

# Cython Tutorial

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# Getting set up

Tutorial source files should be on USB stick. Also:

<http://github.com/dagss/cython-pydata12>

Cython relies on:

- A C/C++ compiler (can be a problem on Windows)
- Python development headers  
(Ubuntu: `sudo apt-get install python-dev`)

Using scientific Python distributions (such as EPD) solve both of these.

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If you distribute software in source code form, your users will need the above too.

# Cython at a glance

- Cython is used for compiling Python-like code to machine-code
  - superset of Python
  - conditions and loops run 2-8x faster, overall 30% faster for plain Python code (vs. Py2.5, using PyBench)

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- How it works: Cython code is turned into C code which uses the CPython API and runtime.
  - Generated C code can be built and run without Cython installed
- Has its share of warts, but works now!

**Coding in Cython is like coding in Python and C at the same time!**

# Usecase 1: Library wrapping

- Cython is a popular choice for writing Python interface modules for C libraries
- Works very well for writing a higher-level Pythonized wrapper
- For 1:1 wrapping other tools might be better suited, depending on the exact usecase

Examples: Pytables, hdf4py, mpi4py, pyzmq, ...



## Usecase 2: Performance-critical code

Python	↔	C/C++/Fortran
High-level		Lower-level
Slow		Fast
No variables typed		All variables typed

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- Common procedure: Where speed is needed, use a compiled language, then wrap the code for use from Python
- Cython: Incremental optimization workflow
  - Optimize, don't re-write
  - Only the pieces you need

Examples: scikits-image, pandas, Sage, ...

# Not a usecase: Static type checking

- Cython is (partially) statically typed because it has too, not because it wants to
- You still need to run the program to catch a typo

# How Cython works

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- 1 A .pyx file is compiled by Cython to a .c file, containing the code of a Python extension module
- 2 The .c file is compiled by a C compiler
  - Special compiler flags dictated by the Python installation must be used

The result is a .so file (or .pyd on Windows) which can be `import`-ed directly into a Python session.

If you are wrapping a C++ library, one can use C++ instead of C.

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- distutils: `setup.py`
- Simple cases: `pyximport` automatically compiles on Python import
- Advanced cases: Use a *real* build tool
  - CMake, waf, SCons, Unix Makefiles, IDE projects...



## Exercise 1: Building a Cython module

- 1 Write some Python code in `example.pyx`
- 2 Get <https://github.com/dagss/cython-pydata12/hello>
- 3 To build: `python setup.py build_ext -i`
  - `python setup.py install` installs
- 4 Then simply `import example`
- 5 Finally have a look at the generated C code

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  - Purpose: Get better timer resolution
- Make sure the Cython-part of the benchmark does enough work, or you'll be benchmarking the (slow) speed of a Python for-loop

# Faster code: Adding types

Variables can be typed with a C-like notation:

```
cdef int two = 2
def func(int x):
    cdef int i, y = two * x
    cdef float z
    z = x / 3
    print z**2
    return z
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- All C types are available
- Conversion to and from Python objects happen automatically.
- Note that Python float and int and C float and int are different things.



# Faster code: cdef functions

Python function calls can be expensive – in Cython doubly so because one might need to convert to and from Python objects to do the call.

Therefore Cython provides a syntax for declaring a Cython-only function:

```
cdef double f(double x): return x**3 + 2*x**2
```

The downside is that the function is not available from Python-space. Using `cpdef` makes a fast version available to Cython and a slower one to Python:

```
cpdef double f(double x): return x**3 + 2*x**2
```

## Exercise 2: Adding types

Add types etc. to speed up the following code (name the file `integrate.pyx` for future reference):

```
from __future__ import division
def f(x): return 1/(x**3 + 2*x**2)
def integrate_f(a, b, N):
    s = 0
    dx = (b-a)/N
    for i in range(N):
        s += f(a+i*dx)
    return s * dx
```

- Use the `double` type for function values and domain, and `ssize_t` for integers.
- Expect about 100x speedup. It is easy to miss typing a variable; experiment and see what happens to speed then.
- Use the `-a` switch to the `cython` command-line tool; the generated view of the code explains the speed differences
- Experiment with letting `f` be declared `cdef` vs. `cpdef`.

# Raising exceptions from cdef functions

For speed reasons, some manual exception declarations must be done on cdef functions capable of raising exceptions.

You can always add "except \*" and not worry about this though.

```
cdef int is_monday() except -2:
    # Must never return -2 explicitly!
    return time.localtime().tm_wday == 0

cdef int divide(int a, int b) except? 45345:
    # If result is 45345, make an additional check
    return a // b # possible ZeroDivisionError

cdef int divide(int a, int b) except *:
    # I'd rather not bother, just ask Python
    return a // b
```

# Calling C functions

One *can* do “from math import sin” to get Python’s sin function. Calling C’s sin function is faster though:

```
cdef extern from "math.h":  
    double sin(double)  
# or:  
# from libc.math cimport sin  
  
cdef double f(double x):  
    return sin(x * x)
```

Note that one must “redeclare” the function from `math.h` for the benefit of Cython. In the C compilation stage, only the declaration in `math.h` is seen.

# Calling C functions

When calling C functions, one must take care to link in the appropriate libraries. In `setup.py`:

```
...  
    Extension("integrate", ["integrate.pyx"],  
              libraries=["m"]) # Unix-like specific  
...
```

### Exercise 3: Call a C function

Just make sure you now know how to calculate  $\int_a^b \sin(x^2) dx$ .  
Check the speed difference between calling Python's `sin` and C's `sin`.

# NumPy and Cython

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- Optimize an array expression like `1.2 * a + b + np.sqrt(c)`
  - Helps because it reduces memory bandwidth
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- Optimize an array expression like `1.2 * a + b + np.sqrt(c)`
  - Helps because it reduces memory bandwidth
  - `numexpr` and `Theano` solves the same problem
- Push data between NumPy arrays and C/C++/Fortran libraries

## Exercise 4: Optimize pixel-domain convolution

Check out the `integrate` example and speed it up.

- Use the `float` type (32-bit floating point data) for values, `ssize_t` for indices
- NumPy arrays should be typed:

```
import numpy as np
cimport numpy as cnp
cnp.import_array()
def convolve2d(cnp.ndarray[float, ndim=2] f, ...)
```

- Headers needed for the C compiler as well. In `setup.py`:

```
Extension("cy_convolve", ["cy_convolve.pyx"],
          include_dirs=[np.get_include()])
```

# Object-oriented programming

Cython has two kinds of classes:

- Normal Python classes. These are exactly like Python's classes.
- Extension types/ “cdef classes”
  - Store typed attributes (avoid converting to/from Python object)
  - Faster method calls when called from Cython
  - Between different Cython modules, .pxd-files are needed to export the cdef class interface

```
cdef class MyClass:  
    cdef int value  
    cpdef int some_method(self, int arg):  
        ...
```

Normal Python classes (also in pure Python code) can inherit from cdef classes, but not the other way around.

# cdef class polymorphism

Methods of cdef class objects can be called much faster than methods on regular objects, *if* the variable is typed.

```
untyped = MyClass(arg1, arg2)
cdef MyClass typed = untyped
untyped.some_cpdef_method() # slow
typed.some_cpdef_method()  # fast
```

Regular Python classes can not be used as the type of a variable.

# cdef class attributes

Attributes are different from regular classes:

- All attributes must be pre-declared at compile-time
- Attributes are by default only accessible from Cython (typed access)
- Properties can be declared to make the attribute accessible from Python-space

```
cdef class SineWave(DoubleFunction):  
    cdef double offset # not available in Python-space  
    cdef public double frequency # available in Python-space  
    property period:  
        def __get__(self): return 1.0 / self.frequency  
        def __set__(self, value): self.frequency = 1.0 / value  
    ...
```

Special methods have some differences from regular classes:

- `__cinit__` is, unlike `__init__`, guaranteed to be called exactly once per object
  - `__init__` is available as well
  - Take care: Might be called before the Python object has been fully constructed!
  - Rationale: Improper initialization of C attributes can cause leaks or crashes.

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- `__dealloc__` is called when the object is deallocated
- Arithmetic operators, pickling etc. are different as well

# The None issue

- For convenience, variables declared as having a cdef class type can be assigned None.
- By default, accessing None in such a “typed” fashion will lead to undefined behaviour (hopefully a crash). Always test with `is None` first!
- The `nonecheck` *compiler directive* will raise an exception instead; but slows down all such accesses.

```
import cython
@cython.nonecheck(True)
def func():
    cdef MyClass obj = None
    try:
        print obj.myfunc() # raises exception
    except AttributeError:
        pass
    with cython.nonecheck(False):
        print obj.myfunc() # hope for a crash!
```

## Exercise 5: Using cdef classes in the integration example

Until now, the function to integrate has been hardcoded. Let's use cdef classes to create callbacks without too much of a penalty.