GENERAL ASSEMBLY

INTERMEDIATE PYTHON FOR DATA SCIENCE

Nicolas Paris
CTO, Healint

HELLO!

NICOLAS PARIS

- 2005-2013 Business Intelligence / Finance
- 2014 Head of Data at Healint [python]
- 2017 CTO at Healint [python, AWS]

Healint:
>> 300.000 Monthly Active users on the platform
>> 500 GB of data per week

ni.paris@gmail.com

GETTING TO KNOW YOU

http://bit.ly/python-intermediate-start

https://github.com/niparis/ga-intermediate-python-ds

AGENDA

I. PANDAS

- 1. Overview / Pandas workflow
- 2. Filtering
- 3. Transformations: apply
- 4. Aggregations: Group By
- 5. Comments on data visualisation
- 6. Understanding vectorized operations
- 7. When to use pandas vs other tools
- 8. Hands On

II. PERFORMANCE TIPS

- Why/When
- Non technical tips

III. ML PIPELINE

- Why/When
- Benefits
- Examples
- Implementation

GETTING STARTED

CONNECT TO WIFI

1. WIFI: GA / Password: yellowpencil

CLONE THE FOLLOWING GITHUB REPO

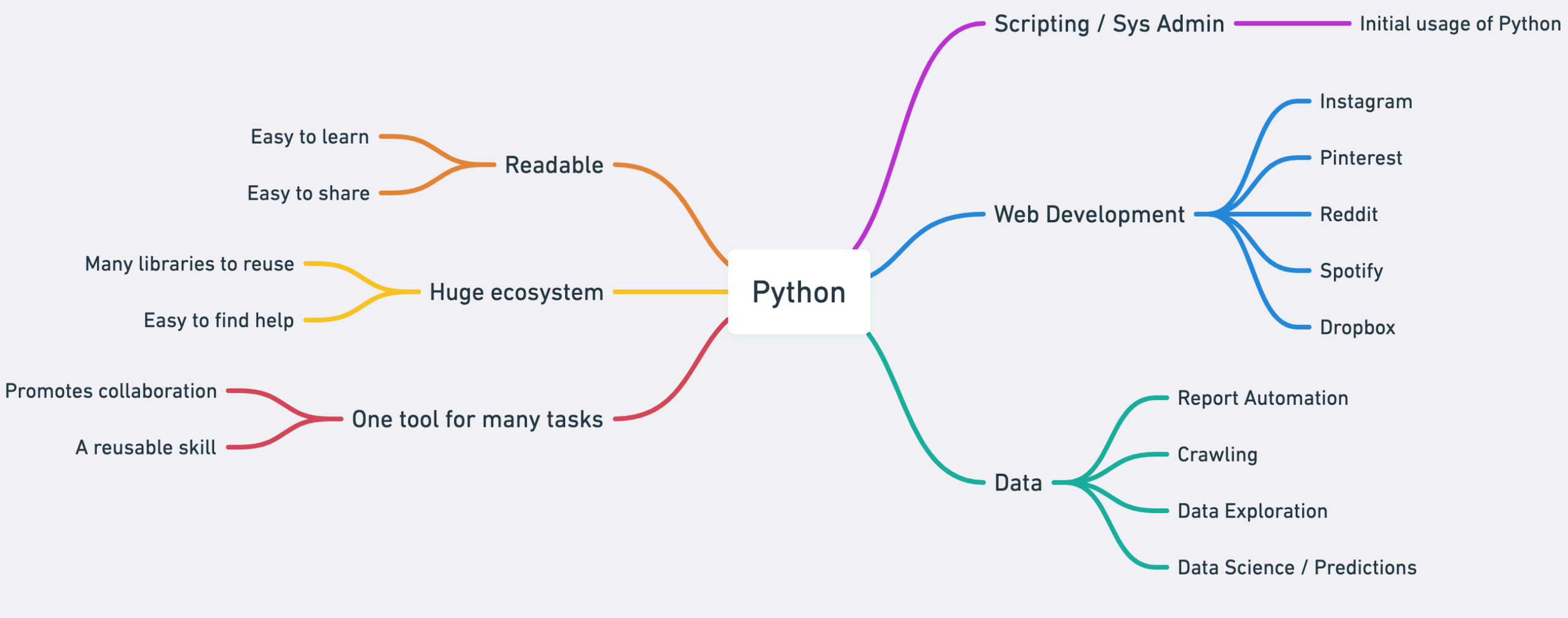
https://github.com/niparis/ga-intermediate-python-ds

START A PYTHON NOTEBOOK - PYTHON 3!

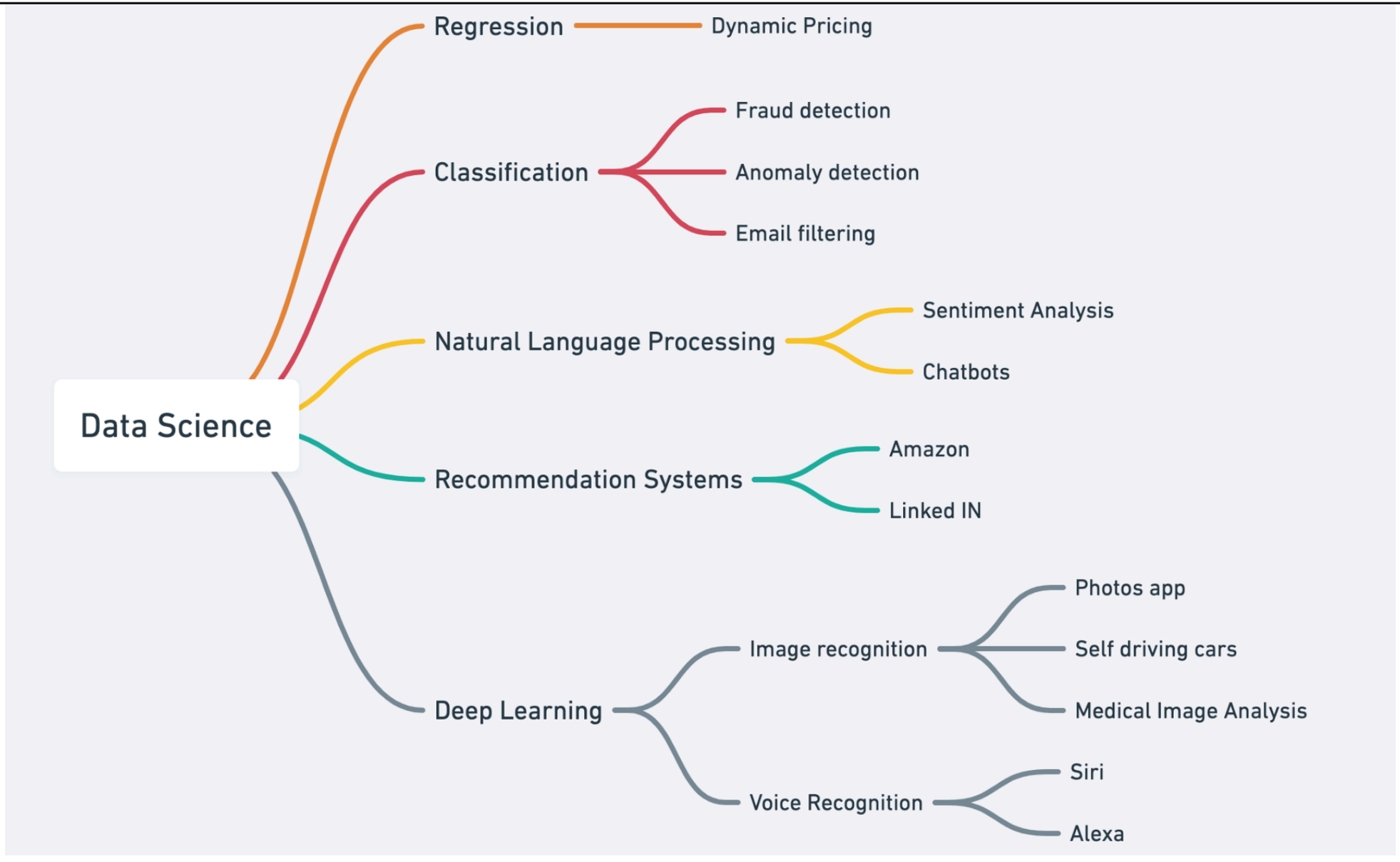
- Option A: You already have it !
- Option B: Use google colab (colab.research.google.com)
- Option C: Download Anaconda (https://www.anaconda.com/distribution/)

PYTHON

PYTHON: WHY & WHAT



DATA SCIENCE: PRACTICAL CASES



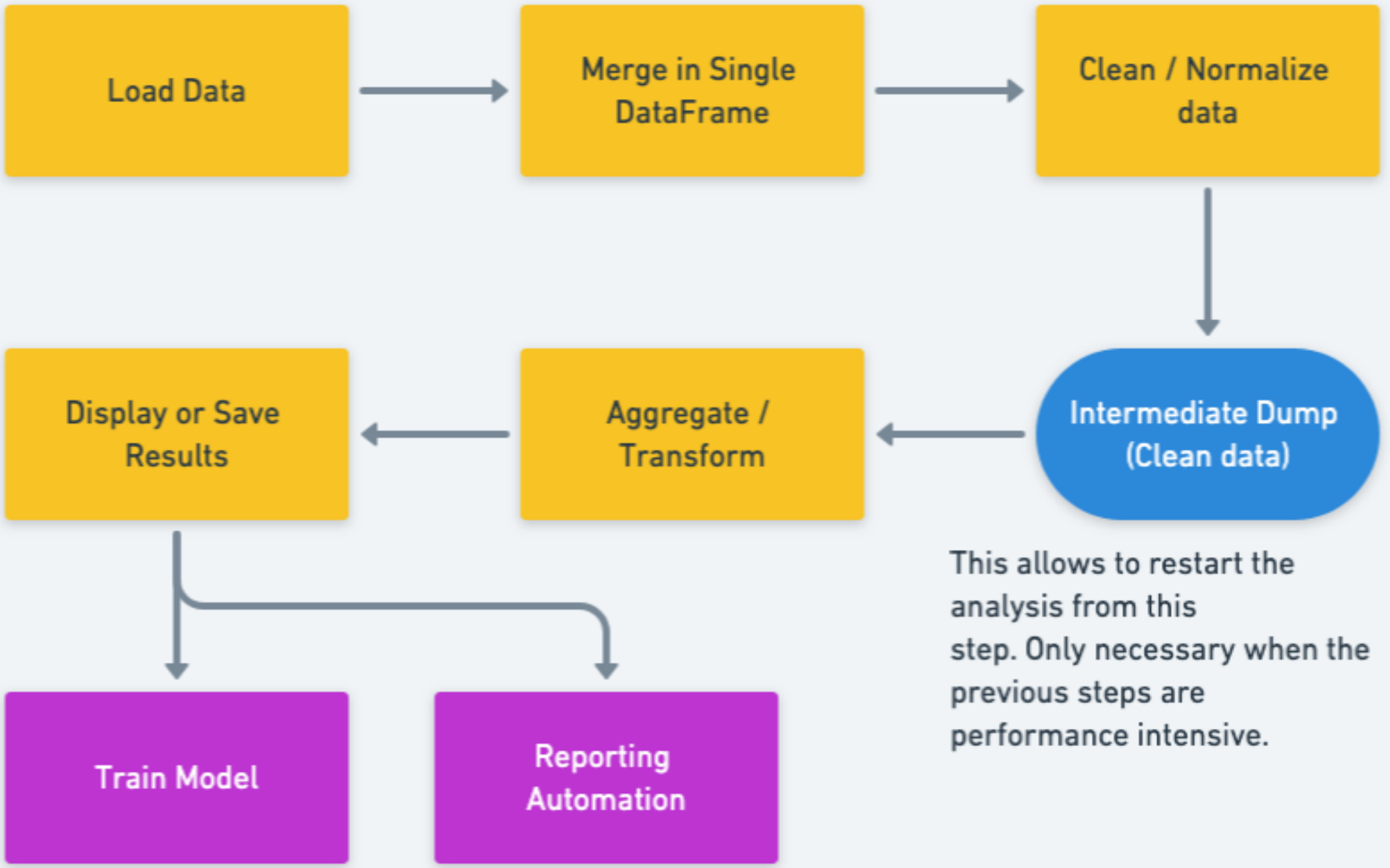
PANDAS

PANDAS: A DATA TOOLBOX

Pandas is a python library that has become the de-facto standard for:

1. Merging datasets (especially when coming from different sources)
2. Cleaning data, which involves
    A. Filtering to remove irrelevant data
    B. Impute missing data
3. Creating aggregations
4. Creating new features
5. Generating data ready to be used by a model

Pandas Workflow



PANDAS: A DATA TOOLBOX

Pandas is a huge library - it's impossible to learn everything. Besides, the doc is great, so why learn everything ?
However there are some fundamental building blocks of pandas that you have to know to be productive:

DataFrame [object]: *The main pandas object. Represents a table. Think of it as an excel table.*

.Loc / .Query: *Each of these* allows to filter dataframes. They have different syntax, the `.Query` being the more modern approach.

.Apply: To transform some existing column (or create new columns from an existing one)

.GroupBy / .agg: *The core of the pandas workload. Allows to do any aggregation.*

PANDAS: A DATA TOOLBOX

FILTERING

PANDAS ESSENTIALS: FILTERING

WHY: To keep only part of the data, either to :

HOW: Use the `.query` function. Here's the basic syntax:

<dataframe>.query("column operation value")

NOTE: "column operation value" is a STRING.

EXAMPLES:

A. df.query("column > 4")
Filters any row where the value of column is greater than 4

B. df.query("column > second-column")
Filters any row where the value of column is greater is greater than the value in second-column

PANDAS ESSENTIALS: FILTERING WITH .LOC [1]

NEXT: Once you're comfortable with **.query**, learn **.loc**.

Benefits of **.loc:**

- **A. Can add /change a value in the filtered expression**
- **B. complex filtering logic**

PANDAS ESSENTIALS: FILTERING WITH .LOC [2]

A. Add /change a value in the filtered expression with .loc

Example:

```
df.loc[df[”column_to_filter”] == “critera” , “cats”] = “meow”
```

Explanation:

For all rows where the value in the column “column_to_filter” is strictly equal to “criteria”, ASSIGN the value “meow” in the column ”cats”

Note:
If the column “cats” does not exist, it will be created on the fly.
Any value not filtered will become “None”

PANDAS ESSENTIALS: FILTERING WITH .LOC [3]

B. Can do more complex filtering logic (multi criterias, mixing AND / OR)

Example:

```
df.loc[(df[”column_to_filter”] == “critera”) | (df[”second_criteria”] > 4)]
```

Explanation:
Filters any row having **either** “criteria” as the value in the column “column_to_filter”
OR strictly more than 4 as the value in the column “second_criteria”

Note: pipe (|) is used for logical OR, ampersand (&) is used for logical ANDS

PANDAS: A DATA TOOLBOX

TRANSFORMING

PANDAS: TRANSFORMATIONS [1]

WHY: To transform some existing column, or create a new column from an existing one

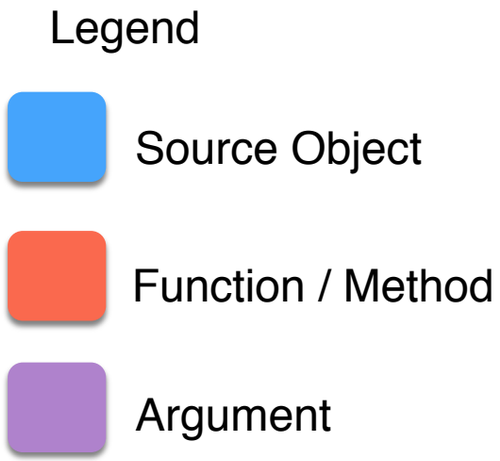
HOW: Use the `.apply` function. Here's the basic syntax:

<dataframe>[<column-selection>].apply(<function>)

The DataFrame object + the column selection. It returns a single column (pd.Series). The transformation will be applied on *each element* of the column

The .apply function

A function that will be applied on EACH ELEMENT of the source object



The main advantage of `.apply` is its versatility.

PANDAS: TRANSFORMATIONS [2]

EXAMPLE:

```python
def transform_to_date(elem: dt.datetime):
    # extract the date from a datetime.
    # date is a method of the datetime object, that's why it has to be called with `()`
    return elem.date()
```

```python
df['date'] = df['utc'].apply(transform_to_date)
df.head(2)
```

	username	subreddit	utc	date
0	kabanossi	photoshopbattles	2016-12-26 10:24:59	2016-12-26
1	kabanossi	GetMotivated	2016-12-26 10:23:14	2016-12-26

PANDAS: A DATA TOOLBOX

AGGREGATING

PANDAS: AGGREGATIONS [1]

WHY: To transform some existing column, or create a new column from an existing one

HOW: Use the `.groupby` function. Here's the basic syntax:

<dataframe>.groupby(<column_to_reduce>).agg({"target_column" : "function"})

Legend

- Source Object
- Function / Method
- Argument

Source DataFrame

The .groupby function

A column (or list of columns). The dataframe will be reduced until only UNIQUE ELEMENTS of that column are left.

The .agg function

Which column we want to perform computation on. Ex: if we perform an average, this will define the values we average.

This function will be applied on each element of "target_column", and generate a single value for each unique element of "column_to_reduce"

PANDAS: GROUP BY [SQL EQUIVALENT]

PANDAS

Df.gr*oupby(“country”)[“id”].count()*

OR
Df.groupby(“country”).agg({“id” : “count”})

SQL

SELECT country, count(id)
FROM table
GROUP BY country

HANDS ON

OPEN THE NOTEBOOK INTRO-TO-PANDAS.IPYNB

FROM THE FOLDER “01 - PANDAS” (IN THE REPO YOU DOWNLOADED)

PANDAS: A DATA TOOLBOX

MORE PANDAS

PANDAS: VECTORIZED OPERATIONS

Pandas is fast because it executes its operations on “vectors”

Vectorized operations are operations performed on entire columns at once.

To keep pandas fast avoid looping through rows.
It’s a pandas anti-pattern, it will be much SLOWER than standard python

PANDAS: HOW TO THINK ABOUT DATA VIZ

It's easy to spend hours creating very nifty charts in python.
They do look cool, but I'd suggest not investing too much time in learning how to create charts:

1. It can be VERY time consuming to create charts if you want to control the look in depth
2. The code is typically not very reusable
3. You're not improving your coding skills.
4. Many charts can be done easily with GUI

Don't spend more time creating charts than working the data

PANDAS: HOW TO THINK ABOUT DATA VIZ

You're working on an EDA (exploratory data analysis)
Use pandas ".plot" methods, as it takes no effort. Install the "seaborn" library to prevent your eyes from bleeding

You're working on a deliverable (slides, paper, etc..)
For a business audience, consider Tableau / Excel, unless there is a strong need to give a "sciency" vibe.

You're automating a report (charts need to be generated automatically)
Code is necessary. No choice.

You're working on a dashboard / web application that displays charts
Consider hosted dashboards (hosted tableau, mode, metabase, holistics, …). If your needs are too specific, have a look at plotly.

PANDAS: WHEN TO USE OTHER TOOLS

Excel

Yes, it’s not code. But if you have some quick calculations to do on a small file, or if you need a very dynamic interaction with your data (ie: lots of filtering), don’t hesitate to save your dataframe as an excel file.

Databases

A lot of pandas operations can be done by a database (merging, filters, aggregations). Many of them will be faster on a database, so learn SQL, and extract just the data you need from the database (rather than complete tables)

PANDAS: MOST IMPORTANT DOC REFERENCE

Group By: split-apply-combine

Indexing and selecting data

Most important part of the pandas doc

Tom Augspurger: Modern Pandas

The best pandas tutorial

PERFORMANCE

ALWAYS OPTIMIZE YOUR TIME !!!

INTERMEDIATE PYTHON FOR DATA

WHEN PERFORMANCE MATTERS

- You can perceive the slowness and it can be fixed faster than the time it wastes for you
- You understand how to fix it
- It’s preventing from getting results quickly (waiting hours to get the model ready)

WHEN PERFORMANCE DOES NOT MATTERS

- “I can make this 3 x faster” >> pride
- It just saves machine time (worth much less than dev time)

PERFORMANCE PRACTICAL TIPS

- Use a very small subset of your dataset when you're bug fixing (ie: still figuring some syntax, not yet reasoning about the data itself)
- Add timers to your (slow) loops, so you know when to expect your code to complete (do you need to wait 20 minutes or 20 days ?)
- When you're working with an algo that can use multiple CPU, always double check CPU usage on your machine to make sure that it's actually using them

These tips may look obvious, but I consistently see data scientists and analysts losing hours because they don't respect them.

MACHINE LEARNING PIPELINE

WHAT IS A PIPELINE AND WHY WE NEED IT

- A pipeline is a set of automated processed that allows to automatically execute tasks.

- When starting on an ML model, most data scientists start by their code in a notebook, cell by cell, without functions.

- This works perfectly for EDA (Exploratory Data Analysis), but is not an ideal way to build a machine learning model.

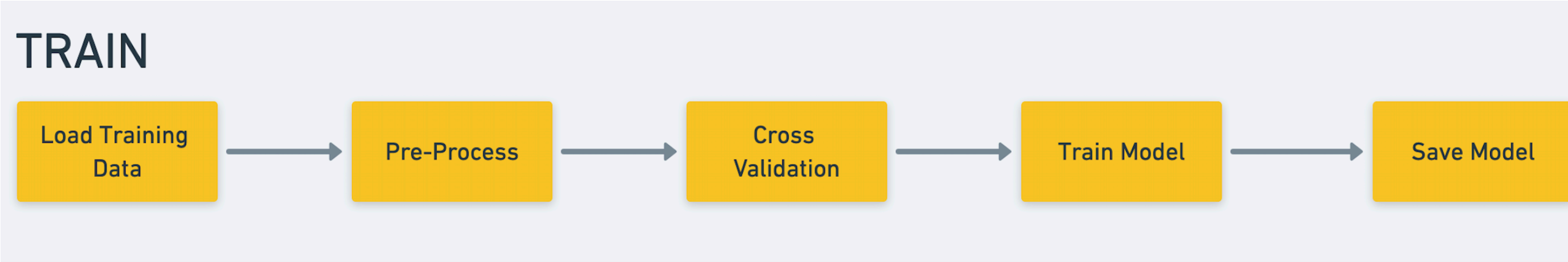
KEY BENEFITS OF BUILDING MODELS AS PIPELINES [1/2]

- 1. Less bugs: by compartmenting your code into `functions`, each `function` will take care of a single part of the pipeline, making bugs discovery/fixing much easier
- 2. Readablity: by breaking your code in small pieces, it becomes more readable, easier to document and share - essential if you're working in a team
- 3. Flexibility: much easier to adjust parts of the model without risking breaking / impacting the rest
- 4. Reproducibility: it's quite easy to produce unstable code in notebooks (execution order of cells is not fixed, easy to shadow variables)

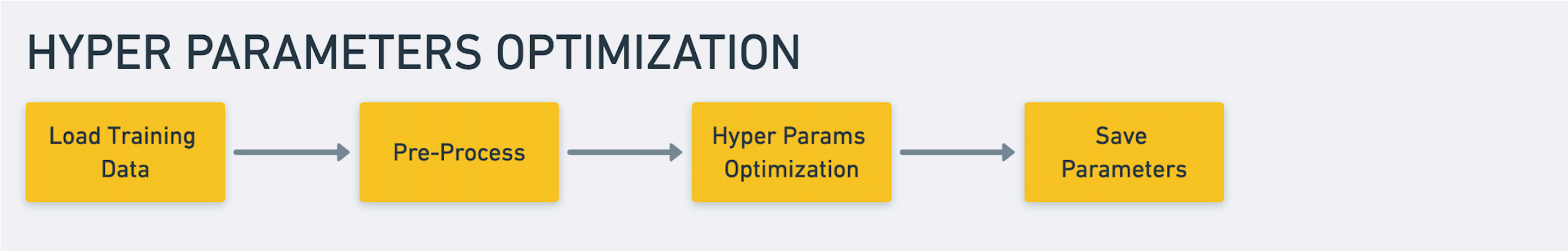
A PRACTICAL IMPLEMENTATION

- A PIPELINE IS:
- A SERIE OF FUNCTION
- WHERE EACH FUNCTION
- USES THE RESULT OF THE PREVIOUS FUNCTION AS ITS INPUT

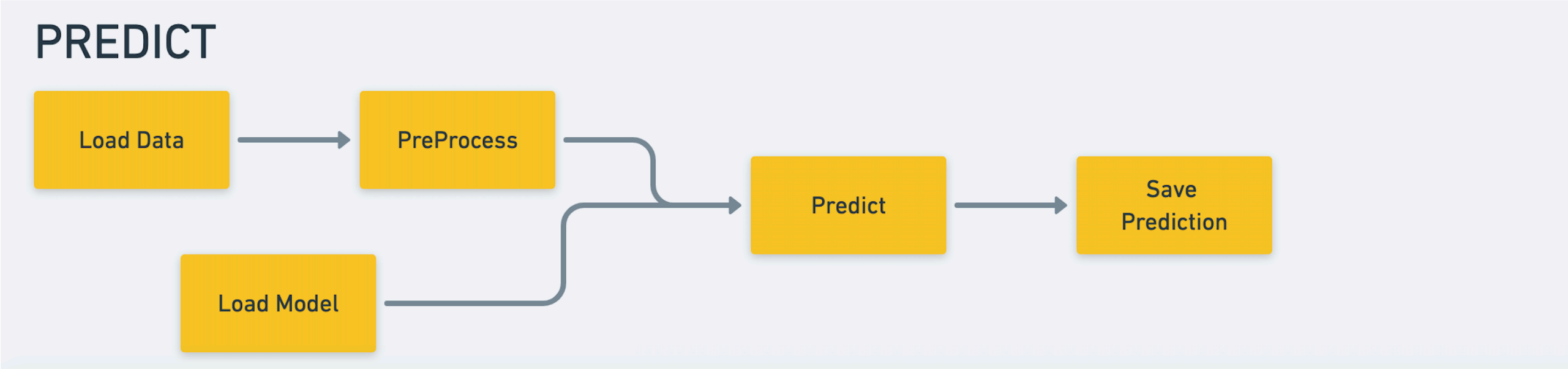
EXAMPLE OF PIPELINES



EXAMPLE OF PIPELINES



EXAMPLE OF PIPELINES



NOTEBOOK EXAMPLE

Open the notebook ml-pipeline.ipynb

From the folder “02 - ml pipeline” (in the repo you downloaded)

WHAT'S NEXT

INSTALLING PYTHON

WINDOWS: ANACONDA

Download Anaconda

https://www.anaconda.com/distribution/

MAC OS: BREW

On Mac, use Anaconda if you plan to use python ONLY for data science. Else use Brew, it's extra effort but will save you trouble.

https://docs.python-guide.org/starting/install3/osx/

KEEP LEARNING - PRACTICE

- I. Work with the other notebooks
  - Flights Delays & Youtube
  - They include some examples and some exercises
- II. Download some data and perform your own notebooks
  - https://www.kaggle.com/datasets
  - Data from your job

PRACTICE UNTIL YOU CAN USE THE SYNTAX SEEN IN THE INTRO NOTEBOOK WITHOUT TOO MUCH EFFORT

FEEDBACK FORM

http://bit.ly/2LGGpJW

Q&A