Speeding up scientific Python code using Cython

Advanced Python Summer School, Kiel

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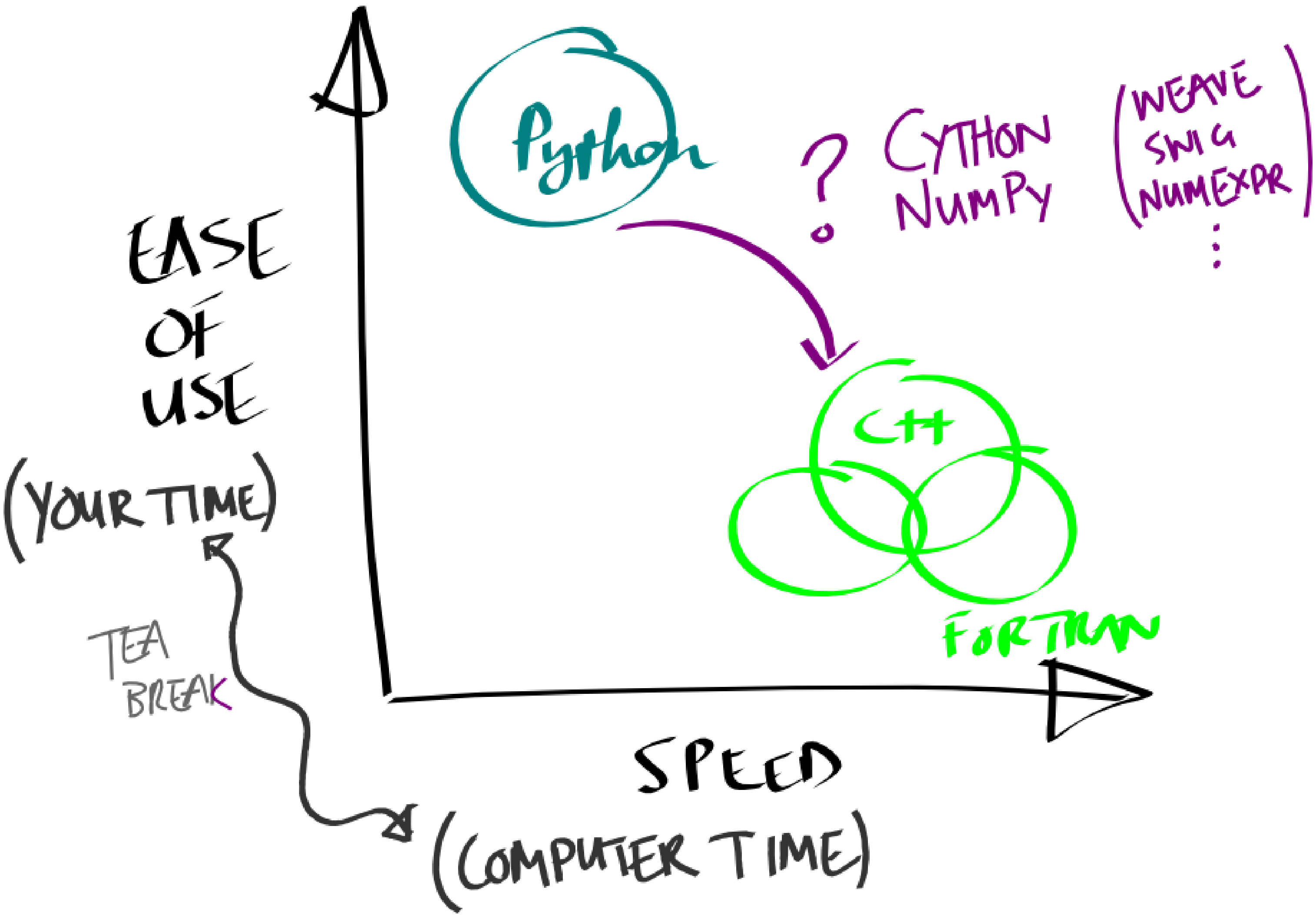
Example Code

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

Introduction

Motivation



Python
?
CYTHON
NUMPY
WEAVE
SWIG
NUMEXPR
C++
FORTRAN
EASE OF USE
(YOUR TIME)
TEA BREAK
SPEED
(COMPUTER TIME)

Motivation (continued)

- 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?*
- Conditions / loops approx. 2–8x speed increase, 30% overall; with annotations: hundreds of times faster

Use Cases

- Optimize execution of Python code (profile, if possible! – demo)
- 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

Tutorial Overview

For this quick introduction, we'll take the following approach:

1. Take a piece of pure Python code and benchmark (we'll find that it is too slow)
2. 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 much faster)

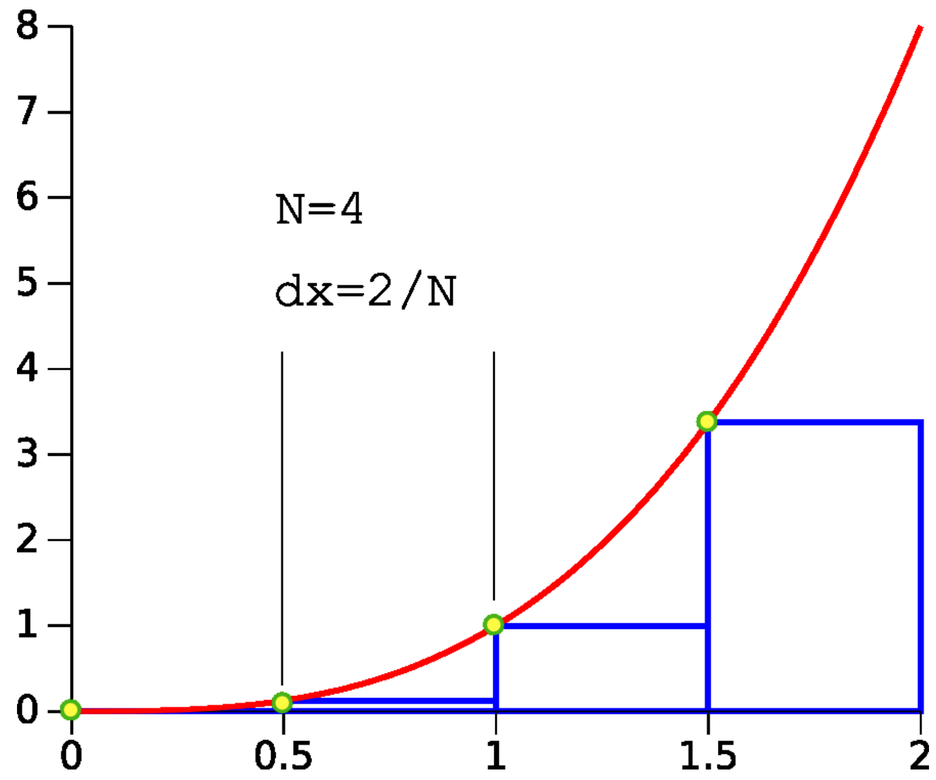
Then we'll look at how Cython allows us to

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

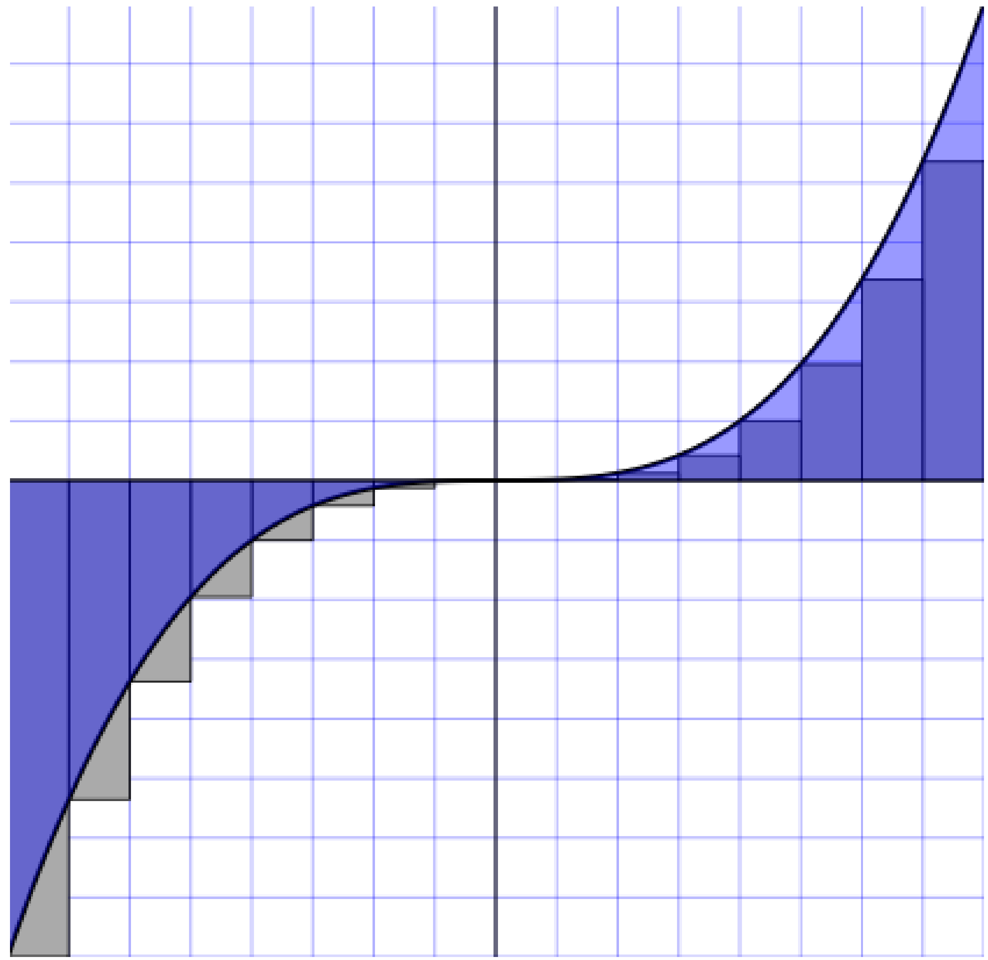
From Python to Cython

Benchmark Python code

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



More Segments



Benchmark Python Code

```
from __future__ import division

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

def integrate_f(a, b, N):
    """Rectangle integration of a function.

    Parameters
    ----------
    a, b : int
        Interval over which to integrate.
    N : int
        Number of intervals to use in the discretisation.

    """
    s = 0
    dx = (b - a) / N
    for i in range(N):
        s += f(a + i * dx)
    return s * dx
```

Compile the code with Cython

- `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.*

Compile generated code

```
$ gcc -O2 -fPIC -I/usr/include/python2.7
  -c integrate.c -o integrate_compiled.o
```

Easier yet, construct `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 extensions «in-place».`

Benchmark the new code

- `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

```
from __future__ import division

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

def integrate_f(double a, double b, int N):
    """Rectangle integration of a function.
    ...
    """
    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
```

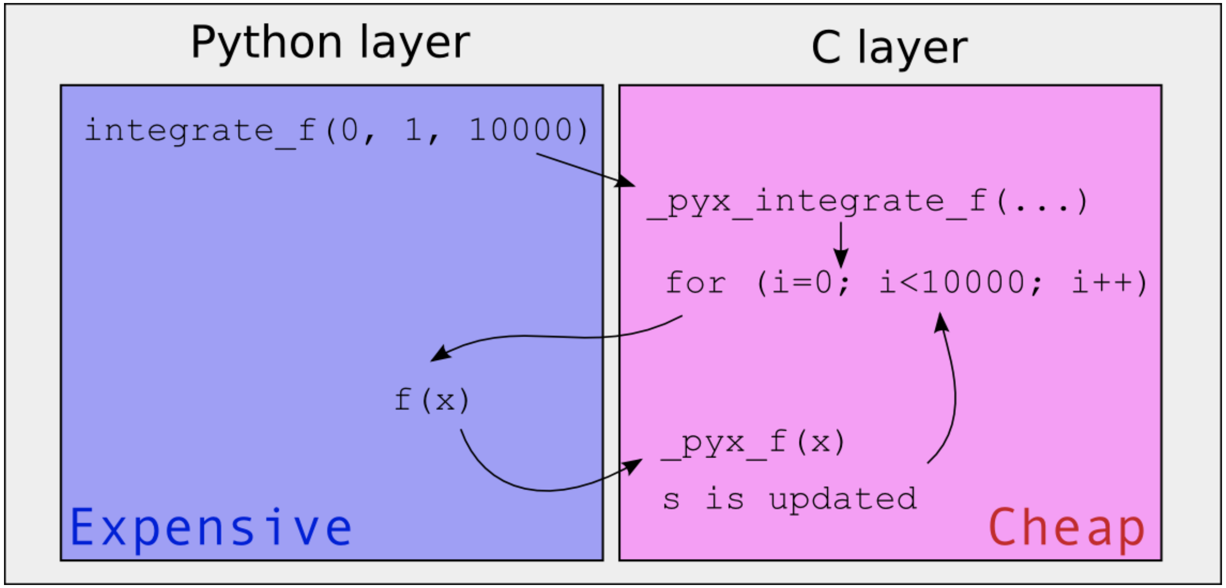
Benchmark...

Expense of Python Function Calls

```
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

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
        size_t i

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

Benchmark!

Integrating Arbitrary Functions (callbacks)


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

Exploring Cython Further

Handling NumPy Arrays

Declaring the MemoryView type


```
import numpy as np

def foo(double[:, ::1] arr):
    cdef double[:, ::1] = np.zeros_like(arr)
    cdef size_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)
```

Declaring the Numpy Array type

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, ndim=2] arr):
    cdef cnp.ndarray[cnp.float64, ndim=2] out = np.zer
    cdef size_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`.

Matrix Multiplication

```
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):
        s = 0
        for k in \
            range(cols_A):
            s = s + A[i, k] *
                    B[k, j]

        out[i, j] = s
```

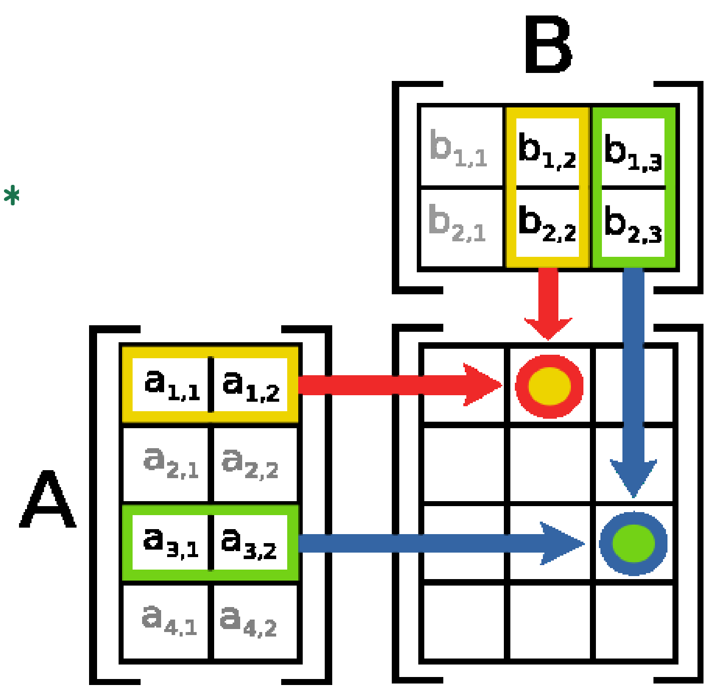


Image credits: http://en.wikipedia.org/wiki/File:Matrix_multiplication_diagram_2.svg

Our Own MatMul

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

```
def dot(double[:, ::1] A,
        double[:, ::1] B,
        double[:, ::1] out):

    cdef:
        size_t rows_A, cols_A, rows_B, cols_B
        size_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):
            s = 0
            for k in range(cols_A):
                s = s + A[i, k] * B[k, j]
            out[i, j] = s
```

Parallelization

Parallel Loops with «prange»


```
@cython.boundscheck(False)
@cython.wraparound(False)
def pdot(double[:, ::1] A,
         double[:, ::1] B,
         double[:, ::1] out):
    cdef:
        size_t rows_A, cols_A, rows_B, cols_B
        size_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]

                out[i, j] = s
```

Benchmark!

Wrapping C and C++ Libraries

Fortran

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

External Definitions

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)
```

Build: Link Math Library


```
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("trig" ,
                  ["trig.pyx"],
                  libraries=["m"] ,
        ),
])
```

C++ Class Wrapper


```
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;
    };
}
```

C++ Class Wrapper


```
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)
```

C++ Class Wrapper

```
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
    def center(self):
        return (self.thisptr.getX(), self.thisptr.getY
```

C++ Class Wrapper


```
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("circ", ["circ.pyx", "Circle.cpp"],
                       language="c++"),
        Extension("trig", ["trig.pyx"],
                      libraries=["m"]),
])
```

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.]