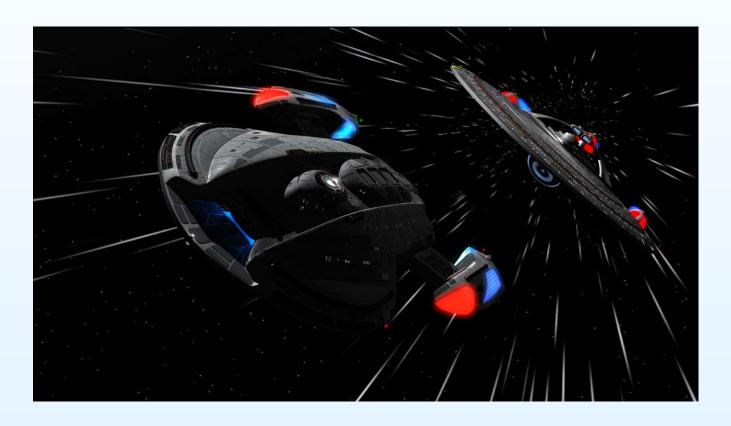
Speeding up scientific Python code using Cython

ASPP, Reading, UK



Stéfan van der Walt (@stefanvdwalt)

Lecture Material

https://python.g-node.org/wiki/cython

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Motivation

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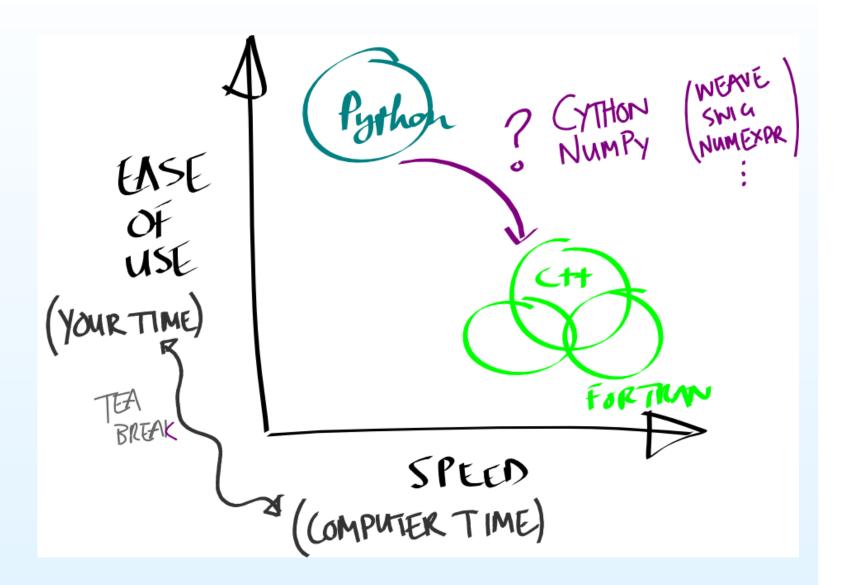
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Motivation (continued)

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Wrapping C and C++ Libraries

- Cython allows us to cross the gap
- This is good news because
 - we get to keep coding in Python (or, at least, a superset)
 - but with the speed advantage of C
- You can't have your cake and eat it. Or can you?

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Use Cases

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Wrapping C and C++ Libraries

- Optimize execution of Python code (profile, like shown by Pietro yesterday)
- Wrap existing C and C++ code
- Breaking out of the Global Interpreter Lock; openmp
- Mixing C and Python, but without the pain of the Python C API

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Tutorial Overview

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Wrapping C and C++ Libraries For this quick introduction, we'll take the following approach:

- Take a piece of pure Python code and benchmark (we'll find that it is too slow)
- Run the code through Cython, compile and benchmark (we'll find that it is somewhat faster)
- 3. Annotate the types and benchmark (we'll find that it is quite a bit faster)

Then we'll look at how Cython allows us to

- Work with NumPy arrays
- Use multiple threads from Python
- Wrap native C libraries

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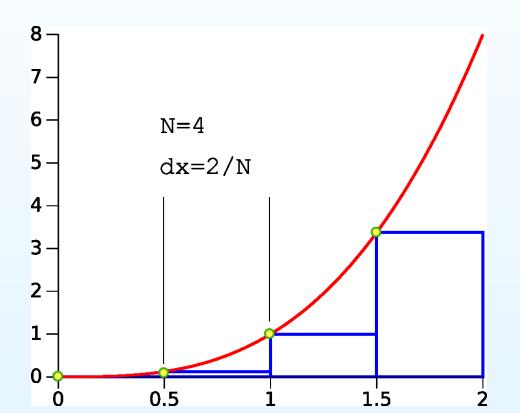
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Benchmark Python code

Our code aims to compute (an approximation of) $\int_a^b f(x)dx$



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More Segments

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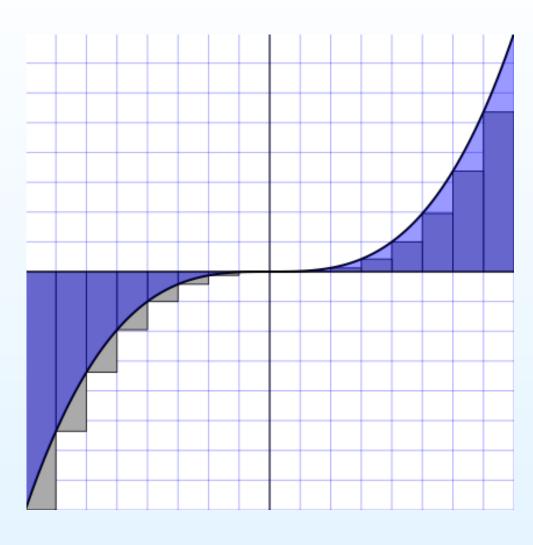
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Benchmark Python Code

return s * dx

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Wrapping C and C++ Libraries

```
def f(x):
    return x**4 - 3 * x
def integrate_f(a, b, N):
    """Rectangle integration of a function.
    Parameters
    a, b: float
        Interval over which to integrate.
    N : int
        Number of intervals to use in the discretisation.
    11 11 11
    s = 0
    dx = (b - a) / N
    for i in range(N):
        s += f(a + i * dx)
```

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Compile the code with Cython

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Wrapping C and C++ Libraries

cython filename.[py|pyx]
What is happening behind the scenes? cython -a filename.[py|pyx]

 Cython translates Python to C, using the Python C API (let's have a look)

This code has some serious bottlenecks.

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Compile generated code

By hand you would do (but don't do this):

```
$ gcc -02 -fPIC -I/usr/include/python2.7
-c integrate.c -o integrate_compiled.so
```

Easier yet, construct a setup.py:

```
from distutils.core import setup
from distutils.extension import Extension
from Cython.Distutils import build_ext

setup(
  cmdclass = {'build_ext': build_ext},
  ext_modules = [
    Extension("integrate", ["integrate.pyx"]),
  ])
```

Run using python setup.py build_ext -i. This means: build the extensions & in-place >> .

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Benchmark the new code

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Parallelization

Wrapping C and C++
Libraries

 Use IPython's %timeit (could do this manually using from timeit import timeit; timeit(...))

- Slight speed increase ($\approx 1.4 \times$) probably not worth it.
- Can we help Cython to do even better?
 - Yes—by giving it some clues.
 - Cython has a basic type inferencing engine, but it is very conservative for safety reasons.
 - Why does type information allow such vast speed increases?

Providing type information

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Parallelization

Wrapping C and C++
Libraries

```
def f(double x):
   return x**4 - 3 * x
def integrate_f( double a, double b, int N ):
    """Rectangle integration of a function.
    11 11 11
     cdef:
         double s = 0
         double dx = (b - a) / N
         Py_ssize_t i
    for i in range(N):
         s += f(a + i * dx)
    return s * dx
```

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Benchmark...

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Expense of Python Function Calls

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Handling NumPy Arrays

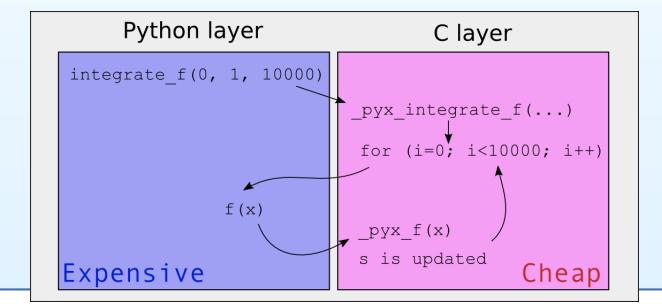
Parallelization

Wrapping C and C++
Libraries

```
def f(double x):
    return x**4 - 3 * x

def integrate_f(double a, double b, int N):
    cdef:
        double s = 0
        double dx = (b - a) / N
        size_t i

for i in range(N):
        s += f(a + i * dx)
    return s * dx
```



The Last Bottlenecks

cython: cdivision=True

return s * dx

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Parallelization

Wrapping C and C++
Libraries

```
cdef double f(double x):
    return x*x*x*x - 3 * x

def integrate_f(double a, double b, int N):
    cdef:
        double s = 0
        double dx = (b - a) / N
        Py_ssize_t i

for i in range(N):
    s += f(a + i * dx)
```

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Benchmark!

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Integrating Arbitrary Functions (callbacks)

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Wrapping C and C++ Libraries

```
# cython: cdivision=True
cdef class Integrand:
     cdef double f(self, double x):
         raise NotImplementedError()
cdef class MyFunc(Integrand):
     cdef double f(self, double x):
          return x*x*x*x - 3 * x
def integrate_f(Integrand integrand,
                double a, double b, int N):
    cdef double s = 0
    cdef double dx = (b - a) / N
    cdef Py_ssize_t i
    for i in range(N):
        s += integrand.f(a + i * dx)
    return s * dx
```

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Exploring Cython Further

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Handling NumPy Arrays

- Declaring the MemoryView type
- Declaring the Numpy Array type
- Matrix Multiplication
- Our Own MatMul

Parallelization

Wrapping C and C++
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Declaring the MemoryView type

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Declaring the MemoryView type

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Parallelization

Wrapping C and C++ Libraries

```
import numpy as np

def foo( double[:, ::1] arr ):
    cdef double[:, ::1] out = np.zeros_like(arr)
    cdef Py_ssize_t i, j
    for i in range( arr.shape[0] ):
        for j in range(arr.shape[1]):
        out[i, j] = arr[i, j] * i + j

    return np.asarray(out)
```

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Declaring the Numpy Array type

Lecture Material

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Handling NumPy Arrays

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- Declaring the Numpy Array type
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Parallelization

Wrapping C and C++ Libraries

An alternative to the MemoryView syntax that corresponds more closely with ndarray dtypes:

```
cimport numpy as cnp
import numpy as np

def foo( cnp.ndarray[cnp.float64_t, ndim=2] arr ):
    cdef cnp.ndarray[cnp.float64\_t, ndim=2] out =
        np.zeros_like(arr)
    cdef Py_ssize_t i, j
    for i in range(arr.shape[0]):
        for j in range(arr.shape[1]):
        arr[i, j] = i + j

    return out
```

Different types are defined in Cython/Includes/numpy.pxd.

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Matrix Multiplication

Lecture Material

Introduction

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Handling NumPy Arrays

- Declaring the MemoryView type
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- Matrix Multiplication
- Our Own MatMul

Parallelization

Wrapping C and C++
Libraries

```
rows_A, cols_A = A.shape[0], A.shape[1]
rows_B, cols_B = B.shape[0], B.shape[1]
out = np.zeros(rows_A, cols_B)
# Take each row in A
for i in range(rows_A):
    # And multiply by each column in B
    for j in range(cols_B):
         for k in \
              range(cols_A):
                                                       b<sub>1,2</sub>
              s = s + A[i, k] *
                                                       b<sub>2,2</sub>
                        B[k, j]
         out[i, j] = s
                                        a<sub>1,1</sub> a<sub>1,2</sub>
```

Our Own MatMul

We won't even try this in pure Python (way too slow).

```
def dot( double[:, ::1] A,
```

double[:, ::1] B,

s = 0

double[:, ::1] out):

Handling NumPy Arrays

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 Declaring the MemoryView type

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Wrapping C and C++ Libraries

```
Py_ssize_t rows_A, cols_A, rows_B, cols_B
Py_ssize_t i, j, k

double s

rows_A, cols_A = A.shape[0], A.shape[1]
rows_B, cols_B = B.shape[0], B.shape[1]

# Take each row in A
for i in range(rows_A):
    # And multiply by every column in B
    for j in range(cols_B):
```

for k in range(cols_A):

= s + A[i, k] * B[k, i]

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Parallel Loops with «prange»

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- Parallel Loops with
- «prange»

Wrapping C and C++ Libraries

```
@cython.boundscheck(False)
@cython.wraparound(False)
def pdot(double[:, ::1] A,
         double[:, ::1] B,
         double[:, ::1] out):
    cdef:
        Py_ssize_t rows_A, cols_A, rows_B, cols_B
        Py_ssize_t i, j, k
        double s
    rows_A, cols_A = A.shape[0], A.shape[1]
    rows_B, cols_B = B.shape[0], B.shape[1]
    with nogil:
        # Take each row in A
        for i in prange (rows_A):
            # And multiply by every column in B
            for j in range(cols_B):
                 s = 0
                 for k in range(cols_A):
                     s = s + A[i, k] * B[k, j]
```

Benchmark!

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Wrapping C and C++ Libraries

- Fortran
- External Definitions
- Build: Link Math Library
- C++ Class Wrapper
- C++ Class Wrapper
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- C++ Class Wrapper
- In conclusion...

Wrapping C and C++ Libraries

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Fortran

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- Build: Link Math Library
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- C++ Class Wrapper
- C++ Class Wrapper
- C++ Class Wrapper
- In conclusion...

We won't be talking about that here, but Ondrej Certik has some excellent notes:

http://fortran90.org/src/best-practices.html#interfacing-with-python

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External Definitions

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- C++ Class Wrapper
- In conclusion...

Create a file, trig.pyx, with the following content:

```
cdef extern from "math.h":
    double cos(double x)
    double sin(double x)
    double tan(double x)

    double M_PI

def test_trig():
    print('Some trig functions from C:',
        cos(0), cos(M_PI))
```

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Build: Link Math Library

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- C++ Class Wrapper
- In conclusion...

```
namespace geom {
    class Circle {
    public:
        Circle(double x, double y, double r);
        ~Circle();
        double getX();
        double getY();
        double getRadius();
        double getArea();
        void setCenter(double x, double y);
        void setRadius(double r);
    private:
        double x;
        double y;
        double r;
    };
```

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```
cdef extern from "Circle.h" namespace "geom":
    cdef cppclass Circle:
        Circle(double, double, double)
        double getX()
        double getY()
        double getRadius()
        double getArea()
        void setCenter(double, double)
        void setRadius(double)
```

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```
cdef class PyCircle:
    cdef Circle *thisptr

def __cinit__(self, double x, double y, double r):
    self.thisptr = new Circle(x, y, r)
```

```
def __dealloc__(self):
    del self.thisptr
```

```
@property
def area(self):
    return self.thisptr.getArea()
```

```
@property
def radius(self):
    return self.thisptr.getRadius()

def set_radius(self, r):
    self.thisptr.setRadius(r)

@property
```

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- In conclusion...

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In conclusion...

- Build functional and tested code
- Profile
- Re-implement bottlenecks (behavior verified by tests)
- Et voilà—high-level code, low-level performance. [It's no silver bullet, but it's still pretty good.]



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