(4)
    z = y[:]
    for i in prange(n):
        z += x[i]
    return y
```

1.9.3 Examples

In this section, we give an example of how this feature helps parallelize Logistic Regression:

```
@numba.jit(nopython=True, parallel=True)
def logistic_regression(Y, X, w, iterations):
    for i in range(iterations):
        w -= np.dot(((1.0 / (1.0 + np.exp(-Y * np.dot(X, w))) - 1.0) * Y), X)
    return w
```

We will not discuss details of the algorithm, but instead focus on how this program behaves with auto-parallelization:

1. Input `Y` is a vector of size `N`, `X` is an `N x D` matrix, and `w` is a vector of size `D`.
2. The function body is an iterative loop that updates variable `w`. The loop body consists of a sequence of vector and matrix operations.
3. The inner `dot` operation produces a vector of size `N`, followed by a sequence of arithmetic operations either between a scalar and vector of size `N`, or two vectors both of size `N`.
4. The outer `dot` produces a vector of size `D`, followed by an inplace array subtraction on variable `w`.
5. With auto-parallelization, all operations that produce array of size `N` are fused together to become a single parallel kernel. This includes the inner `dot` operation and all point-wise array operations following it.
6. The outer `dot` operation produces a result array of different dimension, and is not fused with the above kernel.

Here, the only thing required to take advantage of parallel hardware is to set the *parallel* option for *jit()*, with no modifications to the `logistic_regression` function itself. If we were to give an equivalence parallel implementation using *guvectorize()*, it would require a pervasive change that rewrites the code to extract kernel computation that can be parallelized, which was both tedious and challenging.

1.9.4 Unsupported Operations

This section contains a non-exhaustive list of commonly encountered but currently unsupported features:

1. **Mutating a list is not threadsafe**

   Concurrent write operations on container types (i.e. lists, sets and dictionaries) in a `prange` parallel region are not threadsafe e.g.:

   ```
   @njit(parallel=True)
   def invalid():
   ```

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```
    z = []
    for i in prange(10000):
        z.append(i)
    return z
```

It is highly likely that the above will result in corruption or an access violation as containers require thread-safety under mutation but this feature is not implemented.

2. **Induction variables are not associated with thread ID**

   The use of the induction variable induced by a `prange` based loop in conjunction with `get_num_threads` as a method of ensuring safe writes into a pre-sized container is not valid e.g.:

```
@njit(parallel=True)
def invalid():
    n = get_num_threads()
    z = [0 for _ in range(n)]
    for i in prange(100):
        z[i % n] += i
    return z
```

   The above can on occasion appear to work, but it does so by luck. There's no guarantee about which indexes are assigned to which executing threads or the order in which the loop iterations execute.

1.9.5 Diagnostics

Note: At present not all parallel transforms and functions can be tracked through the code generation process. Occasionally diagnostics about some loops or transforms may be missing.

The *parallel* option for *jit()* can produce diagnostic information about the transforms undertaken in automatically parallelizing the decorated code. This information can be accessed in two ways, the first is by setting the environment variable *NUMBA_PARALLEL_DIAGNOSTICS*, the second is by calling *parallel_diagnostics()*, both methods give the same information and print to STDOUT. The level of verbosity in the diagnostic information is controlled by an integer argument of value between 1 and 4 inclusive, 1 being the least verbose and 4 the most. For example:

```
@njit(parallel=True)
def test(x):
    n = x.shape[0]
    a = np.sin(x)
    b = np.cos(a * a)
    acc = 0
    for i in prange(n - 2):
        for j in prange(n - 1):
            acc += b[i] + b[j + 1]
    return acc

test(np.arange(10))

test.parallel_diagnostics(level=4)
```

produces:

```
================================================================================
======= Parallel Accelerator Optimizing:  Function test, example.py (4)  =======
================================================================================


Parallel loop listing for  Function test, example.py (4)
-------------------------------------|loop #ID
@njit(parallel=True)                 |
def test(x):                         |
    n = x.shape[0]                   |
    a = np.sin(x)--------------------| #0
    b = np.cos(a * a)----------------| #1
    acc = 0                          |
    for i in prange(n - 2):----------| #3
        for j in prange(n - 1):------| #2
            acc += b[i] + b[j + 1]   |
    return acc                       |
--------------------------------- Fusing loops ---------------------------------
Attempting fusion of parallel loops (combines loops with similar properties)...
Trying to fuse loops #0 and #1:
    - fusion succeeded: parallel for-loop #1 is fused into for-loop #0.
Trying to fuse loops #0 and #3:
    - fusion failed: loop dimension mismatched in axis 0. slice(0, x_size0.1, 1)
!= slice(0, $40.4, 1)
------------------------------ Before Optimization ------------------------------
Parallel region 0:
+--0 (parallel)
+--1 (parallel)


Parallel region 1:
+--3 (parallel)
+--2 (parallel)


--------------------------------------------------------------------------------
------------------------------- After Optimization -------------------------------
Parallel region 0:
+--0 (parallel, fused with loop(s): 1)


Parallel region 1:
+--3 (parallel)
+--2 (serial)



Parallel region 0 (loop #0) had 1 loop(s) fused.

Parallel region 1 (loop #3) had 0 loop(s) fused and 1 loop(s) serialized as part
of the larger parallel loop (#3).
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
```

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```
--------------------------Loop invariant code motion--------------------------

Instruction hoisting:
loop #0:
Failed to hoist the following:
    dependency: $arg_out_var.10 = getitem(value=x, index=$parfor__index_5.99)
    dependency: $0.6.11 = getattr(value=$0.5, attr=sin)
    dependency: $expr_out_var.9 = call $0.6.11($arg_out_var.10, func=$0.6.11, args=[Var(
↪$arg_out_var.10, example.py (7))], kws=(), vararg=None)
    dependency: $arg_out_var.17 = $expr_out_var.9 * $expr_out_var.9
    dependency: $0.10.20 = getattr(value=$0.9, attr=cos)
    dependency: $expr_out_var.16 = call $0.10.20($arg_out_var.17, func=$0.10.20,␣
↪args=[Var($arg_out_var.17, example.py (8))], kws=(), vararg=None)
loop #3:
Has the following hoisted:
    $const58.3 = const(int, 1)
    $58.4 = _n_23 - $const58.3
--------------------------------------------------------------------------------
```

To aid users unfamiliar with the transforms undertaken when the *parallel* option is used, and to assist in the understanding of the subsequent sections, the following definitions are provided:

- **Loop fusion**
  Loop fusion is a technique whereby loops with equivalent bounds may be combined under certain conditions to produce a loop with a larger body (aiming to improve data locality).
- **Loop serialization**
  Loop serialization occurs when any number of `prange` driven loops are present inside another `prange` driven loop. In this case the outermost of all the `prange` loops executes in parallel and any inner `prange` loops (nested or otherwise) are treated as standard `range` based loops. Essentially, nested parallelism does not occur.
- **Loop invariant code motion**
  Loop invariant code motion is an optimization technique that analyses a loop to look for statements that can be moved outside the loop body without changing the result of executing the loop, these statements are then "hoisted" out of the loop to save repeated computation.
- **Allocation hoisting**
  Allocation hoisting is a specialized case of loop invariant code motion that is possible due to the design of some common NumPy allocation methods. Explanation of this technique is best driven by an example:

```
@njit(parallel=True)
def test(n):
    for i in prange(n):
        temp = np.zeros((50, 50)) # <--- Allocate a temporary array with np.
↪zeros()
        for j in range(50):
            temp[j, j] = i

    # ...do something with temp
```

  internally, this is transformed to approximately the following:

```
@njit(parallel=True)
def test(n):
    for i in prange(n):
        temp = np.empty((50, 50)) # <--- np.zeros() is rewritten as np.empty()
        temp[:] = 0               # <--- and then a zero initialisation
        for j in range(50):
            temp[j, j] = i

    # ...do something with temp
```

then after hoisting:

```
@njit(parallel=True)
def test(n):
    temp = np.empty((50, 50)) # <--- allocation is hoisted as a loop invariant␣
↪as `np.empty` is considered pure
    for i in prange(n):
        temp[:] = 0           # <--- this remains as assignment is a side effect
        for j in range(50):
            temp[j, j] = i

    # ...do something with temp
```

it can be seen that the `np.zeros` allocation is split into an allocation and an assignment, and then the allocation is hoisted out of the loop in `i`, this producing more efficient code as the allocation only occurs once.

The parallel diagnostics report sections

The report is split into the following sections:

1. **Code annotation**

   This is the first section and contains the source code of the decorated function with loops that have parallel semantics identified and enumerated. The `loop #ID` column on the right of the source code lines up with identified parallel loops. From the example, `#0` is `np.sin`, `#1` is `np.cos` and `#2` and `#3` are `prange()`:

```
Parallel loop listing for  Function test, example.py (4)
-------------------------------------|loop #ID
@njit(parallel=True)                 |
def test(x):                         |
    n = x.shape[0]                   |
    a = np.sin(x)--------------------| #0
    b = np.cos(a * a)----------------| #1
    acc = 0                          |
    for i in prange(n - 2):----------| #3
        for j in prange(n - 1):------| #2
            acc += b[i] + b[j + 1]   |
    return acc                       |
```

   It is worth noting that the loop IDs are enumerated in the order they are discovered which is not necessarily the same order as present in the source. Further, it should also be noted that the parallel transforms use a static counter for loop ID indexing. As a consequence it is possible for the loop ID index to not start at 0 due to use of the same counter for internal optimizations/transforms taking place that are invisible to the user.

2. **Fusing loops**
   This section describes the attempts made at fusing discovered loops noting which succeeded and which failed. In the case of failure to fuse a reason is given (e.g. dependency on other data). From the example:

```
--------------------------------- Fusing loops ---------------------------------
Attempting fusion of parallel loops (combines loops with similar properties)...
Trying to fuse loops #0 and #1:
    - fusion succeeded: parallel for-loop #1 is fused into for-loop #0.
Trying to fuse loops #0 and #3:
    - fusion failed: loop dimension mismatched in axis 0. slice(0, x_size0.1, 1)
!= slice(0, $40.4, 1)
```

   It can be seen that fusion of loops `#0` and `#1` was attempted and this succeeded (both are based on the same dimensions of `x`). Following the successful fusion of `#0` and `#1`, fusion was attempted between `#0` (now including the fused `#1` loop) and `#3`. This fusion failed because there is a loop dimension mismatch, `#0` is size `x.shape` whereas `#3` is size `x.shape[0] - 2`.

3. **Before Optimization**
   This section shows the structure of the parallel regions in the code before any optimization has taken place, but with loops associated with their final parallel region (this is to make before/after optimization output directly comparable). Multiple parallel regions may exist if there are loops which cannot be fused, in this case code within each region will execute in parallel, but each parallel region will run sequentially. From the example:

```
Parallel region 0:
+--0 (parallel)
+--1 (parallel)


Parallel region 1:
+--3 (parallel)
+--2 (parallel)
```

   As alluded to by the *Fusing loops* section, there are necessarily two parallel regions in the code. The first contains loops `#0` and `#1`, the second contains `#3` and `#2`, all loops are marked `parallel` as no optimization has taken place yet.

4. **After Optimization**
   This section shows the structure of the parallel regions in the code after optimization has taken place. Again, parallel regions are enumerated with their corresponding loops but this time loops which are fused or serialized are noted and a summary is presented. From the example:

```
Parallel region 0:
+--0 (parallel, fused with loop(s): 1)


Parallel region 1:
+--3 (parallel)
   +--2 (serial)

Parallel region 0 (loop #0) had 1 loop(s) fused.

Parallel region 1 (loop #3) had 0 loop(s) fused and 1 loop(s) serialized as part
of the larger parallel loop (#3).
```

   It can be noted that parallel region 0 contains loop `#0` and, as seen in the *fusing loops* section, loop `#1` is

fused into loop #0. It can also be noted that parallel region 1 contains loop #3 and that loop #2 (the inner prange()) has been serialized for execution in the body of loop #3.

5. **Loop invariant code motion**
   This section shows for each loop, after optimization has occurred:

   - the instructions that failed to be hoisted and the reason for failure (dependency/impure).
   - the instructions that were hoisted.
   - any allocation hoisting that may have occurred.

   From the example:

```
Instruction hoisting:
loop #0:
Failed to hoist the following:
    dependency: $arg_out_var.10 = getitem(value=x, index=$parfor__index_5.99)
    dependency: $0.6.11 = getattr(value=$0.5, attr=sin)
    dependency: $expr_out_var.9 = call $0.6.11($arg_out_var.10, func=$0.6.11,␣
↪args=[Var($arg_out_var.10, example.py (7))], kws=(), vararg=None)
    dependency: $arg_out_var.17 = $expr_out_var.9 * $expr_out_var.9
    dependency: $0.10.20 = getattr(value=$0.9, attr=cos)
    dependency: $expr_out_var.16 = call $0.10.20($arg_out_var.17, func=$0.10.20,
↪ args=[Var($arg_out_var.17, example.py (8))], kws=(), vararg=None)
loop #3:
Has the following hoisted:
    $const58.3 = const(int, 1)
    $58.4 = _n_23 - $const58.3
```

   The first thing to note is that this information is for advanced users as it refers to the *Numba IR* of the function being transformed. As an example, the expression `a * a` in the example source partly translates to the expression `$arg_out_var.17 = $expr_out_var.9 * $expr_out_var.9` in the IR, this clearly cannot be hoisted out of `loop #0` because it is not loop invariant! Whereas in `loop #3`, the expression `$const58.3 = const(int, 1)` comes from the source `b[j + 1]`, the number 1 is clearly a constant and so can be hoisted out of the loop.

1.9.6 Scheduling

By default, Numba divides the iterations of a parallel region into approximately equal sized chunks and gives one such chunk to each configured thread. (See *Setting the Number of Threads*). This scheduling approach is equivalent to OpenMP's static schedule with no specified chunk size and is appropriate when the work required for each iteration is nearly constant. Conversely, if the work required per iteration, as shown in the `prange` loop below, varies significantly then this static scheduling approach can lead to load imbalances and longer execution times.

Listing 27: from `test_unbalanced_example` of `numba/tests/doc_examples/test_parallel_chunksize.py`

```
1 from numba import (njit,
2                    prange,
3                    )
4 import numpy as np
5
6 @njit(parallel=True)
7 def func1():
```

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```
    n = 100
    vals = np.empty(n)
    # The work in each iteration of the following prange
    # loop is proportional to its index.
    for i in prange(n):
        cur = i + 1
        for j in range(i):
            if cur % 2 == 0:
                cur //= 2
            else:
                cur = cur * 3 + 1
        vals[i] = cur
    return vals

result = func1()
```

In such cases, Numba provides a mechanism to control how many iterations of a parallel region (i.e., the chunk size) go into each chunk. Numba then computes the number of required chunks which is equal to the number of iterations divided by the chunk size, truncated to the nearest integer. All of these chunks are then approximately, equally sized. Numba then gives one such chunk to each configured thread as above and when a thread finishes a chunk, Numba gives that thread the next available chunk. This scheduling approach is similar to OpenMP's dynamic scheduling option with the specified chunk size. (Note that Numba is only capable of supporting this dynamic scheduling of parallel regions if the underlying Numba threading backend, *The Threading Layers*, is also capable of dynamic scheduling. At the moment, only the `tbb` backend is capable of dynamic scheduling and so is required if any performance benefit is to be achieved from this chunk size selection mechanism.) To minimize execution time, the programmer must pick a chunk size that strikes a balance between greater load balancing with smaller chunk sizes and less scheduling overhead with larger chunk sizes. See *Parallel Chunksize Details* for additional details on the internal implementation of chunk sizes.

The number of iterations of a parallel region in a chunk is stored as a thread-local variable and can be set using `numba.set_parallel_chunksize()`. This function takes one integer parameter whose value must be greater than or equal to 0. A value of 0 is the default value and instructs Numba to use the static scheduling approach above. Values greater than 0 instruct Numba to use that value as the chunk size in the dynamic scheduling approach described above. `numba.set_parallel_chunksize()` returns the previous value of the chunk size. The current value of this thread local variable is used as the chunk size for all subsequent parallel regions invoked by this thread. However, upon entering a parallel region, Numba sets the chunk size thread local variable for each of the threads executing that parallel region back to the default of 0, since it is unlikely that any nested parallel regions would require the same chunk size. If the same thread is used to execute a sequential and parallel region then that thread's chunk size variable is set to 0 at the beginning of the parallel region and restored to its original value upon exiting the parallel region. This behavior is demonstrated in `func1` in the example below in that the reported chunk size inside the `prange` parallel region is 0 but is 4 outside the parallel region. Note that if the `prange` is not executed in parallel for any reason (e.g., setting `parallel=False`) then the chunk size reported inside the non-parallel prange would be reported as 4. This behavior may initially be counterintuitive to programmers as it differs from how thread local variables typically behave in other languages. A programmer may use the chunk size API described in this section within the threads executing a parallel region if the programmer wishes to specify a chunk size for any nested parallel regions that may be launched. The current value of the parallel chunk size can be obtained by calling `numba.get_parallel_chunksize()`. Both of these functions can be used from standard Python and from within Numba JIT compiled functions as shown below. Both invocations of `func1` would be executed with a chunk size of 4 whereas `func2` would use a chunk size of 8.

Listing 28: from `test_chunksize_manual` of `numba/tests/doc_examples/test_parallel_chunksize.py`

```
from numba import (njit,
                   prange,
```

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```
                    set_parallel_chunksize,
                    get_parallel_chunksize,
                    )

@njit(parallel=True)
def func1(n):
    acc = 0
    print(get_parallel_chunksize()) # Will print 4.
    for i in prange(n):
        print(get_parallel_chunksize()) # Will print 0.
        acc += i
    print(get_parallel_chunksize()) # Will print 4.
    return acc

@njit(parallel=True)
def func2(n):
    acc = 0
    # This version gets the previous chunksize explicitly.
    old_chunksize = get_parallel_chunksize()
    set_parallel_chunksize(8)
    for i in prange(n):
        acc += i
    set_parallel_chunksize(old_chunksize)
    return acc

# This version saves the previous chunksize as returned
# by set_parallel_chunksize.
old_chunksize = set_parallel_chunksize(4)
result1 = func1(12)
result2 = func2(12)
result3 = func1(12)
set_parallel_chunksize(old_chunksize)
```

Since this idiom of saving and restoring is so common, Numba provides the `parallel_chunksize()` with clause context-manager to simplify the idiom. As shown below, this with clause can be invoked from both standard Python and within Numba JIT compiled functions. As with other Numba context-managers, be aware that the raising of exceptions is not supported from within a context managed block that is part of a Numba JIT compiled function.

Listing 29: from `test_chunksize_with` of `numba/tests/doc_examples/test_parallel_chunksize.py`

```
from numba import njit, prange, parallel_chunksize

@njit(parallel=True)
def func1(n):
    acc = 0
    for i in prange(n):
        acc += i
    return acc

@njit(parallel=True)
def func2(n):
```

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```
    acc = 0
    with parallel_chunksize(8):
        for i in prange(n):
            acc += i
    return acc

with parallel_chunksize(4):
    result1 = func1(12)
    result2 = func2(12)
    result3 = func1(12)
```

Note that these functions to set the chunk size only have an effect on Numba automatic parallelization with the *parallel* option. Chunk size specification has no effect on the *vectorize()* decorator or the *guvectorize()* decorator.

See also:

parallel, *Parallel FAQs*

1.10 Using the `@stencil` decorator

Stencils are a common computational pattern in which array elements are updated according to some fixed pattern called the stencil kernel. Numba provides the `@stencil` decorator so that users may easily specify a stencil kernel and Numba then generates the looping code necessary to apply that kernel to some input array. Thus, the stencil decorator allows clearer, more concise code and in conjunction with *the parallel jit option* enables higher performance through parallelization of the stencil execution.

1.10.1 Basic usage

An example use of the `@stencil` decorator:

```
from numba import stencil

@stencil
def kernel1(a):
    return 0.25 * (a[0, 1] + a[1, 0] + a[0, -1] + a[-1, 0])
```

The stencil kernel is specified by what looks like a standard Python function definition but there are different semantics with respect to array indexing. Stencils produce an output array of the same size and shape as the input array although depending on the kernel definition may have a different type. Conceptually, the stencil kernel is run once for each element in the output array. The return value from the stencil kernel is the value written into the output array for that particular element.

The parameter `a` represents the input array over which the kernel is applied. Indexing into this array takes place with respect to the current element of the output array being processed. For example, if element `(x, y)` is being processed then `a[0, 0]` in the stencil kernel corresponds to `a[x + 0, y + 0]` in the input array. Similarly, `a[-1, 1]` in the stencil kernel corresponds to `a[x - 1, y + 1]` in the input array.

Depending on the specified kernel, the kernel may not be applicable to the borders of the output array as this may cause the input array to be accessed out-of-bounds. The way in which the stencil decorator handles this situation is dependent upon which *func_or_mode* is selected. The default mode is for the stencil decorator to set the border elements of the output array to zero.

To invoke a stencil on an input array, call the stencil as if it were a regular function and pass the input array as the argument. For example, using the kernel defined above:

```
>>> import numpy as np
>>> input_arr = np.arange(100).reshape((10, 10))
array([[ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9],
       [10, 11, 12, 13, 14, 15, 16, 17, 18, 19],
       [20, 21, 22, 23, 24, 25, 26, 27, 28, 29],
       [30, 31, 32, 33, 34, 35, 36, 37, 38, 39],
       [40, 41, 42, 43, 44, 45, 46, 47, 48, 49],
       [50, 51, 52, 53, 54, 55, 56, 57, 58, 59],
       [60, 61, 62, 63, 64, 65, 66, 67, 68, 69],
       [70, 71, 72, 73, 74, 75, 76, 77, 78, 79],
       [80, 81, 82, 83, 84, 85, 86, 87, 88, 89],
       [90, 91, 92, 93, 94, 95, 96, 97, 98, 99]])
>>> output_arr = kernel1(input_arr)
array([[  0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.],
       [  0.,  11.,  12.,  13.,  14.,  15.,  16.,  17.,  18.,   0.],
       [  0.,  21.,  22.,  23.,  24.,  25.,  26.,  27.,  28.,   0.],
       [  0.,  31.,  32.,  33.,  34.,  35.,  36.,  37.,  38.,   0.],
       [  0.,  41.,  42.,  43.,  44.,  45.,  46.,  47.,  48.,   0.],
       [  0.,  51.,  52.,  53.,  54.,  55.,  56.,  57.,  58.,   0.],
       [  0.,  61.,  62.,  63.,  64.,  65.,  66.,  67.,  68.,   0.],
       [  0.,  71.,  72.,  73.,  74.,  75.,  76.,  77.,  78.,   0.],
       [  0.,  81.,  82.,  83.,  84.,  85.,  86.,  87.,  88.,   0.],
       [  0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.]])
>>> input_arr.dtype
dtype('int64')
>>> output_arr.dtype
dtype('float64')
```

Note that the stencil decorator has determined that the output type of the specified stencil kernel is `float64` and has thus created the output array as `float64` while the input array is of type `int64`.

1.10.2 Stencil Parameters

Stencil kernel definitions may take any number of arguments with the following provisions. The first argument must be an array. The size and shape of the output array will be the same as that of the first argument. Additional arguments may either be scalars or arrays. For array arguments, those arrays must be at least as large as the first argument (array) in each dimension. Array indexing is relative for all such input array arguments.

1.10.3 Kernel shape inference and border handling

In the above example and in most cases, the array indexing in the stencil kernel will exclusively use `Integer` literals. In such cases, the stencil decorator is able to analyze the stencil kernel to determine its size. In the above example, the stencil decorator determines that the kernel is `3 x 3` in shape since indices `-1` to `1` are used for both the first and second dimensions. Note that the stencil decorator also correctly handles non-symmetric and non-square stencil kernels.

Based on the size of the stencil kernel, the stencil decorator is able to compute the size of the border in the output array. If applying the kernel to some element of input array would cause an index to be out-of-bounds then that element belongs to the border of the output array. In the above example, points `-1` and `+1` are accessed in each dimension and thus the output array has a border of size one in all dimensions.

The parallel mode is able to infer kernel indices as constants from simple expressions if possible. For example:

```
@njit(parallel=True)
def stencil_test(A):
    c = 2
    B = stencil(
        lambda a, c: 0.3 * (a[-c+1] + a[0] + a[c-1]))(A, c)
    return B
```

1.10.4 Stencil decorator options

Note: The stencil decorator may be augmented in the future to provide additional mechanisms for border handling. At present, only one behaviour is implemented, `"constant"` (see `func_or_mode` below for details).

neighborhood

Sometimes it may be inconvenient to write the stencil kernel exclusively with `Integer` literals. For example, let us say we would like to compute the trailing 30-day moving average of a time series of data. One could write `(a[-29] + a[-28] + ... + a[-1] + a[0]) / 30` but the stencil decorator offers a more concise form using the `neighborhood` option:

```
@stencil(neighborhood = ((-29, 0),))
def kernel2(a):
    cumul = 0
    for i in range(-29, 1):
        cumul += a[i]
    return cumul / 30
```

The neighborhood option is a tuple of tuples. The outer tuple's length is equal to the number of dimensions of the input array. The inner tuple's lengths are always two because each element of the inner tuple corresponds to minimum and maximum index offsets used in the corresponding dimension.

If a user specifies a neighborhood but the kernel accesses elements outside the specified neighborhood, **the behavior is undefined.**

func_or_mode

The optional `func_or_mode` parameter controls how the border of the output array is handled. Currently, there is only one supported value, `"constant"`. In `constant` mode, the stencil kernel is not applied in cases where the kernel would access elements outside the valid range of the input array. In such cases, those elements in the output array are assigned to a constant value, as specified by the `cval` parameter.

cval

The optional cval parameter defaults to zero but can be set to any desired value, which is then used for the border of the output array if the `func_or_mode` parameter is set to `constant`. The cval parameter is ignored in all other modes. The type of the cval parameter must match the return type of the stencil kernel. If the user wishes the output array to be constructed from a particular type then they should ensure that the stencil kernel returns that type.

standard_indexing

By default, all array accesses in a stencil kernel are processed as relative indices as described above. However, sometimes it may be advantageous to pass an auxiliary array (e.g. an array of weights) to a stencil kernel and have that array use standard Python indexing rather than relative indexing. For this purpose, there is the stencil decorator option `standard_indexing` whose value is a collection of strings whose names match those parameters to the stencil function that are to be accessed with standard Python indexing rather than relative indexing:

```
@stencil(standard_indexing=("b",))
def kernel3(a, b):
    return a[-1] * b[0] + a[0] + b[1]
```

1.10.5 StencilFunc

The stencil decorator returns a callable object of type `StencilFunc`. A `StencilFunc` object contains a number of attributes but the only one of potential interest to users is the `neighborhood` attribute. If the `neighborhood` option was passed to the stencil decorator then the provided neighborhood is stored in this attribute. Else, upon first execution or compilation, the system calculates the neighborhood as described above and then stores the computed neighborhood into this attribute. A user may then inspect the attribute if they wish to verify that the calculated neighborhood is correct.

1.10.6 Stencil invocation options

Internally, the stencil decorator transforms the specified stencil kernel into a regular Python function. This function will have the same parameters as specified in the stencil kernel definition but will also include the following optional parameter.

out

The optional `out` parameter is added to every stencil function generated by Numba. If specified, the `out` parameter tells Numba that the user is providing their own pre-allocated array to be used for the output of the stencil. In this case, the stencil function will not allocate its own output array. Users should assure that the return type of the stencil kernel can be safely cast to the element-type of the user-specified output array following the NumPy ufunc casting rules.

An example usage is shown below:

```
>>> import numpy as np
>>> input_arr = np.arange(100).reshape((10, 10))
>>> output_arr = np.full(input_arr.shape, 0.0)
>>> kernel1(input_arr, out=output_arr)
```

1.11 Callback into the Python Interpreter from within JIT'ed code

There are rare but real cases when a nopython-mode function needs to callback into the Python interpreter to invoke code that cannot be compiled by Numba. Such cases include:

- logging progress for long running JIT'ed functions;
- use data structures that are not currently supported by Numba;
- debugging inside JIT'ed code using the Python debugger.

When Numba callbacks into the Python interpreter, the following has to happen:

- acquire the GIL;
- convert values in native representation back into Python objects;
- call-back into the Python interpreter;
- convert returned values from the Python-code into native representation;
- release the GIL.

These steps can be expensive. Users **should not** rely on the feature described here on performance-critical paths.

1.11.1 The `objmode` context-manager

Warning: This feature can be easily mis-used. Users should first consider alternative approaches to achieve their intended goal before using this feature.

numba.**objmode**(**args*, ***kwargs*)

Creates a contextmanager to be used inside jitted functions to enter *object-mode* for using interpreter features. The body of the with-context is lifted into a function that is compiled in *object-mode*. This transformation process is limited and cannot process all possible Python code. However, users can wrap complicated logic in another Python function, which will then be executed by the interpreter.

Use this as a function that takes keyword arguments only. The argument names must correspond to the output variables from the with-block. Their respective values can be:

1. strings representing the expected types; i.e. `"float32"`.
2. compile-time bound global or nonlocal variables referring to the expected type. The variables are read at compile time.

When exiting the with-context, the output variables are converted to the expected nopython types according to the annotation. This process is the same as passing Python objects into arguments of a nopython function.

Example:

```
import numpy as np
from numba import njit, objmode, types

def bar(x):
    # This code is executed by the interpreter.
    return np.asarray(list(reversed(x.tolist())))

# Output type as global variable
```

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```
out_ty = types.intp[:]

@njit
def foo():
    x = np.arange(5)
    y = np.zeros_like(x)
    with objmode(y='intp[:]', z=out_ty):  # annotate return type
        # this region is executed by object-mode.
        y += bar(x)
        z = y
    return y, z
```

Note: Known limitations:

- with-block cannot use incoming list objects.
- with-block cannot use incoming function objects.
- with-block cannot `yield`, `break`, `return` or `raise` such that the execution will leave the with-block immediately.
- with-block cannot contain *with* statements.
- random number generator states do not synchronize; i.e. nopython-mode and object-mode uses different RNG states.

Note: When used outside of no-python mode, the context-manager has no effect.

Warning: This feature is experimental. The supported features may change with or without notice.

1.12 Automatic module jitting with `jit_module`

A common usage pattern is to have an entire module containing user-defined functions that all need to be jitted. One option to accomplish this is to manually apply the `@jit` decorator to each function definition. This approach works and is great in many cases. However, for large modules with many functions, manually `jit`-wrapping each function definition can be tedious. For these situations, Numba provides another option, the `jit_module` function, to automatically replace functions declared in a module with their `jit`-wrapped equivalents.

It's important to note the conditions under which `jit_module` will *not* impact a function:

1. Functions which have already been wrapped with a Numba decorator (e.g. `jit`, `vectorize`, `cfunc`, etc.) are not impacted by `jit_module`.
2. Functions which are declared outside the module from which `jit_module` is called are not automatically `jit`-wrapped.
3. Function declarations which occur logically after calling `jit_module` are not impacted.

All other functions in a module will have the `@jit` decorator automatically applied to them. See the following section for an example use case.

Note: This feature is for use by module authors. `jit_module` should not be called outside the context of a module containing functions to be jitted.

1.12.1 Example usage

Let's assume we have a Python module we've created, `mymodule.py` (shown below), which contains several functions. Some of these functions are defined in `mymodule.py` while others are imported from other modules. We wish to have all the functions which are defined in `mymodule.py` jitted using `jit_module`.

```
# mymodule.py

from numba import jit, jit_module

def inc(x):
   return x + 1

def add(x, y):
   return x + y

import numpy as np
# Use NumPy's mean function
mean = np.mean

@jit(nogil=True)
def mul(a, b):
   return a * b

jit_module(nopython=True, error_model="numpy")

def div(a, b):
    return a / b
```

There are several things to note in the above example:

- Both the `inc` and `add` functions will be replaced with their `jit`-wrapped equivalents with *compilation options* `nopython=True` and `error_model="numpy"`.
- The `mean` function, because it's defined *outside* of `mymodule.py` in NumPy, will not be modified.
- `mul` will not be modified because it has been manually decorated with `jit`.
- `div` will not be automatically `jit`-wrapped because it is declared after `jit_module` is called.

When the above module is imported, we have:

```
>>> import mymodule
>>> mymodule.inc
CPUDispatcher(<function inc at 0x1032f86a8>)
>>> mymodule.mean
<function mean at 0x1096b8950>
```

1.12.2 API

Warning: This feature is experimental. The supported features may change with or without notice.

numba.**jit_module**(***kwargs*)

Automatically `jit`-wraps functions defined in a Python module

Note that `jit_module` should only be called at the end of the module to be jitted. In addition, only functions which are defined in the module `jit_module` is called from are considered for automatic jit-wrapping. See the Numba documentation for more information about what can/cannot be jitted.

Parameters

kwargs – Keyword arguments to pass to `jit` such as `nopython` or `error_model`.

1.13 Performance Tips

This is a short guide to features present in Numba that can help with obtaining the best performance from code. Two examples are used, both are entirely contrived and exist purely for pedagogical reasons to motivate discussion. The first is the computation of the trigonometric identity `cos(x)^2 + sin(x)^2`, the second is a simple element wise square root of a vector with reduction over summation. All performance numbers are indicative only and unless otherwise stated were taken from running on an Intel `i7-4790` CPU (4 hardware threads) with an input of `np.arange(1.e7)`.

Note: A reasonably effective approach to achieving high performance code is to profile the code running with real data and use that to guide performance tuning. The information presented here is to demonstrate features, not to act as canonical guidance!

1.13.1 NoPython mode

The default mode in which Numba's `@jit` decorator operates is *nopython mode*. This mode is most restrictive about what can be compiled, but results in faster executable code.

Note: Historically (prior to 0.59.0) the default compilation mode was a fall-back mode whereby the compiler would try to compile in *nopython mode* and if it failed it would fall-back to *object mode*. It is likely that you'll see `@jit(nopython=True)`, or its alias `@njit`, in use in code/documentation as this was the recommended best practice method to force use of *nopython mode*. Since Numba 0.59.0 this is no long necessary as *nopython mode* is the default mode for `@jit`.

1.13.2 Loops

Whilst NumPy has developed a strong idiom around the use of vector operations, Numba is perfectly happy with loops too. For users familiar with C or Fortran, writing Python in this style will work fine in Numba (after all, LLVM gets a lot of use in compiling C lineage languages). For example:

```
@njit
def ident_np(x):
    return np.cos(x) ** 2 + np.sin(x) ** 2

@njit
def ident_loops(x):
    r = np.empty_like(x)
    n = len(x)
    for i in range(n):
        r[i] = np.cos(x[i]) ** 2 + np.sin(x[i]) ** 2
    return r
```

The above run at almost identical speeds when decorated with `@njit`, without the decorator the vectorized function is a couple of orders of magnitude faster.

Function Name	@njit	Execution time
`ident_np`	No	0.581s
`ident_np`	Yes	0.659s
`ident_loops`	No	25.2s
`ident_loops`	Yes	0.670s

1.13.3 A Case for Object mode: LoopLifting

Some functions may be incompatible with the restrictive *nopython mode* but contain compatible loops. You can enable these functions to attempt nopython mode on their loops by setting `@jit(forceobj=True)`. The incompatible code segments will run in object mode.

Whilst using looplifting in object mode can provide some performance increase, compiling functions entirely in *nopython mode* is key to achieving optimal performance.

1.13.4 Fastmath

In certain classes of applications strict IEEE 754 compliance is less important. As a result it is possible to relax some numerical rigour with view of gaining additional performance. The way to achieve this behaviour in Numba is through the use of the `fastmath` keyword argument:

```
@njit(fastmath=False)
def do_sum(A):
    acc = 0.
    # without fastmath, this loop must accumulate in strict order
    for x in A:
        acc += np.sqrt(x)
    return acc

@njit(fastmath=True)
def do_sum_fast(A):
```

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```
    acc = 0.
    # with fastmath, the reduction can be vectorized as floating point
    # reassociation is permitted.
    for x in A:
        acc += np.sqrt(x)
    return acc
```

Function Name	Execution time
do_sum	35.2 ms
do_sum_fast	17.8 ms

In some cases you may wish to opt-in to only a subset of possible fast-math optimizations. This can be done by supplying a set of LLVM fast-math flags to `fastmath`.:

```
def add_assoc(x, y):
    return (x - y) + y

print(njit(fastmath=False)(add_assoc)(0, np.inf)) # nan
print(njit(fastmath=True) (add_assoc)(0, np.inf)) # 0.0
print(njit(fastmath={'reassoc', 'nsz'})(add_assoc)(0, np.inf)) # 0.0
print(njit(fastmath={'reassoc'})       (add_assoc)(0, np.inf)) # nan
print(njit(fastmath={'nsz'})           (add_assoc)(0, np.inf)) # nan
```

1.13.5 Parallel=True

If code contains operations that are parallelisable (*and supported*) Numba can compile a version that will run in parallel on multiple native threads (no GIL!). This parallelisation is performed automatically and is enabled by simply adding the `parallel` keyword argument:

```
@njit(parallel=True)
def ident_parallel(x):
    return np.cos(x) ** 2 + np.sin(x) ** 2
```

Executions times are as follows:

Function Name	Execution time
ident_parallel	112 ms

The execution speed of this function with `parallel=True` present is approximately 5x that of the NumPy equivalent and 6x that of standard `@njit`.

Numba parallel execution also has support for explicit parallel loop declaration similar to that in OpenMP. To indicate that a loop should be executed in parallel the `numba.prange` function should be used, this function behaves like Python `range` and if `parallel=True` is not set it acts simply as an alias of `range`. Loops induced with `prange` can be used for embarrassingly parallel computation and also reductions.

Revisiting the reduce over sum example, assuming it is safe for the sum to be accumulated out of order, the loop in `n` can be parallelised through the use of `prange`. Further, the `fastmath=True` keyword argument can be added without concern in this case as the assumption that out of order execution is valid has already been made through the use of `parallel=True` (as each thread computes a partial sum).

```
@njit(parallel=True)
def do_sum_parallel(A):
    # each thread can accumulate its own partial sum, and then a cross
    # thread reduction is performed to obtain the result to return
    n = len(A)
    acc = 0.
    for i in prange(n):
        acc += np.sqrt(A[i])
    return acc

@njit(parallel=True, fastmath=True)
def do_sum_parallel_fast(A):
    n = len(A)
    acc = 0.
    for i in prange(n):
        acc += np.sqrt(A[i])
    return acc
```

Execution times are as follows, `fastmath` again improves performance.

Function Name	Execution time
`do_sum_parallel`	9.81 ms
`do_sum_parallel_fast`	5.37 ms

1.13.6 Intel SVML

Intel provides a short vector math library (SVML) that contains a large number of optimised transcendental functions available for use as compiler intrinsics. If the `intel-cmplr-lib-rt` package is present in the environment (or the SVML libraries are simply locatable!) then Numba automatically configures the LLVM back end to use the SVML intrinsic functions where ever possible. SVML provides both high and low accuracy versions of each intrinsic and the version that is used is determined through the use of the `fastmath` keyword. The default is to use high accuracy which is accurate to within `1 ULP`, however if `fastmath` is set to `True` then the lower accuracy versions of the intrinsics are used (answers to within `4 ULP`).

First obtain SVML, using conda for example:

```
conda install intel-cmplr-lib-rt
```

Note: The SVML library was previously provided through the `icc_rt` conda package. The `icc_rt` package has since become a meta-package and as of version `2021.1.1` it has `intel-cmplr-lib-rt` amongst other packages as a dependency. Installing the recommended `intel-cmplr-lib-rt` package directly results in fewer installed packages.

Rerunning the identity function example `ident_np` from above with various combinations of options to `@njit` and with/without SVML yields the following performance results (input size `np.arange(1.e8)`). For reference, with just NumPy the function executed in `5.84s`:

`@njit` kwargs	SVML	Execution time
`None`	No	5.95s
`None`	Yes	2.26s
`fastmath=True`	No	5.97s
`fastmath=True`	Yes	1.8s
`parallel=True`	No	1.36s
`parallel=True`	Yes	0.624s
`parallel=True, fastmath=True`	No	1.32s
`parallel=True, fastmath=True`	Yes	0.576s

It is evident that SVML significantly increases the performance of this function. The impact of `fastmath` in the case of SVML not being present is zero, this is expected as there is nothing in the original function that would benefit from relaxing numerical strictness.

1.13.7 Linear algebra

Numba supports most of `numpy.linalg` in no Python mode. The internal implementation relies on a LAPACK and BLAS library to do the numerical work and it obtains the bindings for the necessary functions from SciPy. Therefore, to achieve good performance in `numpy.linalg` functions with Numba it is necessary to use a SciPy built against a well optimised LAPACK/BLAS library. In the case of the Anaconda distribution SciPy is built against Intel's MKL which is highly optimised and as a result Numba makes use of this performance.

1.14 The Threading Layers

This section is about the Numba threading layer, this is the library that is used internally to perform the parallel execution that occurs through the use of the `parallel` targets for CPUs, namely:

- The use of the `parallel=True` kwarg in `@jit` and `@njit`.
- The use of the `target='parallel'` kwarg in `@vectorize` and `@guvectorize`.

Note: If a code base does not use the `threading` or `multiprocessing` modules (or any other sort of parallelism) the defaults for the threading layer that ship with Numba will work well, no further action is required!

1.14.1 Which threading layers are available?

There are three threading layers available and they are named as follows:

- `tbb` - A threading layer backed by Intel TBB.
- `omp` - A threading layer backed by OpenMP.
- `workqueue` -A simple built-in work-sharing task scheduler.

In practice, the only threading layer guaranteed to be present is `workqueue`. The `omp` layer requires the presence of a suitable OpenMP runtime library. The `tbb` layer requires the presence of Intel's TBB libraries, these can be obtained via the conda command:

```
$ conda install tbb
```

If you installed Numba with `pip`, TBB can be enabled by running:

```
$ pip install tbb
```

Note: The default manner in which Numba searches for and loads a threading layer is tolerant of missing libraries, incompatible runtimes etc.

1.14.2 Setting the threading layer

The threading layer is set via the environment variable `NUMBA_THREADING_LAYER` or through assignment to `numba.config.THREADING_LAYER`. If the programmatic approach to setting the threading layer is used it must occur logically before any Numba based compilation for a parallel target has occurred. There are two approaches to choosing a threading layer, the first is by selecting a threading layer that is safe under various forms of parallel execution, the second is through explicit selection via the threading layer name (e.g. `tbb`).

1.14.3 Setting the threading layer selection priority

By default the threading layers are searched in the order of `'tbb'`, `'omp'`, then `'workqueue'`. To change this search order whilst maintaining the selection of a threading layer based on availability, the environment variable *NUMBA_THREADING_LAYER_PRIORITY* can be used.

Note that it can also be set via `numba.config.THREADING_LAYER_PRIORITY`. Similar to `numba.config.THREADING_LAYER`, it must occur logically before any Numba based compilation for a parallel target has occurred.

For example, to instruct Numba to choose `omp` first if available, then `tbb` and so on, set the environment variable as `NUMBA_THREADING_LAYER_PRIORITY="omp tbb workqueue"`. Or programmatically, `numba.config.THREADING_LAYER_PRIORITY = ["omp", "tbb", "workqueue"]`.

Selecting a threading layer for safe parallel execution

Parallel execution is fundamentally derived from core Python libraries in four forms (the first three also apply to code using parallel execution via other means!):

- `threads` from the `threading` module.
- `spawn` ing processes from the `multiprocessing` module via `spawn` (default on Windows, only available in Python 3.4+ on Unix)
- `fork` ing processes from the `multiprocessing` module via `fork` (default on Unix).
- `fork` ing processes from the `multiprocessing` module through the use of a `forkserver` (only available in Python 3 on Unix). Essentially a new process is spawned and then forks are made from this new process on request.

Any library in use with these forms of parallelism must exhibit safe behaviour under the given paradigm. As a result, the threading layer selection methods are designed to provide a way to choose a threading layer library that is safe for a given paradigm in an easy, cross platform and environment tolerant manner. The options that can be supplied to the *setting mechanisms* are as follows:

- `default` provides no specific safety guarantee and is the default.
- `safe` is both fork and thread safe, this requires the `tbb` package (Intel TBB libraries) to be installed.
- `forksafe` provides a fork safe library.
- `threadsafe` provides a thread safe library.

To discover the threading layer that was selected, the function `numba.threading_layer()` may be called after parallel execution. For example, on a Linux machine with no TBB installed:

```
from numba import config, njit, threading_layer
import numpy as np

# set the threading layer before any parallel target compilation
config.THREADING_LAYER = 'threadsafe'

@njit(parallel=True)
def foo(a, b):
    return a + b

x = np.arange(10.)
y = x.copy()

# this will force the compilation of the function, select a threading layer
# and then execute in parallel
foo(x, y)

# demonstrate the threading layer chosen
print("Threading layer chosen: %s" % threading_layer())
```

which produces:

```
Threading layer chosen: omp
```

and this makes sense as GNU OpenMP, as present on Linux, is thread safe.

Selecting a named threading layer

Advanced users may wish to select a specific threading layer for their use case, this is done by directly supplying the threading layer name to the *setting mechanisms*. The options and requirements are as follows:

Threading Layer Name	Platform	Requirements
`tbb`	All	The `tbb` package (`$ conda install tbb`)
`omp`	Linux Windows OSX	GNU OpenMP libraries (very likely this will already exist) MS OpenMP libraries (very likely this will already exist) Either the `intel-openmp` package or the `llvm-openmp` package (`conda install` the package as named).
`workqueue`	All	None

Should the threading layer not load correctly Numba will detect this and provide a hint about how to resolve the problem. It should also be noted that the Numba diagnostic command `numba -s` has a section `__Threading Layer Information__` that reports on the availability of threading layers in the current environment.

1.14.4 Extra notes

The threading layers have fairly complex interactions with CPython internals and system level libraries, some additional things to note:

- The installation of Intel's TBB libraries vastly widens the options available in the threading layer selection process.
- On Linux, the `omp` threading layer is not fork safe due to the GNU OpenMP runtime library (`libgomp`) not being fork safe. If a fork occurs in a program that is using the `omp` threading layer, a detection mechanism is present that will try and gracefully terminate the forked child and print an error message to `STDERR`.
- On systems with the `fork(2)` system call available, if the TBB backed threading layer is in use and a `fork` call is made from a thread other than the thread that launched TBB (typically the main thread) then this results in undefined behaviour and a warning will be displayed on `STDERR`. As `spawn` is essentially `fork` followed by `exec` it is safe to `spawn` from a non-main thread, but as this cannot be differentiated from just a `fork` call the warning message will still be displayed.
- On OSX, the `intel-openmp` package is required to enable the OpenMP based threading layer.

1.14.5 Setting the Number of Threads

The number of threads used by numba is based on the number of CPU cores available (see *numba.config.NUMBA_DEFAULT_NUM_THREADS*), but it can be overridden with the *NUMBA_NUM_THREADS* environment variable.

The total number of threads that numba launches is in the variable *numba.config.NUMBA_NUM_THREADS*.

For some use cases, it may be desirable to set the number of threads to a lower value, so that numba can be used with higher level parallelism.

The number of threads can be set dynamically at runtime using *numba.set_num_threads()*. Note that *set_num_threads()* only allows setting the number of threads to a smaller value than *NUMBA_NUM_THREADS*. Numba always launches *numba.config.NUMBA_NUM_THREADS* threads, but *set_num_threads()* causes it to mask out unused threads so they aren't used in computations.

The current number of threads used by numba can be accessed with *numba.get_num_threads()*. Both functions work inside of a jitted function.

Example of Limiting the Number of Threads

In this example, suppose the machine we are running on has 8 cores (so *numba.config.NUMBA_NUM_THREADS* would be 8). Suppose we want to run some code with `@njit(parallel=True)`, but we also want to run our code concurrently in 4 different processes. With the default number of threads, each Python process would run 8 threads, for a total in 4*8 = 32 threads, which is oversubscription for our 8 cores. We should rather limit each process to 2 threads, so that the total will be 4*2 = 8, which matches our number of physical cores.

There are two ways to do this. One is to set the *NUMBA_NUM_THREADS* environment variable to 2.

```
$ NUMBA_NUM_THREADS=2 python ourcode.py
```

However, there are two downsides to this approach:

1. *NUMBA_NUM_THREADS* must be set before Numba is imported, and ideally before Python is launched. As soon as Numba is imported the environment variable is read and that number of threads is locked in as the number of threads Numba launches.

2. If we want to later increase the number of threads used by the process, we cannot. *NUMBA_NUM_THREADS* sets the *maximum* number of threads that are launched for a process. Calling *set_num_threads()* with a value greater than *numba.config.NUMBA_NUM_THREADS* results in an error.

The advantage of this approach is that we can do it from outside of the process without changing the code.

Another approach is to use the *numba.set_num_threads()* function in our code

```
from numba import njit, set_num_threads

@njit(parallel=True)
def func():
    ...

set_num_threads(2)
func()
```

If we call `set_num_threads(2)` before executing our parallel code, it has the same effect as calling the process with `NUMBA_NUM_THREADS=2`, in that the parallel code will only execute on 2 threads. However, we can later call `set_num_threads(8)` to increase the number of threads back to the default size. And we do not have to worry about setting it before Numba gets imported. It only needs to be called before the parallel function is run.

1.14.6 Getting a Thread ID

In some cases it may be beneficial to have access to a unique identifier for the current thread that is executing a parallel region in Numba. For that purpose, Numba provides the *numba.get_thread_id()* function. This function is the corollary of OpenMP's function `omp_get_thread_num` and returns an integer between 0 (inclusive) and the number of configured threads as described above (exclusive).

API Reference

numba.config.**NUMBA_NUM_THREADS**

The total (maximum) number of threads launched by numba.

Defaults to *numba.config.NUMBA_DEFAULT_NUM_THREADS*, but can be overridden with the *NUMBA_NUM_THREADS* environment variable.

numba.config.**NUMBA_DEFAULT_NUM_THREADS**

The number of usable CPU cores on the system (as determined by `len(os.sched_getaffinity(0))`, if supported by the OS, or `multiprocessing.cpu_count()` if not). This is the default value for *numba.config.NUMBA_NUM_THREADS* unless the *NUMBA_NUM_THREADS* environment variable is set.

numba.**set_num_threads**(*n*)

Set the number of threads to use for parallel execution.

By default, all *numba.config.NUMBA_NUM_THREADS* threads are used.

This functionality works by masking out threads that are not used. Therefore, the number of threads *n* must be less than or equal to *NUMBA_NUM_THREADS*, the total number of threads that are launched. See its documentation for more details.

This function can be used inside of a jitted function.

Parameters

n: The number of threads. Must be between 1 and NUMBA_NUM_THREADS.

See also:

get_num_threads, *numba.config.NUMBA_NUM_THREADS*
numba.config.NUMBA_DEFAULT_NUM_THREADS, *NUMBA_NUM_THREADS*

numba.**get_num_threads**()

Get the number of threads used for parallel execution.

By default (if *set_num_threads()* is never called), all *numba.config.NUMBA_NUM_THREADS* threads are used.

This number is less than or equal to the total number of threads that are launched, *numba.config.NUMBA_NUM_THREADS*.

This function can be used inside of a jitted function.

Returns

The number of threads.

See also:

set_num_threads, *numba.config.NUMBA_NUM_THREADS*
numba.config.NUMBA_DEFAULT_NUM_THREADS, *NUMBA_NUM_THREADS*

numba.**get_thread_id**()

Returns a unique ID for each thread in the range 0 (inclusive) to *get_num_threads()* (exclusive).

1.15 Command line interface

Numba is a Python package, usually you `import numba` from Python and use the Python application programming interface (API). However, Numba also ships with a command line interface (CLI), i.e. a tool `numba` that is installed when you install Numba.

Currently, the only purpose of the CLI is to allow you to quickly show some information about your system and installation, or to quickly get some debugging information for a Python script using Numba.

1.15.1 Usage

To use the Numba CLI from the terminal, use `numba` followed by the options and arguments like `--help` or `-s`, as explained below.

Sometimes it can happen that you get a "command not found" error when you type `numba`, because your `PATH` isn't configured properly. In that case you can use the equivalent command `python -m numba`. If that still gives "command not found", try to `import numba` as suggested here: *Dependency List*.

The two versions `numba` and `python -m numba` are the same. The first is shorter to type, but if you get a "command not found" error because your `PATH` doesn't contain the location where `numba` is installed, having the `python -m numba` variant is useful.

To use the Numba CLI from IPython or Jupyter, use `!numba`, i.e. prefix the command with an exclamation mark. This is a general IPython/Jupyter feature to execute shell commands, it is not available in the regular `python` terminal.

1.15.2 Help

To see all available options, use `numba --help`:

```
$ numba --help
usage: numba [-h] [--annotate] [--dump-llvm] [--dump-optimized]
             [--dump-assembly] [--annotate-html ANNOTATE_HTML] [-s]
             [--sys-json SYS_JSON]
             [filename]

positional arguments:
filename              Python source filename

optional arguments:
-h, --help            show this help message and exit
--annotate            Annotate source
--dump-llvm           Print generated llvm assembly
--dump-optimized      Dump the optimized llvm assembly
--dump-assembly       Dump the LLVM generated assembly
--annotate-html ANNOTATE_HTML
                        Output source annotation as html
-s, --sysinfo         Output system information for bug reporting
--sys-json SYS_JSON   Saves the system info dict as a json file
```

1.15.3 System information

The `numba -s` (or the equivalent `numba --sysinfo`) command prints a lot of information about your system and your Numba installation and relevant dependencies.

Remember: you can use `!numba -s` with an exclamation mark to see this information from IPython or Jupyter.

Example output:

```
$ numba -s

System info:
--------------------------------------------------------------------------------
__Time Stamp__
Report started (local time)                  : 2022-11-30 15:40:42.368114
UTC start time                               : 2022-11-30 15:40:42.368129
Running time (s)                             : 2.563586

__Hardware Information__
Machine                                      : x86_64
CPU Name                                     : ivybridge
CPU Count                                    : 3
Number of accessible CPUs                    : ?
List of accessible CPUs cores                : ?
CFS Restrictions (CPUs worth of runtime)     : None

CPU Features                                 : 64bit aes avx cmov cx16 cx8 f16c
                                               fsgsbase fxsr mmx pclmul popcnt
                                               rdrnd sahf sse sse2 sse3 sse4.1
```

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```
                                        sse4.2 ssse3 xsave

Memory Total (MB)                     : 14336
Memory Available (MB)                 : 11540

__OS Information__
Platform Name                         : macOS-10.16-x86_64-i386-64bit
Platform Release                      : 20.6.0
OS Name                               : Darwin
OS Version                            : Darwin Kernel Version 20.6.0: Thu Sep 29␣
↪20:15:11 PDT 2022; root:xnu-7195.141.42~1/RELEASE_X86_64
OS Specific Version                   : 10.16   x86_64
Libc Version                          : ?

__Python Information__
Python Compiler                       : Clang 14.0.6
Python Implementation                 : CPython
Python Version                        : 3.10.8
Python Locale                         : en_US.UTF-8

__Numba Toolchain Versions__
Numba Version                         : 0+untagged.gb91eec710
llvmlite Version                      : 0.40.0dev0+43.g7783803

__LLVM Information__
LLVM Version                          : 11.1.0

__CUDA Information__
CUDA Device Initialized               : False
CUDA Driver Version                   : ?
CUDA Runtime Version                  : ?
CUDA NVIDIA Bindings Available        : ?
CUDA NVIDIA Bindings In Use           : ?
CUDA Detect Output:
None
CUDA Libraries Test Output:
None

__NumPy Information__
NumPy Version                         : 1.23.4
NumPy Supported SIMD features         : ('MMX', 'SSE', 'SSE2', 'SSE3', 'SSSE3',
↪'SSE41', 'POPCNT', 'SSE42', 'AVX', 'F16C')
NumPy Supported SIMD dispatch         : ('SSSE3', 'SSE41', 'POPCNT', 'SSE42',
↪'AVX', 'F16C', 'FMA3', 'AVX2', 'AVX512F', 'AVX512CD', 'AVX512_KNL', 'AVX512_SKX',
↪'AVX512_CLX', 'AVX512_CNL', 'AVX512_ICL')
NumPy Supported SIMD baseline         : ('SSE', 'SSE2', 'SSE3')
NumPy AVX512_SKX support detected     : False

__SVML Information__
SVML State, config.USING_SVML         : False
SVML Library Loaded                   : False
llvmlite Using SVML Patched LLVM      : True
```

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```
SVML Operational                                : False

__Threading Layer Information__
TBB Threading Layer Available                   : True
+-->TBB imported successfully.
OpenMP Threading Layer Available                : True
+-->Vendor: Intel
Workqueue Threading Layer Available             : True
+-->Workqueue imported successfully.

__Numba Environment Variable Information__
None found.

__Conda Information__
Conda Build                                     : not installed
Conda Env                                       : 4.12.0
Conda Platform                                  : osx-64
Conda Python Version                            : 3.9.12.final.0
Conda Root Writable                             : True

__Installed Packages__
(output truncated due to length)
```

1.15.4 Debugging

As shown in the help output above, the `numba` command includes options that can help you to debug Numba compiled code.

To try it out, create an example script called `myscript.py`:

```
import numba

@numba.jit
def f(x):
    return 2 * x

f(42)
```

and then execute one of the following commands:

```
$ numba myscript.py --annotate
$ numba myscript.py --annotate-html myscript.html
$ numba myscript.py --dump-llvm
$ numba myscript.py --dump-optimized
$ numba myscript.py --dump-assembly
```

1.16 Code Coverage for Compiled Code

Numba, a just-in-time compiler for Python, transforms Python code into machine code for optimized execution. This process, however, poses a challenge for traditional code coverage tools, as they typically operate within the Python interpreter and thus miss the lines of code compiled by Numba. To address this issue, Numba opts for a compile-time notification to coverage tools, rather than during execution, to minimize performance penalties. This approach helps prevent significant coverage gaps in projects utilizing Numba, without incurring substantial performance costs.

No additional effort is required to generate compile-time coverage data. By running a Numba application under the `coverage` tool (e.g. `coverage run ...`), the compiler automatically detects the active coverage session and emits data accordingly. This mechanism ensures that coverage data is generated seamlessly, without the need for manual intervention.

The coverage data is emitted during the lowering phase, which involves the generation of LLVM-IR. This phase inherently excludes lines of code that are statically identified as dead code, ensuring that the coverage data accurately reflects the executable code paths.

1.17 Troubleshooting and tips

1.17.1 What to compile

The general recommendation is that you should only try to compile the critical paths in your code. If you have a piece of performance-critical computational code amongst some higher-level code, you may factor out the performance-critical code in a separate function and compile the separate function with Numba. Letting Numba focus on that small piece of performance-critical code has several advantages:

- it reduces the risk of hitting unsupported features;
- it reduces the compilation times;
- it allows you to evolve the higher-level code which is outside of the compiled function much easier.

1.17.2 My code doesn't compile

There can be various reasons why Numba cannot compile your code, and raises an error instead. One common reason is that your code relies on an unsupported Python feature, especially in *nopython mode*. Please see the list of *Supported Python features*. If you find something that is listed there and still fails compiling, please *report a bug*.

When Numba tries to compile your code it first tries to work out the types of all the variables in use, this is so it can generate a type specific implementation of your code that can be compiled down to machine code. A common reason for Numba failing to compile (especially in *nopython mode*) is a type inference failure, essentially Numba cannot work out what the type of all the variables in your code should be.

For example, let's consider this trivial function:

```
@jit(nopython=True)
def f(x, y):
    return x + y
```

If you call it with two numbers, Numba is able to infer the types properly:

```
>>> f(1, 2)
    3
```

If however you call it with a tuple and a number, Numba is unable to say what the result of adding a tuple and number is, and therefore compilation errors out:

```
>>> f(1, (2,))
Traceback (most recent call last):
File "<stdin>", line 1, in <module>
File "<path>/numba/numba/dispatcher.py", line 339, in _compile_for_args
    reraise(type(e), e, None)
File "<path>/numba/numba/six.py", line 658, in reraise
    raise value.with_traceback(tb)
numba.errors.TypingError: Failed at nopython (nopython frontend)
Invalid use of + with parameters (int64, tuple(int64 x 1))
Known signatures:
* (int64, int64) -> int64
* (int64, uint64) -> int64
* (uint64, int64) -> int64
* (uint64, uint64) -> uint64
* (float32, float32) -> float32
* (float64, float64) -> float64
* (complex64, complex64) -> complex64
* (complex128, complex128) -> complex128
* (uint16,) -> uint64
* (uint8,) -> uint64
* (uint64,) -> uint64
* (uint32,) -> uint64
* (int16,) -> int64
* (int64,) -> int64
* (int8,) -> int64
* (int32,) -> int64
* (float32,) -> float32
* (float64,) -> float64
* (complex64,) -> complex64
* (complex128,) -> complex128
* parameterized
[1] During: typing of intrinsic-call at <stdin> (3)

File "<stdin>", line 3:
```

The error message helps you find out what went wrong: “Invalid use of + with parameters (int64, tuple(int64 x 1))” is to be interpreted as “Numba encountered an addition of variables typed as integer and 1-tuple of integer, respectively, and doesn’t know about any such operation”.

Note that if you allow object mode:

```
@jit
def g(x, y):
    return x + y
```

compilation will succeed and the compiled function will raise at runtime as Python would do:

```
>>> g(1, (2,))
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: unsupported operand type(s) for +: 'int' and 'tuple'
```

1.17.3 My code has a type unification problem

Another common reason for Numba not being able to compile your code is that it cannot statically determine the return type of a function. The most likely cause of this is the return type depending on a value that is available only at runtime. Again, this is most often problematic when using *nopython mode*. The concept of type unification is simply trying to find a type in which two variables could safely be represented. For example a 64 bit float and a 64 bit complex number could both be represented in a 128 bit complex number.

As an example of type unification failure, this function has a return type that is determined at runtime based on the value of *x*:

```
In [1]: from numba import jit

In [2]: @jit(nopython=True)
...: def f(x):
...:     if x > 10:
...:         return (1,)
...:     else:
...:         return 1
...:

In [3]: f(10)
```

Trying to execute this function, errors out as follows:

```
TypingError: Failed at nopython (nopython frontend)
Can't unify return type from the following types: tuple(int64 x 1), int64
Return of: IR name '$8.2', type '(int64 x 1)', location:
File "<ipython-input-2-51ef1cc64bea>", line 4:
def f(x):
    <source elided>
    if x > 10:
        return (1,)
        ^
Return of: IR name '$12.2', type 'int64', location:
File "<ipython-input-2-51ef1cc64bea>", line 6:
def f(x):
    <source elided>
    else:
        return 1
```

The error message "Can't unify return type from the following types: tuple(int64 x 1), int64" should be read as "Numba cannot find a type that can safely represent a 1-tuple of integer and an integer".

1.17.4 My code has an untyped list problem

As *noted previously* the first part of Numba compiling your code involves working out what the types of all the variables are. In the case of lists, a list must contain items that are of the same type or can be empty if the type can be inferred from some later operation. What is not possible is to have a list which is defined as empty and has no inferable type (i.e. an untyped list).

For example, this is using a list of a known type:

```
from numba import jit
@jit(nopython=True)
def f():
    return [1, 2, 3] # this list is defined on construction with `int` type
```

This is using an empty list, but the type can be inferred:

```
from numba import jit
@jit(nopython=True)
def f(x):
    tmp = [] # defined empty
    for i in range(x):
        tmp.append(i) # list type can be inferred from the type of `i`
    return tmp
```

This is using an empty list and the type cannot be inferred:

```
from numba import jit
@jit(nopython=True)
def f(x):
    tmp = [] # defined empty
    return (tmp, x) # ERROR: the type of `tmp` is unknown
```

Whilst slightly contrived, if you need an empty list and the type cannot be inferred but you know what type you want the list to be, this "trick" can be used to instruct the typing mechanism:

```
from numba import jit
import numpy as np
@jit(nopython=True)
def f(x):
    # define empty list, but instruct that the type is np.complex64
    tmp = [np.complex64(x) for x in range(0)]
    return (tmp, x) # the type of `tmp` is known, but it is still empty
```

1.17.5 *Object mode* or `@jit(forceobj=True)` is too slow

object mode provides little to no speedup compared to regular Python interpretation, its main point is to allow an internal optimization known as *loop-lifting*. This optimization will allow compilation of inner loops in *nopython mode* regardless of what code surrounds those inner loops. The compilation of inner loops can still fallback to *object mode* if they use types or operations that *nopython mode* does not support.

1.17.6 Disabling JIT compilation

In order to debug code, it is possible to disable JIT compilation, which makes the `jit` decorator (and the `njit` decorator) act as if they perform no operation, and the invocation of decorated functions calls the original Python function instead of a compiled version. This can be toggled by setting the *NUMBA_DISABLE_JIT* environment variable to 1.

When this mode is enabled, the `vectorize` and `guvectorize` decorators will still result in compilation of a ufunc, as there is no straightforward pure Python implementation of these functions.

1.17.7 Debugging JIT compiled code with GDB

Setting the `debug` keyword argument in the `jit` decorator (e.g. `@jit(debug=True)`) enables the emission of debug info in the jitted code. To debug, GDB version 7.0 or above is required. Currently, the following debug info is available:

- Function name will be shown in the backtrace along with type information and values (if available).
- Source location (filename and line number) is available. For example, users can set a break point by the absolute filename and line number; e.g. `break /path/to/myfile.py:6`.
- Arguments to the current function can be show with `info args`
- Local variables in the current function can be shown with `info locals`.
- The type of variables can be shown with `whatis myvar`.
- The value of variables can be shown with `print myvar` or `display myvar`.
  - Simple numeric types, i.e. int, float and double, are shown in their native representation.
  - Other types are shown as a structure based on Numba's memory model representation of the type.

Further, the Numba `gdb` printing extension can be loaded into `gdb` (if the `gdb` has Python support) to permit the printing of variables as they would be in native Python. The extension does this by reinterpreting Numba's memory model representations as Python types. Information about the `gdb` installation that Numba is using, including the path to load the `gdb` printing extension, can be displayed by using the `numba -g` command. For best results ensure that the Python that `gdb` is using has a NumPy module accessible. An example output of the `gdb` information follows:

```
$ numba -g
GDB info:
--------------------------------------------------------------------------------
Binary location                                : <some path>/gdb
Print extension location                       : <some python path>/numba/misc/gdb_
↪print_extension.py
Python version                                 : 3.8
NumPy version                                  : 1.20.0
Numba printing extension supported             : True

To load the Numba gdb printing extension, execute the following from the gdb prompt:

source <some python path>/numba/misc/gdb_print_extension.py

--------------------------------------------------------------------------------
```

Known issues:

- Stepping depends heavily on optimization level. At full optimization (equivalent to O3), most of the variables are optimized out. It is often beneficial to use the jit option `_dbg_optnone=True` or the environment variable *NUMBA_OPT* to adjust the optimization level and the jit option `_dbg_extend_lifetimes=True` (which is on by default if `debug=True`) or *NUMBA_EXTEND_VARIABLE_LIFETIMES* to extend the lifetime of variables to the end of their scope so as to get a debugging experience closer to the semantics of Python execution.
- Memory consumption increases significantly with debug info enabled. The compiler emits extra information (DWARF) along with the instructions. The emitted object code can be 2x bigger with debug info.

Internal details:

- Since Python semantics allow variables to bind to value of different types, Numba internally creates multiple versions of the variable for each type. So for code like:

```
x = 1          # type int
x = 2.3        # type float
x = (1, 2, 3) # type 3-tuple of int
```

Each assignments will store to a different variable name. In the debugger, the variables will be `x`, `x$1` and `x$2`. (In the Numba IR, they are `x`, `x.1` and `x.2`.)

- When debug is enabled, inlining of functions at LLVM IR level is disabled.

JIT options for debug

- `debug` (bool). Set to `True` to enable debug info. Defaults to `False`.
- `_dbg_optnone` (bool). Set to `True` to disable all LLVM optimization passes on the function. Defaults to `False`. See *NUMBA_OPT* for a global setting to disable optimization.
- `_dbg_extend_lifetimes` (bool). Set to `True` to extend the lifetime of objects such that they more closely follow the semantics of Python. Automatically set to `True` when `debug=True`; otherwise, defaults to `False`. Users can explicitly set this option to `False` to retain the normal execution semantics of compiled code. See *NUMBA_EXTEND_VARIABLE_LIFETIMES* for a global option to extend object lifetimes.

Example debug usage

The python source:

```
from numba import njit

@njit(debug=True)
def foo(a):
    b = a + 1
    c = a * 2.34
    d = (a, b, c)
    print(a, b, c, d)

r = foo(123)
print(r)
```

In the terminal:

```
$ NUMBA_OPT=0 NUMBA_EXTEND_VARIABLE_LIFETIMES=1 gdb -q python
Reading symbols from python...
(gdb) break test1.py:5
No source file named test1.py.
Make breakpoint pending on future shared library load? (y or [n]) y
Breakpoint 1 (test1.py:5) pending.
(gdb) run test1.py
Starting program: <path>/bin/python test1.py
...
Breakpoint 1, __main__::foo_241[abi:c8tJTC_2fWgEeGLSgydRTQUgiqKEZ6gEoDvQJmaQIA](long␣
↪long) (a=123) at test1.py:5
5           b = a + 1
(gdb) info args
a = 123
```

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```
(gdb) n
6           c = a * 2.34
(gdb) info locals
b = 124
c = 0
d = {f0 = 0, f1 = 0, f2 = 0}
(gdb) n
7           d = (a, b, c)
(gdb) info locals
b = 124
c = 287.81999999999999
d = {f0 = 0, f1 = 0, f2 = 0}
(gdb) whatis b
type = int64
(gdb) whatis d
type = Tuple(int64, int64, float64) ({i64, i64, double})
(gdb) n
8           print(a, b, c, d)
(gdb) print b
$1 = 124
(gdb) print d
$2 = {f0 = 123, f1 = 124, f2 = 287.81999999999999}
(gdb) bt
#0  __main__::foo_241[abi:c8tJTC_2fWgEeGLSgydRTQUgiqKEZ6gEoDvQJmaQIA](long long)␣
↪(a=123) at test1.py:8
#1  0x00007ffff06439fa in cpython::__main__::foo_241[abi:c8tJTC_
↪2fWgEeGLSgydRTQUgiqKEZ6gEoDvQJmaQIA](long long) ()
```

Another example follows that makes use of the Numba `gdb` printing extension mentioned above, note the change in the print format once the extension is loaded with `source` :

The Python source:

```
from numba import njit
import numpy as np

@njit(debug=True)
def foo(n):
    x = np.arange(n)
    y = (x[0], x[-1])
    return x, y

foo(4)
```

In the terminal:

```
$ NUMBA_OPT=0 NUMBA_EXTEND_VARIABLE_LIFETIMES=1 gdb -q python
Reading symbols from python...
(gdb) set breakpoint pending on
(gdb) break test2.py:8
No source file named test2.py.
Breakpoint 1 (test2.py:8) pending.
(gdb) run test2.py
```

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```
Starting program: <path>/bin/python test2.py
...
Breakpoint 1, __main__::foo_241[abi:c8tJTC_2fWgEeGLSgydRTQUgiqKEZ6gEoDvQJmaQIA](long␣
↪long) (n=4) at test2.py:8
8           return x, y
(gdb) print x
$1 = {meminfo = 0x55555688f470 "\001", parent = 0x0, nitems = 4, itemsize = 8, data =␣
↪0x55555688f4a0, shape = {4}, strides = {8}}
(gdb) print y
$2 = {0, 3}
(gdb) source numba/misc/gdb_print_extension.py
(gdb) print x
$3 =
[0 1 2 3]
(gdb) print y
$4 = (0, 3)
```

Globally override debug setting

It is possible to enable debug for the full application by setting environment variable `NUMBA_DEBUGINFO=1`. This sets the default value of the `debug` option in `jit`. Debug can be turned off on individual functions by setting `debug=False`.

Beware that enabling debug info significantly increases the memory consumption for each compiled function. For large application, this may cause out-of-memory error.

1.17.8 Using Numba's direct `gdb` bindings in `nopython` mode

Numba (version 0.42.0 and later) has some additional functions relating to `gdb` support for CPUs that make it easier to debug programs. All the `gdb` related functions described in the following work in the same manner irrespective of whether they are called from the standard CPython interpreter or code compiled in either *nopython mode* or *object mode*.

Note: This feature is experimental!

Warning: This feature does unexpected things if used from Jupyter or alongside the `pdb` module. It's behaviour is harmless, just hard to predict!

Set up

Numba's `gdb` related functions make use of a `gdb` binary, the location and name of this binary can be configured via the *NUMBA_GDB_BINARY* environment variable if desired.

Note: Numba's `gdb` support requires the ability for `gdb` to attach to another process. On some systems (notably Ubuntu Linux) default security restrictions placed on `ptrace` prevent this from being possible. This restriction is enforced at the system level by the Linux security module *Yama*. Documentation for this module and the security implications of making changes to its behaviour can be found in the Linux Kernel documentation. The Ubuntu Linux security

documentation discusses how to adjust the behaviour of *Yama* on with regards to `ptrace_scope` so as to permit the required behaviour.

Basic gdb support

Warning: Calling `numba.gdb()` and/or `numba.gdb_init()` more than once in the same program is not advisable, unexpected things may happen. If multiple breakpoints are desired within a program, launch `gdb` once via `numba.gdb()` or `numba.gdb_init()` and then use `numba.gdb_breakpoint()` to register additional breakpoint locations.

The most simple function for adding `gdb` support is `numba.gdb()`, which, at the call location, will:

- launch `gdb` and attach it to the running process.
- create a breakpoint at the site of the `numba.gdb()` function call, the attached `gdb` will pause execution here awaiting user input.

use of this functionality is best motivated by example, continuing with the example used above:

```
from numba import njit, gdb

@njit(debug=True)
def foo(a):
    b = a + 1
    gdb() # instruct Numba to attach gdb at this location and pause execution
    c = a * 2.34
    d = (a, b, c)
    print(a, b, c, d)

r= foo(123)
print(r)
```

In the terminal (`...` on a line by itself indicates output that is not presented for brevity):

```
$ NUMBA_OPT=0 NUMBA_EXTEND_VARIABLE_LIFETIMES=1 python demo_gdb.py
...
Breakpoint 1, 0x00007fb75238d830 in numba_gdb_breakpoint () from numba/_helperlib.
↪cpython-39-x86_64-linux-gnu.so
(gdb) s
Single stepping until exit from function numba_gdb_breakpoint,
which has no line number information.
0x00007fb75233e1cf in numba::misc::gdb_hook::hook_gdb::_3clocals_3e::impl_
↪242[abi:c8tJTIeFCjyCbUFRqqOAK_2f6h0phxApMogijRBAA_3d](StarArgTuple) ()
(gdb) s
Single stepping until exit from function _ZN5numba4misc8gdb_hook8hook_gdb12_3clocals_
↪3e8impl_242B44c8tJTIeFCjyCbUFRqqOAK_2f6h0phxApMogijRBAA_3dE12StarArgTuple,
which has no line number information.
__main__::foo_241[abi:c8tJTC_2fWgEeGLSgydRTQUgiqKEZ6gEoDvQJmaQIA](long long) (a=123) at␣
↪demo_gdb.py:7
7           c = a * 2.34
(gdb) l
2
```

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```
3       @njit(debug=True)
4       def foo(a):
5           b = a + 1
6           gdb() # instruct Numba to attach gdb at this location and pause execution
7           c = a * 2.34
8           d = (a, b, c)
9           print(a, b, c, d)
10
11      r= foo(123)
(gdb) p a
$1 = 123
(gdb) p b
$2 = 124
(gdb) p c
$3 = 0
(gdb) b 9
Breakpoint 2 at 0x7fb73d1f7287: file demo_gdb.py, line 9.
(gdb) c
Continuing.

Breakpoint 2, __main__::foo_241[abi:c8tJTC_2fWgEeGLSgydRTQUgiqKEZ6gEoDvQJmaQIA](long␣
↪long) (a=123) at demo_gdb.py:9
9           print(a, b, c, d)
(gdb) info locals
b = 124
c = 287.81999999999999
d = {f0 = 123, f1 = 124, f2 = 287.81999999999999}
```

It can be seen in the above example that execution of the code is paused at the location of the `gdb()` function call at end of the `numba_gdb_breakpoint` function (this is the Numba internal symbol registered as breakpoint with `gdb`). Issuing a `step` twice at this point moves to the stack frame of the compiled Python source. From there, it can be seen that the variables `a` and `b` have been evaluated but `c` has not, as demonstrated by printing their values, this is precisely as expected given the location of the `gdb()` call. Issuing a `break` on line 9 and then continuing execution leads to the evaluation of line 7. The variable `c` is assigned a value as a result of the execution and this can be seen in output of `info locals` when the breakpoint is hit.

Running with `gdb` enabled

The functionality provided by `numba.gdb()` (launch and attach `gdb` to the executing process and pause on a breakpoint) is also available as two separate functions:

- `numba.gdb_init()` this function injects code at the call site to launch and attach `gdb` to the executing process but does not pause execution.
- `numba.gdb_breakpoint()` this function injects code at the call site that will call the special `numba_gdb_breakpoint` function that is registered as a breakpoint in Numba's `gdb` support. This is demonstrated in the next section.

This functionality enables more complex debugging capabilities. Again, motivated by example, debugging a 'segfault' (memory access violation signalling `SIGSEGV`):

```
1  from numba import njit, gdb_init
2  import numpy as np
```

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```
3
4   # NOTE debug=True switches bounds-checking on, but for the purposes of this
5   # example it is explicitly turned off so that the out of bounds index is
6   # not caught!
7   @njit(debug=True, boundscheck=False)
8   def foo(a, index):
9       gdb_init() # instruct Numba to attach gdb at this location, but not to pause␣
    ↪execution
10      b = a + 1
11      c = a * 2.34
12      d = c[index] # access an address that is a) invalid b) out of the page
13      print(a, b, c, d)
14
15  bad_index = int(1e9) # this index is invalid
16  z = np.arange(10)
17  r = foo(z, bad_index)
18  print(r)
```

In the terminal (`...` on a line by itself indicates output that is not presented for brevity):

```
$ NUMBA_OPT=0 python demo_gdb_segfault.py
...
Program received signal SIGSEGV, Segmentation fault.
0x00007f5a4ca655eb in __main__::foo_241[abi:c8tJTC_
↪2fWgEeGLSgydRTQUgiqKEZ6gEoDvQJmaQIA](Array<long long, 1, C, mutable, aligned>, long␣
↪long) (a=..., index=1000000000) at demo_gdb_segfault.py:12
12          d = c[index] # access an address that is a) invalid b) out of the page
(gdb) p index
$1 = 1000000000
(gdb) p c
$2 = {meminfo = 0x5586cfb95830 "\001", parent = 0x0, nitems = 10, itemsize = 8, data =␣
↪0x5586cfb95860, shape = {10}, strides = {8}}
(gdb) whatis c
type = array(float64, 1d, C) ({i8*, i8*, i64, i64, double*, [1 x i64], [1 x i64]})
(gdb) p c.nitems
$3 = 10
```

In the `gdb` output it can be noted that a `SIGSEGV` signal was caught, and the line in which the access violation occurred is printed.

Continuing the example as a debugging session demonstration, first `index` can be printed, and it is evidently 1e9. Printing `c` shows that it is a structure, so the type needs looking up and it can be seen that it is an `array(float64, 1d, C)` type. Given the segfault came from an invalid access it would be informative to check the number of items in the array and compare that to the index requested. Inspecting the `nitems` member of the structure `c` shows 10 items. It's therefore clear that the segfault comes from an invalid access of index `1000000000` in an array containing `10` items.

Adding breakpoints to code

The next example demonstrates using multiple breakpoints that are defined through the invocation of the `numba.gdb_breakpoint()` function:

```
from numba import njit, gdb_init, gdb_breakpoint

@njit(debug=True)
def foo(a):
    gdb_init() # instruct Numba to attach gdb at this location
    b = a + 1
    gdb_breakpoint() # instruct gdb to break at this location
    c = a * 2.34
    d = (a, b, c)
    gdb_breakpoint() # and to break again at this location
    print(a, b, c, d)

r= foo(123)
print(r)
```

In the terminal (`...` on a line by itself indicates output that is not presented for brevity):

```
$ NUMBA_OPT=0 python demo_gdb_breakpoints.py
...
Breakpoint 1, 0x00007fb65bb4c830 in numba_gdb_breakpoint () from numba/_helperlib.
↪cpython-39-x86_64-linux-gnu.so
(gdb) step
Single stepping until exit from function numba_gdb_breakpoint,
which has no line number information.
__main__::foo_241[abi:c8tJTC_2fWgEeGLSgydRTQUgiqKEZ6gEoDvQJmaQIA](long long) (a=123) at␣
↪demo_gdb_breakpoints.py:8
8           c = a * 2.34
(gdb) l
3       @njit(debug=True)
4       def foo(a):
5           gdb_init() # instruct Numba to attach gdb at this location
6           b = a + 1
7           gdb_breakpoint() # instruct gdb to break at this location
8           c = a * 2.34
9           d = (a, b, c)
10          gdb_breakpoint() # and to break again at this location
11          print(a, b, c, d)
12
(gdb) p b
$1 = 124
(gdb) p c
$2 = 0
(gdb) c
Continuing.

Breakpoint 1, 0x00007fb65bb4c830 in numba_gdb_breakpoint ()
from numba/_helperlib.cpython-39-x86_64-linux-gnu.so
(gdb) step
11          print(a, b, c, d)
```

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```
(gdb) p c
$3 = 287.81999999999999
```

From the gdb output it can be seen that execution paused at line 8 as a breakpoint was hit, and after a `continue` was issued, it broke again at line 11 where the next breakpoint was hit.

Debugging in parallel regions

The following example is quite involved, it executes with gdb instrumentation from the outset as per the example above, but it also uses threads and makes use of the breakpoint functionality. Further, the last iteration of the parallel section calls the function `work`, which is actually just a binding to `glibc`'s `free(3)` in this case, but could equally be some involved function that is presenting a segfault for unknown reasons.

```
1  from numba import njit, prange, gdb_init, gdb_breakpoint
2  import ctypes
3
4  def get_free():
5      lib = ctypes.cdll.LoadLibrary('libc.so.6')
6      free_binding = lib.free
7      free_binding.argtypes = [ctypes.c_void_p,]
8      free_binding.restype = None
9      return free_binding
10
11 work = get_free()
12
13 @njit(debug=True, parallel=True)
14 def foo():
15     gdb_init() # instruct Numba to attach gdb at this location, but not to pause␣
   ↪execution
16     counter = 0
17     n = 9
18     for i in prange(n):
19         if i > 3 and i < 8: # iterations 4, 5, 6, 7 will break here
20             gdb_breakpoint()
21
22         if i == 8: # last iteration segfaults
23             work(0xBADADD)
24
25         counter += 1
26     return counter
27
28 r = foo()
29 print(r)
```

In the terminal (`...` on a line by itself indicates output that is not presented for brevity), note the setting of `NUMBA_NUM_THREADS` to 4 to ensure that there are 4 threads running in the parallel section:

```
$ NUMBA_NUM_THREADS=4 NUMBA_OPT=0 python demo_gdb_threads.py
Attaching to PID: 21462
...
Attaching to process 21462
[New LWP 21467]
```

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```
[New LWP 21468]
[New LWP 21469]
[New LWP 21470]
[Thread debugging using libthread_db enabled]
Using host libthread_db library "/lib64/libthread_db.so.1".
0x00007f59ec31756d in nanosleep () at ../sysdeps/unix/syscall-template.S:81
81      T_PSEUDO (SYSCALL_SYMBOL, SYSCALL_NAME, SYSCALL_NARGS)
Breakpoint 1 at 0x7f59d631e8f0: file numba/_helperlib.c, line 1090.
Continuing.
[Switching to Thread 0x7f59d1fd1700 (LWP 21470)]

Thread 5 "python" hit Breakpoint 1, numba_gdb_breakpoint () at numba/_helperlib.c:1090
1090    }
(gdb) info threads
Id   Target Id         Frame
1    Thread 0x7f59eca2f740 (LWP 21462) "python" pthread_cond_wait@@GLIBC_2.3.2 ()
    at ../nptl/sysdeps/unix/sysv/linux/x86_64/pthread_cond_wait.S:185
2    Thread 0x7f59d37d4700 (LWP 21467) "python" pthread_cond_wait@@GLIBC_2.3.2 ()
    at ../nptl/sysdeps/unix/sysv/linux/x86_64/pthread_cond_wait.S:185
3    Thread 0x7f59d2fd3700 (LWP 21468) "python" pthread_cond_wait@@GLIBC_2.3.2 ()
    at ../nptl/sysdeps/unix/sysv/linux/x86_64/pthread_cond_wait.S:185
4    Thread 0x7f59d27d2700 (LWP 21469) "python" numba_gdb_breakpoint () at numba/_
↪helperlib.c:1090
* 5    Thread 0x7f59d1fd1700 (LWP 21470) "python" numba_gdb_breakpoint () at numba/_
↪helperlib.c:1090
(gdb) thread apply 2-5 info locals

Thread 2 (Thread 0x7f59d37d4700 (LWP 21467)):
No locals.

Thread 3 (Thread 0x7f59d2fd3700 (LWP 21468)):
No locals.

Thread 4 (Thread 0x7f59d27d2700 (LWP 21469)):
No locals.

Thread 5 (Thread 0x7f59d1fd1700 (LWP 21470)):
sched$35 = '\000' <repeats 55 times>
counter__arr = '\000' <repeats 16 times>, "\001\000\000\000\000\000\000\b\000\000\
↪000\000\000\000\000\370B]\"hU\000\000\001", '\000' <repeats 14 times>
counter = 0
(gdb) continue
Continuing.
[Switching to Thread 0x7f59d27d2700 (LWP 21469)]

Thread 4 "python" hit Breakpoint 1, numba_gdb_breakpoint () at numba/_helperlib.c:1090
1090    }
(gdb) continue
Continuing.
[Switching to Thread 0x7f59d1fd1700 (LWP 21470)]

Thread 5 "python" hit Breakpoint 1, numba_gdb_breakpoint () at numba/_helperlib.c:1090
```

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```
1090    }
(gdb) continue
Continuing.
[Switching to Thread 0x7f59d27d2700 (LWP 21469)]

Thread 4 "python" hit Breakpoint 1, numba_gdb_breakpoint () at numba/_helperlib.c:1090
1090    }
(gdb) continue
Continuing.

Thread 5 "python" received signal SIGSEGV, Segmentation fault.
[Switching to Thread 0x7f59d1fd1700 (LWP 21470)]
__GI___libc_free (mem=0xbadadd) at malloc.c:2935
2935      if (chunk_is_mmapped(p))                       /* release mmapped memory. */
(gdb) bt
#0  __GI___libc_free (mem=0xbadadd) at malloc.c:2935
#1  0x00007f59d37ded84 in $3cdynamic$3e::__numba_parfor_gufunc__0x7ffff80a61ae3e31
↪$244(Array<unsigned long long, 1, C, mutable, aligned>, Array<long long, 1, C, mutable,
↪ aligned>) () at <string>:24
#2  0x00007f59d17ce326 in __gufunc__._ZN13$3cdynamic$3e45__numba_parfor_gufunc__
↪0x7ffff80a61ae3e31$244E5ArrayIyLi1E1C7mutable7alignedE5ArrayIxLi1E1C7mutable7alignedE␣
↪()
#3  0x00007f59d37d7320 in thread_worker ()
from <path>/numba/numba/npyufunc/workqueue.cpython-37m-x86_64-linux-gnu.so
#4  0x00007f59ec626e25 in start_thread (arg=0x7f59d1fd1700) at pthread_create.c:308
#5  0x00007f59ec350bad in clone () at ../sysdeps/unix/sysv/linux/x86_64/clone.S:113
```

In the output it can be seen that there are 4 threads launched and that they all break at the breakpoint, further that `Thread 5` receives a signal `SIGSEGV` and that back tracing shows that it came from `__GI___libc_free` with the invalid address in `mem`, as expected.

Using the `gdb` command language

Both the `numba.gdb()` and `numba.gdb_init()` functions accept unlimited string arguments which will be passed directly to `gdb` as command line arguments when it initializes, this makes it easy to set breakpoints on other functions and perform repeated debugging tasks without having to manually type them every time. For example, this code runs with `gdb` attached and sets a breakpoint on `_dgesdd` (say for example the arguments passed to the LAPACK's double precision divide and conqueror SVD function need debugging).

```
1  from numba import njit, gdb
2  import numpy as np
3
4  @njit(debug=True)
5  def foo(a):
6      # instruct Numba to attach gdb at this location and on launch, switch
7      # breakpoint pending on , and then set a breakpoint on the function
8      # _dgesdd, continue execution, and once the breakpoint is hit, backtrace
9      gdb('-ex', 'set breakpoint pending on',
10         '-ex', 'b dgesdd_',
11         '-ex','c',
12         '-ex','bt')
```

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```
    b = a + 10
    u, s, vh = np.linalg.svd(b)
    return s # just return singular values

z = np.arange(70.).reshape(10, 7)
r = foo(z)
print(r)
```

In the terminal (... on a line by itself indicates output that is not presented for brevity), note that no interaction is required to break and backtrace:

```
$ NUMBA_OPT=0 python demo_gdb_args.py
Attaching to PID: 22300
GNU gdb (GDB) Red Hat Enterprise Linux 8.0.1-36.el7
...
Attaching to process 22300
Reading symbols from <py_env>/bin/python3.7...done.
0x00007f652305a550 in __nanosleep_nocancel () at ../sysdeps/unix/syscall-template.S:81
81      T_PSEUDO (SYSCALL_SYMBOL, SYSCALL_NAME, SYSCALL_NARGS)
Breakpoint 1 at 0x7f650d0618f0: file numba/_helperlib.c, line 1090.
Continuing.

Breakpoint 1, numba_gdb_breakpoint () at numba/_helperlib.c:1090
1090    }
Breakpoint 2 at 0x7f65102322e0 (2 locations)
Continuing.

Breakpoint 2, 0x00007f65182be5f0 in mkl_lapack.dgesdd_ ()
from <py_env>/lib/python3.7/site-packages/numpy/core/../../../../libmkl_rt.so
#0  0x00007f65182be5f0 in mkl_lapack.dgesdd_ ()
from <py_env>/lib/python3.7/site-packages/numpy/core/../../../../libmkl_rt.so
#1  0x00007f650d065b71 in numba_raw_rgesdd (kind=kind@entry=100 'd', jobz=<optimized out>
↪, jobz@entry=65 'A', m=m@entry=10,
    n=n@entry=7, a=a@entry=0x561c6fbb20c0, lda=lda@entry=10, s=0x561c6facf3a0,␣
↪u=0x561c6fb680e0, ldu=10, vt=0x561c6fd375c0,
    ldvt=7, work=0x7fff4c926c30, lwork=-1, iwork=0x7fff4c926c40, info=0x7fff4c926c20) at␣
↪numba/_lapack.c:1277
#2  0x00007f650d06768f in numba_ez_rgesdd (ldvt=7, vt=0x561c6fd375c0, ldu=10,␣
↪u=0x561c6fb680e0, s=0x561c6facf3a0, lda=10,
    a=0x561c6fbb20c0, n=7, m=10, jobz=65 'A', kind=<optimized out>) at numba/_lapack.
↪c:1307
#3  numba_ez_gesdd (kind=<optimized out>, jobz=<optimized out>, m=10, n=7,␣
↪a=0x561c6fbb20c0, lda=10, s=0x561c6facf3a0,
    u=0x561c6fb680e0, ldu=10, vt=0x561c6fd375c0, ldvt=7) at numba/_lapack.c:1477
#4  0x00007f650a3147a3 in numba::targets::linalg::svd_impl::$3clocals$3e::svd_impl
↪$243(Array<double, 2, C, mutable, aligned>, omitted$28default$3d1$29) ()
#5  0x00007f650a1c0489 in __main__::foo$241(Array<double, 2, C, mutable, aligned>) () at␣
↪demo_gdb_args.py:15
#6  0x00007f650a1c2110 in cpython::__main__::foo$241(Array<double, 2, C, mutable,␣
↪aligned>) ()
#7  0x00007f650cd096a4 in call_cfunc ()
from <path>/numba/numba/_dispatcher.cpython-37m-x86_64-linux-gnu.so
```

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```
...
```

How does the gdb binding work?

For advanced users and debuggers of Numba applications it's important to know some of the internal implementation details of the outlined `gdb` bindings. The `numba.gdb()` and `numba.gdb_init()` functions work by injecting the following into the function's LLVM IR:

- At the call site of the function first inject a call to `getpid(3)` to get the PID of the executing process and store this for use later, then inject a `fork(3)` call:
  - In the parent:
    * Inject a call `sleep(3)` (hence the pause whilst `gdb` loads).
    * Inject a call to the `numba_gdb_breakpoint` function (only `numba.gdb()` does this).
  - In the child:
    * Inject a call to `execl(3)` with the arguments `numba.config.GDB_BINARY`, the `attach` command and the PID recorded earlier. Numba has a special `gdb` command file that contains instructions to break on the symbol `numba_gdb_breakpoint` and then `finish`, this is to make sure that the program stops on the breakpoint but the frame it stops in is the compiled Python frame (or one `step` away from, depending on optimisation). This command file is also added to the arguments and finally and any user specified arguments are added.

At the call site of a `numba.gdb_breakpoint()` a call is injected to the special `numba_gdb_breakpoint` symbol, which is already registered and instrumented as a place to break and `finish` immediately.

As a result of this, a e.g. `numba.gdb()` call will cause a fork in the program, the parent will sleep whilst the child launches `gdb` and attaches it to the parent and tells the parent to continue. The launched `gdb` has the `numba_gdb_breakpoint` symbol registered as a breakpoint and when the parent continues and stops sleeping it will immediately call `numba_gdb_breakpoint` on which the child will break. Additional `numba.gdb_breakpoint()` calls create calls to the registered breakpoint hence the program will also break at these locations.

1.17.9 Debugging CUDA Python code

Using the simulator

CUDA Python code can be run in the Python interpreter using the CUDA Simulator, allowing it to be debugged with the Python debugger or with print statements. To enable the CUDA simulator, set the environment variable *NUMBA_ENABLE_CUDASIM* to 1. For more information on the CUDA Simulator, see *the CUDA Simulator documentation*.

Debug Info

By setting the `debug` argument to `cuda.jit` to `True` (`@cuda.jit(debug=True)`), Numba will emit source location in the compiled CUDA code. Unlike the CPU target, only filename and line information are available, but no variable type information is emitted. The information is sufficient to debug memory error with cuda-memcheck.

For example, given the following cuda python code:

```
import numpy as np
from numba import cuda

@cuda.jit(debug=True)
def foo(arr):
    arr[cuda.threadIdx.x] = 1

arr = np.arange(30)
foo[1, 32](arr)   # more threads than array elements
```

We can use `cuda-memcheck` to find the memory error:

```
$ cuda-memcheck python chk_cuda_debug.py
========= CUDA-MEMCHECK
========= Invalid __global__ write of size 8
=========     at 0x00000148 in /home/user/chk_cuda_debug.py:6:cudapy::__main__::foo
↪$241(Array<__int64, int=1, C, mutable, aligned>)
=========     by thread (31,0,0) in block (0,0,0)
=========     Address 0x500a600f8 is out of bounds
...
=========
========= Invalid __global__ write of size 8
=========     at 0x00000148 in /home/user/chk_cuda_debug.py:6:cudapy::__main__::foo
↪$241(Array<__int64, int=1, C, mutable, aligned>)
=========     by thread (30,0,0) in block (0,0,0)
=========     Address 0x500a600f0 is out of bounds
...
```

1.18 Frequently Asked Questions

1.18.1 Installation

Numba could not be imported

If you are seeing an exception on importing Numba with an error message that starts with:

```
ImportError: Numba could not be imported.
```

here are some common issues and things to try to fix it.

1. Your installation has more than one version of Numba a given environment.

   Common ways this occurs include:

   - Installing Numba with conda and then installing again with pip.
   - Installing Numba with pip and then updating to a new version with pip (pip re-installations don't seem to always clean up very well).

   To fix this the best approach is to create an entirely new environment and install a single version of Numba in that environment using a package manager of your choice.

2. Your installation has Numba for Python version X but you are running with Python version Y.

This occurs due to a variety of Python environment mix-up/mismatch problems. The most common mismatch comes from installing Numba into the site-packages/environment of one version of Python by using a base or system installation of Python that is a different version, this typically happens through the use of the "wrong" `pip` binary. This will obviously cause problems as the C-Extensions on which Numba relies are bound to specific Python versions. A way to check if this likely the problem is to see if the path to the `python` binary at:

```
python -c 'import sys; print(sys.executable)'
```

matches the path to your installation tool and/or matches the reported installation location and if the Python versions match up across all of these. Note that Python version `X.Y.A` is compatible with `X.Y.B`.

To fix this the best approach is to create an entirely new environment and ensure that the installation tool used to install Numba is the one from that environment/the Python versions at install and run time match.

3. Your core system libraries are too old.

   This is a somewhat rare occurrence, but there are occasions when a very old (typically out of support) version of Linux is in use it doesn't have a `glibc` library with sufficiently new versioned symbols for Numba's shared libraries to resolve against. The fix for this is to update your OS system libraries/update your OS.

4. You are using an IDE e.g. Spyder.

   There are some unknown issues in relation to installing Numba via IDEs, but it would appear that these are likely variations of 1. or 2. with the same suggested fixes. Also, try installation from outside of the IDE with the command line.

If you have an installation problem which is not one of the above problems, please do ask on numba.discourse.group and if possible include the path where Numba is installed and also the output of:

```
python -c 'import sys; print(sys.executable)'
```

1.18.2 Programming

Can I pass a function as an argument to a jitted function?

As of Numba 0.39, you can, so long as the function argument has also been JIT-compiled:

```
@jit(nopython=True)
def f(g, x):
    return g(x) + g(-x)

result = f(jitted_g_function, 1)
```

However, dispatching with arguments that are functions has extra overhead. If this matters for your application, you can also use a factory function to capture the function argument in a closure:

```
def make_f(g):
    # Note: a new f() is created each time make_f() is called!
    @jit(nopython=True)
    def f(x):
        return g(x) + g(-x)
    return f

f = make_f(jitted_g_function)
result = f(1)
```

Improving the dispatch performance of functions in Numba is an ongoing task.

Numba doesn't seem to care when I modify a global variable

Numba considers global variables as compile-time constants. If you want your jitted function to update itself when you have modified a global variable's value, one solution is to recompile it using the *recompile()* method. This is a relatively slow operation, though, so you may instead decide to rearchitect your code and turn the global variable into a function argument.

Can I debug a jitted function?

Calling into pdb or other such high-level facilities is currently not supported from Numba-compiled code. However, you can temporarily disable compilation by setting the *NUMBA_DISABLE_JIT* environment variable.

How can I create a Fortran-ordered array?

Numba currently doesn't support the `order` argument to most Numpy functions such as `numpy.empty()` (because of limitations in the *type inference* algorithm). You can work around this issue by creating a C-ordered array and then transposing it. For example:

```
a = np.empty((3, 5), order='F')
b = np.zeros(some_shape, order='F')
```

can be rewritten as:

```
a = np.empty((5, 3)).T
b = np.zeros(some_shape[::-1]).T
```

How can I increase integer width?

By default, Numba will generally use machine integer width for integer variables. On a 32-bit machine, you may sometimes need the magnitude of 64-bit integers instead. You can simply initialize relevant variables as `np.int64` (for example `np.int64(0)` instead of `0`). It will propagate to all computations involving those variables.

How can I tell if `parallel=True` worked?

If the `parallel=True` transformations failed for a function decorated as such, a warning will be displayed. See also *Diagnostics* for information about parallel diagnostics.

1.18.3 Performance

Does Numba inline functions?

Numba gives enough information to LLVM so that functions short enough can be inlined. This only works in *nopython mode*.

Does Numba vectorize array computations (SIMD)?

Numba doesn't implement such optimizations by itself, but it lets LLVM apply them.

Why has my loop not vectorized?

Numba enables the loop-vectorize optimization in LLVM by default. While it is a powerful optimization, not all loops are applicable. Sometimes, loop-vectorization may fail due to subtle details like memory access pattern. To see additional diagnostic information from LLVM, add the following lines:

```
import llvmlite.binding as llvm
llvm.set_option('', '--debug-only=loop-vectorize')
```

This tells LLVM to print debug information from the **loop-vectorize** pass to stderr. Each function entry looks like:

Note: Using `--debug-only` requires LLVM to be build with assertions enabled to work. Use the build of llvmlite in the Numba channel which is linked against LLVM with assertions enabled.

```
LV: Checking a loop in "<low-level symbol name>" from <function name>
LV: Loop hints: force=? width=0 unroll=0
...
LV: Vectorization is possible but not beneficial.
LV: Interleaving is not beneficial.
```

Each function entry is separated by an empty line. The reason for rejecting the vectorization is usually at the end of the entry. In the example above, LLVM rejected the vectorization because doing so will not speedup the loop. In this case, it can be due to memory access pattern. For instance, the array being looped over may not be in contiguous layout.

When memory access pattern is non-trivial such that it cannot determine the access memory region, LLVM may reject with the following message:

```
LV: Can't vectorize due to memory conflicts
```

Another common reason is:

```
LV: Not vectorizing: loop did not meet vectorization requirements.
```

In this case, vectorization is rejected because the vectorized code may behave differently. This is a case to try turning on `fastmath=True` to allow fastmath instructions.

Why are the `typed` containers slower when used from the interpreter?

The Numba `typed` containers found in `numba.typed` e.g. `numba.typed.List` store their data in an efficient form for access from JIT compiled code. When these containers are used from the CPython interpreter, the data involved has to be converted from/to the container format. This process is relatively costly and as a result impacts performance. In JIT compiled code no such penalty exists and so operations on the containers are much quicker and often faster than the pure Python equivalent.

Does Numba automatically parallelize code?

It can, in some cases:

- Ufuncs and gufuncs with the `target="parallel"` option will run on multiple threads.
- The `parallel=True` option to `@jit` will attempt to optimize array operations and run them in parallel. It also adds support for `prange()` to explicitly parallelize a loop.

You can also manually run computations on multiple threads yourself and use the `nogil=True` option (see *releasing the GIL*). Numba can also target parallel execution on GPU architectures using its CUDA and HSA backends.

Can Numba speed up short-running functions?

Not significantly. New users sometimes expect to JIT-compile such functions:

```
def f(x, y):
    return x + y
```

and get a significant speedup over the Python interpreter. But there isn't much Numba can improve here: most of the time is probably spent in CPython's function call mechanism, rather than the function itself. As a rule of thumb, if a function takes less than 10 µs to execute: leave it.

The exception is that you *should* JIT-compile that function if it is called from another jitted function.

There is a delay when JIT-compiling a complicated function, how can I improve it?

Try to pass `cache=True` to the `@jit` decorator. It will keep the compiled version on disk for later use.

A more radical alternative is *ahead-of-time compilation*.

1.18.4 GPU Programming

How do I work around the `CUDA initialized before forking` error?

On Linux, the `multiprocessing` module in the Python standard library defaults to using the `fork` method for creating new processes. Because of the way process forking duplicates state between the parent and child processes, CUDA will not work correctly in the child process if the CUDA runtime was initialized *prior* to the fork. Numba detects this and raises a `CudaDriverError` with the message `CUDA initialized before forking`.

One approach to avoid this error is to make all calls to `numba.cuda` functions inside the child processes or after the process pool is created. However, this is not always possible, as you might want to query the number of available GPUs before starting the process pool. In Python 3, you can change the process start method, as described in the multiprocessing documentation. Switching from `fork` to `spawn` or `forkserver` will avoid the CUDA initialization issue, although the child processes will not inherit any global variables from their parent.

1.18.5 Integration with other utilities

Can I "freeze" an application which uses Numba?

If you're using PyInstaller or a similar utility to freeze an application, you may encounter issues with llvmlite. llvmlite needs a non-Python DLL for its working, but it won't be automatically detected by freezing utilities. You have to inform the freezing utility of the DLL's location: it will usually be named `llvmlite/binding/libllvmlite.so` or `llvmlite/binding/llvmlite.dll`, depending on your system.

I get errors when running a script twice under Spyder

When you run a script in a console under Spyder, Spyder first tries to reload existing modules. This doesn't work well with Numba, and can produce errors like `TypeError: No matching definition for argument type(s)`.

There is a fix in the Spyder preferences. Open the "Preferences" window, select "Console", then "Advanced Settings", click the "Set UMR excluded modules" button, and add `numba` inside the text box that pops up.

To see the setting take effect, be sure to restart the IPython console or kernel.

Why does Numba complain about the current locale?

If you get an error message such as the following:

```
RuntimeError: Failed at nopython (nopython mode backend)
LLVM will produce incorrect floating-point code in the current locale
```

it means you have hit a LLVM bug which causes incorrect handling of floating-point constants. This is known to happen with certain third-party libraries such as the Qt backend to matplotlib.

To work around the bug, you need to force back the locale to its default value, for example:

```
import locale
locale.setlocale(locale.LC_NUMERIC, 'C')
```

How do I get Numba development builds?

Pre-release versions of Numba can be installed with conda:

```
$ conda install -c numba/label/dev numba
```

1.18.6 Miscellaneous

Where does the project name "Numba" come from?

"Numba" is a combination of "NumPy" and "Mamba". Mambas are some of the fastest snakes in the world, and Numba makes your Python code fast.

How do I reference/cite/acknowledge Numba in other work?

For academic use, the best option is to cite our ACM Proceedings: Numba: a LLVM-based Python JIT compiler. You can also find the sources on github, including a pre-print pdf, in case you don't have access to the ACM site but would like to read the paper.

Other related papers

A paper describing ParallelAccelerator technology, that is activated when the `parallel=True` jit option is used, can be found here.

How do I write a minimal working reproducer for a problem with Numba?

A minimal working reproducer for Numba should include:

1. The source code of the function(s) that reproduce the problem.
2. Some example data and a demonstration of calling the reproducing code with that data. As Numba compiles based on type information, unless your problem is numerical, it's fine to just provide dummy data of the right type, e.g. use `numpy.ones` of the correct `dtype`/size/shape for arrays.
3. Ideally put 1. and 2. into a script with all the correct imports. Make sure your script actually executes and reproduces the problem before submitting it! The target is to make it so that the script can just be copied directly from the issue tracker and run by someone else such that they can see the same problem as you are having.

Having made a reproducer, now remove every part of the code that does not contribute directly to reproducing the problem to create a "minimal" reproducer. This means removing imports that aren't used, removing variables that aren't used or have no effect, removing lines of code which have no effect, reducing the complexity of expressions, and shrinking input data to the minimal amount required to trigger the problem.

Doing the above really helps out the Numba issue triage process and will enable a faster response to your problem!

Suggested further reading on writing minimal working reproducers.

1.19 Examples

1.19.1 Mandelbrot

Listing 30: from `test_mandelbrot` of `numba/tests/doc_examples/test_examples.py`

```
from timeit import default_timer as timer
try:
    from matplotlib.pylab import imshow, show
    have_mpl = True
except ImportError:
    have_mpl = False
import numpy as np
from numba import jit

@jit(nopython=True)
def mandel(x, y, max_iters):
```

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```
    """
    Given the real and imaginary parts of a complex number,
    determine if it is a candidate for membership in the Mandelbrot
    set given a fixed number of iterations.
    """
    i = 0
    c = complex(x,y)
    z = 0.0j
    for i in range(max_iters):
        z = z * z + c
        if (z.real * z.real + z.imag * z.imag) >= 4:
            return i

    return 255

@jit(nopython=True)
def create_fractal(min_x, max_x, min_y, max_y, image, iters):
    height = image.shape[0]
    width = image.shape[1]

    pixel_size_x = (max_x - min_x) / width
    pixel_size_y = (max_y - min_y) / height
    for x in range(width):
        real = min_x + x * pixel_size_x
        for y in range(height):
            imag = min_y + y * pixel_size_y
            color = mandel(real, imag, iters)
            image[y, x] = color

    return image

image = np.zeros((500 * 2, 750 * 2), dtype=np.uint8)
s = timer()
create_fractal(-2.0, 1.0, -1.0, 1.0, image, 20)
e = timer()
print(e - s)
if have_mpl:
    imshow(image)
    show()
```

1.19.2 Moving average

Listing 31: from test_moving_average of numba/tests/doc_examples/test_examples.py

```
import numpy as np

from numba import guvectorize

@guvectorize(['void(float64[:], intp[:], float64[:])'],
```

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```
            '(n),()->(n)')
def move_mean(a, window_arr, out):
    window_width = window_arr[0]
    asum = 0.0
    count = 0
    for i in range(window_width):
        asum += a[i]
        count += 1
        out[i] = asum / count
    for i in range(window_width, len(a)):
        asum += a[i] - a[i - window_width]
        out[i] = asum / count

arr = np.arange(20, dtype=np.float64).reshape(2, 10)
print(arr)
print(move_mean(arr, 3))
```

1.19.3 Multi-threading

The code below showcases the potential performance improvement when using the *nogil* feature. For example, on a 4-core machine, the following results were printed:

```
numpy (1 thread)        145 ms
numba (1 thread)        128 ms
numba (4 threads)        35 ms
```

Note: If preferred it's possible to use the standard concurrent.futures module rather than spawn threads and dispatch tasks by hand.

Listing 32: from `test_no_gil` of `numba/tests/doc_examples/test_examples.py`

```
import math
import threading
from timeit import repeat

import numpy as np
from numba import jit

nthreads = 4
size = 10**6

def func_np(a, b):
    """
    Control function using Numpy.
    """
    return np.exp(2.1 * a + 3.2 * b)

@jit('void(double[:], double[:], double[:])', nopython=True,
```

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```
     nogil=True)
def inner_func_nb(result, a, b):
    """
    Function under test.
    """
    for i in range(len(result)):
        result[i] = math.exp(2.1 * a[i] + 3.2 * b[i])

def timefunc(correct, s, func, *args, **kwargs):
    """
    Benchmark *func* and print out its runtime.
    """
    print(s.ljust(20), end=" ")
    # Make sure the function is compiled before the benchmark is
    # started
    res = func(*args, **kwargs)
    if correct is not None:
        assert np.allclose(res, correct), (res, correct)
    # time it
    print('{:>5.0f} ms'.format(min(repeat(
        lambda: func(*args, **kwargs), number=5, repeat=2)) * 1000))
    return res

def make_singlethread(inner_func):
    """
    Run the given function inside a single thread.
    """
    def func(*args):
        length = len(args[0])
        result = np.empty(length, dtype=np.float64)
        inner_func(result, *args)
        return result
    return func

def make_multithread(inner_func, numthreads):
    """
    Run the given function inside *numthreads* threads, splitting
    its arguments into equal-sized chunks.
    """
    def func_mt(*args):
        length = len(args[0])
        result = np.empty(length, dtype=np.float64)
        args = (result,) + args
        chunklen = (length + numthreads - 1) // numthreads
        # Create argument tuples for each input chunk
        chunks = [[arg[i * chunklen:(i + 1) * chunklen] for arg in
                   args] for i in range(numthreads)]
        # Spawn one thread per chunk
        threads = [threading.Thread(target=inner_func, args=chunk)
                   for chunk in chunks]
        for thread in threads:
            thread.start()
```

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```
        for thread in threads:
            thread.join()
        return result
    return func_mt

func_nb = make_singlethread(inner_func_nb)
func_nb_mt = make_multithread(inner_func_nb, nthreads)

a = np.random.rand(size)
b = np.random.rand(size)

correct = timefunc(None, "numpy (1 thread)", func_np, a, b)
timefunc(correct, "numba (1 thread)", func_nb, a, b)
timefunc(correct, "numba (%d threads)" % nthreads, func_nb_mt, a, b)
```

1.20 Talks and Tutorials

Note: This is a selection of talks and tutorials that have been given by members of the Numba team as well as Numba users. If you know of a Numba-related talk that should be included on this list, please open an issue.

1.20.1 Talks on Numba

- AnacondaCON 2018 - Accelerating Scientific Workloads with Numba - Siu Kwan Lam (Video)
- DIANA-HEP Meeting, 23 April 2018 - Overview of Numba - Stan Seibert

1.20.2 Talks on Applications of Numba

- GPU Technology Conference 2016 - Accelerating a Spectral Algorithm for Plasma Physics with Python/Numba on GPU - Manuel Kirchen & Rémi Lehe (Slides)
- DIANA-HEP Meeting, 23 April 2018 - Use of Numba in XENONnT - Chris Tunnell
- DIANA-HEP Meeting, 23 April 2018 - Extending Numba for HEP data types - Jim Pivarski
- STAC Summit, Nov 1 2017 - Scaling High-Performance Python with Minimal Effort - Ehsan Totoni (Video, Slides)
- SciPy 2018 - UMAP: Uniform Manifold Approximation and Projection for Dimensional Reduction - Leland McInnes (Video, Github)
- PyData Berlin 2018 - Extending Pandas using Apache Arrow and Numba - Uwe L. Korn (Video, Blog)
- FOSDEM 2019 - Extending Numba - Joris Geessels (Video, Slides & Examples)
- PyCon India 2019 - Real World Numba: Taking the Path of Least Resistance - Ankit Mahato (Video)
- SciPy 2019 - How to Accelerate an Existing Codebase with Numba - Siu Kwan Lam & Stanley Seibert (Video)
- SciPy 2019 - Real World Numba: Creating a Skeleton Analysis Library - Juan Nunez-Iglesias (Video)
- SciPy 2019 - Fast Gradient Boosting Decision Trees with PyGBM and Numba - Nicholas Hug (Video)

- PyCon Sweden 2020 - Accelerating Scientific Computing using Numba - Ankit Mahato (Video)

1.20.3 Tutorials

- SciPy 2017 - Numba: Tell those C++ Bullies to Get Lost - Gil Forsyth & Lorena Barba (Video, Notebooks)
- GPU Technology Conference 2018 - GPU Computing in Python with Numba - Stan Seibert (Notebooks)
- PyData Amsterdam 2019 - Create CUDA kernels from Python using Numba and CuPy - Valentin Haenel (Video)

CHAPTER

TWO

REFERENCE MANUAL

2.1 Types and signatures

2.1.1 Rationale

As an optimizing compiler, Numba needs to decide on the type of each variable to generate efficient machine code. Python's standard types are not precise enough for that, so we had to develop our own fine-grained type system.

You will encounter Numba types mainly when trying to inspect the results of Numba's type inference, for *debugging* or *educational* purposes. However, you need to use types explicitly if compiling code *ahead-of-time*.

2.1.2 Signatures

A signature specifies the type of a function. Exactly which kind of signature is allowed depends on the context (*AOT* or *JIT* compilation), but signatures always involve some representation of Numba types to specify the concrete types for the function's arguments and, if required, the function's return type.

An example function signature would be the string `"f8(i4, i4)"` (or the equivalent `"float64(int32, int32)"`) which specifies a function taking two 32-bit integers and returning a double-precision float.

2.1.3 Basic types

The most basic types can be expressed through simple expressions. The symbols below refer to attributes of the main `numba` module (so if you read "boolean", it means that symbol can be accessed as `numba.boolean`). Many types are available both as a canonical name and a shorthand alias, following NumPy's conventions.

Numbers

The following table contains the elementary numeric types currently defined by Numba and their aliases.

Type name(s)	Shorthand	Comments
boolean	b1	represented as a byte
uint8, byte	u1	8-bit unsigned byte
uint16	u2	16-bit unsigned integer
uint32	u4	32-bit unsigned integer
uint64	u8	64-bit unsigned integer
int8, char	i1	8-bit signed byte
int16	i2	16-bit signed integer
int32	i4	32-bit signed integer
int64	i8	64-bit signed integer
intc	–	C int-sized integer
uintc	–	C int-sized unsigned integer
intp	–	pointer-sized integer
uintp	–	pointer-sized unsigned integer
ssize_t	–	C ssize_t
size_t	–	C size_t
float32	f4	single-precision floating-point number
float64, double	f8	double-precision floating-point number
complex64	c8	single-precision complex number
complex128	c16	double-precision complex number

Arrays

The easy way to declare *Array* types is to subscript an elementary type according to the number of dimensions. For example a 1-dimension single-precision array:

```
>>> numba.float32[:]
array(float32, 1d, A)
```

or a 3-dimension array of the same underlying type:

```
>>> numba.float32[:, :, :]
array(float32, 3d, A)
```

This syntax defines array types with no particular layout (producing code that accepts both non-contiguous and contiguous arrays), but you can specify a particular contiguity by using the `::1` index either at the beginning or the end of the index specification:

```
>>> numba.float32[::1]
array(float32, 1d, C)
>>> numba.float32[:, :, ::1]
array(float32, 3d, C)
>>> numba.float32[::1, :, :]
array(float32, 3d, F)
```

This style of type declaration is supported within Numba compiled-functions, e.g. declaring the type of a *typed.List*.:

```
from numba import njit, types, typed

@njit
def example():
    return typed.List.empty_list(types.float64[:, ::1])
```

Note that this feature is only supported for simple numerical types. Application to compound types, e.g. record types, is not supported.

Functions

Warning: The feature of considering functions as first-class type objects is under development.

Functions are often considered as certain transformations of input arguments to output values. Within Numba *JIT* compiled functions, the functions can also be considered as objects, that is, functions can be passed around as arguments or return values, or used as items in sequences, in addition to being callable.

First-class function support is enabled for all Numba *JIT* compiled functions and Numba `cfunc` compiled functions except when:

- using a non-CPU compiler,
- the compiled function is a Python generator,
- the compiled function has Omitted arguments,
- or the compiled function returns Optional value.

To disable first-class function support, use `no_cfunc_wrapper=True` decorator option.

For instance, consider an example where the Numba *JIT* compiled function applies user-specified functions as a composition to an input argument:

```
>>> @numba.njit
... def composition(funcs, x):
...     r = x
...     for f in funcs[::-1]:
...         r = f(r)
...     return r
...
>>> @numba.cfunc("double(double)")
... def a(x):
...     return x + 1.0
...
>>> @numba.njit
... def b(x):
...     return x * x
...
>>> composition((a, b), 0.5), 0.5 ** 2 + 1
(1.25, 1.25)
>>> composition((b, a, b, b, a), 0.5), b(a(b(b(a(0.5)))))
(36.75390625, 36.75390625)
```

Here, `cfunc` compiled functions `a` and `b` are considered as first-class function objects because these are passed in to the Numba *JIT* compiled function `composition` as arguments, that is, the `composition` is *JIT* compiled independently from its argument function objects (that are collected in the input argument `funcs`).

Currently, first-class function objects can be Numba `cfunc` compiled functions, *JIT* compiled functions, and objects that implement the Wrapper Address Protocol (WAP, see below) with the following restrictions:

Context	JIT compiled	cfunc compiled	WAP objects
Can be used as arguments	yes	yes	yes
Can be called	yes	yes	yes
Can be used as items	yes*	yes	yes
Can be returned	yes	yes	yes
Namespace scoping	yes	yes	yes
Automatic overload	yes	no	no

* at least one of the items in a sequence of first-class function objects must have a precise type.

Wrapper Address Protocol - WAP

Wrapper Address Protocol provides an API for making any Python object a first-class function for Numba *JIT* compiled functions. This assumes that the Python object represents a compiled function that can be called via its memory address (function pointer value) from Numba *JIT* compiled functions. The so-called WAP objects must define the following two methods:

__wrapper_address__(*self*) → int

Return the memory address of a first-class function. This method is used when a Numba *JIT* compiled function tries to call the given WAP instance.

signature(*self*) → numba.typing.Signature

Return the signature of the given first-class function. This method is used when passing in the given WAP instance to a Numba *JIT* compiled function.

In addition, the WAP object may implement the `__call__` method. This is necessary when calling WAP objects from Numba *JIT* compiled functions in *object mode*.

As an example, let us call the standard math library function `cos` within a Numba *JIT* compiled function. The memory address of `cos` can be established after loading the math library and using the `ctypes` package:

```
>>> import numba, ctypes, ctypes.util, math
>>> libm = ctypes.cdll.LoadLibrary(ctypes.util.find_library('m'))
>>> class LibMCos(numba.types.WrapperAddressProtocol):
...     def __wrapper_address__(self):
...         return ctypes.cast(libm.cos, ctypes.c_voidp).value
...     def signature(self):
...         return numba.float64(numba.float64)
...
>>> @numba.njit
... def foo(f, x):
...     return f(x)
...
>>> foo(LibMCos(), 0.0)
1.0
>>> foo(LibMCos(), 0.5), math.cos(0.5)
(0.8775825618903728, 0.8775825618903728)
```

Miscellaneous Types

There are some non-numerical types that do not fit into the other categories.

Type name(s)	Comments
pyobject	generic Python object
voidptr	raw pointer, no operations can be performed on it

2.1.4 Advanced types

For more advanced declarations, you have to explicitly call helper functions or classes provided by Numba.

Warning: The APIs documented here are not guaranteed to be stable. Unless necessary, it is recommended to let Numba infer argument types by using the *signature-less variant of @jit*.

Inference

numba.**typeof**(*value*)

Create a Numba type accurately describing the given Python *value*. `ValueError` is raised if the value isn't supported in *nopython mode*.

```
>>> numba.typeof(np.empty(3))
array(float64, 1d, C)
>>> numba.typeof((1, 2.0))
(int64, float64)
>>> numba.typeof([0])
reflected list(int64)
```

NumPy scalars

Instead of using *typeof()*, non-trivial scalars such as structured types can also be constructed programmatically.

numba.**from_dtype**(*dtype*)

Create a Numba type corresponding to the given NumPy *dtype*:

```
>>> struct_dtype = np.dtype([('row', np.float64), ('col', np.float64)])
>>> ty = numba.from_dtype(struct_dtype)
>>> ty
Record([('row', '<f8'), ('col', '<f8')])
>>> ty[:, :]
unaligned array(Record([('row', '<f8'), ('col', '<f8')]), 2d, A)
```

class numba.types.**NPDatetime**(*unit*)

Create a Numba type for NumPy datetimes of the given *unit*. *unit* should be a string amongst the codes recognized by NumPy (e.g. `Y`, `M`, `D`, etc.).

class numba.types.**NPTimedelta**(*unit*)

Create a Numba type for NumPy timedeltas of the given *unit*. *unit* should be a string amongst the codes recognized by NumPy (e.g. `Y`, `M`, `D`, etc.).

See also:

NumPy datetime units.

Arrays

class numba.types.**Array**(*dtype*, *ndim*, *layout*)

Create an array type. *dtype* should be a Numba type. *ndim* is the number of dimensions of the array (a positive integer). *layout* is a string giving the layout of the array: `A` means any layout, `C` means C-contiguous and `F` means Fortran-contiguous.

Optional types

class numba.**optional**(*typ*)

Create an optional type based on the underlying Numba type *typ*. The optional type will allow any value of either *typ* or `None`.

```
>>> @jit((optional(intp),))
... def f(x):
...     return x is not None
...
>>> f(0)
True
>>> f(None)
False
```

Type annotations

numba.extending.**as_numba_type**(*py_type*)

Create a Numba type corresponding to the given Python *type annotation*. `TypingError` is raised if the type annotation can't be mapped to a Numba type. This function is meant to be used at statically compile time to evaluate Python type annotations. For runtime checking of Python objects see `typeof` above.

For any numba type, `as_numba_type(nb_type) == nb_type`.

```
>>> numba.extending.as_numba_type(int)
int64
>>> import typing  # the Python library, not the Numba one
>>> numba.extending.as_numba_type(typing.List[float])
ListType[float64]
>>> numba.extending.as_numba_type(numba.int32)
int32
```

`as_numba_type` is automatically updated to include any `@jitclass`.

```
>>> @jitclass
... class Counter:
...     x: int
...
...     def __init__(self):
...         self.x = 0
```

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```
...
...     def inc(self):
...         old_val = self.x
...         self.x += 1
...         return old_val
...
>>> numba.extending.as_numba_type(Counter)
instance.jitclass.Counter#11bad4278<x:int64>
```

Currently `as_numba_type` is only used to infer fields for `@jitclass`.

2.2 Just-in-Time compilation

2.2.1 JIT functions

`@numba.jit`(*signature=None*, *nopython=False*, *nogil=False*, *cache=False*, *forceobj=False*, *parallel=False*, *error_model='python'*, *fastmath=False*, *locals={}*, *boundscheck=False*)

Compile the decorated function on-the-fly to produce efficient machine code. All parameters are optional.

If present, the *signature* is either a single signature or a list of signatures representing the expected *Types and signatures* of function arguments and return values. Each signature can be given in several forms:

- A tuple of *Types and signatures* arguments (for example `(numba.int32, numba.double)`) representing the types of the function's arguments; Numba will then infer an appropriate return type from the arguments.
- A call signature using *Types and signatures*, specifying both return type and argument types. This can be given in intuitive form (for example `numba.void(numba.int32, numba.double)`).
- A string representation of one of the above, for example `"void(int32, double)"`. All type names used in the string are assumed to be defined in the `numba.types` module.

nopython and *nogil* are boolean flags. *locals* is a mapping of local variable names to *Types and signatures*.

This decorator has several modes of operation:

- If one or more signatures are given in *signature*, a specialization is compiled for each of them. Calling the decorated function will then try to choose the best matching signature, and raise a `TypeError` if no appropriate conversion is available for the function arguments. If converting succeeds, the compiled machine code is executed with the converted arguments and the return value is converted back according to the signature.
- If no *signature* is given, the decorated function implements lazy compilation. Each call to the decorated function will try to re-use an existing specialization if it exists (for example, a call with two integer arguments may re-use a specialization for argument types `(numba.int64, numba.int64)`). If no suitable specialization exists, a new specialization is compiled on-the-fly, stored for later use, and executed with the converted arguments.

If true, *nopython* forces the function to be compiled in *nopython mode*. If not possible, compilation will raise an error.

If true, *forceobj* forces the function to be compiled in *object mode*. Since object mode is slower than nopython mode, this is mostly useful for testing purposes.

If true, *nogil* tries to release the global interpreter lock inside the compiled function. The GIL will only be released if Numba can compile the function in *nopython mode*, otherwise a compilation warning will be printed.

If true, *cache* enables a file-based cache to shorten compilation times when the function was already compiled in a previous invocation. The cache is maintained in the `__pycache__` subdirectory of the directory containing the source file; if the current user is not allowed to write to it, though, it falls back to a platform-specific user-wide cache directory (such as `$HOME/.cache/numba` on Unix platforms).

If true, *parallel* enables the automatic parallelization of a number of common NumPy constructs as well as the fusion of adjacent parallel operations to maximize cache locality.

The *error_model* option controls the divide-by-zero behavior. Setting it to 'python' causes divide-by-zero to raise exception like CPython. Setting it to 'numpy' causes divide-by-zero to set the result to *+/-inf* or *nan*.

Not all functions can be cached, since some functionality cannot be always persisted to disk. When a function cannot be cached, a warning is emitted.

If true, *fastmath* enables the use of otherwise unsafe floating point transforms as described in the LLVM documentation. Further, if *Intel SVML* is installed faster but less accurate versions of some math intrinsics are used (answers to within `4 ULP`).

If true, *boundscheck* enables bounds checking for array indices. Out of bounds accesses will raise IndexError. The default is to not do bounds checking. If bounds checking is disabled, out of bounds accesses can produce garbage results or segfaults. However, enabling bounds checking will slow down typical functions, so it is recommended to only use this flag for debugging. You can also set the *NUMBA_BOUNDSCHECK* environment variable to 0 or 1 to globally override this flag.

The *locals* dictionary may be used to force the *Types and signatures* of particular local variables, for example if you want to force the use of single precision floats at some point. In general, we recommend you let Numba's compiler infer the types of local variables by itself.

Here is an example with two signatures:

```
@jit(["int32(int32)", "float32(float32)"], nopython=True)
def f(x): ...
```

Not putting any parentheses after the decorator is equivalent to calling the decorator without any arguments, i.e.:

```
@jit
def f(x): ...
```

is equivalent to:

```
@jit()
def f(x): ...
```

The decorator returns a *Dispatcher* object.

Note: If no *signature* is given, compilation errors will be raised when the actual compilation occurs, i.e. when the function is first called with some given argument types.

Note: Compilation can be influenced by some dedicated *Environment variables*.

2.2.2 Generated JIT functions

Like the *jit()* decorator, but calls the decorated function at compile-time, passing the *types* of the function's arguments. The decorated function must return a callable which will be compiled as the function's implementation for those types, allowing flexible kinds of specialization.

If you are looking for this functionality, see the *high-level extension API* `@overload` family of decorators.

2.2.3 Dispatcher objects

class Dispatcher

The class of objects created by calling *jit()*. You shouldn't try to create such an object in any other way. Calling a Dispatcher object calls the compiled specialization for the arguments with which it is called, letting it act as an accelerated replacement for the Python function which was compiled.

In addition, Dispatcher objects have the following methods and attributes:

py_func

The pure Python function which was compiled.

inspect_types(*file=None*, *pretty=False*)

Print out a listing of the function source code annotated line-by-line with the corresponding Numba IR, and the inferred types of the various variables. If *file* is specified, printing is done to that file object, otherwise to sys.stdout. If *pretty* is set to True then colored ANSI will be produced in a terminal and HTML in a notebook.

See also:

Numba architecture

inspect_llvm(*signature=None*)

Return a dictionary keying compiled function signatures to the human readable LLVM IR generated for the function. If the signature keyword is specified a string corresponding to that individual signature is returned.

inspect_asm(*signature=None*)

Return a dictionary keying compiled function signatures to the human-readable native assembly code for the function. If the signature keyword is specified a string corresponding to that individual signature is returned.

inspect_cfg(*signature=None*, *show_wrapped*)

Return a dictionary keying compiled function signatures to the control-flow graph objects for the function. If the signature keyword is specified a string corresponding to that individual signature is returned.

The control-flow graph objects can be stringified (`str` or `repr`) to get the textual representation of the graph in DOT format. Or, use its `.display(filename=None, view=False)` method to plot the graph. The *filename* option can be set to a specific path for the rendered output to write to. If *view* option is True, the plot is opened by the system default application for the image format (PDF). In IPython notebook, the returned object can be plot inlined.

Usage:

```
@jit
def foo():
  ...
```

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```
# opens the CFG in system default application
foo.inspect_cfg(foo.signatures[0]).display(view=True)
```

inspect_disasm_cfg(*signature=None*)

Return a dictionary keying compiled function signatures to the control-flow graph of the disassembly of the underlying compiled ELF object. If the signature keyword is specified a control-flow graph corresponding to that individual signature is returned. This function is execution environment aware and will produce SVG output in Jupyter notebooks and ASCII in terminals.

Example:

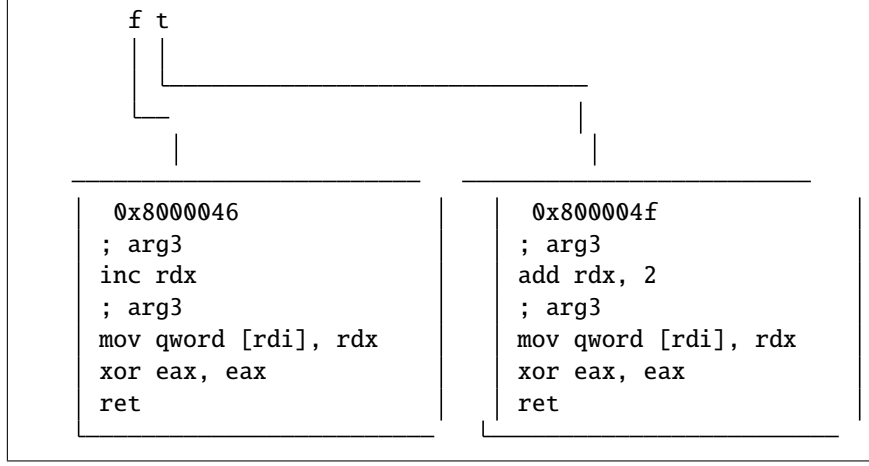
```
@njit
def foo(x):
    if x < 3:
        return x + 1
    return x + 2

foo(10)

print(foo.inspect_disasm_cfg(signature=foo.signatures[0]))
```

Gives:

```
[0x08000040]>  # method.__main__.foo_241_long_long (int64_t arg1, int64_t arg3);
 ──────────────────────────────────────────────────────────────────────────────
 0x8000040
; arg3 ; [02] -r-x section size 279 named .text
  ;-- section..text:
  ;-- .text:
  ;-- __main__::foo$241(long long):
  ;-- rip:
25: method.__main__.foo_241_long_long (int64_t arg1, int64_t arg3);
; arg int64_t arg1 @ rdi
; arg int64_t arg3 @ rdx
; 2
cmp rdx, 2
jg 0x800004f
```



recompile()

Recompile all existing signatures. This can be useful for example if a global or closure variable was frozen by your function and its value in Python has changed. Since compiling isn't cheap, this is mainly for testing and interactive use.

parallel_diagnostics(*signature=None*, *level=1*)

Print parallel diagnostic information for the given signature. If no signature is present it is printed for all known signatures. `level` is used to adjust the verbosity, `level=1` (default) is minimum verbosity, levels 2, 3, and 4 provide increasing levels of verbosity.

get_metadata(*signature=None*)

Obtain the compilation metadata for a given signature. This is useful for developers of Numba and Numba extensions.

2.2.4 Vectorized functions (ufuncs and DUFuncs)

@numba.**vectorize**(*, *signatures=[]*, *identity=None*, *nopython=True*, *target='cpu'*, *forceobj=False*, *cache=False*, *locals={}*)

Compile the decorated function and wrap it either as a NumPy ufunc or a Numba *DUFunc*. The optional *nopython*, *forceobj* and *locals* arguments have the same meaning as in *numba.jit()*.

signatures is an optional list of signatures expressed in the same form as in the *numba.jit()* *signature* argument. If *signatures* is non-empty, then the decorator will compile the user Python function into a NumPy ufunc. If no *signatures* are given, then the decorator will wrap the user Python function in a *DUFunc* instance, which will compile the user function at call time whenever NumPy can not find a matching loop for the input arguments. *signatures* is required if *target* is `"parallel"`.

identity is the identity (or unit) value of the function being implemented. Possible values are 0, 1, None, and the string `"reorderable"`. The default is None. Both None and `"reorderable"` mean the function has no identity value; `"reorderable"` additionally specifies that reductions along multiple axes can be reordered.

If there are several *signatures*, they must be ordered from the more specific to the least specific. Otherwise, NumPy's type-based dispatching may not work as expected. For example, the following is wrong:

```
@vectorize(["float64(float64)", "float32(float32)"])
def f(x): ...
```

as running it over a single-precision array will choose the `float64` version of the compiled function, leading to much less efficient execution. The correct invocation is:

```
@vectorize(["float32(float32)", "float64(float64)"])
def f(x): ...
```

target is a string for backend target; Available values are "cpu", "parallel", and "cuda". To use a multithreaded version, change the target to "parallel" (which requires signatures to be specified):

```
@vectorize(["float64(float64)", "float32(float32)"], target='parallel')
def f(x): ...
```

For the CUDA target, use "cuda":

```
@vectorize(["float64(float64)", "float32(float32)"], target='cuda')
def f(x): ...
```

The compiled function can be cached to reduce future compilation time. It is enabled by setting *cache* to True. Only the "cpu" and "parallel" targets support caching.

The ufuncs created by this function respect NEP-13, NumPy's mechanism for overriding ufuncs. If any of the arguments of the ufunc's `__call__` have a `__array_ufunc__` method, that method will be called (in Python, not the compiled context), which may pre-process and/or post-process the arguments and return value of the compiled ufunc (or might not even call it).

`@numba.guvectorize`(*signatures*, *layout*, *, *identity=None*, *nopython=True*, *target='cpu'*, *forceobj=False*, *cache=False*, *locals={}*)

Generalized version of *numba.vectorize()*. While *numba.vectorize()* will produce a simple ufunc whose core functionality (the function you are decorating) operates on scalar operands and returns a scalar value, *numba.guvectorize()* allows you to create a NumPy ufunc whose core function takes array arguments of various dimensions.

The additional argument *layout* is a string specifying, in symbolic form, the dimensionality and size relationship of the argument types and return types. For example, a matrix multiplication will have a layout string of `"(m,n),(n,p)->(m,p)"`. Its definition might be (function body omitted):

```
@guvectorize(["void(float64[:,:], float64[:,:], float64[:,:])"],
             "(m,n),(n,p)->(m,p)")
def f(a, b, result):
    """Fill-in *result* matrix such as result := a * b"""
    ...
```

If one of the arguments should be a scalar, the corresponding layout specification is `()` and the argument will really be given to you as a zero-dimension array (you have to dereference it to get the scalar value). For example, a *one-dimension moving average* with a parameterable window width may have a layout string of `"(n),()->(n)"`.

Note that any output will be given to you preallocated as an additional function argument: your code has to fill it with the appropriate values for the function you are implementing.

If your function doesn't take an output array, you should omit the "arrow" in the layout string (e.g. `"(n),(n)"`). When doing this, it is important to be aware that changes to the input arrays cannot always be relied on to be visible outside the execution of the ufunc, as NumPy may pass in temporary arrays as inputs (for example, if a cast is required).

See also:

Specification of the layout string as supported by NumPy. Note that NumPy uses the term "signature", which we unfortunately use for something else.

The compiled function can be cached to reduce future compilation time. It is enabled by setting *cache* to True. Only the "cpu" and "parallel" targets support caching.

`class numba.DUFunc`

The class of objects created by calling *numba.vectorize()* with no signatures.

DUFunc instances should behave similarly to NumPy `ufunc` objects with one important difference: call-time loop generation. When calling a ufunc, NumPy looks at the existing loops registered for that ufunc, and will raise a `TypeError` if it cannot find a loop that it cannot safely cast the inputs to suit. When calling a DUFunc, Numba delegates the call to NumPy. If the NumPy ufunc call fails, then Numba attempts to build a new loop for the given input types, and calls the ufunc again. If this second call attempt fails or a compilation error occurs, then DUFunc passes along the exception to the caller.

See also:

The "*Dynamic universal functions*" section in the user's guide demonstrates the call-time behavior of *DUFunc*, and discusses the impact of call order on how Numba generates the underlying `ufunc`.

ufunc

The actual NumPy `ufunc` object being built by the *DUFunc* instance. Note that the *DUFunc* object maintains several important data structures required for proper ufunc functionality (specifically the dynamically compiled loops). Users should not pass the `ufunc` value around without ensuring the underlying *DUFunc* will not be garbage collected.

nin

The number of DUFunc (ufunc) inputs. See ufunc.nin.

nout

The number of DUFunc outputs. See ufunc.nout.

nargs

The total number of possible DUFunc arguments (should be *nin* + *nout*). See ufunc.nargs.

ntypes

The number of input types supported by the DUFunc. See ufunc.ntypes.

types

A list of the supported types given as strings. See ufunc.types.

identity

The identity value when using the ufunc as a reduction. See ufunc.identity.

reduce(*A*, *, *axis*, *dtype*, *out*, *keepdims*)

Reduces *A*'s dimension by one by applying the DUFunc along one axis. See ufunc.reduce.

accumulate(*A*, *, *axis*, *dtype*, *out*)

Accumulate the result of applying the operator to all elements. See ufunc.accumulate.

reduceat(*A*, *indices*, *, *axis*, *dtype*, *out*)

Performs a (local) reduce with specified slices over a single axis. See ufunc.reduceat.

outer(*A*, *B*)

Apply the ufunc to all pairs (*a*, *b*) with *a* in *A*, and *b* in *B*. See ufunc.outer.

at(*A*, *indices*, *, *B*)

Performs unbuffered in place operation on operand *A* for elements specified by *indices*. If you are using NumPy 1.7 earlier, this method will not be present. See ufunc.at.

Note: Vectorized functions can, in rare circumstances, show *unexpected warnings or errors*.

2.2.5 C callbacks

@numba.**cfunc**(*signature*, *nopython=False*, *cache=False*, *locals={}*)

Compile the decorated function on-the-fly to produce efficient machine code. The compiled code is wrapped in a thin C callback that makes it callable using the natural C ABI.

The *signature* is a single signature representing the signature of the C callback. It must have the same form as in *jit()*. The decorator does not check that the types in the signature have a well-defined representation in C.

nopython and *cache* are boolean flags. *locals* is a mapping of local variable names to *Types and signatures*. They all have the same meaning as in *jit()*.

The decorator returns a *CFunc* object.

Note: C callbacks currently do not support *object mode*.

class CFunc

The class of objects created by *cfunc()*. *CFunc* objects expose the following attributes and methods:

address

The address of the compiled C callback, as an integer.

cffi

A cffi function pointer instance, to be passed as an argument to cffi-wrapped functions. The pointer's type is `void *`, so only minimal type checking will happen when passing it to cffi.

ctypes

A `ctypes` callback instance, as if it were created using `ctypes.CFUNCTYPE()`.

native_name

The name of the compiled C callback.

inspect_llvm()

Return the human-readable LLVM IR generated for the C callback. *native_name* is the name under which this callback is defined in the IR.

2.3 Ahead-of-Time compilation

Note: This module is pending deprecation. Please see *Deprecation of the numba.pycc module* for more information.

class numba.pycc.**CC**(*extension_name*, *source_module=None*)

An object used to generate compiled extensions from Numba-compiled Python functions. *extension_name* is the name of the extension to be generated. *source_module* is the Python module containing the functions; if `None`, it is inferred by examining the call stack.

CC instances have the following attributes and methods:

name

(read-only attribute) The name of the extension module to be generated.

output_dir

(read-write attribute) The directory the extension module will be written into. By default it is the directory the *source_module* is located in.

output_file

(read-write attribute) The name of the file the extension module will be written to. By default this follows the Python naming convention for the current platform.

target_cpu

(read-write attribute) The name of the CPU model to generate code for. This will select the appropriate instruction set extensions. By default, a generic CPU is selected in order to produce portable code.

Recognized names for this attribute depend on the current architecture and LLVM version. If you have LLVM installed, `llc -mcpu=help` will give you a list. Examples on x86-64 are `"ivybridge"`, `"haswell"`, `"skylake"` or `"broadwell"`. You can also give the value `"host"` which will select the current host CPU.

verbose

(read-write attribute) If true, print out information while compiling the extension. False by default.

@export(*exported_name*, *sig*)

Mark the decorated function for compilation with the signature *sig*. The compiled function will be exposed as *exported_name* in the generated extension module.

All exported names within a given *CC* instance must be distinct, otherwise an exception is raised.

compile()

Compile all exported functions and generate the extension module as specified by *output_dir* and *output_file*.

distutils_extension(***kwargs*)

Return a `distutils.core.Extension` instance allowing to integrate generation of the extension module in a conventional `setup.py`-driven build process. The optional *kwargs* let you pass optional parameters to the `Extension` constructor.

In this mode of operation, it is not necessary to call *compile()* yourself. Also, *output_dir* and *output_file* will be ignored.

2.4 Utilities

2.4.1 Dealing with pointers

These functions can be called from pure Python as well as in *nopython mode*.

numba.**carray**(*ptr*, *shape*, *dtype=None*)

Return a Numpy array view over the data pointed to by *ptr* with the given *shape*, in C order. If *dtype* is given, it is used as the array's dtype, otherwise the array's dtype is inferred from *ptr*'s type. As the returned array is a view, not a copy, writing to it will modify the original data.

ptr should be a ctypes pointer object (either a typed pointer as created using `POINTER()`, or a `c_void_p`).

shape should be an integer or a tuple of integers.

dtype should be a Numpy dtype or scalar class (i.e. both `np.dtype('int8')` and `np.int8` are accepted).

numba.**farray**(*ptr*, *shape*, *dtype=None*)

Same as *carray()*, but the data is assumed to be laid out in Fortran order, and the array view is constructed accordingly.

2.5 Environment variables

Note: This section relates to environment variables that impact Numba's runtime, for compile time environment variables see *Build time environment variables and configuration of optional components*.

Numba allows its behaviour to be changed through the use of environment variables. Unless otherwise mentioned, those variables have integer values and default to zero.

For convenience, Numba also supports the use of a configuration file to persist configuration settings. Note: To use this feature `pyyaml` must be installed.

The configuration file must be named `.numba_config.yaml` and be present in the directory from which the Python interpreter is invoked. The configuration file, if present, is read for configuration settings before the environment variables are searched. This means that the environment variable settings will override the settings obtained from a configuration file (the configuration file is for setting permanent preferences whereas the environment variables are for ephemeral preferences).

The format of the configuration file is a dictionary in `YAML` format that maps the environment variables below (without the `NUMBA_` prefix) to a desired value. For example, to permanently switch on developer mode (`NUMBA_DEVELOPER_MODE` environment variable) and control flow graph printing (`NUMBA_DUMP_CFG` environment variable), create a configuration file with the contents:

```
developer_mode: 1
dump_cfg: 1
```

This can be especially useful in the case of wanting to use a set color scheme based on terminal background color. For example, if the terminal background color is black, the `dark_bg` color scheme would be well suited and can be set for permanent use by adding:

```
color_scheme: dark_bg
```

2.5.1 Jit flags

These variables globally override flags to the *jit()* decorator.

NUMBA_BOUNDSCHECK

If set to 0 or 1, globally disable or enable bounds checking, respectively. The default if the variable is not set or set to an empty string is to use the `boundscheck` flag passed to the *jit()* decorator for a given function. See the documentation of *@jit* for more information.

Note, due to limitations in numba, the bounds checking currently produces exception messages that do not match those from NumPy. If you set `NUMBA_FULL_TRACEBACKS=1`, the full exception message with the axis, index, and shape information will be printed to the terminal.

2.5.2 Debugging

These variables influence what is printed out during compilation of *JIT functions*.

NUMBA_DEVELOPER_MODE

If set to non-zero, developer mode produces full tracebacks and disables help instructions. Default is zero.

NUMBA_FULL_TRACEBACKS

If set to non-zero, enable full tracebacks when an exception occurs. Defaults to the value set by *NUMBA_DEVELOPER_MODE*.

NUMBA_SHOW_HELP

If set to non-zero, show resources for getting help. Default is zero.

NUMBA_DISABLE_ERROR_MESSAGE_HIGHLIGHTING

If set to non-zero error message highlighting is disabled. This is useful for running the test suite on CI systems.

NUMBA_COLOR_SCHEME

Alters the color scheme used in error reporting (requires the `colorama` package to be installed to work). Valid values are:

- `no_color` No color added, just bold font weighting.

- `dark_bg` Suitable for terminals with a dark background.
- `light_bg` Suitable for terminals with a light background.
- `blue_bg` Suitable for terminals with a blue background.
- `jupyter_nb` Suitable for use in Jupyter Notebooks.

Default value: `no_color`. The type of the value is `string`.

NUMBA_HIGHLIGHT_DUMPS

If set to non-zero and `pygments` is installed, syntax highlighting is applied to Numba IR, LLVM IR and assembly dumps. Default is zero.

NUMBA_DISABLE_PERFORMANCE_WARNINGS

If set to non-zero the issuing of performance warnings is disabled. Default is zero.

NUMBA_DEBUG

If set to non-zero, print out all possible debugging information during function compilation. Finer-grained control can be obtained using other variables below.

NUMBA_DEBUG_FRONTEND

If set to non-zero, print out debugging information during operation of the compiler frontend, up to and including generation of the Numba Intermediate Representation.

NUMBA_DEBUG_NRT

If set to non-zero, print out debugging information at runtime about the use of *Numba run time (NRT)* reference count operations. If set to non-zero, this also switches on the filling of all NRT allocated regions with an identifiable "marker" byte pattern, `0xCB` on allocation and `0xDE` on deallocation, both to help with debugging memory leaks.

NUMBA_NRT_STATS

If set to non-zero, enable the *Numba run time (NRT)* statistics counters. These counters are enabled process wide on import of Numba and are atomic.

NUMBA_DEBUGINFO

If set to non-zero, enable debug for the full application by setting the default value of the `debug` option in `jit`. Beware that enabling debug info significantly increases the memory consumption for each compiled function. Default value equals to the value of *NUMBA_ENABLE_PROFILING*.

NUMBA_EXTEND_VARIABLE_LIFETIMES

If set to non-zero, extend the lifetime of variables to the end of the block in which their lifetime ends. This is particularly useful in conjunction with *NUMBA_DEBUGINFO* as it helps with introspection of values. Default is zero.

NUMBA_GDB_BINARY

Set the `gdb` binary for use in Numba's `gdb` support. This takes one of two forms: 1) a path and full name of the binary to explicitly express which binary to use 2) just the name of the binary and the current path will be searched using the standard path resolution rules. For example: `/path/from/root/to/binary/name_of_gdb_binary` or `custom_gdb_binary_name`. This is to permit the use of a `gdb` from a non-default location with a non-default name. The default value is `gdb`.

NUMBA_DEBUG_TYPEINFER

If set to non-zero, print out debugging information about type inference.

NUMBA_ENABLE_SYS_MONITORING

Controls support for Python's `sys.monitoring` feature in Numba. Disabled (set to zero) by default. When enabled (set to non-zero), allows profiling tools that use `sys.monitoring` to work with Numba code. Currently tested with `cProfile`, other monitoring tools may work but are not guaranteed.

Only available for Python 3.12 and above. Otherwise, it has no effect.

NUMBA_ENABLE_PROFILING

Enables JIT events of LLVM in order to support profiling of jitted functions. This option is automatically enabled under certain profilers.

NUMBA_TRACE

If set to non-zero, trace certain function calls (function entry and exit events, including arguments and return values).

NUMBA_CHROME_TRACE

If defined, chrome tracing is enabled and this variable specifies the filepath of the chrome tracing json file output. The emitted file can be opened by a Chromium-based browser using the profile viewer at *chrome://tracing/*.

> **Warning:** This feature is not supported in multi-process applications.

NUMBA_DUMP_BYTECODE

If set to non-zero, print out the Python *bytecode* of compiled functions.

NUMBA_DUMP_CFG

If set to non-zero, print out information about the Control Flow Graph of compiled functions.

NUMBA_DUMP_IR

If set to non-zero, print out the Numba Intermediate Representation of compiled functions.

NUMBA_DUMP_SSA

If set to non-zero, print out the Numba Intermediate Representation of compiled functions after conversion to Static Single Assignment (SSA) form.

NUMBA_DEBUG_PRINT_AFTER

Dump the Numba IR after declared pass(es). This is useful for debugging IR changes made by given passes. Accepted values are:

- Any pass name (as given by the `.name()` method on the class)
- Multiple pass names as a comma separated list, i.e. `"foo_pass,bar_pass"`
- The token `"all"`, which will print after all passes.

The default value is `"none"` so as to prevent output.

NUMBA_DUMP_ANNOTATION

If set to non-zero, print out types annotations for compiled functions.

NUMBA_DUMP_LLVM

Dump the unoptimized LLVM assembly source of compiled functions. Unoptimized code is usually very verbose; therefore, *NUMBA_DUMP_OPTIMIZED* is recommended instead.

NUMBA_DUMP_FUNC_OPT

Dump the LLVM assembly source after the LLVM "function optimization" pass, but before the "module optimization" pass. This is useful mostly when developing Numba itself, otherwise use *NUMBA_DUMP_OPTIMIZED*.

NUMBA_DUMP_OPTIMIZED

Dump the LLVM assembly source of compiled functions after all optimization passes. The output includes the raw function as well as its CPython-compatible wrapper (whose name begins with `wrapper.`). Note that the function is often inlined inside the wrapper, as well.

NUMBA_DEBUG_ARRAY_OPT

Dump debugging information related to the processing associated with the `parallel=True` jit decorator option.

NUMBA_DEBUG_ARRAY_OPT_RUNTIME

Dump debugging information related to the runtime scheduler associated with the `parallel=True` jit decorator option.

NUMBA_DEBUG_ARRAY_OPT_STATS

Dump statistics about how many operators/calls are converted to parallel for-loops and how many are fused together, which are associated with the `parallel=True` jit decorator option.

NUMBA_PARALLEL_DIAGNOSTICS

If set to an integer value between 1 and 4 (inclusive) diagnostic information about parallel transforms undertaken by Numba will be written to STDOUT. The higher the value set the more detailed the information produced.

NUMBA_DUMP_ASSEMBLY

Dump the native assembly code of compiled functions.

NUMBA_LLVM_PASS_TIMINGS

Set to 1 to enable recording of pass timings in LLVM; e.g. `NUMBA_LLVM_PASS_TIMINGS=1`. See *Notes on timing LLVM*.

Default value: `0` (Off)

NUMBA_JIT_COVERAGE

Set to 1 to enable coverage data reporting by the JIT compiler on compiled source lines. Default to `0` (Off).

See also:

Troubleshooting and tips and *Numba architecture*.

2.5.3 Compilation options

NUMBA_OPT

The optimization level; typically this option is passed straight to LLVM. It may take one of the values `0`, `1`, `2` or `3` which correspond approximately to the `-O{value}` flag found in many command line compilation tools. The value `max` is also supported, this is Numba specific, it has the effect of running with the optimization level set at `3` both before and after a pass which in which reference count operation pruning takes place. In some cases this may increase performance, in other cases it may impede performance, the same can be said for compilation time. This option is present to give users the opportunity to choose a value suitable for their application.

Default value: 3

NUMBA_LOOP_VECTORIZE

If set to non-zero, enable LLVM loop vectorization.

Default value: 1

NUMBA_SLP_VECTORIZE

If set to non-zero, enable LLVM superword-level parallelism vectorization. Note that use of this feature has occasionally resulted in LLVM producing miscompilations, hence it is off by default.

Default value: 0

NUMBA_ENABLE_AVX

If set to non-zero, enable AVX optimizations in LLVM. This is disabled by default on Sandy Bridge and Ivy Bridge architectures as it can sometimes result in slower code on those platforms.

NUMBA_DISABLE_INTEL_SVML

If set to non-zero and Intel SVML is available, the use of SVML will be disabled.

NUMBA_DISABLE_JIT

Disable JIT compilation entirely. The *jit()* decorator acts as if it performs no operation, and the invocation of decorated functions calls the original Python function instead of a compiled version. This can be useful if you want to run the Python debugger over your code.

NUMBA_CPU_NAME

NUMBA_CPU_FEATURES

Override CPU and CPU features detection. By setting `NUMBA_CPU_NAME=generic`, a generic CPU model is picked for the CPU architecture and the feature list (`NUMBA_CPU_FEATURES`) defaults to empty. CPU features must be listed with the format `+feature1,-feature2` where `+` indicates enable and `-` indicates disable. For example, `+sse,+sse2,-avx,-avx2` enables SSE and SSE2, and disables AVX and AVX2.

These settings are passed to LLVM for configuring the compilation target. To get a list of available options, use the `llc` commandline tool from LLVM, for example:

```
llc -march=x86 -mattr=help
```

Tip: To force all caching functions (`@jit(cache=True)`) to emit portable code (portable within the same architecture and OS), simply set `NUMBA_CPU_NAME=generic`.

NUMBA_FUNCTION_CACHE_SIZE

Override the size of the function cache for retaining recently deserialized functions in memory. In systems like Dask, it is common for functions to be deserialized multiple times. Numba will cache functions as long as there is a reference somewhere in the interpreter. This cache size variable controls how many functions that are no longer referenced will also be retained, just in case they show up in the future. The implementation of this is not a true LRU, but the large size of the cache should be sufficient for most situations.

Note: this is unrelated to the compilation cache.

Default value: 128

NUMBA_LLVM_REFPRUNE_PASS

Turns on the LLVM pass level reference-count pruning pass and disables the regex based implementation in Numba.

Default value: 1 (On)

NUMBA_LLVM_REFPRUNE_FLAGS

When `NUMBA_LLVM_REFPRUNE_PASS` is on, this allows configuration of subpasses in the reference-count pruning LLVM pass.

Valid values are any combinations of the below separated by `,` (case-insensitive):

- `all`: enable all subpasses.
- `per_bb`: enable per-basic-block level pruning, which is same as the old regex based implementation.
- `diamond`: enable inter-basic-block pruning that is a diamond shape pattern, i.e. a single-entry single-exit CFG subgraph where has an incref in the entry and a corresponding decref in the exit.
- `fanout`: enable inter-basic-block pruning that has a fanout pattern, i.e. a single-entry multiple-exit CFG subgraph where the entry has an incref and every exit has a corresponding decref.
- `fanout_raise`: same as `fanout` but allow subgraph exit nodes to be raising an exception and not have a corresponding decref.

For example, `all` is the same as `per_bb, diamond, fanout, fanout_raise`

Default value: "all"

NUMBA_USE_LLVMLITE_MEMORY_MANAGER

Whether llvmlite's built-in memory manager is enabled. The default is to enable it on 64-bit ARM platforms (macOS on Apple Silicon and Linux on AArch64), where it is needed to ensure ABI compliance, specifically conformance with the requirements for GOT and text segment placement in the large code model.

This environment variable can be used to override the default setting and force it to be enabled (`1`) or disabled (`0`). This should not normally be required, but it is provided as an option for debugging and potential workaround situations.

Default value: None (Use the default for the system)

2.5.4 Caching options

Options for the compilation cache.

NUMBA_DEBUG_CACHE

If set to non-zero, print out information about operation of the *JIT compilation cache*.

NUMBA_CACHE_DIR

Override the location of the cache directory. If defined, this should be a valid directory path.

If not defined, Numba picks the cache directory in the following order:

1. In-tree cache. Put the cache next to the corresponding source file under a `__pycache__` directory following how `.pyc` files are stored.
2. User-wide cache. Put the cache in the user's application directory using `appdirs.user_cache_dir` from the Appdirs package.
3. IPython cache. Put the cache in an IPython specific application directory. Stores are made under the `numba_cache` in the directory returned by `IPython.paths.get_ipython_cache_dir()`.

Also see *docs on cache sharing* and *docs on cache clearing*

2.5.5 GPU support

NUMBA_DISABLE_CUDA

If set to non-zero, disable CUDA support.

NUMBA_FORCE_CUDA_CC

If set, force the CUDA compute capability to the given version (a string of the type `major.minor`), regardless of attached devices.

NUMBA_CUDA_DEFAULT_PTX_CC

The default compute capability (a string of the type `major.minor`) to target when compiling to PTX using `cuda.compile_ptx`. The default is 5.0, which is the lowest non-deprecated compute capability in the most recent version of the CUDA toolkit supported (12.4 at present).

NUMBA_ENABLE_CUDASIM

If set, don't compile and execute code for the GPU, but use the CUDA Simulator instead. For debugging purposes.

NUMBA_CUDA_ARRAY_INTERFACE_SYNC

Whether to synchronize on streams provided by objects imported using the CUDA Array Interface. This defaults to 1. If set to 0, then no synchronization takes place, and the user of Numba (and other CUDA libraries) is responsible for ensuring correctness with respect to synchronization on streams.

NUMBA_CUDA_LOG_LEVEL

For debugging purposes. If no other logging is configured, the value of this variable is the logging level for CUDA API calls. The default value is `CRITICAL` - to trace all API calls on standard error, set this to `DEBUG`.

NUMBA_CUDA_LOG_API_ARGS

By default the CUDA API call logs only give the names of functions called. Setting this variable to 1 also includes the values of arguments to Driver API calls in the logs.

NUMBA_CUDA_DRIVER

Path of the directory in which the CUDA driver libraries are to be found. Normally this should not need to be set as Numba can locate the driver in standard locations. However, this variable can be used if the driver is in a non-standard location.

NUMBA_CUDA_LOG_SIZE

Buffer size for logs produced by CUDA driver API operations. This defaults to 1024 and should not normally need to be modified - however, if an error in an API call produces a large amount of output that appears to be truncated (perhaps due to multiple long function names, for example) then this variable can be used to increase the buffer size and view the full error message.

NUMBA_CUDA_VERBOSE_JIT_LOG

Whether the CUDA driver should produce verbose log messages. Defaults to 1, indicating that verbose messaging is enabled. This should not need to be modified under normal circumstances.

NUMBA_CUDA_PER_THREAD_DEFAULT_STREAM

When set to 1, the default stream is the per-thread default stream. When set to 0, the default stream is the legacy default stream. This defaults to 0, for the legacy default stream. See Stream Synchronization Behavior for an explanation of the legacy and per-thread default streams.

This variable only takes effect when using Numba's internal CUDA bindings; when using the NVIDIA bindings, use the environment variable `CUDA_PYTHON_CUDA_PER_THREAD_DEFAULT_STREAM` instead.

See also:

The Default Stream section in the NVIDIA Bindings documentation.

NUMBA_CUDA_LOW_OCCUPANCY_WARNINGS

Enable warnings if the grid size is too small relative to the number of streaming multiprocessors (SM). This option is on by default (default value is 1).

The heuristic checked is whether `gridsize < 2 * (number of SMs)`. NOTE: The absence of a warning does not imply a good gridsize relative to the number of SMs. Disabling this warning will reduce the number of CUDA API calls (during JIT compilation), as the heuristic needs to check the number of SMs available on the device in the current context.

NUMBA_CUDA_WARN_ON_IMPLICIT_COPY

Enable warnings if a kernel is launched with host memory which forces a copy to and from the device. This option is on by default (default value is 1).

NUMBA_CUDA_USE_NVIDIA_BINDING

When set to 1, Numba will attempt to use the NVIDIA CUDA Python binding to make calls to the driver API instead of using its own ctypes binding. This defaults to 0 (off), as the NVIDIA binding is currently missing support for Per-Thread Default Streams and the profiler APIs.

NUMBA_CUDA_INCLUDE_PATH

The location of the CUDA include files. This is used when linking CUDA C/C++ sources to Python kernels, and needs to be correctly set for CUDA includes to be available to linked C/C++ sources. On Linux, it defaults to `/usr/local/cuda/include`. On Windows, the default is `$env:CUDA_PATH\include`.

2.5.6 Threading Control

NUMBA_NUM_THREADS

If set, the number of threads in the thread pool for the parallel CPU target will take this value. Must be greater than zero. This value is independent of `OMP_NUM_THREADS` and `MKL_NUM_THREADS`.

Default value: The number of CPU cores on the system as determined at run time. This can be accessed via *numba.config.NUMBA_DEFAULT_NUM_THREADS*.

See also the section on *Setting the Number of Threads* for information on how to set the number of threads at runtime.

NUMBA_THREADING_LAYER

This environment variable controls the library used for concurrent execution for the CPU parallel targets (`@vectorize(target='parallel')`, `@guvectorize(target='parallel')` and `@njit(parallel=True)`). The variable type is string and by default is `default` which will select a threading layer based on what is available in the runtime. The valid values are (for more information about these see *the threading layer documentation*):

- `default` - select a threading layer based on what is available in the current runtime.
- `safe` - select a threading layer that is both fork and thread safe (requires the TBB package).
- `forksafe` - select a threading layer that is fork safe.
- `threadsafe` - select a threading layer that is thread safe.
- `tbb` - A threading layer backed by Intel TBB.
- `omp` - A threading layer backed by OpenMP.
- `workqueue` - A simple built-in work-sharing task scheduler.

NUMBA_THREADING_LAYER_PRIORITY

This environment variable controls the order in which the libraries used for concurrent execution, for the CPU parallel targets (`@vectorize(target='parallel')`, `@guvectorize(target='parallel')` and `@njit(parallel=True)`), are prioritized for use. The variable type is string and by default is `tbb omp workqueue`, with the priority taken based on position from the left of the string, left most being the highest. Valid values are any permutation of the three choices (for more information about these see *the threading layer documentation*.)

2.6 Supported Python features

Apart from the *Language* part below, which applies to both *object mode* and *nopython mode*, this page only lists the features supported in *nopython mode*.

Warning: Numba behavior differs from Python semantics in some situations. We strongly advise reviewing *Deviations from Python Semantics* to become familiar with these differences.

2.6.1 Language

Constructs

Numba strives to support as much of the Python language as possible, but some language features are not available inside Numba-compiled functions. Below is a quick reference for the support level of Python constructs.

Supported constructs:

- conditional branch: `if .. elif .. else`
- loops: `while`, `for .. in`, `break`, `continue`
- basic generator: `yield`
- assertion: `assert`

Partially supported constructs:

- exceptions: `try .. except`, `raise`, `else` and `finally` (See details in this *section*)
- context manager: `with` (only support *numba.objmode()*)
- list comprehension (see details in this *section*)

Unsupported constructs:

- async features: `async with`, `async for` and `async def`
- class definition: `class` (except for *@jitclass*)
- set, dict and generator comprehensions
- generator delegation: `yield from`
- Deletion with `del` statements

Functions

Function calls

Numba supports function calls using positional and named arguments, as well as arguments with default values and `*args` (note the argument for `*args` can only be a tuple, not a list). Explicit `**kwargs` are not supported.

Function calls to locally defined inner functions are supported as long as they can be fully inlined.

Functions as arguments

Functions can be passed as argument into another function. But, they cannot be returned. For example:

```
from numba import jit

@jit
def add1(x):
    return x + 1

@jit
def bar(fn, x):
    return fn(x)
```

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```
@jit
def foo(x):
    return bar(add1, x)

# Passing add1 within numba compiled code.
print(foo(1))
# Passing add1 into bar from interpreted code
print(bar(add1, 1))
```

Note: Numba does not handle function objects as real objects. Once a function is assigned to a variable, the variable cannot be re-assigned to a different function.

Inner function and closure

Numba now supports inner functions as long as they are non-recursive and only called locally, but not passed as argument or returned as result. The use of closure variables (variables defined in outer scopes) within an inner function is also supported.

Recursive calls

Most recursive call patterns are supported. The only restriction is that the recursive callee must have a control-flow path that returns without recursing. Numba is able to type-infer recursive functions without specifying the function type signature (which is required in numba 0.28 and earlier). Recursive calls can even call into a different overload of the function.

Generators

Numba supports generator functions and is able to compile them in *object mode* and *nopython mode*. The returned generator can be used both from Numba-compiled code and from regular Python code.

Coroutine features of generators are not supported (i.e. the `generator.send()`, `generator.throw()`, `generator.close()` methods).

Exception handling

`raise` statement

The `raise` statement is only supported in the following forms:

- `raise SomeException`
- `raise SomeException(<arguments>)`

It is currently unsupported to re-raise an exception created in compiled code.

try .. except

The `try .. except` construct is partially supported. The following forms of are supported:

- the *bare* except that captures all exceptions:

```
try:
    ...
except:
    ...
```

- using exactly the `Exception` class in the `except` clause:

```
try:
  ...
except Exception:
  ...
```

  This will match any exception that is a subclass of `Exception` as expected. Currently, instances of `Exception` and it's subclasses are the only kind of exception that can be raised in compiled code.

Warning: Numba currently masks signals like `KeyboardInterrupt` and `SystemExit`. These signaling exceptions are ignored during the execution of Numba compiled code. The Python interpreter will handle them as soon as the control is returned to it.

Currently, exception objects are not materialized inside compiled functions. As a result, it is not possible to store an exception object into a user variable or to re-raise an exception. With this limitation, the only realistic use-case would look like:

```
try:
   do_work()
except Exception:
   handle_error_case()
   return error_code
```

try .. except .. else .. finally

The `else` block and the `finally` block of a `try .. except` are supported:

```
>>> @jit(nopython=True)
... def foo():
...     try:
...         print('main block')
...     except Exception:
...         print('handler block')
...     else:
...         print('else block')
...     finally:
...         print('final block')
...
>>> foo()
```

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```
main block
else block
final block
```

The `try .. finally` construct without the `except` clause is also supported.

2.6.2 Built-in types

int, bool

Arithmetic operations as well as truth values are supported.

The following attributes and methods are supported:

- `.conjugate()`
- `.real`
- `.imag`

float, complex

Arithmetic operations as well as truth values are supported.

The following attributes and methods are supported:

- `.conjugate()`
- `.real`
- `.imag`

str

Numba supports (Unicode) strings in Python 3. Strings can be passed into *nopython mode* as arguments, as well as constructed and returned from *nopython mode*. As in Python, slices (even of length 1) return a new, reference counted string. Optimized code paths for efficiently accessing single characters may be introduced in the future.

The in-memory representation is the same as was introduced in Python 3.4, with each string having a tag to indicate whether the string is using a 1, 2, or 4 byte character width in memory. When strings of different encodings are combined (as in concatenation), the resulting string automatically uses the larger character width of the two input strings. String slices also use the same character width as the original string, even if the slice could be represented with a narrower character width. (These details are invisible to the user, of course.)

The following constructors, functions, attributes and methods are currently supported:

- `str(int)`
- `len()`
- + (concatenation of strings)
- * (repetition of strings)
- `in`, `.contains()`
- ==, <, <=, >, >= (comparison)
- `.capitalize()`

- .casefold()
- .center()
- .count()
- .endswith()
- .endswith()
- .expandtabs()
- .find()
- .index()
- .isalnum()
- .isalpha()
- .isdecimal()
- .isdigit()
- .isidentifier()
- .islower()
- .isnumeric()
- .isprintable()
- .isspace()
- .istitle()
- .isupper()
- .join()
- .ljust()
- .lower()
- .lstrip()
- .partition()
- .replace()
- .rfind()
- .rindex()
- .rjust()
- .rpartition()
- .rsplit()
- .rstrip()
- .split()
- .splitlines()
- .startswith()
- .strip()
- .swapcase()

- `.title()`
- `.upper()`
- `.zfill()`

Regular string literals (e.g. `"ABC"`) as well as f-strings without format specs (e.g. `"ABC_{a+1}"`) that only use string and integer variables (types with `str()` overload) are supported in *nopython mode*.

Additional operations as well as support for Python 2 strings / Python 3 bytes will be added in a future version of Numba. Python 2 Unicode objects will likely never be supported.

Warning: The performance of some operations is known to be slower than the CPython implementation. These include substring search (`in`, `.contains()` and `find()`) and string creation (like `.split()`). Improving the string performance is an ongoing task, but the speed of CPython is unlikely to be surpassed for basic string operation in isolation. Numba is most successfully used for larger algorithms that happen to involve strings, where basic string operations are not the bottleneck.

tuple

Tuple support is categorised into two categories based on the contents of a tuple. The first category is homogeneous tuples, these are tuples where the type of all the values in the tuple are the same, the second is heterogeneous tuples, these are tuples where the types of the values are different.

Note: The `tuple()` constructor itself is NOT supported.

homogeneous tuples

An example of a homogeneous tuple:

```
homogeneous_tuple = (1, 2, 3, 4)
```

The following operations are supported on homogeneous tuples:

- Tuple construction.
- Tuple unpacking.
- Comparison between tuples.
- Iteration and indexing.
- Addition (concatenation) between tuples.
- Slicing tuples with a constant slice.
- The index method on tuples.

heterogeneous tuples

An example of a heterogeneous tuple:

```
heterogeneous_tuple = (1, 2j, 3.0, "a")
```

The following operations are supported on heterogeneous tuples:

- Comparison between tuples.
- Indexing using an index value that is a compile time constant e.g. `mytuple[7]`, where `7` is evidently a constant.
- Iteration over a tuple (requires experimental `literal_unroll()` feature, see below).

Warning: The following feature (`literal_unroll()`) is experimental and was added in version 0.47.

To permit iteration over a heterogeneous tuple the special function `numba.literal_unroll()` must be used. This function has no effect other than to act as a token to permit the use of this feature. Example use:

```
from numba import njit, literal_unroll

@njit
def foo():
    heterogeneous_tuple = (1, 2j, 3.0, "a")
    for i in literal_unroll(heterogeneous_tuple):
        print(i)
```

Warning: The following restrictions apply to the use of `literal_unroll()`:

- `literal_unroll()` can only be used on tuples and constant lists of compile time constants, e.g. `[1, 2j, 3, "a"]` and the list not being mutated.
- The only supported use pattern for `literal_unroll()` is loop iteration.
- Only one `literal_unroll()` call is permitted per loop nest (i.e. nested heterogeneous tuple iteration loops are forbidden).
- The usual type inference/stability rules still apply.

A more involved use of `literal_unroll()` might be type specific dispatch, recall that string and integer literal values are considered their own type, for example:

```
from numba import njit, types, literal_unroll
from numba.extending import overload

def dt(x):
    # dummy function to overload
    pass

@overload(dt, inline='always')
def ol_dt(li):
    if isinstance(li, types.StringLiteral):
        value = li.literal_value
        if value == "apple":
```

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```
            def impl(li):
                return 1
        elif value == "orange":
            def impl(li):
                return 2
        elif value == "banana":
            def impl(li):
                return 3
        return impl
    elif isinstance(li, types.IntegerLiteral):
        value = li.literal_value
        if value == 0xca11ab1e:
            def impl(li):
                # capture the dispatcher literal value
                return 0x5ca1ab1e + value
            return impl

@njit
def foo():
    acc = 0
    for t in literal_unroll(('apple', 'orange', 'banana', 3390155550)):
        acc += dt(t)
    return acc

print(foo())
```

list

Warning: As of version 0.45.x the internal implementation for the list datatype in Numba is changing. Until recently, only a single implementation of the list datatype was available, the so-called *reflected-list* (see below). However, it was scheduled for deprecation from version 0.44.0 onwards due to its limitations. As of version 0.45.0 a new implementation, the so-called *typed-list* (see below), is available as an experimental feature. For more information, please see: *Deprecation Notices*.

Creating and returning lists from JIT-compiled functions is supported, as well as all methods and operations. Lists must be strictly homogeneous: Numba will reject any list containing objects of different types, even if the types are compatible (for example, `[1, 2.5]` is rejected as it contains a `int` and a `float`).

For example, to create a list of arrays:

```
In [1]: from numba import njit

In [2]: import numpy as np

In [3]: @njit
  ...: def foo(x):
  ...:     lst = []
  ...:     for i in range(x):
  ...:         lst.append(np.arange(i))
  ...:     return lst
```

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```
  ...:

In [4]: foo(4)
Out[4]: [array([], dtype=int64), array([0]), array([0, 1]), array([0, 1, 2])]
```

List Reflection

In nopython mode, Numba does not operate on Python objects. `list` are compiled into an internal representation. Any `list` arguments must be converted into this representation on the way in to nopython mode and their contained elements must be restored in the original Python objects via a process called *reflection*. Reflection is required to maintain the same semantics as found in regular Python code. However, the reflection process can be expensive for large lists and it is not supported for lists that contain reflected data types. Users cannot use list-of-list as an argument because of this limitation.

Note: When passing a list into a JIT-compiled function, any modifications made to the list will not be visible to the Python interpreter until the function returns. (A limitation of the reflection process.)

Warning: List sorting currently uses a quicksort algorithm, which has different performance characterics than the algorithm used by Python.

Initial Values

Warning: This is an experimental feature!

Lists that:

- Are constructed using the square braces syntax
- Have values of a literal type

will have their initial value stored in the `.initial_value` property on the type so as to permit inspection of these values at compile time. If required, to force value based dispatch the *literally* function will accept such a list.

Example:

Listing 1: from `test_ex_initial_value_list_compile_time_consts` of `numba/tests/doc_examples/test_literal_container_usage.py`

```
from numba import njit, literally
from numba.extending import overload

# overload this function
def specialize(x):
    pass

@overload(specialize)
```

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```
def ol_specialize(x):
    iv = x.initial_value
    if iv is None:
        return lambda x: literally(x) # Force literal dispatch
    assert iv == [1, 2, 3] # INITIAL VALUE
    return lambda x: x

@njit
def foo():
    l = [1, 2, 3]
    l[2] = 20 # no impact on .initial_value
    l.append(30) # no impact on .initial_value
    return specialize(l)

result = foo()
print(result) # [1, 2, 20, 30] # NOT INITIAL VALUE!
```

Typed List

Note: `numba.typed.List` is an experimental feature, if you encounter any bugs in functionality or suffer from unexpectedly bad performance, please report this, ideally by opening an issue on the Numba issue tracker.

As of version 0.45.0 a new implementation of the list data type is available, the so-called *typed-list*. This is compiled library backed, type-homogeneous list data type that is an improvement over the *reflected-list* mentioned above. Additionally, lists can now be arbitrarily nested. Since the implementation is considered experimental, you will need to import it explicitly from the *numba.typed* module:

```
In [1]: from numba.typed import List

In [2]: from numba import njit

In [3]: @njit
...: def foo(l):
...:     l.append(23)
...:     return l
...:

In [4]: mylist = List()

In [5]: mylist.append(1)

In [6]: foo(mylist)
Out[6]: ListType[int64]([1, 23])
```

Note: As the typed-list stabilizes it will fully replace the reflected-list and the constructors *[]* and *list()* will create a typed-list instead of a reflected one.

Here's an example using `List()` to create `numba.typed.List` inside a jit-compiled function and letting the compiler

infer the item type:

Listing 2: from ex_inferred_list_jit of numba/tests/doc_examples/test_typed_list_usage.py

```
from numba import njit
from numba.typed import List

@njit
def foo():
    # Instantiate a typed-list
    l = List()
    # Append a value to it, this will set the type to int32/int64
    # (depending on platform)
    l.append(42)
    # The usual list operations, getitem, pop and length are
    # supported
    print(l[0])   # 42
    l[0] = 23
    print(l[0])   # 23
    print(len(l)) # 1
    l.pop()
    print(len(l)) # 0
    return l

foo()

```

Here's an example of using `List()` to create a `numba.typed.List` outside of a jit-compiled function and then using it as an argument to a jit-compiled function:

Listing 3: from ex_inferred_list of numba/tests/doc_examples/test_typed_list_usage.py

```
from numba import njit
from numba.typed import List

@njit
def foo(mylist):
    for i in range(10, 20):
        mylist.append(i)
    return mylist

# Instantiate a typed-list, outside of a jit context
l = List()
# Append a value to it, this will set the type to int32/int64
# (depending on platform)
l.append(42)
# The usual list operations, getitem, pop and length are supported
print(l[0])   # 42
l[0] = 23
print(l[0])   # 23
print(len(l)) # 1
l.pop()
```

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```
print(len(l)) # 0

# And you can use the typed-list as an argument for a jit compiled
# function
l = foo(l)
print(len(l)) # 10

# You can also directly construct a typed-list from an existing
# Python list
py_list = [2, 3, 5]
numba_list = List(py_list)
print(len(numba_list)) # 3

```

Finally, here's an example of using a nested *List()*:

Listing 4: from `ex_nested_list` of `numba/tests/doc_examples/test_typed_list_usage.py`

```
from numba.typed import List

# typed-lists can be nested in typed-lists
mylist = List()
for i in range(10):
    l = List()
    for i in range(10):
        l.append(i)
    mylist.append(l)
# mylist is now a list of 10 lists, each containing 10 integers
print(mylist)

```

Literal List

Warning: This is an experimental feature!

Numba supports the use of literal lists containing any values, for example:

```
l = ['a', 1, 2j, np.zeros(5,)]
```

the predominant use of these lists is for use as a configuration object. The lists appear as a `LiteralList` type which inherits from `Literal`, as a result the literal values of the list items are available at compile time. For example:

Listing 5: from `test_ex_literal_list` of `numba/tests/doc_examples/test_literal_container_usage.py`

```
from numba import njit
from numba.extending import overload

# overload this function
```

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```
def specialize(x):
    pass

@overload(specialize)
def ol_specialize(x):
    l = x.literal_value
    const_expr = []
    for v in l:
        const_expr.append(str(v))
    const_strings = tuple(const_expr)

    def impl(x):
        return const_strings
    return impl

@njit
def foo():
    const_list = ['a', 10, 1j, ['another', 'list']]
    return specialize(const_list)

result = foo()
print(result) # ('Literal[str](a)', 'Literal[int](10)', 'complex128', 'list(unicode_type)') #␣
↪noqa E501
```

Important things to note about these kinds of lists:

1. They are immutable, use of mutating methods e.g. `.pop()` will result in compilation failure. Read-only static access and read only methods are supported e.g. `len()`.
2. Dynamic access of items is not possible, e.g. `some_list[x]`, for a value `x` which is not a compile time constant. This is because it's impossible to statically determine the type of the item being accessed.
3. Inside the compiler, these lists are actually just tuples with some extra things added to make them look like they are lists.
4. They cannot be returned to the interpreter from a compiled function.

List comprehension

Numba supports list comprehension. For example:

```
In [1]: from numba import njit

In [2]: @njit
  ...: def foo(x):
  ...:     return [[i for i in range(n)] for n in range(x)]
  ...:

In [3]: foo(3)
Out[3]: [[], [0], [0, 1]]
```

Note: Prior to version 0.39.0, Numba did not support the creation of nested lists.

Numba also supports "array comprehension" that is a list comprehension followed immediately by a call to `numpy.array()`. The following is an example that produces a 2D Numpy array:

```
from numba import jit
import numpy as np

@jit(nopython=True)
def f(n):
  return np.array([ [ x * y for x in range(n) ] for y in range(n) ])
```

In this case, Numba is able to optimize the program to allocate and initialize the result array directly without allocating intermediate list objects. Therefore, the nesting of list comprehension here is not a problem since a multi-dimensional array is being created here instead of a nested list.

Additionally, Numba supports parallel array comprehension when combined with the *parallel* option on CPUs.

set

All methods and operations on sets are supported in JIT-compiled functions.

Sets must be strictly homogeneous: Numba will reject any set containing objects of different types, even if the types are compatible (for example, `{1, 2.5}` is rejected as it contains a `int` and a `float`). The use of reference counted types, e.g. strings, in sets is unsupported.

Note: When passing a set into a JIT-compiled function, any modifications made to the set will not be visible to the Python interpreter until the function returns.

Typed Dict

Warning: `numba.typed.Dict` is an experimental feature. The API may change in the future releases.

Note: `dict()` was not supported in versions prior to 0.44. Currently, calling `dict()` translates to calling `numba.typed.Dict()`.

Numba supports the use of `dict()`. Such use is semantically equivalent to `{}` and `numba.typed.Dict()`. It will create an instance of `numba.typed.Dict` where the key-value types will be later inferred by usage. Numba also supports, explicitly, the `dict(iterable)` constructor.

Numba does not fully support the Python `dict` because it is an untyped container that can have any Python types as members. To generate efficient machine code, Numba needs the keys and the values of the dictionary to have fixed types, declared in advance. To achieve this, Numba has a typed dictionary, `numba.typed.Dict`, for which the type-inference mechanism must be able to infer the key-value types by use, or the user must explicitly declare the key-value type using the `Dict.empty()` constructor method. This typed dictionary has the same API as the Python `dict`, it implements the `collections.MutableMapping` interface and is usable in both interpreted Python code and JIT-compiled Numba functions. Because the typed dictionary stores keys and values in Numba's native, unboxed data layout, passing a Numba dictionary into nopython mode has very low overhead. However, this means that using a typed dictionary from the Python interpreter is slower than a regular dictionary because Numba has to box and unbox key and value objects when getting or setting items.

An important difference of the typed dictionary in comparison to Python's `dict` is that **implicit casting** occurs when a key or value is stored. As a result the *setitem* operation may fail should the type-casting fail.

It should be noted that the Numba typed dictionary is implemented using the same algorithm as the CPython 3.7 dictionary. As a consequence, the typed dictionary is ordered and has the same collision resolution as the CPython implementation.

Further to the above in relation to type specification, there are limitations placed on the types that can be used as keys and/or values in the typed dictionary, most notably the Numba `Set` and `List` types are currently unsupported. Acceptable key/value types include but are not limited to: unicode strings, arrays (value only), scalars, tuples. It is expected that these limitations will be relaxed as Numba continues to improve.

Here's an example of using `dict()` and `{}` to create `numba.typed.Dict` instances and letting the compiler infer the key-value types:

Listing 6: from `test_ex_inferred_dict_njit` of `numba/tests/doc_examples/test_typed_dict_usage.py`

```
from numba import njit
import numpy as np

@njit
def foo():
    d = dict()
    k = {1: np.arange(1), 2: np.arange(2)}
    # The following tells the compiler what the key type and the
    # value
    # type are for `d`.
    d[3] = np.arange(3)
    d[5] = np.arange(5)
    return d, k

d, k = foo()
print(d)    # {3: [0 1 2], 5: [0 1 2 3 4]}
print(k)    # {1: [0], 2: [0 1]}
```

Here's an example of creating a `numba.typed.Dict` instance from interpreted code and using the dictionary in jit code:

Listing 7: from `test_ex_typed_dict_from_cpython` of `numba/tests/doc_examples/test_typed_dict_usage.py`

```
import numpy as np
from numba import njit
from numba.core import types
from numba.typed import Dict

# The Dict.empty() constructs a typed dictionary.
# The key and value typed must be explicitly declared.
d = Dict.empty(
    key_type=types.unicode_type,
    value_type=types.float64[:],
)

# The typed-dict can be used from the interpreter.
```

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```
d['posx'] = np.asarray([1, 0.5, 2], dtype='f8')
d['posy'] = np.asarray([1.5, 3.5, 2], dtype='f8')
d['velx'] = np.asarray([0.5, 0, 0.7], dtype='f8')
d['vely'] = np.asarray([0.2, -0.2, 0.1], dtype='f8')

# Here's a function that expects a typed-dict as the argument
@njit
def move(d):
    # inplace operations on the arrays
    d['posx'] += d['velx']
    d['posy'] += d['vely']

print('posx: ', d['posx'])  # Out: posx:  [1.  0.5 2. ]
print('posy: ', d['posy'])  # Out: posy:  [1.5 3.5 2. ]

# Call move(d) to inplace update the arrays in the typed-dict.
move(d)

print('posx: ', d['posx'])  # Out: posx:  [1.5 0.5 2.7]
print('posy: ', d['posy'])  # Out: posy:  [1.7 3.3 2.1]
```

Here's an example of creating a `numba.typed.Dict` instance from jit code and using the dictionary in interpreted code:

Listing 8: from `test_ex_typed_dict_njit` of `numba/tests/doc_examples/test_typed_dict_usage.py`

```
import numpy as np
from numba import njit
from numba.core import types
from numba.typed import Dict

# Make array type.  Type-expression is not supported in jit
# functions.
float_array = types.float64[:]

@njit
def foo():
    # Make dictionary
    d = Dict.empty(
        key_type=types.unicode_type,
        value_type=float_array,
    )
    # Fill the dictionary
    d["posx"] = np.arange(3).astype(np.float64)
    d["posy"] = np.arange(3, 6).astype(np.float64)
    return d

d = foo()
# Print the dictionary
print(d)  # Out: {posx: [0. 1. 2.], posy: [3. 4. 5.]}
```

It should be noted that `numba.typed.Dict` is not thread-safe. Specifically, functions which modify a dictionary from

multiple threads will potentially corrupt memory, causing a range of possible failures. However, the dictionary can be safely read from multiple threads as long as the contents of the dictionary do not change during the parallel access.

Dictionary comprehension

Numba supports dictionary comprehension under the assumption that a `numba.typed.Dict` instance can be created from the comprehension. For example:

```
In [1]: from numba import njit

In [2]: @njit
   ...: def foo(n):
   ...:     return {i: i**2 for i in range(n)}
   ...:

In [3]: foo(3)
Out[3]: DictType[int64,int64]<iv=None>({0: 0, 1: 1, 2: 4})
```

Initial Values

Warning: This is an experimental feature!

Typed dictionaries that:

- Are constructed using the curly braces syntax
- Have literal string keys
- Have values of a literal type

will have their initial value stored in the `.initial_value` property on the type so as to permit inspection of these values at compile time. If required, to force value based dispatch the *literally* function will accept a typed dictionary.

Example:

Listing 9: from `test_ex_initial_value_dict_compile_time_consts` of `numba/tests/doc_examples/test_literal_container_usage.py`

```
from numba import njit, literally
from numba.extending import overload

# overload this function
def specialize(x):
    pass

@overload(specialize)
def ol_specialize(x):
    iv = x.initial_value
    if iv is None:
        return lambda x: literally(x) # Force literal dispatch
    assert iv == {'a': 1, 'b': 2, 'c': 3} # INITIAL VALUE
```

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```
    return lambda x: literally(x)

@njit
def foo():
    d = {'a': 1, 'b': 2, 'c': 3}
    d['c'] = 20 # no impact on .initial_value
    d['d'] = 30 # no impact on .initial_value
    return specialize(d)

result = foo()
print(result) # {a: 1, b: 2, c: 20, d: 30} # NOT INITIAL VALUE!
```

Heterogeneous Literal String Key Dictionary

Warning: This is an experimental feature!

Numba supports the use of statically declared string key to any value dictionaries, for example:

```
d = {'a': 1, 'b': 'data', 'c': 2j}
```

the predominant use of these dictionaries is to orchestrate advanced compilation dispatch or as a container for use as a configuration object. The dictionaries appear as a `LiteralStrKeyDict` type which inherits from `Literal`, as a result the literal values of the keys and the types of the items are available at compile time. For example:

Listing 10: from `test_ex_literal_dict_compile_time_consts` of `numba/tests/doc_examples/test_literal_container_usage.py`

```
import numpy as np
from numba import njit, types
from numba.extending import overload

# overload this function
def specialize(x):
    pass

@overload(specialize)
def ol_specialize(x):
    ld = x.literal_value
    const_expr = []
    for k, v in ld.items():
        if isinstance(v, types.Literal):
            lv = v.literal_value
            if lv == 'cat':
                const_expr.append("Meow!")
            elif lv == 'dog':
                const_expr.append("Woof!")
            elif isinstance(lv, int):
                const_expr.append(k.literal_value * lv)
```

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```
        else: # it's an array
            const_expr.append("Array(dim={dim}".format(dim=v.ndim))
    const_strings = tuple(const_expr)

    def impl(x):
        return const_strings
    return impl

@njit
def foo():
    pets_ints_and_array = {'a': 1,
                           'b': 2,
                           'c': 'cat',
                           'd': 'dog',
                           'e': np.ones(5,)}
    return specialize(pets_ints_and_array)

result = foo()
print(result) # ('a', 'bb', 'Meow!', 'Woof!', 'Array(dim=1')
```

Important things to note about these kinds of dictionaries:

1. They are immutable, use of mutating methods e.g. `.pop()` will result in compilation failure. Read-only static access and read only methods are supported e.g. `len()`.
2. Dynamic access of items is not possible, e.g. `some_dictionary[x]`, for a value `x` which is not a compile time constant. This is because it's impossible statically determine the type of the item being accessed.
3. Inside the compiler, these dictionaries are actually just named tuples with some extra things added to make them look like they are dictionaries.
4. They cannot be returned to the interpreter from a compiled function.
5. The `.keys()`, `.values()` and `.items()` methods all functionally operate but return tuples opposed to iterables.

None

The None value is supported for identity testing (when using an *optional* type).

bytes, bytearray, memoryview

The `bytearray` type and, on Python 3, the `bytes` type support indexing, iteration and retrieving the len().

The `memoryview` type supports indexing, slicing, iteration, retrieving the len(), and also the following attributes:

- `contiguous`
- `c_contiguous`
- `f_contiguous`
- `itemsize`
- `nbytes`
- `ndim`
- `readonly`

- shape
- strides

2.6.3 Built-in functions

The following built-in functions are supported:

- abs()
- bool
- chr()
- complex
- divmod()
- enumerate()
- filter()
- float
- getattr(): the attribute must be a string literal and the return type cannot be a function type (e.g. `getattr(numpy, 'cos')` is not supported as it returns a function type).
- hasattr()
- hash() (see *Hashing* below)
- int: only the one-argument form
- iter(): only the one-argument form
- isinstance()
- len()
- min()
- map()
- max()
- next(): only the one-argument form
- ord()
- print(): only numbers and strings; no `file` or `sep` argument
- range: The only permitted use of range is as a callable function (cannot pass range as an argument to a jitted function or return a range from a jitted function).
- repr()
- round()
- sorted(): the `key` argument is not supported
- sum()
- str()
- type(): only the one-argument form, and only on some types (e.g. numbers and named tuples)
- zip()

Hashing

The hash() built-in is supported and produces hash values for all supported hashable types with the following Python version specific behavior:

Under Python 3, hash values computed by Numba will exactly match those computed in CPython under the condition that the sys.hash_info.algorithm is siphash24 (default).

The PYTHONHASHSEED environment variable influences the hashing behavior in precisely the manner described in the CPython documentation.

Note: From NumPy 2.2 onwards, hash values for numpy.timedelta64 and numpy.datetime64 instances computed in Numba compiled code do not match the NumPy hash values of the same. Prior to NumPy 2.2, NumPy hash values for numpy.timedelta64 and numpy.datetime64 instances were equivalent to their integer value representation. From NumPy 2.2 onwards, their hash value is the same as the hash of the equivalent type from the datetime module, Numba does not replicate this behaviour.

2.6.4 Standard library modules

array

Limited support for the array.array type is provided through the buffer protocol. Indexing, iteration and taking the len() is supported. All type codes are supported except for "u".

cmath

The following functions from the cmath module are supported:

- cmath.acos()
- cmath.acosh()
- cmath.asin()
- cmath.asinh()
- cmath.atan()
- cmath.atanh()
- cmath.cos()
- cmath.cosh()
- cmath.exp()
- cmath.isfinite()
- cmath.isinf()
- cmath.isnan()
- cmath.log()
- cmath.log10()
- cmath.phase()
- cmath.polar()

- cmath.rect()
- cmath.sin()
- cmath.sinh()
- cmath.sqrt()
- cmath.tan()
- cmath.tanh()

collections

Named tuple classes, as returned by collections.namedtuple(), are supported in the same way regular tuples are supported. Attribute access and named parameters in the constructor are also supported.

Creating a named tuple class inside Numba code is *not* supported; the class must be created at the global level.

ctypes

Numba is able to call ctypes-declared functions with the following argument and return types:

- ctypes.c_int8
- ctypes.c_int16
- ctypes.c_int32
- ctypes.c_int64
- ctypes.c_uint8
- ctypes.c_uint16
- ctypes.c_uint32
- ctypes.c_uint64
- ctypes.c_float
- ctypes.c_double
- ctypes.c_void_p

enum

Both enum.Enum and enum.IntEnum subclasses are supported.

math

The following functions from the math module are supported:

- math.acos()
- math.acosh()
- math.asin()
- math.asinh()
- math.atan()

- math.atan2()
- math.atanh()
- math.ceil()
- math.copysign()
- math.cos()
- math.cosh()
- math.degrees()
- math.erf()
- math.erfc()
- math.exp()
- math.expm1()
- math.fabs()
- math.floor()
- math.frexp()
- math.gamma()
- math.gcd()
- math.hypot()
- math.isfinite()
- math.isinf()
- math.isnan()
- math.ldexp()
- math.lgamma()
- math.log()
- math.log2()
- math.log10()
- math.log1p()
- math.nextafter()
- math.pow()
- math.radians()
- math.sin()
- math.sinh()
- math.sqrt()
- math.tan()
- math.tanh()
- math.trunc()

operator

The following functions from the operator module are supported:

- operator.add()
- operator.and_()
- operator.eq()
- operator.floordiv()
- operator.ge()
- operator.gt()
- operator.iadd()
- operator.iand()
- operator.ifloordiv()
- operator.ilshift()
- operator.imatmul() (Python 3.5 and above)
- operator.imod()
- operator.imul()
- operator.invert()
- operator.ior()
- operator.ipow()
- operator.irshift()
- operator.isub()
- operator.itruediv()
- operator.ixor()
- operator.le()
- operator.lshift()
- operator.lt()
- operator.matmul() (Python 3.5 and above)
- operator.mod()
- operator.mul()
- operator.ne()
- operator.neg()
- operator.not_()
- operator.or_()
- operator.pos()
- operator.pow()
- operator.rshift()
- operator.sub()

- operator.truediv()
- operator.xor()

functools

The functools.reduce() function is supported but the *initializer* argument is required.

random

Numba supports top-level functions from the random module, but does not allow you to create individual Random instances. A Mersenne-Twister generator is used, with a dedicated internal state. It is initialized at startup with entropy drawn from the operating system.

- random.betavariate()
- random.expovariate()
- random.gammavariate()
- random.gauss()
- random.getrandbits(): number of bits must not be greater than 64
- random.lognormvariate()
- random.normalvariate()
- random.paretovariate()
- random.randint()
- random.random()
- random.randrange()
- random.seed(): with an integer argument only
- random.shuffle(): the sequence argument must be a one-dimension Numpy array or buffer-providing object (such as a bytearray or array.array); the second (optional) argument is not supported
- random.uniform()
- random.triangular()
- random.vonmisesvariate()
- random.weibullvariate()

Warning: Calling random.seed() from non-Numba code (or from *object mode* code) will seed the Python random generator, not the Numba random generator. To seed the Numba random generator, see the example below.

```
from numba import njit
import random

@njit
def seed(a):
    random.seed(a)
```

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```
@njit
def rand():
    return random.random()


# Incorrect seeding
random.seed(1234)
print(rand())

random.seed(1234)
print(rand())

# Correct seeding
seed(1234)
print(rand())

seed(1234)
print(rand())
```

Note: Since version 0.28.0, the generator is thread-safe and fork-safe. Each thread and each process will produce independent streams of random numbers.

See also:

Numba also supports most additional distributions from the *Numpy random module*.

heapq

The following functions from the `heapq` module are supported:

- `heapq.heapify()`
- `heapq.heappop()`
- `heapq.heappush()`
- `heapq.heappushpop()`
- `heapq.heapreplace()`
- `heapq.nlargest()` : first two arguments only
- `heapq.nsmallest()` : first two arguments only

Note: the heap must be seeded with at least one value to allow its type to be inferred; heap items are assumed to be homogeneous in type.

2.6.5 Third-party modules

cffi

Similarly to ctypes, Numba is able to call into cffi-declared external functions, using the following C types and any derived pointer types:

- char
- short
- int
- long
- long long
- unsigned char
- unsigned short
- unsigned int
- unsigned long
- unsigned long long
- int8_t
- uint8_t
- int16_t
- uint16_t
- int32_t
- uint32_t
- int64_t
- uint64_t
- float
- double
- ssize_t
- size_t
- void

The from_buffer() method of cffi.FFI and CompiledFFI objects is supported for passing Numpy arrays and other buffer-like objects. Only *contiguous* arguments are accepted. The argument to from_buffer() is converted to a raw pointer of the appropriate C type (for example a double * for a float64 array).

Additional type mappings for the conversion from a buffer to the appropriate C type may be registered with Numba. This may include struct types, though it is only permitted to call functions that accept pointers to structs - passing a struct by value is unsupported. For registering a mapping, use:

numba.core.typing.cffi_utils.**register_type**(*cffi_type*, *numba_type*)

Out-of-line cffi modules must be registered with Numba prior to the use of any of their functions from within Numba-compiled functions:

numba.core.typing.cffi_utils.**register_module**(*mod*)

Register the cffi out-of-line module `mod` with Numba.

Inline cffi modules require no registration.

2.7 Supported NumPy features

One objective of Numba is having a seamless integration with NumPy. NumPy arrays provide an efficient storage method for homogeneous sets of data. NumPy dtypes provide type information useful when compiling, and the regular, structured storage of potentially large amounts of data in memory provides an ideal memory layout for code generation. Numba excels at generating code that executes on top of NumPy arrays.

NumPy support in Numba comes in many forms:

- Numba understands calls to NumPy ufuncs and is able to generate equivalent native code for many of them.
- NumPy arrays are directly supported in Numba. Access to NumPy arrays is very efficient, as indexing is lowered to direct memory accesses when possible.
- Numba is able to generate ufuncs and gufuncs. This means that it is possible to implement ufuncs and gufuncs within Python, getting speeds comparable to that of ufuncs/gufuncs implemented in C extension modules using the NumPy C API.

The following sections focus on the NumPy features supported in *nopython mode*, unless otherwise stated.

2.7.1 Scalar types

Numba supports the following NumPy scalar types:

- **Integers**: all integers of either signedness, and any width up to 64 bits
- **Booleans**
- **Real numbers:** single-precision (32-bit) and double-precision (64-bit) reals
- **Complex numbers:** single-precision (2x32-bit) and double-precision (2x64-bit) complex numbers
- **Datetimes and timestamps:** of any unit
- **Character sequences** (but no operations are available on them)
- **Structured scalars:** structured scalars made of any of the types above and arrays of the types above

The following scalar types and features are not supported:

- **Arbitrary Python objects**
- **Half-precision and extended-precision** real and complex numbers
- **Nested structured scalars** the fields of structured scalars may not contain other structured scalars

The operations supported on NumPy scalars are almost the same as on the equivalent built-in types such as `int` or `float`. You can use a type's constructor to convert from a different type or width. In addition you can use the `view(np.<dtype>)` method to bitcast all `int` and `float` types within the same width. However, you must define the scalar using a NumPy constructor within a jitted function. For example, the following will work:

```
>>> import numpy as np
>>> from numba import njit
>>> @njit
... def bitcast():
```

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```
...     i = np.int64(-1)
...     print(i.view(np.uint64))
...
>>> bitcast()
18446744073709551615
```

Whereas the following will not work:

```
>>> import numpy as np
>>> from numba import njit
>>> @njit
... def bitcast(i):
...     print(i.view(np.uint64))
...
>>> bitcast(np.int64(-1))
---------------------------------------------------------------------------
TypingError                               Traceback (most recent call last)
    ...
TypingError: Failed in nopython mode pipeline (step: ensure IR is legal prior to␣
↪lowering)
'view' can only be called on NumPy dtypes, try wrapping the variable with 'np.<dtype>()'

File "<ipython-input-3-fc40aaab84c4>", line 3:
def bitcast(i):
    print(i.view(np.uint64))
```

Structured scalars support attribute getting and setting, as well as member lookup using constant strings. Strings stored in a local or global tuple are considered constant strings and can be used for member lookup.

```
import numpy as np
from numba import njit

arr = np.array([(1, 2)], dtype=[('a1', 'f8'), ('a2', 'f8')])
fields_gl = ('a1', 'a2')

@njit
def get_field_sum(rec):
    fields_lc = ('a1', 'a2')
    field_name1 = fields_lc[0]
    field_name2 = fields_gl[1]
    return rec[field_name1] + rec[field_name2]

get_field_sum(arr[0])  # returns 3
```

It is also possible to use local or global tuples together with `literal_unroll`:

```
import numpy as np
from numba import njit, literal_unroll

arr = np.array([(1, 2)], dtype=[('a1', 'f8'), ('a2', 'f8')])
fields_gl = ('a1', 'a2')

@njit
```

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```
def get_field_sum(rec):
    out = 0
    for f in literal_unroll(fields_gl):
        out += rec[f]
    return out

get_field_sum(arr[0])   # returns 3
```

Record subtyping

Warning: This is an experimental feature.

Numba allows width subtyping of structured scalars. For example, `dtype([('a', 'f8'), ('b', 'i8')])` will be considered a subtype of `dtype([('a', 'f8')]`, because the second is a strict subset of the first, i.e. field `a` is of the same type and is in the same position in both types. The subtyping relationship will matter in cases where compilation for a certain input is not allowed, but the input is a subtype of another, allowed type.

```
import numpy as np
from numba import njit, typeof
from numba.core import types
record1 = np.array([1], dtype=[('a', 'f8')])[0]
record2 = np.array([(2,3)], dtype=[('a', 'f8'), ('b', 'f8')])[0]

@njit(types.float64(typeof(record1)))
def foo(rec):
    return rec['a']

foo(record1)
foo(record2)
```

Without subtyping the last line would fail. With subtyping, no new compilation will be triggered, but the compiled function for `record1` will be used for `record2`.

See also:

NumPy scalars reference.

2.7.2 Array types

NumPy arrays of any of the scalar types above are supported, regardless of the shape or layout.

Note: NumPy MaskedArrays are not supported.

Array access

Arrays support normal iteration. Full basic indexing and slicing is supported along with passing `None` / `np.newaxis` as indices for additional resulting dimensions. A subset of advanced indexing is also supported: only one advanced index is allowed, and it has to be a one-dimensional array (it can be combined with an arbitrary number of basic indices as well).

See also:

NumPy indexing reference.

Structured array access

Numba presently supports accessing fields of individual elements in structured arrays by attribute as well as by getting and setting. This goes slightly beyond the NumPy API, which only allows accessing fields by getting and setting. For example:

```
from numba import njit
import numpy as np

record_type = np.dtype([("ival", np.int32), ("fval", np.float64)], align=True)

def f(rec):
    value = 2.5
    rec[0].ival = int(value)
    rec[0].fval = value
    return rec

arr = np.ones(1, dtype=record_type)

cfunc = njit(f)

# Works
print(cfunc(arr))

# Does not work
print(f(arr))
```

The above code results in the output:

```
[(2, 2.5)]
Traceback (most recent call last):
  File "repro.py", line 22, in <module>
    print(f(arr))
  File "repro.py", line 9, in f
    rec[0].ival = int(value)
AttributeError: 'numpy.void' object has no attribute 'ival'
```

The Numba-compiled version of the function executes, but the pure Python version raises an error because of the unsupported use of attribute access.

Note: This behavior will eventually be deprecated and removed.

Attributes

The following attributes of NumPy arrays are supported:

- `dtype`
- `flags`
- `flat`
- `itemsize`
- `nbytes`
- `ndim`
- `shape`
- `size`
- `strides`
- `T`
- `real`
- `imag`

The `flags` object

The object returned by the `flags` attribute supports the `contiguous`, `c_contiguous` and `f_contiguous` attributes.

The `flat` object

The object returned by the `flat` attribute supports iteration and indexing, but be careful: indexing is very slow on non-C-contiguous arrays.

The `real` and `imag` attributes

NumPy supports these attributes regardless of the dtype but Numba chooses to limit their support to avoid potential user error. For numeric dtypes, Numba follows NumPy's behavior. The `real` attribute returns a view of the real part of the complex array and it behaves as an identity function for other numeric dtypes. The `imag` attribute returns a view of the imaginary part of the complex array and it returns a zero array with the same shape and dtype for other numeric dtypes. For non-numeric dtypes, including all structured/record dtypes, using these attributes will result in a compile-time (*TypingError*) error. This behavior differs from NumPy's but it is chosen to avoid the potential confusion with field names that overlap these attributes.

Calculation

The following methods of NumPy arrays are supported in their basic form (without any optional arguments):

- `all()`
- `any()`
- `clip()`
- `conj()`
- `conjugate()`
- `cumprod()`
- `cumsum()`
- `max()`
- `mean()`
- `min()`
- `nonzero()`
- `prod()`
- `std()`
- `take()`
- `var()`

The corresponding top-level NumPy functions (such as `numpy.prod()`) are similarly supported.

Other methods

The following methods of NumPy arrays are supported:

- `argmax()` (`axis` keyword argument supported).
- `argmin()` (`axis` keyword argument supported).
- `numpy.argpartition()` (only the 2 first arguments)
- `argsort()` (`kind` key word argument supported for values `'quicksort'` and `'mergesort'`)
- `astype()` (only the 1-argument form)
- `copy()` (without arguments)
- `dot()` (only the 1-argument form)
- `flatten()` (no order argument; 'C' order only)
- `item()` (without arguments)
- `itemset()` (only the 1-argument form)
- `ptp()` (without arguments)
- `ravel()` (no order argument; 'C' order only)
- `repeat()` (no axis argument)
- `reshape()` (only the 1-argument form)
- `sort()` (without arguments)

- sum() (with or without the axis and/or dtype arguments.)
  - axis only supports integer values.
  - If the axis argument is a compile-time constant, all valid values are supported. An out-of-range value will result in a LoweringError at compile-time.
  - If the axis argument is not a compile-time constant, only values from 0 to 3 are supported. An out-of-range value will result in a runtime exception.
  - All numeric dtypes are supported in the dtype parameter. timedelta arrays can be used as input arrays but timedelta is not supported as dtype parameter.
  - When a dtype is given, it determines the type of the internal accumulator. When it is not, the selection is made automatically based on the input array's dtype, mostly following the same rules as NumPy. However, on 64-bit Windows, Numba uses a 64-bit accumulator for integer inputs (int64 for int32 inputs and uint64 for uint32 inputs), while NumPy would use a 32-bit accumulator in those cases.
- tobytes() (without arguments)
- transpose()
- view() (only the 1-argument form)
- __contains__()

Where applicable, the corresponding top-level NumPy functions (such as numpy.argmax()) are similarly supported.

Warning: Sorting may be slightly slower than NumPy's implementation.

2.7.3 Functions

Linear algebra

Basic linear algebra is supported on 1-D and 2-D contiguous arrays of floating-point and complex numbers:

- numpy.dot()
- numpy.kron() ('C' and 'F' order only)
- numpy.outer()
- numpy.trace() (only the first argument).
- numpy.vdot()
- On Python 3.5 and above, the matrix multiplication operator from **PEP 465** (i.e. a @ b where a and b are 1-D or 2-D arrays).
- numpy.linalg.cholesky()
- numpy.linalg.cond() (only non string values in p).
- numpy.linalg.det()
- numpy.linalg.eig() (only running with data that does not cause a domain change is supported e.g. real input -> real output, complex input -> complex output).
- numpy.linalg.eigh() (only the first argument).
- numpy.linalg.eigvals() (only running with data that does not cause a domain change is supported e.g. real input -> real output, complex input -> complex output).

- numpy.linalg.eigvalsh() (only the first argument).
- numpy.linalg.inv()
- numpy.linalg.lstsq()
- numpy.linalg.matrix_power()
- numpy.linalg.matrix_rank()
- numpy.linalg.norm() (only the 2 first arguments and only non string values in ord).
- numpy.linalg.pinv()
- numpy.linalg.qr() (only the first argument).
- numpy.linalg.slogdet()
- numpy.linalg.solve()
- numpy.linalg.svd() (only the 2 first arguments).

Note: The implementation of these functions needs SciPy to be installed.

Reductions

The following reduction functions are supported:

- numpy.diff() (only the 2 first arguments)
- numpy.amin() (only the first argument, also aliased as np.min)
- numpy.amax() (only the first argument, also aliased as np.max)
- numpy.median() (only the first argument)
- numpy.nancumprod() (only the first argument)
- numpy.nancumsum() (only the first argument)
- numpy.nanmax() (only the first argument)
- numpy.nanmean() (only the first argument)
- numpy.nanmedian() (only the first argument)
- numpy.nanmin() (only the first argument)
- numpy.nanpercentile() (only the 2 first arguments, complex dtypes unsupported)
- numpy.nanquantile() (only the 2 first arguments, complex dtypes unsupported)
- numpy.nanprod() (only the first argument)
- numpy.nanstd() (only the first argument)
- numpy.nansum() (only the first argument)
- numpy.nanvar() (only the first argument)
- numpy.percentile() (only the 2 first arguments, complex dtypes unsupported)
- numpy.quantile() (only the 2 first arguments, complex dtypes unsupported)

Polynomials

The following polynomial classes are supported: * numpy.polynomial.polynomial.Polynomial (only the first three arguments)

The following polynomial functions are supported: * numpy.polynomial.polynomial.polyadd() * numpy.polynomial.polynomial.polydiv() * numpy.polynomial.polynomial.polyint() (only the 2 first arguments) * numpy.polynomial.polynomial.polymul() * numpy.polynomial.polynomial.polysub() * numpy.polynomial.polynomial.polyval() (the argument `tensor` must be a boolean constant) * numpy.polynomial.polyutils.as_series() * numpy.polynomial.polyutils.trimseq()

Other functions

The following top-level functions are supported:

- numpy.allclose()
- numpy.append()
- numpy.arange()
- numpy.argsort() (`kind` key word argument supported for values `'quicksort'` and `'mergesort'`)
- numpy.argwhere()
- numpy.around()
- numpy.array() (only the 2 first arguments)
- numpy.array_equal()
- numpy.array_split()
- numpy.asarray() (only the 2 first arguments)
- numpy.asarray_chkfinite() (only the 2 first arguments)
- numpy.ascontiguousarray() (only the first argument)
- numpy.asfarray()
- numpy.asfortranarray() (only the first argument)
- numpy.atleast_1d()
- numpy.atleast_2d()
- numpy.atleast_3d()
- numpy.bartlett()
- numpy.bincount()
- numpy.blackman()
- numpy.broadcast_to() (only the 2 first arguments)
- numpy.broadcast_arrays() (only the first argument)
- numpy.broadcast_shapes()
- numpy.column_stack()
- numpy.concatenate() (only supports tuple arguments)
- numpy.convolve() (all arguments)

- numpy.copy() (only the first argument)
- numpy.corrcoef() (only the 3 first arguments, requires SciPy)
- numpy.correlate() (all arguments)
- numpy.count_nonzero() (axis only supports scalar values)
- numpy.cov() (only the 5 first arguments)
- numpy.cross() (only the 2 first arguments; at least one of the input arrays should have `shape[-1] == 3`)
  - If `shape[-1] == 2` for both inputs, please replace your numpy.cross() call with `numba.np.extensions.cross2d()`.
- numpy.delete() (only the 2 first arguments)
- numpy.diag()
- numpy.diagflat()
- numpy.digitize()
- numpy.dsplit()
- numpy.dstack()
- `numpy.dtype()` (only the first argument)
- numpy.ediff1d()
- numpy.empty() (only the 2 first arguments)
- numpy.empty_like() (only the 2 first arguments)
- numpy.expand_dims()
- numpy.extract()
- numpy.eye()
- numpy.fill_diagonal()
- `numpy.flatten()` (no order argument; 'C' order only)
- numpy.flatnonzero()
- numpy.flip() (no axis argument)
- numpy.fliplr()
- numpy.flipud()
- numpy.frombuffer() (only the 2 first arguments)
- numpy.full() (only the 3 first arguments)
- numpy.full_like() (only the 3 first arguments)
- numpy.geomspace() (only the 3 first arguments)
- numpy.hamming()
- numpy.hanning()
- numpy.histogram() (only the 3 first arguments)
- numpy.hsplit()
- numpy.hstack()

- numpy.identity()
- numpy.indices() (only the first argument)
- numpy.isclose()
- numpy.kaiser()
- numpy.iscomplex()
- numpy.iscomplexobj()
- numpy.isin() (matching pre-1.24 behaviour without the kind keyword)
- numpy.isneginf()
- numpy.isposinf()
- numpy.isreal()
- numpy.isrealobj()
- numpy.isscalar()
- numpy.interp() (only the 3 first arguments)
- numpy.intersect1d() (only 3 first arguments: ar1, ar2, and assume_unique)
- numpy.in1d() (matching pre-1.24 behaviour without the kind keyword)
- numpy.linspace() (only the 3-argument form)
- numpy.logspace() (only the 3 first arguments)
- numpy.nan_to_num() (only the 3 first arguments)
- numpy.ndenumerate
- numpy.ndindex
- numpy.nditer (only the first argument)
- numpy.ones() (only the 2 first arguments)
- numpy.ones_like() (only the 2 first arguments)
- numpy.partition() (only the 2 first arguments)
- numpy.ptp() (only the first argument)
- numpy.ravel() (no order argument; 'C' order only)
- numpy.repeat() (no axis argument)
- numpy.reshape() (no order argument; 'C' order only)
- numpy.resize()
- numpy.roll() (only the 2 first arguments; second argument shift must be an integer)
- numpy.roots()
- numpy.rot90() (only the 2 first arguments)
- numpy.round_()
- numpy.row_stack()
- numpy.searchsorted() (only the 3 first arguments)

- numpy.select() (only using homogeneous lists or tuples for the first two arguments, condlist and choicelist). Additionally, these two arguments can only contain arrays (unlike NumPy that also accepts tuples).
- numpy.setxor1d()
- numpy.setdiff1d()
- numpy.shape()
- numpy.sinc()
- numpy.sort() (no optional arguments, quicksort accepts multi-dimensional array and sorts its last axis).
- numpy.split()
- numpy.stack() (only the first two arguments are supported)
- numpy.swapaxes()
- numpy.take() (only the 2 first arguments)
- numpy.take_along_axis() (the axis argument must be a literal value)
- numpy.transpose()
- numpy.trapezoid() (only the 3 first arguments)
- numpy.trapz() (only the 3 first arguments)
- numpy.tri() (only the 3 first arguments; third argument `k` must be an integer)
- numpy.tril() (second argument `k` must be an integer)
- numpy.tril_indices() (all arguments must be integer)
- numpy.tril_indices_from() (second argument `k` must be an integer)
- numpy.trim_zeros() (for NumPy array arguments only)
- numpy.triu() (second argument `k` must be an integer)
- numpy.triu_indices() (all arguments must be integer)
- numpy.triu_indices_from() (second argument `k` must be an integer)
- numpy.union1d() (For unicode arrays, only supports arrays of the same dtype)
- numpy.unique() (only the first argument)
- numpy.unwrap() (third argument `axis` must equal -1)
- numpy.vander()
- numpy.vsplit()
- numpy.vstack()
- numpy.where()
- numpy.zeros() (only the 2 first arguments)
- numpy.zeros_like() (only the 2 first arguments)

The following constructors are supported, both with a numeric input (to construct a scalar) or a sequence (to construct an array):

- numpy.bool_
- numpy.complex64
- numpy.complex128

- numpy.float32
- numpy.float64
- numpy.int8
- numpy.int16
- numpy.int32
- numpy.int64
- numpy.intc
- numpy.intp
- numpy.uint8
- numpy.uint16
- numpy.uint32
- numpy.uint64
- numpy.uintc
- numpy.uintp

The following machine parameter classes are supported, with all purely numerical attributes:

- numpy.iinfo
- numpy.finfo (machar attribute not supported)
- numpy.MachAr (with no arguments to the constructor)

Literal arrays

Neither Python nor Numba has actual array literals, but you can construct arbitrary arrays by calling numpy.array() on a nested tuple:

```
a = numpy.array(((a, b, c), (d, e, f)))
```

(nested lists are not yet supported by Numba)

2.7.4 Modules

random

Generator Objects

Numba supports numpy.random.Generator() objects. As of version 0.56, users can pass individual NumPy Generator objects into Numba functions and use their methods inside the functions. The same algorithms are used as NumPy for random number generation hence maintaining parity between the random number generated using NumPy and Numba under identical arguments (also the same documentation notes as NumPy Generator methods apply). The current Numba support for Generator is not thread-safe, hence we do not recommend using Generator methods in methods with parallel execution logic.

Note: NumPy's Generator objects rely on BitGenerator to manage state and generate the random bits, which are then transformed into random values from useful distributions. Numba will unbox the Generator objects and

will maintain a reference to the underlying `BitGenerator` objects using NumPy's `ctypes` interface bindings. Hence `Generator` objects can cross the JIT boundary and their functions be used within Numba-Jit code. Note that since only references to `BitGenerator` objects are maintained, any change to the state of a particular `Generator` object outside Numba code would affect the state of `Generator` inside the Numba code.

```
x = np.random.default_rng(1)
y = np.random.default_rng(1)

size = 10

@numba.njit
def do_stuff(gen):
    return gen.random(size=int(size / 2))

original = x.random(size=size)
# [0.51182162 0.9504637  0.14415961 0.94864945 0.31183145
#  0.42332645 0.82770259 0.40919914 0.54959369 0.02755911]

numba_func_res = do_stuff(y)
# [0.51182162 0.9504637  0.14415961 0.94864945 0.31183145]

after_numba = y.random(size=int(size / 2))
# [0.42332645 0.82770259 0.40919914 0.54959369 0.02755911]
```

The following `Generator` methods are supported:

- `numpy.random.Generator().beta()`
- `numpy.random.Generator().chisquare()`
- `numpy.random.Generator().exponential()`
- `numpy.random.Generator().f()`
- `numpy.random.Generator().gamma()`
- `numpy.random.Generator().geometric()`
- `numpy.random.Generator().integers()` (Both *low* and *high* are required arguments. Array values for low and high are currently not supported.)
- `numpy.random.Generator().laplace()`
- `numpy.random.Generator().logistic()`
- `numpy.random.Generator().lognormal()`
- `numpy.random.Generator().logseries()` (Accepts float values as well as data types that cast to floats. Array values for `p` are currently not supported.)
- `numpy.random.Generator().negative_binomial()`
- `numpy.random.Generator().noncentral_chisquare()` (Accepts float values as well as data types that cast to floats. Array values for `dfnum` and `nonc` are currently not supported.)
- `numpy.random.Generator().noncentral_f()` (Accepts float values as well as data types that cast to floats. Array values for `dfnum`, `dfden` and `nonc` are currently not supported.)
- `numpy.random.Generator().normal()`

- numpy.random.Generator().pareto()
- numpy.random.Generator().permutation() (Only accepts NumPy ndarrays and integers.)
- numpy.random.Generator().poisson()
- numpy.random.Generator().power()
- numpy.random.Generator().random()
- numpy.random.Generator().rayleigh()
- numpy.random.Generator().shuffle() (Only accepts NumPy ndarrays.)
- numpy.random.Generator().standard_cauchy()
- numpy.random.Generator().standard_exponential()
- numpy.random.Generator().standard_gamma()
- numpy.random.Generator().standard_normal()
- numpy.random.Generator().standard_t()
- numpy.random.Generator().triangular()
- numpy.random.Generator().uniform()
- numpy.random.Generator().wald()
- numpy.random.Generator().weibull()
- numpy.random.Generator().zipf()

Note: Due to instruction selection differences across compilers, there may be discrepancies, when compared to NumPy, in the order of 1000s of ULPs on 32-bit architectures as well as linux-aarch64 and linux- ppc64le platforms. For Linux-x86_64, Windows-x86_64 and macOS these discrepancies are less pronounced (order of 10s of ULPs) but are not guaranteed to follow the exception pattern and may increase in some cases.

The differences are unlikely to impact the "quality" of the random number generation as they occur through changes in rounding that happen when fused-multiply-add is used instead of multiplication followed by addition.

RandomState and legacy Random number generation

Numba supports top-level functions from the numpy.random module, but does not allow you to create individual RandomState instances. The same algorithms are used as for *the standard random module* (and therefore the same notes apply), but with an independent internal state: seeding or drawing numbers from one generator won't affect the other.

The following functions are supported.

Initialization

- numpy.random.seed(): with an integer argument only

Warning: Calling numpy.random.seed() from interpreted code (including from *object mode* code) will seed the NumPy random generator, not the Numba random generator. To seed the Numba random generator, see the example below.

```
from numba import njit
import numpy as np

@njit
def seed(a):
    np.random.seed(a)

@njit
def rand():
    return np.random.rand()


# Incorrect seeding
np.random.seed(1234)
print(rand())

np.random.seed(1234)
print(rand())

# Correct seeding
seed(1234)
print(rand())

seed(1234)
print(rand())
```

Simple random data

- numpy.random.rand()
- numpy.random.randint() (only the first two arguments)
- numpy.random.randn()
- numpy.random.random()
- numpy.random.random_sample()
- numpy.random.ranf()
- numpy.random.sample()

Permutations

- numpy.random.choice(): the optional *p* argument (probabilities array) is not supported
- numpy.random.permutation()
- numpy.random.shuffle(): the sequence argument must be a one-dimension NumPy array or buffer-providing object (such as a bytearray or array.array)

Distributions

The following functions support all arguments.

- numpy.random.beta()
- numpy.random.binomial()
- numpy.random.chisquare()
- numpy.random.dirichlet()
- numpy.random.exponential()
- numpy.random.f()
- numpy.random.gamma()
- numpy.random.geometric()
- numpy.random.gumbel()
- numpy.random.hypergeometric()
- numpy.random.laplace()
- numpy.random.logistic()
- numpy.random.lognormal()
- numpy.random.logseries()
- numpy.random.multinomial()
- numpy.random.negative_binomial()
- numpy.random.noncentral_chisquare()
- numpy.random.normal()
- numpy.random.pareto()
- numpy.random.poisson()
- numpy.random.power()
- numpy.random.rayleigh()
- numpy.random.standard_cauchy()
- numpy.random.standard_exponential()
- numpy.random.standard_gamma()
- numpy.random.standard_normal()
- numpy.random.standard_t()
- numpy.random.triangular()

- numpy.random.uniform()
- numpy.random.vonmises()
- numpy.random.wald()
- numpy.random.weibull()
- numpy.random.zipf()

Note: Calling numpy.random.seed() from non-Numba code (or from *object mode* code) will seed the NumPy random generator, not the Numba random generator.

Note: Since version 0.28.0, the generator is thread-safe and fork-safe. Each thread and each process will produce independent streams of random numbers.

stride_tricks

The following functions from the numpy.lib.stride_tricks module are supported:

- as_strided() (the *strides* argument is mandatory, the *subok* argument is not supported)
- sliding_window_view() (the *subok* argument is not supported, the *writeable* argument is not supported with the returned view always being writeable)

2.7.5 Standard ufuncs

One objective of Numba is having all the standard ufuncs in NumPy understood by Numba. When a supported ufunc is found when compiling a function, Numba maps the ufunc to equivalent native code. This allows the use of those ufuncs in Numba code that gets compiled in *nopython mode*.

Limitations

Right now, only a selection of the standard ufuncs work in *nopython mode*. Following is a list of the different standard ufuncs that Numba is aware of, sorted in the same way as in the NumPy documentation.

Math operations

UFUNC	MODE	
name	object mode	nopython mode
add	Yes	Yes
subtract	Yes	Yes
multiply	Yes	Yes
divide	Yes	Yes
logaddexp	Yes	Yes
logaddexp2	Yes	Yes
true_divide	Yes	Yes
floor_divide	Yes	Yes
negative	Yes	Yes

continues on next page

Table 1 – continued from previous page

UFUNC	MODE	
name	object mode	nopython mode
power	Yes	Yes
float_power	Yes	Yes
remainder	Yes	Yes
mod	Yes	Yes
fmod	Yes	Yes
divmod (*)	Yes	Yes
abs	Yes	Yes
absolute	Yes	Yes
fabs	Yes	Yes
rint	Yes	Yes
sign	Yes	Yes
conj	Yes	Yes
exp	Yes	Yes
exp2	Yes	Yes
log	Yes	Yes
log2	Yes	Yes
log10	Yes	Yes
expm1	Yes	Yes
log1p	Yes	Yes
sqrt	Yes	Yes
square	Yes	Yes
cbrt	Yes	Yes
reciprocal	Yes	Yes
conjugate	Yes	Yes
gcd	Yes	Yes
lcm	Yes	Yes

(*) not supported on timedelta types

Trigonometric functions

UFUNC	MODE	
name	object mode	nopython mode
sin	Yes	Yes
cos	Yes	Yes
tan	Yes	Yes
arcsin	Yes	Yes
arccos	Yes	Yes
arctan	Yes	Yes
arctan2	Yes	Yes
hypot	Yes	Yes
sinh	Yes	Yes
cosh	Yes	Yes
tanh	Yes	Yes
arcsinh	Yes	Yes
arccosh	Yes	Yes
arctanh	Yes	Yes
deg2rad	Yes	Yes
rad2deg	Yes	Yes
degrees	Yes	Yes
radians	Yes	Yes

Bit-twiddling functions

UFUNC	MODE	
name	object mode	nopython mode
bitwise_and	Yes	Yes
bitwise_or	Yes	Yes
bitwise_xor	Yes	Yes
bitwise_not	Yes	Yes
invert	Yes	Yes
left_shift	Yes	Yes
right_shift	Yes	Yes

Comparison functions

UFUNC	MODE	
name	object mode	nopython mode
greater	Yes	Yes
greater_equal	Yes	Yes
less	Yes	Yes
less_equal	Yes	Yes
not_equal	Yes	Yes
equal	Yes	Yes
logical_and	Yes	Yes
logical_or	Yes	Yes
logical_xor	Yes	Yes
logical_not	Yes	Yes
maximum	Yes	Yes
minimum	Yes	Yes
fmax	Yes	Yes
fmin	Yes	Yes

Floating functions

UFUNC	MODE	
name	object mode	nopython mode
isfinite	Yes	Yes
isinf	Yes	Yes
isnan	Yes	Yes
signbit	Yes	Yes
copysign	Yes	Yes
nextafter	Yes	Yes
modf	Yes	No
ldexp	Yes	Yes
frexp	Yes	No
floor	Yes	Yes
ceil	Yes	Yes
trunc	Yes	Yes
spacing	Yes	Yes

Datetime functions

UFUNC	MODE	
name	object mode	nopython mode
isnat	Yes	Yes

2.8 Deviations from Python Semantics

2.8.1 Bounds Checking

By default, instead of causing an `IndexError`, accessing an out-of-bound index of an array in a Numba-compiled function will return invalid values or lead to an access violation error (it's reading from invalid memory locations). Bounds checking can be enabled on a specific function via the *boundscheck* option of the jit decorator. Additionally, the *NUMBA_BOUNDSCHECK* can be set to 0 or 1 to globally override this flag.

Note: Bounds checking will slow down typical functions so it is recommended to only use this flag for debugging purposes.

2.8.2 Exceptions and Memory Allocation

Due to limitations in the current compiler when handling exceptions, memory allocated (almost always NumPy arrays) within a function that raises an exception will **leak**. This is a known issue that will be fixed, but in the meantime, it is best to do memory allocation outside of functions that can also raise exceptions.

2.8.3 Integer width

While Python has arbitrary-sized integers, integers in Numba-compiled functions get a fixed size through *type inference* (usually, the size of a machine integer). This means that arithmetic operations can wraparound or produce undefined results or overflow.

Type inference can be overridden by an explicit type specification, if fine-grained control of integer width is desired.

See also:

Enhancement proposal 1: Changes in integer typing

2.8.4 Boolean inversion

Calling the bitwise complement operator (the ~ operator) on a Python boolean returns an integer, while the same operator on a Numpy boolean returns another boolean:

```
>>> ~True
-2
>>> ~np.bool_(True)
False
```

Numba follows the Numpy semantics.

2.8.5 Global and closure variables

In *nopython mode*, global and closure variables are *frozen* by Numba: a Numba-compiled function sees the value of those variables at the time the function was compiled. Also, it is not possible to change their values from the function.

Numba **may or may not** copy global variables referenced inside a compiled function. Small global arrays are copied for potential compiler optimization with immutability assumption. However, large global arrays are not copied to conserve memory. The definition of "small" and "large" may change.

2.8.6 Zero initialization of variables

Numba does not track variable liveness at runtime. For simplicity of implementation, all variables are zero-initialized. Example:

```
from numba import njit

@njit
def foo():
    for i in range(0):
        pass
    print(i) # will print 0 and not raise UnboundLocalError

foo()
```

2.9 Floating-point pitfalls

2.9.1 Precision and accuracy

For some operations, Numba may use a different algorithm than Python or Numpy. The results may not be bit-by-bit compatible. The difference should generally be small and within reasonable expectations. However, small accumulated differences might produce large differences at the end, especially if a divergent function is involved.

Math library implementations

Numba supports a variety of platforms and operating systems, each of which has its own math library implementation (referred to as `libm` from here in). The majority of math functions included in `libm` have specific requirements as set out by the IEEE 754 standard (like `sin()`, `exp()` etc.), but each implementation may have bugs. Thus, on some platforms Numba has to exercise special care in order to workaround known `libm` issues.

Another typical problem is when an operating system's `libm` function set is incomplete and needs to be supplemented by additional functions. These are provided with reference to the IEEE 754 and C99 standards and are often implemented in Numba in a manner similar to equivalent CPython functions.

Linear algebra

Numpy forces some linear algebra operations to run in double-precision mode even when a `float32` input is given. Numba will always observe the input's precision, and invoke single-precision linear algebra routines when all inputs are `float32` or `complex64`.

The implementations of the `numpy.linalg` routines in Numba only support the floating point types that are used in the LAPACK functions that provide the underlying core functionality. As a result only `float32`, `float64`, `complex64` and `complex128` types are supported. If a user has e.g. an `int32` type, an appropriate type conversion must be performed to a floating point type prior to its use in these routines. The reason for this decision is to essentially avoid having to replicate type conversion choices made in Numpy and to also encourage the user to choose the optimal floating point type for the operation they are undertaking.

Mixed-types operations

Numpy will most often return a `float64` as a result of a computation with mixed integer and floating-point operands (a typical example is the power operator `**`). Numba by contrast will select the highest precision amongst the floating-point operands, so for example `float32 ** int32` will return a `float32`, regardless of the input values. This makes performance characteristics easier to predict, but you should explicitly cast the input to `float64` if you need the extra precision.

2.9.2 Warnings and errors

When calling a *ufunc* created with *vectorize()*, Numpy will determine whether an error occurred by examining the FPU error word. It may then print out a warning or raise an exception (such as `RuntimeWarning: divide by zero encountered`), depending on the current error handling settings.

Depending on how LLVM optimized the ufunc's code, however, some spurious warnings or errors may appear. If you get caught by this issue, we recommend you call `numpy.seterr()` to change Numpy's error handling settings, or the `numpy.errstate` context manager to switch them temporarily:

```
with np.errstate(all='ignore'):
    x = my_ufunc(y)
```

2.10 Deprecation Notices

This section contains information about deprecation of behaviours, features and APIs that have become undesirable/obsolete. Any information about the schedule for their deprecation and reasoning behind the changes, along with examples, is provided. However, first is a small section on how to suppress deprecation warnings that may be raised from Numba so as to prevent warnings propagating into code that is consuming Numba.

2.10.1 Suppressing Deprecation warnings

All Numba deprecations are issued via `NumbaDeprecationWarning` or `NumbaPendingDeprecationWarning` s, to suppress the reporting of these the following code snippet can be used:

```
from numba.core.errors import NumbaDeprecationWarning, NumbaPendingDeprecationWarning
import warnings

warnings.simplefilter('ignore', category=NumbaDeprecationWarning)
warnings.simplefilter('ignore', category=NumbaPendingDeprecationWarning)
```

The `action` used above is `'ignore'`, other actions are available, see The Warnings Filter documentation for more information.

Note: It is **strongly recommended** that applications and libraries which choose to suppress these warnings should pin their Numba dependency to a suitable version because their users will no longer be aware of the coming incompatibility.

2.10.2 Deprecation of reflection for List and Set types

Reflection (*reflection*) is the jargon used in Numba to describe the process of ensuring that changes made by compiled code to arguments that are mutable Python container data types are visible in the Python interpreter when the compiled function returns. Numba has for some time supported reflection of `list` and `set` data types and it is support for this reflection that is scheduled for deprecation with view to replace with a better implementation.

Reason for deprecation

First recall that for Numba to be able to compile a function in `nopython` mode all the variables must have a concrete type ascertained through type inference. In simple cases, it is clear how to reflect changes to containers inside `nopython` mode back to the original Python containers. However, reflecting changes to complex data structures with nested container types (for example, lists of lists of integers) quickly becomes impossible to do efficiently and consistently. After a number of years of experience with this problem, it is clear that providing this behaviour is both fraught with difficulty and often leads to code which does not have good performance (all reflected data has to go through special APIs to convert the data to native formats at call time and then back to CPython formats at return time). As a result of this, the sheer number of reported problems in the issue tracker, and how well a new approach that was taken with `typed.Dict` (typed dictionaries) has gone, the core developers have decided to deprecate the noted `reflection` behaviour.

Example(s) of the impact

At present only a warning of the upcoming change is issued. In future code such as:

```
from numba import njit

@njit
def foo(x):
    x.append(10)

a = [1, 2, 3]
foo(a)
```

will require adjustment to use a `typed.List` instance, this typed container is synonymous to the *Typed Dict*. An example of translating the above is:

```
from numba import njit
from numba.typed import List

@njit
def foo(x):
    x.append(10)

a = [1, 2, 3]
typed_a = List()
[typed_a.append(x) for x in a]
foo(typed_a)
```

For more information about `typed.List` see *Typed List*. Further usability enhancements for this feature were made in the 0.47.0 release cycle.

Schedule

This feature will be removed with respect to this schedule:

- Pending-deprecation warnings will be issued in version 0.44.0
- Prominent notice will be given for a minimum of two releases prior to full removal.

Recommendations

Projects that need/rely on the deprecated behaviour should pin their dependency on Numba to a version prior to removal of this behaviour, or consider following replacement instructions that will be issued outlining how to adjust to the change.

Expected Replacement

As noted above `typed.List` will be used to permit similar functionality to reflection in the case of `list` s, a `typed.Set` will provide the equivalent for `set` (not implemented yet!). The advantages to this approach are:

- That the containers are typed means type inference has to work less hard.
- Nested containers (containers of containers of ...) are more easily supported.
- Performance penalties currently incurred translating data to/from native formats are largely avoided.
- Numba's `typed.Dict` will be able to use these containers as values.

2.10.3 Deprecation of object mode *fall-back* behaviour when using `@jit`

Note: This feature was removed in 0.59.0, see the schedule section below.

The `numba.jit` decorator has for a long time followed the behaviour of first attempting to compile the decorated function in *nopython mode* and should this compilation fail it will *fall-back* and try again to compile but this time in *object mode*. It is this *fall-back* behaviour which is being deprecated, the result of which will be that `numba.jit` will by default compile in *nopython mode* and *object mode* compilation will become *opt-in* only.

Note: It is relatively common for the `numba.jit` decorator to be used within other decorators to provide an easy path to compilation. Due to this change, deprecation warnings may be raised from such call sites. To avoid these warnings, it's recommended to either *suppress them* if the application does not rely on *object mode fall-back* or to check the documentation for the decorator to see how to pass application appropriate options through to the wrapped `numba.jit` decorator. An example of this within the Numba API would be `numba.vectorize`. This decorator simply forwards keyword arguments to the internal `numba.jit` decorator call site such that e.g. `@vectorize(nopython=True)` would be an appropriate declaration for a `nopython=True` mode use of `@vectorize`.

Reason for deprecation

The *fall-back* has repeatedly caused confusion for users as seemingly innocuous changes in user code can lead to drastic performance changes as code which may have once compiled in *nopython mode* mode may silently switch to compiling in *object mode* e.g:

```
from numba import jit

@jit
def foo():
    l = []
    for x in range(10):
        l.append(x)
    return l

foo()

assert foo.nopython_signatures # this was compiled in nopython mode

@jit
def bar():
    l = []
    for x in range(10):
        l.append(x)
    return reversed(l) # innocuous change, but no reversed support in nopython mode

bar()

assert not bar.nopython_signatures # this was not compiled in nopython mode
```

Another reason to remove the *fall-back* is that it is confusing for the compiler engineers developing Numba as it causes internal state problems that are really hard to debug and it makes manipulating the compiler pipelines incredibly challenging.

Further, it has long been considered best practice that the *nopython mode* keyword argument in the `numba.jit` decorator is set to `True` and that any user effort spent should go into making code work in this mode as there's very little gain if it does not. The result is that, as Numba has evolved, the amount of use *object mode* gets in practice and its general utility has decreased. It can be noted that there are some minor improvements available through the notion of *loop-lifting*, the cases of this being used in practice are, however, rare and often a legacy from use of less-recent Numba whereby such behaviour was better accommodated/the use of `@jit` with *fall-back* was recommended.

Example(s) of the impact

At present a warning of the upcoming change is issued if `@jit` decorated code uses the *fall-back* compilation path. In future code such as:

```
@jit
def bar():
    l = []
    for x in range(10):
        l.append(x)
    return reversed(l)

bar()
```

will simply not compile, a `TypingError` would be raised.

A further consequence of this change is that the `nopython` keyword argument will become redundant as *nopython mode* will be the default. As a result, following this change, supplying the keyword argument as `nopython=False` will trigger a warning stating that the implicit default has changed to `True`. Essentially this keyword will have no effect following removal of this feature.

Schedule

This feature was removed with respect to this schedule:

- Deprecation warnings were issued in version 0.44.0.
- Prominent notice was given in 0.57.0.
- The feature was removed in 0.59.0.

Recommendations

Projects that need/rely on the deprecated behaviour should pin their dependency on Numba to a version prior to removal of this behaviour.

General advice to accommodate the scheduled deprecation:

Users with code compiled at present with `@jit` can supply the `nopython=True` keyword argument, if the code continues to compile then the code is already ready for this change. If the code does not compile, continue using the `@jit` decorator without `nopython=True` and profile the performance of the function. Then remove the decorator and again check the performance of the function. If there is no benefit to having the `@jit` decorator present consider removing it! If there is benefit to having the `@jit` decorator present, then to be future proof supply the keyword argument `forceobj=True` to ensure the function is always compiled in *object mode*.

Advice for users of the "loop-lifting" feature:

If object mode compilation with loop-lifting is needed it should be explicitly declared through supplying the keyword arguments `forceobj=True` and `looplift=True` to the `@jit` decorator.

Advice for users setting `nopython=False`:

This is essentially specifying the implicit default prior to removal of this feature, either remove the keyword argument or change the value to `True`.

2.10.4 Deprecation of `generated_jit`

The top level API function `numba.generated_jit` provides functionality that allows users to write JIT compilable functions that have different implementations based on the types of the arguments to the function. This is a hugely useful concept and is also key to Numba's internal implementation.

Reason for deprecation

There are a number of reasons for this deprecation.

First, `generated_jit` breaks the concept of "JIT transparency" in that if the JIT compiler is disabled, the source code does not execute the same way as it would were the JIT compiler present.

Second, internally Numba uses the `numba.extending.overload` family of decorators to access an equivalent functionality to `generated_jit`. The `overload` family of decorators are more powerful than `generated_jit` as they support far more options and both the CPU and CUDA targets. Essentially a replacement for `generated_jit` already exists and has been recommended and preferred for a long while.

Third, the public extension API decorators are far better maintained than `generated_jit`. This is an important consideration due to Numba's limited resources, fewer duplicated pieces of functionality to maintain will reduce pressure on these resources.

For more information on the `overload` family of decorators see the *high level extension API documentation*.

Example(s) of the impact

Any source code using `generated_jit` would fail to work once the functionality has been removed.

Schedule

This feature was removed with respect to this schedule:

- Deprecation warnings were issued in version 0.57.0.
- Removal took place in version 0.59.0.

Recommendations

Projects that need/rely on the deprecated behaviour should pin their dependency on Numba to a version prior to removal of this behaviour, or consider following replacement instructions below that outline how to adjust to the change.

Replacement

The `overload` decorator offers a replacement for the functionality available through `generated_jit`. An example follows of translating from one to the other. First define a type specialised function dispatch with the `generated_jit` decorator:

```
from numba import njit, generated_jit, types

@generated_jit
def select(x):
    if isinstance(x, types.Float):
        def impl(x):
            return x + 1
        return impl
    elif isinstance(x, types.UnicodeType):
        def impl(x):
            return x + " the number one"
        return impl
    else:
        raise TypeError("Unsupported Type")

@njit
def foo(x):
    return select(x)

print(foo(1.))
print(foo("a string"))
```

Conceptually, `generated_jit` is like `overload`, but with `generated_jit` the overloaded function is the decorated function. Taking the example above and adjusting it to use the `overload` API:

```
from numba import njit, types
from numba.extending import overload

# A pure python implementation that will run if the JIT compiler is disabled.
def select(x):
    if isinstance(x, float):
        return x + 1
    elif isinstance(x, str):
        return x + " the number one"
    else:
        raise TypeError("Unsupported Type")

# An overload for the `select` function cf. generated_jit
@overload(select)
def ol_select(x):
    if isinstance(x, types.Float):
        def impl(x):
            return x + 1
        return impl
    elif isinstance(x, types.UnicodeType):
        def impl(x):
            return x + " the number one"
        return impl
```

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```
    else:
        raise TypeError("Unsupported Type")

@njit
def foo(x):
    return select(x)

print(foo(1.))
print(foo("a string"))
```

Further, users that are using `generated_jit` to dispatch on some of the more primitive types may find that Numba's support for `isinstance` is sufficient, for example:

```
@njit # NOTE: standard @njit decorator.
def select(x):
    if isinstance(x, float):
        return x + 1
    elif isinstance(x, str):
        return x + " the number one"
    else:
        raise TypeError("Unsupported Type")

@njit
def foo(x):
    return select(x)

print(foo(1.))
print(foo("a string"))
```

2.10.5 Deprecation of the `numba.pycc` module

Numba has supported some degree of Ahead-of-Time (AOT) compilation through the use of the tools in the `numba.pycc` module. This capability is very important to the Numba project and following an assessment of the viability of the current approach, it was decided to deprecate it in favour of developing new technology to better meet current needs.

Reason for deprecation

There are a number of reasons for this deprecation.

- `numba.pycc` tools create C-Extensions that have symbols that are only usable from the Python interpreter, they are not compatible with calls made from within code compiled using Numba's JIT compiler. This drastically reduces the utility of AOT compiled functions.
- `numba.pycc` has some reliance on `setuptools` (and `distutils`) which is something Numba is trying to reduce, particularly due to the upcoming removal of `distutils` in Python 3.12.
- The `numba.pycc` compilation chain is very limited in terms of its feature set in comparison to Numba's JIT compiler, it also has numerous technical issues to do with declaring and linking both internal and external libraries.
- The number of users of `numba.pycc` is assumed to be quite small, this was indicated through discussions at a Numba public meeting on 2022-10-04 and issue #8509.

- The Numba project is working on new innovations in the AOT compiler space and the maintainers consider it a better use of resources to develop these than maintain and develop `numba.pycc`.

Example(s) of the impact

Any source code using `numba.pycc` would fail to work once the functionality has been removed.

Schedule

This feature will be removed with respect to this schedule:

- Pending-deprecation warnings will be issued in version 0.57.0.
- Deprecation warnings will be issued once a replacement is developed.
- Deprecation warnings will be given for a minimum of two releases prior to full removal.

Recommendations

Projects that need/rely on the deprecated behaviour should pin their dependency on Numba to a version prior to removal of this behaviour, or consider following replacement instructions below that outline how to adjust to the change.

Replacement

A replacement for this functionality is being developed as part of the Numba 2023 development focus. The `numba.pycc` module will not be removed until this replacement functionality is able to provide similar utility and offer an upgrade path. At the point of the new technology being deemed suitable, replacement instructions will be issued.

2.10.6 Deprecation and removal of CUDA Toolkits < 11.2 and devices with CC < 5.0

- Support for CUDA toolkits less than 11.2 has been removed.
- Support for devices with Compute Capability < 5.0 is deprecated and will be removed in the future.

Recommendations

- For devices of Compute Capability 3.0 and 3.2, Numba 0.55.1 or earlier will be required.
- CUDA toolkit 11.2 or later should be installed.

Schedule

- In Numba 0.55.1: support for CC < 5.0 and CUDA toolkits < 10.2 was deprecated.
- In Numba 0.56: support for CC < 3.5 and CUDA toolkits < 10.2 was removed.
- In Numba 0.57: Support for CUDA toolkit 10.2 was removed.
- In Numba 0.58: Support CUDA toolkits 11.0 and 11.1 was removed.
- In a future release: Support for CC < 5.0 will be removed.

2.10.7 Deprecation of old-style `NUMBA_CAPTURED_ERRORS`

The use of the `NUMBA_CAPTURED_ERRORS` environment variable is deprecated and removed.

Reason for deprecation

Previously, this variable allowed controlling how Numba handles exceptions during compilation that do not inherit from `numba.core.errors.NumbaError`. The default "old_style" behavior was to capture and wrap these errors, often obscuring the original exception.

The new "new_style" option treats non-`NumbaError` exceptions as hard errors, propagating them without capturing. This differentiates compilation errors from unintended exceptions during compilation.

The old style was removed in favor of the new behavior.

Impact

The impact of this deprecation will only affect those who are extending Numba functionality.

Recommendations

- Modify any code that raises a non-`NumbaError` to indicate a compilation error to raise a subclass of `NumbaError` instead. For example, instead of raising a `TypeError`, raise a `numba.core.errors.NumbaTypeError`.

Schedule

- In Numba 0.58: `NUMBA_CAPTURED_ERRORS=old_style` was deprecated. Warnings will be raised when *old_style* error capturing is used.
- In Numba 0.59: explicitly setting `NUMBA_CAPTURED_ERRORS=old_style` will raise deprecation warnings.
- In Numba 0.60: `NUMBA_CAPTURED_ERRORS=new_style` became the default.
- In Numba 0.61: support for `NUMBA_CAPTURED_ERRORS=old_style` was removed.

2.10.8 Deprecation of the built-in CUDA target

The CUDA target is now maintained in a separate package, numba-cuda, and the built-in CUDA target is deprecated.

Reason for deprecation

Development of the CUDA target has been moved to the `numba-cuda` package to proceed independently of Numba development. See *Built-in CUDA target deprecation and maintenance status*.

Impact

The built-in CUDA target is still supported by Numba 0.61 and will continue to be provided through at least Numba 0.62, but new changes to the built-in target are not expected; bug fixes and new features will be added in `numba-cuda`. No code changes are required to any code that uses the CUDA target.

Recommendations

Users should install the `numba-cuda` package when using the CUDA target.

To install `numba-cuda` with `pip`:

```
pip install numba-cuda
```

To install `numba-cuda` with `conda`, for example from the `conda-forge` channel:

```
conda install conda-forge::numba-cuda
```

Maintainers of packages that use the CUDA target should add `numba-cuda` as a dependency in addition to `numba`, or replace the `numba` dependency with `numba-cuda` if the CUDA target is used exclusively.

Schedule

- In Numba 0.61: The built-in CUDA target is deprecated.
- In Numba 0.62: Use of the CUDA target when the `numba-cuda` package is not installed will cause the emission of a warning prompting the installation of `numba-cuda`.
- In a future version of Numba no less than 0.63: The built-in CUDA target will be removed, and use of the CUDA target in the absence of the `numba-cuda` package will raise an error.

CHAPTER

THREE

NUMBA FOR CUDA GPUS

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

3.1 Overview

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

3.1.1 Built-in CUDA target deprecation and maintenance status

Numba's CUDA target is now maintained in a separate package, numba-cuda. This enables improvements in the development of the CUDA target:

- The time and effort required to incorporate new features and bug fixes into the CUDA target is decreased - its development cycle is now decoupled from the Numba development process, so "upstream" reviews from Numba maintainers and test runs on the Anaconda internal CI systems are no longer required as part of the standard process for CUDA target pull requests. This lightening of process enables development to proceed at an increased cadence.
- Similarly, releases of the CUDA target can be made independently of Numba releases, at a more frequent pace.
- Numba is sufficiently mature as a compiler platform to support out-of-tree targets. The CUDA target, whilst maintained upstream, had been migrated to use the externally-facing APIs for target implementation. The continued development of the CUDA target outside of the main Numba repository ensures the continued development and robustness of these target extension APIs.

With development proceeding outside of the main Numba package, the built-in CUDA target is now deprecated, but is still supported in Numba 0.61. It will continue to be provided by Numba through at least version 0.62, but no new functionality is expected to be added to it. New functionality and bug fixes will be implemented in the `numba-cuda` package.

Users are encouraged to install `numba-cuda` in addition to Numba when using the CUDA target. No code changes are required - the `numba-cuda` package will continue to implement functionality under the `numba.cuda` namespace.

To install `numba-cuda` with `pip`:

```
pip install numba-cuda
```

To install `numba-cuda` with `conda`, for example from the `conda-forge` channel:

```
conda install conda-forge::numba-cuda
```

For further information, see the *deprecation notice and schedule*.

3.1.2 Introduction

Numba supports CUDA GPU programming by directly compiling a restricted subset of Python code into CUDA kernels and device functions following the CUDA execution model. Kernels written in Numba appear to have direct access to NumPy arrays. NumPy arrays are transferred between the CPU and the GPU automatically.

3.1.3 Terminology

Several important terms in the topic of CUDA programming are listed here:

- *host*: the CPU
- *device*: the GPU
- *host memory*: the system main memory
- *device memory*: onboard memory on a GPU card
- *kernels*: a GPU function launched by the host and executed on the device
- *device function*: a GPU function executed on the device which can only be called from the device (i.e. from a kernel or another device function)

3.1.4 Programming model

Most CUDA programming facilities exposed by Numba map directly to the CUDA C language offered by NVidia. Therefore, it is recommended you read the official CUDA C programming guide.

3.1.5 Requirements

Supported GPUs

Numba supports CUDA-enabled GPUs with Compute Capability 3.5 or greater. Support for devices with Compute Capability less than 5.0 is deprecated, and will be removed in a future Numba release.

Devices with Compute Capability 5.0 or greater include (but are not limited to):

- Embedded platforms: NVIDIA Jetson Nano, Jetson Orin Nano, TX1, TX2, Xavier NX, AGX Xavier, AGX Orin.
- Desktop / Server GPUs: All GPUs with Maxwell microarchitecture or later. E.g. GTX 9 / 10 / 16 series, RTX 20 / 30 / 40 series, Quadro / Tesla M / P / V / RTX series, RTX A series, RTX Ada / SFF, A / L series, H100.
- Laptop GPUs: All GPUs with Maxwell microarchitecture or later. E.g. MX series, Quadro M / P / T series (mobile), RTX 20 / 30 series (mobile), RTX A series (mobile).

Software

Numba aims to support CUDA Toolkit versions released within the last 3 years. Presently 11.2 is the minimum required toolkit version. An NVIDIA driver sufficient for the toolkit version is also required (see also *CUDA Minor Version Compatibility*).

Conda users can install the CUDA Toolkit into a conda environment.

For CUDA 12, `cuda-nvcc` and `cuda-nvrtc` are required:

```
$ conda install -c conda-forge cuda-nvcc cuda-nvrtc "cuda-version>=12.0"
```

For CUDA 11, `cudatoolkit` is required:

```
$ conda install -c conda-forge cudatoolkit "cuda-version>=11.2,<12.0"
```

If you are not using Conda or if you want to use a different version of CUDA toolkit, the following describes how Numba searches for a CUDA toolkit installation.

CUDA Bindings

Numba supports interacting with the CUDA Driver API via the NVIDIA CUDA Python bindings and its own ctypes-based bindings. Functionality is equivalent between the two bindings. The ctypes-based bindings are presently the default, but the NVIDIA bindings will be used by default (if they are available in the environment) in a future Numba release.

You can install the NVIDIA bindings with:

```
$ conda install -c conda-forge cuda-python
```

if you are using Conda, or:

```
$ pip install cuda-python
```

if you are using pip.

The use of the NVIDIA bindings is enabled by setting the environment variable *NUMBA_CUDA_USE_NVIDIA_BINDING* to `"1"`.

Setting CUDA Installation Path

Numba searches for a CUDA toolkit installation in the following order:

1. Conda installed CUDA Toolkit packages
2. Environment variable `CUDA_HOME`, which points to the directory of the installed CUDA toolkit (i.e. `/home/user/cuda-12`)
3. System-wide installation at exactly `/usr/local/cuda` on Linux platforms. Versioned installation paths (i.e. `/usr/local/cuda-12.0`) are intentionally ignored. Users can use `CUDA_HOME` to select specific versions.

In addition to the CUDA toolkit libraries, which can be installed by conda into an environment or installed system-wide by the CUDA SDK installer, the CUDA target in Numba also requires an up-to-date NVIDIA graphics driver. Updated graphics drivers are also installed by the CUDA SDK installer, so there is no need to do both. If the `libcuda` library is in a non-standard location, users can set environment variable `NUMBA_CUDA_DRIVER` to the file path (not the directory path) of the shared library file.

3.1.6 Missing CUDA Features

Numba does not implement all features of CUDA, yet. Some missing features are listed below:

- dynamic parallelism
- texture memory

3.2 Writing CUDA Kernels

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

3.2.1 Introduction

CUDA has an execution model unlike the traditional sequential model used for programming CPUs. In CUDA, the code you write will be executed by multiple threads at once (often hundreds or thousands). Your solution will be modeled by defining a thread hierarchy of *grid*, *blocks* and *threads*.

Numba's CUDA support exposes facilities to declare and manage this hierarchy of threads. The facilities are largely similar to those exposed by NVidia's CUDA C language.

Numba also exposes three kinds of GPU memory: global *device memory* (the large, relatively slow off-chip memory that's connected to the GPU itself), on-chip *shared memory* and *local memory*. For all but the simplest algorithms, it is important that you carefully consider how to use and access memory in order to minimize bandwidth requirements and contention.

3.2.2 Kernel declaration

A *kernel function* is a GPU function that is meant to be called from CPU code (*). It gives it two fundamental characteristics:

- kernels cannot explicitly return a value; all result data must be written to an array passed to the function (if computing a scalar, you will probably pass a one-element array);
- kernels explicitly declare their thread hierarchy when called: i.e. the number of thread blocks and the number of threads per block (note that while a kernel is compiled once, it can be called multiple times with different block sizes or grid sizes).

At first sight, writing a CUDA kernel with Numba looks very much like writing a *JIT function* for the CPU:

```
@cuda.jit
def increment_by_one(an_array):
    """
    Increment all array elements by one.
    """
    # code elided here; read further for different implementations
```

(*) Note: newer CUDA devices support device-side kernel launching; this feature is called *dynamic parallelism* but Numba does not support it currently)

3.2.3 Kernel invocation

A kernel is typically launched in the following way:

```
threadsperblock = 32
blockspergrid = (an_array.size + (threadsperblock - 1)) // threadsperblock
increment_by_one[blockspergrid, threadsperblock](an_array)
```

We notice two steps here:

- Instantiate the kernel proper, by specifying a number of blocks (or "blocks per grid"), and a number of threads per block. The product of the two will give the total number of threads launched. Kernel instantiation is done by taking the compiled kernel function (here `increment_by_one`) and indexing it with a tuple of integers.
- Running the kernel, by passing it the input array (and any separate output arrays if necessary). Kernels run asynchronously: launches queue their execution on the device and then return immediately. You can use *cuda.synchronize()* to wait for all previous kernel launches to finish executing.

Note: Passing an array that resides in host memory will implicitly cause a copy back to the host, which will be synchronous. In this case, the kernel launch will not return until the data is copied back, and therefore appears to execute synchronously.

Choosing the block size

It might seem curious to have a two-level hierarchy when declaring the number of threads needed by a kernel. The block size (i.e. number of threads per block) is often crucial:

- On the software side, the block size determines how many threads share a given area of *shared memory*.
- On the hardware side, the block size must be large enough for full occupation of execution units; recommendations can be found in the CUDA C Programming Guide.

Multi-dimensional blocks and grids

To help deal with multi-dimensional arrays, CUDA allows you to specify multi-dimensional blocks and grids. In the example above, you could make `blockspergrid` and `threadsperblock` tuples of one, two or three integers. Compared to 1D declarations of equivalent sizes, this doesn't change anything to the efficiency or behaviour of generated code, but can help you write your algorithms in a more natural way.

3.2.4 Thread positioning

When running a kernel, the kernel function's code is executed by every thread once. It therefore has to know which thread it is in, in order to know which array element(s) it is responsible for (complex algorithms may define more complex responsibilities, but the underlying principle is the same).

One way is for the thread to determine its position in the grid and block and manually compute the corresponding array position:

```
@cuda.jit
def increment_by_one(an_array):
    # Thread id in a 1D block
    tx = cuda.threadIdx.x
```

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```
    # Block id in a 1D grid
    ty = cuda.blockIdx.x
    # Block width, i.e. number of threads per block
    bw = cuda.blockDim.x
    # Compute flattened index inside the array
    pos = tx + ty * bw
    if pos < an_array.size:  # Check array boundaries
        an_array[pos] += 1
```

Note: Unless you are sure the block size and grid size is a divisor of your array size, you **must** check boundaries as shown above.

threadIdx, *blockIdx*, *blockDim* and *gridDim* are special objects provided by the CUDA backend for the sole purpose of knowing the geometry of the thread hierarchy and the position of the current thread within that geometry.

These objects can be 1D, 2D or 3D, depending on how the kernel was *invoked*. To access the value at each dimension, use the `x`, `y` and `z` attributes of these objects, respectively.

numba.cuda.**threadIdx**

The thread indices in the current thread block. For 1D blocks, the index (given by the `x` attribute) is an integer spanning the range from 0 inclusive to *numba.cuda.blockDim* exclusive. A similar rule exists for each dimension when more than one dimension is used.

numba.cuda.**blockDim**

The shape of the block of threads, as declared when instantiating the kernel. This value is the same for all threads in a given kernel, even if they belong to different blocks (i.e. each block is "full").

numba.cuda.**blockIdx**

The block indices in the grid of threads launched a kernel. For a 1D grid, the index (given by the `x` attribute) is an integer spanning the range from 0 inclusive to *numba.cuda.gridDim* exclusive. A similar rule exists for each dimension when more than one dimension is used.

numba.cuda.**gridDim**

The shape of the grid of blocks, i.e. the total number of blocks launched by this kernel invocation, as declared when instantiating the kernel.

Absolute positions

Simple algorithms will tend to always use thread indices in the same way as shown in the example above. Numba provides additional facilities to automate such calculations:

numba.cuda.**grid**(*ndim*)

Return the absolute position of the current thread in the entire grid of blocks. *ndim* should correspond to the number of dimensions declared when instantiating the kernel. If *ndim* is 1, a single integer is returned. If *ndim* is 2 or 3, a tuple of the given number of integers is returned.

numba.cuda.**gridsize**(*ndim*)

Return the absolute size (or shape) in threads of the entire grid of blocks. *ndim* has the same meaning as in *grid()* above.

With these functions, the incrementation example can become:

```
@cuda.jit
def increment_by_one(an_array):
    pos = cuda.grid(1)
    if pos < an_array.size:
        an_array[pos] += 1
```

The same example for a 2D array and grid of threads would be:

```
@cuda.jit
def increment_a_2D_array(an_array):
    x, y = cuda.grid(2)
    if x < an_array.shape[0] and y < an_array.shape[1]:
       an_array[x, y] += 1
```

Note the grid computation when instantiating the kernel must still be done manually, for example:

```
threadsperblock = (16, 16)
blockspergrid_x = math.ceil(an_array.shape[0] / threadsperblock[0])
blockspergrid_y = math.ceil(an_array.shape[1] / threadsperblock[1])
blockspergrid = (blockspergrid_x, blockspergrid_y)
increment_a_2D_array[blockspergrid, threadsperblock](an_array)
```

Further Reading

Please refer to the the CUDA C Programming Guide for a detailed discussion of CUDA programming.

3.3 Memory management

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

3.3.1 Data transfer

Even though Numba can automatically transfer NumPy arrays to the device, it can only do so conservatively by always transferring device memory back to the host when a kernel finishes. To avoid the unnecessary transfer for read-only arrays, you can use the following APIs to manually control the transfer:

`numba.cuda.`**`device_array`**(*shape*, *dtype=np.float64*, *strides=None*, *order='C'*, *stream=0*)

Allocate an empty device ndarray. Similar to `numpy.empty()`.

`numba.cuda.`**`device_array_like`**(*ary*, *stream=0*)

Call *device_array()* with information from the array.

`numba.cuda.`**`to_device`**(*obj*, *stream=0*, *copy=True*, *to=None*)

Allocate and transfer a numpy ndarray or structured scalar to the device.

To copy host->device a numpy array:

```
ary = np.arange(10)
d_ary = cuda.to_device(ary)
```

To enqueue the transfer to a stream:

```
stream = cuda.stream()
d_ary = cuda.to_device(ary, stream=stream)
```

The resulting `d_ary` is a `DeviceNDArray`.

To copy device->host:

```
hary = d_ary.copy_to_host()
```

To copy device->host to an existing array:

```
ary = np.empty(shape=d_ary.shape, dtype=d_ary.dtype)
d_ary.copy_to_host(ary)
```

To enqueue the transfer to a stream:

```
hary = d_ary.copy_to_host(stream=stream)
```

In addition to the device arrays, Numba can consume any object that implements *cuda array interface*. These objects also can be manually converted into a Numba device array by creating a view of the GPU buffer using the following APIs:

`numba.cuda.`**`as_cuda_array`**`(`*obj*, *sync=True*`)`

Create a DeviceNDArray from any object that implements the *cuda array interface*.

A view of the underlying GPU buffer is created. No copying of the data is done. The resulting DeviceNDArray will acquire a reference from *obj*.

If `sync` is `True`, then the imported stream (if present) will be synchronized.

`numba.cuda.`**`is_cuda_array`**`(`*obj*`)`

Test if the object has defined the *__cuda_array_interface__* attribute.

Does not verify the validity of the interface.

Device arrays

Device array references have the following methods. These methods are to be called in host code, not within CUDA-jitted functions.

`class` `numba.cuda.cudadrv.devicearray.`**`DeviceNDArray`**`(`*shape*, *strides*, *dtype*, *stream=0*, *gpu_data=None*`)`

An on-GPU array type

`copy_to_host``(`*ary=None*, *stream=0*`)`

Copy `self` to `ary` or create a new Numpy ndarray if `ary` is `None`.

If a CUDA `stream` is given, then the transfer will be made asynchronously as part as the given stream. Otherwise, the transfer is synchronous: the function returns after the copy is finished.

Always returns the host array.

Example:

```
import numpy as np
from numba import cuda

arr = np.arange(1000)
d_arr = cuda.to_device(arr)

my_kernel[100, 100](d_arr)

result_array = d_arr.copy_to_host()
```

is_c_contiguous()

Return true if the array is C-contiguous.

is_f_contiguous()

Return true if the array is Fortran-contiguous.

ravel(*order='C'*, *stream=0*)

Flattens a contiguous array without changing its contents, similar to `numpy.ndarray.ravel()`. If the array is not contiguous, raises an exception.

reshape(**newshape*, ***kws*)

Reshape the array without changing its contents, similarly to `numpy.ndarray.reshape()`. Example:

```
d_arr = d_arr.reshape(20, 50, order='F')
```

Note: DeviceNDArray defines the *cuda array interface*.

3.3.2 Pinned memory

numba.cuda.**pinned**(**arylist*)

A context manager for temporary pinning a sequence of host ndarrays.

numba.cuda.**pinned_array**(*shape*, *dtype=np.float64*, *strides=None*, *order='C'*)

Allocate an `ndarray` with a buffer that is pinned (pagelocked). Similar to `np.empty()`.

numba.cuda.**pinned_array_like**(*ary*)

Call *pinned_array()* with the information from the array.

3.3.3 Mapped memory

numba.cuda.**mapped**(**arylist*, ***kws*)

A context manager for temporarily mapping a sequence of host ndarrays.

numba.cuda.**mapped_array**(*shape*, *dtype=np.float64*, *strides=None*, *order='C'*, *stream=0*, *portable=False*, *wc=False*)

Allocate a mapped ndarray with a buffer that is pinned and mapped on to the device. Similar to np.empty()

Parameters

- **portable** – a boolean flag to allow the allocated device memory to be usable in multiple devices.

- **wc** – a boolean flag to enable writecombined allocation which is faster to write by the host and to read by the device, but slower to write by the host and slower to write by the device.

numba.cuda.**mapped_array_like**(*ary*, *stream=0*, *portable=False*, *wc=False*)

Call *mapped_array()* with the information from the array.

3.3.4 Managed memory

numba.cuda.**managed_array**(*shape*, *dtype=np.float64*, *strides=None*, *order='C'*, *stream=0*, *attach_global=True*)

Allocate a np.ndarray with a buffer that is managed. Similar to np.empty().

Managed memory is supported on Linux / x86 and PowerPC, and is considered experimental on Windows and Linux / AArch64.

Parameters

attach_global – A flag indicating whether to attach globally. Global attachment implies that the memory is accessible from any stream on any device. If `False`, attachment is *host*, and memory is only accessible by devices with Compute Capability 6.0 and later.

3.3.5 Streams

Streams can be passed to functions that accept them (e.g. copies between the host and device) and into kernel launch configurations so that the operations are executed asynchronously.

numba.cuda.**stream**()

Create a CUDA stream that represents a command queue for the device.

numba.cuda.**default_stream**()

Get the default CUDA stream. CUDA semantics in general are that the default stream is either the legacy default stream or the per-thread default stream depending on which CUDA APIs are in use. In Numba, the APIs for the legacy default stream are always the ones in use, but an option to use APIs for the per-thread default stream may be provided in future.

numba.cuda.**legacy_default_stream**()

Get the legacy default CUDA stream.

numba.cuda.**per_thread_default_stream**()

Get the per-thread default CUDA stream.

numba.cuda.**external_stream**(*ptr*)

Create a Numba stream object for a stream allocated outside Numba.

Parameters

ptr (*int*) – Pointer to the external stream to wrap in a Numba Stream

CUDA streams have the following methods:

class numba.cuda.cudadrv.driver.**Stream**(*context*, *handle*, *finalizer*, *external=False*)

auto_synchronize()

A context manager that waits for all commands in this stream to execute and commits any pending memory transfers upon exiting the context.

synchronize()

Wait for all commands in this stream to execute. This will commit any pending memory transfers.

3.3.6 Shared memory and thread synchronization

A limited amount of shared memory can be allocated on the device to speed up access to data, when necessary. That memory will be shared (i.e. both readable and writable) amongst all threads belonging to a given block and has faster access times than regular device memory. It also allows threads to cooperate on a given solution. You can think of it as a manually-managed data cache.

The memory is allocated once for the duration of the kernel, unlike traditional dynamic memory management.

`numba.cuda.shared.array`(*shape*, *type*)

Allocate a shared array of the given *shape* and *type* on the device. This function must be called on the device (i.e. from a kernel or device function). *shape* is either an integer or a tuple of integers representing the array's dimensions and must be a simple constant expression. A "simple constant expression" includes, but is not limited to:

1. A literal (e.g. `10`)
2. A local variable whose right-hand side is a literal or a simple constant expression (e.g. `shape`, where `shape` is defined earlier in the function as `shape = 10`)
3. A global variable that is defined in the jitted function's globals by the time of compilation (e.g. `shape`, where `shape` is defined using any expression at global scope).

The definition must result in a Python `int` (i.e. not a NumPy scalar or other scalar / integer-like type). *type* is a *Numba type* of the elements needing to be stored in the array. The returned array-like object can be read and written to like any normal device array (e.g. through indexing).

A common pattern is to have each thread populate one element in the shared array and then wait for all threads to finish using *`syncthreads()`*.

`numba.cuda.syncthreads`()

Synchronize all threads in the same thread block. This function implements the same pattern as barriers in traditional multi-threaded programming: this function waits until all threads in the block call it, at which point it returns control to all its callers.

See also:

Matrix multiplication example.

Dynamic Shared Memory

In order to use dynamic shared memory in kernel code declare a shared array of size 0:

```
@cuda.jit
def kernel_func(x):
   dyn_arr = cuda.shared.array(0, dtype=np.float32)
   ...
```

and specify the size of dynamic shared memory in bytes during kernel invocation:

```
kernel_func[32, 32, 0, 128](x)
```

In the above code the kernel launch is configured with 4 parameters:

```
kernel_func[grid_dim, block_dim, stream, dyn_shared_mem_size]
```

Note: all dynamic shared memory arrays *alias*, so if you want to have multiple dynamic shared arrays, you need to take *disjoint* views of the arrays. For example, consider:

```
from numba import cuda
import numpy as np

@cuda.jit
def f():
   f32_arr = cuda.shared.array(0, dtype=np.float32)
   i32_arr = cuda.shared.array(0, dtype=np.int32)
   f32_arr[0] = 3.14
   print(f32_arr[0])
   print(i32_arr[0])

f[1, 1, 0, 4]()
cuda.synchronize()
```

This allocates 4 bytes of shared memory (large enough for one `int32` or one `float32`) and declares dynamic shared memory arrays of type `int32` and of type `float32`. When `f32_arr[0]` is set, this also sets the value of `i32_arr[0]`, because they're pointing at the same memory. So we see as output:

```
3.140000
1078523331
```

because 1078523331 is the `int32` represented by the bits of the `float32` value 3.14.

If we take disjoint views of the dynamic shared memory:

```
from numba import cuda
import numpy as np

@cuda.jit
def f_with_view():
   f32_arr = cuda.shared.array(0, dtype=np.float32)
   i32_arr = cuda.shared.array(0, dtype=np.int32)[1:] # 1 int32 = 4 bytes
   f32_arr[0] = 3.14
   i32_arr[0] = 1
   print(f32_arr[0])
   print(i32_arr[0])

f_with_view[1, 1, 0, 8]()
cuda.synchronize()
```

This time we declare 8 dynamic shared memory bytes, using the first 4 for a `float32` value and the next 4 for an `int32` value. Now we can set both the `int32` and `float32` value without them aliasing:

```
3.140000
1
```

3.3.7 Local memory

Local memory is an area of memory private to each thread. Using local memory helps allocate some scratchpad area when scalar local variables are not enough. The memory is allocated once for the duration of the kernel, unlike traditional dynamic memory management.

`numba.cuda.local.array`(*shape*, *type*)

Allocate a local array of the given *shape* and *type* on the device. *shape* is either an integer or a tuple of integers representing the array's dimensions and must be a simple constant expression. A "simple constant expression" includes, but is not limited to:

1. A literal (e.g. `10`)
2. A local variable whose right-hand side is a literal or a simple constant expression (e.g. `shape`, where `shape` is defined earlier in the function as `shape = 10`)
3. A global variable that is defined in the jitted function's globals by the time of compilation (e.g. `shape`, where `shape` is defined using any expression at global scope).

The definition must result in a Python `int` (i.e. not a NumPy scalar or other scalar / integer-like type). *type* is a *Numba type* of the elements needing to be stored in the array. The array is private to the current thread. An array-like object is returned which can be read and written to like any standard array (e.g. through indexing).

See also:

The Local Memory section of Device Memory Accesses in the CUDA programming guide.

3.3.8 Constant memory

Constant memory is an area of memory that is read only, cached and off-chip, it is accessible by all threads and is host allocated. A method of creating an array in constant memory is through the use of:

`numba.cuda.const.array_like`(*arr*)

Allocate and make accessible an array in constant memory based on array-like *arr*.

3.3.9 Deallocation Behavior

This section describes the deallocation behaviour of Numba's internal memory management. If an External Memory Management Plugin is in use (see *External Memory Management (EMM) Plugin interface*), then deallocation behaviour may differ; you may refer to the documentation for the EMM Plugin to understand its deallocation behaviour.

Deallocation of all CUDA resources are tracked on a per-context basis. When the last reference to a device memory is dropped, the underlying memory is scheduled to be deallocated. The deallocation does not occur immediately. It is added to a queue of pending deallocations. This design has two benefits:

1. Resource deallocation API may cause the device to synchronize; thus, breaking any asynchronous execution. Deferring the deallocation could avoid latency in performance critical code section.
2. Some deallocation errors may cause all the remaining deallocations to fail. Continued deallocation errors can cause critical errors at the CUDA driver level. In some cases, this could mean a segmentation fault in the CUDA driver. In the worst case, this could cause the system GUI to freeze and could only recover with a system reset. When an error occurs during a deallocation, the remaining pending deallocations are cancelled. Any deallocation error will be reported. When the process is terminated, the CUDA driver is able to release all allocated resources by the terminated process.

The deallocation queue is flushed automatically as soon as the following events occur:

- An allocation failed due to out-of-memory error. Allocation is retried after flushing all deallocations.

- The deallocation queue has reached its maximum size, which is default to 10. User can override by setting the environment variable *NUMBA_CUDA_MAX_PENDING_DEALLOCS_COUNT*. For example, *NUMBA_CUDA_MAX_PENDING_DEALLOCS_COUNT=20*, increases the limit to 20.
- The maximum accumulated byte size of resources that are pending deallocation is reached. This is default to 20% of the device memory capacity. User can override by setting the environment variable *NUMBA_CUDA_MAX_PENDING_DEALLOCS_RATIO*. For example, *NUMBA_CUDA_MAX_PENDING_DEALLOCS_RATIO=0.5* sets the limit to 50% of the capacity.

Sometimes, it is desired to defer resource deallocation until a code section ends. Most often, users want to avoid any implicit synchronization due to deallocation. This can be done by using the following context manager:

numba.cuda.**defer_cleanup**()

Temporarily disable memory deallocation. Use this to prevent resource deallocation breaking asynchronous execution.

For example:

```
with defer_cleanup():
    # all cleanup is deferred in here
    do_speed_critical_code()
# cleanup can occur here
```

Note: this context manager can be nested.

3.4 Writing Device Functions

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

CUDA device functions can only be invoked from within the device (by a kernel or another device function). To define a device function:

```
from numba import cuda

@cuda.jit(device=True)
def a_device_function(a, b):
    return a + b
```

Unlike a kernel function, a device function can return a value like normal functions.

3.5 Supported Python features in CUDA Python

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

This page lists the Python features supported in the CUDA Python. This includes all kernel and device functions compiled with `@cuda.jit` and other higher level Numba decorators that targets the CUDA GPU.

3.5.1 Language

Execution Model

CUDA Python maps directly to the *single-instruction multiple-thread* execution (SIMT) model of CUDA. Each instruction is implicitly executed by multiple threads in parallel. With this execution model, array expressions are less useful because we don't want multiple threads to perform the same task. Instead, we want threads to perform a task in a cooperative fashion.

For details please consult the CUDA Programming Guide.

Floating Point Error Model

By default, CUDA Python kernels execute with the NumPy error model. In this model, division by zero raises no exception and instead produces a result of `inf`, `-inf` or `nan`. This differs from the normal Python error model, in which division by zero raises a `ZeroDivisionError`.

When debug is enabled (by passing `debug=True` to the *`@cuda.jit`* decorator), the Python error model is used. This allows division-by-zero errors during kernel execution to be identified.

Constructs

The following Python constructs are not supported:

- Exception handling (`try .. except`, `try .. finally`)
- Context management (the `with` statement)
- Comprehensions (either list, dict, set or generator comprehensions)
- Generator (any `yield` statements)

The `raise` and `assert` statements are supported, with the following constraints:

- They can only be used in kernels, not in device functions.
- They only have an effect when `debug=True` is passed to the *`@cuda.jit`* decorator. This is similar to the behavior of the `assert` keyword in CUDA C/C++, which is ignored unless compiling with device debug turned on.

Printing of strings, integers, and floats is supported, but printing is an asynchronous operation - in order to ensure that all output is printed after a kernel launch, it is necessary to call *`numba.cuda.synchronize()`*. Eliding the call to `synchronize` is acceptable, but output from a kernel may appear during other later driver operations (e.g. subsequent kernel launches, memory transfers, etc.), or fail to appear before the program execution completes. Up to 32 arguments may be passed to the `print` function - if more are passed then a format string will be emitted instead and a warning will be produced. This is due to a general limitation in CUDA printing, as outlined in the section on limitations in printing in the CUDA C++ Programming Guide.

Recursion

Self-recursive device functions are supported, with the constraint that recursive calls must have the same argument types as the initial call to the function. For example, the following form of recursion is supported:

```
@cuda.jit("int64(int64)", device=True)
def fib(n):
    if n < 2:
        return n
    return fib(n - 1) + fib(n - 2)
```

(the `fib` function always has an `int64` argument), whereas the following is unsupported:

```
# Called with x := int64, y := float64
@cuda.jit
def type_change_self(x, y):
    if x > 1 and y > 0:
        return x + type_change_self(x - y, y)
    else:
        return y
```

The outer call to `type_change_self` provides `(int64, float64)` arguments, but the inner call uses `(float64, float64)` arguments (because `x - y` / `int64 - float64` results in a `float64` type). Therefore, this function is unsupported.

Mutual recursion between functions (e.g. where a function `func1()` calls `func2()` which again calls `func1()`) is unsupported.

Note: The call stack in CUDA is typically quite limited in size, so it is easier to overflow it with recursive calls on CUDA devices than it is on CPUs.

Stack overflow will result in an Unspecified Launch Failure (ULF) during kernel execution. In order to identify whether a ULF is due to stack overflow, programs can be run under Compute Sanitizer, which explicitly states when stack overflow has occurred.

3.5.2 Built-in types

The following built-in types support are inherited from CPU nopython mode.

- int
- float
- complex
- bool
- None
- tuple
- Enum, IntEnum

See *nopython built-in types*.

There is also some very limited support for character sequences (bytes and unicode strings) used in NumPy arrays. Note that this support can only be used with CUDA 11.2 onwards.

3.5.3 Built-in functions

The following built-in functions are supported:

- `abs()`
- `bool`
- `complex`
- `enumerate()`
- `float`
- `int`: only the one-argument form
- `len()`
- `min()`: only the multiple-argument form
- `max()`: only the multiple-argument form
- `pow()`
- `range`
- `round()`
- `zip()`

3.5.4 Standard library modules

`cmath`

The following functions from the `cmath` module are supported:

- `cmath.acos()`
- `cmath.acosh()`
- `cmath.asin()`
- `cmath.asinh()`
- `cmath.atan()`
- `cmath.atanh()`
- `cmath.cos()`
- `cmath.cosh()`
- `cmath.exp()`
- `cmath.isfinite()`
- `cmath.isinf()`
- `cmath.isnan()`
- `cmath.log()`
- `cmath.log10()`
- `cmath.phase()`
- `cmath.polar()`

- cmath.rect()
- cmath.sin()
- cmath.sinh()
- cmath.sqrt()
- cmath.tan()
- cmath.tanh()

math

The following functions from the math module are supported:

- math.acos()
- math.asin()
- math.atan()
- math.acosh()
- math.asinh()
- math.atanh()
- math.cos()
- math.sin()
- math.tan()
- math.hypot()
- math.cosh()
- math.sinh()
- math.tanh()
- math.atan2()
- math.erf()
- math.erfc()
- math.exp()
- math.expm1()
- math.fabs()
- math.frexp()
- math.ldexp()
- math.gamma()
- math.lgamma()
- math.log()
- math.log2()
- math.log10()
- math.log1p()

- math.sqrt()
- math.remainder()
- math.pow()
- math.ceil()
- math.floor()
- math.copysign()
- math.fmod()
- math.modf()
- math.isnan()
- math.isinf()
- math.isfinite()

operator

The following functions from the operator module are supported:

- operator.add()
- operator.and_()
- operator.eq()
- operator.floordiv()
- operator.ge()
- operator.gt()
- operator.iadd()
- operator.iand()
- operator.ifloordiv()
- operator.ilshift()
- operator.imod()
- operator.imul()
- operator.invert()
- operator.ior()
- operator.ipow()
- operator.irshift()
- operator.isub()
- operator.itruediv()
- operator.ixor()
- operator.le()
- operator.lshift()
- operator.lt()

- operator.mod()
- operator.mul()
- operator.ne()
- operator.neg()
- operator.not_()
- operator.or_()
- operator.pos()
- operator.pow()
- operator.rshift()
- operator.sub()
- operator.truediv()
- operator.xor()

3.5.5 NumPy support

Due to the CUDA programming model, dynamic memory allocation inside a kernel is inefficient and is often not needed. Numba disallows any memory allocating features. This disables a large number of NumPy APIs. For best performance, users should write code such that each thread is dealing with a single element at a time.

Supported NumPy features:

- accessing *ndarray* attributes *.shape*, *.strides*, *.ndim*, *.size*, etc..
- indexing and slicing works.
- A subset of ufuncs are supported, but the output array must be passed in as a positional argument (see *Calling a NumPy UFunc*). Note that ufuncs execute sequentially in each thread - there is no automatic parallelisation of ufuncs across threads over the elements of an input array.

  The following ufuncs are supported:

  - numpy.sin()
  - numpy.cos()
  - numpy.tan()
  - numpy.arcsin()
  - numpy.arccos()
  - numpy.arctan()
  - numpy.arctan2()
  - numpy.hypot()
  - numpy.sinh()
  - numpy.cosh()
  - numpy.tanh()
  - numpy.arcsinh()
  - numpy.arccosh()

  - numpy.arctanh()
  - numpy.deg2rad()
  - numpy.radians()
  - numpy.rad2deg()
  - numpy.degrees()
  - numpy.greater()
  - numpy.greater_equal()
  - numpy.less()
  - numpy.less_equal()
  - numpy.not_equal()
  - numpy.equal()
  - numpy.log()
  - numpy.log2()
  - numpy.log10()
  - numpy.logical_and()
  - numpy.logical_or()
  - numpy.logical_xor()
  - numpy.logical_not()
  - numpy.maximum()
  - numpy.minimum()
  - numpy.fmax()
  - numpy.fmin()
  - numpy.bitwise_and()
  - numpy.bitwise_or()
  - numpy.bitwise_xor()
  - numpy.invert()
  - numpy.bitwise_not()
  - numpy.left_shift()
  - numpy.right_shift()

Unsupported NumPy features:

- array creation APIs.
- array methods.
- functions that returns a new array.

3.5.6 CFFI support

The `from_buffer()` method of `cffi.FFI` objects is supported. This is useful for obtaining a pointer that can be passed to external C / C++ / PTX functions (see the *CUDA FFI documentation*).

3.6 CUDA Fast Math

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

As noted in *Fastmath*, for certain classes of applications that utilize floating point, strict IEEE-754 conformance is not required. For this subset of applications, performance speedups may be possible.

The CUDA target implements *Fastmath* behavior with two differences.

- First, the `fastmath` argument to the *`@jit decorator`* is limited to the values `True` and `False`. When `True`, the following optimizations are enabled:
  - Flushing of denormals to zero.
  - Use of a fast approximation to the square root function.
  - Use of a fast approximation to the division operation.
  - Contraction of multiply and add operations into single fused multiply-add operations.

  See the documentation for nvvmCompileProgram for more details of these optimizations.
- Secondly, calls to a subset of math module functions on `float32` operands will be implemented using fast approximate implementations from the libdevice library.
  - `math.cos()`: Implemented using __nv_fast_cosf.
  - `math.sin()`: Implemented using __nv_fast_sinf.
  - `math.tan()`: Implemented using __nv_fast_tanf.
  - `math.exp()`: Implemented using __nv_fast_expf.
  - `math.log2()`: Implemented using __nv_fast_log2f.
  - `math.log10()`: Implemented using __nv_fast_log10f.
  - `math.log()`: Implemented using __nv_fast_logf.
  - `math.pow()`: Implemented using __nv_fast_powf.

3.7 Supported Atomic Operations

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

Numba provides access to some of the atomic operations supported in CUDA. Those that are presently implemented are as follows:

class numba.cuda.**atomic**

Namespace for atomic operations

class add(*ary*, *idx*, *val*)

Perform atomic `ary[idx] += val`. Supported on int32, float32, and float64 operands only.

Returns the old value at the index location as if it is loaded atomically.

class and_(*ary*, *idx*, *val*)

Perform atomic `ary[idx] &= val`. Supported on int32, int64, uint32 and uint64 operands only.

Returns the old value at the index location as if it is loaded atomically.

class cas(*ary*, *idx*, *old*, *val*)

Conditionally assign `val` to the element `idx` of an array `ary` if the current value of `ary[idx]` matches `old`.

Supported on int32, int64, uint32, uint64 operands only.

Returns the old value as if it is loaded atomically.

class compare_and_swap(*ary*, *old*, *val*)

Conditionally assign `val` to the first element of an 1D array `ary` if the current value matches `old`.

Supported on int32, int64, uint32, uint64 operands only.

Returns the old value as if it is loaded atomically.

class dec(*ary*, *idx*, *val*)

Performs:

```
ary[idx] = (value if (array[idx] == 0) or
            (array[idx] > value) else array[idx] - 1)
```

Supported on uint32, and uint64 operands only.

Returns the old value at the index location as if it is loaded atomically.

class exch(*ary*, *idx*, *val*)

Perform atomic `ary[idx] = val`. Supported on int32, int64, uint32 and uint64 operands only.

Returns the old value at the index location as if it is loaded atomically.

class inc(*ary*, *idx*, *val*)

Perform atomic `ary[idx] += 1` up to val, then reset to 0. Supported on uint32, and uint64 operands only.

Returns the old value at the index location as if it is loaded atomically.

class max(*ary*, *idx*, *val*)

Perform atomic `ary[idx] = max(ary[idx], val)`.

Supported on int32, int64, uint32, uint64, float32, float64 operands only.

Returns the old value at the index location as if it is loaded atomically.

class min(*ary*, *idx*, *val*)

Perform atomic `ary[idx] = min(ary[idx], val)`.

Supported on int32, int64, uint32, uint64, float32, float64 operands only.

Returns the old value at the index location as if it is loaded atomically.

class nanmax(*ary*, *idx*, *val*)

Perform atomic `ary[idx] = max(ary[idx], val)`.

NOTE: NaN is treated as a missing value such that: nanmax(NaN, n) == n, nanmax(n, NaN) == n

Supported on int32, int64, uint32, uint64, float32, float64 operands only.

Returns the old value at the index location as if it is loaded atomically.

class nanmin(*ary*, *idx*, *val*)

Perform atomic `ary[idx] = min(ary[idx], val)`.

NOTE: NaN is treated as a missing value, such that: nanmin(NaN, n) == n, nanmin(n, NaN) == n

Supported on int32, int64, uint32, uint64, float32, float64 operands only.

Returns the old value at the index location as if it is loaded atomically.

class or_(*ary*, *idx*, *val*)

Perform atomic `ary[idx] |= val`. Supported on int32, int64, uint32 and uint64 operands only.

Returns the old value at the index location as if it is loaded atomically.

class sub(*ary*, *idx*, *val*)

Perform atomic `ary[idx] -= val`. Supported on int32, float32, and float64 operands only.

Returns the old value at the index location as if it is loaded atomically.

class xor(*ary*, *idx*, *val*)

Perform atomic `ary[idx] ^= val`. Supported on int32, int64, uint32 and uint64 operands only.

Returns the old value at the index location as if it is loaded atomically.

3.7.1 Example

The following code demonstrates the use of *numba.cuda.atomic.max* to find the maximum value in an array. Note that this is not the most efficient way of finding a maximum in this case, but that it serves as an example:

```
from numba import cuda
import numpy as np

@cuda.jit
def max_example(result, values):
    """Find the maximum value in values and store in result[0]"""
    tid = cuda.threadIdx.x
    bid = cuda.blockIdx.x
```

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```
    bdim = cuda.blockDim.x
    i = (bid * bdim) + tid
    cuda.atomic.max(result, 0, values[i])


arr = np.random.rand(16384)
result = np.zeros(1, dtype=np.float64)

max_example[256,64](result, arr)
print(result[0]) # Found using cuda.atomic.max
print(max(arr))  # Print max(arr) for comparison (should be equal!)
```

Multiple dimension arrays are supported by using a tuple of ints for the index:

```
@cuda.jit
def max_example_3d(result, values):
    """
    Find the maximum value in values and store in result[0].
    Both result and values are 3d arrays.
    """
    i, j, k = cuda.grid(3)
    # Atomically store to result[0,1,2] from values[i, j, k]
    cuda.atomic.max(result, (0, 1, 2), values[i, j, k])

arr = np.random.rand(1000).reshape(10,10,10)
result = np.zeros((3, 3, 3), dtype=np.float64)
max_example_3d[(2, 2, 2), (5, 5, 5)](result, arr)
print(result[0, 1, 2], '==', np.max(arr))
```

3.8 Cooperative Groups

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

3.8.1 Supported features

Numba's Cooperative Groups support presently provides grid groups and grid synchronization, along with cooperative kernel launches.

Cooperative groups are supported on Linux, and Windows for devices in TCC mode.

3.8.2 Using Grid Groups

To get the current grid group, use the *cg.this_grid()* function:

```
g = cuda.cg.this_grid()
```

Synchronizing the grid is done with the *sync()* method of the grid group:

```
g.sync()
```

3.8.3 Cooperative Launches

Unlike the CUDA C/C++ API, a cooperative launch is invoked using the same syntax as a normal kernel launch - Numba automatically determines whether a cooperative launch is required based on whether a grid group is synchronized in the kernel.

The grid size limit for a cooperative launch is more restrictive than for a normal launch - the grid must be no larger than the maximum number of active blocks on the device on which it is launched. To get maximum grid size for a cooperative launch of a kernel with a given block size and dynamic shared memory requirement, use the `max_cooperative_grid_blocks()` method of kernel overloads:

_Kernel.**max_cooperative_grid_blocks**(*blockdim*, *dynsmemsize=0*)

Calculates the maximum number of blocks that can be launched for this kernel in a cooperative grid in the current context, for the given block and dynamic shared memory sizes.

Parameters

- **blockdim** – Block dimensions, either as a scalar for a 1D block, or a tuple for 2D or 3D blocks.
- **dynsmemsize** – Dynamic shared memory size in bytes.

Returns

The maximum number of blocks in the grid.

This can be used to ensure that the kernel is launched with no more than the maximum number of blocks. Exceeding the maximum number of blocks for the cooperative launch will result in a `CUDA_ERROR_COOPERATIVE_LAUNCH_TOO_LARGE` error.

3.8.4 Applications and Example

Grid group synchronization can be used to implement a global barrier across all threads in the grid - applications of this include a global reduction to a single value, or looping over rows of a large matrix sequentially using the entire grid to operate on column elements in parallel.

In the following example, rows are written sequentially by the grid. Each thread in the grid reads a value from the previous row written by it's *opposite* thread. A grid sync is needed to ensure that threads in the grid don't run ahead of threads in other blocks, or fail to see updates from their opposite thread.

First we'll define our kernel:

Listing 1: from test_grid_sync of numba/cuda/tests/doc_example/test_cg.py

```
from numba import cuda, int32
import numpy as np

sig = (int32[:,::1],)

@cuda.jit(sig)
def sequential_rows(M):
    col = cuda.grid(1)
    g = cuda.cg.this_grid()

    rows = M.shape[0]
    cols = M.shape[1]

    for row in range(1, rows):
        opposite = cols - col - 1
        # Each row's elements are one greater than the previous row
        M[row, col] = M[row - 1, opposite] + 1
        # Wait until all threads have written their column element,
        # and that the write is visible to all other threads
        g.sync()
```

Then create some empty input data and determine the grid and block sizes:

Listing 2: from test_grid_sync of numba/cuda/tests/doc_example/test_cg.py

```
# Empty input data
A = np.zeros((1024, 1024), dtype=np.int32)
# A somewhat arbitrary choice (one warp), but generally smaller block sizes
# allow more blocks to be launched (noting that other limitations on
# occupancy apply such as shared memory size)
blockdim = 32
griddim = A.shape[1] // blockdim
```

Finally we launch the kernel and print the result:

Listing 3: from test_grid_sync of numba/cuda/tests/doc_example/test_cg.py

```
# Kernel launch - this is implicitly a cooperative launch
sequential_rows[griddim, blockdim](A)

# What do the results look like?
# print(A)
#
# [[   0    0    0 ...    0    0    0]
#  [   1    1    1 ...    1    1    1]
#  [   2    2    2 ...    2    2    2]
#  ...
#  [1021 1021 1021 ... 1021 1021 1021]
#  [1022 1022 1022 ... 1022 1022 1022]
```

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```
#  [1023 1023 1023 ... 1023 1023 1023]]
```

The maximum grid size for `sequential_rows` can be enquired using:

```
overload = sequential_rows.overloads[(int32[:,::1],)
max_blocks = overload.max_cooperative_grid_blocks(blockdim)
print(max_blocks)
# 1152 (e.g. on Quadro RTX 8000 with Numba 0.52.1 and CUDA 11.0)
```

3.9 Random Number Generation

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

Numba provides a random number generation algorithm that can be executed on the GPU. Due to technical issues with how NVIDIA implemented cuRAND, however, Numba's GPU random number generator is not based on cuRAND. Instead, Numba's GPU RNG is an implementation of the xoroshiro128+ algorithm. The xoroshiro128+ algorithm has a period of `2**128 - 1`, which is shorter than the period of the XORWOW algorithm used by default in cuRAND, but xoroshiro128+ still passes the BigCrush tests of random number generator quality.

When using any RNG on the GPU, it is important to make sure that each thread has its own RNG state, and they have been initialized to produce non-overlapping sequences. The numba.cuda.random module provides a host function to do this, as well as CUDA device functions to obtain uniformly or normally distributed random numbers.

Note: Numba (like cuRAND) uses the *Box-Muller transform <https://en.wikipedia.org/wiki/Box%E2%80%93Muller_transform>* to generate normally distributed random numbers from a uniform generator. However, Box-Muller generates pairs of random numbers, and the current implementation only returns one of them. As a result, generating normally distributed values is half the speed of uniformly distributed values.

numba.cuda.random.**create_xoroshiro128p_states**(*n*, *seed*, *subsequence_start=0*, *stream=0*)

Returns a new device array initialized for n random number generators.

This initializes the RNG states so that each state in the array corresponds subsequences in the separated by 2**64 steps from each other in the main sequence. Therefore, as long no CUDA thread requests more than 2**64 random numbers, all of the RNG states produced by this function are guaranteed to be independent.

The subsequence_start parameter can be used to advance the first RNG state by a multiple of 2**64 steps.

Parameters

- **n** (*int*) – number of RNG states to create
- **seed** (*uint64*) – starting seed for list of generators
- **subsequence_start** (*uint64*) –
- **stream** (*CUDA stream*) – stream to run initialization kernel on

numba.cuda.random.**init_xoroshiro128p_states**(*states*, *seed*, *subsequence_start=0*, *stream=0*)

Initialize RNG states on the GPU for parallel generators.

This initializes the RNG states so that each state in the array corresponds subsequences in the separated by 2**64 steps from each other in the main sequence. Therefore, as long no CUDA thread requests more than 2**64 random numbers, all of the RNG states produced by this function are guaranteed to be independent.

The subsequence_start parameter can be used to advance the first RNG state by a multiple of 2**64 steps.

Parameters

- **states** (*1D DeviceNDArray, dtype=xoroshiro128p_dtype*) – array of RNG states
- **seed** (*uint64*) – starting seed for list of generators

numba.cuda.random.**xoroshiro128p_normal_float32**(*states*, *index*)

Return a normally distributed float32 and advance `states[index]`.

The return value is drawn from a Gaussian of mean=0 and sigma=1 using the Box-Muller transform. This advances the RNG sequence by two steps.

Parameters

- **states** (*1D array, dtype=xoroshiro128p_dtype*) – array of RNG states
- **index** (*int64*) – offset in states to update

Return type
float32

numba.cuda.random.**xoroshiro128p_normal_float64**(*states*, *index*)

Return a normally distributed float32 and advance `states[index]`.

The return value is drawn from a Gaussian of mean=0 and sigma=1 using the Box-Muller transform. This advances the RNG sequence by two steps.

Parameters

- **states** (*1D array, dtype=xoroshiro128p_dtype*) – array of RNG states
- **index** (*int64*) – offset in states to update

Return type
float64

numba.cuda.random.**xoroshiro128p_uniform_float32**(*states*, *index*)

Return a float32 in range [0.0, 1.0) and advance `states[index]`.

Parameters

- **states** (*1D array, dtype=xoroshiro128p_dtype*) – array of RNG states
- **index** (*int64*) – offset in states to update

Return type
float32

numba.cuda.random.**xoroshiro128p_uniform_float64**(*states*, *index*)

Return a float64 in range [0.0, 1.0) and advance `states[index]`.

Parameters

- **states** (*1D array, dtype=xoroshiro128p_dtype*) – array of RNG states
- **index** (*int64*) – offset in states to update

Return type
float64

3.9.1 A simple example

Here is a sample program that uses the random number generator:

```
from __future__ import print_function, absolute_import

from numba import cuda
from numba.cuda.random import create_xoroshiro128p_states, xoroshiro128p_uniform_float32
import numpy as np

@cuda.jit
def compute_pi(rng_states, iterations, out):
    """Find the maximum value in values and store in result[0]"""
    thread_id = cuda.grid(1)

    # Compute pi by drawing random (x, y) points and finding what
    # fraction lie inside a unit circle
    inside = 0
    for i in range(iterations):
        x = xoroshiro128p_uniform_float32(rng_states, thread_id)
        y = xoroshiro128p_uniform_float32(rng_states, thread_id)
        if x**2 + y**2 <= 1.0:
            inside += 1

    out[thread_id] = 4.0 * inside / iterations

threads_per_block = 64
blocks = 24
rng_states = create_xoroshiro128p_states(threads_per_block * blocks, seed=1)
out = np.zeros(threads_per_block * blocks, dtype=np.float32)

compute_pi[blocks, threads_per_block](rng_states, 10000, out)
print('pi:', out.mean())
```

3.9.2 An example of managing RNG state size and using a 3D grid

The number of RNG states scales with the number of threads using the RNG, so it is often better to use strided loops in conjunction with the RNG in order to keep the state size manageable.

In the following example, which initializes a large 3D array with random numbers, using one thread per output element would result in 453,617,100 RNG states. This would take a long time to initialize and poorly utilize the GPU. Instead, it uses a fixed size 3D grid with a total of 2,097,152 (`(16 ** 3) * (8 ** 3)`) threads striding over the output array. The 3D thread indices `startx`, `starty`, and `startz` are linearized into a 1D index, `tid`, to index into the 2,097,152 RNG states.

Listing 4: from `test_ex_3d_grid of ``numba/cuda/tests/doc_example/test_random.py`

```
from numba import cuda
from numba.cuda.random import (create_xoroshiro128p_states,
                               xoroshiro128p_uniform_float32)
import numpy as np

```

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```
@cuda.jit
def random_3d(arr, rng_states):
    # Per-dimension thread indices and strides
    startx, starty, startz = cuda.grid(3)
    stridex, stridey, stridez = cuda.gridsize(3)

    # Linearized thread index
    tid = (startz * stridey * stridex) + (starty * stridex) + startx

    # Use strided loops over the array to assign a random value to each entry
    for i in range(startz, arr.shape[0], stridez):
        for j in range(starty, arr.shape[1], stridey):
            for k in range(startx, arr.shape[2], stridex):
                arr[i, j, k] = xoroshiro128p_uniform_float32(rng_states, tid)

# Array dimensions
X, Y, Z = 701, 900, 719

# Block and grid dimensions
bx, by, bz = 8, 8, 8
gx, gy, gz = 16, 16, 16

# Total number of threads
nthreads = bx * by * bz * gx * gy * gz

# Initialize a state for each thread
rng_states = create_xoroshiro128p_states(nthreads, seed=1)

# Generate random numbers
arr = cuda.device_array((X, Y, Z), dtype=np.float32)
random_3d[(gx, gy, gz), (bx, by, bz)](arr, rng_states)
```

3.10 Device management

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

For multi-GPU machines, users may want to select which GPU to use. By default the CUDA driver selects the fastest GPU as the device 0, which is the default device used by Numba.

The features introduced on this page are generally not of interest unless working with systems hosting/offering more than one CUDA-capable GPU.

3.10.1 Device Selection

If at all required, device selection must be done before any CUDA feature is used.

```
from numba import cuda
cuda.select_device(0)
```

The device can be closed by:

```
cuda.close()
```

Users can then create a new context with another device.

```
cuda.select_device(1)  # assuming we have 2 GPUs
```

numba.cuda.**select_device**(*device_id*)

Create a new CUDA context for the selected *device_id*. *device_id* should be the number of the device (starting from 0; the device order is determined by the CUDA libraries). The context is associated with the current thread. Numba currently allows only one context per thread.

If successful, this function returns a device instance.

numba.cuda.**close**()

Explicitly close all contexts in the current thread.

Note: Compiled functions are associated with the CUDA context. This makes it not very useful to close and create new devices, though it is certainly useful for choosing which device to use when the machine has multiple GPUs.

3.11 The Device List

The Device List is a list of all the GPUs in the system, and can be indexed to obtain a context manager that ensures execution on the selected GPU.

numba.cuda.**gpus**

numba.cuda.cudadrv.devices.**gpus**

numba.cuda.gpus is an instance of the `_DeviceList` class, from which the current GPU context can also be retrieved:

class numba.cuda.cudadrv.devices.**_DeviceList**

property current

Returns the active device or None if there's no active device

3.12 Device UUIDs

The UUID of a device (equal to that returned by `nvidia-smi -L`) is available in the *uuid* attribute of a CUDA device object.

For example, to obtain the UUID of the current device:

```
dev = cuda.current_context().device
# prints e.g. "GPU-e6489c45-5b68-3b03-bab7-0e7c8e809643"
print(dev.uuid)
```

3.13 Examples

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

3.13.1 Vector Addition

This example uses Numba to create on-device arrays and a vector addition kernel; it is a warmup for learning how to write GPU kernels using Numba. We'll begin with some required imports:

Listing 5: from `test_ex_vecadd` in `numba/cuda/tests/doc_examples/test_vecadd.py`

```
import numpy as np
from numba import cuda
```

The following function is the kernel. Note that it is defined in terms of Python variables with unspecified types. When the kernel is launched, Numba will examine the types of the arguments that are passed at runtime and generate a CUDA kernel specialized for them.

Note that Numba kernels do not return values and must write any output into arrays passed in as parameters (this is similar to the requirement that CUDA C/C++ kernels have `void` return type). Here we pass in `c` for the results to be written into.

Listing 6: from `test_ex_vecadd` in `numba/cuda/tests/doc_examples/test_vecadd.py`

```
@cuda.jit
def f(a, b, c):
    # like threadIdx.x + (blockIdx.x * blockDim.x)
    tid = cuda.grid(1)
    size = len(c)

    if tid < size:
        c[tid] = a[tid] + b[tid]
```

cuda.to_device() can be used create device-side copies of arrays. *cuda.device_array_like()* creates an uninitialized array of the same shape and type as an existing array. Here we transfer two vectors and create an empty vector to hold our results:

Listing 7: from test_ex_vecadd in numba/cuda/tests/doc_examples/test_vecadd.py

```
N = 100000
a = cuda.to_device(np.random.random(N))
b = cuda.to_device(np.random.random(N))
c = cuda.device_array_like(a)
```

A call to `forall()` generates an appropriate launch configuration with a 1D grid (see *Kernel invocation*) for a given data size and is often the simplest way of launching a kernel:

Listing 8: from test_ex_vecadd in numba/cuda/tests/doc_examples/test_vecadd.py

```
f.forall(len(a))(a, b, c)
print(c.copy_to_host())
```

This prints:

```
[0.73548323 1.32061059 0.12582968 ... 1.25925809 1.49335059 1.59315414]
```

One can also configure the grid manually using the subscripting syntax. The following example launches a grid with sufficient threads to operate on every vector element:

Listing 9: from test_ex_vecadd in numba/cuda/tests/doc_examples/test_vecadd.py

```
# Enough threads per block for several warps per block
nthreads = 256
# Enough blocks to cover the entire vector depending on its length
nblocks = (len(a) // nthreads) + 1
f[nblocks, nthreads](a, b, c)
print(c.copy_to_host())
```

This also prints:

```
[0.73548323 1.32061059 0.12582968 ... 1.25925809 1.49335059 1.59315414]
```

3.13.2 1D Heat Equation

This example solves Laplace's equation in one dimension for a certain set of initial conditions and boundary conditions. A full discussion of Laplace's equation is out of scope for this documentation, but it will suffice to say that it describes how heat propagates through an object over time. It works by discretizing the problem in two ways:

1. The domain is partitioned into a mesh of points that each have an individual temperature.
2. Time is partitioned into discrete intervals that are advanced forward sequentially.

Then, the following assumption is applied: The temperature of a point after some interval has passed is some weighted average of the temperature of the points that are directly adjacent to it. Intuitively, if all the points in the domain are very hot and a single point in the middle is very cold, as time passes, the hot points will cause the cold one to heat up

and the cold point will cause the surrounding hot pieces to cool slightly. Simply put, the heat spreads throughout the object.

We can implement this simulation using a Numba kernel. Let's start simple by assuming we have a one dimensional object which we'll represent with an array of values. The position of the element in the array is the position of a point within the object, and the value of the element represents the temperature.

Listing 10: from test_ex_laplace in numba/cuda/tests/doc_examples/test_laplace.py

```
import numpy as np
from numba import cuda
```

Some initial setup here. Let's make one point in the center of the object very hot.

Listing 11: from test_ex_laplace in numba/cuda/tests/doc_examples/test_laplace.py

```
# Use an odd problem size.
# This is so there can be an element truly in the "middle" for symmetry.
size = 1001
data = np.zeros(size)

# Middle element is made very hot
data[500] = 10000
buf_0 = cuda.to_device(data)

# This extra array is used for synchronization purposes
buf_1 = cuda.device_array_like(buf_0)

niter = 10000
```

The initial state of the problem can be visualized as:

In our kernel each thread will be responsible for managing the temperature update for a single element in a loop over the desired number of timesteps. The kernel is below. Note the use of cooperative group synchronization and the use of two buffers swapped at each iteration to avoid race conditions. See *numba.cuda.cg.this_grid()* for details.

Listing 12: from test_ex_laplace in numba/cuda/tests/doc_examples/test_laplace.py

```
@cuda.jit
def solve_heat_equation(buf_0, buf_1, timesteps, k):
    i = cuda.grid(1)

    # Don't continue if our index is outside the domain
    if i >= len(buf_0):
        return

    # Prepare to do a grid-wide synchronization later
    grid = cuda.cg.this_grid()

    for step in range(timesteps):
        # Select the buffer from the previous timestep
```

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```
        if (step % 2) == 0:
            data = buf_0
            next_data = buf_1
        else:
            data = buf_1
            next_data = buf_0

        # Get the current temperature associated with this point
        curr_temp = data[i]

        # Apply formula from finite difference equation
        if i == 0:
            # Left wall is held at T = 0
            next_temp = curr_temp + k * (data[i + 1] - (2 * curr_temp))
        elif i == len(data) - 1:
            # Right wall is held at T = 0
            next_temp = curr_temp + k * (data[i - 1] - (2 * curr_temp))
        else:
            # Interior points are a weighted average of their neighbors
            next_temp = curr_temp + k * (
                data[i - 1] - (2 * curr_temp) + data[i + 1]
            )

        # Write new value to the next buffer
        next_data[i] = next_temp

        # Wait for every thread to write before moving on
        grid.sync()
```

Calling the kernel:

Listing 13: from `test_ex_laplace` in `numba/cuda/tests/doc_examples/test_laplace.py`

```
solve_heat_equation.forall(len(data))(
    buf_0, buf_1, niter, 0.25
)
```

Plotting the final data shows an arc that is highest where the object was hot initially and gradually sloping down to zero towards the edges where the temperature is fixed at zero. In the limit of infinite time, the arc will flatten out completely.

3.13.3 Shared Memory Reduction

Numba exposes many CUDA features, including *shared memory*. To demonstrate shared memory, let's reimplement a famous CUDA solution for summing a vector which works by "folding" the data up using a successively smaller number of threads.

Note that this is a fairly naive implementation, and there are more efficient ways of implementing reductions using Numba - see *Monte Carlo Integration* for an example.

Listing 14: from test_ex_reduction in numba/cuda/tests/doc_examples/test_reduction.py

```
import numpy as np
from numba import cuda
from numba.types import int32
```

Let's create some one dimensional data that we'll use to demonstrate the kernel itself:

Listing 15: from test_ex_reduction in numba/cuda/tests/doc_examples/test_reduction.py

```
# generate data
a = cuda.to_device(np.arange(1024))
nelem = len(a)
```

Here is a version of the kernel implemented using Numba:

Listing 16: from test_ex_reduction in numba/cuda/tests/doc_examples/test_reduction.py

```
@cuda.jit
def array_sum(data):
    tid = cuda.threadIdx.x
    size = len(data)
    if tid < size:
        i = cuda.grid(1)

        # Declare an array in shared memory
        shr = cuda.shared.array(nelem, int32)
        shr[tid] = data[i]

        # Ensure writes to shared memory are visible
        # to all threads before reducing
        cuda.syncthreads()

        s = 1
        while s < cuda.blockDim.x:
            if tid % (2 * s) == 0:
                # Stride by `s` and add
                shr[tid] += shr[tid + s]
            s *= 2
            cuda.syncthreads()

        # After the loop, the zeroth  element contains the sum
        if tid == 0:
            data[tid] = shr[tid]
```

We can run kernel and verify that the same result is obtained through summing data on the host as follows:

Listing 17: from test_ex_reduction in numba/cuda/tests/doc_examples/test_reduction.py

```
array_sum[1, nelem](a)
print(a[0])                    # 523776
print(sum(np.arange(1024)))    # 523776
```

This algorithm can be greatly improved upon by redesigning the inner loop to use sequential memory accesses, and even further by using strategies that keep more threads active and working, since in this example most threads quickly become idle.

3.13.4 Dividing Click Data into Sessions

A common problem in business analytics is that of grouping the activity of users of an online platform into sessions, called "sessionization". The idea is that users generally traverse through a website and perform various actions (clicking something, filling out a form, etc.) in discrete groups. Perhaps a customer spends some time shopping for an item in the morning and then again at night - often the business is interested in treating these periods as separate interactions with their service, and this creates the problem of programmatically splitting up activity in some agreed-upon way.

Here we'll illustrate how to write a Numba kernel to solve this problem. We'll start with data containing two fields: let `user_id` represent a unique ID corresponding to an individual customer, and let `action_time` be a time that some unknown action was taken on the service. Right now, we'll assume there's only one type of action, so all there is to know is when it happened.

Our goal will be to create a new column called `session_id`, which contains a label corresponding to a unique session. We'll define the boundary between sessions as when there has been at least one hour between clicks.

Listing 18: from test_ex_sessionize in numba/cuda/tests/doc_examples/test_sessionize.py

```
import numpy as np
from numba import cuda

# Set the timeout to one hour
session_timeout = np.int64(np.timedelta64("3600", "s"))
```

Here is a solution using Numba:

Listing 19: from test_ex_sessionize in numba/cuda/tests/doc_examples/test_sessionize.py

```
@cuda.jit
def sessionize(user_id, timestamp, results):
    gid = cuda.grid(1)
    size = len(user_id)

    if gid >= size:
        return

    # Determine session boundaries
    is_first_datapoint = gid == 0
    if not is_first_datapoint:
        new_user = user_id[gid] != user_id[gid - 1]
```

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```
        timed_out = (
            timestamp[gid] - timestamp[gid - 1] > session_timeout
        )
        is_sess_boundary = new_user or timed_out
    else:
        is_sess_boundary = True

    # Determine session labels
    if is_sess_boundary:
        # This thread marks the start of a session
        results[gid] = gid

        # Make sure all session boundaries are written
        # before populating the session id
        grid = cuda.cg.this_grid()
        grid.sync()

        look_ahead = 1
        # Check elements 'forward' of this one
        # until a new session boundary is found
        while results[gid + look_ahead] == 0:
            results[gid + look_ahead] = gid
            look_ahead += 1
            # Avoid out-of-bounds accesses by the last thread
            if gid + look_ahead == size - 1:
                results[gid + look_ahead] = gid
                break
```

Let's generate some data and try out the kernel:

Listing 20: from `test_ex_sessionize` in `numba/cuda/tests/doc_examples/test_sessionize.py`

```
# Generate data
ids = cuda.to_device(
    np.array(
        [
            1, 1, 1, 1, 1, 1,
            2, 2, 2,
            3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
            4, 4, 4, 4, 4, 4, 4, 4, 4,
        ]
    )
)
sec = cuda.to_device(
    np.array(
        [
            1, 2, 3, 5000, 5001, 5002, 1,
            2, 3, 1, 2, 5000, 5001, 10000,
            10001, 10002, 10003, 15000, 150001,
            1, 5000, 50001, 15000, 20000,
            25000, 25001, 25002, 25003,
```

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```
        ],
        dtype="datetime64[ns]",
    ).astype(
        "int64"
    )  # Cast to int64 for compatibility
)
# Create a vector to hold the results
results = cuda.to_device(np.zeros(len(ids)))
```

As can be seen above, the kernel successfully divided the first three datapoints from the second three for the first user ID, and a similar pattern is seen throughout.

3.13.5 JIT Function CPU-GPU Compatibility

This example demonstrates how `numba.jit` can be used to jit compile a function for the CPU, while at the same time making it available for use inside CUDA kernels. This can be very useful for users that are migrating workflows from CPU to GPU as they can directly reuse potential business logic with fewer code changes.

Take the following example function:

Listing 21: from `test_ex_cpu_gpu_compat` in `numba/cuda/tests/doc_examples/test_cpu_gpu_compat.py`

```
@numba.jit
def business_logic(x, y, z):
    return 4 * z * (2 * x - (4 * y) / 2 * pi)
```

The function `business_logic` can be run standalone in compiled form on the CPU:

Listing 22: from `test_ex_cpu_gpu_compat` in `numba/cuda/tests/doc_examples/test_cpu_gpu_compat.py`

```
print(business_logic(1, 2, 3))  # -126.79644737231007
```

It can also be directly reused threadwise inside a GPU kernel. For example one may generate some vectors to represent `x`, `y`, and `z`:

Listing 23: from `test_ex_cpu_gpu_compat` in `numba/cuda/tests/doc_examples/test_cpu_gpu_compat.py`

```
X = cuda.to_device([1, 10, 234])
Y = cuda.to_device([2, 2, 4014])
Z = cuda.to_device([3, 14, 2211])
results = cuda.to_device([0.0, 0.0, 0.0])
```

And a numba kernel referencing the decorated function:

Listing 24: from `test_ex_cpu_gpu_compat` in `numba/cuda/tests/doc_examples/test_cpu_gpu_compat.py`

```
@cuda.jit
def f(res, xarr, yarr, zarr):
    tid = cuda.grid(1)
```

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```
    if tid < len(xarr):
        # The function decorated with numba.jit may be directly reused
        res[tid] = business_logic(xarr[tid], yarr[tid], zarr[tid])
```

This kernel can be invoked in the normal way:

Listing 25: from `test_ex_cpu_gpu_compat` in `numba/cuda/tests/doc_examples/test_cpu_gpu_compat.py`

```
f.forall(len(X))(results, X, Y, Z)
print(results)
# [-126.79644737231007, 416.28324559588634, -218912930.2987788]
```

3.13.6 Monte Carlo Integration

This example shows how to use Numba to approximate the value of a definite integral by rapidly generating random numbers on the GPU. A detailed description of the mathematical mechanics of Monte Carlo integration is out of the scope of the example, but it can briefly be described as an averaging process where the area under the curve is approximated by taking the average of many rectangles formed by its function values.

In addition, this example shows how to perform reductions in numba using the *cuda.reduce()* API.

Listing 26: from `test_ex_montecarlo` in `numba/cuda/tests/doc_examples/test_montecarlo.py`

```
import numba
import numpy as np
from numba import cuda
from numba.cuda.random import (
    create_xoroshiro128p_states,
    xoroshiro128p_uniform_float32,
)
```

Let's create a variable to control the number of samples drawn:

Listing 27: from `test_ex_montecarlo` in `numba/cuda/tests/doc_examples/test_montecarlo.py`

```
# number of samples, higher will lead to a more accurate answer
nsamps = 1000000
```

The following kernel implements the main integration routine:

Listing 28: from `test_ex_montecarlo` in `numba/cuda/tests/doc_examples/test_montecarlo.py`

```
@cuda.jit
def mc_integrator_kernel(out, rng_states, lower_lim, upper_lim):
    """
    kernel to draw random samples and evaluate the function to
    be integrated at those sample values
    """
    size = len(out)
```

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```
    gid = cuda.grid(1)
    if gid < size:
        # draw a sample between 0 and 1 on this thread
        samp = xoroshiro128p_uniform_float32(rng_states, gid)

        # normalize this sample to the limit range
        samp = samp * (upper_lim - lower_lim) + lower_lim

        # evaluate the function to be
        # integrated at the normalized
        # value of the sample
        y = func(samp)
        out[gid] = y
```

This convenience function calls the kernel performs some preprocessing and post processing steps. Note the use of Numba's reduction API to take sum of the array and compute the final result:

Listing 29: from `test_ex_montecarlo` in `numba/cuda/tests/doc_examples/test_montecarlo.py`

```
@cuda.reduce
def sum_reduce(a, b):
    return a + b

def mc_integrate(lower_lim, upper_lim, nsamps):
    """
    approximate the definite integral of `func` from
    `lower_lim` to `upper_lim`
    """
    out = cuda.to_device(np.zeros(nsamps, dtype="float32"))
    rng_states = create_xoroshiro128p_states(nsamps, seed=42)

    # jit the function for use in CUDA kernels

    mc_integrator_kernel.forall(nsamps)(
        out, rng_states, lower_lim, upper_lim
    )
    # normalization factor to convert
    # to the average: (b - a)/(N - 1)
    factor = (upper_lim - lower_lim) / (nsamps - 1)

    return sum_reduce(out) * factor
```

We can now use `mc_integrate` to compute the definite integral of this function between two limits:

Listing 30: from `test_ex_montecarlo` in `numba/cuda/tests/doc_examples/test_montecarlo.py`

```
# define a function to integrate
@numba.jit
def func(x):
    return 1.0 / x
```

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```

mc_integrate(1, 2, nsamps)  # array(0.6929643, dtype=float32)
mc_integrate(2, 3, nsamps)  # array(0.4054021, dtype=float32)
```

3.13.7 Matrix multiplication

First, import the modules needed for this example:

Listing 31: from test_ex_matmul in numba/cuda/tests/doc_examples/test_matmul.py

```
from numba import cuda, float32
import numpy as np
import math
```

Here is a naïve implementation of matrix multiplication using a CUDA kernel:

Listing 32: from test_ex_matmul in numba/cuda/tests/doc_examples/test_matmul.py

```
@cuda.jit
def matmul(A, B, C):
    """Perform square matrix multiplication of C = A * B."""
    i, j = cuda.grid(2)
    if i < C.shape[0] and j < C.shape[1]:
        tmp = 0.
        for k in range(A.shape[1]):
            tmp += A[i, k] * B[k, j]
        C[i, j] = tmp
```

An example usage of this function is as follows:

Listing 33: from test_ex_matmul in numba/cuda/tests/doc_examples/test_matmul.py

```
x_h = np.arange(16).reshape([4, 4])
y_h = np.ones([4, 4])
z_h = np.zeros([4, 4])

x_d = cuda.to_device(x_h)
y_d = cuda.to_device(y_h)
z_d = cuda.to_device(z_h)

threadsperblock = (16, 16)
blockspergrid_x = math.ceil(z_h.shape[0] / threadsperblock[0])
blockspergrid_y = math.ceil(z_h.shape[1] / threadsperblock[1])
blockspergrid = (blockspergrid_x, blockspergrid_y)

matmul[blockspergrid, threadsperblock](x_d, y_d, z_d)
z_h = z_d.copy_to_host()
print(z_h)
print(x_h @ y_h)
```

This implementation is straightforward and intuitive but performs poorly, because the same matrix elements will be loaded multiple times from device memory, which is slow (some devices may have transparent data caches, but they may not be large enough to hold the entire inputs at once).

It will be faster if we use a blocked algorithm to reduce accesses to the device memory. CUDA provides a fast *shared memory* for threads in a block to cooperatively compute on a task. The following implements a faster version of the square matrix multiplication using shared memory:

Listing 34: from `test_ex_matmul` in `numba/cuda/tests/doc_examples/test_matmul.py`

```
# Controls threads per block and shared memory usage.
# The computation will be done on blocks of TPBxTPB elements.
# TPB should not be larger than 32 in this example
TPB = 16

@cuda.jit
def fast_matmul(A, B, C):
    """
    Perform matrix multiplication of C = A * B using CUDA shared memory.

    Reference: https://stackoverflow.com/a/64198479/13697228 by @RobertCrovella
    """
    # Define an array in the shared memory
    # The size and type of the arrays must be known at compile time
    sA = cuda.shared.array(shape=(TPB, TPB), dtype=float32)
    sB = cuda.shared.array(shape=(TPB, TPB), dtype=float32)

    x, y = cuda.grid(2)

    tx = cuda.threadIdx.x
    ty = cuda.threadIdx.y
    bpg = cuda.gridDim.x    # blocks per grid

    # Each thread computes one element in the result matrix.
    # The dot product is chunked into dot products of TPB-long vectors.
    tmp = float32(0.)
    for i in range(bpg):
        # Preload data into shared memory
        sA[ty, tx] = 0
        sB[ty, tx] = 0
        if y < A.shape[0] and (tx + i * TPB) < A.shape[1]:
            sA[ty, tx] = A[y, tx + i * TPB]
        if x < B.shape[1] and (ty + i * TPB) < B.shape[0]:
            sB[ty, tx] = B[ty + i * TPB, x]

        # Wait until all threads finish preloading
        cuda.syncthreads()

        # Computes partial product on the shared memory
        for j in range(TPB):
            tmp += sA[ty, j] * sB[j, tx]

        # Wait until all threads finish computing
```

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```
        cuda.syncthreads()
    if y < C.shape[0] and x < C.shape[1]:
        C[y, x] = tmp
```

Because the shared memory is a limited resource, the code preloads a small block at a time from the input arrays. Then, it calls *syncthreads()* to wait until all threads have finished preloading and before doing the computation on the shared memory. It synchronizes again after the computation to ensure all threads have finished with the data in shared memory before overwriting it in the next loop iteration.

An example usage of the `fast_matmul` function is as follows:

Listing 35: from `test_ex_matmul` in `numba/cuda/tests/doc_examples/test_matmul.py`

```
x_h = np.arange(16).reshape([4, 4])
y_h = np.ones([4, 4])
z_h = np.zeros([4, 4])

x_d = cuda.to_device(x_h)
y_d = cuda.to_device(y_h)
z_d = cuda.to_device(z_h)

threadsperblock = (TPB, TPB)
blockspergrid_x = math.ceil(z_h.shape[0] / threadsperblock[0])
blockspergrid_y = math.ceil(z_h.shape[1] / threadsperblock[1])
blockspergrid = (blockspergrid_x, blockspergrid_y)

fast_matmul[blockspergrid, threadsperblock](x_d, y_d, z_d)
z_h = z_d.copy_to_host()
print(z_h)
print(x_h @ y_h)
```

This passes a *CUDA memory check test*, which can help with debugging. Running the code above produces the following output:

```
$ python fast_matmul.py
[[ 6.  6.  6.  6.]
[22. 22. 22. 22.]
[38. 38. 38. 38.]
[54. 54. 54. 54.]]
[[ 6.  6.  6.  6.]
[22. 22. 22. 22.]
[38. 38. 38. 38.]
[54. 54. 54. 54.]]
```

Note: For high performance matrix multiplication in CUDA, see also the CuPy implementation.

The approach outlined here generalizes to non-square matrix multiplication as follows by adjusting the `blockspergrid` variable:

Again, here is an example usage:

Listing 36: from test_ex_matmul in numba/cuda/tests/doc_examples/test_matmul.py

```
x_h = np.arange(115).reshape([5, 23])
y_h = np.ones([23, 7])
z_h = np.zeros([5, 7])

x_d = cuda.to_device(x_h)
y_d = cuda.to_device(y_h)
z_d = cuda.to_device(z_h)

threadsperblock = (TPB, TPB)
grid_y_max = max(x_h.shape[0], y_h.shape[0])
grid_x_max = max(x_h.shape[1], y_h.shape[1])
blockspergrid_x = math.ceil(grid_x_max / threadsperblock[0])
blockspergrid_y = math.ceil(grid_y_max / threadsperblock[1])
blockspergrid = (blockspergrid_x, blockspergrid_y)

fast_matmul[blockspergrid, threadsperblock](x_d, y_d, z_d)
z_h = z_d.copy_to_host()
print(z_h)
print(x_h @ y_h)
```

and the corresponding output:

```
$ python nonsquare_matmul.py
[[ 253.  253.  253.  253.  253.  253.  253.]
 [ 782.  782.  782.  782.  782.  782.  782.]
 [1311. 1311. 1311. 1311. 1311. 1311. 1311.]
 [1840. 1840. 1840. 1840. 1840. 1840. 1840.]
 [2369. 2369. 2369. 2369. 2369. 2369. 2369.]]
[[ 253.  253.  253.  253.  253.  253.  253.]
 [ 782.  782.  782.  782.  782.  782.  782.]
 [1311. 1311. 1311. 1311. 1311. 1311. 1311.]
 [1840. 1840. 1840. 1840. 1840. 1840. 1840.]
 [2369. 2369. 2369. 2369. 2369. 2369. 2369.]]
```

3.13.8 Calling a NumPy UFunc

UFuncs supported in the CUDA target (see *NumPy support*) can be called inside kernels, but the output array must be passed in as a positional argument. The following example demonstrates a call to `np.sin()` inside a kernel following this pattern:

Listing 37: from test_ex_cuda_ufunc_call in numba/cuda/tests/doc_examples/test_ufunc.py

```
import numpy as np
from numba import cuda

# A kernel calling a ufunc (sin, in this case)
@cuda.jit
def f(r, x):
```

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```
    # Compute sin(x) with result written to r
    np.sin(x, r)

# Declare input and output arrays
x = np.arange(10, dtype=np.float32) - 5
r = np.zeros_like(x)

# Launch kernel that calls the ufunc
f[1, 1](r, x)

# A quick sanity check demonstrating equality of the sine computed by
# the sin ufunc inside the kernel, and NumPy's sin ufunc
np.testing.assert_allclose(r, np.sin(x))
```

3.14 Debugging CUDA Python with the the CUDA Simulator

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

Numba includes a CUDA Simulator that implements most of the semantics in CUDA Python using the Python interpreter and some additional Python code. This can be used to debug CUDA Python code, either by adding print statements to your code, or by using the debugger to step through the execution of an individual thread.

The simulator deliberately allows running non-CUDA code like starting a debugger and printing arbitrary expressions for debugging purposes. Therefore, it is best to start from code that compiles for the CUDA target, and then move over to the simulator to investigate issues.

Execution of kernels is performed by the simulator one block at a time. One thread is spawned for each thread in the block, and scheduling of the execution of these threads is left up to the operating system.

3.14.1 Using the simulator

The simulator is enabled by setting the environment variable *NUMBA_ENABLE_CUDASIM* to 1 prior to importing Numba. CUDA Python code may then be executed as normal. The easiest way to use the debugger inside a kernel is to only stop a single thread, otherwise the interaction with the debugger is difficult to handle. For example, the kernel below will stop in the thread `<<<(3,0,0), (1, 0, 0)>>>`:

```
@cuda.jit
def vec_add(A, B, out):
    x = cuda.threadIdx.x
    bx = cuda.blockIdx.x
    bdx = cuda.blockDim.x
    if x == 1 and bx == 3:
        from pdb import set_trace; set_trace()
    i = bx * bdx + x
    out[i] = A[i] + B[i]
```

when invoked with a one-dimensional grid and one-dimensional blocks.

3.14.2 Supported features

The simulator aims to provide as complete a simulation of execution on a real GPU as possible - in particular, the following are supported:

- Atomic operations
- Constant memory
- Local memory
- Shared memory: declarations of shared memory arrays must be on separate source lines, since the simulator uses source line information to keep track of allocations of shared memory across threads.
- Mapped arrays.
- Host and device memory operations: copying and setting memory.
- *syncthreads()* is supported - however, in the case where divergent threads enter different *syncthreads()* calls, the launch will not fail, but unexpected behaviour will occur. A future version of the simulator may detect this condition.
- The stream API is supported, but all operations occur sequentially and synchronously, unlike on a real device. Synchronising on a stream is therefore a no-op.
- The event API is also supported, but provides no meaningful timing information.
- Data transfer to and from the GPU - in particular, creating array objects with *device_array()* and *device_array_like()*. The APIs for pinned memory *pinned()* and *pinned_array()* are also supported, but no pinning takes place.
- The driver API implementation of the list of GPU contexts (`cuda.gpus` and `cuda.cudadrv.devices.gpus`) is supported, and reports a single GPU context. This context can be closed and reset as the real one would.
- The *detect()* function is supported, and reports one device called *SIMULATOR*.
- Cooperative grids: A cooperative kernel can be launched, but with only one block - the simulator always returns 1 from a kernel overload's *max_cooperative_grid_blocks()* method.

Some limitations of the simulator include:

- It does not perform type checking/type inference. If any argument types to a jitted function are incorrect, or if the specification of the type of any local variables are incorrect, this will not be detected by the simulator.
- Only one GPU is simulated.
- Multithreaded accesses to a single GPU are not supported, and will result in unexpected behaviour.
- Most of the driver API is unimplemented.
- It is not possible to link PTX code with CUDA Python functions.
- Warps and warp-level operations are not yet implemented.
- Because the simulator executes kernels using the Python interpreter, structured array access by attribute that works with the hardware target may fail in the simulator - see *Structured array access*.
- Operations directly against device arrays are only partially supported, that is, testing equality, less than, greater than, and basic mathematical operations are supported, but many other operations, such as the in-place operators and bit operators are not.
- The *ffs()* function only works correctly for values that can be represented using 32-bit integers.

Obviously, the speed of the simulator is also much lower than that of a real device. It may be necessary to reduce the size of input data and the size of the CUDA grid in order to make debugging with the simulator tractable.

3.15 GPU Reduction

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

Writing a reduction algorithm for CUDA GPU can be tricky. Numba provides a `@reduce` decorator for converting a simple binary operation into a reduction kernel. An example follows:

```
import numpy
from numba import cuda

@cuda.reduce
def sum_reduce(a, b):
    return a + b

A = (numpy.arange(1234, dtype=numpy.float64)) + 1
expect = A.sum()      # NumPy sum reduction
got = sum_reduce(A)   # cuda sum reduction
assert expect == got
```

Lambda functions can also be used here:

```
sum_reduce = cuda.reduce(lambda a, b: a + b)
```

3.15.1 The Reduce class

The `reduce` decorator creates an instance of the `Reduce` class. Currently, `reduce` is an alias to `Reduce`, but this behavior is not guaranteed.

class numba.cuda.**Reduce**(*functor*)

Create a reduction object that reduces values using a given binary function. The binary function is compiled once and cached inside this object. Keeping this object alive will prevent re-compilation.

__init__(*functor*)

Parameters

functor – A function implementing a binary operation for reduction. It will be compiled as a CUDA device function using `cuda.jit(device=True)`.

__call__(*arr*, *size=None*, *res=None*, *init=0*, *stream=0*)

Performs a full reduction.

Parameters

- **arr** – A host or device array.
- **size** – Optional integer specifying the number of elements in `arr` to reduce. If this parameter is not specified, the entire array is reduced.
- **res** – Optional device array into which to write the reduction result to. The result is written into the first element of this array. If this parameter is specified, then no communication of the reduction output takes place from the device to the host.

- **init** – Optional initial value for the reduction, the type of which must match `arr.dtype`.
- **stream** – Optional CUDA stream in which to perform the reduction. If no stream is specified, the default stream of 0 is used.

Returns

If `res` is specified, `None` is returned. Otherwise, the result of the reduction is returned.

3.16 CUDA Ufuncs and Generalized Ufuncs

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

This page describes the CUDA ufunc-like object.

To support the programming pattern of CUDA programs, CUDA Vectorize and GUVectorize cannot produce a conventional ufunc. Instead, a ufunc-like object is returned. This object is a close analog but not fully compatible with a regular NumPy ufunc. The CUDA ufunc adds support for passing intra-device arrays (already on the GPU device) to reduce traffic over the PCI-express bus. It also accepts a *stream* keyword for launching in asynchronous mode.

3.16.1 Example: Basic Example

```
import math
from numba import vectorize, cuda
import numpy as np

@vectorize(['float32(float32, float32, float32)',
            'float64(float64, float64, float64)'],
           target='cuda')
def cu_discriminant(a, b, c):
    return math.sqrt(b ** 2 - 4 * a * c)

N = 10000
dtype = np.float32

# prepare the input
A = np.array(np.random.sample(N), dtype=dtype)
B = np.array(np.random.sample(N) + 10, dtype=dtype)
C = np.array(np.random.sample(N), dtype=dtype)

D = cu_discriminant(A, B, C)

print(D)  # print result
```

3.16.2 Example: Calling Device Functions

All CUDA ufunc kernels have the ability to call other CUDA device functions:

```
from numba import vectorize, cuda

# define a device function
@cuda.jit('float32(float32, float32, float32)', device=True, inline=True)
def cu_device_fn(x, y, z):
    return x ** y / z

# define a ufunc that calls our device function
@vectorize(['float32(float32, float32, float32)'], target='cuda')
def cu_ufunc(x, y, z):
    return cu_device_fn(x, y, z)
```

3.16.3 Generalized CUDA ufuncs

Generalized ufuncs may be executed on the GPU using CUDA, analogous to the CUDA ufunc functionality. This may be accomplished as follows:

```
from numba import guvectorize

@guvectorize(['void(float32[:,:], float32[:,:], float32[:,:])'],
             '(m,n),(n,p)->(m,p)', target='cuda')
def matmulcore(A, B, C):
    ...
```

3.17 Sharing CUDA Memory

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

3.17.1 Sharing between process

Sharing between processes is implemented using the Legacy CUDA IPC API (functions whose names begin with `cuIpc`), and is supported only on Linux.

Export device array to another process

A device array can be shared with another process in the same machine using the CUDA IPC API. To do so, use the `.get_ipc_handle()` method on the device array to get a `IpcArrayHandle` object, which can be transferred to another process.

`DeviceNDArray.`**`get_ipc_handle`**`()`

Returns a *IpcArrayHandle* object that is safe to serialize and transfer to another process to share the local allocation.

Note: this feature is only available on Linux.

`class` `numba.cuda.cudadrv.devicearray.`**`IpcArrayHandle`**`(`*ipc_handle*, *array_desc*`)`

An IPC array handle that can be serialized and transfer to another process in the same machine for share a GPU allocation.

On the destination process, use the *.open()* method to creates a new *DeviceNDArray* object that shares the allocation from the original process. To release the resources, call the *.close()* method. After that, the destination can no longer use the shared array object. (Note: the underlying weakref to the resource is now dead.)

This object implements the context-manager interface that calls the *.open()* and *.close()* method automatically:

```
with the_ipc_array_handle as ipc_array:
    # use ipc_array here as a normal gpu array object
    some_code(ipc_array)
# ipc_array is dead at this point
```

`close``()`

Closes the IPC handle to the array.

`open``()`

Returns a new *DeviceNDArray* that shares the allocation from the original process. Must not be used on the original process.

Import IPC memory from another process

The following function is used to open IPC handle from another process as a device array.

`cuda.`**`open_ipc_array`**`(`*shape*, *dtype*, *strides=None*, *offset=0*`)`

A context manager that opens a IPC *handle* (*CUipcMemHandle*) that is represented as a sequence of bytes (e.g. *bytes*, tuple of int) and represent it as an array of the given *shape*, *strides* and *dtype*. The *strides* can be omitted. In that case, it is assumed to be a 1D C contiguous array.

Yields a device array.

The IPC handle is closed automatically when context manager exits.

3.18 CUDA Array Interface (Version 3)

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

The *CUDA Array Interface* (or CAI) is created for interoperability between different implementations of CUDA array-like objects in various projects. The idea is borrowed from the NumPy array interface.

Note: Currently, we only define the Python-side interface. In the future, we may add a C-side interface for efficient exchange of the information in compiled code.

3.18.1 Python Interface Specification

Note: Experimental feature. Specification may change.

The `__cuda_array_interface__` attribute returns a dictionary (`dict`) that must contain the following entries:

- **shape**: `(integer, ...)`

  A tuple of `int` (or `long`) representing the size of each dimension.

- **typestr**: `str`

  The type string. This has the same definition as `typestr` in the NumPy array interface.

- **data**: `(integer, boolean)`

  The **data** is a 2-tuple. The first element is the data pointer as a Python `int` (or `long`). The data must be device-accessible. For zero-size arrays, use `0` here. The second element is the read-only flag as a Python `bool`.

  Because the user of the interface may or may not be in the same context, the most common case is to use `cuPointerGetAttribute` with `CU_POINTER_ATTRIBUTE_DEVICE_POINTER` in the CUDA driver API (or the equivalent CUDA Runtime API) to retrieve a device pointer that is usable in the currently active context.

- **version**: `integer`

  An integer for the version of the interface being exported. The current version is *3*.

The following are optional entries:

- **strides**: `None` or `(integer, ...)`

  If **strides** is not given, or it is `None`, the array is in C-contiguous layout. Otherwise, a tuple of `int` (or `long`) is explicitly given for representing the number of bytes to skip to access the next element at each dimension.

- **descr**

  This is for describing more complicated types. This follows the same specification as in the NumPy array interface.

- **mask**: `None` or object exposing the `__cuda_array_interface__`

  If `None` then all values in **data** are valid. All elements of the mask array should be interpreted only as true or not true indicating which elements of this array are valid. This has the same definition as `mask` in the NumPy array interface.

Note: Numba does not currently support working with masked CUDA arrays and will raise a `NotImplementedError` exception if one is passed to a GPU function.

- **stream**: `None` or `integer`

  An optional stream upon which synchronization must take place at the point of consumption, either by synchronizing on the stream or enqueuing operations on the data on the given stream. Integer values in this entry are as follows:

  - `0`: This is disallowed as it would be ambiguous between `None` and the default stream, and also between the legacy and per-thread default streams. Any use case where `0` might be given should either use `None`, `1`, or `2` instead for clarity.
  - `1`: The legacy default stream.
  - `2`: The per-thread default stream.
  - Any other integer: a `cudaStream_t` represented as a Python integer.

  When `None`, no synchronization is required. See the *Synchronization* section below for further details.

  In a future revision of the interface, this entry may be expanded (or another entry added) so that an event to synchronize on can be specified instead of a stream.

Synchronization

Definitions

When discussing synchronization, the following definitions are used:

- *Producer*: The library / object on which `__cuda_array_interface__` is accessed.
- *Consumer*: The library / function that accesses the `__cuda_array_interface__` of the Producer.
- *User Code*: Code that induces a Producer and Consumer to share data through the CAI.
- *User*: The person writing or maintaining the User Code. The User may implement User Code without knowledge of the CAI, since the CAI accesses can be hidden from their view.

In the following example:

```
import cupy
from numba import cuda

@cuda.jit
def add(x, y, out):
    start = cuda.grid(1)
    stride = cuda.gridsize(1)
    for i in range(start, x.shape[0], stride):
        out[i] = x[i] + y[i]

a = cupy.arange(10)
b = a * 2
out = cupy.zeros_like(a)

add[1, 32](a, b, out)
```

When the `add` kernel is launched:

- `a`, `b`, `out` are Producers.
- The `add` kernel is the Consumer.
- The User Code is specifically `add[1, 32](a, b, out)`.
- The author of the code is the User.

Design Motivations

Elements of the CAI design related to synchronization seek to fulfill these requirements:

1. Producers and Consumers that exchange data through the CAI must be able to do so without data races.
2. Requirement 1 should be met without requiring the user to be aware of any particulars of the CAI - in other words, exchanging data between Producers and Consumers that operate on data asynchronously should be correct by default.
    - An exception to this requirement is made for Producers and Consumers that explicitly document that the User is required to take additional steps to ensure correctness with respect to synchronization. In this case, Users are required to understand the details of the CUDA Array Interface, and the Producer/Consumer library documentation must specify the steps that Users are required to take.

      Use of this exception should be avoided where possible, as it is provided for libraries that cannot implement the synchronization semantics without the involvement of the User - for example, those interfacing with third-party libraries oblivious to the CUDA Array Interface.
3. Where the User is aware of the particulars of the CAI and implementation details of the Producer and Consumer, they should be able to, at their discretion, override some of the synchronization semantics of the interface to reduce the synchronization overhead. Overriding synchronization semantics implies that:
    - The CAI design, and the design and implementation of the Producer and Consumer do not specify or guarantee correctness with respect to data races.
    - Instead, the User is responsible for ensuring correctness with respect to data races.

Interface Requirements

The `stream` entry enables Producers and Consumers to avoid hazards when exchanging data. Expected behaviour of the Consumer is as follows:

- When `stream` is not present or is `None`:
    - No synchronization is required on the part of the Consumer.
    - The Consumer may enqueue operations on the underlying data immediately on any stream.
- When `stream` is an integer, its value indicates the stream on which the Producer may have in-progress operations on the data, and which the Consumer is expected to either:
    - Synchronize on before accessing the data, or
    - Enqueue operations in when accessing the data.

  The Consumer can choose which mechanism to use, with the following considerations:
    - If the Consumer synchronizes on the provided stream prior to accessing the data, then it must ensure that no computation can take place in the provided stream until its operations in its own choice of stream have taken place. This could be achieved by either:

        * Placing a wait on an event in the provided stream that occurs once all of the Consumer's operations on the data are completed, or
        * Avoiding returning control to the user code until after its operations on its own stream have completed.
    - If the consumer chooses to only enqueue operations on the data in the provided stream, then it may return control to the User code immediately after enqueueing its work, as the work will all be serialized on the exported array's stream. This is sufficient to ensure correctness even if the User code were to induce the Producer to subsequently start enqueueing more work on the same stream.
- If the User has set the Consumer to ignore CAI synchronization semantics, the Consumer may assume it can operate on the data immediately in any stream with no further synchronization, even if the `stream` member has an integer value.

When exporting an array through the CAI, Producers must ensure that:

- If there is work on the data enqueued in one or more streams, then synchronization on the provided `stream` is sufficient to ensure synchronization with all pending work.
    - If the Producer has no enqueued work, or work only enqueued on the stream identified by `stream`, then this condition is met.
    - If the Producer has enqueued work on the data on multiple streams, then it must enqueue events on those streams that follow the enqueued work, and then wait on those events in the provided `stream`. For example:
        1. Work is enqueued by the Producer on streams `7`, `9`, and `15`.
        2. Events are then enqueued on each of streams `7`, `9`, and `15`.
        3. Producer then tells stream `3` to wait on the events from Step 2, and the `stream` entry is set to `3`.
- If there is no work enqueued on the data, then the `stream` entry may be either `None`, or not provided.

Optionally, to facilitate the User relaxing conformance to synchronization semantics:

- Producers may provide a configuration option to always set `stream` to `None`.
- Consumers may provide a configuration option to ignore the value of `stream` and act as if it were `None` or not provided. This elides synchronization on the Producer-provided streams, and allows enqueuing work on streams other than that provided by the Producer.

These options should not be set by default in either a Producer or a Consumer. The CAI specification does not prescribe the exact mechanism by which these options are set, or related options that Producers or Consumers might provide to allow the user further control over synchronization behavior.

Synchronization in Numba

Numba is neither strictly a Producer nor a Consumer - it may be used to implement either by a User. In order to facilitate the correct implementation of synchronization semantics, Numba exhibits the following behaviors related to synchronization of the interface:

- When Numba acts as a Consumer (for example when an array-like object is passed to a kernel launch): If `stream` is an integer, then Numba will immediately synchronize on the provided `stream`. A Numba *Device Array* created from an array-like object has its *default stream* set to the provided stream.
- When Numba acts as a Producer (when the `__cuda_array_interface__` property of a Numba CUDA Array is accessed): If the exported CUDA Array has a *default stream*, then it is given as the `stream` entry. Otherwise, `stream` is set to `None`.

Note: In Numba's terminology, an array's *default stream* is a property specifying the stream that Numba will enqueue asynchronous transfers in if no other stream is provided as an argument to the function invoking the transfer. It is not the same as the Default Stream in normal CUDA terminology.

Numba's synchronization behavior results in the following intended consequences:

- Exchanging data either as a Producer or a Consumer will be correct without the need for any further action from the User, provided that the other side of the interaction also follows the CAI synchronization semantics.
- The User is expected to either:
  - Avoid launching kernels or other operations on streams that are not the default stream for their parameters, or
  - When launching operations on a stream that is not the default stream for a given parameter, they should then insert an event into the stream that they are operating in, and wait on that event in the default stream for the parameter. For an example of this, *see below*.

The User may override Numba's synchronization behavior by setting the environment variable `NUMBA_CUDA_ARRAY_INTERFACE_SYNC` or the config variable `CUDA_ARRAY_INTERFACE_SYNC` to `0` (see *GPU Support Environment Variables*). When set, Numba will not synchronize on the streams of imported arrays, and it is the responsibility of the user to ensure correctness with respect to stream synchronization. Synchronization when creating a Numba CUDA Array from an object exporting the CUDA Array Interface may also be elided by passing `sync=False` when creating the Numba CUDA Array with *`numba.cuda.as_cuda_array()`* or *`numba.cuda.from_cuda_array_interface()`*.

There is scope for Numba's synchronization implementation to be optimized in the future, by eliding synchronizations when a kernel or driver API operation (e.g. a memcopy or memset) is launched on the same stream as an imported array.

An example launching on an array's non-default stream

This example shows how to ensure that a Consumer can safely consume an array with a default stream when it is passed to a kernel launched in a different stream.

First we need to import Numba and a consumer library (a fictitious library named `other_cai_library` for this example):

```
from numba import cuda, int32, void
import other_cai_library
```

Now we'll define a kernel - this initializes the elements of the array, setting each entry to its index:

```
@cuda.jit(void, int32[::1])
def initialize_array(x):
    i = cuda.grid(1)
    if i < len(x):
        x[i] = i
```

Next we will create two streams:

```
array_stream = cuda.stream()
kernel_stream = cuda.stream()
```

Then create an array with one of the streams as its default stream:

```
N = 16384
x = cuda.device_array(N, stream=array_stream)
```

Now we launch the kernel in the other stream:

```
nthreads = 256
nblocks = N // nthreads

initialize_array[nthreads, nblocks, kernel_stream](x)
```

If we were to pass `x` to a Consumer now, there is a risk that it may operate on it in `array_stream` whilst the kernel is still running in `kernel_stream`. To prevent operations in `array_stream` starting before the kernel launch is finished, we create an event and wait on it:

```
# Create event
evt = cuda.event()
# Record the event after the kernel launch in kernel_stream
evt.record(kernel_stream)
# Wait for the event in array_stream
evt.wait(array_stream)
```

It is now safe for `other_cai_library` to consume `x`:

```
other_cai_library.consume(x)
```

Lifetime management

Data

Obtaining the value of the `__cuda_array_interface__` property of any object has no effect on the lifetime of the object from which it was created. In particular, note that the interface has no slot for the owner of the data.

The User code must preserve the lifetime of the object owning the data for as long as the Consumer might use it.

Streams

Like data, CUDA streams also have a finite lifetime. It is therefore required that a Producer exporting data on the interface with an associated stream ensures that the exported stream's lifetime is equal to or surpasses the lifetime of the object from which the interface was exported.

Lifetime management in Numba

Producing Arrays

Numba takes no steps to maintain the lifetime of an object from which the interface is exported - it is the user's responsibility to ensure that the underlying object is kept alive for the duration that the exported interface might be used.

The lifetime of any Numba-managed stream exported on the interface is guaranteed to equal or surpass the lifetime of the underlying object, because the underlying object holds a reference to the stream.

Note: Numba-managed streams are those created with `cuda.default_stream()`, `cuda.legacy_default_stream()`, or `cuda.per_thread_default_stream()`. Streams not managed by Numba are created from an external stream with `cuda.external_stream()`.

Consuming Arrays

Numba provides two mechanisms for creating device arrays from objects exporting the CUDA Array Interface. Which to use depends on whether the created device array should maintain the life of the object from which it is created:

- `as_cuda_array`: This creates a device array that holds a reference to the owning object. As long as a reference to the device array is held, its underlying data will also be kept alive, even if all other references to the original owning object have been dropped.
- `from_cuda_array_interface`: This creates a device array with no reference to the owning object by default. The owning object, or some other object to be considered the owner can be passed in the `owner` parameter.

The interfaces of these functions are:

cuda.**as_cuda_array**(*sync=True*)

Create a DeviceNDArray from any object that implements the *cuda array interface*.

A view of the underlying GPU buffer is created. No copying of the data is done. The resulting DeviceNDArray will acquire a reference from *obj*.

If `sync` is `True`, then the imported stream (if present) will be synchronized.

cuda.**from_cuda_array_interface**(*owner=None*, *sync=True*)

Create a DeviceNDArray from a cuda-array-interface description. The `owner` is the owner of the underlying memory. The resulting DeviceNDArray will acquire a reference from it.

If `sync` is `True`, then the imported stream (if present) will be synchronized.

Pointer Attributes

Additional information about the data pointer can be retrieved using `cuPointerGetAttribute` or `cudaPointerGetAttributes`. Such information include:

- the CUDA context that owns the pointer;
- is the pointer host-accessible?
- is the pointer a managed memory?

Differences with CUDA Array Interface (Version 0)

Version 0 of the CUDA Array Interface did not have the optional **mask** attribute to support masked arrays.

Differences with CUDA Array Interface (Version 1)

Versions 0 and 1 of the CUDA Array Interface neither clarified the **strides** attribute for C-contiguous arrays nor specified the treatment for zero-size arrays.

Differences with CUDA Array Interface (Version 2)

Prior versions of the CUDA Array Interface made no statement about synchronization.

Interoperability

The following Python libraries have adopted the CUDA Array Interface:

- Numba
- CuPy
- PyTorch
- PyArrow
- mpi4py
- ArrayViews
- JAX
- PyCUDA
- DALI: the NVIDIA Data Loading Library :
  - TensorGPU objects expose the CUDA Array Interface.
  - The External Source operator consumes objects exporting the CUDA Array Interface.
- The RAPIDS stack:
  - cuDF
  - cuML
  - cuSignal
  - RMM

If your project is not on this list, please feel free to report it on the Numba issue tracker.

3.19 External Memory Management (EMM) Plugin interface

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

The *CUDA Array Interface* enables sharing of data between different Python libraries that access CUDA devices. However, each library manages its own memory distinctly from the others. For example:

- By default, Numba allocates memory on CUDA devices by interacting with the CUDA driver API to call functions such as `cuMemAlloc` and `cuMemFree`, which is suitable for many use cases.

- The RAPIDS libraries (cuDF, cuML, etc.) use the RAPIDS Memory Manager (RMM) for allocating device memory.
- CuPy includes a memory pool implementation for both device and pinned memory.

When multiple CUDA-aware libraries are used together, it may be preferable for Numba to defer to another library for memory management. The EMM Plugin interface facilitates this, by enabling Numba to use another CUDA-aware library for all allocations and deallocations.

An EMM Plugin is used to facilitate the use of an external library for memory management. An EMM Plugin can be a part of an external library, or could be implemented as a separate library.

3.19.1 Overview of External Memory Management

When an EMM Plugin is in use (see *Setting the EMM Plugin*), Numba will make memory allocations and deallocations through the Plugin. It will never directly call functions such as `cuMemAlloc`, `cuMemFree`, etc.

EMM Plugins always take responsibility for the management of device memory. However, not all CUDA-aware libraries also support managing host memory, so a facility for Numba to continue the management of host memory whilst ceding control of device memory to the EMM is provided (see *The Host-Only CUDA Memory Manager*).

Effects on Deallocation Strategies

Numba's internal *Deallocation Behavior* is designed to increase efficiency by deferring deallocations until a significant quantity are pending. It also provides a mechanism for preventing deallocations entirely during critical sections, using the *`defer_cleanup()`* context manager.

When an EMM Plugin is in use, the deallocation strategy is implemented by the EMM, and Numba's internal deallocation mechanism is not used. The EMM Plugin could implement:

- A similar strategy to the Numba deallocation behaviour, or
- Something more appropriate to the plugin - for example, deallocated memory might immediately be returned to a memory pool.

The `defer_cleanup` context manager may behave differently with an EMM Plugin - an EMM Plugin should be accompanied by documentation of the behaviour of the `defer_cleanup` context manager when it is in use. For example, a pool allocator could always immediately return memory to a pool even when the context manager is in use, but could choose not to free empty pools until `defer_cleanup` is not in use.

Management of other objects

In addition to memory, Numba manages the allocation and deallocation of *events*, *streams*, and modules (a module is a compiled object, which is generated from `@cuda.jit`-ted functions). The management of events, streams, and modules is unchanged by the use of an EMM Plugin.

Asynchronous allocation and deallocation

The present EMM Plugin interface does not provide support for asynchronous allocation and deallocation. This may be added to a future version of the interface.

3.19.2 Implementing an EMM Plugin

An EMM Plugin is implemented by deriving from *BaseCUDAMemoryManager*. A summary of considerations for the implementation follows:

- Numba instantiates one instance of the EMM Plugin class per context. The context that owns an EMM Plugin object is accessible through `self.context`, if required.
- The EMM Plugin is transparent to any code that uses Numba - all its methods are invoked by Numba, and never need to be called by code that uses Numba.
- The allocation methods `memalloc`, `memhostalloc`, and `mempin`, should use the underlying library to allocate and/or pin device or host memory, and construct an instance of a *memory pointer* representing the memory to return back to Numba. These methods are always called when the current CUDA context is the context that owns the EMM Plugin instance.
- The `initialize` method is called by Numba prior to the first use of the EMM Plugin object for a context. This method should do anything required to prepare the underlying library for allocations in the current context. This method may be called multiple times, and must not invalidate previous state when it is called.
- The `reset` method is called when all allocations in the context are to be cleaned up. It may be called even prior to `initialize`, and an EMM Plugin implementation needs to guard against this.
- To support inter-GPU communication, the `get_ipc_handle` method should provide an *IpcHandle* for a given *MemoryPointer* instance. This method is part of the EMM interface (rather than being handled within Numba) because the base address of the allocation is only known by the underlying library. Closing an IPC handle is handled internally within Numba.
- It is optional to provide memory info from the `get_memory_info` method, which provides a count of the total and free memory on the device for the context. It is preferable to implement the method, but this may not be practical for all allocators. If memory info is not provided, this method should raise a `RuntimeError`.
- The `defer_cleanup` method should return a context manager that ensures that expensive cleanup operations are avoided whilst it is active. The nuances of this will vary between plugins, so the plugin documentation should include an explanation of how deferring cleanup affects deallocations, and performance in general.
- The `interface_version` property is used to ensure that the plugin version matches the interface provided by the version of Numba. At present, this should always be 1.

Full documentation for the base class follows:

class numba.cuda.**BaseCUDAMemoryManager**(**args*, ***kwargs*)

Abstract base class for External Memory Management (EMM) Plugins.

abstract memalloc(*size*)

Allocate on-device memory in the current context.

Parameters
size (*int*) – Size of allocation in bytes

Returns
A memory pointer instance that owns the allocated memory

Return type
MemoryPointer

abstract memhostalloc(*size*, *mapped*, *portable*, *wc*)

Allocate pinned host memory.

Parameters

- **size** (*int*) – Size of the allocation in bytes
- **mapped** (*bool*) – Whether the allocated memory should be mapped into the CUDA address space.
- **portable** (*bool*) – Whether the memory will be considered pinned by all contexts, and not just the calling context.
- **wc** (*bool*) – Whether to allocate the memory as write-combined.

Returns

A memory pointer instance that owns the allocated memory. The return type depends on whether the region was mapped into device memory.

Return type

MappedMemory or *PinnedMemory*

abstract mempin(*owner*, *pointer*, *size*, *mapped*)

Pin a region of host memory that is already allocated.

Parameters

- **owner** – The object that owns the memory.
- **pointer** (*int*) – The pointer to the beginning of the region to pin.
- **size** (*int*) – The size of the region in bytes.
- **mapped** (*bool*) – Whether the region should also be mapped into device memory.

Returns

A memory pointer instance that refers to the allocated memory.

Return type

MappedMemory or *PinnedMemory*

abstract initialize()

Perform any initialization required for the EMM plugin instance to be ready to use.

Returns

None

abstract get_ipc_handle(*memory*)

Return an IPC handle from a GPU allocation.

Parameters

memory (*MemoryPointer*) – Memory for which the IPC handle should be created.

Returns

IPC handle for the allocation

Return type

IpcHandle

abstract get_memory_info()

Returns `(free, total)` memory in bytes in the context. May raise `NotImplementedError`, if returning such information is not practical (e.g. for a pool allocator).

Returns
Memory info

Return type
MemoryInfo

abstract reset()

Clears up all memory allocated in this context.

Returns
None

abstract defer_cleanup()

Returns a context manager that ensures the implementation of deferred cleanup whilst it is active.

Returns
Context manager

abstract property interface_version

Returns an integer specifying the version of the EMM Plugin interface supported by the plugin implementation. Should always return 1 for implementations of this version of the specification.

The Host-Only CUDA Memory Manager

Some external memory managers will support management of on-device memory but not host memory. For implementing EMM Plugins using one of these memory managers, a partial implementation of a plugin that implements host-side allocation and pinning is provided. To use it, derive from *HostOnlyCUDAMemoryManager* instead of *BaseCUDAMemoryManager*. Guidelines for using this class are:

- The host-only memory manager implements `memhostalloc` and `mempin` - the EMM Plugin should still implement `memalloc`.
- If `reset` is overridden, it must also call `super().reset()` to allow the host allocations to be cleaned up.
- If `defer_cleanup` is overridden, it must hold an active context manager from `super().defer_cleanup()` to ensure that host-side cleanup is also deferred.

Documentation for the methods of *HostOnlyCUDAMemoryManager* follows:

class numba.cuda.**HostOnlyCUDAMemoryManager**(**args*, ***kwargs*)

Base class for External Memory Management (EMM) Plugins that only implement on-device allocation. A subclass need not implement the `memhostalloc` and `mempin` methods.

This class also implements `reset` and `defer_cleanup` (see *numba.cuda.BaseCUDAMemoryManager*) for its own internal state management. If an EMM Plugin based on this class also implements these methods, then its implementations of these must also call the method from `super()` to give `HostOnlyCUDAMemoryManager` an opportunity to do the necessary work for the host allocations it is managing.

This class does not implement `interface_version`, as it will always be consistent with the version of Numba in which it is implemented. An EMM Plugin subclassing this class should implement `interface_version` instead.

memhostalloc(*size*, *mapped=False*, *portable=False*, *wc=False*)

Implements the allocation of pinned host memory.

It is recommended that this method is not overridden by EMM Plugin implementations - instead, use the *BaseCUDAMemoryManager*.

mempin(*owner*, *pointer*, *size*, *mapped=False*)

Implements the pinning of host memory.

It is recommended that this method is not overridden by EMM Plugin implementations - instead, use the *BaseCUDAMemoryManager*.

reset()

Clears up all host memory (mapped and/or pinned) in the current context.

EMM Plugins that override this method must call `super().reset()` to ensure that host allocations are also cleaned up.

defer_cleanup()

Returns a context manager that disables cleanup of mapped or pinned host memory in the current context whilst it is active.

EMM Plugins that override this method must obtain the context manager from this method before yielding to ensure that cleanup of host allocations is also deferred.

The IPC Handle Mixin

An implementation of the `get_ipc_handle()` function is is provided in the `GetIpcHandleMixin` class. This uses the driver API to determine the base address of an allocation for opening an IPC handle. If this implementation is appropriate for an EMM plugin, it can be added by mixing in the `GetIpcHandleMixin` class:

class numba.cuda.**GetIpcHandleMixin**

A class that provides a default implementation of `get_ipc_handle()`.

get_ipc_handle(*memory*)

Open an IPC memory handle by using `cuMemGetAddressRange` to determine the base pointer of the allocation. An IPC handle of type `cu_ipc_mem_handle` is constructed and initialized with `cuIpcGetMemHandle`. A *numba.cuda.IpcHandle* is returned, populated with the underlying `ipc_mem_handle`.

3.19.3 Classes and structures of returned objects

This section provides an overview of the classes and structures that need to be constructed by an EMM Plugin.

Memory Pointers

EMM Plugins should construct memory pointer instances that represent their allocations, for return to Numba. The appropriate memory pointer class to use in each method is:

- *MemoryPointer*: returned from `memalloc`
- *MappedMemory*: returned from `memhostalloc` or `mempin` when the host memory is mapped into the device memory space.
- *PinnedMemory*: return from `memhostalloc` or `mempin` when the host memory is not mapped into the device memory space.

Memory pointers can take a finalizer, which is a function that is called when the buffer is no longer needed. Usually the finalizer will make a call to the memory management library (either internal to Numba, or external if allocated by an EMM Plugin) to inform it that the memory is no longer required, and that it could potentially be freed and/or unpinned. The memory manager may choose to defer actually cleaning up the memory to any later time after the finalizer runs - it is not required to free the buffer immediately.

Documentation for the memory pointer classes follows.

class numba.cuda.**MemoryPointer**(*context*, *pointer*, *size*, *owner=None*, *finalizer=None*)

A memory pointer that owns a buffer, with an optional finalizer. Memory pointers provide reference counting, and instances are initialized with a reference count of 1.

The base `MemoryPointer` class does not use the reference count for managing the buffer lifetime. Instead, the buffer lifetime is tied to the memory pointer instance's lifetime:

- When the instance is deleted, the finalizer will be called.
- When the reference count drops to 0, no action is taken.

Subclasses of `MemoryPointer` may modify these semantics, for example to tie the buffer lifetime to the reference count, so that the buffer is freed when there are no more references.

Parameters

- **context** (*Context*) – The context in which the pointer was allocated.
- **pointer** (*ctypes.c_void_p*) – The address of the buffer.
- **size** (*int*) – The size of the allocation in bytes.
- **owner** (*NoneType*) – The owner is sometimes set by the internals of this class, or used for Numba's internal memory management. It should not be provided by an external user of the `MemoryPointer` class (e.g. from within an EMM Plugin); the default of *None* should always suffice.
- **finalizer** (*function*) – A function that is called when the buffer is to be freed.

The `AutoFreePointer` class need not be used directly, but is documented here as it is subclassed by *numba.cuda.MappedMemory*:

class numba.cuda.cudadrv.driver.**AutoFreePointer**(**args*, ***kwargs*)

Modifies the ownership semantic of the MemoryPointer so that the instance lifetime is directly tied to the number of references.

When the reference count reaches zero, the finalizer is invoked.

Constructor arguments are the same as for *MemoryPointer*.

class numba.cuda.**MappedMemory**(*context*, *pointer*, *size*, *owner=None*, *finalizer=None*)

A memory pointer that refers to a buffer on the host that is mapped into device memory.

Parameters

- **context** (*Context*) – The context in which the pointer was mapped.
- **pointer** (*ctypes.c_void_p*) – The address of the buffer.
- **size** (*int*) – The size of the buffer in bytes.
- **owner** (*NoneType*) – The owner is sometimes set by the internals of this class, or used for Numba's internal memory management. It should not be provided by an external user of the `MappedMemory` class (e.g. from within an EMM Plugin); the default of *None* should always suffice.
- **finalizer** (*function*) – A function that is called when the buffer is to be freed.

class numba.cuda.**PinnedMemory**(*context*, *pointer*, *size*, *owner=None*, *finalizer=None*)

A pointer to a pinned buffer on the host.

Parameters

- **context** (Context) – The context in which the pointer was mapped.
- **owner** – The object owning the memory. For EMM plugin implementation, this ca
- **pointer** (*ctypes.c_void_p*) – The address of the buffer.
- **size** (*int*) – The size of the buffer in bytes.
- **owner** – An object owning the buffer that has been pinned. For EMM plugin implementation, the default of `None` suffices for memory allocated in `memhostalloc` - for `mempin`, it should be the owner passed in to the `mempin` method.
- **finalizer** (*function*) – A function that is called when the buffer is to be freed.

Memory Info

If an implementation of *get_memory_info()* is to provide a result, then it should return an instance of the `MemoryInfo` named tuple:

class numba.cuda.**MemoryInfo**(*free*, *total*)

Free and total memory for a device.

free

Free device memory in bytes.

total

Total device memory in bytes.

IPC

An instance of `IpcHandle` is required to be returned from an implementation of *get_ipc_handle()*:

class numba.cuda.**IpcHandle**(*base*, *handle*, *size*, *source_info=None*, *offset=0*)

CUDA IPC handle. Serialization of the CUDA IPC handle object is implemented here.

Parameters

- **base** (MemoryPointer) – A reference to the original allocation to keep it alive
- **handle** – The CUDA IPC handle, as a ctypes array of bytes.
- **size** (*int*) – Size of the original allocation
- **source_info** (*dict*) – The identity of the device on which the IPC handle was opened.
- **offset** (*int*) – The offset into the underlying allocation of the memory referred to by this IPC handle.

Guidance for constructing an IPC handle in the context of implementing an EMM Plugin:

- The `memory` parameter passed to the `get_ipc_handle` method of an EMM Plugin can be passed as the `base` parameter.
- A suitable type for the `handle` can be constructed as `ctypes.c_byte * 64`. The data for `handle` must be populated using a method for obtaining a CUDA IPC handle appropriate to the underlying library.
- `size` should match the size of the original allocation, which can be obtained with `memory.size` in `get_ipc_handle`.
- An appropriate value for `source_info` can be created by calling `self.context.device.get_device_identity()`.

- If the underlying memory does not point to the base of an allocation returned by the CUDA driver or runtime API (e.g. if a pool allocator is in use) then the `offset` from the base must be provided.

3.19.4 Setting the EMM Plugin

By default, Numba uses its internal memory management - if an EMM Plugin is to be used, it must be configured. There are two mechanisms for configuring the use of an EMM Plugin: an environment variable, and a function.

Environment variable

A module name can be provided in the environment variable, `NUMBA_CUDA_MEMORY_MANAGER`. If this environment variable is set, Numba will attempt to import the module, and and use its `_numba_memory_manager` global variable as the memory manager class. This is primarily useful for running the Numba test suite with an EMM Plugin, e.g.:

```
$ NUMBA_CUDA_MEMORY_MANAGER=rmm python -m numba.runtests numba.cuda.tests
```

Function

The *set_memory_manager()* function can be used to set the memory manager at runtime. This should be called prior to the initialization of any contexts, as EMM Plugin instances are instantiated along with contexts.

numba.cuda.**set_memory_manager**(*mm_plugin*)

Configure Numba to use an External Memory Management (EMM) Plugin. If the EMM Plugin version does not match one supported by this version of Numba, a RuntimeError will be raised.

Parameters
mm_plugin (BaseCUDAMemoryManager) – The class implementing the EMM Plugin.

Returns
None

Resetting the memory manager

It is recommended that the memory manager is set once prior to using any CUDA functionality, and left unchanged for the remainder of execution. It is possible to set the memory manager multiple times, noting the following:

- At the time of their creation, contexts are bound to an instance of a memory manager for their lifetime.
- Changing the memory manager will have no effect on existing contexts - only contexts created after the memory manager was updated will use instances of the new memory manager.
- *numba.cuda.close()* can be used to destroy contexts after setting the memory manager so that they get re-created with the new memory manager.
  - This will invalidate any arrays, streams, events, and modules owned by the context.
  - Attempting to use invalid arrays, streams, or events will likely fail with an exception being raised due to a `CUDA_ERROR_INVALID_CONTEXT` or `CUDA_ERROR_CONTEXT_IS_DESTROYED` return code from a Driver API function.
  - Attempting to use an invalid module will result in similar, or in some cases a segmentation fault / access violation.

Note: The invalidation of modules means that all functions compiled with `@cuda.jit` prior to context destruction will need to be redefined, as the code underlying them will also have been unloaded from the GPU.

3.20 CUDA Bindings

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

Numba supports two bindings to the CUDA Driver APIs: its own internal bindings based on ctypes, and the official NVIDIA CUDA Python bindings. Functionality is equivalent between the two bindings.

The internal bindings are used by default. If the NVIDIA bindings are installed, then they can be used by setting the environment variable `NUMBA_CUDA_USE_NVIDIA_BINDING` to `1` prior to the import of Numba. Once Numba has been imported, the selected binding cannot be changed.

3.20.1 Per-Thread Default Streams

Responsibility for handling Per-Thread Default Streams (PTDS) is delegated to the NVIDIA bindings when they are in use. To use PTDS with the NVIDIA bindings, set the environment variable `CUDA_PYTHON_CUDA_PER_THREAD_DEFAULT_STREAM` to `1` instead of Numba's environmnent variable *`NUMBA_CUDA_PER_THREAD_DEFAULT_STREAM`*.

See also:

The Default Stream section in the NVIDIA Bindings documentation.

3.20.2 Roadmap

In Numba 0.56, the NVIDIA Bindings will be used by default, if they are installed.

In future versions of Numba:

- The internal bindings will be deprecated.
- The internal bindings will be removed.

At present, no specific release is planned for the deprecation or removal of the internal bindings.

3.21 Calling foreign functions from Python kernels

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

Python kernels can call device functions written in other languages. CUDA C/C++, PTX, and binary objects (cubins, fat binaries, etc.) are directly supported; sources in other languages must be compiled to PTX first. The constituent parts of a Python kernel call to a foreign device function are:

- The device function implementation in a foreign language (e.g. CUDA C).
- A declaration of the device function in Python.
- A kernel that links with and calls the foreign function.

3.21.1 Device function ABI

Numba's ABI for calling device functions defines the following prototype in C/C++:

```
extern "C"
__device__ int
function(
  T* return_value,
  ...
);
```

Components of the prototype are as follows:

- `extern "C"` is used to prevent name-mangling so that it is easy to declare the function in Python. It can be removed, but then the mangled name must be used in the declaration of the function in Python.
- `__device__` is required to define the function as a device function.
- The return value is always of type `int`, and is used to signal whether a Python exception occurred. Since Python exceptions don't occur in foreign functions, this should always be set to 0 by the callee.
- The first argument is a pointer to the return value of type `T`, which is allocated in the local address space[1] and passed in by the caller. If the function returns a value, the pointee should be set by the callee to store the return value.
- Subsequent arguments should match the types and order of arguments passed to the function from the Python kernel.

Functions written in other languages must compile to PTX that conforms to this prototype specification.

A function that accepts two floats and returns a float would have the following prototype:

```
extern "C"
__device__ int
mul_f32_f32(
  float* return_value,
  float x,
  float y
);
```

[1] Care must be taken to ensure that any operations on the return value are applicable to data in the local address space. Some operations, such as atomics, cannot be performed on data in the local address space.

Notes

3.21.2 Declaration in Python

To declare a foreign device function in Python, use *declare_device()*:

numba.cuda.**declare_device**(*name*, *sig*)

Declare the signature of a foreign function. Returns a descriptor that can be used to call the function from a Python kernel.

Parameters

- **name** (*str*) – The name of the foreign function.
- **sig** – The Numba signature of the function.

The returned descriptor name need not match the name of the foreign function. For example, when:

```
mul = cuda.declare_device('mul_f32_f32', 'float32(float32, float32)')
```

is declared, calling `mul(a, b)` inside a kernel will translate into a call to `mul_f32_f32(a, b)` in the compiled code.

3.21.3 Passing pointers

Numba's calling convention requires multiple values to be passed for array arguments. These include the data pointer along with shape, stride, and other information. This is incompatible with the expectations of most C/C++ functions, which generally only expect a pointer to the data. To align the calling conventions between C device code and Python kernels it is necessary to declare array arguments using C pointer types.

For example, a function with the following prototype:

Listing 38: numba/cuda/tests/doc_examples/ffi/functions.cu

```
extern "C"
__device__ int
sum_reduce(
  float* return_value,
  float* array,
  int n
);
```

would be declared as follows:

Listing 39: from test_ex_from_buffer in numba/cuda/tests/doc_examples/test_ffi.py

```
signature = 'float32(CPointer(float32), int32)'
sum_reduce = cuda.declare_device('sum_reduce', signature)
```

To obtain a pointer to array data for passing to foreign functions, use the `from_buffer()` method of a `cffi.FFI` instance. For example, a kernel using the `sum_reduce` function could be defined as:

Listing 40: from `test_ex_from_buffer` in `numba/cuda/tests/doc_examples/test_ffi.py`

```
import cffi
ffi = cffi.FFI()

@cuda.jit(link=[functions_cu])
def reduction_caller(result, array):
    array_ptr = ffi.from_buffer(array)
    result[()] = sum_reduce(array_ptr, len(array))
```

where `result` and `array` are both arrays of `float32` data.

3.21.4 Linking and Calling functions

The `link` keyword argument of the *`@cuda.jit`* decorator accepts a list of file names specified by absolute path or a path relative to the current working directory. Files whose name ends in `.cu` will be compiled with the NVIDIA Runtime Compiler (NVRTC) and linked into the kernel as PTX; other files will be passed directly to the CUDA Linker.

For example, the following kernel calls the `mul()` function declared above with the implementation `mul_f32_f32()` in a file called `functions.cu`:

```
@cuda.jit(link=['functions.cu'])
def multiply_vectors(r, x, y):
    i = cuda.grid(1)

    if i < len(r):
        r[i] = mul(x[i], y[i])
```

3.21.5 C/C++ Support

Support for compiling and linking of CUDA C/C++ code is provided through the use of NVRTC subject to the following considerations:

- It is only available when using the NVIDIA Bindings. See *`NUMBA_CUDA_USE_NVIDIA_BINDING`*.
- A suitable version of the NVRTC library for the installed version of the NVIDIA CUDA Bindings must be available.
- The CUDA include path is assumed by default to be `/usr/local/cuda/include` on Linux and `$env:CUDA_PATH\include` on Windows. It can be modified using the environment variable *`NUMBA_CUDA_INCLUDE_PATH`*.
- The CUDA include directory will be made available to NVRTC on the include path; additional includes are not supported.

3.21.6 Complete Example

This example demonstrates calling a foreign function written in CUDA C to multiply pairs of numbers from two arrays.

The foreign function is written as follows:

Listing 41: numba/cuda/tests/doc_examples/ffi/functions.cu

```
// Foreign function example: multiplication of a pair of floats

extern "C" __device__ int
mul_f32_f32(
  float* return_value,
  float x,
  float y)
{
  // Compute result and store in caller-provided slot
  *return_value = x * y;

  // Signal that no Python exception occurred
  return 0;
}
```

The Python code and kernel are:

Listing 42: from test_ex_linking_cu in numba/cuda/tests/doc_examples/test_ffi.py

```
from numba import cuda
import numpy as np
import os

# Declaration of the foreign function
mul = cuda.declare_device('mul_f32_f32', 'float32(float32, float32)')

# Path to the source containing the foreign function
# (here assumed to be in a subdirectory called "ffi")
basedir = os.path.dirname(os.path.abspath(__file__))
functions_cu = os.path.join(basedir, 'ffi', 'functions.cu')

# Kernel that links in functions.cu and calls mul
@cuda.jit(link=[functions_cu])
def multiply_vectors(r, x, y):
    i = cuda.grid(1)

    if i < len(r):
        r[i] = mul(x[i], y[i])

# Generate random data
N = 32
np.random.seed(1)
x = np.random.rand(N).astype(np.float32)
y = np.random.rand(N).astype(np.float32)
r = np.zeros_like(x)
```

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```
27
28 # Run the kernel
29 multiply_vectors[1, 32](r, x, y)
30
31 # Sanity check - ensure the results match those expected
32 np.testing.assert_array_equal(r, x * y)
```

Note: The example above is minimal in order to illustrate a foreign function call - it would not be expected to be particularly performant due to the small grid and light workload of the foreign function.

3.22 Compiling Python functions for use with other languages

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

Numba can compile Python code to PTX or LTO-IR so that Python functions can be incorporated into CUDA code written in other languages (e.g. C/C++). It is commonly used to support User-Defined Functions written in Python within the context of a library or application.

The compilation API can be used without a GPU present, as it uses no driver functions and avoids initializing CUDA in the process. It is invoked through the following function:

numba.cuda.**compile**(*pyfunc*, *sig*, *debug=False*, *lineinfo=False*, *device=True*, *fastmath=False*, *cc=None*, *opt=True*, *abi='c'*, *abi_info=None*, *output='ptx'*)

Compile a Python function to PTX or LTO-IR for a given set of argument types.

Parameters

- **pyfunc** – The Python function to compile.
- **sig** – The signature representing the function's input and output types. If this is a tuple of argument types without a return type, the inferred return type is returned by this function. If a signature including a return type is passed, the compiled code will include a cast from the inferred return type to the specified return type, and this function will return the specified return type.
- **debug** (*bool*) – Whether to include debug info in the compiled code.
- **lineinfo** (*bool*) – Whether to include a line mapping from the compiled code to the source code. Usually this is used with optimized code (since debug mode would automatically include this), so we want debug info in the LLVM IR but only the line mapping in the final output.
- **device** (*bool*) – Whether to compile a device function.
- **fastmath** (*bool*) – Whether to enable fast math flags (ftz=1, prec_sqrt=0, prec_div=, and fma=1)
- **cc** (*tuple*) – Compute capability to compile for, as a tuple `(MAJOR, MINOR)`. Defaults to `(5, 0)`.

- **opt** (*bool*) – Enable optimizations. Defaults to `True`.
- **abi** (*str*) – The ABI for a compiled function - either `"numba"` or `"c"`. Note that the Numba ABI is not considered stable. The C ABI is only supported for device functions at present.
- **abi_info** (*dict*) – A dict of ABI-specific options. The `"c"` ABI supports one option, `"abi_name"`, for providing the wrapper function's name. The `"numba"` ABI has no options.
- **output** (*str*) – Type of output to generate, either `"ptx"` or `"ltoir"`.

Returns
(code, resty): The compiled code and inferred return type

Return type
tuple

If a device is available and compiled code for the compute capability of the current device is required (for example when building a JIT compilation workflow using Numba), the `compile_for_current_device` function can be used:

numba.cuda.**compile_for_current_device**(*pyfunc*, *sig*, *debug=False*, *lineinfo=False*, *device=True*, *fastmath=False*, *opt=True*, *abi='c'*, *abi_info=None*, *output='ptx'*)

Compile a Python function to PTX or LTO-IR for a given signature for the current device's compute capabilility. This calls *compile()* with an appropriate `cc` value for the current device.

Most users should use the two functions described above; for backwards compatibility with existing use cases, the following functions are also provided:

numba.cuda.**compile_ptx**(*pyfunc*, *sig*, *debug=False*, *lineinfo=False*, *device=False*, *fastmath=False*, *cc=None*, *opt=True*, *abi='numba'*, *abi_info=None*)

Compile a Python function to PTX for a given signature. See *compile()*. The defaults for this function are to compile a kernel with the Numba ABI, rather than *compile()*'s default of compiling a device function with the C ABI.

numba.cuda.**compile_ptx_for_current_device**(*pyfunc*, *sig*, *debug=False*, *lineinfo=False*, *device=False*, *fastmath=False*, *opt=True*, *abi='numba'*, *abi_info=None*)

Compile a Python function to PTX for a given signature for the current device's compute capabilility. See *compile_ptx()*.

3.22.1 Using the C ABI

Numba internally uses its own ABI - this is as described in *Device function ABI*, without the `extern "C"` modifier. Calling Numba ABI device functions requires three issues to be addressed:

- The name of the function will be mangled according to Numba's ABI rules - these are based on the Itanium C++ ABI rules, but are extended beyond its specifications.
- The Python return value is expected to be stored into a pointer value passed in the first argument.
- The return value of the compiled function will contain a status code, instead of the return value of the function. For use of Numba-compiled functions outside of Numba, this can generally be ignored.

A simple way to address all these issues is to compile device functions with the C ABI instead. This results in the following:

- The name of the device function in the compiled code can be controlled. By default it will match the name of the function in Python, so it is easy to determine. This is the function's `__name__`, rather than `__qualname__`, because `__qualname__` encodes additional scoping information that would make the function name hard to predict, and in a lot of cases, an illegal identifier in C.
- The returned value of the Python code is placed in the return value of the compiled function.

- Status codes are ignored / unreported, so they do not need to be handled.

If the name of the compiled function needs to be specified, it can be controlled by passing the name in the `abi_info` dict, under the key `'abi_name'`.

Compilation with the C ABI is the default when using the `compile()` and `compile_for_current_device()` functions. The `compile_ptx()` and `compile_ptx_for_current_device()` functions default to the Numba ABI in order to maintain compatibility with existing use cases.

3.22.2 C and Numba ABI examples

The following function:

```
def add(x, y):
    return x + y
```

compiled for the Numba ABI using, for example:

```
ptx, resty = cuda.compile_ptx(add, int32(int32, int32), device=True)
```

results in PTX where the function prototype is:

```
.visible .func  (.param .b32 func_retval0) _ZN8__main__
↪3addB2v1B94cw51cXTLSUwv1sCUt9Uw1VEw0NRRQPKzLTg4gaGKFsG2oMQGEYakJSQB1PQBk0Bynm21OiwU1a0UoLGhDpQE8oxrNQ
↪3dEii(
    .param .b64 _ZN8__main__
↪3addB2v1B94cw51cXTLSUwv1sCUt9Uw1VEw0NRRQPKzLTg4gaGKFsG2oMQGEYakJSQB1PQBk0Bynm21OiwU1a0UoLGhDpQE8oxrNQ
↪3dEii_param_0,
    .param .b32 _ZN8__main__
↪3addB2v1B94cw51cXTLSUwv1sCUt9Uw1VEw0NRRQPKzLTg4gaGKFsG2oMQGEYakJSQB1PQBk0Bynm21OiwU1a0UoLGhDpQE8oxrNQ
↪3dEii_param_1,
    .param .b32 _ZN8__main__
↪3addB2v1B94cw51cXTLSUwv1sCUt9Uw1VEw0NRRQPKzLTg4gaGKFsG2oMQGEYakJSQB1PQBk0Bynm21OiwU1a0UoLGhDpQE8oxrNQ
↪3dEii_param_2
 )
```

Note that there are three parameters, for the pointer to the return value, `x`, and `y`. The name is mangled in a way that is hard to predict outside of Numba internals.

Compiling for the C ABI with:

```
ptx, resty = cuda.compile_ptx(add, int32(int32, int32), device=True, abi="c")
```

instead results in the following PTX prototype:

```
.visible .func  (.param .b32 func_retval0) add(
    .param .b32 add_param_0,
    .param .b32 add_param_1
)
```

The function name matches the Python source function name, and there are exactly two parameters, for `x` and `y`. The result of the function is directly placed in the return value:

```
add.s32      %r3, %r2, %r1;
st.param.b32         [func_retval0+0], %r3;
```

To distinguish one variant of the compiled `add()` function from another, the following example specifies its ABI name in the `abi_info` dict:

```
ptx, resty = cuda.compile_ptx(add, float32(float32, float32), device=True,
                              abi="c", abi_info={"abi_name": "add_f32"})
```

Resulting in the PTX prototype:

```
.visible .func  (.param .b32 func_retval0) add_f32(
    .param .b32 add_f32_param_0,
    .param .b32 add_f32_param_1
)
```

which will not clash with definitions by other names (e.g. the variant for `int32` above).

3.23 On-disk Kernel Caching

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

When the `cache` keyword argument of the *`@cuda.jit`* decorator is `True`, a file-based cache is enabled. This shortens compilation times when the function was already compiled in a previous invocation.

The cache is maintained in the `__pycache__` subdirectory of the directory containing the source file; if the current user is not allowed to write to it, the cache implementation falls back to a platform-specific user-wide cache directory (such as `$HOME/.cache/numba` on Unix platforms).

3.23.1 Compute capability considerations

Separate cache files are maintained for each compute capability. When a cached kernel is loaded, the compute capability of the device the kernel is first launched on in the current run is used to determine which version to load. Therefore, on systems that have multiple GPUs with differing compute capabilities, the cached versions of kernels are only used for one compute capability, and recompilation will occur for other compute capabilities.

For example: if a system has two GPUs, one of compute capability 7.5 and one of 8.0, then:

- If a cached kernel is first launched on the CC 7.5 device, then the cached version for CC 7.5 is used. If it is subsequently launched on the CC 8.0 device, a recompilation will occur.
- If in a subsequent run the cached kernel is first launched on the CC 8.0 device, then the cached version for CC 8.0 is used. A subsequent launch on the CC 7.5 device will require a recompilation.

This limitation is not expected to present issues in most practical scenarios, as multi-GPU production systems tend to have identical GPUs within each node.

3.24 CUDA Minor Version Compatibility

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

CUDA Minor Version Compatibility (MVC) enables the use of a newer CUDA Toolkit version than the CUDA version supported by the driver, provided that the Toolkit and driver both have the same major version. For example, use of CUDA Toolkit 11.5 with CUDA driver 450 (CUDA version 11.0) is supported through MVC.

Numba supports MVC for CUDA 12 on Linux using the external `pynvjitlink` package.

Numba supports MVC for CUDA 11 on Linux using the external `cubinlinker` and `ptxcompiler` packages, subject to the following limitations:

- Linking of archives is unsupported.
- Cooperative Groups are unsupported, because they require an archive to be linked.

MVC is not supported on Windows.

3.24.1 Installation

CUDA 12

To use MVC support, the `pynvjitlink` package must be installed. To install using conda, use:

```
conda install -c rapidsai pynvjitlink
```

To install with pip, use the NVIDIA package index:

```
pip install --extra-index-url https://pypi.nvidia.com pynvjitlink-cu12
```

CUDA 11

To use MVC support, the `cubinlinker` and `ptxcompiler` compiler packages must be installed from the appropriate channels. To install using conda, use:

```
conda install -c rapidsai -c conda-forge cubinlinker ptxcompiler
```

To install with pip, use the NVIDIA package index:

```
pip install --extra-index-url https://pypi.nvidia.com ptxcompiler-cu11 cubinlinker-cu11
```

3.24.2 Enabling MVC Support

MVC support is enabled by setting the environment variable:

```
export NUMBA_CUDA_ENABLE_MINOR_VERSION_COMPATIBILITY=1
```

or by setting a configuration variable prior to using any CUDA functionality in Numba:

```
from numba import config
config.CUDA_ENABLE_MINOR_VERSION_COMPATIBILITY = True
```

3.24.3 References

Further information about Minor Version Compatibility may be found in:

- The CUDA Compatibility Guide.
- The README for pynvjitlink.
- The README for ptxcompiler.

3.25 CUDA Frequently Asked Questions

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

3.25.1 nvprof reports "No kernels were profiled"

When using the `nvprof` tool to profile Numba jitted code for the CUDA target, the output contains `No kernels were profiled` but there are clearly running kernels present, what is going on?

This is quite likely due to the profiling data not being flushed on program exit, see the NVIDIA CUDA documentation for details. To fix this simply add a call to `numba.cuda.profile_stop()` prior to the exit point in your program (or wherever you want to stop profiling). For more on CUDA profiling support in Numba, see *Profiling*.

CHAPTER

FOUR

CUDA PYTHON REFERENCE

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

4.1 CUDA Host API

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

4.1.1 Device Management

Device detection and enquiry

The following functions are available for querying the available hardware:

`numba.cuda.is_available()`

Returns a boolean to indicate the availability of a CUDA GPU.

This will initialize the driver if it hasn't been initialized.

`numba.cuda.detect()`

Detect supported CUDA hardware and print a summary of the detected hardware.

Returns a boolean indicating whether any supported devices were detected.

Context management

CUDA Python functions execute within a CUDA context. Each CUDA device in a system has an associated CUDA context, and Numba presently allows only one context per thread. For further details on CUDA Contexts, refer to the CUDA Driver API Documentation on Context Management and the CUDA C Programming Guide Context Documentation. CUDA Contexts are instances of the *Context* class:

class numba.cuda.cudadrv.driver.**Context**(*device*, *handle*)

This object wraps a CUDA Context resource.

Contexts should not be constructed directly by user code.

get_memory_info()

Returns (free, total) memory in bytes in the context.

pop()

Pops this context off the current CPU thread. Note that this context must be at the top of the context stack, otherwise an error will occur.

push()

Pushes this context on the current CPU Thread.

reset()

Clean up all owned resources in this context.

The following functions can be used to get or select the context:

numba.cuda.**current_context**(*devnum=None*)

Get the current device or use a device by device number, and return the CUDA context.

numba.cuda.**require_context**(*fn*)

A decorator that ensures a CUDA context is available when *fn* is executed.

Note: The function *fn* cannot switch CUDA-context.

The following functions affect the current context:

numba.cuda.**synchronize**()

Synchronize the current context.

numba.cuda.**close**()

Explicitly clears all contexts in the current thread, and destroys all contexts if the current thread is the main thread.

Device management

Numba maintains a list of supported CUDA-capable devices:

numba.cuda.**gpus**

An indexable list of supported CUDA devices. This list is indexed by integer device ID.

Alternatively, the current device can be obtained:

numba.cuda.gpus.**current**

The currently-selected device.

Getting a device through *numba.cuda.gpus* always provides an instance of *numba.cuda.cudadrv.devices._DeviceContextManager*, which acts as a context manager for the selected device:

class numba.cuda.cudadrv.devices.**_DeviceContextManager**(*device*)

Provides a context manager for executing in the context of the chosen device. The normal use of instances of this type is from `numba.cuda.gpus`. For example, to execute on device 2:

```
with numba.cuda.gpus[2]:
    d_a = numba.cuda.to_device(a)
```

to copy the array *a* onto device 2, referred to by *d_a*.

One may also select a context and device or get the current device using the following three functions:

numba.cuda.**select_device**(*device_id*)

Make the context associated with device *device_id* the current context.

Returns a Device instance.

Raises exception on error.

numba.cuda.**get_current_device**()

Get current device associated with the current thread

numba.cuda.**list_devices**()

Return a list of all detected devices

The *numba.cuda.cudadrv.driver.Device* class can be used to enquire about the functionality of the selected device:

class numba.cuda.cudadrv.driver.**Device**

The device associated with a particular context.

compute_capability

A tuple, *(major, minor)* indicating the supported compute capability.

id

The integer ID of the device.

name

The name of the device (e.g. "GeForce GTX 970").

uuid

The UUID of the device (e.g. "GPU-e6489c45-5b68-3b03-bab7-0e7c8e809643").

reset()

Delete the context for the device. This will destroy all memory allocations, events, and streams created within the context.

supports_float16

Return `True` if the device supports float16 operations, `False` otherwise.

4.1.2 Compilation

Numba provides an entry point for compiling a Python function without invoking any of the driver API. This can be useful for:

- Generating PTX that is to be inlined into other PTX code (e.g. from outside the Numba / Python ecosystem).
- Generating PTX or LTO-IR to link with objects from non-Python translation units.
- Generating code when there is no device present.
- Generating code prior to a fork without initializing CUDA.

Note: It is the user's responsibility to manage any ABI issues arising from the use of compilation to PTX / LTO-IR. Passing the `abi="c"` keyword argument can provide a solution to most issues that may arise - see *Using the C ABI*.

`numba.cuda.compile`(*pyfunc*, *sig*, *debug=False*, *lineinfo=False*, *device=True*, *fastmath=False*, *cc=None*, *opt=True*, *abi='c'*, *abi_info=None*, *output='ptx'*)

Compile a Python function to PTX or LTO-IR for a given set of argument types.

Parameters

- **pyfunc** – The Python function to compile.
- **sig** – The signature representing the function's input and output types. If this is a tuple of argument types without a return type, the inferred return type is returned by this function. If a signature including a return type is passed, the compiled code will include a cast from the inferred return type to the specified return type, and this function will return the specified return type.
- **debug** (*bool*) – Whether to include debug info in the compiled code.
- **lineinfo** (*bool*) – Whether to include a line mapping from the compiled code to the source code. Usually this is used with optimized code (since debug mode would automatically include this), so we want debug info in the LLVM IR but only the line mapping in the final output.
- **device** (*bool*) – Whether to compile a device function.
- **fastmath** (*bool*) – Whether to enable fast math flags (ftz=1, prec_sqrt=0, prec_div=, and fma=1)
- **cc** (*tuple*) – Compute capability to compile for, as a tuple `(MAJOR, MINOR)`. Defaults to `(5, 0)`.
- **opt** (*bool*) – Enable optimizations. Defaults to `True`.
- **abi** (*str*) – The ABI for a compiled function - either `"numba"` or `"c"`. Note that the Numba ABI is not considered stable. The C ABI is only supported for device functions at present.
- **abi_info** (*dict*) – A dict of ABI-specific options. The `"c"` ABI supports one option, `"abi_name"`, for providing the wrapper function's name. The `"numba"` ABI has no options.
- **output** (*str*) – Type of output to generate, either `"ptx"` or `"ltoir"`.

Returns

(code, resty): The compiled code and inferred return type

Return type

tuple

The environment variable `NUMBA_CUDA_DEFAULT_PTX_CC` can be set to control the default compute capability targeted by `compile` - see *GPU support*. If code for the compute capability of the current device is required, the `compile_for_current_device` function can be used:

numba.cuda.**compile_for_current_device**(*pyfunc*, *sig*, *debug=False*, *lineinfo=False*, *device=True*, *fastmath=False*, *opt=True*, *abi='c'*, *abi_info=None*, *output='ptx'*)

Compile a Python function to PTX or LTO-IR for a given signature for the current device's compute capabilility. This calls *compile()* with an appropriate `cc` value for the current device.

Numba also provides two functions that may be used in legacy code that specifically compile to PTX only:

numba.cuda.**compile_ptx**(*pyfunc*, *sig*, *debug=False*, *lineinfo=False*, *device=False*, *fastmath=False*, *cc=None*, *opt=True*, *abi='numba'*, *abi_info=None*)

Compile a Python function to PTX for a given signature. See *compile()*. The defaults for this function are to compile a kernel with the Numba ABI, rather than *compile()*'s default of compiling a device function with the C ABI.

numba.cuda.**compile_ptx_for_current_device**(*pyfunc*, *sig*, *debug=False*, *lineinfo=False*, *device=False*, *fastmath=False*, *opt=True*, *abi='numba'*, *abi_info=None*)

Compile a Python function to PTX for a given signature for the current device's compute capabilility. See *compile_ptx()*.

4.1.3 Measurement

Profiling

The NVidia Visual Profiler can be used directly on executing CUDA Python code - it is not a requirement to insert calls to these functions into user code. However, these functions can be used to allow profiling to be performed selectively on specific portions of the code. For further information on profiling, see the NVidia Profiler User's Guide.

numba.cuda.**profile_start**()

Enable profile collection in the current context.

numba.cuda.**profile_stop**()

Disable profile collection in the current context.

numba.cuda.**profiling**()

Context manager that enables profiling on entry and disables profiling on exit.

Events

Events can be used to monitor the progress of execution and to record the timestamps of specific points being reached. Event creation returns immediately, and the created event can be queried to determine if it has been reached. For further information, see the CUDA C Programming Guide Events section.

The following functions are used for creating and measuring the time between events:

numba.cuda.**event**(*timing=True*)

Create a CUDA event. Timing data is only recorded by the event if it is created with `timing=True`.

numba.cuda.**event_elapsed_time**(*evtstart*, *evtend*)

Compute the elapsed time between two events in milliseconds.

Events are instances of the *numba.cuda.cudadrv.driver.Event* class:

class numba.cuda.cudadrv.driver.**Event**(*context*, *handle*, *finalizer=None*)

query()

Returns True if all work before the most recent record has completed; otherwise, returns False.

record(*stream=0*)

Set the record point of the event to the current point in the given stream.

The event will be considered to have occurred when all work that was queued in the stream at the time of the call to `record()` has been completed.

synchronize()

Synchronize the host thread for the completion of the event.

wait(*stream=0*)

All future works submitted to stream will wait util the event completes.

4.1.4 Stream Management

Streams allow concurrency of execution on a single device within a given context. Queued work items in the same stream execute sequentially, but work items in different streams may execute concurrently. Most operations involving a CUDA device can be performed asynchronously using streams, including data transfers and kernel execution. For further details on streams, see the CUDA C Programming Guide Streams section.

Numba defaults to using the legacy default stream as the default stream. The per-thread default stream can be made the default stream by setting the environment variable `NUMBA_CUDA_PER_THREAD_DEFAULT_STREAM` to 1 (see the *CUDA Environment Variables section*). Regardless of this setting, the objects representing the legacy and per-thread default streams can be constructed using the functions below.

Streams are instances of *numba.cuda.cudadrv.driver.Stream*:

class numba.cuda.cudadrv.driver.**Stream**(*context*, *handle*, *finalizer*, *external=False*)

add_callback(*callback*, *arg=None*)

Add a callback to a compute stream. The user provided function is called from a driver thread once all preceding stream operations are complete.

Callback functions are called from a CUDA driver thread, not from the thread that invoked *add_callback*. No CUDA API functions may be called from within the callback function.

The duration of a callback function should be kept short, as the callback will block later work in the stream and may block other callbacks from being executed.

Note: The driver function underlying this method is marked for eventual deprecation and may be replaced in a future CUDA release.

Parameters

- **callback** – Callback function with arguments (stream, status, arg).
- **arg** – Optional user data to be passed to the callback function.

async_done() → Future

Return an awaitable that resolves once all preceding stream operations are complete. The result of the awaitable is the current stream.

auto_synchronize()

A context manager that waits for all commands in this stream to execute and commits any pending memory transfers upon exiting the context.

synchronize()

Wait for all commands in this stream to execute. This will commit any pending memory transfers.

To create a new stream:

numba.cuda.**stream**()

Create a CUDA stream that represents a command queue for the device.

To get the default stream:

numba.cuda.**default_stream**()

Get the default CUDA stream. CUDA semantics in general are that the default stream is either the legacy default stream or the per-thread default stream depending on which CUDA APIs are in use. In Numba, the APIs for the legacy default stream are always the ones in use, but an option to use APIs for the per-thread default stream may be provided in future.

To get the default stream with an explicit choice of whether it is the legacy or per-thread default stream:

numba.cuda.**legacy_default_stream**()

Get the legacy default CUDA stream.

numba.cuda.**per_thread_default_stream**()

Get the per-thread default CUDA stream.

To construct a Numba `Stream` object using a stream allocated elsewhere, the `external_stream` function is provided. Note that the lifetime of external streams must be managed by the user - Numba will not deallocate an external stream, and the stream must remain valid whilst the Numba `Stream` object is in use.

numba.cuda.**external_stream**(*ptr*)

Create a Numba stream object for a stream allocated outside Numba.

Parameters

ptr (*int*) – Pointer to the external stream to wrap in a Numba Stream

4.1.5 Runtime

Numba generally uses the Driver API, but it provides a simple wrapper to the Runtime API so that the version of the runtime in use can be queried. This is accessed through `cuda.runtime`, which is an instance of the *numba.cuda.cudadrv.runtime.Runtime* class:

class numba.cuda.cudadrv.runtime.**Runtime**

Runtime object that lazily binds runtime API functions.

get_version()

Returns the CUDA Runtime version as a tuple (major, minor).

is_supported_version()

Returns True if the CUDA Runtime is a supported version.

property supported_versions

A tuple of all supported CUDA toolkit versions. Versions are given in the form `(major_version, minor_version)`.

Whether the current runtime is officially supported and tested with the current version of Numba can also be queried:

numba.cuda.**is_supported_version**()

Returns True if the CUDA Runtime is a supported version.

Unsupported versions (e.g. newer versions than those known to Numba) may still work; this function provides a facility to check whether the current Numba version is tested and known to work with the current runtime version. If the current version is unsupported, the caller can decide how to act. Options include:

- Continuing silently,
- Emitting a warning,
- Generating an error or otherwise preventing the use of CUDA.

4.2 CUDA Kernel API

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

4.2.1 Kernel declaration

The `@cuda.jit` decorator is used to create a CUDA dispatcher object that can be configured and launched:

numba.cuda.**jit**(*func_or_sig=None*, *device=False*, *inline=False*, *link=None*, *debug=None*, *opt=True*, *lineinfo=False*, *cache=False*, ***kws*)

JIT compile a Python function for CUDA GPUs.

Parameters

- **func_or_sig** – A function to JIT compile, or *signatures* of a function to compile. If a function is supplied, then a *Dispatcher* is returned. Otherwise, `func_or_sig` may be a signature or a list of signatures, and a function is returned. The returned function accepts another function, which it will compile and then return a *Dispatcher*. See *JIT functions* for more information about passing signatures.

  Note: A kernel cannot have any return value.

- **device** (*bool*) – Indicates whether this is a device function.
- **link** (*list*) – A list of files containing PTX or CUDA C/C++ source to link with the function
- **debug** – If True, check for exceptions thrown when executing the kernel. Since this degrades performance, this should only be used for debugging purposes. If set to True, then `opt` should be set to False. Defaults to False. (The default value can be overridden by setting environment variable `NUMBA_CUDA_DEBUGINFO=1`.)
- **fastmath** – When True, enables fastmath optimizations as outlined in the *CUDA Fast Math documentation*.
- **max_registers** – Request that the kernel is limited to using at most this number of registers per thread. The limit may not be respected if the ABI requires a greater number of registers than that requested. Useful for increasing occupancy.

- **opt** (*bool*) – Whether to compile from LLVM IR to PTX with optimization enabled. When `True`, `-opt=3` is passed to NVVM. When `False`, `-opt=0` is passed to NVVM. Defaults to `True`.
- **lineinfo** (*bool*) – If True, generate a line mapping between source code and assembly code. This enables inspection of the source code in NVIDIA profiling tools and correlation with program counter sampling.
- **cache** (*bool*) – If True, enables the file-based cache for this function.

4.2.2 Dispatcher objects

The usual syntax for configuring a Dispatcher with a launch configuration uses subscripting, with the arguments being as in the following:

```
# func is some function decorated with @cuda.jit
func[griddim, blockdim, stream, sharedmem]
```

The `griddim` and `blockdim` arguments specify the size of the grid and thread blocks, and may be either integers or tuples of length up to 3. The `stream` parameter is an optional stream on which the kernel will be launched, and the `sharedmem` parameter specifies the size of dynamic shared memory in bytes.

Subscripting the Dispatcher returns a configuration object that can be called with the kernel arguments:

```
configured = func[griddim, blockdim, stream, sharedmem]
configured(x, y, z)
```

However, it is more idiomatic to configure and call the kernel within a single statement:

```
func[griddim, blockdim, stream, sharedmem](x, y, z)
```

This is similar to launch configuration in CUDA C/C++:

```
func<<<griddim, blockdim, sharedmem, stream>>>(x, y, z)
```

Note: The order of `stream` and `sharedmem` are reversed in Numba compared to in CUDA C/C++.

Dispatcher objects also provide several utility methods for inspection and creating a specialized instance:

class numba.cuda.dispatcher.**CUDADispatcher**(*py_func*, *targetoptions*, *pipeline_class=<class 'numba.cuda.compiler.CUDACompiler'>*)

CUDA Dispatcher object. When configured and called, the dispatcher will specialize itself for the given arguments (if no suitable specialized version already exists) & compute capability, and launch on the device associated with the current context.

Dispatcher objects are not to be constructed by the user, but instead are created using the *numba.cuda.jit()* decorator.

property extensions

A list of objects that must have a *prepare_args* function. When a specialized kernel is called, each argument will be passed through to the *prepare_args* (from the last object in this list to the first). The arguments to *prepare_args* are:

- *ty* the numba type of the argument
- *val* the argument value itself

- *stream* the CUDA stream used for the current call to the kernel
- *retr* a list of zero-arg functions that you may want to append post-call cleanup work to.

The *prepare_args* function must return a tuple *(ty, val)*, which will be passed in turn to the next right-most *extension*. After all the extensions have been called, the resulting *(ty, val)* will be passed into Numba's default argument marshalling logic.

`forall`(*ntasks*, *tpb=0*, *stream=0*, *sharedmem=0*)

Returns a 1D-configured dispatcher for a given number of tasks.

This assumes that:

- the kernel maps the Global Thread ID `cuda.grid(1)` to tasks on a 1-1 basis.
- the kernel checks that the Global Thread ID is upper-bounded by `ntasks`, and does nothing if it is not.

Parameters

- **`ntasks`** – The number of tasks.
- **`tpb`** – The size of a block. An appropriate value is chosen if this parameter is not supplied.
- **`stream`** – The stream on which the configured dispatcher will be launched.
- **`sharedmem`** – The number of bytes of dynamic shared memory required by the kernel.

Returns

A configured dispatcher, ready to launch on a set of arguments.

`get_const_mem_size`(*signature=None*)

Returns the size in bytes of constant memory used by this kernel for the device in the current context.

Parameters

`signature` – The signature of the compiled kernel to get constant memory usage for. This may be omitted for a specialized kernel.

Returns

The size in bytes of constant memory allocated by the compiled variant of the kernel for the given signature and current device.

`get_local_mem_per_thread`(*signature=None*)

Returns the size in bytes of local memory per thread for this kernel.

Parameters

`signature` – The signature of the compiled kernel to get local memory usage for. This may be omitted for a specialized kernel.

Returns

The amount of local memory allocated by the compiled variant of the kernel for the given signature and current device.

`get_max_threads_per_block`(*signature=None*)

Returns the maximum allowable number of threads per block for this kernel. Exceeding this threshold will result in the kernel failing to launch.

Parameters

`signature` – The signature of the compiled kernel to get the max threads per block for. This may be omitted for a specialized kernel.

Returns

The maximum allowable threads per block for the compiled variant of the kernel for the given signature and current device.

`get_regs_per_thread`(*signature=None*)

Returns the number of registers used by each thread in this kernel for the device in the current context.

Parameters
`signature` – The signature of the compiled kernel to get register usage for. This may be omitted for a specialized kernel.

Returns
The number of registers used by the compiled variant of the kernel for the given signature and current device.

`get_shared_mem_per_block`(*signature=None*)

Returns the size in bytes of statically allocated shared memory for this kernel.

Parameters
`signature` – The signature of the compiled kernel to get shared memory usage for. This may be omitted for a specialized kernel.

Returns
The amount of shared memory allocated by the compiled variant of the kernel for the given signature and current device.

`inspect_asm`(*signature=None*)

Return this kernel's PTX assembly code for for the device in the current context.

Parameters
`signature` – A tuple of argument types.

Returns
The PTX code for the given signature, or a dict of PTX codes for all previously-encountered signatures.

`inspect_llvm`(*signature=None*)

Return the LLVM IR for this kernel.

Parameters
`signature` – A tuple of argument types.

Returns
The LLVM IR for the given signature, or a dict of LLVM IR for all previously-encountered signatures.

`inspect_sass`(*signature=None*)

Return this kernel's SASS assembly code for for the device in the current context.

Parameters
`signature` – A tuple of argument types.

Returns
The SASS code for the given signature, or a dict of SASS codes for all previously-encountered signatures.

SASS for the device in the current context is returned.

Requires nvdisasm to be available on the PATH.

`inspect_types`(*file=None*)

Produce a dump of the Python source of this function annotated with the corresponding Numba IR and type information. The dump is written to *file*, or *sys.stdout* if *file* is *None*.

specialize(**args*)

Create a new instance of this dispatcher specialized for the given *args*.

property specialized

True if the Dispatcher has been specialized.

4.2.3 Intrinsic Attributes and Functions

The remainder of the attributes and functions in this section may only be called from within a CUDA Kernel.

Thread Indexing

numba.cuda.**threadIdx**

The thread indices in the current thread block, accessed through the attributes `x`, `y`, and `z`. Each index is an integer spanning the range from 0 inclusive to the corresponding value of the attribute in *numba.cuda.blockDim* exclusive.

numba.cuda.**blockIdx**

The block indices in the grid of thread blocks, accessed through the attributes `x`, `y`, and `z`. Each index is an integer spanning the range from 0 inclusive to the corresponding value of the attribute in *numba.cuda.gridDim* exclusive.

numba.cuda.**blockDim**

The shape of a block of threads, as declared when instantiating the kernel. This value is the same for all threads in a given kernel, even if they belong to different blocks (i.e. each block is "full").

numba.cuda.**gridDim**

The shape of the grid of blocks, accessed through the attributes `x`, `y`, and `z`.

numba.cuda.**laneid**

The thread index in the current warp, as an integer spanning the range from 0 inclusive to the *numba.cuda.warpsize* exclusive.

numba.cuda.**warpsize**

The size in threads of a warp on the GPU. Currently this is always 32.

numba.cuda.**grid**(*ndim*)

Return the absolute position of the current thread in the entire grid of blocks. *ndim* should correspond to the number of dimensions declared when instantiating the kernel. If *ndim* is 1, a single integer is returned. If *ndim* is 2 or 3, a tuple of the given number of integers is returned.

Computation of the first integer is as follows:

```
cuda.threadIdx.x + cuda.blockIdx.x * cuda.blockDim.x
```

and is similar for the other two indices, but using the `y` and `z` attributes.

numba.cuda.**gridsize**(*ndim*)

Return the absolute size (or shape) in threads of the entire grid of blocks. *ndim* should correspond to the number of dimensions declared when instantiating the kernel.

Computation of the first integer is as follows:

```
cuda.blockDim.x * cuda.gridDim.x
```

and is similar for the other two indices, but using the `y` and `z` attributes.

Memory Management

numba.cuda.shared.**array**(*shape*, *dtype*)

Creates an array in the local memory space of the CUDA kernel with the given `shape` and `dtype`.

Returns an array with its content uninitialized.

Note: All threads in the same thread block sees the same array.

---

numba.cuda.local.**array**(*shape*, *dtype*)

Creates an array in the local memory space of the CUDA kernel with the given `shape` and `dtype`.

Returns an array with its content uninitialized.

Note: Each thread sees a unique array.

---

numba.cuda.const.**array_like**(*ary*)

Copies the `ary` into constant memory space on the CUDA kernel at compile time.

Returns an array like the `ary` argument.

Note: All threads and blocks see the same array.

Synchronization and Atomic Operations

numba.cuda.atomic.**add**(*array*, *idx*, *value*)

Perform `array[idx] += value`. Support int32, int64, float32 and float64 only. The `idx` argument can be an integer or a tuple of integer indices for indexing into multiple dimensional arrays. The number of element in `idx` must match the number of dimension of `array`.

Returns the value of `array[idx]` before storing the new value. Behaves like an atomic load.

numba.cuda.atomic.**sub**(*array*, *idx*, *value*)

Perform `array[idx] -= value`. Supports int32, int64, float32 and float64 only. The `idx` argument can be an integer or a tuple of integer indices for indexing into multi-dimensional arrays. The number of elements in `idx` must match the number of dimensions of `array`.

Returns the value of `array[idx]` before storing the new value. Behaves like an atomic load.

numba.cuda.atomic.**and_**(*array*, *idx*, *value*)

Perform `array[idx] &= value`. Supports int32, uint32, int64, and uint64 only. The `idx` argument can be an integer or a tuple of integer indices for indexing into multi-dimensional arrays. The number of elements in `idx` must match the number of dimensions of `array`.

Returns the value of `array[idx]` before storing the new value. Behaves like an atomic load.

numba.cuda.atomic.**or_**(*array*, *idx*, *value*)

Perform `array[idx] |= value`. Supports int32, uint32, int64, and uint64 only. The `idx` argument can be an integer or a tuple of integer indices for indexing into multi-dimensional arrays. The number of elements in `idx` must match the number of dimensions of `array`.

Returns the value of `array[idx]` before storing the new value. Behaves like an atomic load.

numba.cuda.atomic.**xor**(*array*, *idx*, *value*)

Perform `array[idx] ^= value`. Supports int32, uint32, int64, and uint64 only. The `idx` argument can be an integer or a tuple of integer indices for indexing into multi-dimensional arrays. The number of elements in `idx` must match the number of dimensions of `array`.

Returns the value of `array[idx]` before storing the new value. Behaves like an atomic load.

numba.cuda.atomic.**exch**(*array*, *idx*, *value*)

Perform `array[idx] = value`. Supports int32, uint32, int64, and uint64 only. The `idx` argument can be an integer or a tuple of integer indices for indexing into multi-dimensional arrays. The number of elements in `idx` must match the number of dimensions of `array`.

Returns the value of `array[idx]` before storing the new value. Behaves like an atomic load.

numba.cuda.atomic.**inc**(*array*, *idx*, *value*)

Perform `array[idx] = (0 if array[idx] >= value else array[idx] + 1)`. Supports uint32, and uint64 only. The `idx` argument can be an integer or a tuple of integer indices for indexing into multi-dimensional arrays. The number of elements in `idx` must match the number of dimensions of `array`.

Returns the value of `array[idx]` before storing the new value. Behaves like an atomic load.

numba.cuda.atomic.**dec**(*array*, *idx*, *value*)

Perform `array[idx] = (value if (array[idx] == 0) or (array[idx] > value) else array[idx] - 1)`. Supports uint32, and uint64 only. The `idx` argument can be an integer or a tuple of integer indices for indexing into multi-dimensional arrays. The number of elements in `idx` must match the number of dimensions of `array`.

Returns the value of `array[idx]` before storing the new value. Behaves like an atomic load.

numba.cuda.atomic.**max**(*array*, *idx*, *value*)

Perform `array[idx] = max(array[idx], value)`. Support int32, int64, float32 and float64 only. The `idx` argument can be an integer or a tuple of integer indices for indexing into multiple dimensional arrays. The number of element in `idx` must match the number of dimension of `array`.

Returns the value of `array[idx]` before storing the new value. Behaves like an atomic load.

numba.cuda.atomic.**cas**(*array*, *idx*, *old*, *value*)

Perform `if array[idx] == old: array[idx] = value`. Supports int32, int64, uint32, uint64 indexes only. The `idx` argument can be an integer or a tuple of integer indices for indexing into multi-dimensional arrays. The number of elements in `idx` must match the number of dimensions of `array`.

Returns the value of `array[idx]` before storing the new value. Behaves like an atomic compare and swap.

numba.cuda.**syncthreads**()

Synchronize all threads in the same thread block. This function implements the same pattern as barriers in traditional multi-threaded programming: this function waits until all threads in the block call it, at which point it returns control to all its callers.

numba.cuda.**syncthreads_count**(*predicate*)

An extension to *numba.cuda.syncthreads* where the return value is a count of the threads where `predicate` is true.

numba.cuda.**syncthreads_and**(*predicate*)

An extension to *numba.cuda.syncthreads* where 1 is returned if `predicate` is true for all threads or 0 otherwise.

numba.cuda.**syncthreads_or**(*predicate*)

An extension to *numba.cuda.syncthreads* where 1 is returned if `predicate` is true for any thread or 0 otherwise.

> **Warning:** All syncthreads functions must be called by every thread in the thread-block. Falling to do so may result in undefined behavior.

Cooperative Groups

numba.cuda.cg.**this_grid**()

Get the current grid group.

Returns
The current grid group

Return type
numba.cuda.cg.GridGroup

class numba.cuda.cg.**GridGroup**

A grid group. Users should not construct a GridGroup directly - instead, get the current grid group using *cg.this_grid()*.

sync()

Synchronize the current grid group.

Memory Fences

The memory fences are used to guarantee the effect of memory operations are visible by other threads within the same thread-block, the same GPU device, and the same system (across GPUs on global memory). Memory loads and stores are guaranteed to not move across the memory fences by optimization passes.

> **Warning:** The memory fences are considered to be advanced API and most usercases should use the thread barrier (e.g. `syncthreads()`).

numba.cuda.**threadfence**()

A memory fence at device level (within the GPU).

numba.cuda.**threadfence_block**()

A memory fence at thread block level.

numba.cuda.**threadfence_system**()

A memory fence at system level (across GPUs).

Warp Intrinsics

The argument `membermask` is a 32 bit integer mask with each bit corresponding to a thread in the warp, with 1 meaning the thread is in the subset of threads within the function call. The `membermask` must be all 1 if the GPU compute capability is below 7.x.

numba.cuda.**syncwarp**(*membermask*)

Synchronize a masked subset of the threads in a warp.

numba.cuda.**all_sync**(*membermask*, *predicate*)

If the `predicate` is true for all threads in the masked warp, then a non-zero value is returned, otherwise 0 is returned.

numba.cuda.**any_sync**(*membermask*, *predicate*)

If the `predicate` is true for any thread in the masked warp, then a non-zero value is returned, otherwise 0 is returned.

numba.cuda.**eq_sync**(*membermask*, *predicate*)

If the boolean `predicate` is the same for all threads in the masked warp, then a non-zero value is returned, otherwise 0 is returned.

numba.cuda.**ballot_sync**(*membermask*, *predicate*)

Returns a mask of all threads in the warp whose `predicate` is true, and are within the given mask.

numba.cuda.**shfl_sync**(*membermask*, *value*, *src_lane*)

Shuffles `value` across the masked warp and returns the `value` from `src_lane`. If this is outside the warp, then the given `value` is returned.

numba.cuda.**shfl_up_sync**(*membermask*, *value*, *delta*)

Shuffles `value` across the masked warp and returns the `value` from `laneid - delta`. If this is outside the warp, then the given `value` is returned.

numba.cuda.**shfl_down_sync**(*membermask*, *value*, *delta*)

Shuffles `value` across the masked warp and returns the `value` from `laneid + delta`. If this is outside the warp, then the given `value` is returned.

numba.cuda.**shfl_xor_sync**(*membermask*, *value*, *lane_mask*)

Shuffles `value` across the masked warp and returns the `value` from `laneid ^ lane_mask`.

numba.cuda.**match_any_sync**(*membermask*, *value*, *lane_mask*)

Returns a mask of threads that have same `value` as the given `value` from within the masked warp.

numba.cuda.**match_all_sync**(*membermask*, *value*, *lane_mask*)

Returns a tuple of (mask, pred), where mask is a mask of threads that have same `value` as the given `value` from within the masked warp, if they all have the same value, otherwise it is 0. And pred is a boolean of whether or not all threads in the mask warp have the same warp.

numba.cuda.**activemask**()

Returns a 32-bit integer mask of all currently active threads in the calling warp. The Nth bit is set if the Nth lane in the warp is active when activemask() is called. Inactive threads are represented by 0 bits in the returned mask. Threads which have exited the kernel are always marked as inactive.

numba.cuda.**lanemask_lt**()

Returns a 32-bit integer mask of all lanes (including inactive ones) with ID less than the current lane.

Integer Intrinsics

A subset of the CUDA Math API's integer intrinsics are available. For further documentation, including semantics, please refer to the CUDA Toolkit documentation.

numba.cuda.**popc**(*x*)

Returns the number of bits set in `x`.

numba.cuda.**brev**(*x*)

Returns the reverse of the bit pattern of `x`. For example, `0b10110110` becomes `0b01101101`.

numba.cuda.**clz**(*x*)

Returns the number of leading zeros in `x`.

numba.cuda.**ffs**(*x*)

Returns the position of the first (least significant) bit set to 1 in `x`, where the least significant bit position is 1. `ffs(0)` returns 0.

Floating Point Intrinsics

A subset of the CUDA Math API's floating point intrinsics are available. For further documentation, including semantics, please refer to the single and double precision parts of the CUDA Toolkit documentation.

numba.cuda.**fma**()

Perform the fused multiply-add operation. Named after the `fma` and `fmaf` in the C api, but maps to the `fma.rn.f32` and `fma.rn.f64` (round-to-nearest-even) PTX instructions.

numba.cuda.**cbrt**(*x*)

Perform the cube root operation, x ** (1/3). Named after the functions `cbrt` and `cbrtf` in the C api. Supports float32, and float64 arguments only.

16-bit Floating Point Intrinsics

The functions in the `cuda.fp16` module are used to operate on 16-bit floating point operands. These functions return a 16-bit floating point result.

To determine whether Numba supports compiling code that uses the `float16` type in the current configuration, use:

numba.cuda.**is_float16_supported**()

Return `True` if 16-bit floats are supported, `False` otherwise.

To check whether a device supports `float16`, use its *supports_float16* attribute.

numba.cuda.fp16.**hfma**(*a*, *b*, *c*)

Perform the fused multiply-add operation `(a * b) + c` on 16-bit floating point arguments in round to nearest mode. Maps to the `fma.rn.f16` PTX instruction.

Returns the 16-bit floating point result of the fused multiply-add.

numba.cuda.fp16.**hadd**(*a*, *b*)

Perform the add operation `a + b` on 16-bit floating point arguments in round to nearest mode. Maps to the `add.f16` PTX instruction.

Returns the 16-bit floating point result of the addition.

numba.cuda.fp16.**hsub**(*a*, *b*)

Perform the subtract operation `a - b` on 16-bit floating point arguments in round to nearest mode. Maps to the `sub.f16` PTX instruction.

Returns the 16-bit floating point result of the subtraction.

numba.cuda.fp16.**hmul**(*a*, *b*)

Perform the multiply operation `a * b` on 16-bit floating point arguments in round to nearest mode. Maps to the `mul.f16` PTX instruction.

Returns the 16-bit floating point result of the multiplication.

numba.cuda.fp16.**hdiv**(*a*, *b*)

Perform the divide operation `a / b` on 16-bit floating point arguments in round to nearest mode.

Returns the 16-bit floating point result of the division.

numba.cuda.fp16.**hneg**(*a*)

Perform the negation operation `-a` on the 16-bit floating point argument. Maps to the `neg.f16` PTX instruction.

Returns the 16-bit floating point result of the negation.

numba.cuda.fp16.**habs**(*a*)

Perform the absolute value operation `|a|` on the 16-bit floating point argument.

Returns the 16-bit floating point result of the absolute value operation.

numba.cuda.fp16.**hsin**(*a*)

Calculates the trigonometry sine function of the 16-bit floating point argument.

Returns the 16-bit floating point result of the sine operation.

numba.cuda.fp16.**hcos**(*a*)

Calculates the trigonometry cosine function of the 16-bit floating point argument.

Returns the 16-bit floating point result of the cosine operation.

numba.cuda.fp16.**hlog**(*a*)

Calculates the natural logarithm of the 16-bit floating point argument.

Returns the 16-bit floating point result of the natural log operation.

numba.cuda.fp16.**hlog10**(*a*)

Calculates the base 10 logarithm of the 16-bit floating point argument.

Returns the 16-bit floating point result of the log base 10 operation.

numba.cuda.fp16.**hlog2**(*a*)

Calculates the base 2 logarithm on the 16-bit floating point argument.

Returns the 16-bit floating point result of the log base 2 operation.

numba.cuda.fp16.**hexp**(*a*)

Calculates the natural exponential operation of the 16-bit floating point argument.

Returns the 16-bit floating point result of the exponential operation.

numba.cuda.fp16.**hexp10**(*a*)

Calculates the base 10 exponential of the 16-bit floating point argument.

Returns the 16-bit floating point result of the exponential operation.

numba.cuda.fp16.**hexp2**(*a*)

Calculates the base 2 exponential of the 16-bit floating point argument.

Returns the 16-bit floating point result of the exponential operation.

numba.cuda.fp16.**hfloor**(*a*)

Calculates the floor operation, the largest integer less than or equal to `a`, on the 16-bit floating point argument.

Returns the 16-bit floating point result of the floor operation.

numba.cuda.fp16.**hceil**(*a*)

Calculates the ceiling operation, the smallest integer greater than or equal to `a`, on the 16-bit floating point argument.

Returns the 16-bit floating point result of the ceil operation.

numba.cuda.fp16.**hsqrt**(*a*)

Calculates the square root operation of the 16-bit floating point argument.

Returns the 16-bit floating point result of the square root operation.

numba.cuda.fp16.**hrsqrt**(*a*)

Calculates the reciprocal of the square root of the 16-bit floating point argument.

Returns the 16-bit floating point result of the reciprocal square root operation.

numba.cuda.fp16.**hrcp**(*a*)

Calculates the reciprocal of the 16-bit floating point argument.

Returns the 16-bit floating point result of the reciprocal.

numba.cuda.fp16.**hrint**(*a*)

Round the input 16-bit floating point argument to nearest integer value.

Returns the 16-bit floating point result of the rounding.

numba.cuda.fp16.**htrunc**(*a*)

Truncate the input 16-bit floating point argument to the nearest integer that does not exceed the input argument in magnitude.

Returns the 16-bit floating point result of the truncation.

numba.cuda.fp16.**heq**(*a*, *b*)

Perform the comparison operation `a == b` on 16-bit floating point arguments.

Returns a boolean.

numba.cuda.fp16.**hne**(*a*, *b*)

Perform the comparison operation `a != b` on 16-bit floating point arguments.

Returns a boolean.

numba.cuda.fp16.**hgt**(*a*, *b*)

Perform the comparison operation `a > b` on 16-bit floating point arguments.

Returns a boolean.

numba.cuda.fp16.**hge**(*a*, *b*)

Perform the comparison operation `a >= b` on 16-bit floating point arguments.

Returns a boolean.

numba.cuda.fp16.**hlt**(*a*, *b*)

Perform the comparison operation `a < b` on 16-bit floating point arguments.

Returns a boolean.

numba.cuda.fp16.**hle**(*a*, *b*)

Perform the comparison operation `a <= b` on 16-bit floating point arguments.

Returns a boolean.

numba.cuda.fp16.**hmax**(*a*, *b*)

Perform the operation `a if a > b else b.`

Returns a 16-bit floating point value.

numba.cuda.fp16.**hmin**(*a*, *b*)

Perform the operation `a if a < b else b.`

Returns a 16-bit floating point value.

Control Flow Instructions

A subset of the CUDA's control flow instructions are directly available as intrinsics. Avoiding branches is a key way to improve CUDA performance, and using these intrinsics mean you don't have to rely on the `nvcc` optimizer identifying and removing branches. For further documentation, including semantics, please refer to the relevant CUDA Toolkit documentation.

numba.cuda.**selp**()

Select between two expressions, depending on the value of the first argument. Similar to LLVM's `select` instruction.

Timer Intrinsics

numba.cuda.**nanosleep**(*ns*)

Suspends the thread for a sleep duration approximately close to the delay `ns`, specified in nanoseconds.

4.3 CUDA-Specific Types

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

Note: This page is about types specific to CUDA targets. Many other types are also available in the CUDA target - see *Built-in types*.

4.3.1 Vector Types

CUDA Vector Types are usable in kernels. There are two important distinctions from vector types in CUDA C/C++:

First, the recommended names for vector types in Numba CUDA is formatted as <`base_type`>`x`<`N`>, where `base_type` is the base type of the vector, and `N` is the number of elements in the vector. Examples include `int64x3`, `uint16x4`, `float32x4`, etc. For new Numba CUDA kernels, this is the recommended way to instantiate vector types.

For convenience, users adapting existing kernels from CUDA C/C++ to Python may use aliases consistent with the C/C++ namings. For example, `float3` aliases `float32x3`, `long3` aliases `int32x3` or `int64x3` (depending on the platform), etc.

Second, unlike CUDA C/C++ where factory functions are used, vector types are constructed directly with their constructor. For example, to construct a `float32x3`:

```
from numba.cuda import float32x3

# In kernel
f3 = float32x3(0.0, -1.0, 1.0)
```

Additionally, vector types can be constructed from a combination of vector and primitive types, as long as the total number of components matches the result vector type. For example, all of the following constructions are valid:

```
zero = uint32(0)
u2 = uint32x2(1, 2)
# Construct a 3-component vector with primitive type and a 2-component vector
u3 = uint32x3(zero, u2)
# Construct a 4-component vector with 2 2-component vectors
u4 = uint32x4(u2, u2)
```

The 1st, 2nd, 3rd and 4th component of the vector type can be accessed through fields `x`, `y`, `z`, and `w` respectively. The components are immutable after construction in the present version of Numba; it is expected that support for mutating vector components will be added in a future release.

```
v1 = float32x2(1.0, 1.0)
v2 = float32x2(1.0, -1.0)
dotprod = v1.x * v2.x + v1.y * v2.y
```

4.4 Memory Management

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

numba.cuda.**to_device**(*obj*, *stream=0*, *copy=True*, *to=None*)

Allocate and transfer a numpy ndarray or structured scalar to the device.

To copy host->device a numpy array:

```
ary = np.arange(10)
d_ary = cuda.to_device(ary)
```

To enqueue the transfer to a stream:

```
stream = cuda.stream()
d_ary = cuda.to_device(ary, stream=stream)
```

The resulting `d_ary` is a `DeviceNDArray`.

To copy device->host:

```
hary = d_ary.copy_to_host()
```

To copy device->host to an existing array:

```
ary = np.empty(shape=d_ary.shape, dtype=d_ary.dtype)
d_ary.copy_to_host(ary)
```

To enqueue the transfer to a stream:

```
hary = d_ary.copy_to_host(stream=stream)
```

numba.cuda.**device_array**(*shape*, *dtype=np.float64*, *strides=None*, *order='C'*, *stream=0*)

Allocate an empty device ndarray. Similar to `numpy.empty()`.

numba.cuda.**device_array_like**(*ary*, *stream=0*)

Call *device_array()* with information from the array.

numba.cuda.**pinned_array**(*shape*, *dtype=np.float64*, *strides=None*, *order='C'*)

Allocate an `ndarray` with a buffer that is pinned (pagelocked). Similar to `np.empty()`.

numba.cuda.**pinned_array_like**(*ary*)

Call *pinned_array()* with the information from the array.

numba.cuda.**mapped_array**(*shape*, *dtype=np.float64*, *strides=None*, *order='C'*, *stream=0*, *portable=False*, *wc=False*)

Allocate a mapped ndarray with a buffer that is pinned and mapped on to the device. Similar to np.empty()

Parameters

- **portable** – a boolean flag to allow the allocated device memory to be usable in multiple devices.
- **wc** – a boolean flag to enable writecombined allocation which is faster to write by the host and to read by the device, but slower to write by the host and slower to write by the device.

numba.cuda.**mapped_array_like**(*ary*, *stream=0*, *portable=False*, *wc=False*)

Call *mapped_array()* with the information from the array.

numba.cuda.**managed_array**(*shape*, *dtype=np.float64*, *strides=None*, *order='C'*, *stream=0*, *attach_global=True*)

Allocate a np.ndarray with a buffer that is managed. Similar to np.empty().

Managed memory is supported on Linux / x86 and PowerPC, and is considered experimental on Windows and Linux / AArch64.

Parameters

attach_global – A flag indicating whether to attach globally. Global attachment implies that the memory is accessible from any stream on any device. If `False`, attachment is *host*, and memory is only accessible by devices with Compute Capability 6.0 and later.

numba.cuda.**pinned**(**arylist*)

A context manager for temporary pinning a sequence of host ndarrays.

numba.cuda.**mapped**(**arylist*, ***kws*)

A context manager for temporarily mapping a sequence of host ndarrays.

4.4.1 Device Objects

class numba.cuda.cudadrv.devicearray.**DeviceNDArray**(*shape*, *strides*, *dtype*, *stream=0*, *gpu_data=None*)

An on-GPU array type

copy_to_device(*ary*, *stream=0*)

Copy *ary* to *self*.

If *ary* is a CUDA memory, perform a device-to-device transfer. Otherwise, perform a a host-to-device transfer.

copy_to_host(*ary=None*, *stream=0*)

Copy `self` to `ary` or create a new Numpy ndarray if `ary` is `None`.

If a CUDA `stream` is given, then the transfer will be made asynchronously as part as the given stream. Otherwise, the transfer is synchronous: the function returns after the copy is finished.

Always returns the host array.

Example:

```
import numpy as np
from numba import cuda

arr = np.arange(1000)
d_arr = cuda.to_device(arr)

my_kernel[100, 100](d_arr)

result_array = d_arr.copy_to_host()
```

is_c_contiguous()

Return true if the array is C-contiguous.

is_f_contiguous()

Return true if the array is Fortran-contiguous.

ravel(*order='C'*, *stream=0*)

Flattens a contiguous array without changing its contents, similar to `numpy.ndarray.ravel()`. If the array is not contiguous, raises an exception.

reshape(**newshape*, ***kws*)

Reshape the array without changing its contents, similarly to `numpy.ndarray.reshape()`. Example:

```
d_arr = d_arr.reshape(20, 50, order='F')
```

split(*section*, *stream=0*)

Split the array into equal partition of the *section* size. If the array cannot be equally divided, the last section will be smaller.

class numba.cuda.cudadrv.devicearray.**DeviceRecord**(*dtype*, *stream=0*, *gpu_data=None*)

An on-GPU record type

copy_to_device(*ary*, *stream=0*)

Copy *ary* to *self*.

If *ary* is a CUDA memory, perform a device-to-device transfer. Otherwise, perform a a host-to-device transfer.

copy_to_host(*ary=None*, *stream=0*)

Copy `self` to `ary` or create a new Numpy ndarray if `ary` is `None`.

If a CUDA `stream` is given, then the transfer will be made asynchronously as part as the given stream. Otherwise, the transfer is synchronous: the function returns after the copy is finished.

Always returns the host array.

Example:

```
import numpy as np
from numba import cuda

arr = np.arange(1000)
d_arr = cuda.to_device(arr)

my_kernel[100, 100](d_arr)

result_array = d_arr.copy_to_host()
```

class numba.cuda.cudadrv.devicearray.**MappedNDArray**(*shape*, *strides*, *dtype*, *stream=0*, *gpu_data=None*)

A host array that uses CUDA mapped memory.

copy_to_device(*ary*, *stream=0*)

Copy *ary* to *self*.

If *ary* is a CUDA memory, perform a device-to-device transfer. Otherwise, perform a a host-to-device transfer.

copy_to_host(*ary=None*, *stream=0*)

Copy `self` to `ary` or create a new Numpy ndarray if `ary` is `None`.

If a CUDA `stream` is given, then the transfer will be made asynchronously as part as the given stream. Otherwise, the transfer is synchronous: the function returns after the copy is finished.

Always returns the host array.

Example:

```
import numpy as np
from numba import cuda

arr = np.arange(1000)
d_arr = cuda.to_device(arr)

my_kernel[100, 100](d_arr)

result_array = d_arr.copy_to_host()
```

split(*section*, *stream=0*)

Split the array into equal partition of the *section* size. If the array cannot be equally divided, the last section will be smaller.

4.5 Libdevice functions

CUDA Built-in Target deprecation notice

The CUDA target built-in to Numba is deprecated, with further development moved to the NVIDIA numba-cuda package. Please see *Built-in CUDA target deprecation and maintenance status*.

All wrapped libdevice functions are listed in this section. All functions in libdevice are wrapped, with the exception of `__nv_nan` and `__nv_nanf`. These functions return a representation of a quiet NaN, but the argument they take (a pointer to an object specifying the representation) is undocumented, and follows an unusual form compared to the rest of libdevice - it is not an output like every other pointer argument. If a NaN is required, one can be obtained in CUDA Python by other means, e.g. `math.nan`.

4.5.1 Wrapped functions

`numba.cuda.libdevice.abs(x)`

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_abs.html

Parameters
x (*int32*) – Argument.

Return type
int32

`numba.cuda.libdevice.acos(x)`

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_acos.html

Parameters
x (*float64*) – Argument.

Return type
float64

`numba.cuda.libdevice.acosf(x)`

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_acosf.html

Parameters
x (*float32*) – Argument.

Return type
float32

`numba.cuda.libdevice.acosh(x)`

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_acosh.html

Parameters
x (*float64*) – Argument.

Return type
float64

`numba.cuda.libdevice.acoshf(x)`

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_acoshf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**asin**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_asin.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**asinf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_asinf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**asinh**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_asinh.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**asinhf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_asinhf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**atan**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_atan.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**atan2**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_atan2.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**atan2f**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_atan2f.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**atanf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_atanf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**atanh**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_atanh.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**atanhf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_atanhf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**brev**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_brev.html

Parameters
x (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**brevll**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_brevll.html

Parameters
x (*int64*) – Argument.

Return type
int64

numba.cuda.libdevice.**byte_perm**(*x*, *y*, *z*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_byte_perm.html

Parameters

- **x** (*int32*) – Argument.
- **y** (*int32*) – Argument.
- **z** (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**cbrt**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_cbrt.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**cbrtf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_cbrtf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**ceil**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ceil.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**ceilf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ceilf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**clz**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_clz.html

Parameters
x (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**clzll**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_clzll.html

Parameters
x (*int64*) – Argument.

Return type
int32

numba.cuda.libdevice.**copysign**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_copysign.html

Parameters

- **x** (*float64*) – Argument.

- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**copysignf**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_copysignf.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**cos**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_cos.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**cosf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_cosf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**cosh**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_cosh.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**coshf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_coshf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**cospi**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_cospi.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**cospif**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_cospif.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**dadd_rd**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_dadd_rd.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**dadd_rn**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_dadd_rn.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**dadd_ru**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_dadd_ru.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**dadd_rz**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_dadd_rz.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**ddiv_rd**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ddiv_rd.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**ddiv_rn**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ddiv_rn.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**ddiv_ru**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ddiv_ru.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**ddiv_rz**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ddiv_rz.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**dmul_rd**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_dmul_rd.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**dmul_rn**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_dmul_rn.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**dmul_ru**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_dmul_ru.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**dmul_rz**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_dmul_rz.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**double2float_rd**(*d*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2float_rd.html

Parameters
d (*float64*) – Argument.

Return type
float32

numba.cuda.libdevice.**double2float_rn**(*d*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2float_rn.html

Parameters
d (*float64*) – Argument.

Return type
float32

numba.cuda.libdevice.**double2float_ru**(*d*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2float_ru.html

Parameters
d (*float64*) – Argument.

Return type
float32

numba.cuda.libdevice.**double2float_rz**(*d*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2float_rz.html

Parameters
d (*float64*) – Argument.

Return type
float32

numba.cuda.libdevice.**double2hiint**(*d*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2hiint.html

Parameters
d (*float64*) – Argument.

Return type
int32

numba.cuda.libdevice.**double2int_rd**(*d*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2int_rd.html

Parameters
d (*float64*) – Argument.

Return type
int32

numba.cuda.libdevice.**double2int_rn**(*d*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2int_rn.html

Parameters
d (*float64*) – Argument.

Return type
int32

numba.cuda.libdevice.**double2int_ru**(*d*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2int_ru.html

Parameters
d (*float64*) – Argument.

Return type
int32

numba.cuda.libdevice.**double2int_rz**(*d*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2int_rz.html

Parameters
d (*float64*) – Argument.

Return type
int32

numba.cuda.libdevice.**double2ll_rd**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2ll_rd.html

Parameters
f (*float64*) – Argument.

Return type
int64

numba.cuda.libdevice.**double2ll_rn**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2ll_rn.html

Parameters
f (*float64*) – Argument.

Return type
int64

numba.cuda.libdevice.**double2ll_ru**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2ll_ru.html

Parameters
f (*float64*) – Argument.

Return type
int64

numba.cuda.libdevice.**double2ll_rz**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2ll_rz.html

Parameters
f (*float64*) – Argument.

Return type
int64

numba.cuda.libdevice.**double2loint**(*d*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2loint.html

Parameters
d (*float64*) – Argument.

Return type
int32

numba.cuda.libdevice.**double2uint_rd**(*d*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2uint_rd.html

Parameters
d (*float64*) – Argument.

Return type
int32

numba.cuda.libdevice.**double2uint_rn**(*d*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2uint_rn.html

Parameters
d (*float64*) – Argument.

Return type
int32

numba.cuda.libdevice.**double2uint_ru**(*d*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2uint_ru.html

Parameters
d (*float64*) – Argument.

Return type
int32

numba.cuda.libdevice.**double2uint_rz**(*d*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2uint_rz.html

Parameters
d (*float64*) – Argument.

Return type
int32

numba.cuda.libdevice.**double2ull_rd**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2ull_rd.html

Parameters
f (*float64*) – Argument.

Return type
int64

numba.cuda.libdevice.**double2ull_rn**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2ull_rn.html

Parameters
f (*float64*) – Argument.

Return type
int64

numba.cuda.libdevice.**double2ull_ru**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2ull_ru.html

Parameters
f (*float64*) – Argument.

Return type
int64

numba.cuda.libdevice.**double2ull_rz**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double2ull_rz.html

Parameters
f (*float64*) – Argument.

Return type
int64

numba.cuda.libdevice.**double_as_longlong**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_double_as_longlong.html

Parameters
x (*float64*) – Argument.

Return type
int64

numba.cuda.libdevice.**drcp_rd**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_drcp_rd.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**drcp_rn**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_drcp_rn.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**drcp_ru**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_drcp_ru.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**drcp_rz**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_drcp_rz.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**dsqrt_rd**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_dsqrt_rd.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**dsqrt_rn**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_dsqrt_rn.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**dsqrt_ru**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_dsqrt_ru.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**dsqrt_rz**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_dsqrt_rz.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**erf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_erf.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**erfc**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_erfc.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**erfcf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_erfcf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**erfcinv**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_erfcinv.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**erfcinvf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_erfcinvf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**erfcx**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_erfcx.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**erfcxf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_erfcxf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**erff**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_erff.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**erfinv**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_erfinv.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**erfinvf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_erfinvf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**exp**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_exp.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**exp10**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_exp10.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**exp10f**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_exp10f.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**exp2**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_exp2.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**exp2f**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_exp2f.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**expf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_expf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**expm1**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_expm1.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**expm1f**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_expm1f.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fabs**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fabs.html

Parameters
f (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**fabsf**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fabsf.html

Parameters
f (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fadd_rd**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fadd_rd.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fadd_rn**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fadd_rn.html

Parameters

- **x** (*float32*) – Argument.

- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fadd_ru**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fadd_ru.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fadd_rz**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fadd_rz.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fast_cosf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fast_cosf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fast_exp10f**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fast_exp10f.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fast_expf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fast_expf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fast_fdividef**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fast_fdividef.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fast_log10f**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fast_log10f.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fast_log2f**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fast_log2f.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fast_logf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fast_logf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fast_powf**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fast_powf.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fast_sincosf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fast_sincosf.html

Parameters
x (*float32*) – Argument.

Return type
UniTuple(float32 x 2)

numba.cuda.libdevice.**fast_sinf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fast_sinf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fast_tanf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fast_tanf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fdim**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fdim.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**fdimf**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fdimf.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fdiv_rd**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fdiv_rd.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fdiv_rn**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fdiv_rn.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fdiv_ru**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fdiv_ru.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fdiv_rz**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fdiv_rz.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**ffs**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ffs.html

Parameters
x (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**ffsll**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ffsll.html

Parameters
x (*int64*) – Argument.

Return type
int32

numba.cuda.libdevice.**finitef**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_finitef.html

Parameters
x (*float32*) – Argument.

Return type
int32

numba.cuda.libdevice.**float2half_rn**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2half_rn.html

Parameters
f (*float32*) – Argument.

Return type
int16

numba.cuda.libdevice.**float2int_rd**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2int_rd.html

Parameters
in (*float32*) – Argument.

Return type
int32

numba.cuda.libdevice.**float2int_rn**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2int_rn.html

Parameters
in (*float32*) – Argument.

Return type
int32

numba.cuda.libdevice.**float2int_ru**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2int_ru.html

Parameters
in (*float32*) – Argument.

Return type
int32

numba.cuda.libdevice.**float2int_rz**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2int_rz.html

Parameters
in (*float32*) – Argument.

Return type
int32

numba.cuda.libdevice.**float2ll_rd**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2ll_rd.html

Parameters
f (*float32*) – Argument.

Return type
int64

numba.cuda.libdevice.**float2ll_rn**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2ll_rn.html

Parameters
f (*float32*) – Argument.

Return type
int64

numba.cuda.libdevice.**float2ll_ru**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2ll_ru.html

Parameters
f (*float32*) – Argument.

Return type
int64

numba.cuda.libdevice.**float2ll_rz**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2ll_rz.html

Parameters
f (*float32*) – Argument.

Return type
int64

numba.cuda.libdevice.**float2uint_rd**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2uint_rd.html

Parameters
in (*float32*) – Argument.

Return type
int32

numba.cuda.libdevice.**float2uint_rn**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2uint_rn.html

Parameters
in (*float32*) – Argument.

Return type
int32

numba.cuda.libdevice.**float2uint_ru**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2uint_ru.html

Parameters
in (*float32*) – Argument.

Return type
int32

numba.cuda.libdevice.**float2uint_rz**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2uint_rz.html

Parameters
in (*float32*) – Argument.

Return type
int32

numba.cuda.libdevice.**float2ull_rd**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2ull_rd.html

Parameters
f (*float32*) – Argument.

Return type
int64

numba.cuda.libdevice.**float2ull_rn**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2ull_rn.html

Parameters
f (*float32*) – Argument.

Return type
int64

numba.cuda.libdevice.**float2ull_ru**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2ull_ru.html

Parameters
f (*float32*) – Argument.

Return type
int64

numba.cuda.libdevice.**float2ull_rz**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float2ull_rz.html

Parameters
f (*float32*) – Argument.

Return type
int64

numba.cuda.libdevice.**float_as_int**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_float_as_int.html

Parameters
x (*float32*) – Argument.

Return type
int32

numba.cuda.libdevice.**floor**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_floor.html

Parameters
f (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**floorf**(*f*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_floorf.html

Parameters
f (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fma**(*x*, *y*, *z*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fma.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.
- **z** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**fma_rd**(*x*, *y*, *z*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fma_rd.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.
- **z** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**fma_rn**(*x*, *y*, *z*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fma_rn.html

Parameters

- **x** (*float64*) – Argument.

- **y** (*float64*) – Argument.
- **z** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**fma_ru**(*x*, *y*, *z*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fma_ru.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.
- **z** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**fma_rz**(*x*, *y*, *z*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fma_rz.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.
- **z** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**fmaf**(*x*, *y*, *z*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fmaf.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.
- **z** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fmaf_rd**(*x*, *y*, *z*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fmaf_rd.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.
- **z** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fmaf_rn**(*x*, *y*, *z*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fmaf_rn.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.
- **z** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fmaf_ru**(*x*, *y*, *z*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fmaf_ru.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.
- **z** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fmaf_rz**(*x*, *y*, *z*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fmaf_rz.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.
- **z** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fmax**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fmax.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**fmaxf**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fmaxf.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fmin**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fmin.html

Parameters

- **x** (*float64*) – Argument.

- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**fminf**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fminf.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fmod**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fmod.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**fmodf**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fmodf.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fmul_rd**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fmul_rd.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fmul_rn**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fmul_rn.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fmul_ru**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fmul_ru.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fmul_rz**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fmul_rz.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**frcp_rd**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_frcp_rd.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**frcp_rn**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_frcp_rn.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**frcp_ru**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_frcp_ru.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**frcp_rz**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_frcp_rz.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**frexp**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_frexp.html

Parameters
x (*float64*) – Argument.

Return type
Tuple(float64, int32)

numba.cuda.libdevice.**frexpf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_frexpf.html

Parameters
x (*float32*) – Argument.

Return type
Tuple(float32, int32)

numba.cuda.libdevice.**frsqrt_rn**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_frsqrt_rn.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fsqrt_rd**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fsqrt_rd.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fsqrt_rn**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fsqrt_rn.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fsqrt_ru**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fsqrt_ru.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fsqrt_rz**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fsqrt_rz.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fsub_rd**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fsub_rd.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fsub_rn**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fsub_rn.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fsub_ru**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fsub_ru.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**fsub_rz**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_fsub_rz.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**hadd**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_hadd.html

Parameters

- **x** (*int32*) – Argument.
- **y** (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**half2float**(*h*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_half2float.html

Parameters
h (*int16*) – Argument.

Return type
float32

numba.cuda.libdevice.**hiloint2double**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_hiloint2double.html

Parameters

- **x** (*int32*) – Argument.
- **y** (*int32*) – Argument.

Return type
float64

numba.cuda.libdevice.**hypot**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_hypot.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**hypotf**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_hypotf.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**ilogb**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ilogb.html

Parameters
x (*float64*) – Argument.

Return type
int32

numba.cuda.libdevice.**ilogbf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ilogbf.html

Parameters
x (*float32*) – Argument.

Return type
int32

numba.cuda.libdevice.**int2double_rn**(*i*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_int2double_rn.html

Parameters
i (*int32*) – Argument.

Return type
float64

numba.cuda.libdevice.**int2float_rd**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_int2float_rd.html

Parameters
in (*int32*) – Argument.

Return type
float32

numba.cuda.libdevice.**int2float_rn**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_int2float_rn.html

Parameters
in (*int32*) – Argument.

Return type
float32

numba.cuda.libdevice.**int2float_ru**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_int2float_ru.html

Parameters
in (*int32*) – Argument.

Return type
float32

numba.cuda.libdevice.**int2float_rz**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_int2float_rz.html

Parameters
in (*int32*) – Argument.

Return type
float32

numba.cuda.libdevice.**int_as_float**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_int_as_float.html

Parameters
x (*int32*) – Argument.

Return type
float32

numba.cuda.libdevice.**isfinited**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_isfinited.html

Parameters
x (*float64*) – Argument.

Return type
int32

numba.cuda.libdevice.**isinfd**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_isinfd.html

Parameters
x (*float64*) – Argument.

Return type
int32

numba.cuda.libdevice.**isinff**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_isinff.html

Parameters
x (*float32*) – Argument.

Return type
int32

numba.cuda.libdevice.**isnand**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_isnand.html

Parameters
x (*float64*) – Argument.

Return type
int32

numba.cuda.libdevice.**isnanf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_isnanf.html

Parameters
x (*float32*) – Argument.

Return type
int32

numba.cuda.libdevice.**j0**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_j0.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**j0f**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_j0f.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**j1**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_j1.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**j1f**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_j1f.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**jn**(*n*, *x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_jn.html

Parameters

- **n** (*int32*) – Argument.
- **x** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**jnf**(*n*, *x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_jnf.html

Parameters

- **n** (*int32*) – Argument.
- **x** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**ldexp**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ldexp.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*int32*) – Argument.

Return type
float64

numba.cuda.libdevice.**ldexpf**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ldexpf.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*int32*) – Argument.

Return type
float32

numba.cuda.libdevice.**lgamma**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_lgamma.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**lgammaf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_lgammaf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**ll2double_rd**(*l*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ll2double_rd.html

Parameters
l (*int64*) – Argument.

Return type
float64

numba.cuda.libdevice.**ll2double_rn**(*l*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ll2double_rn.html

Parameters
l (*int64*) – Argument.

Return type
float64

numba.cuda.libdevice.**ll2double_ru**(*l*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ll2double_ru.html

Parameters
l (*int64*) – Argument.

Return type
float64

numba.cuda.libdevice.**ll2double_rz**(*l*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ll2double_rz.html

Parameters
l (*int64*) – Argument.

Return type
float64

numba.cuda.libdevice.**ll2float_rd**(*l*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ll2float_rd.html

Parameters
l (*int64*) – Argument.

Return type
float32

numba.cuda.libdevice.**ll2float_rn**(*l*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ll2float_rn.html

Parameters
l (*int64*) – Argument.

Return type
float32

numba.cuda.libdevice.**ll2float_ru**(*l*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ll2float_ru.html

Parameters
l (*int64*) – Argument.

Return type
float32

numba.cuda.libdevice.**ll2float_rz**(*l*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ll2float_rz.html

Parameters
l (*int64*) – Argument.

Return type
float32

numba.cuda.libdevice.**llabs**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_llabs.html

Parameters
x (*int64*) – Argument.

Return type
int64

numba.cuda.libdevice.**llmax**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_llmax.html

Parameters

- **x** (*int64*) – Argument.
- **y** (*int64*) – Argument.

Return type
int64

numba.cuda.libdevice.**llmin**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_llmin.html

Parameters

- **x** (*int64*) – Argument.
- **y** (*int64*) – Argument.

Return type
int64

numba.cuda.libdevice.**llrint**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_llrint.html

Parameters
x (*float64*) – Argument.

Return type
int64

numba.cuda.libdevice.**llrintf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_llrintf.html

Parameters
x (*float32*) – Argument.

Return type
int64

numba.cuda.libdevice.**llround**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_llround.html

Parameters
x (*float64*) – Argument.

Return type
int64

numba.cuda.libdevice.**llroundf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_llroundf.html

Parameters
x (*float32*) – Argument.

Return type
int64

numba.cuda.libdevice.**log**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_log.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**log10**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_log10.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**log10f**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_log10f.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**log1p**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_log1p.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**log1pf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_log1pf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**log2**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_log2.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**log2f**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_log2f.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**logb**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_logb.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**logbf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_logbf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**logf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_logf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**longlong_as_double**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_longlong_as_double.html

Parameters
x (*int64*) – Argument.

Return type
float64

numba.cuda.libdevice.**max**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_max.html

Parameters

- **x** (*int32*) – Argument.
- **y** (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**min**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_min.html

Parameters

- **x** (*int32*) – Argument.
- **y** (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**modf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_modf.html

Parameters
x (*float64*) – Argument.

Return type
UniTuple(float64 x 2)

numba.cuda.libdevice.**modff**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_modff.html

Parameters
x (*float32*) – Argument.

Return type
UniTuple(float32 x 2)

numba.cuda.libdevice.**mul24**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_mul24.html

Parameters

- **x** (*int32*) – Argument.
- **y** (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**mul64hi**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_mul64hi.html

Parameters

- **x** (*int64*) – Argument.
- **y** (*int64*) – Argument.

Return type
int64

numba.cuda.libdevice.**mulhi**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_mulhi.html

Parameters

- **x** (*int32*) – Argument.
- **y** (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**nearbyint**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_nearbyint.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**nearbyintf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_nearbyintf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**nextafter**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_nextafter.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**nextafterf**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_nextafterf.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**normcdf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_normcdf.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**normcdff**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_normcdff.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**normcdfinv**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_normcdfinv.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**normcdfinvf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_normcdfinvf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**popc**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_popc.html

Parameters
x (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**popcll**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_popcll.html

Parameters
x (*int64*) – Argument.

Return type
int32

numba.cuda.libdevice.**pow**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_pow.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**powf**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_powf.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**powi**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_powi.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*int32*) – Argument.

Return type
float64

numba.cuda.libdevice.**powif**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_powif.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*int32*) – Argument.

Return type
float32

numba.cuda.libdevice.**rcbrt**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_rcbrt.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**rcbrtf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_rcbrtf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**remainder**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_remainder.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**remainderf**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_remainderf.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**remquo**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_remquo.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*float64*) – Argument.

Return type
Tuple(float64, int32)

numba.cuda.libdevice.**remquof**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_remquof.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*float32*) – Argument.

Return type
Tuple(float32, int32)

numba.cuda.libdevice.**rhadd**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_rhadd.html

Parameters

- **x** (*int32*) – Argument.
- **y** (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**rint**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_rint.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**rintf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_rintf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**round**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_round.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**roundf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_roundf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**rsqrt**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_rsqrt.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**rsqrtf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_rsqrtf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**sad**(*x*, *y*, *z*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_sad.html

Parameters

- **x** (*int32*) – Argument.
- **y** (*int32*) – Argument.
- **z** (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**saturatef**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_saturatef.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**scalbn**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_scalbn.html

Parameters

- **x** (*float64*) – Argument.
- **y** (*int32*) – Argument.

Return type
float64

numba.cuda.libdevice.**scalbnf**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_scalbnf.html

Parameters

- **x** (*float32*) – Argument.
- **y** (*int32*) – Argument.

Return type
float32

numba.cuda.libdevice.**signbitd**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_signbitd.html

Parameters
x (*float64*) – Argument.

Return type
int32

numba.cuda.libdevice.**signbitf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_signbitf.html

Parameters
x (*float32*) – Argument.

Return type
int32

numba.cuda.libdevice.**sin**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_sin.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**sincos**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_sincos.html

Parameters
x (*float64*) – Argument.

Return type
UniTuple(float64 x 2)

numba.cuda.libdevice.**sincosf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_sincosf.html

Parameters
x (*float32*) – Argument.

Return type
UniTuple(float32 x 2)

numba.cuda.libdevice.**sincospi**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_sincospi.html

Parameters
x (*float64*) – Argument.

Return type
UniTuple(float64 x 2)

numba.cuda.libdevice.**sincospif**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_sincospif.html

Parameters
x (*float32*) – Argument.

Return type
UniTuple(float32 x 2)

numba.cuda.libdevice.**sinf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_sinf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**sinh**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_sinh.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**sinhf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_sinhf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**sinpi**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_sinpi.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**sinpif**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_sinpif.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**sqrt**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_sqrt.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**sqrtf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_sqrtf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**tan**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_tan.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**tanf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_tanf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**tanh**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_tanh.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**tanhf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_tanhf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**tgamma**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_tgamma.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**tgammaf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_tgammaf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**trunc**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_trunc.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**truncf**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_truncf.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**uhadd**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_uhadd.html

Parameters

- **x** (*int32*) – Argument.
- **y** (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**uint2double_rn**(*i*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_uint2double_rn.html

Parameters
i (*int32*) – Argument.

Return type
float64

numba.cuda.libdevice.**uint2float_rd**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_uint2float_rd.html

Parameters
in (*int32*) – Argument.

Return type
float32

numba.cuda.libdevice.**uint2float_rn**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_uint2float_rn.html

Parameters
in (*int32*) – Argument.

Return type
float32

numba.cuda.libdevice.**uint2float_ru**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_uint2float_ru.html

Parameters
in (*int32*) – Argument.

Return type
float32

numba.cuda.libdevice.**uint2float_rz**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_uint2float_rz.html

Parameters
in (*int32*) – Argument.

Return type
float32

numba.cuda.libdevice.**ull2double_rd**(*l*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ull2double_rd.html

Parameters
l (*int64*) – Argument.

Return type
float64

numba.cuda.libdevice.**ull2double_rn**(*l*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ull2double_rn.html

Parameters
l (*int64*) – Argument.

Return type
float64

numba.cuda.libdevice.**ull2double_ru**(*l*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ull2double_ru.html

Parameters
l (*int64*) – Argument.

Return type
float64

numba.cuda.libdevice.**ull2double_rz**(*l*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ull2double_rz.html

Parameters
l (*int64*) – Argument.

Return type
float64

numba.cuda.libdevice.**ull2float_rd**(*l*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ull2float_rd.html

Parameters
l (*int64*) – Argument.

Return type
float32

numba.cuda.libdevice.**ull2float_rn**(*l*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ull2float_rn.html

Parameters
l (*int64*) – Argument.

Return type
float32

numba.cuda.libdevice.**ull2float_ru**(*l*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ull2float_ru.html

Parameters
l (*int64*) – Argument.

Return type
float32

numba.cuda.libdevice.**ull2float_rz**(*l*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ull2float_rz.html

Parameters
l (*int64*) – Argument.

Return type
float32

numba.cuda.libdevice.**ullmax**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ullmax.html

Parameters

- **x** (*int64*) – Argument.
- **y** (*int64*) – Argument.

Return type
int64

numba.cuda.libdevice.**ullmin**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ullmin.html

Parameters

- **x** (*int64*) – Argument.
- **y** (*int64*) – Argument.

Return type
int64

numba.cuda.libdevice.**umax**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_umax.html

Parameters

- **x** (*int32*) – Argument.
- **y** (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**umin**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_umin.html

Parameters

- **x** (*int32*) – Argument.
- **y** (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**umul24**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_umul24.html

Parameters

- **x** (*int32*) – Argument.
- **y** (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**umul64hi**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_umul64hi.html

Parameters

- **x** (*int64*) – Argument.
- **y** (*int64*) – Argument.

Return type
int64

numba.cuda.libdevice.**umulhi**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_umulhi.html

Parameters

- **x** (*int32*) – Argument.
- **y** (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**urhadd**(*x*, *y*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_urhadd.html

Parameters

- **x** (*int32*) – Argument.
- **y** (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**usad**(*x*, *y*, *z*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_usad.html

Parameters

- **x** (*int32*) – Argument.
- **y** (*int32*) – Argument.
- **z** (*int32*) – Argument.

Return type
int32

numba.cuda.libdevice.**y0**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_y0.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**y0f**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_y0f.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**y1**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_y1.html

Parameters
x (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**y1f**(*x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_y1f.html

Parameters
x (*float32*) – Argument.

Return type
float32

numba.cuda.libdevice.**yn**(*n*, *x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_yn.html

Parameters

- **n** (*int32*) – Argument.
- **x** (*float64*) – Argument.

Return type
float64

numba.cuda.libdevice.**ynf**(*n*, *x*)

See https://docs.nvidia.com/cuda/libdevice-users-guide/__nv_ynf.html

Parameters

- **n** (*int32*) – Argument.
- **x** (*float32*) – Argument.

Return type
float32

CHAPTER

FIVE

EXTENDING NUMBA

This chapter describes how to extend Numba to make it recognize and support additional operations, functions or types. Numba provides two categories of APIs to this end:

- The high-level APIs provide abstracted entry points which are sufficient for simple uses. They require little knowledge of Numba's internal compilation chain.
- The low-level APIs reflect Numba's internal compilation chain and allow flexible interaction with its various layers, but require more effort and experience with Numba internals.

It may be helpful for readers of this chapter to also read some of the documents in the *developer manual*, especially the *architecture document*.

5.1 High-level extension API

This extension API is exposed through the *numba.extending* module.

5.1.1 Implementing functions

The `@overload` decorator allows you to implement arbitrary functions for use in *nopython mode* functions. The function decorated with `@overload` is called at compile-time with the *types* of the function's runtime arguments. It should return a callable representing the *implementation* of the function for the given types. The returned implementation is compiled by Numba as if it were a normal function decorated with `@jit`. Additional options to `@jit` can be passed as dictionary using the `jit_options` argument.

For example, let's pretend Numba doesn't support the `len()` function on tuples yet. Here is how to implement it using `@overload`:

```
from numba import types
from numba.extending import overload

@overload(len)
def tuple_len(seq):
   if isinstance(seq, types.BaseTuple):
       n = len(seq)
       def len_impl(seq):
           return n
       return len_impl
```

You might wonder, what happens if `len()` is called with something else than a tuple? If a function decorated with `@overload` doesn't return anything (i.e. returns None), other definitions are tried until one succeeds. Therefore, multiple libraries may overload `len()` for different types without conflicting with each other.

5.1.2 Implementing methods

The `@overload_method` decorator similarly allows implementing a method on a type well-known to Numba.

`numba.core.extending.overload_method(typ, attr, **kwargs)`

A decorator marking the decorated function as typing and implementing method *attr* for the given Numba type in nopython mode.

kwargs are passed to the underlying *@overload* call.

Here is an example implementing .take() for array types:

```
@overload_method(types.Array, 'take')
def array_take(arr, indices):
    if isinstance(indices, types.Array):
        def take_impl(arr, indices):
            n = indices.shape[0]
            res = np.empty(n, arr.dtype)
            for i in range(n):
                res[i] = arr[indices[i]]
            return res
        return take_impl
```

5.1.3 Implementing classmethods

The `@overload_classmethod` decorator similarly allows implementing a classmethod on a type well-known to Numba.

`numba.core.extending.overload_classmethod(typ, attr, **kwargs)`

A decorator marking the decorated function as typing and implementing classmethod *attr* for the given Numba type in nopython mode.

Similar to `overload_method`.

Here is an example implementing a classmethod on the Array type to call `np.arange()`:

```
@overload_classmethod(types.Array, "make")
def ov_make(cls, nitems):
    def impl(cls, nitems):
        return np.arange(nitems)
    return impl
```

The above code will allow the following to work in jit-compiled code:

```
@njit
def foo(n):
    return types.Array.make(n)
```

5.1.4 Implementing attributes

The `@overload_attribute` decorator allows implementing a data attribute (or property) on a type. Only reading the attribute is possible; writable attributes are only supported through the *low-level API*.

The following example implements the `nbytes` attribute on Numpy arrays:

```
@overload_attribute(types.Array, 'nbytes')
def array_nbytes(arr):
   def get(arr):
       return arr.size * arr.itemsize
   return get
```

5.1.5 Importing Cython Functions

The function `get_cython_function_address` obtains the address of a C function in a Cython extension module. The address can be used to access the C function via a `ctypes.CFUNCTYPE()` callback, thus allowing use of the C function inside a Numba jitted function. For example, suppose that you have the file `foo.pyx`:

```
from libc.math cimport exp

cdef api double myexp(double x):
    return exp(x)
```

You can access `myexp` from Numba in the following way:

```
import ctypes
from numba.extending import get_cython_function_address

addr = get_cython_function_address("foo", "myexp")
functype = ctypes.CFUNCTYPE(ctypes.c_double, ctypes.c_double)
myexp = functype(addr)
```

The function `myexp` can now be used inside jitted functions, for example:

```
@njit
def double_myexp(x):
    return 2*myexp(x)
```

One caveat is that if your function uses Cython's fused types, then the function's name will be mangled. To find out the mangled name of your function you can check the extension module's `__pyx_capi__` attribute.

5.1.6 Implementing intrinsics

The `@intrinsic` decorator is used for marking a function *func* as typing and implementing the function in `nopython` mode using the llvmlite IRBuilder API. This is an escape hatch for expert users to build custom LLVM IR that will be inlined into the caller, there is no safety net!

The first argument to *func* is the typing context. The rest of the arguments corresponds to the type of arguments of the decorated function. These arguments are also used as the formal argument of the decorated function. If *func* has the signature `foo(typing_context, arg0, arg1)`, the decorated function will have the signature `foo(arg0, arg1)`.

The return values of *func* should be a 2-tuple of expected type signature, and a code-generation function that will passed to `lower_builtin()`. For an unsupported operation, return `None`.

Here is an example that cast any integer to a byte pointer:

```
from numba import types
from numba.extending import intrinsic

@intrinsic
def cast_int_to_byte_ptr(typingctx, src):
    # check for accepted types
    if isinstance(src, types.Integer):
        # create the expected type signature
        result_type = types.CPointer(types.uint8)
        sig = result_type(types.uintp)
        # defines the custom code generation
        def codegen(context, builder, signature, args):
            # llvm IRBuilder code here
            [src] = args
            rtype = signature.return_type
            llrtype = context.get_value_type(rtype)
            return builder.inttoptr(src, llrtype)
        return sig, codegen
```

it may be used as follows:

```
from numba import njit

@njit('void(int64)')
def foo(x):
    y = cast_int_to_byte_ptr(x)

foo.inspect_types()
```

and the output of `.inspect_types()` demonstrates the cast (note the `uint8*`):

```
def foo(x):

    #   x = arg(0, name=x)  :: int64
    #   $0.1 = global(cast_int_to_byte_ptr: <intrinsic cast_int_to_byte_ptr>)  ::␣
↪Function(<intrinsic cast_int_to_byte_ptr>)
    #   $0.3 = call $0.1(x, func=$0.1, args=[Var(x, check_intrin.py (24))], kws=(),␣
↪vararg=None)  :: (uint64,) -> uint8*
    #   del x
    #   del $0.1
    #   y = $0.3  :: uint8*
    #   del y
    #   del $0.3
    #   $const0.4 = const(NoneType, None)  :: none
    #   $0.5 = cast(value=$const0.4)  :: none
    #   del $const0.4
    #   return $0.5

    y = cast_int_to_byte_ptr(x)
```

5.1.7 Implementing mutable structures

Warning: This is an experimental feature, the API may change without warning.

The `numba.experimental.structref` module provides utilities for defining mutable pass-by-reference structures, a `StructRef`. The following example demonstrates how to define a basic mutable structure:

Defining a StructRef

Listing 1: from numba/tests/doc_examples/test_structref_usage.py

```
import numpy as np

from numba import njit
from numba.core import types
from numba.experimental import structref

from numba.tests.support import skip_unless_scipy


# Define a StructRef.
# `structref.register` associates the type with the default data model.
# This will also install getters and setters to the fields of
# the StructRef.
@structref.register
class MyStructType(types.StructRef):
    def preprocess_fields(self, fields):
        # This method is called by the type constructor for additional
        # preprocessing on the fields.
        # Here, we don't want the struct to take Literal types.
        return tuple((name, types.unliteral(typ)) for name, typ in fields)


# Define a Python type that can be use as a proxy to the StructRef
# allocated inside Numba. Users can construct the StructRef via
# the constructor for this type in python code and jit-code.
class MyStruct(structref.StructRefProxy):
    def __new__(cls, name, vector):
        # Overriding the __new__ method is optional, doing so
        # allows Python code to use keyword arguments,
        # or add other customized behavior.
        # The default __new__ takes `*args`.
        # IMPORTANT: Users should not override __init__.
        return structref.StructRefProxy.__new__(cls, name, vector)

    # By default, the proxy type does not reflect the attributes or
    # methods to the Python side. It is up to users to define
    # these. (This may be automated in the future.)

```

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```
    @property
    def name(self):
        # To access a field, we can define a function that simply
        # return the field in jit-code.
        # The definition of MyStruct_get_name is shown later.
        return MyStruct_get_name(self)

    @property
    def vector(self):
        # The definition of MyStruct_get_vector is shown later.
        return MyStruct_get_vector(self)


@njit
def MyStruct_get_name(self):
    # In jit-code, the StructRef's attribute is exposed via
    # structref.register
    return self.name


@njit
def MyStruct_get_vector(self):
    return self.vector


# This associates the proxy with MyStructType for the given set of
# fields. Notice how we are not constraining the type of each field.
# Field types remain generic.
structref.define_proxy(MyStruct, MyStructType, ["name", "vector"])
```

The following demonstrates using the above mutable struct definition:

Listing 2: from test_type_definition of numba/tests/doc_examples/test_structref_usage.py

```
# Let's test our new StructRef.

# Define one in Python
alice = MyStruct("Alice", vector=np.random.random(3))

# Define one in jit-code
@njit
def make_bob():
    bob = MyStruct("unnamed", vector=np.zeros(3))
    # Mutate the attributes
    bob.name = "Bob"
    bob.vector = np.random.random(3)
    return bob

bob = make_bob()

# Out: Alice: [0.5488135  0.71518937 0.60276338]
```

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```
print(f"{alice.name}: {alice.vector}")
# Out: Bob: [0.88325739 0.73527629 0.87746707]
print(f"{bob.name}: {bob.vector}")

# Define a jit function to operate on the structs.
@njit
def distance(a, b):
    return np.linalg.norm(a.vector - b.vector)

# Out: 0.4332647200356598
print(distance(alice, bob))
```

Defining a method on StructRef

Methods and attributes can be attached using `@overload_*` as shown in the previous sections.

The following demonstrates the use of `@overload_method` to insert a method for instances of `MyStructType`:

Listing 3: from `test_overload_method` of `numba/tests/doc_examples/test_structref_usage.py`

```
from numba.core.extending import overload_method
from numba.core.errors import TypingError

# Use @overload_method to add a method for
# MyStructType.distance(other)
# where *other* is an instance of MyStructType.
@overload_method(MyStructType, "distance")
def ol_distance(self, other):
    # Guard that *other* is an instance of MyStructType
    if not isinstance(other, MyStructType):
        raise TypingError(
            f"*other* must be a {MyStructType}; got {other}"
        )

    def impl(self, other):
        return np.linalg.norm(self.vector - other.vector)

    return impl

# Test
@njit
def test():
    alice = MyStruct("Alice", vector=np.random.random(3))
    bob = MyStruct("Bob", vector=np.random.random(3))
    # Use the method
    return alice.distance(bob)
```

numba.experimental.structref API Reference

Utilities for defining a mutable struct.

A mutable struct is passed by reference; hence, structref (a reference to a struct).

class numba.experimental.structref.**StructRefProxy**(**args*)

A PyObject proxy to the Numba allocated structref data structure.

Notes

- Subclasses should not define `__init__`.
- Subclasses can override `__new__`.

numba.experimental.structref.**define_attributes**(*struct_typeclass*)

Define attributes on *struct_typeclass*.

Defines both setters and getters in jit-code.

This is called directly in *register()*.

numba.experimental.structref.**define_boxing**(*struct_type*, *obj_class*)

Define the boxing & unboxing logic for *struct_type* to *obj_class*.

Defines both boxing and unboxing.

- boxing turns an instance of *struct_type* into a PyObject of *obj_class*
- unboxing turns an instance of *obj_class* into an instance of *struct_type* in jit-code.

Use this directly instead of *define_proxy()* when the user does not want any constructor to be defined.

numba.experimental.structref.**define_constructor**(*py_class*, *struct_typeclass*, *fields*)

Define the jit-code constructor for *struct_typeclass* using the Python type *py_class* and the required *fields*.

Use this instead of *define_proxy()* if the user does not want boxing logic defined.

numba.experimental.structref.**define_proxy**(*py_class*, *struct_typeclass*, *fields*)

Defines a PyObject proxy for a structref.

This makes *py_class* a valid constructor for creating a instance of *struct_typeclass* that contains the members as defined by *fields*.

Parameters

py_class
[type] The Python class for constructing an instance of *struct_typeclass*.

struct_typeclass
[numba.core.types.Type] The structref type class to bind to.

fields
[Sequence[str]] A sequence of field names.

Returns

None

numba.experimental.structref.**register**(*struct_type*)

Register a *numba.core.types.StructRef* for use in jit-code.

This defines the data-model for lowering an instance of *struct_type*. This defines attributes accessor and mutator for an instance of *struct_type*.

Parameters

struct_type
[type] A subclass of *numba.core.types.StructRef*.

Returns

struct_type
[type] Returns the input argument so this can act like a decorator.

Examples

```
class MyStruct(numba.core.types.StructRef):
    ...  # the simplest subclass can be empty

numba.experimental.structref.register(MyStruct)
```

5.1.8 Determining if a function is already wrapped by a `jit` family decorator

The following function is provided for this purpose.

extending.**is_jitted**()

Returns True if a function is wrapped by one of the Numba @jit decorators, for example: numba.jit, numba.njit

The purpose of this function is to provide a means to check if a function is already JIT decorated.

5.2 Low-level extension API

This extension API is available through the *numba.extending* module. It allows you to hook directly into the Numba compilation chain. As such, it distinguished between several compilation phases:

- The *typing* phase deduces the types of variables in a compiled function by looking at the operations performed.
- The *lowering* phase converts high-level Python operations into low-level LLVM code. This phase exploits the typing information derived by the typing phase.
- *Boxing* and *unboxing* convert Python objects into native values, and vice-versa. They occur at the boundaries of calling a Numba function from the Python interpreter.

5.2.1 Typing

Type inference – or simply *typing* – is the process of assigning Numba types to all values involved in a function, so as to enable efficient code generation. Broadly speaking, typing comes in two flavours: typing plain Python *values* (e.g. function arguments or global variables) and typing *operations* (or *functions*) on known value types.

`@typeof_impl.register(`*cls*`)`

Register the decorated function as typing Python values of class *cls*. The decorated function will be called with the signature `(val, c)` where *val* is the Python value being typed and *c* is a context object.

`@type_callable(`*func*`)`

Register the decorated function as typing the callable *func*. *func* can be either an actual Python callable or a string denoting a operation internally known to Numba (for example `'getitem'`). The decorated function is called with a single *context* argument and must return a typer function. The typer function should have the same signature as the function being typed, and it is called with the Numba *types* of the function arguments; it should return either the Numba type of the function's return value, or `None` if inference failed.

`as_numba_type.register(`*py_type*, *numba_type*`)`

Register that the Python type *py_type* corresponds with the Numba type *numba_type*. This can be used to register a new type or overwrite the existing default (e.g. to treat `float` as `numba.float32` instead of `numba.float64`).

This function can also be used as a decorator. It registers the decorated function as a type inference function used by `as_numba_type` when trying to infer the Numba type of a Python type. The decorated function is called with a single *py_type* argument and returns either a corresponding Numba type, or `None` if it cannot infer that *py_type*.

5.2.2 Lowering

The following decorators all take a type specification of some kind. A type specification is usually a type class (such as `types.Float`) or a specific type instance (such as `types.float64`). Some values have a special meaning:

- `types.Any` matches any type; this allows doing your own dispatching inside the implementation
- `types.VarArg(<some type>)` matches any number of arguments of the given type; it can only appear as the last type specification when describing a function's arguments.

A *context* argument in the following APIs is a target context providing various utility methods for code generation (such as creating a constant, converting from a type to another, looking up the implementation of a specific function, etc.). A *builder* argument is a `llvmlite.ir.IRBuilder` instance for the LLVM code being generated.

A *signature* is an object specifying the concrete type of an operation. The `args` attribute of the signature is a tuple of the argument types. The `return_type` attribute of the signature is the type that the operation should return.

Note: Numba always reasons on Numba types, but the values being passed around during lowering are LLVM values: they don't hold the required type information, which is why Numba types are passed explicitly too.

LLVM has its own, very low-level type system: you can access the LLVM type of a value by looking up its `.type` attribute.

Native operations

@lower_builtin(*func*, *typespec*, ...)

Register the decorated function as implementing the callable *func* for the arguments described by the given Numba *typespecs*. As with *type_callable()*, *func* can be either an actual Python callable or a string denoting a operation internally known to Numba (for example `'getitem'`).

The decorated function is called with four arguments `(context, builder, sig, args)`. `sig` is the concrete signature the callable is being invoked with. `args` is a tuple of the values of the arguments the callable is being invoked with; each value in `args` corresponds to a type in `sig.args`. The function must return a value compatible with the type `sig.return_type`.

@lower_getattr(*typespec*, *name*)

Register the decorated function as implementing the attribute *name* of the given *typespec*. The decorated function is called with four arguments `(context, builder, typ, value)`. *typ* is the concrete type the attribute is being looked up on. *value* is the value the attribute is being looked up on.

@lower_getattr_generic(*typespec*)

Register the decorated function as a fallback for attribute lookup on a given *typespec*. Any attribute that does not have a corresponding *lower_getattr()* declaration will go through *lower_getattr_generic()*. The decorated function is called with five arguments `(context, builder, typ, value, name)`. *typ* and *value* are as in *lower_getattr()*. *name* is the name of the attribute being looked up.

@lower_cast(*fromspec*, *tospec*)

Register the decorated function as converting from types described by *fromspec* to types described by *tospec*. The decorated function is called with five arguments `(context, builder, fromty, toty, value)`. *fromty* and *toty* are the concrete types being converted from and to, respectively. *value* is the value being converted. The function must return a value compatible with the type `toty`.

Constants

@lower_constant(*typespec*)

Register the decorated function as implementing the creation of constants for the Numba *typespec*. The decorated function is called with four arguments `(context, builder, ty, pyval)`. *ty* is the concrete type to create a constant for. *pyval* is the Python value to convert into a LLVM constant. The function must return a value compatible with the type `ty`.

Boxing and unboxing

In these functions, *c* is a convenience object with several attributes:

- its `context` attribute is a target context as above
- its `builder` attribute is a `llvmlite.ir.IRBuilder` as above
- its `pyapi` attribute is an object giving access to a subset of the Python interpreter's C API

An object, as opposed to a native value, is a `PyObject *` pointer. Such pointers can be produced or processed by the methods in the `pyapi` object.

@box(*typespec*)

Register the decorated function as boxing values matching the *typespec*. The decorated function is called with three arguments `(typ, val, c)`. *typ* is the concrete type being boxed. *val* is the value being boxed. The function should return a Python object, or NULL to signal an error.

@unbox(*typespec*)

Register the decorated function as unboxing values matching the *typespec*. The decorated function is called with three arguments `(typ, obj, c)`. *typ* is the concrete type being unboxed. *obj* is the Python object (a `PyObject *` pointer, in C terms) being unboxed. The function should return a `NativeValue` object giving the unboxing result value and an optional error bit.

5.3 Example: An Interval Type

In this example, we will extend the Numba frontend to add support for a user-defined class that it does not internally support. This will allow:

- Passing an instance of the class to a Numba function
- Accessing attributes of the class in a Numba function
- Constructing and returning a new instance of the class from a Numba function

(all the above in *nopython mode*)

We will mix APIs from the *high-level extension API* and the *low-level extension API*, depending on what is available for a given task.

The starting point for our example is the following pure Python class:

```
class Interval(object):
    """
    A half-open interval on the real number line.
    """
    def __init__(self, lo, hi):
        self.lo = lo
        self.hi = hi

    def __repr__(self):
        return 'Interval(%f, %f)' % (self.lo, self.hi)

    @property
    def width(self):
        return self.hi - self.lo
```

5.3.1 Extending the typing layer

Creating a new Numba type

As the `Interval` class is not known to Numba, we must create a new Numba type to represent instances of it. Numba does not deal with Python types directly: it has its own type system that allows a different level of granularity as well as various meta-information not available with regular Python types.

We first create a type class `IntervalType` and, since we don't need the type to be parametric, we instantiate a single type instance `interval_type`:

```
from numba import types

class IntervalType(types.Type):
    def __init__(self):
```

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```
        super(IntervalType, self).__init__(name='Interval')

interval_type = IntervalType()
```

Type inference for Python values

In itself, creating a Numba type doesn't do anything. We must teach Numba how to infer some Python values as instances of that type. In this example, it is trivial: any instance of the `Interval` class should be treated as belonging to the type `interval_type`:

```
from numba.extending import typeof_impl

@typeof_impl.register(Interval)
def typeof_index(val, c):
    return interval_type
```

Function arguments and global values will thusly be recognized as belonging to `interval_type` whenever they are instances of `Interval`.

Type inference for Python annotations

While `typeof` is used to infer the Numba type of Python objects, `as_numba_type` is used to infer the Numba type of Python types. For simple cases, we can simply register that the Python type `Interval` corresponds with the Numba type `interval_type`:

```
from numba.extending import as_numba_type

as_numba_type.register(Interval, interval_type)
```

Note that `as_numba_type` is only used to infer types from type annotations at compile time. The `typeof` registry above is used to infer the type of objects at runtime.

Type inference for operations

We want to be able to construct interval objects from Numba functions, so we must teach Numba to recognize the two-argument `Interval(lo, hi)` constructor. The arguments should be floating-point numbers:

```
from numba.extending import type_callable

@type_callable(Interval)
def type_interval(context):
    def typer(lo, hi):
        if isinstance(lo, types.Float) and isinstance(hi, types.Float):
            return interval_type
    return typer
```

The *`type_callable()`* decorator specifies that the decorated function should be invoked when running type inference for the given callable object (here the `Interval` class itself). The decorated function must simply return a typer function that will be called with the argument types. The reason for this seemingly convoluted setup is for the typer function to have *exactly* the same signature as the typed callable. This allows handling keyword arguments correctly.

The *context* argument received by the decorated function is useful in more sophisticated cases where computing the callable's return type requires resolving other types.

5.3.2 Extending the lowering layer

We have finished teaching Numba about our type inference additions. We must now teach Numba how to actually generate code and data for the new operations.

Defining the data model for native intervals

As a general rule, *nopython mode* does not work on Python objects as they are generated by the CPython interpreter. The representations used by the interpreter are far too inefficient for fast native code. Each type supported in *nopython mode* therefore has to define a tailored native representation, also called a *data model*.

A common case of data model is an immutable struct-like data model, that is akin to a C `struct`. Our interval datatype conveniently falls in that category, and here is a possible data model for it:

```
from numba.extending import models, register_model

@register_model(IntervalType)
class IntervalModel(models.StructModel):
    def __init__(self, dmm, fe_type):
        members = [('lo', types.float64),
                   ('hi', types.float64),]
        models.StructModel.__init__(self, dmm, fe_type, members)
```

This instructs Numba that values of type `IntervalType` (or any instance thereof) are represented as a structure of two fields `lo` and `hi`, each of them a double-precision floating-point number (`types.float64`).

Note: Mutable types need more sophisticated data models to be able to persist their values after modification. They typically cannot be stored and passed on the stack or in registers like immutable types do.

Exposing data model attributes

We want the data model attributes `lo` and `hi` to be exposed under the same names for use in Numba functions. Numba provides a convenience function to do exactly that:

```
from numba.extending import make_attribute_wrapper

make_attribute_wrapper(IntervalType, 'lo', 'lo')
make_attribute_wrapper(IntervalType, 'hi', 'hi')
```

This will expose the attributes in read-only mode. As mentioned above, writable attributes don't fit in this model.

Exposing a property

As the `width` property is computed rather than stored in the structure, we cannot simply expose it like we did for `lo` and `hi`. We have to re-implement it explicitly:

```
from numba.extending import overload_attribute

@overload_attribute(IntervalType, "width")
def get_width(interval):
    def getter(interval):
        return interval.hi - interval.lo
    return getter
```

You might ask why we didn't need to expose a type inference hook for this attribute? The answer is that `@overload_attribute` is part of the high-level API: it combines type inference and code generation in a single API.

Implementing the constructor

Now we want to implement the two-argument `Interval` constructor:

```
from numba.extending import lower_builtin
from numba.core import cgutils

@lower_builtin(Interval, types.Float, types.Float)
def impl_interval(context, builder, sig, args):
    typ = sig.return_type
    lo, hi = args
    interval = cgutils.create_struct_proxy(typ)(context, builder)
    interval.lo = lo
    interval.hi = hi
    return interval._getvalue()
```

There is a bit more going on here. `@lower_builtin` decorates the implementation of the given callable or operation (here the `Interval` constructor) for some specific argument types. This allows defining type-specific implementations of a given operation, which is important for heavily overloaded functions such as `len()`.

`types.Float` is the class of all floating-point types (`types.float64` is an instance of `types.Float`). It is generally more future-proof to match argument types on their class rather than on specific instances (however, when *returning* a type – chiefly during the type inference phase –, you must usually return a type instance).

`cgutils.create_struct_proxy()` and `interval._getvalue()` are a bit of boilerplate due to how Numba passes values around. Values are passed as instances of `llvmlite.ir.Value`, which can be too limited: LLVM structure values especially are quite low-level. A struct proxy is a temporary wrapper around a LLVM structure value allowing to easily get or set members of the structure. The `_getvalue()` call simply gets the LLVM value out of the wrapper.

Boxing and unboxing

If you try to use an `Interval` instance at this point, you'll certainly get the error *"cannot convert Interval to native value"*. This is because Numba doesn't yet know how to make a native interval value from a Python `Interval` instance. Let's teach it how to do it:

```
from numba.extending import unbox, NativeValue
from contextlib import ExitStack

@unbox(IntervalType)
def unbox_interval(typ, obj, c):
    """
    Convert a Interval object to a native interval structure.
    """
    is_error_ptr = cgutils.alloca_once_value(c.builder, cgutils.false_bit)
    interval = cgutils.create_struct_proxy(typ)(c.context, c.builder)

    with ExitStack() as stack:
        lo_obj = c.pyapi.object_getattr_string(obj, "lo")
        with cgutils.early_exit_if_null(c.builder, stack, lo_obj):
            c.builder.store(cgutils.true_bit, is_error_ptr)
        lo_native = c.unbox(types.float64, lo_obj)
        c.pyapi.decref(lo_obj)
        with cgutils.early_exit_if(c.builder, stack, lo_native.is_error):
            c.builder.store(cgutils.true_bit, is_error_ptr)

        hi_obj = c.pyapi.object_getattr_string(obj, "hi")
        with cgutils.early_exit_if_null(c.builder, stack, hi_obj):
            c.builder.store(cgutils.true_bit, is_error_ptr)
        hi_native = c.unbox(types.float64, hi_obj)
        c.pyapi.decref(hi_obj)
        with cgutils.early_exit_if(c.builder, stack, hi_native.is_error):
            c.builder.store(cgutils.true_bit, is_error_ptr)

        interval.lo = lo_native.value
        interval.hi = hi_native.value

    return NativeValue(interval._getvalue(), is_error=c.builder.load(is_error_ptr))
```

Unbox is the other name for "convert a Python object to a native value" (it fits the idea of a Python object as a sophisticated box containing a simple native value). The function returns a `NativeValue` object which gives its caller access to the computed native value, the error bit and possibly other information.

The snippet above makes abundant use of the `c.pyapi` object, which gives access to a subset of the Python interpreter's C API. Note the use of `early_exit_if_null` to detect and handle any errors that may have happened when unboxing the object (try passing `Interval('a', 'b')` for example).

We also want to do the reverse operation, called *boxing*, so as to return interval values from Numba functions:

```
from numba.extending import box

@box(IntervalType)
def box_interval(typ, val, c):
    """
    Convert a native interval structure to an Interval object.
```

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```
    """
    ret_ptr = cgutils.alloca_once(c.builder, c.pyapi.pyobj)
    fail_obj = c.pyapi.get_null_object()

    with ExitStack() as stack:
        interval = cgutils.create_struct_proxy(typ)(c.context, c.builder, value=val)
        lo_obj = c.box(types.float64, interval.lo)
        with cgutils.early_exit_if_null(c.builder, stack, lo_obj):
            c.builder.store(fail_obj, ret_ptr)

        hi_obj = c.box(types.float64, interval.hi)
        with cgutils.early_exit_if_null(c.builder, stack, hi_obj):
            c.pyapi.decref(lo_obj)
            c.builder.store(fail_obj, ret_ptr)

        class_obj = c.pyapi.unserialize(c.pyapi.serialize_object(Interval))
        with cgutils.early_exit_if_null(c.builder, stack, class_obj):
            c.pyapi.decref(lo_obj)
            c.pyapi.decref(hi_obj)
            c.builder.store(fail_obj, ret_ptr)

        # NOTE: The result of this call is not checked as the clean up
        # has to occur regardless of whether it is successful. If it
        # fails `res` is set to NULL and a Python exception is set.
        res = c.pyapi.call_function_objargs(class_obj, (lo_obj, hi_obj))
        c.pyapi.decref(lo_obj)
        c.pyapi.decref(hi_obj)
        c.pyapi.decref(class_obj)
        c.builder.store(res, ret_ptr)

    return c.builder.load(ret_ptr)
```

5.3.3 Using it

nopython mode functions are now able to make use of Interval objects and the various operations you have defined on them. You can try for example the following functions:

```
from numba import njit

@njit
def inside_interval(interval, x):
    return interval.lo <= x < interval.hi

@njit
def interval_width(interval):
    return interval.width

@njit
def sum_intervals(i, j):
    return Interval(i.lo + j.lo, i.hi + j.hi)
```

5.3.4 Conclusion

We have shown how to do the following tasks:

- Define a new Numba type class by subclassing the `Type` class
- Define a singleton Numba type instance for a non-parametric type
- Teach Numba how to infer the Numba type of Python values of a certain class, using `typeof_impl.register`
- Teach Numba how to infer the Numba type of the Python type itself, using `as_numba_type.register`
- Define the data model for a Numba type using `StructModel` and `register_model`
- Implementing a boxing function for a Numba type using the `@box` decorator
- Implementing an unboxing function for a Numba type using the `@unbox` decorator and the `NativeValue` class
- Type and implement a callable using the `@type_callable` and `@lower_builtin` decorators
- Expose a read-only structure attribute using the `make_attribute_wrapper` convenience function
- Implement a read-only property using the `@overload_attribute` decorator

5.4 A guide to using `@overload`

As mentioned in the *high-level extension API*, you can use the `@overload` decorator to create a Numba implementation of a function that can be used in *nopython mode* functions. A common use case is to re-implement NumPy functions so that they can be called in `@jit` decorated code. This section discusses how and when to use the `@overload` decorator and what contributing such a function to the Numba code base might entail. This should help you get started when needing to use the `@overload` decorator or when attempting to contribute new functions to Numba itself.

The `@overload` decorator and its variants are useful when you have a third-party library that you do not control and you wish to provide Numba compatible implementations for specific functions from that library.

5.4.1 Concrete Example

Let's assume that you are working on a minimization algorithm that makes use of `scipy.linalg.norm` to find different vector norms and the frobenius norm for matrices. You know that only integer and real numbers will be involved. (While this may sound like an artificial example, especially because a Numba implementation of `numpy.linalg.norm` exists, it is largely pedagogical and serves to illustrate how and when to use `@overload`).

The skeleton might look something like this:

```
def algorithm():
    # setup
    v = ...
    while True:
        # take a step
        d = scipy.linalg.norm(v)
        if d < tolerance:
            break
```

Now, let's further assume, that you have heard of Numba and you now wish to use it to accelerate your function. However, after adding the `jit(nopython=True)` decorator, Numba complains that `scipy.linalg.norm` isn't supported. From looking at the documentation, you realize that a norm is probably fairly easy to implement using NumPy. A good starting point is the following template.

```
# Declare that function `myfunc` is going to be overloaded (have a
# substitutable Numba implementation)
@overload(myfunc)
# Define the overload function with formal arguments
# these arguments must be matched in the inner function implementation
def jit_myfunc(arg0, arg1, arg2, ...):
    # This scope is for typing, access is available to the *type* of all
    # arguments. This information can be used to change the behaviour of the
    # implementing function and check that the types are actually supported
    # by the implementation.

    print(arg0) # this will show the Numba type of arg0

    # This is the definition of the function that implements the `myfunc` work.
    # It does whatever algorithm is needed to implement myfunc.
    def myfunc_impl(arg0, arg1, arg2, ...): # match arguments to jit_myfunc
        # < Implementation goes here >
        return # whatever needs to be returned by the algorithm

    # return the implementation
    return myfunc_impl
```

After some deliberation and tinkering, you end up with the following code:

```
import numpy as np
from numba import njit, types
from numba.extending import overload, register_jitable
from numba.core.errors import TypingError

import scipy.linalg


@register_jitable
def _oneD_norm_2(a):
    # re-usable implementation of the 2-norm
    val = np.abs(a)
    return np.sqrt(np.sum(val * val))


@overload(scipy.linalg.norm)
def jit_norm(a, ord=None):
    if isinstance(ord, types.Optional):
        ord = ord.type
    # Reject non integer, floating-point or None types for ord
    if not isinstance(ord, (types.Integer, types.Float, types.NoneType)):
        raise TypingError("'ord' must be either integer or floating-point")
    # Reject non-ndarray types
    if not isinstance(a, types.Array):
        raise TypingError("Only accepts NumPy ndarray")
    # Reject ndarrays with non integer or floating-point dtype
    if not isinstance(a.dtype, (types.Integer, types.Float)):
        raise TypingError("Only integer and floating point types accepted")
    # Reject ndarrays with unsupported dimensionality
```

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```
    if not (0 <= a.ndim <= 2):
        raise TypingError('3D and beyond are not allowed')
    # Implementation for scalars/0d-arrays
    elif a.ndim == 0:
        return a.item()
    # Implementation for vectors
    elif a.ndim == 1:
        def _oneD_norm_x(a, ord=None):
            if ord == 2 or ord is None:
                return _oneD_norm_2(a)
            elif ord == np.inf:
                return np.max(np.abs(a))
            elif ord == -np.inf:
                return np.min(np.abs(a))
            elif ord == 0:
                return np.sum(a != 0)
            elif ord == 1:
                return np.sum(np.abs(a))
            else:
                return np.sum(np.abs(a)**ord)**(1. / ord)
        return _oneD_norm_x
    # Implementation for matrices
    elif a.ndim == 2:
        def _two_D_norm_2(a, ord=None):
            return _oneD_norm_2(a.ravel())
        return _two_D_norm_2


if __name__ == "__main__":
    @njit
    def use(a, ord=None):
        # simple test function to check that the overload works
        return scipy.linalg.norm(a, ord)

    # spot check for vectors
    a = np.arange(10)
    print(use(a))
    print(scipy.linalg.norm(a))

    # spot check for matrices
    b = np.arange(9).reshape((3, 3))
    print(use(b))
    print(scipy.linalg.norm(b))
```

As you can see, the implementation only supports what you need right now:

- Only supports integer and floating-point types
- All vector norms
- Only the Frobenius norm for matrices
- Code sharing between vector and matrix implementations using `@register_jitable`.
- Norms are implemented using NumPy syntax. (This is possible because Numba is very aware of NumPy and

many functions are supported.)

So what actually happens here? The `overload` decorator registers a suitable implementation for `scipy.linalg.norm` in case a call to this is encountered in code that is being JIT-compiled, for example when you decorate your `algorithm` function with `@jit(nopython=True)`. In that case, the function `jit_norm` will be called with the currently encountered types and will then return either `_oneD_norm_x` in the vector case and `_two_D_norm_2`.

You can download the example code here: `mynorm.py`

5.4.2 Implementing `@overload` for NumPy functions

Numba supports NumPy through the provision of `@jit` compatible re-implementations of NumPy functions. In such cases `@overload` is a very convenient option for writing such implementations, however there are a few additional things to watch out for.

- The Numba implementation should match the NumPy implementation as closely as feasible with respect to accepted types, arguments, raised exceptions and algorithmic complexity (Big-O / Landau order).
- When implementing supported argument types, bear in mind that, due to duck typing, NumPy does tend to accept a multitude of argument types beyond NumPy arrays such as scalar, list, tuple, set, iterator, generator etc. You will need to account for that during type inference and subsequently as part of the tests.
- A NumPy function may return a scalar, array or a data structure which matches one of its inputs, you need to be aware of type unification problems and dispatch to appropriate implementations. For example, `np.corrcoef` may return an array or a scalar depending on its inputs.
- If you are implementing a new function, you should always update the documentation. The sources can be found in `docs/source/reference/numpysupported.rst`. Be sure to mention any limitations that your implementation has, e.g. no support for the `axis` keyword.
- When writing tests for the functionality itself, it's useful to include handling of non-finite values, arrays with different shapes and layouts, complex inputs, scalar inputs, inputs with types for which support is not documented (e.g. a function which the NumPy docs say requires a float or int input might also 'work' if given a bool or complex input).
- When writing tests for exceptions, for example if adding tests to `numba/tests/test_np_functions.py`, you may encounter the following error message:

```
======================================================================
FAIL: test_foo (numba.tests.test_np_functions.TestNPFunctions)
----------------------------------------------------------------------
Traceback (most recent call last):
File "<path>/numba/numba/tests/support.py", line 645, in tearDown
    self.memory_leak_teardown()
File "<path>/numba/numba/tests/support.py", line 619, in memory_leak_teardown
    self.assert_no_memory_leak()
File "<path>/numba/numba/tests/support.py", line 628, in assert_no_memory_leak
    self.assertEqual(total_alloc, total_free)
AssertionError: 36 != 35
```

  This occurs because raising exceptions from jitted code leads to reference leaks. Ideally, you will place all exception testing in a separate test method and then add a call in each test to `self.disable_leak_check()` to disable the leak-check (inherit from `numba.tests.support.TestCase` to make that available).
- For many of the functions that are available in NumPy, there are corresponding methods defined on the NumPy `ndarray` type. For example, the function `repeat` is available as a NumPy module level function and a member function on the `ndarray` class.

```
import numpy as np
a = np.arange(10)
# function
np.repeat(a, 10)
# method
a.repeat(10)
```

Once you have written the function implementation, you can easily use `@overload_method` and reuse it. Just be sure to check that NumPy doesn't diverge in the implementations of its function/method.

As an example, the `repeat` function/method:

```
@extending.overload_method(types.Array, 'repeat')
def array_repeat(a, repeats):
    def array_repeat_impl(a, repeat):
        # np.repeat has already been overloaded
        return np.repeat(a, repeat)

    return array_repeat_impl
```

- If you need to create ancillary functions, for example to re-use a small utility function or to split your implementation across functions for the sake of readability, you can make use of the `@register_jitable` decorator. This will make those functions available from within your `@jit` and `@overload` decorated functions.
- The Numba continuous integration (CI) set up tests a wide variety of NumPy versions, you'll sometimes be alerted to a change in behaviour from some previous NumPy version. If you can find supporting evidence in the NumPy change log / repository, then you'll need to decide whether to create branches and attempt to replicate the logic across versions, or use a version gate (with associated wording in the documentation) to advertise that Numba replicates NumPy from some particular version onwards.
- You can look at the Numba source code for inspiration, many of the overloaded NumPy functions and methods are in `numba/targets/arrayobj.py`. Below, you will find a list of implementations to look at that are well implemented in terms of accepted types and test coverage.
  - `np.repeat`

5.5 Registering Extensions with Entry Points

Often, third party packages will have a user-facing API as well as define extensions to the Numba compiler. In those situations, the new types and overloads can registered with Numba when the package is imported by the user. However, there are situations where a Numba extension would not normally be imported directly by the user, but must still be registered with the Numba compiler. An example of this is the numba-scipy package, which adds support for some SciPy functions to Numba. The end user does not need to `import numba_scipy` to enable compiler support for SciPy, the extension only needs to be installed in the Python environment.

Numba discovers extensions using the entry points feature of `setuptools`. This allows a Python package to register an initializer function that will be called before `numba` compiles for the first time. The delay ensures that the cost of importing extensions is deferred until it is necessary.

5.5.1 Adding Support for the "Init" Entry Point

A package can register an initialization function with Numba by adding the `entry_points` argument to the `setup()` function call in `setup.py`:

```
setup(
    ...,
    entry_points={
        "numba_extensions": [
            "init = numba_scipy:_init_extension",
        ],
    },
    ...
)
```

Numba currently only looks for the `init` entry point in the `numba_extensions` group. The entry point should be a function (any name, as long as it matches what is listed in `setup.py`) that takes no arguments, and the return value is ignored. This function should register types, overloads, or call other Numba extension APIs. The order of initialization of extensions is undefined.

5.5.2 Testing your Entry Point

Numba loads all entry points when the first function is compiled. To test your entry point, it is not sufficient to just `import numba`; you have to define and run a small function, like this:

```
import numba; numba.njit(lambda x: x + 1)(123)
```

It is not necessary to import your module: entry points are identified by the `entry_points.txt` file in your library's `*.egg-info` directory.

The `setup.py build` command does not create eggs, but `setup.py sdist` (for testing in a local directory) and `setup.py install` do. All entry points registered in eggs that are on the Python path are loaded. Be sure to check for stale `entry_points.txt` when debugging.

CHAPTER

SIX

DEVELOPER MANUAL

6.1 Contributing to Numba

We welcome people who want to make contributions to Numba, big or small! Even simple documentation improvements are encouraged. If you have questions, don't hesitate to ask them (see below).

6.1.1 Communication

Real-time Chat

Numba uses Gitter for public real-time chat. To help improve the signal-to-noise ratio, we have two channels:

- numba/numba: General Numba discussion, questions, and debugging help.
- numba/numba-dev: Discussion of PRs, planning, release coordination, etc.

Both channels are public, but we may ask that discussions on numba-dev move to the numba channel. This is simply to ensure that numba-dev is easy for core developers to keep up with.

Note that the Github issue tracker is the best place to report bugs. Bug reports in chat are difficult to track and likely to be lost.

Forum

Numba uses Discourse as a forum for longer running threads such as design discussions and roadmap planning. There are various categories available and it can be reached at: numba.discourse.group.

Weekly Meetings

The core Numba developers have a weekly video conference to discuss roadmap, feature planning, and outstanding issues. These meetings are entirely public, details are posted on numba.discourse.group Announcements and everyone is welcome to join the discussion. Minutes will be taken and will be posted to the Numba wiki.

Bug tracker

We use the Github issue tracker to track both bug reports and feature requests. If you report an issue, please include specifics:

- what you are trying to do;
- which operating system you have and which version of Numba you are running;
- how Numba is misbehaving, e.g. the full error traceback, or the unexpected results you are getting;
- as far as possible, a code snippet that allows full reproduction of your problem.

6.1.2 Getting set up

If you want to contribute, we recommend you fork our Github repository, then create a branch representing your work. When your work is ready, you should submit it as a pull request from the Github interface.

If you want, you can submit a pull request even when you haven't finished working. This can be useful to gather feedback, or to stress your changes against the *continuous integration* platform. In this case, please prepend `[WIP]` to your pull request's title.

Build environment

Numba has a number of dependencies (mostly NumPy and llvmlite) with non-trivial build instructions. Unless you want to build those dependencies yourself, we recommend you use conda to create a dedicated development environment and install precompiled versions of those dependencies there. Read more about the Numba dependencies here: *numba-source-install-check*.

When working with a source checkout of Numba you will also need a development build of llvmlite. These are available from the `numba/label/dev` channel on anaconda.org.

To create an environment with the required dependencies, noting the use of the double-colon syntax (`numba/label/dev::llvmlite`) to install the latest development version of the llvmlite library:

```
$ conda create -n numbaenv python=3.10 numba/label/dev::llvmlite numpy scipy jinja2 cffi
```

Note: This installs an environment based on Python 3.10, but you can of course choose another version supported by Numba. To test additional features, you may also need to install `tbb` and/or `llvm-openmp`. Check the dependency list above for details.

To activate the environment for the current shell session:

```
$ conda activate numbaenv
```

Note: These instructions are for a standard Linux shell. You may need to adapt them for other platforms.

Once the environment is activated, you have a dedicated Python with the required dependencies:

```
$ python
Python 3.10.3 (main, Mar 28 2022, 04:26:28) [Clang 12.0.0 ] on darwin
Type "help", "copyright", "credits" or "license" for more information.
```

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```
>>> import llvmlite
>>> llvmlite.__version__
0.39.0dev0+61.gf27ac6f
```

Building Numba

For a convenient development workflow, we recommend you build Numba inside its source checkout:

```
$ git clone git@github.com:numba/numba.git
$ cd numba
$ python setup.py build_ext --inplace
```

This assumes you have a working C compiler and runtime on your development system. You will have to run this command again whenever you modify C files inside the Numba source tree.

The `build_ext` command in Numba's setup also accepts the following arguments:

- `--noopt`: This disables optimization when compiling Numba's CPython extensions, which makes debugging them much easier. Recommended in conjunction with the standard `build_ext` option `--debug`.
- `--werror`: Compiles Numba's CPython extensions with the `-Werror` flag.
- `--wall`: Compiles Numba's CPython extensions with the `-Wall` flag.

Note that Numba's CI and the conda recipe for Linux build with the `--werror` and `--wall` flags, so any contributions that change the CPython extensions should be tested with these flags too.

Running tests

Numba is validated using a test suite comprised of various kind of tests (unit tests, functional tests). The test suite is written using the standard `unittest` framework.

The tests can be executed via `python -m numba.runtests`. If you are running Numba from a source checkout, you can type `./runtests.py` as a shortcut. Various options are supported to influence test running and reporting. Pass `-h` or `--help` to get a glimpse at those options. Examples:

- to list all available tests:

  ```
  $ python -m numba.runtests -l
  ```

- to list tests from a specific (sub-)suite:

  ```
  $ python -m numba.runtests -l numba.tests.test_usecases
  ```

- to run those tests:

  ```
  $ python -m numba.runtests numba.tests.test_usecases
  ```

- to run all tests in parallel, using multiple sub-processes:

  ```
  $ python -m numba.runtests -m
  ```

- For a detailed list of all options:

```
$ python -m numba.runtests -h
```

The numba test suite can take a long time to complete. When you want to avoid the long wait, it is useful to focus on the failing tests first with the following test runner options:

- The `--failed-first` option is added to capture the list of failed tests and to re-execute them first:

```
$ python -m numba.runtests --failed-first -m -v -b
```

- The `--last-failed` option is used with `--failed-first` to execute the previously failed tests only:

```
$ python -m numba.runtests --last-failed -m -v -b
```

When debugging, it is useful to turn on logging. Numba logs using the standard `logging` module. One can use the standard ways (i.e. `logging.basicConfig`) to configure the logging behavior. To enable logging in the test runner, there is a `--log` flag for convenience:

```
$ python -m numba.runtests --log
```

To enable *runtime type-checking*, set the environment variable `NUMBA_USE_TYPEGUARD=1` and use *runtests.py* from the source root instead. For example:

```
$ NUMBA_USE_TYPEGUARD=1 python runtests.py
```

Running coverage

Coverage reports can be produced using coverage.py. To record coverage info for the test suite, run:

```
coverage run -m numba.runtests <runtests args>
```

Next, combine coverage files (potentially for multiple runs) with:

```
coverage combine
```

The combined output can be transformed into various report formats - see the coverage CLI usage reference. For example, to produce an HTML report, run:

```
coverage html
```

Following this command, the report can be viewed by opening `htmlcov/index.html`.

6.1.3 Development rules

Code reviews

Any non-trivial change should go through a code review by one or several of the core developers. The recommended process is to submit a pull request on github.

A code review should try to assess the following criteria:

- general design and correctness
- code structure and maintainability
- coding conventions

- docstrings, comments and release notes (if necessary)
- test coverage

Policy on large scale changes to code formatting

Please note that pull requests making large scale changes to format the code base are in general not accepted. Such changes often increase the likelihood of merge conflicts for other pull requests, which inevitably take time and resources to resolve. They also require a lot of effort to check as Numba aims to compile code that is valid even if it is not ideal. For example, in a test of `operator.eq`:

```
if x == None: # Valid code, even if the recommended form is `if x is None:`
```

This tests Numba's compilation of comparison with `None`, and therefore should not be changed, even though most style checkers will suggest it should.

This policy has been adopted by the core developers so as to try and make best use of limited resources. Whilst it would be great to have an extremely tidy code base, priority is given to fixes and features over code formatting changes.

Coding conventions

All Python code should follow **PEP 8**. Our C code doesn't have a well-defined coding style (would it be nice to follow **PEP 7**?). Code and documentation should generally fit within 80 columns, for maximum readability with all existing tools (such as code review UIs).

Numba uses Flake8 to ensure a consistent Python code format throughout the project. `flake8` can be installed with `pip` or `conda` and then run from the root of the Numba repository:

```
flake8 numba
```

Optionally, you may wish to setup pre-commit hooks to automatically run `flake8` when you make a git commit. This can be done by installing `pre-commit`:

```
pip install pre-commit
```

and then running:

```
pre-commit install
```

from the root of the Numba repository. Now `flake8` will be run each time you commit changes. You can skip this check with `git commit --no-verify`.

Numba has started the process of using type hints in its code base. This will be a gradual process of extending the number of files that use type hints, as well as going from voluntary to mandatory type hints for new features. Mypy is used for automated static checking.

At the moment, only certain files are checked by mypy. The list can be found in `mypy.ini`. When making changes to those files, it is necessary to add the required type hints such that mypy tests will pass. Only in exceptional circumstances should `type: ignore` comments be used.

If you are contributing a new feature, we encourage you to use type hints, even if the file is not currently in the checklist. If you want to contribute type hints to enable a new file to be in the checklist, please add the file to the `files` variable in `mypy.ini`, and decide what level of compliance you are targeting. Level 3 is basic static checks, while levels 2 and 1 represent stricter checking. The levels are described in details in `mypy.ini`.

There is potential for confusion between the Numba module `typing` and Python built-in module `typing` used for type hints, as well as between Numba types—such as `Dict` or `Literal`—and `typing` types of the same name. To mitigate

the risk of confusion we use a naming convention by which objects of the built-in `typing` module are imported with an `pt` prefix. For example, `typing.Dict` is imported as `from typing import Dict as ptDict`.

Release Notes

Pull Requests that add significant user-facing modifications may need to be mentioned in the release notes. To add a release note, a short `.rst` file needs creating containing a summary of the change and it needs to be placed in `docs/upcoming_changes`. The file `docs/upcoming_changes/README.rst` details the format and file naming conventions.

Stability

The repository's `main` branch is expected to be stable at all times. This translates into the fact that the test suite passes without errors on all supported platforms (see below). This also means that a pull request also needs to pass the test suite before it is merged in.

Platform support

Every commit to the main branch is automatically tested on all of the platforms Numba supports. This includes ARMv8, and NVIDIA GPUs. The build system however is internal to Anaconda, so we also use Azure to provide public continuous integration information for as many combinations as can be supported by the service. Azure CI automatically tests all pull requests on Windows, OS X and Linux, as well as a sampling of different Python and NumPy versions. If you see problems on platforms you are unfamiliar with, feel free to ask for help in your pull request. The Numba core developers can help diagnose cross-platform compatibility issues. Also see the *continuous integration* section on how public CI is implemented.

Continuous integration testing

The Numba test suite causes CI systems a lot of grief:

1. It's huge, 9000+ tests.
2. In part because of 1. and that compilers are pretty involved, the test suite takes a long time to run.
3. There's sections of the test suite that are deliberately designed to stress systems almost to the point of failure (tests which concurrently compile and execute with threads and fork processes etc).
4. The combination of things that Numba has to test well exceeds the capacity of any public CI system, (Python versions x NumPy versions x Operating systems x Architectures x feature libraries (e.g. SVML) x threading backends (e.g. OpenMP, TBB)) and then there's CUDA too and all its version variants.

As a result of the above, public CI is implemented as follows:

1. The combination of OS x Python x NumPy x Various Features in the testing matrix is designed to give a good indicative result for whether "this pull request is probably ok".
2. When public CI runs it:
    1. Looks for files that contain tests that have been altered by the proposed change and runs these on the whole testing matrix.
    2. Runs a subset of the test suite on each part of the testing matrix. i.e. slice the test suite up by the number of combinations in the testing matrix and each combination runs one chunk. This is done for speed, because public CI cannot cope with the load else.

If a Pull Request (PR) changes CUDA code or will affect the CUDA target, it needs to be run on gpuCI. This can be triggered by one of the Numba maintainers commenting `run gpuCI tests` on the PR discussion. This runs the CUDA testsuite with various CUDA toolkit versions on Linux, to provide some initial confidence in the correctness of the changes with respect to CUDA. Following approval, the PR will also be run on Numba's build farm to test other configurations with CUDA (including Windows, which is not tested by gpuCI).

If the PR is not CUDA-related but makes changes to something that the core developers consider risky, then it will also be run on the Numba farm just to make sure. The Numba project's private build and test farm will actually exercise all the applicable tests on all the combinations noted above on real hardware!

Type annotation and runtime type checking

Numba is slowly gaining type annotations. To facilitate the review of pull requests that are incrementally adding type annotations, the test suite uses typeguard to perform runtime type checking. This helps verify the validity of type annotations.

To enable runtime type checking in the test suite, users can use runtests.py in the source root as the test runner and set environment variable `NUMBA_USE_TYPEGUARD=1`. For example:

```
$ NUMBA_USE_TYPEGUARD=1 python runtests.py numba.tests
```

Things that help with pull requests

Even with the mitigating design above public CI can get overloaded which causes a backlog of builds. It's therefore really helpful when opening pull requests if you can limit the frequency of pushing changes. Ideally, please squash commits to reduce the number of patches and/or push as infrequently as possible. Also, once a pull request review has started, please don't rebase/force push/squash or do anything that rewrites history of the reviewed code as GitHub cannot track this and it makes it very hard for reviewers to see what has changed.

The core developers thank everyone for their cooperation with the above!

Why is my pull request/issue seemingly being ignored?

Numba is an open source project and like many similar projects it has limited resources. As a result, it is unfortunately necessary for the core developers to associate a priority with issues/pull requests (PR). A great way to move your issue/PR up the priority queue is to help out somewhere else in the project so as to free up core developer time. Examples of ways to help:

- Perform an initial review on a PR. This often doesn't require compiler engineering knowledge and just involves checking that the proposed patch is of good quality, fixes the problem/implements the feature, is well tested and documented.
- Debug an issue, there are numerous issues which "need triage" which essentially involves debugging the reported problem. Even if you cannot get right to the bottom of a problem, leaving notes about what was discovered for someone else is also helpful.
- Answer questions/provide help for users on discourse and/or gitter.im.

The core developers thank everyone for their understanding with the above!

6.1.4 Documentation

The Numba documentation is split over two repositories:

- This documentation is in the `docs` directory inside the Numba repository.
- The Numba homepage has its sources in a separate repository at https://github.com/numba/numba.github.com.

Main documentation

This documentation is under the `docs` directory of the Numba repository. It is built with Sphinx, numpydoc and the sphinx-rtd-theme.

To install all dependencies for building the documentation, use:

```
$ conda install sphinx numpydoc sphinx_rtd_theme
```

You can edit the source files under `docs/source/`, after which you can build and check the documentation under `docs/`:

```
$ make html
$ open _build/html/index.html
```

Web site homepage

The Numba homepage on https://numba.pydata.org can be fetched from here: https://github.com/numba/numba.github.com

6.2 Numba Release Process

The goal of the Numba release process – from a high level perspective – is to publish source and binary artifacts that correspond to a given version number. This usually involves a sequence of individual tasks that must be performed in the correct order and with diligence. Numba and llvmlite are commonly released in lockstep since there is usually a one-to-one mapping between a Numba version and a corresponding llvmlite version.

This section contains various notes and templates that can be used to create a Numba release checklist on the Numba Github issue tracker. This is an aid for the maintainers during the release process and helps to ensure that all tasks are completed in the correct order and that no tasks are accidentally omitted.

If new or additional items do appear during release, please do remember to add them to the checklist templates. Also note that the release process itself is always a work in progress. This means that some of the information here may be outdated. If you notice this please do remember to submit a pull-request to update this document.

All release checklists are available as Gitub issue templates. To create a new release checklist simply open a new issue and select the correct template.

6.2.1 Primary Release Candidate Checklist

This is for the first/primary release candidate for minor release i.e. the first release of every series. It is special, because during this release, the release branch will have to be created. Release candidate indexing begins at 1.

```
## Numba X.Y.Z

* [ ] Merge to main.
    - [ ] "remaining Pull-Requests from milestone".
* [ ] Check Numba's version support table documentation. Update via PR if
      needed.
* [ ] Review deprecation schedule and notices. Make PRs if need be. (Note that
  deprecation notices for features that have been removed are kept in the
  documentation for two more releases.)
* [ ] Create changelog using instructions at: `docs/source/developer/release.rst`
* [ ] Merge change log changes.
    - [ ] "PR with changelog entries".
* [ ] Create X.Y release branch.
* [ ] Create PR against the release branch to make `numba/testing/main.py`
      to refer to `origin/releaseX.Y` instead of `origin/main`.
* [ ] Dependency version pinning on release branch:
  * [ ] Pin llvmlite to `0.A.*`.
  * [ ] Pin NumPy if needed (see previous release for details).
    * [ ] `buildscripts/condarecipe.local/meta.yaml`
    * [ ] `numba/__init__.py`
    * [ ] `setup.py`
    * [ ] `docs/environment.yml`
  * [ ] Pin TBB if needed.
* [ ] Run the HEAD of the release branch through the build farm and confirm:
  * [ ] Build farm CPU testing has passed.
  * [ ] Build farm CUDA testing has passed.
  * [ ] Build farm wheel testing has passed.
* [ ] Annotated tag `X.Y.Zrc1` on release branch (no `v` prefix).
* [ ] Build and upload conda packages on buildfarm (check "upload").
* [ ] Build wheels and sdist on the buildfarm (check "upload").
* [ ] Verify packages uploaded to Anaconda Cloud and move to `numba/label/main`.
* [ ] Upload wheels and sdist to PyPI (upload from `ci_artifacts`).
* [ ] Verify wheels for all platforms arrived on PyPi.
* [ ] Initialize and verify ReadTheDocs build.
* [ ] Post announcement to discourse group and ping the release testers group
  using `@RC_Testers`.
* [ ] Post link to X and to Mastodon and...

### Post Release:

* [ ] Snapshot Build Farm config.
* [ ] Clean up `ci_artifacts` by moving files to sub-directories.
* [ ] Tag `X.Y+1.0dev0` to start new development cycle on `main`.
* [ ] Update llvmlite dependency via PR to `main`, PR includes version updates
      to:
  * [ ] `setup.py`
  * [ ] `numba/__init__.py`
  * [ ] `docs/environment.yml`
```

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```
  * [ ] `buildscripts/incremental/setup_conda_environment.sh`
  * [ ] `buildscripts/incremental/setup_conda_environment.cmd`
  * [ ] `buildscripts/condarecipe.local/meta.yaml`
* [ ] Update release checklist template with any additional bullet points that
      may have arisen during the release.
* [ ] Close milestone (and then close this release issue).
```

Open a primary release checklist.

6.2.2 Subsequent Release Candidates, Final Releases and Patch Releases

Releases subsequent to the first release in a series usually involves a series of cherry-picks, the recipe is therefore slightly different.

```
## numba X.Y.Z

* [ ] Cherry-pick items from the X.Y.Z milestone into a cherry-pick PR.
* [ ] Update the "version support table" in the documentation with the final
  release date (FINAL ONLY) and add to cherry-pick PR.
* [ ] Update `CHANGE_LOG` on cherry-pick PR.
* [ ] Check if any dependency pinnings need an update (e.g. NumPy).
* [ ] Approve cherry-pick PR.
* [ ] Merge cherry-pick PR to X.Y release branch.
  * [ ] https://github.com/numba/numba/pull/XXXX
* [ ] Run the HEAD of the release branch through the build farm and confirm:
  * [ ] Build farm CPU testing has passed.
  * [ ] Build farm CUDA testing has passed.
  * [ ] Build farm wheel testing has passed.
* [ ] Annotated tag X.Y.Z on release branch (no `v` prefix).
  `git tag -am "Version X.Y.Z" X.Y.Z`
* [ ] Build and upload conda packages on buildfarm (check `upload`).
* [ ] Build wheels and sdist on the buildfarm (check "upload").
* [ ] Verify packages uploaded to Anaconda Cloud and move to
  `numba/label/main`.
* [ ] Upload wheels and sdist to PyPI (upload from `ci_artifacts`).
* [ ] Verify wheels for all platforms arrived on PyPi.
* [ ] Verify ReadTheDocs build.
* [ ] Create a release on Github at https://github.com/numba/numba/releases (FINAL ONLY).
* [ ] Post link to X and to Mastodon and...
* [ ] Post announcement to discourse group and ping the release testers group
  using `@RC_Testers` (RC ONLY).
* [ ] Post link to python-announce-list@python.org.

### Post release

* [ ] Cherry-pick change-log and version support table modifications to `main`.
* [ ] Snapshot Build Farm config.
* [ ] Clean up `ci_artifacts` by moving files to subdirectories.
* [ ] Update release checklist template with any additional bullet points that
      may have arisen during the release.
* [ ] Ping Anaconda Distro team to trigger a build for `defaults` (FINAL ONLY).
* [ ] Close milestone (and then close this release issue).
```

Open a subsequent release checklist.

6.2.3 Generating Release Notes

The Numba release notes consist of two parts and there are two tools which need to be invoked.

- Release summary and overview of noteworthy items: use `towncrier`
- Pull-request and author list: use `maint/gitlog2changelog.py`

Using `towncrier`

Before each release, generate the changelog using Towncrier. This will collect all news fragments, combine them, and output the result to a single changelog file. During the changelog creation user is asked if the existing news fragments are to be deleted. In case of release notes generation, they are to be deleted so that they aren't accidentally included in post-release changelog creation.

towncrier build –version=0.xx.x

Using `maint/gitlog2changelog.py`

The script `maint/gitlog2changelog.py` is used to generate the list of pull-requests and authors. To prepare to use it:

- Install dependencies: `conda install docopt pygithub gitpython`.
- Generate a fine-grained Personal Access Token on Github with read access to public repositories. This can be done in Github Personal Access Tokens settings.
- Establish the base commit for the changelog. There are two known approaches here:
  - Finding a base-commit using `git`. This is the common commit between `main` and the last release branch, which can be determined by running `git merge-base main <branch>`. For example, `branch` may be `release0.58` if generating the release notes for the 0.59 release.
  - Using the development commit for the release. For example for the *0.59.0rc1* release this would be *0.59.0dev0*.

The script can then be invoked in the root of the repository with:

```
python maint/gitlog2changelog.py --token="<token>" --beginning="<base commit>" \
                                 --repo="numba/numba" --digits=4
```

This uses the token and commit established above. The `--digits` arguments specifies the number of digits in pull request numbers - this is presently 4 but will roll over to 5 soon after the time of writing - when that happens, it will be necessary to run the script twice, once with `--digits=4` and once with `--digits=5` and combine the results.

The script should output the release notes in a form that can be pasted into the top of the `CHANGE_LOG` file in the repo root. Truncated example output looks like:

```
Pull-Requests:

* PR `#8990 <https://github.com/numba/numba/pull/8990>`_: Removed extra block copying in␣
↪InlineWorker (`kc611 <https://github.com/kc611>`_)
* PR `#9048 <https://github.com/numba/numba/pull/9048>`_: Dynamically allocate parfor␣
↪schedule. (`DrTodd13 <https://github.com/DrTodd13>`_)
```

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```
<... some output omitted ...>

Authors:

* `apmasell <https://github.com/apmasell>`_
* `DrTodd13 <https://github.com/DrTodd13>`_

<... some output omitted ...>
```

Note that, the list may contain duplicates and thus you need to manually check and eliminate these duplictes! The duplicates are commonly the result of pull-requests that have been commited to the *main* branch and have then been cherry picked to a *release* branch. This can happen when issues are fixed for release candidates or when resolved issues are backported for patch releases.

Note also, that you must manually add the pull-request for the changelog itself once it has been opened. This must be done after opening the pull-request itself, since the link and number for the pull-request will not exists beforehand.

6.3 A Map of the Numba Repository

The Numba repository is quite large, and due to age has functionality spread around many locations. To help orient developers, this document will try to summarize where different categories of functionality can be found.

6.3.1 Support Files

Build and Packaging

- setup.py - Standard Python distutils/setuptools script
- MANIFEST.in - Distutils packaging instructions
- requirements.txt - Pip package requirements, not used by conda
- versioneer.py - Handles automatic setting of version in installed package from git tags
- .flake8 - Preferences for code formatting. Files should be fixed and removed from the exception list as time allows.
- .pre-commit-config.yaml - Configuration file for pre-commit hooks.
- .readthedocs.yml - Configuration file for Read the Docs.
- buildscripts/condarecipe.local - Conda build recipe

Continuous Integration

- azure-pipelines.yml - Azure Pipelines CI config (active: Win/Mac/Linux)
- buildscripts/azure/ - Azure Pipeline configuration for specific platforms
- buildscripts/incremental/ - Generic scripts for building Numba on various CI systems
- codecov.yml - Codecov.io coverage reporting

Documentation

- LICENSE - License for Numba
- LICENSES.third-party - License for third party code vendored into Numba
- README.rst - README for repo, also uploaded to PyPI
- CONTRIBUTING.md - Documentation on how to contribute to project (out of date, should be updated to point to Sphinx docs)
- CHANGE_LOG - History of Numba releases, also directly embedded into Sphinx documentation
- docs/ - Documentation source
- docs/_templates/ - Directory for templates (to override defaults with Sphinx theme)
- docs/Makefile - Used to build Sphinx docs with `make`
- docs/source - ReST source for Numba documentation
- docs/_static/ - Static CSS and image assets for Numba docs
- docs/make.bat - Not used (remove?)
- numba/scripts/generate_lower_listing.py - Dump all registered implementations decorated with `@lower*` for reference documentation. Currently misses implementations from the higher level extension API.

6.3.2 Numba Source Code

Numba ships with both the source code and tests in one package.

- numba/ - all of the source code and tests

Public API

These define aspects of the public Numba interface.

- numba/core/decorators.py - User-facing decorators for compiling regular functions on the CPU
- numba/core/extending.py - Public decorators for extending Numba (`overload`, `intrinsic`, etc) - numba/experimental/structref.py - Public API for defining a mutable struct
- numba/core/ccallback.py - `@cfunc` decorator for compiling functions to a fixed C signature. Used to make callbacks.
- numba/np/ufunc/decorators.py - ufunc/gufunc compilation decorators
- numba/core/config.py - Numba global config options and environment variable handling
- numba/core/annotations - Gathering and printing type annotations of Numba IR

- numba/core/annotations/pretty_annotate.py - Code highlighting of Numba functions and types (both ANSI terminal and HTML)
- numba/core/event.py - A simple event system for applications to listen to specific compiler events.

Dispatching

- numba/core/dispatcher.py - Dispatcher objects are compiled functions produced by `@jit`. A dispatcher has different implementations for different type signatures.
- numba/_dispatcher.cpp - C++ dispatcher implementation (for speed on common data types)

Compiler Pipeline

- numba/core/compiler.py - Compiler pipelines and flags
- numba/core/errors.py - Numba exception and warning classes
- numba/core/ir.py - Numba IR data structure objects
- numba/core/bytecode.py - Bytecode parsing and function identity (??)
- numba/core/interpreter.py - Translate Python interpreter bytecode to Numba IR
- numba/core/analysis.py - Utility functions to analyze Numba IR (variable lifetime, prune branches, etc)
- numba/core/controlflow.py - Control flow analysis of Numba IR and Python bytecode
- numba/core/typeinfer.py - Type inference algorithm
- numba/core/transforms.py - Numba IR transformations
- numba/core/rewrites - Rewrite passes used by compiler
- numba/core/rewrites/__init__.py - Loads all rewrite passes so they are put into the registry
- numba/core/rewrites/registry.py - Registry object for collecting rewrite passes
- numba/core/rewrites/ir_print.py - Write print() calls into special print nodes in the IR
- numba/core/rewrites/static_raise.py - Converts exceptions with static arguments into a special form that can be lowered
- numba/core/rewrites/static_getitem.py - Rewrites getitem and setitem with constant arguments to allow type inference
- numba/core/rewrites/static_binop.py - Rewrites binary operations (specifically **) with constant arguments so faster code can be generated
- numba/core/inline_closurecall.py - Inlines body of closure functions to call site. Support for array comprehensions, reduction inlining, and stencil inlining.
- numba/core/postproc.py - Postprocessor for Numba IR that computes variable lifetime, inserts del operations, and handles generators
- numba/core/lowering.py - General implementation of lowering Numba IR to LLVM numba/core/environment.py - Runtime environment object
- numba/core/withcontexts.py - General scaffolding for implementing context managers in nopython mode, and the objectmode context manager
- numba/core/pylowering.py - Lowering of Numba IR in object mode
- numba/core/pythonapi.py - LLVM IR code generation to interface with CPython API

- numba/core/targetconfig.py - Utils for target configurations such as compiler flags.

Type Management

- numba/core/typeconv/ - Implementation of type casting and type signature matching in both C++ and Python
- numba/capsulethunk.h - Used by typeconv
- numba/core/types/ - definition of the Numba type hierarchy, used everywhere in compiler to select implementations
- numba/core/consts.py - Constant inference (used to make constant values available during codegen when possible)
- numba/core/datamodel - LLVM IR representations of data types in different contexts
- numba/core/datamodel/models.py - Models for most standard types
- numba/core/datamodel/registry.py - Decorator to register new data models
- numba/core/datamodel/packer.py - Pack typed values into a data structure
- numba/core/datamodel/testing.py - Data model tests (this should move??)
- numba/core/datamodel/manager.py - Map types to data models

Compiled Extensions

Numba uses a small amount of compiled C/C++ code for core functionality, like dispatching and type matching where performance matters, and it is more convenient to encapsulate direct interaction with CPython APIs.

- numba/_arraystruct.h - Struct for holding NumPy array attributes. Used in helperlib and the Numba Runtime.
- numba/_helperlib.c - C functions required by Numba compiled code at runtime. Linked into ahead-of-time compiled modules
- numba/_helpermod.c - Python extension module with pointers to functions from `_helperlib.c`
- numba/_dynfuncmod.c - Python extension module exporting _dynfunc.c functionality
- numba/_dynfunc.c - C level Environment and Closure objects (keep in sync with numba/target/base.py)
- numba/mathnames.h - Macros for defining names of math functions
- numba/_pymodule.h - C macros for Python 2/3 portable naming of C API functions
- numba/mviewbuf.c - Handles Python memoryviews
- numba/_typeof.h | numba/_typeof.cpp - C++ implementation of type fingerprinting, used by dispatcher
- numba/_numba_common.h - Portable C macro for marking symbols that can be shared between object files, but not outside the library.

Misc Support

- numba/_version.py - Updated by versioneer
- numba/core/runtime - Language runtime. Currently manages reference-counted memory allocated on the heap by Numba-compiled functions
- numba/core/ir_utils.py - Utility functions for working with Numba IR data structures
- numba/core/cgutils.py - Utility functions for generating common code patterns in LLVM IR
- numba/core/utils.py - Python 2 backports of Python 3 functionality (also imports local copy of `six`)
- numba/misc/appdirs.py - Vendored package for determining application config directories on every platform
- numba/misc/POST.py - A power-on-self-test script Numba uses in CI to make sure the test runner and compilation is working.
- numba/core/compiler_lock.py - Global compiler lock because Numba's usage of LLVM is not thread-safe
- numba/misc/special.py - Python stub implementations of special Numba functions (prange, gdb*)
- numba/core/itanium_mangler.py - Python implementation of Itanium C++ name mangling
- numba/misc/findlib.py - Helper function for locating shared libraries on all platforms
- numba/core/debuginfo.py - Helper functions to construct LLVM IR debug info
- numba/core/unsafe/refcount.py - Read reference count of object
- numba/core/unsafe/eh.py - Exception handling helpers
- numba/core/unsafe/nrt.py - Numba runtime (NRT) helpers
- numba/cpython/unsafe/tuple.py - Replace a value in a tuple slot
- numba/np/unsafe/ndarray.py - NumPy array helpers
- numba/core/unsafe/bytes.py - Copying and dereferencing data from void pointers
- numba/core/callwrapper.py - Handles argument unboxing and releasing the GIL when moving from Python to nopython mode
- numba/np/numpy_support.py - Helper functions for working with NumPy and translating Numba types to and from NumPy dtypes.
- numba/core/tracing.py - Decorator for tracing Python calls and emitting log messages
- numba/core/funcdesc.py - Classes for describing function metadata (used in the compiler)
- numba/core/sigutils.py - Helper functions for parsing and normalizing Numba type signatures
- numba/core/serialize.py - Support for pickling compiled functions
- numba/core/caching.py - Disk cache for compiled functions
- numba/np/npdatetime.py - Helper functions for implementing NumPy datetime64 support
- numba/misc/llvm_pass_timings.py - Helper to record timings of LLVM passes.
- numba/cloudpickle - Vendored cloudpickle subpackage

Core Python Data Types

- numba/_hashtable.h | numba/_hashtable.cpp - Adaptation of the Python 3.7 hash table implementation
- numba/cext/dictobject.h | numba/cext/dictobject.c - C level implementation of typed dictionary
- numba/typed/dictobject.py - Nopython mode wrapper for typed dictionary
- numba/cext/listobject.h | numba/cext/listobject.c - C level implementation of typed list
- numba/typed/listobject.py - Nopython mode wrapper for typed list
- numba/typed/typedobjectutils.py - Common utilities for typed dictionary and list
- numba/cpython/unicode.py - Unicode strings (Python 3.5 and later)
- numba/typed - Python interfaces to statically typed containers
- numba/typed/typeddict.py - Python interface to typed dictionary
- numba/typed/typedlist.py - Python interface to typed list
- numba/experimental/jitclass - Implementation of experimental JIT compilation of Python classes
- numba/core/generators.py - Support for lowering Python generators

Math

- numba/_random.c - Reimplementation of NumPy / CPython random number generator
- numba/_lapack.c - Wrappers for calling BLAS and LAPACK functions (requires SciPy)

ParallelAccelerator

Code transformation passes that extract parallelizable code from a function and convert it into multithreaded gufunc calls.

- numba/parfors/parfor.py - General ParallelAccelerator
- numba/parfors/parfor_lowering.py - gufunc lowering for ParallelAccelerator
- numba/parfors/array_analysis.py - Array analysis passes used in ParallelAccelerator

Stencil

Implementation of `@stencil`:

- numba/stencils/stencil.py - Stencil function decorator (implemented without ParallelAccelerator)
- numba/stencils/stencilparfor.py - ParallelAccelerator implementation of stencil

Debugging Support

- numba/misc/gdb_hook.py - Hooks to jump into GDB from nopython mode
- numba/misc/cmdlang.gdb - Commands to setup GDB for setting explicit breakpoints from Python

Type Signatures (CPU)

Some (usually older) Numba supported functionality separates the declaration of allowed type signatures from the definition of implementations. This package contains registries of type signatures that must be matched during type inference.

- numba/core/typing - Type signature module
- numba/core/typing/templates.py - Base classes for type signature templates
- numba/core/typing/cmathdecl.py - Python complex math (`cmath`) module
- numba/core/typing/bufproto.py - Interpreting objects supporting the buffer protocol
- numba/core/typing/mathdecl.py - Python `math` module
- numba/core/typing/listdecl.py - Python lists
- numba/core/typing/builtins.py - Python builtin global functions and operators
- numba/core/typing/setdecl.py - Python sets
- numba/core/typing/npydecl.py - NumPy ndarray (and operators), NumPy functions
- numba/core/typing/arraydecl.py - Python `array` module
- numba/core/typing/context.py - Implementation of typing context (class that collects methods used in type inference)
- numba/core/typing/collections.py - Generic container operations and namedtuples
- numba/core/typing/ctypes_utils.py - Typing ctypes-wrapped function pointers
- numba/core/typing/enumdecl.py - Enum types
- numba/core/typing/cffi_utils.py - Typing of CFFI objects
- numba/core/typing/typeof.py - Implementation of typeof operations (maps Python object to Numba type)
- numba/core/typing/asnumbatype.py - Implementation of `as_numba_type` operations (maps Python types to Numba type)
- numba/core/typing/npdatetime.py - Datetime dtype support for NumPy arrays

Target Implementations (CPU)

Implementations of Python / NumPy functions and some data models. These modules are responsible for generating LLVM IR during lowering. Note that some of these modules do not have counterparts in the typing package because newer Numba extension APIs (like overload) allow typing and implementation to be specified together.

- numba/core/cpu.py - Context for code gen on CPU
- numba/core/base.py - Base class for all target contexts
- numba/core/codegen.py - Driver for code generation
- numba/core/boxing.py - Boxing and unboxing for most data types

- numba/core/intrinsics.py - Utilities for converting LLVM intrinsics to other math calls
- numba/core/callconv.py - Implements different calling conventions for Numba-compiled functions
- numba/core/options.py - Container for options that control lowering
- numba/core/optional.py - Special type representing value or `None`
- numba/core/registry.py - Registry object for collecting implementations for a specific target
- numba/core/imputils.py - Helper functions for lowering
- numba/core/externals.py - Registers external C functions needed to link generated code
- numba/core/fastmathpass.py - Rewrite pass to add fastmath attributes to function call sites and binary operations
- numba/core/removerefctpass.py - Rewrite pass to remove unnecessary incref/decref pairs
- numba/core/descriptors.py - empty base class for all target descriptors (is this needed?)
- numba/cpython/builtins.py - Python builtin functions and operators
- numba/cpython/cmathimpl.py - Python complex math module
- numba/cpython/enumimpl.py - Enum objects
- numba/cpython/hashing.py - Hashing algorithms
- numba/cpython/heapq.py - Python `heapq` module
- numba/cpython/iterators.py - Iterable data types and iterators
- numba/cpython/listobj.py - Python lists
- numba/cpython/mathimpl.py - Python `math` module
- numba/cpython/numbers.py - Numeric values (int, float, etc)
- numba/cpython/printimpl.py - Print function
- numba/cpython/randomimpl.py - Python and NumPy `random` modules
- numba/cpython/rangeobj.py - Python *range* objects
- numba/cpython/slicing.py - Slice objects, and index calculations used in slicing
- numba/cpython/setobj.py - Python set type
- numba/cpython/tupleobj.py - Tuples (statically typed as immutable struct)
- numba/misc/cffiimpl.py - CFFI functions
- numba/misc/quicksort.py - Quicksort implementation used with list and array objects
- numba/misc/mergesort.py - Mergesort implementation used with array objects
- numba/np/arraymath.py - Math operations on arrays (both Python and NumPy)
- numba/np/arrayobj.py - Array operations (both NumPy and buffer protocol)
- numba/np/linalg.py - NumPy linear algebra operations
- numba/np/npdatetime.py - NumPy datetime operations
- numba/np/npyfuncs.py - Kernels used in generating some NumPy ufuncs
- numba/np/npyimpl.py - Implementations of most NumPy ufuncs
- numba/np/polynomial/polynomial_functions.py - Implementations of NumPy `Polynomial` functions
- numba/np/polynomial/polynomial_core.py - Implementations of NumPy `Polynomial` class

- numba/np/ufunc_db.py - Big table mapping types to ufunc implementations

Ufunc Compiler and Runtime

- numba/np/ufunc - ufunc compiler implementation
- numba/np/ufunc/_internal.h | numba/np/ufunc/_internal.c - Python extension module with helper functions that use CPython & NumPy C API
- numba/np/ufunc/_ufunc.c - Used by *_internal.c*
- numba/np/ufunc/gufunc_scheduler.h | numba/np/ufunc/gufunc_scheduler.cpp - Schedule work chunks to threads
- numba/np/ufunc/dufunc.py - Special ufunc that can compile new implementations at call time
- numba/np/ufunc/ufuncbuilder.py - Top-level orchestration of ufunc/gufunc compiler pipeline
- numba/np/ufunc/sigparse.py - Parser for generalized ufunc indexing signatures
- numba/np/ufunc/parallel.py - Codegen for `parallel` target
- numba/np/ufunc/array_exprs.py - Rewrite pass for turning array expressions in regular functions into ufuncs
- numba/np/ufunc/wrappers.py - Wrap scalar function kernel with loops
- numba/np/ufunc/workqueue.h | numba/np/ufunc/workqueue.c - Threading backend based on pthreads/Windows threads and queues
- numba/np/ufunc/omppool.cpp - Threading backend based on OpenMP
- numba/np/ufunc/tbbpool.cpp - Threading backend based on TBB

Unit Tests (CPU)

CPU unit tests (GPU target unit tests listed in later sections

- runtests.py - Convenience script that launches test runner and turns on full compiler tracebacks
- .coveragerc - Coverage.py configuration
- numba/runtests.py - Entry point to unittest runner
- numba/testing/_runtests.py - Implementation of custom test runner command line interface
- numba/tests/test_* - Test cases
- numba/tests/*_usecases.py - Python functions compiled by some unit tests
- numba/tests/support.py - Helper functions for testing and special TestCase implementation
- numba/tests/dummy_module.py - Module used in `test_dispatcher.py`
- numba/tests/npyufunc - ufunc / gufunc compiler tests
- numba/testing - Support code for testing
- numba/testing/loader.py - Find tests on disk
- numba/testing/notebook.py - Support for testing notebooks
- numba/testing/main.py - Numba test runner

Command Line Utilities

- bin/numba - Command line stub, delegates to main in `numba_entry.py`
- numba/misc/numba_entry.py - Main function for `numba` command line tool
- numba/pycc - Ahead of time compilation of functions to shared library extension
- numba/pycc/__init__.py - Main function for `pycc` command line tool
- numba/pycc/cc.py - User-facing API for tagging functions to compile ahead of time
- numba/pycc/compiler.py - Compiler pipeline for creating standalone Python extension modules
- numba/pycc/llvm_types.py - Aliases to LLVM data types used by `compiler.py`
- numba/pycc/modulemixin.c - C file compiled into every compiled extension. Pulls in C source from Numba core that is needed to make extension standalone
- numba/pycc/platform.py - Portable interface to platform-specific compiler toolchains
- numba/pycc/decorators.py - Deprecated decorators for tagging functions to compile. Use `cc.py` instead.

CUDA GPU Target

Note that the CUDA target does reuse some parts of the CPU target.

- numba/cuda/ - The implementation of the CUDA (NVIDIA GPU) target and associated unit tests
- numba/cuda/decorators.py - Compiler decorators for CUDA kernels and device functions
- numba/cuda/deviceufunc.py - Custom ufunc dispatch for CUDA
- numba/cuda/dispatcher.py - Dispatcher for CUDA JIT functions
- numba/cuda/printimpl.py - Special implementation of device printing
- numba/cuda/libdevice.py - Registers libdevice functions
- numba/cuda/kernels/ - Custom kernels for reduction and transpose
- numba/cuda/device_init.py - Initializes the CUDA target when imported
- numba/cuda/compiler.py - Compiler pipeline for CUDA target
- numba/cuda/intrinsic_wrapper.py - CUDA device intrinsics (shuffle, ballot, etc)
- numba/cuda/initialize.py - Deferred initialization of the CUDA device and subsystem. Called only when user imports `numba.cuda`
- numba/cuda/simulator_init.py - Initializes the CUDA simulator subsystem (only when user requests it with env var)
- numba/cuda/random.py - Implementation of random number generator
- numba/cuda/api.py - User facing APIs imported into `numba.cuda.*`
- numba/cuda/stubs.py - Python placeholders for functions that only can be used in GPU device code
- numba/cuda/simulator/ - Simulate execution of CUDA kernels in Python interpreter
- numba/cuda/vectorizers.py - Subclasses of ufunc/gufunc compilers for CUDA
- numba/cuda/args.py - Management of kernel arguments, including host<->device transfers
- numba/cuda/target.py - Typing and target contexts for GPU
- numba/cuda/cudamath.py - Type signatures for math functions in CUDA Python

- numba/cuda/errors.py - Validation of kernel launch configuration
- numba/cuda/nvvmutils.py - Helper functions for generating NVVM-specific IR
- numba/cuda/testing.py - Support code for creating CUDA unit tests and capturing standard out
- numba/cuda/cudadecl.py - Type signatures of CUDA API (threadIdx, blockIdx, atomics) in Python on GPU
- numba/cuda/cudaimpl.py - Implementations of CUDA API functions on GPU
- numba/cuda/codegen.py - Code generator object for CUDA target
- numba/cuda/cudadrv/ - Wrapper around CUDA driver API
- numba/cuda/cudadrv/dummyarray.py - Used to hold array information on the host, but not the data.
- numba/cuda/tests/ - CUDA unit tests, skipped when CUDA is not detected
- numba/cuda/tests/cudasim/ - Tests of CUDA simulator
- numba/cuda/tests/nocuda/ - Tests for NVVM functionality when CUDA not present
- numba/cuda/tests/cudapy/ - Tests of compiling Python functions for GPU
- numba/cuda/tests/cudadrv/ - Tests of Python wrapper around CUDA API

6.4 Numba architecture

6.4.1 Introduction

Numba is a compiler for Python bytecode with optional type-specialization.

Suppose you enter a function like this into the standard Python interpreter (henceforward referred to as "CPython"):

```
def add(a, b):
    return a + b
```

The interpreter will immediately parse the function and convert it into a bytecode representation that describes how the CPython interpreter should execute the function at a low level. For the example above, it looks something like this:

```
>>> import dis
>>> dis.dis(add)
2           0 LOAD_FAST                0 (a)
            3 LOAD_FAST                1 (b)
            6 BINARY_ADD
            7 RETURN_VALUE
```

CPython uses a stack-based interpreter (much like an HP calculator), so the code first pushes two local variables onto the stack. The `BINARY_ADD` opcode pops the top two arguments off the stack and makes a Python C API function call that is equivalent to calling `a.__add__(b)`. The result is then pushed onto the top of the interpreter stack. Finally, the `RETURN_VALUE` opcode returns value on the top of the stack as the result of the function call.

Numba can take this bytecode and compile it to machine code that performs the same operations as the CPython interpreter, treating `a` and `b` as generic Python objects. The full semantics of Python are preserved, and the compiled function can be used with any kind of objects that have the add operator defined. When a Numba function is compiled this way, we say that it has been compiled in *object mode*, because the code still manipulates Python objects.

Numba code compiled in object mode is not much faster than executing the original Python function in the CPython interpreter. However, if we specialize the function to only run with certain data types, Numba can generate much shorter and more efficient code that manipulates the data natively without any calls into the Python C API. When code

has been compiled for specific data types so that the function body no longer relies on the Python runtime, we say the function has been compiled in *nopython mode*. Numeric code compiled in nopython mode can be hundreds of times faster than the original Python.

6.4.2 Compiler architecture

Like many compilers, Numba can be conceptually divided into a *frontend* and a *backend*.

The Numba *frontend* comprises the stages which analyze the Python bytecode, translate it to *Numba IR* and perform various transformations and analysis steps on the IR. One of the key steps is *type inference*. The frontend must succeed in typing all variables unambiguously in order for the backend to generate code in *nopython mode*, because the backend uses type information to match appropriate code generators with the values they operate on.

The Numba *backend* walks the Numba IR resulting from the frontend analyses and exploits the type information deduced by the type inference phase to produce the right LLVM code for each encountered operation. After LLVM code is produced, the LLVM library is asked to optimize it and generate native processor code for the final, native function.

There are other pieces besides the compiler frontend and backend, such as the caching machinery for JIT functions. Those pieces are not considered in this document.

6.4.3 Contexts

Numba is quite flexible, allowing it to generate code for different hardware architectures like CPUs and GPUs. In order to support these different applications, Numba uses a *typing context* and a *target context*.

A *typing context* is used in the compiler frontend to perform type inference on operations and values in the function. Similar typing contexts could be used for many architectures because for nearly all cases, typing inference is hardware-independent. However, Numba currently has a different typing context for each target.

A *target context* is used to generate the specific instruction sequence required to operate on the Numba types identified during type inference. Target contexts are architecture-specific and are flexible in defining the execution model and available Python APIs. For example, Numba has a "cpu" and a "cuda" context for those two kinds of architecture, and a "parallel" context which produces multithreaded CPU code.

6.4.4 Compiler stages

The *jit()* decorator in Numba ultimately calls `numba.compiler.compile_extra()` which compiles the Python function in a multi-stage process, described below.

Stage 1: Analyze bytecode

At the start of compilation, the function bytecode is passed to an instance of the Numba interpreter (`numba.interpreter`). The interpreter object analyzes the bytecode to find the control flow graph (`numba.controlflow`). The control flow graph (CFG) describes the ways that execution can move from one block to the next inside the function as a result of loops and branches.

The data flow analysis (`numba.dataflow`) takes the control flow graph and traces how values get pushed and popped off the Python interpreter stack for different code paths. This is important to understand the lifetimes of variables on the stack, which are needed in Stage 2.

If you set the environment variable `NUMBA_DUMP_CFG` to 1, Numba will dump the results of the control flow graph analysis to the screen. Our `add()` example is pretty boring, since there is only one statement block:

```
CFG adjacency lists:
{0: []}
CFG dominators:
{0: set([0])}
CFG post-dominators:
{0: set([0])}
CFG back edges: []
CFG loops:
{}
CFG node-to-loops:
{0: []}
```

A function with more complex flow control will have a more interesting control flow graph. This function:

```
def doloops(n):
    acc = 0
    for i in range(n):
        acc += 1
        if n == 10:
            break
    return acc
```

compiles to this bytecode:

```
 9           0 LOAD_CONST               1 (0)
             3 STORE_FAST               1 (acc)

10           6 SETUP_LOOP              46 (to 55)
             9 LOAD_GLOBAL              0 (range)
            12 LOAD_FAST                0 (n)
            15 CALL_FUNCTION            1
            18 GET_ITER
       >>   19 FOR_ITER                32 (to 54)
            22 STORE_FAST               2 (i)

11          25 LOAD_FAST                1 (acc)
            28 LOAD_CONST               2 (1)
            31 INPLACE_ADD
            32 STORE_FAST               1 (acc)

12          35 LOAD_FAST                0 (n)
            38 LOAD_CONST               3 (10)
            41 COMPARE_OP               2 (==)
            44 POP_JUMP_IF_FALSE       19

13          47 BREAK_LOOP
            48 JUMP_ABSOLUTE           19
            51 JUMP_ABSOLUTE           19
       >>   54 POP_BLOCK

14     >>   55 LOAD_FAST                1 (acc)
            58 RETURN_VALUE
```

The corresponding CFG for this bytecode is:

```
CFG adjacency lists:
{0: [6], 6: [19], 19: [54, 22], 22: [19, 47], 47: [55], 54: [55], 55: []}
CFG dominators:
{0: set([0]),
 6: set([0, 6]),
 19: set([0, 6, 19]),
 22: set([0, 6, 19, 22]),
 47: set([0, 6, 19, 22, 47]),
 54: set([0, 6, 19, 54]),
 55: set([0, 6, 19, 55])}
CFG post-dominators:
{0: set([0, 6, 19, 55]),
 6: set([6, 19, 55]),
 19: set([19, 55]),
 22: set([22, 55]),
 47: set([47, 55]),
 54: set([54, 55]),
 55: set([55])}
CFG back edges: [(22, 19)]
CFG loops:
{19: Loop(entries=set([6]), exits=set([54, 47]), header=19, body=set([19, 22]))}
CFG node-to-loops:
{0: [], 6: [], 19: [19], 22: [19], 47: [], 54: [], 55: []}
```

The numbers in the CFG refer to the bytecode offsets shown just to the left of the opcode names above.

Stage 2: Generate the Numba IR

Once the control flow and data analyses are complete, the Numba interpreter can step through the bytecode and translate it into an Numba-internal intermediate representation. This translation process changes the function from a stack machine representation (used by the Python interpreter) to a register machine representation (used by LLVM).

Although the IR is stored in memory as a tree of objects, it can be serialized to a string for debugging. If you set the environment variable `NUMBA_DUMP_IR` equal to 1, the Numba IR will be dumped to the screen. For the `add()` function described above, the Numba IR looks like:

```
label 0:
    a = arg(0, name=a)                       ['a']
    b = arg(1, name=b)                       ['b']
    $0.3 = a + b                             ['$0.3', 'a', 'b']
    del b                                    []
    del a                                    []
    $0.4 = cast(value=$0.3)                  ['$0.3', '$0.4']
    del $0.3                                 []
    return $0.4                              ['$0.4']
```

The `del` instructions are produced by *Live Variable Analysis*. Those instructions ensure references are not leaked. In *nopython mode*, some objects are tracked by the Numba runtime and some are not. For tracked objects, a dereference operation is emitted; otherwise, the instruction is an no-op. In *object mode* each variable contains an owned reference to a PyObject.

Stage 3: Rewrite untyped IR

Before running type inference, it may be desired to run certain transformations on the Numba IR. One such example is to detect `raise` statements which have an implicitly constant argument, so as to support them in *nopython mode*. Let's say you compile the following function with Numba:

```
def f(x):
   if x == 0:
      raise ValueError("x cannot be zero")
```

If you set the *NUMBA_DUMP_IR* environment variable to 1, you'll see the IR being rewritten before the type inference phase:

```
REWRITING:
    del $0.3                                  []
    $12.1 = global(ValueError: <class 'ValueError'>) ['$12.1']
    $const12.2 = const(str, x cannot be zero) ['$const12.2']
    $12.3 = call $12.1($const12.2)            ['$12.1', '$12.3', '$const12.2']
    del $const12.2                            []
    del $12.1                                 []
    raise $12.3                               ['$12.3']
----------------------------------------------------------------
    del $0.3                                  []
    $12.1 = global(ValueError: <class 'ValueError'>) ['$12.1']
    $const12.2 = const(str, x cannot be zero) ['$const12.2']
    $12.3 = call $12.1($const12.2)            ['$12.1', '$12.3', '$const12.2']
    del $const12.2                            []
    del $12.1                                 []
    raise <class 'ValueError'>('x cannot be zero') []
```

Stage 4: Infer types

Now that the Numba IR has been generated, type analysis can be performed. The types of the function arguments can be taken either from the explicit function signature given in the `@jit` decorator (such as `@jit('float64(float64, float64)')`), or they can be taken from the types of the actual function arguments if compilation is happening when the function is first called.

The type inference engine is found in `numba.typeinfer`. Its job is to assign a type to every intermediate variable in the Numba IR. The result of this pass can be seen by setting the *NUMBA_DUMP_ANNOTATION* environment variable to 1:

```
-----------------------------------ANNOTATION-----------------------------------
# File: archex.py
# --- LINE 4 ---

@jit(nopython=True)

# --- LINE 5 ---

def add(a, b):

    # --- LINE 6 ---
    # label 0
```

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```
    #   a = arg(0, name=a)  :: int64
    #   b = arg(1, name=b)  :: int64
    #   $0.3 = a + b  :: int64
    #   del b
    #   del a
    #   $0.4 = cast(value=$0.3)  :: int64
    #   del $0.3
    #   return $0.4

    return a + b
```

If type inference fails to find a consistent type assignment for all the intermediate variables, it will label every variable as type `pyobject` and fall back to object mode. Type inference can fail when unsupported Python types, language features, or functions are used in the function body.

Note: As of Numba 0.59, object mode fall back will only occur when *loop-lifting* is enabled.

Stage 5a: Rewrite typed IR

This pass's purpose is to perform any high-level optimizations that still require, or could at least benefit from, Numba IR type information.

One example of a problem domain that isn't as easily optimized once lowered is the domain of multidimensional array operations. When Numba lowers an array operation, Numba treats the operation like a full ufunc kernel. During lowering a single array operation, Numba generates an inline broadcasting loop that creates a new result array. Then Numba generates an application loop that applies the operator over the array inputs. Recognizing and rewriting these loops once they are lowered into LLVM is hard, if not impossible.

An example pair of optimizations in the domain of array operators is loop fusion and shortcut deforestation. When the optimizer recognizes that the output of one array operator is being fed into another array operator, and only to that array operator, it can fuse the two loops into a single loop. The optimizer can further eliminate the temporary array allocated for the initial operation by directly feeding the result of the first operation into the second, skipping the store and load to the intermediate array. This elimination is known as shortcut deforestation. Numba currently uses the rewrite pass to implement these array optimizations. For more information, please consult the "*Case study: Array Expressions*" subsection, later in this document.

One can see the result of rewriting by setting the *NUMBA_DUMP_IR* environment variable to a non-zero value (such as 1). The following example shows the output of the rewrite pass as it recognizes an array expression consisting of a multiply and add, and outputs a fused kernel as a special operator, `arrayexpr()`:

```
----------------------------------------------------------------------------
REWRITING:
a0 = arg(0, name=a0)                     ['a0']
a1 = arg(1, name=a1)                     ['a1']
a2 = arg(2, name=a2)                     ['a2']
$0.3 = a0 * a1                           ['$0.3', 'a0', 'a1']
del a1                                   []
del a0                                   []
$0.5 = $0.3 + a2                         ['$0.3', '$0.5', 'a2']
del a2                                   []
del $0.3                                 []
```

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```
$0.6 = cast(value=$0.5)                  ['$0.5', '$0.6']
del $0.5                                 []
return $0.6                              ['$0.6']
----------------------------------------------------------------
a0 = arg(0, name=a0)                     ['a0']
a1 = arg(1, name=a1)                     ['a1']
a2 = arg(2, name=a2)                     ['a2']
$0.5 = arrayexpr(ty=array(float64, 1d, C), expr=('+', [('*', [Var(a0, test.py (14)),␣
↪Var(a1, test.py (14))]), Var(a2, test.py (14))])) ['$0.5', 'a0', 'a1', 'a2']
del a0                                   []
del a1                                   []
del a2                                   []
$0.6 = cast(value=$0.5)                  ['$0.5', '$0.6']
del $0.5                                 []
return $0.6                              ['$0.6']
----------------------------------------------------------------------------
```

Following this rewrite, Numba lowers the array expression into a new ufunc-like function that is inlined into a single loop that only allocates a single result array.

Stage 5b: Perform Automatic Parallelization

This pass is only performed if the `parallel` option in the *jit()* decorator is set to `True`. This pass finds parallelism implicit in the semantics of operations in the Numba IR and replaces those operations with explicitly parallel representations of those operations using a special *parfor* operator. Then, optimizations are performed to maximize the number of parfors that are adjacent to each other such that they can then be fused together into one parfor that takes only one pass over the data and will thus typically have better cache performance. Finally, during lowering, these parfor operators are converted to a form similar to guvectorize to implement the actual parallelism.

The automatic parallelization pass has a number of sub-passes, many of which are controllable using a dictionary of options passed via the `parallel` keyword argument to *jit()*:

```
{ 'comprehension': True/False,  # parallel comprehension
  'prange':        True/False,  # parallel for-loop
  'numpy':         True/False,  # parallel numpy calls
  'reduction':     True/False,  # parallel reduce calls
  'setitem':       True/False,  # parallel setitem
  'stencil':       True/False,  # parallel stencils
  'fusion':        True/False,  # enable fusion or not
}
```

The default is set to *True* for all of them. The sub-passes are described in more detail in the following paragraphs.

1. **CFG Simplification**
   Sometimes Numba IR will contain chains of blocks containing no loops which are merged in this sub-pass into single blocks. This sub-pass simplifies subsequent analysis of the IR.
2. **Numpy canonicalization**
   Some Numpy operations can be written as operations on Numpy objects (e.g. `arr.sum()`), or as calls to Numpy taking those objects (e.g. `numpy.sum(arr)`). This sub-pass converts all such operations to the latter form for cleaner subsequent analysis.
3. **Array analysis**
   A critical requirement for later parfor fusion is that parfors have identical iteration spaces and these iteration

spaces typically correspond to the sizes of the dimensions of Numpy arrays. In this sub-pass, the IR is analyzed to determine equivalence classes for the dimensions of Numpy arrays. Consider the example, `a = b + 1`, where `a` and `b` are both Numpy arrays. Here, we know that each dimension of `a` must have the same equivalence class as the corresponding dimension of `b`. Typically, routines rich in Numpy operations will enable equivalence classes to be fully known for all arrays created within a function.

Array analysis will also reason about size equivalence for slice selection, and boolean array masking (one dimensional only). For example, it is able to infer that `a[1 : n-1]` is of the same size as `b[0 : n-2]`.

Array analysis may also insert safety assumptions to ensure pre-conditions related to array sizes are met before an operation can be parallelized. For example, `np.dot(X, w)` between a 2-D matrix `X` and a 1-D vector `w` requires that the second dimension of `X` is of the same size as `w`. Usually this kind of runtime check is automatically inserted, but if array analysis can infer such equivalence, it will skip them.

Users can even help array analysis by turning implicit knowledge about array sizes into explicit assertions. For example, in the code below:

```
@numba.njit(parallel=True)
def logistic_regression(Y, X, w, iterations):
    assert(X.shape == (Y.shape[0], w.shape[0]))
    for i in range(iterations):
        w -= np.dot(((1.0 / (1.0 + np.exp(-Y * np.dot(X, w))) - 1.0) * Y), X)
    return w
```

Making the explicit assertion helps eliminate all bounds checks in the rest of the function.

4. **prange() to parfor**

   The use of prange (*Explicit Parallel Loops*) in a for loop is an explicit indication from the programmer that all iterations of the for loop can execute in parallel. In this sub-pass, we analyze the CFG to locate loops and to convert those loops controlled by a prange object to the explicit *parfor* operator. Each explicit parfor operator consists of:

   a. A list of loop nest information that describes the iteration space of the parfor. Each entry in the loop nest list contains an indexing variable, the start of the range, the end of the range, and the step value for each iteration.

   b. An initialization (init) block which contains instructions to be executed one time before the parfor begins executing.

   c. A loop body comprising a set of basic blocks that correspond to the body of the loop and compute one point in the iteration space.

   d. The index variables used for each dimension of the iteration space.

   For parfor *pranges*, the loop nest is a single entry where the start, stop, and step fields come from the specified *prange*. The init block is empty for *prange* parfors and the loop body is the set of blocks in the loop minus the loop header.

   With parallelization on, array comprehensions (*List comprehension*) will also be translated to prange so as to run in parallel. This behavior be disabled by setting `parallel={'comprehension': False}`.

   Likewise, the overall *prange* to *parfor* translation can be disabled by setting `parallel={'prange': False}`, in which case *prange* is treated the same as *range*.

5. **Numpy to parfor**

   In this sub-pass, Numpy functions such as `ones`, `zeros`, `dot`, most of the random number generating functions, arrayexprs (from Section *Stage 5a: Rewrite typed IR*), and Numpy reductions are converted to parfors. Generally, this conversion creates the loop nest list, whose length is equal to the number of dimensions of the left-hand side of the assignment instruction in the IR. The number and size of the dimensions of the

left-hand-side array is taken from the array analysis information generated in sub-pass 3 above. An instruction to create the result Numpy array is generated and stored in the new parfor's init block. A basic block is created for the loop body and an instruction is generated and added to the end of that block to store the result of the computation into the array at the current point in the iteration space. The result stored into the array depends on the operation that is being converted. For example, for `ones`, the value stored is a constant 1. For calls to generate a random array, the value comes from a call to the same random number function but with the size parameter dropped and therefore returning a scalar. For arrayexpr operators, the arrayexpr tree is converted to Numba IR and the value at the root of that expression tree is used to write into the output array. The translation from Numpy functions and arrayexpr operators to *parfor* can be disabled by setting `parallel={'numpy': False}`.

For reductions, the loop nest list is similarly created using the array analysis information for the array being reduced. In the init block, the initial value is assigned to the reduction variable. The loop body consists of a single block in which the next value in the iteration space is fetched and the reduction operation is applied to that value and the current reduction value and the result stored back into the reduction value. The translation of reduction functions to *parfor* can be disabled by setting `parallel={'reduction': False}`.

Setting the *NUMBA_DEBUG_ARRAY_OPT_STATS* environment variable to 1 will show some statistics about parfor conversions in general.

6. **Setitem to parfor**

   Setting a range of array elements using a slice or boolean array selection can also run in parallel. Statement such as `A[P] = B[Q]` (or a simpler case `A[P] = c`, where `c` is a scalar) is translated to *parfor* if one of the following conditions is met:

   a. `P` and `Q` are slices or multi-dimensional selector involving scalar and slices, and `A[P]` and `B[Q]` are considered size equivalent by array analysis. Only 2-value slice/range is supported, 3-value with a step will not be translated to *parfor*.

   b. `P` and `Q` are the same boolean array.

   This translation can be disabled by setting `parallel={'setitem': False}`.

7. **Simplification**

   Performs a copy propagation and dead code elimination pass.

8. **Fusion**

   This sub-pass first processes each basic block and does a reordering of the instructions within the block with the goal of pushing parfors lower in the block and lifting non-parfors towards the start of the block. In practice, this approach does a good job of getting parfors adjacent to each other in the IR, which enables more parfors to then be fused. During parfor fusion, each basic block is repeatedly scanned until no further fusion is possible. During this scan, each set of adjacent instructions are considered. Adjacent instructions are fused together if:

   a. they are both parfors

   b. the parfors' loop nests are the same size and the array equivalence classes for each dimension of the loop nests are the same, and

   c. the first parfor does not create a reduction variable used by the second parfor.

   The two parfors are fused together by adding the second parfor's init block to the first's, merging the two parfors' loop bodies together and replacing the instances of the second parfor's loop index variables in the second parfor's body with the loop index variables for the first parfor. Fusion can be disabled by setting `parallel={'fusion': False}`.

   Setting the *NUMBA_DEBUG_ARRAY_OPT_STATS* environment variable to 1 will show some statistics about parfor fusions.

9. **Push call objects and compute parfor parameters**

   In the lowering phase described in Section *Stage 6a: Generate nopython LLVM IR*, each parfor becomes a separate function executed in parallel in `guvectorize` (*The @guvectorize decorator*) style. Since parfors may use variables defined previously in a function, when those parfors become separate functions, those variables must be passed to the parfor function as parameters. In this sub-pass, a use-def scan is made over each parfor body and liveness information is used to determine which variables are used but not defined by the parfor. That list of variables is stored here in the parfor for use during lowering. Function variables are a special case in this process since function variables cannot be passed to functions compiled in nopython mode. Instead, for function variables, this sub-pass pushes the assignment instruction to the function variable into the parfor body so that those do not need to be passed as parameters.

   To see the intermediate IR between the above sub-passes and other debugging information, set the *NUMBA_DEBUG_ARRAY_OPT* environment variable to 1. For the example in Section *Stage 5a: Rewrite typed IR*, the following IR with a parfor is generated during this stage:

```
----------------------------------------------------------------------------
label 0:
    a0 = arg(0, name=a0)                     ['a0']
    a0_sh_attr0.0 = getattr(attr=shape, value=a0) ['a0', 'a0_sh_attr0.0']
    $consta00.1 = const(int, 0)              ['$consta00.1']
    a0size0.2 = static_getitem(value=a0_sh_attr0.0, index_var=$consta00.1,␣
↪index=0) ['$consta00.1', 'a0_sh_attr0.0', 'a0size0.2']
    a1 = arg(1, name=a1)                     ['a1']
    a1_sh_attr0.3 = getattr(attr=shape, value=a1) ['a1', 'a1_sh_attr0.3']
    $consta10.4 = const(int, 0)              ['$consta10.4']
    a1size0.5 = static_getitem(value=a1_sh_attr0.3, index_var=$consta10.4,␣
↪index=0) ['$consta10.4', 'a1_sh_attr0.3', 'a1size0.5']
    a2 = arg(2, name=a2)                     ['a2']
    a2_sh_attr0.6 = getattr(attr=shape, value=a2) ['a2', 'a2_sh_attr0.6']
    $consta20.7 = const(int, 0)              ['$consta20.7']
    a2size0.8 = static_getitem(value=a2_sh_attr0.6, index_var=$consta20.7,␣
↪index=0) ['$consta20.7', 'a2_sh_attr0.6', 'a2size0.8']
---begin parfor 0---
index_var =  parfor_index.9
LoopNest(index_variable=parfor_index.9, range=0,a0size0.2,1 correlation=5)
init block:
    $np_g_var.10 = global(np: <module 'numpy' from '/usr/local/lib/python3.5/
↪dist-packages/numpy/__init__.py'>) ['$np_g_var.10']
    $empty_attr_attr.11 = getattr(attr=empty, value=$np_g_var.10) ['$empty_attr_
↪attr.11', '$np_g_var.10']
    $np_typ_var.12 = getattr(attr=float64, value=$np_g_var.10) ['$np_g_var.10',
↪'$np_typ_var.12']
    $0.5 = call $empty_attr_attr.11(a0size0.2, $np_typ_var.12, kws=(), func=
↪$empty_attr_attr.11, vararg=None, args=[Var(a0size0.2, test2.py (7)), Var($np_
↪typ_var.12, test2.py (7))]) ['$0.5', '$empty_attr_attr.11', '$np_typ_var.12',
↪'a0size0.2']
label 1:
    $arg_out_var.15 = getitem(value=a0, index=parfor_index.9) ['$arg_out_var.15
↪', 'a0', 'parfor_index.9']
    $arg_out_var.16 = getitem(value=a1, index=parfor_index.9) ['$arg_out_var.16
↪', 'a1', 'parfor_index.9']
    $arg_out_var.14 = $arg_out_var.15 * $arg_out_var.16 ['$arg_out_var.14', '
↪$arg_out_var.15', '$arg_out_var.16']
    $arg_out_var.17 = getitem(value=a2, index=parfor_index.9) ['$arg_out_var.17
↪', 'a2', 'parfor_index.9']
```

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```
    $expr_out_var.13 = $arg_out_var.14 + $arg_out_var.17 ['$arg_out_var.14', '
↪$arg_out_var.17', '$expr_out_var.13']
    $0.5[parfor_index.9] = $expr_out_var.13  ['$0.5', '$expr_out_var.13',
↪'parfor_index.9']
----end parfor 0----
    $0.6 = cast(value=$0.5)                  ['$0.5', '$0.6']
    return $0.6                              ['$0.6']
--------------------------------------------------------------------------------
```

Stage 6a: Generate nopython LLVM IR

If type inference succeeds in finding a Numba type for every intermediate variable, then Numba can (potentially) generate specialized native code. This process is called *lowering*. The Numba IR tree is translated into LLVM IR by using helper classes from llvmlite. The machine-generated LLVM IR can seem unnecessarily verbose, but the LLVM toolchain is able to optimize it quite easily into compact, efficient code.

The basic lowering algorithm is generic, but the specifics of how particular Numba IR nodes are translated to LLVM instructions is handled by the target context selected for compilation. The default target context is the "cpu" context, defined in `numba.targets.cpu`.

The LLVM IR can be displayed by setting the *NUMBA_DUMP_LLVM* environment variable to 1. For the "cpu" context, our `add()` example would look like:

```
define i32 @"__main__.add$1.int64.int64"(i64* %"retptr",
                                         {i8*, i32}** %"excinfo",
                                         i8* %"env",
                                         i64 %"arg.a", i64 %"arg.b")
{
   entry:
     %"a" = alloca i64
     %"b" = alloca i64
     %"$0.3" = alloca i64
     %"$0.4" = alloca i64
     br label %"B0"
   B0:
     store i64 %"arg.a", i64* %"a"
     store i64 %"arg.b", i64* %"b"
     %".8" = load i64* %"a"
     %".9" = load i64* %"b"
     %".10" = add i64 %".8", %".9"
     store i64 %".10", i64* %"$0.3"
     %".12" = load i64* %"$0.3"
     store i64 %".12", i64* %"$0.4"
     %".14" = load i64* %"$0.4"
     store i64 %".14", i64* %"retptr"
     ret i32 0
}
```

The post-optimization LLVM IR can be output by setting *NUMBA_DUMP_OPTIMIZED* to 1. The optimizer shortens the code generated above quite significantly:

```
define i32 @"__main__.add$1.int64.int64"(i64* nocapture %retptr,
                                         { i8*, i32 }** nocapture readnone %excinfo,
                                         i8* nocapture readnone %env,
                                         i64 %arg.a, i64 %arg.b)
{
   entry:
     %.10 = add i64 %arg.b, %arg.a
     store i64 %.10, i64* %retptr, align 8
     ret i32 0
}
```

If created during *Stage 5b: Perform Automatic Parallelization*, parfor operations are lowered in the following manner. First, instructions in the parfor's init block are lowered into the existing function using the normal lowering code. Second, the loop body of the parfor is turned into a separate GUFunc. Third, code is emitted for the current function to call the parallel GUFunc.

To create a GUFunc from the parfor body, the signature of the GUFunc is created by taking the parfor parameters as identified in step 9 of Stage *Stage 5b: Perform Automatic Parallelization* and adding to that a special *schedule* parameter, across which the GUFunc will be parallelized. The schedule parameter is in effect a static schedule mapping portions of the parfor iteration space to Numba threads and so the length of the schedule array is the same as the number of configured Numba threads. To make this process easier and somewhat less dependent on changes to Numba IR, this stage creates a Python function as text that contains the parameters to the GUFunc and iteration code that takes the current schedule entry and loops through the specified portion of the iteration space. In the body of that loop, a special sentinel is inserted for subsequent easy location. This code that handles the processing of the iteration space is then `eval`'ed into existence and the Numba compiler's run_frontend function is called to generate IR. That IR is scanned to locate the sentinel and the sentinel is replaced with the loop body of the parfor. Then, the process of creating the parallel GUFunc is completed by compiling this merged IR with the Numba compiler's `compile_ir` function.

To call the parallel GUFunc, the static schedule must be created. Code is inserted to call a function named `do_scheduling`. This function is called with the size of each of the parfor's dimensions and the number *N* of configured Numba threads (*NUMBA_NUM_THREADS*). The `do_scheduling` function will divide the iteration space into N approximately equal sized regions (linear for 1D, rectangular for 2D, or hyperrectangles for 3+D) and the resulting schedule is passed to the parallel GUFunc. The number of threads dedicated to a given dimension of the full iteration space is roughly proportional to the ratio of the size of the given dimension to the sum of the sizes of all the dimensions of the iteration space.

Parallel reductions are not natively provided by GUFuncs but the parfor lowering strategy allows us to use GUFuncs in a way that reductions can be performed in parallel. To accomplish this, for each reduction variable computed by a parfor, the parallel GUFunc and the code that calls it are modified to make the scalar reduction variable into an array of reduction variables whose length is equal to the number of Numba threads. In addition, the GUFunc still contains a scalar version of the reduction variable that is updated by the parfor body during each iteration. One time at the end of the GUFunc this local reduction variable is copied into the reduction array. In this way, false sharing of the reduction array is prevented. Code is also inserted into the main function after the parallel GUFunc has returned that does a reduction across this smaller reduction array and this final reduction value is then stored into the original scalar reduction variable.

The GUFunc corresponding to the example from Section *Stage 5b: Perform Automatic Parallelization* can be seen below:

```
________________________________________________________________________________
label 0:
    sched.29 = arg(0, name=sched)                ['sched.29']
    a0 = arg(1, name=a0)                         ['a0']
    a1 = arg(2, name=a1)                         ['a1']
    a2 = arg(3, name=a2)                         ['a2']
```

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```
    _0_5 = arg(4, name=_0_5)                  ['_0_5']
    $3.1.24 = global(range: <class 'range'>) ['$3.1.24']
    $const3.3.21 = const(int, 0)              ['$const3.3.21']
    $3.4.23 = getitem(value=sched.29, index=$const3.3.21) ['$3.4.23', '$const3.3.21',
↪'sched.29']
    $const3.6.28 = const(int, 1)              ['$const3.6.28']
    $3.7.27 = getitem(value=sched.29, index=$const3.6.28) ['$3.7.27', '$const3.6.28',
↪'sched.29']
    $const3.8.32 = const(int, 1)              ['$const3.8.32']
    $3.9.31 = $3.7.27 + $const3.8.32          ['$3.7.27', '$3.9.31', '$const3.8.32']
    $3.10.36 = call $3.1.24($3.4.23, $3.9.31, kws=[], func=$3.1.24, vararg=None,␣
↪args=[Var($3.4.23, <string> (2)), Var($3.9.31, <string> (2))]) ['$3.1.24', '$3.10.36',
↪'$3.4.23', '$3.9.31']
    $3.11.30 = getiter(value=$3.10.36)        ['$3.10.36', '$3.11.30']
    jump 1                                    []
label 1:
    $28.2.35 = iternext(value=$3.11.30)       ['$28.2.35', '$3.11.30']
    $28.3.25 = pair_first(value=$28.2.35)     ['$28.2.35', '$28.3.25']
    $28.4.40 = pair_second(value=$28.2.35)    ['$28.2.35', '$28.4.40']
    branch $28.4.40, 2, 3                     ['$28.4.40']
label 2:
    $arg_out_var.15 = getitem(value=a0, index=$28.3.25) ['$28.3.25', '$arg_out_var.15',
↪'a0']
    $arg_out_var.16 = getitem(value=a1, index=$28.3.25) ['$28.3.25', '$arg_out_var.16',
↪'a1']
    $arg_out_var.14 = $arg_out_var.15 * $arg_out_var.16 ['$arg_out_var.14', '$arg_out_
↪var.15', '$arg_out_var.16']
    $arg_out_var.17 = getitem(value=a2, index=$28.3.25) ['$28.3.25', '$arg_out_var.17',
↪'a2']
    $expr_out_var.13 = $arg_out_var.14 + $arg_out_var.17 ['$arg_out_var.14', '$arg_out_
↪var.17', '$expr_out_var.13']
    _0_5[$28.3.25] = $expr_out_var.13         ['$28.3.25', '$expr_out_var.13', '_0_5']
    jump 1                                    []
label 3:
    $const44.1.33 = const(NoneType, None)     ['$const44.1.33']
    $44.2.39 = cast(value=$const44.1.33)      ['$44.2.39', '$const44.1.33']
    return $44.2.39                           ['$44.2.39']
--------------------------------------------------------------------------------
```

Stage 6b: Generate object mode LLVM IR

If type inference fails to find Numba types for all values inside a function, the function will be compiled in object mode. The generated LLVM will be significantly longer, as the compiled code will need to make calls to the Python C API to perform basically all operations. The optimized LLVM for our example `add()` function is:

```
@PyExc_SystemError = external global i8
@".const.Numba_internal_error:_object_mode_function_called_without_an_environment" =␣
↪internal constant [73 x i8] c"Numba internal error: object mode function called␣
↪without an environment\00"
@".const.name_'a'_is_not_defined" = internal constant [24 x i8] c"name 'a' is not␣
↪defined\00"
```

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```
@PyExc_NameError = external global i8
@".const.name_'b'_is_not_defined" = internal constant [24 x i8] c"name 'b' is not␣
↪defined\00"

define i32 @"__main__.add$1.pyobject.pyobject"(i8** nocapture %retptr, { i8*, i32 }**␣
↪nocapture readnone %excinfo, i8* readnone %env, i8* %arg.a, i8* %arg.b) {
entry:
  %.6 = icmp eq i8* %env, null
  br i1 %.6, label %entry.if, label %entry.endif, !prof !0

entry.if:                                         ; preds = %entry
  tail call void @PyErr_SetString(i8* @PyExc_SystemError, i8* getelementptr inbounds␣
↪([73 x i8]* @".const.Numba_internal_error:_object_mode_function_called_without_an_
↪environment", i64 0, i64 0))
  ret i32 -1

entry.endif:                                      ; preds = %entry
  tail call void @Py_IncRef(i8* %arg.a)
  tail call void @Py_IncRef(i8* %arg.b)
  %.21 = icmp eq i8* %arg.a, null
  br i1 %.21, label %B0.if, label %B0.endif, !prof !0

B0.if:                                            ; preds = %entry.endif
  tail call void @PyErr_SetString(i8* @PyExc_NameError, i8* getelementptr inbounds ([24␣
↪x i8]* @".const.name_'a'_is_not_defined", i64 0, i64 0))
  tail call void @Py_DecRef(i8* null)
  tail call void @Py_DecRef(i8* %arg.b)
  ret i32 -1

B0.endif:                                         ; preds = %entry.endif
  %.30 = icmp eq i8* %arg.b, null
  br i1 %.30, label %B0.endif1, label %B0.endif1.1, !prof !0

B0.endif1:                                        ; preds = %B0.endif
  tail call void @PyErr_SetString(i8* @PyExc_NameError, i8* getelementptr inbounds ([24␣
↪x i8]* @".const.name_'b'_is_not_defined", i64 0, i64 0))
  tail call void @Py_DecRef(i8* %arg.a)
  tail call void @Py_DecRef(i8* null)
  ret i32 -1

B0.endif1.1:                                      ; preds = %B0.endif
  %.38 = tail call i8* @PyNumber_Add(i8* %arg.a, i8* %arg.b)
  %.39 = icmp eq i8* %.38, null
  br i1 %.39, label %B0.endif1.1.if, label %B0.endif1.1.endif, !prof !0

B0.endif1.1.if:                                   ; preds = %B0.endif1.1
  tail call void @Py_DecRef(i8* %arg.a)
  tail call void @Py_DecRef(i8* %arg.b)
  ret i32 -1

B0.endif1.1.endif:                                ; preds = %B0.endif1.1
  tail call void @Py_DecRef(i8* %arg.b)
```

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```
  tail call void @Py_DecRef(i8* %arg.a)
  tail call void @Py_IncRef(i8* %.38)
  tail call void @Py_DecRef(i8* %.38)
  store i8* %.38, i8** %retptr, align 8
  ret i32 0
}

declare void @PyErr_SetString(i8*, i8*)

declare void @Py_IncRef(i8*)

declare void @Py_DecRef(i8*)

declare i8* @PyNumber_Add(i8*, i8*)
```

The careful reader might notice several unnecessary calls to `Py_IncRef` and `Py_DecRef` in the generated code. Currently Numba isn't able to optimize those away.

Object mode compilation will also attempt to identify loops which can be extracted and statically-typed for "nopython" compilation. This process is called *loop-lifting*, and results in the creation of a hidden nopython mode function just containing the loop which is then called from the original function. Loop-lifting helps improve the performance of functions that need to access uncompilable code (such as I/O or plotting code) but still contain a time-intensive section of compilable code.

Stage 7: Compile LLVM IR to machine code

In both *object mode* and *nopython mode*, the generated LLVM IR is compiled by the LLVM JIT compiler and the machine code is loaded into memory. A Python wrapper is also created (defined in `numba.dispatcher.Dispatcher`) which can do the dynamic dispatch to the correct version of the compiled function if multiple type specializations were generated (for example, for both `float32` and `float64` versions of the same function).

The machine assembly code generated by LLVM can be dumped to the screen by setting the *NUMBA_DUMP_ASSEMBLY* environment variable to 1:

```
        .globl  __main__.add$1.int64.int64
        .align  16, 0x90
        .type   __main__.add$1.int64.int64,@function
__main__.add$1.int64.int64:
        addq    %r8, %rcx
        movq    %rcx, (%rdi)
        xorl    %eax, %eax
        retq
```

The assembly output will also include the generated wrapper function that translates the Python arguments to native data types.

6.5 Polymorphic dispatching

Functions compiled using *jit()* or *vectorize()* are open-ended: they can be called with many different input types and have to select (possibly compile on-the-fly) the right low-level specialization. We hereby explain how this mechanism is implemented.

6.5.1 Requirements

JIT-compiled functions can take several arguments and each of them is taken into account when selecting a specialization. Thus it is a form of multiple dispatch, more complex than single dispatch.

Each argument weighs in the selection based on its *Numba type*. Numba types are often more granular than Python types: for example, Numba types Numpy arrays differently depending on their dimensionality and their layout (C-contiguous, etc.).

Once a Numba type is inferred for each argument, a specialization must be chosen amongst the available ones; or, if not suitable specialization is found, a new one must be compiled. This is not a trivial decision: there can be multiple specializations compatible with a given concrete signature (for example, say a two-argument function has compiled specializations for `(float64, float64)` and `(complex64, complex64)`, and it is called with `(float32, float32)`).

Therefore, there are two crucial steps in the dispatch mechanism:

1. infer the Numba types of the concrete arguments
2. select the best available specialization (or choose to compile a new one) for the inferred Numba types

Compile-time vs. run-time

This document discusses dispatching when it is done at runtime, i.e. when a JIT-compiled function is called from pure Python. In that context, performance is important. To stay in the realm of normal function call overhead in Python, the overhead of dispatching should stay under a microsecond. Of course, *the faster the better...*

When a JIT-compiled function is called from another JIT-compiled function (in *nopython mode*), the polymorphism is resolved at compile-time, using a non-performance critical mechanism, bearing zero runtime performance overhead.

Note: In practice, the performance-critical parts described here are coded in C.

6.5.2 Type resolution

The first step is therefore to infer, at call-time, a Numba type for each of the function's concrete arguments. Given the finer granularity of Numba types compared to Python types, one cannot simply lookup an object's class and key a dictionary with it to obtain the corresponding Numba type.

Instead, there is a machinery to inspect the object and, based on its Python type, query various properties to infer the appropriate Numba type. This can be more or less complex: for example, a Python `int` argument will always infer to a Numba `intp` (a pointer-sized integer), but a Python `tuple` argument can infer to multiple Numba types (depending on the tuple's size and the concrete type of each of its elements).

The Numba type system is high-level and written in pure Python; there is a pure Python machinery, based on a generic function, to do said inference (in `numba.typing.typeof`). That machinery is used for compile-time inference, e.g. on constants. Unfortunately, it is too slow for run-time value-based dispatching. It is only used as a fallback for rarely used (or difficult to infer) types, and exhibits multiple-microsecond overhead.

Typecodes

The Numba type system is really too high-level to be manipulated efficiently from C code. Therefore, the C dispatching layer uses another representation based on integer typecodes. Each Numba type gets a unique integer typecode when constructed; also, an interning system ensure no two instances of same type are created. The dispatching layer is therefore able to *eschew* the overhead of the Numba type system by working with simple integer typecodes, amenable to well-known optimizations (fast hash tables, etc.).

The goal of the type resolution step becomes: infer a Numba *typecode* for each of the function's concrete arguments. Ideally, it doesn't deal with Numba types anymore…

Hard-coded fast paths

While eschewing the abstraction and object-orientation overhead of the type system, the integer typecodes still have the same conceptual complexity. Therefore, an important technique to speed up inference is to first go through checks for the most important types, and hard-code a fast resolution for each of them.

Several types benefit from such an optimization, notably:

- basic Python scalars (`bool`, `int`, `float`, `complex`);
- basic Numpy scalars (the various kinds of integer, floating-point, complex numbers);
- Numpy arrays of certain dimensionalities and basic element types.

Each of those fast paths ideally uses a hard-coded result value or a direct table lookup after a few simple checks.

However, we can't apply that technique to all argument types; there would be an explosion of ad-hoc internal caches, and it would become difficult to maintain. Besides, the recursive application of hard-coded fast paths would not necessarily combine into a low overhead (in the nested tuple case, for example).

Fingerprint-based typecode cache

For non-so-trivial types (imagine a tuple, or a Numpy `datetime64` array, for example), the hard-coded fast paths don't match. Another mechanism then kicks in, more generic.

The principle here is to examine each argument value, as the pure Python machinery would do, and to describe its Numba type unambiguously. The difference is that *we don't actually compute a Numba type*. Instead, we compute a simple bytestring, a low-level possible denotation of that Numba type: a *fingerprint*. The fingerprint format is designed to be short and extremely simple to compute from C code (in practice, it has a bytecode-like format).

Once the fingerprint is computed, it is looked up in a cache mapping fingerprints to typecodes. The cache is a hash table, and the lookup is fast thanks to the fingerprints being generally very short (rarely more than 20 bytes).

If the cache lookup fails, the typecode must first be computed using the slow pure Python machinery. Luckily, this would only happen once: on subsequent calls, the cached typecode would be returned for the given fingerprint.

In rare cases, a fingerprint cannot be computed efficiently. This is the case for some types which cannot be easily inspected from C: for example `cffi` function pointers. Then, the slow Pure Python machinery is invoked at each function call with such an argument.

Note: Two fingerprints may denote a single Numba type. This does not make the mechanism incorrect; it only creates more cache entries.

Summary

Type resolution of a function argument involves the following mechanisms in order:

- Try a few hard-coded fast paths, for common simple types.
- If the above failed, compute a fingerprint for the argument and lookup its typecode in a cache.
- If all the above failed, invoke the pure Python machinery which will determine a Numba type for the argument (and look up its typecode).

6.5.3 Specialization selection

At the previous step, an integer typecode has been determined for each concrete argument to the JIT-compiled function. Now it remains to match that concrete signature against each of the available specializations for the function. There can be three outcomes:

- There is a satisfying best match: the corresponding specialization is then invoked (it will handle argument unboxing and other details).
- There is a tie between two or more "best matches": an exception is raised, refusing to solve the ambiguity.
- There is no satisfying match: a new specialization is compiled tailored for the concrete argument types that were inferred.

The selection works by looping over all available specializations, and computing the compatibility of each concrete argument type with the corresponding type in the specialization's intended signature. Specifically, we are interested in:

1. Whether the concrete argument type is allowed to convert implicitly to the specialization's argument type;
2. If so, at what semantic (user-visible) cost the conversion comes.

Implicit conversion rules

There are five possible kinds of implicit conversion from a source type to a destination type (note this is an asymmetric relationship):

1. *exact match*: the two types are identical; this is the ideal case, since the specialization would behave exactly as intended;
2. *same-kind promotion*: the two types belong to the same "kind" (for example `int32` and `int64` are two integer types), and the source type can be converted losslessly to the destination type (e.g. from `int32` to `int64`, but not the reverse);
3. *safe conversion*: the two types belong to different kinds, but the source type can be reasonably converted to the destination type (e.g. from `int32` to `float64`, but not the reverse);
4. *unsafe conversion*: a conversion is available from the source type to the destination type, but it may lose precision, magnitude, or another desirable quality.
5. *no conversion*: there is no correct or reasonably efficient way to convert between the two types (for example between an `int64` and a `datetime64`, or a C-contiguous array and a Fortran-contiguous array).

When a specialization is examined, the latter two cases eliminate it from the final choice: i.e. when at least one argument has *no conversion* or only an *unsafe conversion* to the signature's argument type.

Note: However, if the function is compiled with explicit signatures in the *jit()* call (and therefore it is not allowed to compile new specializations), *unsafe conversion* is allowed.

Candidates and best match

If a specialization is not eliminated by the rule above, it enters the list of *candidates* for the final choice. Those candidates are ranked by an ordered 4-uple of integers: `(number of unsafe conversions, number of safe conversions, number of same-kind promotions, number of exact matches)` (note the sum of the tuple's elements is equal to the number of arguments). The best match is then the #1 result in sorted ascending order, thereby preferring exact matches over promotions, promotions over safe conversions, safe conversions over unsafe conversions.

Implementation

The above-described mechanism works on integer typecodes, not on Numba types. It uses an internal hash table storing the possible conversion kind for each pair of compatible types. The internal hash table is in part built at startup (for built-in trivial types such as `int32`, `int64` etc.), in part filled dynamically (for arbitrarily complex types such as array types: for example to allow using a C-contiguous 2D array where a function expects a non-contiguous 2D array).

Summary

Selecting the right specialization involves the following steps:

- Examine each available specialization and match it against the concrete argument types.
- Eliminate any specialization where at least one argument doesn't offer sufficient compatibility.
- If there are remaining candidates, choose the best one in terms of preserving the types' semantics.

6.5.4 Miscellaneous

Some benchmarks of dispatch performance exist in the Numba benchmarks repository.

Some unit tests of specific aspects of the machinery are available in `numba.tests.test_typeinfer` and `numba.tests.test_typeof`. Higher-level dispatching tests are in `numba.tests.test_dispatcher`.

6.6 Notes on generators

Numba recently gained support for compiling generator functions. This document explains some of the implementation choices.

6.6.1 Terminology

For clarity, we distinguish between *generator functions* and *generators*. A generator function is a function containing one or several `yield` statements. A generator (sometimes also called "generator iterator") is the return value of a generator function; it resumes execution inside its frame each time `next()` is called.

A *yield point* is the place where a `yield` statement is called. A *resumption point* is the place just after a *yield point* where execution is resumed when `next()` is called again.

6.6.2 Function analysis

Suppose we have the following simple generator function:

```
def gen(x, y):
    yield x + y
    yield x - y
```

Here is its CPython bytecode, as printed out using `dis.dis()`:

```
7           0 LOAD_FAST                0 (x)
            3 LOAD_FAST                1 (y)
            6 BINARY_ADD
            7 YIELD_VALUE
            8 POP_TOP

8           9 LOAD_FAST                0 (x)
           12 LOAD_FAST                1 (y)
           15 BINARY_SUBTRACT
           16 YIELD_VALUE
           17 POP_TOP
           18 LOAD_CONST               0 (None)
           21 RETURN_VALUE
```

When compiling this function with *NUMBA_DUMP_IR* set to 1, the following information is printed out:

```
----------------------------------IR DUMP: gen----------------------------------
label 0:
    x = arg(0, name=x)                       ['x']
    y = arg(1, name=y)                       ['y']
    $0.3 = x + y                             ['$0.3', 'x', 'y']
    $0.4 = yield $0.3                        ['$0.3', '$0.4']
    del $0.4                                 []
    del $0.3                                 []
    $0.7 = x - y                             ['$0.7', 'x', 'y']
    del y                                    []
    del x                                    []
    $0.8 = yield $0.7                        ['$0.7', '$0.8']
    del $0.8                                 []
    del $0.7                                 []
    $const0.9 = const(NoneType, None)        ['$const0.9']
    $0.10 = cast(value=$const0.9)            ['$0.10', '$const0.9']
    del $const0.9                            []
    return $0.10                             ['$0.10']
------------------------------GENERATOR INFO: gen-------------------------------
generator state variables: ['$0.3', '$0.7', 'x', 'y']
yield point #1: live variables = ['x', 'y'], weak live variables = ['$0.3']
yield point #2: live variables = [], weak live variables = ['$0.7']
```

What does it mean? The first part is the Numba IR, as already seen in *Stage 2: Generate the Numba IR*. We can see the two yield points (`yield $0.3` and `yield $0.7`).

The second part shows generator-specific information. To understand it we have to understand what suspending and resuming a generator means.

When suspending a generator, we are not merely returning a value to the caller (the operand of the `yield` statement).

We also have to save the generator's *current state* in order to resume execution. In trivial use cases, perhaps the CPU's register values or stack slots would be preserved until the next call to next(). However, any non-trivial case will hopelessly clobber those values, so we have to save them in a well-defined place.

What are the values we need to save? Well, in the context of the Numba Intermediate Representation, we must save all *live variables* at each yield point. These live variables are computed thanks to the control flow graph.

Once live variables are saved and the generator is suspended, resuming the generator simply involves the inverse operation: the live variables are restored from the saved generator state.

Note: It is the same analysis which helps insert Numba `del` instructions where appropriate.

Let's go over the generator info again:

```
generator state variables: ['$0.3', '$0.7', 'x', 'y']
yield point #1: live variables = ['x', 'y'], weak live variables = ['$0.3']
yield point #2: live variables = [], weak live variables = ['$0.7']
```

Numba has computed the union of all live variables (denoted as "state variables"). This will help define the layout of the *generator structure*. Also, for each yield point, we have computed two sets of variables:

- the *live variables* are the variables which are used by code following the resumption point (i.e. after the `yield` statement)
- the *weak live variables* are variables which are del'ed immediately after the resumption point; they have to be saved in *object mode*, to ensure proper reference cleanup

6.6.3 The generator structure

Layout

Function analysis helps us gather enough information to define the layout of the generator structure, which will store the entire execution state of a generator. Here is a sketch of the generator structure's layout, in pseudo-code:

```
struct gen_struct_t {
   int32_t resume_index;
   struct gen_args_t {
      arg_0_t arg0;
      arg_1_t arg1;
      ...
      arg_N_t argN;
   }
   struct gen_state_t {
      state_0_t state_var0;
      state_1_t state_var1;
      ...
      state_N_t state_varN;
   }
}
```

Let's describe those fields in order.

- The first member, the *resume index*, is an integer telling the generator at which resumption point execution must resume. By convention, it can have two special values: 0 means execution must start at the beginning of the generator (i.e. the first time `next()` is called); -1 means the generator is exhausted and resumption must

immediately raise StopIteration. Other values indicate the yield point's index starting from 1 (corresponding to the indices shown in the generator info above).

- The second member, the *arguments structure* is read-only after it is first initialized. It stores the values of the arguments the generator function was called with. In our example, these are the values of `x` and `y`.
- The third member, the *state structure*, stores the live variables as computed above.

Concretely, our example's generator structure (assuming the generator function is called with floating-point numbers) is then:

```
struct gen_struct_t {
   int32_t resume_index;
   struct gen_args_t {
      double arg0;
      double arg1;
   }
   struct gen_state_t {
      double $0.3;
      double $0.7;
      double x;
      double y;
   }
}
```

Note that here, saving `x` and `y` is redundant: Numba isn't able to recognize that the state variables `x` and `y` have the same value as `arg0` and `arg1`.

Allocation

How does Numba ensure the generator structure is preserved long enough? There are two cases:

- When a Numba-compiled generator function is called from a Numba-compiled function, the structure is allocated on the stack by the callee. In this case, generator instantiation is practically costless.
- When a Numba-compiled generator function is called from regular Python code, a CPython-compatible wrapper is instantiated that has the right amount of allocated space to store the structure, and whose `tp_iternext` slot is a wrapper around the generator's native code.

6.6.4 Compiling to native code

When compiling a generator function, three native functions are actually generated by Numba:

- An initialization function. This is the function corresponding to the generator function itself: it receives the function arguments and stores them inside the generator structure (which is passed by pointer). It also initialized the *resume index* to 0, indicating that the generator hasn't started yet.
- A next() function. This is the function called to resume execution inside the generator. Its single argument is a pointer to the generator structure and it returns the next yielded value (or a special exit code is used if the generator is exhausted, for quick checking when called from Numba-compiled functions).
- An optional finalizer. In object mode, this function ensures that all live variables stored in the generator state are decref'ed, even if the generator is destroyed without having been exhausted.

The next() function

The next() function is the least straight-forward of the three native functions. It starts with a trampoline which dispatches execution to the right resume point depending on the *resume index* stored in the generator structure. Here is how the function start may look like in our example:

```
define i32 @"__main__.gen.next"(
   double* nocapture %retptr,
   { i8*, i32 }** nocapture readnone %excinfo,
   i8* nocapture readnone %env,
   { i32, { double, double }, { double, double, double, double } }* nocapture %arg.gen)
{
  entry:
     %gen.resume_index = getelementptr { i32, { double, double }, { double, double,␣
↪double, double } }* %arg.gen, i64 0, i32 0
     %.47 = load i32* %gen.resume_index, align 4
     switch i32 %.47, label %stop_iteration [
       i32 0, label %B0
       i32 1, label %generator_resume1
       i32 2, label %generator_resume2
     ]

  ; rest of the function snipped
```

(uninteresting stuff trimmed from the LLVM IR to make it more readable)

We recognize the pointer to the generator structure in `%arg.gen`. The trampoline switch has three targets (one for each *resume index* 0, 1 and 2), and a fallback target label named `stop_iteration`. Label `B0` represents the function's start, `generator_resume1` (resp. `generator_resume2`) is the resumption point after the first (resp. second) yield point.

After generation by LLVM, the whole native assembly code for this function may look like this (on x86-64):

```
        .globl  __main__.gen.next
        .align  16, 0x90
__main__.gen.next:
        movl    (%rcx), %eax
        cmpl    $2, %eax
        je      .LBB1_5
        cmpl    $1, %eax
        jne     .LBB1_2
        movsd   40(%rcx), %xmm0
        subsd   48(%rcx), %xmm0
        movl    $2, (%rcx)
        movsd   %xmm0, (%rdi)
        xorl    %eax, %eax
        retq
.LBB1_5:
        movl    $-1, (%rcx)
        jmp     .LBB1_6
.LBB1_2:
        testl   %eax, %eax
        jne     .LBB1_6
        movsd   8(%rcx), %xmm0
        movsd   16(%rcx), %xmm1
        movaps  %xmm0, %xmm2
```

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```
        addsd   %xmm1, %xmm2
        movsd   %xmm1, 48(%rcx)
        movsd   %xmm0, 40(%rcx)
        movl    $1, (%rcx)
        movsd   %xmm2, (%rdi)
        xorl    %eax, %eax
        retq
.LBB1_6:
        movl    $-3, %eax
        retq
```

Note the function returns 0 to indicate a value is yielded, -3 to indicate StopIteration. `%rcx` points to the start of the generator structure, where the resume index is stored.

6.7 Notes on Numba Runtime

The *Numba Runtime (NRT)* provides the language runtime to the *nopython mode* Python subset. NRT is a standalone C library with a Python binding. This allows *NPM* runtime feature to be used without the GIL. Currently, the only language feature implemented in NRT is memory management.

6.7.1 Memory Management

NRT implements memory management for *NPM* code. It uses *atomic reference count* for threadsafe, deterministic memory management. NRT maintains a separate `MemInfo` structure for storing information about each allocation.

Cooperating with CPython

For NRT to cooperate with CPython, the NRT python binding provides adaptors for converting python objects that export a memory region. When such an object is used as an argument to a *NPM* function, a new `MemInfo` is created and it acquires a reference to the Python object. When a *NPM* value is returned to the Python interpreter, the associated `MemInfo` (if any) is checked. If the `MemInfo` references a Python object, the underlying Python object is released and returned instead. Otherwise, the `MemInfo` is wrapped in a Python object and returned. Additional process maybe required depending on the type.

The current implementation supports Numpy array and any buffer-exporting types.

Compiler-side Cooperation

NRT reference counting requires the compiler to emit incref/decref operations according to the usage. When the reference count drops to zero, the compiler must call the destructor routine in NRT.

Optimizations

The compiler is allowed to emit incref/decref operations naively. It relies on an optimization pass to remove redundant reference count operations.

A new optimization pass is implemented in version 0.52.0 to remove reference count operations that fall into the following four categories of control-flow structure—per basic-block, diamond, fanout, fanout+raise. See the documentation for *NUMBA_LLVM_REFPRUNE_FLAGS* for their descriptions.

The old optimization pass runs at block level to avoid control flow analysis. It depends on LLVM function optimization pass to simplify the control flow, stack-to-register, and simplify instructions. It works by matching and removing incref and decref pairs within each block. The old pass can be enabled by setting *NUMBA_LLVM_REFPRUNE_PASS* to *0*.

Important assumptions

Both the old (pre-0.52.0) and the new (post-0.52.0) optimization passes assume that the only function that can consume a reference is `NRT_decref`. It is important that there are no other functions that will consume references. Since the passes operate on LLVM IR, the "functions" here are referring to any callee in a LLVM call instruction.

To summarize, all functions exposed to the refcount optimization pass **must not** consume counted references unless done so via `NRT_decref`.

Quirks of the old optimization pass

Since the pre-0.52.0 *refcount optimization pass* requires the LLVM function optimization pass, the pass works on the LLVM IR as text. The optimized IR is then materialized again as a new LLVM in-memory bitcode object.

Debugging Leaks

To debug reference leaks in NRT MemInfo, each MemInfo python object has a `.refcount` attribute for inspection. To get the MemInfo from a ndarray allocated by NRT, use the `.base` attribute.

To debug memory leaks in NRT, the `numba.core.runtime.rtsys` defines `.get_allocation_stats()`. It returns a namedtuple containing the number of allocation and deallocation since the start of the program. Checking that the allocation and deallocation counters are matching is the simplest way to know if the NRT is leaking.

Debugging Leaks in C

The start of numba/core/runtime/nrt.h has these lines:

```
/* Debugging facilities - enabled at compile-time */
/* #undef NDEBUG */
#if 0
#   define NRT_Debug(X) X
#else
#   define NRT_Debug(X) if (0) { X; }
#endif
```

Undefining NDEBUG (uncomment the `#undef NDEBUG` line) enables the assertion check in NRT.

Enabling the NRT_Debug (replace `#if 0` with `#if 1`) turns on debug print inside NRT.

6.7.2 Recursion Support

During the compilation of a pair of mutually recursive functions, one of the functions will contain unresolved symbol references since the compiler handles one function at a time. The memory for the unresolved symbols is allocated and initialized to the address of the *unresolved symbol abort* function (`nrt_unresolved_abort`) just before the machine code is generated by LLVM. These symbols are tracked and resolved as new functions are compiled. If a bug prevents the resolution of these symbols, the abort function will be called, raising a `RuntimeError` exception.

The *unresolved symbol abort* function is defined in the NRT with a zero-argument signature. The caller is safe to call it with arbitrary number of arguments. Therefore, it is safe to be used inplace of the intended callee.

6.7.3 Using the NRT from C code

Externally compiled C code should use the `NRT_api_functions` struct as a function table to access the NRT API. The struct is defined in numba/core/runtime/nrt_external.h. Users can use the utility function `numba.extending.include_path()` to determine the include directory for Numba provided C headers.

Listing 1: *numba/core/runtime/nrt_external.h*

```
#ifndef NUMBA_NRT_EXTERNAL_H_
#define NUMBA_NRT_EXTERNAL_H_

#include <stdlib.h>

typedef struct MemInfo NRT_MemInfo;

typedef void NRT_managed_dtor(void *data);

typedef void *(*NRT_external_malloc_func)(size_t size, void *opaque_data);
typedef void *(*NRT_external_realloc_func)(void *ptr, size_t new_size, void *opaque_
↪data);
typedef void (*NRT_external_free_func)(void *ptr, void *opaque_data);

struct ExternalMemAllocator {
    NRT_external_malloc_func malloc;
    NRT_external_realloc_func realloc;
    NRT_external_free_func free;
    void *opaque_data;
};

typedef struct ExternalMemAllocator NRT_ExternalAllocator;

typedef struct {
    /* Methods to create MemInfos.

    MemInfos are like smart pointers for objects that are managed by the Numba.
    */

    /* Allocate memory

    *nbytes* is the number of bytes to be allocated

    Returning a new reference.
```

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```
    */
    NRT_MemInfo* (*allocate)(size_t nbytes);
    /* Allocates memory using an external allocator but still using Numba's MemInfo.
     *
     * NOTE: An externally provided allocator must behave the same way as C99
     *       stdlib.h's "malloc" function with respect to return value
     *       (including the behaviour that occurs when requesting an allocation
     *        of size 0 bytes).
     */
    NRT_MemInfo* (*allocate_external)(size_t nbytes, NRT_ExternalAllocator *allocator);

    /* Convert externally allocated memory into a MemInfo.

    *data* is the memory pointer
    *dtor* is the deallocator of the memory
    */
    NRT_MemInfo* (*manage_memory)(void *data, NRT_managed_dtor dtor);

    /* Acquire a reference */
    void (*acquire)(NRT_MemInfo* mi);

    /* Release a reference */
    void (*release)(NRT_MemInfo* mi);

    /* Get MemInfo data pointer */
    void* (*get_data)(NRT_MemInfo* mi);

} NRT_api_functions;



#endif /* NUMBA_NRT_EXTERNAL_H_ */
```

Inside Numba compiled code, the `numba.core.unsafe.nrt.NRT_get_api()` intrinsic can be used to obtain a pointer to the `NRT_api_functions`.

Here is an example that uses the `nrt_external.h`:

```
#include <stdio.h>
#include "numba/core/runtime/nrt_external.h"

void my_dtor(void *ptr) {
    free(ptr);
}

NRT_MemInfo* my_allocate(NRT_api_functions *nrt) {
    /* heap allocate some memory */
    void * data = malloc(10);
    /* wrap the allocated memory; yield a new reference */
    NRT_MemInfo *mi = nrt->manage_memory(data, my_dtor);
    /* acquire reference */
    nrt->acquire(mi);
    /* release reference */
```

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```
    nrt->release(mi);
    return mi;
}
```

It is important to ensure that the NRT is initialized prior to making calls to it, calling `numba.core.runtime.nrt.rtsys.initialize(context)` from Python will have the desired effect. Similarly the code snippet:

```
from numba.core.registry import cpu_target # Get the CPU target singleton
cpu_target.target_context # Access the target_context property to initialize
```

will achieve the same specifically for Numba's CPU target (the default). Failure to initialize the NRT will result in access violations as function pointers for various internal atomic operations will be missing in the `NRT_MemSys` struct.

6.7.4 Future Plan

The plan for NRT is to make a standalone shared library that can be linked to Numba compiled code, including use within the Python interpreter and without the Python interpreter. To make that work, we will be doing some refactoring:

- numba *NPM* code references statically compiled code in "helperlib.c". Those functions should be moved to NRT.

6.8 Using the Numba Rewrite Pass for Fun and Optimization

6.8.1 Overview

This section introduces intermediate representation (IR) rewrites, and how they can be used to implement optimizations.

As discussed earlier in "*Stage 5a: Rewrite typed IR*", rewriting the Numba IR allows us to perform optimizations that would be much more difficult to perform at the lower LLVM level. Similar to the Numba type and lowering subsystems, the rewrite subsystem is user extensible. This extensibility affords Numba the possibility of supporting a wide variety of domain-specific optimizations (DSO's).

The remaining subsections detail the mechanics of implementing a rewrite, registering a rewrite with the rewrite registry, and provide examples of adding new rewrites, as well as internals of the array expression optimization pass. We conclude by reviewing some use cases exposed in the examples, as well as reviewing any points where developers should take care.

6.8.2 Rewriting Passes

Rewriting passes have a simple *`match()`* and *`apply()`* interface. The division between matching and rewriting follows how one would define a term rewrite in a declarative domain-specific languages (DSL's). In such DSL's, one may write a rewrite as follows:

```
<match> => <replacement>
```

The `<match>` and `<replacement>` symbols represent IR term expressions, where the left-hand side presents a pattern to match, and the right-hand side an IR term constructor to build upon matching. Whenever the rewrite matches an IR pattern, any free variables in the left-hand side are bound within a custom environment. When applied, the rewrite uses the pattern matching environment to bind any free variables in the right-hand side.

As Python is not commonly used in a declarative capacity, Numba uses object state to handle the transfer of information between the matching and application steps.

The `Rewrite` Base Class

class Rewrite

The *Rewrite* class simply defines an abstract base class for Numba rewrites. Developers should define rewrites as subclasses of this base type, overloading the *match()* and *apply()* methods.

pipeline

The pipeline attribute contains the `numba.compiler.Pipeline` instance that is currently compiling the function under consideration for rewriting.

__init__(*self*, *pipeline*, **args*, ***kws*)

The base constructor for rewrites simply stashes its arguments into attributes of the same name. Unless being used in debugging or testing, rewrites should only be constructed by the `RewriteRegistry` in the `RewriteRegistry.apply()` method, and the construction interface should remain stable (though the pipeline will commonly contain just about everything there is to know).

match(*self*, *block*, *typemap*, *callmap*)

The *match()* method takes four arguments other than *self*:

- *func_ir*: This is an instance of `numba.ir.FunctionIR` for the function being rewritten.
- *block*: This is an instance of `numba.ir.Block`. The matching method should iterate over the instructions contained in the `numba.ir.Block.body` member.
- *typemap*: This is a Python `dict` instance mapping from symbol names in the IR, represented as strings, to Numba types.
- *callmap*: This is another `dict` instance mapping from calls, represented as `numba.ir.Expr` instances, to their corresponding call site type signatures, represented as a `numba.typing.templates.Signature` instance.

The *match()* method should return a `bool` result. A `True` result should indicate that one or more matches were found, and the *apply()* method will return a new replacement `numba.ir.Block` instance. A `False` result should indicate that no matches were found, and subsequent calls to *apply()* will return undefined or invalid results.

apply(*self*)

The *apply()* method should only be invoked following a successful call to *match()*. This method takes no additional parameters other than *self*, and should return a replacement `numba.ir.Block` instance.

As mentioned above, the behavior of calling *apply()* is undefined unless *match()* has already been called and returned `True`.

Subclassing `Rewrite`

Before going into the expectations for the overloaded methods any *Rewrite* subclass must have, let's step back a minute to review what is taking place here. By providing an extensible compiler, Numba opens itself to user-defined code generators which may be incomplete, or worse, incorrect. When a code generator goes awry, it can cause abnormal program behavior or early termination. User-defined rewrites add a new level of complexity because they must not only generate correct code, but the code they generate should ensure that the compiler does not get stuck in a match/apply loop. Non-termination by the compiler will directly lead to non-termination of user function calls.

There are several ways to help ensure that a rewrite terminates:

- *Typing*: A rewrite should generally attempt to decompose composite types, and avoid composing new types. If the rewrite is matching a specific type, changing expression types to a lower-level type will ensure they will no long match after the rewrite is applied.

- *Special instructions*: A rewrite may synthesize custom operators or use special functions in the target IR. This technique again generates code that is no longer within the domain of the original match, and the rewrite will terminate.

In the "*Case study: Array Expressions*" subsection, below, we'll see how the array expression rewriter uses both of these techniques.

Overloading `Rewrite.match()`

Every rewrite developer should seek to have their implementation of *`match()`* return a `False` value as quickly as possible. Numba is a just-in-time compiler, and adding compilation time ultimately adds to the user's run time. When a rewrite returns `False` for a given block, the registry will no longer process that block with that rewrite, and the compiler is that much closer to proceeding to lowering.

This need for timeliness has to be balanced against collecting the necessary information to make a match for a rewrite. Rewrite developers should be comfortable adding dynamic attributes to their subclasses, and then having these new attributes guide construction of the replacement basic block.

Overloading `Rewrite.apply()`

The *`apply()`* method should return a replacement `numba.ir.Block` instance to replace the basic block that contained a match for the rewrite. As mentioned above, the IR built by *`apply()`* methods should preserve the semantics of the user's code, but also seek to avoid generating another match for the same rewrite or set of rewrites.

6.8.3 The Rewrite Registry

When you want to include a rewrite in the rewrite pass, you should register it with the rewrite registry. The `numba.rewrites` module provides both the abstract base class and a class decorator for hooking into the Numba rewrite subsystem. The following illustrates a stub definition of a new rewrite:

```
from numba import rewrites

@rewrites.register_rewrite
class MyRewrite(rewrites.Rewrite):

    def match(self, block, typemap, calltypes):
        raise NotImplementedError("FIXME")

    def apply(self):
        raise NotImplementedError("FIXME")
```

Developers should note that using the class decorator as shown above will register a rewrite at import time. It is the developer's responsibility to ensure their extensions are loaded before compilation starts.

6.8.4 Case study: Array Expressions

This subsection looks at the array expression rewriter in more depth. The array expression rewriter, and most of its support functionality, are found in the `numba.npyufunc.array_exprs` module. The rewriting pass itself is implemented in the `RewriteArrayExprs` class. In addition to the rewriter, the `array_exprs` module includes a function for lowering array expressions, `_lower_array_expr()`. The overall optimization process is as follows:

- `RewriteArrayExprs.match()`: The rewrite pass looks for one or more array operations that form an array expression.
- `RewriteArrayExprs.apply()`: Once an array expression is found, the rewriter replaces the individual array operations with a new kind of IR expression, the `arrayexpr`.
- `numba.npyufunc.array_exprs._lower_array_expr()`: During lowering, the code generator calls `_lower_array_expr()` whenever it finds an `arrayexpr` IR expression.

More details on each step of the optimization are given below.

The `RewriteArrayExprs.match()` method

The array expression optimization pass starts by looking for array operations, including calls to supported `ufunc`'s and user-defined *`DUFunc`*'s. Numba IR follows the conventions of a static single assignment (SSA) language, meaning that the search for array operators begins with looking for assignment instructions.

When the rewriting pass calls the `RewriteArrayExprs.match()` method, it first checks to see if it can trivially reject the basic block. If the method determines the block to be a candidate for matching, it sets up the following state variables in the rewrite object:

- *crnt_block*: The current basic block being matched.
- *typemap*: The *typemap* for the function being matched.
- *matches*: A list of variable names that reference array expressions.
- *array_assigns*: A map from assignment variable names to the actual assignment instructions that define the given variable.
- *const_assigns*: A map from assignment variable names to the constant valued expression that defines the constant variable.

At this point, the match method iterates over the assignment instructions in the input basic block. For each assignment instruction, the matcher looks for one of two things:

- Array operations: If the right-hand side of the assignment instruction is an expression, and the result of that expression is an array type, the matcher checks to see if the expression is either a known array operation, or a call to a universal function. If an array operator is found, the matcher stores the left-hand variable name and the whole instruction in the *array_assigns* member. Finally, the matcher tests to see if any operands of the array operation have also been identified as targets of other array operations. If one or more operands are also targets of array operations, then the matcher will also append the left-hand side variable name to the *matches* member.
- Constants: Constants (even scalars) can be operands to array operations. Without worrying about the constant being apart of an array expression, the matcher stores constant names and values in the *const_assigns* member.

The end of the matching method simply checks for a non-empty *matches* list, returning `True` if there were one or more matches, and `False` when *matches* is empty.

The `RewriteArrayExprs.apply()` method

When one or matching array expressions are found by `RewriteArrayExprs.match()`, the rewriting pass will call `RewriteArrayExprs.apply()`. The apply method works in two passes. The first pass iterates over the matches found, and builds a map from instructions in the old basic block to new instructions in the new basic block. The second pass iterates over the instructions in the old basic block, copying instructions that are not changed by the rewrite, and replacing or deleting instructions that were identified by the first pass.

The `RewriteArrayExprs._handle_matches()` implements the first pass of the code generation portion of the rewrite. For each match, this method builds a special IR expression that contains an expression tree for the array expression. To compute the leaves of the expression tree, the `_handle_matches()` method iterates over the operands of the identified root operation. If the operand is another array operation, it is translated into an expression sub-tree. If the operand is a constant, `_handle_matches()` copies the constant value. Otherwise, the operand is marked as being used by an array expression. As the method builds array expression nodes, it builds a map from old instructions to new instructions (*replace_map*), as well as sets of variables that may have moved (*used_vars*), and variables that should be removed altogether (*dead_vars*). These three data structures are returned back to the calling `RewriteArrayExprs.apply()` method.

The remaining part of the `RewriteArrayExprs.apply()` method iterates over the instructions in the old basic block. For each instruction, this method either replaces, deletes, or duplicates that instruction based on the results of `RewriteArrayExprs._handle_matches()`. The following list describes how the optimization handles individual instructions:

- When an instruction is an assignment, `apply()` checks to see if it is in the replacement instruction map. When an assignment instruction is found in the instruction map, `apply()` must then check to see if the replacement instruction is also in the replacement map. The optimizer continues this check until it either arrives at a `None` value or an instruction that isn't in the replacement map. Instructions that have a replacement that is `None` are deleted. Instructions that have a non-`None` replacement are replaced. Assignment instructions not in the replacement map are appended to the new basic block with no changes made.
- When the instruction is a delete instruction, the rewrite checks to see if it deletes a variable that may still be used by a later array expression, or if it deletes a dead variable. Delete instructions for used variables are added to a map of deferred delete instructions that `apply()` uses to move them past any uses of that variable. The loop copies delete instructions for non-dead variables, and ignores delete instructions for dead variables (effectively removing them from the basic block).
- All other instructions are appended to the new basic block.

Finally, the `apply()` method returns the new basic block for lowering.

The `_lower_array_expr()` function

If we left things at just the rewrite, then the lowering stage of the compiler would fail, complaining it doesn't know how to lower `arrayexpr` operations. We start by hooking a lowering function into the target context whenever the `RewriteArrayExprs` class is instantiated by the compiler. This hook causes the lowering pass to call `_lower_array_expr()` whenever it encounters an `arrayexr` operator.

This function has two steps:

- Synthesize a Python function that implements the array expression: This new Python function essentially behaves like a Numpy `ufunc`, returning the result of the expression on scalar values in the broadcasted array arguments. The lowering function accomplishes this by translating from the array expression tree into a Python AST.
- Compile the synthetic Python function into a kernel: At this point, the lowering function relies on existing code for lowering ufunc and DUFunc kernels, calling `numba.targets.numpyimpl.numpy_ufunc_kernel()` after defining how to lower calls to the synthetic function.

The end result is similar to loop lifting in Numba's object mode.

6.8.5 Conclusions and Caveats

We have seen how to implement rewrites in Numba, starting with the interface, and ending with an actual optimization. The key points of this section are:

- When writing a good plug-in, the matcher should try to get a go/no-go result as soon as possible.
- The rewrite application portion can be more computationally expensive, but should still generate code that won't cause infinite loops in the compiler.
- We use object state to communicate any results of matching to the rewrite application pass.

6.9 Live Variable Analysis

(Related issue https://github.com/numba/numba/pull/1611)

Numba uses reference-counting for garbage collection, a technique that requires cooperation by the compiler. The Numba IR encodes the location where a decref must be inserted. These locations are determined by live variable analysis. The corresponding source code is the `_insert_var_dels()` method in https://github.com/numba/numba/blob/main/numba/interpreter.py.

In Python semantic, once a variable is defined inside a function, it is alive until the variable is explicitly deleted or the function scope is ended. However, Numba analyzes the code to determine the minimum bound of the lifetime of each variable by its definition and usages during compilation. As soon as a variable is unreachable, a `del` instruction is inserted at the closest basic-block (either at the start of the next block(s) or at the end of the current block). This means variables can be released earlier than in regular Python code.

The behavior of the live variable analysis affects memory usage of the compiled code. Internally, Numba does not differentiate temporary variables and user variables. Since each operation generates at least one temporary variable, a function can accumulate a high number of temporary variables if they are not released as soon as possible. Our generator implementation can benefit from early releasing of variables, which reduces the size of the state to suspend at each yield point.

6.9.1 Notes on behavior of the live variable analysis

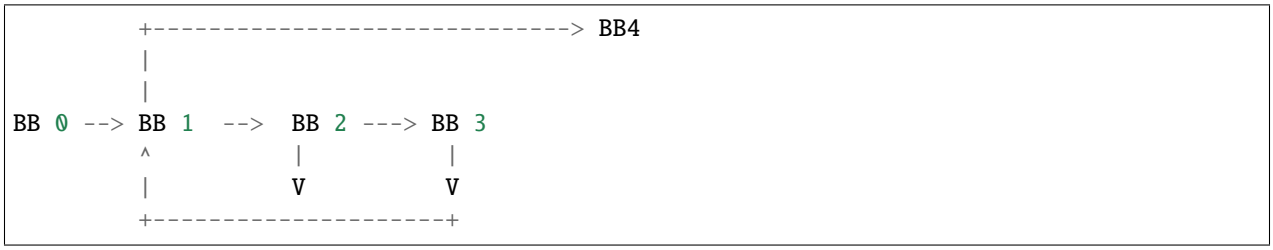
Variable deleted before definition

(Related issue: https://github.com/numba/numba/pull/1738)

When a variable lifetime is confined within the loop body (its definition and usage does not escape the loop body), like:

```
def f(arr):
  # BB 0
  res = 0
  # BB 1
  for i in (0, 1):
      # BB 2
      t = arr[i]
      if t[i] > 1:
          # BB 3
          res += t[i]
  # BB 4
  return res
```

Variable `t` is never referenced outside of the loop. A `del` instruction is emitted for `t` at the head of the loop (BB 1) before a variable is defined. The reason is obvious once we know the control flow graph:



Variable `t` is defined in BB 1. In BB 2, the evaluation of `t[i] > 1` uses `t`, which is the last use if execution takes the false branch and goto BB 1. In BB 3, `t` is only used in `res += t[i]`, which is the last use if execution takes the true branch. Because BB 3, an outgoing branch of BB 2 uses `t`, `t` must be deleted at the common predecessor. The closest point is BB 1, which does not have `t` defined from the incoming edge of BB 0.

Alternatively, if `t` is deleted at BB 4, we will still have to delete the variable before its definition because BB4 can be executed without executing the loop body (BB 2 and BB 3), where the variable is defined.

6.10 Listings

This shows listings from compiler internal registries (e.g. lowering definitions). The information is provided as developer reference. When possible, links to source code are provided via github links.

6.10.1 New style listings

The following listings are generated from `numba.help.inspector.write_listings()`. Users can run `python -m numba.help.inspector --format=rst <package>` to recreate the the documentation.

Listings for builtins

builtins

`builtins.abs()`

- defined by `<class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>`
- defined by `func(x)` at numba/experimental/jitclass/overloads.py:0-34
- defined by `<class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>`

`builtins.chr()`

- defined by `ol_chr(i)` at numba/cpython/unicode.py:2547-2552

`builtins.divmod()`

- defined by `<class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>`

builtins.**getattr**()

- defined by `ol_getattr_2(obj, name)` at numba/cpython/old_builtins.py:952-956
- defined by `ol_getattr_3(obj, name, default)` at numba/cpython/old_builtins.py:963-967

builtins.**hasattr**()

- defined by `ol_hasattr(obj, name)` at numba/cpython/old_builtins.py:996-1000

builtins.**hash**()

- defined by `func(x)` at numba/experimental/jitclass/overloads.py:0-34
- defined by `hash_overload(obj)` at numba/cpython/old_hashing.py:64-76

builtins.**isinstance**()

- defined by `ol_isinstance(var, typs)` at numba/cpython/old_builtins.py:766-864

builtins.**iter**()

- defined by `<class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>`

builtins.**len**()

- defined by `<class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>`
- defined by `func(x)` at numba/experimental/jitclass/overloads.py:0-34
- defined by `unicode_len(s)` at numba/cpython/unicode.py:476-481
- defined by `charseq_len(s)` at numba/cpython/charseq.py:351-372
- defined by `literal_list_len(lst)` at numba/cpython/listobj.py:1234-1239
- defined by `impl_len(d)` at numba/typed/dictobject.py:679-689
- defined by `impl_len_iters(d)` at numba/typed/dictobject.py:692-703
- defined by `literalstrkeydict_impl_len(d)` at numba/typed/dictobject.py:1307-1312
- defined by `impl_len(l)` at numba/typed/listobject.py:407-415
- defined by `<class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>`

builtins.**max**()

- defined by `<class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>`
- defined by `indval_max(indval1, indval2)` at numba/cpython/old_builtins.py:606-632
- defined by `boolval_max(val1, val2)` at numba/cpython/old_builtins.py:635-641
- defined by `iterable_max(iterable)` at numba/cpython/old_builtins.py:666-668

builtins.**min**()

- defined by `<class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>`
- defined by `indval_min(indval1, indval2)` at numba/cpython/old_builtins.py:568-594
- defined by `boolval_min(val1, val2)` at numba/cpython/old_builtins.py:597-603

- defined by `iterable_min(iterable)` at numba/cpython/old_builtins.py:661-663

`builtins.next()`

- defined by `<class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>`

`builtins.ord()`

- defined by `ol_ord(c)` at numba/cpython/unicode.py:2507-2516

`builtins.pow()`

- defined by `<class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>`

`builtins.print()`

- defined by `<class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>`

`builtins.repr()`

- defined by `ol_repr_generic(obj)` at numba/cpython/old_builtins.py:1003-1014

`builtins.round()`

- defined by `<class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>`

`builtins.sorted()`

- defined by `ol_sorted(iterable, key=None, reverse=False)` at numba/cpython/listobj.py:1113-1126

`builtins.sum()`

- defined by `ol_sum(iterable, start=0)` at numba/cpython/old_builtins.py:703-736

Not showing 24 unsupported functions.

supported = 19 / 43 = 44.19%

Listings for math

math

`math.acos()`

- defined by `<class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>`

`math.acosh()`

- defined by `<class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>`

`math.asin()`

- defined by `<class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>`

math.**asinh**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**atan**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**atan2**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**atanh**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**ceil**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**copysign**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**cos**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**cosh**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**degrees**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**erf**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**erfc**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**exp**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**expm1**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**fabs**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**floor**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**frexp**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**gamma**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**gcd**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**hypot**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**isfinite**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**isinf**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**isnan**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**ldexp**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**lgamma**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**log**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**log10**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**log1p**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**log2**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**nextafter**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**pow**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**radians**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**sin**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**sinh**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**sqrt**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**tan**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**tanh**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

math.**trunc**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

Not showing 13 unsupported functions.

supported = 40 / 53 = 75.47%

Listings for cmath

cmath

cmath.**acos**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

cmath.**acosh**()

- defined by impl_cmath_acosh(z) at numba/cpython/cmathimpl.py:413-439

cmath.**asin**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

cmath.**asinh**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

cmath.**atan**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

cmath.**atanh**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

cmath.**cos**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

cmath.**cosh**()

- defined by impl_cmath_cosh(z) at numba/cpython/cmathimpl.py:279-306

cmath.**exp**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

cmath.**isfinite**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

cmath.**isinf**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

cmath.**isnan**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

cmath.**log**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

cmath.**log10**()

- defined by impl_cmath_log10(z) at numba/cpython/cmathimpl.py:169-183

cmath.**phase**()

- defined by phase_impl(x) at numba/cpython/cmathimpl.py:186-195

cmath.**polar**()

- defined by polar_impl(x) at numba/cpython/cmathimpl.py:198-206

cmath.**rect**()

- defined by impl_cmath_rect(r, phi) at numba/cpython/cmathimpl.py:57-81

cmath.**sin**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

cmath.**sinh**()

- defined by impl_cmath_sinh(z) at numba/cpython/cmathimpl.py:319-343

cmath.**sqrt**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

cmath.**tan**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

cmath.**tanh**()

- defined by impl_cmath_tanh(z) at numba/cpython/cmathimpl.py:357-384

Not showing 1 unsupported functions.

supported = 22 / 23 = 95.65%

Listings for numpy

numpy

numpy.**arange**()

- defined by np_arange(start, /, stop=None, step=None, dtype=None) at numba/np/arrayobj.py:4906-4971

numpy.**array**()

- defined by impl_np_array(object, dtype=None) at numba/np/arrayobj.py:5632-5644

numpy.**asarray**()

- defined by np_asarray(a, dtype=None) at numba/np/old_arraymath.py:4263-4316

numpy.**asarray_chkfinite**()

- defined by np_asarray_chkfinite(a, dtype=None) at numba/np/old_arraymath.py:4428-4450

numpy.**ascontiguousarray**()

- defined by array_ascontiguousarray(a) at numba/np/arrayobj.py:5153-5164

numpy.**asfortranarray**()

- defined by array_asfortranarray(a) at numba/np/arrayobj.py:5167-5179

numpy.**bartlett**()

- defined by window_generator.<locals>.window_overload(M) at numba/np/old_arraymath.py:4558-4570

numpy.**blackman**()

- defined by window_generator.<locals>.window_overload(M) at numba/np/old_arraymath.py:4558-4570

numpy.**broadcast_shapes**()

- defined by ol_numpy_broadcast_shapes(*args) at numba/np/arrayobj.py:1524-1562

numpy.**empty**()

- defined by ol_np_empty(shape, dtype=<class 'float'>) at numba/np/arrayobj.py:4441-4460

numpy.**eye**()

- defined by numpy_eye(N, M=None, k=0, dtype=<class 'float'>) at numba/np/arrayobj.py:4633-4656

numpy.**frombuffer**()

- defined by impl_np_frombuffer(buffer, dtype=<class 'float'>) at numba/np/arrayobj.py:5308-5333

numpy.**full**()

- defined by impl_np_full(shape, fill_value, dtype=None) at numba/np/arrayobj.py:4556-4570

numpy.**hamming**()

- defined by window_generator.<locals>.window_overload(M) at numba/np/old_arraymath.py:4558-4570

numpy.**hanning**()

- defined by window_generator.<locals>.window_overload(M) at numba/np/old_arraymath.py:4558-4570

numpy.**identity**()

- defined by impl_np_identity(n, dtype=None) at numba/np/arrayobj.py:4602-4615

numpy.**indices**()

- defined by numpy_indices(dimensions) at numba/np/arrayobj.py:4698-4723

numpy.**isscalar**()

- defined by np_isscalar(element) at numba/np/old_arraymath.py:1014-1020

numpy.**kaiser**()

- defined by np_kaiser(M, beta) at numba/np/old_arraymath.py:4676-4695

numpy.**ones**()

- defined by ol_np_ones(shape, dtype=None) at numba/np/arrayobj.py:4587-4599

numpy.**row_stack**()

- defined by impl_np_vstack(tup) at numba/np/arrayobj.py:6254-6259

numpy.**trapz**()

- defined by np_trapz(y, x=None, dx=1.0) at numba/np/old_arraymath.py:2218-2237

numpy.**tri**()

- defined by np_tri(N, M=None, k=0) at numba/np/old_arraymath.py:1947-1958

numpy.**tril_indices**()

- defined by np_tril_indices(n, k=0, m=None) at numba/np/old_arraymath.py:2011-2022

numpy.**triu_indices**()

- defined by np_triu_indices(n, k=0, m=None) at numba/np/old_arraymath.py:2071-2082

numpy.**zeros**()

- defined by ol_np_zeros(shape, dtype=<class 'float'>) at numba/np/arrayobj.py:4519-4527

Not showing 42 unsupported functions.

supported = 26 / 68 = 38.24%

numpy.char

This module is not supported.

numpy.compat

This module is not supported.

numpy.compat.py3k

This module is not supported.

numpy.core

This module is not supported.

numpy.core.arrayprint

This module is not supported.

numpy.core.defchararray

This module is not supported.

numpy.core.einsumfunc

This module is not supported.

numpy.core.fromnumeric

This module is not supported.

numpy.core.function_base

This module is not supported.

numpy.core.getlimits

This module is not supported.

numpy.core.multiarray

This module is not supported.

numpy.core.numeric

This module is not supported.

numpy.core.numerictypes

This module is not supported.

numpy.core.overrides

This module is not supported.

numpy.core.records

This module is not supported.

numpy.core.shape_base

This module is not supported.

numpy.core.umath

This module is not supported.

numpy.ctypeslib

This module is not supported.

numpy.distutils

This module is not supported.

numpy.distutils.armccompiler

This module is not supported.

numpy.distutils.ccompiler

This module is not supported.

numpy.distutils.ccompiler_opt

This module is not supported.

numpy.distutils.command

This module is not supported.

numpy.distutils.command.autodist

This module is not supported.

numpy.distutils.command.bdist_rpm

This module is not supported.

numpy.distutils.command.build

This module is not supported.

numpy.distutils.command.build_clib

This module is not supported.

numpy.distutils.command.build_ext

This module is not supported.

numpy.distutils.command.build_py

This module is not supported.

numpy.distutils.command.build_scripts

This module is not supported.

numpy.distutils.command.build_src

This module is not supported.

numpy.distutils.command.config

This module is not supported.

numpy.distutils.command.config_compiler

This module is not supported.

numpy.distutils.command.develop

This module is not supported.

numpy.distutils.command.egg_info

This module is not supported.

numpy.distutils.command.install

This module is not supported.

numpy.distutils.command.install_clib

This module is not supported.

numpy.distutils.command.install_data

This module is not supported.

numpy.distutils.command.install_headers

This module is not supported.

numpy.distutils.command.sdist

This module is not supported.

numpy.distutils.conv_template

This module is not supported.

numpy.distutils.core

This module is not supported.

numpy.distutils.cpuinfo

This module is not supported.

numpy.distutils.exec_command

This module is not supported.

numpy.distutils.extension

This module is not supported.

numpy.distutils.fcompiler

This module is not supported.

numpy.distutils.fcompiler.absoft

This module is not supported.

numpy.distutils.fcompiler.arm

This module is not supported.

numpy.distutils.fcompiler.compaq

This module is not supported.

numpy.distutils.fcompiler.environment

This module is not supported.

numpy.distutils.fcompiler.fujitsu

This module is not supported.

numpy.distutils.fcompiler.g95

This module is not supported.

numpy.distutils.fcompiler.gnu

This module is not supported.

numpy.distutils.fcompiler.hpux

This module is not supported.

numpy.distutils.fcompiler.ibm

This module is not supported.

numpy.distutils.fcompiler.intel

This module is not supported.

numpy.distutils.fcompiler.lahey

This module is not supported.

numpy.distutils.fcompiler.mips

This module is not supported.

numpy.distutils.fcompiler.nag

This module is not supported.

numpy.distutils.fcompiler.none

This module is not supported.

numpy.distutils.fcompiler.nv

This module is not supported.

numpy.distutils.fcompiler.pathf95

This module is not supported.

numpy.distutils.fcompiler.pg

This module is not supported.

numpy.distutils.fcompiler.sun

This module is not supported.

numpy.distutils.fcompiler.vast

This module is not supported.

numpy.distutils.from_template

This module is not supported.

numpy.distutils.fujitsuccompiler

This module is not supported.

numpy.distutils.intelccompiler

This module is not supported.

numpy.distutils.lib2def

This module is not supported.

numpy.distutils.line_endings

This module is not supported.

numpy.distutils.log

This module is not supported.

numpy.distutils.mingw32ccompiler

This module is not supported.

numpy.distutils.misc_util

numpy.distutils.misc_util.**reduce**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

Not showing 63 unsupported functions.

supported = 1 / 64 = 1.56%

numpy.distutils.msvccompiler

This module is not supported.

numpy.distutils.npy_pkg_config

This module is not supported.

numpy.distutils.numpy_distribution

This module is not supported.

numpy.distutils.pathccompiler

This module is not supported.

numpy.distutils.system_info

numpy.distutils.system_info.**reduce**()

Alias to: numpy.distutils.misc_util.reduce

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

Not showing 16 unsupported functions.

supported = 1 / 17 = 5.88%

numpy.distutils.unixccompiler

This module is not supported.

numpy.dtypes

This module is not supported.

numpy.exceptions

This module is not supported.

numpy.f2py

This module is not supported.

numpy.f2py.auxfuncs

numpy.f2py.auxfuncs.**reduce**()

Alias to: numpy.distutils.misc_util.reduce

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

Not showing 114 unsupported functions.

supported = 1 / 115 = 0.87%

numpy.f2py.capi_maps

This module is not supported.

numpy.f2py.cb_rules

This module is not supported.

numpy.f2py.cfuncs

This module is not supported.

numpy.f2py.common_rules

This module is not supported.

numpy.f2py.crackfortran

This module is not supported.

numpy.f2py.diagnose

This module is not supported.

numpy.f2py.f2py2e

This module is not supported.

numpy.f2py.f90mod_rules

This module is not supported.

numpy.f2py.func2subr

This module is not supported.

numpy.f2py.rules

This module is not supported.

numpy.f2py.symbolic

numpy.f2py.symbolic.**gcd**()

- defined by <class 'numba.core.typing.templates.Registry.register_global.<locals>.decorate.<locals>.Template'>

Not showing 29 unsupported functions.

supported = 1 / 30 = 3.33%

numpy.f2py.use_rules

This module is not supported.

numpy.fft

This module is not supported.

numpy.fft.helper

This module is not supported.

numpy.lib

This module is not supported.

numpy.lib.array_utils

This module is not supported.

numpy.lib.format

This module is not supported.

numpy.lib.introspect

This module is not supported.

numpy.lib.mixins

This module is not supported.

numpy.lib.npyio

This module is not supported.

numpy.lib.recfunctions

This module is not supported.

numpy.lib.scimath

This module is not supported.

numpy.lib.stride_tricks

numpy.lib.stride_tricks.**as_strided**()

- defined by `as_strided(x, shape=None, strides=None)` at numba/np/arrayobj.py:6742-6768

Not showing 0 unsupported functions.

supported = 1 / 1 = 100.00%

numpy.lib.user_array

This module is not supported.

numpy.linalg

This module is not supported.

numpy.linalg.lapack_lite

This module is not supported.

numpy.linalg.linalg

This module is not supported.

numpy.ma

This module is not supported.

numpy.ma.core

numpy.ma.core.**narray**()

Alias to: `numpy.array`

- defined by `impl_np_array(object, dtype=None)` at numba/np/arrayobj.py:5632-5644

Not showing 84 unsupported functions.

supported = 1 / 85 = 1.18%

numpy.ma.extras

numpy.ma.extras.**nxarray**()

Alias to: numpy.array

- defined by impl_np_array(object, dtype=None) at numba/np/arrayobj.py:5632-5644

Not showing 49 unsupported functions.

supported = 1 / 50 = 2.00%

numpy.ma.mrecords

This module is not supported.

numpy.ma.testutils

This module is not supported.

numpy.ma.timer_comparison

This module is not supported.

numpy.matlib

numpy.matlib.**arange**()

Alias to: numpy.arange

- defined by np_arange(start, /, stop=None, step=None, dtype=None) at numba/np/arrayobj.py:4906-4971

numpy.matlib.**array**()

Alias to: numpy.array

- defined by impl_np_array(object, dtype=None) at numba/np/arrayobj.py:5632-5644

numpy.matlib.**asarray**()

Alias to: numpy.asarray

- defined by np_asarray(a, dtype=None) at numba/np/old_arraymath.py:4263-4316

numpy.matlib.**asarray_chkfinite**()

Alias to: numpy.asarray_chkfinite

- defined by np_asarray_chkfinite(a, dtype=None) at numba/np/old_arraymath.py:4428-4450

numpy.matlib.**ascontiguousarray**()

Alias to: numpy.ascontiguousarray

- defined by array_ascontiguousarray(a) at numba/np/arrayobj.py:5153-5164

numpy.matlib.**asfortranarray**()

Alias to: numpy.asfortranarray

- defined by array_asfortranarray(a) at numba/np/arrayobj.py:5167-5179

numpy.matlib.**bartlett**()

Alias to: numpy.bartlett

- defined by window_generator.<locals>.window_overload(M) at numba/np/old_arraymath.py:4558-4570

numpy.matlib.**blackman**()

Alias to: numpy.blackman

- defined by window_generator.<locals>.window_overload(M) at numba/np/old_arraymath.py:4558-4570

numpy.matlib.**broadcast_shapes**()

Alias to: numpy.broadcast_shapes

- defined by ol_numpy_broadcast_shapes(*args) at numba/np/arrayobj.py:1524-1562

numpy.matlib.**frombuffer**()

Alias to: numpy.frombuffer

- defined by impl_np_frombuffer(buffer, dtype=<class 'float'>) at numba/np/arrayobj.py:5308-5333

numpy.matlib.**full**()

Alias to: numpy.full

- defined by impl_np_full(shape, fill_value, dtype=None) at numba/np/arrayobj.py:4556-4570

numpy.matlib.**hamming**()

Alias to: numpy.hamming

- defined by window_generator.<locals>.window_overload(M) at numba/np/old_arraymath.py:4558-4570

numpy.matlib.**hanning**()

Alias to: numpy.hanning

- defined by window_generator.<locals>.window_overload(M) at numba/np/old_arraymath.py:4558-4570

numpy.matlib.**indices**()

Alias to: numpy.indices

- defined by numpy_indices(dimensions) at numba/np/arrayobj.py:4698-4723

numpy.matlib.**isscalar**()

Alias to: numpy.isscalar

- defined by np_isscalar(element) at numba/np/old_arraymath.py:1014-1020

numpy.matlib.**kaiser**()

Alias to: numpy.kaiser

- defined by np_kaiser(M, beta) at numba/np/old_arraymath.py:4676-4695

numpy.matlib.**row_stack**()

Alias to: numpy.row_stack

- defined by impl_np_vstack(tup) at numba/np/arrayobj.py:6254-6259

numpy.matlib.**trapz**()

Alias to: numpy.trapz

- defined by np_trapz(y, x=None, dx=1.0) at numba/np/old_arraymath.py:2218-2237

numpy.matlib.**tri**()

Alias to: numpy.tri

- defined by np_tri(N, M=None, k=0) at numba/np/old_arraymath.py:1947-1958

numpy.matlib.**tril_indices**()

Alias to: numpy.tril_indices

- defined by np_tril_indices(n, k=0, m=None) at numba/np/old_arraymath.py:2011-2022

numpy.matlib.**triu_indices**()

Alias to: numpy.triu_indices

- defined by np_triu_indices(n, k=0, m=None) at numba/np/old_arraymath.py:2071-2082

Not showing 50 unsupported functions.

supported = 21 / 71 = 29.58%

numpy.matrixlib

This module is not supported.

numpy.matrixlib.defmatrix

numpy.matrixlib.defmatrix.**isscalar**()

Alias to: numpy.isscalar

- defined by np_isscalar(element) at numba/np/old_arraymath.py:1014-1020

Not showing 3 unsupported functions.

supported = 1 / 4 = 25.00%

numpy.polynomial

This module is not supported.

numpy.polynomial.chebyshev

This module is not supported.

numpy.polynomial.hermite

This module is not supported.

numpy.polynomial.hermite_e

This module is not supported.

numpy.polynomial.laguerre

This module is not supported.

numpy.polynomial.legendre

This module is not supported.

numpy.polynomial.polynomial

numpy.polynomial.polynomial.**polyadd**()

- defined by `numpy_polyadd(c1, c2)` at numba/np/polynomial/polynomial_functions.py:186-208

numpy.polynomial.polynomial.**polydiv**()

- defined by `numpy_polydiv(c1, c2)` at numba/np/polynomial/polynomial_functions.py:342-375

numpy.polynomial.polynomial.**polyint**()

- defined by `poly_polyint(c, m=1)` at numba/np/polynomial/polynomial_functions.py:301-339

numpy.polynomial.polynomial.**polymul**()

- defined by `numpy_polymul(c1, c2)` at numba/np/polynomial/polynomial_functions.py:236-251

numpy.polynomial.polynomial.**polysub**()

- defined by `numpy_polysub(c1, c2)` at numba/np/polynomial/polynomial_functions.py:211-233

numpy.polynomial.polynomial.**polyval**()

- defined by `poly_polyval(x, c, tensor=True)` at numba/np/polynomial/polynomial_functions.py:254-298

Not showing 18 unsupported functions.

supported = 6 / 24 = 25.00%

numpy.polynomial.polyutils

numpy.polynomial.polyutils.**as_series**()

- defined by `polyutils_as_series(alist, trim=True)` at numba/np/polynomial/polynomial_functions.py:90-145

numpy.polynomial.polyutils.**trimseq**()

- defined by `polyutils_trimseq(seq)` at numba/np/polynomial/polynomial_functions.py:64-87

Not showing 7 unsupported functions.

supported = 2 / 9 = 22.22%

numpy.random

This module is not supported.

numpy.random.bit_generator

This module is not supported.

numpy.random.mtrand

This module is not supported.

numpy.rec

This module is not supported.

numpy.strings

This module is not supported.

numpy.testing

This module is not supported.

numpy.testing.overrides

This module is not supported.

numpy.testing.print_coercion_tables

This module is not supported.

numpy.typing

This module is not supported.

numpy.typing.mypy_plugin

This module is not supported.

numpy.version

This module is not supported.

6.10.2 Old style listings

Lowering Listing

This lists all lowering definition registered to the CPU target. Each subsection corresponds to a Python function that is supported by numba nopython mode. These functions have one or more lower implementation with different signatures. The compiler chooses the most specific implementation from all overloads.

`'array.argsort'`

Signature	Definition
(Array, StringLiteral)	`array_argsort` numba/np/arrayobj.py lines 6637-6652

`'array.astype'`

Signature	Definition
(Array, DTypeSpec)	`array_astype` numba/np/arrayobj.py lines 5182-5210
(Array, StringLiteral)	`array_astype` numba/np/arrayobj.py lines 5182-5210

`'array.copy'`

Signature	Definition
(Array)	`array_copy` numba/np/arrayobj.py lines 5063-5065

'array.flatten'

Signature	Definition
(Array)	`array_flatten` numba/np/arrayobj.py lines 2331-2339

'array.item'

Signature	Definition
(Array)	`array_item` numba/np/arrayobj.py lines 576-588

'array.nonzero'

Signature	Definition
(Array)	`array_nonzero` numba/np/old_arraymath.py lines 3265-3320

'array.ravel'

Signature	Definition
(Array)	`array_ravel` numba/np/arrayobj.py lines 2300-2320

'array.reshape'

Signature	Definition
*(Array, *any)*	`array_reshape_vararg` numba/np/arrayobj.py lines 2207-2210
(Array, BaseTuple)	`array_reshape` numba/np/arrayobj.py lines 2142-2204

'array.sort'

Signature	Definition
(Array)	`array_sort` numba/np/arrayobj.py lines 6610-6621

'array.sum'

Signature	Definition
(Array)	`array_sum` numba/np/old_arraymath.py lines 160-173
(Array, DTypeSpec)	`array_sum_dtype` numba/np/old_arraymath.py lines 289-302
(Array, IntegerLiteral)	`array_sum_axis` numba/np/old_arraymath.py lines 305-346
(Array, IntegerLiteral, DTypeSpec)	`array_sum_axis_dtype` numba/np/old_arraymath.py lines 246-286
(Array, int64)	`array_sum_axis` numba/np/old_arraymath.py lines 305-346
(Array, int64, DTypeSpec)	`array_sum_axis_dtype` numba/np/old_arraymath.py lines 246-286

'array.transpose'

Signature	Definition
(Array)	`array_transpose` numba/np/arrayobj.py lines 1840-1842
*(Array, *any)*	`array_transpose_vararg` numba/np/arrayobj.py lines 1915-1918
(Array, BaseTuple)	`array_transpose_tuple` numba/np/arrayobj.py lines 1860-1912

'array.view'

Signature	Definition
(Array, DTypeSpec)	`array_view` numba/np/arrayobj.py lines 2786-2817

'complex.conjugate'

Signature	Definition
(Complex)	`complex_conjugate_impl` numba/cpython/old_numbers.py lines 967-973
(Float)	`real_conjugate_impl` numba/cpython/old_numbers.py lines 982-983
(Integer)	`real_conjugate_impl` numba/cpython/old_numbers.py lines 982-983

'ffi.from_buffer'

Signature	Definition
(Buffer)	`from_buffer` numba/misc/cffiimpl.py lines 12-22

'getiter'

Signature	Definition
(Buffer)	`getiter_array` numba/np/arrayobj.py lines 304-325
(DictItemsIterableType)	`impl_iterable_getiter` numba/typed/dictobject.py lines 987-1018
(DictKeysIterableType)	`impl_iterable_getiter` numba/typed/dictobject.py lines 987-1018
(DictType)	`impl_dict_getiter` numba/typed/dictobject.py lines 1021-1052
(DictValuesIterableType)	`impl_iterable_getiter` numba/typed/dictobject.py lines 987-1018
(IteratorType)	`iterator_getiter` numba/cpython/iterators.py lines 12-15
(List)	`getiter_list` numba/cpython/listobj.py lines 490-493
(ListType)	`getiter_list` numba/typed/listobject.py lines 1516-1520
(NamedUniTuple)	`getiter_unituple` numba/cpython/old_tupleobj.py lines 138-154
(Set)	`getiter_set` numba/cpython/setobj.py lines 1284-1287
(UniTuple)	`getiter_unituple` numba/cpython/old_tupleobj.py lines 138-154
(UnicodeType)	`getiter_unicode` numba/cpython/unicode.py lines 2611-2632
(range_state_int32)	`make_range_impl.<locals>.getiter_range32_impl` numba/cpython/rangeobj.py lines 87-95
(range_state_int64)	`make_range_impl.<locals>.getiter_range32_impl` numba/cpython/rangeobj.py lines 87-95
(range_state_uint64)	`make_range_impl.<locals>.getiter_range32_impl` numba/cpython/rangeobj.py lines 87-95

'iternext'

Signature	Definition
(ArrayIterator)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347
(DictIteratorType)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347
(EnumerateType)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347
(Generator)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347
(ListIter)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347
(ListTypeIteratorType)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347
(NumpyFlatType)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347
(NumpyNdEnumerate-Type)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347
(NumpyNdIndexType)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347
(NumpyNdIterType)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347
(SetIter)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347
(UniTupleIter)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347
(UnicodeIteratorType)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347
(ZipType)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347
(range_iter_int32)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347
(range_iter_int64)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347
(range_iter_uint64)	`iternext_impl.<locals>.outer.<locals>.wrapper` numba/core/imputils.py lines 333-347

'list.append'

Signature	Definition
(List, any)	`list_append` numba/cpython/listobj.py lines 868-878

'list.clear'

Signature	Definition
(List)	`list_clear` numba/cpython/listobj.py lines 880-885

'list.extend'

Signature	Definition
(List, IterableType)	`list_extend` numba/cpython/listobj.py lines 926-939

'list.insert'

Signature	Definition
(List, Integer, any)	`list_insert` numba/cpython/listobj.py lines 974-989

'list.pop'

Signature	Definition
(List)	`list_pop` numba/cpython/listobj.py lines 991-1003
(List, Integer)	`list_pop` numba/cpython/listobj.py lines 1005-1021

'not in'

Signature	Definition
(any, any)	`not_in` numba/cpython/old_builtins.py lines 414-420

'number.item'

Signature	Definition
(Boolean)	`number_item_impl` numba/cpython/old_numbers.py lines 1198-1204
(Number)	`number_item_impl` numba/cpython/old_numbers.py lines 1198-1204

'print_item'

Signature	Definition
(Literal)	`print_item_impl` numba/cpython/printimpl.py lines 15-30
(any)	`print_item_impl` numba/cpython/printimpl.py lines 33-61

'set.add'

Signature	Definition
(Set, any)	`set_add` numba/cpython/setobj.py lines 1301-1307

'set.update'

Signature	Definition
(Set, IterableType)	`set_update` numba/cpython/setobj.py lines 1468-1496

'slice.indices'

Signature	Definition
(SliceType, Integer)	`slice_indices` numba/cpython/slicing.py lines 218-240

'static_getitem'

Signature	Definition
(Array, StringLiteral)	`array_record_getitem` numba/np/arrayobj.py lines 3193-3199
(BaseTuple, IntegerLiteral)	`static_getitem_tuple` numba/cpython/old_tupleobj.py lines 346-371
(BaseTuple, SliceLiteral)	`static_getitem_tuple` numba/cpython/old_tupleobj.py lines 346-371
(EnumClass, StringLiteral)	`enum_class_getitem` numba/cpython/enumimpl.py lines 73-81
(LiteralList, IntegerLiteral)	`static_getitem_tuple` numba/cpython/old_tupleobj.py lines 346-371
(LiteralList, SliceLiteral)	`static_getitem_tuple` numba/cpython/old_tupleobj.py lines 346-371
(LiteralStrKeyDict, StringLiteral)	`static_getitem_tuple` numba/cpython/old_tupleobj.py lines 346-371
(NumberClass, any)	`static_getitem_number_clazz` numba/np/arrayobj.py lines 3113-3131
(Record, IntegerLiteral)	`record_static_getitem_int` numba/np/arrayobj.py lines 3281-3290
(Record, StringLiteral)	`record_static_getitem_str` numba/np/arrayobj.py lines 3272-3278

'static_setitem'

Signature	Definition
(Record, IntegerLiteral, any)	`record_static_setitem_int` numba/np/arrayobj.py lines 3306-3317
(Record, StringLiteral, any)	`record_static_setitem_str` numba/np/arrayobj.py lines 3293-3303

'typed_getitem'

Signature	Definition
(BaseTuple, any)	`getitem_typed` numba/cpython/old_tupleobj.py lines 206-288

(<class 'numba.core.types.containers.BaseTuple'>, '__hash__')

Signature	Definition
*(BaseTuple, *any)*	`_OverloadMethodTemplate._init_once.<locals>.method_impl` numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.BaseTuple'>, 'index')

Signature	Definition
*(BaseTuple, *any)*	`_OverloadMethodTemplate._init_once.<locals>.method_impl` numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Bytes'>, '_to_str')

Signature	Definition
*(Bytes, *any)*	`_OverloadMethodTemplate._init_once.<locals>.method_impl` numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Bytes'>, 'center')

Signature	Definition
*(Bytes, *any)*	`_OverloadMethodTemplate._init_once.<locals>.method_impl` numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Bytes'>, 'endswith')

Signature	Definition
*(Bytes, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Bytes'>, 'find')

Signature	Definition
*(Bytes, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Bytes'>, 'isascii')

Signature	Definition
*(Bytes, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Bytes'>, 'join')

Signature	Definition
*(Bytes, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Bytes'>, 'ljust')

Signature	Definition
*(Bytes, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Bytes'>, 'lstrip')

Signature	Definition
*(Bytes, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Bytes'>, 'rfind')

Signature	Definition
*(Bytes, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Bytes'>, 'rjust')

Signature	Definition
*(Bytes, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Bytes'>, 'rstrip')

Signature	Definition
*(Bytes, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Bytes'>, 'split')

Signature	Definition
*(Bytes, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Bytes'>, 'startswith')

Signature	Definition
*(Bytes, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Bytes'>, 'strip')

Signature	Definition
*(Bytes, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Bytes'>, 'zfill')

Signature	Definition
*(Bytes, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.DictType'>, '__setitem__')

Signature	Definition
*(DictType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.DictType'>, 'clear')

Signature	Definition
*(DictType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.DictType'>, 'copy')

Signature	Definition
*(DictType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.DictType'>, 'get')

Signature	Definition
*(DictType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.DictType'>, 'items')

Signature	Definition
*(DictType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.DictType'>, 'keys')

Signature	Definition
*(DictType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.DictType'>, 'pop')

Signature	Definition
*(DictType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.DictType'>, 'popitem')

Signature	Definition
*(DictType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.DictType'>, 'setdefault')

Signature	Definition
*(DictType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.DictType'>, 'update')

Signature	Definition
*(DictType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.DictType'>, 'values')

Signature	Definition
*(DictType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.List'>, 'copy')

Signature	Definition
*(List, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.List'>, 'count')

Signature	Definition
*(List, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.List'>, 'index')

Signature	Definition
*(List, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.List'>, 'remove')

Signature	Definition
*(List, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.List'>, 'reverse')

Signature	Definition
*(List, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.List'>, 'sort')

Signature	Definition
*(List, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.ListType'>, '_allocated')

Signature	Definition
*(ListType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.ListType'>, '_is_mutable')

Signature	Definition
*(ListType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.ListType'>, '_make_immutable')

Signature	Definition
*(ListType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.ListType'>, '_make_mutable')

Signature	Definition
*(ListType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.ListType'>, 'append')

Signature	Definition
*(ListType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.ListType'>, 'clear')

Signature	Definition
*(ListType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.ListType'>, 'copy')

Signature	Definition
*(ListType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.ListType'>, 'count')

Signature	Definition
*(ListType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.ListType'>, 'extend')

Signature	Definition
*(ListType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.ListType'>, 'getitem_unchecked')

Signature	Definition
*(ListType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.ListType'>, 'index')

Signature	Definition
*(ListType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.ListType'>, 'insert')

Signature	Definition
*(ListType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.ListType'>, 'pop')

Signature	Definition
*(ListType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.ListType'>, 'remove')

Signature	Definition
*(ListType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.ListType'>, 'reverse')

Signature	Definition
*(ListType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.ListType'>, 'sort')

Signature	Definition
*(ListType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralList'>, 'append')

Signature	Definition
*(LiteralList, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralList'>, 'clear')

Signature	Definition
*(LiteralList, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralList'>, 'copy')

Signature	Definition
*(LiteralList, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralList'>, 'count')

Signature	Definition
*(LiteralList, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralList'>, 'extend')

Signature	Definition
*(LiteralList, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralList'>, 'index')

Signature	Definition
*(LiteralList, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralList'>, 'insert')

Signature	Definition
*(LiteralList, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralList'>, 'pop')

Signature	Definition
*(LiteralList, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralList'>, 'remove')

Signature	Definition
*(LiteralList, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralList'>, 'reverse')

Signature	Definition
*(LiteralList, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralList'>, 'sort')

Signature	Definition
*(LiteralList, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralStrKeyDict'>, 'clear')

Signature	Definition
*(LiteralStrKeyDict, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralStrKeyDict'>, 'copy')

Signature	Definition
*(LiteralStrKeyDict, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralStrKeyDict'>, 'get')

Signature	Definition
*(LiteralStrKeyDict, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralStrKeyDict'>, 'items')

Signature	Definition
*(LiteralStrKeyDict, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralStrKeyDict'>, 'keys')

Signature	Definition
*(LiteralStrKeyDict, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralStrKeyDict'>, 'pop')

Signature	Definition
*(LiteralStrKeyDict, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralStrKeyDict'>, 'popitem')

Signature	Definition
*(LiteralStrKeyDict, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralStrKeyDict'>, 'setdefault')

Signature	Definition
*(LiteralStrKeyDict, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralStrKeyDict'>, 'update')

Signature	Definition
*(LiteralStrKeyDict, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.LiteralStrKeyDict'>, 'values')

Signature	Definition
*(LiteralStrKeyDict, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Set'>, 'clear')

Signature	Definition
*(Set, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Set'>, 'copy')

Signature	Definition
*(Set, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Set'>, 'difference')

Signature	Definition
*(Set, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Set'>, 'difference_update')

Signature	Definition
*(Set, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Set'>, 'discard')

Signature	Definition
*(Set, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Set'>, 'intersection')

Signature	Definition
*(Set, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Set'>, 'intersection_update')

Signature	Definition
*(Set, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Set'>, 'isdisjoint')

Signature	Definition
*(Set, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Set'>, 'issubset')

Signature	Definition
*(Set, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Set'>, 'issuperset')

Signature	Definition
*(Set, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Set'>, 'pop')

Signature	Definition
*(Set, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Set'>, 'remove')

Signature	Definition
*(Set, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Set'>, 'symmetric_difference')

Signature	Definition
*(Set, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Set'>, 'symmetric_difference_update')

Signature	Definition
*(Set, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.containers.Set'>, 'union')

Signature	Definition
*(Set, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, '__hash__')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, '__repr__')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, '__str__')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, '_to_bytes')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'capitalize')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'casefold')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'center')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'count')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'endswith')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'expandtabs')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'find')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'index')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'isalnum')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'isalpha')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'isascii')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'isdecimal')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'isdigit')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'isidentifier')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'islower')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'isnumeric')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'isprintable')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'isspace')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'istitle')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'isupper')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'join')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'ljust')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'lower')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'lstrip')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'partition')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'replace')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'rfind')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'rindex')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'rjust')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'rpartition')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'rsplit')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'rstrip')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'split')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'splitlines')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'startswith')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'strip')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'swapcase')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'title')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'upper')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.misc.UnicodeType'>, 'zfill')

Signature	Definition
*(UnicodeType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, '_zero_fill')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'all')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'allclose')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'any')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'argmax')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'argmin')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'clip')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'conj')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'conjugate')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'cumprod')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'cumsum')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'dot')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'fill')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'max')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'mean')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'min')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'prod')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'repeat')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'std')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'take')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'tobytes')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.Array'>, 'var')

Signature	Definition
*(Array, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.CharSeq'>, '__hash__')

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.CharSeq'>, '_get_kind')

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.CharSeq'>, '_to_str')

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.CharSeq'>, 'center')

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.CharSeq'>, 'endswith')

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

```
(<class 'numba.core.types.npytypes.CharSeq'>, 'find')
```

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

```
(<class 'numba.core.types.npytypes.CharSeq'>, 'isascii')
```

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

```
(<class 'numba.core.types.npytypes.CharSeq'>, 'isupper')
```

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

```
(<class 'numba.core.types.npytypes.CharSeq'>, 'join')
```

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

```
(<class 'numba.core.types.npytypes.CharSeq'>, 'ljust')
```

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

```
(<class 'numba.core.types.npytypes.CharSeq'>, 'lstrip')
```

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.CharSeq'>, 'rfind')

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.CharSeq'>, 'rjust')

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.CharSeq'>, 'rstrip')

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.CharSeq'>, 'split')

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.CharSeq'>, 'startswith')

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.CharSeq'>, 'strip')

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.CharSeq'>, 'upper')

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.CharSeq'>, 'zfill')

Signature	Definition
*(CharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'beta')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'binomial')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'chisquare')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'exponential')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'f')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'gamma')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'geometric')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'integers')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'laplace')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'logistic')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'lognormal')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'logseries')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'negative_binomial')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'noncentral_chisquare')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'noncentral_f')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'normal')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'pareto')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'permutation')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'poisson')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'power')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'random')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'rayleigh')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'shuffle')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'standard_cauchy')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'standard_exponential')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'standard_gamma')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'standard_normal')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'standard_t')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'triangular')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'uniform')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'wald')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'weibull')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.NumPyRandomGeneratorType'>, 'zipf')

Signature	Definition
*(NumPyRandomGeneratorType, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, '__hash__')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, '__str__')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, '_get_kind')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, 'center')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, 'endswith')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, 'find')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, 'isascii')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, 'isupper')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, 'join')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, 'ljust')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, 'lstrip')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, 'rfind')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, 'rjust')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, 'rstrip')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, 'split')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, 'startswith')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, 'strip')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, 'upper')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.npytypes.UnicodeCharSeq'>, 'zfill')

Signature	Definition
*(UnicodeCharSeq, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.old_scalars.Boolean'>, '__hash__')

Signature	Definition
*(Boolean, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.old_scalars.Boolean'>, '__repr__')

Signature	Definition
*(Boolean, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.old_scalars.Boolean'>, '__str__')

Signature	Definition
*(Boolean, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.old_scalars.Complex'>, '__hash__')

Signature	Definition
*(Complex, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.old_scalars.Float'>, '__hash__')

Signature	Definition
*(Float, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.old_scalars.Float'>, 'view')

Signature	Definition
*(Float, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.old_scalars.IntEnumMember'>, '__hash__')

Signature	Definition
*(IntEnumMember, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.old_scalars.Integer'>, '__hash__')

Signature	Definition
*(Integer, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.old_scalars.Integer'>, '__repr__')

Signature	Definition
*(Integer, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.old_scalars.Integer'>, '__str__')

Signature	Definition
*(Integer, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.old_scalars.Integer'>, 'view')

Signature	Definition
*(Integer, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(<class 'numba.core.types.old_scalars.NPDatetime'>, '__hash__')

Signature	Definition
*(NPDatetime, *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(typeref[<class 'numba.core.types.containers.DictType'>], 'empty')

Signature	Definition
*(typeref[<class 'numba.core.types.containers.DictType'>], *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(typeref[<class 'numba.core.types.containers.ListType'>], 'empty_list')

Signature	Definition
*(typeref[<class 'numba.core.types.containers.ListType'>], *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

(typeref[<class 'numba.core.types.npytypes.Array'>], '_allocate')

Signature	Definition
*(typeref[<class 'numba.core.types.npytypes.Array'>], *any)*	_OverloadMethodTemplate._init_once.<locals>.method_impl numba/core/typing/templates.py lines 1108-1117

_operator.add

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Array, any)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(BaseTuple, BaseTuple)	tuple_add numba/cpython/old_tupleobj.py lines 29-34
(Complex, Complex)	complex_add_impl numba/cpython/old_numbers.py lines 1035-1048
(Float, Float)	real_add_impl numba/cpython/old_numbers.py lines 614-616
(Integer, Integer)	int_add_impl numba/cpython/old_numbers.py lines 35-41
(List, List)	list_add numba/cpython/listobj.py lines 687-707
(NPDatetime, NPTimedelta)	datetime_plus_timedelta numba/np/npdatetime.py lines 591-600
(NPTimedelta, NPDatetime)	timedelta_plus_datetime numba/np/npdatetime.py lines 603-612
(NPTimedelta, NPTimedelta)	timedelta_add_impl numba/np/npdatetime.py lines 183-194
(any, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769

operator.and

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Array, any)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Boolean, Boolean)	int_and_impl numba/cpython/old_numbers.py lines 431-437
(Integer, Integer)	int_and_impl numba/cpython/old_numbers.py lines 431-437
(any, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769

_operator.contains

Signature	Definition
(Sequence, any)	in_seq numba/cpython/listobj.py lines 661-669
(Set, any)	in_set numba/cpython/setobj.py lines 1279-1282

_operator.delitem

Signature	Definition
(List, Integer)	delitem_list_index numba/cpython/listobj.py lines 617-623
(List, SliceType)	delitem_list numba/cpython/listobj.py lines 626-656

_operator.eq

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Array, any)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(BaseTuple, BaseTuple)	tuple_eq numba/cpython/old_tupleobj.py lines 58-71
(Complex, Complex)	complex_eq_impl numba/cpython/old_numbers.py lines 1141-1150
(DType, DType)	dtype_eq_impl numba/np/arrayobj.py lines 4232-4236
(EnumMember, EnumMember)	enum_eq numba/cpython/enumimpl.py lines 13-19
(Float, Float)	real_eq_impl numba/cpython/old_numbers.py lines 862-864
(Integer, Integer)	int_eq_impl numba/cpython/old_numbers.py lines 354-356
(IntegerLiteral, IntegerLiteral)	const_eq_impl numba/cpython/old_builtins.py lines 107-115
(List, List)	list_eq numba/cpython/listobj.py lines 773-795
(Literal, Literal)	const_eq_impl numba/cpython/old_builtins.py lines 107-115
(LiteralStrKeyDict, LiteralStrKeyDict)	literalstrkeydict_impl_equals numba/typed/dictobject.py lines 1225-1231
(NPDatetime, NPDatetime)	_create_datetime_comparison_impl.<locals>.impl numba/np/npdatetime.py lines 651-673
(NPTimedelta, NPTimedelta)	_create_timedelta_comparison_impl.<locals>.impl numba/np/npdatetime.py lines 372-394
(any, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(bool, bool)	int_eq_impl numba/cpython/old_numbers.py lines 354-356

_operator.floordiv

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Array, any)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Float, Float)	real_floordiv_impl numba/cpython/old_numbers.py lines 811-827
(Integer, Integer)	int_floordiv_impl numba/cpython/old_numbers.py lines 168-173
(NPTimedelta, Float)	timedelta_over_number numba/np/npdatetime.py lines 250-278
(NPTimedelta, Integer)	timedelta_over_number numba/np/npdatetime.py lines 250-278
(NPTimedelta, NPTimedelta)	timedelta_floor_div_timedelta numba/np/npdatetime.py lines 299-332
(any, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769

_operator.ge

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Array, any)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(BaseTuple, BaseTuple)	tuple_ge numba/cpython/old_tupleobj.py lines 93-96
(Float, Float)	real_ge_impl numba/cpython/old_numbers.py lines 857-859
(IntegerLiteral, IntegerLiteral)	int_slt_impl numba/cpython/old_numbers.py lines 314-316
(NPDatetime, NPDatetime)	_create_datetime_comparison_impl.<locals>.impl numba/np/npdatetime.py lines 651-673
(NPTimedelta, NPTimedelta)	_create_timedelta_ordering_impl.<locals>.impl numba/np/npdatetime.py lines 400-413
(any, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(bool, bool)	int_uge_impl numba/cpython/old_numbers.py lines 349-351
(int16, int16)	int_sge_impl numba/cpython/old_numbers.py lines 329-331
(int32, int32)	int_sge_impl numba/cpython/old_numbers.py lines 329-331
(int64, int64)	int_sge_impl numba/cpython/old_numbers.py lines 329-331
(int8, int8)	int_sge_impl numba/cpython/old_numbers.py lines 329-331
(uint16, uint16)	int_uge_impl numba/cpython/old_numbers.py lines 349-351
(uint32, uint32)	int_uge_impl numba/cpython/old_numbers.py lines 349-351
(uint64, uint64)	int_uge_impl numba/cpython/old_numbers.py lines 349-351
(uint8, uint8)	int_uge_impl numba/cpython/old_numbers.py lines 349-351

_operator.getitem

Signature	Definition
(Buffer, Array)	fancy_getitem_array numba/np/arrayobj.py lines 1141-1158
(Buffer, BaseTuple)	getitem_array_tuple numba/np/arrayobj.py lines 499-521
(Buffer, Integer)	getitem_arraynd_intp numba/np/arrayobj.py lines 482-496
(Buffer, SliceType)	getitem_arraynd_intp numba/np/arrayobj.py lines 482-496
(CPointer, Integer)	getitem_cpointer numba/cpython/old_builtins.py lines 178-183
(List, Integer)	getitem_list numba/cpython/listobj.py lines 510-519
(List, SliceType)	getslice_list numba/cpython/listobj.py lines 533-554
(NamedUniTuple, int64)	getitem_unituple numba/cpython/old_tupleobj.py lines 291-343
(NamedUniTuple, uint64)	getitem_unituple numba/cpython/old_tupleobj.py lines 291-343
(NumpyFlatType, Integer)	iternext_numpy_getitem numba/np/arrayobj.py lines 4074-4087
(UniTuple, int64)	getitem_unituple numba/cpython/old_tupleobj.py lines 291-343
(UniTuple, uint64)	getitem_unituple numba/cpython/old_tupleobj.py lines 291-343

_operator.gt

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Array, any)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(BaseTuple, BaseTuple)	tuple_gt numba/cpython/old_tupleobj.py lines 88-91
(Float, Float)	real_gt_impl numba/cpython/old_numbers.py lines 852-854
(IntegerLiteral, IntegerLiteral)	int_slt_impl numba/cpython/old_numbers.py lines 314-316
(NPDatetime, NPDatetime)	_create_datetime_comparison_impl.<locals>.impl numba/np/npdatetime.py lines 651-673
(NPTimedelta, NPTimedelta)	_create_timedelta_ordering_impl.<locals>.impl numba/np/npdatetime.py lines 400-413
(any, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(bool, bool)	int_ugt_impl numba/cpython/old_numbers.py lines 344-346
(int16, int16)	int_sgt_impl numba/cpython/old_numbers.py lines 324-326
(int32, int32)	int_sgt_impl numba/cpython/old_numbers.py lines 324-326
(int64, int64)	int_sgt_impl numba/cpython/old_numbers.py lines 324-326
(int8, int8)	int_sgt_impl numba/cpython/old_numbers.py lines 324-326
(uint16, uint16)	int_ugt_impl numba/cpython/old_numbers.py lines 344-346
(uint32, uint32)	int_ugt_impl numba/cpython/old_numbers.py lines 344-346
(uint64, uint64)	int_ugt_impl numba/cpython/old_numbers.py lines 344-346
(uint8, uint8)	int_ugt_impl numba/cpython/old_numbers.py lines 344-346

_operator.iadd

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Array, any)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Complex, Complex)	complex_add_impl numba/cpython/old_numbers.py lines 1035-1048
(Float, Float)	real_add_impl numba/cpython/old_numbers.py lines 614-616
(Integer, Integer)	int_add_impl numba/cpython/old_numbers.py lines 35-41
(List, List)	list_add_inplace numba/cpython/listobj.py lines 709-714
(NPDatetime, NPTimedelta)	datetime_plus_timedelta numba/np/npdatetime.py lines 591-600
(NPTimedelta, NPDatetime)	timedelta_plus_datetime numba/np/npdatetime.py lines 603-612
(NPTimedelta, NPTimedelta)	timedelta_add_impl numba/np/npdatetime.py lines 183-194
(any, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777

_operator.iand

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Array, any)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Boolean, Boolean)	int_and_impl numba/cpython/old_numbers.py lines 431-437
(Integer, Integer)	int_and_impl numba/cpython/old_numbers.py lines 431-437
(any, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777

_operator.ifloordiv

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Array, any)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Float, Float)	real_floordiv_impl numba/cpython/old_numbers.py lines 811-827
(Integer, Integer)	int_floordiv_impl numba/cpython/old_numbers.py lines 168-173
(NPTimedelta, Float)	timedelta_over_number numba/np/npdatetime.py lines 250-278
(NPTimedelta, Integer)	timedelta_over_number numba/np/npdatetime.py lines 250-278
(any, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777

_operator.ilshift

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Array, any)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Integer, Integer)	int_shl_impl numba/cpython/old_numbers.py lines 410-416
(any, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777

_operator.imod

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Array, any)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Float, Float)	real_mod_impl numba/cpython/old_numbers.py lines 792-808
(Integer, Integer)	int_rem_impl numba/cpython/old_numbers.py lines 189-194
(any, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777

_operator.imul

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Array, any)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Complex, Complex)	complex_mul_impl numba/cpython/old_numbers.py lines 1067-1087
(Float, Float)	real_mul_impl numba/cpython/old_numbers.py lines 624-626
(Float, NPTimedelta)	number_times_timedelta numba/np/npdatetime.py lines 239-247
(Integer, Integer)	int_mul_impl numba/cpython/old_numbers.py lines 53-59
(Integer, NPTimedelta)	number_times_timedelta numba/np/npdatetime.py lines 239-247
(List, Integer)	list_mul_inplace numba/cpython/listobj.py lines 742-759
(NPTimedelta, Float)	timedelta_times_number numba/np/npdatetime.py lines 228-236
(NPTimedelta, Integer)	timedelta_times_number numba/np/npdatetime.py lines 228-236
(any, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777

_operator.invert

Signature	Definition
(Array)	register_unary_operator_kernel.<locals>.lower_unary_operator numba/np/npyimpl.py lines 761-762
(Boolean)	int_invert_impl numba/cpython/old_numbers.py lines 474-480
(Integer)	int_invert_impl numba/cpython/old_numbers.py lines 474-480

_operator.ior

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Array, any)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Boolean, Boolean)	int_or_impl numba/cpython/old_numbers.py lines 440-446
(Integer, Integer)	int_or_impl numba/cpython/old_numbers.py lines 440-446
(any, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777

_operator.ipow

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Array, any)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Complex, Complex)	complex_power_impl numba/cpython/old_numbers.py lines 991-1033
(Float, Float)	real_power_impl numba/cpython/old_numbers.py lines 830-839
(Float, IntegerLiteral)	static_power_impl numba/cpython/old_numbers.py lines 249-311
(Float, int16)	int_power_impl numba/cpython/old_numbers.py lines 206-246
(Float, int32)	int_power_impl numba/cpython/old_numbers.py lines 206-246
(Float, int64)	int_power_impl numba/cpython/old_numbers.py lines 206-246
(Float, int8)	int_power_impl numba/cpython/old_numbers.py lines 206-246
(Float, uint16)	int_power_impl numba/cpython/old_numbers.py lines 206-246
(Float, uint32)	int_power_impl numba/cpython/old_numbers.py lines 206-246
(Float, uint64)	int_power_impl numba/cpython/old_numbers.py lines 206-246
(Float, uint8)	int_power_impl numba/cpython/old_numbers.py lines 206-246
(Integer, Integer)	int_power_impl numba/cpython/old_numbers.py lines 206-246
(Integer, IntegerLiteral)	static_power_impl numba/cpython/old_numbers.py lines 249-311
(any, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777

_operator.irshift

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Array, any)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Integer, Integer)	int_shr_impl numba/cpython/old_numbers.py lines 419-428
(any, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777

operator.is

Signature	Definition
(Array, Array)	array_is numba/np/arrayobj.py lines 3354-3365
(Boolean, Boolean)	bool_is_impl numba/cpython/old_builtins.py lines 88-103
(EnumMember, EnumMember)	enum_is numba/cpython/enumimpl.py lines 22-31
(List, List)	list_is numba/cpython/listobj.py lines 765-771
(ListType, ListType)	list_is numba/typed/listobject.py lines 222-228
(Opaque, Opaque)	opaque_is numba/cpython/old_builtins.py lines 72-85
(Optional, none)	optional_is_none numba/core/optional.py lines 18-35
(Set, Set)	set_is numba/cpython/setobj.py lines 1695-1701
(any, any)	generic_is numba/cpython/old_builtins.py lines 46-69
(none, Optional)	optional_is_none numba/core/optional.py lines 18-35
(none, none)	always_return_true_impl numba/core/optional.py lines 10-11

_operator.is_not

Signature	Definition
(any, any)	generic_is_not numba/cpython/old_builtins.py lines 37-43

_operator.isub

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Array, any)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Complex, Complex)	complex_sub_impl numba/cpython/old_numbers.py lines 1051-1064
(Float, Float)	real_sub_impl numba/cpython/old_numbers.py lines 619-621
(Integer, Integer)	int_sub_impl numba/cpython/old_numbers.py lines 44-50
(NPDatetime, NPTimedelta)	datetime_minus_timedelta numba/np/npdatetime.py lines 617-626
(NPTimedelta, NPTimedelta)	timedelta_sub_impl numba/np/npdatetime.py lines 197-208
(any, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777

_operator.itruediv

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Array, any)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Complex, Complex)	complex_div_impl numba/cpython/old_numbers.py lines 1092-1121
(Float, Float)	real_div_impl numba/cpython/old_numbers.py lines 629-633
(Integer, Integer)	int_truediv_impl numba/cpython/old_numbers.py lines 176-186
(NPTimedelta, Float)	timedelta_over_number numba/np/npdatetime.py lines 250-278
(NPTimedelta, Integer)	timedelta_over_number numba/np/npdatetime.py lines 250-278
(NPTimedelta, NPTimedelta)	timedelta_over_timedelta numba/np/npdatetime.py lines 281-296
(any, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777

_operator.ixor

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Array, any)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777
(Boolean, Boolean)	int_xor_impl numba/cpython/old_numbers.py lines 449-455
(Integer, Integer)	int_xor_impl numba/cpython/old_numbers.py lines 449-455
(any, Array)	register_binary_operator_kernel.<locals>.lower_inplace_operator numba/np/npyimpl.py lines 771-777

_operator.le

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Array, any)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(BaseTuple, BaseTuple)	tuple_le numba/cpython/old_tupleobj.py lines 83-86
(Float, Float)	real_le_impl numba/cpython/old_numbers.py lines 847-849
(IntegerLiteral, IntegerLiteral)	int_slt_impl numba/cpython/old_numbers.py lines 314-316
(NPDatetime, NPDatetime)	_create_datetime_comparison_impl.<locals>.impl numba/np/npdatetime.py lines 651-673
(NPTimedelta, NPTimedelta)	_create_timedelta_ordering_impl.<locals>.impl numba/np/npdatetime.py lines 400-413
(any, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(bool, bool)	int_ule_impl numba/cpython/old_numbers.py lines 339-341
(int16, int16)	int_sle_impl numba/cpython/old_numbers.py lines 319-321
(int32, int32)	int_sle_impl numba/cpython/old_numbers.py lines 319-321
(int64, int64)	int_sle_impl numba/cpython/old_numbers.py lines 319-321
(int8, int8)	int_sle_impl numba/cpython/old_numbers.py lines 319-321
(uint16, uint16)	int_ule_impl numba/cpython/old_numbers.py lines 339-341
(uint32, uint32)	int_ule_impl numba/cpython/old_numbers.py lines 339-341
(uint64, uint64)	int_ule_impl numba/cpython/old_numbers.py lines 339-341
(uint8, uint8)	int_ule_impl numba/cpython/old_numbers.py lines 339-341

_operator.lshift

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Array, any)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Integer, Integer)	int_shl_impl numba/cpython/old_numbers.py lines 410-416
(any, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769

_operator.lt

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Array, any)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(BaseTuple, BaseTuple)	tuple_lt numba/cpython/old_tupleobj.py lines 78-81
(Float, Float)	real_lt_impl numba/cpython/old_numbers.py lines 842-844
(IntegerLiteral, IntegerLiteral)	int_slt_impl numba/cpython/old_numbers.py lines 314-316
(NPDatetime, NPDatetime)	_create_datetime_comparison_impl.<locals>.impl numba/np/npdatetime.py lines 651-673
(NPTimedelta, NPTimedelta)	_create_timedelta_ordering_impl.<locals>.impl numba/np/npdatetime.py lines 400-413
(any, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(bool, bool)	int_ult_impl numba/cpython/old_numbers.py lines 334-336
(int16, int16)	int_slt_impl numba/cpython/old_numbers.py lines 314-316
(int32, int32)	int_slt_impl numba/cpython/old_numbers.py lines 314-316
(int64, int64)	int_slt_impl numba/cpython/old_numbers.py lines 314-316
(int8, int8)	int_slt_impl numba/cpython/old_numbers.py lines 314-316
(uint16, uint16)	int_ult_impl numba/cpython/old_numbers.py lines 334-336
(uint32, uint32)	int_ult_impl numba/cpython/old_numbers.py lines 334-336
(uint64, uint64)	int_ult_impl numba/cpython/old_numbers.py lines 334-336
(uint8, uint8)	int_ult_impl numba/cpython/old_numbers.py lines 334-336

_operator.mod

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Array, any)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Float, Float)	real_mod_impl numba/cpython/old_numbers.py lines 792-808
(Integer, Integer)	int_rem_impl numba/cpython/old_numbers.py lines 189-194
(any, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769

_operator.mul

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Array, any)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Complex, Complex)	complex_mul_impl numba/cpython/old_numbers.py lines 1067-1087
(Float, Float)	real_mul_impl numba/cpython/old_numbers.py lines 624-626
(Float, NPTimedelta)	number_times_timedelta numba/np/npdatetime.py lines 239-247
(Integer, Integer)	int_mul_impl numba/cpython/old_numbers.py lines 53-59
(Integer, List)	list_mul numba/cpython/listobj.py lines 717-740
(Integer, NPTimedelta)	number_times_timedelta numba/np/npdatetime.py lines 239-247
(List, Integer)	list_mul numba/cpython/listobj.py lines 717-740
(NPTimedelta, Float)	timedelta_times_number numba/np/npdatetime.py lines 228-236
(NPTimedelta, Integer)	timedelta_times_number numba/np/npdatetime.py lines 228-236
(any, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769

_operator.ne

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Array, any)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(BaseTuple, BaseTuple)	tuple_ne numba/cpython/old_tupleobj.py lines 73-76
(Complex, Complex)	complex_ne_impl numba/cpython/old_numbers.py lines 1153-1162
(EnumMember, EnumMember)	enum_ne numba/cpython/enumimpl.py lines 34-40
(Float, Float)	real_ne_impl numba/cpython/old_numbers.py lines 867-869
(Integer, Integer)	int_ne_impl numba/cpython/old_numbers.py lines 359-361
(IntegerLiteral, IntegerLiteral)	const_ne_impl numba/cpython/old_builtins.py lines 119-127
(Literal, Literal)	const_ne_impl numba/cpython/old_builtins.py lines 119-127
(NPDatetime, NPDatetime)	_create_datetime_comparison_impl.<locals>.impl numba/np/npdatetime.py lines 651-673
(NPTimedelta, NPTimedelta)	_create_timedelta_comparison_impl.<locals>.impl numba/np/npdatetime.py lines 372-394
(any, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(bool, bool)	int_ne_impl numba/cpython/old_numbers.py lines 359-361

_operator.neg

Signature	Definition
(Array)	register_unary_operator_kernel.<locals>.lower_unary_operator numba/np/npyimpl.py lines 761-762
(Complex)	complex_negate_impl numba/cpython/old_numbers.py lines 1124-1133
(Float)	real_negate_impl numba/cpython/old_numbers.py lines 879-882
(Integer)	int_negate_impl numba/cpython/old_numbers.py lines 458-464
(NPTimedelta)	timedelta_neg_impl numba/np/npdatetime.py lines 142-145
(bool)	bool_negate_impl numba/cpython/old_numbers.py lines 525-530

operator.not

Signature	Definition
(Complex)	number_not_impl numba/cpython/old_numbers.py lines 1210-1215
(Float)	number_not_impl numba/cpython/old_numbers.py lines 1210-1215
(Integer)	number_not_impl numba/cpython/old_numbers.py lines 1210-1215
(bool)	number_not_impl numba/cpython/old_numbers.py lines 1210-1215

operator.or

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Array, any)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Boolean, Boolean)	int_or_impl numba/cpython/old_numbers.py lines 440-446
(Integer, Integer)	int_or_impl numba/cpython/old_numbers.py lines 440-446
(any, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769

_operator.pos

Signature	Definition
(Array)	array_positive_impl numba/np/npyimpl.py lines 792-804
(Array)	register_unary_operator_kernel.<locals>.lower_unary_operator numba/np/npyimpl.py lines 761-762
(Complex)	complex_positive_impl numba/cpython/old_numbers.py lines 1136-1138
(Float)	real_positive_impl numba/cpython/old_numbers.py lines 885-889
(Integer)	int_positive_impl numba/cpython/old_numbers.py lines 467-471
(NPTimedelta)	timedelta_pos_impl numba/np/npdatetime.py lines 136-139
(bool)	bool_unary_positive_impl numba/cpython/old_numbers.py lines 533-537

_operator.pow

Signature	Definition
(Array, Array)	`register_binary_operator_kernel.<locals>.lower_binary_operator` numba/np/npyimpl.py lines 768-769
(Array, any)	`register_binary_operator_kernel.<locals>.lower_binary_operator` numba/np/npyimpl.py lines 768-769
(Complex, Complex)	`complex_power_impl` numba/cpython/old_numbers.py lines 991-1033
(Float, Float)	`real_power_impl` numba/cpython/old_numbers.py lines 830-839
(Float, IntegerLiteral)	`static_power_impl` numba/cpython/old_numbers.py lines 249-311
(Float, int16)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Float, int32)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Float, int64)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Float, int8)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Float, uint16)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Float, uint32)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Float, uint64)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Float, uint8)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Integer, Integer)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Integer, IntegerLiteral)	`static_power_impl` numba/cpython/old_numbers.py lines 249-311
(any, Array)	`register_binary_operator_kernel.<locals>.lower_binary_operator` numba/np/npyimpl.py lines 768-769

_operator.rshift

Signature	Definition
(Array, Array)	`register_binary_operator_kernel.<locals>.lower_binary_operator` numba/np/npyimpl.py lines 768-769
(Array, any)	`register_binary_operator_kernel.<locals>.lower_binary_operator` numba/np/npyimpl.py lines 768-769
(Integer, Integer)	`int_shr_impl` numba/cpython/old_numbers.py lines 419-428
(any, Array)	`register_binary_operator_kernel.<locals>.lower_binary_operator` numba/np/npyimpl.py lines 768-769

_operator.setitem

Signature	Definition
(Buffer, any, any)	`setitem_array` numba/np/arrayobj.py lines 524-562
(CPointer, Integer, any)	`setitem_cpointer` numba/cpython/old_builtins.py lines 186-190
(List, Integer, any)	`setitem_list` numba/cpython/listobj.py lines 521-530
(List, SliceType, any)	`setitem_list` numba/cpython/listobj.py lines 556-613
(NumpyFlatType, Integer, any)	`iternext_numpy_getitem_any` numba/np/arrayobj.py lines 4090-4104

_operator.sub

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Array, any)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Complex, Complex)	complex_sub_impl numba/cpython/old_numbers.py lines 1051-1064
(Float, Float)	real_sub_impl numba/cpython/old_numbers.py lines 619-621
(Integer, Integer)	int_sub_impl numba/cpython/old_numbers.py lines 44-50
(NPDatetime, NPDatetime)	datetime_minus_datetime numba/np/npdatetime.py lines 631-645
(NPDatetime, NPTimedelta)	datetime_minus_timedelta numba/np/npdatetime.py lines 617-626
(NPTimedelta, NPTimedelta)	timedelta_sub_impl numba/np/npdatetime.py lines 197-208
(any, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769

_operator.truediv

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Array, any)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Complex, Complex)	complex_div_impl numba/cpython/old_numbers.py lines 1092-1121
(Float, Float)	real_div_impl numba/cpython/old_numbers.py lines 629-633
(Integer, Integer)	int_truediv_impl numba/cpython/old_numbers.py lines 176-186
(NPTimedelta, Float)	timedelta_over_number numba/np/npdatetime.py lines 250-278
(NPTimedelta, Integer)	timedelta_over_number numba/np/npdatetime.py lines 250-278
(NPTimedelta, NPTimedelta)	timedelta_over_timedelta numba/np/npdatetime.py lines 281-296
(any, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769

_operator.xor

Signature	Definition
(Array, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Array, any)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769
(Boolean, Boolean)	int_xor_impl numba/cpython/old_numbers.py lines 449-455
(Integer, Integer)	int_xor_impl numba/cpython/old_numbers.py lines 449-455
(any, Array)	register_binary_operator_kernel.<locals>.lower_binary_operator numba/np/npyimpl.py lines 768-769

builtins.abs

Signature	Definition
(Complex)	complex_abs_impl numba/cpython/old_numbers.py lines 1165-1173
(Float)	real_abs_impl numba/cpython/old_numbers.py lines 872-876
(NPTimedelta)	timedelta_abs_impl numba/np/npdatetime.py lines 148-158
(int16)	int_abs_impl numba/cpython/old_numbers.py lines 396-402
(int32)	int_abs_impl numba/cpython/old_numbers.py lines 396-402
(int64)	int_abs_impl numba/cpython/old_numbers.py lines 396-402
(int8)	int_abs_impl numba/cpython/old_numbers.py lines 396-402
(uint16)	uint_abs_impl numba/cpython/old_numbers.py lines 405-407
(uint32)	uint_abs_impl numba/cpython/old_numbers.py lines 405-407
(uint64)	uint_abs_impl numba/cpython/old_numbers.py lines 405-407
(uint8)	uint_abs_impl numba/cpython/old_numbers.py lines 405-407

builtins.bool

Signature	Definition
(Boolean)	bool_as_bool numba/cpython/old_numbers.py lines 1217-1220
(Complex)	complex_as_bool numba/cpython/old_numbers.py lines 1232-1241
(Float)	float_as_bool numba/cpython/old_numbers.py lines 1227-1230
(Integer)	int_as_bool numba/cpython/old_numbers.py lines 1222-1225
(Sequence)	sequence_bool numba/cpython/listobj.py lines 671-676
(Sized)	sized_bool numba/cpython/old_builtins.py lines 433-439

builtins.complex

Signature	Definition
*(*any)*	`complex_impl` numba/cpython/old_builtins.py lines 310-335

builtins.dict

Signature	Definition
()	`impl_dict` numba/typed/dictimpl.py lines 30-43
(IterableType)	`dict_constructor` numba/typed/dictimpl.py lines 14-27

builtins.divmod

Signature	Definition
(Float, Float)	`real_divmod_impl` numba/cpython/old_numbers.py lines 766-789
(Integer, Integer)	`int_divmod_impl` numba/cpython/old_numbers.py lines 159-165

builtins.enumerate

Signature	Definition
(IterableType)	`make_enumerate_object` numba/cpython/iterators.py lines 20-44
(IterableType, Integer)	`make_enumerate_object` numba/cpython/iterators.py lines 20-44

builtins.float

Signature	Definition
(StringLiteral)	`float_literal_impl` numba/cpython/old_builtins.py lines 303-307
(any)	`int_impl` numba/cpython/old_builtins.py lines 294-300

builtins.int

Signature	Definition
(any)	`int_impl` numba/cpython/old_builtins.py lines 294-300

builtins.iter

Signature	Definition
(IterableType)	`iter_impl` numba/cpython/old_builtins.py lines 391-396

builtins.len

Signature	Definition
(Buffer)	`array_len` numba/np/arrayobj.py lines 565-573
(ConstSized)	`constsized_len` numba/cpython/old_builtins.py lines 425-430
(List)	`list_len` numba/cpython/listobj.py lines 485-488
(NumpyFlatType)	`iternext_numpy_getitem_flat` numba/np/arrayobj.py lines 4107-4115
(Set)	`set_len` numba/cpython/setobj.py lines 1274-1277
(range_state_int32)	`make_range_impl.<locals>.range_len` numba/cpython/rangeobj.py lines 77-85
(range_state_int64)	`make_range_impl.<locals>.range_len` numba/cpython/rangeobj.py lines 77-85
(range_state_uint64)	`make_range_impl.<locals>.range_len` numba/cpython/rangeobj.py lines 77-85

builtins.list

Signature	Definition
()	`list_constructor` numba/cpython/listobj.py lines 475-480
(IterableType)	`list_constructor` numba/cpython/listobj.py lines 465-473

builtins.max

Signature	Definition
*(*any)*	`max_vararg` numba/cpython/old_builtins.py lines 225-227
(BaseTuple)	`max_iterable` numba/cpython/old_builtins.py lines 219-223

builtins.min

Signature	Definition
*(*any)*	`min_vararg` numba/cpython/old_builtins.py lines 235-237
(BaseTuple)	`min_iterable` numba/cpython/old_builtins.py lines 229-233

builtins.next

Signature	Definition
(IteratorType)	`next_impl` numba/cpython/old_builtins.py lines 399-409

builtins.pow

Signature	Definition
(Complex, Complex)	`complex_power_impl` numba/cpython/old_numbers.py lines 991-1033
(Float, Float)	`real_power_impl` numba/cpython/old_numbers.py lines 830-839
(Float, int16)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Float, int32)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Float, int64)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Float, int8)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Float, uint16)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Float, uint32)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Float, uint64)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Float, uint8)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246
(Integer, Integer)	`int_power_impl` numba/cpython/old_numbers.py lines 206-246

builtins.print

Signature	Definition
*(*any)*	`print_varargs_impl` numba/cpython/printimpl.py lines 64-82

builtins.range

Signature	Definition
(int32)	`make_range_impl.<locals>.range1_impl` numba/cpython/rangeobj.py lines 26-41
(int32, int32)	`make_range_impl.<locals>.range2_impl` numba/cpython/rangeobj.py lines 43-58
(int32, int32, int32)	`make_range_impl.<locals>.range3_impl` numba/cpython/rangeobj.py lines 60-75
(int64)	`make_range_impl.<locals>.range1_impl` numba/cpython/rangeobj.py lines 26-41
(int64, int64)	`make_range_impl.<locals>.range2_impl` numba/cpython/rangeobj.py lines 43-58
(int64, int64, int64)	`make_range_impl.<locals>.range3_impl` numba/cpython/rangeobj.py lines 60-75
(uint64)	`make_range_impl.<locals>.range1_impl` numba/cpython/rangeobj.py lines 26-41
(uint64, uint64)	`make_range_impl.<locals>.range2_impl` numba/cpython/rangeobj.py lines 43-58
(uint64, uint64, uint64)	`make_range_impl.<locals>.range3_impl` numba/cpython/rangeobj.py lines 60-75

builtins.round

Signature	Definition
(Float)	`round_impl_unary` numba/cpython/old_builtins.py lines 244-254
(Float, Integer)	`round_impl_binary` numba/cpython/old_builtins.py lines 256-288

builtins.set

Signature	Definition
()	`set_empty_constructor` numba/cpython/setobj.py lines 1244-1248
(IterableType)	`set_constructor` numba/cpython/setobj.py lines 1250-1268

builtins.slice

Signature	Definition
*(*any)*	`slice_constructor_impl` numba/cpython/slicing.py lines 151-196

builtins.tuple

Signature	Definition
()	`lower_empty_tuple` numba/cpython/old_builtins.py lines 441-445
(BaseTuple)	`lower_tuple` numba/cpython/old_builtins.py lines 447-450

builtins.type

Signature	Definition
(any)	`type_impl` numba/cpython/old_builtins.py lines 383-388

builtins.zip

Signature	Definition
*(*any)*	`make_zip_object` numba/cpython/iterators.py lines 71-83

cmath.acos

Signature	Definition
(Complex)	`acos_impl` numba/cpython/cmathimpl.py lines 387-411

cmath.asin

Signature	Definition
(Complex)	`asin_impl` numba/cpython/cmathimpl.py lines 466-474

cmath.asinh

Signature	Definition
(Complex)	`asinh_impl` numba/cpython/cmathimpl.py lines 442-464

cmath.atan

Signature	Definition
(Complex)	`atan_impl` numba/cpython/cmathimpl.py lines 476-488

cmath.atanh

Signature	Definition
(Complex)	`atanh_impl` numba/cpython/cmathimpl.py lines 490-542

cmath.cos

Signature	Definition
(Complex)	`cos_impl` numba/cpython/cmathimpl.py lines 270-277

cmath.exp

Signature	Definition
(Complex)	`intrinsic_complex_unary.<locals>.wrapper` numba/cpython/cmathimpl.py lines 85-99

cmath.isfinite

Signature	Definition
(Complex)	`isfinite_float_impl` numba/cpython/cmathimpl.py lines 48-54

cmath.isinf

Signature	Definition
(Complex)	`isinf_float_impl` numba/cpython/cmathimpl.py lines 39-45

cmath.isnan

Signature	Definition
(Complex)	`isnan_float_impl` numba/cpython/cmathimpl.py lines 31-37

cmath.log

Signature	Definition
(Complex)	`intrinsic_complex_unary.<locals>.wrapper` numba/cpython/cmathimpl.py lines 85-99
(Complex, Complex)	`log_base_impl` numba/cpython/cmathimpl.py lines 157-166

cmath.sin

Signature	Definition
(Complex)	`sin_impl` numba/cpython/cmathimpl.py lines 309-317

cmath.sqrt

Signature	Definition
(Complex)	`sqrt_impl` numba/cpython/cmathimpl.py lines 209-267

cmath.tan

Signature	Definition
(Complex)	`tan_impl` numba/cpython/cmathimpl.py lines 346-354

math.acos

Signature	Definition
(Float)	`unary_math_extern.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 149-165
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.acosh

Signature	Definition
(Float)	`unary_math_extern.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 149-165
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.asin

Signature	Definition
(Float)	`unary_math_extern.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 149-165
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.asinh

Signature	Definition
(Float)	`unary_math_extern.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 149-165
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.atan

Signature	Definition
(Float)	`unary_math_extern.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 149-165
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.atan2

Signature	Definition
(Float, Float)	`atan2_float_impl` numba/cpython/old_mathimpl.py lines 310-323
(int64, int64)	`atan2_s64_impl` numba/cpython/old_mathimpl.py lines 294-300
(uint64, uint64)	`atan2_u64_impl` numba/cpython/old_mathimpl.py lines 302-308

math.atanh

Signature	Definition
(Float)	`unary_math_extern.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 149-165
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.ceil

Signature	Definition
(Float)	`unary_math_extern.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 149-165
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.copysign

Signature	Definition
(Float, Float)	`copysign_float_impl` numba/cpython/old_mathimpl.py lines 247-254

math.cos

Signature	Definition
(Float)	unary_math_intr.<locals>.float_impl numba/cpython/old_mathimpl.py lines 131-134
(Integer)	_unary_int_input_wrapper_impl.<locals>.implementer numba/cpython/old_mathimpl.py lines 113-119

math.cosh

Signature	Definition
(Float)	unary_math_extern.<locals>.float_impl numba/cpython/old_mathimpl.py lines 149-165
(Integer)	_unary_int_input_wrapper_impl.<locals>.implementer numba/cpython/old_mathimpl.py lines 113-119

math.degrees

Signature	Definition
(Float)	degrees_float_impl numba/cpython/old_mathimpl.py lines 391-396
(Integer)	_unary_int_input_wrapper_impl.<locals>.implementer numba/cpython/old_mathimpl.py lines 113-119

math.erf

Signature	Definition
(Float)	unary_math_extern.<locals>.float_impl numba/cpython/old_mathimpl.py lines 149-165
(Integer)	_unary_int_input_wrapper_impl.<locals>.implementer numba/cpython/old_mathimpl.py lines 113-119

math.erfc

Signature	Definition
(Float)	unary_math_extern.<locals>.float_impl numba/cpython/old_mathimpl.py lines 149-165
(Integer)	_unary_int_input_wrapper_impl.<locals>.implementer numba/cpython/old_mathimpl.py lines 113-119

math.exp

Signature	Definition
(Float)	`unary_math_intr.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 131-134
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.expm1

Signature	Definition
(Float)	`unary_math_extern.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 149-165
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.fabs

Signature	Definition
(Float)	`unary_math_intr.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 131-134
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.floor

Signature	Definition
(Float)	`unary_math_extern.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 149-165
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.frexp

Signature	Definition
(Float)	`frexp_impl` numba/cpython/old_mathimpl.py lines 260-274

math.gamma

Signature	Definition
(Float)	`unary_math_extern.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 149-165
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.gcd

Signature	Definition
(Integer, Integer)	`gcd_impl` numba/cpython/old_mathimpl.py lines 439-466

math.hypot

Signature	Definition
(Float, Float)	`hypot_float_impl` numba/cpython/old_mathimpl.py lines 349-375
(int64, int64)	`hypot_s64_impl` numba/cpython/old_mathimpl.py lines 329-336
(uint64, uint64)	`hypot_u64_impl` numba/cpython/old_mathimpl.py lines 339-346

math.isfinite

Signature	Definition
(Float)	`isfinite_float_impl` numba/cpython/old_mathimpl.py lines 234-238
(Integer)	`isfinite_int_impl` numba/cpython/old_mathimpl.py lines 241-244

math.isinf

Signature	Definition
(Float)	`isinf_float_impl` numba/cpython/old_mathimpl.py lines 222-226
(Integer)	`isinf_int_impl` numba/cpython/old_mathimpl.py lines 228-231

math.isnan

Signature	Definition
(Float)	`isnan_float_impl` numba/cpython/old_mathimpl.py lines 210-214
(Integer)	`isnan_int_impl` numba/cpython/old_mathimpl.py lines 216-219

math.ldexp

Signature	Definition
(Float, int32)	`ldexp_impl` numba/cpython/old_mathimpl.py lines 277-288

math.lgamma

Signature	Definition
(Float)	`unary_math_extern.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 149-165
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.log

Signature	Definition
(Float)	`unary_math_intr.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 131-134
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.log10

Signature	Definition
(Float)	`unary_math_intr.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 131-134
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.log1p

Signature	Definition
(Float)	`unary_math_extern.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 149-165
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.log2

Signature	Definition
(Float)	`unary_math_intr.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 131-134
(Float)	`unary_math_extern.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 149-165
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.nextafter

Signature	Definition
(Float, Float)	`nextafter_impl` numba/cpython/old_mathimpl.py lines 410-422

math.pow

Signature	Definition
(Float, Float)	`pow_impl` numba/cpython/old_mathimpl.py lines 402-406
(Float, Integer)	`pow_impl` numba/cpython/old_mathimpl.py lines 402-406

math.radians

Signature	Definition
(Float)	`radians_float_impl` numba/cpython/old_mathimpl.py lines 380-385
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.sin

Signature	Definition
(Float)	`unary_math_intr.<locals>.float_impl` numba/cpython/old_mathimpl.py lines 131-134
(Integer)	`_unary_int_input_wrapper_impl.<locals>.implementer` numba/cpython/old_mathimpl.py lines 113-119

math.sinh

Signature	Definition
(Float)	unary_math_extern.<locals>.float_impl numba/cpython/old_mathimpl.py lines 149-165
(Integer)	_unary_int_input_wrapper_impl.<locals>.implementer numba/cpython/old_mathimpl.py lines 113-119

math.sqrt

Signature	Definition
(Float)	unary_math_extern.<locals>.float_impl numba/cpython/old_mathimpl.py lines 149-165
(Integer)	_unary_int_input_wrapper_impl.<locals>.implementer numba/cpython/old_mathimpl.py lines 113-119

math.tan

Signature	Definition
(Float)	unary_math_extern.<locals>.float_impl numba/cpython/old_mathimpl.py lines 149-165
(Integer)	_unary_int_input_wrapper_impl.<locals>.implementer numba/cpython/old_mathimpl.py lines 113-119

math.tanh

Signature	Definition
(Float)	unary_math_extern.<locals>.float_impl numba/cpython/old_mathimpl.py lines 149-165
(Integer)	_unary_int_input_wrapper_impl.<locals>.implementer numba/cpython/old_mathimpl.py lines 113-119

math.trunc

Signature	Definition
(Float)	unary_math_extern.<locals>.float_impl numba/cpython/old_mathimpl.py lines 149-165
(Integer)	_unary_int_input_wrapper_impl.<locals>.implementer numba/cpython/old_mathimpl.py lines 113-119

numba.core.types.abstract.TypeRef

Signature	Definition
*(*any)*	`redirect_type_ctor` numba/cpython/old_builtins.py lines 671-700

numba.core.types.functions.NamedTupleClass

Signature	Definition
*(*any)*	`namedtuple_constructor` numba/cpython/old_tupleobj.py lines 15-27

numba.core.types.functions.NumberClass

Signature	Definition
(any)	`number_constructor` numba/cpython/old_builtins.py lines 338-354

numba.core.types.misc.ClassType

Signature	Definition
*(*any)*	`ctor_impl` numba/experimental/jitclass/base.py lines 553-595

numba.core.typing.old_builtins.IndexValue

Signature	Definition
(int64, Type)	`impl_index_value` numba/cpython/old_builtins.py lines 557-565
(uint64, Type)	`impl_index_value` numba/cpython/old_builtins.py lines 557-565

numba.cpython.old_builtins.get_type_max_value

Signature	Definition
(DType)	`lower_get_type_max_value` numba/cpython/old_builtins.py lines 525-550
(NumberClass)	`lower_get_type_max_value` numba/cpython/old_builtins.py lines 525-550

numba.cpython.old_builtins.get_type_min_value

Signature	Definition
(DType)	lower_get_type_min_value numba/cpython/old_builtins.py lines 498-523
(NumberClass)	lower_get_type_min_value numba/cpython/old_builtins.py lines 498-523

numba.misc.special.pndindex

Signature	Definition
(<class 'numba.core.types.old_scalars.Integer'>)*	make_array_ndindex numba/np/arrayobj.py lines 4152-4164
(BaseTuple)	make_array_ndindex_tuple numba/np/arrayobj.py lines 4167-4187

numba.misc.special.prange

Signature	Definition
(int32)	make_range_impl.<locals>.range1_impl numba/cpython/rangeobj.py lines 26-41
(int32, int32)	make_range_impl.<locals>.range2_impl numba/cpython/rangeobj.py lines 43-58
(int32, int32, int32)	make_range_impl.<locals>.range3_impl numba/cpython/rangeobj.py lines 60-75
(int64)	make_range_impl.<locals>.range1_impl numba/cpython/rangeobj.py lines 26-41
(int64, int64)	make_range_impl.<locals>.range2_impl numba/cpython/rangeobj.py lines 43-58
(int64, int64, int64)	make_range_impl.<locals>.range3_impl numba/cpython/rangeobj.py lines 60-75
(uint64)	make_range_impl.<locals>.range1_impl numba/cpython/rangeobj.py lines 26-41
(uint64, uint64)	make_range_impl.<locals>.range2_impl numba/cpython/rangeobj.py lines 43-58
(uint64, uint64, uint64)	make_range_impl.<locals>.range3_impl numba/cpython/rangeobj.py lines 60-75

numba.np.arrayobj.reshape_unchecked

Signature	Definition
(Array, BaseTuple, BaseTuple)	impl_shape_unchecked numba/np/arrayobj.py lines 6720-6739

numba.np.npdatetime_helpers.datetime_maximum

Signature	Definition
(NPDatetime, NPDatetime)	_gen_datetime_max_impl.<locals>.datetime_max_impl numba/np/npdatetime.py lines 698-712
(NPTimedelta, NPTimedelta)	_gen_datetime_max_impl.<locals>.datetime_max_impl numba/np/npdatetime.py lines 698-712

numba.np.npdatetime_helpers.datetime_minimum

Signature	Definition
(NPDatetime, NPDatetime)	`_gen_datetime_min_impl.<locals>.datetime_min_impl` numba/np/npdatetime.py lines 719-733
(NPTimedelta, NPTimedelta)	`_gen_datetime_min_impl.<locals>.datetime_min_impl` numba/np/npdatetime.py lines 719-733

numba.parfors.parfor.internal_prange

Signature	Definition
(int32)	`make_range_impl.<locals>.range1_impl` numba/cpython/rangeobj.py lines 26-41
(int32, int32)	`make_range_impl.<locals>.range2_impl` numba/cpython/rangeobj.py lines 43-58
(int32, int32, int32)	`make_range_impl.<locals>.range3_impl` numba/cpython/rangeobj.py lines 60-75
(int64)	`make_range_impl.<locals>.range1_impl` numba/cpython/rangeobj.py lines 26-41
(int64, int64)	`make_range_impl.<locals>.range2_impl` numba/cpython/rangeobj.py lines 43-58
(int64, int64, int64)	`make_range_impl.<locals>.range3_impl` numba/cpython/rangeobj.py lines 60-75
(uint64)	`make_range_impl.<locals>.range1_impl` numba/cpython/rangeobj.py lines 26-41
(uint64, uint64)	`make_range_impl.<locals>.range2_impl` numba/cpython/rangeobj.py lines 43-58
(uint64, uint64, uint64)	`make_range_impl.<locals>.range3_impl` numba/cpython/rangeobj.py lines 60-75

numba.stencils.stencil.stencil

Signature	Definition
()	`stencil_dummy_lower` numba/stencils/stencil.py lines 833-836

numpy.absolute

Signature	Definition
(any)	`register_ufunc_kernel.<locals>.do_ufunc` numba/np/npyimpl.py lines 744-745
(any, Array)	`register_ufunc_kernel.<locals>.do_ufunc` numba/np/npyimpl.py lines 744-745

numpy.add

Signature	Definition
(any, any)	`register_ufunc_kernel.<locals>.do_ufunc` numba/np/npyimpl.py lines 744-745
(any, any, Array)	`register_ufunc_kernel.<locals>.do_ufunc` numba/np/npyimpl.py lines 744-745

numpy.arccos

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.arccosh

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.arcsin

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.arcsinh

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.arctan

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.arctan2

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.arctanh

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.argsort

Signature	Definition
(Array, StringLiteral)	array_argsort numba/np/arrayobj.py lines 6637-6652

numpy.bitwise_and

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.bitwise_or

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.bitwise_xor

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.cbrt

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.ceil

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.conjugate

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.copysign

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.cos

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.cosh

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.deg2rad

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.degrees

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.divide

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.divmod

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.equal

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.exp

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.exp2

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.expm1

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.fabs

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.float_power

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.floor

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.floor_divide

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.fmax

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.fmin

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.fmod

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.gcd

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.greater

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.greater_equal

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.hypot

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.invert

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.isfinite

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.isinf

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.isnan

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.isnat

Signature	Definition
(NPDatetime)	_np_isnat_impl numba/np/npdatetime.py lines 795-798
(NPTimedelta)	_np_isnat_impl numba/np/npdatetime.py lines 795-798
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.lcm

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.ldexp

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.left_shift

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.less

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.less_equal

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.log

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.log10

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.log1p

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.log2

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.logaddexp

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.logaddexp2

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.logical_and

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.logical_not

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.logical_or

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.logical_xor

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.maximum

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.minimum

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.multiply

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.ndenumerate

Signature	Definition
(Array)	make_array_ndenumerate numba/np/arrayobj.py lines 4118-4133

numpy.ndindex

Signature	Definition
(<class 'numba.core.types.old_scalars.Integer'>)*	make_array_ndindex numba/np/arrayobj.py lines 4152-4164
(BaseTuple)	make_array_ndindex_tuple numba/np/arrayobj.py lines 4167-4187

numpy.nditer

Signature	Definition
(any)	make_array_nditer numba/np/arrayobj.py lines 4202-4219

numpy.negative

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.nextafter

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.nonzero

Signature	Definition
(Array)	array_nonzero numba/np/old_arraymath.py lines 3265-3320

numpy.not_equal

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.polynomial.polynomial.Polynomial

Signature	Definition
(Array)	impl_polynomial1 numba/np/polynomial/polynomial_core.py lines 73-94
(Array, Array, Array)	impl_polynomial3 numba/np/polynomial/polynomial_core.py lines 97-148

numpy.positive

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.power

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.rad2deg

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.radians

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.ravel

Signature	Definition
(Array)	np_ravel numba/np/arrayobj.py lines 2323-2328

numpy.reciprocal

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.remainder

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.right_shift

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.rint

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.sign

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.signbit

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.sin

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.sinh

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.spacing

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.sqrt

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.square

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.subtract

Signature	Definition
(any, any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.sum

Signature	Definition
(Array)	array_sum numba/np/old_arraymath.py lines 160-173
(Array, DTypeSpec)	array_sum_dtype numba/np/old_arraymath.py lines 289-302
(Array, IntegerLiteral)	array_sum_axis numba/np/old_arraymath.py lines 305-346
(Array, IntegerLiteral, DTypeSpec)	array_sum_axis_dtype numba/np/old_arraymath.py lines 246-286
(Array, int64)	array_sum_axis numba/np/old_arraymath.py lines 305-346
(Array, int64, DTypeSpec)	array_sum_axis_dtype numba/np/old_arraymath.py lines 246-286

numpy.tan

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.tanh

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

numpy.trunc

Signature	Definition
(any)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745
(any, Array)	register_ufunc_kernel.<locals>.do_ufunc numba/np/npyimpl.py lines 744-745

6.11 Notes on stencils

Numba provides the *@stencil decorator* to represent stencil computations. This document explains how this feature is implemented in the several different modes available in Numba. Currently, calls to the stencil from non-jitted code is supported as well as calls from jitted code, either with or without the *parallel=True* option.

6.11.1 The stencil decorator

The stencil decorator itself just returns a `StencilFunc` object. This object encapsulates the original stencil kernel function as specified in the program and the options passed to the stencil decorator. Also of note is that after the first compilation of the stencil, the computed neighborhood of the stencil is stored in the `StencilFunc` object in the `neighborhood` attribute.

6.11.2 Handling the three modes

As mentioned above, Numba supports the calling of stencils from inside or outside a `@jit` compiled function, with or without the *parallel=True* option.

Outside jit context

`StencilFunc` overrides the `__call__` method so that calls to `StencilFunc` objects execute the stencil:

```
def __call__(self, *args, **kwargs):
    result = kwargs.get('out')

    new_stencil_func = self._stencil_wrapper(result, None, *args)

    if result is None:
        return new_stencil_func.entry_point(*args)
    else:
        return new_stencil_func.entry_point(*args, result)
```

First, the presence of the optional *out* parameter is checked. If it is present then the output array is stored in `result`. Then, the call to `_stencil_wrapper` generates the stencil function given the result and argument types and finally the generated stencil function is executed and its result returned.

Jit without `parallel=True`

When constructed, a `StencilFunc` inserts itself into the typing context's set of user functions and provides the `_type_me` callback. In this way, the standard Numba compiler is able to determine the output type and signature of a `StencilFunc`. Each `StencilFunc` maintains a cache of previously seen combinations of input argument types and keyword types. If previously seen, the `StencilFunc` returns the computed signature. If not previously computed, the `StencilFunc` computes the return type of the stencil by running the Numba compiler frontend on the stencil kernel and then performing type inference on the *Numba IR* (IR) to get the scalar return type of the kernel. From that, a Numpy array type is constructed whose element type matches that scalar return type.

After computing the signature of the stencil for a previously unseen combination of input and keyword types, the `StencilFunc` then *creates the stencil function* itself. `StencilFunc` then installs the new stencil function's definition in the target context so that jitted code is able to call it.

Thus, in this mode, the generated stencil function is a stand-alone function called like a normal function from within jitted code.

Jit with `parallel=True`

When calling a `StencilFunc` from a jitted context with `parallel=True`, a separate stencil function as generated by *Creating the stencil function* is not used. Instead, *parfors* (*Stage 5b: Perform Automatic Parallelization*) are created within the current function that implements the stencil. This code again starts with the stencil kernel and does a similar kernel size computation but then rather than standard Python looping syntax, corresponding *parfors* are created so that the execution of the stencil will take place in parallel.

The stencil to *parfor* translations can also be selectively disabled by setting `parallel={'stencil': False}`, among other sub-options described in *Stage 5b: Perform Automatic Parallelization*.

6.11.3 Creating the stencil function

Conceptually, a stencil function is created from the user-specified stencil kernel by adding looping code around the kernel, transforming the relative kernel indices into absolute array indices based on the loop indices, and replacing the kernel's `return` statement with a statement to assign the computed value into the output array.

To accomplish this transformation, first, a copy of the stencil kernel IR is created so that subsequent modifications of the IR for different stencil signatures will not effect each other.

Then, an approach similar to how GUFunc's are created for *parfors* is employed. In a text buffer, a Python function is created with a unique name. The input array parameter is added to the function definition and if the `out` argument type is present then an `out` parameter is added to the stencil function definition. If the `out` argument is not present then first an output array is created with `numpy.zeros` having the same shape as the input array.

The kernel is then analyzed to compute the stencil size and the shape of the boundary (or the `neighborhood` stencil decorator argument is used for this purpose if present). Then, one `for` loop for each dimension of the input array is added to the stencil function definition. The range of each loop is controlled by the stencil kernel size previously computed so that the boundary of the output image is not modified but instead left as is. The body of the innermost `for` loop is a single `sentinel` statement that is easily recognized in the IR. A call to `exec` with the text buffer is used to force the stencil function into existence and an `eval` is used to get access to the corresponding function on which `run_frontend` is used to get the stencil function IR.

Various renaming and relabeling is performed on the stencil function IR and the kernel IR so that the two can be combined without conflict. The relative indices in the kernel IR (i.e., `getitem` calls) are replaced with expressions where the corresponding loop index variables are added to the relative indices. The `return` statement in the kernel IR is replaced with a `setitem` for the corresponding element in the output array. The stencil function IR is then scanned for the sentinel and the sentinel replaced with the modified kernel IR.

Next, `compile_ir` is used to compile the combined stencil function IR. The resulting compile result is cached in the `StencilFunc` so that other calls to the same stencil do not need to undertake this process again.

6.11.4 Exceptions raised

Various checks are performed during stencil compilation to make sure that user-specified options do not conflict with each other or with other runtime parameters. For example, if the user has manually specified a `neighborhood` to the stencil decorator, the length of that neighborhood must match the dimensionality of the input array. If this is not the case, a `ValueError` is raised.

If the neighborhood has not been specified then it must be inferred and a requirement to infer the kernel is that all indices are constant integers. If they are not, a `ValueError` is raised indicating that kernel indices may not be non-constant.

Finally, the stencil implementation detects the output array type by running Numba type inference on the stencil kernel. If the return type of this kernel does not match the type of the value passed to the `cval` stencil decorator option then a `ValueError` is raised.

6.12 Customizing the Compiler

Warning: The custom pipeline feature is for expert use only. Modifying the compiler behavior can invalidate internal assumptions in the numba source code.

For library developers looking for a way to extend or modify the compiler behavior, you can do so by defining a custom compiler by inheriting from `numba.compiler.CompilerBase`. The default Numba compiler is defined as `numba.compiler.Compiler`, implementing the `.define_pipelines()` method, which adds the *nopython-mode*, *object-mode* and *interpreted-mode* pipelines. For convenience these three pipelines are defined in `numba.compiler.DefaultPassBuilder` by the methods:

- `.define_nopython_pipeline()`
- `.define_objectmode_pipeline()`
- `.define_interpreted_pipeline()`

respectively.

To use a custom subclass of `CompilerBase`, supply it as the `pipeline_class` keyword argument to the `@jit` decorator. By doing so, the effect of the custom pipeline is limited to the function being decorated.

6.12.1 Implementing a compiler pass

Numba makes it possible to implement a new compiler pass and does so through the use of an API similar to that of LLVM. The following demonstrates the basic process involved.

Compiler pass classes

All passes must inherit from `numba.compiler_machinery.CompilerPass`, commonly used subclasses are:

- `numba.compiler_machinery.FunctionPass` for describing a pass that operates on a function-at-once level and may mutate the IR state.
- `numba.compiler_machinery.AnalysisPass` for describing a pass that performs analysis only.
- `numba.compiler_machinery.LoweringPass` for describing a pass that performs lowering only.

In this example a new compiler pass will be implemented that will rewrite all `ir.Const(x)` nodes, where `x` is a subclass of `numbers.Number`, such that the value of x is incremented by one. There is no use for this pass other than to serve as a pedagogical vehicle!

The `numba.compiler_machinery.FunctionPass` is appropriate for the suggested pass behavior and so is the base class of the new pass. Further, a `run_pass` method is defined to do the work (this method is abstract, all compiler passes must implement it).

First the new class:

```
from numba import njit
from numba.core import ir
from numba.core.compiler import CompilerBase, DefaultPassBuilder
from numba.core.compiler_machinery import FunctionPass, register_pass
from numba.core.untyped_passes import IRProcessing
from numbers import Number
```

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```
# Register this pass with the compiler framework, declare that it will not
# mutate the control flow graph and that it is not an analysis_only pass (it
# potentially mutates the IR).
@register_pass(mutates_CFG=False, analysis_only=False)
class ConstsAddOne(FunctionPass):
    _name = "consts_add_one" # the common name for the pass

    def __init__(self):
        FunctionPass.__init__(self)

    # implement method to do the work, "state" is the internal compiler
    # state from the CompilerBase instance.
    def run_pass(self, state):
        func_ir = state.func_ir # get the FunctionIR object
        mutated = False # used to record whether this pass mutates the IR
        # walk the blocks
        for blk in func_ir.blocks.values():
            # find the assignment nodes in the block and walk them
            for assgn in blk.find_insts(ir.Assign):
                # if an assignment value is a ir.Consts
                if isinstance(assgn.value, ir.Const):
                    const_val = assgn.value
                    # if the value of the ir.Const is a Number
                    if isinstance(const_val.value, Number):
                        # then add one!
                        const_val.value += 1
                        mutated |= True
        return mutated # return True if the IR was mutated, False if not.
```

Note also that the class must be registered with Numba's compiler machinery using `@register_pass`. This in part is to allow the declaration of whether the pass mutates the control flow graph and whether it is an analysis only pass.

Next, define a new compiler based on the existing `numba.compiler.CompilerBase`. The compiler pipeline is defined through the use of an existing pipeline and the new pass declared above is added to be run after the `IRProcessing` pass.

```
class MyCompiler(CompilerBase): # custom compiler extends from CompilerBase

    def define_pipelines(self):
        # define a new set of pipelines (just one in this case) and for ease
        # base it on an existing pipeline from the DefaultPassBuilder,
        # namely the "nopython" pipeline
        pm = DefaultPassBuilder.define_nopython_pipeline(self.state)
        # Add the new pass to run after IRProcessing
        pm.add_pass_after(ConstsAddOne, IRProcessing)
        # finalize
        pm.finalize()
        # return as an iterable, any number of pipelines may be defined!
        return [pm]
```

Finally update the `@njit` decorator at the call site to make use of the newly defined compilation pipeline.

```
@njit(pipeline_class=MyCompiler) # JIT compile using the custom compiler
def foo(x):
    a = 10
    b = 20.2
    c = x + a + b
    return c

print(foo(100)) # 100 + 10 + 20.2 (+ 1 + 1), extra + 1 + 1 from the rewrite!
```

6.12.2 Debugging compiler passes

Observing IR Changes

It is often useful to be able to see the changes a pass makes to the IR. Numba conveniently permits this through the use of the environment variable *NUMBA_DEBUG_PRINT_AFTER*. In the case of the above pass, running the example code with `NUMBA_DEBUG_PRINT_AFTER="ir_processing,consts_add_one"` gives:

```
---------------------------nopython: ir_processing-----------------------------
label 0:
    x = arg(0, name=x)                       ['x']
    $const0.1 = const(int, 10)               ['$const0.1']
    a = $const0.1                            ['$const0.1', 'a']
    del $const0.1                            []
    $const0.2 = const(float, 20.2)           ['$const0.2']
    b = $const0.2                            ['$const0.2', 'b']
    del $const0.2                            []
    $0.5 = x + a                             ['$0.5', 'a', 'x']
    del x                                    []
    del a                                    []
    $0.7 = $0.5 + b                          ['$0.5', '$0.7', 'b']
    del b                                    []
    del $0.5                                 []
    c = $0.7                                 ['$0.7', 'c']
    del $0.7                                 []
    $0.9 = cast(value=c)                     ['$0.9', 'c']
    del c                                    []
    return $0.9                              ['$0.9']
---------------------------nopython: consts_add_one----------------------------
label 0:
    x = arg(0, name=x)                       ['x']
    $const0.1 = const(int, 11)               ['$const0.1']
    a = $const0.1                            ['$const0.1', 'a']
    del $const0.1                            []
    $const0.2 = const(float, 21.2)           ['$const0.2']
    b = $const0.2                            ['$const0.2', 'b']
    del $const0.2                            []
    $0.5 = x + a                             ['$0.5', 'a', 'x']
    del x                                    []
    del a                                    []
    $0.7 = $0.5 + b                          ['$0.5', '$0.7', 'b']
    del b                                    []
```

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```
    del $0.5                                 []
    c = $0.7                                 ['$0.7', 'c']
    del $0.7                                 []
    $0.9 = cast(value=c)                     ['$0.9', 'c']
    del c                                    []
    return $0.9                              ['$0.9']
```

Note the change in the values in the `const` nodes.

Pass execution times

Numba has built-in support for timing all compiler passes, the execution times are stored in the metadata associated with a compilation result. This demonstrates one way of accessing this information based on the previously defined function, `foo`:

```
compile_result = foo.overloads[foo.signatures[0]]
nopython_times = compile_result.metadata['pipeline_times']['nopython']
for k in nopython_times.keys():
    if ConstsAddOne._name in k:
        print(nopython_times[k])
```

the output of which is, for example:

```
pass_timings(init=1.914000677061267e-06, run=4.308700044930447e-05, finalize=1.
↪7400006981915794e-06)
```

this displaying the pass initialization, run and finalization times in seconds.

6.13 Notes on Inlining

There are occasions where it is useful to be able to inline a function at its call site, at the Numba IR level of representation. The decorators such as *numba.jit()*, `numba.extending.overload()` and `register_jitable()` support the keyword argument `inline`, to facilitate this behaviour.

When attempting to inline at this level, it is important to understand what purpose this serves and what effect this will have. In contrast to the inlining performed by LLVM, which is aimed at improving performance, the main reason to inline at the Numba IR level is to allow type inference to cross function boundaries.

As an example, consider the following snippet:

```
from numba import njit


@njit
def bar(a):
    a.append(10)


@njit
def foo():
    z = []
```

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```
    bar(z)


foo()
```

This will fail to compile and run, because the type of `z` can not be inferred as it will only be refined within `bar`. If we now add `inline=True` to the decorator for `bar` the snippet will compile and run. This is because inlining the call to `a.append(10)` will mean that `z` will be refined to hold integers and so type inference will succeed.

So, to recap, inlining at the Numba IR level is unlikely to have a performance benefit. Whereas inlining at the LLVM level stands a better chance.

The `inline` keyword argument can be one of three values:

- The string `'never'`, this is the default and results in the function not being inlined under any circumstances.
- The string `'always'`, this results in the function being inlined at all call sites.
- A python function that takes three arguments. The first argument is always the `ir.Expr` node that is the `call` requesting the inline, this is present to allow the function to make call contextually aware decisions. The second and third arguments are:
  - In the case of an untyped inline, i.e. that which occurs when using the *numba.jit()* family of decorators, both arguments are `numba.ir.FunctionIR` instances. The second argument corresponding to the IR of the caller, the third argument corresponding to the IR of the callee.
  - In the case of a typed inline, i.e. that which occurs when using `numba.extending.overload()`, both arguments are instances of a `namedtuple` with fields (corresponding to their standard use in the compiler internals):
    - `func_ir` - the function's Numba IR.
    - `typemap` - the function's type map.
    - `calltypes` - the call types of any calls in the function.
    - `signature` - the function's signature.

    The second argument holds the information from the caller, the third holds the information from the callee.

  In all cases the function should return True to inline and return False to not inline, this essentially permitting custom inlining rules (typical use might be cost models).
- Recursive functions with `inline='always'` will result in a non-terminating compilation. If you wish to avoid this, supply a function to limit the recursion depth (see below).

Note: No guarantee is made about the order in which functions are assessed for inlining or about the order in which they are inlined.

6.13.1 Example using `numba.jit()`

An example of using all three options to `inline` in the `numba.njit()` decorator:

```
from numba import njit
import numba
from numba.core import ir


@njit(inline='never')
def never_inline():
    return 100


@njit(inline='always')
def always_inline():
    return 200


def sentinel_cost_model(expr, caller_info, callee_info):
    # this cost model will return True (i.e. do inlining) if either:
    # a) the callee IR contains an `ir.Const(37)`
    # b) the caller IR contains an `ir.Const(13)` logically prior to the call
    #    site

    # check the callee
    for blk in callee_info.blocks.values():
        for stmt in blk.body:
            if isinstance(stmt, ir.Assign):
                if isinstance(stmt.value, ir.Const):
                    if stmt.value.value == 37:
                        return True

    # check the caller
    before_expr = True
    for blk in caller_info.blocks.values():
        for stmt in blk.body:
            if isinstance(stmt, ir.Assign):
                if isinstance(stmt.value, ir.Expr):
                    if stmt.value == expr:
                        before_expr = False
                if isinstance(stmt.value, ir.Const):
                    if stmt.value.value == 13:
                        return True & before_expr
    return False


@njit(inline=sentinel_cost_model)
def maybe_inline1():
    # Will not inline based on the callee IR with the declared cost model
    # The following is ir.Const(300).
    return 300
```

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```
@njit(inline=sentinel_cost_model)
def maybe_inline2():
    # Will inline based on the callee IR with the declared cost model
    # The following is ir.Const(37).
    return 37


@njit
def foo():
    a = never_inline()  # will never inline
    b = always_inline()  # will always inline

    # will not inline as the function does not contain a magic constant known to
    # the cost model, and the IR up to the call site does not contain a magic
    # constant either
    d = maybe_inline1()

    # declare this magic constant to trigger inlining of maybe_inline1 in a
    # subsequent call
    magic_const = 13

    # will inline due to above constant declaration
    e = maybe_inline1()

    # will inline as the maybe_inline2 function contains a magic constant known
    # to the cost model
    c = maybe_inline2()

    return a + b + c + d + e + magic_const


foo()
```

which produces the following when executed (with a print of the IR after the legalization pass, enabled via the environment variable `NUMBA_DEBUG_PRINT_AFTER="ir_legalization"`):

```
label 0:
    $0.1 = global(never_inline: CPUDispatcher(<function never_inline at 0x7f890ccf9048>
↪)) ['$0.1']
    $0.2 = call $0.1(func=$0.1, args=[], kws=(), vararg=None) ['$0.1', '$0.2']
    del $0.1                                []
    a = $0.2                                ['$0.2', 'a']
    del $0.2                                []
    $0.3 = global(always_inline: CPUDispatcher(<function always_inline at 0x7f890ccf9598>
↪)) ['$0.3']
    del $0.3                                []
    $const0.1.0 = const(int, 200)           ['$const0.1.0']
    $0.2.1 = $const0.1.0                    ['$0.2.1', '$const0.1.0']
    del $const0.1.0                         []
    $0.4 = $0.2.1                           ['$0.2.1', '$0.4']
    del $0.2.1                              []
```

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```
    b = $0.4                                    ['$0.4', 'b']
    del $0.4                                    []
    $0.5 = global(maybe_inline1: CPUDispatcher(<function maybe_inline1 at 0x7f890ccf9ae8>
↪)) ['$0.5']
    $0.6 = call $0.5(func=$0.5, args=[], kws=(), vararg=None) ['$0.5', '$0.6']
    del $0.5                                    []
    d = $0.6                                    ['$0.6', 'd']
    del $0.6                                    []
    $const0.7 = const(int, 13)                  ['$const0.7']
    magic_const = $const0.7                     ['$const0.7', 'magic_const']
    del $const0.7                               []
    $0.8 = global(maybe_inline1: CPUDispatcher(<function maybe_inline1 at 0x7f890ccf9ae8>
↪)) ['$0.8']
    del $0.8                                    []
    $const0.1.2 = const(int, 300)               ['$const0.1.2']
    $0.2.3 = $const0.1.2                        ['$0.2.3', '$const0.1.2']
    del $const0.1.2                             []
    $0.9 = $0.2.3                               ['$0.2.3', '$0.9']
    del $0.2.3                                  []
    e = $0.9                                    ['$0.9', 'e']
    del $0.9                                    []
    $0.10 = global(maybe_inline2: CPUDispatcher(<function maybe_inline2 at␣
↪0x7f890ccf9b70>)) ['$0.10']
    del $0.10                                   []
    $const0.1.4 = const(int, 37)                ['$const0.1.4']
    $0.2.5 = $const0.1.4                        ['$0.2.5', '$const0.1.4']
    del $const0.1.4                             []
    $0.11 = $0.2.5                              ['$0.11', '$0.2.5']
    del $0.2.5                                  []
    c = $0.11                                   ['$0.11', 'c']
    del $0.11                                   []
    $0.14 = a + b                               ['$0.14', 'a', 'b']
    del b                                       []
    del a                                       []
    $0.16 = $0.14 + c                           ['$0.14', '$0.16', 'c']
    del c                                       []
    del $0.14                                   []
    $0.18 = $0.16 + d                           ['$0.16', '$0.18', 'd']
    del d                                       []
    del $0.16                                   []
    $0.20 = $0.18 + e                           ['$0.18', '$0.20', 'e']
    del e                                       []
    del $0.18                                   []
    $0.22 = $0.20 + magic_const                 ['$0.20', '$0.22', 'magic_const']
    del magic_const                             []
    del $0.20                                   []
    $0.23 = cast(value=$0.22)                   ['$0.22', '$0.23']
    del $0.22                                   []
    return $0.23                                ['$0.23']
```

Things to note in the above:

1. The call to the function `never_inline` remains as a call.

2. The `always_inline` function has been inlined, note its `const(int, 200)` in the caller body.
3. There is a call to `maybe_inline1` before the `const(int, 13)` declaration, the cost model prevented this from being inlined.
4. After the `const(int, 13)` the subsequent call to `maybe_inline1` has been inlined as shown by the `const(int, 300)` in the caller body.
5. The function `maybe_inline2` has been inlined as demonstrated by `const(int, 37)` in the caller body.
6. That dead code elimination has not been performed and as a result there are superfluous statements present in the IR.

6.13.2 Example using `numba.extending.overload()`

An example of using inlining with the `numba.extending.overload()` decorator. It is most interesting to note that if a function is supplied as the argument to `inline` a lot more information is available via the supplied function arguments for use in decision making. Also that different `@overload` s can have different inlining behaviours, with multiple ways to achieve this:

```
import numba
from numba.extending import overload
from numba import njit, types


def bar(x):
    """A function stub to overload"""
    pass


@overload(bar, inline='always')
def ol_bar_tuple(x):
    # An overload that will always inline, there is a type guard so that this
    # only applies to UniTuples.
    if isinstance(x, types.UniTuple):
        def impl(x):
            return x[0]
        return impl


def cost_model(expr, caller, callee):
    # Only inline if the type of the argument is an Integer
    return isinstance(caller.typemap[expr.args[0].name], types.Integer)


@overload(bar, inline=cost_model)
def ol_bar_scalar(x):
    # An overload that will inline based on a cost model, it only applies to
    # scalar values in the numerical domain as per the type guard on Number
    if isinstance(x, types.Number):
        def impl(x):
            return x + 1
        return impl
```

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```
@njit
def foo():

    # This will resolve via `ol_bar_tuple` as the argument is a types.UniTuple
    # instance. It will always be inlined as specified in the decorator for this
    # overload.
    a = bar((1, 2, 3))

    # This will resolve via `ol_bar_scalar` as the argument is a types.Number
    # instance, hence the cost_model will be used to determine whether to
    # inline.
    # The function will be inlined as the value 100 is an IntegerLiteral which
    # is an instance of a types.Integer as required by the cost_model function.
    b = bar(100)

    # This will also resolve via `ol_bar_scalar` as the argument is a
    # types.Number instance, again the cost_model will be used to determine
    # whether to inline.
    # The function will not be inlined as the complex value is not an instance
    # of a types.Integer as required by the cost_model function.
    c = bar(300j)

    return a + b + c


foo()
```

which produces the following when executed (with a print of the IR after the legalization pass, enabled via the environment variable `NUMBA_DEBUG_PRINT_AFTER="ir_legalization"`):

```
label 0:
    $const0.2 = const(tuple, (1, 2, 3))      ['$const0.2']
    x.0 = $const0.2                          ['$const0.2', 'x.0']
    del $const0.2                            []
    $const0.2.2 = const(int, 0)              ['$const0.2.2']
    $0.3.3 = getitem(value=x.0, index=$const0.2.2) ['$0.3.3', '$const0.2.2', 'x.0']
    del x.0                                  []
    del $const0.2.2                          []
    $0.4.4 = $0.3.3                          ['$0.3.3', '$0.4.4']
    del $0.3.3                               []
    $0.3 = $0.4.4                            ['$0.3', '$0.4.4']
    del $0.4.4                               []
    a = $0.3                                 ['$0.3', 'a']
    del $0.3                                 []
    $const0.5 = const(int, 100)              ['$const0.5']
    x.5 = $const0.5                          ['$const0.5', 'x.5']
    del $const0.5                            []
    $const0.2.7 = const(int, 1)              ['$const0.2.7']
    $0.3.8 = x.5 + $const0.2.7               ['$0.3.8', '$const0.2.7', 'x.5']
    del x.5                                  []
    del $const0.2.7                          []
```

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```
    $0.4.9 = $0.3.8                          ['$0.3.8', '$0.4.9']
    del $0.3.8                               []
    $0.6 = $0.4.9                            ['$0.4.9', '$0.6']
    del $0.4.9                               []
    b = $0.6                                 ['$0.6', 'b']
    del $0.6                                 []
    $0.7 = global(bar: <function bar at 0x7f6c3710d268>) ['$0.7']
    $const0.8 = const(complex, 300j)         ['$const0.8']
    $0.9 = call $0.7($const0.8, func=$0.7, args=[Var($const0.8, inline_overload_example.
↪py (56))], kws=(), vararg=None) ['$0.7', '$0.9', '$const0.8']
    del $const0.8                            []
    del $0.7                                 []
    c = $0.9                                 ['$0.9', 'c']
    del $0.9                                 []
    $0.12 = a + b                            ['$0.12', 'a', 'b']
    del b                                    []
    del a                                    []
    $0.14 = $0.12 + c                        ['$0.12', '$0.14', 'c']
    del c                                    []
    del $0.12                                []
    $0.15 = cast(value=$0.14)                ['$0.14', '$0.15']
    del $0.14                                []
    return $0.15                             ['$0.15']
```

Things to note in the above:

1. The first highlighted section is the always inlined overload for the `UniTuple` argument type.
2. The second highlighted section is the overload for the `Number` argument type that has been inlined as the cost model function decided to do so as the argument was an `Integer` type instance.
3. The third highlighted section is the overload for the `Number` argument type that has not inlined as the cost model function decided to reject it as the argument was an `Complex` type instance.
4. That dead code elimination has not been performed and as a result there are superfluous statements present in the IR.

6.13.3 Using a function to limit the inlining depth of a recursive function

When using recursive inlines, you can terminate the compilation by using a cost model.

```
from numba import njit
import numpy as np

class CostModel(object):
    def __init__(self, max_inlines):
        self._count = 0
        self._max_inlines = max_inlines

    def __call__(self, expr, caller, callee):
        ret = self._count < self._max_inlines
        self._count += 1
        return ret
```

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```
@njit(inline=CostModel(3))
def factorial(n):
    if n <= 0:
        return 1
    return n * factorial(n - 1)

factorial(5)
```

6.14 Environment Object

The Environment object (Env) is used to maintain references to python objects that are needed to support compiled functions for both object-mode and nopython-mode.

In nopython-mode, the Env is used for:

- Storing pyobjects for reconstruction from native values, such as:
  - for printing native values of NumPy arrays;
  - for returning or yielding native values back to the interpreter.

In object-mode, the Env is used for:

- storing constant values referenced in the code.
- storing a reference to the function's global dictionary to load global values.

6.14.1 The Implementation

The Env is implemented in two parts. In `_dynfunc.c`, the Env is defined as `EnvironmentObject` as a Python C-extension type. In `lowering.py`, the *EnvironmentObject`* (exported as `_dynfunc.Environment`) is extended to support necessary operations needed at lowering.

Serialization

The Env supports being pickled. Compilation cache files and ahead-of-time compiled modules serialize all the used Envs for recreation at the runtime.

Usage

At the start of the lowering for a function or a generator, an Env is created. Throughout the compilation, the Env is mutated to attach additional information. The compiled code references an Env via a global variable in the emitted LLVM IR. The global variable is zero-initialized with "common" linkage, which is the default linkage for C global values. The use of this linkage allows multiple definitions of the global variable to be merged into a single definition when the modules are linked together. The name of the global variable is computed from the name of the function (see `FunctionDescriptor.env_name` and `.get_env_name()` of the target context).

The Env is initialized when the compiled-function is loaded. The JIT engine finds the address of the associated global variable for the Env and stores the address of the Env into it. For cached functions, the same process applies. For ahead-of-time compiled functions, the module initializer in the generated library is responsible for initializing the global variables of all the Envs in the module.

6.15 Notes on Hashing

Numba supports the built-in `hash()` and does so by simply calling the `__hash__()` member function on the supplied argument. This makes it trivial to add hash support for new types as all that is required is the application of the extension API `overload_method()` decorator to overload a function for computing the hash value for the new type registered to the type's `__hash__()` method. For example:

```
from numba.extending import overload_method

@overload_method(myType, '__hash__')
def myType_hash_overload(obj):
    # implementation details
```

6.15.1 The Implementation

The implementation of the Numba hashing functions strictly follows that of Python 3. The only exception to this is that for hashing Unicode and bytes (for content longer than `sys.hash_info.cutoff`) the only supported algorithm is `siphash24` (default in CPython 3). As a result Numba will match Python 3 hash values for all supported types under the default conditions described.

Unicode hash cache differences

Both Numba and CPython Unicode string internal representations have a `hash` member for the purposes of caching the string's hash value. This member is always checked ahead of computing a hash value with the view of simply providing a value from cache as it is considerably cheaper to do so. The Numba Unicode string hash caching implementation behaves in a similar way to that of CPython's. The only notable behavioral change (and its only impact is a minor potential change in performance) is that Numba always computes and caches the hash for Unicode strings created in `nopython mode` at the time they are boxed for reuse in Python, this is too eager in some cases in comparison to CPython which may delay hashing a new Unicode string depending on creation method. It should also be noted that Numba copies in the `hash` member of the CPython internal representation for Unicode strings when unboxing them to its own representation so as to not recompute the hash of a string that already has a hash value associated with it.

The accommodation of `PYTHONHASHSEED`

The `PYTHONHASHSEED` environment variable can be used to seed the CPython hashing algorithms for e.g. the purposes of reproducibility. The Numba hashing implementation directly reads the CPython hashing algorithms' internal state and as a result the influence of `PYTHONHASHSEED` is replicated in Numba's hashing implementations.

6.16 Notes on `sys.monitoring`

Note: This documentation was written at the advent of Python 3.12. Future versions of Python may behave differently. It is however hoped that most of the concepts herein will remain relevant.

Python 3.12 introduced a new monitoring system under `sys.monitoring`. This system lets users monitor a selection of events that may be interesting for e.g. performance profiling or debugging purposes. Event monitoring is set "per tool", so that multiple tools can be running at the same time. For each tool the events can be monitored globally per thread or locally per code object (or a mixture of both). For each tool-event combination a callback can be registered that will be called on the occurrence of the event. The callbacks are just regular functions and can do most of the

things supported by Python, they also have the ability to return a special value to tell the monitoring system to disable triggering future events for the current code location.

6.16.1 What does this mean for Numba?

When the interpreter "encounters" a monitoring event (it actually issues them) it triggers any callbacks that are associated with that event across all tools that have registered monitoring for said event. In the case of Numba there are problems...

Numba has made it so that there's no Python interpreter involved in the execution of a function, the function is compiled and its execution path exists only in machine code. To get to the machine code from the interpreter the Numba dispatcher is invoked, this is the last place in the stack where (in `nopython` mode) the Python interpreter is readily available. The dispatcher is also in some way part of the execution of the function, without the dispatcher the call to the machine code cannot easily happen from user space. As a result of this, the monitoring types and event types that Numba can support are somewhat limited as there's such limited interpreter involvement in execution!

Looking at monitoring types in turn. Local monitoring is requested by setting monitoring on a code object. In practice this instructs the interpreter to augment the bytecode at runtime by switching certain opcodes for "instrumented" opcodes. These instrumented opcodes go via a special path in the interpreter loop whereby they will issue an "event" in association with a particular instruction at a particular offset. For example, a `RETURN` opcode might be replaced by an `INSTRUMENTED_RETURN` and a `PY_RETURN` event would by issued when the instrumented instruction is interpreted. This event and the offset at which it occurred being forwarded to the monitoring system. Unfortunately this presents an issue for Numba, there is no interpreter involved with execution and so events will not be emitted. It does seem like it would be possible to handle a few types of event, such as `PY_START` and `PY_RETURN` by analysing the code object at dispatch time. However, it's possible for a user to de-instrument the code object and/or dynamically disable monitoring at a particular code location whilst executing, and as a result emulating the semantics of this would be prohibitively challenging and would likely require constant interaction with the interpreter. As a result, Numba does not support local event monitoring, the compiled function will still execute correctly if it has been set, it just has no effect on `sys.monitoring`.

Considering per-thread global monitoring, this manifests as the user setting some global state on the interpreter for a given thread. This state can be accessed via the `sys.monitoring` Python API, it's also accessible via CPython internals. This kind of monitoring is a little more amenable to working with Numba as there's no code object involved and state mutation during execution can only occur via object mode calls.

6.16.2 What does Numba do in practice?

As there's no Python or C API to issue events (the concept is heavily linked to the interpreter itself), Numba has to look for tool-event combinations at appropriate locations in the dispatch sequence and then manually call the associated callbacks (essentially doing what the interpreter does when it issues an event). In the case of the Numba dispatcher, only a few events are relevant and only four are supported, namely

- `sys.monitoring.events.PY_START` (Python function starting).
- `sys.monitoring.events.PY_RETURN` (Python function returning).
- `sys.monitoring.events.RAISE` (Python function raised an exception).
- `sys.monitoring.events.PY_UNWIND` (Python function exiting during exception unwinding).

These events don't really exist in the machine code, but would exist had the interpreter interpreted the equivalent bytecode. The dispatcher therefore checks for monitoring of `PY_START` just before control is transferred to the machine code and calls any associated callbacks. The same is done for `PY_RETURN` just after control is transferred back to the dispatcher from the machine code. This behaviour essentially emulates the interpreter executing bytecode and lets tools such as `cProfile` be able to "see" the Numba compiled function as part of the standard interpreted execution. In the case of an exception being raised in the machine code, the associated error state is handled just after control

is transferred back to the dispatcher, at this point `RAISE` and `PY_UNWIND` event monitoring is checked and registered callbacks are invoked.

A note on offsets. The callback functions often take an "offset" argument which is the bytecode offset at which the event triggering the callback was encountered. In the case of `PY_START` this seems to be associated with the offset of the `RESUME` bytecode. In the case of `PY_RETURN` this is associated with the offset of one of the `RETURN` bytecodes, most generally this would only be known at runtime as there could be multiple return paths. As a result, Numba elects to just set all offsets to zero. It may eventually be possible to do some analysis and transfer the appropriate runtime information to the dispatcher from the machine code, however, at the present time the effort to do this vastly outweighs the gain.

6.17 Notes on Caching

Numba supports caching of compiled functions into the filesystem for future use of the same functions.

6.17.1 The Implementation

Caching is done by saving the compiled *object code*, the ELF object of the executable code. By using the *object code*, cached functions have minimal overhead because no compilation is needed. The cached data is saved under the cache directory (see *NUMBA_CACHE_DIR*). The index of the cache is stored in a `.nbi` file, with one index per function, and it lists all the overloaded signatures compiled for the function. The *object code* is stored in files with an `.nbc` extension, one file per overload. The data in both files is serialized with `pickle`.

Requirements for Cacheability

Developers should note the requirements of a function to permit it to be cached to ensure that the features they are working on are compatible with caching.

Requirements for cacheable function:

- The LLVM module must be *self-contained*, meaning that it cannot rely on other compiled units without linking to them.
- The only allowed external symbols are from the *NRT* or other common symbols from system libraries (i.e. libc and libm).

Debugging note:

- Look for the usage of `inttoptr` in the LLVM IR or `target_context.add_dynamic_add()` in the lowering code in Python. They indicate potential usage of runtime address. Not all uses are problematic and some are necessary. Only the conversion of constant integers into pointers will affect caching.
- Misuse of dynamic address or dynamic symbols will likely result in a segfault.
- Linking order matters because unused symbols are dropped after linking. Linking should start from the leaf nodes of the dependency graph.

Features Compatible with Caching

The following features are explicitly verified to work with caching.

- ufuncs and gufuncs for the `cpu` and `parallel` target
- parallel accelerator features (i.e. `parallel=True`)

Caching Limitations

This is a list of known limitation of the cache:

- Cache invalidation fails to recognize changes in symbols defined in a different file.
- Global variables are treated as constants. The cache will remember the value of the global variable at compilation time. On cache load, the cached function will not rebind to the new value of the global variable.

Cache Sharing

It is safe to share and reuse the contents in the cache directory on a different machine. The cache remembers the CPU model and the available CPU features during compilation. If the CPU model and the CPU features do not match exactly, the cache contents will not be considered. (Also see *NUMBA_CPU_NAME*)

If the cache directory is shared on a network filesystem, concurrent read/write of the cache is safe only if file replacement operation is atomic for the filesystem. Numba always writes to a unique temporary file first, it then replaces the target cache file path with the temporary file. Numba is tolerant against lost cache files and lost cache entries.

Cache Clearing

The cache is invalidated when the corresponding source file is modified. However, it is necessary sometimes to clear the cache directory manually. For instance, changes in the compiler will not be recognized because the source files are not modified.

To clear the cache, the cache directory can be simply removed.

Removing the cache directory when a Numba application is running may cause an `OSError` exception to be raised at the compilation site.

Related Environment Variables

See *env-vars for caching*.

6.18 Notes on Numba's threading implementation

The execution of the work presented by the Numba `parallel` targets is undertaken by the Numba threading layer. Practically, the "threading layer" is a Numba built-in library that can perform the required concurrent execution. At the time of writing there are three threading layers available, each implemented via a different lower level native threading library. More information on the threading layers and appropriate selection of a threading layer for a given application/system can be found in the *threading layer documentation*.

The pertinent information to note for the following sections is that the function in the threading library that performs the parallel execution is the `parallel_for` function. The job of this function is to both orchestrate and execute the parallel tasks.

The relevant source files referenced in this document are

- `numba/np/ufunc/tbbpool.cpp`
- `numba/np/ufunc/omppool.cpp`
- `numba/np/ufunc/workqueue.c`

  These files contain the TBB, OpenMP, and workqueue threadpool implementations, respectively. Each includes the functions `set_num_threads()`, `get_num_threads()`, and `get_thread_id()`, as well as the relevant logic for thread masking in their respective schedulers. Note that the basic thread local variable logic is duplicated in each of these files, and not shared between them.

- `numba/np/ufunc/parallel.py`

  This file contains the Python and JIT compatible wrappers for `set_num_threads()`, `get_num_threads()`, and `get_thread_id()`, as well as the code that loads the above libraries into Python and launches the threadpool.

- `numba/parfors/parfor_lowering.py`

  This file contains the main logic for generating code for the parallel backend. The thread mask is accessed in this file in the code that generates scheduler code, and passed to the relevant backend scheduler function (see below).

6.18.1 Thread masking

As part of its design, Numba never launches new threads beyond the threads that are launched initially with `numba.np.ufunc.parallel._launch_threads()` when the first parallel execution is run. This is due to the way threads were already implemented in Numba prior to thread masking being implemented. This restriction was kept to keep the design simple, although it could be removed in the future. Consequently, it's possible to programmatically set the number of threads, but only to less than or equal to the total number that have already been launched. This is done by "masking" out unused threads, causing them to do no work. For example, on a 16 core machine, if the user were to call `set_num_threads(4)`, Numba would always have 16 threads present, but 12 of them would sit idle for parallel computations. A further call to `set_num_threads(16)` would cause those same threads to do work in later computations.

Thread masking was added to make it possible for a user to programmatically alter the number of threads performing work in the threading layer. Thread masking proved challenging to implement as it required the development of a programming model that is suitable for users, easy to reason about, and could be implemented safely, with consistent behavior across the various threading layers.

Programming model

The programming model chosen is similar to that found in OpenMP. The reasons for this choice were that it is familiar to a lot of users, restricted in scope and also simple. The number of threads in use is specified by calling `set_num_threads` and the number of threads in use can be queried by calling `get_num_threads`.These two functions are synonymous with their OpenMP counterparts (with the above restriction that the mask must be less than or equal to the number of launched threads). The execution semantics are also similar to OpenMP in that once a parallel region is launched, altering the thread mask has no impact on the currently executing region, but will have an impact on parallel regions executed subsequently.

The Implementation

So as to place no further restrictions on user code other than those that already existed in the threading layer libraries, careful consideration of the design of thread masking was required. The "thread mask" cannot be stored in a global value as concurrent use of the threading layer may result in classic forms of race conditions on the value itself. Numerous designs were discussed involving various types of mutex on such a global value, all of which were eventually broken through thought experiment alone. It eventually transpired that, following some OpenMP implementations, the "thread mask" is best implemented as a `thread local`. This means each thread that executes a Numba parallel function will have a thread local storage (TLS) slot that contains the value of the thread mask to use when scheduling threads in the `parallel_for` function.

The above notion of TLS use for a thread mask is relatively easy to implement, `get_num_threads` and `set_num_threads` simply need to address the TLS slot in a given threading layer. This also means that the execution schedule for a parallel region can be derived from a run time call to `get_num_threads`. This is achieved via a well known and relatively easy to implement pattern of a `C` library function registration and wrapping it in the internal Numba implementation.

In addition to satisfying the original upfront thread masking requirements, a few more complicated scenarios needed consideration as follows.

Nested parallelism

In all threading layers a "main thread" will invoke the `parallel_for` function and then in the parallel region, depending on the threading layer, some number of additional threads will assist in doing the actual work. If the work contains a call to another parallel function (i.e. nested parallelism) it is necessary for the thread making the call to know what the "thread mask" of the main thread is so that it can propagate it into the `parallel_for` call it makes when executing the nested parallel function. The implementation of this behavior is threading layer specific but the general principle is for the "main thread" to always "send" the value of the thread mask from its TLS slot to all threads in the threading layer that are active in the parallel region. These active threads then update their TLS slots with this value prior to performing any work. The net result of this implementation detail is that:

- thread masks correctly propagate into nested functions
- it's still possible for each thread in a parallel region to safely have a different mask with which to call nested functions, if it's not set explicitly then the inherited mask from the "main thread" is used
- threading layers which have dynamic scheduling with threads potentially joining and leaving the active pool during a `parallel_for` execution are successfully accommodated
- any "main thread" thread mask is entirely decoupled from the in-flux nature of the thread masks of the threads in the active thread pool

Python threads independently invoking parallel functions

The threading layer launch sequence is heavily guarded to ensure that the launch is both thread and process safe and run once per process. In a system with numerous Python `threading` module threads all using Numba, the first thread through the launch sequence will get its thread mask set appropriately, but no further threads can run the launch sequence. This means that other threads will need their initial thread mask set some other way. This is achieved when `get_num_threads` is called and no thread mask is present, in this case the thread mask will be set to the default. In the implementation, "no thread mask is present" is represented by the value `-1` and the "default thread mask" (unset) is represented by the value `0`. The implementation also immediately calls `set_num_threads(NUMBA_NUM_THREADS)` after doing this, so if either `-1` or `0` is encountered as a result from `get_num_threads()` it indicates a bug in the above processes.

OS `fork()` calls

The use of TLS was also in part driven by the Linux (the most popular platform for Numba use by far) having a `fork(2, 3P)` call that will do TLS propagation into child processes, see `clone(2)`'s `CLONE_SETTLS`.

Thread ID

A private `get_thread_id()` function was added to each threading backend, which returns a unique ID for each thread. This can be accessed from Python by `numba.np.ufunc.parallel._get_thread_id()` (it can also be used inside a JIT compiled function). The thread ID function is useful for testing that the thread masking behavior is correct, but it should not be used outside of the tests. For example, one can call `set_num_threads(4)` and then collect all unique `_get_thread_id()`s in a parallel region to verify that only 4 threads are run.

Caveats

Some caveats to be aware of when testing thread masking:

- The TBB backend may choose to schedule fewer than the given mask number of threads. Thus a test such as the one described above may return fewer than 4 unique threads.
- The workqueue backend is not threadsafe, so attempts to do multithreading nested parallelism with it may result in deadlocks or other undefined behavior. The workqueue backend will raise a SIGABRT signal if it detects nested parallelism.
- Certain backends may reuse the main thread for computation, but this behavior shouldn't be relied upon (for instance, if propagating exceptions).

Use in Code Generation

The general pattern for using `get_num_threads` in code generation is

```
from llvmlite import ir as llvmir

get_num_threads = cgutils.get_or_insert_function(builder.module
    llvmir.FunctionType(llvmir.IntType(types.intp.bitwidth), []),
    name="get_num_threads")

num_threads = builder.call(get_num_threads, [])

with cgutils.if_unlikely(builder, builder.icmp_signed('<=', num_threads,
                                            num_threads.type(0))):
    cgutils.printf(builder, "num_threads: %d\n", num_threads)
    context.call_conv.return_user_exc(builder, RuntimeError,
                                            ("Invalid number of threads. "
                                             "This likely indicates a bug in Numba.",))

# Pass num_threads through to the appropriate backend function here
```

See the code in `numba/parfors/parfor_lowering.py`.

The guard against `num_threads` being <= 0 is not strictly necessary, but it can protect against accidentally incorrect behavior in case the thread masking logic contains a bug.

The num_threads variable should be passed through to the appropriate backend function, such as do_scheduling or parallel_for. If it's used in some way other than passing it through to the backend function, the above considerations should be taken into account to ensure the use of the num_threads variable is safe. It would probably be better to keep such logic in the threading backends, rather than trying to do it in code generation.

Parallel Chunksize Details

There are some cases in which the actual parallel work chunk sizes may differ from the requested chunk size that is requested through numba.set_parallel_chunksize(). First, if the number of required chunks based on the specified chunk size is less than the number of configured threads then Numba will use all of the configured threads to execute the parallel region. In this case, the actual chunk size will be less than the requested chunk size. Second, due to truncation, in cases where the iteration count is slightly less than a multiple of the chunk size (e.g., 14 iterations and a specified chunk size of 5), the actual chunk size will be larger than the specified chunk size. As in the given example, the number of chunks would be 2 and the actual chunk size would be 7 (i.e. 14 / 2). Lastly, since Numba divides an N-dimensional iteration space into N-dimensional (hyper)rectangular chunks, it may be the case there are not N integer factors whose product is equal to the chunk size. In this case, some chunks will have an area/volume larger than the chunk size whereas others will be less than the specified chunk size.

6.19 Notes on Literal Types

Note: This document describes an advanced feature designed to overcome some limitations of the compilation mechanism relating to types.

Some features need to specialize based on the literal value during compilation to produce type stable code necessary for successful compilation in Numba. This can be achieved by propagating the literal value through the type system. Numba recognizes inline literal values as *numba.types.Literal*. For example:

```
def foo(x):
    a = 123
    return bar(x, a)
```

Numba will infer the type of a as Literal[int](123). The definition of bar() can subsequently specialize its implementation knowing that the second argument is an int with the value 123.

6.19.1 Literal Type

Classes and methods related to the Literal type.

class numba.types.**Literal**(**args*, ***kwargs*)

Base class for Literal types. Literal types contain the original Python value in the type.

A literal type should always be constructed from the *literal(val)* function.

numba.types.**literal**(*value*)

Returns a Literal instance or raise LiteralTypingError

numba.types.**unliteral**(*lit_type*)

Get base type from Literal type.

numba.types.**maybe_literal**(*value*)

Get a Literal type for the value or None.

6.19.2 Specifying for Literal Typing

To specify a value as a `Literal` type in code scheduled for JIT compilation, use the following function:

`numba.literally(obj)`

Forces Numba to interpret *obj* as an Literal value.

obj must be either a literal or an argument of the caller function, where the argument must be bound to a literal. The literal requirement propagates up the call stack.

This function is intercepted by the compiler to alter the compilation behavior to wrap the corresponding function parameters as `Literal`. It has **no effect** outside of nopython-mode (interpreter, and objectmode).

The current implementation detects literal arguments in two ways:

1. Scans for uses of `literally` via a compiler pass.
2. `literally` is overloaded to raise `numba.errors.ForceLiteralArg` to signal the dispatcher to treat the corresponding parameter differently. This mode is to support indirect use (via a function call).

The execution semantic of this function is equivalent to an identity function.

See numba/tests/test_literal_dispatch.py for examples.

Code Example

Listing 2: from `test_literally_usage` of `numba/tests/doc_examples/test_literally_usage.py`

```
import numba

def power(x, n):
    raise NotImplementedError

@numba.extending.overload(power)
def ov_power(x, n):
    if isinstance(n, numba.types.Literal):
        # only if `n` is a literal
        if n.literal_value == 2:
            # special case: square
            print("square")
            return lambda x, n: x * x
        elif n.literal_value == 3:
            # special case: cubic
            print("cubic")
            return lambda x, n: x * x * x
    else:
        # If `n` is not literal, request literal dispatch
        return lambda x, n: numba.literally(n)

    print("generic")
    return lambda x, n: x ** n

@numba.njit
def test_power(x, n):
    return power(x, n)
```

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```
28
29          # should print "square" and "9"
30          print(test_power(3, 2))
31
32          # should print "cubic" and "27"
33          print(test_power(3, 3))
34
35          # should print "generic" and "81"
36          print(test_power(3, 4))
37
```

Internal Details

Internally, the compiler raises a `ForceLiteralArgs` exception to signal the dispatcher to wrap specified arguments using the `Literal` type.

class numba.errors.**ForceLiteralArg**(*arg_indices*, *fold_arguments=None*, *loc=None*)

A Pseudo-exception to signal the dispatcher to type an argument literally

Attributes

requested_args
[frozenset[int]] requested positions of the arguments.

__init__(*arg_indices*, *fold_arguments=None*, *loc=None*)

Parameters

arg_indices
[Sequence[int]] requested positions of the arguments.

fold_arguments: callable
A function `(tuple, dict) -> tuple` that binds and flattens the `args` and `kwargs`.

loc
[numba.ir.Loc or None]

__or__(*other*)

Same as self.combine(other)

combine(*other*)

Returns a new instance by or'ing the requested_args.

6.19.3 Inside Extensions

`@overload` extensions can use `literally` inside the implementation body like in normal jit-code.

Explicit handling of literal requirements is possible through use of the following:

class numba.extending.**SentryLiteralArgs**(*literal_args*)

Parameters

literal_args
[Sequence[str]] A sequence of names for literal arguments

Examples

The following line:

```
>>> SentryLiteralArgs(literal_args).for_pysig(pysig).bind(*args, **kwargs)
```

is equivalent to:

```
>>> sentry_literal_args(pysig, literal_args, args, kwargs)
```

for_function(*func*)

Bind the sentry to the signature of *func*.

Parameters

func
[Function] A python function.

Returns

obj
[BoundLiteralArgs]

for_pysig(*pysig*)

Bind the sentry to the given signature *pysig*.

Parameters

pysig
[inspect.Signature]

Returns

obj
[BoundLiteralArgs]

class numba.extending.**BoundLiteralArgs**(*pysig*, *literal_args*)

This class is usually created by SentryLiteralArgs.

bind(**args*, ***kwargs*)

Bind to argument types.

numba.extending.**sentry_literal_args**(*pysig*, *literal_args*, *args*, *kwargs*)

Ensures that the given argument types (in *args* and *kwargs*) are literally typed for a function with the python signature *pysig* and the list of literal argument names in *literal_args*.

Alternatively, this is the same as:

```
SentryLiteralArgs(literal_args).for_pysig(pysig).bind(*args, **kwargs)
```

6.20 Notes on timing LLVM

6.20.1 Getting LLVM Pass Timings

The dispatcher stores LLVM pass timings in the dispatcher object metadata under the `llvm_pass_timings` key when *NUMBA_LLVM_PASS_TIMINGS* is enabled or `numba.config.LLVM_PASS_TIMINGS` is set to truthy. The timings information contains details on how much time has been spent in each pass. The pass timings are also grouped by their purpose. For example, there will be pass timings for function-level pre-optimizations, module-level optimizations, and object code generation.

Code Example

Listing 3: from `test_pass_timings` of `numba/tests/doc_examples/test_llvm_pass_timings.py`

```
import numba

@numba.njit
def foo(n):
    c = 0
    for i in range(n):
        for j in range(i):
            c += j
    return c

foo(10)
md = foo.get_metadata(foo.signatures[0])
print(md['llvm_pass_timings'])
```

Example output:

```
Printing pass timings for JITCodeLibrary('DocsLLVMPassTimings.test_pass_timings.<locals>.
↪foo')
Total time: 0.0376
== #0 Function passes on '_ZN5numba5tests12doc_examples22test_llvm_pass_
↪timings19DocsLLVMPassTimings17test_pass_timings12$3clocals$3e7foo$241Ex'
Percent: 4.8%
Total 0.0018s
Top timings:
  0.0015s ( 81.6%) SROA #3
  0.0002s (  9.3%) Early CSE #2
  0.0001s (  4.0%) Simplify the CFG #9
  0.0000s (  1.5%) Prune NRT refops #4
  0.0000s (  1.1%) Post-Dominator Tree Construction #5
== #1 Function passes on '_ZN7cpython5numba5tests12doc_examples22test_llvm_pass_
↪timings19DocsLLVMPassTimings17test_pass_timings12$3clocals$3e7foo$241Ex'
Percent: 0.8%
Total 0.0003s
Top timings:
  0.0001s ( 30.4%) Simplify the CFG #10
  0.0001s ( 24.1%) Early CSE #3
  0.0001s ( 17.8%) SROA #4
```

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```
  0.0000s (  8.8%) Prune NRT refops #5
  0.0000s (  5.6%) Post-Dominator Tree Construction #6
== #2 Function passes on 'cfunc._ZN5numba5tests12doc_examples22test_llvm_pass_
↪timings19DocsLLVMPassTimings17test_pass_timings12$3clocals$3e7foo$241Ex'
Percent: 0.5%
Total 0.0002s
Top timings:
  0.0001s ( 27.7%) Early CSE #4
  0.0001s ( 26.8%) Simplify the CFG #11
  0.0000s ( 13.8%) Prune NRT refops #6
  0.0000s (  7.4%) Post-Dominator Tree Construction #7
  0.0000s (  6.7%) Dominator Tree Construction #29
== #3 Module passes (cheap optimization for refprune)
Percent: 3.7%
Total 0.0014s
Top timings:
  0.0007s ( 52.0%) Combine redundant instructions
  0.0001s (  5.4%) Function Integration/Inlining
  0.0001s (  4.9%) Prune NRT refops #2
  0.0001s (  4.8%) Natural Loop Information
  0.0001s (  4.6%) Post-Dominator Tree Construction #2
== #4 Module passes (full optimization)
Percent: 43.9%
Total 0.0165s
Top timings:
  0.0032s ( 19.5%) Combine redundant instructions #9
  0.0022s ( 13.5%) Combine redundant instructions #7
  0.0010s (  6.1%) Induction Variable Simplification
  0.0008s (  4.8%) Unroll loops #2
  0.0007s (  4.5%) Loop Vectorization
== #5 Finalize object
Percent: 46.3%
Total 0.0174s
Top timings:
  0.0060s ( 34.6%) X86 DAG->DAG Instruction Selection #2
  0.0019s ( 11.0%) Greedy Register Allocator #2
  0.0013s (  7.4%) Machine Instruction Scheduler #2
  0.0012s (  7.1%) Loop Strength Reduction
  0.0004s (  2.3%) Induction Variable Users
```

API for custom analysis

It is possible to get more details then the summary text in the above example. The pass timings are stored in a *numba.misc.llvm_pass_timings.PassTimingsCollection*, which contains methods for accessing individual record for each pass.

class numba.misc.llvm_pass_timings.**PassTimingsCollection**(*name*)

A collection of pass timings.

This class implements the `Sequence` protocol for accessing the individual timing records.

__getitem__(*i*)

Get the i-th timing record.

Returns

res: (name, timings)
A named tuple with two fields:

- name: str
- timings: ProcessedPassTimings

`__len__()`

Length of this collection.

`get_total_time()`

Computes the sum of the total time across all contained timings.

Returns

res: float or None
Returns the total number of seconds or None if no timings were recorded

`list_longest_first()`

Returns the timings in descending order of total time duration.

Returns

res: List[ProcessedPassTimings]

`summary(`*topn=5*`)`

Return a string representing the summary of the timings.

Parameters

topn: int; optional, default=5.
This limits the maximum number of items to show. This function will show the `topn` most time-consuming passes.

Returns

res: str
See also `ProcessedPassTimings.summary()`

`class` numba.misc.llvm_pass_timings.`ProcessedPassTimings(`*raw_data*`)`

A class for processing raw timing report from LLVM.

The processing is done lazily so we don't waste time processing unused timing information.

`get_raw_data()`

Returns the raw string data.

Returns

res: str

`get_total_time()`

Compute the total time spend in all passes.

Returns

res: float

`list_records()`

Get the processed data for the timing report.

Returns

res: List[PassTimingRecord]

`list_top`(*n*)

Returns the top(n) most time-consuming (by wall-time) passes.

Parameters

n: int
This limits the maximum number of items to show. This function will show the `n` most time-consuming passes.

Returns

res: List[PassTimingRecord]
Returns the top(n) most time-consuming passes in descending order.

`summary`(*topn=5*, *indent=0*)

Return a string summarizing the timing information.

Parameters

topn: int; optional
This limits the maximum number of items to show. This function will show the `topn` most time-consuming passes.

indent: int; optional
Set the indentation level. Defaults to 0 for no indentation.

Returns

res: str

`class numba.misc.llvm_pass_timings.PassTimingRecord`(*user_time*, *user_percent*, *system_time*, *system_percent*, *user_system_time*, *user_system_percent*, *wall_time*, *wall_percent*, *pass_name*, *instruction*)

6.21 Notes on Debugging

This section describes techniques that can be useful in debugging the compilation and execution of generated code.

See also:

Debugging JIT compiled code with GDB

6.21.1 Memcheck

Memcheck is a memory error detector implemented using Valgrind. It is useful for detecting memory errors in compiled code, particularly out-of-bounds accesses and use-after-free errors. Buggy or miscompiled native code can generate these kinds of errors. The Memcheck documentation explains its usage; here, we discuss only the specifics of using it with Numba.

The Python interpreter and some of the libraries used by Numba can generate false positives with Memcheck - see this section of the manual for more information on why false positives occur. The false positives can make it difficult to determine when an actual error has occurred, so it is helpful to suppress known false positives. This can be done by supplying a suppressions file, which instructs Memcheck to ignore errors that match the suppressions defined in it.

The CPython source distribution includes a suppressions file, in the file `Misc/valgrind-python.supp`. Using this file prevents a lot of spurious errors generated by Python's memory allocation implementation. Additionally, the Numba repository includes a suppressions file in `contrib/valgrind-numba.supp`.

Note: It is important to use the suppressions files from the versions of the Python interpreter and Numba that you are using - these files evolve over time, so non-current versions can fail to suppress some errors, or erroneously suppress actual errors.

To run the Python interpreter under Memcheck with both suppressions files, it is invoked with the following command:

```
valgrind --tool=memcheck \
         --suppressions=${CPYTHON_SRC_DIR}/Misc/valgrind-python.supp \
         --suppressions=${NUMBA_SRC_DIR}/contrib/valgrind-numba.supp \
         python ${PYTHON_ARGS}
```

where `${CPYTHON_SRC_DIR}` is set to the location of the CPython source distribution, `${NUMBA_SRC_DIR}` is the location of the Numba source dir, and `${PYTHON_ARGS}` are the arguments to the Python interpreter.

If there are errors, then messages describing them will be printed to standard error. An example of an error is:

```
==77113==    at 0x24169A: PyLong_FromLong (longobject.c:251)
==77113==    by 0x241881: striter_next (bytesobject.c:3084)
==77113==    by 0x2D3C95: _PyEval_EvalFrameDefault (ceval.c:2809)
==77113==    by 0x21B499: _PyEval_EvalCodeWithName (ceval.c:3930)
==77113==    by 0x26B436: _PyFunction_FastCallKeywords (call.c:433)
==77113==    by 0x2D3605: call_function (ceval.c:4616)
==77113==    by 0x2D3605: _PyEval_EvalFrameDefault (ceval.c:3124)
==77113==    by 0x21B977: _PyEval_EvalCodeWithName (ceval.c:3930)
==77113==    by 0x21C2A4: _PyFunction_FastCallDict (call.c:376)
==77113==    by 0x2D5129: do_call_core (ceval.c:4645)
==77113==    by 0x2D5129: _PyEval_EvalFrameDefault (ceval.c:3191)
==77113==    by 0x21B499: _PyEval_EvalCodeWithName (ceval.c:3930)
==77113==    by 0x26B436: _PyFunction_FastCallKeywords (call.c:433)
==77113==    by 0x2D46DA: call_function (ceval.c:4616)
==77113==    by 0x2D46DA: _PyEval_EvalFrameDefault (ceval.c:3139)
==77113==
==77113== Use of uninitialised value of size 8
```

The traceback provided only outlines the C call stack, which can make it difficult to determine what the Python interpreter was doing at the time of the error. One can learn more about the state of the stack by looking at the backtrace in the GNU Debugger (GDB). Launch `valgrind` with an additional argument, `--vgdb-error=0` and attach to the process using GDB as instructed by the output. Once an error is encountered, GDB will stop at the error and the stack can be inspected.

GDB does provide support for backtracing through the Python stack, but this requires symbols which may not be easily available in your Python distribution. In this case, it is still possible to determine some information about what was happening in Python, but this depends on examining the backtrace closely. For example, in a backtrace corresponding to the above error, we see items such as:

```
#18 0x0000000002722da in slot_tp_call (
    self=<_wrap_impl(_callable=<_wrap_missing_loc(func=<function at remote
    0x1cf66c20>) at remote 0x1d200bd0>, _imp=<function at remote 0x1d0e7440>,
    _context=<CUDATargetContext(address_size=64,
    typing_context=<CUDATypingContext(_registries={<Registry(functions=[<type
```

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```
    at remote 0x65be5e0>, <type at remote 0x65be9d0>, <type at remote
    0x65bedc0>, <type at remote 0x65bf1b0>, <type at remote 0x8b78000>, <type
    at remote 0x8b783f0>, <type at remote 0x8b787e0>, <type at remote
    0x8b78bd0>, <type at remote 0x8b78fc0>, <type at remote 0x8b793b0>, <type
    at remote 0x8b797a0>, <type at remote 0x8b79b90>, <type at remote
    0x8b79f80>, <type at remote 0x8b7a370>, <type at remote 0x8b7a760>, <type
    at remote 0x8b7ab50>, <type at remote 0x8b7af40>, <type at remote
    0x8b7b330>, <type at remote 0x8b7b720>, <type at remote 0x8b7bf00>, <type
    at remote 0x8b7c2f0>, <type at remote 0x8b7c6e0>], attributes=[<type at
    remote 0x8b7cad0>, <type at remote 0x8b7cec0>, <type at remote
    0x8b7d2b0>, <type at remote 0x8b7d6a0>, <type at remote 0x8b7da90>,
    <t...(truncated),
    args=(<Builder(_block=<Block(parent=<Function(parent=<Module(context=<Context(scope=
↪<NameScope(_useset={''},
    _basenamemap={}) at remote 0xbb5ae10>, identified_types={}) at remote
    0xbb5add0>, name='cuconstRecAlign$7',
    data_layout='e-p:64:64:64-i1:8:8-i8:8:8-i16:16:16-i32:32:32-i64:64:64-f32:32:32-
↪f64:64:64-v16:16:16-v32:32:32-v64:64:64-v128:128:128-n16:32:64',
    scope=<NameScope(_useset={'',
    '_ZN08NumbaEnv5numba4cuda5tests6cudapy13test_constmem19cuconstRecAlign
↪$247E5ArrayIdLi1E1C7mutable7alignedE5ArrayIdLi1E1C7mutable7alignedE5ArrayIdLi1E1C7mutable7alignedE5Ar
↪',
    '_ZN5numba4cuda5tests6cudapy13test_constmem19cuconstRecAlign
↪$247E5ArrayIdLi1E1C7mutable7alignedE5ArrayIdLi1E1C7mutable7alignedE5ArrayIdLi1E1C7mutable7alignedE5Ar
↪'},
    _basenamemap={}) at remote 0x1d27bf10>, triple='nvptx64-nvidia-cuda',
    globals={'_ZN08NumbaEnv5numba4cuda5tests6cudapy13test_constmem19cuconstRecAlign
↪$247E5ArrayIdLi1E1C7mutable7ali...(truncated),
    kwds=0x0)
```

We can see some of the arguments, in particular the names of the compiled functions, e.g:

```
_ZN5numba4cuda5tests6cudapy13test_constmem19cuconstRecAlign
↪$247E5ArrayIdLi1E1C7mutable7alignedE5ArrayIdLi1E1C7mutable7alignedE5ArrayIdLi1E1C7mutable7alignedE5Ar
```

We can run this through `c++filt` to see a more human-readable representation:

```
numba::cuda::tests::cudapy::test_constmem::cuconstRecAlign$247(
  Array<double, 1, C, mutable, aligned>,
  Array<double, 1, C, mutable, aligned>,
  Array<double, 1, C, mutable, aligned>,
  Array<double, 1, C, mutable, aligned>,
  Array<double, 1, C, mutable, aligned>)
```

which is the fully qualified name of a jitted function and the types with which it was called.

6.22 Event API

The `numba.core.event` module provides a simple event system for applications to register callbacks to listen to specific compiler events.

The following events are built in:

- `"numba:compile"` is broadcast when a dispatcher is compiling. Events of this kind have `data` defined to be a `dict` with the following key-values:
  - `"dispatcher"`: the dispatcher object that is compiling.
  - `"args"`: the argument types.
  - `"return_type"`: the return type.
- `"numba:compiler_lock"` is broadcast when the internal compiler-lock is acquired. This is mostly used internally to measure time spent with the lock acquired.
- `"numba:llvm_lock"` is broadcast when the internal LLVM-lock is acquired. This is used internally to measure time spent with the lock acquired.
- `"numba:run_pass"` is broadcast when a compiler pass is running.
  - `"name"`: pass name.
  - `"qualname"`: qualified name of the function being compiled.
  - `"module"`: module name of the function being compiled.
  - `"flags"`: compilation flags.
  - `"args"`: argument types.
  - `"return_type"` return type.

Applications can register callbacks that are listening for specific events using `register(kind: str, listener: Listener)`, where `listener` is an instance of `Listener` that defines custom actions on occurrence of the specific event.

`class numba.core.event.Event(`*kind*, *status*, *data=None*, *exc_details=None*`)`

An event.

Parameters

kind
[str]

status
[EventStatus]

data
[any; optional] Additional data for the event.

exc_details
[3-tuple; optional] Same 3-tuple for `__exit__`.

`property data`

Event data

Returns

res
[object]

property is_end

Is it an *END* event?

Returns

res
[bool]

property is_failed

Is the event carrying an exception?

This is used for *END* event. This method will never return `True` in a *START* event.

Returns

res
[bool]

property is_start

Is it a *START* event?

Returns

res
[bool]

property kind

Event kind

Returns

res
[str]

property status

Event status

Returns

res
[EventStatus]

class numba.core.event.**EventStatus**(*value*)

Status of an event.

class numba.core.event.**Listener**

Base class for all event listeners.

notify(*event*)

Notify this Listener with the given Event.

Parameters

event
[Event]

abstract on_end(*event*)

Called when there is a *END* event.

Parameters

event
[Event]

abstract on_start(*event*)

Called when there is a *START* event.

Parameters

event
[Event]

class numba.core.event.RecordingListener

A listener that records all events and stores them in the `.buffer` attribute as a list of 2-tuple `(float, Event)`, where the first element is the time the event occurred as returned by `time.time()` and the second element is the event.

on_end(*event*)

Called when there is a *END* event.

Parameters

event
[Event]

on_start(*event*)

Called when there is a *START* event.

Parameters

event
[Event]

class numba.core.event.TimingListener

A listener that measures the total time spent between *START* and *END* events during the time this listener is active.

property done

Returns a `bool` indicating whether a measurement has been made.

When this returns `False`, the matching event has never fired. If and only if this returns `True`, `.duration` can be read without error.

property duration

Returns the measured duration.

This may raise `AttributeError`. Users can use `.done` to check that a measurement has been made.

on_end(*event*)

Called when there is a *END* event.

Parameters

event
[Event]

on_start(*event*)

Called when there is a *START* event.

Parameters

event
[Event]

numba.core.event.**broadcast**(*event*)

Broadcast an event to all registered listeners.

Parameters

event
[Event]

numba.core.event.**end_event**(*kind*, *data=None*, *exc_details=None*)

Trigger the end of an event of *kind*, *exc_details*.

Parameters

kind
[str] Event kind.

data
[any; optional] Extra event data.

exc_details
[3-tuple; optional] Same 3-tuple for `__exit__`. Or, `None` if no error.

numba.core.event.**install_listener**(*kind*, *listener*)

Install a listener for event "kind" temporarily within the duration of the context.

Returns

res
[Listener] The *listener* provided.

Examples

```
>>> with install_listener("numba:compile", listener):
>>>     some_code()  # listener will be active here.
>>> other_code()     # listener will be unregistered by this point.
```

numba.core.event.**install_recorder**(*kind*)

Install a RecordingListener temporarily to record all events.

Once the context is closed, users can use `RecordingListener.buffer` to access the recorded events.

Returns

res
[RecordingListener]

Examples

This is equivalent to:

```
>>> with install_listener(kind, RecordingListener()) as res:
>>>     ...
```

numba.core.event.**install_timer**(*kind*, *callback*)

Install a TimingListener temporarily to measure the duration of an event.

If the context completes successfully, the *callback* function is executed. The *callback* function is expected to take a float argument for the duration in seconds.

Returns

res
[TimingListener]

Examples

This is equivalent to:

```
>>> with install_listener(kind, TimingListener()) as res:
>>>     ...
```

numba.core.event.**register**(*kind*, *listener*)

Register a listener for a given event kind.

Parameters

kind
[str]

listener
[Listener]

numba.core.event.**start_event**(*kind*, *data=None*)

Trigger the start of an event of *kind* with *data*.

Parameters

kind
[str] Event kind.

data
[any; optional] Extra event data.

numba.core.event.**trigger_event**(*kind*, *data=None*)

A context manager to trigger the start and end events of *kind* with *data*. The start event is triggered when entering the context. The end event is triggered when exiting the context.

Parameters

kind
[str] Event kind.

data
[any; optional] Extra event data.

numba.core.event.**unregister**(*kind*, *listener*)

Unregister a listener for a given event kind.

Parameters

kind
[str]

listener
[Listener]

6.23 Notes on Target Extensions

Warning: All features and APIs described in this page are in-development and may change at any time without deprecation notices being issued.

6.23.1 Inheriting compiler flags from the caller

Compiler flags, i.e. options such as `fastmath`, `nrt` in `@jit(nrt=True, fastmath=True)` are specified per-function but their effects are not well-defined—some flags affect the entire callgraph, some flags affect only the current function. Sometimes it is necessary for callees to inherit flags from the caller; for example the `fastmath` flag should be infectious.

To address the problem, the following are needed:

1. Better definitions for the semantics of compiler flags. Preferably, all flags should limit their effect to the current function. (TODO)
2. Allow compiler flags to be inherited from the caller. (Done)
3. Consider compiler flags in function resolution. (TODO)

numba.core.targetconfig.ConfigStack is used to propagate the compiler flags throughout the compiler. At the start of the compilation, the flags are pushed into the `ConfigStack`, which maintains a thread-local stack for the compilation. Thus, callees can check the flags in the caller.

class numba.core.targetconfig.**ConfigStack**

A stack for tracking target configurations in the compiler.

It stores the stack in a thread-local class attribute. All instances in the same thread will see the same stack.

enter(*flags*)

Returns a contextmanager that performs `push(flags)` on enter and `pop()` on exit.

classmethod top_or_none()

Get the TOS or return None if no config is set.

Compiler flags

Compiler flags are defined as a subclass of `TargetConfig`:

class numba.core.targetconfig.**TargetConfig**(*copy_from=None*)

Base class for `TargetConfig`.

Subclass should fill class members with `Option`. For example:

```
>>> class MyTargetConfig(TargetConfig):
>>>     a_bool_option = Option(type=bool, default=False, doc="a bool")
>>>     an_int_option = Option(type=int, default=0, doc="an int")
```

The metaclass will insert properties for each `Option`. For example:

```
>>> tc = MyTargetConfig()
>>> tc.a_bool_option = True  # invokes the setter
>>> print(tc.an_int_option)  # print the default
```

`copy`()

Clone this instance.

`classmethod demangle`(*mangled: str*) → str

Returns the demangled result from `.get_mangle_string()`

`discard`(*name*)

Remove the option by name if it is defined.

After this, the value for the option will be set to its default value.

`get_mangle_string`() → str

Return a string suitable for symbol mangling.

`inherit_if_not_set`(*name*, *default=<NotSet>*)

Inherit flag from `ConfigStack`.

Parameters

name
[str] Option name.

default
[optional] When given, it overrides the default value. It is only used when the flag is not defined locally and there is no entry in the `ConfigStack`.

`is_set`(*name*)

Is the option set?

`summary`() → str

Returns a `str` that summarizes this instance.

In contrast to `__repr__`, only options that are explicitly set will be shown.

`values`()

Returns a dict of all the values

These are internal compiler flags and they are different from the user-facing options used in the jit decorators.

Internally, the user-facing options are mapped to the internal compiler flags by *numba.core.options.TargetOptions*. Each target can override the default compiler flags and control the flag inheritance in `TargetOptions.finalize`. The CPU target overrides it.

`class numba.core.options.TargetOptions`

Target options maps user options from decorators to the `numba.core.compiler.Flags` used by lowering and target context.

`finalize`(*flags*, *options*)

Subclasses can override this method to make target specific customizations of default flags.

Parameters

flags
[Flags]

options
[dict]

In *numba.core.options.TargetOptions.finalize()*, use *numba.core.targetconfig.TargetConfig.inherit_if_not_set()* to request a compiler flag from the caller if it is not set for the current function.

6.24 Notes on Bytecode Handling

6.24.1 `LOAD_FAST_AND_CLEAR` opcode, `Expr.undef` IR Node, `UndefVar` type

Python 3.12 introduced a new bytecode `LOAD_FAST_AND_CLEAR` which is solely used in comprehensions. The common pattern is:

```
In [1]: def foo(x):
...:       # 6 LOAD_FAST_AND_CLEAR      0 (x)  # push x and clear from scope
...:       y = [x for x in (1, 2)]              # comprehension
...:       # 30 STORE_FAST              0 (x)  # restore x
...:       return x
...:

In [2]: import dis

In [3]: dis.dis(foo)
1           0 RESUME                   0

3           2 LOAD_CONST               1 ((1, 2))
            4 GET_ITER
            6 LOAD_FAST_AND_CLEAR      0 (x)
            8 SWAP                     2
           10 BUILD_LIST               0
           12 SWAP                     2
      >>   14 FOR_ITER                 4 (to 26)
           18 STORE_FAST               0 (x)
           20 LOAD_FAST                0 (x)
           22 LIST_APPEND              2
           24 JUMP_BACKWARD            6 (to 14)
      >>   26 END_FOR
           28 STORE_FAST               1 (y)
           30 STORE_FAST               0 (x)

5          32 LOAD_FAST_CHECK          0 (x)
           34 RETURN_VALUE
      >>   36 SWAP                     2
           38 POP_TOP

3          40 SWAP                     2
           42 STORE_FAST               0 (x)
           44 RERAISE                  0
ExceptionTable:
10 to 26 -> 36 [2]
```

Numba handles the `LOAD_FAST_AND_CLEAR` bytecode differently to CPython because it relies on static instead of dynamic semantics.

In Python, comprehensions can shadow variables from the enclosing function scope. To handle this, `LOAD_FAST_AND_CLEAR` snapshots the value of a potentially shadowed variable and clears it from the scope. This gives the illusion that comprehensions execute in a new scope, even though they are fully inlined in Python 3.12. The snapshotted value is later restored with `STORE_FAST` after the comprehension.

Since Numba uses static semantics, it cannot precisely model the dynamic behavior of `LOAD_FAST_AND_CLEAR`. In-

stead, Numba checks if a variable is used in previous opcodes to determine if it must be defined. If so, Numba treats it like a regular `LOAD_FAST`. Otherwise, Numba emits an Expr.undef IR node to mark the stack value as undefined. Type inference assigns the UndefVar type to this node, allowing the value to be zero-initialized and implicitly cast to other types.

In object mode, Numba uses the _UNDEFINED sentinel object to indicate undefined values.

Numba does not raise `UnboundLocalError` if an undefined value is used.

Special case 1: `LOAD_FAST_AND_CLEAR` may load an undefined variable

```
In [1]: def foo(a, v):
...:       if a:
...:           x = v
...:       y = [x for x in (1, 2)]
...:       return x
```

In the above example, the variable `x` may or may not be defined before the list comprehension, depending on the truth value of `a`. If `a` is `True`, then `x` is defined and execution proceeds as described in the common case. However, if `a` is `False`, then `x` is undefined. In this case, the Python interpreter would raise an `UnboundLocalError` at the `return x` line. Numba cannot determine whether `x` was previously defined, therefore it assumes `x` is defined to avoid the error. This deviates from Python's official semantics, since Numba will use a zero-initialized `x` even if it was not defined earlier.

```
In [1]: from numba import njit

In [2]: def foo(a, v):
...:     if a:
...:         x = v
...:     y = [x for x in (1, 2)]
...:     return x
...:

In [3]: foo(0, 123)
---------------------------------------------------------------------------
UnboundLocalError                         Traceback (most recent call last)
Cell In[3], line 1
----> 1 foo(0, 123)

Cell In[2], line 5, in foo(a, v)
    3     x = v
    4 y = [x for x in (1, 2)]
----> 5 return x

UnboundLocalError: cannot access local variable 'x' where it is not associated with a␣
↪value

In [4]: njit(foo)(0, 123)
Out[4]: 0
```

As shown in the above example, Numba does not raise `UnboundLocalError` and allows the function to return normally.

Special case 2: `LOAD_FAST_AND_CLEAR` loads undefined variable

If Numba can statically determine that a variable must be undefined, the type system will raise a `TypingError` instead of raising a `NameError` like the Python interpreter does.

```
In [1]: def foo():
...:     y = [x for x in (1, 2)]
...:     return x
...:

In [2]: foo()
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[2], line 1
----> 1 foo()

Cell In[1], line 3, in foo()
    1 def foo():
    2     y = [x for x in (1, 2)]
----> 3     return x

NameError: name 'x' is not defined

In [3]: from numba import njit

In [4]: njit(foo)()
---------------------------------------------------------------------------
TypingError                               Traceback (most recent call last)
Cell In[4], line 1
----> 1 njit(foo)()

File /numba/numba/core/dispatcher.py:468, in _DispatcherBase._compile_for_args(self,␣
↪*args, **kws)
    464         msg = (f"{str(e).rstrip()} \n\nThis error may have been caused "
    465                f"by the following argument(s):\n{args_str}\n")
    466         e.patch_message(msg)
--> 468     error_rewrite(e, 'typing')
    469 except errors.UnsupportedError as e:
    470     # Something unsupported is present in the user code, add help info
    471     error_rewrite(e, 'unsupported_error')

File /numba/numba/core/dispatcher.py:409, in _DispatcherBase._compile_for_args.<locals>.
↪error_rewrite(e, issue_type)
    407     raise e
    408 else:
--> 409     raise e.with_traceback(None)

TypingError: Failed in nopython mode pipeline (step: nopython frontend)
NameError: name 'x' is not defined
```

6.25 Numba Mission Statement

6.25.1 Introduction

This document is the mission statement for the Numba project. It exists to provide a clear description of the purposes and goals of the project. As such, this document provides background on Numba's users and use-cases, and outlines the project's overall goals.

This is a living document:

The first revision date is:	May 2022
The last updated date is:	May 2022
The next review date is:	November 2022

6.25.2 Background

The Numba project provides tools to improve the performance of Python software. It comprises numerous facilities including just-in-time (JIT) compilation, extension points for library authors, and a compiler toolkit on which new computational acceleration technologies can be explored and built.

The range of use-cases and applications that can be targeted by Numba includes, but is not limited to:

- Scientific Computing
- Computationally intensive tasks
- Numerically oriented applications
- Data science utilities and programs

The user base of Numba includes anyone needing to perform intensive computational work, including users from a wide range of disciplines, examples include:

- The most common use case, a user wanting to JIT compile some numerical functions.
- Users providing JIT accelerated libraries for domain specific use cases e.g. scientific researchers.
- Users providing JIT accelerated libraries for use as part of the numerical Python ecosystem.
- Those writing more advanced JIT accelerated libraries containing their own domain specific data types etc.
- Compiler engineers who explore new compiler use-cases and/or need a custom compiler.
- Hardware vendors looking to extend Numba to provide Python support for their custom silicon or new hardware.

6.25.3 Project Goals

The primary aims of the Numba project are:

- To make it easier for Python users to write high performance code.
- To have a core package with a well defined and pragmatically selected feature scope that meets the needs of the user base without being overly complex.
- To provide a compiler toolkit for Python that is extensible and can be customized to meet the needs of the user base. This comes with the expectation that users potentially need to invest time and effort to extend and/or customize the software themselves.
- To support both the Python core language/standard libraries and NumPy.

- To consistently produce high quality software:
  - Feature stability across versions.
  - Well established and tested public APIs.
  - Clearly documented deprecation cycles.
  - Internally stable code base.
  - Externally tested release candidates.
  - Regular releases with a predictable and published release cycle.
  - Maintain suitable infrastructure for both testing and releasing. With as much in public as feasible.
- To make it as easy as possible for people to contribute.
- To have a maintained public roadmap which will also include areas under active development.
- To have a governance document in place and it working in practice.
- To ensure that Numba receives timely updates for its core dependencies: LLVM, NumPy and Python.

CHAPTER

SEVEN

NUMBA ENHANCEMENT PROPOSALS

Numba Enhancement Proposals (not really abbreviated "NEPs", since "NEP" is already taken by the Numpy project) describe proposed changes to Numba. They are modeled on Python Enhancement Proposals (PEPs) and Numpy Enhancement Proposals, and are typically written up when important changes (behavioural changes, feature additions…) to Numba are proposed.

This page provides an overview of all proposals, making only a distinction between the ones that have been implemented and those that have not been implemented.

7.1 Implemented proposals

7.1.1 NBEP 1: Changes in integer typing

Author
Antoine Pitrou

Date
July 2015

Status
Final

Current semantics

Type inference of integers in Numba currently has some subtleties and some corner cases. The simple case is when some variable has an obvious Numba type (for example because it is the result of a constructor call to a Numpy scalar type such as `np.int64`). That case suffers no ambiguity.

The less simple case is when a variable doesn't bear such explicit information. This can happen because it is inferred from a built-in Python `int` value, or from an arithmetic operation between two integers, or other cases yet. Then Numba has a number of rules to infer the resulting Numba type, especially its signedness and bitwidth.

Currently, the generic case could be summarized as: *start small, grow bigger as required*. Concretely:

1. Each constant or pseudo-constant is inferred using the *smallest signed integer type* that can correctly represent it (or, possibly, `uint64` for positive integers between `2**63` and `2**64 - 1`).
2. The result of an operation is typed so as to ensure safe representation in the face of overflow and other magnitude increases (for example, `int32 + int32` would be typed `int64`).
3. As an exception, a Python `int` used as function argument is always typed `intp`, a pointer-size integer. This is to avoid the proliferation of compiled specializations, as otherwise various integer bitwidths in input arguments may produce multiple signatures.

Note: The second rule above (the "respect magnitude increases" rule) reproduces Numpy's behaviour with arithmetic on scalar values. Numba, however, has different implementation and performance constraints than Numpy scalars.

It is worth nothing, by the way, that Numpy arrays do not implement said rule (i.e. `array(int32) + array(int32)` is typed `array(int32)`, not `array(int64)`). Probably because this makes performance more controllable.

This has several non-obvious side-effects:

1. It is difficult to predict the precise type of a value inside a function, after several operations. The basic operands in an expression tree may for example be `int8` but the end result may be `int64`. Whether this is desirable or not is an open question; it is good for correctness, but potentially bad for performance.
2. In trying to follow the correctness over predictability rule, some values can actually leave the integer realm. For example, `int64 + uint64` is typed `float64` in order to avoid magnitude losses (but incidentally will lose precision on large integer values...), again following Numpy's semantics for scalars. This is usually not intended by the user.
3. More complicated scenarios can produce unexpected errors at the type unification stage. An example is at Github issue 1299, the gist of which is reproduced here:

```
@jit(nopython=True)
def f():
    variable = 0
    for i in range(1):
        variable = variable + 1
    return np.arange(variable)
```

At the time of this writing, this fails compiling, on a 64-bit system, with the error:

```
numba.errors.TypingError: Failed at nopython (nopython frontend)
Can't unify types of variable '$48.4': $48.4 := {array(int32, 1d, C), array(int64,␣
↪1d, C)}
```

People expert with Numba's type unification system can understand why. But the user is caught in mystery.

Proposal: predictable width-conserving typing

We propose to turn the current typing philosophy on its head. Instead of "*start small and grow as required*", we propose "*start big and keep the width unchanged*".

Concretely:

1. The typing of Python `int` values used as function arguments doesn't change, as it works satisfyingly and doesn't surprise the user.
2. The typing of integer *constants* (and pseudo-constants) changes to match the typing of integer arguments. That is, every non-explicitly typed integer constant is typed `intp`, the pointer-sized integer; except for the rare cases where `int64` (on 32-bit systems) or `uint64` is required.
3. Operations on integers promote bitwidth to `intp`, if smaller, otherwise they don't promote. For example, on a 32-bit machine, `int8 + int8` is typed `int32`, as is `int32 + int32`. However, `int64 + int64` is typed `int64`.
4. Furthermore, mixed operations between signed and unsigned fall back to signed, while following the same bitwidth rule. For example, on a 32-bit machine, `int8 + uint16` is typed `int32`, as is `uint32 + int32`.

Proposal impact

Semantics

With this proposal, the semantics become clearer. Regardless of whether the arguments and constants of a function were explicitly typed or not, the results of various expressions at any point in the function have easily predictable types.

When using built-in Python `int`, the user gets acceptable magnitude (32 or 64 bits depending on the system's bitness), and the type remains the same across all computations.

When explicitly using smaller bitwidths, intermediate results don't suffer from magnitude loss, since their bitwidth is promoted to `intp`.

There is also less potential for annoyances with the type unification system as demonstrated above. The user would have to force several different types to be faced with such an error.

One potential cause for concern is the discrepancy with Numpy's scalar semantics; but at the same time this brings Numba scalar semantics closer to array semantics (both Numba's and Numpy's), which seems a desirable outcome as well.

It is worth pointing out that some sources of integer numbers, such as the `range()` built-in, always yield 32-bit integers or larger. This proposal could be an opportunity to standardize them on `intp`.

Performance

Except in trivial cases, it seems unlikely that the current "best fit" behaviour for integer constants really brings a performance benefit. After all, most integers in Numba code would either be stored in arrays (with well-known types, chosen by the user) or be used as indices, where a `int8` is highly unlikely to fare better than a `intp` (actually, it may be worse, if LLVM isn't able to optimize away the required sign-extension).

As a side note, the default use of `intp` rather than `int64` ensures that 32-bit systems won't suffer from poor arithmetic performance.

Implementation

Optimistically, this proposal may simplify some Numba internals a bit. Or, at least, it doesn't threaten to make them significantly more complicated.

Limitations

This proposal doesn't really solve the combination of signed and unsigned integers. It is geared mostly at solving the bitwidth issues, which are a somewhat common cause of pain for users. Unsigned integers are in practice very uncommon in Numba-compiled code, except when explicitly asked for, and therefore much less of a pain point.

On the bitwidth front, 32-bit systems could still show discrepancies based on the values of constants: if a constant is too large to fit in 32 bits, it is typed `int64`, which propagates through other computations. This would be a reminiscence of the current behaviour, but rarer and much more controlled still.

Long-term horizon

While we believe this proposal makes Numba's behaviour more regular and more predictable, it also pulls it further from general compatibility with pure Python semantics, where users can assume arbitrary-precision integers without any truncation issues.

7.1.2 NBEP 7: CUDA External Memory Management Plugins

Author
Graham Markall, NVIDIA

Contributors
Thomson Comer, Peter Entschev, Leo Fang, John Kirkham, Keith Kraus

Date
March 2020

Status
Final

Background and goals

The *CUDA Array Interface* enables sharing of data between different Python libraries that access CUDA devices. However, each library manages its own memory distinctly from the others. For example:

- Numba internally manages memory for the creation of device and mapped host arrays.
- The RAPIDS libraries (cuDF, cuML, etc.) use the Rapids Memory Manager for allocating device memory.
- CuPy includes a memory pool implementation for both device and pinned memory.

The goal of this NBEP is to describe a plugin interface that enables Numba's internal memory management to be replaced with an external memory manager by the user. When the plugin interface is in use, Numba no longer directly allocates or frees any memory when creating arrays, but instead requests allocations and frees through the external manager.

Requirements

Provide an *External Memory Manager (EMM)* interface in Numba.

- When the EMM is in use, Numba will make all memory allocation using the EMM. It will never directly call functions such as `CuMemAlloc`, `cuMemFree`, etc.
- When not using an *External Memory Manager (EMM)*, Numba's present behaviour is unchanged (at the time of writing, the current version is the 0.48 release).

If an EMM is to be used, it will entirely replace Numba's internal memory management for the duration of program execution. An interface for setting the memory manager will be provided.

Device vs. Host memory

An EMM will always take responsibility for the management of device memory. However, not all CUDA memory management libraries also support managing host memory, so a facility for Numba to continue the management of host memory whilst ceding control of device memory to the EMM will be provided.

Deallocation strategies

Numba's internal memory management uses a *deallocation strategy* designed to increase efficiency by deferring deallocations until a significant quantity are pending. It also provides a mechanism for preventing deallocations entirely during critical sections, using the *defer_cleanup()* context manager.

- When the EMM is not in use, the deallocation strategy and operation of `defer_cleanup` remain unchanged.
- When the EMM is in use, the deallocation strategy is implemented by the EMM, and Numba's internal deallocation mechanism is not used. For example:
  - A similar strategy to Numba's could be implemented by the EMM, or
  - Deallocated memory might immediately be returned to a memory pool.
- The `defer_cleanup` context manager may behave differently with an EMM - an EMM should be accompanied by documentation of the behaviour of the `defer_cleanup` context manager when it is in use.
  - For example, a pool allocator could always immediately return memory to a pool even when the context manager is in use, but could choose not to free empty pools until `defer_cleanup` is not in use.

Management of other objects

In addition to memory, Numba manages the allocation and deallocation of *events*, *streams*, and modules (a module is a compiled object, which is generated from `@cuda.jit`-ted functions). The management of streams, events, and modules should be unchanged by the presence or absence of an EMM.

Asynchronous allocation / deallocation

An asynchronous memory manager might provide the facility for an allocation or free to take a CUDA stream and execute asynchronously. For freeing, this is unlikely to cause issues since it operates at a layer beneath Python, but for allocations this could be problematic if the user tries to then launch a kernel on the default stream from this asynchronous memory allocation.

The interface described in this proposal will not be required to support asynchronous allocation and deallocation, and as such these use cases will not be considered further. However, nothing in this proposal should preclude the straightforward addition of asynchronous operations in future versions of the interface.

Non-requirements

In order to minimise complexity and constrain this proposal to a reasonable scope, the following will not be supported:

- Using different memory manager implementations for different contexts. All contexts will use the same memory manager implementation - either the Numba internal implementation or an external implementation.
- Changing the memory manager once execution has begun. It is not practical to change the memory manager and retain all allocations. Cleaning up the entire state and then changing to a different memory allocator (rather than starting a new process) appears to be a rather niche use case.
- Any changes to the `__cuda_array_interface__` to further define its semantics, e.g. for acquiring / releasing memory as discussed in Numba Issue #4886 - these are independent, and can be addressed as part of separate proposals.
- Managed memory / UVM is not supported. At present Numba does not support UVM - see Numba Issue #4362 for discussion of support.

Interface for Plugin developers

New classes and functions will be added to `numba.cuda.cudadrv.driver`:

- `BaseCUDAMemoryManager` and `HostOnlyCUDAMemoryManager`: base classes for EMM plugin implementations.
- `set_memory_manager`: a method for registering an external memory manager with Numba.

These will be exposed through the public API, in the `numba.cuda` module. Additionally, some classes that are already part of the *driver* module will be exposed as part of the public API:

- `MemoryPointer`: used to encapsulate information about a pointer to device memory.
- `MappedMemory`: used to hold information about host memory that is mapped into the device address space (a subclass of `MemoryPointer`).
- `PinnedMemory`: used to hold information about host memory that is pinned (a subclass of `mviewbuf.MemAlloc`, a class internal to Numba).

As an alternative to calling the `set_memory_manager` function, an environment variable can be used to set the memory manager. The value of the environment variable should be the name of the module containing the memory manager in its global scope, named `_numba_memory_manager`:

```
export NUMBA_CUDA_MEMORY_MANAGER="<module>"
```

When this variable is set, Numba will automatically use the memory manager from the specified module. Calls to `set_memory_manager` will issue a warning, but otherwise be ignored.

Plugin Base Classes

An EMM plugin is implemented by inheriting from the `BaseCUDAMemoryManager` class, which is defined as:

```
class BaseCUDAMemoryManager(object, metaclass=ABCMeta):
    @abstractmethod
    def memalloc(self, size):
        """
        Allocate on-device memory in the current context. Arguments:

```

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```
        - `size`: Size of allocation in bytes

        Returns: a `MemoryPointer` to the allocated memory.
        """

    @abstractmethod
    def memhostalloc(self, size, mapped, portable, wc):
        """
        Allocate pinned host memory. Arguments:

        - `size`: Size of the allocation in bytes
        - `mapped`: Whether the allocated memory should be mapped into the CUDA
                    address space.
        - `portable`: Whether the memory will be considered pinned by all
                      contexts, and not just the calling context.
        - `wc`: Whether to allocate the memory as write-combined.

        Returns a `MappedMemory` or `PinnedMemory` instance that owns the
        allocated memory, depending on whether the region was mapped into
        device memory.
        """

    @abstractmethod
    def mempin(self, owner, pointer, size, mapped):
        """
        Pin a region of host memory that is already allocated. Arguments:

        - `owner`: An object owning the memory - e.g. a `DeviceNDArray`.
        - `pointer`: The pointer to the beginning of the region to pin.
        - `size`: The size of the region to pin.
        - `mapped`: Whether the region should also be mapped into device memory.

        Returns a `MappedMemory` or `PinnedMemory` instance that refers to the
        allocated memory, depending on whether the region was mapped into device
        memory.
        """

    @abstractmethod
    def initialize(self):
        """
        Perform any initialization required for the EMM plugin to be ready to
        use.
        """

    @abstractmethod
    def get_memory_info(self):
        """
        Returns (free, total) memory in bytes in the context
        """

    @abstractmethod
    def get_ipc_handle(self, memory):
```

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```
        """
        Return an `IpcHandle` from a GPU allocation. Arguments:

        - `memory`: A `MemoryPointer` for which the IPC handle should be created.
        """

    @abstractmethod
    def reset(self):
        """
        Clear up all memory allocated in this context.
        """

    @abstractmethod
    def defer_cleanup(self):
        """
        Returns a context manager that ensures the implementation of deferred
        cleanup whilst it is active.
        """

    @property
    @abstractmethod
    def interface_version(self):
        """
        Returns an integer specifying the version of the EMM Plugin interface
        supported by the plugin implementation. Should always return 1 for
        implementations described in this proposal.
        """
```

All of the methods of an EMM plugin are called from within Numba - they never need to be invoked directly by a Numba user.

The `initialize` method is called by Numba prior to any memory allocations being requested. This gives the EMM an opportunity to initialize any data structures, etc., that it needs for its normal operations. The method may be called multiple times during the lifetime of the program - subsequent calls should not invalidate or reset the state of the EMM.

The `memalloc`, `memhostalloc`, and `mempin` methods are called when Numba requires an allocation of device or host memory, or pinning of host memory. Device memory should always be allocated in the current context.

`get_ipc_handle` is called when an IPC handle for an array is required. Note that there is no method for closing an IPC handle - this is because the `IpcHandle` object constructed by `get_ipc_handle` contains a `close()` method as part of its definition in Numba, which closes the handle by calling `cuIpcCloseMemHandle`. It is expected that this is sufficient for general use cases, so no facility for customising the closing of IPC handles is provided by the EMM Plugin interface.

`get_memory_info` may be called at any time after `initialize`.

`reset` is called as part of resetting a context. Numba does not normally call reset spontaneously, but it may be called at the behest of the user. Calls to `reset` may even occur before `initialize` is called, so the plugin should be robust against this occurrence.

`defer_cleanup` is called when the `numba.cuda.defer_cleanup` context manager is used from user code.

`interface_version` is called by Numba when the memory manager is set, to ensure that the version of the interface implemented by the plugin is compatible with the version of Numba in use.

Representing pointers

Device Memory

The `MemoryPointer` class is used to represent a pointer to memory. Whilst there are various details of its implementation, the only aspect relevant to EMM plugin development is its initialization. The `__init__` method has the following interface:

```
class MemoryPointer:
    def __init__(self, context, pointer, size, owner=None, finalizer=None):
```

- `context`: The context in which the pointer was allocated.
- `pointer`: A `ctypes` pointer (e.g. `ctypes.c_uint64`) holding the address of the memory.
- `size`: The size of the allocation in bytes.
- `owner`: The owner is sometimes set by the internals of the class, or used for Numba's internal memory management, but need not be provided by the writer of an EMM plugin - the default of `None` should always suffice.
- `finalizer`: A method that is called when the last reference to the `MemoryPointer` object is released. Usually this will make a call to the external memory management library to inform it that the memory is no longer required, and that it could potentially be freed (though the EMM is not required to free it immediately).

Host Memory

Memory mapped into the CUDA address space (which is created when the `memhostalloc` or `mempin` methods are called with `mapped=True`) is managed using the `MappedMemory` class:

```
class MappedMemory(AutoFreePointer):
    def __init__(self, context, pointer, size, owner, finalizer=None):
```

- `context`: The context in which the pointer was allocated.
- `pointer`: A `ctypes` pointer (e.g. `ctypes.c_void_p`) holding the address of the allocated memory.
- `size`: The size of the allocated memory in bytes.
- `owner`: A Python object that owns the memory, e.g. a `DeviceNDArray` instance.
- `finalizer`: A method that is called when the last reference to the `MappedMemory` object is released. For example, this method could call `cuMemFreeHost` on the pointer to deallocate the memory immediately.

Note that the inheritance from `AutoFreePointer` is an implementation detail and need not concern the developer of an EMM plugin - `MemoryPointer` is higher in the MRO of `MappedMemory`.

Memory that is only in the host address space and has been pinned is represented with the `PinnedMemory` class:

```
class PinnedMemory(mviewbuf.MemAlloc):
    def __init__(self, context, pointer, size, owner, finalizer=None):
```

- `context`: The context in which the pointer was allocated.
- `pointer`: A `ctypes` pointer (e.g. `ctypes.c_void_p`) holding the address of the pinned memory.
- `size`: The size of the pinned region in bytes.
- `owner`: A Python object that owns the memory, e.g. a `DeviceNDArray` instance.

- `finalizer`: A method that is called when the last reference to the `PinnedMemory` object is released. This method could e.g. call `cuMemHostUnregister` on the pointer to unpin the memory immediately.

Providing device memory management only

Some external memory managers will support management of on-device memory but not host memory. To make it easy to implement an EMM plugin using one of these managers, Numba will provide a memory manager class with implementations of the `memhostalloc` and `mempin` methods. An abridged definition of this class follows:

```
class HostOnlyCUDAMemoryManager(BaseCUDAMemoryManager):
    # Unimplemented methods:
    #
    # - memalloc
    # - get_memory_info

    def memhostalloc(self, size, mapped, portable, wc):
        # Implemented.

    def mempin(self, owner, pointer, size, mapped):
        # Implemented.

    def initialize(self):
        # Implemented.
        #
        # Must be called by any subclass when its initialize() method is
        # called.

    def reset(self):
        # Implemented.
        #
        # Must be called by any subclass when its reset() method is
        # called.

    def defer_cleanup(self):
        # Implemented.
        #
        # Must be called by any subclass when its defer_cleanup() method is
        # called.
```

A class can subclass the `HostOnlyCUDAMemoryManager` and then it only needs to add implementations of methods for on-device memory. Any subclass must observe the following rules:

- If the subclass implements `__init__`, then it must also call `HostOnlyCUDAMemoryManager.__init__`, as this is used to initialize some of its data structures (`self.allocations` and `self.deallocations`).
- The subclass must implement `memalloc` and `get_memory_info`.
- The `initialize` and `reset` methods perform initialisation of structures used by the `HostOnlyCUDAMemoryManager`.
  - If the subclass has nothing to do on initialisation (possibly) or reset (unlikely) then it need not implement these methods.
  - However, if it does implement these methods then it must also call the methods from `HostOnlyCUDAMemoryManager` in its own implementations.

- Similarly if `defer_cleanup` is implemented, it should enter the context provided by `HostOnlyCUDAManager.defer_cleanup()` prior to `yield`ing (or in the `__enter__` method) and release it prior to exiting (or in the `__exit__` method).

Import order

The order in which Numba and the library implementing an EMM Plugin should not matter. For example, if `rmm` were to implement and register an EMM Plugin, then:

```
from numba import cuda
import rmm
```

and

```
import rmm
from numba import cuda
```

are equivalent - this is because Numba does not initialize CUDA or allocate any memory until the first call to a CUDA function - neither instantiating and registering an EMM plugin, nor importing `numba.cuda` causes a call to a CUDA function.

Numba as a Dependency

Adding the implementation of an EMM Plugin to a library naturally makes Numba a dependency of the library where it may not have been previously. In order to make the dependency optional, if this is desired, one might conditionally instantiate and register the EMM Plugin like:

```
try:
    import numba
    from mylib.numba_utils import MyNumbaMemoryManager
    numba.cuda.cudadrv.driver.set_memory_manager(MyNumbaMemoryManager)
except:
    print("Numba not importable - not registering EMM Plugin")
```

so that `mylib.numba_utils`, which contains the implementation of the EMM Plugin, is only imported if Numba is already present. If Numba is not available, then `mylib.numba_utils` (which necessarily imports `numba`), will never be imported.

It is recommended that any library with an EMM Plugin includes at least some environments with Numba for testing with the EMM Plugin in use, as well as some environments without Numba, to avoid introducing an accidental Numba dependency.

Example implementation - A RAPIDS Memory Manager (RMM) Plugin

An implementation of an EMM plugin within the Rapids Memory Manager (RMM) is sketched out in this section. This is intended to show an overview of the implementation in order to support the descriptions above and to illustrate how the plugin interface can be used - different choices may be made for a production-ready implementation.

The plugin implementation consists of additions to python/rmm/rmm.py:

```
# New imports:
from contextlib import context_manager
```

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```
# RMM already has Numba as a dependency, so these imports need not be guarded
# by a check for the presence of numba.
from numba.cuda import (HostOnlyCUDAMemoryManager, MemoryPointer, IpcHandle,
                        set_memory_manager)


# New class implementing the EMM Plugin:
class RMMNumbaManager(HostOnlyCUDAMemoryManager):
    def memalloc(self, size):
        # Allocates device memory using RMM functions. The finalizer for the
        # allocated memory calls back to RMM to free the memory.
        addr = librmm.rmm_alloc(bytesize, 0)
        ctx = cuda.current_context()
        ptr = ctypes.c_uint64(int(addr))
        finalizer = _make_finalizer(addr, stream)
        return MemoryPointer(ctx, ptr, size, finalizer=finalizer)

   def get_ipc_handle(self, memory):
        """
        Get an IPC handle for the memory with offset modified by the RMM memory
        pool.
        """
        # This implementation provides a functional implementation and illustrates
        # what get_ipc_handle needs to do, but it is not a very "clean"
        # implementation, and it relies on borrowing bits of Numba internals to
        # initialise ipchandle.
        #
        # A more polished implementation might make use of additional functions in
        # the RMM C++ layer for initialising IPC handles, and not use any Numba
        # internals.
        ipchandle = (ctypes.c_byte * 64)()  # IPC handle is 64 bytes
        cuda.cudadrv.memory.driver_funcs.cuIpcGetMemHandle(
            ctypes.byref(ipchandle),
            memory.owner.handle,
        )
        source_info = cuda.current_context().device.get_device_identity()
        ptr = memory.device_ctypes_pointer.value
        offset = librmm.rmm_getallocationoffset(ptr, 0)
        return IpcHandle(memory, ipchandle, memory.size, source_info,
                         offset=offset)

    def get_memory_info(self):
        # Returns a tuple of (free, total) using RMM functionality.
        return get_info() # Function defined in rmm.py

    def initialize(self):
        # Nothing required to initialize RMM here, but this method is added
        # to illustrate that the super() method should also be called.
        super().initialize()

    @contextmanager
    def defer_cleanup(self):
```

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```
        # Does nothing to defer cleanup - a full implementation may choose to
        # implement a different policy.
        with super().defer_cleanup():
            yield

    @property
    def interface_version(self):
        # As required by the specification
        return 1

# The existing _make_finalizer function is used by RMMNumbaManager:
def _make_finalizer(handle, stream):
    """
    Factory to make the finalizer function.
    We need to bind *handle* and *stream* into the actual finalizer, which
    takes no args.
    """

    def finalizer():
        """
        Invoked when the MemoryPointer is freed
        """
        librmm.rmm_free(handle, stream)

    return finalizer

# Utility function register `RMMNumbaManager` as an EMM:
def use_rmm_for_numba():
    set_memory_manager(RMMNumbaManager)

# To support `NUMBA_CUDA_MEMORY_MANAGER=rmm`:
_numba_memory_manager = RMMNumbaManager
```

Example usage

A simple example that configures Numba to use RMM for memory management and creates a device array is as follows:

```
# example.py
import rmm
import numpy as np

from numba import cuda

rmm.use_rmm_for_numba()

a = np.zeros(10)
d_a = cuda.to_device(a)
del(d_a)
print(rmm.csv_log())
```

Running this should result in output similar to the following:

```
Event Type,Device ID,Address,Stream,Size (bytes),Free Memory,Total Memory,Current Allocs,
↪Start,End,Elapsed,Location
Alloc,0,0x7fae06600000,0,80,0,0,1,1.10549,1.1074,0.00191666,<path>/numba/numba/cuda/
↪cudadrv/driver.py:683
Free,0,0x7fae06600000,0,0,0,0,0,1.10798,1.10921,0.00122238,<path>/numba/numba/utils.
↪py:678
```

Note that there is some scope for improvement in RMM for detecting the line number at which the allocation / free occurred, but this is outside the scope of the example in this proposal.

Setting the memory manager through the environment

Rather than calling `rmm.use_rmm_for_numba()` in the example above, the memory manager could also be set to use RMM globally with an environment variable, so the Python interpreter is invoked to run the example as:

```
NUMBA_CUDA_MEMORY_MANAGER="rmm.RMMNumbaManager" python example.py
```

Numba internal changes

This section is intended primarily for Numba developers - those with an interest in the external interface for implementing EMM plugins may choose to skip over this section.

Current model / implementation

At present, memory management is implemented in the *Context* class. It maintains lists of allocations and deallocations:

- `allocations` is a `numba.core.utils.UniqueDict`, created at context creation time.
- `deallocations` is an instance of the `_PendingDeallocs` class, and is created when `Context.prepare_for_use()` is called.

These are used to track allocations and deallocations of:

- Device memory
- Pinned memory
- Mapped memory
- Streams
- Events
- Modules

The `_PendingDeallocs` class implements the deferred deallocation strategy - cleanup functions (such as `cuMemFree`) for the items above are added to its list of pending deallocations by the finalizers of objects representing allocations. These finalizers are run when the objects owning them are garbage-collected by the Python interpreter. When the addition of a new cleanup function to the deallocation list causes the number or size of pending deallocations to exceed a configured ratio, the `_PendingDeallocs` object runs deallocators for all items it knows about and then clears its internal pending list.

See *Deallocation Behavior* for more details of this implementation.

Proposed changes

This section outlines the major changes that will be made to support the EMM plugin interface - there will be various small changes to other parts of Numba that will be required in order to adapt to these changes; an exhaustive list of these is not provided.

Context changes

The `numba.cuda.cudadrv.driver.Context` class will no longer directly allocate and free memory. Instead, the context will hold a reference to a memory manager instance, and its memory allocation methods will call into the memory manager, e.g.:

```
def memalloc(self, size):
    return self.memory_manager.memalloc(size)

def memhostalloc(self, size, mapped=False, portable=False, wc=False):
    return self.memory_manager.memhostalloc(size, mapped, portable, wc)

def mempin(self, owner, pointer, size, mapped=False):
    if mapped and not self.device.CAN_MAP_HOST_MEMORY:
        raise CudaDriverError("%s cannot map host memory" % self.device)
    return self.memory_manager.mempin(owner, pointer, size, mapped)

def prepare_for_use(self):
    self.memory_manager.initialize()

def get_memory_info(self):
    self.memory_manager.get_memory_info()

def get_ipc_handle(self, memory):
    return self.memory_manager.get_ipc_handle(memory)

def reset(self):
    # ... Already-extant reset logic, plus:
    self._memory_manager.reset()
```

The `memory_manager` member is initialised when the context is created.

The `memunpin` method (not shown above but currently exists in the `Context` class) has never been implemented - it presently raises a `NotImplementedError`. This method arguably un-needed - pinned memory is immediately unpinned by its finalizer, and unpinning before a finalizer runs would invalidate the state of `PinnedMemory` objects for which references are still held. It is proposed that this is removed when making the other changes to the `Context` class.

The `Context` class will still instantiate `self.allocations` and `self.deallocations` as before - these will still be used by the context to manage the allocations and deallocations of events, streams, and modules, which are not handled by the EMM plugin.

New components of the `driver` module

- `BaseCUDAMemoryManager`: An abstract class, as defined in the plugin interface above.
- `HostOnlyCUDAMemoryManager`: A subclass of `BaseCUDAMemoryManager`, with the logic from `Context.memhostalloc` and `Context.mempin` moved into it. This class will also create its own `allocations` and `deallocations` members, similarly to how the `Context` class creates them. These are used to manage the allocations and deallocations of pinned and mapped host memory.
- `NumbaCUDAMemoryManager`: A subclass of `HostOnlyCUDAMemoryManager`, which also contains an implementation of `memalloc` based on that presently existing in the `Context` class. This is the default memory manager, and its use preserves the behaviour of Numba prior to the addition of the EMM plugin interface - that is, all memory allocation and deallocation for Numba arrays is handled within Numba.
  - This class shares the `allocations` and `deallocations` members with its parent class `HostOnlyCUDAMemoryManager`, and it uses these for the management of device memory that it allocates.
- The `set_memory_manager` function, which sets a global pointing to the memory manager class. This global initially holds `NumbaCUDAMemoryManager` (the default).

Staged IPC

Staged IPC should not take ownership of the memory that it allocates. When the default internal memory manager is in use, the memory allocated for the staging array is already owned. When an EMM plugin is in use, it is not legitimate to take ownership of the memory.

This change can be made by applying the following small patch, which has been tested to have no effect on the CUDA test suite:

```
diff --git a/numba/cuda/cudadrv/driver.py b/numba/cuda/cudadrv/driver.py
index 7832955..f2c1352 100644
--- a/numba/cuda/cudadrv/driver.py
+++ b/numba/cuda/cudadrv/driver.py
@@ -922,7 +922,11 @@ class _StagedIpcImpl(object):
         with cuda.gpus[srcdev.id]:
             impl.close()

-        return newmem.own()
+        return newmem
```

Testing

Alongside the addition of appropriate tests for new functionality, there will be some refactoring of existing tests required, but these changes are not substantial. Tests of the deallocation strategy (e.g. `TestDeallocation`, `TestDeferCleanup`) will need to be modified to ensure that they are examining the correct set of deallocations. When an EMM plugin is in use, they will need to be skipped.

Prototyping / experimental implementation

Some prototype / experimental implementations have been produced to guide the designs presented in this document. The current implementations can be found in:

- Numba branch: https://github.com/gmarkall/numba/tree/grm-numba-nbep-7.
- RMM branch: https://github.com/gmarkall/rmm/tree/grm-numba-nbep-7.
- CuPy implementation: https://github.com/gmarkall/nbep-7/blob/master/nbep7/cupy_mempool.py - uses an unmodified CuPy.
  - See CuPy memory management docs.

Current implementation status

RMM Plugin

For a minimal example, a simple allocation and free using RMM works as expected. For the example code (similar to the RMM example above):

```
import rmm
import numpy as np

from numba import cuda

rmm.use_rmm_for_numba()

a = np.zeros(10)
d_a = cuda.to_device(a)
del(d_a)
print(rmm.csv_log())
```

We see the following output:

```
Event Type,Device ID,Address,Stream,Size (bytes),Free Memory,Total Memory,Current Allocs,
↪Start,End,Elapsed,Location
Alloc,0,0x7f96c7400000,0,80,0,0,1,1.13396,1.13576,0.00180059,<path>/numba/numba/cuda/
↪cudadrv/driver.py:686
Free,0,0x7f96c7400000,0,0,0,0,0,1.13628,1.13723,0.000956004,<path>/numba/numba/utils.
↪py:678
```

This output is similar to the expected output from the example usage presented above (though note that the pointer addresses and timestamps vary compared to the example), and provides some validation of the example use case.

CuPy Plugin

```
from nbep7.cupy_mempool import use_cupy_mm_for_numba
import numpy as np

from numba import cuda

use_cupy_mm_for_numba()

a = np.zeros(10)
d_a = cuda.to_device(a)
del(d_a)
```

The prototype CuPy plugin has somewhat primitive logging, so we see the output:

```
Allocated 80 bytes at 7f004d400000
Freeing 80 bytes at 7f004d400000
```

Numba CUDA Unit tests

As well as providing correct execution of a simple example, all relevant Numba CUDA unit tests also pass with the prototype branch, for both the internal memory manager and the RMM EMM Plugin.

RMM

The unit test suite can be run with the RMM EMM Plugin with:

```
NUMBA_CUDA_MEMORY_MANAGER=rmm python -m numba.runtests numba.cuda.tests
```

A summary of the unit test suite output is:

```
Ran 564 tests in 142.211s

OK (skipped=11)
```

When running with the built-in Numba memory management, the output is:

```
Ran 564 tests in 133.396s

OK (skipped=5)
```

i.e. the changes for using an external memory manager do not break the built-in Numba memory management. There are an additional 6 skipped tests, from:

- `TestDeallocation`: skipped as it specifically tests Numba's internal deallocation strategy.
- `TestDeferCleanup`: skipped as it specifically tests Numba's implementation of deferred cleanup.
- `TestCudaArrayInterface.test_ownership`: skipped as Numba does not own memory when an EMM Plugin is used, but ownership is assumed by this test case.

CuPy

The test suite can be run with the CuPy plugin using:

```
NUMBA_CUDA_MEMORY_MANAGER=nbep7.cupy_mempool python -m numba.runtests numba.cuda.tests
```

This plugin implementation is presently more primitive than the RMM implementation, and results in some errors with the unit test suite:

```
Ran 564 tests in 111.699s

FAILED (errors=8, skipped=11)
```

The 8 errors are due to a lack of implementation of `get_ipc_handle` in the CuPy EMM Plugin implementation. It is expected that this implementation will be re-visited and completed so that CuPy can be used stably as an allocator for Numba in the future.

7.2 Other proposals

7.2.1 NBEP 2: Extension points

Author
Antoine Pitrou

Date
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Status
Draft

Implementing new types or functions in Numba requires hooking into various mechanisms along the compilation chain (and potentially outside of it). This document aims, first, at examining the current ways of doing so and, second, at making proposals to make extending easier.

If some of the proposals are implemented, we should first strive to use and exercise them internally, before exposing the APIs to the public.

Note: This document doesn't cover CUDA or any other non-CPU backend.

High-level API

There is currently no high-level API, making some use cases more complicated than they should be.

Proposed changes

Dedicated module

We propose the addition of a `numba.extending` module exposing the main APIs useful for extending Numba.

Implementing a function

We propose the addition of a `@overload` decorator allowing the implementation of a given function for use in *nopython mode*. The overloading function has the same formal signature as the implemented function, and receives the actual argument types. It should return a Python function implementing the overloaded function for the given types.

The following example implements `numpy.where()` with this approach.

```
import numpy as np

from numba.core import types
from numba.extending import overload

@overload(np.where)
def where(cond, x, y):
    """
    Implement np.where().
    """
    # Choose implementation based on argument types.
    if isinstance(cond, types.Array):
        # Array where() => return an array of the same shape
        if all(ty.layout == 'C' for ty in (cond, x, y)):
            def where_impl(cond, x, y):
                """
                Fast implementation for C-contiguous arrays
                """
                shape = cond.shape
                if x.shape != shape or y.shape != shape:
                    raise ValueError("all inputs should have the same shape")
                res = np.empty_like(x)
                cf = cond.flat
                xf = x.flat
                yf = y.flat
                rf = res.flat
                for i in range(cond.size):
                    rf[i] = xf[i] if cf[i] else yf[i]
                return res
        else:
            def where_impl(cond, x, y):
                """
                Generic implementation for other arrays
                """
                shape = cond.shape
                if x.shape != shape or y.shape != shape:
                    raise ValueError("all inputs should have the same shape")
                res = np.empty_like(x)
```

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```
                for idx, c in np.ndenumerate(cond):
                    res[idx] = x[idx] if c else y[idx]
                return res

    else:
        def where_impl(cond, x, y):
            """
            Scalar where() => return a 0-dim array
            """
            scal = x if cond else y
            return np.full_like(scal, scal)

    return where_impl
```

It is also possible to implement functions already known to Numba, to support additional types. The following example implements the built-in function `len()` for tuples with this approach:

```
@overload(len)
def tuple_len(x):
   if isinstance(x, types.BaseTuple):
      # The tuple length is known at compile-time, so simply reify it
      # as a constant.
      n = len(x)
      def len_impl(x):
         return n
      return len_impl
```

Implementing an attribute

We propose the addition of a `@overload_attribute` decorator allowing the implementation of an attribute getter for use in *nopython mode*.

The following example implements the `.nbytes` attribute on Numpy arrays:

```
@overload_attribute(types.Array, 'nbytes')
def array_nbytes(arr):
   def get(arr):
       return arr.size * arr.itemsize
   return get
```

Note: The overload_attribute() signature allows for expansion to also define setters and deleters, by letting the decorated function return a `getter, setter, deleter` tuple instead of a single `getter`.

Implementing a method

We propose the addition of a `@overload_method` decorator allowing the implementation of an instance method for use in *nopython mode*.

The following example implements the `.take()` method on Numpy arrays:

```
@overload_method(types.Array, 'take')
def array_take(arr, indices):
   if isinstance(indices, types.Array):
       def take_impl(arr, indices):
           n = indices.shape[0]
           res = np.empty(n, arr.dtype)
           for i in range(n):
               res[i] = arr[indices[i]]
           return res
       return take_impl
```

Exposing a structure member

We propose the addition of a `make_attribute_wrapper()` function exposing an internal field as a visible read-only attribute, for those types backed by a `StructModel` data model.

For example, assuming `PdIndexType` is the Numba type of pandas indices, here is how to expose the underlying Numpy array as a `._data` attribute:

```
@register_model(PdIndexType)
class PdIndexModel(models.StructModel):
    def __init__(self, dmm, fe_type):
        members = [
            ('values', fe_type.as_array),
            ]
        models.StructModel.__init__(self, dmm, fe_type, members)

make_attribute_wrapper(PdIndexType, 'values', '_data')
```

Typing

Numba types

Numba's standard types are declared in `numba.types`. To declare a new type, one subclasses the base `Type` class or one of its existing abstract subclasses, and implements the required functionality.

Proposed changes

No change required.

Type inference on values

Values of a new type need to be type-inferred if they can appear as function arguments or constants. The core machinery is in `numba.typing.typeof`.

In the common case where some Python class or classes map exclusively to the new type, one can extend a generic function to dispatch on said classes, e.g.:

```
from numba.typing.typeof import typeof_impl

@typeof_impl(MyClass)
def _typeof_myclass(val, c):
   if "some condition":
      return MyType(...)
```

The `typeof_impl` specialization must return a Numba type instance, or None if the value failed typing.

(when one controls the class being type-inferred, an alternative to `typeof_impl` is to define a `_numba_type_` property on the class)

In the rarer case where the new type can denote various Python classes that are impossible to enumerate, one must insert a manual check in the fallback implementation of the `typeof_impl` generic function.

Proposed changes

Allow people to define a generic hook without monkeypatching the fallback implementation.

Fast path for type inference on function arguments

Optionally, one may want to allow a new type to participate in the fast type resolution (written in C code) to minimize function call overhead when a JIT-compiled function is called with the new type. One must then insert the required checks and implementation in the `_typeof.c` file, presumably inside the `compute_fingerprint()` function.

Proposed changes

None. Adding generic hooks to C code embedded in a C Python extension is too delicate a change.

Type inference on operations

Values resulting from various operations (function calls, operators, etc.) are typed using a set of helpers called "templates". One can define a new template by subclass one of the existing base classes and implement the desired inference mechanism. The template is explicitly registered with the type inference machinery using a decorator.

The `ConcreteTemplate` base class allows one to define inference as a set of supported signatures for a given operation. The following example types the modulo operator:

```
@builtin
class BinOpMod(ConcreteTemplate):
    key = "%"
    cases = [signature(op, op, op)
             for op in sorted(types.signed_domain)]
    cases += [signature(op, op, op)
              for op in sorted(types.unsigned_domain)]
    cases += [signature(op, op, op) for op in sorted(types.real_domain)]
```

(note that type *instances* are used in the signatures, severely limiting the amount of genericity that can be expressed)

The `AbstractTemplate` base class allows to define inference programmatically, giving it full flexibility. Here is a simplistic example of how tuple indexing (i.e. the `__getitem__` operator) can be expressed:

```
@builtin
class GetItemUniTuple(AbstractTemplate):
    key = "getitem"

    def generic(self, args, kws):
        tup, idx = args
        if isinstance(tup, types.UniTuple) and isinstance(idx, types.Integer):
            return signature(tup.dtype, tup, idx)
```

The `AttributeTemplate` base class allows to type the attributes and methods of a given type. Here is an example, typing the `.real` and `.imag` attributes of complex numbers:

```
@builtin_attr
class ComplexAttribute(AttributeTemplate):
    key = types.Complex

    def resolve_real(self, ty):
        return ty.underlying_float

    def resolve_imag(self, ty):
        return ty.underlying_float
```

Note: `AttributeTemplate` only works for getting attributes. Setting an attribute's value is hardcoded in `numba.typeinfer`.

The `CallableTemplate` base class offers an easier way to parse flexible function signatures, by letting one define a callable that has the same definition as the function being typed. For example, here is how one could hypothetically type Python's `sorted` function if Numba supported lists:

```
@builtin
class Sorted(CallableTemplate):
    key = sorted

    def generic(self):
        def typer(iterable, key=None, reverse=None):
            if reverse is not None and not isinstance(reverse, types.Boolean):
                return
            if key is not None and not isinstance(key, types.Callable):
                return
            if not isinstance(iterable, types.Iterable):
                return
            return types.List(iterable.iterator_type.yield_type)

        return typer
```

(note you can return just the function's return type instead of the full signature)

Proposed changes

Naming of the various decorators is quite vague and confusing. We propose renaming `@builtin` to `@infer`, `@builtin_attr` to `@infer_getattr` and `builtin_global` to `infer_global`.

The two-step declaration for global values is a bit verbose, we propose simplifying it by allowing the use of `infer_global` as a decorator:

```
@infer_global(len)
class Len(AbstractTemplate):
    key = len

    def generic(self, args, kws):
        assert not kws
        (val,) = args
        if isinstance(val, (types.Buffer, types.BaseTuple)):
            return signature(types.intp, val)
```

The class-based API can feel clumsy, we can add a functional API for some of the template kinds:

```
@type_callable(sorted)
def type_sorted(context):
    def typer(iterable, key=None, reverse=None):
        # [same function as above]

    return typer
```

Code generation

Concrete representation of values of a Numba type

Any concrete Numba type must be able to be represented in LLVM form (for variable storage, argument passing, etc.). One defines that representation by implementing a datamodel class and registering it with a decorator. Datamodel classes for standard types are defined in `numba.datamodel.models`.

Proposed changes

No change required.

Conversion between types

Implicit conversion between Numba types is currently implemented as a monolithic sequence of choices and type checks in the `BaseContext.cast()` method. To add a new implicit conversion, one appends a type-specific check in that method.

Boolean evaluation is a special case of implicit conversion (the destination type being `types.Boolean`).

Note: Explicit conversion is seen as a regular operation, e.g. a constructor call.

Proposed changes

Add a generic function for implicit conversion, with multiple dispatch based on the source and destination types. Here is an example showing how to write a float-to-integer conversion:

```
@lower_cast(types.Float, types.Integer)
def float_to_integer(context, builder, fromty, toty, val):
    lty = context.get_value_type(toty)
    if toty.signed:
        return builder.fptosi(val, lty)
    else:
        return builder.fptoui(val, lty)
```

Implementation of an operation

Other operations are implemented and registered using a set of generic functions and decorators. For example, here is how lookup for a the `.ndim` attribute on Numpy arrays is implemented:

```
@builtin_attr
@impl_attribute(types.Kind(types.Array), "ndim", types.intp)
def array_ndim(context, builder, typ, value):
    return context.get_constant(types.intp, typ.ndim)
```

And here is how calling `len()` on a tuple value is implemented:

```
@builtin
@implement(types.len_type, types.Kind(types.BaseTuple))
def tuple_len(context, builder, sig, args):
    tupty, = sig.args
    retty = sig.return_type
    return context.get_constant(retty, len(tupty.types))
```

Proposed changes

Review and streamine the API. Drop the requirement to write `types.Kind(...)` explicitly. Remove the separate `@implement` decorator and rename `@builtin` to `@lower_builtin`, `@builtin_attr` to `@lower_getattr`, etc.

Add decorators to implement `setattr()` operations, named `@lower_setattr` and `@lower_setattr_generic`.

Conversion from / to Python objects

Some types need to be converted from or to Python objects, if they can be passed as function arguments or returned from a function. The corresponding boxing and unboxing operations are implemented using a generic function. The implementations for standard Numba types are in `numba.targets.boxing`. For example, here is the boxing implementation for a boolean value:

```
@box(types.Boolean)
def box_bool(c, typ, val):
    longval = c.builder.zext(val, c.pyapi.long)
    return c.pyapi.bool_from_long(longval)
```

Proposed changes

Change the implementation signature from `(c, typ, val)` to `(typ, val, c)`, to match the one chosen for the `typeof_impl` generic function.

7.2.2 NBEP 3: JIT Classes

Author
Siu Kwan Lam

Date
Dec 2015

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Draft

Introduction

Numba does not yet support user-defined classes. Classes provide useful abstraction and promote modularity when used right. In the simplest sense, a class specifies the set of data and operations as attributes and methods, respectively. A class instance is an instantiation of that class. This proposal will focus on supporting this simple usecase of classes–with just attributes and methods. Other features, such as class methods, static methods, and inheritance are deferred to another proposal, but we believe these features can be easily implemented given the foundation described here.

Proposal: jit-classes

A JIT-classes is more restricted than a Python class. We will focus on the following operations on a class and its instance:

- Instantiation: create an instance of a class using the class object as the constructor: `cls(*args, **kwargs)`
- Destruction: remove resources allocated during instantiation and release all references to other objects.
- Attribute access: loading and storing attributes using `instance.attr` syntax.
- Method access: loading methods using `instance.method` syntax.

With these operations, a class object (not the instance) does not need to be materialize. Using the class object as a constructor is fully resolved (a runtime implementation is picked) during the typing phase in the compiler. This means **a class object will not be first class**. On the other hand, implementing a first-class class object will require an "interface" type, or the type of class.

The instantiation of a class will allocate resources for storing the data attributes. This is described in the "Storage model" section. Methods are never stored in the instance. They are information attached to the class. Since a class object only exists in the type domain, the methods will also be fully resolved at the typing phase. Again, numba do not have first-class function value and each function type maps uniquely to each function implementation (this needs to be changed to support function value as argument).

A class instance can contain other NRT reference-counted object as attributes. To properly clean up an instance, a destructor is called when the reference count of the instance is dropped to zero. This is described in the "Reference count and descructor" section.

Storage model

For compatibility with C, attributes are stored in a simple plain-old-data structure. Each attribute are stored in a user-defined order in a padded (for proper alignment), contiguous memory region. An instance that contains three fields of int32, float32, complex64 will be compatible with the following C structure:

```
struct {
    int32     field0;
    float32   field1;
    complex64 field2;
};
```

This will also be compatible with an aligned NumPy structured dtype.

Methods

Methods are regular function that can be bounded to an instance. They can be compiled as regular function by numba. The operation `getattr(instance, name)` (getting an attribute `name` from `instance`) binds the instance to the requested method at runtime.

The special `__init__` method is also handled like regular functions.

`__del__` is not supported at this time.

Reference count and destructor

An instance of jit-class is reference-counted by NRT. Since it may contain other NRT tracked object, it must call a destructor when its reference count dropped to zero. The destructor will decrement the reference count of all attributes by one.

At this time, there is no support for user defined `__del__` method.

Proper cleanup for cyclic reference is not handled at this time. Cycles will cause memory leak.

Type inference

So far we have not described the type of the attributes or the methods. Type information is necessary to materailize the instance (e.g. allocate the storage). The simplest way is to let user provide the type of each attributes as well as the ordering; for instance:

```
dct = OrderedDict()
dct['x'] = int32
dct['y'] = float32
```

Allowing user to supply an ordered dictionary will provide the name, ordering and types of the attributes. However, this statically typed semantic is not as flexible as the Python semantic which behaves like a generic class.

Inferring the type of attributes is difficult. In a previous attempt to implement JIT classes, the `__init__` method is specialized to capture the type stored into the attributes. Since the method can contain arbitrary logic, the problem can become a dependent typing problem if types are assigned conditionally depending on the value. (Very few languages implement dependent typing and those that does are mostly theorem provers.)

Example: typing function using an OrderedDict

```
spec = OrderedDict()
spec['x'] = numba.int32
spec['y'] = numba.float32

@jitclass(spec)
class Vec(object):
    def __init__(self, x, y):
        self.x = x
        self.y = y

    def add(self, dx, dy):
        self.x += dx
        self.y += dy
```

Example: typing function using a list of 2-tuples

```
spec = [('x', numba.int32),
        ('y', numba.float32)]

@jitclass(spec)
class Vec(object):
    ...
```

Creating multiple jitclasses from a single class object

The *jitclass(spec)* decorator creates a new jitclass type even when applied to the same class object and the same type specification.

```
class Vec(object):
  ...

Vec1 = jitclass(spec)(Vec)
Vec2 = jitclass(spec)(Vec)
# Vec1 and Vec2 are two different jitclass types
```

Usage from the Interpreter

When constructing a new instance of a jitclass, a "box" is created that wraps the underlying jitclass instance from numba. Attributes and methods are accessible from the interpreter. The actual implementation will be in numba compiled code. Any Python object is converted to its native representation for consumption in numba. Similarly, the returned value is converted to its Python representation. As a result, there may be overhead in manipulating jitclass instances in the interpreter. This overhead is minimal and should be easily amortized by more efficient computation in the compiled methods.

Support for property, staticmethod and classmethod

The use of `property` is accepted for getter and setter only. Deleter is not supported.

The use of `staticmethod` is not supported.

The use of `classmethod` is not supported.

Inheritance

Class inheritance is not considered in this proposal. The only accepted base class for a jitclass is *object*.

Supported targets

Only the CPU target (including the parallel target) is supported. GPUs (e.g. CUDA and HSA) targets are supported via an immutable version of the jitclass instance, which will be described in a separate NBEP.

Other properties

Given:

```
spec = [('x', numba.int32),
        ('y', numba.float32)]

@jitclass(spec)
class Vec(object):
    ...
```

- `isinstance(Vec(1, 2), Vec)` is True.
- `type(Vec(1, 2))` may not be `Vec`.

Future enhancements

This proposal has only described the basic semantic and functionality of a jitclass. Additional features will be described in future enhancement proposals.

7.2.3 NBEP 4: Defining C callbacks

Author
Antoine Pitrou

Date
April 2016

Status
Draft

Interfacing with some native libraries (for example written in C or C++) can necessitate writing native callbacks to provide business logic to the library. Some Python-facing libraries may also provide the alternative of passing a ctypes-wrapped native callback instead of a Python callback for better performance. A simple example is the `scipy.integrate` package where the user passes the function to be integrated as a callback.

Users of those libraries may want to benefit from the performance advantage of running purely native code, while writing their code in Python. This proposal outlines a scheme to provide such a functionality in Numba.

Basic usage

We propose adding a new decorator, `@cfunc`, importable from the main package. This decorator allows defining a callback as in the following example:

```
from numba import cfunc
from numba.types import float64

# A callback with the C signature `double(double)`

@cfunc(float64(float64), nopython=True)
def integrand(x):
    return 1 / x
```

The `@cfunc` decorator returns a "C function" object holding the resources necessary to run the given compiled function (for example its LLVM module). This object has several attributes and methods:

- the `ctypes` attribute is a ctypes function object representing the native function.
- the `address` attribute is the address of the native function code, as an integer (note this can also be computed from the `ctypes` attribute).
- the `native_name` attribute is the symbol under which the function can be looked up inside the current process.
- the `inspect_llvm()` method returns the IR for the LLVM module in which the function is compiled. It is expected that the `native_name` attribute corresponds to the function's name in the LLVM IR.

The general signature of the decorator is `cfunc(signature, **options)`.

The `signature` must specify the argument types and return type of the function using Numba types. In contrary to `@jit`, the return type cannot be omitted.

The `options` are keyword-only parameters specifying compilation options. We are expecting that the standard `@jit` options (`nopython`, `forceobj`, `cache`) can be made to work with `@cfunc`.

Calling from Numba-compiled functions

While the intended use is to pass a callback's address to foreign C code expecting a function pointer, it should be made possible to call the C callback from a Numba-compiled function.

Passing array data

Native platform ABIs as used by C or C++ don't have the notion of a shaped array as in Numpy. One common solution is to pass a raw data pointer and one or several size arguments (depending on dimensionality). Numba must provide a way to rebuild an array view of this data inside the callback.

```
from numba import cfunc, carray
from numba.types import float64, CPointer, void, intp

# A callback with the C signature `void(double *, double *, size_t)`

@cfunc(void(CPointer(float64), CPointer(float64), intp))
def invert(in_ptr, out_ptr, n):
    in_ = carray(in_ptr, (n,))
    out = carray(out_ptr, (n,))
```

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```
    for i in range(n):
        out[i] = 1 / in_[i]
```

The `carray` function takes `(pointer, shape, dtype)` arguments (`dtype` being optional) and returns a C-layout array view over the data *pointer*, with the given *shape* and *dtype*. *pointer* must be a ctypes pointer object (not a Python integer). The array's dimensionality corresponds to the *shape* tuple's length. If *dtype* is not given, the array's dtype corresponds to the *pointer*'s pointee type.

The `farray` function is similar except that it returns a F-layout array view.

Error handling

There is no standard mechanism in C for error reporting. Unfortunately, Numba currently doesn't handle `try..except` blocks, which makes it more difficult for the user to implement the required error reporting scheme. The current stance of this proposal is to let users guard against invalid arguments where necessary, and do whatever is required to inform the caller of the error.

Based on user feedback, we can later add support for some error reporting schemes, such as returning an integer error code depending on whether an exception was raised, or setting `errno`.

Deferred topics

Ahead-of-Time compilation

This proposal doesn't make any provision for AOT compilation of C callbacks. It would probably necessitate a separate API (a new method on the `numba.pycc.CC` object), and the implementation would require exposing a subset of the C function object's functionality from the compiled C extension module.

Opaque data pointers

Some libraries allow passing an opaque data pointer (`void *`) to a user-provided callback, to provide any required context for execution of the callback. Taking advantage of this functionality would require adding specific support in Numba, for example the ability to do generic conversion from `types.voidptr` and to take the address of a Python-facing `jitclass` instance.

7.2.4 NBEP 5: Type Inference

Author
Siu Kwan Lam

Date
Sept 2016

Status
Draft

This document describes the current type inference implementation in numba.

Introduction

Numba uses type information to ensure that every variable in the user code can be correctly lowered (translated into a low-level representation). The type of a variable describes the set of valid operations and available attributes. Resolving this information during compilation avoids the overhead of type checking and dispatching at runtime. However, Python is dynamically typed and the user does not declare variable types. Since type information is absent, we use type inference to reconstruct the missing information.

Numba Type Semantic

Type inference operates on *Numba IR*, a mostly static-single-assignment (SSA) encoding of the Python bytecode. Conceptually, all intermediate values in the Python code are explicitly assigned to a variable in the IR. Numba enforces that each IR variable to have one type only. A user variable (from the Python source code) can be mapped to multiple variables in the IR. They are *versions* of a variable. Each time a user variable is assigned to, a new version is created. From that point, all subsequent references will use the new version. The user variable *evolves* as the function logic updates its type. Merge points (e.g. subsequent block to an if-else, the loop body, etc..) in the control flow need extra care. At each merge point, a new version is implicitly created to merge the different variable versions from the incoming paths. The merging of the variable versions may translate into an implicit cast.

Numba uses function overloading to emulate Python duck-typing. The type of a function can contain multiple call signatures that accept different argument types and yield different return types. The process to decide the best signature for an overloaded function is called *overload resolution*. Numba partially implements the C++ overload resolution scheme (ISOCPP 13.3 Overload Resolution). The scheme uses a "best fit" algorithm by ranking each argument symmetrically. The five possible rankings in increasing order of penalty are:

- *Exact*: the expected type is the same as the actual type.
- *Promotion*: the actual type can be upcast to the expected type by extending the precision without changing the behavior.
- *Safe conversion*: the actual type can be cast to the expected type by changing the type without losing information.
- *Unsafe conversion*: the actual type can be cast to the expected type by changing the type or downcasting the type even if it is imprecise.
- *No match*: no valid operation can convert the actual type to the expected type.

It is possible to have an ambiguous resolution. For example, a function with signatures `(int16, int32)` and `(int32, int16)` can become ambiguous if presented with the argument types `(int32, int32)`, because demoting either argument to `int16` is equally "fit". Fortunately, numba can usually resolve such ambiguity by compiling a new version with the exact signature `(int32, int32)`. When compilation is disabled and there are multiple signatures with equal fit, an exception is raised.

Type Inference

The type inference in numba has three important components—type variable, constraint network, and typing context.

- The *typing context* provides all the type information and typing related operations, including the logic for type unification, and the logic for typing of global and constant values. It defines the semantic of the language that can be compiled by numba.
- A *type variable* holds the type of each variable (in the Numba IR). Conceptually, it is initialized to the universal type and, as it is re-assigned, it stores a common type by unifying the new type with the existing type. The common type must be able to represent values of the new type and the existing type. Type conversion is applied as necessary and precision loss is accepted for usability reason.
- The *constraint network* is a dependency graph built from the IR. Each node represents an operation in the Numba IR and updates at least one type variable. There may be cycles due to loops in user code.

The type inference process starts by seeding the argument types. These initial types are propagated in the constraint network, which eventually fills all the type variables. Due to cycles in the network, the process repeats until all type variables converge or it fails with undecidable types.

Type unification always returns a more "general" (quoted because unsafe conversion is allowed) type. Types will converge to the least "general" type that can represent all possible values that the variable can hold. Since unification will never move down the type hierarchy and there is a single top type, the universal type—`object`, the type inference is guaranteed to converge.

A failure in type inference can be caused by two reasons. The first reason is user error due to incorrect use of a type. This type of error will also trigger an exception in regular python execution. The second reason is due to the use of an unsupported feature, but the code is otherwise valid in regular python execution. Upon an error, the type inference will set all types to the object type. As a result, numba will fallback to *object-mode*.

Since functions can be overloaded, the type inference needs to decide the type signature used at each call site. The overload resolution is applied to all known overload versions of the callee function described in *call-templates*. A call-template can either be concrete or abstract. A concrete call-template defines a fixed list of all possible signatures. An abstract call-template defines the logic to compute the accepted signature and it is used to implement generic functions.

Numba-compiled functions are generic functions due to their ability to compile new versions. When it sees a new set of argument types, it triggers type inference to validate and determine the return type. When there are nested calls for numba-compiled functions, each call-site triggers type inference. This poses a problem to recursive functions because the type inference will also be triggered recursively. Currently, simple single recursion is supported if the signature is user-annotated by the user, which avoids unbound recursion in type inference that will never terminate.

7.2.5 NBEP 6: Typing Recursion

Author
Siu Kwan Lam

Date
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Status
Draft

Introduction

This document proposes an enhancement to the type inference algorithm to support recursion without explicitly annotating the function signature. As a result, the proposal enables numba to type-infer both self-recursive and mutual-recursive functions under some limitations. In practice, these limitations can be easily overcome by specifying a compilation order.

The Current State

Recursion support in numba is currently limited to self-recursion with explicit type annotation for the function. This limitation comes from the inability to determine the return type of a recursive call. This is because the callee is either the current function (for self-recursion) or a parent function (mutual-recursion) and its type inference process has been suspended while waiting for the function-type of its callee. This results in the formation of a cyclic dependency. For example, given a function `foo()` that calls `bar()`, which in turns call `foo()`:

```
def foo(x):
    if x > 0:
        return bar(x)
```

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```
    else:
        return 1

def bar(x):
    return foo(x - 1)
```

The type inference process of `foo()` depends on that of `bar()`, which depends on `foo()`. Therefore `foo()` depends on itself and the type inference algorithm cannot terminate.

The Solution

The proposed solution has two components:

1. The introduction of a compile-time *callstack* that tracks the compiling functions.
2. The allowance of a partial type inference on functions by leveraging the return type on non-recursive control-flow paths.

The compile-time callstack stores typing information of the functions being compiled. Like an ordinary callstack, it pushes a new record every time a function is "called". Since this occurs at compile-time, a "call" triggers a compilation of the callee.

To detect recursion, the compile-time callstack is searched bottom-up (stack grows downward) for a record that matches the callee. As the record contains a reference to the type inference state, the type inference process can be resumed to determine the return type.

Recall that the type inference process cannot be resumed normally because of the cyclic dependency of the return type. In practice, we can assume that a useful program must have a terminating condition, a path that does not recurse. So, the type inference process can make an initial guess for the return-type at the recursive call by using the return-type determined by the non-recursive paths. This allows type information to propagate on the recursive paths to generate the final return type, which is used to refine the type information by the subsequent iteration in the type inference process.

The following figure illustrates the compile-time callstack when the compiler reaches the recursive call to `foo()` from `bar()`:

At this time, the type inference process of `foo()` is suspended and that of `bar()` is active. The compiler can see that the callee is already compiling by searching the callstack. Knowing that it is a recursive call, the compiler can resume the type-inference on `foo()` by ignoring the paths that contain recursive calls. This means only the `else` branch is considered and we can easily tell that `foo()` returns an `int` in this case. The compiler will then set the initial return type of `foo()` and `bar()` to `int`. The subsequent type propagation can use this information to complete the type inference of both functions, unifying the return-type of all returning paths.

Limitations

For the proposed type inference algorithm to terminate, it assumes that at least one of the control path leads to a return-statement without undertaking a recursive call. Should this not be the case, the algorithm will raise an exception indicating a potential runaway recursion.

For example:

```
@jit
def first(x):
    # The recursing call must have a path that is non-recursing.
```

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```
    if x > 0:
        return second(x)
    else:
        return 1

@jit
def second(x):
    return third(x)

@jit
def third(x):
    return first(x - 1)
```

The `first()` function must be the compiled first for the type inference algorithm to complete successfully. Compiling any other function first will lead to a failure in type inference. The type inference algorithm will treat it as a runaway recursion due to the lack of a non-recursive exit in the recursive callee.

For example, compiling `second()` first will move the recursive call to `first()`. When the compiler tries to resume the type inference process of `second()`, it will fail to find a non-recursive path.

This is a small limitation and can be overcome easily by code restructuring or precompiling in a specific order.

CHAPTER

EIGHT

GLOSSARY

ahead-of-time compilation
AOT compilation
AOT
: Compilation of a function in a separate step before running the program code, producing an on-disk binary object which can be distributed independently. This is the traditional kind of compilation known in languages such as C, C++ or Fortran.

bytecode
Python bytecode
: The original form in which Python functions are executed. Python bytecode describes a stack-machine executing abstract (untyped) operations using operands from both the function stack and the execution environment (e.g. global variables).

compile-time constant
: An expression whose value Numba can infer and freeze at compile-time. Global variables and closure variables are compile-time constants.

just-in-time compilation
JIT compilation
JIT
: Compilation of a function at execution time, as opposed to *ahead-of-time compilation*.

JIT function
: Shorthand for "a function *JIT-compiled* with Numba using the *@jit* decorator."

lifted loops
loop-lifting
loop-jitting
: A feature of compilation in *object mode* where a loop can be automatically extracted and compiled in *nopython mode*. This allows functions with operations unsupported in nopython mode to see significant performance improvements if they contain loops with only nopython-supported operations.

lowering
: The act of translating *Numba IR* into LLVM IR. The term "lowering" stems from the fact that LLVM IR is low-level and machine-specific while Numba IR is high-level and abstract.

NPM
nopython mode
: A Numba compilation mode that generates code that does not access the Python C API. This compilation mode produces the highest performance code, but requires that the native types of all values in the function can be *inferred*.

Note: Prior to Numba 0.59, `@jit` did not set `nopython=True` by default and allowed automatic fall back to

object mode.

Numba IR
Numba intermediate representation
A representation of a piece of Python code which is more amenable to analysis and transformations than the original Python *bytecode*.

object mode
A Numba compilation mode that generates code that handles all values as Python objects and uses the Python C API to perform all operations on those objects. Code compiled in object mode will often run no faster than Python interpreted code, unless the Numba compiler can take advantage of *loop-jitting*.

`OptionalType`
An `OptionalType` is effectively a type union of a `type` and `None`. They typically occur in practice due to a variable being set to `None` and then in a branch the variable being set to some other value. It's often not possible at compile time to determine if the branch will execute so to permit *type inference* to complete, the type of the variable becomes the union of a `type` (from the value) and `None`, i.e. `OptionalType(type)`.

type inference
The process by which Numba determines the specialized types of all values within a function being compiled. Type inference can fail if arguments or globals have Python types unknown to Numba, or if functions are used that are not recognized by Numba. Successful type inference is a prerequisite for compilation in *nopython mode*.

typing
The act of running *type inference* on a value or operation.

ufunc
A NumPy universal function. Numba can create new compiled ufuncs with the *@vectorize* decorator.

reflection
In numba, when a mutable container is passed as argument to a nopython function from the Python interpreter, the container object and all its contained elements are converted into nopython values. To match the semantics of Python, any mutation on the container inside the nopython function must be visible in the Python interpreter. To do so, Numba must update the container and its elements and convert them back into Python objects during the transition back into the interpreter.

Not to be confused with Python's "reflection" in the context of binary operators (see https://docs.python.org/3.5/reference/datamodel.html).

CHAPTER

NINE

RELEASE NOTES

9.1 Towncrier generated notes:

9.1.1 Version 0.61.0 (16 January 2025)

Table of Contents

This is a major Numba release. Numba now supports Python 3.13 as well as NumPy 2.1. The minimum supported Python and NumPy versions have been bumped to 3.10 and 1.24 respectively. The built-in CUDA target `numba.cuda` is now deprecated and `numba-cuda` is the preferred place to get CUDA support from this release onwards. LLVM 15 is now supported via llmlite 0.44.0 as the default LLVM version.

Please find a summary of all noteworthy items below.

Highlights

Add initial implementation for a new type system

This adds a new type system that will allow Numba to differentiate between Python and NumPy scalars.

This has been achieved as follows:

- Retain Numba's old type system as default.
- Add a config flag `USE_LEGACY_TYPE_SYSTEM` set to `1` (on) by default. Switching it to `0` (off) will activate new type system.
- Within the new type system, Python and NumPy scalars will be treated and returned separately as different entities through JIT compiled functions.

(PR-#9662)

Python 3.13 support

Support for Python 3.13 is added. Note that this does not include support for free-threading.

(PR-#9682)

Dropped support for Python 3.9

This release drops official support for Python 3.9. Numba now supports Python 3.10 and later.

(PR-#9726)

Update the minimum supported NumPy version to 1.24

This release updates the minimum supported version of NumPy to 1.24.

(PR-#9739)

Added Support for NumPy 2.1

This release adds support for NumPy 2.1 (excluding the NEP-050 semantics).

(PR-#9741)

New Features

Schedule guvectorize'd functions over `dask.distributed`

Functions decorated with `@guvectorize` can now be scheduled over distributed Dask clusters.

(PR-#9495)

Added compile-time code coverage

Support for emitting compile-time coverage data is added. This feature is automatically activated when running Python under `coverage`. It collects data during the compiler's lowering phase, showing source lines compiled into LLVM-IR, excluding dead-code eliminated lines.

(PR-#9508)

Improvements

First-class function improvements

Passing a jit function as a parameter to another jit function that accepts it as a `FunctionType` has two new improvements.

First, the compiler can now inline a jit function that is passed as a non-local variable (like a global variable) to another jit function. Previously, the interpreter had to introspect the function address for first-class function calls, which prevented inlining. With this improvement, the compiler can statically determine the referenced jit function and link in the corresponding LLVM module for optimization, bypassing the need for the GIL entirely.

Second, jit functions used as first-class functions can now raise exceptions. Before this improvement, they were subject to the same restrictions as `@cfunc` decorated functions, where any exceptions raised were ignored.

(PR-#9077)

Improve reorderable ufunc support and add NumPy reduce related tests

Improve reorderable ufunc support and add NumPy ufunc.reduce related tests.

(PR-#9295)

Add `axis` support to `np.take`

Add support for `axis` keyword in `np.take`.

(PR-#9297)

Allow caching of Numba functions within Zip files

This change enables Numba functions imported from a file within a Zip archive to be cached, by recognizing a Zip file and using a user-wide cache directory for the cache. Previously, Numba would fail.

For context, Zip archives are a supported-but-less-common way to distribute Python packages, and heavily used in PySpark.

(PR-#9630)

Improvements in how Pass Manager objects are created for optimizations

Move creation of `ModulePassManager` object to `_optimize_final_module` function, preventing the usage of the same pass manager object for compiling multiple Python functions. This would allow for better control while optimizing unrelated modules and possibly under different settings (degree of vectorization, optimization level, etc.).

(PR-#9670)

Fixed `typed.List __repr__()` to display ellipsis appropriately

`typed.List __repr__()` has been fixed to display the list elements without appending the ellipsis at the end, up until a maximum of 1000 elements. Previously, the list `repr` would append the ellipsis at the end of the list regardless of the number of elements in the list.

(PR-#9693)

Use of dead branch pruning improved

Dead-branch pruning use is improved to support cases when the predicate expression is dependent on a variable that later changes type.

(PR-#9711)

`find_topo_sort` reliabililty improvement

Improves the reliability of the `find_topo_sort` function for complex CFGs (typically through generated code) by replacing the recursive post order traversal with an iterative one. This removes a risk of hitting the Python recursion limit.

(PR-#9718)

NumPy Support

Added support for `np.setdiff1d()`, `np.setxor1d()`, and `np.in1d()` functions, as well as argument `assume_unique` in `np.intersect1d()`

Support is added for: `numpy.setdiff1d()`, `np.setxor1d()`, `np.in1d()`, and `np.isin()`; and the argument `assume_unique` in `np.intersect1d()`. For `np.in1d()`, and `np.isin()`, the keyword `kind` is *not* supported, and the behaviour reflects that of NumPy prior to version 1.24. This is equivalent to setting `kind="sort"` in NumPy 1.24 and later.

(PR-#9338)

Support for `np.trapezoid`

Add support for NumPy 2.0 new function `numpy.trapezoid`.

(PR-#9719)

Bug Fixes

`memcpy` static buffer content into newly allocated buffer

Fix a bug where the static buffer used to store typecode representation is not copied to the new allocated buffer as part of a `realloc` operation.

(PR-#9119)

Fix parfor hoisting

Traverse blocks in the right order so that getattrs will precede calls so that the object of the getattr can be marked as multiply defined.

(PR-#9397)

Fix ParallelAccelerator hoisting logic bug

A bug in the hoisting logic of the ParallelAccelerator is fixed. The bug caused invalid hoisting of operations that depended on non-hoistable operations, leading to incorrect execution. With this fix, the hoisting logic now correctly identifies and handles dependencies on non-hoistable operations, ensuring that operations are hoisted and executed correctly.

(PR-#9586)

Fix calls to `numpy.random` distributions with `size=()`

Calling any of the `numpy.random` distributions with `size=()` is now supported; previously it used to raise a `TypingError` while being supported by NumPy.

(PR-#9636)

Fix incorrect return type of `numpy.sum` on boolean arrays

Calling `numpy.sum` with `axis` parameter on boolean arrays incorrectly returns bool type, while it should return int type. Consequently, calling `numpy.count_nonzero` on boolean arrays also incorrectly returns bool type. This is now fixed.

(PR-#9705)

Fixed numerical error and infinite loop bug in `numpy.random.Generator.binomial`

A bug impacting the correctness of numerical results is fixed alongside an issue which led to executing an infinite loop under specific circumstances most easily triggered by the aforementioned correctness bug.

(PR-#9747)

Fix 0.60.0 objectmode fallback regression due to bug in label renaming

A regression in objectmode fallback introduced in Numba 0.60 is fixed. The issue relates to the "label renaming" code mutating the IR directly opposed to constructing new terminator nodes, the mutations would impact copies of the IR as present in objectmode fallback.

(PR-#9755)

Fix Python reference leaks in unboxing of `numpy.random.Generator` instances

Some Python reference leaks in the unboxing of `numpy.random.Generator` instances have been fixed. Note that it was actually the referenced `numpy.random.BitGenerator` that was leaking on unboxing, but it is rare to use these objects themselves as arguments.

(PR-#9756)

Fix excessive memory use/poor memory behaviour in the dispatcher for non-fingerprintable types

In the case of repeated dispatch on non-fingerprintable types, the dispatcher now uses memory in proportion to the number of unique types seen opposed to in proportion to the number of types in total.

(PR-#9757)

Fix miscompile in branch pruning of SSA form IR

A miscompile occurring when a binop expression with constant arguments is used as a predicate in SSA form IR is now fixed.

(PR-#9758)

Fix regression in type-inference for star-arg arguments

A regression, that occurred between versions 0.59.0 and 0.60.0, in the type-inference associated with star-arg arguments has been fixed. The cause of the regression was the code for star-args handling in type-inference not being updated following the switch to use new-style error handling by default.

(PR-#9799)

Make Numba internally compliant under "new_style" error handling.

Numba now uses `new_style` error handling by default with no alternative available. Numba's internal code is now compliant with this error handling style, this to continue to allow extension writers the ability to add further implementations of "overloads" without the compiler encountering "hard errors".

(PR-#9837)

Fix for Python 3.13.1 comprehension bytecode change

Python 3.13.1 introduces an extra `GET_ITER` bytecode in comprehension processing. This change breaks Numba's comprehension support. This patch adds logic to ignore the new `GET_ITER` bytecode to maintain compatibility.

(PR-#9848)

Changes

Add `NUMBA_JIT_COVERAGE` to control coverage support

The new `NUMBA_JIT_COVERAGE` environment variable enables or disables coverage support. Coverage is disabled by default.

(PR-#9887)

Removal of experimental RVSDG frontend

The experimental RVSDG frontend has been removed from the main Numba codebase. This strategic decision allows for more focused and independent development of the RVSDG frontend as a reusable component. Future development and updates will be available at https://github.com/numba/numba-rvsdg and other new repositories as they are developed.

(PR-#9738)

POWER Support Update

The Numba maintainers have not been actively testing or building packages for the POWER architecture for some time. The code will be retained to ensure compatibility with Linux distributions that may still support Power8, but POWER support is now downgraded to unofficial status.

(PR-#9763)

Disabling `sys.monitoring` support by default

The `sys.monitoring` support is disabled by default due to compatibility issues with native code. In Python 3.12, the implementation and documentation lacks clarity on native code support, which led to tools making incorrect assumptions about Python frames and code objects. While Python 3.13 improves this situation, many tools have not yet adapted to these changes. Consequently, tools may crash when monitoring Numba-compiled functions. To address this, Numba disables `sys.monitoring` by default. Users can opt-in by setting the environment variable `NUMBA_ENABLE_SYS_MONITORING`.

(PR-#9780)

Deprecations

Built-in CUDA target deprecation

The CUDA target built in to Numba (under `numba.cuda`) is deprecated in favour of further development in the NVIDIA `numba-cuda` package. Backward compatibility is maintained between `numba-cuda` and `numba.cuda`, and no user code changes are needed.

(PR-#9768)

Removal of `NUMBA_CAPTURED_ERRORS`

The `NUMBA_CAPTURED_ERRORS` environment variable and `CAPTURED_ERRORS` configuration variable have been removed, as per the deprecation schedule.

(PR-#9773)

Infrastructure Related Changes

Updated GHA versioning in towncrier script

Following recent updates in GitHub Actions, the version for the checkout action has been updated to v4 along with the version for setup-python GHA, which has been updated to v5.

(PR-#9743)

Pull-Requests:

- PR #9076: Add shape context to slicing errors (kklocker guilhermeleobas)
- PR #9077: Enable inlining of first-class function when it is statically known to be a dispatcher (sklam)
- PR #9119: *memcpy* static buffer content into newly allocated buffer (guilhermeleobas)
- PR #9295: Improve reorderable ufunc support (guilhermeleobas)
- PR #9297: Add axis support to np.take (guilhermeleobas)
- PR #9338: Add np.in1d, np.isin, np.setxor1d, np.setdiff1d, extend np.intersect1d. (synapticarbors jaredjeya)
- PR #9397: Reorder block traversal order for correct hoisting. (DrTodd13)
- PR #9495: Schedule guvectorize'd functions over dask.distributed (crusaderky)
- PR #9508: Add compile-time coverage for compiled code (sklam)
- PR #9543: Prevent setting an undeclared attribute in Flags. (sklam)
- PR #9575: initialize 0.61.0dev0 : bump llvmlite to next dev version (esc)
- PR #9583: Remove *resolve_argument_type()* from typing context (gmarkall)
- PR #9593: Explicitly state that *del* is unsupported (gmarkall)
- PR #9600: Update release checklist post 0.60.0rc1 (esc)
- PR #9613: Move a couple of CUDA-specific items into the CUDA target (gmarkall)
- PR #9614: Backport #9596 into main (gmarkall kc611)

- PR #9617: Cherry-Pick: Merge pull request #9568 from esc/fix_parfors_test_sigabrt (esc)
- PR #9619: remove rc1 suffix from checklist (esc)
- PR #9621: Misc/changelog 0.60.0 for main (esc)
- PR #9629: Add CUDA target implementation to sysinfo and module (gmarkall)
- PR #9630: Allow numba functions within zip files to be cached (max-sixty)
- PR #9631: Move Azure to use macos-12 (gmarkall)
- PR #9636: Fix #8975: TypingError raised when calling any of the np.random distributions with size being an empty tuple (NSchiffmacher)
- PR #9643: Fix pythonapi wrapper for some PyTuple API (sklam)
- PR #9662: Type system implementation #1: Added initial implementation for a new type system using redundancies. (kc611)
- PR #9663: Fixes for LLVM 15 (gmarkall)
- PR #9666: Trigger towncrier workflow when label changes (sklam)
- PR #9670: Move creation of mpm to optimize_final_module (yashssh)
- PR #9675: Fix compiler error on RTD (sklam)
- PR #9682: Python 3.13 support (sklam)
- PR #9683: Fix C99 *I* not working with NumPy 2.0.1 (sklam)
- PR #9686: Type system implementation #1: Added initial implementation for a new type system using redundancies. (kc611)
- PR #9691: Fix #9678. parfor issue with build_map (sklam)
- PR #9693: Fix #9677. Fixed list repr in ipython environments (kc611 alok-m)
- PR #9701: update flake8 version in pre-commit config (esc)
- PR #9705: Fix sum_expand return_type missing cast to integer for bool arrays (luyiming)
- PR #9709: activate compilers for linux-aarch64 (esc)
- PR #9711: Add dead-branch-prune pass after SSA pass (sklam)
- PR #9715: Replace uses of *pprint.pformat* for *_lazy_pformat* in logging (srilman)
- PR #9718: Replace find_topo_order with an iterative implementation (njriasan)
- PR #9719: add supported np.trapezoid (holymonson)
- PR #9726: Remove Python 3.9 support (kc611)
- PR #9727: Revert Junit XML PR that may be causing buildfarm issue related to multiprocessing.Pool error (sklam)
- PR #9738: Revert RVSDG frontend. (sklam)
- PR #9739: Update the minimum supported NumPy to 1.24 (kc611)
- PR #9741: Add Support for NumPy 2.1 (kc611)
- PR #9743: Fixed GHA versions in towncrier script (kc611)
- PR #9746: Move Azure to use macos-13 (gmarkall)
- PR #9747: Fix two bugs in Generator.binomial(). (stuartarchibald)

- PR #9755: Fix issue with IR mutation in label renaming. (stuartarchibald)
- PR #9756: Fix PyRef leaks in unboxing of np.random.Generator (stuartarchibald)
- PR #9757: Fix some memory leaks/poor memory behaviour (stuartarchibald)
- PR #9758: Fix miscompile in branch pruning of SSA form IR. (stuartarchibald)
- PR #9761: Add CI for py313 (sklam)
- PR #9763: Update docs regarding power8 support. (sklam)
- PR #9768: Deprecation of built-in CUDA target (gmarkall)
- PR #9772: Emit warnings when missing authors are dectected in *gitlog2changelog* (kc611)
- PR #9773: Remove old-style captured errors for 0.61 (gmarkall)
- PR #9774: Test on gpuCI with supported NumPy and Python versions (gmarkall)
- PR #9780: Default to turn off *sys.monitoring* (sklam)
- PR #9799: Fix regression in exception handling against 0.60. (stuartarchibald)
- PR #9821: Add debug print to debug test_monitoring_multiple_threads failing on win-02 (sklam)
- PR #9837: Replace "hard-errors" with NumbaErrors. (stuartarchibald lericson for #9816)
- PR #9887: Add env-var NUMBA_JIT_COVERAGE to disable coverage (sklam)
- PR #9848: Fix #9846. GET_ITER in comprehension changed to NOP. (sklam)

Authors:

- alok-m
- crusaderky
- DrTodd13
- esc
- gmarkall
- guilhermeleobas
- holymonson
- jaredjeya
- kc611
- kklocker
- luyiming
- max-sixty
- njriasan
- NSchiffmacher
- sklam
- srilman
- stuartarchibald
- synapticarbors

- yashssh
- lericson

9.1.2 Version 0.60.0 (13 June 2024)

Table of Contents

This is a major Numba release. Numba now has binary support for NumPy 2.0. Users should note that this does NOT yet include NEP 50 related type-level changes which are still in progress. This release does not guarantee execution level compatibility with NumPy 2.0 and hence users should expect some type and numerical deviations with respect to normal Python behavior while using Numba with NumPy 2.0.

Please find a summary of all noteworthy items below.

Highlights

NumPy 2.0 Binary Support

Added Binary Support for NumPy 2.0. However, this does not yet include NEP 50 related type-level changes which are still in progress.

Following is a summary of the user facing changes:

- The `ptp()` method previously available for arrays has been deprecated. Instead, it is recommended to use the `np.ptp(arr)` function.
- The data type `np.bool8` has been deprecated and replaced with `np.bool`.
- The `np.product` function is deprecated; users are advised to use `np.prod` instead.
- Starting from NumPy version 2.0, the `itemset()` method has been removed from the `ndarray` class. To achieve the same functionality, utilize the assignment operation `arr[index] = value`.
- Deprecated constants `np.PINF` and `np.NINF` should be replaced with `np.inf` for positive infinity and `-np.inf` for negative infinity, respectively.

(PR-#9466)

New Features

Enhance guvectorize support in JIT code

Generalized universal function support is extended, it is now possible to call a `@guvectorize` decorated function from within a JIT-compiled function. However, please note that broadcasting is not supported yet. Calling a guvectorize function in a scenario where broadcast is needed may result in incorrect behavior.

(PR-#8984)

Add experimental support for ufunc.at

Experimental support for `ufunc.at` is added.

(PR-#9239)

Add `float(<string literal>)` ctor

Support for `float(<string literal>)` is added.

(PR-#9378)

Add support for `math.log2`.

Support for `math.log2` is added.

(PR-#9416)

Add math.nextafter support for nopython mode.

Support `math.nextafter` in nopython mode.

(PR-#9438)

Add support for parfor binop reductions.

Previously, only operations with inplace operations like += could be used as reductions in *prange`s. Now, with this PR, binop reductions of the form `a = a binop b* can be used.

(PR-#9521)

Improvements

Expand `isinstance()` support for NumPy datetime types

Adds support of `numpy.datetime64` and `numpy.timedelta64` types in `isinstance()`.

(PR-#9455)

Python 3.12 `sys.monitoring` support is added to Numba's dispatcher.

Python 3.12 introduced a new module `sys.monitoring` that makes available an event driven monitoring API for use in tools that need to monitor execution e.g. debuggers or profilers. Numba's dispatcher class (the code that handles transfer of control between the Python interpreter and compiled code) has been updated to emit `sys.monitoring.events.PY_START` and `sys.monitoring.events.PY_RETURN` as appropriate. This allows tools that are watching for these events to identify when control has entered and returned from compiled code. As a result of this change, Numba compiled code is now identified by `cProfile` in the same way that it has been historically i.e. it will be present in performance profiles.

(PR-#9482)

NumPy Support

Added support for `np.size()`

Added `np.size()` support for NumPy, which was previously unsupported.

(PR-#9504)

CUDA API Changes

Support for compilation to LTO-IR

Support for compiling device functions to LTO-IR in the compilation API is added.

(PR-#9274)

Support math.log, math.log2 and math.log10 in CUDA

CUDA target now supports `np.log`, `np.log2` and `np.log10`.

(PR-#9417)

Bug Fixes

Fix parfor variable hoisting analysis.

If a variable is used to build a container (e.g., tuple, list, map, set) or is passed as an argument to a call then conservatively assume it could escape the current iteration of the parfor and so should not be hoisted.

(PR-#9532)

Deprecations

Deprecate *old_style* error-capturing

Per deprecation schedule, *old_style* error-capturing is deprecated and the *default* is now *new_style*.

(PR-#9549)

Expired Deprecations

Removal of `numba.core.retarget`

The experimental features implemented in `numba.core.retarget` have been removed. These features were primarily used in numba-dpex, but that project has replaced its use of `numba.core.retarget` with a preference for *target extension API*.

(PR-#9539)

Documentation Changes

`numba.cuda.gpus.current` documentation correction

`numba.cuda.gpus.current` was erroneously described as a function, is now described as an attribute.

(PR-#9394)

CUDA 12 conda installation documentation

Installation instructions have been added for CUDA 12 conda users.

(PR-#9487)

Pull-Requests:

- PR #8984: Support @gufunc inside @jit (guilhermeleobas)
- PR #9239: ufunc.at (guilhermeleobas)
- PR #9274: CUDA: Add support for compilation to LTO-IR (gmarkall)
- PR #9364: Release notes fixes for appropriate Towncrier header underlines (kc611)
- PR #9367: Document release notes generation (gmarkall)
- PR #9368: Added 0.59.0 release notes (kc611)

- PR #9369: Fix release notes link in bug report template (gmarkall)
- PR #9378: Add *float(<string literal>)* ctor (guilhermeleobas)
- PR #9394: fix *TypeError: '_DeviceContextManager' object is not callable* (i7878)
- PR #9411: Doc updates for 0.59.0 final. (stuartarchibald)
- PR #9416: Add math.log2 support (guilhermeleobas)
- PR #9417: Add np.log* bindings for CUDA (guilhermeleobas gmarkall)
- PR #9425: Post release for 0.59.0 (sklam)
- PR #9436: Add timing and junit xml output to testsuite (sklam)
- PR #9437: Remove dependencies between Numba's Cpython and NumPy module (kc611)
- PR #9438: Add math.nextafter support for nopython mode. (groutr)
- PR #9454: Don't attempt to register overloads that aren't for this target in *BaseContext* and related fixes (gmarkall)
- PR #9455: Support datetime types in *isinstance()* (sklam)
- PR #9456: Update release checklist (sklam)
- PR #9466: Numpy 2.0 binary support testing (kc611)
- PR #9468: adding git-copy.py script (esc)
- PR #9482: Add support for *sys.monitoring* events. (stuartarchibald)
- PR #9487: Add CUDA 12 conda installation docs (bdice gmarkall)
- PR #9488: Update overview.rst (jftsang)
- PR #9502: Post release task for 0.59.1 (sklam)
- PR #9504: added np.size() overload and added tests (shourya5)
- PR #9521: Support binop reduction. (DrTodd13)
- PR #9531: Module pass manager: Don't add passes for unsupported LLVM versions (gmarkall)
- PR #9532: Fix hoisting bug to exclude variables used in containers or calls. (DrTodd13)
- PR #9539: Revert PR #6870 *numba.core.retarget* (sklam)
- PR #9549: Make new_style the default error capturing mode (gmarkall sklam)
- PR #9558: Added 0.60.0 release notes (kc611)
- PR #9559: Update version support table 0.60 (esc)
- PR #9568: fix sigabrt in parfors tests (esc stuartarchibald)
- PR #9586: Hoisting logic needs to consider dependency on prior unhoistable variable (sklam)
- PR #9596: Added inline_closurecall as an import during registry loading (kc611)
- PR #9602: Fix numpy2.0 incompatbility issues (sklam)
- PR #9603: Disable AVX for nocona (sklam)

Authors:

- bdice
- DrTodd13
- esc
- gmarkall
- groutr
- guilhermeleobas
- i7878
- jftsang
- kc611
- shourya5
- sklam
- stuartarchibald

9.1.3 Version 0.59.1 (18 March 2024)

This is a bug-fix release to fix regressions in 0.59.0.

CUDA API Changes

Fixed caching of kernels that use target-specific overloads

Caching of kernels using target-specific overloads now works. This includes use of cooperative group sync, which is now implemented with a target-specific overload.

(PR-#9447)

Performance Improvements and Changes

Improvement to `np.searchsorted`

Fixed a performance regression introduced in Numba 0.59 which made `np.searchsorted` considerably slower.

(PR-#9448)

Bug Fixes

Fix issues with `np.searchsorted` not handling `np.datetime64`

This patch fixes two issues with `np.searchsorted`. First, a regression is fixed in the support of `np.datetime64`. Second, adopt `NAT`-aware comparisons to fix mishandling of `NAT` value.

(PR-#9445)

Allow use of Python 3.12 PEP-695 type parameter syntax

A patch is added to properly parse the PEP 695 syntax. While Numba does not yet take advantage of type parameters, it will no longer erroneously reject functions defined with the new Python 3.12 syntax.

(PR-#9459)

Pull-Requests:

- PR #9445: Fix #9427 np.searchsorted on datetime64 (sklam)
- PR #9447: Fix Issue #9432, caching of kernels using target-specific overloads (such as CG sync) (gmarkall sklam)
- PR #9448: Fix *np.searchsorted* regression (guilhermeleobas)
- PR #9449: Remove deprecated CondaEnvironment@1 (sklam)
- PR #9450: Fix gpuci versions (gmarkall)
- PR #9459: Support pep695 type param syntax (sklam)
- PR #9491: Fix non-deterministic bug caused by unstableness in SSA (sklam, loicdtx)

Authors:

- gmarkall
- guilhermeleobas
- sklam
- loicdtx

9.1.4 Version 0.59.0 (31 January 2024)

Table of Contents

This is a major Numba release. Numba now supports Python 3.12, please find a summary of all noteworthy items below.

Highlights

Python 3.12 Support

The standout feature of this release is the official support for Python 3.12 in Numba.

Please note that profiling support is temporarily disabled in this release (for Python 3.12) and several known issues have been identified during development. The Numba team is actively working on resolving them. Please refer to the respective issue pages (Numba #9289 and Numba #9291) for a list of ongoing issues and updates on progress.

(PR-#9246)

Move minimum supported Python version to 3.9.

Support for Python 3.8 has been removed, Numba's minimum supported Python version is now Python 3.9.

(PR-#9310)

New Features

Add support for ufunc attributes and reduce

Support for `ufunc.reduce` and most ufunc attributes is added.

(PR-#9123)

Add a config variable to enable / disable the llvmlite memory manager

A config variable to force enable or disable the llvmlite memory manager is added.

(PR-#9341)

Improvements

Add `TargetLibraryInfo` pass to CPU LLVM pipeline.

The `TargetLibraryInfo` pass makes sure that the optimisations that take place during call simplification are appropriate for the target, without this the target is assumed to be Linux and code will be optimised to produce e.g. math symbols that do not exit on Windows. Historically this issue has been avoided through the use of Numba internal libraries carrying wrapped symbols, but doing so potentially detriments performance. As a result of this change Numba internal libraries are smaller and there is an increase in optimisation opportunity in code using `exp2` and `log2` functions.

(PR-#9336)

Numba deprecation warning classes are now subclasses of builtin ones

To help users manage and suppress deprecation warnings from Numba, the `NumbaDeprecationWarning` and `NumbaPendingDeprecationWarning` classes are now subclasses of the builtin `DeprecationWarning` and `PendingDeprecationWarning` respectively. Therefore, warning filters on `DeprecationWarning` and `PendingDeprecationWarning` will apply to Numba deprecation warnings.

(PR-#9347)

NumPy Support

Added support for np.indices() function.

Support is added for `numpy.indices()`.

(PR-#9126)

Added support for `np.polynomial.polynomial.Polynomial` class.

Support is added for the *Polynomial* class from the package `np.polynomial.polynomial`.

(PR-#9140)

Added support for functions `np.polynomial.polyutils.as_series()`, as well as functions `polydiv()`, `polyint()`, `polyval()` from `np.polynomial.polynomial`.

Support is added for `np.polynomial.polyutils.as_series()`, `np.polynomial.polynomial.polydiv()`, `np.polynomial.polynomial.polyint()` (only the first 2 arguments), `np.polynomial.polynomial.polyval()` (only the first 2 arguments).

(PR-#9141)

Added support for np.unwrap() function.

Support is added for `numpy.unwrap()`. The `axis` argument is only supported when its value equals -1.

(PR-#9154)

Adds support for checking if dtypes are equal.

Support is added for checking if two dtype objects are equal, for example `assert X.dtype == np.dtype(np.float64)`.

(PR-#9249)

CUDA API Changes

Added support for compiling device functions with a C ABI

Support for compiling device functions with a C ABI through the *compile_ptx()* API, for easier interoperability with CUDA C/C++ and other languages.

(PR-#9223)

Make grid() and gridsize() use 64-bit integers

`cuda.grid()` and `cuda.gridsize()` now use 64-bit integers, so they no longer overflow when the grid contains more than `2 ** 31` threads.

(PR-#9235)

Prevent kernels being dropped by implementing the used list

Kernels are no longer dropped when being compiled and linked using nvJitLink, because they are added to the `@"llvm.used"` list.

(PR-#9267)

Support for Windows CUDA 12.0 toolkit conda packages

The library paths used in CUDA toolkit 12.0 conda packages on Windows are added to the search paths used when detecting CUDA libraries.

(PR-#9279)

Performance Improvements and Changes

Improvement to IR copying speed

Improvements were made to the deepcopying of `FunctionIR`. In one case, the `InlineInlineables` pass is 3x faster.

(PR-#9245)

Bug Fixes

Dynamically Allocate Parfor Schedules

This PR fixes an issue where a parallel region is executed in a loop many times. The previous code used an alloca to allocate the parfor schedule on the stack but if there are many such parfors in a loop then the stack will overflow. The new code does a pair of allocation/deallocation calls into the Numba parallel runtime before and after the parallel region respectively. At the moment, these calls redirect to malloc/free although other mechanisms such as pooling are possible and may be implemented later. This PR also adds a warning in cases where a prange loop is not converted to a parfor. This can happen if there is exceptional control flow in the loop. These are related in that the original issue had a prange loop that wasn't converted to a parfor and therefore all the parfors inside the body of the prange were running in parallel and adding to the stack each time.

(PR-#9048)

Support multiple outputs in a `@guvectorize` function

This PR fixes Numba #9058 where it is now possible to call a guvectorize with multiple outputs.

(PR-#9049)

Handling of `None` args fixed in `PythonAPI.call`.

Fixing segfault when `args=None` was passed to `PythonAPI.call`.

(PR-#9089)

Fix propagation of literal values in PHI nodes.

Fixed a bug in the literal propagation pass where a PHI node could be wrongly replaced by a constant.

(PR-#9144)

`numpy.digitize` implementation behaviour aligned with numpy

The implementation of `numpy.digitize` is updated to behave per numpy in a wider set of cases, including where the supplied bins are not in fact monotonic.

(PR-#9169)

`numpy.searchsorted` and `numpy.sort` behaviour updates

- `numpy.searchsorted` implementation updated to produce identical outputs to numpy for a wider set of use cases, including where the provided array *a* is in fact not properly sorted.
- `numpy.searchsorted` implementation bugfix for the case where side='right' and the provided array *a* contains NaN(s).
- `numpy.searchsorted` implementation extended to support complex inputs.
- `numpy.sort` (and `array.sort`) implementation extended to support sorting of complex data.

(PR-#9189)

Fix SSA to consider variables where use is not dominated by the definition

A SSA problem is fixed such that a conditionally defined variable will receive a phi node showing that there is a path where the variable is undefined. This affects extension code that relies on SSA behavior.

(PR-#9242)

Fixed `RecursionError` in `prange`

A problem with certain loop patterns using `prange` leading to `RecursionError` in the compiler is fixed. An example of such loop is shown below. The problem would cause the compiler to fall into an infinite recursive cycle trying to determine the definition of `var1` and `var2`. The pattern involves definitions of variables within an if-else tree and not all branches are defining the variables.

```
for i in prange(N):
    for j in inner:
        if cond1:
            var1 = ...
        elif cond2:
            var1, var2 = ...

        elif cond3:
            pass

        if cond4:
            use(var1)
            use(var2)
```

(PR-#9244)

Support negative axis in ufunc.reduce

Fixed a bug in ufunc.reduce to correctly handle negative axis values.

(PR-#9296)

Fix issue with parfor reductions and Python 3.12.

The parfor reduction code has certain expectations on the order of statements that it discovers, these are based on the code that previous versions of Numba generated. With Python 3.12, one assignment that used to follow the reduction operator statement, such as a binop, is now moved to its own basic block. This change reorders the set of discovered reduction nodes so that this assignment is right after the reduction operator as it was in previous Numba versions. This only affects internal parfor reduction code and doesn't actually change the Numba IR.

(PR-#9334)

Changes

Make test listing not invoke CPU compilation.

Numba's test listing command `python -m numba.runtests -l` has historically triggered CPU target compilation due to the way in which certain test functions were declared within the test suite. It has now been made such that the CPU target compiler is not invoked on test listing and a test is added to ensure that it remains the case.

(PR-#9309)

Semantic differences due to Python 3.12 variable shadowing in comprehensions

Python 3.12 introduced a new bytecode `LOAD_FAST_AND_CLEAR` that is only used in comprehensions. It has dynamic semantics that Numba cannot model.

For example,

```
def foo():
    if False:
        x = 1
    [x for x in (1,)]
    return x  # This return uses undefined variable
```

The variable *x* is undefined at the return statement. Instead of raising an `UnboundLocalError`, Numba will raise a `TypingError` at compile time if an undefined variable is used.

However, Numba cannot always detect undefined variables.

For example,

```
def foo(a):
    [x for x in (0,)]
    if a:
        x = 3 + a
    x += 10
    return x
```

Calling `foo(0)` returns `10` instead of raising `UnboundLocalError`. This is because Numba does not track variable liveness at runtime. The return value is `0 + 10` since Numba zero-initializes undefined variables.

(PR-#9315)

Refactor and remove legacy APIs/testing internals.

A number of internally used functions have been removed to aid with general maintenance by reducing the number of ways in which it is possible to invoke compilation, specifically:

- `numba.core.compiler.compile_isolated` is removed.
- `numba.tests.support.TestCase::run_nullary_func` is removed.
- `numba.tests.support.CompilationCache` is removed.

Additionally, the concept of "nested context" is removed from `numba.core.registry.CPUTarget` along with the implementation details. Maintainers of target extensions (those using the API in `numba.core.target_extension` to extend Numba support to custom/synthetic hardware) should note that the same can be deleted from target extension implementations of `numba.core.descriptor.TargetDescriptor` if it is present. i.e. the `nested_context` method and associated implementation details can just be removed from the custom target's `TargetDescriptor`.

Further, a bug was discovered, during the refactoring, in the typing of record arrays. It materialised that two record types that only differed in their mutability could alias, this has now been fixed.

(PR-#9330)

Deprecations

Explicitly setting `NUMBA_CAPTURED_ERRORS=old_style` will raise deprecation warnings

As per deprecation schedule of old-style error-capturing, explicitly setting `NUMBA_CAPTURED_ERRORS=old_style` will raise deprecation warnings. This release is the last to use "old_style" as the default. Details are documented at https://numba.readthedocs.io/en/0.58.1/reference/deprecation.html#deprecation-of-old-style-numba-captured-errors

(PR-#9346)

Expired Deprecations

Object mode *fall-back* support has been removed.

As per the deprecation schedule for Numba 0.59.0, support for "object mode fall-back" is removed from all Numba `jit`-family decorators. Further, the default for the `nopython` key-word argument has been changed to `True`, this means that all Numba `jit`-family decorated functions will now compile in `nopython` mode by default.

(PR-#9352)

Removal of deprecated API `@numba.generated_jit`.

As per the deprecation schedule for 0.59.0, support for `@numba.generated_jit` has been removed. Use of `@numba.extending.overload` and the high-level extension API is recommended as a replacement.

(PR-#9353)

Infrastructure Related Changes

Add validation capability for user generated towncrier `.rst` files.

Added a validation script for user generated towncrier `.rst` files. The script will run as a part of towncrier Github workflow automatically on every PR.

(PR-#9335)

Pull-Requests:

- PR #8990: Removed extra block copying in InlineWorker (kc611)
- PR #9048: Dynamically allocate parfor schedule. (DrTodd13)
- PR #9058: Fix gufunc with multiple outputs (guilhermeleobas)
- PR #9089: Fix segfault on passing *None* for args in PythonAPI.call (hellozee)
- PR #9101: Add misc script to find missing towncrier news files (sklam)
- PR #9123: Implement most ufunc attributes and ufunc.reduce (guilhermeleobas)
- PR #9126: Add support for np.indices() (KrisMinchev)
- PR #9140: Add support for Polynomial class (KrisMinchev)
- PR #9141: Add support for *as_series()* from *np.polynomial.polyutils* and *polydiv()*, *polyint()*, *polyval()* from *np.polynomial.polynomial* (KrisMinchev)

- PR #9142: Removed out of date comment handled by PR#8338 (njriasan)
- PR #9144: Fix error when literal is wrongly propagated in a PHI node (guilhermeleobas)
- PR #9148: bump llvmdev dependency to 0.42.0dev for next development cycle (esc)
- PR #9149: update release checklist post 0.58.0rc1 (esc)
- PR #9154: Add support for np.unwrap() (KrisMinchev)
- PR #9155: Remove unused test.cmd (sklam)
- PR #9168: fix the *get_template_info* method in *overload_method* template (dlee992 sklam)
- PR #9169: Update *np.digitize* handling of np.nan bin edge(s) (rjenc29)
- PR #9170: Fix an inappropriate test expression to remove a logical short circuit (munahaf)
- PR #9171: Fix the implementation of a special method (munahaf)
- PR #9189: Align *searchsorted* behaviour with numpy (rjenc29)
- PR #9191: Add a Numba power-on-self-test script and use in CI. (stuartarchibald)
- PR #9205: release notes and version support updates from release0.58 branch (esc)
- PR #9223: CUDA: Add support for compiling device functions with C ABI (gmarkall)
- PR #9235: CUDA: Make *grid()* and *gridsize()* use 64-bit integers (gmarkall)
- PR #9236: Fixes numba/numba#9234 (SridharCR)
- PR #9244: Fix Recursion error in parfor lookup (sklam)
- PR #9245: Fix slow InlineInlineable (sklam)
- PR #9246: Support for Python 3.12 (stuartarchibald kc611 esc)
- PR #9249: add support for checking dtypes equal (saulshanabrook)
- PR #9255: Fix SSA to consider variables whose use is not dominated by the definition (sklam)
- PR #9258: [docs] Typo in overloading-guide.rst (kinow)
- PR #9267: CUDA: Fix dropping of kernels by nvjitlink, by implementing the used list (gmarkall)
- PR #9279: CUDA: Add support for CUDA 12.0 Windows conda packages (gmarkall)
- PR #9292: CUDA: Switch cooperative groups to use overloads (gmarkall)
- PR #9296: Fix bug when axis is negative and check when axis is invalid (guilhermeleobas)
- PR #9301: Release Notes 0.58.1 for main (esc)
- PR #9302: add missing backtick to example git tag command (esc)
- PR #9303: Add category to warning (kkokkoros)
- PR #9307: Upgrade to cloudpickle 3.0.0 (sklam)
- PR #9308: Fix typo in azure ci script (sklam)
- PR #9309: Continue #9044, prevent compilation on the CPU target when listing tests. (stuartarchibald apmasell)
- PR #9310: Remove Python 3.8 support. (stuartarchibald)
- PR #9315: Fix support for LOAD_FAST_AND_CLEAR (sklam)
- PR #9318: GPU CI: Test with Python 3.9-3.12 (gmarkall)
- PR #9325: Fix GPUCI (gmarkall)

- PR #9326: Add docs for LOAD_FAST_AND_CLEAR changes (sklam)
- PR #9330: Refactor and remove legacy APIs/testing internals. (stuartarchibald)
- PR #9331: Fix Syntax and Deprecation Warnings from 3.12. (stuartarchibald)
- PR #9334: Fix parfor reduction issue with Python 3.12. (DrTodd13)
- PR #9335: Add validation capability for user generated towncrier .rst files. (kc611)
- PR #9336: Add TargetLibraryInfo pass to CPU LLVM pipeline. (stuartarchibald)
- PR #9337: Revert #8583 which skip tests due to M1 RuntimeDyLd Assertion error (sklam)
- PR #9341: Add configuration variable to force llvmlite memory manager on / off (gmarkall)
- PR #9342: Fix flake8 checks for v6.1.0 (gmarkall)
- PR #9346: Setting `NUMBA_CAPTURED_ERRORS=old_style` will now raise warnings. (sklam)
- PR #9347: Make Numba's deprecation warnings subclasses of the builtin ones. (sklam)
- PR #9351: Made Python 3.12 support rst note more verbose (kc611)
- PR #9352: Removing object mode fallback from *@jit*. (stuartarchibald)
- PR #9353: Remove *numba.generated_jit* (stuartarchibald)
- PR #9356: Refactor print tests to avoid NRT leak issue. (stuartarchibald)
- PR #9357: Fix a typo in *_set_init_process_lock* warning. (stuartarchibald)
- PR #9358: Remove note about OpenMP restriction in wheels. (stuartarchibald)
- PR #9359: Fix test_jit_module test against objmode fallback. (stuartarchibald)
- PR #9360: AzureCI changes. RVSDG test config should still test its assigned test slice (sklam)
- PR #9362: Fix `np.MachAr` warning matching in test. (sklam)
- PR #9402: Doc updates for 0.59 final (sklam stuartarchibald)
- PR #9403: Fix test isolation for stateful configurations in the testsuite (sklam stuartarchibald)
- PR #9404: Fix skipped test stderr change for Python 3.12.1. (stuartarchibald)
- PR #9407: Fix incorrect cycle detection (sklam)

Authors:

- apmasell
- dlee992
- DrTodd13
- esc
- gmarkall
- guilhermeleobas
- hellozee
- kc611
- kinow
- kkokkoros

- KrisMinchev
- munahaf
- njriasan
- rjenc29
- saulshanabrook
- sklam
- SridharCR
- stuartarchibald

9.1.5 Version 0.58.1 (17 October 2023)

This is a maintenance release that adds support for NumPy 1.26 and fixes a bug.

NumPy Support

Support NumPy 1.26

Support for NumPy 1.26 is added.

(PR-#9227)

Bug Fixes

Fixed handling of float default arguments in inline closures

Float default arguments in inline closures would produce incorrect results since updates for Python 3.11 - these are now handled correctly again.

(PR-#9222)

Pull-Requests

- PR #9220: Support passing arbitrary flags to NVVM (gmarkall)
- PR #9227: Support NumPy 1.26 (PR aimed at review / merge) (Tialo gmarkall)
- PR #9228: Fix #9222 - Don't replace . with _ in func arg names in inline closures (gmarkall)

Authors

- gmarkall
- Tialo

9.1.6 Version 0.58.0 (20 September 2023)

Table of Contents

This is a major Numba release. Numba now uses towncrier to create the release notes, so please find a summary of all noteworthy items below.

Highlights

Added towncrier

This PR adds towncrier as a GitHub workflow for checking release notes. From this PR onwards every PR made in Numba will require a appropriate release note associated with it. The reviewer may decide to skip adding release notes in smaller PRs with minimal impact by addition of a `skip_release_notes` label to the PR.

(PR-#8792)

The minimum supported NumPy version is 1.22.

Following NEP-0029, the minimum supported NumPy version is now 1.22.

(PR-#9093)

Add support for NumPy 1.25

Extend Numba to support new and changed features released in NumPy 1.25.

(PR-#9011)

Remove NVVM 3.4 and CTK 11.0 / 11.1 support

Support for CUDA toolkits < 11.2 is removed.

(PR-#9040)

Removal of Windows 32-bit Support

This release onwards, Numba has discontinued support for Windows 32-bit operating systems.

(PR-#9083)

The minimum llvmlite version is now 0.41.0.

The minimum required version of llvmlite is now version 0.41.0.

(PR-#8916)

Added RVSDG-frontend

This PR is a preliminary work on adding a RVSDG-frontend for processing bytecode. RVSDG (Regionalized Value-State Dependence Graph) allows us to have a dataflow-centric view instead of a traditional SSA-CFG view. This allows us to simplify the compiler in the future.

(PR-#9012)

New Features

`numba.experimental.jitclass` gains support for `__*matmul__` methods.

`numba.experimental.jitclass` now has support for the following methods:

- `__matmul__`
- `__imatmul__`
- `__rmatmul__`

(PR-#8892)

`numba.experimental.jitclass` gains support for reflected -dunder- methods.

`numba.experimental.jitclass` now has support for the following methods:

- `__radd__`
- `__rand_`
- `__rfloordiv__`
- `__rlshift__`
- `__ror_`
- `__rmod_`

- `__rmul_`
- `__rpow_`
- `__rrshift_`
- `__rsub_`
- `__rtruediv_`
- `__rxor_`

(PR-#8906)

Add support for value `max` to `NUMBA_OPT`.

The optimisation level that Numba applies when compiling can be set through the environment variable `NUMBA_OPT`. This has historically been a value between 0 and 3 (inclusive). Support for the value `max` has now been added, this is a Numba-specific optimisation level which indicates that the user would like Numba to try running the most optimisation possible, potentially trading a longer compilation time for better run-time performance. In practice, use of the `max` level of optimisation may or may not benefit the run-time or compile-time performance of user code, but it has been added to present an easy to access option for users to try if they so wish.

(PR-#9094)

Improvements

Updates to `numba.core.pythonapi`.

Support for Python C-API functions `PyBytes_AsString` and `PyBytes_AsStringAndSize` is added to `numba.core.pythonapi.PythonAPI` as `bytes_as_string` and `bytes_as_string_and_size` methods respectively.

(PR-#8462)

Support for `isinstance` is now non-experimental.

Support for the `isinstance` built-in function has moved from being considered an experimental feature to a fully supported feature.

(PR-#8911)

NumPy Support

All modes are supported in `numpy.correlate` and `numpy.convolve`.

All values for the `mode` argument to `numpy.correlate` and `numpy.convolve` are now supported.

(PR-#7543)

`@vectorize` accommodates arguments implementing `__array_ufunc__`.

Universal functions (`ufunc`s) created with `numba.vectorize` will now respect arguments implementing `__array_ufunc__` (NEP-13) to allow pre- and post-processing of arguments and return values when the ufunc is called from the interpreter.

(PR-#8995)

Added support for `np.geomspace` function.

This PR improves on #4074 by adding support for `np.geomspace`. The current implementation only supports scalar `start` and `stop` parameters.

(PR-#9068)

Added support for `np.vsplit`, `np.hsplit`, `np.dsplit`.

This PR improves on #4074 by adding support for `np.vsplit`, `np.hsplit`, and `np.dsplit`.

(PR-#9082)

Added support for `np.row_stack` function.

Support is added for `numpy.row_stack`.

(PR-#9085)

Added support for functions `np.polynomial.polyutils.trimseq`, as well as functions `polyadd`, `polysub`, `polymul` from `np.polynomial.polynomial`.

Support is added for `np.polynomial.polyutils.trimseq`, `np.polynomial.polynomial.polyadd`, `np.polynomial.polynomial.polysub`, `np.polynomial.polynomial.polymul`.

(PR-#9087)

Added support for `np.diagflat` function.

Support is added for `numpy.diagflat`.

(PR-#9113)

Added support for `np.resize` function.

Support is added for `numpy.resize`.

(PR-#9118)

Add np.trim_zeros

Support for `np.trim_zeros()` is added.

(PR-#9074)

CUDA Changes

Bitwise operation `ufunc` support for the CUDA target.

Support is added for some `ufunc`s associated with bitwise operation on the CUDA target. Namely:

- `numpy.bitwise_and`
- `numpy.bitwise_or`
- `numpy.bitwise_not`
- `numpy.bitwise_xor`
- `numpy.invert`
- `numpy.left_shift`
- `numpy.right_shift`

(PR-#8974)

Add support for the latest CUDA driver codes.

Support is added for the latest set of CUDA driver codes.

(PR-#8988)

Add NumPy comparison ufunc in CUDA

this PR adds support for comparison ufuncs for the CUDA target (eg. `numpy.greater`, `numpy.greater_equal`, `numpy.less_equal`, etc.).

(PR-#9007)

Report absolute path of `libcuda.so` on Linux

`numba -s` now reports the absolute path to `libcuda.so` on Linux, to aid troubleshooting driver issues, particularly on WSL2 where a Linux driver can incorrectly be installed in the environment.

(PR-#9034)

Add debuginfo support to `nvdisasm` output.

Support is added for debuginfo (source line and inlining information) in functions that make calls through `nvdisasm`. For example the CUDA dispatcher `.inspect_sass` method output is now augmented with this information.

(PR-#9035)

Add CUDA SASS CFG Support

This PR adds support for getting the SASS CFG in dot language format. It adds an `inspect_sass_cfg()` method to CUDADispatcher and the `-cfg` flag to the nvdisasm command line tool.

(PR-#9051)

Support NVRTC using the ctypes binding

NVRTC can now be used when the ctypes binding is in use, enabling float16, and linking CUDA C / C++ sources without needing the NVIDIA CUDA Python bindings.

(PR-#9086)

Fix CUDA atomics tests with toolkit 12.2

CUDA 12.2 generates slightly different PTX for some atomics, so the relevant tests are updated to look for the correct instructions when 12.2 is used.

(PR-#9088)

Bug Fixes

Handling of different sized unsigned integer indexes are fixed in `numba.typed.List`.

An issue with the order of truncation/extension and casting of unsigned integer indexes in `numba.typed.List` has been fixed.

(PR-#7262)

Prevent invalid fusion

This PR fixes an issue in which an array first read in a parfor and later written in the same parfor would only be classified as used in the parfor. When a subsequent parfor also used the same array then fusion of the parfors was happening which should have been forbidden given that that the first parfor was also writing to the array. This PR treats such arrays in a parfor as being both used and defined so that fusion will be prevented.

(PR-#7582)

The `numpy.allclose` implementation now correctly handles default arguments.

The implementation of `numpy.allclose` is corrected to use `TypingError` to report typing errors.

(PR-#8885)

Add type validation to `numpy.isclose`.

Type validation is added to the implementation of `numpy.isclose`.

(PR-#8944)

Fix support for overloading dispatcher with non-compatible first-class functions

Fixes an error caused by not handling compilation error during casting of `Dispatcher` objects into first-class functions. With the fix, users can now overload a dispatcher with non-compatible first-class functions. Refer to https://github.com/numba/numba/issues/9071 for details.

(PR-#9072)

Support `dtype` keyword argument in `numpy.arange` with `parallel=True`

Fixes parfors transformation to support the use of `dtype` keyword argument in `numpy.arange(..., dtype=dtype)`.

(PR-#9095)

Fix all `@overload`s to use parameter names that match public APIs.

Some of the Numba `@overload`s for functions in NumPy and Python's built-ins were written using parameter names that did not match those used in API they were overloading. The result of this being that calling a function with such a mismatch using the parameter names as key-word arguments at the call site would result in a compilation error. This has now been universally fixed throughout the code base and a unit test is running with a best-effort attempt to prevent reintroduction of similar mistakes in the future. Fixed functions include:

From Python built-ins:

- `complex`

From the Python `random` module:

- `random.seed`
- `random.gauss`
- `random.normalvariate`
- `random.randrange`
- `random.randint`
- `random.uniform`
- `random.shuffle`

From the `numpy` module:

- `numpy.argmin`

- numpy.argmax
- numpy.array_equal
- numpy.average
- numpy.count_nonzero
- numpy.flip
- numpy.fliplr
- numpy.flipud
- numpy.iinfo
- numpy.isscalar
- numpy.imag
- numpy.real
- numpy.reshape
- numpy.rot90
- numpy.swapaxes
- numpy.union1d
- numpy.unique

From the numpy.linalg module:

- numpy.linalg.norm
- numpy.linalg.cond
- numpy.linalg.matrix_rank

From the numpy.random module:

- numpy.random.beta
- numpy.random.chisquare
- numpy.random.f
- numpy.random.gamma
- numpy.random.hypergeometric
- numpy.random.lognormal
- numpy.random.pareto
- numpy.random.randint
- numpy.random.random_sample
- numpy.random.ranf
- numpy.random.rayleigh
- numpy.random.sample
- numpy.random.shuffle
- numpy.random.standard_gamma
- numpy.random.triangular

- `numpy.random.weibull`

(PR-#9099)

Changes

Support for `@numba.extending.intrinsic(prefer_literal=True)`

In the high level extension API, the `prefer_literal` option is added to the `numba.extending.intrinsic` decorator to prioritize the use of literal types when available. This has the same behavior as in the `prefer_literal` option in the `numba.extending.overload` decorator.

(PR-#6647)

Deprecations

Deprecation of old-style `NUMBA_CAPTURED_ERRORS`

Added deprecation schedule of `NUMBA_CAPTURED_ERRORS=old_style`. `NUMBA_CAPTURED_ERRORS=new_style` will become the default in future releases. Details are documented at https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-of-old-style-numba-captured-errors

(PR-#9090)

Pull-Requests

- PR #6647: Support prefer_literal option for intrinsic decorator (ashutoshvarma sklam)
- PR #7262: fix order of handling and casting (esc)
- PR #7543: Support for all modes in np.correlate and np.convolve (jeertmans)
- PR #7582: Use get_parfor_writes to detect illegal array access that prevents fusion. (DrTodd13)
- PR #8371: Added binomial distribution (esc kc611)
- PR #8462: Add PyBytes_AsString and PyBytes_AsStringAndSize (ianna)
- PR #8633: DOC: Convert vectorize and guvectorize examples to doctests (Matt711)
- PR #8730: Update dev-docs (sgbaird esc)
- PR #8792: Added towncrier as a github workflow (kc611)
- PR #8854: Updated mk_alloc to support Numba-Dpex compute follows data. (mingjie-intel)
- PR #8861: CUDA: Don't add device kwarg for jit registry (gmarkall)
- PR #8871: Don't return the function in CallConv.decorate_function() (gmarkall)
- PR #8885: Fix np.allclose not handling default args (guilhermeleobas)
- PR #8892: Add support for __*matmul__ methods in jitclass (louisamand)
- PR #8895: CUDA: Enable caching functions that use CG (gmarkall)
- PR #8906: Add support for reflected dunder methods in jitclass (louisamand)
- PR #8911: Remove isinstance experimental feature warning (guilhermeleobas)
- PR #8916: Bump llvmlite requirement to 0.41.0dev0 (sklam)

- PR #8925: Update release checklist template (sklam)
- PR #8937: Remove old Website development documentation (esc gmarkall)
- PR #8944: Add exceptions to np.isclose (guilhermeleobas)
- PR #8974: CUDA: Add binary ufunc support (Matt711)
- PR #8976: Fix index URL for ptxcompiler/cubinlinker packages. (bdice)
- PR #8978: Import MVC packages when using MVCLinker. (bdice)
- PR #8983: Fix typo in deprecation.rst (dsgibbons)
- PR #8988: support for latest CUDA driver codes #8363 (s1Sharp)
- PR #8995: Allow libraries that implement __array_ufunc__ to override DUFunc.__c… (jpivarski)
- PR #9007: CUDA: Add comparison ufunc support (Matt711)
- PR #9012: RVSDG-frontend (sklam)
- PR #9021: update the release checklist following 0.57.1rc1 (esc)
- PR #9022: fix: update the C++ ABI repo reference (emmanuel-ferdman)
- PR #9028: Replace use of imp module removed in 3.12 (hauntsaninja)
- PR #9034: CUDA libs test: Report the absolute path of the loaded libcuda.so on Linux, + other improvements (gmarkall)
- PR #9035: CUDA: Allow for debuginfo in nvdisasm output (Matt711)
- PR #9037: Recognize additional functions as being pure or not having side effects. (DrTodd13)
- PR #9039: Correct git clone link in installation instructions. (ellifteria)
- PR #9040: Remove NVVM 3.4 and CTK 11.0 / 11.1 support (gmarkall)
- PR #9046: copy the change log changes for 0.57.1 to main (esc)
- PR #9050: Update CODEOWNERS (sklam)
- PR #9051: Add CUDA CFG support (Matt711)
- PR #9056: adding weekly meeting notes script (esc)
- PR #9068: Adding np.geomspace (KrisMinchev)
- PR #9069: Fix towncrier error due to importlib_resources upgrade (sklam)
- PR #9072: Fix support for overloading dispatcher with non-compatible first-class functions (gmarkall sklam)
- PR #9074: Add np.trim_zeros (sungraek guilhermeleobas)
- PR #9082: Add np.vsplit, np.hsplit, and np.dsplit (KrisMinchev)
- PR #9083: Removed windows 32 references from code and documentation (kc611)
- PR #9085: Add tests for np.row_stack (KrisMinchev)
- PR #9086: Support NVRTC using ctypes binding (testhound gmarkall)
- PR #9087: Add trimseq from np.polynomial.polyutils and polyadd, polysub, polymul from np.polynomial.polynomial (KrisMinchev)
- PR #9088: Fix: Issue 9063 - CUDA atomics tests failing with CUDA 12.2 (gmarkall)
- PR #9090: Add deprecation notice for old_style error capturing. (esc sklam)
- PR #9094: Add support for a ‘max’ level to NUMBA_OPT environment variable. (stuartarchibald)

- PR #9095: Support dtype keyword in arange_parallel_impl (DrTodd13 sklam)
- PR #9105: NumPy 1.25 support (PR #9011) continued (gmarkall apmasell)
- PR #9111: Fixes ReST syntax error in PR#9099 (stuartarchibald gmarkall sklam apmasell)
- PR #9112: Fixups for PR#9100 (stuartarchibald sklam)
- PR #9113: Add support for np.diagflat (KrisMinchev)
- PR #9114: update np min to 122 (stuartarchibald esc)
- PR #9117: Fixed towncrier template rendering (kc611)
- PR #9118: Add support for np.resize() (KrisMinchev)
- PR #9120: Update conda-recipe for numba-rvsdg (sklam)
- PR #9127: Fix accidental cffi test deps, refactor cffi skipping (gmarkall)
- PR #9128: Merge rvsdg_frontend branch to main (esc sklam)
- PR #9152: Fix old_style error capturing deprecation warnings (sklam)
- PR #9159: Fix uncaught exception in find_file() (gmarkall)
- PR #9173: Towncrier fixups (Continue #9158 and retarget to main branch) (sklam)
- PR #9181: Remove extra decrefs in RNG (sklam)
- PR #9190: Fix issue with incompatible multiprocessing context in test. (stuartarchibald)

Authors

- apmasell
- ashutoshvarma
- bdice
- DrTodd13
- dsgibbons
- ellifteria
- emmanuel-ferdman
- esc
- gmarkall
- guilhermeleobas
- hauntsaninja
- ianna
- jeertmans
- jpivarski
- jtilly
- kc611
- KrisMinchev
- louisamand

- Matt711
- mingjie-intel
- s1Sharp
- sgbaird
- sklam
- stuartarchibald
- sungraek
- testhound

9.2 Non-Towncrier generated notes:

9.2.1 Version 0.57.1 (21 June, 2023)

Pull-Requests:

- PR #8964: fix missing nopython keyword in cuda random module (esc)
- PR #8965: fix return dtype for np.angle (guilhermeleobas esc)
- PR #8982: Don't do the parfor diagnostics pass for the parfor gufunc. (DrTodd13)
- PR #8996: adding a test for 8940 (esc)
- PR #8958: resurrect the import, this time in the registry initialization (esc)
- PR #8947: Introduce internal _isinstance_no_warn (guilhermeleobas esc)
- PR #8998: Fix 8939 (second attempt) (esc)
- PR #8978: Import MVC packages when using MVCLinker. (bdice)
- PR #8895: CUDA: Enable caching functions that use CG (gmarkall)
- PR #8976: Fix index URL for ptxcompiler/cubinlinker packages. (bdice)
- PR #9004: Skip MVC test when libraries unavailable (gmarkall esc)
- PR #9006: link to version support table instead of using explicit versions (esc)
- PR #9005: Fix: Issue #8923 - avoid spurious device-to-host transfers in CUDA ufuncs (gmarkall)

Authors:

- bdice
- DrTodd13
- esc
- gmarkall

9.2.2 Version 0.57.0 (1 May, 2023)

This release continues to add new features, bug fixes and stability improvements to Numba. Please note that this release contains a significant number of both deprecation and pending-deprecation notices with view of making it easier to develop new technology for Numba in the future. Also note that this will be the last release to support Windows 32-bit packages produced by the Numba team.

Highlights of core dependency upgrades:

- Support for Python 3.11 (minimum is moved to 3.8)
- Support for NumPy 1.24 (minimum is moved to 1.21)

Python language support enhancements:

- Exception classes now support arguments that are not compile time constant.
- The built-in functions `hasattr` and `getattr` are supported for compile time constant attributes.
- The built-in functions `str` and `repr` are now implemented similarly to their Python implementations. Custom `__str__` and `__repr__` functions can be associated with types and work as expected.
- Numba's unicode functionality in `str.startswith` now supports kwargs `start` and `end`.
- `min` and `max` now support boolean types.
- Support is added for the `dict(iterable)` constructor.

NumPy features/enhancements:

- The largest set of new features is within the `numpy.random.Generator` support, the vast majority of commonly used distributions are now supported. Namely:
  - `Generator.beta`
  - `Generator.chisquare`
  - `Generator.exponential`
  - `Generator.f`
  - `Generator.gamma`
  - `Generator.geometric`
  - `Generator.integers`
  - `Generator.laplace`
  - `Generator.logistic`
  - `Generator.lognormal`
  - `Generator.logseries`
  - `Generator.negative_binomial`
  - `Generator.noncentral_chisquare`
  - `Generator.noncentral_f`
  - `Generator.normal`
  - `Generator.pareto`
  - `Generator.permutation`
  - `Generator.poisson`

  - `Generator.power`
  - `Generator.random`
  - `Generator.rayleigh`
  - `Generator.shuffle`
  - `Generator.standard_cauchy`
  - `Generator.standard_exponential`
  - `Generator.standard_gamma`
  - `Generator.standard_normal`
  - `Generator.standard_t`
  - `Generator.triangular`
  - `Generator.uniform`
  - `Generator.wald`
  - `Generator.weibull`
  - `Generator.zipf`
- The `nbytes` property on NumPy `ndarray` types is implemented.
- Nesting of nested-array types is now supported.
- `datetime` and `timedelta` types can be cast to `int`.
- `F`-order iteration is supported in `ufunc` generation for increased performance when using combinations of predominantly `F`-order arrays.
- The following functions are also now supported:
  - `np.argpartition`
  - `np.isclose`
  - `np.nan_to_num`
  - `np.new_axis`
  - `np.union1d`

Highlights of core changes:

- A large amount of refactoring has taken place to convert many of Numba's internal implementations, of both Python and NumPy functions, from the low-level extension API to the high-level extension API (`numba.extending`).
- The `__repr__` method is supported for Numba types.
- The default `target` for applicable functions in the extension API (`numba.extending`) is now `"generic"`. This means that `@overload*` and `@intrinsic` functions will by default be accepted by both the CPU and CUDA targets.
- The use of `__getitem__` on Numba types is now supported in compiled code. i.e. `types.float64[:, ::1]` is now compilable.

Performance:

- The performance of `str.find()` and `str.rfind()` has been improved.
- Unicode support for `__getitem__` now avoids allocation and returns a view.

- The `numba.typed.Dict` dictionary now accepts an `n_keys` option to enable allocating the dictionary instance to a predetermined initial size (useful to avoid resizes!).
- The Numba Run-time (NRT) has been improved in terms of performance and safety:
  - The NRT internal statistics counters are now off by default (removes atomic lock contentions).
  - Debug cache line filling is off by default.
  - The NRT is only compiled once a compilation starts opposed to at function decoration time, this improves import speed.
  - The NRT allocation calls are all made through a "checked" layer by default.

CUDA:

- New NVIDIA hardware and software compatibility / support:
  - Toolkits: CUDA 11.8 and 12, with Minor Version Compatibility for 11.x.
  - Packaging: NVIDIA-packaged CUDA toolkit conda packages.
  - Hardware: Hopper, Ada Lovelace, and AGX Orin.
- `float16` support:
  - Arithmetic operations are now fully supported.
  - A new method, `is_fp16_supported()`, and device property, `supports_float16`, for checking the availability of `float16` support.
- Functionality:
  - The high-level extension API is now fully-supported in the CUDA target.
  - Eager compilation of multiple signatures, multiple outputs from generalized ufuncs, and specifying the return type of ufuncs are now supported.
  - A limited set of NumPy ufuncs (trigonometric functions) can now be called inside kernels.
- Lineinfo quality improvement: enabling lineinfo no longer results in any changes to generated code.

Deprecations:

- The `numba.pycc` module and everything in it is now pending deprecation.
- The long awaited full deprecation of `object mode` *fall-back* is underway. This change means `@jit` with no keyword arguments will eventually alias `@njit`.
- The `@generated_jit` decorator is deprecated as the Numba extension API provides a better supported superset of the same functionality, particularly through `@numba.extending.overload`.

Version support/dependency changes:

- The `setuptools` package is now an optional run-time dependency opposed to a required run-time dependency.
- The TBB threading-layer now requires version 2021.6 or later.
- LLVM 14 is now supported on all platforms via `llvmlite`.

Pull-Requests:

- PR #5113: Fix error handling in the Interval extending example (esc eric-wieser)
- PR #5544: Add support for np.union1d (shangbol gmarkall)
- PR #7009: Add writable args (dmbelov)
- PR #7067: Implement np.isclose (guilhermeleobas)

- PR #7255: CUDA: Support CUDA Toolkit conda packages from NVIDIA (gmarkall)
- PR #7622: Support fortran loop ordering for ufunc generation (sklam)
- PR #7733: fix for /tmp/tmp access issues (ChiCheng45)
- PR #7884: Implement getattr builtin. (stuartarchibald)
- PR #7885: Adds CUDA FP16 arithmetic operators (testhound)
- PR #7920: Drop pre-3.7 code path (CPU only) (sklam)
- PR #8001: CUDA fp16 math functions (testhound gmarkall)
- PR #8010: Add support for fp16 comparison native operators (testhound)
- PR #8024: Allow converting NumPy datetimes to int (apmasell)
- PR #8038: Support for Numpy BitGenerators PR#2: Standard Distributions support (kc611)
- PR #8040: Support for Numpy BitGenerators PR#3: Advanced Distributions Support. (kc611)
- PR #8041: Support for Numpy BitGenerators PR#4: Generator().integers() Support. (kc611)
- PR #8042: Support for NumPy BitGenerators PR#5: Generator Shuffling Methods. (kc611)
- PR #8061: Migrate random `glue_lowering` to `overload` where easy (apmasell)
- PR #8106: Remove injection of atomic JIT functions into NRT memsys. (stuartarchibald)
- PR #8120: Support nesting of nested array types (gmarkall)
- PR #8134: Support non-constant exception values in JIT (guilhermeleobas sklam)
- PR #8147: Adds size variable at runtime for arrays that cannot be inferred (njriasan)
- PR #8154: Testhound/native cast 8138 (testhound)
- PR #8158: adding -pthread for linux-ppc64le in setup.py (esc)
- PR #8164: remove myself from automatic reviewer assignment (esc)
- PR #8167: CUDA: Facilitate and document passing arrays / pointers to foreign functions (gmarkall)
- PR #8180: CUDA: Initial support for Minor Version Compatibility (gmarkall)
- PR #8183: Add `n_keys` option to Dict.empty() (stefanfed gmarkall)
- PR #8198: Update the release template to include updating the version table. (stuartarchibald)
- PR #8200: Make the NRT use the "unsafe" allocation API by default. (stuartarchibald)
- PR #8201: Bump llvmlite dependency to 0.40.dev0 for Numba 0.57.0dev0 (stuartarchibald)
- PR #8207: development tag should be in monofont (esc)
- PR #8212: release checklist: include a note to ping @RC_testers on discourse (esc)
- PR #8216: chore: Set permissions for GitHub actions (naveensrinivasan)
- PR #8217: Fix syntax in docs (jorgepiloto)
- PR #8220: Added the interval example as doctest (kc611)
- PR #8221: CUDA stubs docstring: Replace illegal escape sequence (gmarkall)
- PR #8228: Fix typo in @vectorize docstring and a NumPy spelling. (stuartarchibald)
- PR #8229: Remove `mk_unique_var` in `inline_closurecall.py` (sklam)
- PR #8234: Replace @overload_glue by @overload for 20 NumPy functions (guilhermeleobas)

- PR #8235: Make the NRT stats counters optional. (stuartarchibald)
- PR #8238: Advanced Indexing Support #1 (kc611)
- PR #8240: Add get_shared_mem_per_block method to Dispatcher (testhound)
- PR #8241: Reorder typeof checks to avoid infinite loops on StructrefProxy __hash__ (DannyWeitekamp)
- PR #8243: Add a note to `reference/numpysupported.rst` ()
- PR #8245: Fix links in `CONTRIBUTING.md` ()
- PR #8247: Fix issue 8127 (bszollosinagy)
- PR #8250: Fix issue 8161 (bszollosinagy)
- PR #8253: CUDA: Verify NVVM IR prior to compilation (gmarkall)
- PR #8255: CUDA: Make numba.cuda.tests.doc_examples.ffi a module to fix #8252 (gmarkall)
- PR #8256: Migrate linear algebra functions from glue_lowering (apmasell)
- PR #8258: refactor np.where to use overload (guilhermeleobas)
- PR #8259: Add `np.broadcast_to(scalar_array, ())` (guilhermeleobas)
- PR #8264: remove `mk_unique_var` from `parfor_lowering_utils.py` (guilhermeleobas)
- PR #8265: Remove `mk_unique_var` from `array_analysis.py` (guilhermeleobas)
- PR #8266: Remove `mk_unique_var` in `untyped_passes.py` (guilhermeleobas)
- PR #8267: Fix segfault for invalid axes in np.split (aseyboldt)
- PR #8271: Implement some CUDA intrinsics with `@overload`, `@overload_attribute`, and `@intrinsic` (gmarkall)
- PR #8274: Update version support table doc for 0.56. (stuartarchibald)
- PR #8275: Update CHANGE_LOG for 0.56.0 final (stuartarchibald)
- PR #8283: Clean up / remove support for old NumPy versions (gmarkall)
- PR #8287: Drop CUDA 10.2 (gmarkall)
- PR #8289: Revert #8265. (stuartarchibald)
- PR #8290: CUDA: Replace use of deprecated NVVM IR features, questionable constructs (gmarkall)
- PR #8292: update checklist (esc)
- PR #8294: CUDA: Add trig ufunc support (gmarkall)
- PR #8295: Add get_const_mem_size method to Dispatcher (testhound gmarkall)
- PR #8297: Add __name__ attribute to CUDAUFuncDispatcher and test case (testhound)
- PR #8299: Fix build for mingw toolchain (Biswa96)
- PR #8302: CUDA: Revert numba_nvvm intrinsic name workaround (gmarkall)
- PR #8308: CUDA: Support for multiple signatures (gmarkall)
- PR #8315: Add get_local_mem_per_thread method to Dispatcher (testhound)
- PR #8319: Bump minimum supported Python version to 3.8 (esc stuartarchibald jamesobutler)
- PR #8320: Add __name__ support for GUFuncs (testhound)
- PR #8321: Fix literal_unroll pass erroneously exiting on non-conformant loop. (stuartarchibald)

- PR #8325: Remove use of mk_unique_var in stencil.py (bszollosinagy)
- PR #8326: Remove `mk_unique_var` from `parfor_lowering.py` (guilhermeleobas)
- PR #8331: Extend docs with info on how to call C functions from Numba (guilhermeleobas)
- PR #8334: Add dict(*iterable) constructor (guilhermeleobas)
- PR #8335: Remove deprecated pycc script and related source. (stuartarchibald)
- PR #8336: Fix typos of "Generalized" in GUFunc-related code (gmarkall)
- PR #8338: Calculate reductions before fusion so that use of reduction vars can stop fusion. (DrTodd13)
- PR #8339: Fix #8291 parfor leak of redtoset variable (sklam)
- PR #8341: CUDA: Support multiple outputs for Generalized Ufuncs (gmarkall)
- PR #8343: Eliminate references to type annotation in compile_ptx (testhound)
- PR #8348: Add get_max_threads_per_block method to Dispatcher (testhound)
- PR #8354: pin setuptools to < 65 and switch from mamba to conda on RTD (esc gmarkall)
- PR #8357: Clean up the buildscripts directory. (stuartarchibald)
- PR #8359: adding warnings about cache behaviour (luk-f-a)
- PR #8368: Remove `glue_lowering` in random math that requires IR (apmasell)
- PR #8376: Fix issue 8370 (bszollosinagy)
- PR #8387: Add support for compute capability in IR Lowering (testhound)
- PR #8388: Remove more references to the pycc binary. (stuartarchibald)
- PR #8389: Make C++ extensions compile with correct compiler (apmasell)
- PR #8390: Use NumPy logic for lessthan in sort to move NaNs to the back. (sklam)
- PR #8401: Remove Cuda toolkit version check (testhound)
- PR #8415: Refactor `numba.np.arraymath` methods from lower_builtins to overloads (kc611)
- PR #8418: Fixes ravel failure on 1d arrays (#5229) (cako)
- PR #8421: Update release checklist: add a task to check dependency pinnings on subsequent releases (e.g. PATCH) (esc)
- PR #8422: Switch public CI builds to use gdb from conda packages. (stuartarchibald)
- PR #8423: Remove public facing and CI references to 32 bit linux support. (stuartarchibald, in addition, we are grateful for the contribution of jamesobutler towards a similar goal in PR #8319)
- PR #8425: Post 0.56.2 cleanup (esc)
- PR #8427: Shorten the time to verify test discovery. (stuartarchibald)
- PR #8429: changelog generator script (esc)
- PR #8431: Replace `@overload_glue` by `@overload` for `np.linspace` and `np.take` (guilhermeleobas)
- PR #8432: Refactor carray/farray to use @overload (guilhermeleobas)
- PR #8435: Migrate `np.atleast_?` functions from `glue_lowering` to `overload` (apmasell)
- PR #8438: Make the initialisation of the NRT more lazy for the njit decorator. (stuartarchibald)
- PR #8439: Update the contributing docs to include a policy on formatting changes. (stuartarchibald)
- PR #8440: [DOC]: Replaces icc_rt with intel-cmplr-lib-rt (oleksandr-pavlyk)

- PR #8442: Implement hasattr(), str() and repr(). (stuartarchibald)
- PR #8446: add version info in ImportError's (raybellwaves)
- PR #8450: remove GitHub username from changelog generation script (esc)
- PR #8467: Convert implementations using generated_jit to overload (gmarkall)
- PR #8468: Reference test suite in installation documentation (apmasell)
- PR #8469: Correctly handle optional types in parfors lowering (apmasell)
- PR #8473: change the include style in _pymodule.h and remove unused or duplicate headers in two header files ()
- PR #8476: Make setuptools optional at runtime. (stuartarchibald)
- PR #8490: Restore installing SciPy from defaults instead of conda-forge on public CI (esc)
- PR #8494: Remove `context.compile_internal` where easy on `numba/cpython/cmathimpl.py` (guilhermeleobas)
- PR #8495: Removes context.compile_internal where easy on `numba/cpython/listobj.py` (guilhermeleobas)
- PR #8496: Rewrite most of the set API to use overloads (guilhermeleobas)
- PR #8499: Deprecate numba.generated_jit (stuartarchibald)
- PR #8508: This updates the release checklists to capture some more checks. (stuartarchibald)
- PR #8513: Added support for numpy.newaxis (kc611)
- PR #8517: make some typedlist C-APIs public ()
- PR #8518: Adjust stencil tests to use hardcoded python source opposed to AST. (stuartarchibald)
- PR #8520: Added noncentral-chisquared, noncentral-f and logseries distributions (kc611)
- PR #8522: Import jitclass from numba.experimental in jitclass documentation (armgabrielyan)
- PR #8524: Fix grammar in stencil.rst (armgabrielyan)
- PR #8525: Making CUDA specific datamodel manager (sklam)
- PR #8526: Fix broken url (Nimrod0901)
- PR #8527: Fix grammar in troubleshoot.rst (armgabrielyan)
- PR #8532: Vary NumPy version on gpuCI (gmarkall)
- PR #8535: LLVM14 (apmasell)
- PR #8536: Fix fusion bug. (DrTodd13)
- PR #8539: Fix #8534, np.broadcast_to should update array size attr. (stuartarchibald)
- PR #8541: Remove restoration of "free" channel in Azure CI windows builds. (stuartarchibald)
- PR #8542: CUDA: Make arg optional for Stream.add_callback() (gmarkall)
- PR #8544: Remove reliance on npy_<impl> ufunc loops. (stuartarchibald)
- PR #8545: Py3.11 basic support (esc sklam)
- PR #8547: [Unicode] Add more string view usages for unicode operations ()
- PR #8549: Fix rstcheck in Azure CI builds, update sphinx dep and docs to match (stuartarchibald)
- PR #8550: Changes how tests are split between test instances (apmasell)
- PR #8554: Make target for `@overload` have 'generic' as default. (stuartarchibald gmarkall)

- PR #8557: [Unicode] support startswith with args, start and end. ()
- PR #8566: Update workqueue abort message on concurrent access. (stuartarchibald)
- PR #8572: CUDA: Reduce memory pressure from local memory tests (gmarkall)
- PR #8579: CUDA: Add CUDA 11.8 / Hopper support and required fixes (gmarkall)
- PR #8580: adding note about doing a wheel test build prior to tagging (esc)
- PR #8583: Skip tests that contribute to M1 RuntimeDyLd Assertion error (sklam)
- PR #8587: Remove unused refcount removal code, clean `core/cpu.py` module. (stuartarchibald)
- PR #8588: Remove lowering extension hooks, replace with pass infrastructure. (stuartarchibald)
- PR #8590: Py3.11 support continues (sklam)
- PR #8592: fix failure of test_cache_invalidate due to read-only install (tpwrules)
- PR #8593: Adjusted ULP precesion for noncentral distribution test (kc611)
- PR #8594: Fix various CUDA lineinfo issues (gmarkall)
- PR #8597: Prevent use of NumPy's MaskedArray. (stuartarchibald)
- PR #8598: Setup Azure CI to test py3.11 (sklam)
- PR #8600: Chrome trace timestamp should be in microseconds not seconds. (sklam)
- PR #8602: Throw error for unsupported dunder methods (apmasell)
- PR #8605: Support for CUDA fp16 math functions (part 1) (testhound)
- PR #8606: [Doc] Make the RewriteArrayExprs doc more precise ()
- PR #8619: Added flat iteration logic for random distributions (kc611)
- PR #8623: Adds support for np.nan_to_num (thomasjpfan)
- PR #8624: DOC: Add guvectorize scalar return example (Matt711)
- PR #8625: Refactor `test_ufuncs` (gmarkall)
- PR #8626: [unicode-PERF]: use optmized BM algorithm to replace the brute-force finder (dlee992)
- PR #8630: Fix #8628: Don't test math.trunc with non-float64 NumPy scalars (gmarkall)
- PR #8634: Add new method is_fp16_supported (testhound)
- PR #8636: CUDA: Skip `test_ptds` on Windows (gmarkall)
- PR #8639: Python 3.11 - fix majority of remaining test failures. (stuartarchibald)
- PR #8644: Fix bare reraise support (sklam)
- PR #8649: Remove `numba.core.overload_glue` module. (apmasell)
- PR #8659: Preserve module name of jitted class (neilflood)
- PR #8661: Make external compiler discovery lazy in the test suite. (stuartarchibald)
- PR #8662: Add support for `.nbytes` accessor for numpy arrays (alanhdu)
- PR #8666: Updates for Python 3.8 baseline/Python 3.11 migration (stuartarchibald)
- PR #8673: Enable the CUDA simulator tests on Windows builds in Azure CI. (stuartarchibald)
- PR #8675: Make `always_run` test decorator a tag and improve shard tests. (stuartarchibald)
- PR #8677: Add support for min and max on boolean types. (DrTodd13)

- PR #8680: Adjust flake8 config to be compatible with flake8=6.0.0 (thomasjpfan)
- PR #8685: Implement `__repr__` for numba types (luk-f-a)
- PR #8691: NumPy 1.24 (gmarkall)
- PR #8697: Close stale issues after 7 days (gmarkall)
- PR #8701: Relaxed ULP testing precision for NumPy Generator tests across all systems (kc611)
- PR #8702: Supply concrete timeline for objmode fallback deprecation/removal. (stuartarchibald)
- PR #8706: Fix doctest for `@vectorize` (sklam)
- PR #8711: Python 3.11 tracing support (continuation of #8670). (AndrewVallette sklam)
- PR #8716: CI: Use `set -e` in "Before Install" step and fix install (gmarkall)
- PR #8720: Enable coverage for subprocess testing (sklam)
- PR #8723: Check for void return type in `cuda.compile_ptx` (brandonwillard)
- PR #8726: Make Numba dependency check run ahead of Numba internal imports. (stuartarchibald)
- PR #8728: Fix flake8 checks since upgrade to flake8=6.x (stuartarchibald)
- PR #8729: Run flake8 CI step in multiple processes. (stuartarchibald)
- PR #8732: Add numpy argpartition function support ()
- PR #8735: Update bot to close PRs waiting on authors for more than 3 months (guilhermeleobas)
- PR #8736: Implement np.lib.stride_tricks.sliding_window_view ()
- PR #8744: Update CtypesLinker::add_cu error message to include fp16 usage (testhound gmarkall)
- PR #8746: Fix failing test_dispatcher test case (testhound)
- PR #8748: Suppress known test failures for py3.11 (sklam)
- PR #8751: Recycle test runners more aggressively (apmasell)
- PR #8752: Flake8 fixes for py311 branch (esc sklam)
- PR #8760: Bump llvmlite PR in py3.11 branch testing (sklam)
- PR #8764: CUDA tidy-up: remove some unneeded methods (gmarkall)
- PR #8765: BLD: remove distutils (fangchenli)
- PR #8766: Stale bot: Use `abandoned - stale` label for closed PRs (gmarkall)
- PR #8771: Update vendored Versioneer from 0.14 to 0.28 (oscargus gmarkall)
- PR #8775: Revert PR#8751 for buildfarm stability (sklam)
- PR #8780: Improved documentation for Atomic CAS (MiloniAtal)
- PR #8781: Ensure gc.collect() is called before checking refcount in tests. (sklam)
- PR #8782: Changed wording of the escape error (MiloniAtal)
- PR #8786: Upgrade stale GitHub action (apmasell)
- PR #8788: CUDA: Fix returned dtype of vectorized functions (Issue #8400) (gmarkall)
- PR #8790: CUDA compare and swap with index (ianthomas23)
- PR #8795: Add pending-deprecation warnings for `numba.pycc` (stuartarchibald)
- PR #8802: Move the minimum supported NumPy version to 1.21 (stuartarchibald)

- PR #8803: Attempted fix to #8789 by changing `compile_ptx` to accept a signature instead of argument tuple (KyanCheung)
- PR #8804: Split parfor pass into 3 parts (DrTodd13)
- PR #8809: Update LLVM versions for 0.57 release (apmasell)
- PR #8810: Fix llvmlite dependency in meta.yaml (sklam)
- PR #8816: Fix some buildfarm test failures (sklam)
- PR #8819: Support "static" __getitem__ on Numba types in `@njit` code. (stuartarchibald)
- PR #8822: Merge py3.11 branch to main (esc AndrewVallette stuartarchibald sklam)
- PR #8826: CUDA CFFI test: conditionally require cffi module (gmarkall)
- PR #8831: Redo py3.11 sync branch with main (sklam)
- PR #8833: Fix typeguard import hook location. (stuartarchibald)
- PR #8836: Fix failing typeguard test. (stuartarchibald)
- PR #8837: Update AzureCI matrix for Python 3.11/NumPy 1.21..1.24 (stuartarchibald)
- PR #8839: Add Dynamic Shared Memory example. (k1m190r)
- PR #8842: Fix buildscripts, setup.py, docs for setuptools becoming optional. (stuartarchibald)
- PR #8843: Pin typeguard to 3.0.1 in AzureCI. (stuartarchibald)
- PR #8848: added lifted loops to glossary term (cherieliu)
- PR #8852: Disable SLP vectorisation due to miscompilations. (stuartarchibald)
- PR #8855: DOC: `pip` into double backticks in installing.rst (F3eQnxN3RriK)
- PR #8856: Update TBB to use >= 2021.6 by default. (kozlov-alexey stuartarchibald)
- PR #8858: Update deprecation notice for objmode fallback RE `@jit` use. (stuartarchibald)
- PR #8864: Remove obsolete deprecation notices (gmarkall)
- PR #8866: Revise CUDA deprecation notices (gmarkall)
- PR #8869: Update CHANGE_LOG for 0.57.0rc1 (stuartarchibald esc gmarkall)
- PR #8870: Fix opcode "spelling" change since Python 3.11 in CUDA debug test. (stuartarchibald)
- PR #8879: Remove use of `compile_isolated` from generator tests. (stuartarchibald)
- PR #8880: Fix missing dependency guard on pyyaml in `test_azure_config`. (stuartarchibald)
- PR #8881: Replace use of compile_isolated in test_obj_lifetime (sklam)
- PR #8884: Pin llvmlite and NumPy on release branch (sklam)
- PR #8887: Update PyPI supported version tags (bryant1410)
- PR #8896: Remove codecov install (now deleted from PyPI) (gmarkall)
- PR #8902: Enable CALL_FUNCTION_EX fix for py3.11 (sklam)
- PR #8907: Work around issue #8898. Defer `exp2` (and `log2`) calls to Numba internal symbols. (stuartarchibald)
- PR #8909: Fix #8903. `NumbaDeprecationWarning``s raised from ``@{gu,}vectorize`. (stuartarchibald)
- PR #8929: Update CHANGE_LOG for 0.57.0 final. (stuartarchibald)
- PR #8930: Fix year in change log (jtilly)

- PR #8932: Fix 0.57 release changelog (sklam)

Authors:

- alanhdu
- AndrewVallette
- apmasell
- armgabrielyan
- aseyboldt
- Biswa96
- brandonwillard
- bryant1410
- bszollosinagy
- cako
- cherieliu
- ChiCheng45
- DannyWeitekamp
- dlee992
- dmbelov
- DrTodd13
- eric-wieser
- esc
- F3eQnxN3RriK
- fangchenli
- gmarkall
- guilhermeleobas
- ianthomas23
- jamesobutler
- jorgepiloto
- jtilly
- k1m190r
- kc611
- kozlov-alexey
- KyanCheung
- luk-f-a
- Matt711
- MiloniAtal
- naveensrinivasan

- neilflood
- Nimrod0901
- njriasan
- oleksandr-pavlyk
- oscargus
- raybellwaves
- shangbol
- sklam
- stefanfed
- stuartarchibald
- testhound
- thomasjpfan
- tpwrules

9.2.3 Version 0.56.4 (3 November, 2022)

This is a bugfix release to fix a regression in the CUDA target in relation to the `.view()` method on CUDA device arrays that is present when using NumPy version 1.23.0 or later.

Pull-Requests:

- PR #8537: Make ol_compatible_view accessible on all targets (gmarkall)
- PR #8552: Update version support table for 0.56.4. (stuartarchibald)
- PR #8553: Update CHANGE_LOG for 0.56.4 (stuartarchibald)
- PR #8570: Release 0.56 branch: Fix overloads with `target="generic"` for CUDA (gmarkall)
- PR #8571: Additional update to CHANGE_LOG for 0.56.4 (stuartarchibald)

Authors:

- gmarkall
- stuartarchibald

9.2.4 Version 0.56.3 (13 October, 2022)

This is a bugfix release to remove the version restriction applied to the `setuptools` package and to fix a bug in the CUDA target in relation to copying zero length device arrays to zero length host arrays.

Pull-Requests:

- PR #8475: Remove setuptools version pin (gmarkall)
- PR #8482: Fix #8477: Allow copies with different strides for 0-length data (gmarkall)
- PR #8486: Restrict the TBB development package to supported version in Azure. (stuartarchibald)
- PR #8503: Update version support table for 0.56.3 (stuartarchibald)
- PR #8504: Update CHANGE_LOG for 0.56.3 (stuartarchibald)

Authors:

- gmarkall
- stuartarchibald

9.2.5 Version 0.56.2 (1 September, 2022)

This is a bugfix release that supports NumPy 1.23 and fixes CUDA function caching.

Pull-Requests:

- PR #8239: Add decorator to run a test in a subprocess (stuartarchibald)
- PR #8276: Move Azure to use macos-11 (stuartarchibald)
- PR #8310: CUDA: Fix Issue #8309 - atomics don't work on complex components (Graham Markall)
- PR #8342: Upgrade to ubuntu-20.04 for azure pipeline CI (jamesobutler)
- PR #8356: Update setup.py, buildscripts, CI and docs to require setuptools<60 (stuartarchibald)
- PR #8374: Don't pickle LLVM IR for CUDA code libraries (Graham Markall)
- PR #8377: Add support for NumPy 1.23 (stuartarchibald)
- PR #8384: Move strace() check into tests that actually need it (stuartarchibald)
- PR #8386: Fix the docs for numba.get_thread_id (stuartarchibald)
- PR #8407: Pin NumPy version to 1.18-1.24 (Andre Masella)
- PR #8411: update version support table for 0.56.1 (esc)
- PR #8412: Create changelog for 0.56.1 (Andre Masella)
- PR #8413: Fix Azure CI for NumPy 1.23 and use conda-forge scipy (Siu Kwan Lam)
- PR #8414: Hotfix for 0.56.2 (Siu Kwan Lam)

Authors:

- Andre Masella
- esc
- Graham Markall
- jamesobutler
- Siu Kwan Lam
- stuartarchibald

9.2.6 Version 0.56.1 (NO RELEASE)

The release was skipped due to issues during the release process.

9.2.7 Version 0.56.0 (25 July, 2022)

This release continues to add new features, bug fixes and stability improvements to Numba. Please note that this will be the last release that has support for Python 3.7 as the next release series (Numba 0.57) will support Python 3.11! Also note that, this will be the last release to support linux-32 packages produced by the Numba team.

Python language support enhancements:

- Previously missing support for large, in-line dictionaries and internal calls to functions with large numbers of keyword arguments in Python 3.10 has been added.
- `operator.mul` now works for `list` s.
- Literal slices, e.g. `slice(1, 10, 2)` can be returned from `nopython` mode functions.
- The `len` function now works on `dict_keys`, `dict_values` and `dict_items` .
- Numba's `set` implementation now supports reference counted items e.g. strings.

Numba specific feature enhancements:

- The experimental `jitclass` feature gains support for a large number of `builtin` methods e.g. declaring `__hash__` or `__getitem__` for a `jitclass` type.
- It's now possible to use `@vectorize` on an already `@jit` family decorated function.
- Name mangling has been updated to emit compiled function names that exactly match the function name in Python. This means debuggers, like GDB, can be set to break directly on Python function names.
- A GDB "pretty printing" support module has been added, when loaded into GDB Numba's internal representations of Python/NumPy types are rendered inside GDB as they would be in Python.
- An experimental option is added to the `@jit` family decorators to entirely turn off LLVM's optimisation passes for a given function (see `_dbg_optnone` kwarg in the `@jit` decorator family).
- A new environment variable is added `NUMBA_EXTEND_VARIABLE_LIFETIMES`, which if set will extend the lifetime of variables to the end of their basic block, this to permit a debugging experience in GDB similar to that found in compiled C/C++/Fortran code.

NumPy features/enhancements:

- Initial support for passing, using and returning `numpy.random.Generator` instances has been added, this currently includes support for the `random` distribution.
- The broadcasting functions `np.broadcast_shapes` and `np.broadcast_arrays` are now supported.
- The `min` and `max` functions now work with `np.timedelta64` and `np.datetime64` types.
- Sorting multi-dimensional arrays along the last axis is now supported in `np.sort()`.
- The `np.clip` function is updated to accept NumPy arrays for the `a_min` and `a_max` arguments.
- The NumPy allocation routines (`np.empty` , `np.ones` etc.) support shape arguments specified using members of `enum.IntEnum` s.
- The function `np.random.noncentral_chisquare` is now supported.
- The performance of functions `np.full` and `np.ones` has been improved.

Parallel Accelerator enhancements:

- The `parallel=True` functionality is enhanced through the addition of the functions `numba.set_parallel_chunksize` and `numba.get_parallel_chunksize` to permit a more fine grained scheduling of work defined in a parallel region. There is also support for adjusting the `chunksize` via a context manager.

- The `ID` of a thread is now defined to be predictable and within a known range, it is available through calling the function `numba.get_thread_id`.
- The performance of `@stencil` s has been improved in both serial and parallel execution.

CUDA enhancements:

- New functionality:
  - Self-recursive device functions.
  - Vector type support (`float4`, `int2`, etc.).
  - Shared / local arrays of extension types can now be created.
  - Support for linking CUDA C / C++ device functions into Python kernels.
  - PTX generation for Compute Capabilities 8.6 and 8.7 - e.g. RTX A series, GTX 3000 series.
  - Comparison operations for `float16` types.
- Performance improvements:
  - Context queries are no longer made during launch configuration.
  - Launch configurations are now LRU cached.
  - On-disk caching of CUDA kernels is now supported.
- Documentation: many new examples added.

Docs:

- Numba now has an official "mission statement".
- There's now a "version support table" in the documentation to act as an easy to use, single reference point, for looking up information about Numba releases and their required/supported dependencies.

General Enhancements:

- Numba imports more quickly in environments with large numbers of packages as it now uses `importlib-metadata` for querying other packages.
- Emission of chrome tracing output is now supported for the internal compilation event handling system.
- This release is tested and known to work when using the Pyston Python interpreter.

Pull-Requests:

- PR #5209: Use importlib to load numba extensions (Stepan Rakitin Graham Markall stuartarchibald)
- PR #5877: Jitclass builtin methods (Ethan Pronovost Graham Markall)
- PR #6490: Stencil output allocated with np.empty now and new code to initialize the borders. (Todd A. Anderson)
- PR #7005: Make *numpy.searchsorted* match NumPy when first argument is unsorted (Brandon T. Willard)
- PR #7363: Update cuda.local.array to clarify "simple constant expression" (e.g. no NumPy ints) (Sterling Baird)
- PR #7364: Removes an instance of signed integer overflow undefined behaviour. (Tobias Sargeant)
- PR #7537: Add chrome tracing (Hadia Ahmed Siu Kwan Lam)
- PR #7556: Testhound/fp16 comparison (Michael Collison Graham Markall)
- PR #7586: Support for len on dict.keys, dict.values, and dict.items (Nick Riasanovsky)
- PR #7617: Numba gdb-python extension for printing (stuartarchibald)

- PR #7619: CUDA: Fix linking with PTX when compiling lazily (Graham Markall)
- PR #7621: Add support for linking CUDA C / C++ with *@cuda.jit* kernels (Graham Markall)
- PR #7625: Combined parfor chunking and caching PRs. (stuartarchibald Todd A. Anderson Siu Kwan Lam)
- PR #7651: DOC: pypi and conda-forge badges (Ray Bell)
- PR #7660: Add support for np.broadcast_arrays (Guilherme Leobas)
- PR #7664: Flatten mangling dicts into a single dict (Graham Markall)
- PR #7680: CUDA Docs: include example calling slow matmul (Graham Markall)
- PR #7682: performance improvements to np.full and np.ones (Rishi Kulkarni)
- PR #7684: DOC: remove incorrect warning in np.random reference (Rishi Kulkarni)
- PR #7685: Don't convert setitems that have dimension mismatches to parfors. (Todd A. Anderson)
- PR #7690: Implemented np.random.noncentral_chisquare for all size arguments (Rishi Kulkarni)
- PR #7695: *IntEnumMember* support for *np.empty*, *np.zeros*, and *np.ones* (Benjamin Graham)
- PR #7699: CUDA: Provide helpful error if the return type is missing for *declare_device* (Graham Markall)
- PR #7700: Support for scalar arguments in Np.ascontiguousarray (Dhruv Patel)
- PR #7703: Ignore unsupported types in *ShapeEquivSet._getnames()* (Benjamin Graham)
- PR #7704: Move the type annotation pass to post legalization. (stuartarchibald)
- PR #7709: CUDA: Fixes missing type annotation pass following #7704 (stuartarchibald)
- PR #7712: Fixing issue 7693 (stuartarchibald Graham Markall luk-f-a)
- PR #7714: Support for boxing SliceLiteral type (Nick Riasanovsky)
- PR #7718: Bump llvmlite dependency to 0.39.0dev0 for Numba 0.56.0dev0 (stuartarchibald)
- PR #7724: Update URLs in error messages to refer to RTD docs. (stuartarchibald)
- PR #7728: Document that AOT-compiled functions do not check arg types (Graham Markall)
- PR #7729: Handle Omitted/OmittedArgDataModel in DI generation. (stuartarchibald)
- PR #7732: update release checklist following 0.55.0 RC1 (esc)
- PR #7736: Update CHANGE_LOG for 0.55.0 final. (stuartarchibald)
- PR #7740: CUDA Python 11.6 support (Graham Markall)
- PR #7744: Fix issues with locating/parsing source during DebugInfo emission. (stuartarchibald)
- PR #7745: Fix the release year for Numba 0.55 change log entry. (stuartarchibald)
- PR #7748: Fix #7713: Ensure _prng_random_hash return has correct bitwidth (Graham Markall)
- PR #7749: Refactor threading layer priority tests to not use stdout/stderr (stuartarchibald)
- PR #7752: Fix #7751: Use original filename for array exprs (Graham Markall)
- PR #7755: CUDA: Deprecate support for CC < 5.3 and CTK < 10.2 (Graham Markall)
- PR #7763: Update Read the Docs configuration (automatic) (readthedocs-assistant)
- PR #7764: Add dbg_optnone and dbg_extend_lifetimes flags (Siu Kwan Lam)
- PR #7771: Move function unique ID to abi-tags (stuartarchibald Siu Kwan Lam)
- PR #7772: CUDA: Add Support to Creating *StructModel* Array (Michael Wang)

- PR #7776: Updates coverage.py config (stuartarchibald)
- PR #7777: Remove reference existing issue from GH template. (stuartarchibald)
- PR #7778: Remove long deprecated flags from the CLI. (stuartarchibald)
- PR #7780: Fix sets with reference counted items (Benjamin Graham)
- PR #7782: adding reminder to check on deprecations (esc)
- PR #7783: remove upper limit on Python version (esc)
- PR #7786: Remove dependency on intel-openmp for OSX (stuartarchibald)
- PR #7788: Avoid issue with DI gen for arrayexprs. (stuartarchibald)
- PR #7796: update change-log for 0.55.1 (esc)
- PR #7797: prune README (esc)
- PR #7799: update the release checklist post 0.55.1 (esc)
- PR #7801: add sdist command and umask reminder (esc)
- PR #7804: update local references from master -> main (esc)
- PR #7805: Enhance source line finding logic for debuginfo (Siu Kwan Lam)
- PR #7809: Updates the gdb configuration to accept a binary name or a path. (stuartarchibald)
- PR #7813: Extend parfors test timeout for aarch64. (stuartarchibald)
- PR #7814: CUDA Dispatcher refactor (Graham Markall)
- PR #7815: CUDA Dispatcher refactor 2: inherit from *dispatcher.Dispatcher* (Graham Markall)
- PR #7817: Update intersphinx URLs for NumPy and llvmlite. (stuartarchibald)
- PR #7823: Add renamed vars to callee scope such that it is self consistent. (stuartarchibald)
- PR #7829: CUDA: Support *Enum/IntEnum* in Kernel (Michael Wang)
- PR #7833: Add version support information table to docs. (stuartarchibald)
- PR #7835: Fix pickling error when module cannot be imported (idorrington)
- PR #7836: min() and max() support for np.datetime and np.timedelta (Benjamin Graham)
- PR #7837: Initial refactoring of parfor reduction lowering (Siu Kwan Lam)
- PR #7845: change time.time() to time.perf_counter() in docs (Nopileos2)
- PR #7846: Fix CUDA enum vectorize test on Windows (Graham Markall)
- PR #7848: Support for int * list (Nick Riasanovsky)
- PR #7850: CUDA: Pass *fastmath* compiler flag down to *compile_ptx* and *compile_device*; Improve *fastmath* tests (Michael Wang)
- PR #7855: Ensure np.argmin/no.argmax return type is intp (stuartarchibald)
- PR #7858: CUDA: Deprecate *ptx* Attribute and Update Tests (Graham Markall Michael Wang)
- PR #7861: Fix a spelling mistake in README (Zizheng Guo)
- PR #7864: Fix cross_iter_dep check. (Todd A. Anderson)
- PR #7865: Remove add_user_function (Graham Markall)
- PR #7866: Support for large numbers of args/kws with Python 3.10 (Nick Riasanovsky)

- PR #7878: CUDA: Remove some deprecated support, add CC 8.6 and 8.7 (Graham Markall)
- PR #7893: Use uuid.uuid4() as the key in serialization. (stuartarchibald)
- PR #7895: Remove use of *llvmlite.llvmpy* (Andre Masella)
- PR #7898: Skip test_ptds under cuda-memcheck (Graham Markall)
- PR #7901: Pyston compatibility for the test suite (Kevin Modzelewski)
- PR #7904: Support m1 (esc)
- PR #7911: added sys import (Nightfurex)
- PR #7915: CUDA: Fix test checking debug info rendering. (stuartarchibald)
- PR #7918: Add JIT examples to CUDA docs (brandon-b-miller Graham Markall)
- PR #7919: Disallow //= reductions in pranges. (Todd A. Anderson)
- PR #7924: Retain non-modified index tuple components. (Todd A. Anderson)
- PR #7939: Fix rendering in feature request template. (stuartarchibald)
- PR #7940: Implemented *np.allclose* in *numba/np/arraymath.py* (Gagandeep Singh)
- PR #7941: Remove debug dump output from closure inlining pass. (stuartarchibald)
- PR #7946: instructions for creating a build environment were outdated (esc)
- PR #7949: Add Cuda Vector Types (Michael Wang)
- PR #7950: mission statement (esc)
- PR #7956: Stop using pip for 3.10 on public ci (Revert "start testing Python 3.10 on public CI") (esc)
- PR #7957: Use cloudpickle for disk caches (Siu Kwan Lam)
- PR #7958: *numpy.clip* accept *numpy.array* for *a_min*, *a_max* (Gagandeep Singh)
- PR #7959: Permit a new array model to have a super set of array model fields. (stuartarchibald)
- PR #7961: *numba.typed.typeddict.Dict.get* uses *castedkey* to avoid returning default value even if the key is present (Gagandeep Singh)
- PR #7963: remove the roadmap from the sphinx based docs (esc)
- PR #7964: Support for large constant dictionaries in Python 3.10 (Nick Riasanovsky)
- PR #7965: Use uuid4 instead of PID in cache temp name to prevent collisions. (stuartarchibald)
- PR #7971: lru cache for configure call (Tingkai Liu)
- PR #7972: Fix fp16 support for cuda shared array (Michael Collison Graham Markall)
- PR #7986: Small caching refactor to support target cache implementations (Graham Markall)
- PR #7994: Supporting multidimensional arrays in quick sort (Gagandeep Singh Siu Kwan Lam)
- PR #7996: Fix binding logic in @*overload_glue*. (stuartarchibald)
- PR #7999: Remove @*overload_glue* for NumPy allocators. (stuartarchibald)
- PR #8003: Add np.broadcast_shapes (Guilherme Leobas)
- PR #8004: CUDA fixes for Windows (Graham Markall)
- PR #8014: Fix support for {real,imag} array attrs in Parfors. (stuartarchibald)
- PR #8016: [Docs] [Very Minor] Make *numba.jit* boundscheck doc line consistent (Kyle Martin)

- PR #8017: Update FAQ to include details about using debug-only option (Guilherme Leobas)
- PR #8027: Support for NumPy 1.22 (stuartarchibald)
- PR #8031: Support for Numpy BitGenerators PR#1 - Core Generator Support (Kaustubh)
- PR #8035: Fix a couple of typos RE implementation (stuartarchibald)
- PR #8037: CUDA self-recursion tests (Graham Markall)
- PR #8044: Make Python 3.10 kwarg peephole less restrictive (Nick Riasanovsky)
- PR #8046: Fix caching test failures (Siu Kwan Lam)
- PR #8049: support str(bool) syntax (LI Da)
- PR #8052: Ensure pthread is linked in when building for ppc64le. (Siu Kwan Lam)
- PR #8056: Move caching tests from test_dispatcher to test_caching (Graham Markall)
- PR #8057: Fix coverage checking (Graham Markall)
- PR #8064: Rename “nb:run_pass” to “numba:run_pass” and document it. (Siu Kwan Lam)
- PR #8065: Fix PyLowering mishandling starargs (Siu Kwan Lam)
- PR #8068: update changelog for 0.55.2 (esc)
- PR #8077: change return type of np.broadcast_shapes to a tuple (Guilherme Leobas)
- PR #8080: Fix windows test failure due to timeout when the machine is slow poss… (Siu Kwan Lam)
- PR #8081: Fix erroneous array count in parallel gufunc kernel generation. (stuartarchibald)
- PR #8089: Support on-disk caching in the CUDA target (Graham Markall)
- PR #8097: Exclude libopenblas 0.3.20 on osx-arm64 (esc)
- PR #8099: Fix Py_DECREF use in case of error state (for devicearray). (stuartarchibald)
- PR #8102: Combine numpy run_constrained in meta.yaml to the run requirements (Siu Kwan Lam)
- PR #8109: Pin TBB support with respect to incompatible 2021.6 API. (stuartarchibald)
- PR #8118: Update release checklists post 0.55.2 (esc)
- PR #8123: Fix CUDA print tests on Windows (Graham Markall)
- PR #8124: Add explicit checks to all allocators in the NRT. (stuartarchibald)
- PR #8126: Mark gufuncs as having mutable outputs (Andre Masella)
- PR #8133: Fix #8132. Regression in Record.make_c_struct for handling nestedarray (Siu Kwan Lam)
- PR #8137: CUDA: Fix #7806, Division by zero stops the kernel (Graham Markall)
- PR #8142: CUDA: Fix some missed changes from dropping 9.2 (Graham Markall)
- PR #8144: Fix NumPy capitalisation in docs. (stuartarchibald)
- PR #8145: Allow ufunc builder to use previously JITed function (Andre Masella)
- PR #8151: pin NumPy to build 0 of 1.19.2 on public CI (esc)
- PR #8163: CUDA: Remove context query in launch config (Graham Markall)
- PR #8165: Restrict strace based tests to be linux only via support feature. (stuartarchibald)
- PR #8170: CUDA: Fix missing space in low occupancy warning (Graham Markall)
- PR #8175: make build and upload order consistent (esc)

- PR #8181: Fix various typos (luzpaz)
- PR #8187: Update CHANGE_LOG for 0.55.2 (stuartarchibald esc)
- PR #8189: updated version support information for 0.55.2/0.57 (esc)
- PR #8191: CUDA: Update deprecation notes for 0.56. (Graham Markall)
- PR #8192: Update CHANGE_LOG for 0.56.0 (stuartarchibald esc Siu Kwan Lam)
- PR #8195: Make the workqueue threading backend once again fork safe. (stuartarchibald)
- PR #8196: Fix numerical tolerance in parfors caching test. (stuartarchibald)
- PR #8197: Fix *isinstance* warning check test. (stuartarchibald)
- PR #8203: pin llvmlite 0.39 for public CI builds (esc)
- PR #8255: CUDA: Make numba.cuda.tests.doc_examples.ffi a module to fix #8252 (Graham Markall)
- PR #8274: Update version support table doc for 0.56. (stuartarchibald)
- PR #8275: Update CHANGE_LOG for 0.56.0 final (stuartarchibald)

Authors:

- Andre Masella
- Benjamin Graham
- brandon-b-miller
- Brandon T. Willard
- Gagandeep Singh
- Dhruv Patel
- LI Da
- Todd A. Anderson
- Ethan Pronovost
- esc
- Tobias Sargeant
- Graham Markall
- Guilherme Leobas
- Zizheng Guo
- Hadia Ahmed
- idorrington
- Michael Wang
- Kaustubh
- Kevin Modzelewski
- luk-f-a
- luzpaz
- Kyle Martin
- Nightfurex

- Nick Riasanovsky
- Nopileos2
- Ray Bell
- readthedocs-assistant
- Rishi Kulkarni
- Sterling Baird
- Siu Kwan Lam
- stuartarchibald
- Stepan Rakitin
- Michael Collison
- Tingkai Liu

9.2.8 Version 0.55.2 (25 May, 2022)

This is a maintenance release to support NumPy 1.22 and Apple M1.

Pull-Requests:

- PR #8067: Backport #8027: Support for NumPy 1.22 (stuartarchibald)
- PR #8069: Install llvmlite 0.38 for Numba 0.55.* (esc)
- PR #8075: update max NumPy for 0.55.2 (esc)
- PR #8078: Backport #7804: update local references from master -> main (esc)
- PR #8082: Backport #8080: fix windows failure due to timeout (Siu Kwan Lam)
- PR #8084: Pin meta.yaml to llvmlite 0.38 series (Siu Kwan Lam)
- PR #8093: Backport #7904: Support m1 (esc)
- PR #8094: Backport #8052 Ensure pthread is linked in when building for ppc64le. (Siu Kwan Lam)
- PR #8098: Backport #8097: Exclude libopenblas 0.3.20 on osx-arm64 (esc)
- PR #8100: Backport #7786 for 0.55.2: Remove dependency on intel-openmp for OSX (stuartarchibald)
- PR #8103: Backport #8102 to fix numpy requirements (Siu Kwan Lam)
- PR #8114: Backport #8109 Pin TBB support with respect to incompatible 2021.6 API. (stuartarchibald)

Total PRs: 12

Authors:

- esc
- Siu Kwan Lam
- stuartarchibald

Total authors: 3

9.2.9 Version 0.55.1 (27 January, 2022)

This is a bugfix release that closes all the remaining issues from the accelerated release of 0.55.0 and also any release critical regressions discovered since then.

CUDA target deprecation notices:

- Support for CUDA toolkits < 10.2 is deprecated and will be removed in Numba 0.56.
- Support for devices with Compute Capability < 5.3 is deprecated and will be removed in Numba 0.56.

Pull-Requests:

- PR #7755: CUDA: Deprecate support for CC < 5.3 and CTK < 10.2 (Graham Markall)
- PR #7749: Refactor threading layer priority tests to not use stdout/stderr (stuartarchibald)
- PR #7744: Fix issues with locating/parsing source during DebugInfo emission. (stuartarchibald)
- PR #7712: Fixing issue 7693 (Graham Markall luk-f-a stuartarchibald)
- PR #7729: Handle Omitted/OmittedArgDataModel in DI generation. (stuartarchibald)
- PR #7788: Avoid issue with DI gen for arrayexprs. (stuartarchibald)
- PR #7752: Fix #7751: Use original filename for array exprs (Graham Markall)
- PR #7748: Fix #7713: Ensure _prng_random_hash return has correct bitwidth (Graham Markall)
- PR #7745: Fix the release year for Numba 0.55 change log entry. (stuartarchibald)
- PR #7740: CUDA Python 11.6 support (Graham Markall)
- PR #7724: Update URLs in error messages to refer to RTD docs. (stuartarchibald)
- PR #7709: CUDA: Fixes missing type annotation pass following #7704 (stuartarchibald)
- PR #7704: Move the type annotation pass to post legalization. (stuartarchibald)
- PR #7619: CUDA: Fix linking with PTX when compiling lazily (Graham Markall)

Authors:

- Graham Markall
- luk-f-a
- stuartarchibald

9.2.10 Version 0.55.0 (13 January, 2022)

This release includes a significant number important dependency upgrades along with a number of new features and bug fixes.

NOTE: Due to NumPy CVE-2021-33430 this release has bypassed the usual release process so as to promptly provide a Numba release that supports NumPy 1.21. A single release candidate (RC1) was made and a few issues were reported, these are summarised as follows and will be fixed in a subsequent 0.55.1 release.

Known issues with this release:

- Incorrect result copying array-typed field of structured array (#7693)
- Two issues in DebugInfo generation (#7726, #7730)
- Compilation failure for `hash` of floating point values on 32 bit Windows when using Python 3.10 (#7713).

Highlights of core dependency upgrades:

- Support for Python 3.10
- Support for NumPy 1.21

Python language support enhancements:

- Experimental support for `isinstance`.

NumPy features/enhancements:

The following functions are now supported:

- `np.broadcast_to`
- `np.float_power`
- `np.cbrt`
- `np.logspace`
- `np.take_along_axis`
- `np.average`
- `np.argmin` gains support for the `axis` kwarg.
- `np.ndarray.astype` gains support for types expressed as literal strings.

Highlights of core changes:

- For users of the Numba extension API, Numba now has a new error handling mode whereby it will treat all exceptions that do not inherit from `numba.errors.NumbaException` as a "hard error" and immediately unwind the stack. This makes it much easier to debug when writing `@overload`s etc from the extension API as there's now no confusion between Python errors and Numba errors. This feature can be enabled by setting the environment variable: `NUMBA_CAPTURED_ERRORS='new_style'`.
- The threading layer selection priority can now be changed via the environment variable `NUMBA_THREADING_LAYER_PRIORITY`.

Highlights of changes for the CUDA target:

- Support for NVIDIA's CUDA Python bindings.
- Support for 16-bit floating point numbers and their basic operations via intrinsics.
- Streams are provided in the `Stream.async_done` result, making it easier to implement asynchronous work queues.
- Support for structured types in device arrays, character sequences in NumPy arrays, and some array operations on nested arrays.
- Much underlying refactoring to align the CUDA target more closely with the CPU target, which lays the groundwork for supporting the high level extension API in CUDA in future releases.

Intel also kindly sponsored research and development into native debug (DWARF) support and handling per-function compilation flags:

- Line number/location tracking is much improved.
- Numba's internal representation of containers (e.g. tuples, arrays) are now encoded as structures.
- Numba's per-function compilation flags are encoded into the ABI field of the mangled name of the function such that it's possible to compile and differentiate between versions of the same function with different flags set.

General deprecation notices:

- There are no new general deprecations.

CUDA target deprecation notices:

- There are no new CUDA target deprecations.

Version support/dependency changes:

- Python 3.10 is supported.
- NumPy version 1.21 is supported.
- The minimum supported NumPy version is raised to 1.18 for runtime (compilation however remains compatible with NumPy 1.11).

Pull-Requests:

- PR #6075: add np.float_power and np.cbrt (Guilherme Leobas)
- PR #7047: Support __hash__ for numpy.datetime64 (Guilherme Leobas stuartarchibald)
- PR #7057: Fix #7041: Add charseq registry to CUDA target (Graham Markall stuartarchibald)
- PR #7082: Added Add/Sub between datetime64 array and timedelta64 scalar (Nick Riasanovsky stuartarchibald)
- PR #7119: Add support for *np.broadcast_to* (Guilherme Leobas)
- PR #7129: Add support for axis keyword argument to np.argmin() (Itamar Turner-Trauring)
- PR #7132: gh #7131 Support for astype with literal strings (Nick Riasanovsky)
- PR #7177: Add debug infomation support based on datamodel. (stuartarchibald)
- PR #7185: Add get_impl_key as abstract method to types.Callable (Alexey Kozlov)
- PR #7186: Add support for np.logspace. (Guoqiang QI)
- PR #7189: CUDA: Skip IPC tests on ARM (Graham Markall)
- PR #7190: CUDA: Fix test_pinned on Jetson (Graham Markall)
- PR #7192: Fix missing import in array.argsort impl and add more tests. (stuartarchibald)
- PR #7196: Fixes for lineinfo emission (stuartarchibald)
- PR #7197: don't post to python announce on the first RC (esc)
- PR #7202: Initial implementation of np.take_along_axis (Itamar Turner-Trauring)
- PR #7203: remove duplicate changelog entries (esc)
- PR #7216: Update CHANGE_LOG for 0.54.0rc2 (stuartarchibald)
- PR #7219: bump llvmlite dependency to 0.38.0dev0 for Numba 0.55.0dev0 (esc)
- PR #7220: update release checklist post 0.54rc1+2 (esc)
- PR #7221: Show GPU UUIDs in cuda.detect() output (Graham Markall)
- PR #7222: CUDA: Warn when debug=True and opt=True (Graham Markall)
- PR #7223: Replace assertion errors on IR assumption violation (Siu Kwan Lam)
- PR #7226: Add support for structured types in Device Arrays (Michael Collison)
- PR #7227: FIX: Typo (Srinath Kailasa)
- PR #7230: PR #7171 bugfix only (stuartarchibald Todd A. Anderson)
- PR #7234: add THREADING_LAYER_PRIORITY & NUMBA_THREADING_LAYER_PRIORITY (Kolen Cheung)
- PR #7235: replace wordings of WIP by draft PR (Kolen Cheung)

- PR #7236: CUDA: Skip managed alloc tests on ARM (Graham Markall)
- PR #7237: fix a typo in a string (Kolen Cheung)
- PR #7241: Set aliasing information for inplace_binops.. (Todd A. Anderson)
- PR #7242: FIX: typo (Srinath Kailasa)
- PR #7244: Implement partial literal propagation pass (support 'isinstance') (Guilherme Leobas stuartarchibald)
- PR #7247: Solve memory leak to fix issue #7210 (Siu Kwan Lam Graham Markall ysheffer)
- PR #7251: Fix #6001: typed.List ignores ctor arguments with JIT disabled (Graham Markall)
- PR #7256: Fix link to the discourse forum in README (Kenichi Maehashi)
- PR #7257: Use normal list constructor in List.__new__() (Graham Markall)
- PR #7260: Support typed lists in *heapq* (Graham Markall)
- PR #7263: Updated issue URL for error messages #7261 (DeviousLab)
- PR #7265: Fix linspace to use np.divide and clamp to stop. (stuartarchibald)
- PR #7266: CUDA: Skip multi-GPU copy test with peer access disabled (Graham Markall)
- PR #7267: Fix #7258. Bug in SROA optimization (Siu Kwan Lam)
- PR #7271: Update 3rd party license text. (stuartarchibald)
- PR #7272: Allow annotations in njit-ed functions (LunarLanding)
- PR #7273: Update CHANGE_LOG for 0.54.0rc3. (stuartarchibald)
- PR #7283: Added NPM to Glossary and linked to mentions (Nihal Shetty)
- PR #7285: CUDA: Fix OOB in test_kernel_arg (Graham Markall)
- PR #7288: Handle cval as a np attr in stencil generation. (stuartarchibald)
- PR #7294: Continuation of PR #7280, fixing lifetime of TBB task_scheduler_handle (Sergey Pokhodenko stuartarchibald)
- PR #7296: Fix generator lowering not casting to the actual yielded type (Siu Kwan Lam)
- PR #7298: Use CBC to pin GCC to 7 on most linux and 9 on aarch64. (stuartarchibald)
- PR #7304: Continue PR#3655: add support for np.average (Hadia Ahmed slnguyen)
- PR #7307: Prevent mutation of arrays in global tuples. (stuartarchibald)
- PR #7309: Update MapConstraint to handle type coercion for typed.Dict correctly. (stuartarchibald)
- PR #7312: Fix #7302. Workaround missing pthread problem on ppc64le (Siu Kwan Lam)
- PR #7315: Link ELF obj as DSO for radare2 disassembly CFG (stuartarchibald)
- PR #7316: Use float64 for consistent typing in heapq tests. (stuartarchibald)
- PR #7317: In TBB tsh test switch os.fork for mp fork ctx (stuartarchibald)
- PR #7319: Update CHANGE_LOG for 0.54.0 final. (stuartarchibald)
- PR #7329: Improve documentation in reference to CUDA local memory (Sterling Baird)
- PR #7330: Cuda matmul docs (Sterling Baird)
- PR #7340: Add size_t and ssize_t types (Bruce Merry)
- PR #7345: Add check for ipykernel file in IPython cache locator (Sahil Gupta)

- PR #7347: fix:updated url for error report and feature rquest using issue template (DEBARGHA SAHA)
- PR #7349: Allow arbitrary walk-back in reduction nodes to find inplace_binop. (Todd A. Anderson)
- PR #7359: Extend support for nested arrays inside numpy records (Graham Markall luk-f-a)
- PR #7375: CUDA: Run doctests as part of numba.cuda.tests and fix test_cg (Graham Markall)
- PR #7395: Fix #7394 and #6550 & Added test & improved error message (MegaIng)
- PR #7397: Add option to catch only Numba *numba.core.errors* derived exceptions. (stuartarchibald)
- PR #7398: Add support for arrayanalysis of tuple args. (Todd A. Anderson)
- PR #7403: Fix for issue 7402: implement missing numpy ufunc interface (Guilherme Leobas)
- PR #7404: fix typo in literal_unroll docs (esc)
- PR #7419: insert missing backtick in comment (esc)
- PR #7422: Update Omitted Type to use Hashable Values as Keys for Caching (Nick Riasanovsky)
- PR #7429: Update CHANGE_LOG for 0.54.1 (stuartarchibald)
- PR #7432: add github release task to checklist (esc)
- PR #7440: Refactor TargetConfig naming. (stuartarchibald)
- PR #7441: Permit any string as a key in literalstrkeydict type. (stuartarchibald)
- PR #7442: Add some diagnostics to SVML test failures. (stuartarchibald)
- PR #7443: Refactor template selection logic for targets. (stuartarchibald)
- PR #7444: use correct variable name in closure (esc)
- PR #7447: cleanup Numba metadata (esc)
- PR #7453: CUDA: Provide stream in async_done result (Graham Markall)
- PR #7456: Fix invalid codegen for #7451. (stuartarchibald)
- PR #7457: Factor out target registry selection logic (stuartarchibald)
- PR #7459: Include compiler flags in symbol mangling (Siu Kwan Lam)
- PR #7460: Add FP16 support for CUDA (Michael Collison Graham Markall)
- PR #7461: Support NVIDIA's CUDA Python bindings (Graham Markall)
- PR #7465: Update changelog for 0.54.1 release (Siu Kwan Lam)
- PR #7477: Fix unicode operator.eq handling of Optional types. (stuartarchibald)
- PR #7479: CUDA: Print format string and warn for > 32 print() args (Graham Markall)
- PR #7483: NumPy 1.21 support (Sebastian Berg stuartarchibald)
- PR #7484: Fixed outgoing link to nvidia documentation. (Dhruv Patel)
- PR #7493: Consolidate TLS stacks in target configuration (Siu Kwan Lam)
- PR #7496: CUDA: Use a single dispatcher class for all kinds of functions (Graham Markall)
- PR #7498: refactor with-detection logic (stuartarchibald esc)
- PR #7499: Add build scripts for CUDA testing on gpuCI (Charles Blackmon-Luca Graham Markall)
- PR #7500: Update parallel.rst (Julius Bier Kirkegaard)
- PR #7506: Enhance Flags mangling/demangling (Siu Kwan Lam)

- PR #7514: Fixup cuda debuginfo emission for 7177 (Siu Kwan Lam)
- PR #7525: Make sure` demangle()` returns *str* type. (Siu Kwan Lam)
- PR #7538: Fix *@overload_glue* performance regression. (stuartarchibald)
- PR #7539: Fix str decode issue from merge #7525/#7506 (stuartarchibald)
- PR #7546: Fix handling of missing const key in LiteralStrKeyDict (Siu Kwan Lam stuartarchibald)
- PR #7547: Remove 32bit linux scipy installation. (stuartarchibald)
- PR #7548: Correct evaluation order in assert statement (Graham Markall)
- PR #7552: Prepend the inlined function name to inlined variables. (stuartarchibald)
- PR #7557: Python3.10 v2 (stuartarchibald esc)
- PR #7560: Refactor with detection py310 (Siu Kwan Lam esc)
- PR #7561: fix a typo (Kolen Cheung)
- PR #7567: Update docs to note meetings are public. (stuartarchibald)
- PR #7570: Update the docs and error message for errors when importing Numba. (stuartarchibald)
- PR #7580: Fix #7507. catch *NotImplementedError* in *.get_function()* (Siu Kwan Lam)
- PR #7581: Add support for casting from int enums (Michael Collison)
- PR #7583: Make numba.types.Optional __str__ less verbose. (stuartarchibald)
- PR #7588: Fix casting of start/stop in linspace (stuartarchibald)
- PR #7591: Remove deprecations (Graham Markall)
- PR #7596: Fix max symbol match length for r2 (stuartarchibald)
- PR #7597: Update gdb docs for new DWARF enhancements. (stuartarchibald)
- PR #7603: Fix list.insert() for refcounted values (Ehsan Totoni)
- PR #7605: Fix TBB 2021 DSO names on OSX/Win and make TBB reporting consistent (stuartarchibald)
- PR #7606: Ensure a prescribed threading layer can load in CI. (stuartarchibald)
- PR #7610: Fix #7609. Type should not be mutated. (Siu Kwan Lam)
- PR #7618: Fix the doc build: docutils 0.18 not compatible with pinned sphinx (stuartarchibald)
- PR #7626: Fix issues with package dependencies. (stuartarchibald esc)
- PR #7627: PR 7321 continued (stuartarchibald Eric Wieser)
- PR #7628: Move to using windows-2019 images in Azure (stuartarchibald)
- PR #7632: Capture output in CUDA matmul doctest (Graham Markall)
- PR #7636: Copy prange loop header to after the parfor. (Todd A. Anderson)
- PR #7637: Increase the timeout on the SVML tests for loaded machines. (stuartarchibald)
- PR #7645: In debuginfo, do not add noinline to functions marked alwaysinline (stuartarchibald)
- PR #7650: Move Azure builds to OSX 10.15 (stuartarchibald esc Siu Kwan Lam)

Authors:

- Bruce Merry
- Charles Blackmon-Luca

- DeviousLab
- Dhruv Patel
- Todd A. Anderson
- Ehsan Totoni
- Eric Wieser
- esc
- Graham Markall
- Guilherme Leobas
- Guoqiang QI
- Hadia Ahmed
- Kolen Cheung
- Itamar Turner-Trauring
- Julius Bier Kirkegaard
- Kenichi Maehashi
- Alexey Kozlov
- luk-f-a
- LunarLanding
- MegaIng
- Nihal Shetty
- Nick Riasanovsky
- Sergey Pokhodenko
- Sahil Gupta
- Sebastian Berg
- Sterling Baird
- Srinath Kailasa
- Siu Kwan Lam
- slnguyen
- DEBARGHA SAHA
- stuartarchibald
- Michael Collison
- ysheffer

9.2.11 Version 0.54.1 (7 October, 2021)

This is a bugfix release for 0.54.0. It fixes a regression in structured array type handling, a potential leak on initialization failure in the CUDA target, a regression caused by Numba's vendored cloudpickle module resetting dynamic classes and a few minor testing/infrastructure related problems.

- PR #7348: test_inspect_cli: Decode exception with default (utf-8) codec (Graham Markall)
- PR #7360: CUDA: Fix potential leaks when initialization fails (Graham Markall)
- PR #7386: Ensure the NRT is initialized prior to use in external NRT tests. (stuartarchibald)
- PR #7388: Patch cloudpickle to not reset dynamic class each time it is unpickled (Siu Kwan Lam)
- PR #7393: skip azure pipeline test if file not present (esc)
- PR #7428: Fix regression #7355: cannot set items in structured array data types (Siu Kwan Lam)

Authors:

- esc
- Graham Markall
- Siu Kwan Lam
- stuartarchibald

9.2.12 Version 0.54.0 (19 August, 2021)

This release includes a significant number of new features, important refactoring, critical bug fixes and a number of dependency upgrades.

Python language support enhancements:

- Basic support for `f-strings`.
- `dict` comprehensions are now supported.
- The `sum` built-in function is implemented.

NumPy features/enhancements:

The following functions are now supported:

- `np.clip`
- `np.iscomplex`
- `np.iscomplexobj`
- `np.isneginf`
- `np.isposinf`
- `np.isreal`
- `np.isrealobj`
- `np.isscalar`
- `np.random.dirichlet`
- `np.rot90`
- `np.swapaxes`

Also `np.argmax` has gained support for the `axis` keyword argument and it's now possible to use `0d` NumPy arrays as scalars in `__setitem__` calls.

Internal changes:

- Debugging support through DWARF has been fixed and enhanced.
- Numba now optimises the way in which locals are emitted to help reduce time spent in LLVM's SROA passes.

CUDA target changes:

- Support for emitting `lineinfo` to be consumed by profiling tools such as Nsight Compute
- Improved fastmath code generation for various trig, division, and other functions
- Faster compilation using lazy addition of libdevice to compiled units
- Support for IPC on Windows
- Support for passing tuples to CUDA ufuncs
- Performance warnings:
  - When making implicit copies by calling a kernel on arrays in host memory
  - When occupancy is poor due to kernel or ufunc/gufunc configuration
- Support for implementing warp-aggregated intrinsics:
  - Using support for more CUDA functions: `activemask()`, `lanemask_lt()`
  - The `ffs()` function now works correctly!
- Support for `@overload` in the CUDA target

Intel kindly sponsored research and development that lead to a number of new features and internal support changes:

- Dispatchers can now be retargetted to a new target via a user defined context manager.
- Support for custom NumPy array subclasses has been added (including an overloadable memory allocator).
- An inheritance based model for targets that permits targets to share `@overload` implementations.
- Per function compiler flags with inheritance behaviours.
- The extension API now has support for overloading class methods via the `@overload_classmethod` decorator.

Deprecations:

- The `ROCm` target (for AMD ROC GPUs) has been moved to an "unmaintained" status and a seperate repository stub has been created for it at: https://github.com/numba/numba-rocm

CUDA target deprecations and breaking changes:

- Relaxed strides checking is now the default when computing the contiguity of device arrays.
- The `inspect_ptx()` method is deprecated. For use cases that obtain PTX for further compilation outside of Numba, use `compile_ptx()` instead.
- Eager compilation of device functions (the case when `device=True` and a signature is provided) is deprecated.

Version support/dependency changes:

- LLVM 11 is now supported on all platforms via llvmlite.
- The minimum supported Python version is raised to 3.7.
- NumPy version 1.20 is supported.

- The minimum supported NumPy version is raised to 1.17 for runtime (compilation however remains compatible with NumPy 1.11).
- Vendor cloudpickle *v1.6.0* – now used for all `pickle` operations.
- TBB >= 2021 is now supported and all prior versions are unsupported (not easily possible to maintain the ABI breaking changes).

Pull-Requests:

- PR #4516: Make setitem accept 0d np-arrays (Guilherme Leobas)
- PR #4610: Implement np.is* functions (Guilherme Leobas)
- PR #5984: Handle idx and size unification in wrap_index manually. (Todd A. Anderson)
- PR #6468: Access `replace_functions_map` via PreParforPass instance (Sergey Pokhodenko Reazul Hoque)
- PR #6469: Add address space in pointer type (Sergey Pokhodenko Reazul Hoque)
- PR #6608: Support f-strings for common cases (Ehsan Totoni)
- PR #6619: Improved fastmath code generation for trig, log, and exp/pow. (Graham Markall Michael Collison)
- PR #6681: Explicitly catch `with..as` and raise error. (stuartarchibald)
- PR #6689: Fix setup.py build command detection (Hannes Pahl)
- PR #6695: Enable negative indexing for cuda atomic operations (Ashutosh Varma)
- PR #6696: flake8: made more files flake8 compliant (Ashutosh Varma)
- PR #6698: Fix #6697: Wrong dtype when using np.asarray on DeviceNDArray (Ashutosh Varma)
- PR #6700: Add UUID to CUDA devices (Graham Markall)
- PR #6709: Block matplotlib in test examples (Graham Markall)
- PR #6718: doc: fix typo in rewrites.rst (extra iterates) (Alexander-Makaryev)
- PR #6720: Faster compile (Siu Kwan Lam)
- PR #6730: Fix Typeguard error (Graham Markall)
- PR #6731: Add CUDA-specific pipeline (Graham Markall)
- PR #6735: CUDA: Don't parse IR for modules with llvmlite (Graham Markall)
- PR #6736: Support for dict comprehension (stuartarchibald)
- PR #6742: Do not add overload function definitions to index. (stuartarchibald)
- PR #6750: Bump to llvmlite 0.37 series (Siu Kwan Lam)
- PR #6751: Suppress typeguard warnings that affect testing. (Siu Kwan Lam)
- PR #6753: The check for internal types in RewriteArrayExprs (Alexander-Makaryev)
- PR #6755: install llvmlite from numba/label/dev (esc)
- PR #6758: patch to compile _devicearray.cpp with c++11 (esc)
- PR #6760: Fix scheduler bug where it rounds to 0 divisions for a chunk. (Todd A. Anderson)
- PR #6762: Glue wrappers to create @overload from split typing and lowering. (stuartarchibald Siu Kwan Lam)
- PR #6766: Fix DeviceNDArray null shape issue (Michael Collison)
- PR #6769: CUDA: Replace `CachedPTX` and `CachedCUFunction` with `CUDACodeLibrary` functionality (Graham Markall)

- PR #6776: Fix issue with TBB interface causing warnings and parfors counting them (stuartarchibald)
- PR #6779: Fix wrap_index type unification. (Todd A. Anderson)
- PR #6786: Fix gufunc kwargs support (Siu Kwan Lam)
- PR #6788: Add support for fastmath 32-bit floating point divide (Michael Collison)
- PR #6789: Fix warnings struct ref typeguard (stuartarchibald Siu Kwan Lam esc)
- PR #6794: refactor and move create_temp_module into numba.tests.support (Alexander-Makaryev)
- PR #6795: CUDA: Lazily add libdevice to compilation units (Graham Markall)
- PR #6798: CUDA: Add optional Driver API argument logging (Graham Markall)
- PR #6799: Print Numba and llvmlite versions in sysinfo (Graham Markall)
- PR #6800: Make a common standard API for querying ufunc impl (Sergey Pokhodenko Siu Kwan Lam)
- PR #6801: ParallelAccelerator no long will convert StaticSetItem to SetItem because record arrays require StaticSetItems. (Todd A. Anderson)
- PR #6802: Add lineinfo flag to PTX and SASS compilation (Graham Markall Max Katz)
- PR #6804: added runtime version to `numba -s` (Kalyan)
- PR #6808: #3468 continued: Add support for `np.clip` (Graham Markall Aaron Russell Voelker)
- PR #6809: #3203 additional info in cuda detect (Kalyan)
- PR #6810: Fix tiny formatting error in ROC kernel docs (Felix Divo)
- PR #6811: CUDA: Remove test of runtime being a supported version (Graham Markall)
- PR #6813: Mostly CUDA: Replace llvmpy API usage with llvmlite APIs (Graham Markall)
- PR #6814: Improving context stack (stuartarchibald Siu Kwan Lam)
- PR #6818: CUDA: Support IPC on Windows (Graham Markall)
- PR #6822: Add support for np.rot90 (stuartarchibald Daniel Nagel)
- PR #6829: Fix accuracy of np.arange and np.linspace (stuartarchibald)
- PR #6830: CUDA: Use relaxed strides checking to compute contiguity (Graham Markall)
- PR #6833: Raise TypeError exception if numpy array is cast to scalar (Michael Collison)
- PR #6834: Remove illegal “debug” kw argument (Shaun Cutts)
- PR #6836: CUDA: Documentation updates (Graham Markall)
- PR #6840: CUDA: Remove items deprecated in 0.53 + simulator test fixes (Graham Markall)
- PR #6841: CUDA: Fix source location on kernel entry and enable breakpoints to be set on kernels by mangled name (Graham Markall)
- PR #6843: cross-referenced Array type in docs (Kalyan)
- PR #6844: CUDA: Remove NUMBAPRO env var warnings, envvars.py + other small tidy-ups (Graham Markall)
- PR #6848: Ignore .ycm_extra_conf.py (Graham Markall)
- PR #6849: Add __hash__ for IntEnum (Hannes Pahl)
- PR #6850: Fix up more internal warnings (stuartarchibald)
- PR #6854: PR 6096 continued (stuartarchibald Ivan Butygin)
- PR #6861: updated reference to hsa with roc (Kalyan)

- PR #6867: Update changelog for 0.53.1 (esc)
- PR #6869: Implement builtin sum() (stuartarchibald)
- PR #6870: Add support for dispatcher retargeting using with-context (stuartarchibald Siu Kwan Lam)
- PR #6871: Force text-align:left when using Annotate (Guilherme Leobas)
- PR #6873: docs: Update reference to @jitclass location (David Nadlinger)
- PR #6876: Add trailing slashes to dir paths in CODEOWNERS (Graham Markall)
- PR #6877: Add doc for recent target extension features (Siu Kwan Lam)
- PR #6878: CUDA: Support passing tuples to ufuncs (Graham Markall)
- PR #6879: CUDA: NumPy and string dtypes for local and shared arrays (Graham Markall)
- PR #6880: Add attribute lower_extension to CPUContext (Reazul Hoque)
- PR #6883: Add support of np.swapaxes #4074 (Daniel Nagel)
- PR #6885: CUDA: Explicitly specify objmode + looplifting for jit functions in cuda.random (Graham Markall)
- PR #6886: CUDA: Fix parallel testing for all testsuite submodules (Graham Markall)
- PR #6888: Get overload to consider compiler flags in cache lookup (Siu Kwan Lam)
- PR #6889: Address guvectorize too slow for cuda target (Michael Collison)
- PR #6890: fixes #6884 (Kalyan)
- PR #6898: Work on overloading by hardware target. (stuartarchibald)
- PR #6911: CUDA: Add support for activemask(), lanemask_lt(), and nanosleep() (Graham Markall)
- PR #6912: Prevent use of varargs in closure calls. (stuartarchibald)
- PR #6913: Add runtests option to gitdiff on the common ancestor (Siu Kwan Lam)
- PR #6915: Update _Intrinsic for sphinx to capture the inner docstring (Guilherme Leobas)
- PR #6917: Add type conversion for StringLiteral to unicode_type and test. (stuartarchibald)
- PR #6918: Start section on commonly encounted unsupported parfors code. (stuartarchibald)
- PR #6924: CUDA: Fix `ffs` (Graham Markall)
- PR #6928: Add support for axis keyword arg to numpy.argmax() (stuartarchibald Itamar Turner-Trauring)
- PR #6929: Fix CI failure when gitpython is missing. (Siu Kwan Lam)
- PR #6935: fixes broken link in numba-runtime.rst (Kalyan)
- PR #6936: CUDA: Implement support for PTDS globally (Graham Markall)
- PR #6937: Fix memory leak in bytes boxing (stuartarchibald)
- PR #6940: Fix function resolution for intrinsics across hardware. (stuartarchibald)
- PR #6941: ABC the target descriptor and make consistent throughout. (stuartarchibald)
- PR #6944: CUDA: Support for `@overload` (Graham Markall)
- PR #6945: Fix issue with array analysis tests needing scipy. (stuartarchibald)
- PR #6948: Refactor registry init. (stuartarchibald Graham Markall Siu Kwan Lam)
- PR #6953: CUDA: Fix and deprecate `inspect_ptx()`, fix NVVM option setup for device functions (Graham Markall)

- PR #6958: Inconsistent behavior of reshape between numpy and numba/cuda device array (Lauren Arnett)
- PR #6961: Update overload glue to deal with typing_key (stuartarchibald)
- PR #6964: Move minimum supported Python version to 3.7 (stuartarchibald)
- PR #6966: Fix issue with TBB test detecting forks from incorrect state. (stuartarchibald)
- PR #6971: Fix CUDA `@intrinsic` use (stuartarchibald)
- PR #6977: Vendor cloudpickle (Siu Kwan Lam)
- PR #6978: Implement operator.contains for empty Tuples (Brandon T. Willard)
- PR #6981: Fix LLVM IR parsing error on use of `np.bool_` in globals (stuartarchibald)
- PR #6983: Support Optional types in ufuncs. (stuartarchibald)
- PR #6985: Implement static set/get items on records with integer index (stuartarchibald)
- PR #6986: document release checklist (esc)
- PR #6989: update threading docs for function loading (esc)
- PR #6990: Refactor hardware extension API to refer to "target" instead. (stuartarchibald)
- PR #6991: Move ROCm target status to "unmaintained". (stuartarchibald)
- PR #6995: Resolve issue where nan was being assigned to int type numpy array (Michael Collison)
- PR #6996: Add constant lowering support for SliceType`s (`Brandon T. Willard)
- PR #6997: CUDA: Remove catch of NotImplementedError in target.py (Graham Markall)
- PR #6999: Fix errors introduced by the cloudpickle patch (Siu Kwan Lam)
- PR #7003: More mainline fixes (stuartarchibald Graham Markall Siu Kwan Lam)
- PR #7004: Test extending the CUDA target (Graham Markall)
- PR #7007: Made stencil compilation not fail for arrays of conflicting types. (MegaIng)
- PR #7008: Added support for np.random.dirichlet with all size arguments (Rishi Kulkarni)
- PR #7016: Docs: Add DALI to list of CAI-supporting libraries (Graham Markall)
- PR #7018: Remove cu{blas,sparse,rand,fft} from library checks (Graham Markall)
- PR #7019: Support NumPy 1.20 (stuartarchibald)
- PR #7020: Fix #7017. Adds util class PickleCallableByPath (Siu Kwan Lam)
- PR #7024: fixed llvmir usage in create_module method (stuartarchibald Kalyan)
- PR #7027: Fix nrt debug print (MegaIng)
- PR #7031: Fix inliner to use a single scope for all blocks (Alexey Kozlov Siu Kwan Lam)
- PR #7040: Add Github action to mark issues as stale (Graham Markall)
- PR #7044: Fixes for LLVM 11 (stuartarchibald)
- PR #7049: Make NumPy random module use @overload_glue (stuartarchibald)
- PR #7050: Add overload_classmethod (Siu Kwan Lam)
- PR #7052: Fix string support in CUDA target (Graham Markall)
- PR #7056: Change prange conversion approach to reuse header block. (Todd A. Anderson)
- PR #7061: Add ndarray allocator classmethod (stuartarchibald Siu Kwan Lam)

- PR #7064: Testhound/host array performance warning (Michael Collison)
- PR #7066: Fix #7065: Add expected exception messages for NumPy 1.20 to tests (Graham Markall)
- PR #7068: Enhancing docs about PRNG seeding (Jérome Eertmans)
- PR #7070: Improve the issue templates and pull request template. (Guoqiang QI)
- PR #7080: Fix `__eq__` for Flags and cpu_options classes (Siu Kwan Lam)
- PR #7087: Add note to docs about zero-initialization of variables. (stuartarchibald)
- PR #7088: Initialize NUMBA_DEFAULT_NUM_THREADS with a batch scheduler aware value (Thomas VINCENT)
- PR #7100: Replace deprecated call to cuDeviceComputeCapability (Graham Markall)
- PR #7113: Temporarily disable debug env export. (stuartarchibald)
- PR #7114: CUDA: Deprecate eager compilation of device functions (Graham Markall)
- PR #7116: Fix various issues with dwarf emission: (stuartarchibald vlad-perevezentsev)
- PR #7118: Remove print to stdout (stuartarchibald)
- PR #7121: Continue work on numpy subclasses (Todd A. Anderson Siu Kwan Lam)
- PR #7122: Rtd/sphinx compat (esc)
- PR #7134: Move minimum LLVM version to 11. (stuartarchibald)
- PR #7137: skip pycc test on Python 3.7 + macOS because of distutils issue (esc)
- PR #7138: Update the Azure default linux image to Ubuntu 18.04 (stuartarchibald)
- PR #7141: Require llvmlite 0.37 as minimum supported. (stuartarchibald)
- PR #7143: Update version checks in __init__ for np 1.17 (stuartarchibald)
- PR #7145: Fix mainline (stuartarchibald)
- PR #7146: Fix `inline_closurecall` may not be imported (Siu Kwan Lam)
- PR #7147: Revert "Workaround gitpython 3.1.18 dependency issue" (stuartarchibald)
- PR #7149: Fix issue in bytecode analysis where target and next are same. (stuartarchibald)
- PR #7152: Fix iterators in CUDA (Graham Markall)
- PR #7156: Fix `ir_utils._max_label` being updated incorrectly (Siu Kwan Lam)
- PR #7160: Split parfors tests (stuartarchibald)
- PR #7161: Update README for 0.54 (stuartarchibald)
- PR #7162: CUDA: Fix linkage of device functions when compiling for debug (Graham Markall)
- PR #7163: Split legalization pass to consider IR and features separately. (stuartarchibald)
- PR #7165: Fix use of np.clip where out is not provided. (stuartarchibald)
- PR #7189: CUDA: Skip IPC tests on ARM (Graham Markall)
- PR #7190: CUDA: Fix test_pinned on Jetson (Graham Markall)
- PR #7192: Fix missing import in array.argsort impl and add more tests. (stuartarchibald)
- PR #7196: Fixes for lineinfo emission. (stuartarchibald)
- PR #7203: remove duplicate changelog entries (esc)

- PR #7209: Clamp numpy (esc)
- PR #7216: Update CHANGE_LOG for 0.54.0rc2. (stuartarchibald)
- PR #7223: Replace assertion errors on IR assumption violation (Siu Kwan Lam)
- PR #7230: PR #7171 bugfix only (Todd A. Anderson stuartarchibald)
- PR #7236: CUDA: Skip managed alloc tests on ARM (Graham Markall)
- PR #7267: Fix #7258. Bug in SROA optimization (Siu Kwan Lam)
- PR #7271: Update 3rd party license text. (stuartarchibald)
- PR #7272: Allow annotations in njit-ed functions (LunarLanding)
- PR #7273: Update CHANGE_LOG for 0.54.0rc3. (stuartarchibald)
- PR #7285: CUDA: Fix OOB in test_kernel_arg (Graham Markall)
- PR #7294: Continuation of PR #7280, fixing lifetime of TBB task_scheduler_handle (Sergey Pokhodenko stuartarchibald)
- PR #7298: Use CBC to pin GCC to 7 on most linux and 9 on aarch64. (stuartarchibald)
- PR #7312: Fix #7302. Workaround missing pthread problem on ppc64le (Siu Kwan Lam)
- PR #7317: In TBB tsh test switch os.fork for mp fork ctx (stuartarchibald)
- PR #7319: Update CHANGE_LOG for 0.54.0 final. (stuartarchibald)

Authors:

- Alexander-Makaryev
- Todd A. Anderson
- Hannes Pahl
- Ivan Butygin
- MegaIng
- Sergey Pokhodenko
- Aaron Russell Voelker
- Ashutosh Varma
- Ben Greiner
- Brandon T. Willard
- Daniel Nagel
- David Nadlinger
- Ehsan Totoni
- esc
- Felix Divo
- Graham Markall
- Guilherme Leobas
- Guoqiang QI
- Itamar Turner-Trauring

- Jérome Eertmans
- Alexey Kozlov
- Lauren Arnett
- LunarLanding
- Max Katz
- Kalyan
- Reazul Hoque
- Rishi Kulkarni
- Shaun Cutts
- Siu Kwan Lam
- stuartarchibald
- Thomas VINCENT
- Michael Collison
- vlad-perevezentsev

9.2.13 Version 0.53.1 (25 March, 2021)

This is a bugfix release for 0.53.0. It contains the following four pull-requests which fix two critical regressions and two build failures reported by the openSuSe team:

- PR #6826 Fix regression on gufunc serialization
- PR #6828 Fix regression in CUDA: Set stream in mapped and managed array device_setup
- PR #6837 Ignore warnings from packaging module when testing import behaviour.
- PR #6851 set non-reported llvm timing values to 0.0

Authors:

- Ben Greiner
- Graham Markall
- Siu Kwan Lam
- Stuart Archibald

9.2.14 Version 0.53.0 (11 March, 2021)

This release continues to add new features, bug fixes and stability improvements to Numba.

Highlights of core changes:

- Support for Python 3.9 (Stuart Archibald).
- Function sub-typing (Lucio Fernandez-Arjona).
- Initial support for dynamic `gufuncs` (i.e. from `@guvectorize`) (Guilherme Leobas).
- Parallel Accelerator (`@njit(parallel=True)` now supports Fortran ordered arrays (Todd A. Anderson and Siu Kwan Lam).

Intel also kindly sponsored research and development that lead to two new features:

- Exposing LLVM compilation pass timings for diagnostic purposes (Siu Kwan Lam).
- An event system for broadcasting compiler events (Siu Kwan Lam).

Highlights of changes for the CUDA target:

- CUDA 11.2 onwards (versions of the toolkit using NVVM IR 1.6 / LLVM IR 7.0.1) are now supported (Graham Markall).
- A fast cube root function is added (Michael Collison).
- Support for atomic `xor`, increment, decrement, exchange, are added, and compare-and-swap is extended to support 64-bit integers (Michael Collison).
- Addition of `cuda.is_supported_version()` to check if the CUDA runtime version is supported (Graham Markall).
- The CUDA dispatcher now shares infrastructure with the CPU dispatcher, improving launch times for lazily-compiled kernels (Graham Markall).
- The CUDA Array Interface is updated to version 3, with support for streams added (Graham Markall).
- Tuples and `namedtuples` can now be passed to kernels (Graham Markall).
- Initial support for Cooperative Groups is added, with support for Grid Groups and Grid Sync (Graham Markall and Nick White).
- Support for `math.log2` and `math.remainder` is added (Guilherme Leobas).

General deprecation notices:

- There are no new general deprecations.

CUDA target deprecation notices:

- CUDA support on macOS is deprecated with this release (it still works, it is just unsupported).
- The `argtypes`, `restypes`, and `bind` keyword arguments to the `cuda.jit` decorator, deprecated since 0.51.0, are removed
- The `Device.COMPUTE_CAPABILITY` property, deprecated since 2014, has been removed (use `compute_capability` instead).
- The `to_host` method of device arrays is removed (use `copy_to_host` instead).

General Enhancements:

- PR #4769: objmode complex type spelling (Siu Kwan Lam)
- PR #5579: Function subtyping (Lucio Fernandez-Arjona)
- PR #5659: Add support for parfors creating 'F'ortran layout Numpy arrays. (Todd A. Anderson)
- PR #5936: Improve array analysis for user-defined data types. (Todd A. Anderson)
- PR #5938: Initial support for dynamic gufuncs (Guilherme Leobas)
- PR #5958: Making typed.List a typing Generic (Lucio Fernandez-Arjona)
- PR #6334: Support attribute access from other modules (Farah Hariri)
- PR #6373: Allow Dispatchers to be cached (Eric Wieser)
- PR #6519: Avoid unnecessary ir.Del generation and removal (Ehsan Totoni)
- PR #6545: Refactoring ParforDiagnostics (Elena Totmenina)

- PR #6560: Add LLVM pass timer (Siu Kwan Lam)
- PR #6573: Improve `__str__` for typed.List when invoked from IPython shell (Amin Sadeghi)
- PR #6575: Avoid temp variable assignments (Ehsan Totoni)
- PR #6578: Add support for numpy `intersect1d` and basic test cases (`@caljrobe`)
- PR #6579: Python 3.9 support. (Stuart Archibald)
- PR #6580: Store partial typing errors in compiler state (Ehsan Totoni)
- PR #6626: A simple event system to broadcast compiler events (Siu Kwan Lam)
- PR #6635: Try to resolve dynamic getitems as static post unroll transform. (Stuart Archibald)
- PR #6636: Adds llvm_lock event (Siu Kwan Lam)
- PR #6664: Adds tests for PR 5659 (Siu Kwan Lam)
- PR #6680: Allow getattr to work in objmode output type spec (Siu Kwan Lam)

Fixes:

- PR #6176: Remove references to deprecated numpy globals (Eric Wieser)
- PR #6374: Use Python 3 style OSError handling (Eric Wieser)
- PR #6402: Fix `typed.Dict` and `typed.List` crashing on parametrized types (Andreas Sodeur)
- PR #6403: Add `types.ListType.key` (Andreas Sodeur)
- PR #6410: Fixes issue #6386 (Danny Weitekamp)
- PR #6425: Fix unicode join for issue #6405 (Teugea Ioan-Teodor)
- PR #6437: Don't pass reduction variables known in an outer parfor to inner parfors when analyzing reductions. (Todd A. Anderson)
- PR #6453: Keep original variable names in metadata to improve diagnostics (Ehsan Totoni)
- PR #6454: FIX: Fixes for literals (Eric Larson)
- PR #6463: Bump llvmlite to 0.36 series (Stuart Archibald)
- PR #6466: Remove the misspelling of finalize_dynamic_globals (Sergey Pokhodenko)
- PR #6489: Improve the error message for unsupported Buffer in Buffer situation. (Stuart Archibald)
- PR #6503: Add test to ensure Numba imports without warnings. (Stuart Archibald)
- PR #6508: Defer requirements to setup.py (Siu Kwan Lam)
- PR #6521: Skip annotated jitclass test if typeguard is running. (Stuart Archibald)
- PR #6524: Fix typed.List return value (Lucio Fernandez-Arjona)
- PR #6562: Correcting typo in numba sysinfo output (Nick Sutcliffe)
- PR #6574: Run parfor fusion if 2 or more parfors (Ehsan Totoni)
- PR #6582: Fix typed dict error with uninitialized padding bytes (Siu Kwan Lam)
- PR #6584: Remove jitclass from `__init__` `__all__`. (Stuart Archibald)
- PR #6586: Run closure inlining ahead of branch pruning in case of nonlocal (Stuart Archibald)
- PR #6591: Fix inlineasm test failure. (Siu Kwan Lam)
- PR #6622: Fix 6534, handle unpack of assign-like tuples. (Stuart Archibald)

- PR #6652: Simplify PR-6334 (Siu Kwan Lam)
- PR #6653: Fix get_numba_envvar (Siu Kwan Lam)
- PR #6654: Fix #6632 support alternative dtype string spellings (Stuart Archibald)
- PR #6685: Add Python 3.9 to classifiers. (Stuart Archibald)
- PR #6693: patch to compile _devicearray.cpp with c++11 (Valentin Haenel)
- PR #6716: Consider assignment lhs live if used in rhs (Fixes #6715) (Ehsan Totoni)
- PR #6727: Avoid errors in array analysis for global tuples with non-int (Ehsan Totoni)
- PR #6733: Fix segfault and errors in #6668 (Siu Kwan Lam)
- PR #6741: Enable SSA in IR inliner (Ehsan Totoni)
- PR #6763: use an alternative constraint for the conda packages (Valentin Haenel)
- PR #6786: Fix gufunc kwargs support (Siu Kwan Lam)

CUDA Enhancements/Fixes:

- PR #5162: Specify synchronization semantics of CUDA Array Interface (Graham Markall)
- PR #6245: CUDA Cooperative grid groups (Graham Markall and Nick White)
- PR #6333: Remove dead `_Kernel.__call__` (Graham Markall)
- PR #6343: CUDA: Add support for passing tuples and namedtuples to kernels (Graham Markall)
- PR #6349: Refactor Dispatcher to remove unnecessary indirection (Graham Markall)
- PR #6358: Add log2 and remainder implementations for cuda (Guilherme Leobas)
- PR #6376: Added a fixed seed in test_atomics.py for issue #6370 (Teugea Ioan-Teodor)
- PR #6377: CUDA: Fix various issues in test suite (Graham Markall)
- PR #6409: Implement cuda atomic xor (Michael Collison)
- PR #6422: CUDA: Remove deprecated items, expect CUDA 11.1 (Graham Markall)
- PR #6427: Remove duplicate repeated definition of gufunc (Amit Kumar)
- PR #6432: CUDA: Use `_dispatcher.Dispatcher` as base Dispatcher class (Graham Markall)
- PR #6447: CUDA: Add get_regs_per_thread method to Dispatcher (Graham Markall)
- PR #6499: CUDA atomic increment, decrement, exchange and compare and swap (Michael Collison)
- PR #6510: CUDA: Make device array assignment synchronous where necessary (Graham Markall)
- PR #6517: CUDA: Add NVVM test of all 8-bit characters (Graham Markall)
- PR #6567: Refactor llvm replacement code into separate function (Michael Collison)
- PR #6642: Testhound/cuda cuberoot (Michael Collison)
- PR #6661: CUDA: Support NVVM70 / CUDA 11.2 (Graham Markall)
- PR #6663: Fix error caused by missing "-static" libraries defined for some platforms (Siu Kwan Lam)
- PR #6666: CUDA: Add a function to query whether the runtime version is supported. (Graham Markall)
- PR #6725: CUDA: Fix compile to PTX with debug for CUDA 11.2 (Graham Markall)

Documentation Updates:

- PR #5740: Add FAQ entry on how to create a MWR. (Stuart Archibald)

- PR #6346: DOC: add where to get dev builds from to FAQ (Eyal Trabelsi)
- PR #6418: docs: use https for homepage (`@imba-tjd`)
- PR #6430: CUDA docs: Add RNG example with 3D grid and strided loops (Graham Markall)
- PR #6436: docs: remove typo in Deprecation Notices (Thibault Ballier)
- PR #6440: Add note about performance of typed containers from the interpreter. (Stuart Archibald)
- PR #6457: Link to read the docs instead of numba homepage (Hannes Pahl)
- PR #6470: Adding PyCon Sweden 2020 talk on numba (Ankit Mahato)
- PR #6472: Document `numba.extending.is_jitted` (Stuart Archibald)
- PR #6495: Fix typo in literal list docs. (Stuart Archibald)
- PR #6501: Add doc entry on Numba's limited resources and how to help. (Stuart Archibald)
- PR #6502: Add CODEOWNERS file. (Stuart Archibald)
- PR #6531: Update canonical URL. (Stuart Archibald)
- PR #6544: Minor typo / grammar fixes to 5 minute guide (Ollin Boer Bohan)
- PR #6599: docs: fix simple typo, consevatively -> conservatively (Tim Gates)
- PR #6609: Recommend miniforge instead of c4aarch64 (Isuru Fernando)
- PR #6671: Update environment creation example to python 3.8 (Lucio Fernandez-Arjona)
- PR #6676: Update hardware and software versions in various docs. (Stuart Archibald)
- PR #6682: Update deprecation notices for 0.53 (Stuart Archibald)

CI/Infrastructure Updates:

- PR #6458: Enable typeguard in CI (Siu Kwan Lam)
- PR #6500: Update bug and feature request templates. (Stuart Archibald)
- PR #6516: Fix RTD build by using conda. (Stuart Archibald)
- PR #6587: Add zenodo badge (Siu Kwan Lam)

Authors:

- Amin Sadeghi
- Amit Kumar
- Andreas Sodeur
- Ankit Mahato
- Chris Barnes
- Danny Weitekamp
- Ehsan Totoni (core dev)
- Eric Larson
- Eric Wieser
- Eyal Trabelsi
- Farah Hariri
- Graham Markall

- Guilherme Leobas
- Hannes Pahl
- Isuru Fernando
- Lucio Fernandez-Arjona
- Michael Collison
- Nick Sutcliffe
- Nick White
- Ollin Boer Bohan
- Sergey Pokhodenko
- Siu Kwan Lam (core dev)
- Stuart Archibald (core dev)
- Teugea Ioan-Teodor
- Thibault Ballier
- Tim Gates
- Todd A. Anderson (core dev)
- Valentin Haenel (core dev)
- `@caljrobe`
- `@imba-tjd`

9.2.15 Version 0.52.0 (30 November, 2020)

This release focuses on performance improvements, but also adds some new features and contains numerous bug fixes and stability improvements.

Highlights of core performance improvements include:

- Intel kindly sponsored research and development into producing a new reference count pruning pass. This pass operates at the LLVM level and can prune a number of common reference counting patterns. This will improve performance for two primary reasons:
  - There will be less pressure on the atomic locks used to do the reference counting.
  - Removal of reference counting operations permits more inlining and the optimisation passes can in general do more with what is present.

  (Siu Kwan Lam).
- Intel also sponsored work to improve the performance of the `numba.typed.List` container, particularly in the case of `__getitem__` and iteration (Stuart Archibald).
- Superword-level parallelism vectorization is now switched on and the optimisation pipeline has been lightly analysed and tuned so as to be able to vectorize more and more often (Stuart Archibald).

Highlights of core feature changes include:

- The `inspect_cfg` method on the JIT dispatcher object has been significantly enhanced and now includes highlighted output and interleaved line markers and Python source (Stuart Archibald).
- The BSD operating system is now unofficially supported (Stuart Archibald).

- Numerous features/functionality improvements to NumPy support, including support for:
  - `np.asfarray` (Guilherme Leobas)
  - "subtyping" in record arrays (Lucio Fernandez-Arjona)
  - `np.split` and `np.array_split` (Isaac Virshup)
  - `operator.contains` with `ndarray` (`@mugoh`).
  - `np.asarray_chkfinite` (Rishabh Varshney).
  - NumPy 1.19 (Stuart Archibald).
  - the `ndarray` allocators, `empty`, `ones` and `zeros`, accepting a `dtype` specified as a string literal (Stuart Archibald).
- Booleans are now supported as literal types (Alexey Kozlov).
- On the CUDA target:
  - CUDA 9.0 is now the minimum supported version (Graham Markall).
  - Support for Unified Memory has been added (Max Katz).
  - Kernel launch overhead is reduced (Graham Markall).
  - Cudasim support for mapped array, memcopies and memset has been added (Mike Williams).
  - Access has been wired in to all libdevice functions (Graham Markall).
  - Additional CUDA atomic operations have been added (Michael Collison).
  - Additional math library functions (`frexp`, `ldexp`, `isfinite`) (Zhihao Yuan).
  - Support for `power` on complex numbers (Graham Markall).

Deprecations to note:

There are no new deprecations. However, note that "compatibility" mode, which was added some 40 releases ago to help transition from 0.11 to 0.12+, has been removed! Also, the shim to permit the import of `jitclass` from Numba's top level namespace has now been removed as per the deprecation schedule.

General Enhancements:

- PR #5418: Add np.asfarray impl (Guilherme Leobas)
- PR #5560: Record subtyping (Lucio Fernandez-Arjona)
- PR #5609: Jitclass Infer Spec from Type Annotations (Ethan Pronovost)
- PR #5699: Implement np.split and np.array_split (Isaac Virshup)
- PR #6015: Adding BooleanLiteral type (Alexey Kozlov)
- PR #6027: Support operators inlining in InlineOverloads (Alexey Kozlov)
- PR #6038: Closes #6037, fixing FreeBSD compilation (László Károlyi)
- PR #6086: Add more accessible version information (Stuart Archibald)
- PR #6157: Add pipeline_class argument to @cfunc as supported by @jit. (Arthur Peters)
- PR #6262: Support dtype from str literal. (Stuart Archibald)
- PR #6271: Support `ndarray` contains (`@mugoh`)
- PR #6295: Enhance inspect_cfg (Stuart Archibald)
- PR #6304: Support NumPy 1.19 (Stuart Archibald)

- PR #6309: Add suitable file search path for BSDs. (Stuart Archibald)
- PR #6341: Re roll 6279 (Rishabh Varshney and Valentin Haenel)

Performance Enhancements:

- PR #6145: Patch to fingerprint namedtuples. (Stuart Archibald)
- PR #6202: Speed up str(int) (Stuart Archibald)
- PR #6261: Add np.ndarray.ptp() support. (Stuart Archibald)
- PR #6266: Use custom LLVM refcount pruning pass (Siu Kwan Lam)
- PR #6275: Switch on SLP vectorize. (Stuart Archibald)
- PR #6278: Improve typed list performance. (Stuart Archibald)
- PR #6335: Split optimisation passes. (Stuart Archibald)
- PR #6455: Fix refprune on obfuscated refs and stabilize optimisation WRT wrappers. (Stuart Archibald)

Fixes:

- PR #5639: Make UnicodeType inherit from Hashable (Stuart Archibald)
- PR #6006: Resolves incorrectly hoisted list in parfor. (Todd A. Anderson)
- PR #6126: fix version_info if version can not be determined (Valentin Haenel)
- PR #6137: Remove references to Python 2's long (Eric Wieser)
- PR #6139: Use direct syntax instead of the `add_metaclass` decorator (Eric Wieser)
- PR #6140: Replace calls to utils.iteritems(d) with d.items() (Eric Wieser)
- PR #6141: Fix #6130 objmode cache segfault (Siu Kwan Lam)
- PR #6156: Remove callers of `reraise` in favor of using `with_traceback` directly (Eric Wieser)
- PR #6162: Move charseq support out of init (Stuart Archibald)
- PR #6165: #5425 continued (Amos Bird and Stuart Archibald)
- PR #6166: Remove Python 2 compatibility from numba.core.utils (Eric Wieser)
- PR #6185: Better error message on NotDefinedError (Luiz Almeida)
- PR #6194: Remove recursion from traverse_types (Radu Popovici)
- PR #6200: Workaround #5973 (Stuart Archibald)
- PR #6203: Make find_callname only lookup functions that are likely part of NumPy. (Stuart Archibald)
- PR #6204: Fix unicode kind selection for getitem. (Stuart Archibald)
- PR #6206: Build all extension modules with -g -Wall -Werror on Linux x86, provide -O0 flag option (Graham Markall)
- PR #6212: Fix for objmode recompilation issue (Alexey Kozlov)
- PR #6213: Fix #6177. Remove AOT dependency on the Numba package (Siu Kwan Lam)
- PR #6224: Add support for tuple concatenation to array analysis. (#5396 continued) (Todd A. Anderson)
- PR #6231: Remove compatibility mode (Graham Markall)
- PR #6254: Fix win-32 hashing bug (from Stuart Archibald) (Ray Donnelly)
- PR #6265: Fix #6260 (Stuart Archibald)

- PR #6267: speed up a couple of really slow unittests (Stuart Archibald)
- PR #6281: Remove numba.jitclass shim as per deprecation schedule. (Stuart Archibald)
- PR #6294: Make return type propagate to all return variables (Andreas Sodeur)
- PR #6300: Un-skip tests that were skipped because of #4026. (Owen Anderson)
- PR #6307: Remove restrictions on SVML version due to bug in LLVM SVML CC (Stuart Archibald)
- PR #6316: Make IR inliner tests not self mutating. (Stuart Archibald)
- PR #6318: PR #5892 continued (Todd A. Anderson, via Stuart Archibald)
- PR #6319: Permit switching off boundschecking when debug is on. (Stuart Archibald)
- PR #6324: PR 6208 continued (Ivan Butygin and Stuart Archibald)
- PR #6337: Implements `key` on `types.TypeRef` (Andreas Sodeur)
- PR #6354: Bump llvmlite to 0.35. series. (Stuart Archibald)
- PR #6357: Fix enumerate invalid decref (Siu Kwan Lam)
- PR #6359: Fixes typed list indexing on 32bit (Stuart Archibald)
- PR #6378: Fix incorrect CPU override in vectorization test. (Stuart Archibald)
- PR #6379: Use O0 to enable inline and not affect loop-vectorization by later O3… (Siu Kwan Lam)
- PR #6384: Fix failing tests to match on platform invariant int spelling. (Stuart Archibald)
- PR #6390: Updates inspect_cfg (Stuart Archibald)
- PR #6396: Remove hard dependency on tbb package. (Stuart Archibald)
- PR #6408: Don't do array analysis for tuples that contain arrays. (Todd A. Anderson)
- PR #6441: Fix ASCII flag in Unicode slicing (0.52.0rc2 regression) (Ehsan Totoni)
- PR #6442: Fix array analysis regression in 0.52 RC2 for tuple of 1D arrays (Ehsan Totoni)
- PR #6446: Fix #6444: pruner issues with reference stealing functions (Siu Kwan Lam)
- PR #6450: Fix asfarray kwarg default handling. (Stuart Archibald)
- PR #6486: fix abstract base class import (Valentin Haenel)
- PR #6487: Restrict maximum version of python (Siu Kwan Lam)
- PR #6527: setup.py: fix py version guard (Chris Barnes)

CUDA Enhancements/Fixes:

- PR #5465: Remove macro expansion and replace uses with FE typing + BE lowering (Graham Markall)
- PR #5741: CUDA: Add two-argument implementation of round() (Graham Markall)
- PR #5900: Enable CUDA Unified Memory (Max Katz)
- PR #6042: CUDA: Lower launch overhead by launching kernel directly (Graham Markall)
- PR #6064: Lower math.frexp and math.ldexp in numba.cuda (Zhihao Yuan)
- PR #6066: Lower math.isfinite in numba.cuda (Zhihao Yuan)
- PR #6092: CUDA: Add mapped_array_like and pinned_array_like (Graham Markall)
- PR #6127: Fix race in reduction kernels on Volta, require CUDA 9, add syncwarp with default mask (Graham Markall)

- PR #6129: Extend Cudasim to support most of the memory functionality. (Mike Williams)
- PR #6150: CUDA: Turn on flake8 for cudadrv and fix errors (Graham Markall)
- PR #6152: CUDA: Provide wrappers for all libdevice functions, and fix typing of math function (#4618) (Graham Markall)
- PR #6227: Raise exception when no supported architectures are found (Jacob Tomlinson)
- PR #6244: CUDA Docs: Make workflow using simulator more explicit (Graham Markall)
- PR #6248: Add support for CUDA atomic subtract operations (Michael Collison)
- PR #6289: Refactor atomic test cases to reduce code duplication (Michael Collison)
- PR #6290: CUDA: Add support for complex power (Graham Markall)
- PR #6296: Fix flake8 violations in numba.cuda module (Graham Markall)
- PR #6297: Fix flake8 violations in numba.cuda.tests.cudapy module (Graham Markall)
- PR #6298: Fix flake8 violations in numba.cuda.tests.cudadrv (Graham Markall)
- PR #6299: Fix flake8 violations in numba.cuda.simulator (Graham Markall)
- PR #6306: Fix flake8 in cuda atomic test from merge. (Stuart Archibald)
- PR #6325: Refactor code for atomic operations (Michael Collison)
- PR #6329: Flake8 fix for a CUDA test (Stuart Archibald)
- PR #6331: Explicitly state that NUMBA_ENABLE_CUDASIM needs to be set before import (Graham Markall)
- PR #6340: CUDA: Fix #6339, performance regression launching specialized kernels (Graham Markall)
- PR #6380: Only test managed allocations on Linux (Graham Markall)

Documentation Updates:

- PR #6090: doc: Add doc on direct creation of Numba typed-list (`@rht`)
- PR #6110: Update CONTRIBUTING.md (Stuart Archibald)
- PR #6128: CUDA Docs: Restore Dispatcher.forall() docs (Graham Markall)
- PR #6277: fix: cross2d wrong doc. reference (issue #6276) (`@jeertmans`)
- PR #6282: Remove docs on Python 2(.7) EOL. (Stuart Archibald)
- PR #6283: Add note on how public CI is impl and what users can do to help. (Stuart Archibald)
- PR #6292: Document support for structured array attribute access (Graham Markall)
- PR #6310: Declare unofficial *BSD support (Stuart Archibald)
- PR #6342: Fix docs on literally usage. (Stuart Archibald)
- PR #6348: doc: fix typo in jitclass.rst (“initilising” -> “initialising”) (`@muxator`)
- PR #6362: Move llvmlite support in README to 0.35 (Stuart Archibald)
- PR #6363: Note that reference counted types are not permitted in set(). (Stuart Archibald)
- PR #6364: Move deprecation schedules for 0.52 (Stuart Archibald)

CI/Infrastructure Updates:

- PR #6252: Show channel URLs (Siu Kwan Lam)
- PR #6338: Direct user questions to Discourse instead of the Google Group. (Stan Seibert)

- PR #6474: Add skip on PPC64LE for tests causing SIGABRT in LLVM. (Stuart Archibald)

Authors:

- Alexey Kozlov
- Amos Bird
- Andreas Sodeur
- Arthur Peters
- Chris Barnes
- Ehsan Totoni (core dev)
- Eric Wieser
- Ethan Pronovost
- Graham Markall
- Guilherme Leobas
- Isaac Virshup
- Ivan Butygin
- Jacob Tomlinson
- Luiz Almeida
- László Károlyi
- Lucio Fernandez-Arjona
- Max Katz
- Michael Collison
- Mike Williams
- Owen Anderson
- Radu Popovici
- Ray Donnelly
- Rishabh Varshney
- Siu Kwan Lam (core dev)
- Stan Seibert (core dev)
- Stuart Archibald (core dev)
- Todd A. Anderson (core dev)
- Valentin Haenel (core dev)
- Zhihao Yuan
- `@jeertmans`
- `@mugoh`
- `@muxator`
- `@rht`

9.2.16 Version 0.51.2 (September 2, 2020)

This is a bugfix release for 0.51.1. It fixes a critical performance bug in the CFG back edge computation algorithm that leads to exponential time complexity arising in compilation for use cases with certain pathological properties.

- PR #6195: PR 6187 Continue. Don't visit already checked successors

Authors:

- Graham Markall
- Siu Kwan Lam (core dev)

9.2.17 Version 0.51.1 (August 26, 2020)

This is a bugfix release for 0.51.0, it fixes a critical bug in caching, another critical bug in the CUDA target initialisation sequence and also fixes some compile time performance regressions:

- PR #6141: Fix #6130 objmode cache segfault
- PR #6146: Fix compilation slowdown due to controlflow analysis
- PR #6147: CUDA: Don't make a runtime call on import
- PR #6153: Fix for #6151. Make UnicodeCharSeq into str for comparison.
- PR #6168: Fix Issue #6167: Failure in test_cuda_submodules

Authors:

- Graham Markall
- Siu Kwan Lam (core dev)
- Stuart Archibald (core dev)

9.2.18 Version 0.51.0 (August 12, 2020)

This release continues to add new features to Numba and also contains a significant number of bug fixes and stability improvements.

Highlights of core feature changes include:

- The compilation chain is now based on LLVM 10 (Valentin Haenel).
- Numba has internally switched to prefer non-literal types over literal ones so as to reduce function over-specialisation, this with view of speeding up compile times (Siu Kwan Lam).
- On the CUDA target: Support for CUDA Toolkit 11, Ampere, and Compute Capability 8.0; Printing of `SASS` code for kernels; Callbacks to Python functions can be inserted into CUDA streams, and streams are async awaitable; Atomic `nanmin` and `nanmax` functions are added; Fixes for various miscompilations and segfaults. (mostly Graham Markall; call backs on streams by Peter Würtz).

Intel also kindly sponsored research and development that lead to some exciting new features:

- Support for heterogeneous immutable lists and heterogeneous immutable string key dictionaries. Also optional initial/construction value capturing for all lists and dictionaries containing literal values (Stuart Archibald).
- A new pass-by-reference mutable structure extension type `StructRef` (Siu Kwan Lam).
- Object mode blocks are now cacheable, with the side effect of numerous bug fixes and performance improvements in caching. This also permits caching of functions defined in closures (Siu Kwan Lam).

Deprecations to note:

To align with other targets, the `argtypes` and `restypes` kwargs to `@cuda.jit` are now deprecated, the `bind` kwarg is also deprecated. Further the `target` kwarg to the `numba.jit` decorator family is deprecated.

General Enhancements:

- PR #5463: Add str(int) impl
- PR #5526: Impl. np.asarray(literal)
- PR #5619: Add support for multi-output ufuncs
- PR #5711: Division with timedelta input
- PR #5763: Support minlength argument to np.bincount
- PR #5779: Return zero array from np.dot when the arguments are empty.
- PR #5796: Add implementation for np.positive
- PR #5849: Setitem for records when index is StringLiteral, including literal unroll
- PR #5856: Add support for conversion of inplace_binop to parfor.
- PR #5893: Allocate 1D iteration space one at a time for more even distribution.
- PR #5922: Reduce objmode and unpickling overhead
- PR #5944: re-enable OpenMP in wheels
- PR #5946: Implement literal dictionaries and lists.
- PR #5956: Update numba_sysinfo.py
- PR #5978: Add structref as a mutable struct that is pass-by-ref
- PR #5980: Deprecate target kwarg for numba.jit.
- PR #6058: Add prefer_literal option to overload API

Fixes:

- PR #5674: Fix #3955. Allow *with objmode* to be cached
- PR #5724: Initialize process lock lazily to prevent multiprocessing issue
- PR #5783: Make np.divide and np.remainder code more similar
- PR #5808: Fix 5665 Block jit(nopython=True, forceobj=True) and suppress njit(forceobj=True)
- PR #5834: Fix the is operator on Ellipsis
- PR #5838: Ensure `Dispatcher.__eq__` always returns a bool
- PR #5841: cleanup: Use PythonAPI.bool_from_bool in more places
- PR #5862: Do not leak loop iteration variables into the numba.np.npyimpl namespace
- PR #5869: Update repomap
- PR #5879: Fix erroneous input mutation in linalg routines
- PR #5882: Type check function in jit decorator
- PR #5925: Use np.inf and -np.inf for max and min float values respectively.
- PR #5935: Fix default arguments with multiprocessing
- PR #5952: Fix "Internal error ... local variable 'errstr' referenced before assignment during BoundFunction(...)"

- PR #5962: Fix SVML tests with LLVM 10 and AVX512
- PR #5972: fix flake8 for numba/runtests.py
- PR #5995: Update setup.py with new llvmlite versions
- PR #5996: Set lower bound for llvmlite to 0.33
- PR #6004: Fix problem in branch pruning with LiteralStrKeyDict
- PR #6017: Fixing up numba_do_raise
- PR #6028: Fix #6023
- PR #6031: Continue 5821
- PR #6035: Fix overspecialize of literal
- PR #6046: Fixes statement reordering bug in maximize fusion step.
- PR #6056: Fix issue on invalid inlining of non-empty build_list by inline_arraycall
- PR #6057: fix aarch64/python_3.8 failure on master
- PR #6070: Fix overspecialized containers
- PR #6071: Remove f-strings in setup.py
- PR #6072: Fix for #6005
- PR #6073: Fixes invalid C prototype in helper function.
- PR #6078: Duplicate NumPy's PyArray_DescrCheck macro
- PR #6081: Fix issue with cross drive use and relpath.
- PR #6083: Fix bug in initial value unify.
- PR #6087: remove invalid sanity check from randrange tests
- PR #6089: Fix invalid reference to TypingError
- PR #6097: Add function code and closure bytes into cache key
- PR #6099: Restrict upper limit of TBB version due to ABI changes.
- PR #6101: Restrict lower limit of icc_rt version due to assumed SVML bug.
- PR #6107: Fix and test #6095
- PR #6109: Fixes an issue reported in #6094
- PR #6111: Decouple LiteralList and LiteralStrKeyDict from tuple
- PR #6116: Fix #6102. Problem with non-unique label.

CUDA Enhancements/Fixes:

- PR #5359: Remove special-casing of 0d arrays
- PR #5709: CUDA: Refactoring of cuda.jit and kernel / dispatcher abstractions
- PR #5732: CUDA Docs: document `forall` method of kernels
- PR #5745: CUDA stream callbacks and async awaitable streams
- PR #5761: Add implmentation for int types for isnan and isinf for CUDA
- PR #5819: Add support for CUDA 11 and Ampere / CC 8.0
- PR #5826: CUDA: Add function to get SASS for kernels

- PR #5846: CUDA: Allow disabling NVVM optimizations, and fix debug issues
- PR #5851: CUDA EMM enhancements - add default get_ipc_handle implementation, skip a test conditionally
- PR #5852: CUDA: Fix `cuda.test()`
- PR #5857: CUDA docs: Add notes on resetting the EMM plugin
- PR #5859: CUDA: Fix reduce docs and style improvements
- PR #6016: Fixes change of list spelling in a cuda test.
- PR #6020: CUDA: Fix #5820, adding atomic nanmin / nanmax
- PR #6030: CUDA: Don't optimize IR before sending it to NVVM
- PR #6052: Fix dtype for atomic_add_double testsuite
- PR #6080: CUDA: Prevent auto-upgrade of atomic intrinsics
- PR #6123: Fix #6121

Documentation Updates:

- PR #5782: Host docs on Read the Docs
- PR #5830: doc: Mention that caching uses pickle
- PR #5963: Fix broken link to numpy ufunc signature docs
- PR #5975: restructure communication section
- PR #5981: Document bounds-checking behavior in python deviations page
- PR #5993: Docs for structref
- PR #6008: Small fix so bullet points are rendered by sphinx
- PR #6013: emphasize cuda kernel functions are asynchronous
- PR #6036: Update deprecation doc from numba.errors to numba.core.errors
- PR #6062: Change references to numba.pydata.org to https

CI updates:

- PR #5850: Updates the "New Issue" behaviour to better redirect users.
- PR #5940: Add discourse badge
- PR #5960: Setting mypy on CI

Enhancements from user contributed PRs (with thanks!):

- Aisha Tammy added the ability to switch off TBB support at compile time in #5821 (continued in #6031 by Stuart Archibald).
- Alexander Stiebing fixed a reference before assignment bug in #5952.
- Alexey Kozlov fixed a bug in tuple getitem for literals in #6028.
- Andrew Eckart updated the repomap in #5869, added support for Read the Docs in #5782, fixed a bug in the `np.dot` implementation to correctly handle empty arrays in #5779 and added support for `minlength` to `np.bincount` in #5763.
- `@bitsisbits` updated `numba_sysinfo.py` to handle HSA agents correctly in #5956.
- Daichi Suzuo Fixed a bug in the threading backend initialisation sequence such that it is now correctly a lazy lock in #5724.

- Eric Wieser contributed a number of patches, particularly in enhancing and improving the `ufunc` capabilities:
  - #5359: Remove special-casing of 0d arrays
  - #5834: Fix the is operator on Ellipsis
  - #5619: Add support for multi-output ufuncs
  - #5841: cleanup: Use PythonAPI.bool_from_bool in more places
  - #5862: Do not leak loop iteration variables into the numba.np.npyimpl namespace
  - #5838: Ensure `Dispatcher.__eq__` always returns a bool
  - #5830: doc: Mention that caching uses pickle
  - #5783: Make np.divide and np.remainder code more similar
- Ethan Pronovost added a guard to prevent the common mistake of applying a jit decorator to the same function twice in #5881.
- Graham Markall contributed many patches to the CUDA target, as follows:
  - #6052: Fix dtype for atomic_add_double tests
  - #6030: CUDA: Don't optimize IR before sending it to NVVM
  - #5846: CUDA: Allow disabling NVVM optimizations, and fix debug issues
  - #5826: CUDA: Add function to get SASS for kernels
  - #5851: CUDA EMM enhancements - add default get_ipc_handle implementation, skip a test conditionally
  - #5709: CUDA: Refactoring of cuda.jit and kernel / dispatcher abstractions
  - #5819: Add support for CUDA 11 and Ampere / CC 8.0
  - #6020: CUDA: Fix #5820, adding atomic nanmin / nanmax
  - #5857: CUDA docs: Add notes on resetting the EMM plugin
  - #5859: CUDA: Fix reduce docs and style improvements
  - #5852: CUDA: Fix `cuda.test()`
  - #5732: CUDA Docs: document `forall` method of kernels
- Guilherme Leobas added support for `str(int)` in #5463 and `np.asarray(literal value)` in #5526.
- Hameer Abbasi deprecated the `target` kwarg for `numba.jit` in #5980.
- Hannes Pahl added a badge to the Numba github page linking to the new discourse forum in #5940 and also fixed a bug that permitted illegal combinations of flags to be passed into `@jit` in #5808.
- Kayran Schmidt emphasized that CUDA kernel functions are asynchronous in the documentation in #6013.
- Leonardo Uieda fixed a broken link to the NumPy ufunc signature docs in #5963.
- Lucio Fernandez-Arjona added mypy to CI and started adding type annotations to the code base in #5960, also fixed a (de)serialization problem on the dispatcher in #5935, improved the undefined variable error message in #5876, added support for division with timedelta input in #5711 and implemented `setitem` for records when the index is a `StringLiteral` in #5849.
- Ludovic Tiako documented Numba's bounds-checking behavior in the python deviations page in #5981.
- Matt Roeschke changed all `http` references `https` in #6062.
- `@niteya-shah` implemented `isnan` and `isinf` for integer types on the CUDA target in #5761 and implemented `np.positive` in #5796.

- Peter Würtz added CUDA stream callbacks and async awaitable streams in #5745.
- `@rht` fixed an invalid import referred to in the deprecation documentation in #6036.
- Sergey Pokhodenko updated the SVML tests for LLVM 10 in #5962.
- Shyam Saladi fixed a Sphinx rendering bug in #6008.

Authors:

- Aisha Tammy
- Alexander Stiebing
- Alexey Kozlov
- Andrew Eckart
- `@bitsisbits`
- Daichi Suzuo
- Eric Wieser
- Ethan Pronovost
- Graham Markall
- Guilherme Leobas
- Hameer Abbasi
- Hannes Pahl
- Kayran Schmidt
- Kozlov, Alexey
- Leonardo Uieda
- Lucio Fernandez-Arjona
- Ludovic Tiako
- Matt Roeschke
- `@niteya-shah`
- Peter Würtz
- Sergey Pokhodenko
- Shyam Saladi
- `@rht`
- Siu Kwan Lam (core dev)
- Stuart Archibald (core dev)
- Todd A. Anderson (core dev)
- Valentin Haenel (core dev)

9.2.19 Version 0.50.1 (Jun 24, 2020)

This is a bugfix release for 0.50.0, it fixes a critical bug in error reporting and a number of other smaller issues:

- PR #5861: Added except for possible Windows get_terminal_size exception
- PR #5876: Improve undefined variable error message
- PR #5884: Update the deprecation notices for 0.50.1
- PR #5889: Fixes literally not forcing re-dispatch for inline='always'
- PR #5912: Fix bad attr access on certain typing templates breaking exceptions.
- PR #5918: Fix cuda test due to #5876

Authors:

- `@pepping_dore`
- Lucio Fernandez-Arjona
- Siu Kwan Lam (core dev)
- Stuart Archibald (core dev)

9.2.20 Version 0.50.0 (Jun 10, 2020)

This is a more usual release in comparison to the others that have been made in the last six months. It comprises the result of a number of maintenance tasks along with some new features and a lot of bug fixes.

Highlights of core feature changes include:

- The compilation chain is now based on LLVM 9.
- The error handling and reporting system has been improved to reduce the size of error messages, and also improve quality and specificity.
- The CUDA target has more stream constructors available and a new function for compiling to PTX without linking and loading the code to a device. Further, the macro-based system for describing CUDA threads and blocks has been replaced with standard typing and lowering implementations, for improved debugging and extensibility.

IMPORTANT: The backwards compatibility shim, that was present in 0.49.x to accommodate the refactoring of Numba's internals, has been removed. If a module is imported from a moved location an `ImportError` will occur.

General Enhancements:

- PR #5060: Enables np.sum for timedelta64
- PR #5225: Adjust interpreter to make conditionals predicates via bool() call.
- PR #5506: Jitclass static methods
- PR #5580: Revert shim
- PR #5591: Fix #5525 Add figure for total memory to `numba -s` output.
- PR #5616: Simplify the ufunc kernel registration
- PR #5617: Remove /examples from the Numba repo.
- PR #5673: Fix inliners to run all passes on IR and clean up correctly.
- PR #5700: Make it easier to understand type inference: add SSA dump, use for `DEBUG_TYPEINFER`
- PR #5702: Fixes for LLVM 9

- PR #5722: Improve error messages.
- PR #5758: Support NumPy 1.18

Fixes:

- PR #5390: add error handling for lookup_module
- PR #5464: Jitclass drops annotations to avoid error
- PR #5478: Fix #5471. Issue with omitted type not recognized as literal value.
- PR #5517: Fix numba.typed.List extend for singleton and empty iterable
- PR #5549: Check type getitem
- PR #5568: Add skip to entrypoint test on windows
- PR #5581: Revert #5568
- PR #5602: Fix segfault caused by pop from numba.typed.List
- PR #5645: Fix SSA redundant CFG computation
- PR #5686: Fix issue with SSA not minimal
- PR #5689: Fix bug in unified_function_type (issue 5685)
- PR #5694: Skip part of slice array analysis if any part is not analyzable.
- PR #5697: Fix usedef issue with parfor loopnest variables.
- PR #5705: A fix for cases where SSA looks like a reduction variable.
- PR #5714: Fix bug in test
- PR #5717: Initialise Numba extensions ahead of any compilation starting.
- PR #5721: Fix array iterator layout.
- PR #5738: Unbreak master on buildfarm
- PR #5757: Force LLVM to use ZMM registers for vectorization.
- PR #5764: fix flake8 errors
- PR #5768: Interval example: fix import
- PR #5781: Moving record array examples to a test module
- PR #5791: Fix up no cgroups problem
- PR #5795: Restore refct removal pass and make it strict
- PR #5807: Skip failing test on POWER8 due to PPC CTR Loop problem.
- PR #5812: Fix side issue from #5792, @overload inliner cached IR being mutated.
- PR #5815: Pin llvmlite to 0.33
- PR #5833: Fixes the source location appearing incorrectly in error messages.

CUDA Enhancements/Fixes:

- PR #5347: CUDA: Provide more stream constructors
- PR #5388: CUDA: Fix OOB write in test_round{f4,f8}
- PR #5437: Fix #5429: Exception using `.get_ipc_handle(...)` on array from `as_cuda_array(...)`
- PR #5481: CUDA: Replace macros with typing and lowering implementations

- PR #5556: CUDA: Make atomic semantics match Python / NumPy, and fix #5458
- PR #5558: CUDA: Only release primary ctx if retained
- PR #5561: CUDA: Add function for compiling to PTX (+ other small fixes)
- PR #5573: CUDA: Skip tests under cuda-memcheck that hang it
- PR #5578: Implement math.modf for CUDA target
- PR #5704: CUDA Eager compilation: Fix max_registers kwarg
- PR #5718: CUDA lib path tests: unset CUDA_PATH when CUDA_HOME unset
- PR #5800: Fix LLVM 9 IR for NVVM
- PR #5803: CUDA Update expected error messages to fix #5797

Documentation Updates:

- PR #5546: DOC: Add documentation about cost model to inlining notes.
- PR #5653: Update doc with respect to try-finally case

Enhancements from user contributed PRs (with thanks!):

- Elias Kuthe fixed in issue with imports in the Interval example in #5768
- Eric Wieser Simplified the ufunc kernel registration mechanism in #5616
- Ethan Pronovost patched a problem with `__annotations__` in `jitclass` in #5464, fixed a bug that lead to infinite loops in Numba's `Type.__getitem__` in #5549, fixed a bug in `np.arange` testing in #5714 and added support for `@staticmethod` to `jitclass` in #5506.
- Gabriele Gemmi implemented `math.modf` for the CUDA target in #5578
- Graham Markall contributed many patches, largely to the CUDA target, as follows:
  - #5347: CUDA: Provide more stream constructors
  - #5388: CUDA: Fix OOB write in test_round{f4,f8}
  - #5437: Fix #5429: Exception using `.get_ipc_handle(...)` on array from `as_cuda_array(...)`
  - #5481: CUDA: Replace macros with typing and lowering implementations
  - #5556: CUDA: Make atomic semantics match Python / NumPy, and fix #5458
  - #5558: CUDA: Only release primary ctx if retained
  - #5561: CUDA: Add function for compiling to PTX (+ other small fixes)
  - #5573: CUDA: Skip tests under cuda-memcheck that hang it
  - #5648: Unset the memory manager after EMM Plugin tests
  - #5700: Make it easier to understand type inference: add SSA dump, use for `DEBUG_TYPEINFER`
  - #5704: CUDA Eager compilation: Fix max_registers kwarg
  - #5718: CUDA lib path tests: unset CUDA_PATH when CUDA_HOME unset
  - #5800: Fix LLVM 9 IR for NVVM
  - #5803: CUDA Update expected error messages to fix #5797
- Guilherme Leobas updated the documentation surrounding try-finally in #5653
- Hameer Abbasi added documentation about the cost model to the notes on inlining in #5546

- Jacques Gaudin rewrote `numba -s` to produce and consume a dictionary of output about the current system in #5591
- James Bourbeau Updated min/argmin and max/argmax to handle non-leading nans (via #5758)
- Lucio Fernandez-Arjona moved the record array examples to a test module in #5781 and added `np.timedelta64` handling to `np.sum` in #5060
- Pearu Peterson Fixed a bug in unified_function_type in #5689
- Sergey Pokhodenko fixed an issue impacting LLVM 10 regarding vectorization widths on Intel SkyLake processors in #5757
- Shan Sikdar added error handling for `lookup_module` in #5390
- @toddrme2178 add CI testing for NumPy 1.18 (via #5758)

Authors:

- Elias Kuthe
- Eric Wieser
- Ethan Pronovost
- Gabriele Gemmi
- Graham Markall
- Guilherme Leobas
- Hameer Abbasi
- Jacques Gaudin
- James Bourbeau
- Lucio Fernandez-Arjona
- Pearu Peterson
- Sergey Pokhodenko
- Shan Sikdar
- Siu Kwan Lam (core dev)
- Stuart Archibald (core dev)
- Todd A. Anderson (core dev)
- `@toddrme2178`
- Valentin Haenel (core dev)

9.2.21 Version 0.49.1 (May 7, 2020)

This is a bugfix release for 0.49.0, it fixes some residual issues with SSA form, a critical bug in the branch pruning logic and a number of other smaller issues:

- PR #5587: Fixed #5586 Threading Implementation Typos
- PR #5592: Fixes #5583 Remove references to cffi_support from docs and examples
- PR #5614: Fix invalid type in resolve for comparison expr in parfors.
- PR #5624: Fix erroneous rewrite of predicate to bit const on prune.

- PR #5627: Fixes #5623, SSA local def scan based on invalid equality assumption.
- PR #5629: Fixes naming error in array_exprs
- PR #5630: Fix #5570. Incorrect race variable detection due to SSA naming.
- PR #5638: Make literal_unroll function work as a freevar.
- PR #5648: Unset the memory manager after EMM Plugin tests
- PR #5651: Fix some SSA issues
- PR #5652: Pin to sphinx=2.4.4 to avoid problem with C declaration
- PR #5658: Fix unifying undefined first class function types issue
- PR #5669: Update example in 5m guide WRT SSA type stability.
- PR #5676: Restore `numba.types` as public API

Authors:

- Graham Markall
- Juan Manuel Cruz Martinez
- Pearu Peterson
- Sean Law
- Stuart Archibald (core dev)
- Siu Kwan Lam (core dev)

9.2.22 Version 0.49.0 (Apr 16, 2020)

This release is very large in terms of code changes. Large scale removal of unsupported Python and NumPy versions has taken place along with a significant amount of refactoring to simplify the Numba code base to make it easier for contributors. Numba's intermediate representation has also undergone some important changes to solve a number of long standing issues. In addition some new features have been added and a large number of bugs have been fixed!

IMPORTANT: In this release Numba's internals have moved about a lot. A backwards compatibility "shim" is provided for this release so as to not immediately break projects using Numba's internals. If a module is imported from a moved location the shim will issue a deprecation warning and suggest how to update the import statement for the new location. The shim will be removed in 0.50.0!

Highlights of core feature changes include:

- Removal of all Python 2 related code and also updating the minimum supported Python version to 3.6, the minimum supported NumPy version to 1.15 and the minimum supported SciPy version to 1.0. (Stuart Archibald).
- Refactoring of the Numba code base. The code is now organised into submodules by functionality. This cleans up Numba's top level namespace. (Stuart Archibald).
- Introduction of an `ir.Del` free static single assignment form for Numba's intermediate representation (Siu Kwan Lam and Stuart Archibald).
- An OpenMP-like thread masking API has been added for use with code using the parallel CPU backends (Aaron Meurer and Stuart Archibald).
- For the CUDA target, all kernel launches now require a configuration, this preventing accidental launches of kernels with the old default of a single thread in a single block. The hard-coded autotuner is also now removed, such tuning is deferred to CUDA API calls that provide the same functionality (Graham Markall).

- The CUDA target also gained an External Memory Management plugin interface to allow Numba to use another CUDA-aware library for all memory allocations and deallocations (Graham Markall).
- The Numba Typed List container gained support for construction from iterables (Valentin Haenel).
- Experimental support was added for first-class function types (Pearu Peterson).

Enhancements from user contributed PRs (with thanks!):

- Aaron Meurer added support for thread masking at runtime in #4615.
- Andreas Sodeur fixed a long standing bug that was preventing `cProfile` from working with Numba JIT compiled functions in #4476.
- Arik Funke fixed error messages in `test_array_reductions` (#5278), fixed an issue with test discovery (#5239), made it so the documentation would build again on windows (#5453) and fixed a nested list problem in the docs in #5489.
- Antonio Russo fixed a SyntaxWarning in #5252.
- Eric Wieser added support for inferring the types of object arrays (#5348) and iterating over 2D arrays (#5115), also fixed some compiler warnings due to missing (void) in #5222. Also helped improved the "shim" and associated warnings in #5485, #5488, #5498 and partly #5532.
- Ethan Pronovost fixed a problem with the shim erroneously warning for jitclass use in #5454 and also prevented illegal return values in jitclass `__init__` in #5505.
- Gabriel Majeri added SciPy 2019 talks to the docs in #5106.
- Graham Markall changed the Numba HTML documentation theme to resolve a number of long standing issues in #5346. Also contributed were a large number of CUDA enhancements and fixes, namely:
  - #5519: CUDA: Silence the test suite - Fix #4809, remove autojit, delete prints
  - #5443: Fix #5196: Docs: assert in CUDA only enabled for debug
  - #5436: Fix #5408: test_set_registers_57 fails on Maxwell
  - #5423: Fix #5421: Add notes on printing in CUDA kernels
  - #5400: Fix #4954, and some other small CUDA testsuite fixes
  - #5328: NBEP 7: External Memory Management Plugin Interface
  - #5144: Fix #4875: Make #2655 test with debug expect to pass
  - #5323: Document lifetime semantics of CUDA Array Interface
  - #5061: Prevent kernel launch with no configuration, remove autotuner
  - #5099: Fix #5073: Slices of dynamic shared memory all alias
  - #5136: CUDA: Enable asynchronous operations on the default stream
  - #5085: Support other itemsizes with view
  - #5059: Docs: Explain how to use Memcheck with Numba, fixups in CUDA documentation
  - #4957: Add notes on overwriting gufunc inputs to docs
- Greg Jennings fixed an issue with `np.random.choice` not acknowledging the RNG seed correctly in #3897/#5310.
- Guilherme Leobas added support for `np.isnat` in #5293.
- Henry Schreiner made the llvmlite requirements more explicit in requirements.txt in #5150.
- Ivan Butygin helped fix an issue with parfors sequential lowering in #5114/#5250.

- Jacques Gaudin fixed a bug for Python >= 3.8 in `numba -s` in #5548.
- Jim Pivarski added some hints for debugging entry points in #5280.
- John Kirkham added `numpy.dtype` coercion for the `dtype` argument to CUDA device arrays in #5252.
- Leo Fang added a list of libraries that support `__cuda_array_interface__` in #5104.
- Lucio Fernandez-Arjona added `getitem` for the NumPy record type when the index is a `StringLiteral` type in #5182 and improved the documentation rendering via additions to the TOC and removal of numbering in #5450.
- Mads R. B. Kristensen fixed an issue with `__cuda_array_interface__` not requiring the context in #5189.
- Marcin Tolysz added support for nested modules in AOT compilation in #5174.
- Mike Williams fixed some issues with NumPy records and `getitem` in the CUDA simulator in #5343.
- Pearu Peterson added experimental support for first-class function types in #5287 (and fixes in #5459, #5473/#5429, and #5557).
- Ravi Teja Gutta added support for `np.flip` in #4376/#5313.
- Rohit Sanjay fixed an issue with type refinement for unicode input supplied to typed-list `extend()` (#5295) and fixed unicode `.strip()` to strip all whitespace characters in #5213.
- Vladimir Lukyanov fixed an awkward bug in `typed.dict` in #5361, added a fix to ensure the LLVM and assembly dumps are highlighted correctly in #5357 and implemented a Numba IR Lexer and added highlighting to Numba IR dumps in #5333.
- hdf fixed an issue with the `boundscheck` flag in the CUDA jit target in #5257.

General Enhancements:

- PR #4615: Allow masking threads out at runtime
- PR #4798: Add branch pruning based on raw predicates.
- PR #5115: Add support for iterating over 2D arrays
- PR #5117: Implement ord()/chr()
- PR #5122: Remove Python 2.
- PR #5127: Calling convention adaptor for boxer/unboxer to call jitcode
- PR #5151: implement None-typed typed-list
- PR #5174: Nested modules https://github.com/numba/numba/issues/4739
- PR #5182: Add getitem for Record type when index is StringLiteral
- PR #5185: extract code-gen utilities from closures
- PR #5197: Refactor Numba, part I
- PR #5210: Remove more unsupported Python versions from build tooling.
- PR #5212: Adds support for viewing the CFG of the ELF disassembly.
- PR #5227: Immutable typed-list
- PR #5231: Added support for `np.asarray` to be used with `numba.typed.List`
- PR #5235: Added property `dtype` to `numba.typed.List`
- PR #5272: Refactor parfor: split up ParforPass
- PR #5281: Make IR ir.Del free until legalized.
- PR #5287: First-class function type

- PR #5293: np.isnat
- PR #5294: Create typed-list from iterable
- PR #5295: refine typed-list on unicode input to extend
- PR #5296: Refactor parfor: better exception from passes
- PR #5308: Provide `numba.extending.is_jitted`
- PR #5320: refactor array_analysis
- PR #5325: Let literal_unroll accept types.Named*Tuple
- PR #5330: refactor common operation in parfor lowering into a new util
- PR #5333: Add: highlight Numba IR dump
- PR #5342: Support for tuples passed to parfors.
- PR #5348: Add support for inferring the types of object arrays
- PR #5351: SSA again
- PR #5352: Add shim to accommodate refactoring.
- PR #5356: implement allocated parameter in njit
- PR #5369: Make test ordering more consistent across feature availability
- PR #5428: Wip/deprecate jitclass location
- PR #5441: Additional changes to first class function
- PR #5455: Move to llvmlite 0.32.*
- PR #5457: implement repr for untyped lists

Fixes:

- PR #4476: Another attempt at fixing frame injection in the dispatcher tracing path
- PR #4942: Prevent some parfor aliasing. Rename copied function var to prevent recursive type locking.
- PR #5092: Fix 5087
- PR #5150: More explicit llvmlite requirement in requirements.txt
- PR #5172: fix version spec for llvmlite
- PR #5176: Normalize kws going into fold_arguments.
- PR #5183: pass 'inline' explicitly to overload
- PR #5193: Fix CI failure due to missing files when installed
- PR #5213: Fix `.strip()` to strip all whitespace characters
- PR #5216: Fix namedtuple mistreated by dispatcher as simple tuple
- PR #5222: Fix compiler warnings due to missing (void)
- PR #5232: Fixes a bad import that breaks master
- PR #5239: fix test discovery for unittest
- PR #5247: Continue PR #5126
- PR #5250: Part fix/5098
- PR #5252: Trivially fix SyntaxWarning

- PR #5276: Add prange variant to has_no_side_effect.
- PR #5278: fix error messages in test_array_reductions
- PR #5310: PR #3897 continued
- PR #5313: Continues PR #4376
- PR #5318: Remove AUTHORS file reference from MANIFEST.in
- PR #5327: Add warning if FNV hashing is found as the default for CPython.
- PR #5338: Remove refcount pruning pass
- PR #5345: Disable test failing due to removed pass.
- PR #5357: Small fix to have llvm and asm highlighted properly
- PR #5361: 5081 typed.dict
- PR #5431: Add tolerance to numba extension module entrypoints.
- PR #5432: Fix code causing compiler warnings.
- PR #5445: Remove undefined variable
- PR #5454: Don't warn for numba.experimental.jitclass
- PR #5459: Fixes issue 5448
- PR #5480: Fix for #5477, literal_unroll KeyError searching for getitems
- PR #5485: Show the offending module in "no direct replacement" error message
- PR #5488: Add missing `numba.config` shim
- PR #5495: Fix missing null initializer for variable after phi strip
- PR #5498: Make the shim deprecation warnings work on python 3.6 too
- PR #5505: Better error message if __init__ returns value
- PR #5527: Attempt to fix #5518
- PR #5529: PR #5473 continued
- PR #5532: Make `numba.<mod>` available without an import
- PR #5542: Fixes RC2 module shim bug
- PR #5548: Fix #5537 Removed reference to `platform.linux_distribution`
- PR #5555: Fix #5515 by reverting changes to ArrayAnalysis
- PR #5557: First-class function call cannot use keyword arguments
- PR #5569: Fix RewriteConstGetitems not registering calltype for new expr
- PR #5571: Pin down llvmlite requirement

CUDA Enhancements/Fixes:

- PR #5061: Prevent kernel launch with no configuration, remove autotuner
- PR #5085: Support other itemsizes with view
- PR #5099: Fix #5073: Slices of dynamic shared memory all alias
- PR #5104: Add a list of libraries that support __cuda_array_interface__
- PR #5136: CUDA: Enable asynchronous operations on the default stream

- PR #5144: Fix #4875: Make #2655 test with debug expect to pass
- PR #5189: __cuda_array_interface__ not requiring context
- PR #5253: Coerce `dtype` to `numpy.dtype`
- PR #5257: boundscheck fix
- PR #5319: Make user facing error string use abs path not rel.
- PR #5323: Document lifetime semantics of CUDA Array Interface
- PR #5328: NBEP 7: External Memory Management Plugin Interface
- PR #5343: Fix cuda spoof
- PR #5400: Fix #4954, and some other small CUDA testsuite fixes
- PR #5436: Fix #5408: test_set_registers_57 fails on Maxwell
- PR #5519: CUDA: Silence the test suite - Fix #4809, remove autojit, delete prints

Documentation Updates:

- PR #4957: Add notes on overwriting gufunc inputs to docs
- PR #5059: Docs: Explain how to use Memcheck with Numba, fixups in CUDA documentation
- PR #5106: Add SciPy 2019 talks to docs
- PR #5147: Update master for 0.48.0 updates
- PR #5155: Explain what inlining at Numba IR level will do
- PR #5161: Fix README.rst formatting
- PR #5207: Remove AUTHORS list
- PR #5249: fix target path for See also
- PR #5262: fix typo in inlining docs
- PR #5270: fix 'see also' in typeddict docs
- PR #5280: Added some hints for debugging entry points.
- PR #5297: Update docs with intro to {g,}ufuncs.
- PR #5326: Update installation docs with OpenMP requirements.
- PR #5346: Docs: use sphinx_rtd_theme
- PR #5366: Remove reference to Python 2.7 in install check output
- PR #5423: Fix #5421: Add notes on printing in CUDA kernels
- PR #5438: Update package deps for doc building.
- PR #5440: Bump deprecation notices.
- PR #5443: Fix #5196: Docs: assert in CUDA only enabled for debug
- PR #5450: Docs: remove numbers and add titles to TOC
- PR #5453: fix building docs on windows
- PR #5489: docs: fix rendering of nested bulleted list

CI updates:

- PR #5314: Update the image used in Azure CI for OSX.

- PR #5360: Remove Travis CI badge.

Authors:

- Aaron Meurer
- Andreas Sodeur
- Antonio Russo
- Arik Funke
- Eric Wieser
- Ethan Pronovost
- Gabriel Majeri
- Graham Markall
- Greg Jennings
- Guilherme Leobas
- hdf
- Henry Schreiner
- Ivan Butygin
- Jacques Gaudin
- Jim Pivarski
- John Kirkham
- Leo Fang
- Lucio Fernandez-Arjona
- Mads R. B. Kristensen
- Marcin Tolysz
- Mike Williams
- Pearu Peterson
- Ravi Teja Gutta
- Rohit Sanjay
- Siu Kwan Lam (core dev)
- Stan Seibert (core dev)
- Stuart Archibald (core dev)
- Todd A. Anderson (core dev)
- Valentin Haenel (core dev)
- Vladimir Lukyanov

9.2.23 Version 0.48.0 (Jan 27, 2020)

This release is particularly small as it was present to catch anything that missed the 0.47.0 deadline (the deadline deliberately coincided with the end of support for Python 2.7). The next release will be considerably larger.

The core changes in this release are dominated by the start of the clean up needed for the end of Python 2.7 support, improvements to the CUDA target and support for numerous additional unicode string methods.

Enhancements from user contributed PRs (with thanks!):

- Brian Wignall fixed more spelling typos in #4998.
- Denis Smirnov added support for string methods `capitalize` (#4823), `casefold` (#4824), `swapcase` (#4825), `rsplit` (#4834), `partition` (#4845) and `splitlines` (#4849).
- Elena Totmenina extended support for string methods `startswith` (#4867) and added `endswith` (#4868).
- Eric Wieser made `type_callable` return the decorated function itself in #4760
- Ethan Pronovost added support for `np.argwhere` in #4617
- Graham Markall contributed a large number of CUDA enhancements and fixes, namely:
  - #5068: Remove Python 3.4 backports from utils
  - #4975: Make `device_array_like` create contiguous arrays (Fixes #4832)
  - #5023: Don't launch ForAll kernels with 0 elements (Fixes #5017)
  - #5016: Fix various issues in CUDA library search (Fixes #4979)
  - #5014: Enable use of records and bools for shared memory, remove ddt, add additional transpose tests
  - #4964: Fix #4628: Add more appropriate typing for CUDA device arrays
  - #5007: test_consuming_strides: Keep dev array alive
  - #4997: State that CUDA Toolkit 8.0 required in docs
- James Bourbeau added the Python 3.8 classifier to setup.py in #5027.
- John Kirkham added a clarification to the `__cuda_array_interface__` documentation in #5049.
- Leo Fang Fixed an indexing problem in `dummyarray` in #5012.
- Marcel Bargull fixed a build and test issue for Python 3.8 in #5029.
- Maria Rubtsov added support for string methods `isdecimal` (#4842), `isdigit` (#4843), `isnumeric` (#4844) and `replace` (#4865).

General Enhancements:

- PR #4760: Make type_callable return the decorated function
- PR #5010: merge string prs

  This merge PR included the following:
  - PR #4823: Implement str.capitalize() based on CPython
  - PR #4824: Implement str.casefold() based on CPython
  - PR #4825: Implement str.swapcase() based on CPython
  - PR #4834: Implement str.rsplit() based on CPython
  - PR #4842: Implement str.isdecimal
  - PR #4843: Implement str.isdigit

  - PR #4844: Implement str.isnumeric
  - PR #4845: Implement str.partition() based on CPython
  - PR #4849: Implement str.splitlines() based on CPython
  - PR #4865: Implement str.replace
  - PR #4867: Functionality extension str.startswith() based on CPython
  - PR #4868: Add functionality for str.endswith()
- PR #5039: Disable help messages.
- PR #4617: Add coverage for `np.argwhere`

Fixes:

- PR #4724: Only use lives (and not aliases) to create post parfor live set.
- PR #4998: Fix more spelling typos
- PR #5024: Propagate semantic constants ahead of static rewrites.
- PR #5027: Add Python 3.8 classifier to setup.py
- PR #5046: Update setup.py and buildscripts for dependency requirements
- PR #5053: Convert from arrays to names in define() and don't invalidate for multiple consistent defines.
- PR #5058: Permit mixed int types in wrap_index
- PR #5078: Catch the use of global typed-list in JITed functions
- PR #5092: Fix #5087, bug in bytecode analysis.

CUDA Enhancements/Fixes:

- PR #4964: Fix #4628: Add more appropriate typing for CUDA device arrays
- PR #4975: Make `device_array_like` create contiguous arrays (Fixes #4832)
- PR #4997: State that CUDA Toolkit 8.0 required in docs
- PR #5007: test_consuming_strides: Keep dev array alive
- PR #5012: Fix IndexError when accessing the "-1" element of dummyarray
- PR #5014: Enable use of records and bools for shared memory, remove ddt, add additional transpose tests
- PR #5016: Fix various issues in CUDA library search (Fixes #4979)
- PR #5023: Don't launch ForAll kernels with 0 elements (Fixes #5017)
- PR #5068: Remove Python 3.4 backports from utils

Documentation Updates:

- PR #5049: Clarify what dictionary means
- PR #5062: Update docs for updated version requirements
- PR #5090: Update deprecation notices for 0.48.0

CI updates:

- PR #5029: Install optional dependencies for Python 3.8 tests
- PR #5040: Drop Py2.7 and Py3.5 from public CI
- PR #5048: Fix CI py38

Authors:

- Brian Wignall
- Denis Smirnov
- Elena Totmenina
- Eric Wieser
- Ethan Pronovost
- Graham Markall
- James Bourbeau
- John Kirkham
- Leo Fang
- Marcel Bargull
- Maria Rubtsov
- Siu Kwan Lam (core dev)
- Stan Seibert (core dev)
- Stuart Archibald (core dev)
- Todd A. Anderson (core dev)
- Valentin Haenel (core dev)

9.2.24 Version 0.47.0 (Jan 2, 2020)

This release expands the capability of Numba in a number of important areas and is also significant as it is the last major point release with support for Python 2 and Python 3.5 included. The next release (0.48.0) will be for Python 3.6+ only! (This follows NumPy's deprecation schedule as specified in NEP 29.)

Highlights of core feature changes include:

- Full support for Python 3.8 (Siu Kwan Lam)
- Opt-in bounds checking (Aaron Meurer)
- Support for `map`, `filter` and `reduce` (Stuart Archibald)

Intel also kindly sponsored research and development that lead to some exciting new features:

- Initial support for basic `try/except` use (Siu Kwan Lam)
- The ability to pass functions created from closures/lambdas as arguments (Stuart Archibald)
- `sorted` and `list.sort()` now accept the `key` argument (Stuart Archibald and Siu Kwan Lam)
- A new compiler pass triggered through the use of the function `numba.literal_unroll` which permits iteration over heterogeneous tuples and constant lists of constants. (Stuart Archibald)

Enhancements from user contributed PRs (with thanks!):

- Ankit Mahato added a reference to a new talk on Numba at PyCon India 2019 in #4862
- Brian Wignall kindly fixed some spelling mistakes and typos in #4909
- Denis Smirnov wrote numerous methods to considerable enhance string support including:
  - `str.rindex()` in #4861

  - `str.isprintable()` in #4836
  - `str.index()` in #4860
  - `start/end` parameters for `str.find()` in #4866
  - `str.isspace()` in #4835
  - `str.isidentifier()` #4837
  - `str.rpartition()` in #4841
  - `str.lower()` and `str.islower()` in #4651
- Elena Totmenina implemented both `str.isalnum()`, `str.isalpha()` and `str.isascii` in #4839, #4840 and #4847 respectively.
- Eric Larson fixed a bug in literal comparison in #4710
- Ethan Pronovost updated the `np.arange` implementation in #4770 to allow the use of the `dtype` key word argument and also added `bool` implementations for several types in #4715.
- Graham Markall fixed some issues with the CUDA target, namely:
  - #4931: Added physical limits for CC 7.0 / 7.5 to CUDA autotune
  - #4934: Fixed bugs in TestCudaWarpOperations
  - #4938: Improved errors / warnings for the CUDA vectorize decorator
- Guilherme Leobas fixed a typo in the `urem` implementation in #4667
- Isaac Virshup contributed a number of patches that fixed bugs, added support for more NumPy functions and enhanced Python feature support. These contributions included:
  - #4729: Allow array construction with mixed type shape tuples
  - #4904: Implementing `np.lcm`
  - #4780: Implement np.gcd and math.gcd
  - #4779: Make slice constructor more similar to python.
  - #4707: Added support for slice.indices
  - #4578: Clarify numba ufunc supported features
- James Bourbeau fixed some issues with tooling, #4794 add `setuptools` as a dependency and #4501 add pre-commit hooks for `flake8` compliance.
- Leo Fang made `numba.dummyarray.Array` iterable in #4629
- Marc Garcia fixed the `numba.jit` parameter name signature_or_function in #4703
- Marcelo Duarte Trevisani patched the llvmlite requirement to `>=0.30.0` in #4725
- Matt Cooper fixed a long standing CI problem in #4737 by remove maxParallel
- Matti Picus fixed an issue with `collections.abc` in #4734 from Azure Pipelines.
- Rob Ennis patched a bug in `np.interp` `float32` handling in #4911
- VDimir fixed a bug in array transposition layouts in #4777 and re-enabled and fixed some idle tests in #4776.
- Vyacheslav Smirnov Enable support for *str.istitle()`* in #4645

General Enhancements:

- PR #4432: Bounds checking

- PR #4501: Add pre-commit hooks
- PR #4536: Handle kw args in inliner when callee is a function
- PR #4599: Permits closures to become functions, enables map(), filter()
- PR #4611: Implement method title() for unicode based on Cpython
- PR #4645: Enable support for istitle() method for unicode string
- PR #4651: Implement str.lower() and str.islower()
- PR #4652: Implement str.rfind()
- PR #4695: Refactor *overload** and support *jit_options* and *inline*
- PR #4707: Added support for slice.indices
- PR #4715: Add *bool* overload for several types
- PR #4729: Allow array construction with mixed type shape tuples
- PR #4755: Python3.8 support
- PR #4756: Add parfor support for ndarray.fill.
- PR #4768: Update typeconv error message to ask for sys.executable.
- PR #4770: Update *np.arange* implementation with *@overload*
- PR #4779: Make slice constructor more similar to python.
- PR #4780: Implement np.gcd and math.gcd
- PR #4794: Add setuptools as a dependency
- PR #4802: put git hash into build string
- PR #4803: Better compiler error messages for improperly used reduction variables.
- PR #4817: Typed list implement and expose allocation
- PR #4818: Typed list faster copy
- PR #4835: Implement str.isspace() based on CPython
- PR #4836: Implement str.isprintable() based on CPython
- PR #4837: Implement str.isidentifier() based on CPython
- PR #4839: Implement str.isalnum() based on CPython
- PR #4840: Implement str.isalpha() based on CPython
- PR #4841: Implement str.rpartition() based on CPython
- PR #4847: Implement str.isascii() based on CPython
- PR #4851: Add graphviz output for FunctionIR
- PR #4854: Python3.8 looplifting
- PR #4858: Implement str.expandtabs() based on CPython
- PR #4860: Implement str.index() based on CPython
- PR #4861: Implement str.rindex() based on CPython
- PR #4866: Support params start/end for str.find()
- PR #4874: Bump to llvmlite 0.31

- PR #4896: Specialise arange dtype on arch + python version.
- PR #4902: basic support for try except
- PR #4904: Implement np.lcm
- PR #4910: loop canonicalisation and type aware tuple unroller/loop body versioning passes
- PR #4961: Update hash(tuple) for Python 3.8.
- PR #4977: Implement sort/sorted with key.
- PR #4987: Add *is_internal* property to all Type classes.

Fixes:

- PR #4090: Update to LLVM8 memset/memcpy intrinsic
- PR #4582: Convert sub to add and div to mul when doing the reduction across the per-thread reduction array.
- PR #4648: Handle 0 correctly as slice parameter.
- PR #4660: Remove multiply defined variables from all blocks' equivalence sets.
- PR #4672: Fix pickling of dufunc
- PR #4710: BUG: Comparison for literal
- PR #4718: Change get_call_table to support intermediate Vars.
- PR #4725: Requires llvmlite >=0.30.0
- PR #4734: prefer to import from collections.abc
- PR #4736: fix flake8 errors
- PR #4776: Fix and enable idle tests from test_array_manipulation
- PR #4777: Fix transpose output array layout
- PR #4782: Fix issue with SVML (and knock-on function resolution effects).
- PR #4785: Treat 0d arrays like scalars.
- PR #4787: fix missing incref on flags
- PR #4789: fix typos in numba/targets/base.py
- PR #4791: fix typos
- PR #4811: fix spelling in now-failing tests
- PR #4852: windowing test should check equality only up to double precision errors
- PR #4881: fix refining list by using extend on an iterator
- PR #4882: Fix return type in arange and zero step size handling.
- PR #4885: suppress spurious RuntimeWarning about ufunc sizes
- PR #4891: skip the xfail test for now. Py3.8 CFG refactor seems to have changed the test case
- PR #4892: regex needs to accept singular form of "argument"
- PR #4901: fix typed list equals
- PR #4909: Fix some spelling typos
- PR #4911: np.interp bugfix for float32 handling
- PR #4920: fix creating list with JIT disabled

- PR #4921: fix creating dict with JIT disabled
- PR #4935: Better handling of prange with multiple reductions on the same variable.
- PR #4946: Improve the error message for *raise <string>*.
- PR #4955: Move overload of literal_unroll to avoid circular dependency that breaks Python 2.7
- PR #4962: Fix test error on windows
- PR #4973: Fixes a bug in the relabelling logic in literal_unroll.
- PR #4978: Fix overload_method problem with stararg
- PR #4981: Add ind_to_const to enable fewer equivalence classes.
- PR #4991: Continuation of #4588 (Let dead code removal handle removing more of the unneeded code after prange conversion to parfor)
- PR #4994: Remove xfail for test which has since had underlying issue fixed.
- PR #5018: Fix #5011.
- PR #5019: skip pycc test on Python 3.8 + macOS because of distutils issue

CUDA Enhancements/Fixes:

- PR #4629: Make numba.dummyarray.Array iterable
- PR #4675: Bump cuda array interface to version 2
- PR #4741: Update choosing the "CUDA_PATH" for windows
- PR #4838: Permit ravel('A') for contig device arrays in CUDA target
- PR #4931: Add physical limits for CC 7.0 / 7.5 to autotune
- PR #4934: Fix fails in TestCudaWarpOperations
- PR #4938: Improve errors / warnings for cuda vectorize decorator

Documentation Updates:

- PR #4418: Directed graph task roadmap
- PR #4578: Clarify numba ufunc supported features
- PR #4655: fix sphinx build warning
- PR #4667: Fix typo on urem implementation
- PR #4669: Add link to ParallelAccelerator paper.
- PR #4703: Fix numba.jit parameter name signature_or_function
- PR #4862: Addition of PyCon India 2019 talk on Numba
- PR #4947: Document jitclass with numba.typed use.
- PR #4958: Add docs for *try..except*
- PR #4993: Update deprecations for 0.47

CI Updates:

- PR #4737: remove maxParallel from Azure Pipelines
- PR #4767: pin to 2.7.16 for py27 on osx
- PR #4781: WIP/runtest cf pytest

Authors:

- Aaron Meurer
- Ankit Mahato
- Brian Wignall
- Denis Smirnov
- Ehsan Totoni (core dev)
- Elena Totmenina
- Eric Larson
- Ethan Pronovost
- Giovanni Cavallin
- Graham Markall
- Guilherme Leobas
- Isaac Virshup
- James Bourbeau
- Leo Fang
- Marc Garcia
- Marcelo Duarte Trevisani
- Matt Cooper
- Matti Picus
- Rob Ennis
- Rujal Desai
- Siu Kwan Lam (core dev)
- Stan Seibert (core dev)
- Stuart Archibald (core dev)
- Todd A. Anderson (core dev)
- VDimir
- Valentin Haenel (core dev)
- Vyacheslav Smirnov

9.2.25 Version 0.46.0

This release significantly reworked one of the main parts of Numba, the compiler pipeline, to make it more extensible and easier to use. The purpose of this was to continue enhancing Numba's ability for use as a compiler toolkit. In a similar vein, Numba now has an extension registration mechanism to allow other Numba-using projects to automatically have their Numba JIT compilable functions discovered. There were also a number of other related compiler toolkit enhancement added along with some more NumPy features and a lot of bug fixes.

This release has updated the CUDA Array Interface specification to version 2, which clarifies the *strides* attribute for C-contiguous arrays and specifies the treatment for zero-size arrays. The implementation in Numba has been changed and may affect downstream packages relying on the old behavior (see issue #4661).

Enhancements from user contributed PRs (with thanks!):

- Aaron Meurer fixed some Python issues in the code base in #4345 and #4341.
- Ashwin Srinath fixed a CUDA performance bug via #4576.
- Ethan Pronovost added support for triangular indices functions in #4601 (the NumPy functions `tril_indices`, `tril_indices_from`, `triu_indices`, and `triu_indices_from`).
- Gerald Dalley fixed a tear down race occurring in Python 2.
- Gregory R. Lee fixed the use of deprecated `inspect.getargspec`.
- Guilherme Leobas contributed five PRs, adding support for `np.append` and `np.count_nonzero` in #4518 and #4386. The typed List was fixed to accept unsigned integers in #4510. #4463 made a fix to NamedTuple internals and #4397 updated the docs for `np.sum`.
- James Bourbeau added a new feature to permit the automatic application of the *jit* decorator to a whole module in #4331. Also some small fixes to the docs and the code base were made in #4447 and #4433, and a fix to inplace array operation in #4228.
- Jim Crist fixed a bug in the rendering of patched errors in #4464.
- Leo Fang updated the CUDA Array Interface contract in #4609.
- Pearu Peterson added support for Unicode based NumPy arrays in #4425.
- Peter Andreas Entschev fixed a CUDA concurrency bug in #4581.
- Lucio Fernandez-Arjona extended Numba's `np.sum` support to now accept the `dtype` kwarg in #4472.
- Pedro A. Morales Maries added support for `np.cross` in #4128 and also added the necessary extension `numba.numpy_extensions.cross2d` in #4595.
- David Hoese, Eric Firing, Joshua Adelman, and Juan Nunez-Iglesias all made documentation fixes in #4565, #4482, #4455, #4375 respectively.
- Vyacheslav Smirnov and Rujal Desai enabled support for `count()` on unicode strings in #4606.

General Enhancements:

- PR #4113: Add rewrite for semantic constants.
- PR #4128: Add np.cross support
- PR #4162: Make IR comparable and legalize it.
- PR #4208: R&D inlining, jitted and overloaded.
- PR #4331: Automatic JIT of called functions
- PR #4353: Inspection tool to check what numba supports
- PR #4386: Implement np.count_nonzero
- PR #4425: Unicode array support
- PR #4427: Entrypoints for numba extensions
- PR #4467: Literal dispatch
- PR #4472: Allow dtype input argument in np.sum
- PR #4513: New compiler.
- PR #4518: add support for np.append
- PR #4554: Refactor NRT C-API

- PR #4556: 0.46 scheduled deprecations
- PR #4567: Add env var to disable performance warnings.
- PR #4568: add np.array_equal support
- PR #4595: Implement numba.cross2d
- PR #4601: Add triangular indices functions
- PR #4606: Enable support for count() method for unicode string

Fixes:

- PR #4228: Fix inplace operator error for arrays
- PR #4282: Detect and raise unsupported on generator expressions
- PR #4305: Don't allow the allocation of mutable objects written into a container to be hoisted.
- PR #4311: Avoid deprecated use of inspect.getargspec
- PR #4328: Replace GC macro with function call
- PR #4330: Loosen up typed container casting checks
- PR #4341: Fix some coding lines at the top of some files (utf8 -> utf-8)
- PR #4345: Replace "import *" with explicit imports in numba/types
- PR #4346: Fix incorrect alg in isupper for ascii strings.
- PR #4349: test using jitclass in typed-list
- PR #4361: Add allocation hoisting info to LICM section at diagnostic L4
- PR #4366: Offset search box to avoid wrapping on some pages with Safari. Fixes #4365.
- PR #4372: Replace all "except BaseException" with "except Exception".
- PR #4407: Restore the "free" conda channel for NumPy 1.10 support.
- PR #4408: Add lowering for constant bytes.
- PR #4409: Add exception chaining for better error context
- PR #4411: Name of type should not contain user facing description for debug.
- PR #4412: Fix #4387. Limit the number of return types for recursive functions
- PR #4426: Fixed two module teardown races in py2.
- PR #4431: Fix and test numpy.random.random_sample(n) for np117
- PR #4463: NamedTuple - Raises an error on non-iterable elements
- PR #4464: Add a newline in patched errors
- PR #4474: Fix liveness for remove dead of parfors (and other IR extensions)
- PR #4510: Make List.__getitem__ accept unsigned parameters
- PR #4512: Raise specific error at typing time for iteration on >1D array.
- PR #4532: Fix static_getitem with Literal type as index
- PR #4547: Update to inliner cost model information.
- PR #4557: Use specific random number seed when generating arbitrary test data
- PR #4559: Adjust test timeouts

- PR #4564: Skip unicode array tests on ppc64le that trigger an LLVM bug
- PR #4621: Fix packaging issue due to missing numba/cext
- PR #4623: Fix issue 4520 due to storage model mismatch
- PR #4644: Updates for llvmlite 0.30.0

CUDA Enhancements/Fixes:

- PR #4410: Fix #4111. cudasim mishandling recarray
- PR #4576: Replace use of *np.prod* with *functools.reduce* for computing size from shape
- PR #4581: Prevent taking the GIL in ForAll
- PR #4592: Fix #4589. Just pass NULL for b2d_func for constant dynamic sharedmem
- PR #4609: Update CUDA Array Interface & Enforce Numba compliance
- PR #4619: Implement math.{degrees, radians} for the CUDA target.
- PR #4675: Bump cuda array interface to version 2

Documentation Updates:

- PR #4317: Add docs for ARMv8/AArch64
- PR #4318: Add supported platforms to the docs. Closes #4316
- PR #4375: Add docstrings to inspect methods
- PR #4388: Update Python 2.7 EOL statement
- PR #4397: Add note about np.sum
- PR #4447: Minor parallel performance tips edits
- PR #4455: Clarify docs for typed dict with regard to arrays
- PR #4482: Fix example in guvectorize docstring.
- PR #4541: fix two typos in architecture.rst
- PR #4548: Document numba.extending.intrinsic and inlining.
- PR #4565: Fix typo in jit-compilation docs
- PR #4607: add dependency list to docs
- PR #4614: Add documentation for implementing new compiler passes.

CI Updates:

- PR #4415: Make 32bit incremental builds on linux not use free channel
- PR #4433: Removes stale azure comment
- PR #4493: Fix Overload Inliner wrt CUDA Intrinsics
- PR #4593: Enable Azure CI batching

Contributors:

- Aaron Meurer
- Ashwin Srinath
- David Hoese
- Ehsan Totoni (core dev)

- Eric Firing
- Ethan Pronovost
- Gerald Dalley
- Gregory R. Lee
- Guilherme Leobas
- James Bourbeau
- Jim Crist
- Joshua Adelman
- Juan Nunez-Iglesias
- Leo Fang
- Lucio Fernandez-Arjona
- Pearu Peterson
- Pedro A. Morales Marie
- Peter Andreas Entschev
- Rujal Desai
- Siu Kwan Lam (core dev)
- Stan Seibert (core dev)
- Stuart Archibald (core dev)
- Todd A. Anderson (core dev)
- Valentin Haenel (core dev)
- Vyacheslav Smirnov

9.2.26 Version 0.45.1

This patch release addresses some regressions reported in the 0.45.0 release and adds support for NumPy 1.17:

- PR #4325: accept scalar/0d-arrays
- PR #4338: Fix #4299. Parfors reduction vars not deleted.
- PR #4350: Use process level locks for fork() only.
- PR #4354: Try to fix #4352.
- PR #4357: Fix np1.17 isnan, isinf, isfinite ufuncs
- PR #4363: Fix np.interp for np1.17 nan handling
- PR #4371: Fix nump1.17 random function non-aliasing

Contributors:

- Siu Kwan Lam (core dev)
- Stuart Archibald (core dev)
- Valentin Haenel (core dev)

9.2.27 Version 0.45.0

In this release, Numba gained an experimental *numba.typed.List* container as a future replacement of the *reflected list*. In addition, functions decorated with `parallel=True` can now be cached to reduce compilation overhead associated with the auto-parallelization.

Enhancements from user contributed PRs (with thanks!):

- James Bourbeau added the Numba version to reportable error messages in #4227, added the `signature` parameter to `inspect_types` in #4200, improved the docstring of `normalize_signature` in #4205, and fixed #3658 by adding reference counting to `register_dispatcher` in #4254
- Guilherme Leobas implemented the dominator tree and dominance frontier algorithms in #4216 and #4149, respectively.
- Nick White fixed the issue with `round` in the CUDA target in #4137.
- Joshua Adelman added support for determining if a value is in a *range* (i.e. `x in range(...)`) in #4129, and added windowing functions (`np.bartlett`, `np.hamming`, `np.blackman`, `np.hanning`, `np.kaiser`) from NumPy in #4076.
- Lucio Fernandez-Arjona added support for `np.select` in #4077
- Rob Ennis added support for `np.flatnonzero` in #4157
- Keith Kraus extended the `__cuda_array_interface__` with an optional mask attribute in #4199.
- Gregory R. Lee replaced deprecated use of `inspect.getargspec` in #4311.

General Enhancements:

- PR #4328: Replace GC macro with function call
- PR #4311: Avoid deprecated use of inspect.getargspec
- PR #4296: Slacken window function testing tol on ppc64le
- PR #4254: Add reference counting to register_dispatcher
- PR #4239: Support len() of multi-dim arrays in array analysis
- PR #4234: Raise informative error for np.kron array order
- PR #4232: Add unicodetype db, low level str functions and examples.
- PR #4229: Make hashing cacheable
- PR #4227: Include numba version in reportable error message
- PR #4216: Add dominator tree
- PR #4200: Add signature parameter to inspect_types
- PR #4196: Catch missing imports of internal functions.
- PR #4180: Update use of unlowerable global message.
- PR #4166: Add tests for PR #4149
- PR #4157: Support for np.flatnonzero
- PR #4149: Implement dominance frontier for SSA for the Numba IR
- PR #4148: Call branch pruning in inline_closure_call()
- PR #4132: Reduce usage of inttoptr
- PR #4129: Support contains for range

- PR #4112: better error messages for np.transpose and tuples
- PR #4110: Add range attrs, start, stop, step
- PR #4077: Add np select
- PR #4076: Add numpy windowing functions support (np.bartlett, np.hamming, np.blackman, np.hanning, np.kaiser)
- PR #4095: Support ir.Global/FreeVar in find_const()
- PR #3691: Make TypingError abort compiling earlier
- PR #3646: Log internal errors encountered in typeinfer

Fixes:

- PR #4303: Work around scipy bug 10206
- PR #4302: Fix flake8 issue on master
- PR #4301: Fix integer literal bug in np.select impl
- PR #4291: Fix pickling of jitclass type
- PR #4262: Resolves #4251 - Fix bug in reshape analysis.
- PR #4233: Fixes issue revealed by #4215
- PR #4224: Fix #4223. Looplifting error due to StaticSetItem in objectmode
- PR #4222: Fix bad python path.
- PR #4178: Fix unary operator overload, check with unicode impl
- PR #4173: Fix return type in np.bincount with weights
- PR #4153: Fix slice shape assignment in array analysis
- PR #4152: fix status check in dict lookup
- PR #4145: Use callable instead of checking __module__
- PR #4118: Fix inline assembly support on CPU.
- PR #4088: Resolves #4075 - parfors array_analysis bug.
- PR #4085: Resolves #3314 - parfors array_analysis bug with reshape.

CUDA Enhancements/Fixes:

- PR #4199: Extend *__cuda_array_interface__* with optional mask attribute, bump version to 1
- PR #4137: CUDA - Fix round Builtin
- PR #4114: Support 3rd party activated CUDA context

Documentation Updates:

- PR #4317: Add docs for ARMv8/AArch64
- PR #4318: Add supported platforms to the docs. Closes #4316
- PR #4295: Alter deprecation schedules
- PR #4253: fix typo in pysupported docs
- PR #4252: fix typo on repomap
- PR #4241: remove unused import

- PR #4240: fix typo in jitclass docs
- PR #4205: Update return value order in normalize_signature docstring
- PR #4237: Update doc links to point to latest not dev docs.
- PR #4197: hyperlink repomap
- PR #4170: Clarify docs on accumulating into arrays in prange
- PR #4147: fix docstring for DictType iterables
- PR #3951: A guide to overloading

CI Updates:

- PR #4300: AArch64 has no faulthandler package
- PR #4273: pin to MKL BLAS for testing to get consistent results
- PR #4209: Revert previous network tol patch and try with conda config
- PR #4138: Remove tbb before Azure test only on Python 3, since it was already removed for Python 2

Contributors:

- Ehsan Totoni (core dev)
- Gregory R. Lee
- Guilherme Leobas
- James Bourbeau
- Joshua L. Adelman
- Keith Kraus
- Lucio Fernandez-Arjona
- Nick White
- Rob Ennis
- Siu Kwan Lam (core dev)
- Stan Seibert (core dev)
- Stuart Archibald (core dev)
- Todd A. Anderson (core dev)
- Valentin Haenel (core dev)

9.2.28 Version 0.44.1

This patch release addresses some regressions reported in the 0.44.0 release:

- PR #4165: Fix #4164 issue with NUMBAPRO_NVVM.
- PR #4172: Abandon branch pruning if an arg name is redefined. (Fixes #4163)
- PR #4183: Fix #4156. Problem with defining in-loop variables.

9.2.29 Version 0.44.0

IMPORTANT: In this release a few significant deprecations (and some less significant ones) are being made, users are encouraged to read the related documentation.

General enhancements in this release include:

- Numba is backed by LLVM 8 on all platforms apart from ppc64le, which, due to bugs, remains on the LLVM 7.x series.
- Numba's dictionary support now includes type inference for keys and values.
- The .view() method now works for NumPy scalar types.
- Newly supported NumPy functions added: np.delete, np.nanquantile, np.quantile, np.repeat, np.shape.

In addition considerable effort has been made to fix some long standing bugs and a large number of other bugs, the "Fixes" section is very large this time!

Enhancements from user contributed PRs (with thanks!):

- Max Bolingbroke added support for the selective use of `fastmath` flags in #3847.
- Rob Ennis made min() and max() work on iterables in #3820 and added np.quantile and np.nanquantile in #3899.
- Sergey Shalnov added numerous unicode string related features, zfill in #3978, ljust in #4001, rjust and center in #4044 and strip, lstrip and rstrip in #4048.
- Guilherme Leobas added support for np.delete in #3890
- Christoph Deil exposed the Numba CLI via `python -m numba` in #4066 and made numerous documentation fixes.
- Leo Schwarz wrote the bulk of the code for jitclass default constructor arguments in #3852.
- Nick White enhanced the CUDA backend to use min/max PTX instructions where possible in #4054.
- Lucio Fernandez-Arjona implemented the unicode string `__mul__` function in #3952.
- Dimitri Vorona wrote the bulk of the code to implement getitem and setitem for jitclass in #3861.

General Enhancements:

- PR #3820: Min max on iterables
- PR #3842: Unicode type iteration
- PR #3847: Allow fine-grained control of fastmath flags to partially address #2923
- PR #3852: Continuation of PR #2894
- PR #3861: Continuation of PR #3730
- PR #3890: Add support for np.delete
- PR #3899: Support for np.quantile and np.nanquantile
- PR #3900: Fix 3457 :: Implements np.repeat
- PR #3928: Add .view() method for NumPy scalars
- PR #3939: Update icc_rt clone recipe.
- PR #3952: __mul__ for strings, initial implementation and tests
- PR #3956: Type-inferred dictionary
- PR #3959: Create a view for string slicing to avoid extra allocations

- PR #3978: zfill operation implementation
- PR #4001: ljust operation implementation
- PR #4010: Support *dict()* and *{}*
- PR #4022: Support for llvm 8
- PR #4034: Make type.Optional str more representative
- PR #4041: Deprecation warnings
- PR #4044: rjust and center operations implementation
- PR #4048: strip, lstrip and rstrip operations implementation
- PR #4066: Expose numba CLI via python -m numba
- PR #4081: Impl *np.shape* and support function for *asarray*.
- PR #4091: Deprecate the use of iternext_impl without RefType

CUDA Enhancements/Fixes:

- PR #3933: Adds *.nbytes* property to CUDA device array objects.
- PR #4011: Add .inspect_ptx() to cuda device function
- PR #4054: CUDA: Use min/max PTX Instructions
- PR #4096: Update env-vars for CUDA libraries lookup

Documentation Updates:

- PR #3867: Code repository map
- PR #3918: adding Joris' Fosdem 2019 presentation
- PR #3926: order talks on applications of Numba by date
- PR #3943: fix two small typos in vectorize docs
- PR #3944: Fixup jitclass docs
- PR #3990: mention preprint repo in FAQ. Fixes #3981
- PR #4012: Correct runtests command in contributing.rst
- PR #4043: fix typo
- PR #4047: Ambiguous Documentation fix for guvectorize.
- PR #4060: Remove remaining mentions of autojit in docs
- PR #4063: Fix annotate example in docstring
- PR #4065: Add FAQ entry explaining Numba project name
- PR #4079: Add Documentation for atomicity of typed.Dict
- PR #4105: Remove info about CUDA ENVVAR potential replacement

Fixes:

- PR #3719: Resolves issue #3528. Adds support for slices when not using parallel=True.
- PR #3727: Remove dels for known dead vars.
- PR #3845: Fix mutable flag transmission in .astype
- PR #3853: Fix some minor issues in the C source.

- PR #3862: Correct boolean reinterpretation of data
- PR #3863: Comments out the appveyor badge
- PR #3869: fixes flake8 after merge
- PR #3871: Add assert to ir.py to help enforce correct structuring
- PR #3881: fix preparfor dtype transform for datetime64
- PR #3884: Prevent mutation of objmode fallback IR.
- PR #3885: Updates for llvmlite 0.29
- PR #3886: Use *safe_load* from pyyaml.
- PR #3887: Add tolerance to network errors by permitting conda to retry
- PR #3893: Fix casting in namedtuple ctor.
- PR #3894: Fix array inliner for multiple array definition.
- PR #3905: Cherrypick #3903 to main
- PR #3920: Raise better error if unsupported jump opcode found.
- PR #3927: Apply flake8 to the numpy related files
- PR #3935: Silence DeprecationWarning
- PR #3938: Better error message for unknown opcode
- PR #3941: Fix typing of ufuncs in parfor conversion
- PR #3946: Return variable renaming dict from inline_closurecall
- PR #3962: Fix bug in alignment computation of *Record.make_c_struct*
- PR #3967: Fix error with pickling unicode
- PR #3964: Unicode split algo versioning
- PR #3975: Add handler for unknown locale to numba -s
- PR #3991: Permit Optionals in ufunc machinery
- PR #3995: Remove assert in type inference causing poor error message.
- PR #3996: add is_ascii flag to UnicodeType
- PR #4009: Prevent zero division error in np.linalg.cond
- PR #4014: Resolves #4007.
- PR #4021: Add a more specific error message for invalid write to a global.
- PR #4023: Fix handling of titles in record dtype
- PR #4024: Do a check if a call is const before saying that an object is multiply defined.
- PR #4027: Fix issue #4020. Turn off no_cpython_wrapper flag when compiling for…
- PR #4033: [WIP] Fixing wrong dtype of array inside reflected list #4028
- PR #4061: Change IPython cache dir name to numba_cache
- PR #4067: Delete examples/notebooks/LinearRegr.py
- PR #4070: Catch writes to global typed.Dict and raise.
- PR #4078: Check tuple length

- PR #4084: Fix missing incref on optional return None
- PR #4089: Make the warnings fixer flush work for warning comparing on type.
- PR #4094: Fix function definition finding logic for commented def
- PR #4100: Fix alignment check on 32-bit.
- PR #4104: Use PEP 508 compliant env markers for install deps

Contributors:

- Benjamin Zaitlen
- Christoph Deil
- David Hirschfeld
- Dimitri Vorona
- Ehsan Totoni (core dev)
- Guilherme Leobas
- Leo Schwarz
- Lucio Fernandez-Arjona
- Max Bolingbroke
- NanduTej
- Nick White
- Ravi Teja Gutta
- Rob Ennis
- Sergey Shalnov
- Siu Kwan Lam (core dev)
- Stan Seibert (core dev)
- Stuart Archibald (core dev)
- Todd A. Anderson (core dev)
- Valentin Haenel (core dev)

9.2.30 Version 0.43.1

This is a bugfix release that provides minor changes to fix: a bug in branch pruning, bugs in *np.interp* functionality, and also fully accommodate the NumPy 1.16 release series.

- PR #3826: NumPy 1.16 support
- PR #3850: Refactor np.interp
- PR #3883: Rewrite pruned conditionals as their evaluated constants.

Contributors:

- Rob Ennis
- Siu Kwan Lam (core dev)
- Stuart Archibald (core dev)

9.2.31 Version 0.43.0

In this release, the major new features are:

- Initial support for statically typed dictionaries
- Improvements to *hash()* to match Python 3 behavior
- Support for the heapq module
- Ability to pass C structs to Numba
- More NumPy functions: asarray, trapz, roll, ptp, extract

NOTE:

The vast majority of NumPy 1.16 behaviour is supported, however `datetime` and `timedelta` use involving `NaT` matches the behaviour present in earlier release. The ufunc suite has not been extending to accommodate the two new time computation related additions present in NumPy 1.16. In addition the functions `ediff1d` and `interp` have known minor issues in replicating outputs exactly when `NaN`'s occur in certain input patterns.

General Enhancements:

- PR #3563: Support for np.roll
- PR #3572: Support for np.ptp
- PR #3592: Add dead branch prune before type inference.
- PR #3598: Implement np.asarray()
- PR #3604: Support for np.interp
- PR #3607: Some simplication to lowering
- PR #3612: Exact match flag in dispatcher
- PR #3627: Support for np.trapz
- PR #3630: np.where with broadcasting
- PR #3633: Support for np.extract
- PR #3657: np.max, np.min, np.nanmax, np.nanmin - support for complex dtypes
- PR #3661: Access C Struct as Numpy Structured Array
- PR #3678: Support for str.split and str.join
- PR #3684: Support C array in C struct
- PR #3696: Add intrinsic to help debug refcount
- PR #3703: Implementations of type hashing.
- PR #3715: Port CPython3.7 dictionary for numba internal use
- PR #3716: Support inplace concat of strings
- PR #3718: Add location to ConstantInferenceError exceptions.
- PR #3720: improve error msg about invalid signature
- PR #3731: Support for heapq
- PR #3754: Updates for llvmlite 0.28
- PR #3760: Overloadable operator.setitem
- PR #3775: Support overloading operator.delitem

- PR #3777: Implement compiler support for dictionary
- PR #3791: Implement interpreter-side interface for numba dict
- PR #3799: Support refcount'ed types in numba dict

CUDA Enhancements/Fixes:

- PR #3713: Fix the NvvmSupportError message when CC too low
- PR #3722: Fix #3705: slicing error with negative strides
- PR #3755: Make cuda.to_device accept readonly host array
- PR #3773: Adapt library search to accommodate multiple locations

Documentation Updates:

- PR #3651: fix link to berryconda in docs
- PR #3668: Add Azure Pipelines build badge
- PR #3749: DOC: Clarify when prange is different from range
- PR #3771: fix a few typos
- PR #3785: Clarify use of range as function only.
- PR #3829: Add docs for typed-dict

Fixes:

- PR #3614: Resolve #3586
- PR #3618: Skip gdb tests on ARM.
- PR #3643: Remove support_literals usage
- PR #3645: Enforce and fix that AbstractTemplate.generic must be returning a Signature
- PR #3648: Fail on @overload signature mismatch.
- PR #3660: Added Ignore message to test numba.tests.test_lists.TestLists.test_mul_error
- PR #3662: Replace six with numba.six
- PR #3663: Removes coverage computation from travisci builds
- PR #3672: Avoid leaking memory when iterating over uniform tuple
- PR #3676: Fixes constant string lowering inside tuples
- PR #3677: Ensure all referenced compiled functions are linked properly
- PR #3692: Fix test failure due to overly strict test on floating point values.
- PR #3693: Intercept failed import to help users.
- PR #3694: Fix memory leak in enumerate iterator
- PR #3695: Convert return of None from intrinsic implementation to dummy value
- PR #3697: Fix for issue #3687
- PR #3701: Fix array.T analysis (fixes #3700)
- PR #3704: Fixes for overload_method
- PR #3706: Don't push call vars recursively into nested parfors. Resolves #3686.
- PR #3710: Set as non-hoistable if a mutable variable is passed to a function in a loop. Resolves #3699.

- PR #3712: parallel=True to use better builtin mechanism to resolve call types. Resolves issue #3671
- PR #3725: Fix invalid removal of dead empty list
- PR #3740: add uintp as a valid type to the tuple operator.getitem
- PR #3758: Fix target definition update in inlining
- PR #3782: Raise typing error on yield optional.
- PR #3792: Fix non-module object used as the module of a function.
- PR #3800: Bugfix for np.interp
- PR #3808: Bump macro to include VS2014 to fix py3.5 build
- PR #3809: Add debug guard to debug only C function.
- PR #3816: Fix array.sum(axis) 1d input return type.
- PR #3821: Replace PySys_WriteStdout with PySys_FormatStdout to ensure no truncation.
- PR #3830: Getitem should not return optional type
- PR #3832: Handle single string as path in find_file()

Contributors:

- Ehsan Totoni
- Gryllos Prokopis
- Jonathan J. Helmus
- Kayla Ngan
- lalitparate
- luk-f-a
- Matyt
- Max Bolingbroke
- Michael Seifert
- Rob Ennis
- Siu Kwan Lam
- Stan Seibert
- Stuart Archibald
- Todd A. Anderson
- Tao He
- Valentin Haenel

9.2.32 Version 0.42.1

Bugfix release to fix the incorrect hash in OSX wheel packages. No change in source code.

9.2.33 Version 0.42.0

In this release the major features are:

- The capability to launch and attach the GDB debugger from within a jitted function.
- The upgrading of LLVM to version 7.0.0.

We added a draft of the project roadmap to the developer manual. The roadmap is for informational purposes only as priorities and resources may change.

Here are some enhancements from contributed PRs:

- #3532. Daniel Wennberg improved the `cuda.{pinned, mapped}` API so that the associated memory is released immediately at the exit of the context manager.
- #3531. Dimitri Vorona enabled the inlining of jitclass methods.
- #3516. Simon Perkins added the support for passing numpy dtypes (i.e. `np.dtype("int32")`) and their type constructor (i.e. `np.int32`) into a jitted function.
- #3509. Rob Ennis added support for `np.corrcoef`.

A regression issue (#3554, #3461) relating to making an empty slice in parallel mode is resolved by #3558.

General Enhancements:

- PR #3392: Launch and attach gdb directly from Numba.
- PR #3437: Changes to accommodate LLVM 7.0.x
- PR #3509: Support for np.corrcoef
- PR #3516: Typeof dtype values
- PR #3520: Fix @stencil ignoring cval if out kwarg supplied.
- PR #3531: Fix jitclass method inlining and avoid unnecessary increfs
- PR #3538: Avoid future C-level assertion error due to invalid visibility
- PR #3543: Avoid implementation error being hidden by the try-except
- PR #3544: Add *long_running* test flag and feature to exclude tests.
- PR #3549: ParallelAccelerator caching improvements
- PR #3558: Fixes array analysis for inplace binary operators.
- PR #3566: Skip alignment tests on armv7l.
- PR #3567: Fix unifying literal types in namedtuple
- PR #3576: Add special copy routine for NumPy out arrays
- PR #3577: Fix example and docs typos for *objmode* context manager. reorder statements.
- PR #3580: Use alias information when determining whether it is safe to
- PR #3583: Use *ir.unknown_loc* for unknown *Loc*, as #3390 with tests
- PR #3587: Fix llvm.memset usage changes in llvm7

- PR #3596: Fix Array Analysis for Global Namedtuples
- PR #3597: Warn users if threading backend init unsafe.
- PR #3605: Add guard for writing to read only arrays from ufunc calls
- PR #3606: Improve the accuracy of error message wording for undefined type.
- PR #3611: gdb test guard needs to ack ptrace permissions
- PR #3616: Skip gdb tests on ARM.

CUDA Enhancements:

- PR #3532: Unregister temporarily pinned host arrays at once
- PR #3552: Handle broadcast arrays correctly in host->device transfer.
- PR #3578: Align cuda and cuda simulator kwarg names.

Documentation Updates:

- PR #3545: Fix @njit description in 5 min guide
- PR #3570: Minor documentation fixes for numba.cuda
- PR #3581: Fixing minor typo in *reference/types.rst*
- PR #3594: Changing *@stencil* docs to correctly reflect *func_or_mode* param
- PR #3617: Draft roadmap as of Dec 2018

Contributors:

- Aaron Critchley
- Daniel Wennberg
- Dimitri Vorona
- Dominik Stańczak
- Ehsan Totoni (core dev)
- Iskander Sharipov
- Rob Ennis
- Simon Muller
- Simon Perkins
- Siu Kwan Lam (core dev)
- Stan Seibert (core dev)
- Stuart Archibald (core dev)
- Todd A. Anderson (core dev)

9.2.34 Version 0.41.0

This release adds the following major features:

- Diagnostics showing the optimizations done by ParallelAccelerator
- Support for profiling Numba-compiled functions in Intel VTune
- Additional NumPy functions: partition, nancumsum, nancumprod, ediff1d, cov, conj, conjugate, tri, tril, triu
- Initial support for Python 3 Unicode strings

General Enhancements:

- PR #1968: armv7 support
- PR #2983: invert mapping b/w binop operators and the operator module #2297
- PR #3160: First attempt at parallel diagnostics
- PR #3307: Adding NUMBA_ENABLE_PROFILING envvar, enabling jit event
- PR #3320: Support for np.partition
- PR #3324: Support for np.nancumsum and np.nancumprod
- PR #3325: Add location information to exceptions.
- PR #3337: Support for np.ediff1d
- PR #3345: Support for np.cov
- PR #3348: Support user pipeline class in with lifting
- PR #3363: string support
- PR #3373: Improve error message for empty imprecise lists.
- PR #3375: Enable overload(operator.getitem)
- PR #3402: Support negative indexing in tuple.
- PR #3414: Refactor Const type
- PR #3416: Optimized usage of alloca out of the loop
- PR #3424: Updates for llvmlite 0.26
- PR #3462: Add support for *np.conj/np.conjugate*.
- PR #3480: np.tri, np.tril, np.triu - default optional args
- PR #3481: Permit dtype argument as sole kwarg in np.eye

CUDA Enhancements:

- PR #3399: Add max_registers Option to cuda.jit

Continuous Integration / Testing:

- PR #3303: CI with Azure Pipelines
- PR #3309: Workaround race condition with apt
- PR #3371: Fix issues with Azure Pipelines
- PR #3362: Fix #3360: *RuntimeWarning: 'numba.runtests' found in sys.modules*
- PR #3374: Disable openmp in wheel building
- PR #3404: Azure Pipelines templates

- PR #3419: Fix cuda tests and error reporting in test discovery
- PR #3491: Prevent faulthandler installation on armv7l
- PR #3493: Fix CUDA test that used negative indexing behaviour that's fixed.
- PR #3495: Start Flake8 checking of Numba source

Fixes:

- PR #2950: Fix dispatcher to only consider contiguous-ness.
- PR #3124: Fix 3119, raise for 0d arrays in reductions
- PR #3228: Reduce redundant module linking
- PR #3329: Fix AOT on windows.
- PR #3335: Fix memory management of __cuda_array_interface__ views.
- PR #3340: Fix typo in error name.
- PR #3365: Fix the default unboxing logic
- PR #3367: Allow non-global reference to objmode() context-manager
- PR #3381: Fix global reference in objmode for dynamically created function
- PR #3382: CUDA_ERROR_MISALIGNED_ADDRESS Using Multiple Const Arrays
- PR #3384: Correctly handle very old versions of colorama
- PR #3394: Add 32bit package guard for non-32bit installs
- PR #3397: Fix with-objmode warning
- PR #3403 Fix label offset in call inline after parfor pass
- PR #3429: Fixes raising of user defined exceptions for exec(<string>).
- PR #3432: Fix error due to function naming in CI in py2.7
- PR #3444: Fixed TBB's single thread execution and test added for #3440
- PR #3449: Allow matching non-array objects in find_callname()
- PR #3455: Change getiter and iternext to not be pure. Resolves #3425
- PR #3467: Make ir.UndefinedType singleton class.
- PR #3478: Fix np.random.shuffle sideeffect
- PR #3487: Raise unsupported for kwargs given to *print()*
- PR #3488: Remove dead script.
- PR #3498: Fix stencil support for boolean as return type
- PR #3511: Fix handling make_function literals (regression of #3414)
- PR #3514: Add missing unicode != unicode
- PR #3527: Fix complex math sqrt implementation for large -ve values
- PR #3530: This adds arg an check for the pattern supplied to Parfors.
- PR #3536: Sets list dtor linkage to *linkonce_odr* to fix visibility in AOT

Documentation Updates:

- PR #3316: Update 0.40 changelog with additional PRs

- PR #3318: Tweak spacing to avoid search box wrapping onto second line
- PR #3321: Add note about memory leaks with exceptions to docs. Fixes #3263
- PR #3322: Add FAQ on CUDA + fork issue. Fixes #3315.
- PR #3343: Update docs for argsort, kind kwarg partially supported.
- PR #3357: Added mention of njit in 5minguide.rst
- PR #3434: Fix parallel reduction example in docs.
- PR #3452: Fix broken link and mark up problem.
- PR #3484: Size Numba logo in docs in em units. Fixes #3313
- PR #3502: just two typos
- PR #3506: Document string support
- PR #3513: Documentation for parallel diagnostics.
- PR #3526: Fix 5 min guide with respect to @njit decl

Contributors:

- Alex Ford
- Andreas Sodeur
- Anton Malakhov
- Daniel Stender
- Ehsan Totoni (core dev)
- Henry Schreiner
- Marcel Bargull
- Matt Cooper
- Nick White
- Nicolas Hug
- rjenc29
- Siu Kwan Lam (core dev)
- Stan Seibert (core dev)
- Stuart Archibald (core dev)
- Todd A. Anderson (core dev)

9.2.35 Version 0.40.1

This is a PyPI-only patch release to ensure that PyPI wheels can enable the TBB threading backend, and to disable the OpenMP backend in the wheels. Limitations of manylinux1 and variation in user environments can cause segfaults when OpenMP is enabled on wheel builds. Note that this release has no functional changes for users who obtained Numba 0.40.0 via conda.

Patches:

- PR #3338: Accidentally left Anton off contributor list for 0.40.0
- PR #3374: Disable OpenMP in wheel building

- PR #3376: Update 0.40.1 changelog and docs on OpenMP backend

9.2.36 Version 0.40.0

This release adds a number of major features:

- A new GPU backend: kernels for AMD GPUs can now be compiled using the ROCm driver on Linux.
- The thread pool implementation used by Numba for automatic multithreading is configurable to use TBB, OpenMP, or the old "workqueue" implementation. (TBB is likely to become the preferred default in a future release.)
- New documentation on thread and fork-safety with Numba, along with overall improvements in thread-safety.
- Experimental support for executing a block of code inside a nopython mode function in object mode.
- Parallel loops now allow arrays as reduction variables
- CUDA improvements: FMA, faster float64 atomics on supporting hardware, records in const memory, and improved datatime dtype support
- More NumPy functions: vander, tri, triu, tril, fill_diagonal

General Enhancements:

- PR #3017: Add facility to support with-contexts
- PR #3033: Add support for multidimensional CFFI arrays
- PR #3122: Add inliner to object mode pipeline
- PR #3127: Support for reductions on arrays.
- PR #3145: Support for np.fill_diagonal
- PR #3151: Keep a queue of references to last N deserialized functions. Fixes #3026
- PR #3154: Support use of list() if typeable.
- PR #3166: Objmode with-block
- PR #3179: Updates for llvmlite 0.25
- PR #3181: Support function extension in alias analysis
- PR #3189: Support literal constants in typing of object methods
- PR #3190: Support passing closures as literal values in typing
- PR #3199: Support inferring stencil index as constant in simple unary expressions
- PR #3202: Threading layer backend refactor/rewrite/reinvention!
- PR #3209: Support for np.tri, np.tril and np.triu
- PR #3211: Handle unpacking in building tuple (BUILD_TUPLE_UNPACK opcode)
- PR #3212: Support for np.vander
- PR #3227: Add NumPy 1.15 support
- PR #3272: Add MemInfo_data to runtime._nrt_python.c_helpers
- PR #3273: Refactor. Removing thread-local-storage based context nesting.
- PR #3278: compiler threadsafety lockdown
- PR #3291: Add CPU count and CFS restrictions info to numba -s.

CUDA Enhancements:

- PR #3152: Use cuda driver api to get best blocksize for best occupancy
- PR #3165: Add FMA intrinsic support
- PR #3172: Use float64 add Atomics, Where Available
- PR #3186: Support Records in CUDA Const Memory
- PR #3191: CUDA: fix log size
- PR #3198: Fix GPU datetime timedelta types usage
- PR #3221: Support datetime/timedelta scalar argument to a CUDA kernel.
- PR #3259: Add DeviceNDArray.view method to reinterpret data as a different type.
- PR #3310: Fix IPC handling of sliced cuda array.

ROCm Enhancements:

- PR #3023: Support for AMDGCN/ROCm.
- PR #3108: Add ROC info to *numba -s* output.
- PR #3176: Move ROC vectorize init to npyufunc
- PR #3177: Add auto_synchronize support to ROC stream
- PR #3178: Update ROC target documentation.
- PR #3294: Add compiler lock to ROC compilation path.
- PR #3280: Add wavebits property to the HSA Agent.
- PR #3281: Fix ds_permute types and add tests

Continuous Integration / Testing:

- PR #3091: Remove old recipes, switch to test config based on env var.
- PR #3094: Add higher ULP tolerance for products in complex space.
- PR #3096: Set exit on error in incremental scripts
- PR #3109: Add skip to test needing jinja2 if no jinja2.
- PR #3125: Skip cudasim only tests
- PR #3126: add slack, drop flowdock
- PR #3147: Improve error message for arg type unsupported during typing.
- PR #3128: Fix recipe/build for jetson tx2/ARM
- PR #3167: In build script activate env before installing.
- PR #3180: Add skip to broken test.
- PR #3216: Fix libcuda.so loading in some container setup
- PR #3224: Switch to new Gitter notification webhook URL and encrypt it
- PR #3235: Add 32bit Travis CI jobs
- PR #3257: This adds scipy/ipython back into windows conda test phase.

Fixes:

- PR #3038: Fix random integer generation to match results from NumPy.

- PR #3045: Fix #3027 - Numba reassigns sys.stdout
- PR #3059: Handler for known LoweringErrors.
- PR #3060: Adjust attribute error for NumPy functions.
- PR #3067: Abort simulator threads on exception in thread block.
- PR #3079: Implement +/-(types.boolean) Fix #2624
- PR #3080: Compute np.var and np.std correctly for complex types.
- PR #3088: Fix #3066 (array.dtype.type in prange)
- PR #3089: Fix invalid ParallelAccelerator hoisting issue.
- PR #3136: Fix #3135 (lowering error)
- PR #3137: Fix for issue3103 (race condition detection)
- PR #3142: Fix Issue #3139 (parfors reuse of reduction variable across prange blocks)
- PR #3148: Remove dead array equal @infer code
- PR #3153: Fix canonicalize_array_math typing for calls with kw args
- PR #3156: Fixes issue with missing pygments in testing and adds guards.
- PR #3168: Py37 bytes output fix.
- PR #3171: Fix #3146. Fix CFUNCTYPE void* return-type handling
- PR #3193: Fix setitem/getitem resolvers
- PR #3222: Fix #3214. Mishandling of POP_BLOCK in while True loop.
- PR #3230: Fixes liveness analysis issue in looplifting
- PR #3233: Fix return type difference for 32bit ctypes.c_void_p
- PR #3234: Fix types and layout for *np.where*.
- PR #3237: Fix DeprecationWarning about imp module
- PR #3241: Fix #3225. Normalize 0nd array to scalar in typing of indexing code.
- PR #3256: Fix #3251: Move imports of ABCs to collections.abc for Python >= 3.3
- PR #3292: Fix issue3279.
- PR #3302: Fix error due to mismatching dtype

Documentation Updates:

- PR #3104: Workaround for #3098 (test_optional_unpack Heisenbug)
- PR #3132: Adds an ~5 minute guide to Numba.
- PR #3194: Fix docs RE: np.random generator fork/thread safety
- PR #3242: Page with Numba talks and tutorial links
- PR #3258: Allow users to choose the type of issue they are reporting.
- PR #3260: Fixed broken link
- PR #3266: Fix cuda pointer ownership problem with user/externally allocated pointer
- PR #3269: Tweak typography with CSS
- PR #3270: Update FAQ for functions passed as arguments

- PR #3274: Update installation instructions
- PR #3275: Note pyobject and voidptr are types in docs
- PR #3288: Do not need to call parallel optimizations "experimental" anymore
- PR #3318: Tweak spacing to avoid search box wrapping onto second line

Contributors:

- Anton Malakhov
- Alex Ford
- Anthony Bisulco
- Ehsan Totoni (core dev)
- Leonard Lausen
- Matthew Petroff
- Nick White
- Ray Donnelly
- rjenc29
- Siu Kwan Lam (core dev)
- Stan Seibert (core dev)
- Stuart Archibald (core dev)
- Stuart Reynolds
- Todd A. Anderson (core dev)

9.2.37 Version 0.39.0

Here are the highlights for the Numba 0.39.0 release.

- This is the first version that supports Python 3.7.
- With help from Intel, we have fixed the issues with SVML support (related issues #2938, #2998, #3006).
- List has gained support for containing reference-counted types like NumPy arrays and *list*. Note, list still cannot hold heterogeneous types.
- We have made a significant change to the internal calling-convention, which should be transparent to most users, to allow for a future feature that will permitting jumping back into python-mode from a nopython-mode function. This also fixes a limitation to *print* that disabled its use from nopython functions that were deep in the call-stack.
- For CUDA GPU support, we added a *__cuda_array_interface__* following the NumPy array interface specification to allow Numba to consume externally defined device arrays. We have opened a corresponding pull request to CuPy to test out the concept and be able to use a CuPy GPU array.
- The Numba dispatcher *inspect_types()* method now supports the kwarg *pretty* which if set to *True* will produce ANSI/HTML output, showing the annotated types, when invoked from ipython/jupyter-notebook respectively.
- The NumPy functions *ndarray.dot*, *np.percentile* and *np.nanpercentile*, and *np.unique* are now supported.
- Numba now supports the use of a per-project configuration file to permanently set behaviours typically set via *NUMBA_** family environment variables.
- Support for the *ppc64le* architecture has been added.

Enhancements:

- PR #2793: Simplify and remove javascript from html_annotate templates.
- PR #2840: Support list of refcounted types
- PR #2902: Support for np.unique
- PR #2926: Enable fence for all architecture and add developer notes
- PR #2928: Making error about untyped list more informative.
- PR #2930: Add configuration file and color schemes.
- PR #2932: Fix encoding to 'UTF-8' in *check_output* decode.
- PR #2938: Python 3.7 compat: _Py_Finalizing becomes _Py_IsFinalizing()
- PR #2939: Comprehensive SVML unit test
- PR #2946: Add support for *ndarray.dot* method and tests.
- PR #2953: percentile and nanpercentile
- PR #2957: Add new 3.7 opcode support.
- PR #2963: Improve alias analysis to be more comprehensive
- PR #2984: Support for namedtuples in array analysis
- PR #2986: Fix environment propagation
- PR #2990: Improve function call matching for intrinsics
- PR #3002: Second pass at error rewrites (interpreter errors).
- PR #3004: Add numpy.empty to the list of pure functions.
- PR #3008: Augment SVML detection with llvmlite SVML patch detection.
- PR #3012: Make use of the common spelling of heterogeneous/homogeneous.
- PR #3032: Fix pycc ctypes test due to mismatch in calling-convention
- PR #3039: Add SVML detection to Numba environment diagnostic tool.
- PR #3041: This adds @needs_blas to tests that use BLAS
- PR #3056: Require llvmlite>=0.24.0

CUDA Enhancements:

- PR #2860: __cuda_array_interface__
- PR #2910: More CUDA intrinsics
- PR #2929: Add Flag To Prevent Unneccessary D->H Copies
- PR #3037: Add CUDA IPC support on non-peer-accessible devices

CI Enhancements:

- PR #3021: Update appveyor config.
- PR #3040: Add fault handler to all builds
- PR #3042: Add catchsegv
- PR #3077: Adds optional number of processes for *-m* in testing

Fixes:

- PR #2897: Fix line position of delete statement in numba ir
- PR #2905: Fix for #2862
- PR #3009: Fix optional type returning in recursive call
- PR #3019: workaround and unittest for issue #3016
- PR #3035: [TESTING] Attempt delayed removal of Env
- PR #3048: [WIP] Fix cuda tests failure on buildfarm
- PR #3054: Make test work on 32-bit
- PR #3062: Fix cuda.In freeing devary before the kernel launch
- PR #3073: Workaround #3072
- PR #3076: Avoid ignored exception due to missing globals at interpreter teardown

Documentation Updates:

- PR #2966: Fix syntax in env var docs.
- PR #2967: Fix typo in CUDA kernel layout example.
- PR #2970: Fix docstring copy paste error.

Contributors:

The following people contributed to this release.

- Anton Malakhov
- Ehsan Totoni (core dev)
- Julia Tatz
- Matthias Bussonnier
- Nick White
- Ray Donnelly
- Siu Kwan Lam (core dev)
- Stan Seibert (core dev)
- Stuart Archibald (core dev)
- Todd A. Anderson (core dev)
- Rik-de-Kort
- rjenc29

9.2.38 Version 0.38.1

This is a critical bug fix release addressing: https://github.com/numba/numba/issues/3006

The bug does not impact users using conda packages from Anaconda or Intel Python Distribution (but it does impact conda-forge). It does not impact users of pip using wheels from PyPI.

This only impacts a small number of users where:

- The ICC runtime (specifically libsvml) is present in the user's environment.
- The user is using an llvmlite statically linked against a version of LLVM that has not been patched with SVML support.

- The platform is 64-bit.

The release fixes a code generation path that could lead to the production of incorrect results under the above situation.

Fixes:

- PR #3007: Augment SVML detection with llvmlite SVML patch detection.

Contributors:

The following people contributed to this release.

- Stuart Archibald (core dev)

9.2.39 Version 0.38.0

Following on from the bug fix focus of the last release, this release swings back towards the addition of new features and usability improvements based on community feedback. This release is comparatively large! Three key features/ changes to note are:

- Numba (via llvmlite) is now backed by LLVM 6.0, general vectorization is improved as a result. A significant long standing LLVM bug that was causing corruption was also found and fixed.
- Further considerable improvements in vectorization are made available as Numba now supports Intel's short vector math library (SVML). Try it out with *conda install -c numba icc_rt*.
- CUDA 8.0 is now the minimum supported CUDA version.

Other highlights include:

- Bug fixes to *parallel=True* have enabled more vectorization opportunities when using the ParallelAccelerator technology.
- Much effort has gone into improving error reporting and the general usability of Numba. This includes highlighted error messages and performance tips documentation. Try it out with *conda install colorama*.
- A number of new NumPy functions are supported, *np.convolve*, *np.correlate np.reshape*, *np.transpose*, *np.permutation*, *np.real*, *np.imag*, and *np.searchsorted* now supports the`side` kwarg. Further, *np.argsort* now supports the *kind* kwarg with *quicksort* and *mergesort* available.
- The Numba extension API has gained the ability operate more easily with functions from Cython modules through the use of *numba.extending.get_cython_function_address* to obtain function addresses for direct use in *ctypes.CFUNCTYPE*.
- Numba now allows the passing of jitted functions (and containers of jitted functions) as arguments to other jitted functions.
- The CUDA functionality has gained support for a larger selection of bit manipulation intrinsics, also SELP, and has had a number of bugs fixed.
- Initial work to support the PPC64LE platform has been added, full support is however waiting on the LLVM 6.0.1 release as it contains critical patches not present in 6.0.0. It is hoped that any remaining issues will be fixed in the next release.
- The capacity for advanced users/compiler engineers to define their own compilation pipelines.

Enhancements:

- PR #2660: Support bools from cffi in nopython.
- PR #2741: Enhance error message for undefined variables.
- PR #2744: Add diagnostic error message to test suite discovery failure.
- PR #2748: Added Intel SVML optimizations as opt-out choice working by default

- PR #2762: Support transpose with axes arguments.
- PR #2777: Add support for np.correlate and np.convolve
- PR #2779: Implement np.random.permutation
- PR #2801: Passing jitted functions as args
- PR #2802: Support np.real() and np.imag()
- PR #2807: Expose *import_cython_function*
- PR #2821: Add kwarg 'side' to np.searchsorted
- PR #2822: Adds stable argsort
- PR #2832: Fixups for llvmlite 0.23/llvm 6
- PR #2836: Support *index* method on tuples
- PR #2839: Support for np.transpose and np.reshape.
- PR #2843: Custom pipeline
- PR #2847: Replace signed array access indices in unsiged prange loop body
- PR #2859: Add support for improved error reporting.
- PR #2880: This adds a github issue template.
- PR #2881: Build recipe to clone Intel ICC runtime.
- PR #2882: Update TravisCI to test SVML
- PR #2893: Add reference to the data buffer in array.ctypes object
- PR #2895: Move to CUDA 8.0

Fixes:

- PR #2737: Fix #2007 (part 1). Empty array handling in np.linalg.
- PR #2738: Fix install_requires to allow pip getting pre-release version
- PR #2740: Fix 2208. Generate better error message.
- PR #2765: Fix Bit-ness
- PR #2780: PowerPC reference counting memory fences
- PR #2805: Fix six imports.
- PR #2813: Fix #2812: gufunc scalar output bug.
- PR #2814: Fix the build post #2727
- PR #2831: Attempt to fix #2473
- PR #2842: Fix issue with test discovery and broken CUDA drivers.
- PR #2850: Add rtsys init guard and test.
- PR #2852: Skip vectorization test with targets that are not x86
- PR #2856: Prevent printing to stdout in *test_extending.py*
- PR #2864: Correct C code to prevent compiler warnings.
- PR #2889: Attempt to fix #2386.
- PR #2891: Removed test skipping for inspect_cfg

- PR #2898: Add guard to parallel test on unsupported platforms
- PR #2907: Update change log for PPC64LE LLVM dependency.
- PR #2911: Move build requirement to llvmlite>=0.23.0dev0
- PR #2912: Fix random permutation test.
- PR #2914: Fix MD list syntax in issue template.

Documentation Updates:

- PR #2739: Explicitly state default value of error_model in docstring
- PR #2803: DOC: parallel vectorize requires signatures
- PR #2829: Add Python 2.7 EOL plan to docs
- PR #2838: Use automatic numbering syntax in list.
- PR #2877: Add performance tips documentation.
- PR #2883: Fix #2872: update rng doc about thread/fork-safety
- PR #2908: Add missing link and ref to docs.
- PR #2909: Tiny typo correction

ParallelAccelerator enhancements/fixes:

- PR #2727: Changes to enable vectorization in ParallelAccelerator.
- PR #2816: Array analysis for transpose with arbitrary arguments
- PR #2874: Fix dead code eliminator not to remove a call with side-effect
- PR #2886: Fix ParallelAccelerator arrayexpr repr

CUDA enhancements:

- PR #2734: More Constants From cuda.h
- PR #2767: Add len(..) Support to DeviceNDArray
- PR #2778: Add More Device Array API Functions to CUDA Simulator
- PR #2824: Add CUDA Primitives for Population Count
- PR #2835: Emit selp Instructions to Avoid Branching
- PR #2867: Full support for CUDA device attributes

CUDA fixes: * PR #2768: Don't Compile Code on Every Assignment * PR #2878: Fixes a Win64 issue with the test in Pr/2865

Contributors:

The following people contributed to this release.

- Abutalib Aghayev
- Alex Olivas
- Anton Malakhov
- Dong-hee Na
- Ehsan Totoni (core dev)
- John Zwinck

- Josh Wilson
- Kelsey Jordahl
- Nick White
- Olexa Bilaniuk
- Rik-de-Kort
- Siu Kwan Lam (core dev)
- Stan Seibert (core dev)
- Stuart Archibald (core dev)
- Thomas Arildsen
- Todd A. Anderson (core dev)

9.2.40 Version 0.37.0

This release focuses on bug fixing and stability but also adds a few new features including support for Numpy 1.14. The key change for Numba core was the long awaited addition of the final tranche of thread safety improvements that allow Numba to be run concurrently on multiple threads without hitting known thread safety issues inside LLVM itself. Further, a number of fixes and enhancements went into the CUDA implementation and ParallelAccelerator gained some new features and underwent some internal refactoring.

Misc enhancements:

- PR #2627: Remove hacks to make llvmlite threadsafe
- PR #2672: Add ascontiguousarray
- PR #2678: Add Gitter badge
- PR #2691: Fix #2690: add intrinsic to convert array to tuple
- PR #2703: Test runner feature: failed-first and last-failed
- PR #2708: Patch for issue #1907
- PR #2732: Add support for array.fill

Misc Fixes:

- PR #2610: Fix #2606 lowering of optional.setattr
- PR #2650: Remove skip for win32 cosine test
- PR #2668: Fix empty_like from readonly arrays.
- PR #2682: Fixes 2210, remove _DisableJitWrapper
- PR #2684: Fix #2340, generator error yielding bool
- PR #2693: Add travis-ci testing of NumPy 1.14, and also check on Python 2.7
- PR #2694: Avoid type inference failure due to a typing template rejection
- PR #2695: Update llvmlite version dependency.
- PR #2696: Fix tuple indexing codegeneration for empty tuple
- PR #2698: Fix #2697 by deferring deletion in the simplify_CFG loop.
- PR #2701: Small fix to avoid tempfiles being created in the current directory

- PR #2725: Fix 2481, LLVM IR parsing error due to mutated IR
- PR #2726: Fix #2673: incorrect fork error msg.
- PR #2728: Alternative to #2620. Remove dead code ByteCodeInst.get.
- PR #2730: Add guard for test needing SciPy/BLAS

Documentation updates:

- PR #2670: Update communication channels
- PR #2671: Add docs about diagnosing loop vectorizer
- PR #2683: Add docs on const arg requirements and on const mem alloc
- PR #2722: Add docs on numpy support in cuda
- PR #2724: Update doc: warning about unsupported arguments

ParallelAccelerator enhancements/fixes:

Parallel support for *np.arange* and *np.linspace*, also *np.mean*, *np.std* and *np.var* are added. This was performed as part of a general refactor and cleanup of the core ParallelAccelerator code.

- PR #2674: Core pa
- PR #2704: Generate Dels after parfor sequential lowering
- PR #2716: Handle matching directly supported functions

CUDA enhancements:

- PR #2665: CUDA DeviceNDArray: Support numpy tranpose API
- PR #2681: Allow Assigning to DeviceNDArrays
- PR #2702: Make DummyArray do High Dimensional Reshapes
- PR #2714: Use CFFI to Reuse Code

CUDA fixes:

- PR #2667: Fix CUDA DeviceNDArray slicing
- PR #2686: Fix #2663: incorrect offset when indexing cuda array.
- PR #2687: Ensure Constructed Stream Bound
- PR #2706: Workaround for unexpected warp divergence due to exception raising code
- PR #2707: Fix regression: cuda test submodules not loading properly in runtests
- PR #2731: Use more challenging values in slice tests.
- PR #2720: A quick testsuite fix to not run the new cuda testcase in the multiprocess pool

Contributors:

The following people contributed to this release.

- Coutinho Menezes Nilo
- Daniel
- Ehsan Totoni
- Nick White
- Paul H. Liu

- Siu Kwan Lam
- Stan Seibert
- Stuart Archibald
- Todd A. Anderson

9.2.41 Version 0.36.2

This is a bugfix release that provides minor changes to address:

- PR #2645: Avoid CPython bug with `exec` in older 2.7.x.
- PR #2652: Add support for CUDA 9.

9.2.42 Version 0.36.1

This release continues to add new features to the work undertaken in partnership with Intel on ParallelAccelerator technology. Other changes of note include the compilation chain being updated to use LLVM 5.0 and the production of conda packages using conda-build 3 and the new compilers that ship with it.

NOTE: A version 0.36.0 was tagged for internal use but not released.

ParallelAccelerator:

NOTE: The ParallelAccelerator technology is under active development and should be considered experimental.

New features relating to ParallelAccelerator, from work undertaken with Intel, include the addition of the *@stencil* decorator for ease of implementation of stencil-like computations, support for general reductions, and slice and range fusion for parallel slice/bit-array assignments. Documentation on both the use and implementation of the above has been added. Further, a new debug environment variable *NUMBA_DEBUG_ARRAY_OPT_STATS* is made available to give information about which operators/calls are converted to parallel for-loops.

ParallelAccelerator features:

- PR #2457: Stencil Computations in ParallelAccelerator
- PR #2548: Slice and range fusion, parallelizing bitarray and slice assignment
- PR #2516: Support general reductions in ParallelAccelerator

ParallelAccelerator fixes:

- PR #2540: Fix bug #2537
- PR #2566: Fix issue #2564.
- PR #2599: Fix nested multi-dimensional parfor type inference issue
- PR #2604: Fixes for stencil tests and cmath sin().
- PR #2605: Fixes issue #2603.

Additional features of note:

This release of Numba (and llvmlite) is updated to use LLVM version 5.0 as the compiler back end, the main change to Numba to support this was the addition of a custom symbol tracker to avoid the calls to LLVM's *ExecutionEngine* that was crashing when asking for non-existent symbol addresses. Further, the conda packages for this release of Numba are built using conda build version 3 and the new compilers/recipe grammar that are present in that release.

- PR #2568: Update for LLVM 5
- PR #2607: Fixes abort when getting address to "nrt_unresolved_abort"

- PR #2615: Working towards conda build 3

Thanks to community feedback and bug reports, the following fixes were also made.

Misc fixes/enhancements:

- PR #2534: Add tuple support to np.take.
- PR #2551: Rebranding fix
- PR #2552: relative doc links
- PR #2570: Fix issue #2561, handle missing successor on loop exit
- PR #2588: Fix #2555. Disable libpython.so linking on linux
- PR #2601: Update llvmlite version dependency.
- PR #2608: Fix potential cache file collision
- PR #2612: Fix NRT test failure due to increased overhead when running in coverage
- PR #2619: Fix dubious pthread_cond_signal not in lock
- PR #2622: Fix *np.nanmedian* for all NaN case.
- PR #2633: Fix markdown in CONTRIBUTING.md
- PR #2635: Make the dependency on compilers for AOT optional.

CUDA support fixes:

- PR #2523: Fix invalid cuda context in memory transfer calls in another thread
- PR #2575: Use CPU to initialize xoroshiro states for GPU RNG. Fixes #2573
- PR #2581: Fix cuda gufunc mishandling of scalar arg as array and out argument

9.2.43 Version 0.35.0

This release includes some exciting new features as part of the work performed in partnership with Intel on ParallelAccelerator technology. There are also some additions made to Numpy support and small but significant fixes made as a result of considerable effort spent chasing bugs and implementing stability improvements.

ParallelAccelerator:

NOTE: The ParallelAccelerator technology is under active development and should be considered experimental.

New features relating to ParallelAccelerator, from work undertaken with Intel, include support for a larger range of *np.random* functions in *parallel* mode, printing Numpy arrays in no Python mode, the capacity to initialize Numpy arrays directly from list comprehensions, and the axis argument to *.sum()*. Documentation on the ParallelAccelerator technology implementation has also been added. Further, a large amount of work on equivalence relations was undertaken to enable runtime checks of broadcasting behaviours in parallel mode.

ParallelAccelerator features:

- PR #2400: Array comprehension
- PR #2405: Support printing Numpy arrays
- PR #2438: from Support more np.random functions in ParallelAccelerator
- PR #2482: Support for sum with axis in nopython mode.
- PR #2487: Adding developer documentation for ParallelAccelerator technology.
- PR #2492: Core PA refactor adds assertions for broadcast semantics

ParallelAccelerator fixes:

- PR #2478: Rename cfg before parfor translation (#2477)
- PR #2479: Fix broken array comprehension tests on unsupported platforms
- PR #2484: Fix array comprehension test on win64
- PR #2506: Fix for 32-bit machines.

Additional features of note:

Support for *np.take*, *np.finfo*, *np.iinfo* and *np.MachAr* in no Python mode is added. Further, three new environment variables are added, two for overriding CPU target/features and another to warn if *parallel=True* was set no such transform was possible.

- PR #2490: Implement np.take and ndarray.take
- PR #2493: Display a warning if parallel=True is set but not possible.
- PR #2513: Add np.MachAr, np.finfo, np.iinfo
- PR #2515: Allow environ overriding of cpu target and cpu features.

Due to expansion of the test farm and a focus on fixing bugs, the following fixes were also made.

Misc fixes/enhancements:

- PR #2455: add contextual information to runtime errors
- PR #2470: Fixes #2458, poor performance in np.median
- PR #2471: Ensure LLVM threadsafety in {g,}ufunc building.
- PR #2494: Update doc theme
- PR #2503: Remove hacky code added in 2482 and feature enhancement
- PR #2505: Serialise env mutation tests during multithreaded testing.
- PR #2520: Fix failing cpu-target override tests

CUDA support fixes:

- PR #2504: Enable CUDA toolkit version testing
- PR #2509: Disable tests generating code unavailable in lower CC versions.
- PR #2511: Fix Windows 64 bit CUDA tests.

9.2.44 Version 0.34.0

This release adds a significant set of new features arising from combined work with Intel on ParallelAccelerator technology. It also adds list comprehension and closure support, support for Numpy 1.13 and a new, faster, CUDA reduction algorithm. For Linux users this release is the first to be built on Centos 6, which will be the new base platform for future releases. Finally a number of thread-safety, type inference and other smaller enhancements and bugs have been fixed.

ParallelAccelerator features:

NOTE: The ParallelAccelerator technology is under active development and should be considered experimental.

The ParallelAccelerator technology is accessed via a new "nopython" mode option "parallel". The ParallelAccelerator technology attempts to identify operations which have parallel semantics (for instance adding a scalar to a vector), fuse together adjacent such operations, and then parallelize their execution across a number of CPU cores. This is essentially auto-parallelization.

In addition to the auto-parallelization feature, explicit loop based parallelism is made available through the use of *prange* in place of *range* as a loop iterator.

More information and examples on both auto-parallelization and *prange* are available in the documentation and examples directory respectively.

As part of the necessary work for ParallelAccelerator, support for closures and list comprehensions is added:

- PR #2318: Transfer ParallelAccelerator technology to Numba
- PR #2379: ParallelAccelerator Core Improvements
- PR #2367: Add support for len(range(...))
- PR #2369: List comprehension
- PR #2391: Explicit Parallel Loop Support (prange)

The ParallelAccelerator features are available on all supported platforms and Python versions with the exceptions of (with view of supporting in a future release):

- The combination of Windows operating systems with Python 2.7.
- Systems running 32 bit Python.

CUDA support enhancements:

- PR #2377: New GPU reduction algorithm

CUDA support fixes:

- PR #2397: Fix #2393, always set alignment of cuda static memory regions

Misc Fixes:

- PR #2373, Issue #2372: 32-bit compatibility fix for parfor related code
- PR #2376: Fix #2375 missing stdint.h for py2.7 vc9
- PR #2378: Fix deadlock in parallel gufunc when kernel acquires the GIL.
- PR #2382: Forbid unsafe casting in bitwise operation
- PR #2385: docs: fix Sphinx errors
- PR #2396: Use 64-bit RHS operand for shift
- PR #2404: Fix threadsafety logic issue in ufunc compilation cache.
- PR #2424: Ensure consistent iteration order of blocks for type inference.
- PR #2425: Guard code to prevent the use of 'parallel' on win32 + py27
- PR #2426: Basic test for Enum member type recovery.
- PR #2433: Fix up the parfors tests with respect to windows py2.7
- PR #2442: Skip tests that need BLAS/LAPACK if scipy is not available.
- PR #2444: Add test for invalid array setitem
- PR #2449: Make the runtime initialiser threadsafe
- PR #2452: Skip CFG test on 64bit windows

Misc Enhancements:

- PR #2366: Improvements to IR utils
- PR #2388: Update README.rst to indicate the proper version of LLVM

- PR #2394: Upgrade to llvmlite 0.19.*
- PR #2395: Update llvmlite version to 0.19
- PR #2406: Expose environment object to ufuncs
- PR #2407: Expose environment object to target-context inside lowerer
- PR #2413: Add flags to pass through to conda build for buildbot
- PR #2414: Add cross compile flags to local recipe
- PR #2415: A few cleanups for rewrites
- PR #2418: Add getitem support for Enum classes
- PR #2419: Add support for returning enums in vectorize
- PR #2421: Add copyright notice for Intel contributed files.
- PR #2422: Patch code base to work with np 1.13 release
- PR #2448: Adds in warning message when using 'parallel' if cache=True
- PR #2450: Add test for keyword arg on .sum-like and .cumsum-like array methods

9.2.45 Version 0.33.0

This release resolved several performance issues caused by atomic reference counting operations inside loop bodies. New optimization passes have been added to reduce the impact of these operations. We observe speed improvements between 2x-10x in affected programs due to the removal of unnecessary reference counting operations.

There are also several enhancements to the CUDA GPU support:

- A GPU random number generator based on xoroshiro128+ algorithm is added. See details and examples in *documentation*.
- `@cuda.jit` CUDA kernels can now call `@jit` and `@njit` CPU functions and they will automatically be compiled as CUDA device functions.
- CUDA IPC memory API is exposed for sharing memory between proceses. See usage details in *documentation*.

Reference counting enhancements:

- PR #2346, Issue #2345, #2248: Add extra refcount pruning after inlining
- PR #2349: Fix refct pruning not removing refct op with tail call.
- PR #2352, Issue #2350: Add refcount pruning pass for function that does not need refcount

CUDA support enhancements:

- PR #2023: Supports CUDA IPC for device array
- PR #2343, Issue #2335: Allow CPU jit decorated function to be used as cuda device function
- PR #2347: Add random number generator support for CUDA device code
- PR #2361: Update autotune table for CC: 5.3, 6.0, 6.1, 6.2

Misc fixes:

- PR #2362: Avoid test failure due to typing to int32 on 32-bit platforms
- PR #2359: Fixed nogil example that threw a TypeError when executed.
- PR #2357, Issue #2356: Fix fragile test that depends on how the script is executed.

- PR #2355: Fix cpu dispatcher referenced as attribute of another module
- PR #2354: Fixes an issue with caching when function needs NRT and refcount pruning
- PR #2342, Issue #2339: Add warnings to inspection when it is used on unserialized cached code
- PR #2329, Issue #2250: Better handling of missing op codes

Misc enhancements:

- PR #2360: Adds missing values in error mesasge interp.
- PR #2353: Handle when get_host_cpu_features() raises RuntimeError
- PR #2351: Enable SVML for erf/erfc/gamma/lgamma/log2
- PR #2344: Expose error_model setting in jit decorator
- PR #2337: Align blocking terminate support for fork() with new TBB version
- PR #2336: Bump llvmlite version to 0.18
- PR #2330: Core changes in PR #2318

9.2.46 Version 0.32.0

In this release, we are upgrading to LLVM 4.0. A lot of work has been done to fix many race-condition issues inside LLVM when the compiler is used concurrently, which is likely when Numba is used with Dask.

Improvements:

- PR #2322: Suppress test error due to unknown but consistent error with tgamma
- PR #2320: Update llvmlite dependency to 0.17
- PR #2308: Add details to error message on why cuda support is disabled.
- PR #2302: Add os x to travis
- PR #2294: Disable remove_module on MCJIT due to memory leak inside LLVM
- PR #2291: Split parallel tests and recycle workers to tame memory usage
- PR #2253: Remove the pointer-stuffing hack for storing meminfos in lists

Fixes:

- PR #2331: Fix a bug in the GPU array indexing
- PR #2326: Fix #2321 docs referring to non-existing function.
- PR #2316: Fixing more race-condition problems
- PR #2315: Fix #2314. Relax strict type check to allow optional type.
- PR #2310: Fix race condition due to concurrent compilation and cache loading
- PR #2304: Fix intrinsic 1st arg not a typing.Context as stated by the docs.
- PR #2287: Fix int64 atomic min-max
- PR #2286: Fix #2285 *@overload_method* not linking dependent libs
- PR #2303: Missing import statements to interval-example.rst

9.2.47 Version 0.31.0

In this release, we added preliminary support for debugging with GDB version >= 7.0. The feature is enabled by setting the `debug=True` compiler option, which causes GDB compatible debug info to be generated. The CUDA backend also gained limited debugging support so that source locations are showed in memory-checking and profiling tools. For details, see *Troubleshooting and tips*.

Also, we added the `fastmath=True` compiler option to enable unsafe floating-point transformations, which allows LLVM to auto-vectorize more code.

Other important changes include upgrading to LLVM 3.9.1 and adding support for Numpy 1.12.

Improvements:

- PR #2281: Update for numpy1.12
- PR #2278: Add CUDA atomic.{max, min, compare_and_swap}
- PR #2277: Add about section to conda recipies to identify license and other metadata in Anaconda Cloud
- PR #2271: Adopt itanium C++-style mangling for CPU and CUDA targets
- PR #2267: Add fastmath flags
- PR #2261: Support dtype.type
- PR #2249: Changes for llvm3.9
- PR #2234: Bump llvmlite requirement to 0.16 and add install_name_tool_fixer to mviewbuf for OS X
- PR #2230: Add python3.6 to TravisCi
- PR #2227: Enable caching for gufunc wrapper
- PR #2170: Add debugging support
- PR #2037: inspect_cfg() for easier visualization of the function operation

Fixes:

- PR #2274: Fix nvvm ir patch in mishandling “load”
- PR #2272: Fix breakage to cuda7.5
- PR #2269: Fix caching of copy_strides kernel in cuda.reduce
- PR #2265: Fix #2263: error when linking two modules with dynamic globals
- PR #2252: Fix path separator in test
- PR #2246: Fix overuse of memory in some system with fork
- PR #2241: Fix #2240: __module__ in dynamically created function not a str
- PR #2239: Fix fingerprint computation failure preventing fallback

9.2.48 Version 0.30.1

This is a bug-fix release to enable Python 3.6 support. In addition, there is now early Intel TBB support for parallel ufuncs when building from source with TBBROOT defined. The TBB feature is not enabled in our official builds.

Fixes:

- PR #2232: Fix name clashes with _Py_hashtable_xxx in Python 3.6.

Improvements:

- PR #2217: Add Intel TBB threadpool implementation for parallel ufunc.

9.2.49 Version 0.30.0

This release adds preliminary support for Python 3.6, but no official build is available yet. A new system reporting tool (`numba --sysinfo`) is added to provide system information to help core developers in replication and debugging. See below for other improvements and bug fixes.

Improvements:

- PR #2209: Support Python 3.6.
- PR #2175: Support `np.trace()`, `np.outer()` and `np.kron()`.
- PR #2197: Support `np.nanprod()`.
- PR #2190: Support caching for ufunc.
- PR #2186: Add system reporting tool.

Fixes:

- PR #2214, Issue #2212: Fix memory error with ndenumerate and flat iterators.
- PR #2206, Issue #2163: Fix `zip()` consuming extra elements in early exhaustion.
- PR #2185, Issue #2159, #2169: Fix rewrite pass affecting objmode fallback.
- PR #2204, Issue #2178: Fix annotation for liftedloop.
- PR #2203: Fix Appveyor segfault with Python 3.5.
- PR #2202, Issue #2198: Fix target context not initialized when loading from ufunc cache.
- PR #2172, Issue #2171: Fix optional type unpacking.
- PR #2189, Issue #2188: Disable freezing of big (>1MB) global arrays.
- PR #2180, Issue #2179: Fix invalid variable version in looplifting.
- PR #2156, Issue #2155: Fix divmod, floordiv segfault on CUDA.

9.2.50 Version 0.29.0

This release extends the support of recursive functions to include direct and indirect recursion without explicit function type annotations. See new example in *examples/mergesort.py*. Newly supported numpy features include array stacking functions, np.linalg.eig* functions, np.linalg.matrix_power, np.roots and array to array broadcasting in assignments.

This release depends on llvmlite 0.14.0 and supports CUDA 8 but it is not required.

Improvements:

- PR #2130, #2137: Add type-inferred recursion with docs and examples.
- PR #2134: Add `np.linalg.matrix_power`.
- PR #2125: Add `np.roots`.
- PR #2129: Add `np.linalg.{eigvals,eigh,eigvalsh}`.
- PR #2126: Add array-to-array broadcasting.
- PR #2069: Add hstack and related functions.
- PR #2128: Allow for vectorizing a jitted function. (thanks to @dhirschfeld)
- PR #2117: Update examples and make them test-able.
- PR #2127: Refactor interpreter class and its results.

Fixes:

- PR #2149: Workaround MSVC9.0 SP1 fmod bug kb982107.
- PR #2145, Issue #2009: Fixes kwargs for jitclass `__init__` method.
- PR #2150: Fix slowdown in objmode fallback.
- PR #2050, Issue #1259: Fix liveness problem with some generator loops.
- PR #2072, Issue #1995: Right shift of unsigned LHS should be logical.
- PR #2115, Issue #1466: Fix inspect_types() error due to mangled variable name.
- PR #2119, Issue #2118: Fix array type created from record-dtype.
- PR #2122, Issue #1808: Fix returning a generator due to datamodel error.

9.2.51 Version 0.28.1

This is a bug-fix release to resolve packaging issues with setuptools dependency.

9.2.52 Version 0.28.0

Amongst other improvements, this version improves again the level of support for linear algebra – functions from the `numpy.linalg` module. Also, our random generator is now guaranteed to be thread-safe and fork-safe.

Improvements:

- PR #2019: Add the `@intrinsic` decorator to define low-level subroutines callable from JIT functions (this is considered a private API for now).
- PR #2059: Implement `np.concatenate` and `np.stack`.
- PR #2048: Make random generation fork-safe and thread-safe, producing independent streams of random numbers for each thread or process.

- PR #2031: Add documentation of floating-point pitfalls.
- Issue #2053: Avoid polling in parallel CPU target (fixes severe performance regression on Windows).
- Issue #2029: Make default arguments fast.
- PR #2052: Add logging to the CUDA driver.
- PR #2049: Implement the built-in `divmod()` function.
- PR #2036: Implement the `argsort()` method on arrays.
- PR #2046: Improving CUDA memory management by deferring deallocations until certain thresholds are reached, so as to avoid breaking asynchronous execution.
- PR #2040: Switch the CUDA driver implementation to use CUDA's "primary context" API.
- PR #2017: Allow `min(tuple)` and `max(tuple)`.
- PR #2039: Reduce fork() detection overhead in CUDA.
- PR #2021: Handle structured dtypes with titles.
- PR #1996: Rewrite looplifting as a transformation on Numba IR.
- PR #2014: Implement `np.linalg.matrix_rank`.
- PR #2012: Implement `np.linalg.cond`.
- PR #1985: Rewrite even trivial array expressions, which opens the door for other optimizations (for example, `array ** 2` can be converted into `array * array`).
- PR #1950: Have `typeof()` always raise ValueError on failure. Previously, it would either raise or return None, depending on the input.
- PR #1994: Implement `np.linalg.norm`.
- PR #1987: Implement `np.linalg.det` and `np.linalg.slogdet`.
- Issue #1979: Document integer width inference and how to workaround.
- PR #1938: Numba is now compatible with LLVM 3.8.
- PR #1967: Restrict `np.linalg` functions to homogeneous dtypes. Users wanting to pass mixed-typed inputs have to convert explicitly, which makes the performance implications more obvious.

Fixes:

- PR #2006: `array(float32) ** int` should return `array(float32)`.
- PR #2044: Allow reshaping empty arrays.
- Issue #2051: Fix refcounting issue when concatenating tuples.
- Issue #2000: Make Numpy optional for setup.py, to allow `pip install` to work without Numpy pre-installed.
- PR #1989: Fix assertion in `Dispatcher.disable_compile()`.
- Issue #2028: Ignore filesystem errors when caching from multiple processes.
- Issue #2003: Allow unicode variable and function names (on Python 3).
- Issue #1998: Fix deadlock in parallel ufuncs that reacquire the GIL.
- PR #1997: Fix random crashes when AOT compiling on certain Windows platforms.
- Issue #1988: Propagate jitclass docstring.
- Issue #1933: Ensure array constants are emitted with the right alignment.

9.2.53 Version 0.27.0

Improvements:

- Issue #1976: improve error message when non-integral dimensions are given to a CUDA kernel.
- PR #1970: Optimize the power operator with a static exponent.
- PR #1710: Improve contextual information for compiler errors.
- PR #1961: Support printing constant strings.
- PR #1959: Support more types in the print() function.
- PR #1823: Support `compute_50` in CUDA backend.
- PR #1955: Support `np.linalg.pinv`.
- PR #1896: Improve the `SmartArray` API.
- PR #1947: Support `np.linalg.solve`.
- Issue #1943: Improve error message when an argument fails typing.4
- PR #1927: Support `np.linalg.lstsq`.
- PR #1934: Use system functions for hypot() where possible, instead of our own implementation.
- PR #1929: Add cffi support to `@cfunc` objects.
- PR #1932: Add user-controllable thread pool limits for parallel CPU target.
- PR #1928: Support self-recursion when the signature is explicit.
- PR #1890: List all lowering implementations in the developer docs.
- Issue #1884: Support `np.lib.stride_tricks.as_strided()`.

Fixes:

- Issue #1960: Fix sliced assignment when source and destination areas are overlapping.
- PR #1963: Make CUDA print() atomic.
- PR #1956: Allow 0d array constants.
- Issue #1945: Allow using Numpy ufuncs in AOT compiled code.
- Issue #1916: Fix documentation example for `@generated_jit`.
- Issue #1926: Fix regression when caching functions in an IPython session.
- Issue #1923: Allow non-intp integer arguments to carray() and farray().
- Issue #1908: Accept non-ASCII unicode docstrings on Python 2.
- Issue #1874: Allow `del container[key]` in object mode.
- Issue #1913: Fix set insertion bug when the lookup chain contains deleted entries.
- Issue #1911: Allow function annotations on jitclass methods.

9.2.54 Version 0.26.0

This release adds support for `cfunc` decorator for exporting numba jitted functions to 3rd party API that takes C callbacks. Most of the overhead of using jitclasses inside the interpreter are eliminated. Support for decompositions in `numpy.linalg` are added. Finally, Numpy 1.11 is supported.

Improvements:

- PR #1889: Export BLAS and LAPACK wrappers for pycc.
- PR #1888: Faster array power.
- Issue #1867: Allow "out" keyword arg for dufuncs.
- PR #1871: `carray()` and `farray()` for creating arrays from pointers.
- PR #1855: `@cfunc` decorator for exporting as ctypes function.
- PR #1862: Add support for `numpy.linalg.qr`.
- PR #1851: jitclass support for '_' and '__' prefixed attributes.
- PR #1842: Optimize jitclass in Python interpreter.
- Issue #1837: Fix CUDA simulator issues with device function.
- PR #1839: Add support for decompositions from `numpy.linalg`.
- PR #1829: Support Python enums.
- PR #1828: Add support for `numpy.random.rand()` ` and `numpy.random.randn()`
- Issue #1825: Use of 0-darray in place of scalar index.
- Issue #1824: Scalar arguments to object mode gufuncs.
- Issue #1813: Let bitwise bool operators return booleans, not integers.
- Issue #1760: Optional arguments in generators.
- PR #1780: Numpy 1.11 support.

9.2.55 Version 0.25.0

This release adds support for `set` objects in nopython mode. It also adds support for many missing Numpy features and functions. It improves Numba's compatibility and performance when using a distributed execution framework such as dask, distributed or Spark. Finally, it removes compatibility with Python 2.6, Python 3.3 and Numpy 1.6.

Improvements:

- Issue #1800: Add erf(), erfc(), gamma() and lgamma() to CUDA targets.
- PR #1793: Implement more Numpy functions: np.bincount(), np.diff(), np.digitize(), np.histogram(), np.searchsorted() as well as NaN-aware reduction functions (np.nansum(), np.nanmedian(), etc.)
- PR #1789: Optimize some reduction functions such as np.sum(), np.prod(), np.median(), etc.
- PR #1752: Make CUDA features work in dask, distributed and Spark.
- PR #1787: Support np.nditer() for fast multi-array indexing with broadcasting.
- PR #1799: Report JIT-compiled functions as regular Python functions when profiling (allowing to see the filename and line number where a function is defined).
- PR #1782: Support np.any() and np.all().

- Issue #1788: Support the iter() and next() built-in functions.
- PR #1778: Support array.astype().
- Issue #1775: Allow the user to set the target CPU model for AOT compilation.
- PR #1758: Support creating random arrays using the `size` parameter to the np.random APIs.
- PR #1757: Support len() on array.flat objects.
- PR #1749: Remove Numpy 1.6 compatibility.
- PR #1748: Remove Python 2.6 and 3.3 compatibility.
- PR #1735: Support the `not in` operator as well as operator.contains().
- PR #1724: Support homogeneous sets in nopython mode.
- Issue #875: make compilation of array constants faster.

Fixes:

- PR #1795: Fix a massive performance issue when calling Numba functions with distributed, Spark or a similar mechanism using serialization.
- Issue #1784: Make jitclasses usable with NUMBA_DISABLE_JIT=1.
- Issue #1786: Allow using linear algebra functions when profiling.
- Issue #1796: Fix np.dot() memory leak on non-contiguous inputs.
- PR #1792: Fix static negative indexing of tuples.
- Issue #1771: Use fallback cache directory when __pycache__ isn't writable, such as when user code is installed in a system location.
- Issue #1223: Use Numpy error model in array expressions (e.g. division by zero returns `inf` or `nan` instead of raising an error).
- Issue #1640: Fix np.random.binomial() for large n values.
- Issue #1643: Improve error reporting when passing an invalid spec to `@jitclass`.
- PR #1756: Fix slicing with a negative step and an omitted start.

9.2.56 Version 0.24.0

This release introduces several major changes, including the `@generated_jit` decorator for flexible specializations as with Julia's "`@generated`" macro, or the SmartArray array wrapper type that allows seamless transfer of array data between the CPU and the GPU.

This will be the last version to support Python 2.6, Python 3.3 and Numpy 1.6.

Improvements:

- PR #1723: Improve compatibility of JIT functions with the Python profiler.
- PR #1509: Support array.ravel() and array.flatten().
- PR #1676: Add SmartArray type to support transparent data management in multiple address spaces (host & GPU).
- PR #1689: Reduce startup overhead of importing Numba.
- PR #1705: Support registration of CFFI types as corresponding to known Numba types.
- PR #1686: Document the extension API.

- PR #1698: Improve warnings raised during type inference.
- PR #1697: Support np.dot() and friends on non-contiguous arrays.
- PR #1692: cffi.from_buffer() improvements (allow more pointer types, allow non-Numpy buffer objects).
- PR #1648: Add the `@generated_jit` decorator.
- PR #1651: Implementation of np.linalg.inv using LAPACK. Thanks to Matthieu Dartiailh.
- PR #1674: Support np.diag().
- PR #1673: Improve error message when looking up an attribute on an unknown global.
- Issue #1569: Implement runtime check for the LLVM locale bug.
- PR #1612: Switch to LLVM 3.7 in sync with llvmlite.
- PR #1624: Allow slice assignment of sequence to array.
- PR #1622: Support slicing tuples with a constant slice.

Fixes:

- Issue #1722: Fix returning an optional boolean (bool or None).
- Issue #1734: NRT decref bug when variable is del'ed before being defined, leading to a possible memory leak.
- PR #1732: Fix tuple getitem regression for CUDA target.
- PR #1718: Mishandling of optional to optional casting.
- PR #1714: Fix .compile() on a JIT function not respecting ._can_compile.
- Issue #1667: Fix np.angle() on arrays.
- Issue #1690: Fix slicing with an omitted stop and a negative step value.
- PR #1693: Fix gufunc bug in handling scalar formal arg with non-scalar input value.
- PR #1683: Fix parallel testing under Windows.
- Issue #1616: Use system-provided versions of C99 math where possible.
- Issue #1652: Reductions of bool arrays (e.g. sum() or mean()) should return integers or floats, not bools.
- Issue #1664: Fix regression when indexing a record array with a constant index.
- PR #1661: Disable AVX on old Linux kernels.
- Issue #1636: Allow raising an exception looked up on a module.

9.2.57 Version 0.23.1

This is a bug-fix release to address several regressions introduced in the 0.23.0 release, and a couple other issues.

Fixes:

- Issue #1645: CUDA ufuncs were broken in 0.23.0.
- Issue #1638: Check tuple sizes when passing a list of tuples.
- Issue #1630: Parallel ufunc would keep eating CPU even after finishing under Windows.
- Issue #1628: Fix ctypes and cffi tests under Windows with Python 3.5.
- Issue #1627: Fix xrange() support.
- PR #1611: Rewrite variable liveness analysis.

- Issue #1610: Allow nested calls between explicitly-typed ufuncs.
- Issue #1593: Fix **args* in object mode.

9.2.58 Version 0.23.0

This release introduces JIT classes using the new `@jitclass` decorator, allowing user-defined structures for nopython mode. Other improvements and bug fixes are listed below.

Improvements:

- PR #1609: Speed up some simple math functions by inlining them in their caller
- PR #1571: Implement JIT classes
- PR #1584: Improve typing of array indexing
- PR #1583: Allow printing booleans
- PR #1542: Allow negative values in np.reshape()
- PR #1560: Support vector and matrix dot product, including `np.dot()` and the `@` operator in Python 3.5
- PR #1546: Support field lookup on record arrays and scalars (i.e. `array['field']` in addition to `array.field`)
- PR #1440: Support the HSA wavebarrier() and activelanepermute_wavewidth() intrinsics
- PR #1540: Support np.angle()
- PR #1543: Implement CPU multithreaded gufuncs (target=”parallel”)
- PR #1551: Allow scalar arguments in np.where(), np.empty_like().
- PR #1516: Add some more examples from NumbaPro
- PR #1517: Support np.sinc()

Fixes:

- Issue #1603: Fix calling a non-cached function from a cached function
- Issue #1594: Ensure a list is homogeneous when unboxing
- Issue #1595: Replace deprecated use of get_pointer_to_function()
- Issue #1586: Allow tests to be run by different users on the same machine
- Issue #1587: Make CudaAPIError picklable
- Issue #1568: Fix using Numba from inside Visual Studio 2015
- Issue #1559: Fix serializing a jit function referring a renamed module
- PR #1508: Let reshape() accept integer argument(s), not just a tuple
- Issue #1545: Improve error checking when unboxing list objects
- Issue #1538: Fix array broadcasting in CUDA gufuncs
- Issue #1526: Fix a reference count handling bug

9.2.59 Version 0.22.1

This is a bug-fix release to resolve some packaging issues and other problems found in the 0.22.0 release.

Fixes:

- PR #1515: Include MANIFEST.in in MANIFEST.in so that sdist still works from source tar files.
- PR #1518: Fix reference counting bug caused by hidden alias
- PR #1519: Fix erroneous assert when passing nopython=True to guvectorize.
- PR #1521: Fix cuda.test()

9.2.60 Version 0.22.0

This release features several highlights: Python 3.5 support, Numpy 1.10 support, Ahead-of-Time compilation of extension modules, additional vectorization features that were previously only available with the proprietary extension NumbaPro, improvements in array indexing.

Improvements:

- PR #1497: Allow scalar input type instead of size-1 array to @guvectorize
- PR #1480: Add distutils support for AOT compilation
- PR #1460: Create a new API for Ahead-of-Time (AOT) compilation
- PR #1451: Allow passing Python lists to JIT-compiled functions, and reflect mutations on function return
- PR #1387: Numpy 1.10 support
- PR #1464: Support cffi.FFI.from_buffer()
- PR #1437: Propagate errors raised from Numba-compiled ufuncs; also, let "division by zero" and other math errors produce a warning instead of exiting the function early
- PR #1445: Support a subset of fancy indexing
- PR #1454: Support "out-of-line" CFFI modules
- PR #1442: Improve array indexing to support more kinds of basic slicing
- PR #1409: Support explicit CUDA memory fences
- PR #1435: Add support for vectorize() and guvectorize() with HSA
- PR #1432: Implement numpy.nonzero() and numpy.where()
- PR #1416: Add support for vectorize() and guvectorize() with CUDA, as originally provided in NumbaPro
- PR #1424: Support in-place array operators
- PR #1414: Python 3.5 support
- PR #1404: Add the parallel ufunc functionality originally provided in NumbaPro
- PR #1393: Implement sorting on arrays and lists
- PR #1415: Add functions to estimate the occupancy of a CUDA kernel
- PR #1360: The JIT cache now stores the compiled object code, yielding even larger speedups.
- PR #1402: Fixes for the ARMv7 (armv7l) architecture under Linux
- PR #1400: Add the cuda.reduce() decorator originally provided in NumbaPro

Fixes:

- PR #1483: Allow np.empty_like() and friends on non-contiguous arrays
- Issue #1471: Allow caching JIT functions defined in IPython
- PR #1457: Fix flat indexing of boolean arrays
- PR #1421: Allow calling Numpy ufuncs, without an explicit output, on non-contiguous arrays
- Issue #1411: Fix crash when unpacking a tuple containing a Numba-allocated array
- Issue #1394: Allow unifying range_state32 and range_state64
- Issue #1373: Fix code generation error on lists of bools

9.2.61 Version 0.21.0

This release introduces support for AMD's Heterogeneous System Architecture, which allows memory to be shared directly between the CPU and the GPU. Other major enhancements are support for lists and the introduction of an opt-in compilation cache.

Improvements:

- PR #1391: Implement print() for CUDA code
- PR #1366: Implement integer typing enhancement proposal (NBEP 1)
- PR #1380: Support the one-argument type() builtin
- PR #1375: Allow boolean evaluation of lists and tuples
- PR #1371: Support array.view() in CUDA mode
- PR #1369: Support named tuples in nopython mode
- PR #1250: Implement numpy.median().
- PR #1289: Make dispatching faster when calling a JIT-compiled function from regular Python
- Issue #1226: Improve performance of integer power
- PR #1321: Document features supported with CUDA
- PR #1345: HSA support
- PR #1343: Support lists in nopython mode
- PR #1356: Make Numba-allocated memory visible to tracemalloc
- PR #1363: Add an environment variable NUMBA_DEBUG_TYPEINFER
- PR #1051: Add an opt-in, per-function compilation cache

Fixes:

- Issue #1372: Some array expressions would fail rewriting when involved the same variable more than once, or a unary operator
- Issue #1385: Allow CUDA local arrays to be declared anywhere in a function
- Issue #1285: Support datetime64 and timedelta64 in Numpy reduction functions
- Issue #1332: Handle the EXTENDED_ARG opcode.
- PR #1329: Handle the `in` operator in object mode
- Issue #1322: Fix augmented slice assignment on Python 2

- PR #1357: Fix slicing with some negative bounds or step values.

9.2.62 Version 0.20.0

This release updates Numba to use LLVM 3.6 and CUDA 7 for CUDA support. Following the platform deprecation in CUDA 7, Numba's CUDA feature is no longer supported on 32-bit platforms. The oldest supported version of Windows is Windows 7.

Improvements:

- Issue #1203: Support indexing ndarray.flat
- PR #1200: Migrate cgutils to llvmlite
- PR #1190: Support more array methods: .transpose(), .T, .copy(), .reshape(), .view()
- PR #1214: Simplify setup.py and avoid manual maintenance
- PR #1217: Support datetime64 and timedelta64 constants
- PR #1236: Reload environment variables when compiling
- PR #1225: Various speed improvements in generated code
- PR #1252: Support cmath module in CUDA
- PR #1238: Use 32-byte aligned allocator to optimize for AVX
- PR #1258: Support numpy.frombuffer()
- PR #1274: Use TravisCI container infrastructure for lower wait time
- PR #1279: Micro-optimize overload resolution in call dispatch
- Issue #1248: Improve error message when return type unification fails

Fixes:

- Issue #1131: Handling of negative zeros in np.conjugate() and np.arccos()
- Issue #1188: Fix slow array return
- Issue #1164: Avoid warnings from CUDA context at shutdown
- Issue #1229: Respect the writeable flag in arrays
- Issue #1244: Fix bug in refcount pruning pass
- Issue #1251: Fix partial left-indexing of Fortran contiguous array
- Issue #1264: Fix compilation error in array expression
- Issue #1254: Fix error when yielding array objects
- Issue #1276: Fix nested generator use

9.2.63 Version 0.19.2

This release fixes the source distribution on pypi. The only change is in the setup.py file. We do not plan to provide a conda package as this release is essentially the same as 0.19.1 for conda users.

9.2.64 Version 0.19.1

- Issue #1196:
  - fix double-free segfault due to redundant variable deletion in the Numba IR (#1195)
  - fix use-after-delete in array expression rewrite pass

9.2.65 Version 0.19.0

This version introduces memory management in the Numba runtime, allowing to allocate new arrays inside Numba-compiled functions. There is also a rework of the ufunc infrastructure, and an optimization pass to collapse cascading array operations into a single efficient loop.

Warning: Support for Windows XP and Vista with all compiler targets and support for 32-bit platforms (Win/Mac/Linux) with the CUDA compiler target are deprecated. In the next release of Numba, the oldest version of Windows supported will be Windows 7. CPU compilation will remain supported on 32-bit Linux and Windows platforms.

Known issues:

- There are some performance regressions in very short running `nopython` functions due to the additional overhead incurred by memory management. We will work to reduce this overhead in future releases.

Features:

- Issue #1181: Add a Frequently Asked Questions section to the documentation.
- Issue #1162: Support the `cumsum()` and `cumprod()` methods on Numpy arrays.
- Issue #1152: Support the `*args` argument-passing style.
- Issue #1147: Allow passing character sequences as arguments to JIT-compiled functions.
- Issue #1110: Shortcut deforestation and loop fusion for array expressions.
- Issue #1136: Support various Numpy array constructors, for example numpy.zeros() and numpy.zeros_like().
- Issue #1127: Add a CUDA simulator running on the CPU, enabled with the NUMBA_ENABLE_CUDASIM environment variable.
- Issue #1086: Allow calling standard Numpy ufuncs without an explicit output array from `nopython` functions.
- Issue #1113: Support keyword arguments when calling numpy.empty() and related functions.
- Issue #1108: Support the `ctypes.data` attribute of Numpy arrays.
- Issue #1077: Memory management for array allocations in `nopython` mode.
- Issue #1105: Support calling a ctypes function that takes ctypes.py_object parameters.
- Issue #1084: Environment variable NUMBA_DISABLE_JIT disables compilation of `@jit` functions, instead calling into the Python interpreter when called. This allows easier debugging of multiple jitted functions.
- Issue #927: Allow gufuncs with no output array.

- Issue #1097: Support comparisons between tuples.
- Issue #1075: Numba-generated ufuncs can now be called from `nopython` functions.
- Issue #1062: `@vectorize` now allows omitting the signatures, and will compile the required specializations on the fly (like `@jit` does).
- Issue #1027: Support numpy.round().
- Issue #1085: Allow returning a character sequence (as fetched from a structured array) from a JIT-compiled function.

Fixes:

- Issue #1170: Ensure `ndindex()`, `ndenumerate()` and `ndarray.flat` work properly inside generators.
- Issue #1151: Disallow unpacking of tuples with the wrong size.
- Issue #1141: Specify install dependencies in setup.py.
- Issue #1106: Loop-lifting would fail when the lifted loop does not produce any output values for the function tail.
- Issue #1103: Fix mishandling of some inputs when a JIT-compiled function is called with multiple array layouts.
- Issue #1089: Fix range() with large unsigned integers.
- Issue #1088: Install entry-point scripts (numba, pycc) from the conda build recipe.
- Issue #1081: Constant structured scalars now work properly.
- Issue #1080: Fix automatic promotion of booleans to integers.

9.2.66 Version 0.18.2

Bug fixes:

- Issue #1073: Fixes missing template file for HTML annotation
- Issue #1074: Fixes CUDA support on Windows machine due to NVVM API mismatch

9.2.67 Version 0.18.1

Version 0.18.0 is not officially released.

This version removes the old deprecated and undocumented `argtypes` and `restype` arguments to the `@jit` decorator. Function signatures should always be passed as the first argument to `@jit`.

Features:

- Issue #960: Add inspect_llvm() and inspect_asm() methods to JIT-compiled functions: they output the LLVM IR and the native assembler source of the compiled function, respectively.
- Issue #990: Allow passing tuples as arguments to JIT-compiled functions in `nopython` mode.
- Issue #774: Support two-argument round() in `nopython` mode.
- Issue #987: Support missing functions from the math module in nopython mode: frexp(), ldexp(), gamma(), lgamma(), erf(), erfc().
- Issue #995: Improve code generation for round() on Python 3.
- Issue #981: Support functions from the random and numpy.random modules in `nopython` mode.
- Issue #979: Add cuda.atomic.max().

- Issue #1006: Improve exception raising and reporting. It is now allowed to raise an exception with an error message in `nopython` mode.
- Issue #821: Allow ctypes- and cffi-defined functions as arguments to `nopython` functions.
- Issue #901: Allow multiple explicit signatures with `@jit`. The signatures must be passed in a list, as with `@vectorize`.
- Issue #884: Better error message when a JIT-compiled function is called with the wrong types.
- Issue #1010: Simpler and faster CUDA argument marshalling thanks to a refactoring of the data model.
- Issue #1018: Support arrays of scalars inside Numpy structured types.
- Issue #808: Reduce Numba import time by half.
- Issue #1021: Support the buffer protocol in `nopython` mode. Buffer-providing objects, such as `bytearray`, `array.array` or `memoryview` support array-like operations such as indexing and iterating. Furthermore, some standard attributes on the `memoryview` object are supported.
- Issue #1030: Support nested arrays in Numpy structured arrays.
- Issue #1033: Implement the inspect_types(), inspect_llvm() and inspect_asm() methods for CUDA kernels.
- Issue #1029: Support Numpy structured arrays with CUDA as well.
- Issue #1034: Support for generators in nopython and object mode.
- Issue #1044: Support default argument values when calling Numba-compiled functions.
- Issue #1048: Allow calling Numpy scalar constructors from CUDA functions.
- Issue #1047: Allow indexing a multi-dimensional array with a single integer, to take a view.
- Issue #1050: Support len() on tuples.
- Issue #1011: Revive HTML annotation.

Fixes:

- Issue #977: Assignment optimization was too aggressive.
- Issue #561: One-argument round() now returns an int on Python 3.
- Issue #1001: Fix an unlikely bug where two closures with the same name and id() would compile to the same LLVM function name, despite different closure values.
- Issue #1006: Fix reference leak when a JIT-compiled function is disposed of.
- Issue #1017: Update instructions for CUDA in the README.
- Issue #1008: Generate shorter LLVM type names to avoid segfaults with CUDA.
- Issue #1005: Properly clean up references when raising an exception from object mode.
- Issue #1041: Fix incompatibility between Numba and the third-party library "future".
- Issue #1053: Fix the size attribute of CUDA shared arrays.

9.2.68 Version 0.17.0

The major focus in this release has been a rewrite of the documentation. The new documentation is better structured and has more detailed coverage of Numba features and APIs. It can be found online at https://numba.pydata.org/numba-doc/dev/index.html

Features:

- Issue #895: LLVM can now inline nested function calls in `nopython` mode.
- Issue #863: CUDA kernels can now infer the types of their arguments ("autojit"-like).
- Issue #833: Support numpy.{min,max,argmin,argmax,sum,mean,var,std} in `nopython` mode.
- Issue #905: Add a `nogil` argument to the `@jit` decorator, to release the GIL in `nopython` mode.
- Issue #829: Add a `identity` argument to `@vectorize` and `@guvectorize`, to set the identity value of the ufunc.
- Issue #843: Allow indexing 0-d arrays with the empty tuple.
- Issue #933: Allow named arguments, not only positional arguments, when calling a Numba-compiled function.
- Issue #902: Support numpy.ndenumerate() in `nopython` mode.
- Issue #950: AVX is now enabled by default except on Sandy Bridge and Ivy Bridge CPUs, where it can produce slower code than SSE.
- Issue #956: Support constant arrays of structured type.
- Issue #959: Indexing arrays with floating-point numbers isn't allowed anymore.
- Issue #955: Add support for 3D CUDA grids and thread blocks.
- Issue #902: Support numpy.ndindex() in `nopython` mode.
- Issue #951: Numpy number types (`numpy.int8`, etc.) can be used as constructors for type conversion in `nopython` mode.

Fixes:

- Issue #889: Fix `NUMBA_DUMP_ASSEMBLY` for the CUDA backend.
- Issue #903: Fix calling of stdcall functions with ctypes under Windows.
- Issue #908: Allow lazy-compiling from several threads at once.
- Issue #868: Wrong error message when multiplying a scalar by a non-scalar.
- Issue #917: Allow vectorizing with datetime64 and timedelta64 in the signature (only with unit-less values, though, because of a Numpy limitation).
- Issue #431: Allow overloading of cuda device function.
- Issue #917: Print out errors occurred in object mode ufuncs.
- Issue #923: Numba-compiled ufuncs now inherit the name and doc of the original Python function.
- Issue #928: Fix boolean return value in nested calls.
- Issue #915: `@jit` called with an explicit signature with a mismatching type of arguments now raises an error.
- Issue #784: Fix the truth value of NaNs.
- Issue #953: Fix using shared memory in more than one function (kernel or device).
- Issue #970: Fix an uncommon double to uint64 conversion bug on CentOS5 32-bit (C compiler issue).

9.2.69 Version 0.16.0

This release contains a major refactor to switch from llvmpy to llvmlite as our code generation backend. The switch is necessary to reconcile different compiler requirements for LLVM 3.5 (needs C++11) and Python extensions (need specific compiler versions on Windows). As a bonus, we have found the use of llvmlite speeds up compilation by a factor of 2!

Other Major Changes:

- Faster dispatch for numpy structured arrays
- Optimized array.flat()
- Improved CPU feature selection
- Fix constant tuple regression in macro expansion code

Known Issues:

- AVX code generation is still disabled by default due to performance regressions when operating on misaligned NumPy arrays. We hope to have a workaround in the future.
- In *extremely* rare circumstances, a known issue with LLVM 3.5 code generation can cause an ELF relocation error on 64-bit Linux systems.

9.2.70 Version 0.15.1

(This was a bug-fix release that superceded version 0.15 before it was announced.)

Fixes:

- Workaround for missing __ftol2 on Windows XP.
- Do not lift loops for compilation that contain break statements.
- Fix a bug in loop-lifting when multiple values need to be returned to the enclosing scope.
- Handle the loop-lifting case where an accumulator needs to be updated when the loop count is zero.

9.2.71 Version 0.15

Features:

- Support for the Python `cmath` module. (NumPy complex functions were already supported.)
- Support for `.real`, `.imag`, and *.conjugate()* ` on non-complex numbers.
- Add support for `math.isfinite()` and `math.copysign()`.
- Compatibility mode: If enabled (off by default), a failure to compile in object mode will fall back to using the pure Python implementation of the function.
- *Experimental* support for serializing JIT functions with cloudpickle.
- Loop-jitting in object mode now works with loops that modify scalars that are accessed after the loop, such as accumulators.
- `@vectorize` functions can be compiled in object mode.
- Numba can now be built using the Visual C++ Compiler for Python 2.7 on Windows platforms.
- CUDA JIT functions can be returned by factory functions with variables in the closure frozen as constants.
- Support for "optional" types in nopython mode, which allow `None` to be a valid value.

Fixes:

- If nopython mode compilation fails for any reason, automatically fall back to object mode (unless nopython=True is passed to @jit) rather than raise an exeception.
- Allow function objects to be returned from a function compiled in object mode.
- Fix a linking problem that caused slower platform math functions (such as `exp()`) to be used on Windows, leading to performance regressions against NumPy.
- `min()` and `max()` no longer accept scalars arguments in nopython mode.
- Fix handling of ambigous type promotion among several compiled versions of a JIT function. The dispatcher will now compile a new version to resolve the problem. (issue #776)
- Fix float32 to uint64 casting bug on 32-bit Linux.
- Fix type inference to allow forced casting of return types.
- Allow the shape of a 1D `cuda.shared.array` and `cuda.local.array` to be a one-element tuple.
- More correct handling of signed zeros.
- Add custom implementation of `atan2()` on Windows to handle special cases properly.
- Eliminated race condition in the handling of the pagelocked staging area used when transferring CUDA arrays.
- Fix non-deterministic type unification leading to varying performance. (issue #797)

9.2.72 Version 0.14

Features:

- Support for nearly all the Numpy math functions (including comparison, logical, bitwise and some previously missing float functions) in nopython mode.
- The Numpy datetime64 and timedelta64 dtypes are supported in nopython mode with Numpy 1.7 and later.
- Support for Numpy math functions on complex numbers in nopython mode.
- ndarray.sum() is supported in nopython mode.
- Better error messages when unsupported types are used in Numpy math functions.
- Set NUMBA_WARNINGS=1 in the environment to see which functions are compiled in object mode vs. nopython mode.
- Add support for the two-argument pow() builtin function in nopython mode.
- New developer documentation describing how Numba works, and how to add new types.
- Support for Numpy record arrays on the GPU. (Note: Improper alignment of dtype fields will cause an exception to be raised.)
- Slices on GPU device arrays.
- GPU objects can be used as Python context managers to select the active device in a block.
- GPU device arrays can be bound to a CUDA stream. All subsequent operations (such as memory copies) will be queued on that stream instead of the default. This can prevent unnecessary synchronization with other streams.

Fixes:

- Generation of AVX instructions has been disabled to avoid performance bugs when calling external math functions that may use SSE instructions, especially on OS X.
- JIT functions can be removed by the garbage collector when they are no longer accessible.

- Various other reference counting fixes to prevent memory leaks.
- Fixed handling of exception when input argument is out of range.
- Prevent autojit functions from making unsafe numeric conversions when called with different numeric types.
- Fix a compilation error when an unhashable global value is accessed.
- Gracefully handle failure to enable faulthandler in the IPython Notebook.
- Fix a bug that caused loop lifting to fail if the loop was inside an `else` block.
- Fixed a problem with selecting CUDA devices in multithreaded programs on Linux.
- The `pow()` function (and `**` operation) applied to two integers now returns an integer rather than a float.
- Numpy arrays using the object dtype no longer cause an exception in the autojit.
- Attempts to write to a global array will cause compilation to fall back to object mode, rather than attempt and fail at nopython mode.
- `range()` works with all negative arguments (ex: `range(-10, -12, -1)`)

9.2.73 Version 0.13.4

Features:

- Setting and deleting attributes in object mode
- Added documentation of supported and currently unsupported numpy ufuncs
- Assignment to 1-D numpy array slices
- Closure variables and functions can be used in object mode
- All numeric global values in modules can be used as constants in JIT compiled code
- Support for the start argument in enumerate()
- Inplace arithmetic operations (+=, -=, etc.)
- Direct iteration over a 1D numpy array (e.g. "for x in array: ...") in nopython mode

Fixes:

- Support for NVIDIA compute capability 5.0 devices (such as the GTX 750)
- Vectorize no longer crashes/gives an error when bool_ is used as return type
- Return the correct dictionary when globals() is used in JIT functions
- Fix crash bug when creating dictionary literals in object
- Report more informative error message on import if llvmpy is too old
- Temporarily disable pycc –header, which generates incorrect function signatures.

9.2.74 Version 0.13.3

Features:

- Support for enumerate() and zip() in nopython mode
- Increased LLVM optimization of JIT functions to -O1, enabling automatic vectorization of compiled code in some cases
- Iteration over tuples and unpacking of tuples in nopython mode
- Support for dict and set (Python >= 2.7) literals in object mode

Fixes:

- JIT functions have the same __name__ and __doc__ as the original function.
- Numerous improvements to better match the data types and behavior of Python math functions in JIT compiled code on different platforms.
- Importing Numba will no longer throw an exception if the CUDA driver is present, but cannot be initialized.
- guvectorize now properly supports functions with scalar arguments.
- CUDA driver is lazily initialized

9.2.75 Version 0.13.2

Features:

- @vectorize ufunc now can generate SIMD fast path for unit strided array
- Added cuda.gridsize
- Added preliminary exception handling (raise exception class)

Fixes:

- UNARY_POSITIVE
- Handling of closures and dynamically generated functions
- Global None value

9.2.76 Version 0.13.1

Features:

- Initial support for CUDA array slicing

Fixes:

- Indirectly fixes numbapro when the system has a incompatible CUDA driver
- Fix numba.cuda.detect
- Export numba.intp and numba.intc

9.2.77 Version 0.13

Features:

- Opensourcing NumbaPro CUDA python support in *numba.cuda*
- Add support for ufunc array broadcasting
- Add support for mixed input types for ufuncs
- Add support for returning tuple from jitted function

Fixes:

- Fix store slice bytecode handling for Python2
- Fix inplace subtract
- Fix pycc so that correct header is emitted
- Allow vectorize to work on functions with jit decorator

9.2.78 Version 0.12.2

Fixes:

- Improved NumPy ufunc support in nopython mode
- Misc bug fixes

9.2.79 Version 0.12.1

This version fixed many regressions reported by user for the 0.12 release. This release contains a new loop-lifting mechanism that specializes certains loop patterns for nopython mode compilation. This avoid direct support for heap-allocating and other very dynamic operations.

Improvements:

- Add loop-lifting–jit-ing loops in nopython for object mode code. This allows functions to allocate NumPy arrays and use Python objects, while the tight loops in the function can still be compiled in nopython mode. Any arrays that the tight loop uses should be created before the loop is entered.

Fixes:

- Add support for majority of "math" module functions
- Fix for…else handling
- Add support for builtin round()
- Fix tenary if…else support
- Revive "numba" script
- Fix problems with some boolean expressions
- Add support for more NumPy ufuncs

9.2.80 Version 0.12

Version 0.12 contains a big refactor of the compiler. The main objective for this refactor was to simplify the code base to create a better foundation for further work. A secondary objective was to improve the worst case performance to ensure that compiled functions in object mode never run slower than pure Python code (this was a problem in several cases with the old code base). This refactor is still a work in progress and further testing is needed.

Main improvements:

- Major refactor of compiler for performance and maintenance reasons
- Better fallback to object mode when native mode fails
- Improved worst case performance in object mode

The public interface of numba has been slightly changed. The idea is to make it cleaner and more rational:

- jit decorator has been modified, so that it can be called without a signature. When called without a signature, it behaves as the old autojit. Autojit has been deprecated in favour of this approach.
- Jitted functions can now be overloaded.
- Added a "njit" decorator that behaves like "jit" decorator with nopython=True.
- The numba.vectorize namespace is gone. The vectorize decorator will be in the main numba namespace.
- Added a guvectorize decorator in the main numba namespace. It is similar to numba.vectorize, but takes a dimension signature. It generates gufuncs. This is a replacement for the GUVectorize gufunc factory which has been deprecated.

Main regressions (will be fixed in a future release):

- Creating new NumPy arrays is not supported in nopython mode
- Returning NumPy arrays is not supported in nopython mode
- NumPy array slicing is not supported in nopython mode
- lists and tuples are not supported in nopython mode
- string, datetime, cdecimal, and struct types are not implemented yet
- Extension types (classes) are not supported in nopython mode
- Closures are not supported
- Raise keyword is not supported
- Recursion is not support in nopython mode

9.2.81 Version 0.11

- Experimental support for NumPy datetime type

9.2.82 Version 0.10

- Annotation tool (./bin/numba –annotate –fancy) (thanks to Jay Bourque)
- Open sourced prange
- Support for raise statement
- Pluggable array representation
- Support for enumerate and zip (thanks to Eugene Toder)
- Better string formatting support (thanks to Eugene Toder)
- Builtins min(), max() and bool() (thanks to Eugene Toder)
- Fix some code reloading issues (thanks to Björn Linse)
- Recognize NumPy scalar objects (thanks to Björn Linse)

9.2.83 Version 0.9

- Improved math support
- Open sourced generalized ufuncs
- Improved array expressions

9.2.84 Version 0.8

- **Support for autojit classes**
  - Inheritance not yet supported
- Python 3 support for pycc
- **Allow retrieval of ctypes function wrapper**
  - And hence support retrieval of a pointer to the function
- Fixed a memory leak of array slicing views

9.2.85 Version 0.7.2

- Official Python 3 support (python 3.2 and 3.3)
- Support for intrinsics and instructions
- Various bug fixes (see https://github.com/numba/numba/issues?milestone=7&state=closed)

9.2.86 Version 0.7.1

- Various bug fixes

9.2.87 Version 0.7

- Open sourced single-threaded ufunc vectorizer
- Open sourced NumPy array expression compilation
- Open sourced fast NumPy array slicing
- Experimental Python 3 support
- **Support for typed containers**
  - typed lists and tuples
- Support for iteration over objects
- Support object comparisons
- **Preliminary CFFI support**
  - Jit calls to CFFI functions (passed into autojit functions)
  - TODO: Recognize ffi_lib.my_func attributes
- Improved support for ctypes
- Allow declaring extension attribute types as through class attributes
- **Support for type casting in Python**
  - Get the same semantics with or without numba compilation
- **Support for recursion**
  - For jit methods and extension classes
- Allow jit functions as C callbacks
- Friendlier error reporting
- Internal improvements
- A variety of bug fixes

9.2.88 Version 0.6.1

- Support for bitwise operations

9.2.89 Version 0.6

- Python 2.6 support
- **Programmable typing**
  - Allow users to add type inference for external code
- **Better NumPy type inference**
  - outer, inner, dot, vdot, tensordot, nonzero, where, binary ufuncs + methods (reduce, accumulate, reduceat, outer)
- **Type based alias analysis**
  - Support for strict aliasing
- Much faster autojit dispatch when calling from Python
- Faster numerical loops through data and stride pre-loading
- Integral overflow and underflow checking for conversions from objects
- Make Meta dependency optional

9.2.90 Version 0.5

- **SSA-based type inference**
  - Allows variable reuse
  - Allow referring to variables before lexical definition
- Support multiple comparisons
- Support for template types
- List comprehensions
- Support for pointers
- Many bug fixes
- Added user documentation

9.2.91 Version 0.4

9.2.92 Version 0.3.2

- Add support for object arithmetic (issue 56).
- Bug fixes (issue 55).

9.2.93 Version 0.3

- Changed default compilation approach to ast
- Added support for cross-module linking
- Added support for closures (can jit inner functions and return them) (see examples/closure.py)
- Added support for dtype structures (can access elements of structure with attribute access) (see examples/structures.py)
- Added support for extension types (numba classes) (see examples/numbaclasses.py)
- Added support for general Python code (use nopython to raise an error if Python C-API is used to avoid unexpected slowness because of lack of implementation defaulting to generic Python)
- Fixed many bugs
- Added support to detect math operations.
- Added with python and with nopython contexts
- Added more examples

Many features need to be documented still. Look at examples and tests for more information.

9.2.94 Version 0.2

- Added an ast approach to compilation
- Removed d, f, i, b from numba namespace (use f8, f4, i4, b1)
- Changed function to autojit2
- Added autojit function to decorate calls to the function and use types of the variable to create compiled versions.
- changed keyword arguments to jit and autojit functions to restype and argtypes to be consistent with ctypes module.
- Added pycc – a python to shared library compiler

PYTHON MODULE INDEX

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