

Working with (big) data

Data Science for Public Policy

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Law, Economics, and Data Science Group (Prof. Elliott Ash)

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Survey

ETH Edu App



Web app

https://eduapp-app1.ethz.ch/



iOS



Android



Paper Presentations

- From 14 March to 23 May:
 - 1-2 presentations per lecture
- 2-4 students in one group.
- Choose a paper from our list OR propose one in coordination with us.
- Sign up by 11 March.



Course Projects

- Either a research paper or a web app.
- Work on something that you are passionate about!
- Choose a type of project and topic with instructors by 9 April:
 - Research Paper
 - Sergio Galletta (sergio.galletta@gess.ethz.ch)
 - Web App
 - Christoph Goessmann (christoph.goessmann@gess.ethz.ch)

Introductions

- Name, Department / Uni
- What's your background?
- What do you want to:
 - learn?
 - work on?
- Pain points when working with data so far?

Tentative Outline

Technical Part

- How to efficiently work with computers?
 - Computer architecture (I/O, CPU, GPU)
 - Controlling a computer (command line, ssh)
 - Shapes and forms of data (text vs. binary, compression)
 - Reproducibility and automation (virtual environments, logging, git, etc.)
 - Data acquisition (scraping)
- APIs and web apps
- Machine Learning

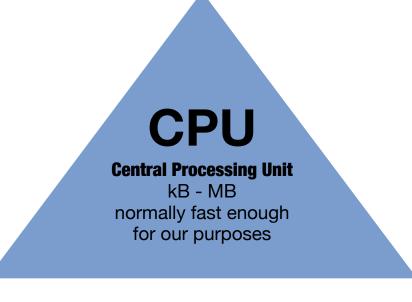


Questions?

- Interrupt with questions / comments anytime!
- Happy to adapt the lectures to your needs.



Typical data flow



RAM (volatile) 8-128 GB

10-50 GB/s > 1,000,000 IOPS \$10k per TB

Virtual Memory

Writes data to your HDD/SSD when you run out of RAM.

HDD Hard Disk Drive (slow random access) ≤ 22 TB 100 MB/s

100 IOPS \$20 per TB

SSD

Solid State Disk (fast random access) ≤ 30 TB 0.5-5 GB/s 10,000 IOPS

\$100 per TB

NAS/SAN

Network Attached Storage Storage Area Network TB - PB > 100 MB/s > 100 IOPS

> \$20 per TB

CPU bound (CPU load ~ 100%)

- increase number of CPUs/cores (parallelization)
- use GPUs instead of CPUs
- change algorithm (e.g., profiling)

I/O bound (CPU load << 100%)

- reduce I/O operations
- switch to faster memory



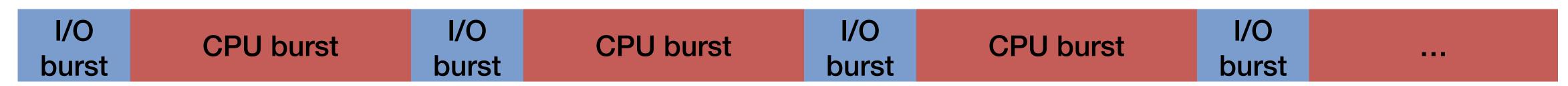
I/O bound vs CPU bound processes

I/O bound



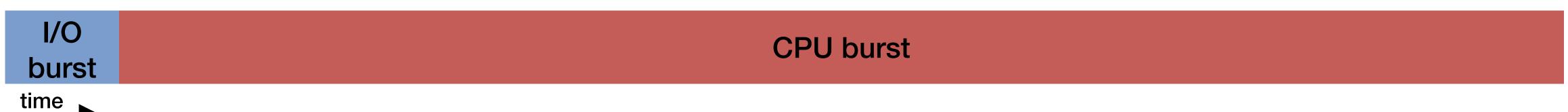
time

Somewhere in between





CPU bound



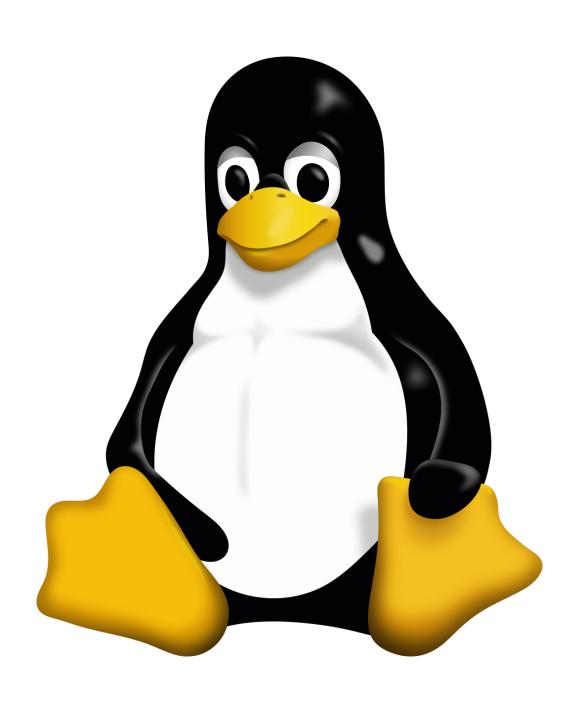


Common data types

Type	Size	Range
boolean	1 byte	0,1
smallint	2 bytes	-32,768 to +32,767
int	4 bytes	-2,147,483,648 to +2,147,483,647
bigint	8 bytes	-9,223,372,036,854,775,808 to +9,223,372,036,854,775,807
real / single precision float	4 bytes	6 decimal digits precision
double precision float	8 bytes	15 decimal digits precision



Operating System



Linux/Unix dominant

- 100% of all TOP500 supercomputers [1]
- > 80% of public servers (web, mail, DNS, etc.) on the internet [2]
- Some packages (e.g., CuPy, PyTorch ROCm) are only fully supported on Linux

^[2] https://w3techs.com/, accessed 28 February 2023



^[1] https://top500.org/statistics/overtime/, accessed 28 February 2023

Basic commands

- \$ pwd (print working directory)
- \$ cd path (change directory)
- \$ mkdir newd (make directory)
- \$ ll / ls -al (list contents
 of working directory)
- \$ cat file (display content of file)
- \$ head -n file (display first
 n lines of file)

- \$ tail -n file (display last n
 lines of file)
- \$ rm file (remove/delete file)
- \$ com > file (write output of command com to file)
- \$ man command (display command's manual)
- \$ CTRL + C (abort command)
- \$ CTRL + D (end of stream)

Text editor

Create new file / edit existing one

\$ vim file.txt

Command mode (default at start, invoke with ESC):

Switch to insert mode: i

Save: :w +Enter

Save and quit: :wq +Enter

Quit without saving: :q! +Enter

Monitoring CPU load & profiling

Task manager

\$ htop / top

Average CPU load of your script

\$ time python my_program.py (local)

\$ myjobs -j **jobid** (ETH Euler cluster)



Profiling with cProfile and SnakeViz

\$ python -m cProfile -o my_program.prof my_program.py

\$ snakeviz my_program.prof



Virtual environments wit pipenv

Install pipenv

\$ pip install pipenv

Change to project directory and install a package

\$ cd myproject

\$ pipenv install package

List of packages and dependencies is written to Pipfile/Pipfile.lock.

Whenever you are in the project directory, you have two options to use the virtual environment:

\$ pipenv shell

\$ pipenv run python
 myscript.py

Use pyenv for managing different python versions on the same machine.

Example

10 million documents

- Each document i has a 128-dim. feature vector $a_{i,*}$ (e.g., LDA topics).
- Want to calculate all cosine similarities between documents *i* and *j*:

$$S_{i,j} = \frac{a_{i,*} \cdot a_{j,*}}{\|a_{i,*}\| \|a_{j,*}\|}$$

(naively corresponds to matrix multiplication of 1e7 x 128 matrix with its transpose)

Feature matrix (1e7 x 128):

$$(a_{i,j}) = \begin{bmatrix} a_{1,1} & a_{1,2} & a_{1,3} & \dots & a_{1,128} \\ a_{2,1} & a_{2,2} & a_{2,3} & \dots & a_{2,128} \\ a_{3,1} & a_{3,2} & a_{3,3} & \dots & a_{3,128} \\ \dots & \dots & \dots & \dots \\ a_{10^7,1} & a_{10^7,2} & a_{10^7,3} & \dots & a_{10^7,128} \end{bmatrix}$$

Similarity matrix (1e7 x 1e7):

$$(s_{i,j}) = (a_{i,j})(a_{i,j})^T$$

First considerations

Document vector (1 x 128):

$$a_{i,*} = [a_{i,1} \quad a_{i,2} \quad a_{i,3} \quad \dots \quad a_{i,128}]$$

→ size = 1e7 * 8 byte = **80 MB**

Feature matrix (1e7 x 128):

$$(a_{i,j}) = \begin{bmatrix} a_{1,1} & a_{1,2} & a_{1,3} & \dots & a_{1,128} \\ a_{2,1} & a_{2,2} & a_{2,3} & \dots & a_{2,128} \\ a_{3,1} & a_{3,2} & a_{3,3} & \dots & a_{3,128} \\ \dots & \dots & \dots & \dots \\ a_{10^7,1} & a_{10^7,2} & a_{10^7,3} & \dots & a_{10^7,128} \end{bmatrix}$$

 \rightarrow size = 1e7 * 128 * 8 byte = **10.2 GB**

Similarity matrix (1e7 x 1e7):

$$(s_{i,j}) = (a_{i,j})(a_{i,j})^T$$

 \rightarrow size = 1e7 * 128 * 8 byte = 800 TB

Is it realistic to calculate all cosine similarities?

1. Create a virtual environment

```
$ pip install pipenv
```

- \$ mkdir session1
- \$ cd session1
- \$ pipenv install numpy
- \$ pipenv install snakeviz
- \$ pipenv shell

2. Write a python script (matrix_math_test.py) that:

- creates a random feature matrix
- computes the cosine similarity between the feature matrix and 100 randomly drawn rows



3. Time your script:

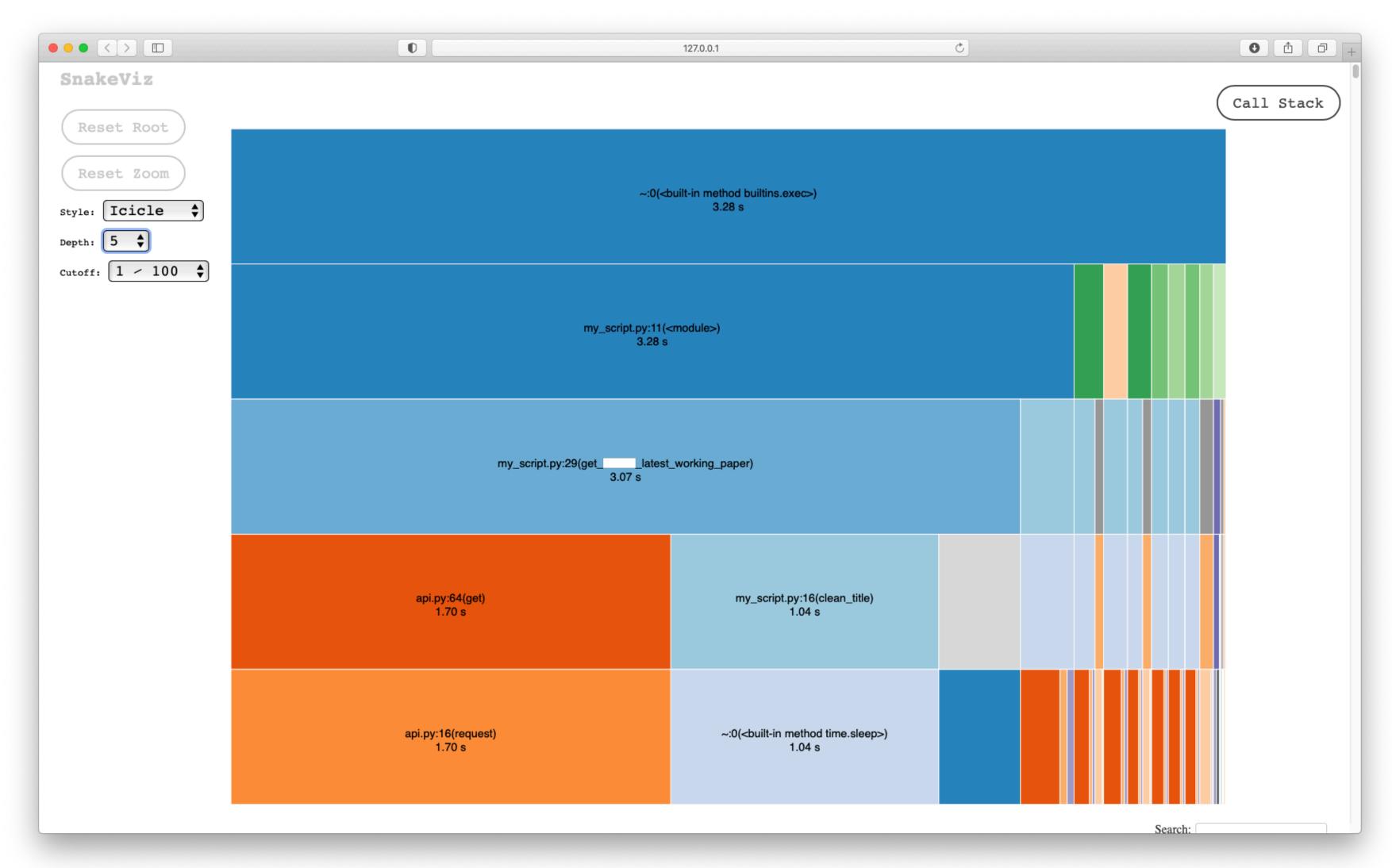
\$ time python my_program.py

Extra: export OPENBLAS_NUM_THREADS=1/0

4. Profile your script with cProfile and SnakeViz

\$ python -m cProfile -o my_program.prof my_program.py

\$ snakeviz my_program.prof





Extras on Euler (Slurm & GPUs) CPU only

```
#!/bin/bash
#SBATCH -n 1
#SBATCH --cpus-per-task=1
#SBATCH --time=4:00:00
#SBATCH --mem-per-cpu=24576
#SBATCH --mail-type=ALL
python matrix_math_test.py
$ sbatch ...
$ myjobs / seff jobid
```

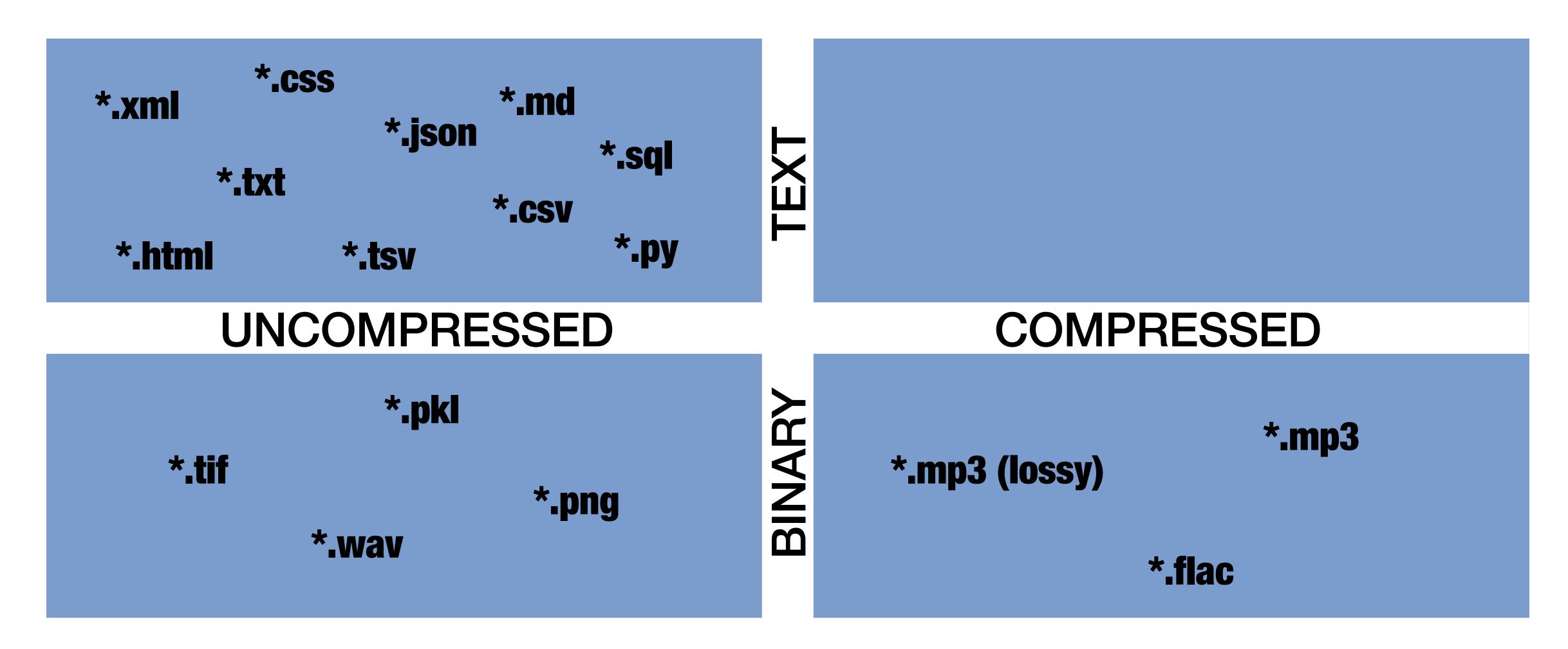
GPU (numpy -> cupy):

```
#!/bin/bash
#SBATCH --gpus=1
#SBATCH --gres=gpumem:22G
#SBATCH --time=4:00:00
#SBATCH --mail-type=ALL
module load gcc/8.2.0 python_gpu && python
matrix_math_test_gpu.py
$ sbatch ...
$ myjobs / seff jobid
```

Runtime: 5s (24 x faster)

Runtime: 120s

Data





End-of-Lecture Survey

ETH Edu App







iOS



Android

