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# Modelling Methodologies

## Data Science

**Irene Torres Valle**

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# ¿Who am I?

# Modelling Methodologies

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## Index

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# Index

# Modelling Methodologies

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## Every day

2,5 trillions of bytes
data

## Every minute

72 hours
video

277.000
tweets

200 millions
emails

Data obtained from “IBM Acelera el BIG DATA”:
https://www.ibm.com/developerworks/community/blogs/insider/entry/acelera_bigdata?lang=en

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*“Data Scientist: The Sexiest Job of the 21st Century.”*

*Harvard Business Review*

# Modelling Methodologies

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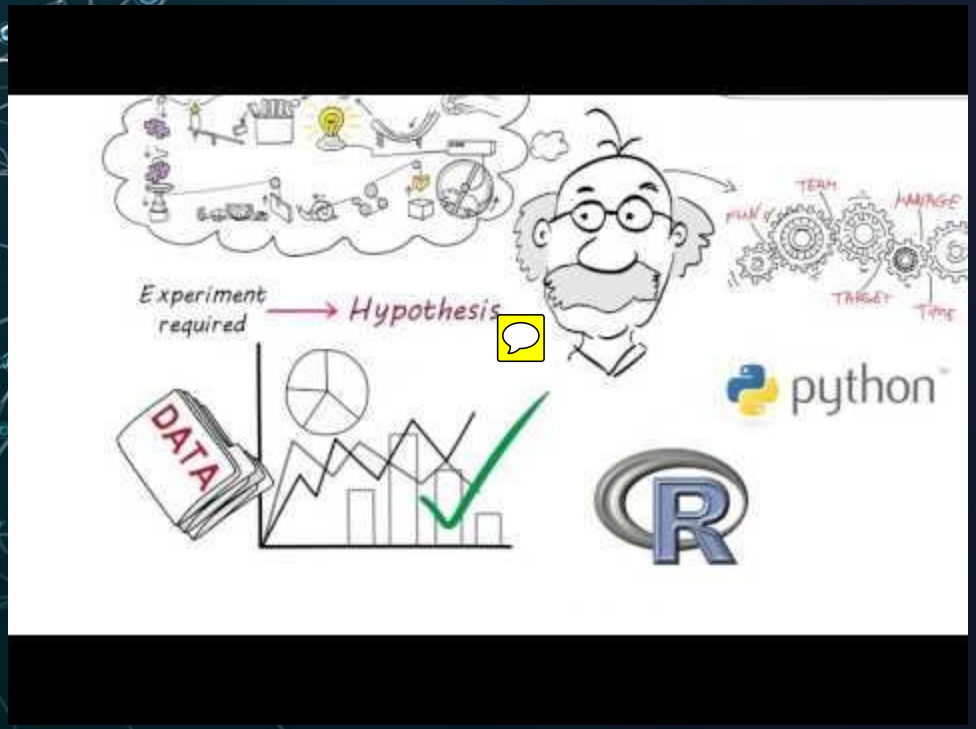

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# Types of data analysis

# Modelling Methodologies

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**Descriptive**

¿What did happen?

**Diagnosis**

¿Why does it happen?

**Predictive**

¿What will happen?

**Prescriptive**

¿What do I need to do?

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# Some questionable conclusions

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Be careful with the arithmetical mean in Descriptive Analysis

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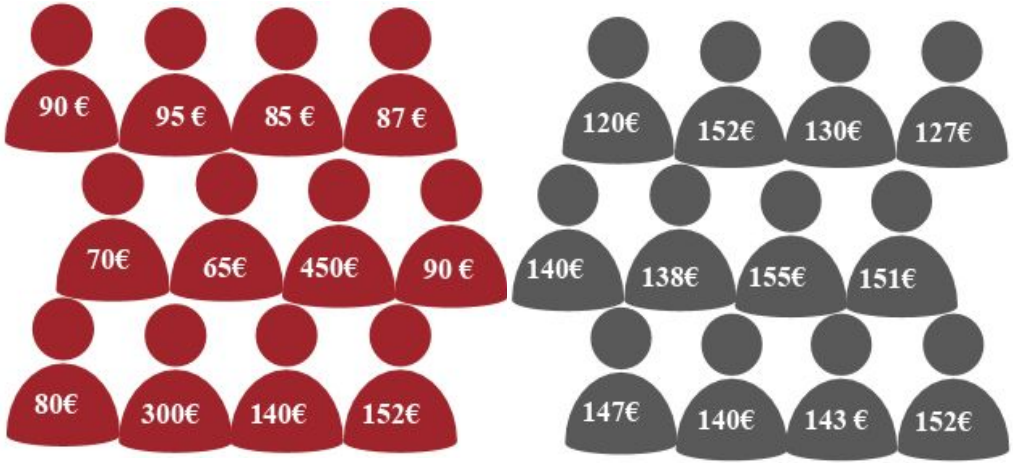
# ¿Which population is better?



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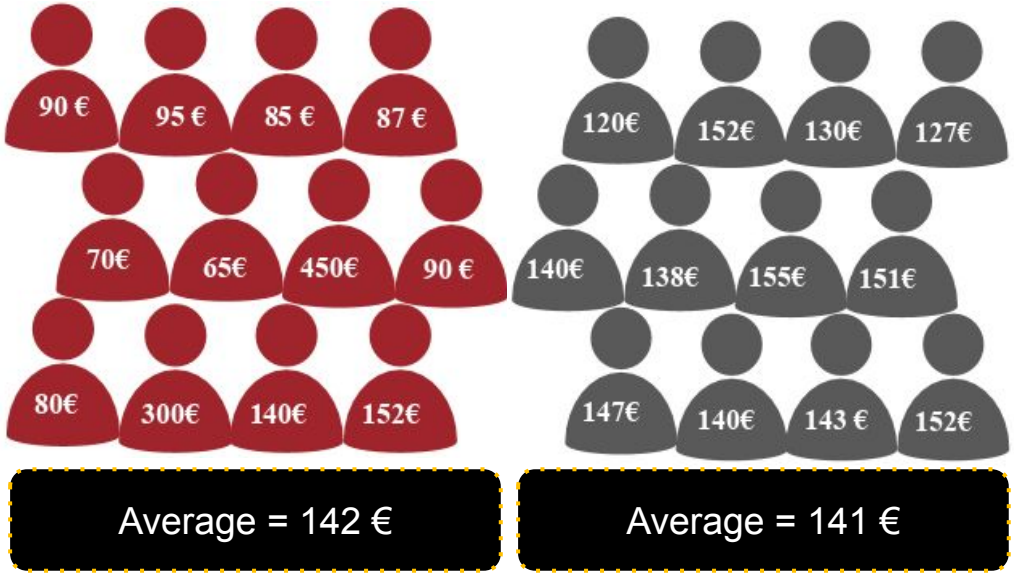
# ¿Which population is better?



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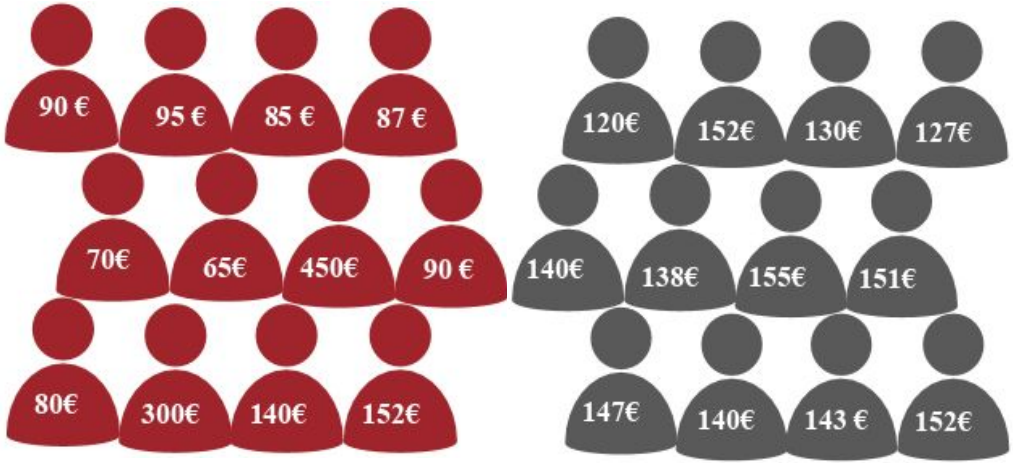
# ¿Which population is better?




Average = 142 €

Average = 141 €

Median = 90 €

Median = 140 €

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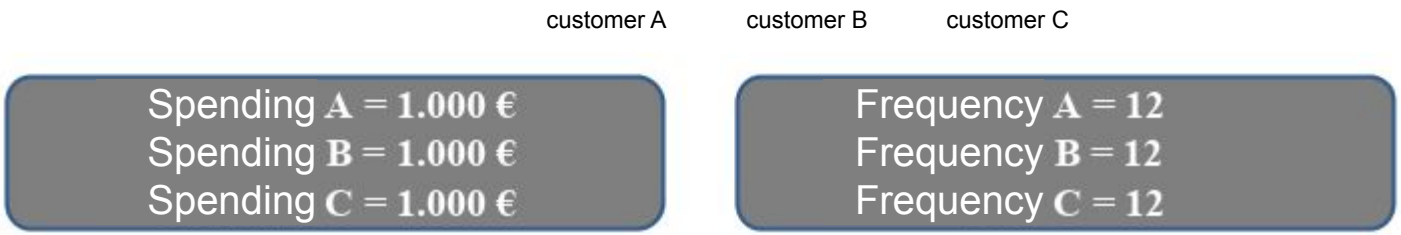
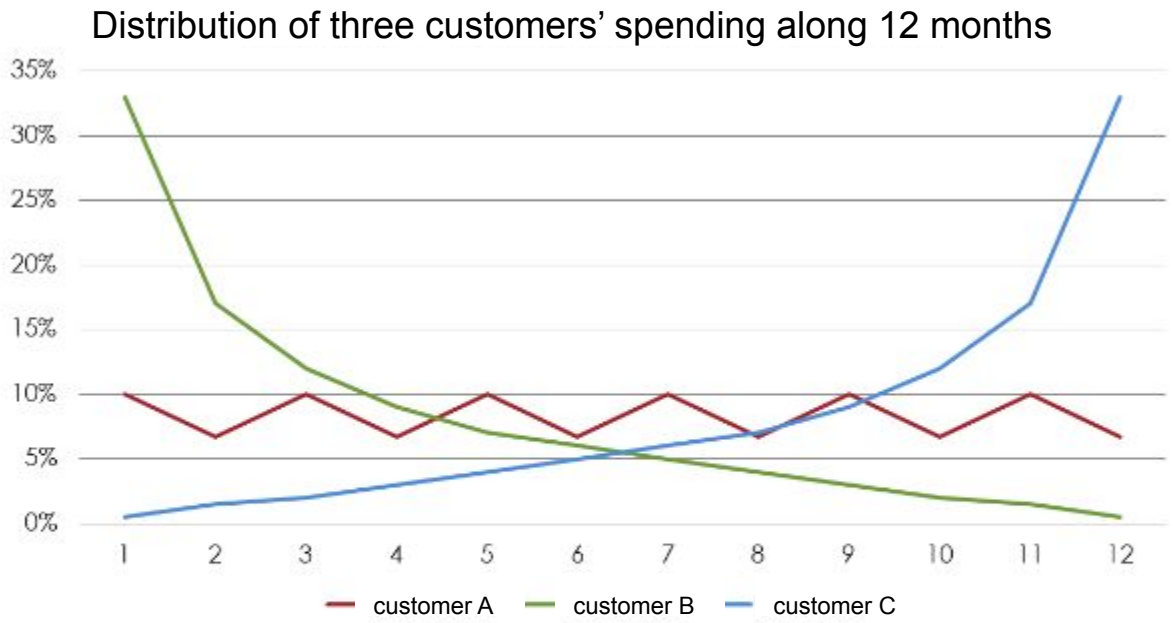
# The importance of the statistical distribution of a variable

# Modelling Methodologies



# Modelling Methodologies




Spending **A** = **1.000 €**
Spending **B** = **1.000 €**
Spending **C** = **1.000 €**

Frequency **A** = **12**
Frequency **B** = **12**
Frequency **C** = **12**

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# Be careful with comparisons

# Modelling Methodologies



Are trully comparable?

- Let's imagine that one of them are women and the other one are men.
- Let's imagine that one of them are customers and the other one are employes.

It is necessary the same starting point.
In another case, we will have the obvious, instead of learnings.


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Relationship between variables does not imply causal relation

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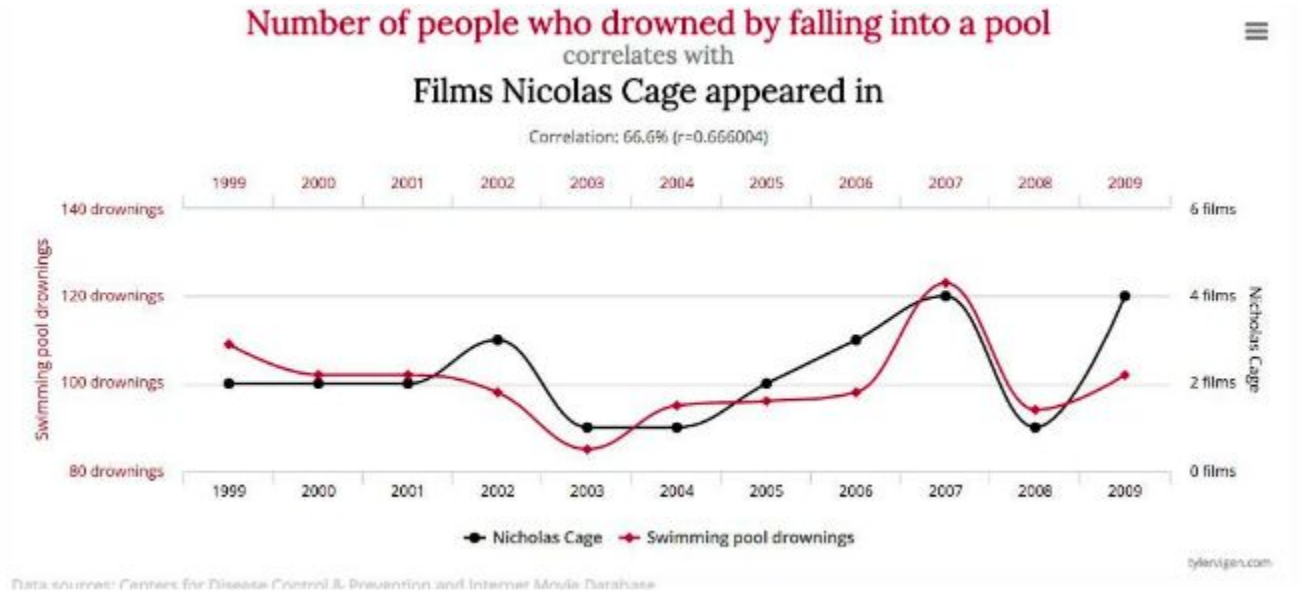
When Nicolas Cage acts, the number of people who drown by falling into a pool increase.



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# A mathematical model

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A mathematical model is a description of a system using mathematical concepts and language. A model may help to explain a system and to study the effects of different components, and to make predictions about behaviour.

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## Example of a model:

Objetive

How could I measure the maximum heart rate?

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## Example of a model:

Data that I have

| | Sexo | Edad | FCM |
|---|---|---|---|
| 1 | Mujer | 37 | 185 |
| 2 | Mujer | 71 | 163 |
| 3 | Hombre | 25 | 210 |
| 4 | Mujer | 22 | 198 |
| 5 | Hombre | 48 | 179 |

each line represents a person

...

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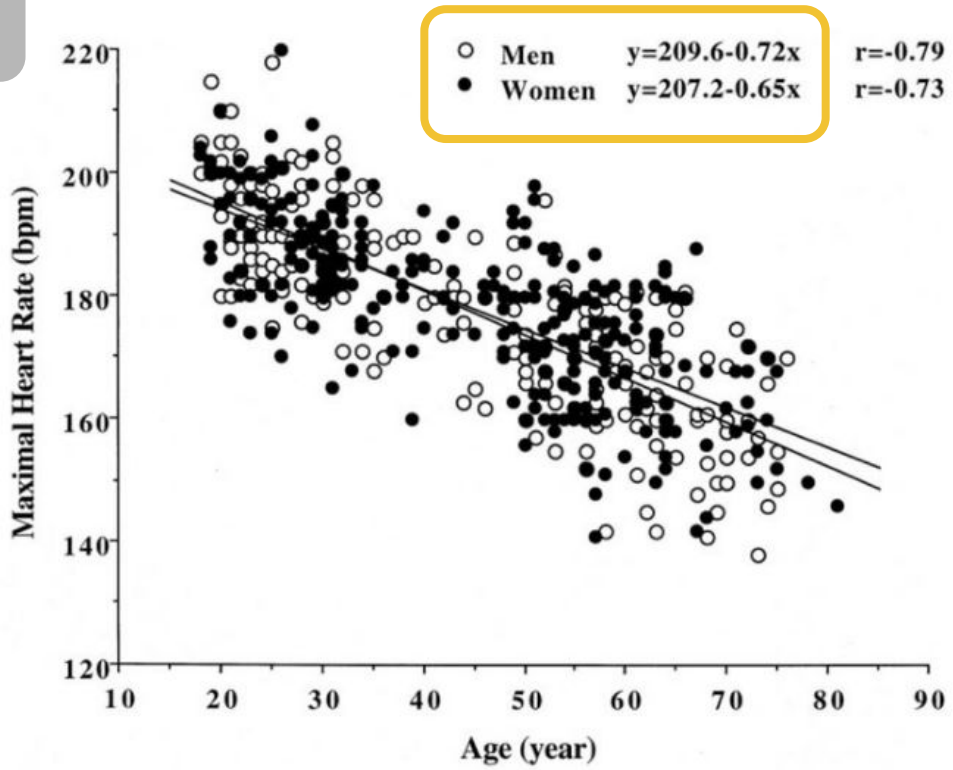
## Example of a model:

### Results



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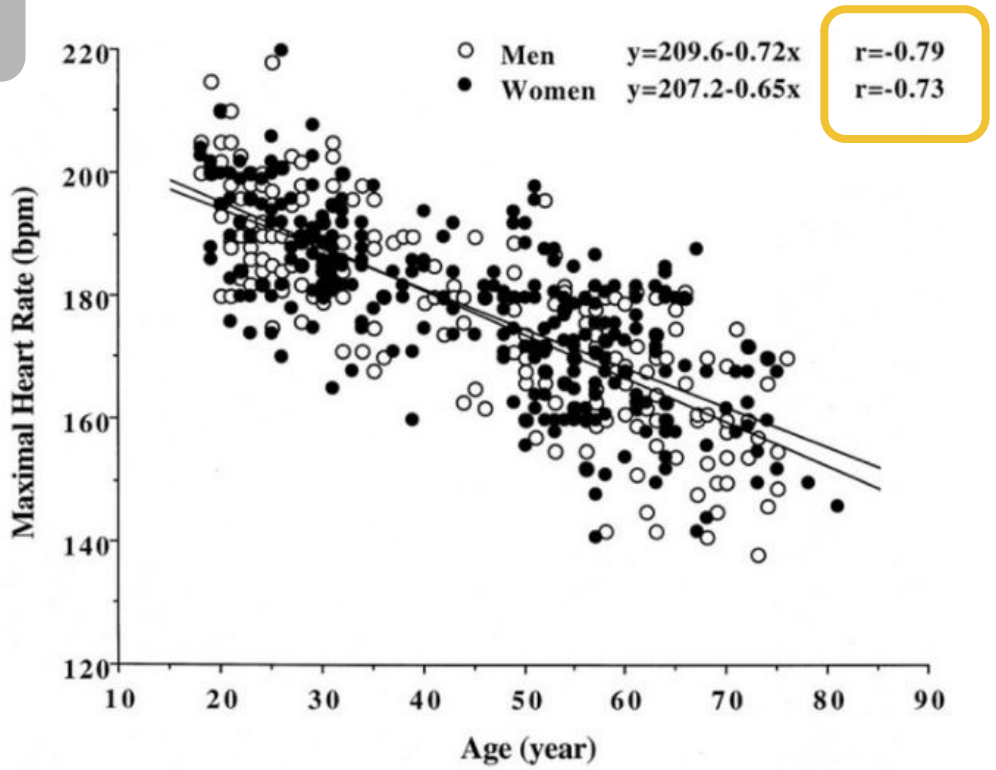
## Example of a model:

### Results



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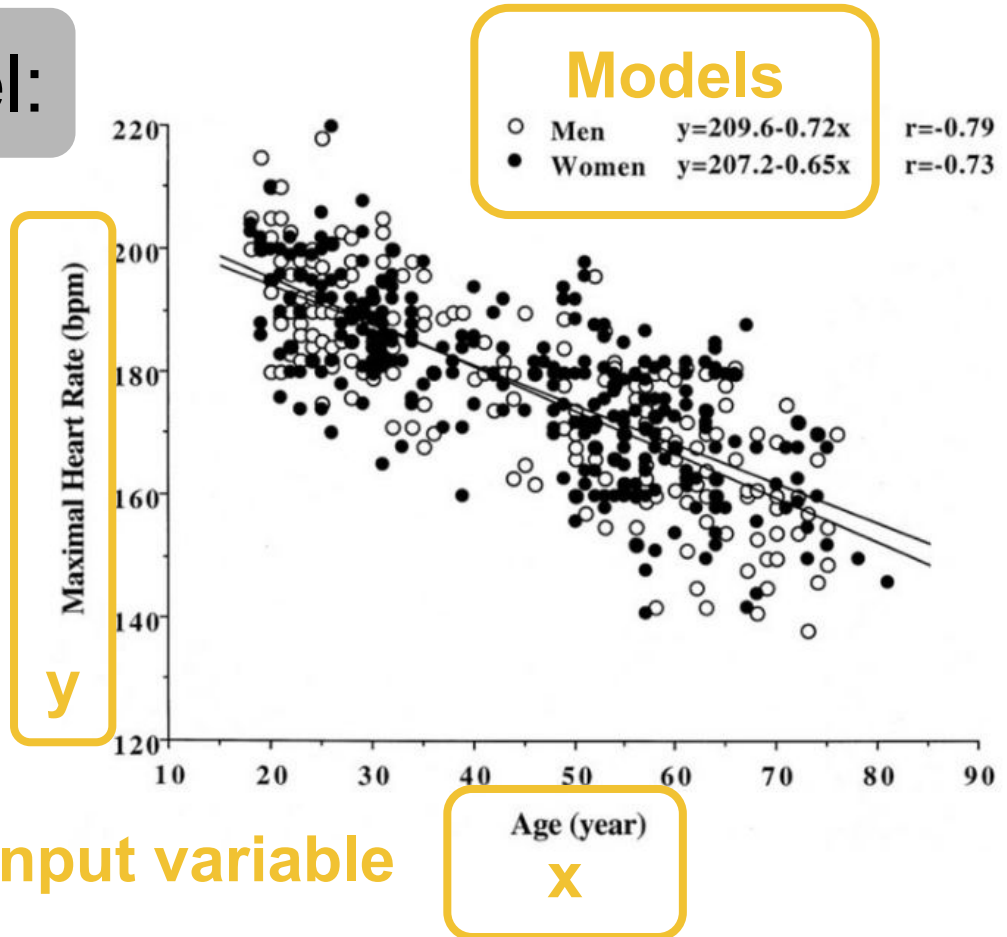
## Example of a model:

Results




output variable **y**

input variable **x**

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# ¿Machine Learning?

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"Machine learning is a field of computer science that uses statistical techniques to give computer systems the ability to "learn" with data, without being explicitly programmed."

Wikipedia

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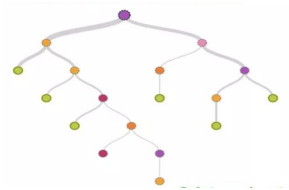
**General types of learnings**

## Supervised learning

Here is the data set where the right answers [labels] are given for each example. Please, produce more right answers.



## Unsupervised learning

Here is the unlabelled data. Please, find peculiarities, similarities or structures (e.g. clusters) in the data yourself.

## Reinforcement learning

Learn to do something yourself purely by maximising your expected reward.

# Modelling Methodologies

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General types of learnings

General types of problems

## Supervised learning

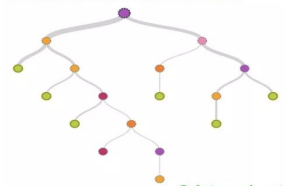
Here is the data set where the right answers [labels] are given for each example. Please, produce more right answers.

### Regression

Predict a continous valued output.

### Classification

Predict a discrete valued output (eg. a label or a class).



## Unsupervised learning

Here is the unlabelled data. Please, find peculiarities, similarities or structures (e.g. clusters) in the data yourself.

### Clustering

Group similar examples into subsets called clusters.

### Dimensionality reduction

Maybe you don't need all the data. What is the essence of the data?

## Reinforcement learning

Learn to do something yourself purely by maximising your expected reward.

This can be a goal on its own but is often used as a pre-processing step for other ML tasks

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## Supervised Learning

Learning from past elements

**Regression**

Predict a number:
eg PRICE

**Classification**

Predict a label:
eg PURCHASE / NON-PURCHASE

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## Unsupervised Learning

Learning by comparison

**Clustering**

Finding elements alike:
eg CUSTOMER SEGMENTATION according to their habits

**Dimensionality Reduction**

Explaining elements with less attributes

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## Example: Predicting House Prices

**Problem Statement**

We would like to predict the price of a house according to its characteristics.

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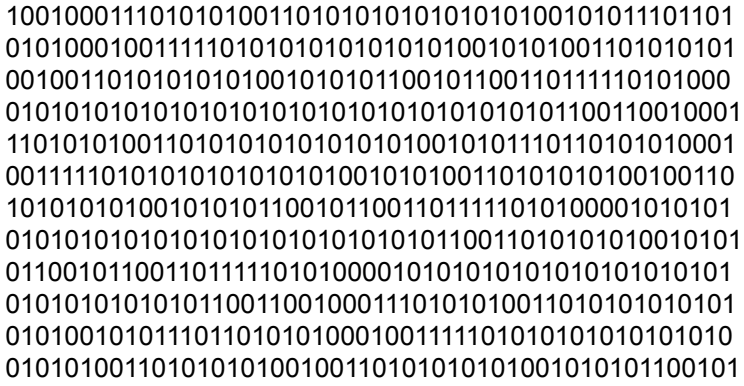
## Example: Predicting House Prices

Machine Learning requires explaining reality as a table of features.

Data



| Id | LotArea | GrLivArea | GarageArea | PoolArea | SalePrice |
|---|---|---|---|---|---|
| 1 | 8450 | 196.0 | 1710 | 548 | 208500 |
| 2 | 9600 | 0.0 | 1262 | 460 | 181500 |
| 3 | 11250 | 162.0 | 1786 | 608 | 223500 |
| 4 | 9550 | 0.0 | 1717 | 642 | 140000 |
| 5 | 14260 | 350.0 | 2198 | 836 | 250000 |

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# Example: Predicting House Prices

## Features Description

each line represents a house

| Id | LotArea | GrLivArea | GarageArea | PoolArea | SalePrice |
|---|---|---|---|---|---|
| 1 | 845 | 196.0 | 171 | 54 | 208500 |
| 2 | 960 | 0.0 | 126 | 46 | 181500 |
| 3 | 1125 | 162.0 | 178 | 60 | 223500 |
| 4 | 955 | 0.0 | 171 | 64 | 140000 |
| 5 | 1426 | 350.0 | 219 | 83 | 250000 |

**target**

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# Example: Predicting House Prices

Machine Learning uses models to explain relationship between features.

In this case, we look for a function that explains the SalePrice:

**SalePrice = f(Features)**

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## Example: Predicting House Prices

Linear Regression

A linear regression tries to find a linear function.

$$SalePrice = a * LotArea + b * GrLivArea + c * GarageArea + d * PoolArea$$

We need to find the best a,b,c,d to have the best relationship.

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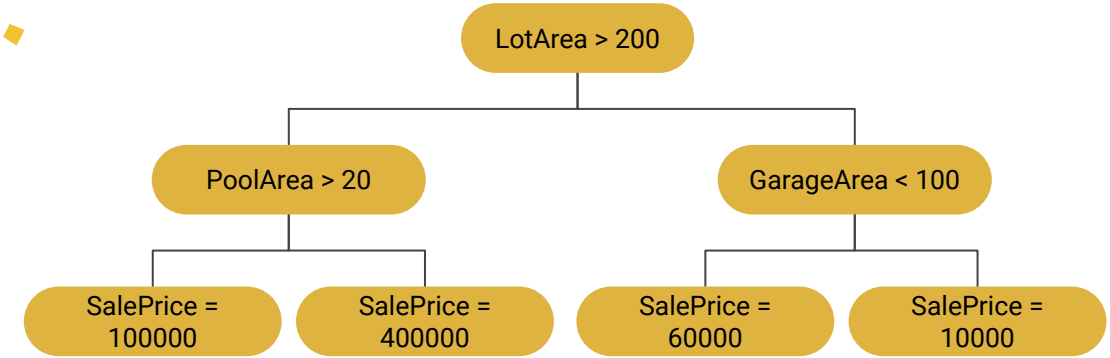
# Example: Predicting House Prices

Decision Tree

A decision tree tries to find a path to explain the target:




We need to find the best splits for our predictions.

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# Example: Predicting House Prices

The Data Scientist works to find the best parameters for the model.

In this case:

- Linear Regression: a,b,c and d.
- Decision Tree: number of splits....

How do you find the best parameters?

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# Example: Predicting House Prices

There are several metrics that can be chosen for this task. For example:

- Bias: Average of the errors
- MAE: Average of the absolute values of errors
- RMSE: Square root of Average of the square of errors

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(x_{f,i} - x_{o,i})$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|x_{f,i} - x_{o,i}|$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_{f,i} - x_{o,i})^2}$$

We chose the model parameters that provide the best METRIC.

In this case, let's use MAE:

$$\frac{|RealPrice1 - PredictedPrice1| + |RealPrice2 - PredictedPrice2| + \cdots}{Number\ of\ houses}$$

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# Example: Predicting House Prices

Once we have the best parameters for a type of model, we can rank the models with the best metric they had

In this case: MAE:

- Linear Regression: 15
- Decision Tree: 10

And we ultimately choose the model with the best metric.

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## Example: Predicting chewing gum buyers

**Problem Statement**

We would like to predict the customers who buy chewing gum.

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# Example: Predicting chewing gum buyers

## Features Description

each line represents a customer

| Id | Sex | Age | Smoker | Sweets | GumBuyer |
|---|---|---|---|---|---|
| 1 | Woman | 19 | Yes | No | Yes |
| 2 | Woman | 45 | No | No | No |
| 3 | Man | 53 | Yes | No | Yes |
| 4 | Woman | 21 | No | Yes | Yes |
| 5 | Man | 35 | No | Yes | No |

**target**

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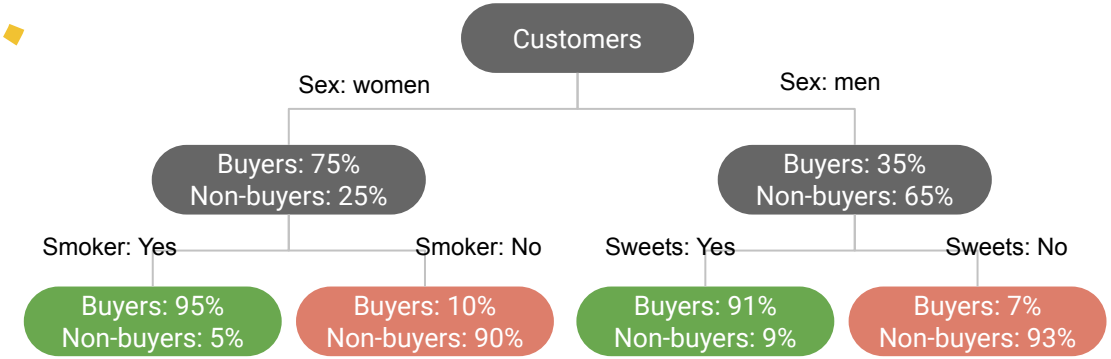
# Example: Predicting chewing gum buyers

Decision Tree

A decision tree tries to find a path to explain the target:




We need to find the best parameters for the model: number of splits, minimum number of member per group...

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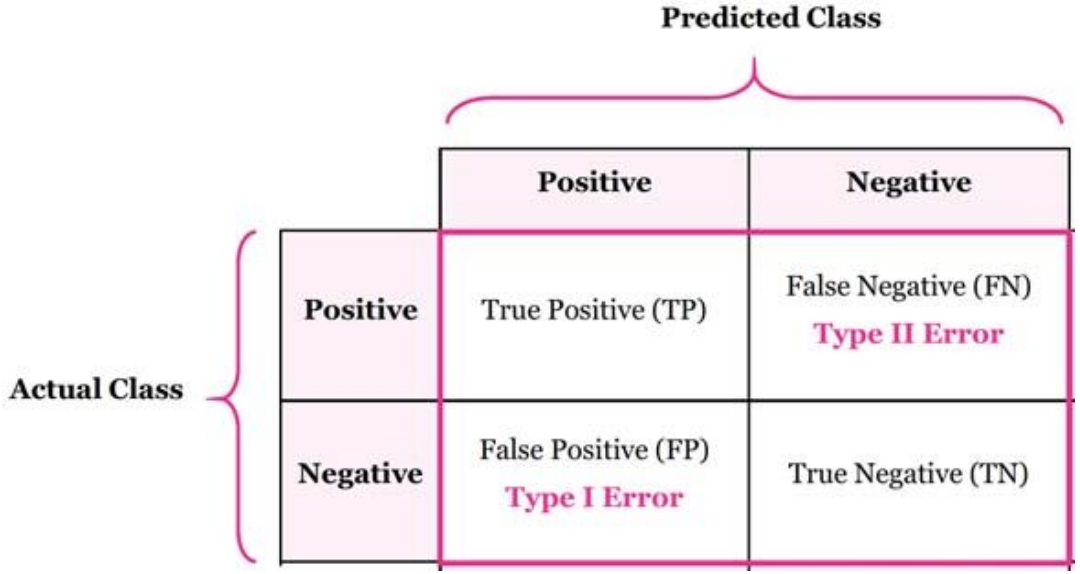
# Classification metrics: Confusion matrix



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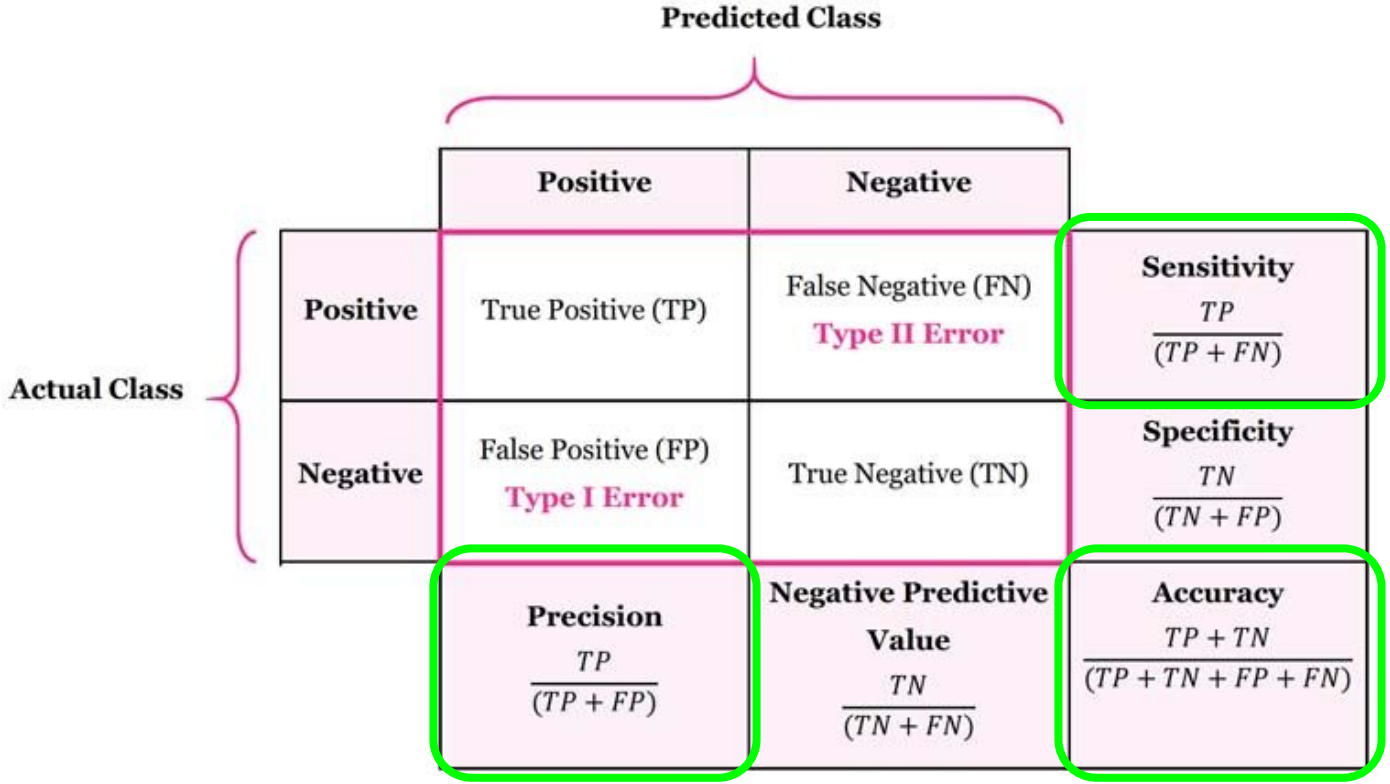
# Classification metrics: Confusion matrix



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## Example: Salmon and sea bass

**Problem Statement**

I would like to discern between salmon and sea bass.

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# Example: Salmon and sea bass

A fish-packing plant wants to automate the process of sorting incoming fish according to species.
As a pilot project, it is decided to try to separate sea bass from salmon using ML.

We know they are different but we don’t know what features make them different.

Let’s go.

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# Example: Salmon and sea bass

Some features to explore:

- Length
- Scale density
- Width
- Position of the mouth
- ...

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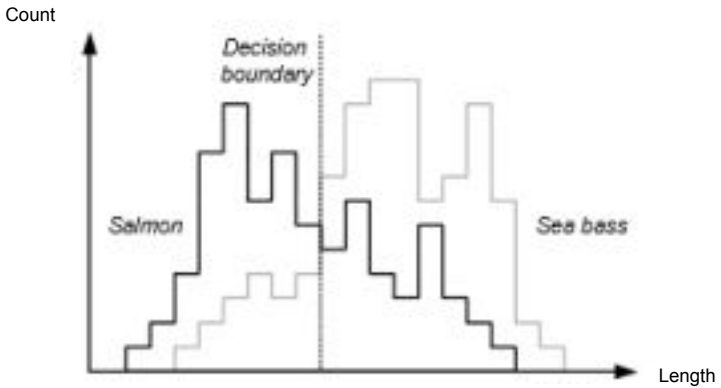
# Example: Salmon and sea bass

Start by checking length of each fish:




They have different distributions. Notice that salmon tends to be shorter than sea bass.

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# Example: Salmon and sea bass

Find the best length L threshold:

fish length < L → classify as a salmon

fish length > L → classify as a sea bass

After searching through all possible thresholds L, the best L= 9, and still 30% of fish is misclassified.

We cannot reliably separate sea bass from salmon by length alone!

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## Example: Salmon and sea bass

I have to continue looking for...

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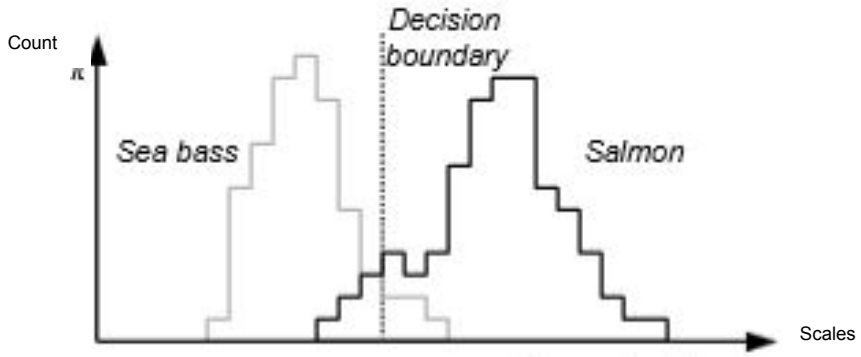
# Example: Salmon and sea bass

Next feature I can consider:

Scale density




The two classes are much better separated!

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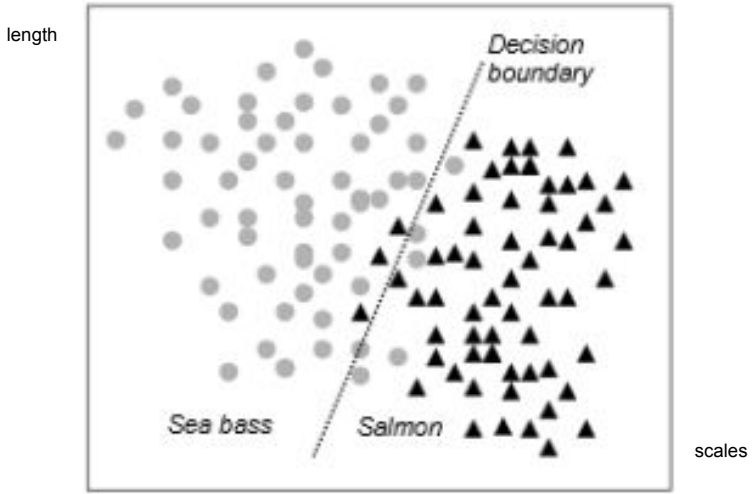
# Example: Salmon and sea bass

Lets to combine the two features:




We have reduced the error rate below 5%.

Should we be satisfied with this result?

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## Example: Salmon and sea bass

And… what could we do now?

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# Example: Salmon and sea bass

**Options we have:**

- Consider additional features:
  - Which ones?
  - Some features may be redundant (e.g., if eye color perfectly correlates with width, then we gain no information by adding eye color as feature.)
  - It may be costly to attain more features
  - Too many features may hurt the performance
- Use a more complex model

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# Example: Salmon and sea bass

**Options we have:**

- Consider additional features:
  - Which ones?
  - Some features may be redundant (e.g., if eye color perfectly correlates with width, then we gain no information by adding eye color as feature.)
  - It may be costly to attain more features
  - Too many features may hurt the performance
- Use a more complex model

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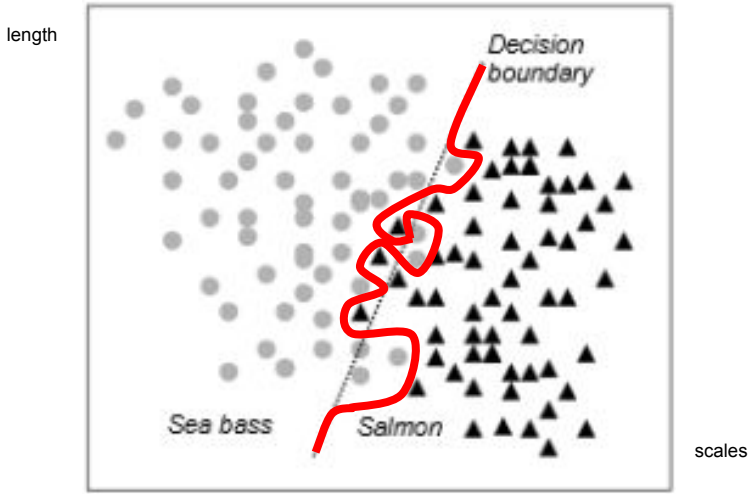
# Example: Salmon and sea bass

With a more complex model all data are perfectly separated :




Should we be satisfied now??

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# Example: Salmon and sea bass

**We must consider:**

Which decisions will the classifier take on novel patterns, i.e. fishes not yet seen?
Will the classifier suggest the correct actions?

This is the issue of GENERALIZATION

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# Measurement of the model

We take the available features table and we split in 2 sets:

1 set to calculate parameters: Training Set

1 set to calculate metrics: Test Set

| | Length | DensityScale | Width | ... |
|---|---|---|---|---|
| 1 | 10000 | 37 | 1385 | ... |
| 2 | 12350 | 71 | 1613 | ... |
| 3 | 9871 | 25 | 2100 | ... |
| 4 | 15431 | 22 | 1985 | ... |
| 5 | 5200 | 48 | 1791 | ... |
| .. | ... | ... | ... | ... |
| ... | ... | ... | ... | ... |
| ... | ... | ... | ... | ... |
| ... | ... | ... | ... | ... |
| ... | ... | ... | ... | ... |
| ... | ... | ... | ... | ... |

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# Summary: ML is about features, models and metrics

- ML requires explaining reality as a table of features
- We then use models to explain relationships between features for the given ML task
- Each model is evaluated according to a metric

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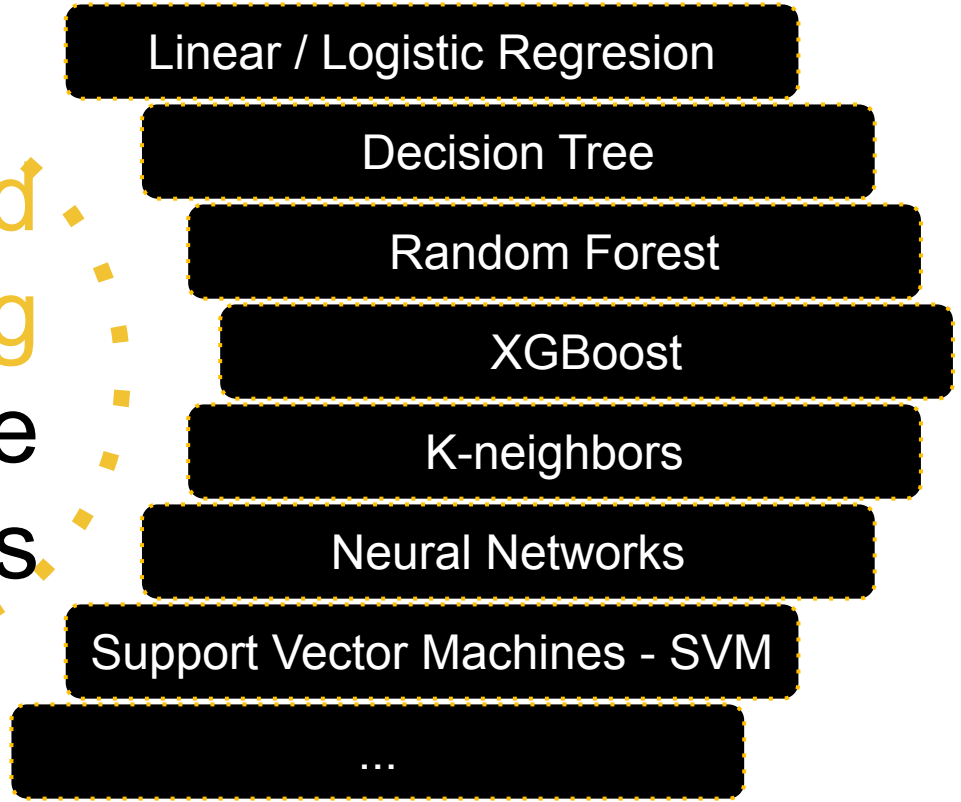
Supervised Learning some of the main techniques




And many others... The list is growing thanks to the active research.

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# Hands on Excercises

Let's try to do next two exercises:

1. Exercise_1: Compare models' predictions and decide which is the best one with different metrics.
2. Exercise_2: Build the confusion matrix and calculate main metrics about it.
   a. Which is the best model in general?
   b. Which identify better the 1 class?

# Modelling Methodologies

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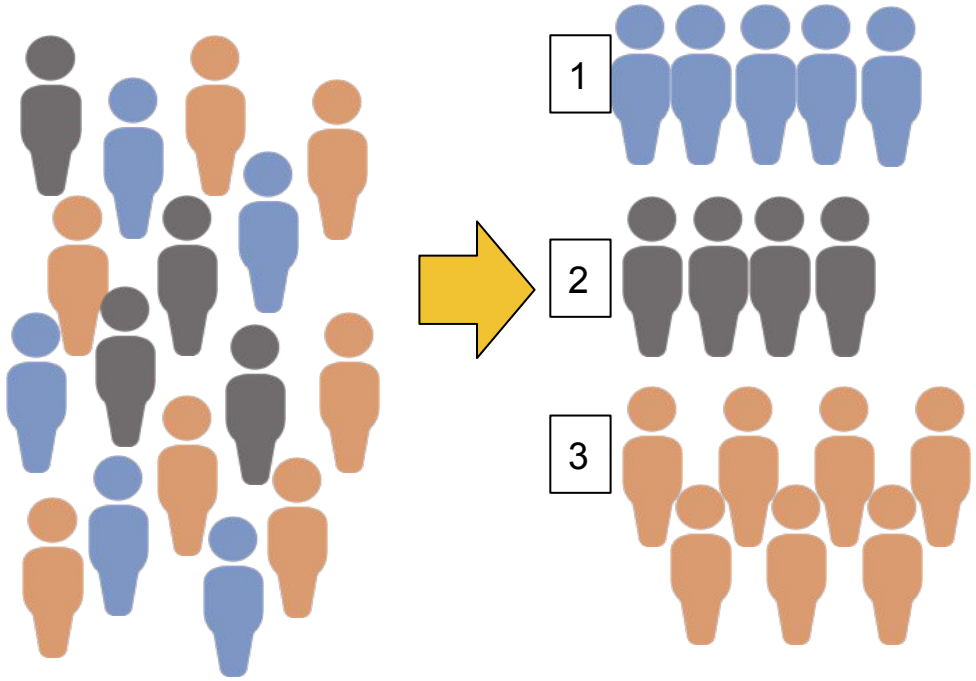
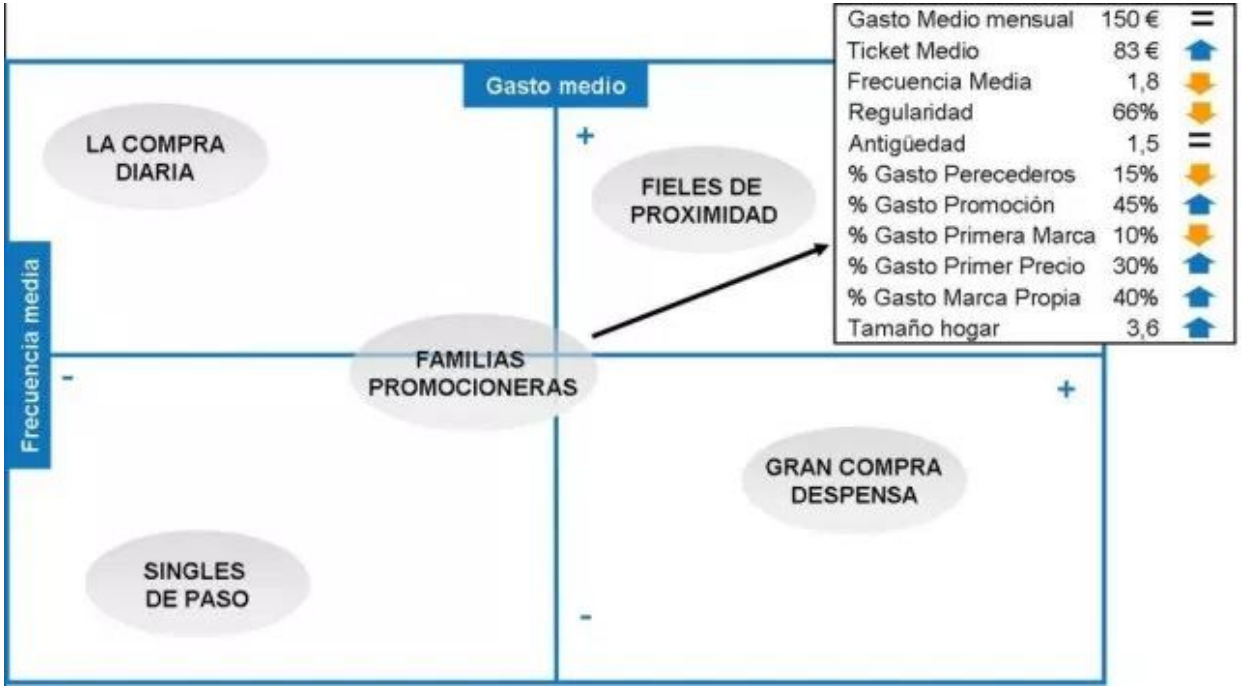
Unsupervised Learning the main type of problems

Clustering



# Example of clustering: department store






Picture from https://www.unica360.com/segmentacion-de-clientes-una-propuesta-de-clasificacion-i.

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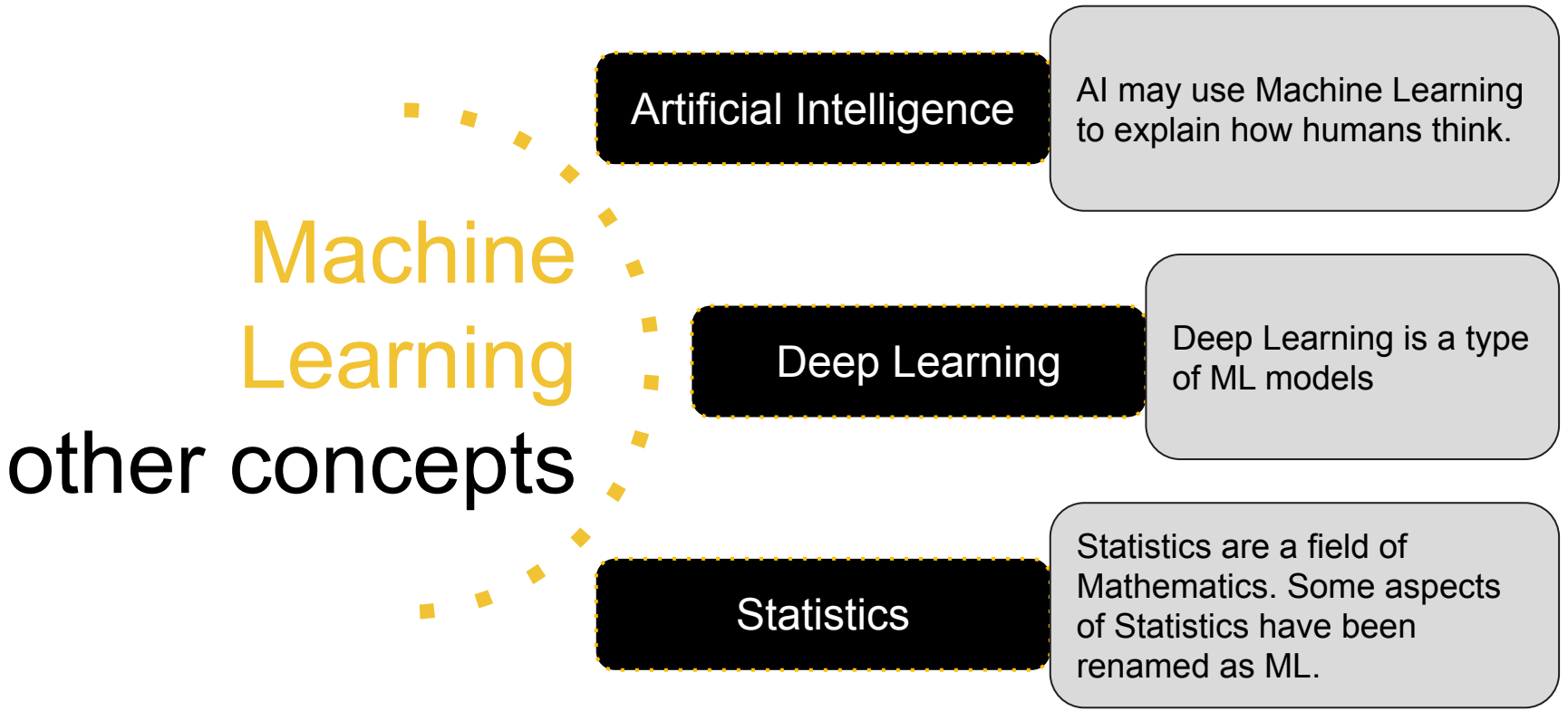

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# ML Canvas

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# Translating a Business Problem to ML

Any Business Problem can be analyzed through the following axes:

1. Business Value and Measure of Success.
2. Data Sources
3. ML task + metric
4. Features Extraction + Model Creation
5. Industrialization and Maintenance

# Modelling Methodologies

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Opportunity:

Estimated Value:

Estimated Cost:

## Value Proposition

Business Description
Resulting Action
Measure of Success (KPI)
ML Initiative Cost

## Machine Learning

ML task
Methods of evaluation

## Data

Sources
Frequency
Legal
History

Acceptable Quality
Main Features

## Ranking of Models

List of the models and their metric

## Industrialization

Description
Implementation Cost
Maintenance Cost
Model Specific Cost

By:

Iteration:

Date:

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# Data Science Process

Once the first version of the canvas is created, Data Scientist perform the following actions:

1. Extraction of features
2. Select of ML task and evaluation
3. Model Creation
4. Quantity of Data > Parameters
5. Loop until satisfied

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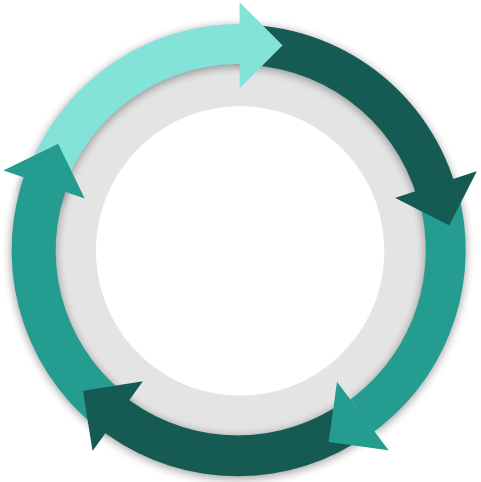
# The whole process is iterative



Product Managers and Data Scientists can revise their initial plans based on discoveries made during the different steps:

- Insufficient Data
- Metric not good enough for the task
- ...

# Modelling Methodologies

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Opportunity: House Price Estimation

Estimated Value:

Estimated Cost:

## Value Proposition

Business Description
Resulting Action
Measure of Success (KPI)
ML Initiative Cost

Business Description:
Negotiate better house prices

Resulting Action:
Daily report of the new houses with offered price and estimated price.

Measure of Success (KPI):
Money saved

ML Initiative Cost:
1 month study

## Machine Learning

ML task
Methods of evaluation

Regression
Method of evaluation: MAE

## Data

Sources
Frequency
Legal
History

Data Sources:
Idealista, Kaggle Data, ...

Frequency:
Weekly

Legal:
Public Data

History:
1 year

Acceptable Quality
Main Features

Acceptable Quality:
Yes

Main Features:
Area of house, Bathrooms, ...

## Ranking of Models

List of the models and their metric

Decision Tree
MAE:

Linear Regression:
MAE:

## Industrialization

Description
Implementation Cost
Maintenance Cost
Model Specific Cost

Weekly job that retrains and produces new model.

Every morning, we run the predictions against a set of newly available houses.

Yearly evaluation to check changes

By:

Iteration:

Date:

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# Hands on Excercises

Let’s try to do that exercise for those 4 use cases:

1. Weather Forecast
2. Movie Recommendation
3. Email Spam Filters
4. Pollution Prediction

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# Some actual examples of Machine Learning

# Modelling Methodologies


Enlace


Enlace


Enlace

**IBM SlamTracker**

Enlace


Enlace


Enlace

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## Data science competitions:

synergic partners™
A Telefónica COMPANY

NETFLIX

BBVA

kaggle

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*“Cuando eres capaz de ver lo sutil, es fácil ganar”*

*Sun Tzu*

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# Thank you!

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