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 …/imf_2024 on β main
❯❯ gcc solow.c -o out -lm

ϕ john on gz-precision …/imf_2024 on β main
❯❯ ./out

k = 6.240251
```

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:

```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

- slow loops / arithmetic

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?

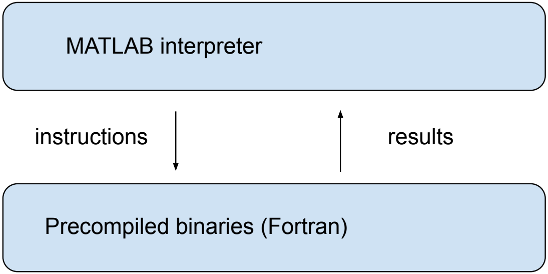
MATLAB

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

b = [0.5, 1.0]';

x = inv(A) * b
```

The vectorization trick



Python + NumPy

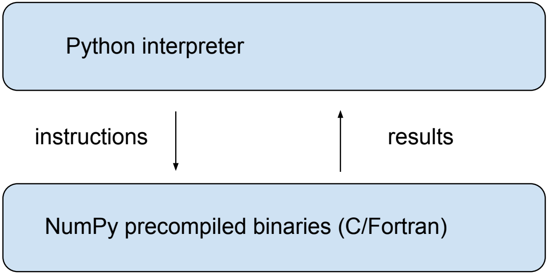
```
import numpy

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.)

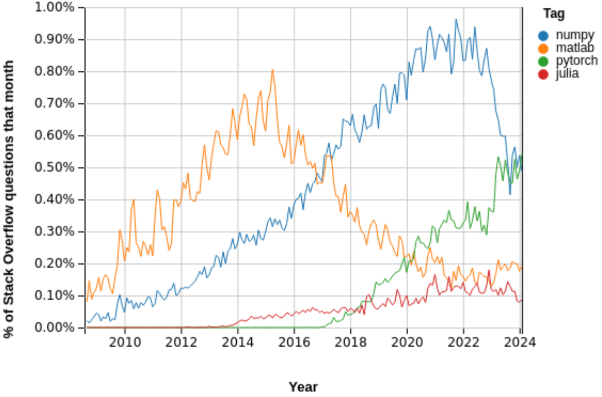
Parallelization is the big game changer powering the AI revolution

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