

Modern Computational Economics and Policy Applications

A workshop for the IMF's Institute for Capacity Development

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Sides, code, personnel, course outline:

https://github.com/QuantEcon/imf_2024

Quick poll:

- Python programmers?
 - NumPy? Numba? PyTorch? JAX?
- Julia programmers?
- MATLAB programmers?
- C?
- Fortran?

This morning:

1. Bird's eye view of scientific computing
2. The AI revolution and its impact on scientific computing
3. The Python language and its scientific ecosystem
4. Working with Jupyter

Bird's eye view of scientific computing

Topics covered in these slides

1. traditional ahead-of-time (AOT) compiled languages
2. interpreted languages and the “vectorization” trick
3. beyond vectorization: modern just-in-time (JIT) compilers
4. parallelization

Traditional paradigm: static types and AOT compilers

Typical languages: Fortran / C / C++

Example. Suppose we want to compute the sequence

$$k_{t+1} = sk_t^\alpha + (1 - \delta)k_t$$

from some given k_0

Let's write a function in C that

1. implements the loop
2. returns the last k_t

```
#include <stdio.h>
```

```
#include <math.h>
```

```
int main() {  
    double k = 0.2;  
    double alpha = 0.4;  
    double s = 0.3;  
    double delta = 0.1;  
    int i;  
    int n = 1000;  
    for (i = 0; i < n; i++) {  
        k = s * pow(k, alpha) + (1 - delta) * k;  
    }  
    printf("k = %f\n", k);  
}
```


Pros

- fast loops / arithmetic

Cons

- low interactivity!
- time consuming to write large programs
- relatively hard to read / debug
- low portability
- hard to parallelize!!

For comparison, the same operation in Python:

```
 $\alpha$  = 0.4  
s = 0.3  
 $\delta$  = 0.1  
n = 1_000  
k = 0.2  
  
for i in range(n):  
    k = s * k** $\alpha$  + (1 -  $\delta$ ) * k  
  
print(k)
```

Pros

- high interactivity
- easy to write
- high portability
- easy to debug

Cons

- slow loops / arithmetic

Why is pure Python slow?

Pros

- high interactivity
- easy to write
- high portability
- easy to debug

Cons

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Why is pure Python slow?

Problem 1: Type checking

Consider the Python code snippets

Ints

$$x, y = 1, 2$$
$$z = x + y \quad \# \quad z = 3$$

Floats

```
x, y = 1.0, 2.0
```

$$z = x + y \quad \# \quad z = 3.0$$

Strings

```
x, y = 'foo', 'bar'
```

```
z = x + y      # z = 'foobar'
```


Problem 2: Memory management

```
>>> import sys
>>> x = [2.56, 3.21]
>>> sys.getsizeof(x) * 8      # number of bits
576                            # whaaaat???
>>> sys.getsizeof(x[0]) * 8   # number of bits
192                            # whaaaat???
```

Also, lists of numbers are pointers to dispersed int/float objects — not contiguous data

So how can we get

good execution speeds **and** high productivity / interactivity?

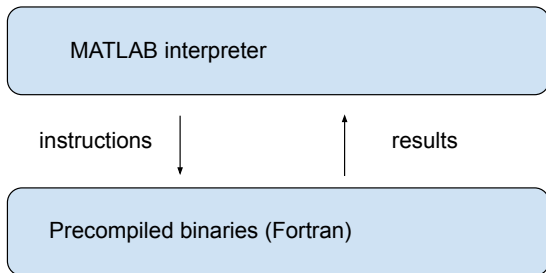
MATLAB

```
A = [2.0, -1.0  
      5.0, -0.5];
```

```
b = [0.5, 1.0]';
```

$$x = \text{inv}(A) * b$$

The vectorization trick



Python + NumPy

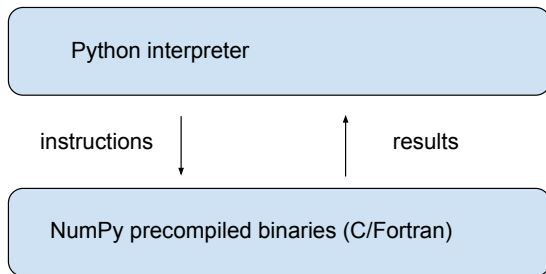
```
import numpy
```

```
A = ((2.0, -1.0),  
      (5.0, -0.5))
```

```
b = (0.5, 1.0)
```

```
A, b = np.array(A), np.array(b)
```

```
x = np.inv(A) @ b
```



Vectorization: the good, the bad and the ugly

Pros

- high interactivity / portability
- many scientific calculations can be framed as operations on arrays

Cons

- some tasks cannot be efficiently vectorized
- precompiled binaries cannot adapt flexibly to function arguments
- precompiled binaries cannot adapt flexibly to hardware

These last two issues turn out to be extremely important

Julia — rise of the JIT compilers

Can do MATLAB / NumPy style vectorized operations

```
A = [2.0  -1.0  
     5.0  -0.5]
```

```
b = [0.5  1.0]'
```

```
x = inv(A) * b
```

But also has fast loops via an efficient JIT compiler

Example. Suppose, again, that we want to compute

$$k_{t+1} = sk_t^\alpha + (1 - \delta)k_t$$

from some given k_0

- Iterative, not easily vectorized

```
function solow(k0, α=0.4, δ=0.1, n=1_000)
    k = k0
    for i in 1:(n-1)
        k = s * k^α + (1 - δ) * k
    end
    return k
end

solow(0.2)
```

Julia accelerates `solow` at runtime via a JIT compiler

Python + Numba copy Julia

```
from numba import jit

@jit
def solow(k0,  $\alpha=0.4$ ,  $\delta=0.1$ , n=1_000):
    k = k0
    for i in range(n-1):
        k = s * k** $\alpha$  + (1 -  $\delta$ ) * k
    return k

solow(0.2)
```

Runs at same speed as Julia / C / Fortran

Parallelization

For tasks that can be divided across multiple “workers,”

$$\text{execution time} = \text{time per worker} / \text{number of workers}$$

So far we have been discussing time per worker

- running code fast along a single thread

The other option for speed gains is

- divide up the execution task
- spread across multiple threads / processes

Parallelization is the big game changer powering the AI revolution

Market Summary > NVIDIA Corp

879.44 USD

✓ Following

+440.44 (100.33%) ↑ past 6 months

Closed: 14 Mar, 7:59 pm GMT-4 • Disclaimer

After hours 872.98 -6.46 (0.73%)

1D | 5D | 1M | **6M** | YTD | 1Y | 5Y | Max

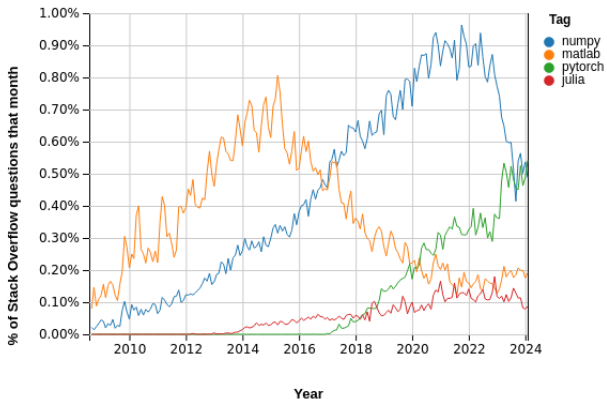


What economists need: software that will parallelize **for us**

- automated intelligent parallelization
- JIT compiled — flexible
- portable
- seamlessly supports most CPUs / GPUs / hardware accelerators

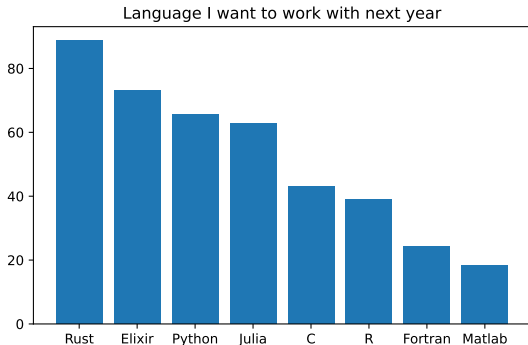
Last topic: Trends and future directions

Some trends:



Source: Stackoverflow Trends

Stack Overflow 2023 Developer Survey (50 languages)



— <https://survey.stackoverflow.co/2023/>