

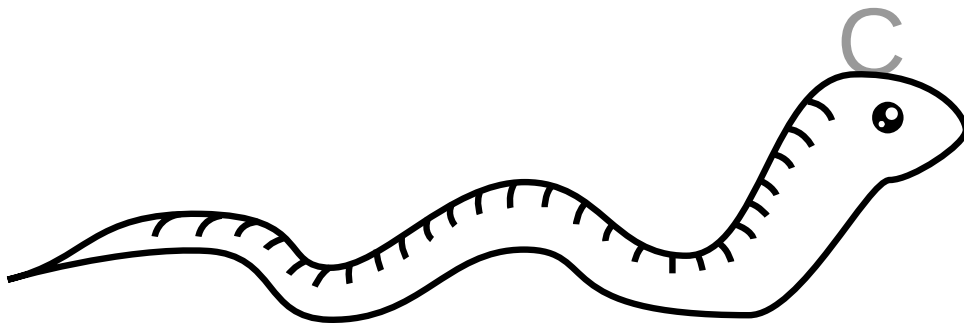
Python 3 for scientific computing

Lecture 8, 28.3.2018

High-performance computing (HPC) in Python

Juha Jeronen

juha.jeronen@tut.fi



Spring 2018, TUT, Tampere
RAK-19006 Various Topics of Civil Engineering



TAMPERE
UNIVERSITY OF
TECHNOLOGY

HPC in Python

- Python itself is a (very) high-level language, and (comparatively speaking) can be slow.
- Performance-critical computations require acceleration tools, such as:

- **NumPy, SciPy**

- *NumPy is already an acceleration tool* (much faster than Python loops), if your math is expressed in the tensor formalism. However, single-core only (**unless multicore BLAS**).
- Similarly, *SciPy already provides excellent performance* for standard math problems, simply by using LAPACK et al.

⚠ Cython not to be confused with CPython, the de-facto standard Python interpreter.



- **Cython**: C-Extensions for Python

- Statically compiled Python with extra syntax for easy embedding of fast C-like code.
- Creates native **extension modules** that can be **imported** like any Python modules.
- For custom low-level code, and for creating Python interfaces to existing low-level libraries.

- **Numexpr**: Fast numerical array expression evaluator

- Further accelerates NumPy. Optimizes memory use, uses multiple cores automatically.

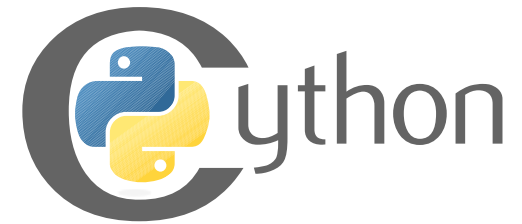
- **Numba**: JIT compiler

- *With a few annotations, array-oriented and math-heavy Python code can be **just-in-time compiled** to native machine instructions, similar in performance to C, C++ and Fortran, without having to switch languages or Python interpreters.*

- **Theano**

- *A Python library that allows you to define, optimize, and evaluate mathematical expressions involving multi-dimensional arrays efficiently.*
- No longer developed.

Cython



- Compiled language.
 - A superset of Python; can use a Python program as a starting point.
 - However, looking at Cython as just a static compiler for Python [is missing the point](#).
 - [Language basics](#) for new users.

Static compilation means offline, before program execution. Contrast [dynamic compilation](#). See also [incremental comp.](#)

- **Two main use cases:**

- **FFI (foreign function interface)**, to connect Python code to libraries written in C or C++.
 - See [simple-cython-example](#) and [scikit-sparse](#) for examples of Cython for FFI.
 - Other possibilities: [CFFI](#) (example in [sparseqr](#)), and [ctypes](#) in the standard library.
 - If you need a Fortran FFI instead, see [F2PY](#).
- ☆ • **Acceleration**, by allowing low-level algorithms to be implemented and manually tuned.
 - The level of abstraction can be closer to the underlying hardware than in pure Python. In effect, Cython transforms Python into a [wide-spectrum language](#).
 - Especially good for exploiting multiple cores: number-crunching code that needs only NumPy arrays does not need to hold the GIL.
- Compiles to C, which is then compiled to machine language via [GCC](#).
 - The result is an extension module, which can be imported just like any Python module.
 - The compiled code skips the Python interpreter, calling directly into the [Python C API](#). This is slightly faster, but not much.
 - Number-crunching loops accessing only NumPy arrays *may compile to native C code, skipping Python altogether!* This may be **up to two orders of magnitude faster**.
 - Ideal for inherently serial algorithms, or when (part of) an algorithm is much easier to express as a traditional loop over array elements rather than as a tensor operation.
 - The C-like extra syntax [has some differences](#) to the actual C language.

Cython



- **Advantages:**

- Approachable to Python users: just Python, with some extra syntax.
- Number-crunching loops compiled to machine language, can be very fast (if the algorithm is).
- True parallelism for custom [multithreaded](#) number-crunching in Python.
 - Also extremely easy to leverage OpenMP for parallel loops over NumPy arrays.
- Excellent integration with Python.
 - Just import your Cython module, no need to care it's written in another language.
- Easy-ish tool for FFI. (So is CFFI.)

- **Drawbacks:**

- Limited support in IDEs and text editors, which tend to focus on pure Python. Acceleration of Python code usually a concern only in the scientific computing community.
 - Spyder has Cython syntax highlighting, but no graphical debugger for Cython.
 - PyCharm has full Cython support, but only in the commercial edition.
 - [Cython syntax highlighting](#) data file for [gedit](#) (actually, for [GtkSourceView](#) that it uses).
- Can be somewhat clumsy:
 - No REPL: must make a module, compile, and import it.
 - Not an inherent limitation of compiled languages; just a common choice in the C family. Python has a REPL, although it internally uses a compiler. Lisps have a REPL; some of them compile to machine code.
 - Need to create and maintain a compile script (*setup.py*).
 - Very basic static type system, just like in C; often gets in your way instead of being helpful.
 - Binaries are platform-dependent; the [distribution process](#) can be much more involved.
- Smaller community, compared to pure Python.
 - May need to look at the generated C code to analyze what exactly is going wrong, instead of just asking the Internet.
 - All input Cython code is included as comments, though, so it's easy to find the right spot.
- To do (or understand) some things, may need to know a bit of C.

Cython



- **Simple example:** a naive `ddot`, let's call it `ddot.pyx`:

```
def ddot(double[:,1] a, double[:,1] b): # vector-vector dot product, double precision
    cdef unsigned int k
    cdef unsigned int n = a.shape[0] # memoryviews have a .shape, just like NumPy arrays
    cdef double out = 0.0

    for k in range(n): # Becomes a C loop when compiled. Cython knows the datatypes
        out += a[k] * b[k] # and memory layouts, and no Python objects are used here.

    return out
```

Memoryviews don't support `out[:] = a[:] * b[:]`, so we loop explicitly.

- New keywords `double`, `unsigned`, `int`, `cdef`, `nogil`
 - The IEEE-754 double precision float datatype is called `double`, like in C
 - `int` is a native integer, either 32 or 64 bits, depending on platform
 - `unsigned` means no sign bit is used; values are 0, 1, ..., $2^m - 1$, where m is 32 or 64.
 - `cdef`, when used for variables, denotes a type declaration.
 - Optional. If a name is used without a `cdef`, the default type is general Python object.
 - Technically speaking, since `k`, `n` and `out` have a primitive datatype, they are **variables** – *names for fixed storage locations*, like in C. Now e.g. `k += 1` **actually mutates** the variable.
- Explicit memory layout: the pythonic syntax `[:,1]` denotes a *contiguous* rank-1 array.
- `range()` now comes from Cython, not from Python, although it looks the same.
- The loop now runs at native speed, but doesn't yet release the GIL. (See next slide.)
- For more, see [Cython for NumPy users](#).

Cython



- Releasing the GIL. A naive $O(n^3)$ `dgemm` (note: *better algorithms exist!*):

```
import numpy as np    # just a usual Python import
```

```
def dgemm(double[:,::1] A, double[:,::1] B):    # matrix-matrix multiply, double precision
    cdef unsigned int i, j, k
    cdef unsigned int n = A.shape[0]
    cdef unsigned int m = B.shape[1]    # the datatype double[:,::1] ensures ndim=2.
    cdef unsigned int p = A.shape[1]
    cdef double[:,::1] out = np.zeros((n,m), dtype=np.float64, order='C') # or empty(), ones(), ...

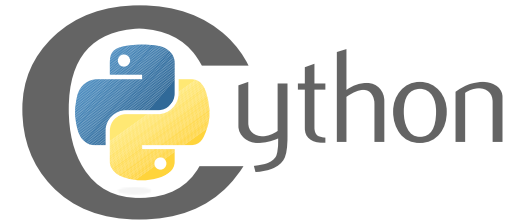
    if B.shape[0] != p:
        raise ValueError('Incompatible input shapes ({:d},{:d}), ({:d},{:d})'.format(n,p,B.shape[0],m))

    with nogil:
        for i in range(n):
            for j in range(m):
                for k in range(p):
                    out[i,j] += A[i,k] * B[k,j]

    return np.asanyarray(out)    # return np.array, not memoryview (with no extra copying of data)
```

- The “context manager” **with nogil**: releases the GIL for the dynamic extent of the **with** block.
- Almost always, `np.array` is a good choice for *dynamically allocated*, but immutable-size arrays.
 - **Cython can use** C primitives `malloc/free` (no need for GIL!), but very painful (just like in C).
- **Memoryviews** talk with `np.arrays` seamlessly, except at output (**return**) must be converted.
 - When creating the array, we use `order='C'` to be explicit that we want a `[:,::1]`.

Cython



- What exactly happens in the *np.array* ↔ *memoryview* conversion:

```
import numpy as np
```

```
def test():
```

```
    A = np.random.random((5,5))
```

```
    cdef double[:,::1] B = A
```

```
    C = np.asanyarray(B)
```

```
    print(A is C)
```

```
    print([type(x) for x in (A,B,C)])
```

```
    addr_A, readonly_flag_A = A.__array_interface__['data']
```

```
    addr_C, readonly_flag_C = C.__array_interface__['data']
```

```
    print("{:x}, {:x}, {:x}".format(addr_A, <unsigned long long>&B[0,0], addr_C)) # same!
```

& is Cython (and C) for “take the memory address of”. Python-level code can use **id** and **is**, as usual.

It **must** work like that, because this line does not refer to “A”.

False; A and C are different np.array instances

B is a memoryview; A and C are np.arrays

- We first create an *np.array*, and bind it to the name *A*, as a general Python object.
- Then, the line with the **cdef**:
 - We first declare a C-contiguous memoryview, with the name “B”.
 - We attempt to bind the name “B” to point to the same object as “A”, but “A” is an *np.array*.
 - Cython **implicitly converts** “A” to a memoryview.
 - ⚠ Recall that pure Python *makes no implicit conversions*. This is different in Cython.
 - Finally, this new memoryview instance is bound to the name “B”.
 - We could put this on one line as **cdef double[:,::1] B = np.random.random((5,5))**
 - In that case, even though the original *np.array* disappears, the data inside it – strictly speaking, the exact same region of memory – lives on in the memoryview instance.
- np.asanyarray()* reverses the conversion, wrapping the same memory back into a new *np.array*.
 - For returning a memoryview, an explicit conversion is needed, because Cython will **return** the exact object instance we tell it to. Alternatively, we can return “A”, already an *np.array*.

Cython



- **C functions.** The previous examples are, in principle, usual Python functions, although they contain some C-like code and they are compiled into a native extension module.
- To avoid Python's [high overhead for function calls](#), Cython provides **C functions**, which are:
 - “called at the C level”, using the faster C [calling conventions](#).
 - **not visible to Python modules** – can only be called from Cython code.
 - “Cython code” includes also any regular (**def**) functions in Cython modules.

```
cdef double cddot(double[:,1] a, double[:,1] b) nogil: # keyword cdef makes a C function.
    cdef unsigned int k
    cdef unsigned int n = a.shape[0]
    cdef double out = 0.0

    for k in range(n):
        out += a[k] * b[k]

    return out
```

- Note optional C-like type declaration for the return value, just before the function name.
- **nogil** at the end of the function signature means that this C function **may be called also** when the GIL is not held. (This implies the function cannot use any Python objects!)
 - *This does not release the GIL*; it allows calls **also** without the GIL.
- C functions, by default, **cannot propagate Python exceptions** to the caller, but they can tag a special [error return value](#) to add this functionality. Use an **except** keyword at the end of the function signature, just use exceptions as usual, and **never manually return the tagged value**.
- See also [Cython Function Declarations](#); and [Early Binding for Speed](#).
- Beside **cdef**, there is also **cpdef**, which means “define this function for both C and Python”.

Cython



- **Summary, language basics:**

- Cython significantly accelerates **for** loops that use only *np.arrays* ($\approx 100\times$ over pure Python).
 - Needs static type information so that the loop can be compiled to C.
 - Must be provided by the programmer, in the form of type declarations (**cdef**).
- To avoid Python's high overhead for function calls, Cython provides **C functions** (also **cdef**).
 - A C function can be declared callable without the GIL by appending **nogil** to the signature.
- When you don't need Python objects except *np.arrays*, you can **release the GIL with nogil**:
 - **Danger: with nogil**: is in effect *during the dynamic extent of the with block* – not lexically!
 - In other words, it behaves just like a context manager.
 - **Danger**: Trying to release the GIL when it is already released **will crash the program**.
 - **Design carefully**; combine with **nogil**. In each thread, use at most one **with nogil**: at a time; but it may safely call, also in a nested manner, any C functions which are **nogil**.
- NumPy arrays in Cython:
 - A good choice for **dynamically allocated**, but immutable-size arrays. Garbage-collected.
 - At the C level, access via typed **memoryviews**. At the Python level, just use as usual.
 - **Memory layout** can be C-contiguous **[::1]**, Fortran-contiguous **[::1, ..., :]**, or general.
 - General layouts are denoted by predefined constants; to use them, **cimport cython.view**
 - **Important**: A fast C loop will only be generated **if the array is contiguous, and Cython knows it** (from a datatype declaration)!
 - Access to a fully general memory layout cannot be accelerated (as much), because then the only way to find out where the data is, is to ask the memoryview for that information.

Cython



- Parallel loops:

```
import numpy as np
```

→ `cimport cython.parallel` # note **cimport** instead of **import** (explanation on next slide)

```
def pdgemm(double[:,::1] A, double[:,::1] B): # parallel dgemm
```

```
    cdef int i, j, k
```

```
    cdef int n = A.shape[0] # indices are signed in OpenMP < 3.0
```

```
    cdef int m = B.shape[1]
```

```
    cdef int p = A.shape[1]
```

```
    cdef double[:,::1] out = np.zeros((n,m), dtype=np.float64, order='C')
```

```
    if B.shape[0] != p:
```

```
        raise ValueError('Incompatible input shapes ({:d},{:d}), ({:d},{:d})'.format(n,p,B.shape[0],m))
```

```
    with nogil:
```

→ `for i in cython.parallel.prange(n):` # ← parallel loop

```
        for j in range(m):
```

```
            for k in range(p):
```

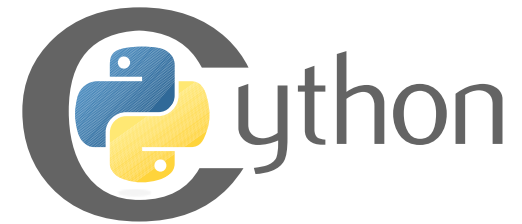
```
                out[i,j] += A[i,k] * B[k,j] # arrays can be accessed as usual
```

```
    return np.asarray(out)
```

⚠ **OpenMP** not to be confused with **Open MPI**.

- Uses **OpenMP** (Open Multi-Processing). Needs compiler and linker options to enable OpenMP.
- **Available only at the C level**; no access to Python objects in parallel code.
- `prange()` must either be inside a **with nogil**: block, or use the magic kwarg `nogil=True`.
- May only be used from the main thread or parallel regions due to OpenMP restrictions.
- For more (e.g. thread-local variables), see **Parallelism** in the Cython documentation.

Cython



- **Cython's import system.** Both of these are valid, but each works for a different reason:

```
cimport cython.parallel
```

```
def do_stuff():  
    cdef unsigned int i, n=10  
    ...  
    with nogil:  
        for i in cython.parallel.prange(n):  
            ...  
    ...
```

```
import cython.parallel
```

```
def do_stuff():  
    cdef unsigned int i, n=10  
    ...  
    for i in cython.parallel.prange(n, nogil=True):  
        ...  
    ...
```

-
- **cimport** is like C's `#include <something.h>`
 - Brings in **C-level definitions**
 - Just like **cdef**, seen only by Cython code
 - **import** is just Python's **import**
 - Brings in **Python modules or objects**, as usual
 - Works just like in any Python code
-
- **Be precise.** For example, trying to **import** `cython.parallel` and then use it in a **with nogil**: block *is a compile-time error*, because **Python objects** cannot be used with the GIL released! But using a **C-level definition** with the GIL released is fine.
 - `cython.view` must be **cimported** (not **imported**!), because the things that are used to denote general memory layouts are defined as **C-level constants**.
 - NumPy must be **imported** (not **cimported**!), because the things we need from it (such as `np.empty()`, `np.asarray()`) are **Python functions**.

Cython



- **Definition files:**
 - Like in C, Cython code can be split to separate *definition* and *implementation* files. For example, for functions:
 - A *definition* states that a function with a certain name exists, and specifies its signature.
 - An *implementation* contains the actual code.
 - Definition files are used to export functions at the C level – i.e. to make them available for other Cython modules to **cimport**.
 - If a module is intended not to export anything at the C level, no definition file is needed.
- **Implementation files** have the file extension **.pyx**
- **Definition files** have the file extension **.pxd**; they play a role similar to C's **header files** (.h).
- Roughly, in C terms a *declaration* corresponds to a Cython *definition*, and a C *definition* corresponds to a Cython *implementation*. (Edge cases **slightly complicate matters**.)
- Contrast pure Python, which requires only an implementation. Separate definitions are typically a feature of statically compiled languages; functions are looked up statically instead of at runtime, as in Python.
 - Roughly speaking. We have ignored C++'s **virtual methods**, which use a limited form of runtime lookup to account for the object's *dynamic type*. (Recall lecture 3, slide 45.)
 - A declaration gives the *compiler* enough information to resolve the reference, whereas the definition provides what the **linker** needs to concretely fix the function to be called.
- See **Sharing Declarations Between Cython Modules** in the Cython documentation.

Cython



- Definition files – example:

```
# mysum.pxd
cdef double sum(double[:,1] a) nogil
```

```
# mysum.pyx
cdef double sum(double[:,1] a) nogil:
    cdef unsigned int k, n = a.shape[0]
    cdef double out = 0.0
    for k in range(n):
        out += a[k]
    return out
```

```
# mysum_test.pyx
import numpy as np
cimport mysum
```

```
def test():
    a = np.arange(10, dtype=np.float64)
    print(mysum.sum(a)) # use just like any Python function (as long as the datatypes match)
```

```
# mysum_run.sh
python3 -c "from mysum_test import test; test()"
```

- Cython must be able to find *mysum.pxd* when compiling *mysum_test.pyx*.
 - This can sometimes be a source of headaches, especially when writing libraries. In Python 3, libraries use relative **imports**, but Cython doesn't fully seem to understand that.
 - One possible solution is to use absolute(-ish) **cimports**; see [setup-template-cython](#).

Cython



- **Extension types** (a.k.a. **cdef classes**):
 - On equal footing with Python's built-in types. Uses less memory and is faster than a class.
 - Uses a **C struct** to store fields and methods, instead of a Python dict.
 - Can store **arbitrary C types** in the fields without requiring a Python wrapper.
 - Can access fields and methods directly at the C level (without a dict lookup).
 - Cannot add or remove fields, or change their datatype, at runtime.
 - **Example**: creating a Python-level wrapper for a **generic C pointer** (a.k.a. *void pointer*, **void ***):

```
# ptrwrap.pxd
cdef class PointerWrapper:
    cdef void * data
    cdef set(self, void * p)
```

```
# ptrwrap.pyx
cdef class PointerWrapper:
    cdef set(self, void * p):
        self.data = p
```

```
# ptrwrap_test.pyx
import numpy as np
from ptrwrap cimport PointerWrapper
def test():
    cdef double[:,::1] A = np.empty((3,5), dtype=np.float64, order='C')
    cdef PointerWrapper pw = PointerWrapper()
    pw.set(&A[0,0])
    cdef double[:,::1] B = <double [:3,:5:1]>pw.data # specify size, a C pointer doesn't know!
main()
```

Where is this needed? To Python, a *PointerWrapper* is a Python object; it can be passed into a function as an argument, returned from a function, stored into the usual Python containers such as *list*, etc.

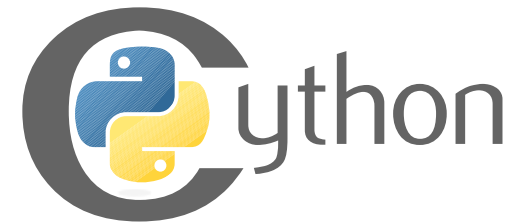
This can be convenient if your Cython code needs to pass pointers around internally, but the function to be called is a regular **def** function (Python function).

In real code, if a *PointerWrapper* is passed/stored as a Python object, cast it explicitly to a *PointerWrapper* before trying to access its *data* field, because it's a C field, not a Python attribute! [Code example](#).

Cast to the right type to later access the data.

In Cython, the size is specified using the slice syntax.

Cython



- The **Cython and C compilation steps** are separate; different compilers, different languages.
- Example: embedding [SSE2](#) assembly (for the [x86](#) family), via C FFI to SIMD [intrinsics](#).
- No ready-made *.pxd* for this exists. To declare (i.e. write Cython definitions for) the existing, external C functions we want to use, we must first tell Cython about the datatype `__m128d`, which is a pair of **double**s packed into one 128-bit item for SSE2-based [SIMD](#) processing:

```
cdef extern from "emmintrin.h": # emmintrin for SSE2
    typedef double __m128d

    __m128d _mm_loadu_pd (double * __P) nogil # (__P[0], __P[1]) are the input doubles
    __m128d _mm_add_pd (__m128d __A, __m128d __B) nogil
    __m128d _mm_mul_pd (__m128d __A, __m128d __B) nogil
    void _mm_store_pd (double * __P, __m128d __A) nogil # result written to (__P[0], __P[1])
```

- **Cython and GCC need different information:**
 - Cython must be told, within the constraints of its syntax, that *an* `__m128d` behaves *somewhat like a* **double** – so that it knows how to generate the C code correctly.
 - But the C compiler needs the exact definition – *an* `__m128d` is *not a* **double**, *but a pair of* **double**s. To get the Cython-generated C code to *#include* the actual original definition, so that the C compile step can work, we must **cdef extern from** the original header.
- [Full example on GitHub](#). (**Danger:** GCC-optimized C may be faster than manual assembly!)

Cython



- **Compiling**, or how to write a *setup.py*
 - Closely related to packaging and distributing Python projects; uses the same tools.
 - A large topic. See the [Packaging and Distributing Projects](#) tutorial by PyPA.
 - Still a moving target; update your skills regularly.
 - As of early 2018, the recommended framework is *setuptools*.
 - Cython's [documentation](#) is based on the older *distutils*, but the relevant parts are somewhat compatible.
 - [GCC compiler options for x86](#) may come in handy.
 - Examples too long to fit on a slide; see online:
 - A very minimal example for Cython compilation and distribution in [cython-sse-example](#).
 - A template for number-crunching projects using Cython: [setup-template-cython](#)
 - For compile only, no distribution, see its [test subfolder](#).
 - A template for FFI projects using Cython: [simple-cython-example](#)
 - Cf. a distribution script for a project using CFFI, but no Cython, in [sparseqr](#).
 - Cf. a distribution script for a pure-Python project, no compile, in PyPA's [sampleproject](#).
 - In simple cases, invoke with ***python setup.py build_ext --inplace***
 - *build_ext* compiles; *build* just copies .py files declared as belonging to packages.
 - If you know what you are doing, invoke with ***python setup.py build_ext***
 - The folder structure generated by this variant is very useful for making a package.

Cython



- **Performance:**

- Some [compiler directives](#) can be used to enable a significant performance boost.
 - [How to set them](#): per-function decorators, magic comments at start of file.
- Default settings:
 - *boundscheck=True*: Array accesses are bounds-checked, like in Python.
 - Safe (no mysterious crashes or program state corruption), but slow.
 - Once sure that there are no indexing-past-end bugs, consider disabling.
 - *wraparound=True*: Negative indices are allowed, like in Python.
 - Convenient, but slow. Disable, if sure that no negative indices are used.
 - *cdivision=False*: The division operator [uses Python semantics](#). Very slow!
 - Almost always, switch to C semantics.
- If your code is running suspiciously slowly:
 - First, invoke ***cython -a mymodule.pyx***
 - This produces ***mymodule.html***, showing the relative efficiency of the generated code.
 - Open it in a web browser to see your source, annotated (-a) with the generated C code.
 - Click on any line with a “+” in front of it to expand.
 - The more yellow a line is, the more Python work it is doing.
 - Lines that translate to pure C appear white.
 - For more detail, look at the generated C code. See e.g. if one of your loops:
 - queries the array for its [strides](#); if so, Cython doesn't know the array is contiguous. Likely the datatype declaration for the array variable is missing, or is missing the [::1](#).
 - calls any Python functions when manipulating the loop counter variable; if so, the datatype declaration for the loop counter is missing.

Cython

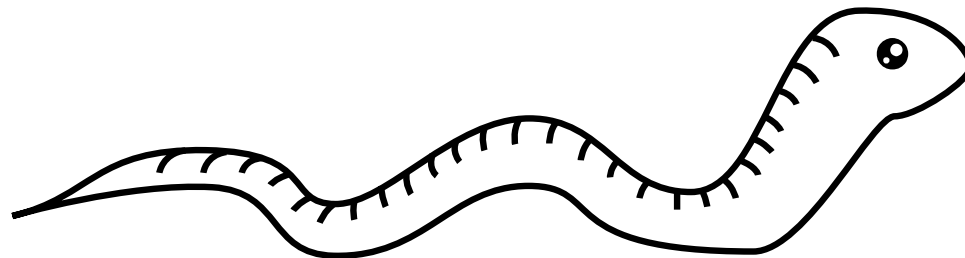


- **Final words:**
 - Regular Python modules can **import** Cython modules just fine – which is the point of Cython, i.e. providing acceleration selectively where needed. Usually there is a *main.py*, no *main.pyx*.
 - Our examples have used Cython only, just because we have concentrated on demonstrating Cython's C-level features.
 - We looked at **cdef extern from** to declare external functions when no ready-made *.pxd* definition file exists; but often there is one, such as *libc.math* or *scipy.linalg.cython_lapack*, so you can just **cimport** it. See [Calling C functions](#), and [includes provided with Cython](#).
 - In Cython modules, function signatures do not automatically appear in *help()*.
 - To work around this, manually copy the signature to the beginning of the function docstring – users will expect to see it.
 - (And remember to update the manual copy if you change the signature later.)
 - **Is it worth it?** If you need to write custom low-level code, **yes**.
 - Achieve true parallelism for CPU-bound workloads.
 - Achieve native speed – [the real deal](#), **-O3 C** – for number-crunching loops.
 - Eliminate [the cost of Python function calls](#).
 - ...all while not deviating *that* far from Python.
 - But keep in mind the [Pareto principle](#) – very often, it happens that 80% of your run time comes from 20% of the code.
 - **Identify that 20% before working too much on acceleration.**
 - “Premature optimization is the root of all evil” – [Donald Knuth](#)

Meta

Code examples

- The code examples shown in this slide set are [available on GitHub](#).
 - Some examples, particularly *ptrwrap*, have been slightly extended.
- A compile script (*setup.py*) is provided.
 - Simple, minimal, compile only; no distribution logic.
 - To use: ***python3 setup.py build_ext -inplace***
 - This command is also documented as *compile.sh*.
 - Feel free to use this *setup.py* as a template for your own Cython projects.
- All main programs have been packaged into *main.py*; except for *mysum* and *ptrwrap*, which have their own main programs.
- To run these two examples, import the relevant module and call its *test()* function; example invocations given in *mysum_run.sh* and *ptrwrap_run.sh*.



Meta

Next time

- Introduction to software engineering
 - I.e. *how to develop correct and maintainable software quickly*
 - Tools of the trade:
 - Basics of version control with *git* and GitHub
 - Debuggers
 - Profilers (finding that 20%, reliably)
 - How to write informative comments
 - Assertions, ensuring internal consistency
 - Automated [unit testing](#) to avoid new bugs, and catch [regressions](#)
- See you next week!

