# Modern Computational Economics and Policy Applications

CBC Workshop 2024

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Slides, code, personnel, course outline:

https://github.com/QuantEcon/cbc_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 $k_t$

```c
#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);
}
```

```
ϕ john on gz-precision …/cbc_2024 on β main
❯❯ gcc solow.c -o out -lm

ϕ john on gz-precision …/cbc_2024 on β main
❯❯ ./out

k = 6.240251
```

```
program main
 implicit none
 integer, parameter :: dp=kind(0.d0)
 integer :: n=1000
 real(dp) :: s=0.3_dp
 real(dp) :: a=1.0_dp
 real(dp) :: delta=0.1_dp
 real(dp) :: alpha=0.4_dp
 real(dp) :: k=0.2_dp
 integer :: i
 do i = 1, n - 1
  k = a * s * k**alpha + (1 - delta) * k
 end do
 print *,'k = ', k
end program main
```

```
ϕ john on gz-precision …/cbc_2024 on β main
❯❯ gfortran solow.f90 -o out

ϕ john on gz-precision …/cbc_2024 on β main
❯❯ ./out

k = 6.240251
```

## Pros of low-level languages

- 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:

```python
α = 0.4
s = 0.3
δ = 0.1
n = 1_000
k = 0.2

for i in range(n):
    k = s * k**α + (1 - δ) * 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

```python
# Ints
x, y = 1, 2
z = x + y        # z = 3

# Floats
x, y = 1.0, 2.0
z = x + y        # z = 3.0

# Strings
x, y = 'foo', 'bar'
z = x + y        # z = 'foobar'
```

How does Python know which operation to perform?

Answer: Python checks the type of the objects first

```
>> x = 1
>> type(x)
int
```

```
>> x = 'foo'
>> type(x)
str
```

In a large loop, this type checking generates massive overhead

# 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?

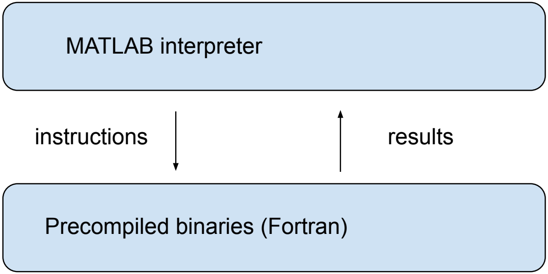
# MATLAB

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

b = [0.5, 1.0]';

x = inv(A) * b
```

# The vectorization trick



# Python + NumPy

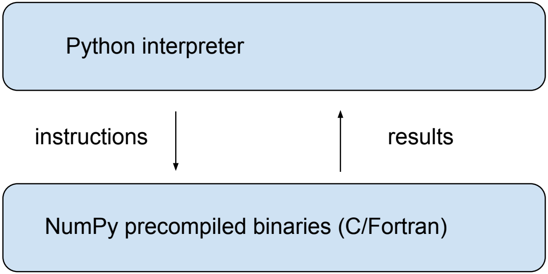
```python
import numpy

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
```


Python interpreter
instructions
results
NumPy precompiled binaries (C/Fortran)

# 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 / hardware

# 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

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

from some given $k_0$

- Iterative, not easily vectorized

```julia
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, α=0.4, δ=0.1, n=1_000):
    k = k0
    for i in range(n-1):
        k = s * k**α + (1 - δ) * k
    return k

solow(0.2)
```

Runs at same speed as Julia / C / Fortran

# Parallelization

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

execution time = time per worker / 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

# Types of parallelization

**Multithreading**: multiple threads with shared memory

- inverting a matrix in Matlab / NumPy using MKL
- graphics calculations on a GPU

**Multiprocessing**: multiple processes with individual memory

- using a cluster
- splitting calculations across multiple GPUs

Comments

- Multithreading is faster with lower overheads – our focus
- Multiprocessing can be used on top of multithreading (training ChatGPT, etc.)

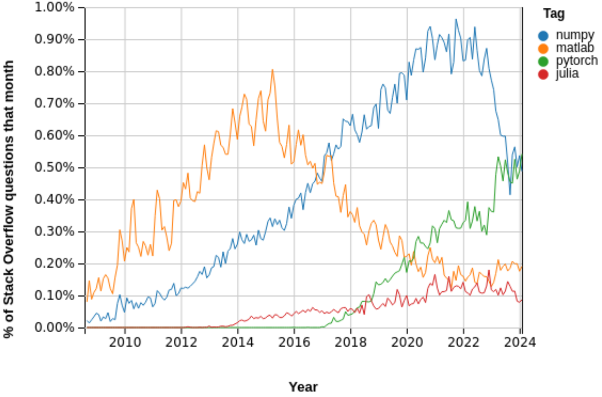
Parallelization is the big game changer powering the AI revolution

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