

# A Whirlwind Tour of Numba

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Python Users Berlin - Thursday 19 Feb 2026

Version: 2026-02-19-python-users-berlin    <https://github.com/esc/numba-talk>  
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# whoami

- Senior Software Engineer at Anaconda
- Working on Numba full-time
- Doing this for almost 7 years
- Actively involved in:
  - Typed containers
  - Release and community management
  - Structured Control Flow Graphs

# Outline

1 Introduction

2 Going Deeper

3 NumPy Support

4 Tips and Tricks

5 Compiler Toolkit

6 Summary



# Numba in a Nutshell

- A compiler that might make your code faster
- Requires importing a decorator: `@jit`
- And decorating functions with it
- Numba = NumPy + Mamba (fast snake)

# Numba Explained

- Numba is a
  - just-in-time
  - type-specializing
  - function compiler
  - for accelerating numerically-focused Python

# LLVM

- LLVM is a compiler toolkit
- Numba uses it as a compiler backend
- Access via `llvmlite`

# Example

- Sieve of Erastothenes

	2	3	4	5	6	7	8	9	10	Prime numbers
11	12	13	14	15	16	17	18	19	20	2 3 5 7
21	22	23	24	25	26	27	28	29	30	11 13 17 19
31	32	33	34	35	36	37	38	39	40	23 29 31 37
41	42	43	44	45	46	47	48	49	50	41 43 47 53
51	52	53	54	55	56	57	58	59	60	59 61 67 71
61	62	63	64	65	66	67	68	69	70	73 79 83 89
71	72	73	74	75	76	77	78	79	80	97 101 103 107
81	82	83	84	85	86	87	88	89	90	109 113
91	92	93	94	95	96	97	98	99	100	
101	102	103	104	105	106	107	108	109	110	
111	112	113	114	115	116	117	118	119	120	

# Example

```
import numpy as np
from numba import jit

@jit # simply add the jit decorator
def primes(max=100000):
    numbers = np.ones(max, dtype=np.uint8) # initialize the boolean sieve
    for i in range(2, max):
        if numbers[i] == 0: # has previously been crossed off
            continue
        else: # it is a prime, cross off all multiples
            x = i + i
            while x < max:
                numbers[x] = 0
                x += i
    # return all primes, as indicated by boolean positions that have value 1
    return np.nonzero(numbers)[0][2:]
```

## Example

```
In [2]: %timeit sieve.primes.py_func()
11.8 ms ± 109 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

```
In [3]: %timeit sieve.primes()
177 µs ± 11.2 µs per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

# Open Source Status

- Several companies and many open source contributors
  - several FTE funded to contribute to Numba
  - several non-core contributors per release
- Issue and PR lists growing
- Very active community on GitHub, Discourse

# Community Usage

- Download rate via PyPi is ~21 Hz (audible by goldfish)
- GitHub: 163126 Repositories and 6513 Packages
- Several high-profile libraries use it:
  - PyData Sparse → sparse matrix implementation
  - UMAP → Uniform Manifold Approximation
  - librosa → Music analysis
  - Tardis-SN → Super Nova Simulator for Type 1a (White Dwarf Nova)
  - Pandas → Dataframe Library
  - NumbaDuck → Fully jitted DuckDB interface
  - numba-cuda, pyOMP, numba-hip → GPU Programming
  - Caterva-2 → Compressed Compute Engine based on Blosc
  - many, many more, we eventually stopped keeping track

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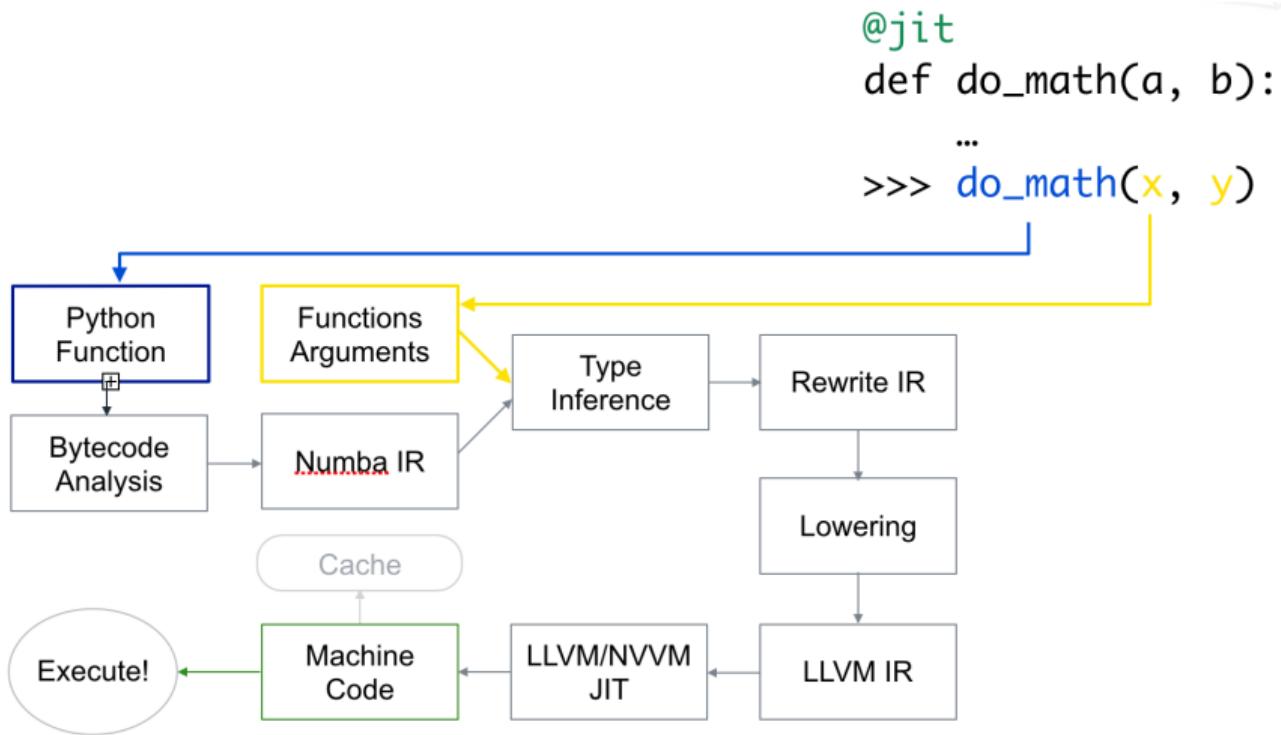
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# Numba Flow



# Internals

- Translate Python objects of supported types into representations with no CPython dependencies ("unboxing")
- Compile Python bytecode from your decorated function into machine code.
- Swap calls to builtins and NumPy functions for implementations provided by Numba (or 3rd party Numba extensions)
- Allow LLVM to inline functions, autovectorize loops, and do other optimizations you would expect from a C compiler
- Allow LLVM to exploit the instruction sets of your hardware (SSE, AVX)
- When calling the function, release the GIL if requested
- Convert return values back to Python objects ("boxing")

## What Numba does not do

- Automated translation of CPython or NumPy implementations
- Automatic compilation of 3rd party libraries
- Partial compilation
- Automatic conversion of arbitrary Python types
- Change the layout of data allocated in the interpreter
- Translate entire programs
- Magically make individual NumPy functions faster

## When is Numba unlikely to help?

- Whole program compilation
- Critical functions have already been converted to C or optimized Cython
- Need to interface directly with C++
- Algorithms that are not primarily numerical, e.g. string manipulation
- Exception: Numba can do pretty well at bit manipulation

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# Implementing NumPy

- Numba does not use much of the NumPy C implementations
- (Only some ufuncs are "borrowed".)
- We implement the NumPy API using Numba compatible/supported Python
- Treat NumPy as DSL for array oriented computing

# Implementing Numpy

- Implement: `numpy.linalg.norm`
- For vectors, `ord` is:
  - `inf` → `min(abs(x))`
  - `0` → `sum(x != 0)`
- Implemented in: `numba.targets.linalg.py`

# Implementing Numpy

```
elif ord == -np.inf:  
    # min(abs(a))  
    ret = abs(a[0])  
    for k in range(1, n):  
        val = abs(a[k])  
        if val < ret:  
            ret = val  
    return ret  
  
elif ord == 0:  
    # sum(a != 0)  
    ret = 0.0  
    for k in range(n):  
        if a[k] != 0.:  
            ret += 1.  
    return ret
```

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# Tips and Tricks

- Always use `@jit`
- Prefer NumPy arrays for numerical data
- Use typed containers from `numba.typed` for nested data
- `for` loops are fine
- Array expressions are fused if on the same line, so those are fine too

# Typed Containers

```
from numba import njit
from numba.typed import List

l = List() # instantiate a new typed list
l1 = List(); [l1.append(i) for i in range(5)]
l.append(l1) # add the first sub-list
l2 = List(); [l2.append(i) for i in range(10)]
l.append(l2) # add the second sub-list
print(l)

@njit
def func(my_list):
    # modify list in a compiled context
    for i in range(10):
        my_list[1][i] = 23

func(l)
print(l)
```

# Typed Containers

```
$ python code/typed.py
[[0, 1, 2, 3, 4], [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]]
[[0, 1, 2, 3, 4], [23, 23, 23, 23, 23, 23, 23, 23, 23]]
```

# Fused Expressions

```
import numpy as np
from numba import njit

a, b = np.arange(1e6), np.arange(1e6)

@njit
def func(a, b):
    return a*b-4.1*a > 2.5*b
```

# Fused Expressions

```
In [1]: from fused import a,b,func
```

```
In [2]: %timeit func.py_func(a,b)
```

```
4.68 ms ± 89.7 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

```
In [3]: %timeit func(a,b)
```

```
626 µs ± 22.4 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)
```

# OS and Hardware Support

- osx-arm64
- linux-64
- linux-aarch64
- win-64

# Python versions

- Python 3.10 - 3.14 as of Numba 0.64 and llvmlite 0.46

# Packaging

- You can depend on Numba to perform the heavy lifting!
- We run CI on most Python/NumPy/OS/Hardware combinations
- You can ship a single source package
  - PyPi
  - anaconda.org
- No need to pre-compile binaries for your users
- Reduced code needed for distribution

# Testing

- Ported CI from custom server farm to GHA last year
- Testing matrix is a cross-product: Python x NumPy x Platform
- GHA runs for 12 hours on a single commit during release process

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## inspect methods

- There are various `inspect` methods on compiled functions
  - `inspect_types` → Prints out results from type-inference
  - `inspect_llvm` → Obtain LLVM IR
  - `inspect_asm` → Obtain print out of function assembly
  - `inspect_cfg` → Obtain Control Flow Graph
  - `inspect_dissam_cfg` → Control Flow Graph and disassembly from reversing generated ELF

# Custom Compiler Passes

```
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

# 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)
```

# Custom Compiler Passes

```
# 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.
```

# Custom Compiler Passes

```
class MyCompiler(CompilerBase): # custom compiler extends from CompilerBase

    def define_pipelines(self):
        # define a new set of pipelines (just one in this case)
        pm = DefaultPassBuilder.define_nopython_pipeline(self.state)
        # Add the new pass to run after IRProcessing
        pm.add_pass_after(ConstsAddOne, IRProcessing)
        pm.finalize()
    return [pm]
```

# Custom Compiler Passes

```
@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!
```

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# Understood Numba?

- Numba is a
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  - function compiler
  - for accelerating numerically-focused Python

# What is Cooking?

- Currently in a PR cleanup, hoping to reduce number of open PRs
- Next gen: numbacc compiler based on Equality Saturation
- PIXIE based backend, toolchain and executable format

# Getting in Touch

- <https://numba.pydata.org>
- <https://github.com/numba>
- <https://numba.discourse.group/>
- Preferred: GitHub + Discourse
- Stuck? It can't hurt to ask. ;-)