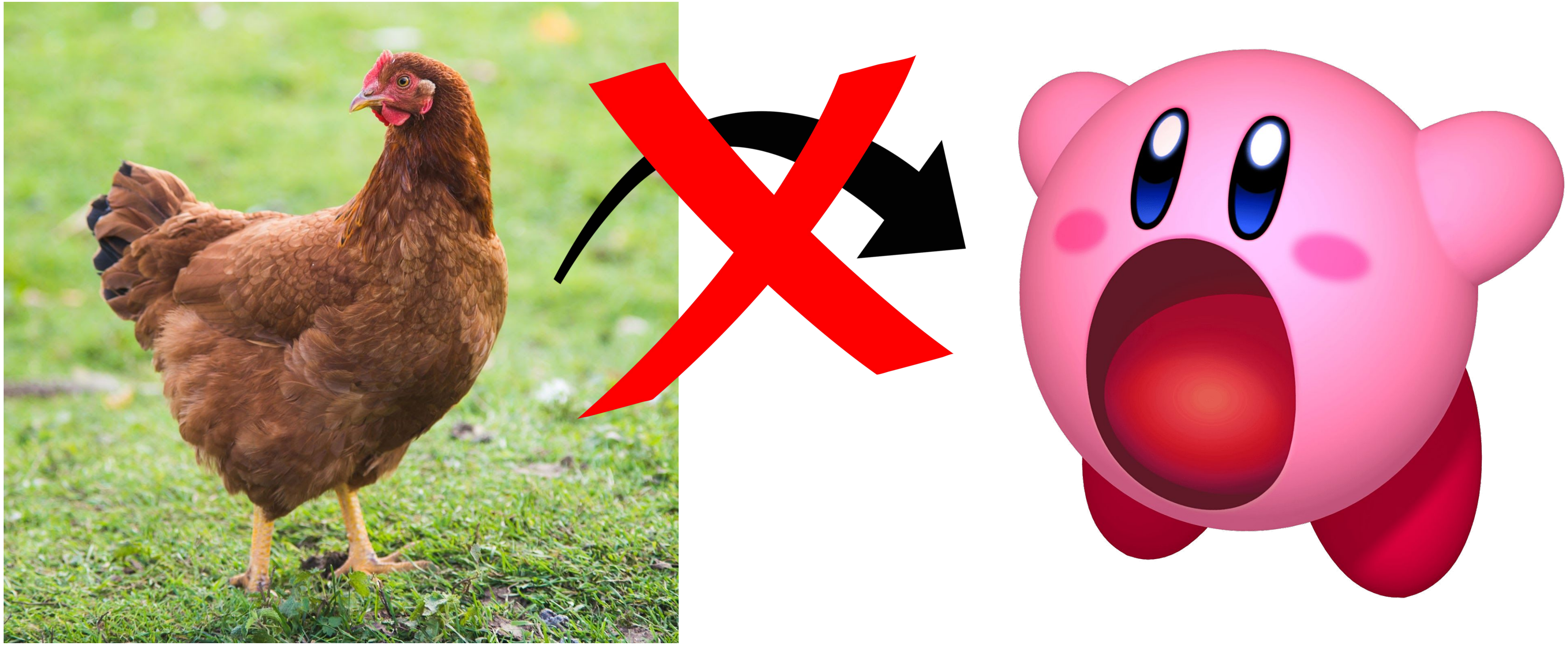
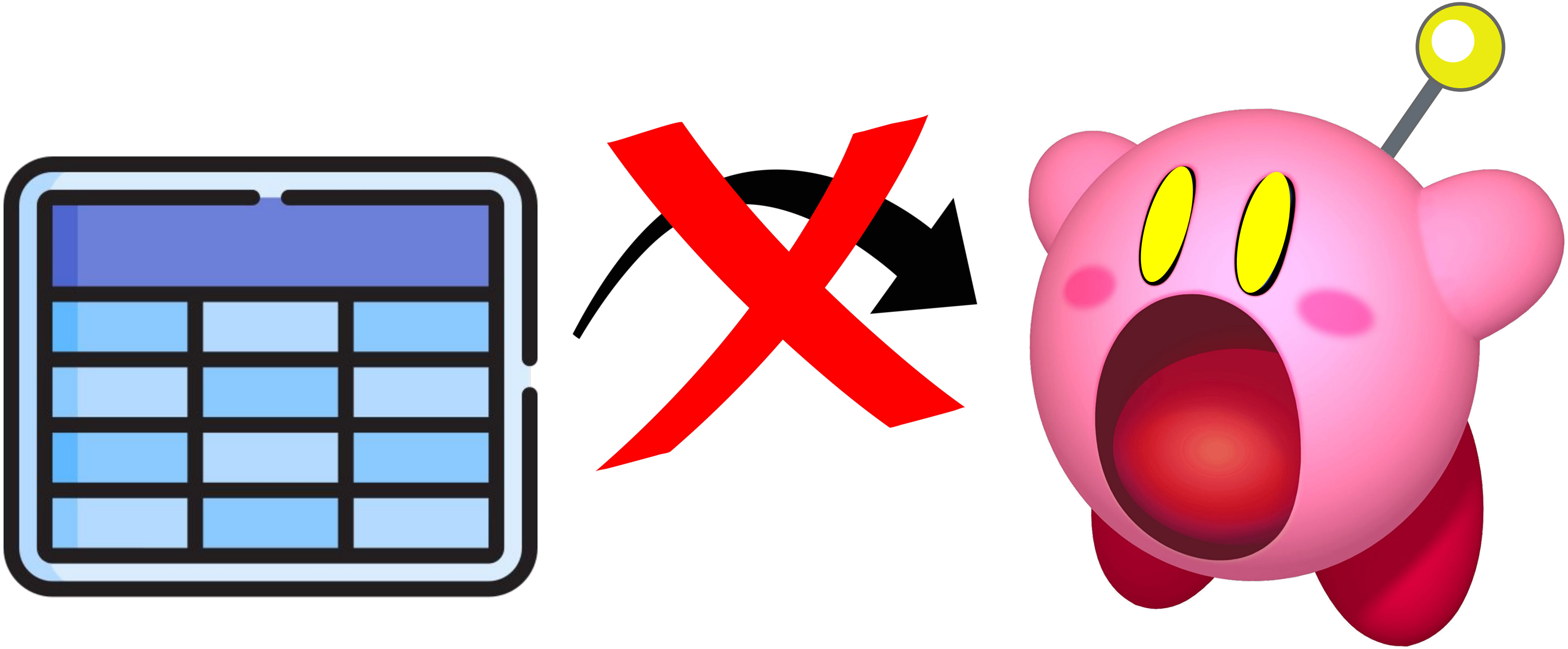
Would you eat a raw chicken ?



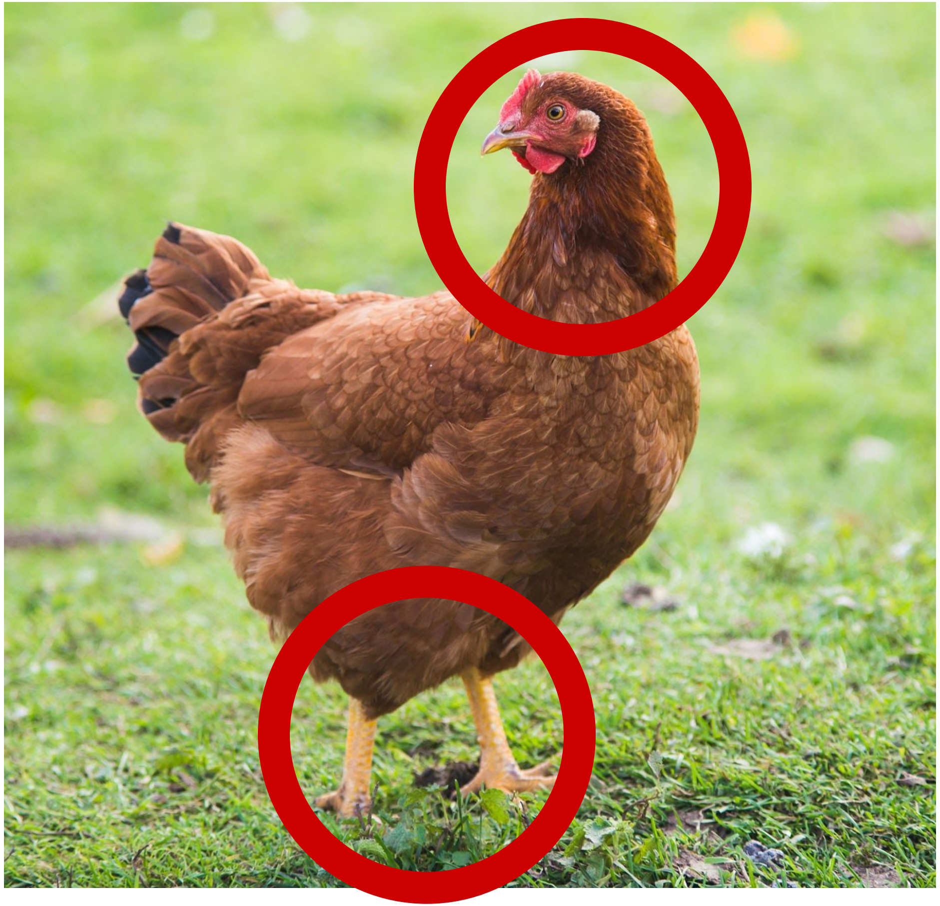
You don’t eat raw chicken…

You eat chicken nuggets!

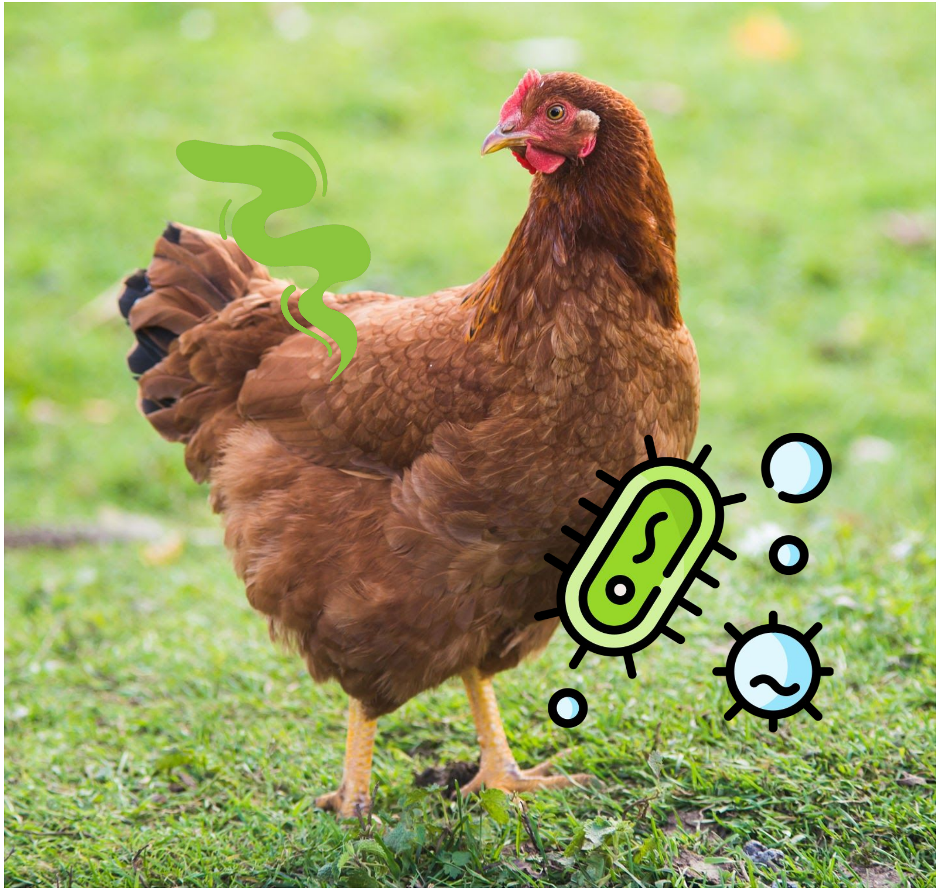


Similarly, you don’t feed raw data to an algorithm

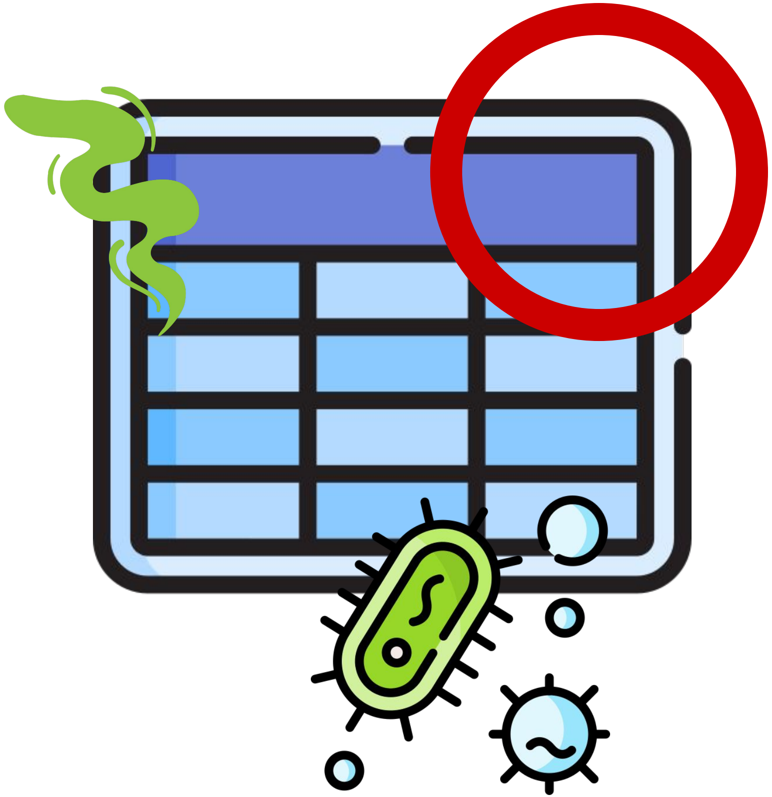
There are things you don’t eat in the chicken



The chicken itself is not clean



Your data is the exact same!



Data Science

Session 1 - Understanding data

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introduction-to-data-science

Introduction
The importance of data

DATA

Value carrying information

Literal, numerical, boolean, etc.

Amounts, facts, statistics, etc.

⇒ Using data is using information to your advantage

Each and every activity generates data - [What is Data Science? on hackr.io]

Vocabulary

Dataset

Big Data

Data Analysis

Data Engineering

Data Science

Vocabulary

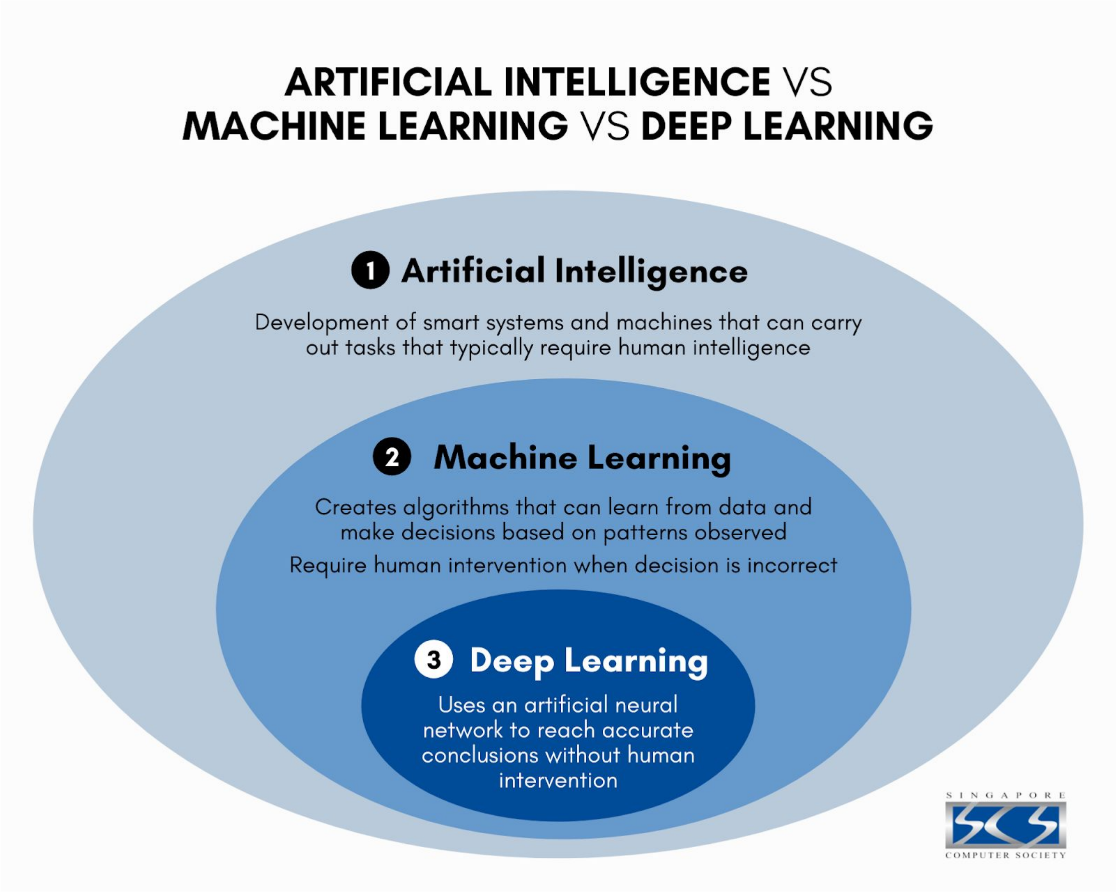
Dataset
An organised structure containing data

Big Data
A lot of data

Data Analysis
Analyse data to understand it

Data Engineering
Prepare data for future use

Data Science
Modelling data



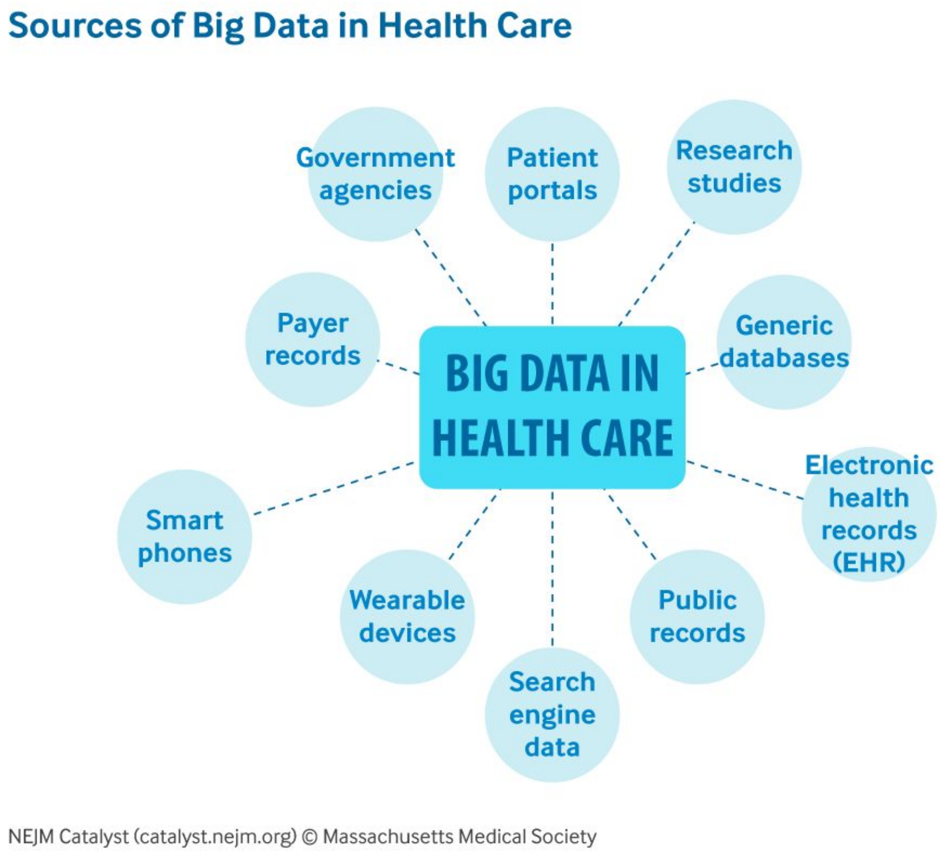
More vocabulary

Image source : [Singapore Computer Society]

Examples in healthcare

There are many applications for data exploitation in healthcare, both in research and in the industry.

- Disease prediction
- Chat bots
- Appointments management
- Alerting patients
- … etc.



The healthcare sector involves many actors who generate data

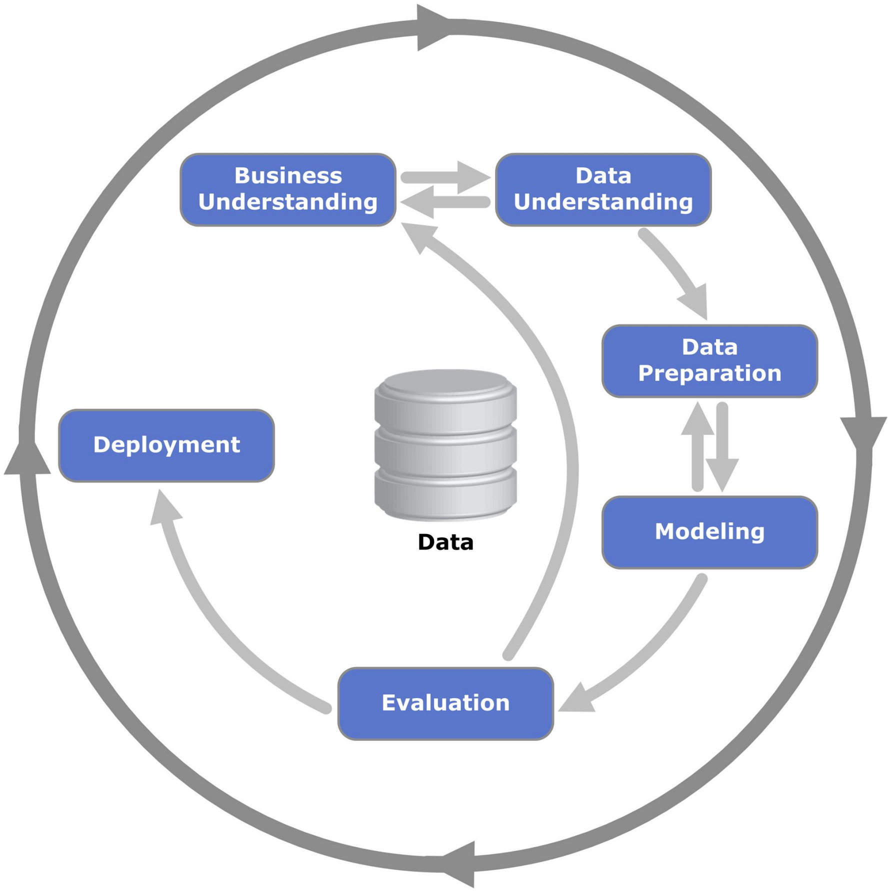
Image source

The healthcare sector can be difficult to work with

Healthcare is a high-impact subject involving many actors with conflictual interests.

- Heavy legal constraints
- Political issues
- Reluctance of certain actors
- Abundant but unclean data
- … etc.

How does one leverage data?

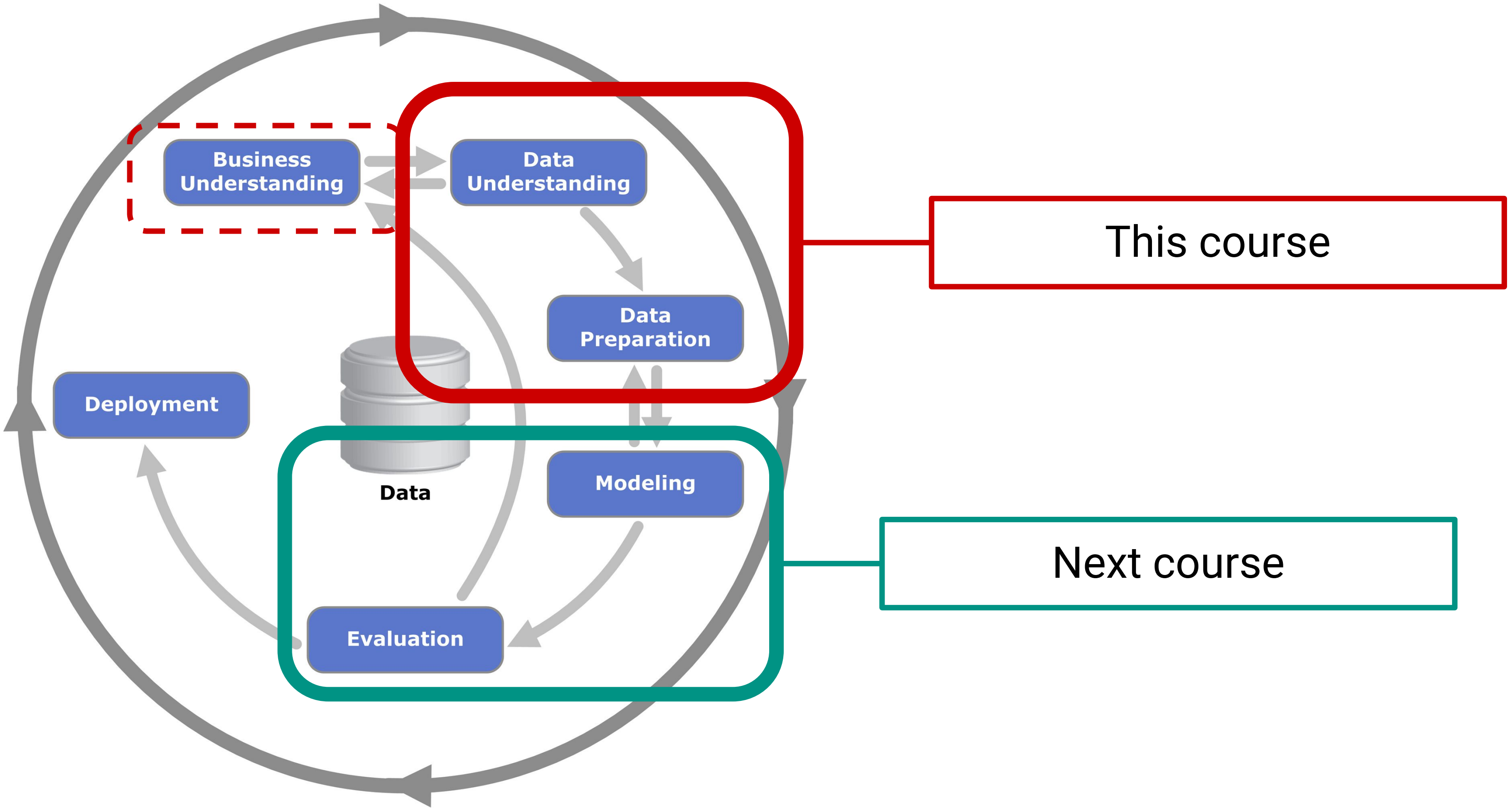


The CRISP-DM method

Cross-**I**ndustry **S**tandard **P**rocess for **D**ata **M**ining

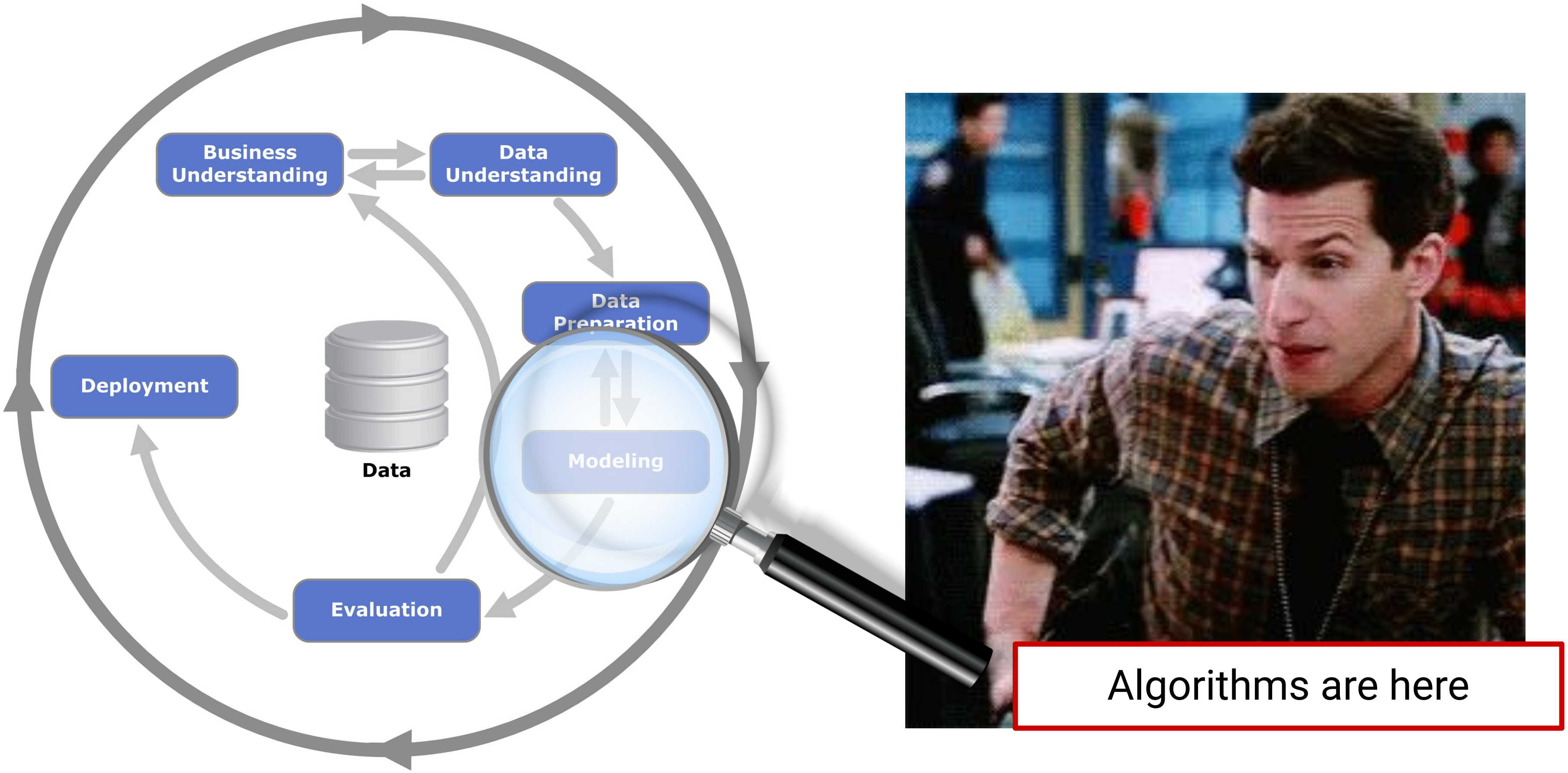
- ➔ Published in 1999
- ➔ Common in the industry
- ➔ Still relevant today

The CRISP-DM method to carry out data-driven projects *(Image source: Wikipedia)*



The CRISP-DM method to carry out data-driven projects

(Image source: Wikipedia)



The CRISP-DM method to carry out data-driven projects

(Image source: Wikipedia)

Leveraging data is a **complex subject** that goes beyond using algorithms

Course outline

Data science course

Session 1: **Understanding data**

Session 2: **Collaborative development**

Session 3: **Preparing data - Managing missing data**

Session 4: **Preparing data - Dimensionality reduction**

Session 5: **Imbalanced data and deidentification**

Session 6: **Working with text**

↓

Machine learning course

Workflow

1. Introduction - Reminders - Questions
2. Theoretical elements for the day's subject
3. Practical application
4. Correction
5. Debrief

Assessments

- Some practicals will be graded
  - Approach and reasoning
  - Code quality
- Project at the end of the machine learning course

Philosophy

In this first course, we focus **only** on the preparation of data. Machine learning algorithms may be used, but will be explained in the dedicated course.

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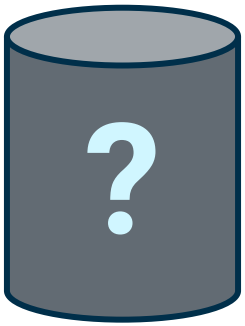
introduction-to-data-science

Exploratory data analysis

Introduction

Exploratory data analysis

Learning to know your data
is always the first step



What are we trying to learn ?

What are we trying to learn ?

General questions (observe and count)

- What data is contained in the dataset?
- How is this data represented?
- What is the type of each feature?
- Are there “holes” in the data?
- Are there duplicates in the data?
- Is there imbalance in the data?

Questions plus avancées (understand)

- What is the statistical distribution of this data?
- Are some features correlated?
- If there are, which ones and why?

⇒ The more you explore, the more questions you will find, and the more specific the questions will be

Exploratory data analysis
Practical application

What languages for data analysis?

Python and R are the most common, but there are many more (e.g. Kotlin, Java, etc.).

These languages offer many packages to analyse and model your data.

python™

We will be using Python

What software for data analysis?

We will be using jupyter notebooks to run code and visualize results.

Which packages for data analysis?

Different libraries cover different aspects of data science.

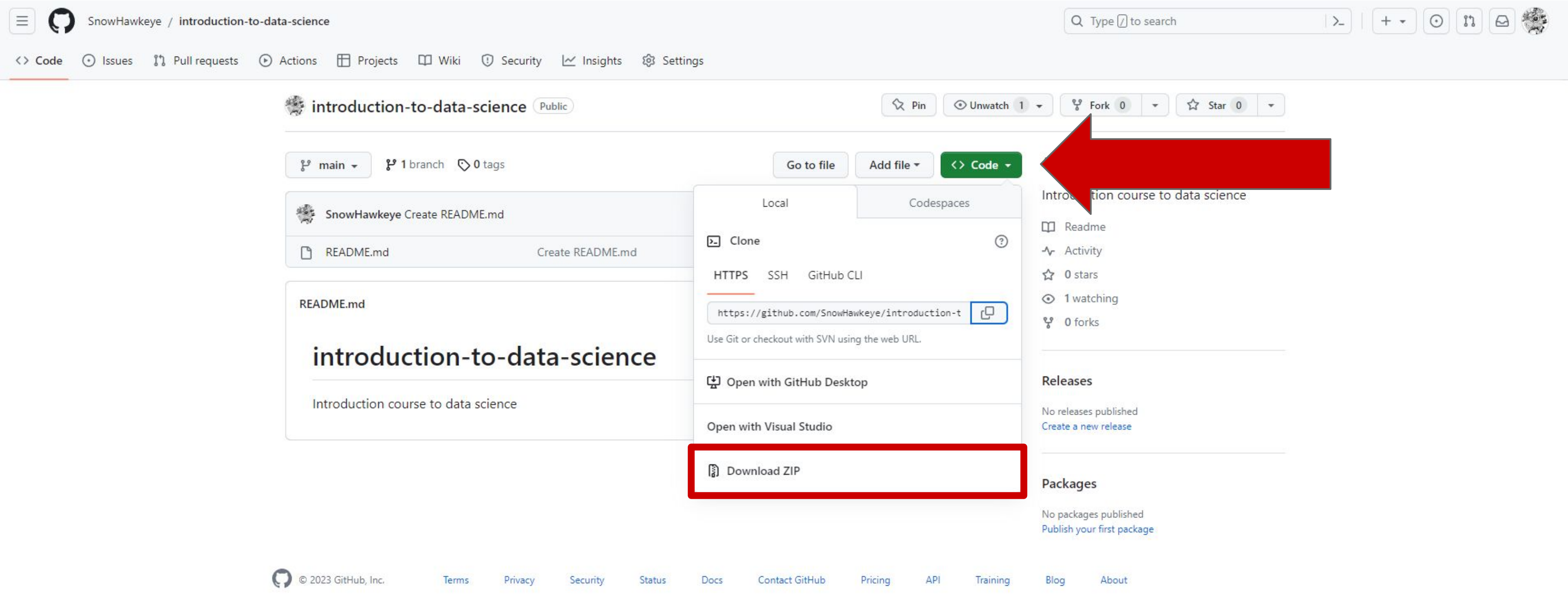
NumPy — **Mathématiques**

pandas — **Manipulation de datasets**

scikit learn — **Machine Learning (hors Deep learning)**

matplotlib, seaborn — **Affichages**

Course material

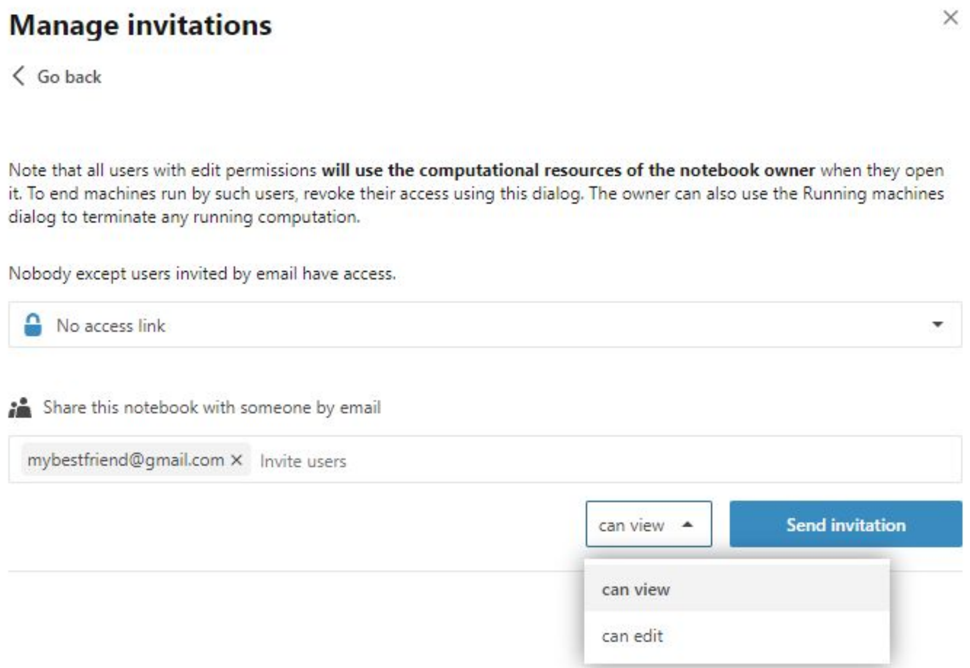


https://github.com/SnowHawkeye/introduction-to-data-science

Opening the notebook

It can be imported in any IDE.

Datalore allows for simultaneous editing between several collaborators.
(Share > Manage invitations)



Practical work

The notebook contains all the necessary instructions

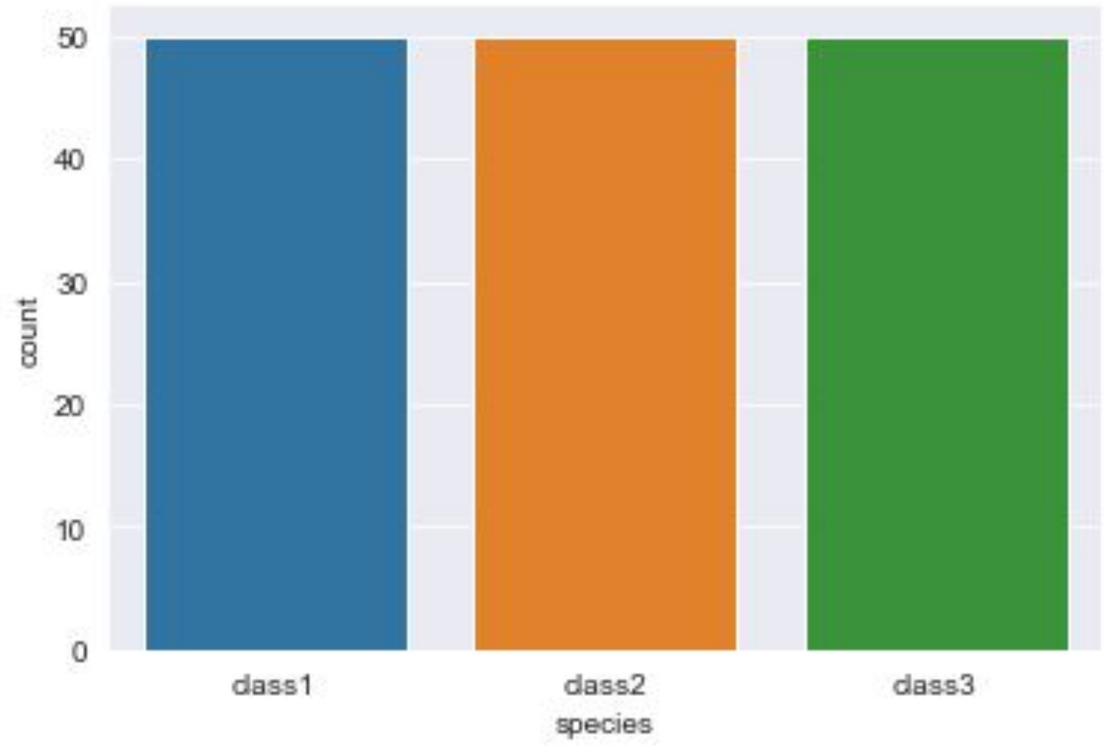
Data visualization

Why do we want to visualize our data?

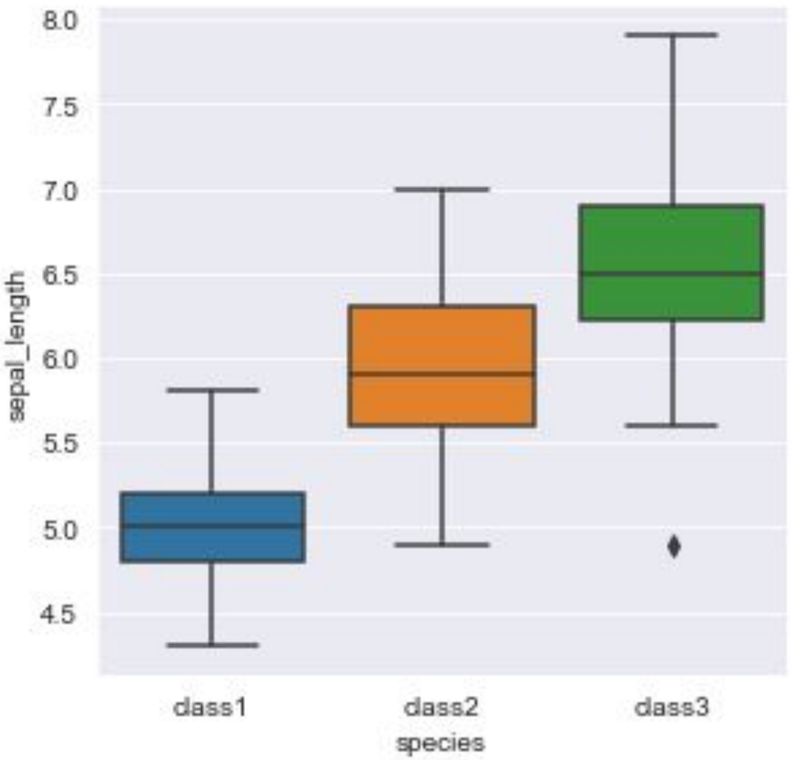
Why do we want to visualize our data?

The benefits of data visualization

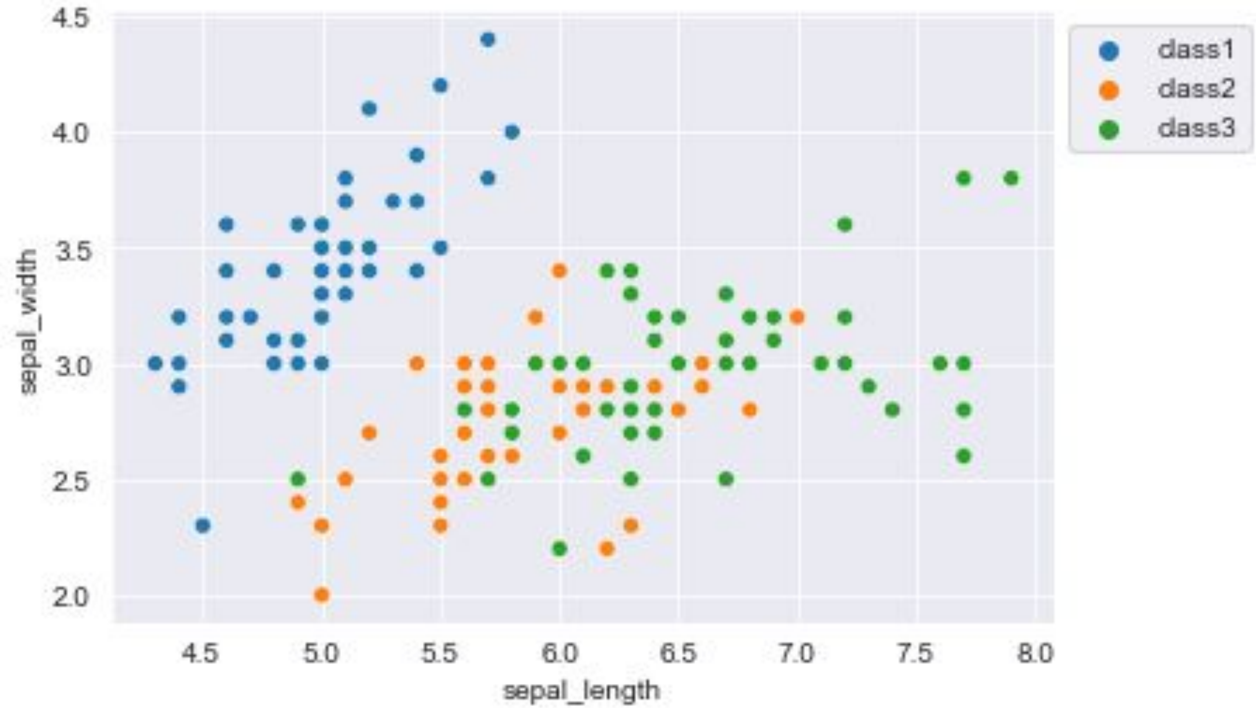
- Visualization helps **understanding the data**: detect outliers, understand the distribution of a variable, the number of elements in a class, feature correlation, feature importance, etc.
- It can help you **choose an algorithm** (in particular if your data is linearly separable)
- Graphs are essential for **communication**, in particular with non-technicians



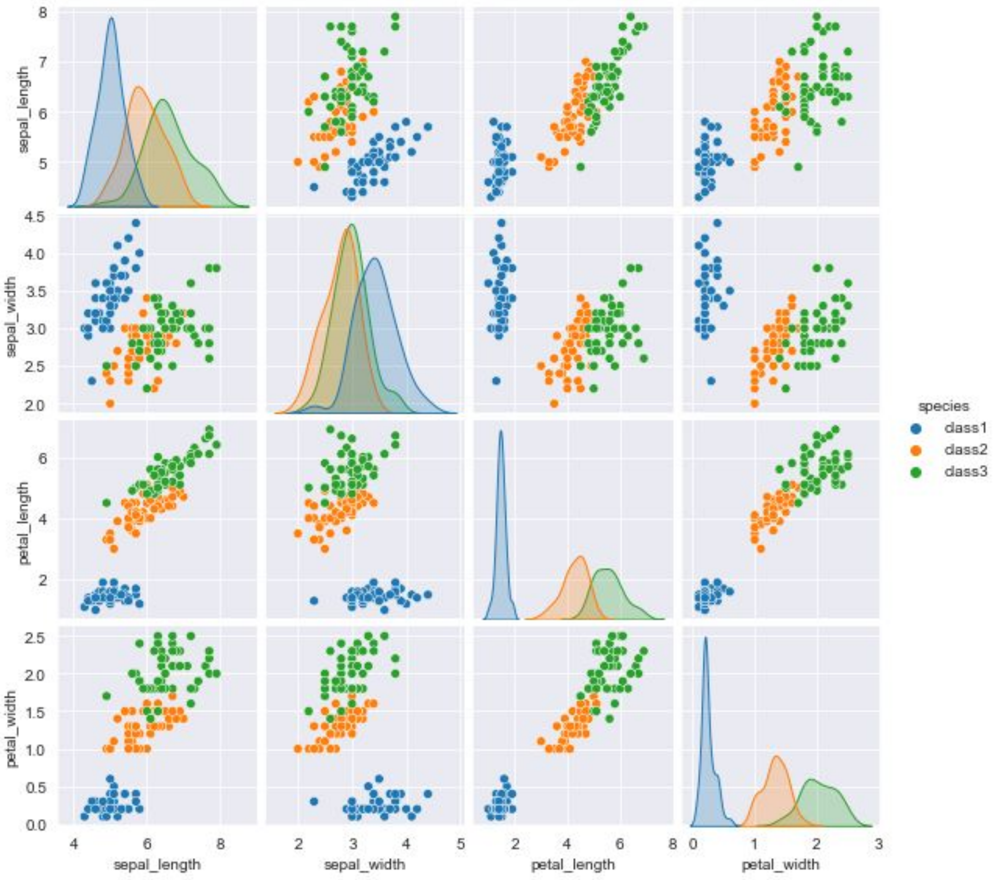
Graphs to count your data: `countplots`



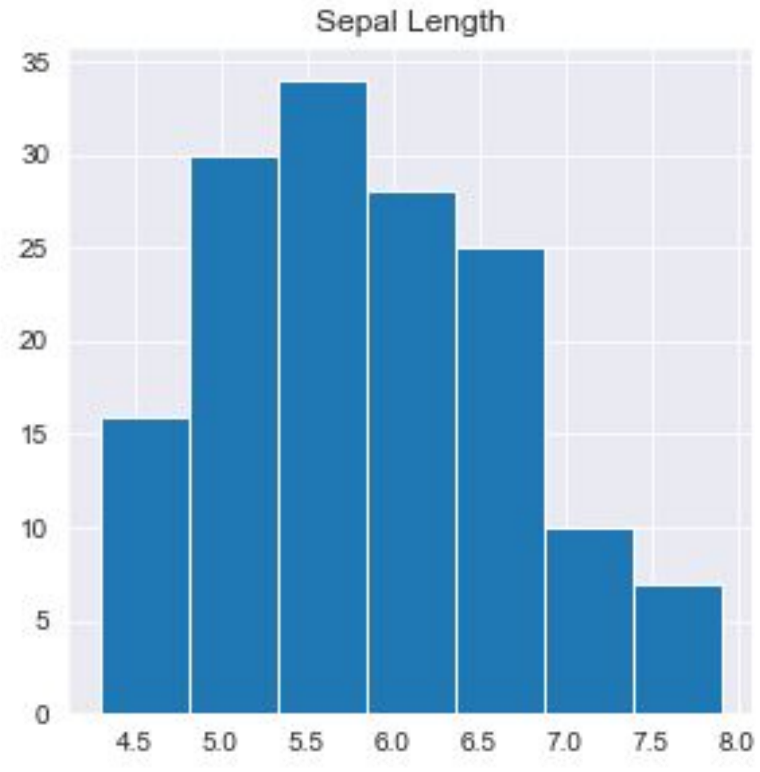
Graphs to understand the data distribution: `boxplots`



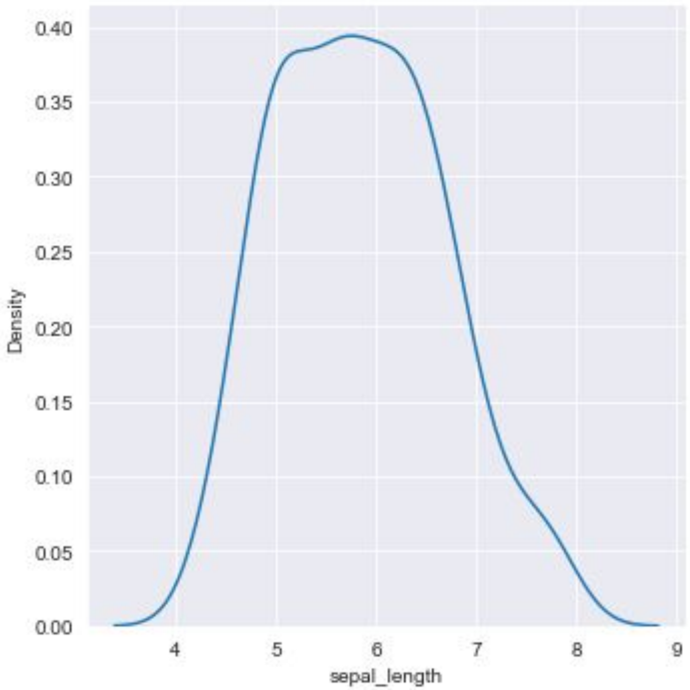
Graphs to visualize your features: `scatterplots`

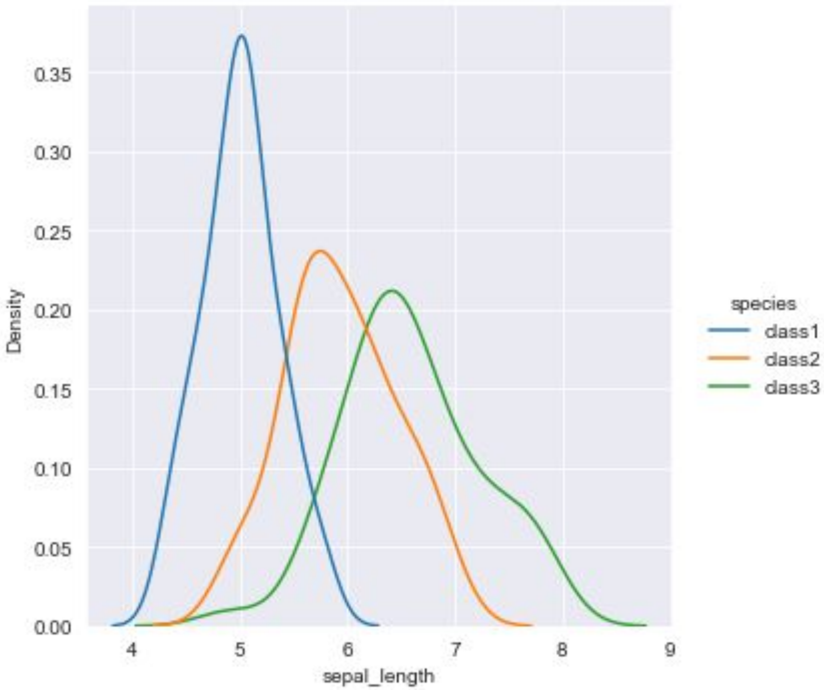


Graphs to visualize your features: `pairplot`

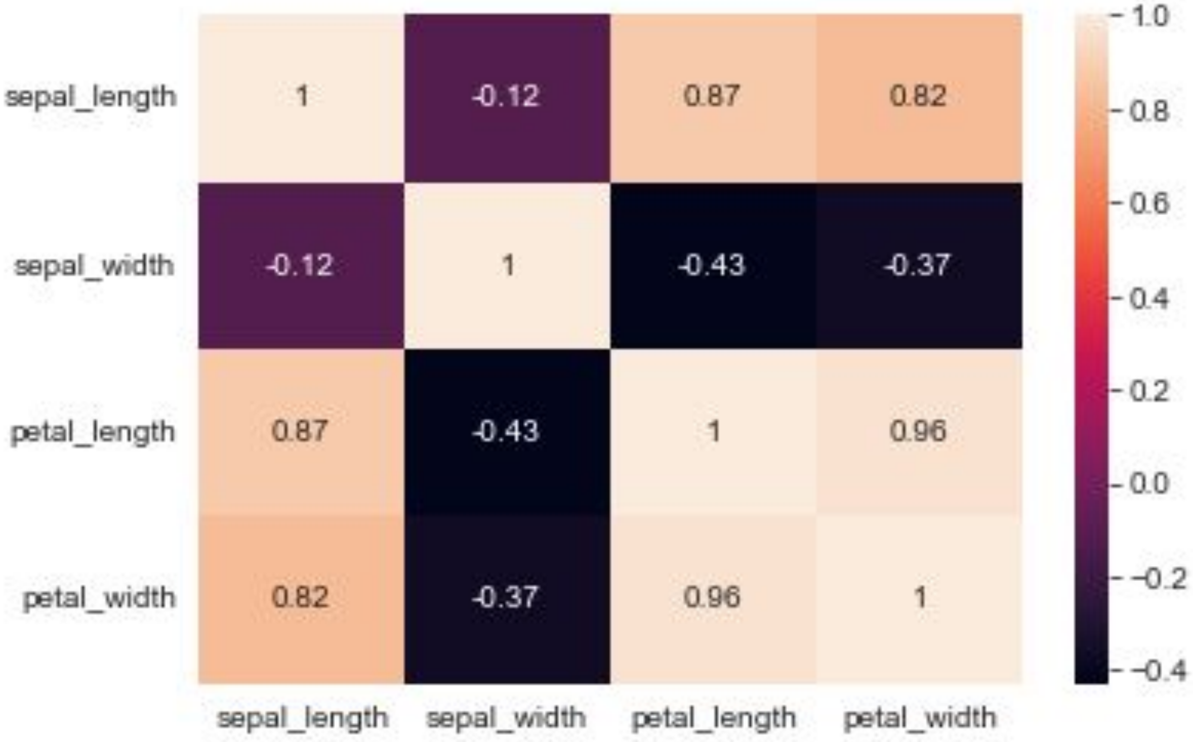


Graphs to understand the distribution of your features: `histogram`





Graphs to understand the distribution of your features: `displot`



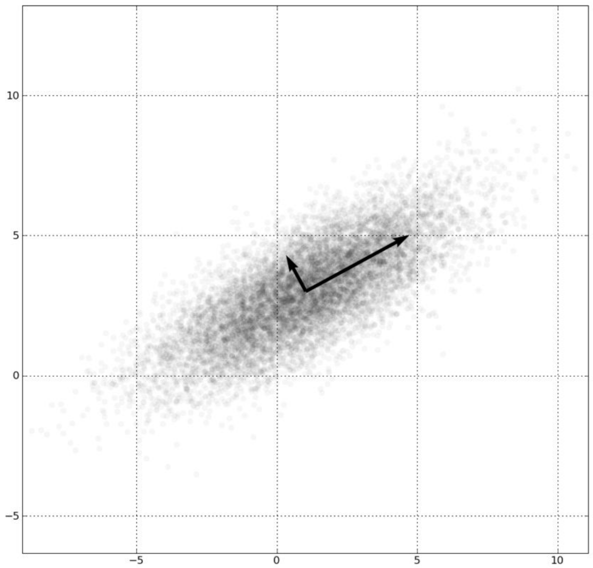
Graphs to understand relations within your features: `heatmap`

$$\mathrm{Cov}(X,Y) \equiv \mathrm{E}[(X-\mathrm{E}[X])\,(Y-\mathrm{E}[Y])]$$

Covariance of two random variables

Quantifies to what extent a change in one variable implies a change in the other variable.

In machine learning, we tend to like high (co)variance (high amount of information)



To represent with a `heatmap`: covariance

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

Pearson’s correlation coefficient

Quantifies to what extent the variables evolve similarly

To represent with a `heatmap`: correlation

Debrief

Debrief

What did we learn today?

What could we have done better?

What are we doing next time?