Python for Data processing

Lecture 6:
EDA, rules of thumb and big picture

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What we already know

- NumPy
- PyTorch
- Pandas
- plotting
- basic EDA

Today

- **exploratory data analysis** discussion
- **rules of thumb** and common mistakes
- **big picture** of DS and ML

Exploratory data analysis

Origin

It all starts with **questions**.

Not about data, but **about real world**.

Why it works like this?

Can we explain why something happens?

Can we predict X?

Can we reinvent our product with data?

Why DS and ML

Two reasons:

- **create** something new
- **improve** something existing

Questions and answers

When answering the questions we look at data

Do we **have** the data needed?

Is quality of this data **good enough**?

Can we process this data?

Can we answer the questions with this data?

It’s iterative

You start answering questions, and you discover **new questions** worth asking

Target may **shift**

Questions may turn out to be **trivial**

You may **hit a wall**

That’s ok.

Walls

Sometimes it's not possible to either answer the questions you have, or ask new ones: **data is too weak.**

Find new one, or **drop** it.

Not just questions

We do not want to just know something new about the world outside.

We want to have **actionable insights**.

And because they are actionable, it’s your responsibility to provide **deep** and **accurate** insights.

Exploring the data

Goals:

- assess data **quality**
- understand data **structure**
- get basic (or complex) **insights**
- plan **modeling**
- plan **presentation** of your results
- plan **integration**

Data quality

Problem: **data is usually quite bad**

- missing values
- errors
- biases
- signal may be not there
- not enough data

Data structure

Problem:

- **types** and **meaning** of variables
- **ranges**
- **statistics** (histograms, counts)
- internal **relationships**
- potential **derived features**
- potential **external/additional data sources**

Insights

You may discover:

- **tricky facts** about the world
- **potential problems** in your reality on the ground
- sources of **improvement**
- new ways of doing things

Presenting

Visualizations matter

- help you to understand data
- ~~help you to~~ **communicate your results**

But they only matter, if they are **clear enough**

Presenting: mistakes

Presenting with notebooks:

- stakeholders may be **overwhelmed**
- **notebooks are fluid**, your “report” may be gone very soon

Remedies:

- plain old **slides**: concise and short
- Viola, Bokeh, Dash, etc.

Presenting: mistakes

Visualizations:

- visualizations are **not “readable”**
- over-visualization

Remedies:

- try to stick to **classical** visualizations (line/scatter/bar/pie)
- if there’s no choice, consider simple **interactive dashboard**

Presenting: mistakes

Context:

- not setting the **stage**
- reporting **process**, not **results**

Remedies:

- explain the **goal**
- support your **approach**, describe process **shortly**
- focus on **results**(both + and -) and **next steps**

Best and worst practices

Code quality

Code quality **matters**: we're doing ML, but technically it's still **software development.**

Low code quality:

- bugs,
- delayed deployment,
- unneeded iterations,
- sub-optimal performance.

Code quality

High code quality:

- read **PEP8** (or similar style guide for your language of choice)
- use linter,
- prefer **readability** and **transparency**,
- **structure**, but **not over-structure**.

Reproducibility

You results **must** be reproducible:

- same computation must produce same results,
- **plan** experiments,
- **log** experiments,
- create **artefacts**,
- **split configuration** and **parameters** from code,
- set **random seeds**.

Versioning

No version control = no reproducibility. Period.

Code versioning:

- nothing is lost,
- one experiment = one commit,
- streamline deployment.

Git.

Versioning

No version control = no reproducibility. Period.

Artefacts(models, features, etc.) and **pipelines** versioning:

- experiments can be reproduced,
- experiments can be compared,
- streamline deployment.

DVC, Kedro, MLFlow.

Project structure

Separate:

- code from configuration and parameters,
- code and config from data,
- generally useful utilities from exploratory and training code.

Benefits:

- easily to extend later on,
- streamline deployment.

Black boxing

Main and most severe ML sin:

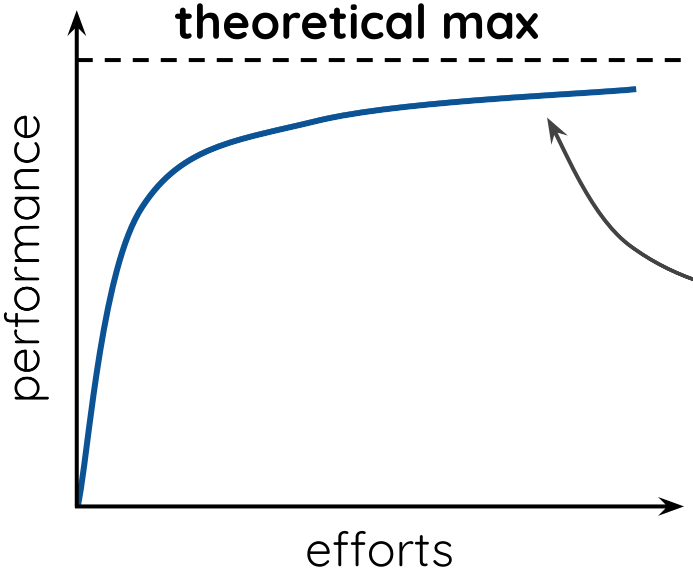
- throwing data into a model without understanding,
- throwing data into a model without rationale,
- not trying simple models first.

Consequences:

- actual performance hard to put into context,
- various deployment-time surprises.

Black boxing

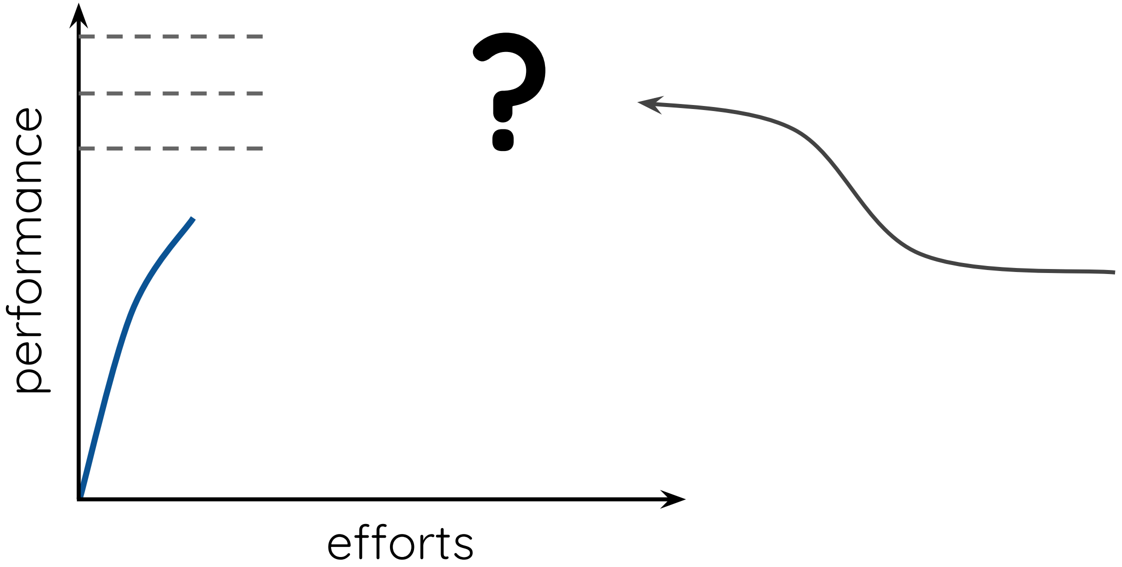
Diminishing returns:



You want to jump **here** with the best and most advanced model

Black boxing

Diminishing returns:



In reality, you jump **here**

Baselines

Instead of jumping into the most advanced model:

- establish robust baseline,
- try to preserve interpretability,
- move incrementally(this has nothing to do with speed)

Benefits:

- progress is quantifiable,
- less surprises,
- more trust.

Big picture:
Python ecosystem

Combine tools to solve large problems

Steps to build something:

- get data
- explore
- model
- present
- deploy
- iterate (usually in explore - model - present cycle)

Slow and fast data

Slow data is sitting in DBs and is updated from time to time

- dump, queues

Fast data is hitting your backend systems at a very high rate and must be processed quickly

- streaming processing or alike

Get data

From SQL DB:

- SqlAlchemy

Web:

- Requests

From other storage systems:

- specific APIs and packages

Get data

To process it immediately/quickly:

- Queues
- Dask/Ray/Faust
- Spark/Storm/Kafka

Explore

Structured data:

- Pandas

Images:

- OpenCV, SkImage

Use:

- notebooks (**tqdm** is useful)
- visualizations

Model

For structured data:

- sklearn estimators
- XGBoost, CatBoost, LightGBM

For images and other unstructured data:

- PyTorch, TensorFlow/Keras

Distributed:

- Dask, Ray

Present

Visualizations matter:

- Matplotlib, Seaborn, Bokeh, Plotly

Dashboards may help:

- Bokeh, Dash, Grafana

Viola, reveal.js instead of PDF’s

Deploy

For **classical** models:

- RESTful API with Falcon, FastAPI or Flask

For **deep learning** models:

- GraphPipe
- PyML
- TensorFlow serving

Tools have finite lifetime

PyTorch/Tensorflow:

- tremendous and confusing codebase
- multiple languages
- architecture is problematic

At least two large attempts to replace them:

- Swift for Tensorflow (dead)
- JAX

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Next gen tools for DL

At least:

- transparent and extendable device handling
- language-level (or alike) autodiff
- JIT (for any device)
- high flexibility and composability

JAX? Julia Flux?

Compute faster/easier

Julia

But why?

- C/C++ is costly in development, but fast at runtime
- Python is cheap, but is slow at runtime
- Python has too many layers of abstraction

Julia promises to be **the best of two worlds**

Julia

Features:

- Julia is **fast**
- Julia is **JIT-compiled**
- **multiple dispatch**
- **parallel and distributed** computing
- calls to C functions are **native**
- calls to Python are **simple**
- great support of **GPU computing**

Oldie, but goodie

R

Robust and well respected tool for statistical computing

- **long history**
- **great community**
- **problems** with integration
- **non-uniform interfaces**

Big picture:

Data, it’s all about data

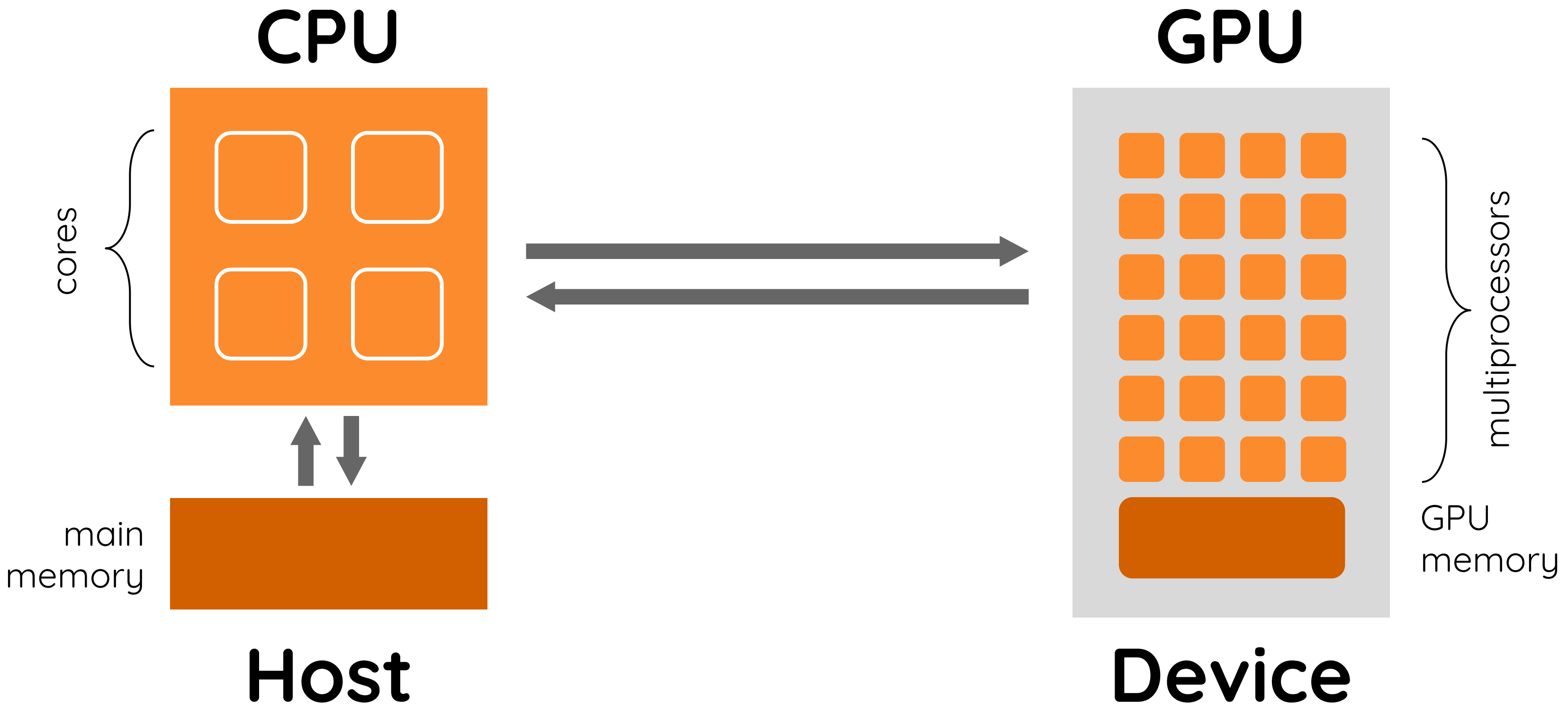
Three pillars of DL revolution

Main DL algorithms have been available for many years.

Why the DL domination since 2012?

- **data:** ImageNet in 2009
- **hardware:** CUDA in 2007
- algorithms

GPUs: the cornerstone



Data is different now

Data from **IoT** devices:

- streaming
- columnar
- graph

And **more** to come:

- edge computing
- distributed computing

Columnar databases

Data may be inherently (time) **ordered**:

- row storage is **inefficient**
- traditional databases are really **bad** in analytic workloads

Columnar engines and databases to the rescue:

- PostgreSQL + cstore_fdw
- ClickHouse (Yandex)

Columnar formats

Apache **Arrow**

Apache **Parquet**

When data is huge

Data may still be either too large, or coming to fast:

Hadoop stack

It's Java

But there's Scala

When data is huge

Apache Spark: distributed analytics engine

- in memory
- can handle streaming jobs
- knows about ML
- and graph data
- and even TensorFlow!

When data is huge

Native way to use Spark is with **Scala**

Scala may look a bit crazy at first, but it’s **powerful and flexible**

Saves a lot of time compared to Java

When data is huge

Scala:

- functional or object-oriented
- strong typing
- but with type inference
- works on JVM
- interoperate with Java

Wrap-up

Next

New hardware is coming and **IoT** is on the rise

New ways to compute: edge and **distributed**

Quantum computing?

Decline of 1-st gen deep learning?

Decline of Python?

AI nationalism

Takeaway note

Rely on **fundamentals**

Keep an eye on **modern developments**

Adapt, as only few things remain constant:

- **probability** theory,
- **first principles** approach,
- general engineering **craftsmanship**.

Takeaway note

Have fun in this fascinating journey :)

questions?