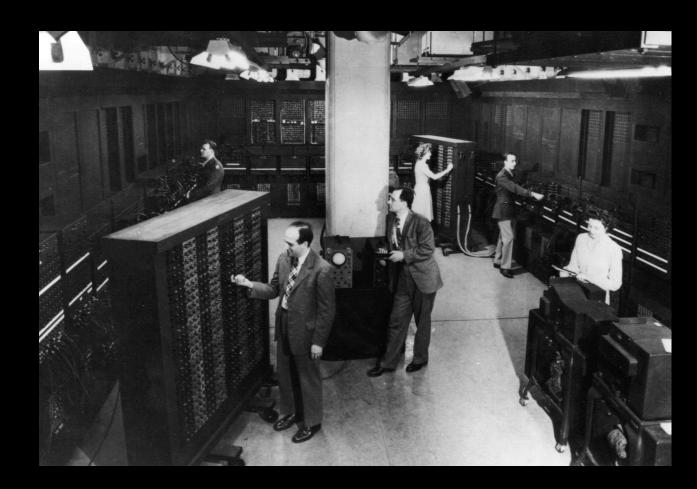
Week 5: performance | QOL

NRSC 7657 Workshop in Advanced Programming for Neuroscientists

course business

Processors: digital computers

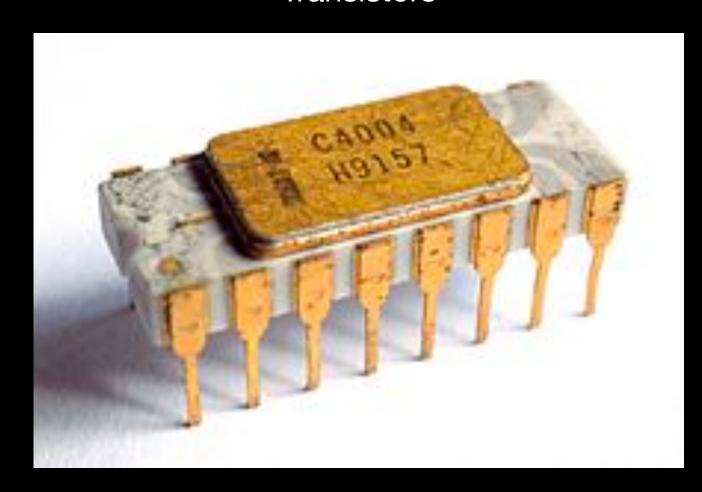
vacuum tubes



ENIAC

18,000 vacuum tubes
5,000,000 hand-soldered joints
27 tons
150 kW

Transistors



Intel 4004
2250 transistors
MOS gates
< 27 tons
1W

Integrated circuits: CPUs



your computer, your phone
< 100,000 transistors
many Integrates gates
also < 27 tons
~100s of watts

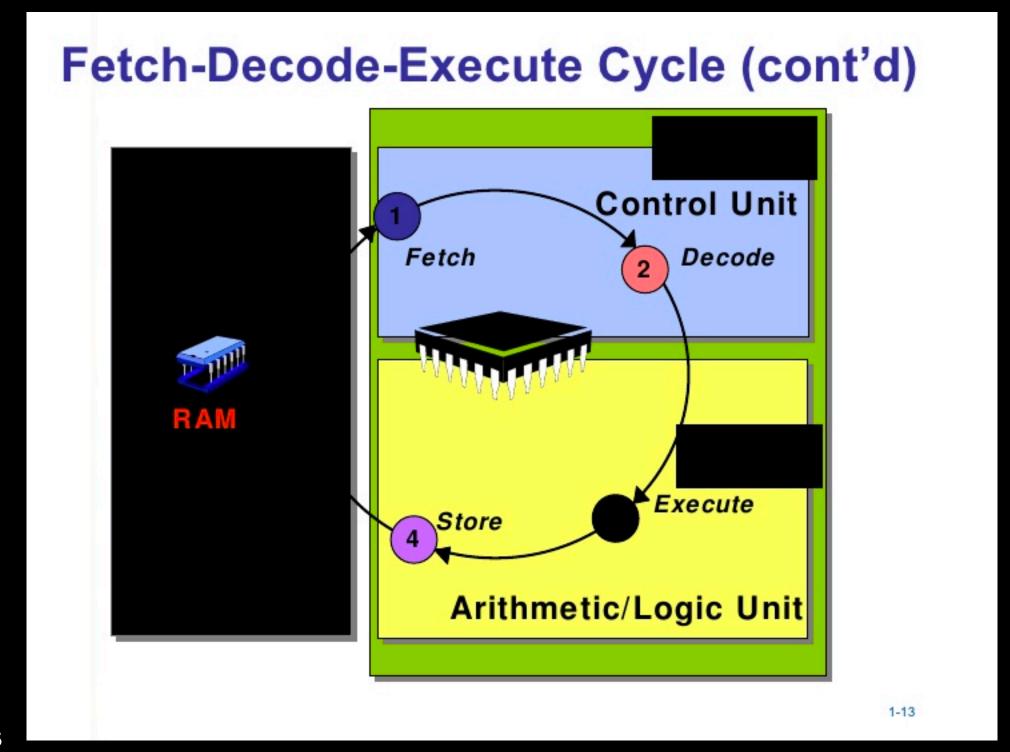
Processors: CPU

- The CPU is (mostly) what is doing the heavy lifting when you ask python to do some calculation.
- The python interpreter converts your code to machine language (a set of instructions for what memory addresses to operate on), and then:
 - 1. Puts that machine language set of instruction in RAM
 - 2. the CPU does its thing (fetch-decode-execute-store)

Processors: CPU machine cycle

Clock speed





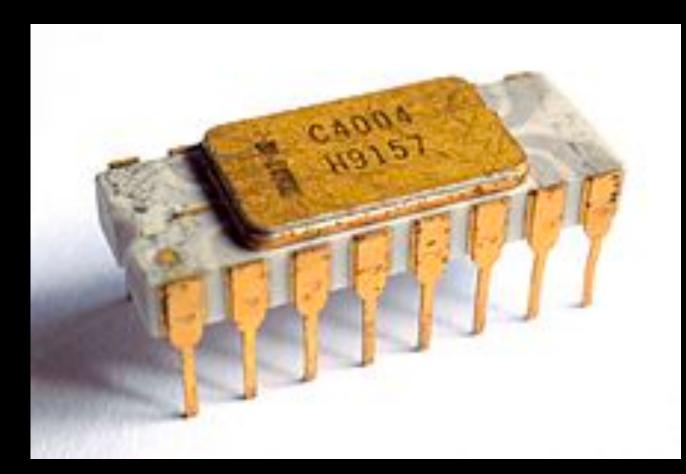
Processors: digital computers

vacuum tubes



ENIAC 100 kHz Machine cycle: 200 μs

Transistors



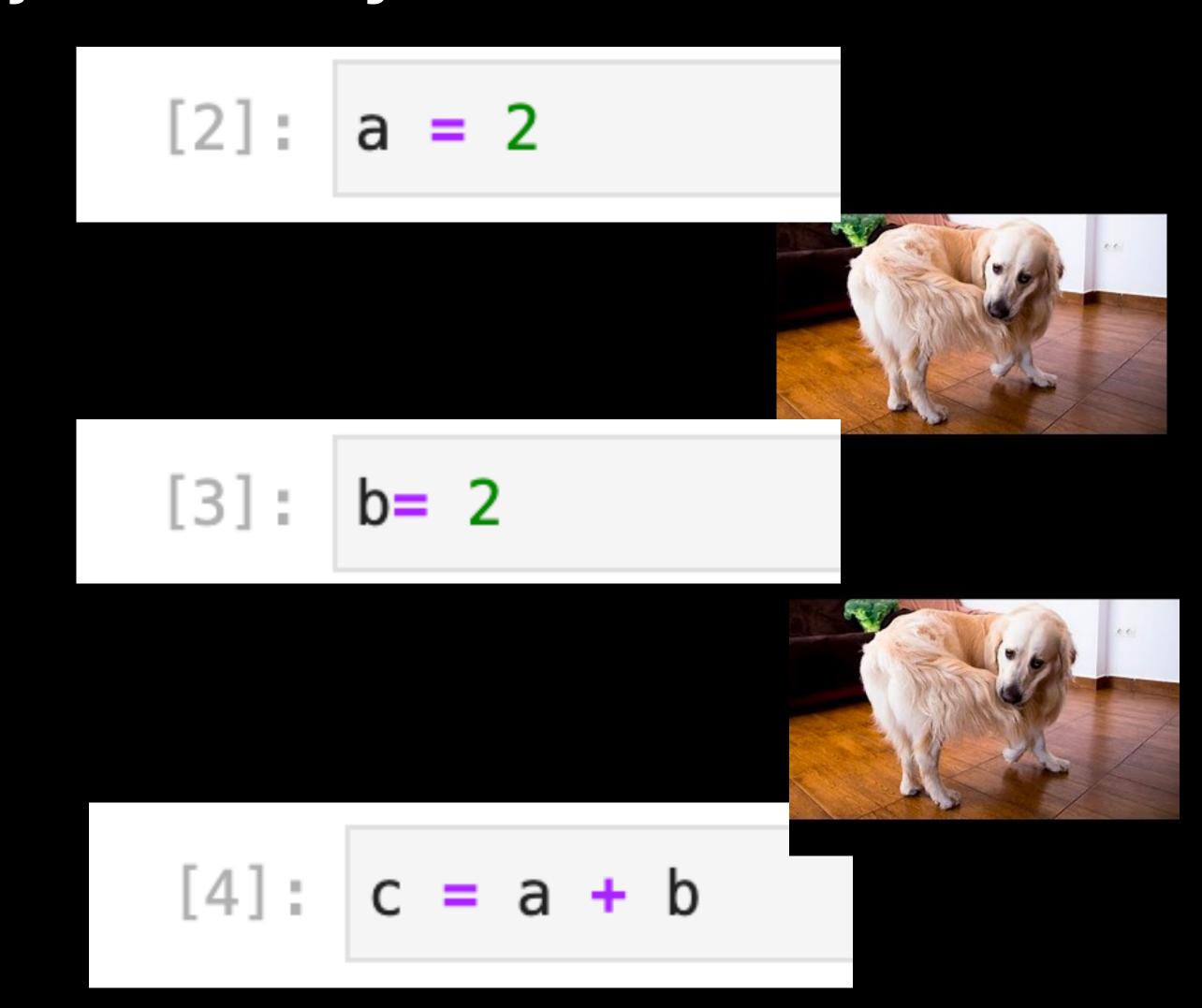
Intel 4004
740 kHz
Machine cycle: 10.8 μs

Integrated circuits: CPUs

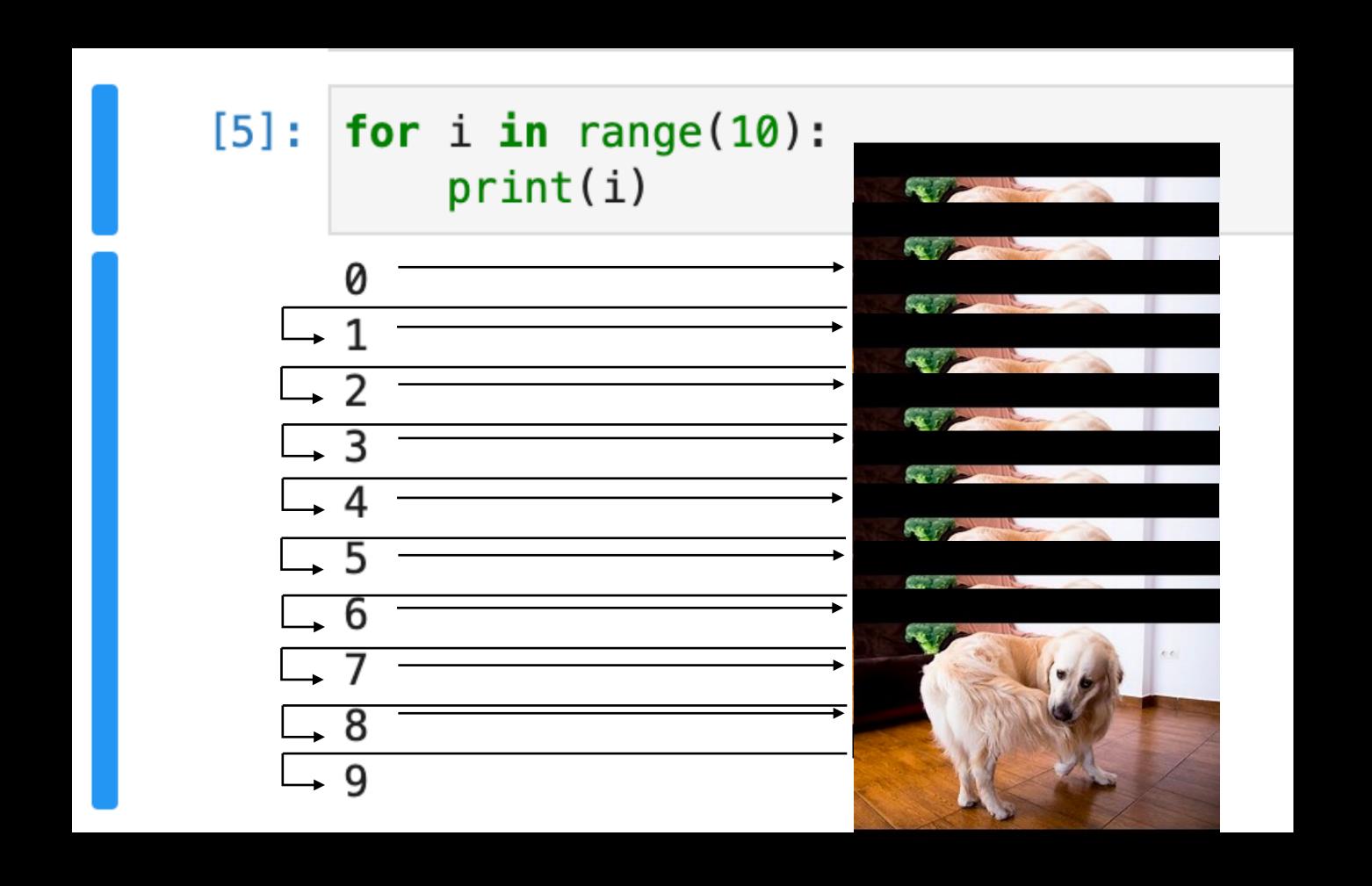


your computer, your phone 2 - 4Ghz 0.3 - 3 ns

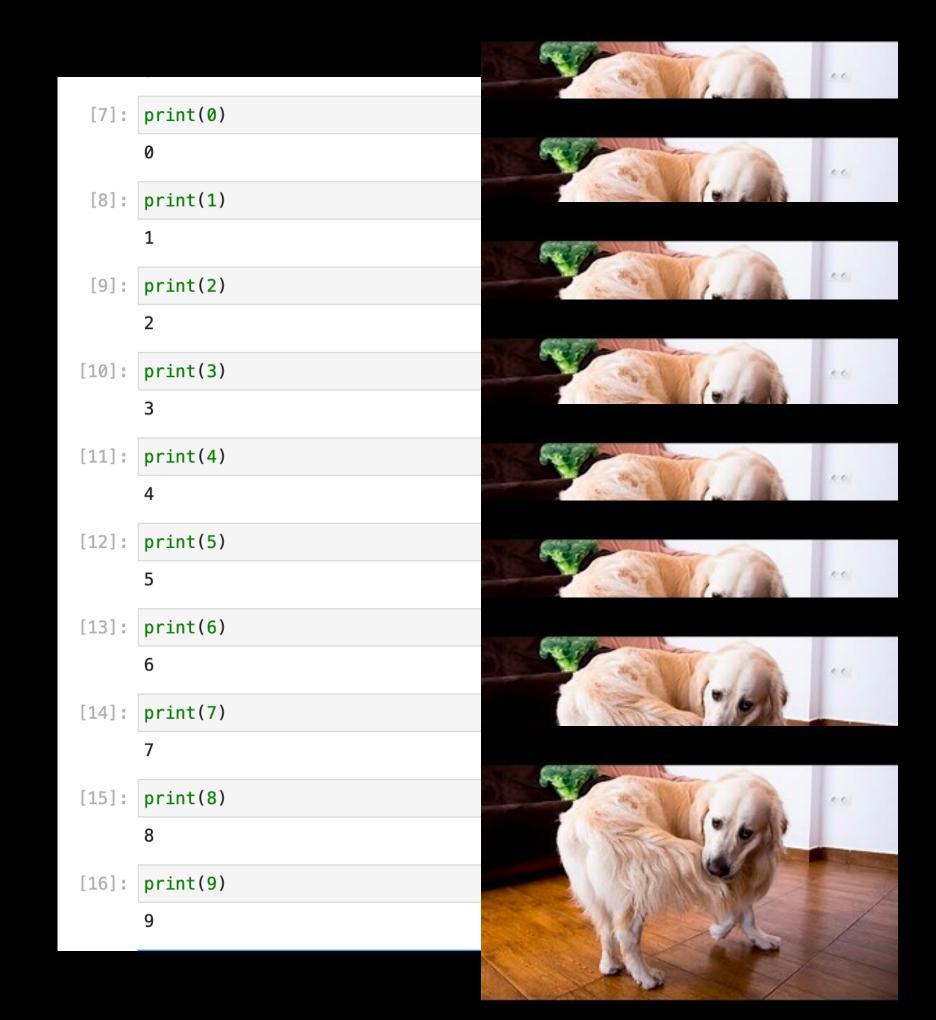
Iteration: serial just like any other line



Iteration: serial just like any other line



Iteration: serial just like any other line



Iteration: data types, speeding it up

- Sorting tuples
- filtering
- Built-in methods (including filtering)
- List comprehension
- Avoiding it (but don't try too hard unless you need to)

Iteration: parallel









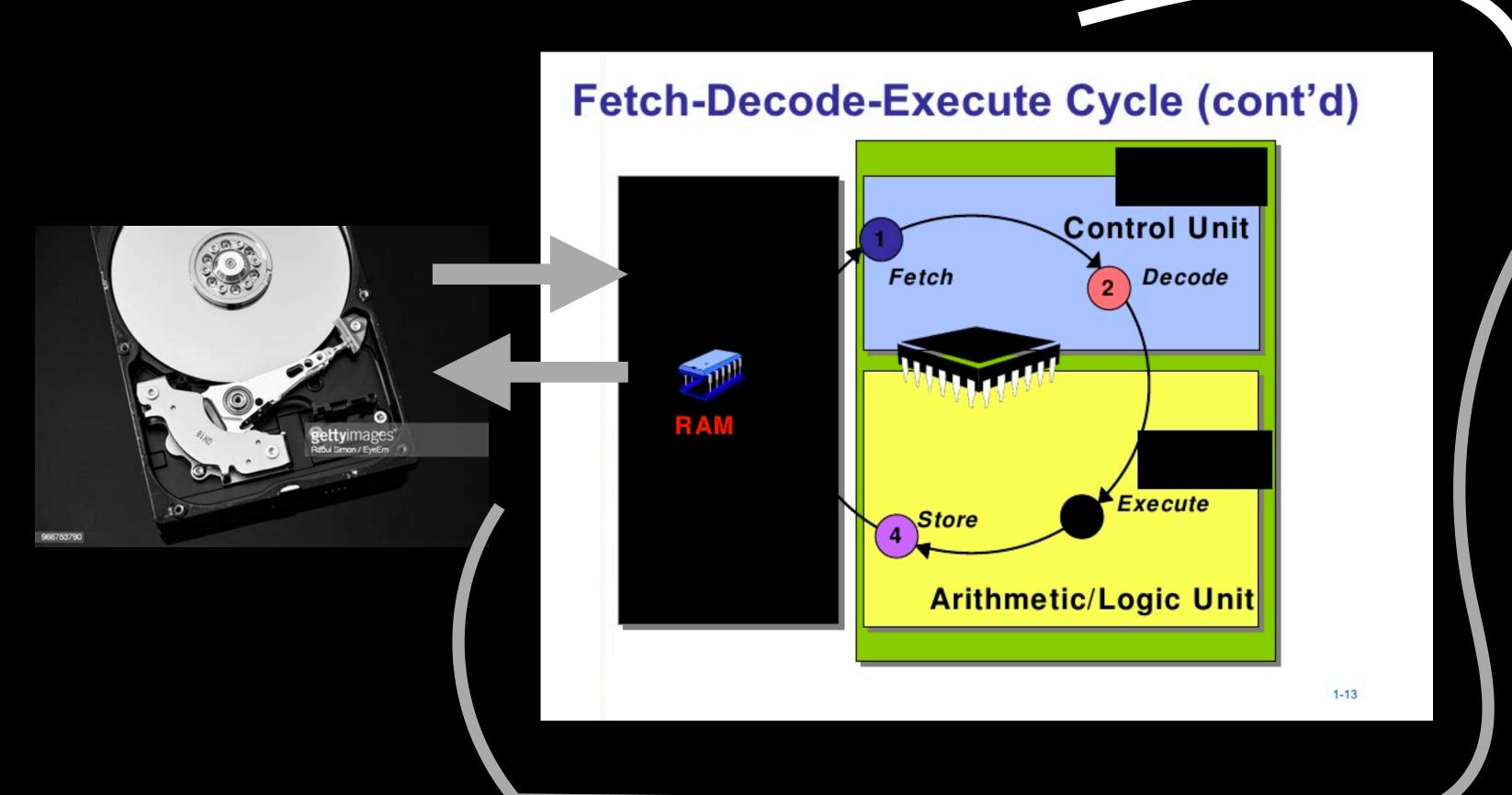
Performance Parallel CPU usage

- Split a computation into parts, ship it off to a number of processors, stitch the results back together
- Not all computations benefit from this, but some do. The computations that be broken into parts that don't depend on each other are called "embarrassingly parallel"
 - Arrays where you do the same thing to chunks
 - Deep learning

- multiprocessing
- joblib
- asyncio
- dask

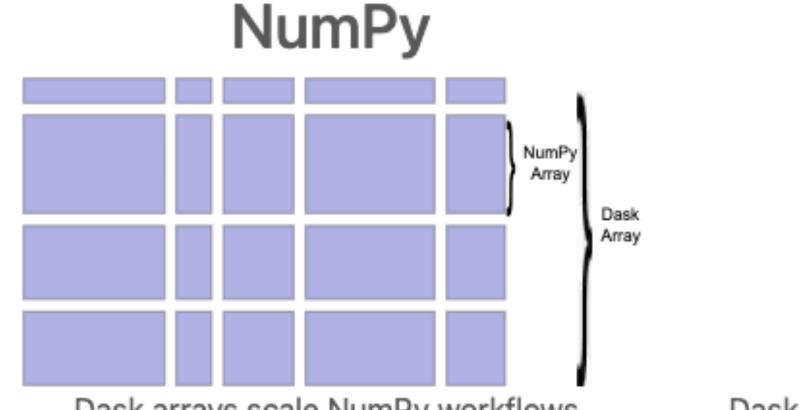
Performance Parallel CPU usage

With standard package helpers



- multiprocessing
- joblib
- asyncio
- dask

Performance Parallel CPU usage: dask



Dask arrays scale NumPy workflows, enabling multi-dimensional data analysis in earth science, satellite imagery, genomics, biomedical applications, and

machine learning algorithms

January, 2016 February, 2016 Pandas Dataframe

March, 2016

April, 2016

Dask dataframes scale pandas workflows enabling applications in time series, business intelligence, and general data munging on big data.

Dataframe

Google Cloud VMs

class dask_cloudprovider.gcp.GCPCluster(projectid=None, zone=None, network=None, machine_type=None, on_host_maintenance=None, source_image=None, docker_image=None, ngpus=None, gpu_type=None, filesystem_size=None, disk_type=None, auto_shutdown=None, bootstrap=True, preemptible=None, debug=False, **kwargs) [source]

Cluster running on GCP VM Instances.

```
# Dask-ML implements the scikit-learn API
from dask_ml.linear_model \
  import LogisticRegression
lr = LogisticRegression()
lr.fit(train, test)
```

Dataframes implement the pandas API

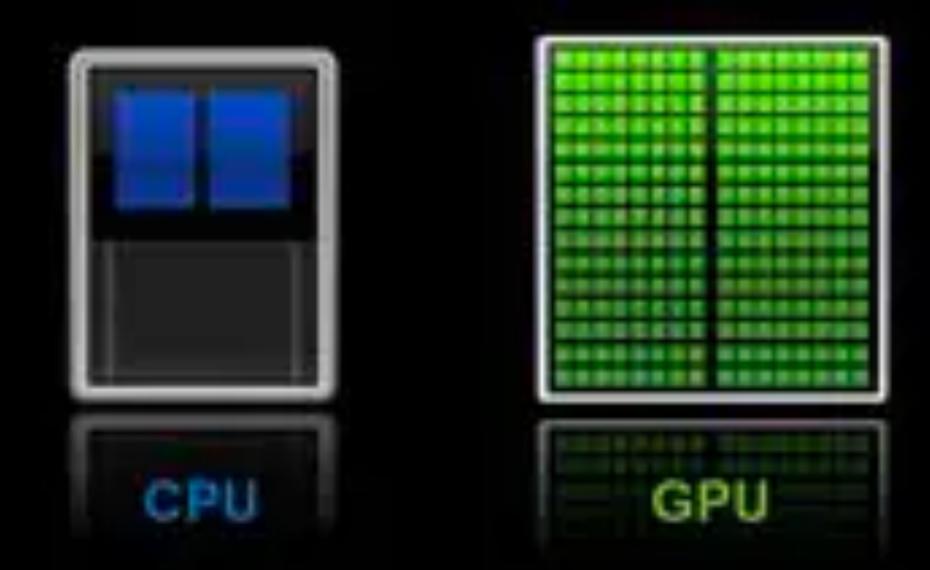
df = dd.read_csv('s3://.../2018-*-*.csv')

df.groupby(df.account_id).balance.sum()

import dask.dataframe as dd

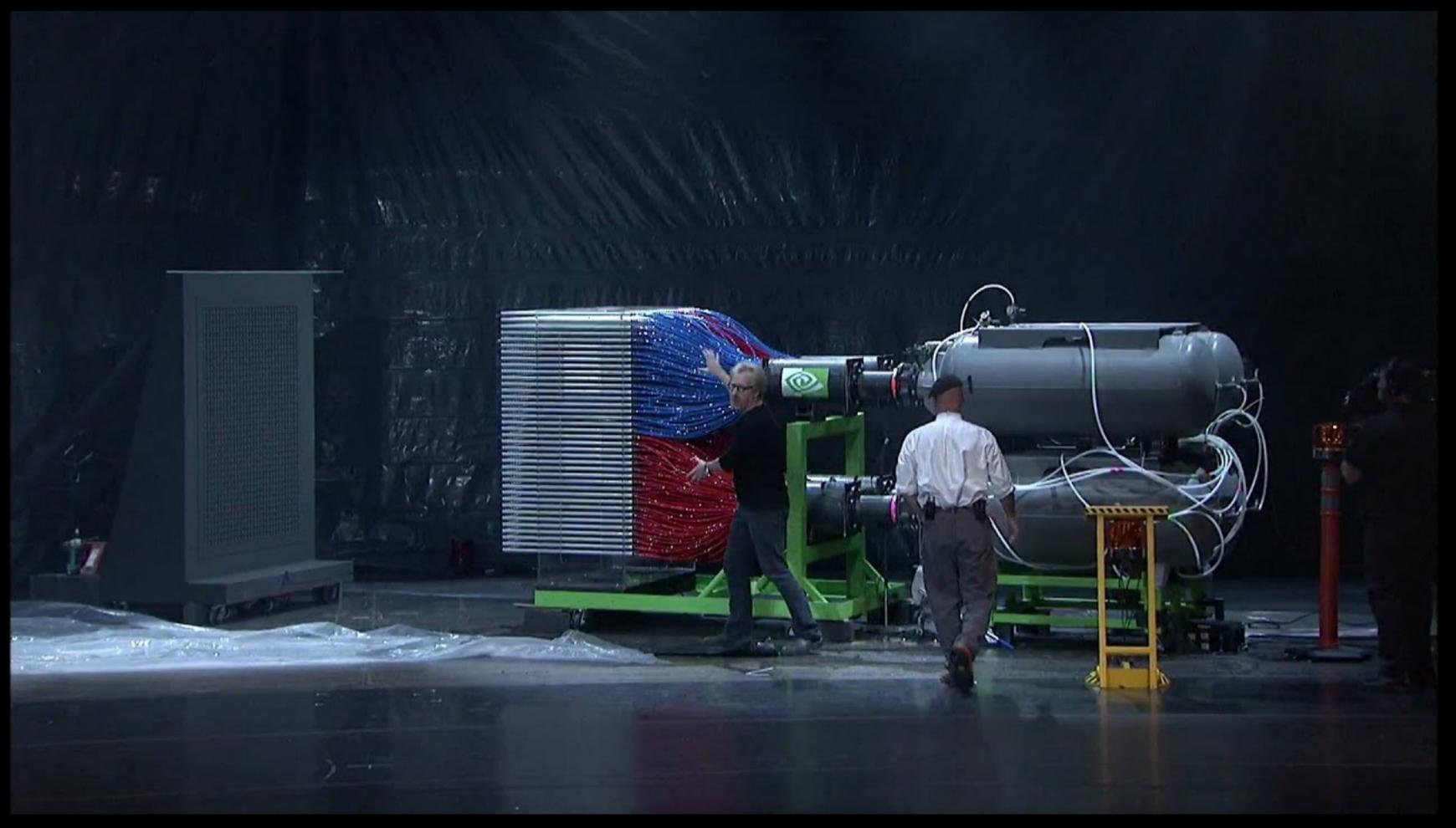
GPUs: many tiny cores for parallel things

The Difference between a CPU and GPU



nVidia

GPUs: many tiny cores for parallel things



nVidia, https://youtu.be/-P28LKWTzrl

Performance GPUs: many tiny cores for parallel things



- PyTorch
- TensorFlow
- MATLAB: Parallel Processing

Performance Profiling

- %%time and %%timeit
 - Note: %%timeit will run multiple times by default, so use some caution

Code. QOL Tips and tricks

- tqdm
- os, sys, glob
- pprint