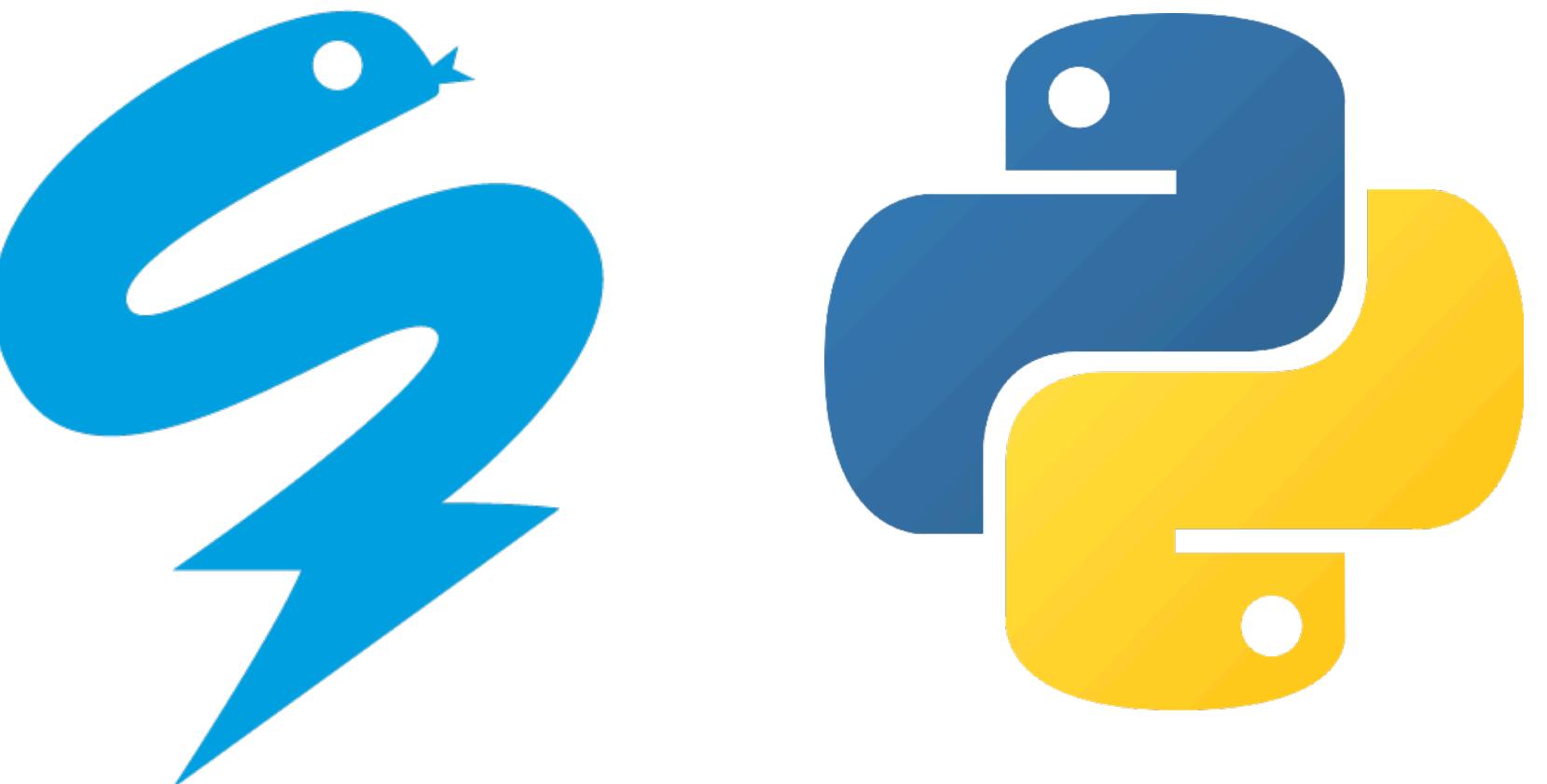


# UNDERSTANDING NUMBA THE PYTHON AND NUMPY COMPILER

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*Christoph Deil & EuroPython 2019*  
Slides at <https://christophdeil.com>



**DISCLAIMER: I DON'T  
UNDERSTAND NUMBA!**

# ABOUT ME

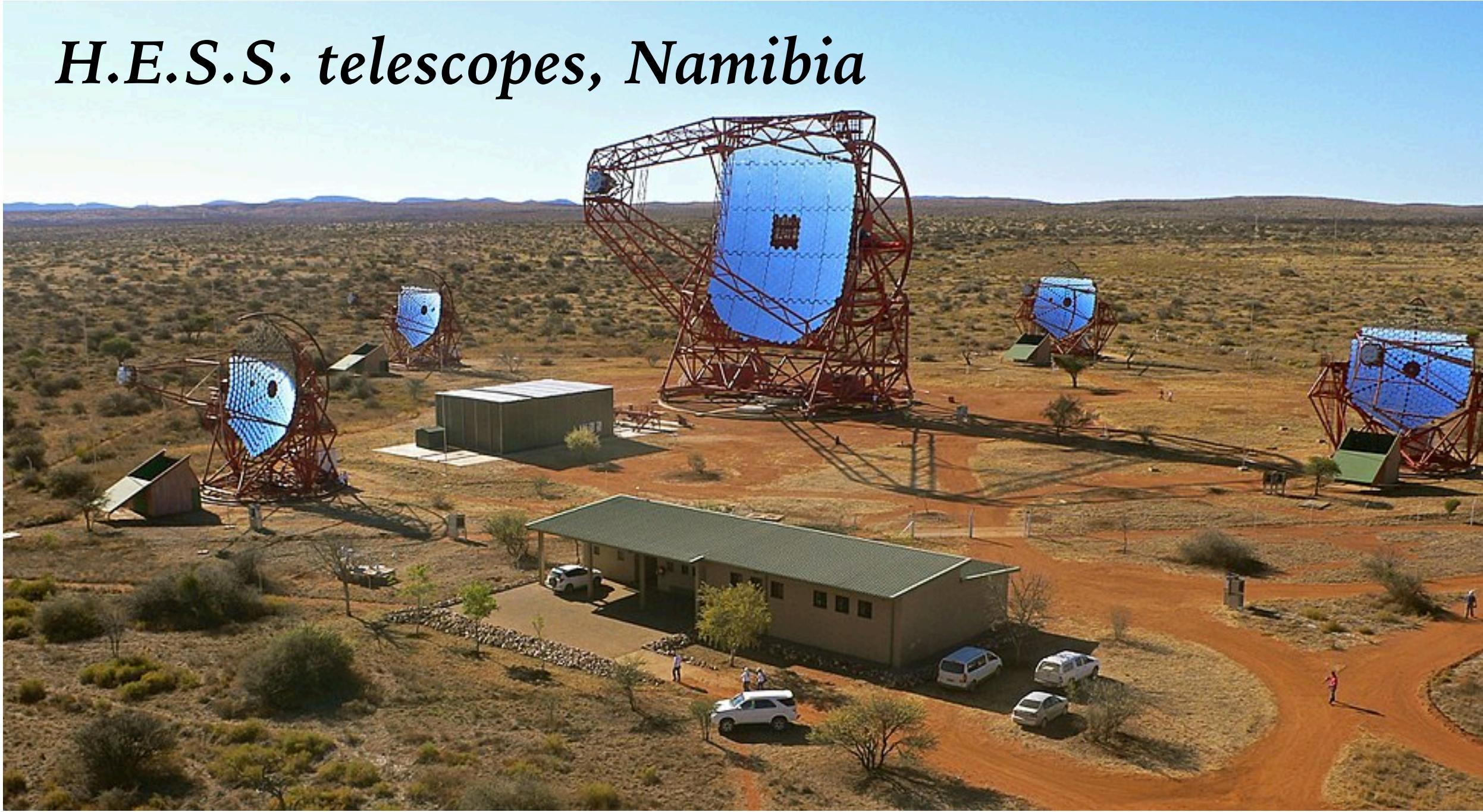
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- Christoph Deil, Gamma-ray astronomer from Heidelberg
- Not a Numba, compiler, CPU expert
- Recently started to use Numba, think it's awesome.  
This is an introduction.



# WHY USE NUMBA?

*H.E.S.S. telescopes, Namibia*



*Cherenkov Telescope Array (CTA)  
Southern array (Chile) - coming soon*



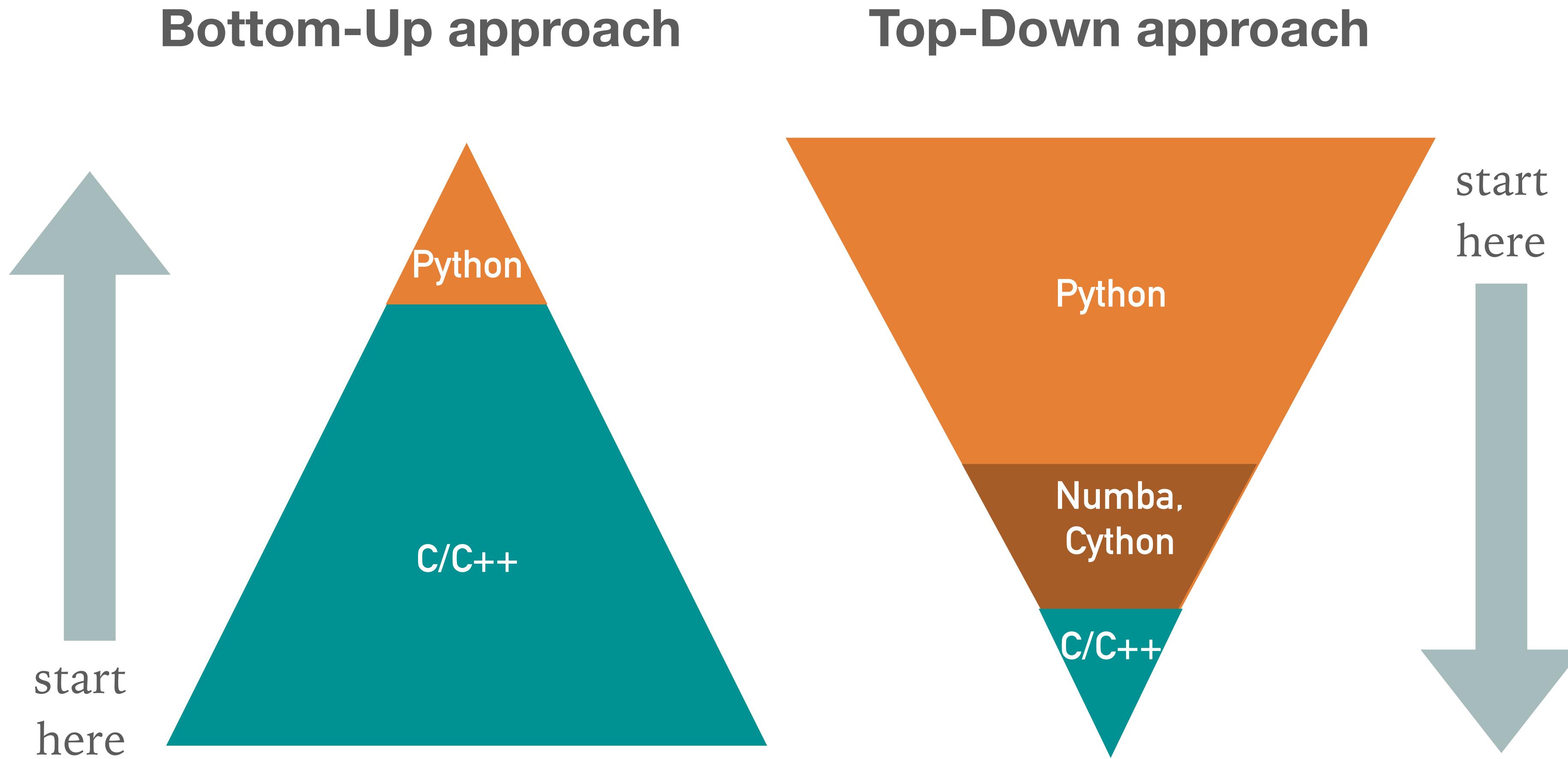
## GAMMA-RAY ASTRONOMY

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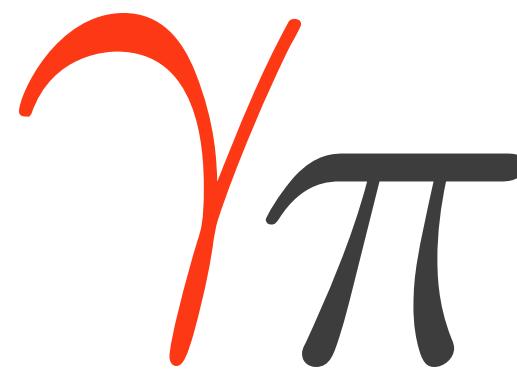
- Lots of numerical computing: data calibration, reduction, analysis
- Need both interactive data and method exploration and production pipelines.
- Software often written by astronomers, not professional programmers

# TWO APPROACHES TO WRITE SCIENTIFIC OR NUMERIC SOFTWARE

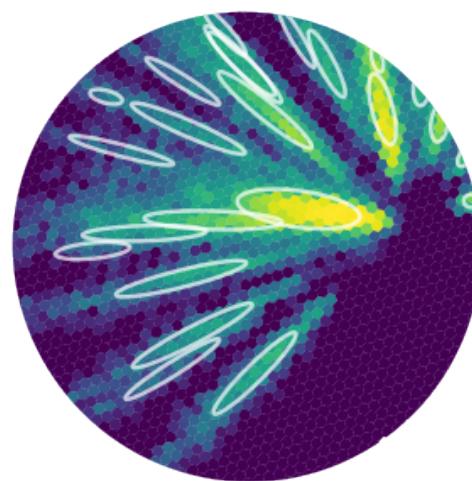
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*Image credit: Karl Kosack*



A **Python** package for  
**gamma-ray** astronomy



**ctapipe**



The  
**Astropy**  
Project



**PyData**



**python**<sup>TM</sup>

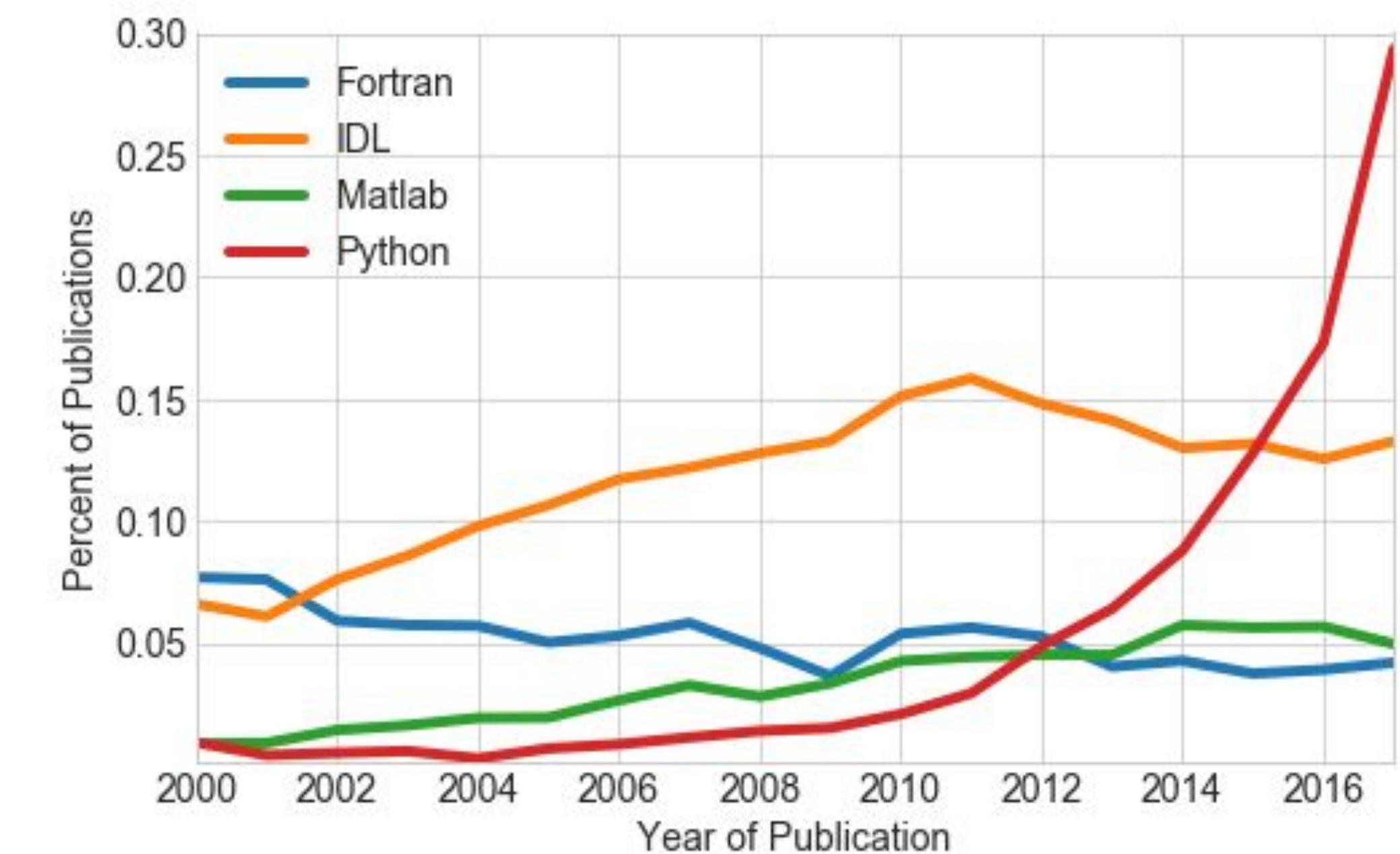
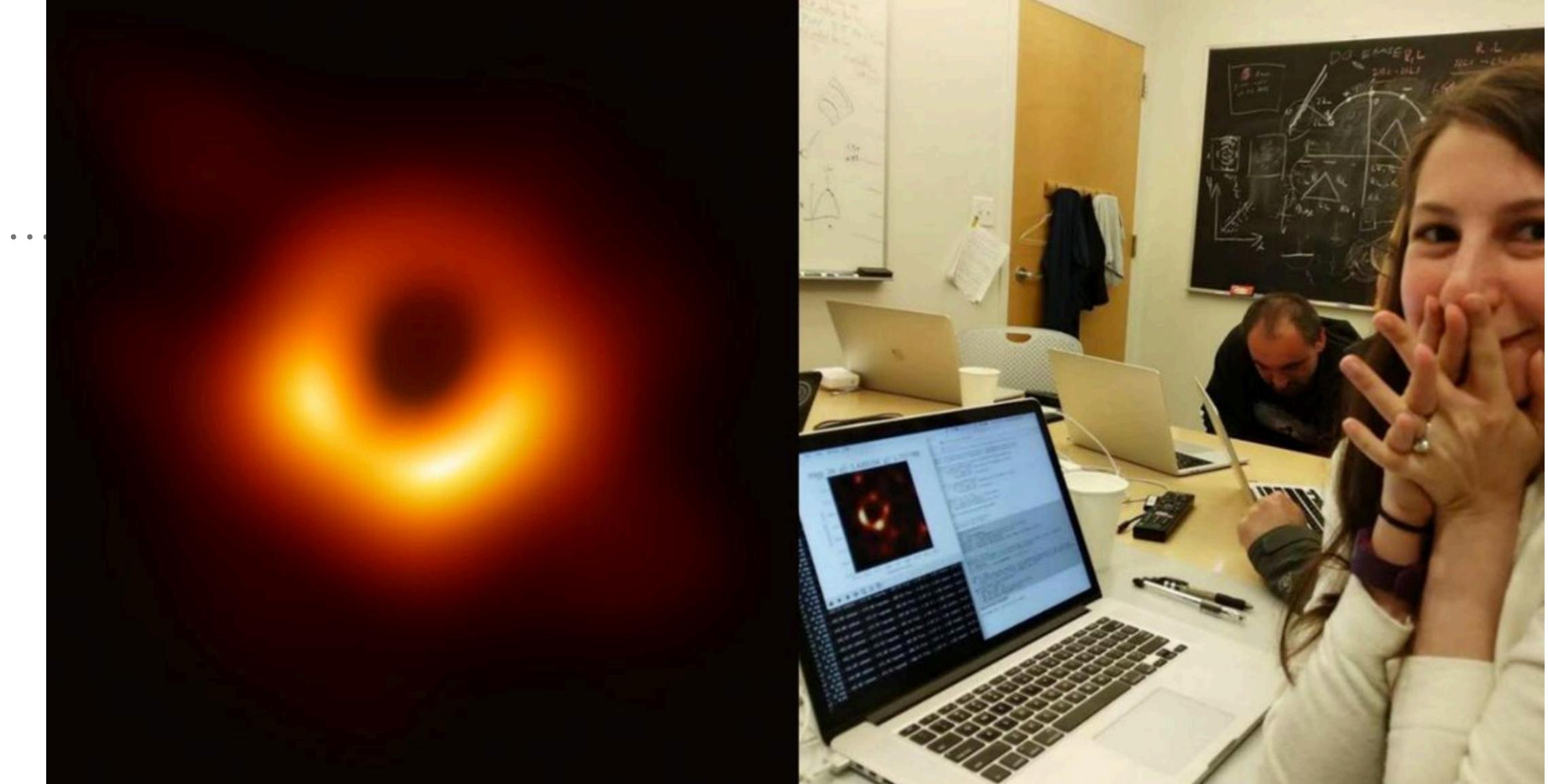
## CTA SOFTWARE

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- Prototyping the Python first approach
- Use Python/Numpy/PyData/Astropy
- Use Numba/Cython/C/C++ for few % of performance-critical functions

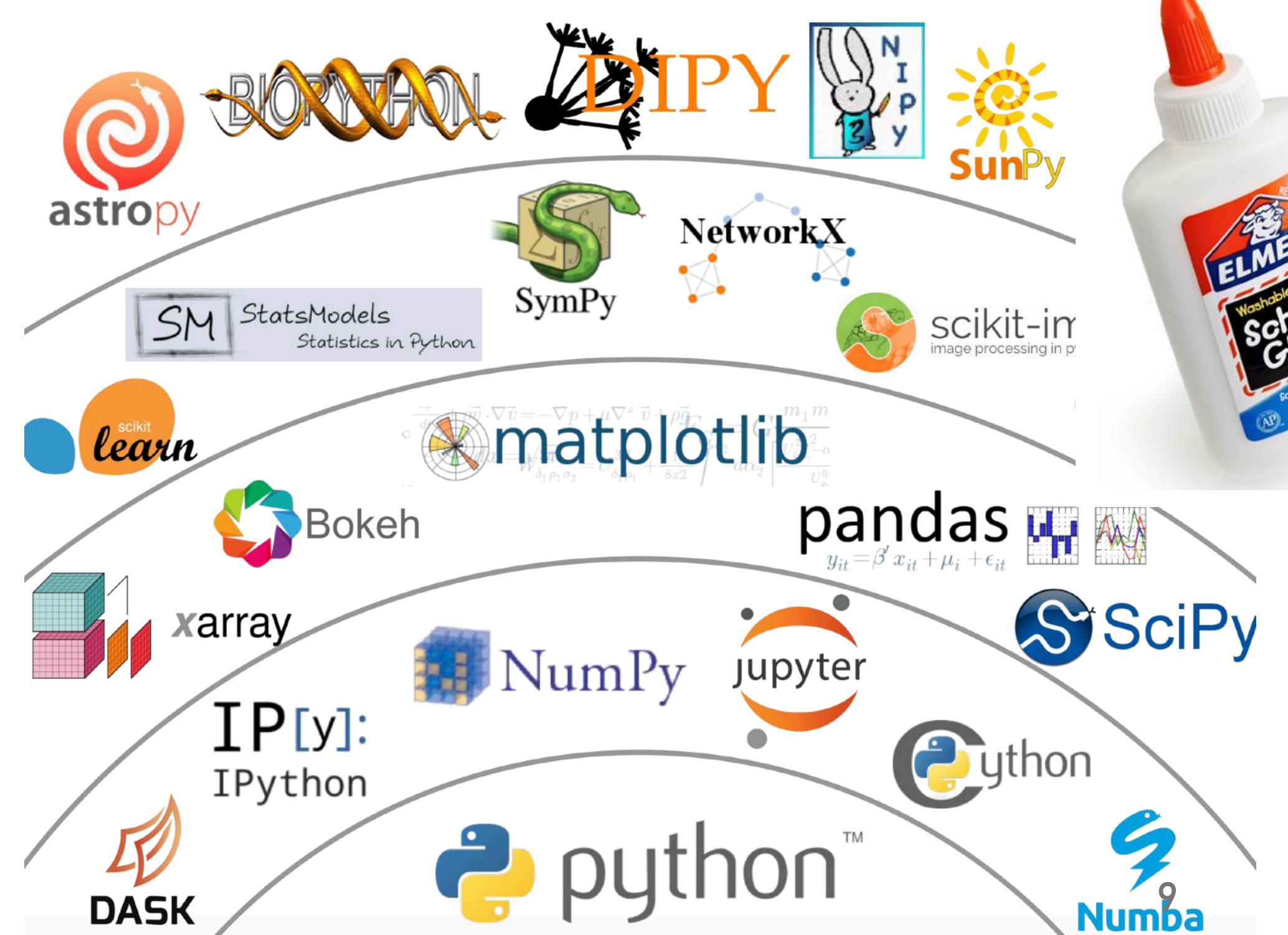
# PYTHON IN ASTRONOMY

- “Python is a language that is very powerful for developers, but is also accessible to Astronomers.”  
— Perry Greenfield, STScI, at PyAstro 2015



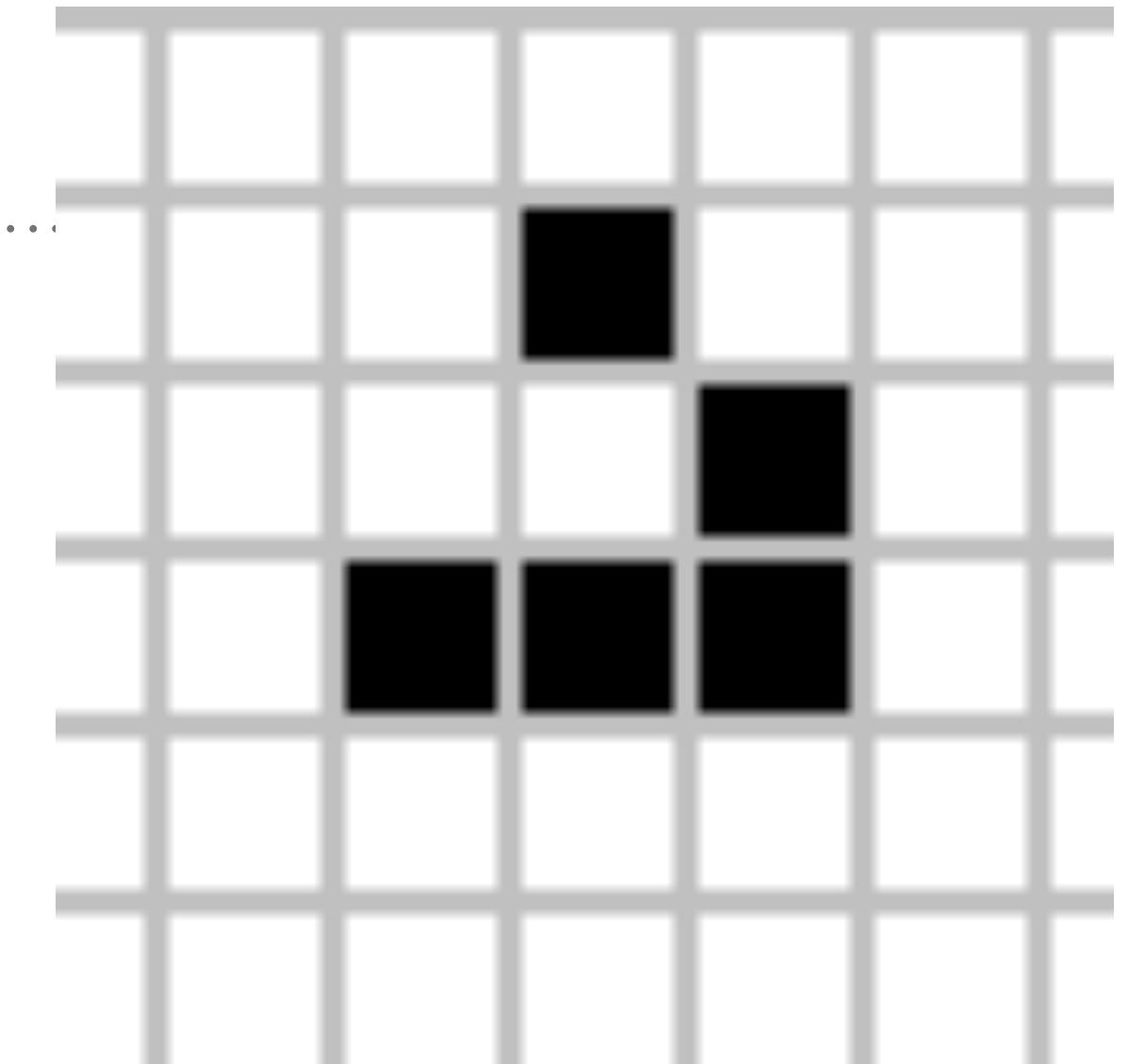
# THE UNEXPECTED EFFECTIVENESS OF PYTHON IN SCIENCE

- Keynote PyCon 2017 by Jake VanderPlas
- “*For scientific data exploration, speed of development is primary, and speed of execution is often secondary.*”
- “*Python has libraries for nearly everything ... it is the glue to combine the scientific codes*”



# WHY DO WE NEED NUMBA?

- Some algorithms are hard to write in Python & Numpy.
- Example: Conway's game of life  
*See <https://jakevdp.github.io/blog/2013/08/07/conways-game-of-life/>*
- Writing C and wrapping it for Python can be tedious.



```
def life_step(X):
    """Game of life step using generator expressions"""
    nbrs_count = sum(np.roll(np.roll(X, i, 0), j, 1)
                    for i in (-1, 0, 1) for j in (-1, 0, 1)
                    if (i != 0 or j != 0))
    return (nbrs_count == 3) | (X & (nbrs_count == 2))
```



*“Don’t write Numpy Haikus. If loops are simpler, write loops and use Numba!”*  
— Stan Seibert, Numba team, Anaconda

# INTRODUCING NUMBA

# WHAT IS NUMBA? — [HTTPS://NUMBA.PYDATA.ORG](https://numba.pydata.org)

---



Numba makes Python code fast

Numba is an open source JIT compiler that translates a subset of Python and NumPy code into fast machine code.

[Learn More](#) [Try Numba »](#)

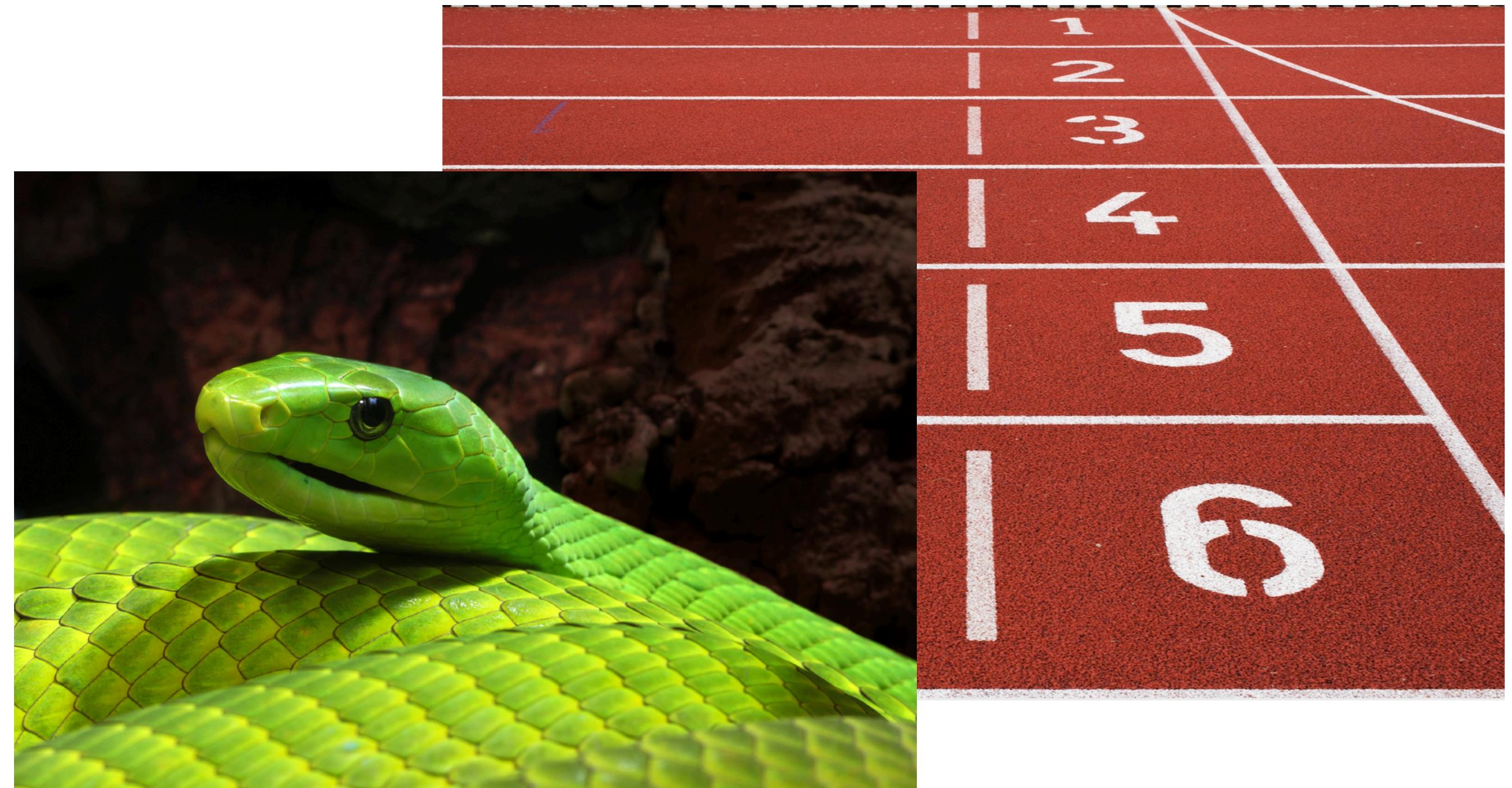
# WHAT IS NUMBA?

---



Numba logo (<https://numba.pydata.org>)

“Numba” = “NumPy”+ “Mamba”  
*Numba crunching in Python, fast like Mambas.*



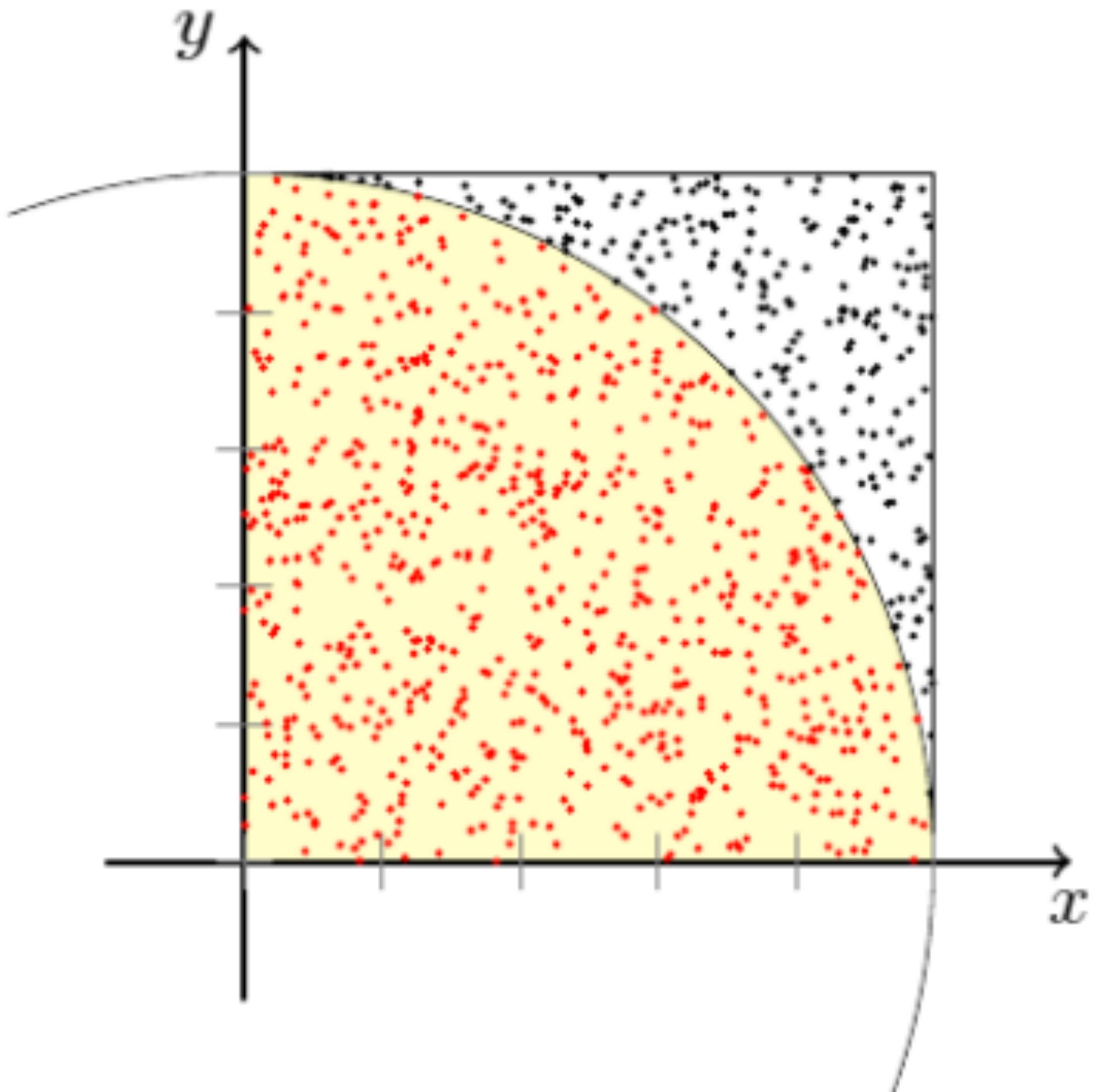
# NUMBA ACCELERATES NUMERICAL PYTHON FUNCTIONS

```
import random

def monte_carlo_pi(nsamples):
    acc = 0
    for i in range(nsamples):
        x = random.random()
        y = random.random()
        if (x ** 2 + y ** 2) < 1.0:
            acc += 1
    return 4.0 * acc / nsamples
```

```
%timeit monte_carlo_pi(1_000_000)
```

*400 ms — very slow*



# NUMBA ACCELERATES NUMERICAL PYTHON FUNCTIONS

```
import random
```

```
import numba
```

*Tell Numba to JIT  
your function*

```
@numba.jit
```

```
def monte_carlo_pi(nsamples):
```

```
    acc = 0
```

```
    for i in range(nsamples):
```

```
        x = random.random()
```

```
        y = random.random()
```

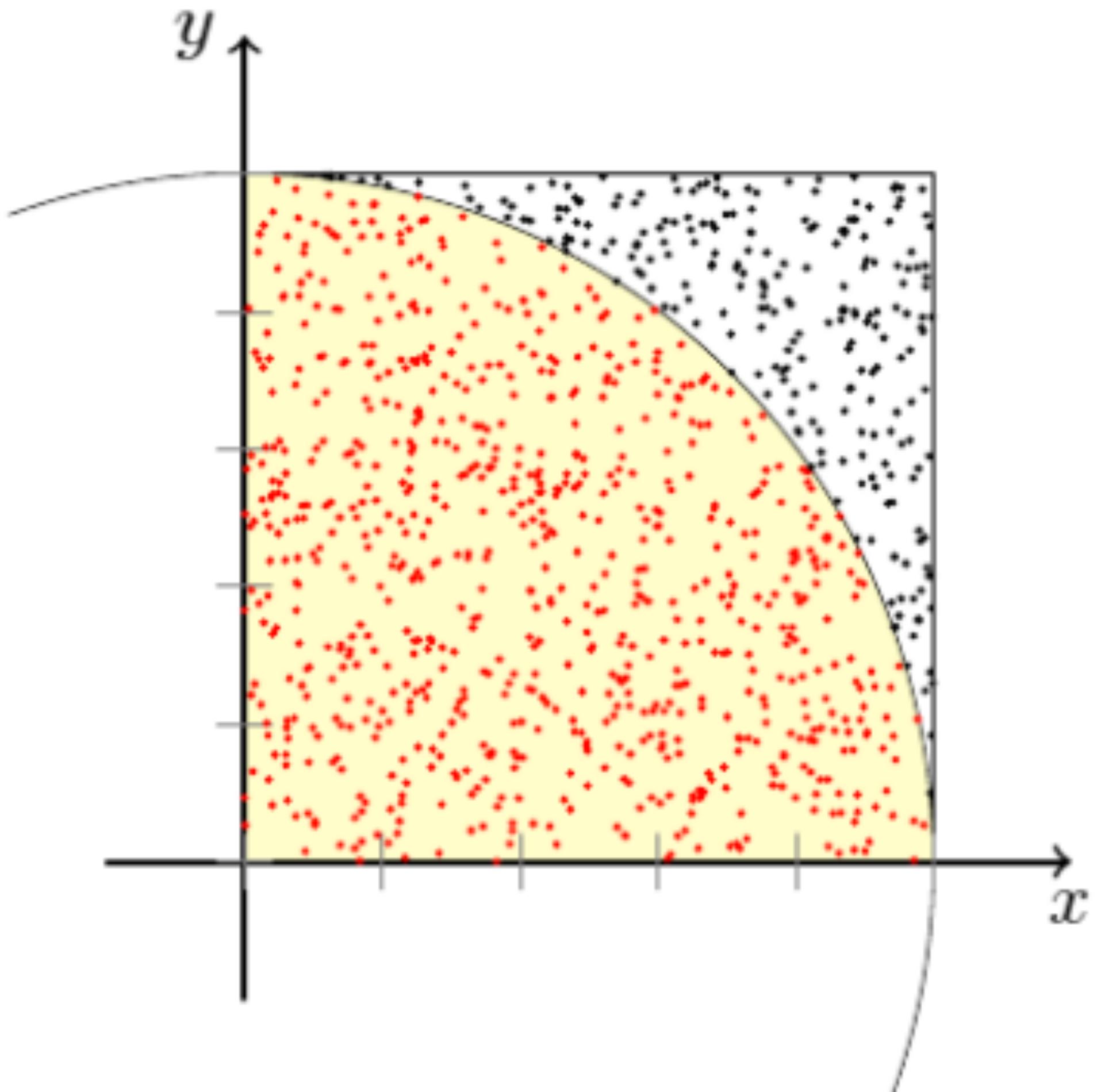
```
        if (x ** 2 + y ** 2) < 1.0:
```

```
            acc += 1
```

```
    return 4.0 * acc / nsamples
```

```
%timeit monte_carlo_pi(1_000_000)
```

*13 ms — Numba/Python speedup: 30x*



# NUMBA UNDERSTANDS NUMPY

```
import numpy as np
x = np.random.random(1_000_000)
y = np.random.random(1_000_000)

def monte_carlo_pi(x, y):
    acc = np.sum(x ** 2 + y ** 2 < 1)
    return 4 * acc / len(x)

%timeit monte_carlo_pi(x, y)
```

4.07 ms

```
@numba.jit
def monte_carlo_pi(x, y):
    count = np.sum(x ** 2 + y ** 2 < 1)
    return 4 * count / len(x)

%timeit monte_carlo_pi(x, y)
```

1.01 ms

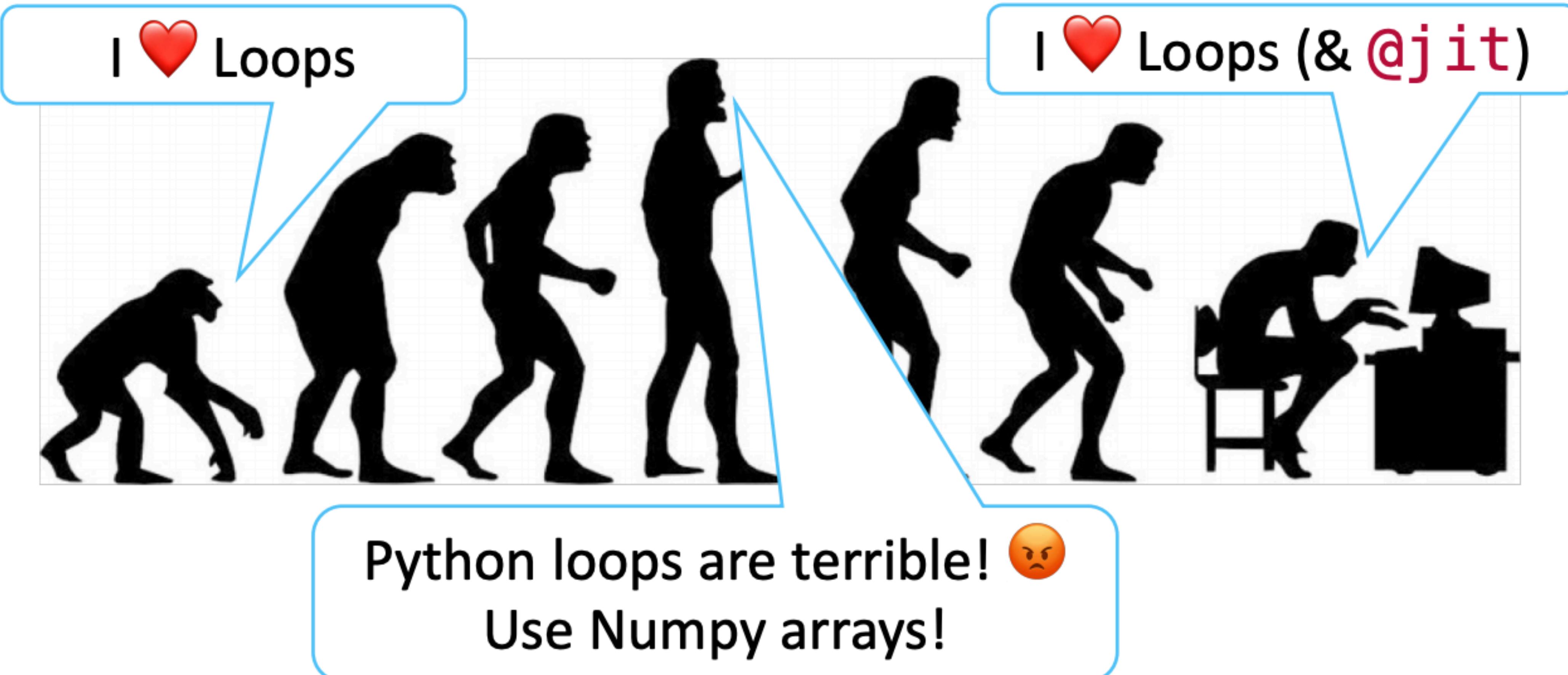
- Use Numpy if you want!
- Use Python for loops if you want!
- Numba will compile either way to optimised machine code

```
@numba.jit
def monte_carlo_pi(x, y):
    acc = 0
    for i in range(x.shape[0]):
        if (x[i] ** 2 + y[i] ** 2) < 1:
            acc += 1
    return 4.0 * acc / x.shape[0]
```

```
%timeit monte_carlo_pi(x, y)
```

692 µs

# EVOLUTION OF A SCIENTIFIC PROGRAMMER COMING TO PYTHON



# NUMBA LIMITATIONS

---

- Numba compiles individual functions.  
Not whole programs like e.g. PyPy
- Numba supports a subset of Python.  
Some dict/list/set support, but not mixed types for keys or values
- Numba supports a subset of Numpy.  
Ever growing, but not all functions and all arguments are available.
- Numba does not support pandas or other PyData or Python packages.

```
def spam(n):
    return n * ["spam", 42]

spam(3)

['spam', 42, 'spam', 42, 'spam', 42]
```

```
@numba.jit(nopython=True)
def spam(n):
    return n * ["spam", 42]

spam(3)
```

*TypingError: Failed in nopython mode pipeline*

```
@numba.jit  
def spam(n):  
    return n * ["spam"]  
  
spam(3)
```

*NumbaWarning: Compilation is falling back to object mode*  
[‘spam’, 42, ‘spam’, 42, ‘spam’, 42]

```
@numba.jit(nopython=True)  
def spam(n):  
    return n * ["spam"]  
  
spam(3)
```

*TypingError: Failed in nopython mode pipeline*

## NUMBA.JIT MODES

---

- @numba.jit has a fallback “object” mode, which allows any Python code.
- This “object” mode results in machine code, but with PyObject and Python C API calls, and same performance as using Python directly without Numba
- Not what you want 99% of the time
- To get either the desired “nopython” mode, or a TypingError you can use @numba.jit(nopython=True) or the equivalent @numba.njit

# NUMBA.OBJMODE CONTEXT MANAGER

---

- To call back to Python there is `numba.objmode` (rarely needed)
- Can be useful in long-running functions e.g. to log or update a progress bar

```
@numba.njit
def foo():
    x = np.arange(5)
    with numba.objmode(y='intp[:]'): # annotate return type
        # this region is executed by object-mode.
        y = np.asarray(list(reversed(x.tolist())))
    return y
```

# **UNDERSTANDING NUMBA**

## **( A LITTLE BIT )**

# UNDERSTANDING NUMBA

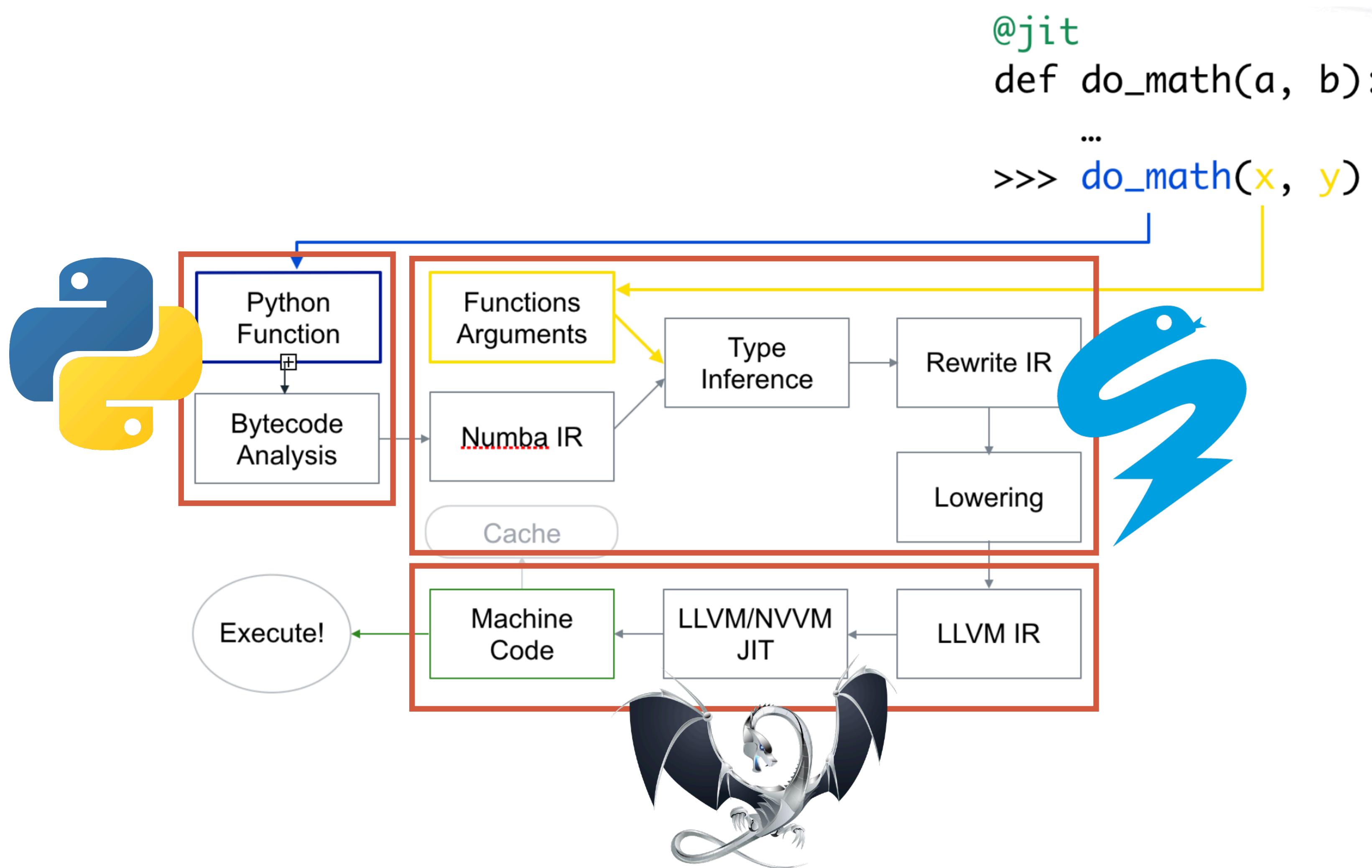
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“Numba is a type-specialising JIT compiler from Python bytecode using LLVM”



<https://youtu.be/LLpIMRowndg>

# PYTHON & NUMBA & LLVM



```
>>> def cond():
...     x = 3
...     if x < 5:
...         return 'yes'
...     else:
...         return 'no'
...
...
```

```
>>> dis.dis(cond)
 2      0 LOAD_CONST
 3      3 STORE_FAST

 3      6 LOAD_FAST
 9      9 LOAD_CONST
12     12 COMPARE_OP
15     15 POP_JUMP_IF_FALSE

 4     18 LOAD_CONST
21     21 RETURN_VALUE

 6   >> 22 LOAD_CONST
25     25 RETURN_VALUE
26     26 LOAD_CONST
29     29 RETURN_VALUE
```



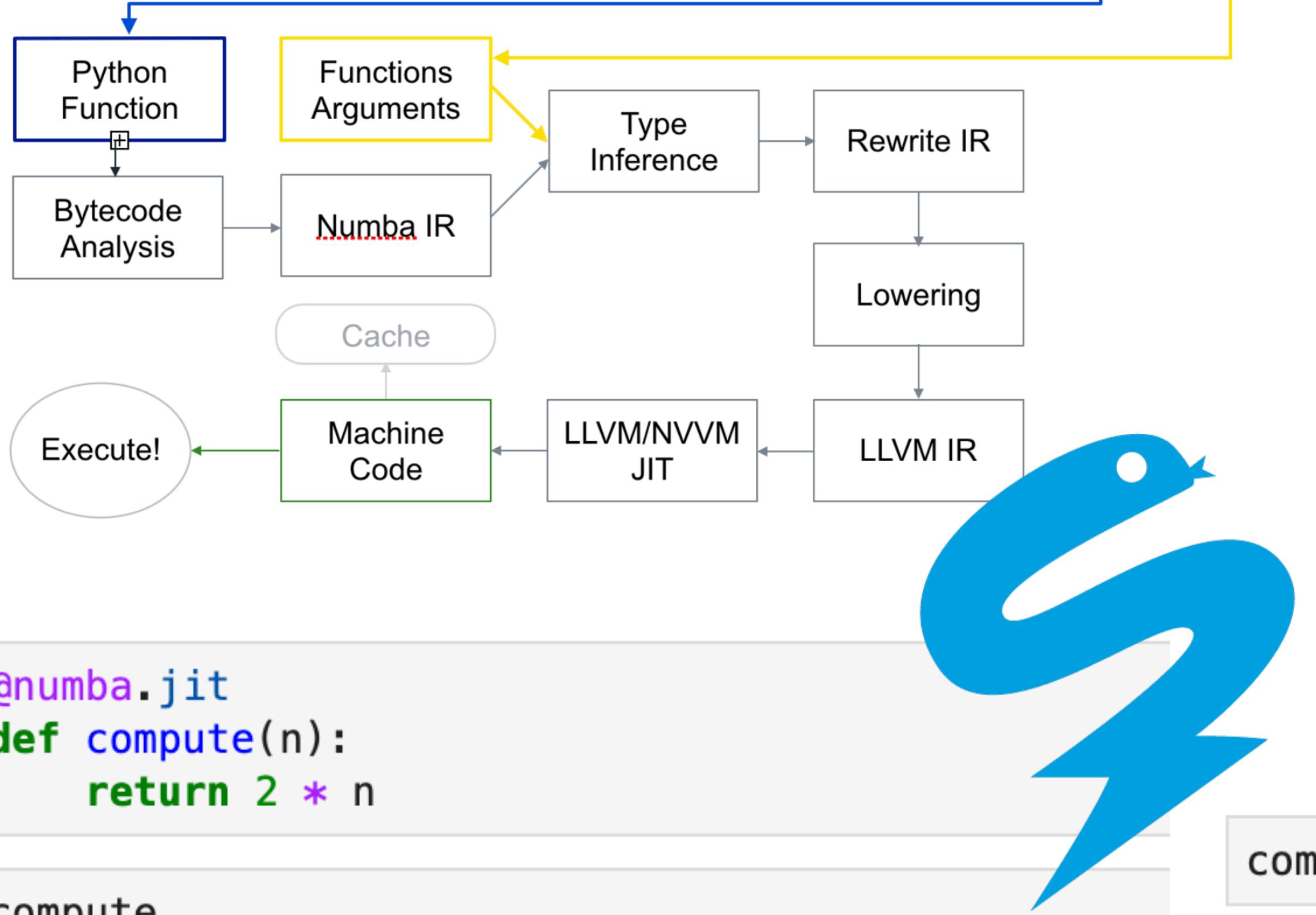
## PYTHON

---

- Python compiler starts with source code, parses it into an Abstract Syntax Tree (AST), then transforms it to Bytecode
- Happens on import of a module
- Bytecode for a function is attached to the Python function object (code=data)

```
>>> cond.__code__.co_code # the bytecode as raw bytes
b'd\x01\x00}\x00\x00|\x00\x00d\x02\x00k\x00\x00r\x16\x00d\x03\x00Sd\x04\x00Sd\x00
\x00S'
>>> list(cond.__code__.co_code) # the bytecode as numbers
[100, 1, 0, 125, 0, 0, 124, 0, 0, 100, 2, 0, 107, 0, 0, 114, 22, 0, 100, 3, 0, 83,
 100, 4, 0, 83, 100, 0, 0, 83]
```

```
@jit
def do_math(a, b):
...
>>> do_math(x, y)
```



```
@numba.jit
def compute(n):
    return 2 * n
```

```
compute
```

```
CPUDispatcher(<function compute at 0x6261a0e18>)
```

```
compute.overloads
```

```
OrderedDict()
```

# NUMBA

- On `@numba.jit` decorator call, Numba makes a CPUDispatcher proxy object.
- On function call, Numba will:
  - JIT compile Bytecode to LLVM IR exactly for the input types
  - Manage LLVM compilation
  - Execute compiled function

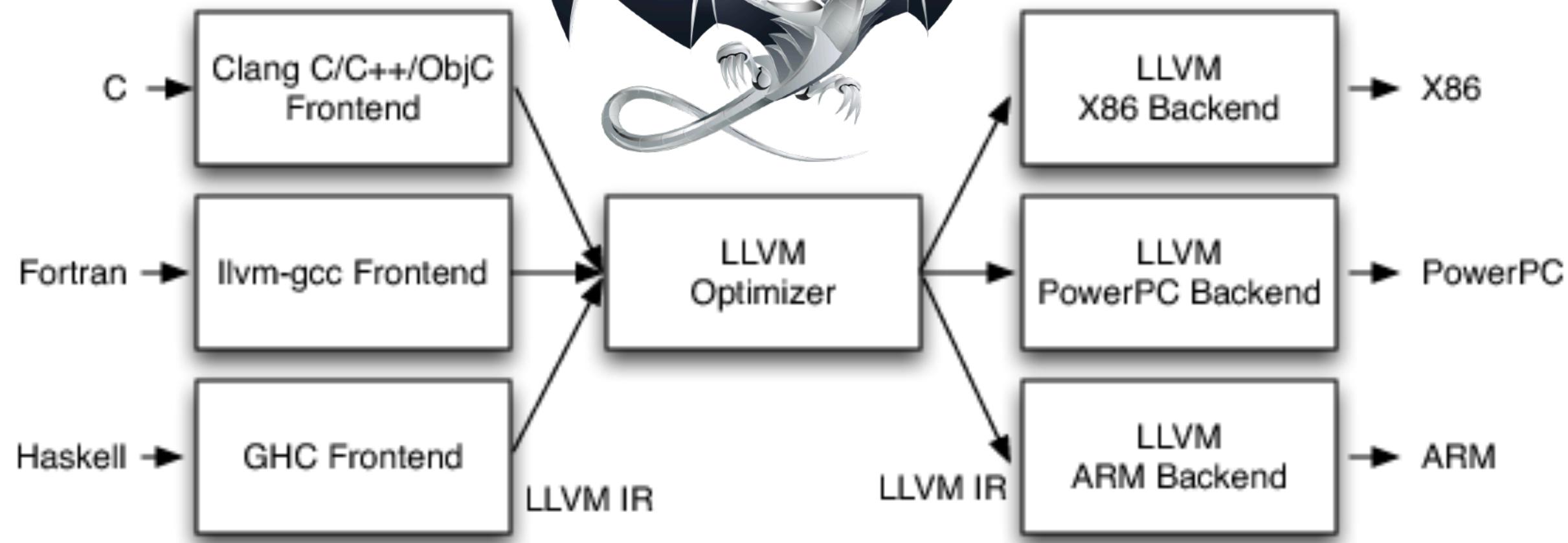
```
compute(3)
```

```
6
```

```
compute.overloads
```

```
OrderedDict([(int64,),  
            CompileResult(typing_context=<numba
```

# LLVM



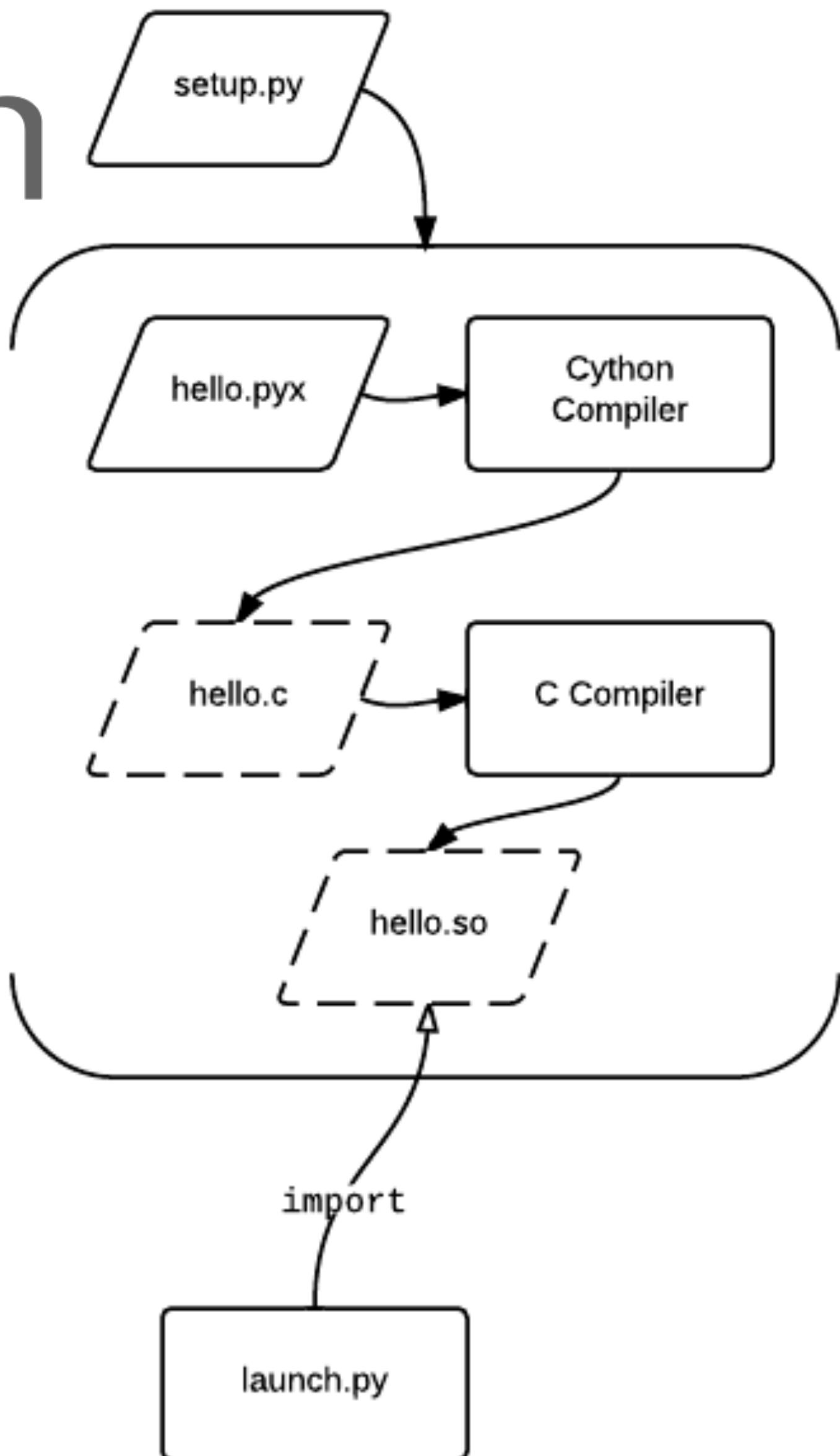
*LLVM intermediate representation (IR) example:*

```
define i32 @add1(i32 %a, i32 %b) {  
entry:  
    %tmp1 = add i32 %a, %b  
    ret i32 %tmp1  
}  
  
define i32 @add2(i32 %a, i32 %b) {  
entry:  
    %tmp1 = icmp eq i32 %a, 0  
    br i1 %tmp1, label %done, label %recurse
```

- LLVM is a compiler infrastructure project
- Many frontends for languages: C, C++, Fortran, Haskell, Rust, Julia, Swift, ...
- Many backends for hardware: almost all CPU vendors add support and optimise
- Numba could be considered the Python front-end to LLVM
- LLVM is shipped as a Python package "llvmlite" that Numba depends on
- Numba team at Anaconda Inc. builds numba and llvmlite for conda and pip



```
In [1]: %load_ext Cython  
  
In [2]: %%cython  
...: def f(n):  
...:     a = 0  
...:     for i in range(n):  
...:         a += i  
...:     return a  
  
...: cpdef g(int n):  
...:     cdef long a = 0  
...:     cdef int i  
...:     for i in range(n):  
...:         a += i  
...:     return a  
  
In [3]: %timeit f(1000000)  
10 loops, best of 3: 26.5 ms per  
  
In [4]: %timeit g(1000000)  
1000 loops, best of 3: 279 µs per
```



## CYTHON VS. NUMBA

- Like Numba, Cython is often used to speed up numeric Python code
- Cython is an “ahead of time” (AOT) compiler of type-annotated Python to C
- Cython is more widely used, easier to debug, very good at interfacing C/C++
- Numba is easier to use: no type annotations, no C compiler, but sometimes harder to debug (LLVM IR)
- Numba optimises JIT for your CPU or GPU, no need to build and distribute binaries for many architectures

Source: <https://en.wikipedia.org/wiki/Cython>

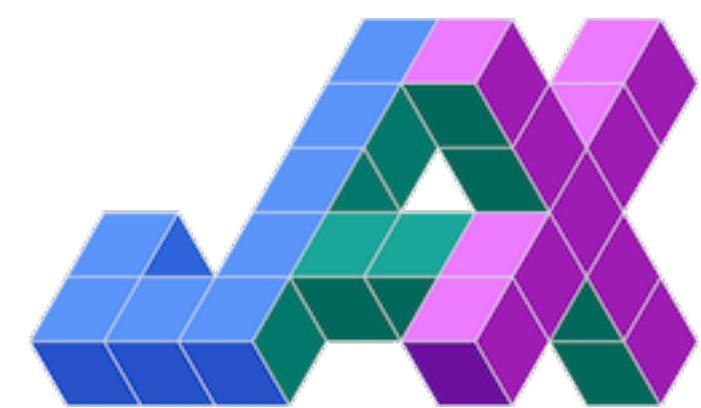
## NUMBA ALTERNATIVES

---

- Many other great tools exist for high-performance computing with Python
- Cython/C/C++/pybind11 to create Python C extensions
- PyPy is an alternative to CPython, that JIT-compiles the whole program
- TensorFlow, JAX, PyTorch, Dask, ... use Python & Numpy as the language to specify computation, but then compile and execute in various ways
- How to do HPC from Python?  
Not an easy choice!



TensorFlow



# MORE NUMBA

```

$ numba -s
__Hardware Information__
Machine : x86_64
CPU Name : haswell
CPU count : 8
CPU Features :
aes avx avx2 bmi bmi2 cmov cx16 f16c fma fsgsbase invpcid lzcnt mmx movbe pclmul
popcnt rdrnd sahf sse sse2 sse3 sse4.1 sse4.2 ssse3 xsave xsaveopt

__OS Information__
Platform : Darwin-18.5.0-x86_64-i386-64bit

__Python Information__
Python Compiler : Clang 4.0.1 (tags/RELEASE_401/final)
Python Implementation : CPython
Python Version : 3.7.3

__LLVM information__
LLVM version : 7.0.0

__CUDA Information__
CUDA driver library cannot be found or no CUDA enabled devices are present.

__ROC Information__
ROC available : False

__SVML Information__
SVML operational : True

__Threading Layer Information__
TBB Threading layer available : True
OpenMP Threading layer available : True
Workqueue Threading layer available : True

```

# NUMBA -S

---

- From the command line:  
**numba -s**  
**numba --sysinfo**
- From IPython or Jupyter:  
**!numba -s**
- Gives you all relevant information:
  - Hardware: CPU & GPU
  - Python, Numba, LLVM versions
  - SVML: Intel short vector math library
  - TBB: Intel threading building blocks
  - CUDA & ROC

# PARALLEL ACCELERATOR

---

```
data = np.random.random(1_000_000)
```

```
@numba.jit
def f(x):
    return np.cos(x) ** 2 + np.sin(x) ** 2

%timeit f(data)
```

11.3 ms

```
@numba.jit(parallel=True)
def f(x):
    return np.cos(x) ** 2 + np.sin(x) ** 2

%timeit f(data)
```

3.51 ms

*3.2x speedup on my 4-core CPU*

- Add `parallel=True` to use multi-core CPU via threading
- Backends: openmp, tbb, workqueue
- Intel Threading Building Blocks needs \$ conda install tbb
- Works automatically for Numpy array expressions - no code changes needed

```

@numba.jit
def compute(x):
    s = 0
    for i in numba.prange(x.shape[0]):
        s += x[i]
    return s

%timeit compute(data)

```

855 µs

```

@numba.jit(parallel=True)
def compute(x):
    s = 0
    for i in numba.prange(x.shape[0]):
        s += x[i]
    return s

%timeit compute(data)

```

388 µs

*2.2x speedup on my 4-core CPU*

## PARALLEL ACCELERATOR

- Use `numba.prange` with `parallel=True` if you have for loops
- With the default `parallel=False`, `numba.prange` is the same as `range`.
- You can try out different options:

```

def compute(x):
    s = 0
    for i in numba.prange(x.shape[0]):
        s += x[i]
    return s

```

```
compute1 = numba.jit(compute)
```

```
compute2 = numba.jit(parallel=True)(compute)
```

# FASTMATH

---

```
def compute(x):
    acc = 0.0
    for item in x:
        acc += np.sqrt(item)
    return acc
```

```
data = np.random.random(1_000_000)
```

```
c1 = numba.jit(compute)
%timeit c1(data)
```

3.92 ms

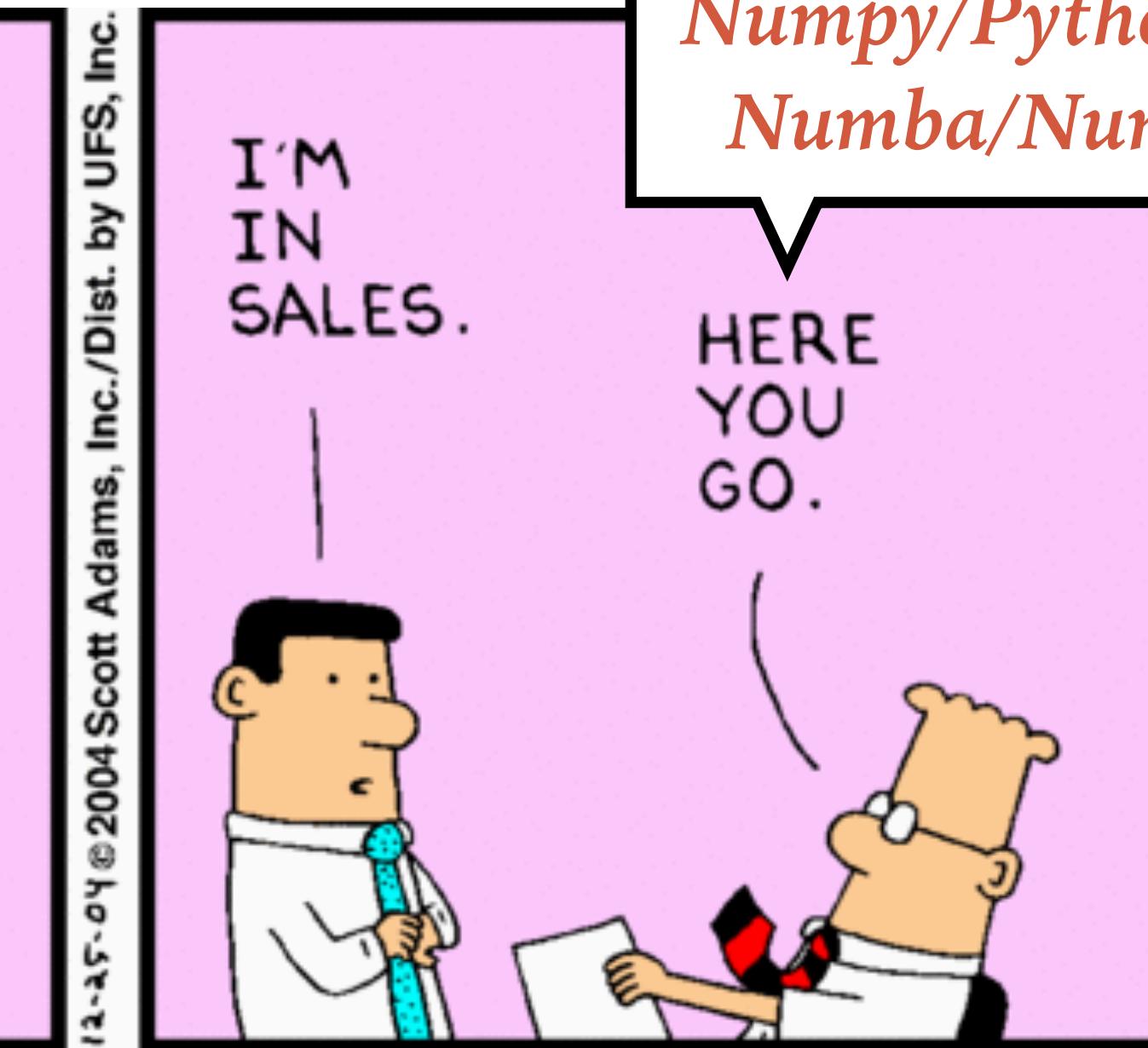
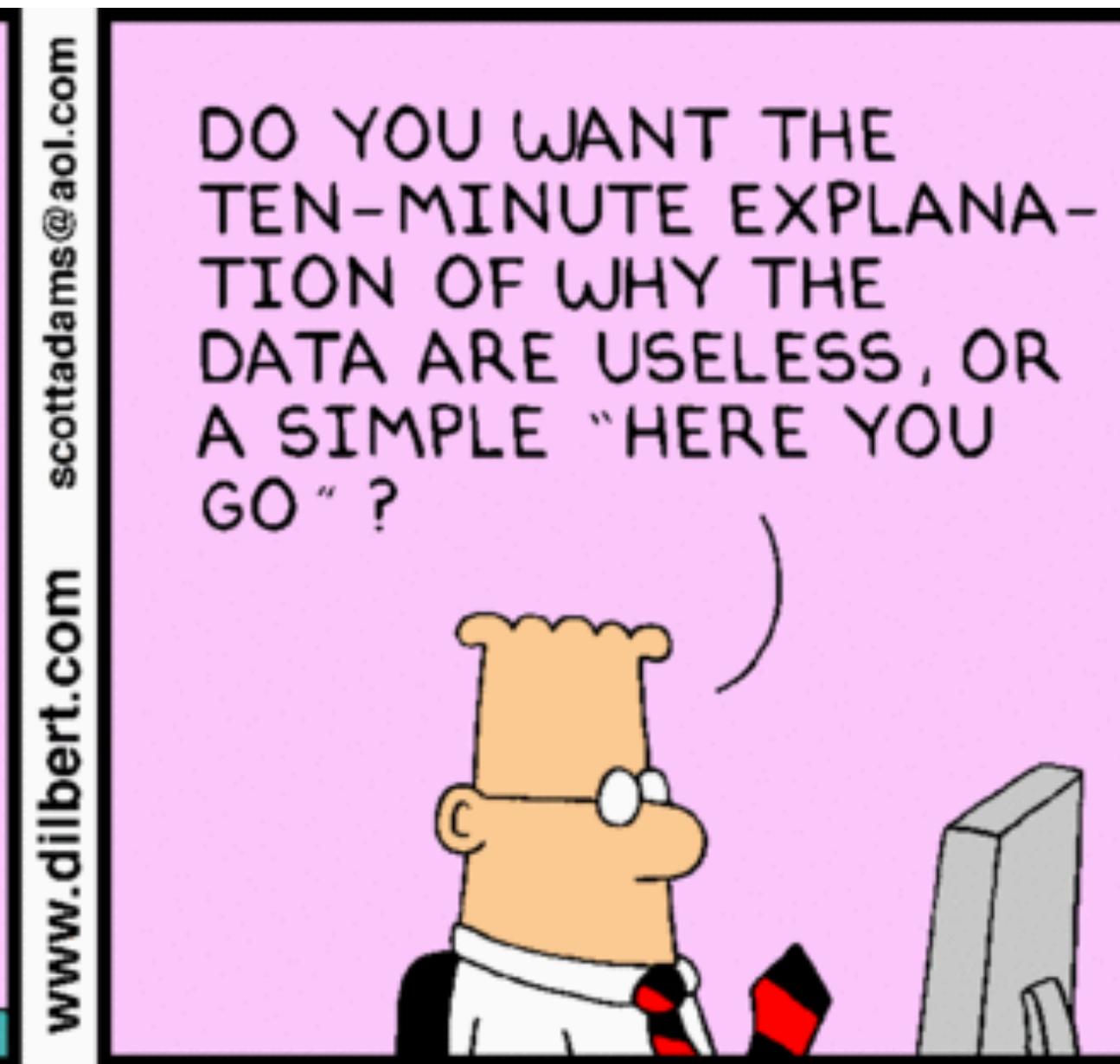
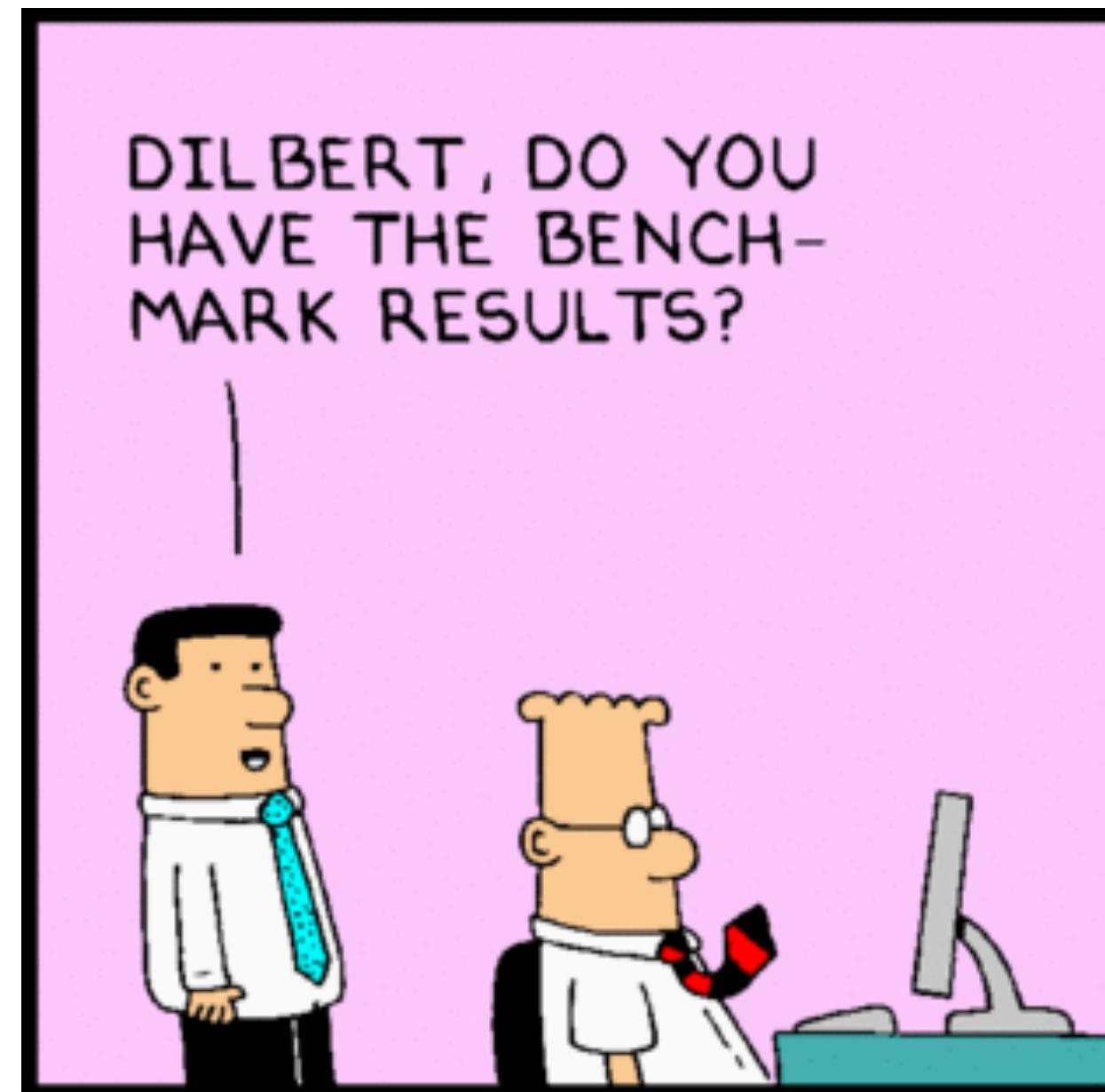
```
c2 = numba.jit(fastmath=True)(compute)
%timeit c2(data)
```

2.17 ms

- Add `fastmath=True` to trade accuracy for speed in some computations
- IEEE 754 floating point standard requires that loop must accumulate in order
- With `fastmath=True`, vectorised reduction is used, which is faster
- Another way to speed up math functions like `sin`, `exp`, `tanh`, ... is this:  
`$ conda install -c numba icc_rt`
- If available, Numba will tell LLVM to use Intel Short Vector Math Library (SVML)

# HOW FAST IS NUMBA?

- Numba gives very good performance, and many options to tweak the computation
- There is no simple answer how Numba compares to Python, Cython, Numpy, C, ...
- Always define a benchmark for your application and measure!



*Numpy/Python speedup: 100x  
Numba/Numpy speedup: 2x*

# NUMPY UFUNCTIONS

---

```
import numpy as np
```

```
np.add(1, 2)
```

```
3
```

```
np.add(1, [2, 3])
```

```
array([3, 4])
```

```
np.add([[1, 2]], [[3], [4]])
```

```
array([[4, 5],  
       [5, 6]])
```

```
np.add.accumulate([2, 3, 4, 5])
```

```
array([ 2,  5,  9, 14])
```

- Numpy functions like add, sin, ... are universal functions (“ufuncs”)
- They all support array broadcasting, data type handling, and some other features like accumulate or reduce.
- So far, you had to write C and use the Numpy C API to make your own ufunc

# NUMBA.VECTORIZE

---

```
@numba.vectorize("(int64, int64)")  
def add(x, y):  
    # Write operation for one element  
    return x + y
```

```
add(1, 2)
```

```
3
```

```
add(1, [2, 3, 4])
```

```
array([3, 4, 5])
```

```
add.accumulate([2, 3, 4, 5])
```

```
array([ 2,  5,  9, 14])
```

- The `@numba.vectorize` decorator makes it easy to write Numpy ufuncs.
- Just write operation for one element
- You can give a type signature, or list of types to support, and Numba will generate one ufunc on vectorize call
- If no signature is given, a DUFunc dispatcher is created, which dynamically will create ufunc for given input types on function call.

# NUMBA - A FAMILY OF COMPILERS

---

- Numba has more compilers, all implemented as Python decorators.  
This was just a quick introduction, see <http://numba.pydata.org/>
- **@numba.jit** — regular function
- **@numba.vectorize** — Numpy ufunc
- **@numba.guvectorize** — Numpy generalised ufunc
- **@numba.stencil** — neighbourhood computation
- **@numba.cfunc** — C callbacks
- **@numba.cuda.jit** — NVidia CUDA kernels
- **@numba.roc.jit** — ARM ROCm kernels

# WHO USES NUMBA?

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“I’m becoming more and more convinced that Numba is the future of fast scientific computing in Python.”  
— *Jake Vanderplas (2013)*

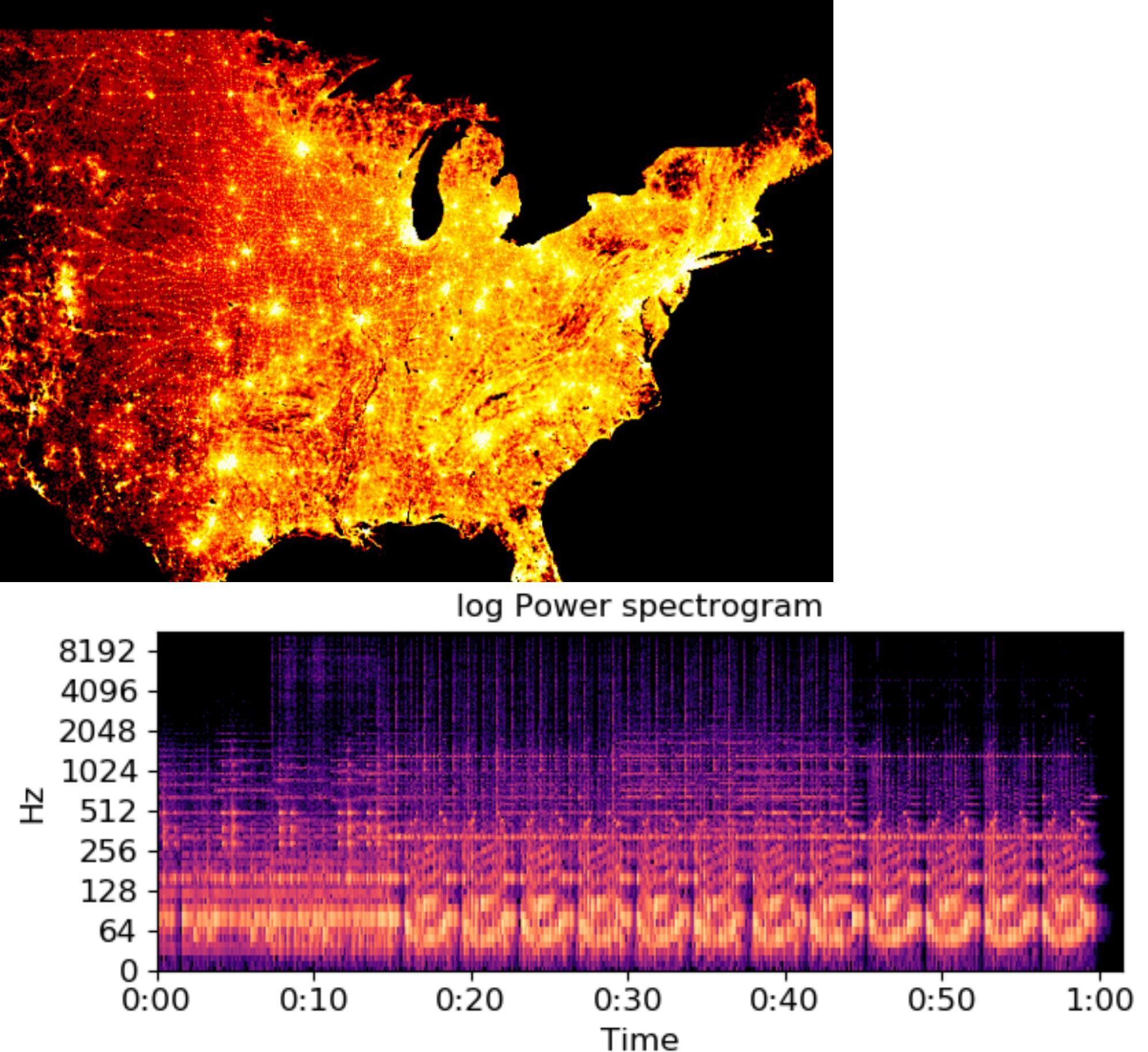


“The numeric Python community should consider adopting Numba more widely within community code.”  
— *Matthew Rocklin (2018)*

# WHO USES NUMBA?

---

- Many people and applications use it for their work and projects
- Large libraries like Numpy, Scipy, pandas, scikit-learn, ... not yet.
- Some nice examples using Numba:
  - Datashader - large data visualisation
  - LibROSA - audio & music analysis
  - HPAT - Intel High Performance Toolkit for big data, supports pandas



```
@hpat.jit
def logistic_regression(iterations):
    f = h5py.File("lr.hdf5", "r")
    X = f['points'][:]
    Y = f['responses'][:]
    D = X.shape[1]
    w = np.random.ranf(D)
    t1 = time.time()
    for i in range(iterations):
        z = ((1.0 / (1.0 + np.exp(-Y * np.dot(X, w)))) - 1.0) * Y
        w -= np.dot(z, X)
    return w
```

# SUMMARY & CONCLUSIONS

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- Numba is a type-specialising JIT compiler from Python byte code to LLVM IR
- Started 2012, current version is v0.44, well on the road to v1.0.
- Use your CPU or GPU well, just by writing Python and adding a decorator
- Use `@numba.jit` for normal functions, and `@numba.vectorize` for Numpy ufuncs  
To check your machine & installation: `numba -s`  
Consider `parallel=True` and `fastmath=True` to run faster on the CPU  
To get Intel SVML: `conda install -c numba icc_rt`
- Thanks to the Numba devs at Anaconda, and contributions by Intel and others!!!

