Python for Data processing

Lecture 1:
Jupyter, Arrays, tensors and computations - Part I

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Gleb Ivashkevich

doing **deep learning** - time series, satellite imagery

PhD in theoretical physics

6 years in **academia** doing numerical simulations

8 years in **data science** and **machine learning**


datarythmics **effimly**
data driven manufacturing efficiency

Our TA

Anatoly Bardukov

applied math from HSE

senior full stack Developer at Nvidia

author at [Industrial Machine Learning (Coursera)]

Course logistics

Each week:

- lecture slides (released on Tue, lecture based)
- Jupyter notebooks (released on Tue, topic based)
- one graded assignment (released on Wed, deadline on Wed/Thu in a week)
- one or more optional materials (released during a week)

+ online discussions (Slack)
+ office hours, Q’s during lectures, quizzes

Course logistics

Graded assignments:

- we run them with Papermill
- they should not fail
- partially autograded
- you have one week

Course logistics

Study groups (pairs, for both Python and Probability courses)**:**

- <u>Oct 19:</u> form study groups (if you don't, we assign you randomly)
- <u>Oct 24:</u> tell us, if randomly assigned group is not working for you (logistics, whatever)
- do homework together, discuss, have fun

Why Python?

Why Python?

Python is:

- simple enough
- flexible
- general purpose
- has huge ecosystem for DS and ML

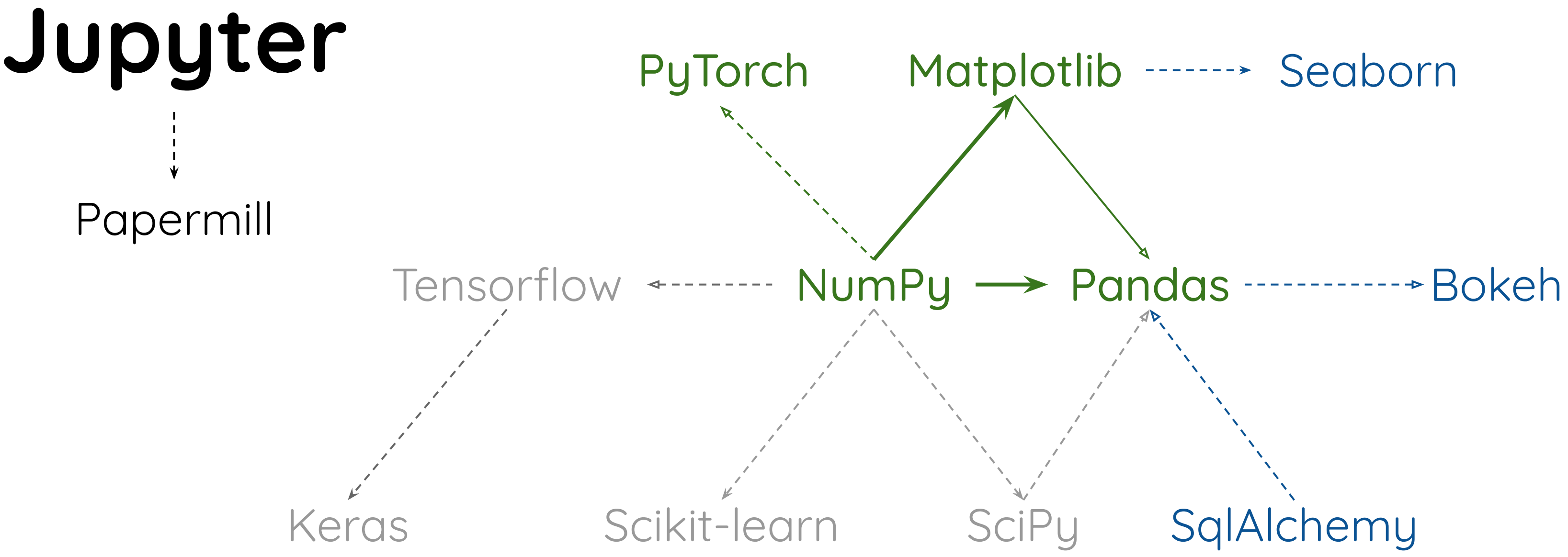
Why Python?

But it’s interpreted! **Isn’t it slow?**

Short answer is: **No. It’s ok.**

Long answer is: **No, it’s not slow,** cause all the heavy lifting is done in **C/C++/Fortran** under the hood. Thank you, Python C API!

Python ecosystem for ML

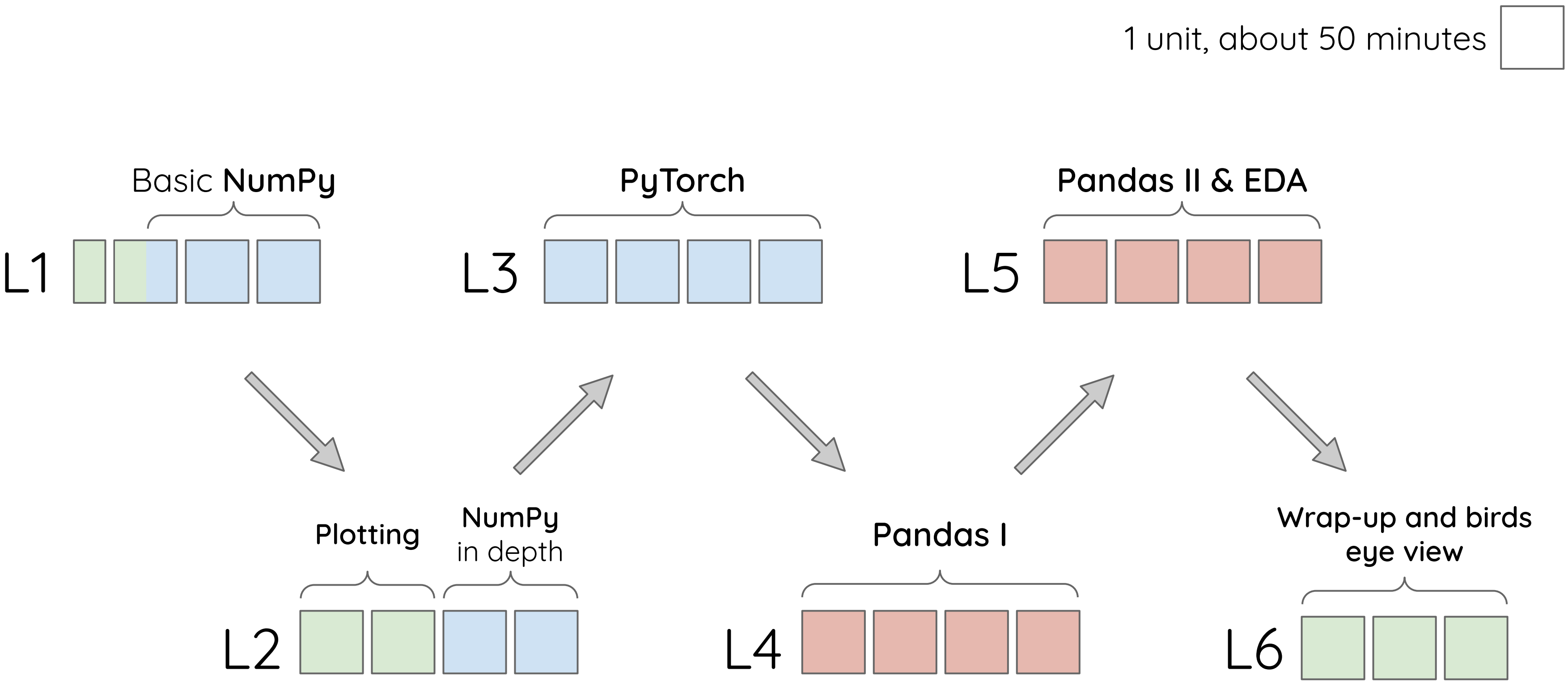


Syllabus

Main parts of the course are:

- NumPy (+ PyTorch as a topping)
- Matplotlib (+ Seaborn and Bokeh)
- Pandas
- basics of **exploratory data analysis**
- tools for **reproducibility**, project structuring and more

Syllabus



1 unit, about 50 minutes
Basic NumPy
L1
PyTorch
L3
Pandas II & EDA
L5
Plotting
NumPy in depth
L2
Pandas I
L4
Wrap-up and birds eye view
L6

→let’s try it out!

(i.e. we’re going to switch to notebook, terminal or whatever)

Resources worth reading

Python for Data Analysis by Wes McKinney

[PyData YouTube channel]

[From Python to Numpy] by Nicolas P. Rougier

[Scientific Computing in Python] by Sebastian Raschka

…and there will be more along the way.

This lecture

- environment review: **Jupyter**
- high-performance Python arrays: **NumPy**
- creating and indexing arrays, linear algebra and more

Jupyter and other tools

Jupyter

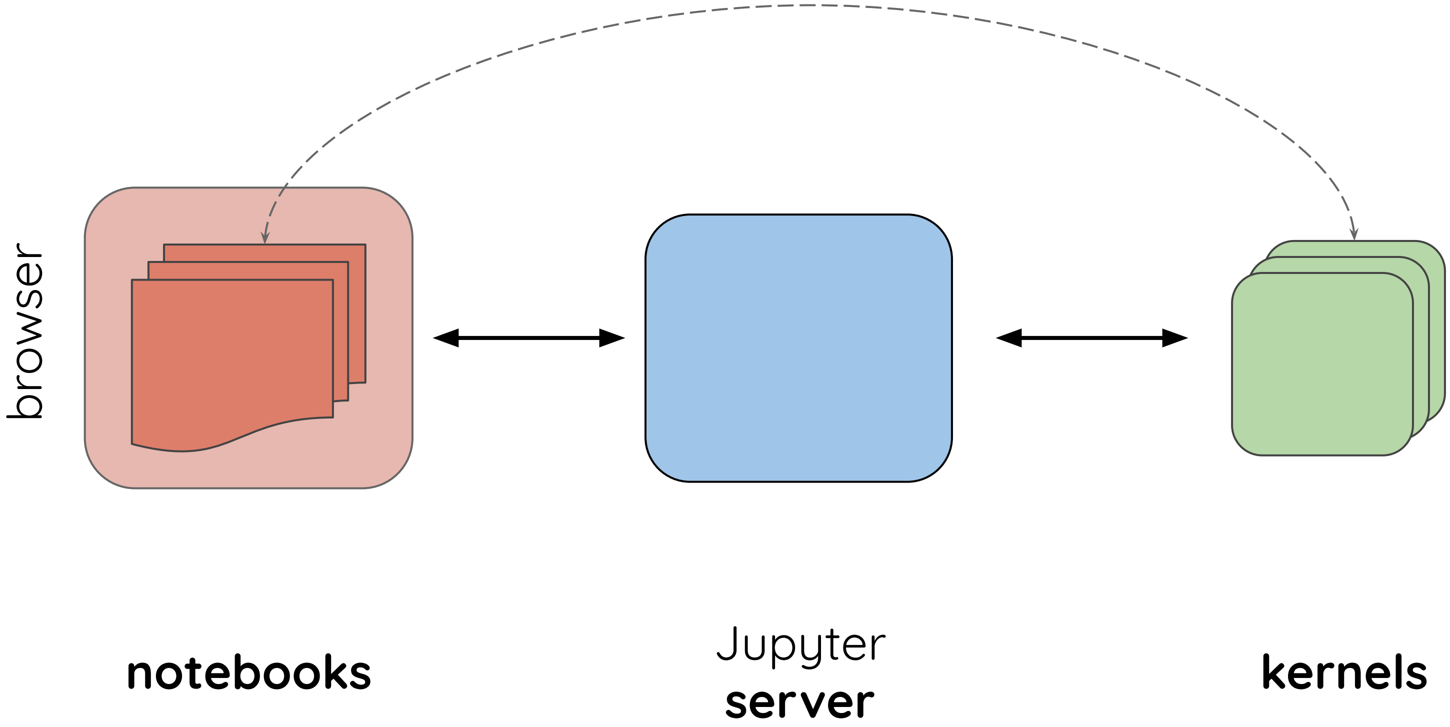
web-based interactive environment

extremely suitable for exploration

originate in IPython project, but is largely **language agnostic now**

→let’s try it out!

Jupyter

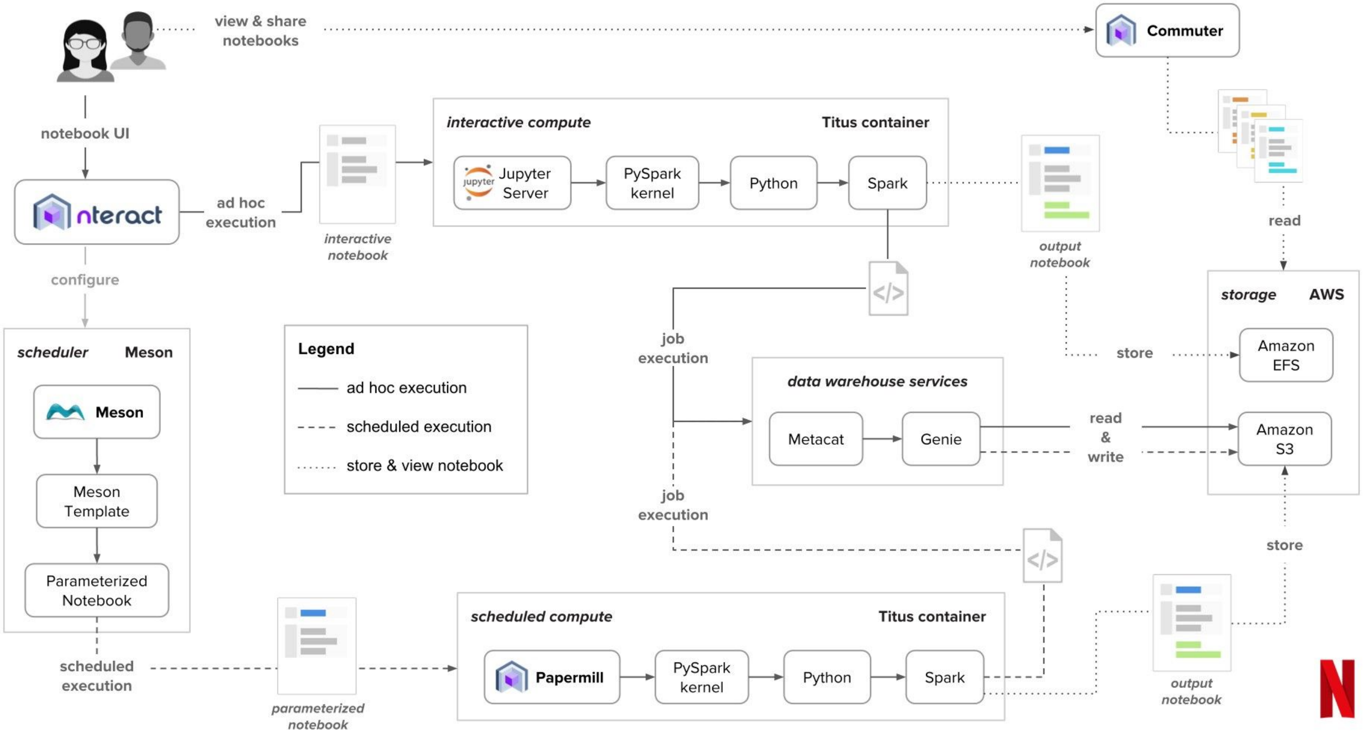


Other notebook envs

Hosted:

- Google Colab
- Yandex DataSphere
- Nextjournal
- more...

Beyond exploration



[Beyond Interactive: Notebook Innovation at Netflix]()

Beyond exploration

Papermill and others:

- Beyond Interactive: Notebook Innovation at Netflix
- Part 2: Scheduling Notebooks at Netflix | by Netflix Technology Blog
- Automating Jupyter notebooks with Papermill

Jupyter: a bit of safety

Jupyter server, when running on a cloud/remote machine **should not be open** to the outside world.

Use password and **https** or **ssh** tunneling.

NumPy: basics of high performance arrays

Why NumPy?

Pure Python:

- is slow (everything works through Python interpreter)
- lacks strong numerical infrastructure (**math** module? really?)

NumPy:

- fast (it's C/C++/Fortran and battle tested BLAS etc. implementations)
- a lot of routines for virtually any generic use case

ndarray

- core data structure in **numpy**
- container with **known number** of elements of the **same** (known) **size**
- supports **indexing** and **vectorized** operations
- allows to **share** data
- **fundamental** for most other numerical packages (Pandas, Matplotlib, SkLearn, etc.)

Creating arrays: naive

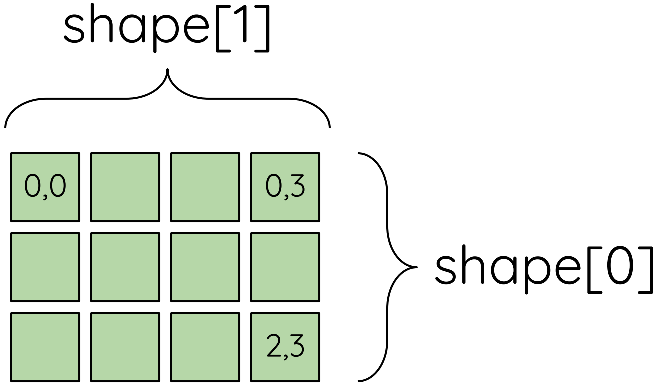
- let's use **np.ndarray** directly!
- Or, better, let's create an array from Python sequence

→let's try it out!

Array: basic properties

- shape: `arr.shape`
- type of elements: `arr.dtype`, `arr.itemsize`
- number of dimensions: `arr.ndim`, `ar.size`

Python list vs. ndarray



len = 5
element size = ?

shape = (3, 4) (**elements**)
ndim = 2
element size = fixed

Creating arrays: advanced

We rarely need to create arrays from Python sequences (and **np.ndarray** should be avoided altogether)

Instead we need:

- arrays of **specific structure or type**
- arrays, filled with some **numeric pattern**

→let's try it out!

Array: basic indexing

NumPy arrays support slicing syntax:

- **a[0, 1]** is ok
- **a[0, :3]** is ok
- **a[1:, :3]** is ok
- **a[0, :-9]** and even this is also ok

→let's try it out!

Array: boolean and fancy indexing

Basic indexing may be (and for large arrays it usually is) insufficient:

- boolean: **a[boolean_mask]**
- fancy: **a[int_idx]** (remember about **np.where**)

→let's try it out!

Array: view vs. copy

Basic indexing returns a **view**(same memory is used)**,** fancy and boolean indexing return a **new array**.

But you can mix them.

And it's a bit different for **setting** values.

→let's try it out!

Array: changing shape

Sometimes we need to **change array shape**:

- flat vector to row or column vector
- row vector to column vector
- transpose

`arr.reshape`, `np.expand_dims`, `arr.T`

`arr.flatten`, `arr.ravel`

Array: changing type

Sometimes we need to **change array type**:

- to create integer mask
- to reduce memory consumption
- to conform with external API

Array: stack

Sometimes we need to **combine** multiple arrays:

- to create a matrix from several vectors
- to combine results from different sources

→let's try it out!

Array: universal functions

Fast, vectorized functions, operating element-wise.

- **unary: np.sum, np.mean** and so on
- **binary: np.maximum, np.logical_and** and so on

Array: universal functions

ufuncs support common arguments:

- **axis**: operate over this axis
- **where**: masking
- **keepdims**: do not drop reduced dimensions

NumPy: basics of linear algebra

Linear algebra: basics

Linear algebra works on vectors (1D), matrices (2D) and tensors (>3D).

Typical operations:

- dot-product of vector and matrix
- matrix operations: invert, get eigenvalues
- decompositions

Linear algebra: np.linalg

Entry point for linear algebra operations:

- np.linalg.inv, np.linalg.det, np.linalg.trace
- np.linalg.eig
- matrix decompositions

→let's try it out!

Linear algebra: eigenvalues and eigenvectors

The simplest possible decomposition for square matrices

Plays huge role in many algorithms
(often in extended ways)

→let's try it out!

Reading and writing data with NumPy

Reading and writing NumPy arrays

Array can be saved to a file with **np.save**:

- binary format
- read with **np.load**

→let's try it out!

Reading and writing NumPy arrays

Multiple array can be saved to a single file with **np.savez**:

- it's zip, but uncompressed
- use **np.load** to read it (return dict-like object, no data is actually read)

→let's try it out!

Reading and writing text files

np.loadtxt and **np.savetxt**: to read text files (mostly CSV)

But **Pandas** is much better in this!

→let's try it out!

Other formats and options

Natively or through scipy.io:

- binary data (from files)
- **mat** files
- WAV files

Using 3rd party packages:

- HDF5 (**h5py**)
- images (**skimage**, **opencv**)

What we’ve learned

- creating and indexing arrays
- changing array properties
- calculate with arrays
- basics of linear algebra operations
- I/O

Assignment

- Exploring NumPy: array creation, indexing
- ufunc's

questions?