CBC QuantEcon Workshop

Introduction

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Plan

- Introduction to scientific computing with Python
- Fixed points and job search
- Dynamic programming: theory and algorithms
- Parallelization on the GPU

Assumptions:

- You have read lectures 1-3 at

  https://python-programming.quantecon.org/intro.html

- some basic familiarity with programming
- linear algebra, multivariate calculus, etc.

Resources:

- https://github.com/QuantEcon/cbc_workshops

Background

The theme of these lectures is dynamic programming in Python

Why use Python for DP?

In fact, why use Python for scientific computing?

Let's compare Python to some of the alternatives

Language Types

Low level

- C/C++
- Fortran
- assembly

High level

- Python
- Ruby
- TypeScript

Low level languages give us fine grained control

Example. $1 + 1$ in assembly

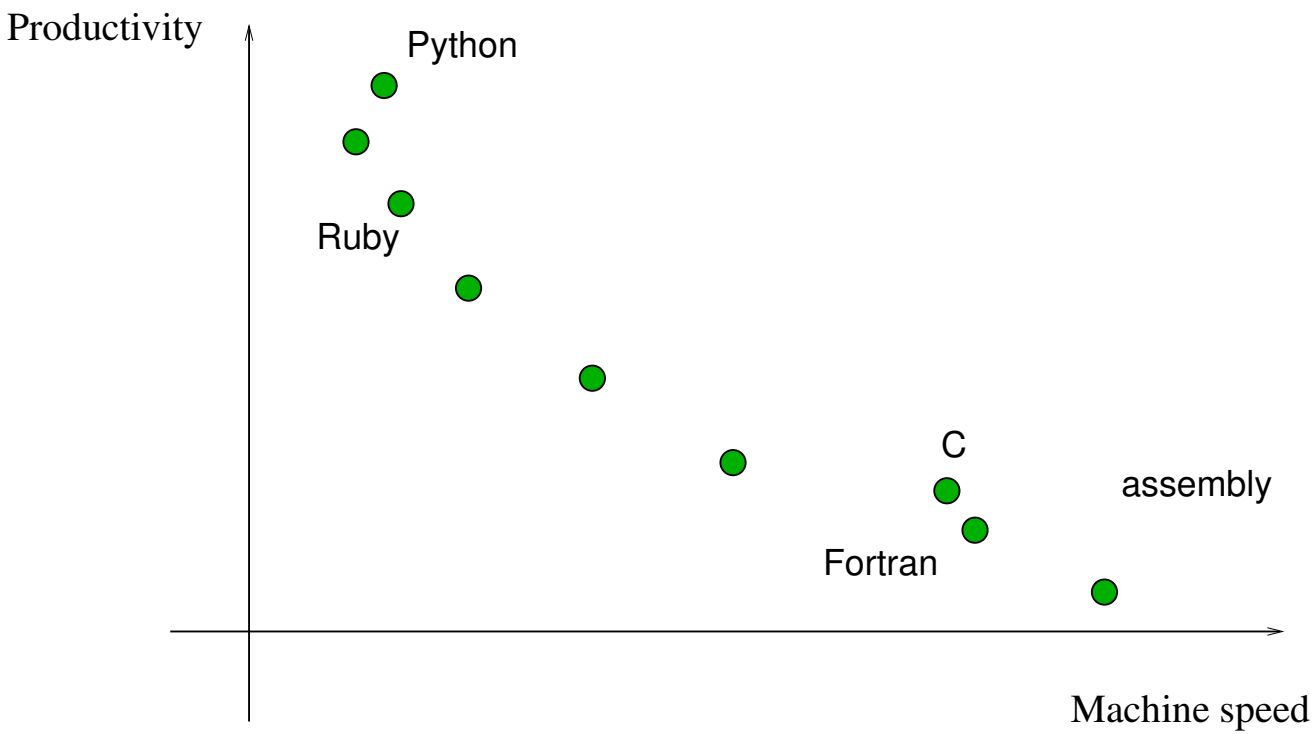
```
pushq   %rbp
movq    %rsp, %rbp
movl    $1, -12(%rbp)
movl    $1, -8(%rbp)
movl    -12(%rbp), %edx
movl    -8(%rbp), %eax
addl    %edx, %eax
movl    %eax, -4(%rbp)
movl    -4(%rbp), %eax
popq    %rbp
```

High level languages give us abstraction, automation, etc.

Example. Reading from a file in Python

```
data_file = open("data.txt")
for line in data_file:
    print(line.capitalize())
data_file.close()
```

Trade-Offs

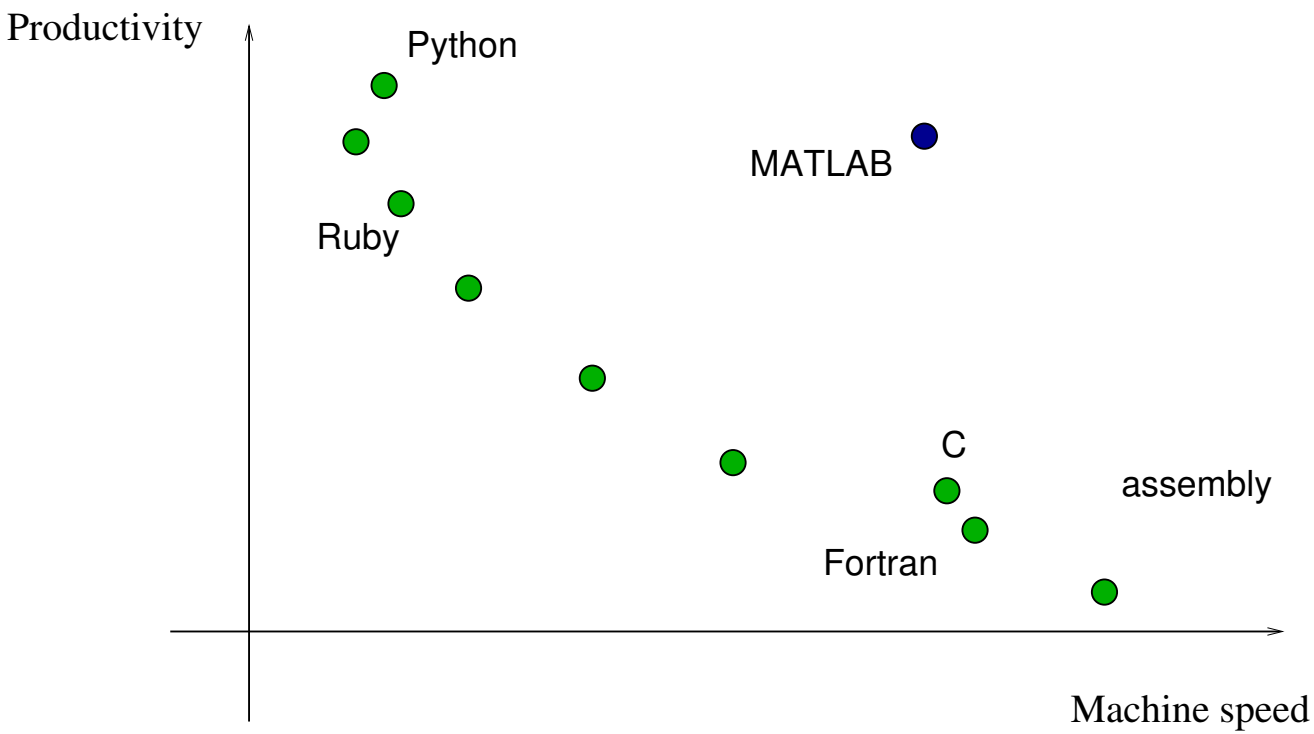

Productivity
Python
Ruby
C
assembly
Fortran
Machine speed

But what about scientific computing?

Requirements

- Productive — easy to read, write, debug, explore
- Fast computations

Trade-Offs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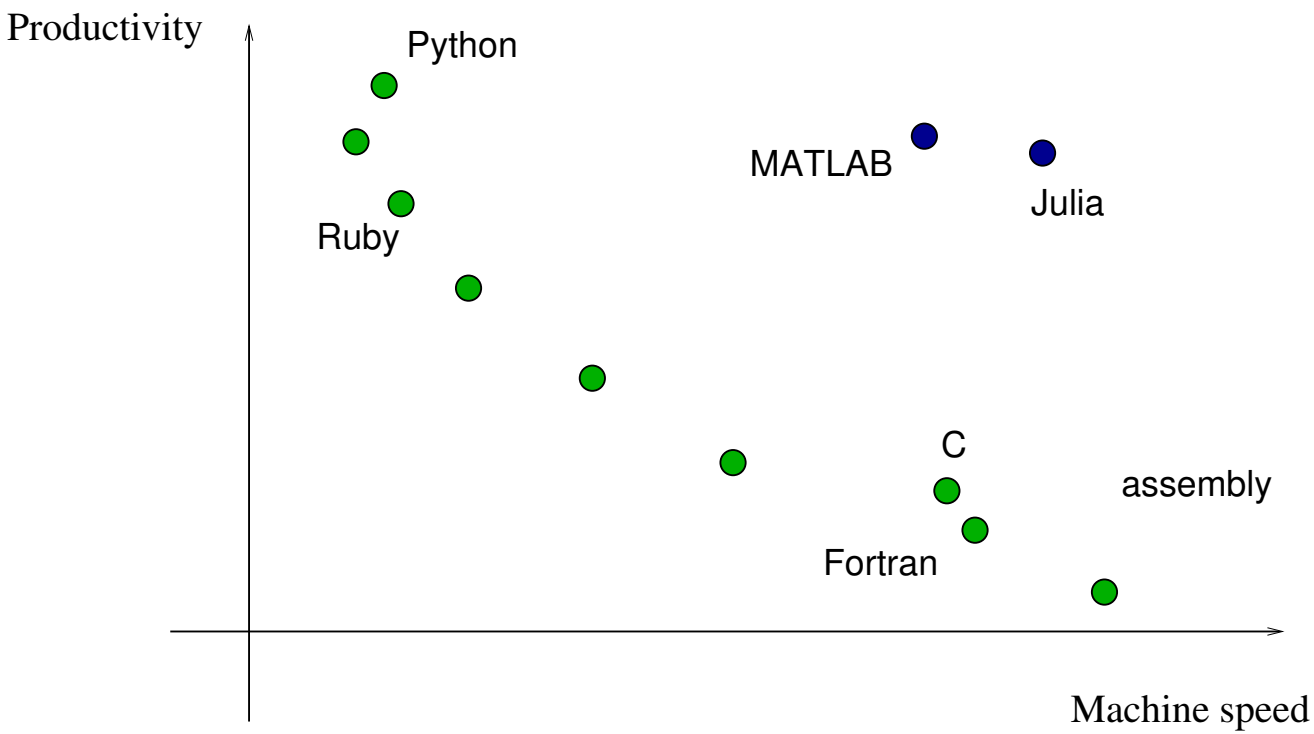
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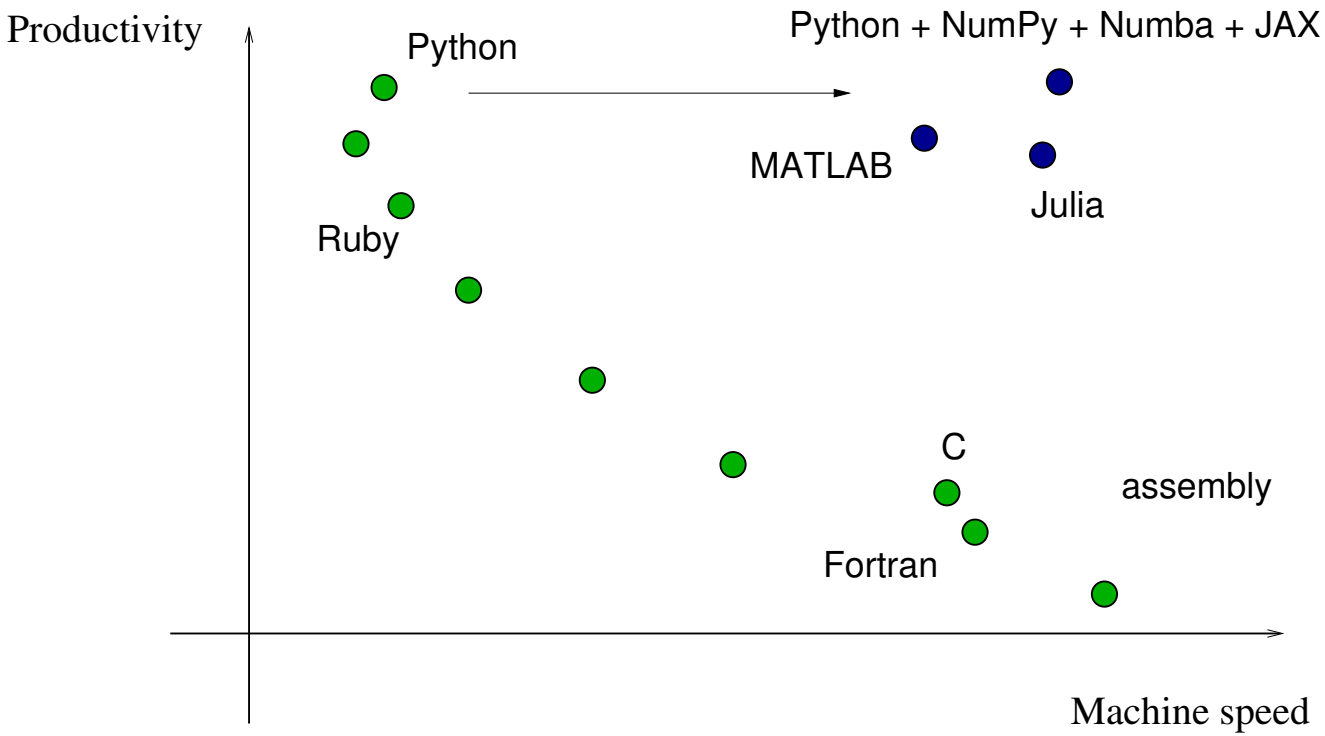

Productivity
Python
Python + NumPy + Numba + JAX
MATLAB
Julia
Ruby
C
assembly
Fortran
Machine speed

Which Language

How about R?

- Specialized to statistics
- Easy to learn, well designed
- Huge range of estimation routines
- Significant demand for R programmers
- Popular in academia

Loosing some ground to Python

Example. Chris Wiggins, Chief Data Scientist at The New York Times:

"Python has gotten sufficiently weapons grade that we don't descend into R anymore. Sorry, R people. I used to be one of you but we no longer descend into R."

Julia

Pros:

- Fast and elegant
- Many scientific routines
- Julia is written in Julia

Cons:

- Some stability issues
- Yet to achieve rapid growth

Python

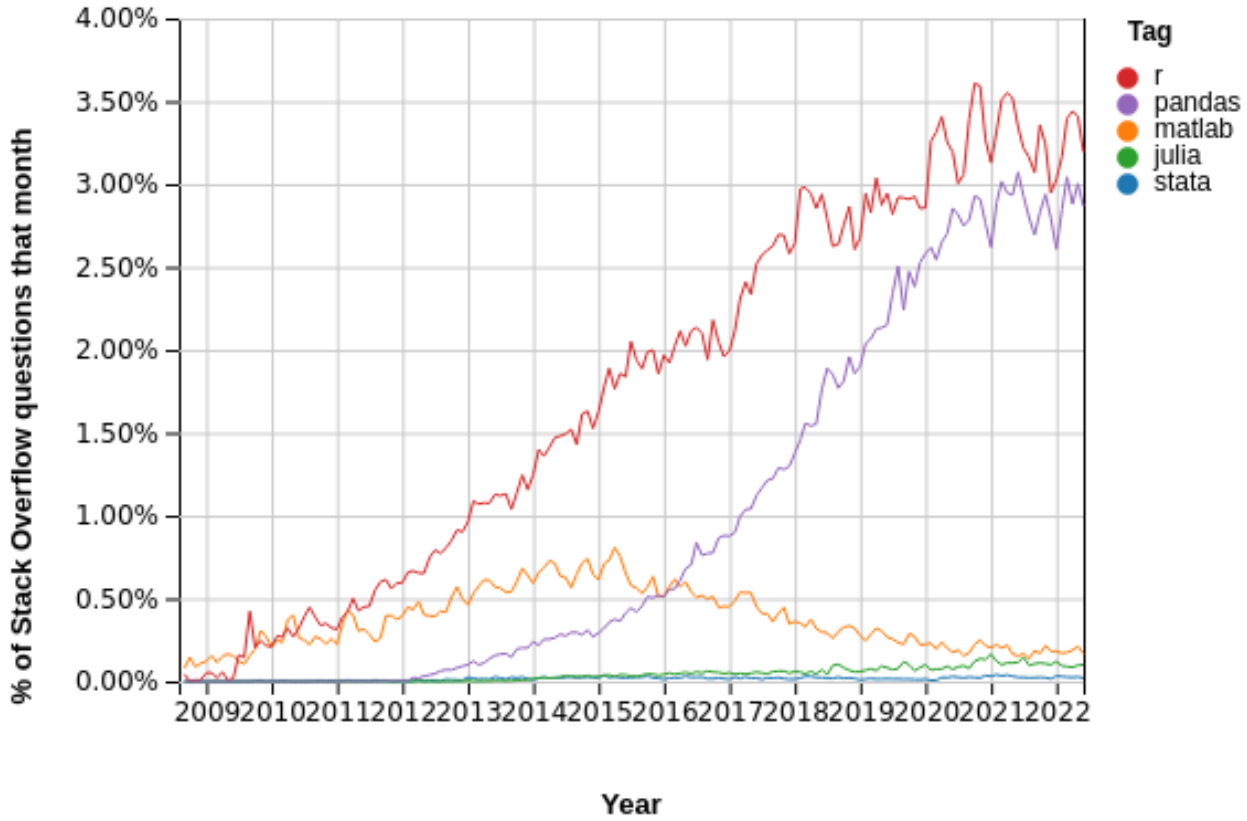
Pros:

- Massive scientific ecosystem
- Strong investment from Google, Facebook (Meta), etc.
- Huge demand for tech-savvy Python programmers

Cons:

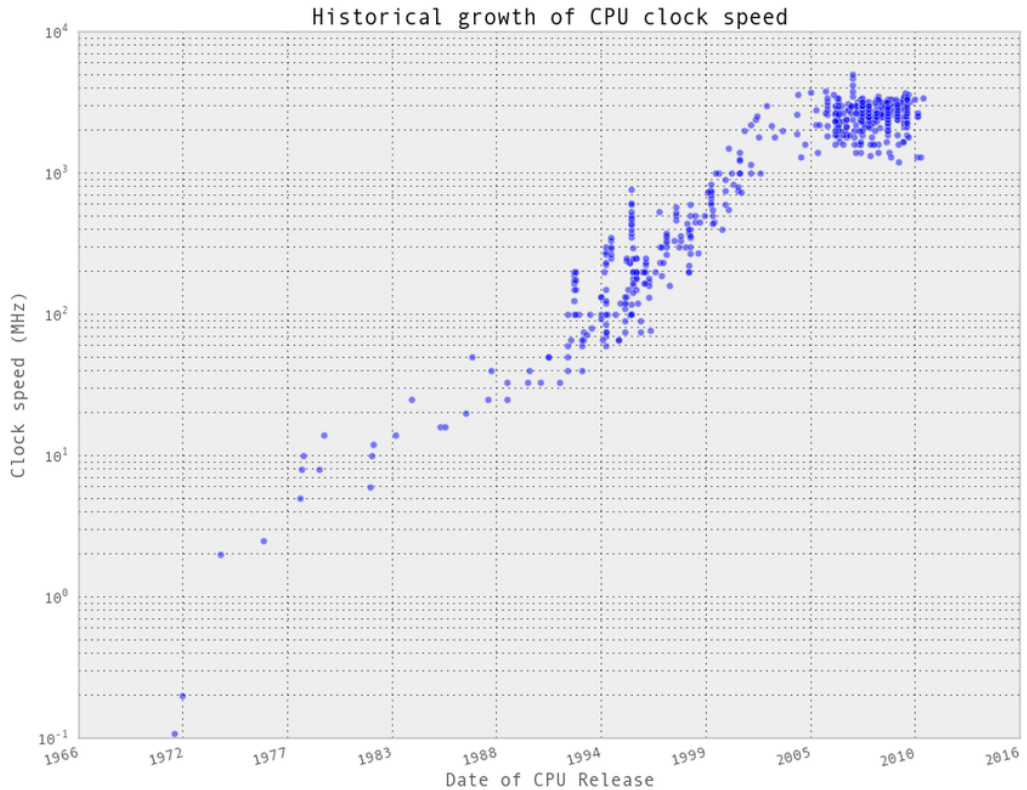
- Numerical code not as clean as Julia
- Econometrics libraries less developed than R/STATA

Popularity, others vs one Python library (pandas)

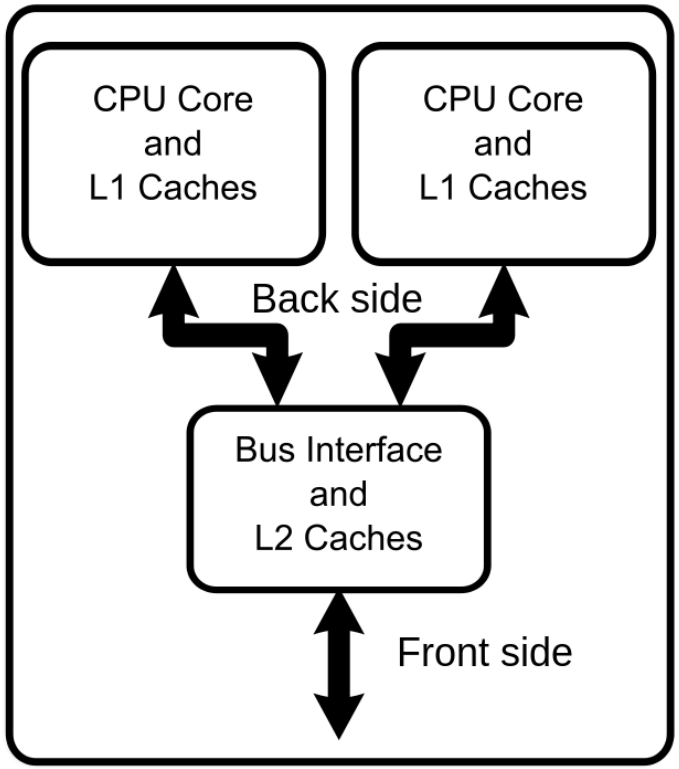


Current Trend 1: Parallelization

CPU frequency (clock speed) growth is slowing

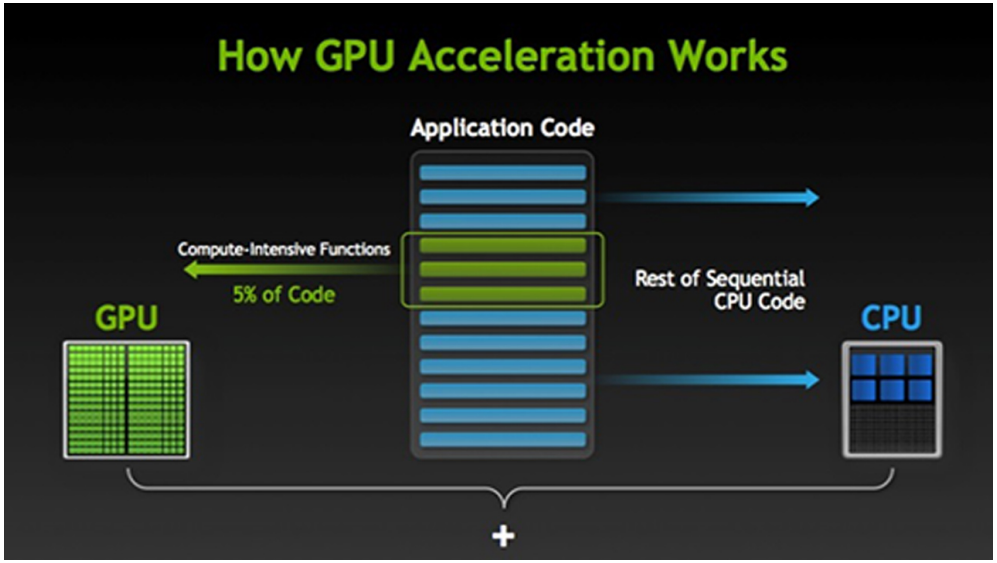


Chip makers have responded by developing multi-core processors



Source: Wikipedia

GPUs / TPUs are becoming more and more important



Applications:

- machine learning, deep learning, etc.
- dynamic programming!

Trend 2: Distributed Computing

Advantages:

- run code on big machines we don't have to buy
- circumvent internal IT departments

Options:

- Google Colab, PythonAnywhere, etc.
- AWS
- Supercomputers

Downloads / Installation / Remote Options

Install Python + scientific libraries (optional)

- Install Anaconda from https://www.anaconda.com/
  - Select latest version
  - For your OS
  - Say "yes" at prompts
- Not plain vanilla Python

Remote options

- https://colab.research.google.com

Notebooks

Now let's move on to

- `python_by_example.ipynb`
- `finite_markov.ipynb`
- `equilibrium.ipynb`
- `numba.ipynb`
- `european_option_numba.ipynb`