Machine Learning

Session 2 - Supervised classification


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introduction-to-data-science

Introduction

What did we do last time?

Course outline

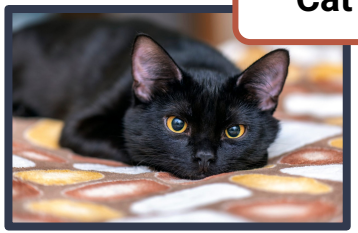
Intro to ML course

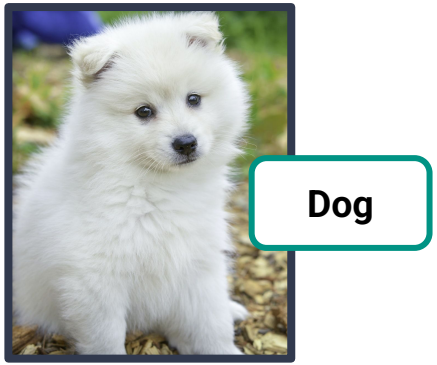
Session 1: Introduction to ML & Regression

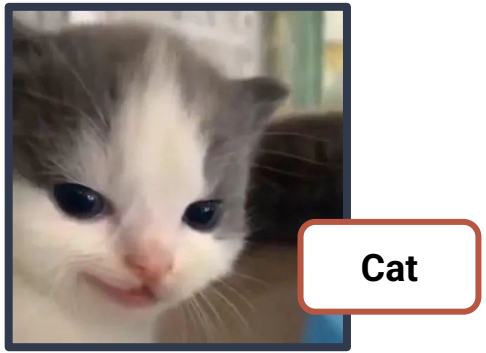
Session 2: Supervised classification

Session 3: Neural networks

What is classification?







Intuitively, classification is giving objects the right label

$$f^*(x) = \arg\max_k \mathbb{P}(C_k|x)$$

Where *f** is a rule for classification, C_k are the **classes**, and *x* the **examples**

The goal of a classification algorithm is to find this rule

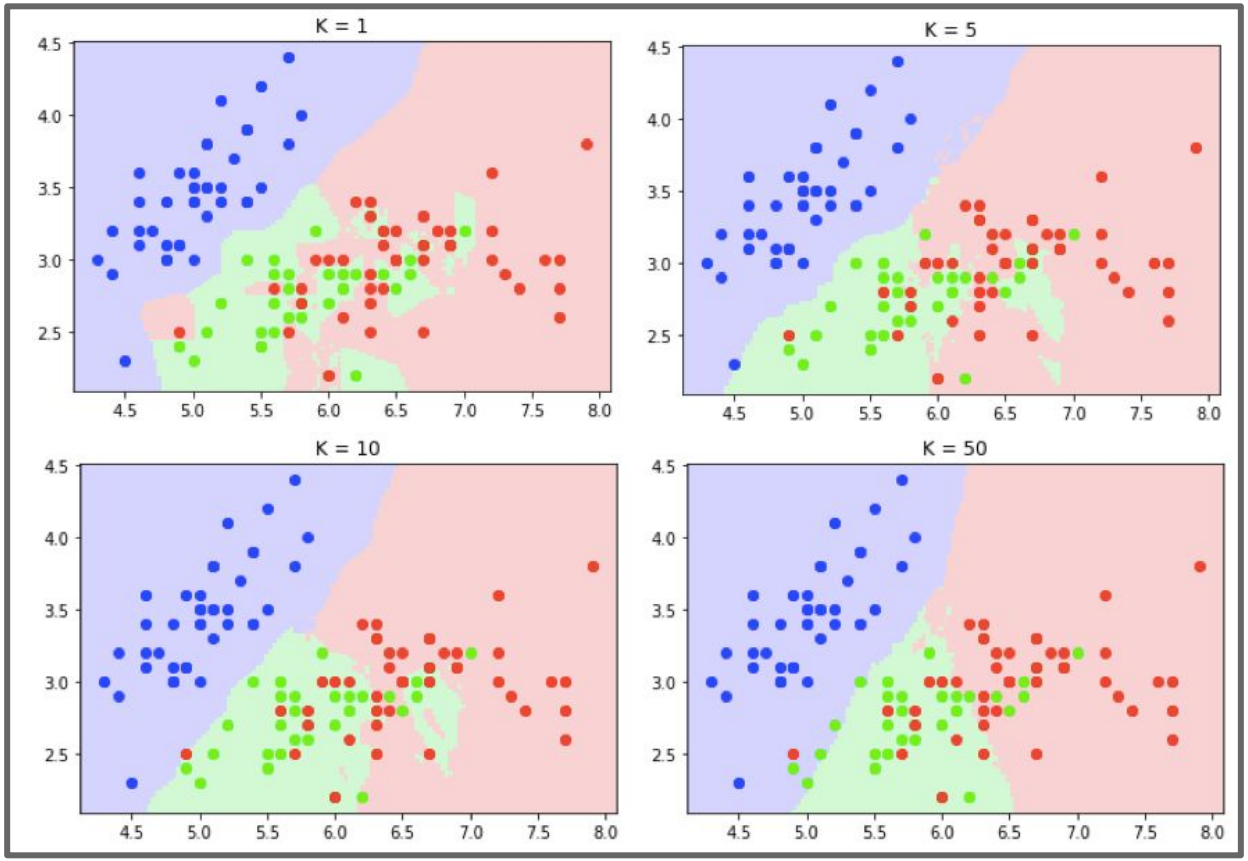
Formally, classification is finding the most probable class for an example

Families of classification models

While they are all classification models, they have different purposes

There are three main families of classification models

- **Discriminant functions**
  - The algorithm learns a function that finds the class directly
  - *Example*: K-nearest-neighbours
- **Discriminant models**
  - The algorithm models the decision boundary
  - *Example*: Support Vector Machines
- **Generative models**
  - The algorithm models the data distribution (meaning you can generate your own data)
  - *Example*: Gaussian Mixture Model

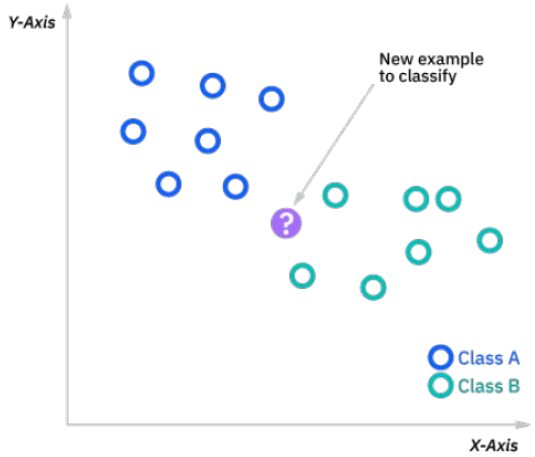


When K is small, the algorithm is very sensitive to **local variations** (risk of overfitting)

When K is large, the algorithm is **more stable**, but **does not take small variations into account** (risk of underfitting)

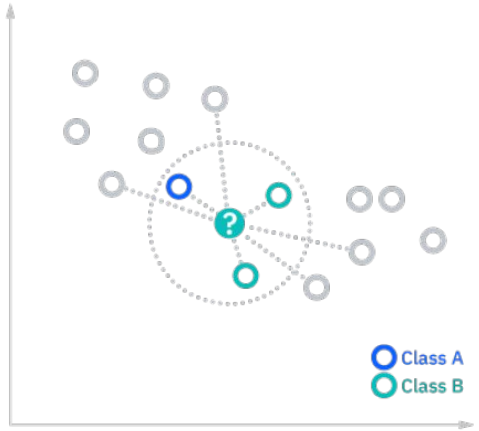
⇒ **When choosing the parameters, there is a compromise between the two**

Common classification algorithms



Introduce a new example

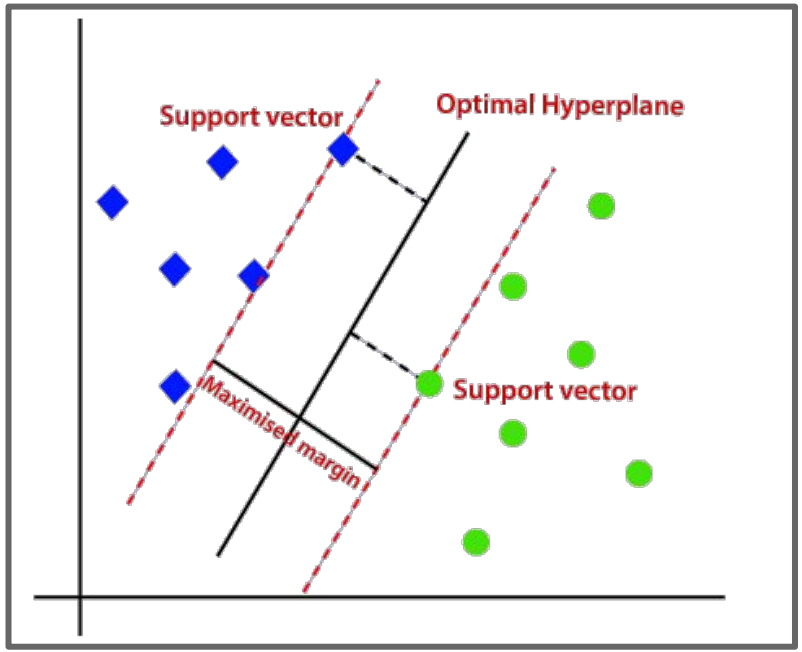
Compute distances



Majority vote

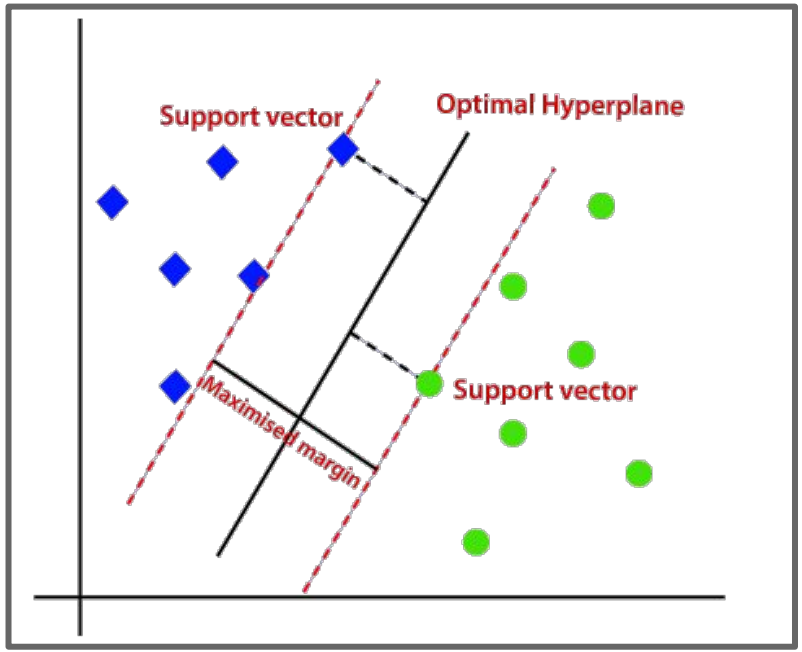
K-nearest neighbours

Decision boundary	Non-linear
Advantages	• Easy to use and understand • No assumptions
Disadvantages	• Slow for large datasets • Inefficient in high dimension



The objective is to **find a hyperplane** such that the **margin between the two classes is maximized**.

Data can be transformed into a higher-dimensional space if it is not linearly separable in the feature space. This is achieved with **kernels** (e.g. polynomial, sigmoid, etc.).

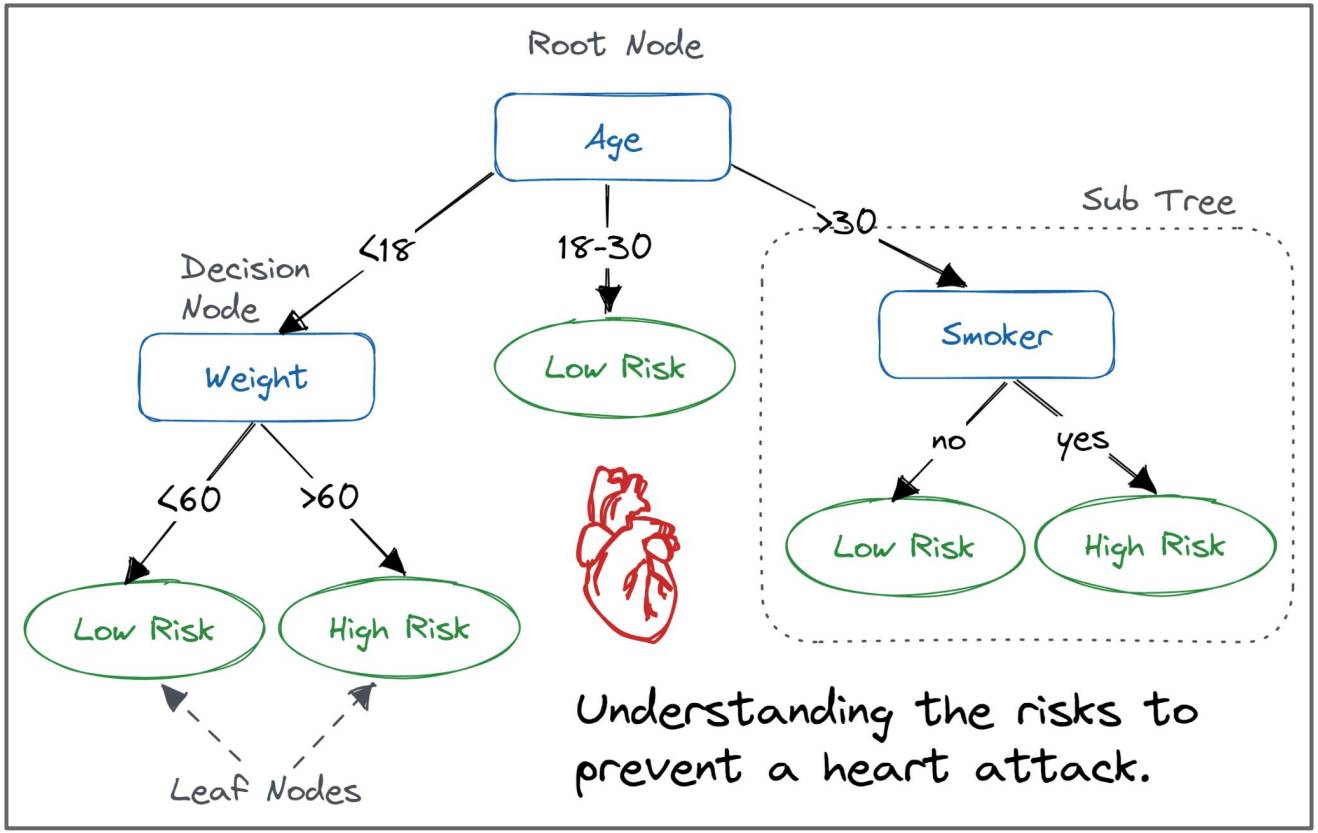


Decision boundary	Linear in the transformed space, can be non-linear in the feature space
Advantages	• Works well in high dimension • Robust to outliers • Low memory consumption
Disadvantages	• Slow for large datasets • Choosing a kernel can be difficult

Other methods for supervised classification

- **Logistic Regression**
  - THIS IS A CLASSIFICATION METHOD
  - Only works when data is linearly separable
  - Easy to use, good baseline method
- **Naive Bayes**
  - Assumes that features are independent
  - Non-linear decision boundary (computes class membership probabilities)
  - Low-cost, also good baseline
- **Linear / Quadratic discriminant analysis**
  - Assumes that data follows a normal distribution
  - Limited to linear / quadratic decision boundaries
  - Good baseline
- **And other algorithms we will study later**
  - Decision trees / Random Forests
  - Ensemble methods
  - Neural networks

Decision trees



Decision trees - Example

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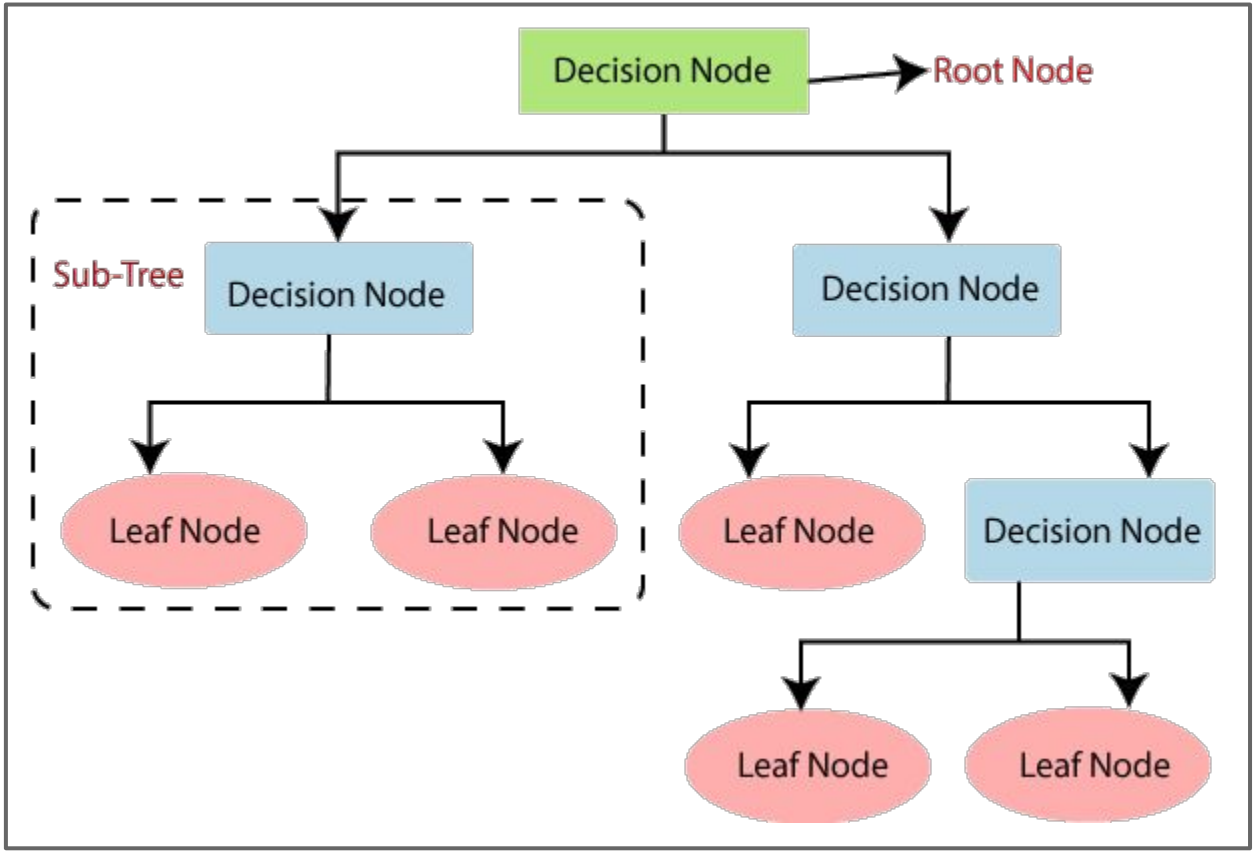


Vocabulary

Image source

Definition

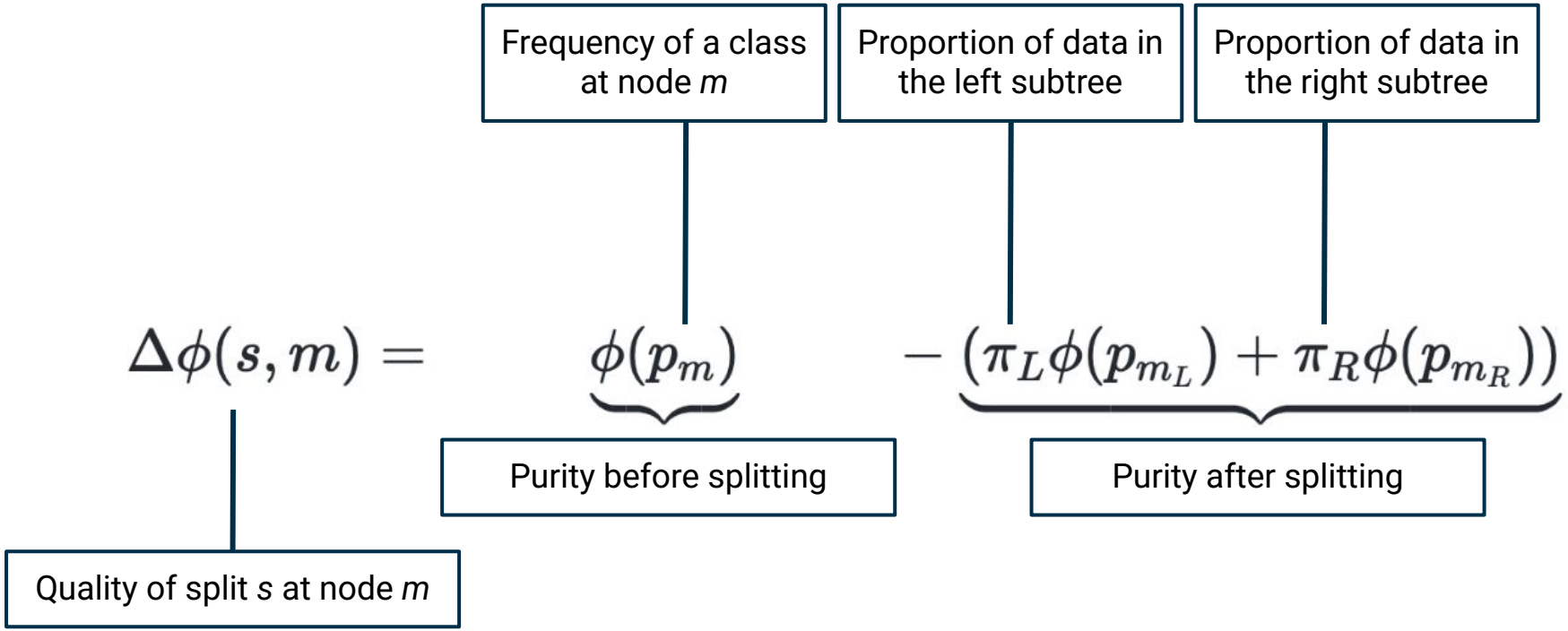
Purity of a node

A node is 100% pure when all of its data belongs to a single class.

It is 100% impure when it contains the same proportion of each class.
(e.g. 50/50 for binary classification)

Several functions can be used to compute the impurity of a node:

- **Gini Index**
- **Cross-entropy**
- **Misclassification error**



Different splits are tested recursively to find the best partitioning

Strength and weaknesses of decision trees

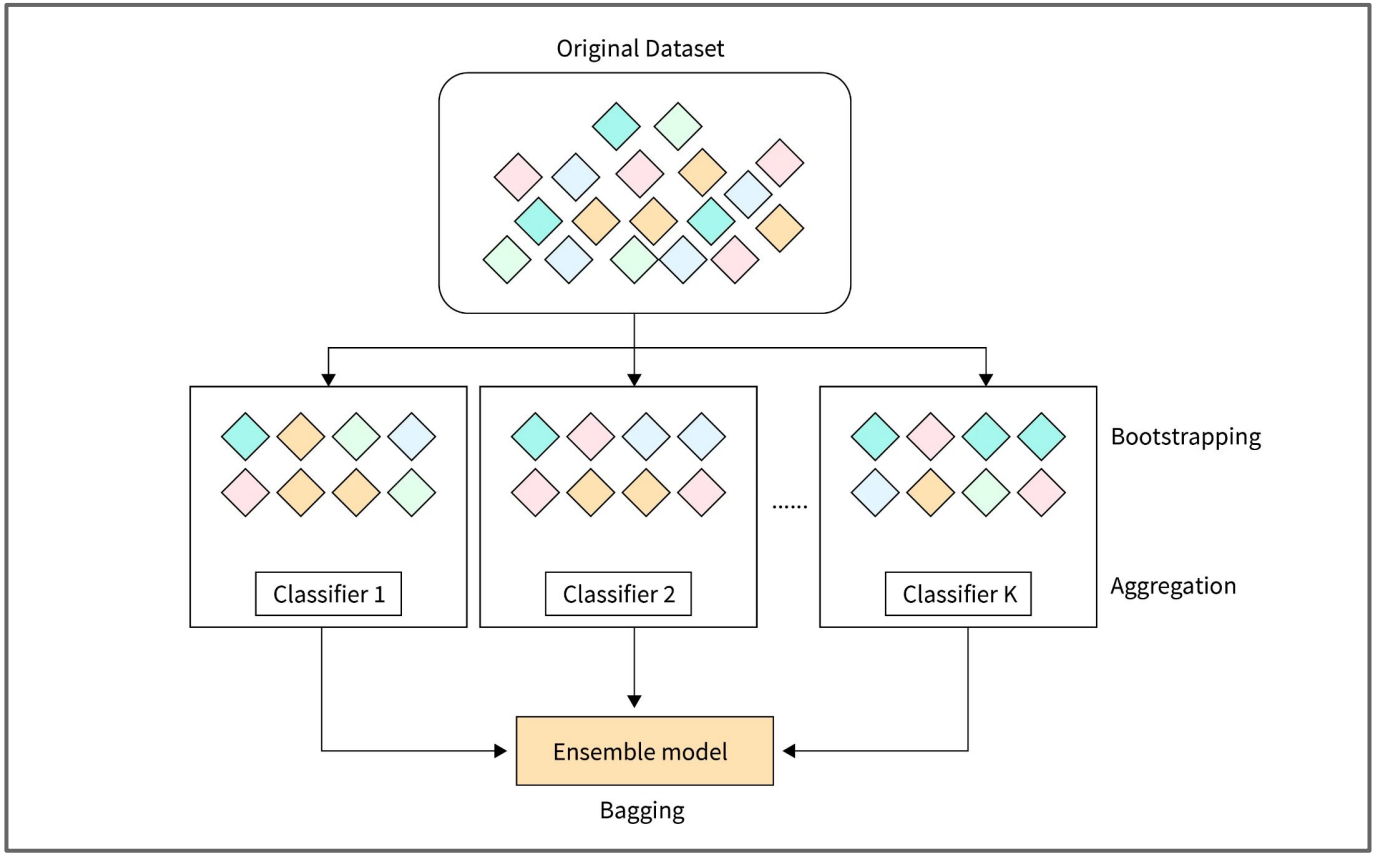
Strengths

- **Flexible** (few hypotheses)
  - They can also apply to regression!
- Easy to **interpret** (explicit rules)
- **Non-linear** (complex decision boundaries)

Weaknesses

- Prone to **overfitting**
- Unstable to **noise**
- **Expensive** on large datasets

Ensemble methods



Bootstrapping
Recombining existing data to create datasets

Aggregating
Training an algorithm for each dataset

Bagging (Bootstraping + Aggregating)

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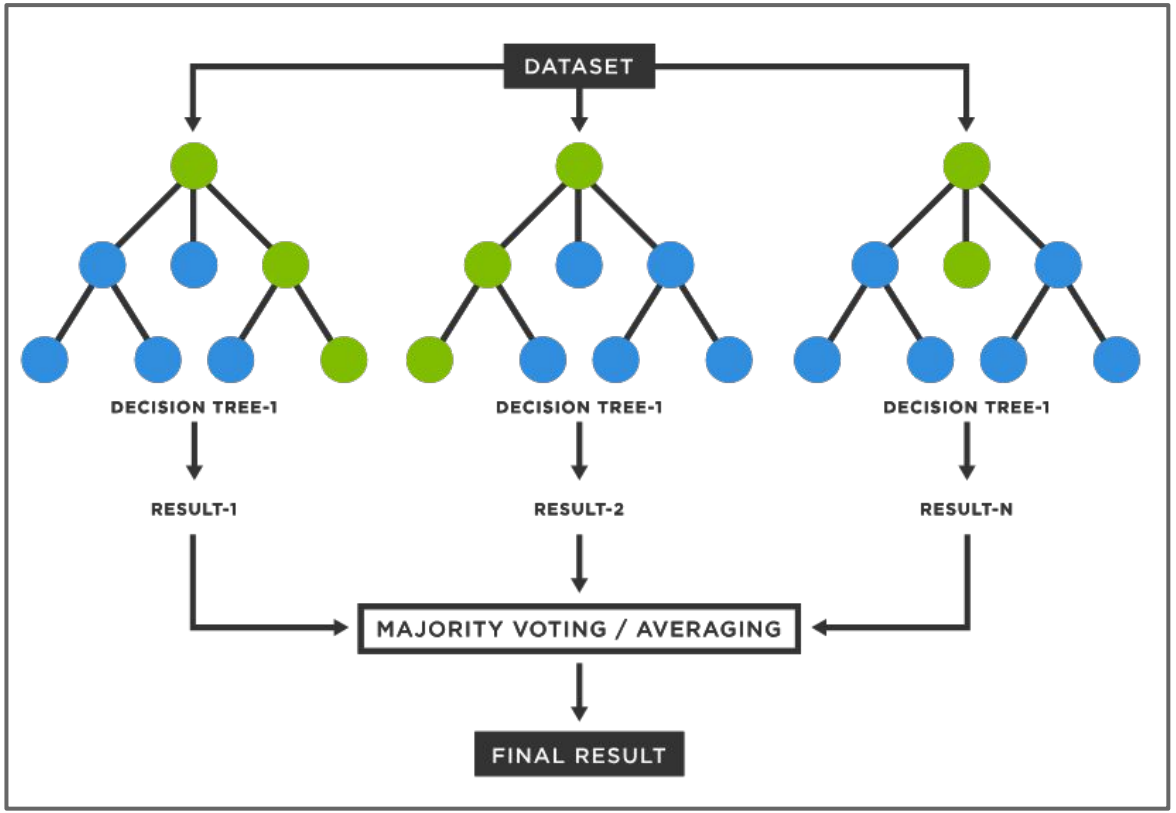

The principle is similar to bagging, except **trees are built upon random subsets of features**

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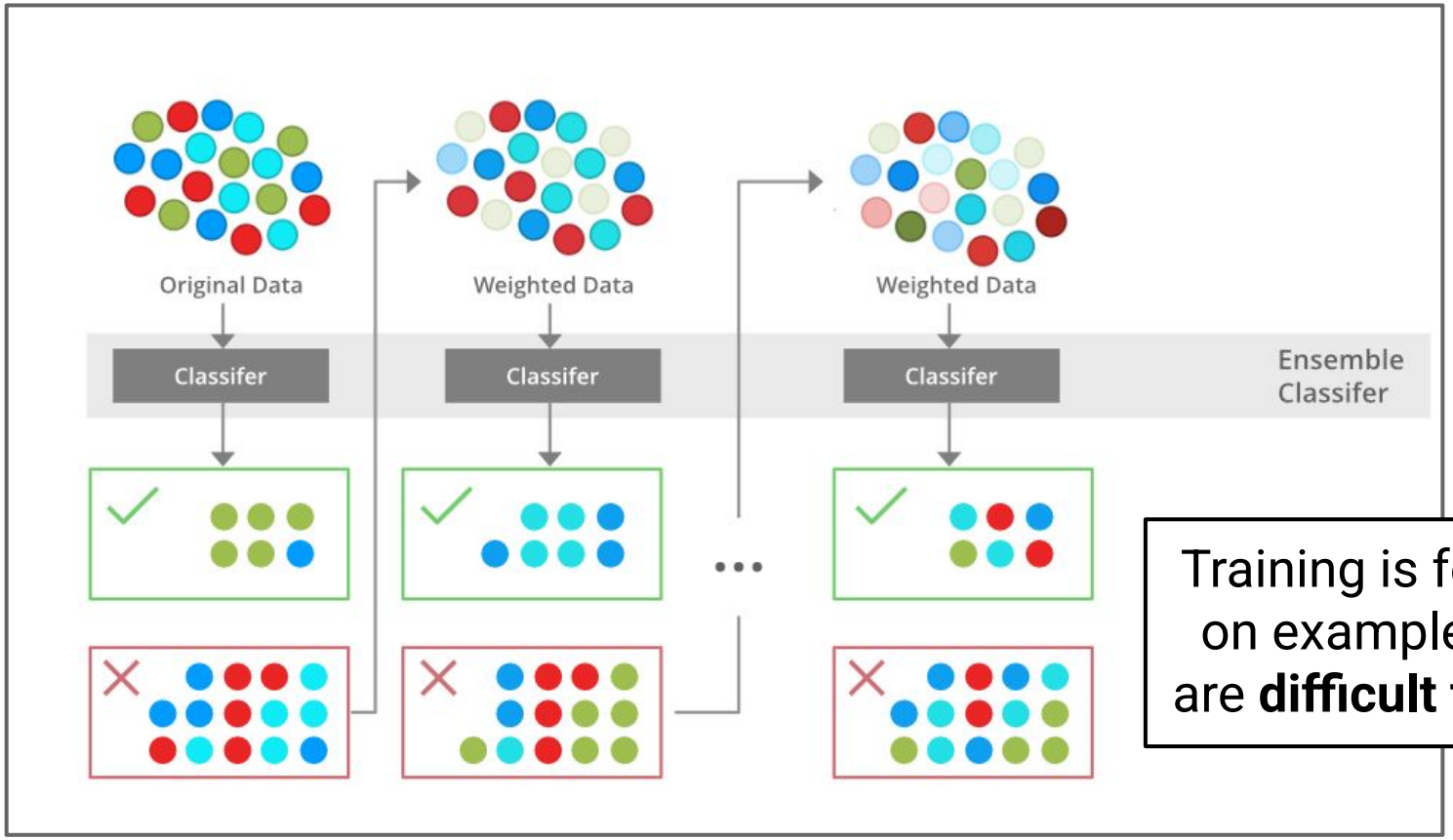

Training is focused on examples that are **difficult to learn**

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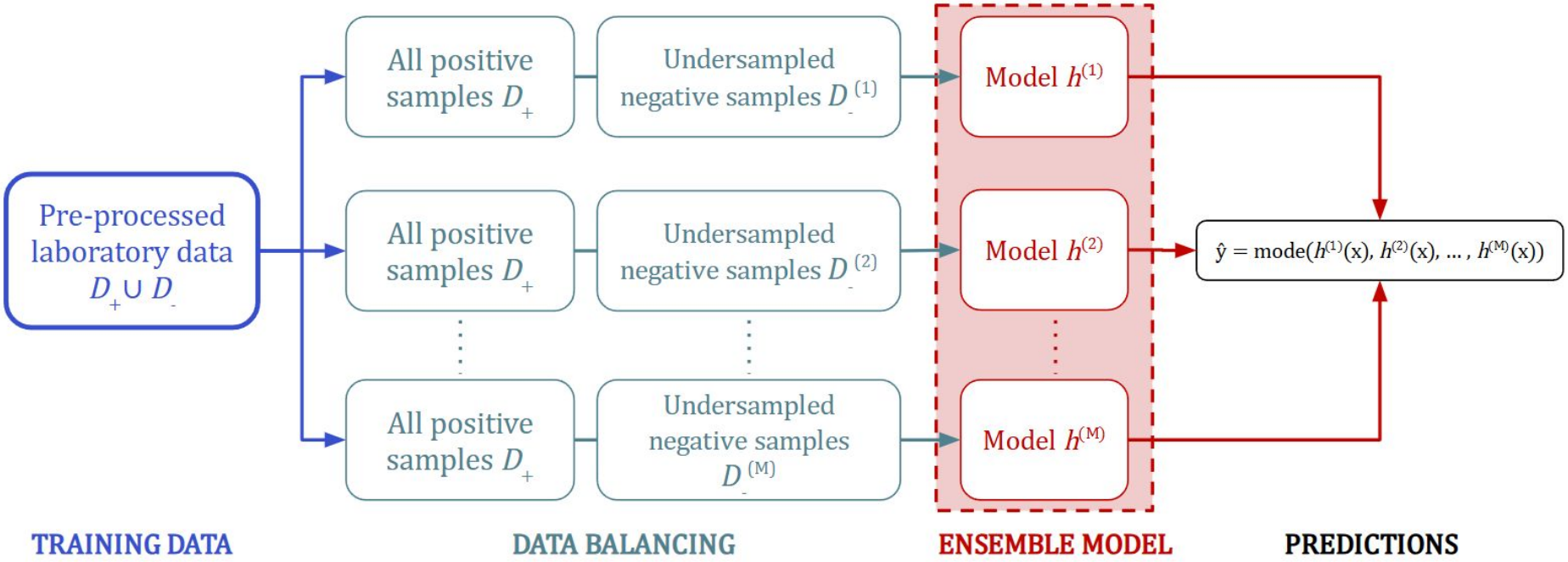


EasyEnsemble (example application to laboratory data)

Strength and weaknesses of ensemble methods

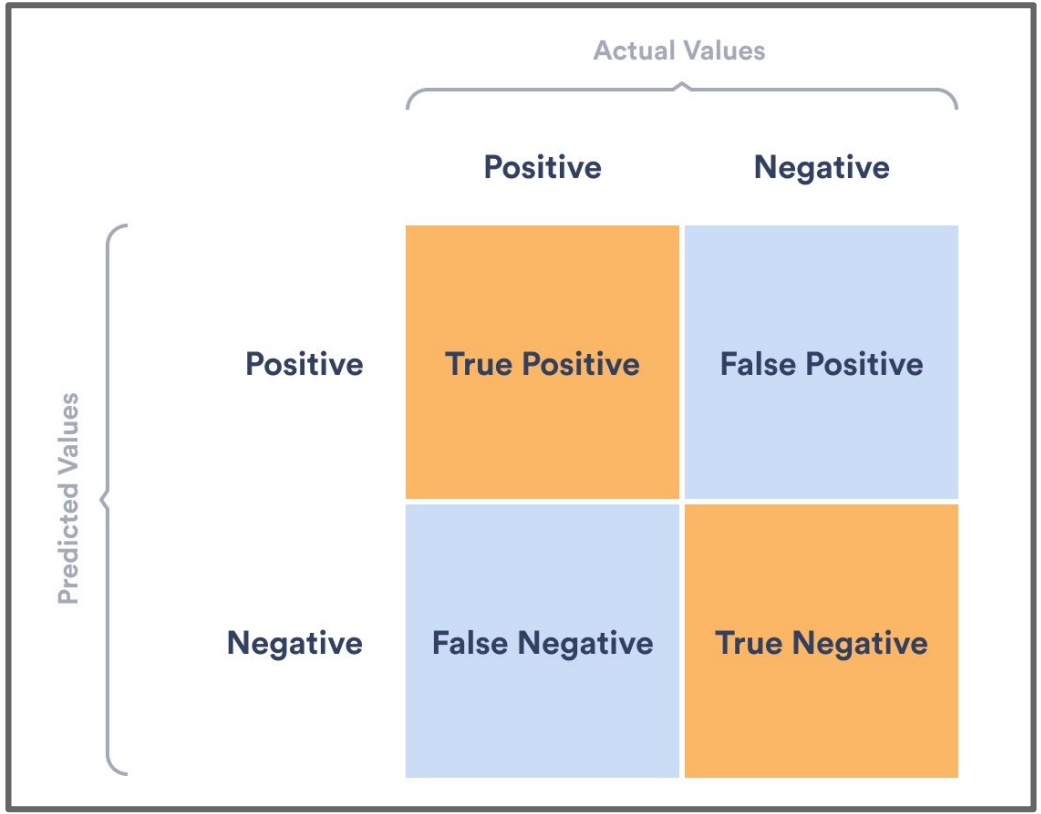
Strengths

- Tends to increase accuracy
- Robust to noise
- Helps reduce overfitting

Weaknesses

- Requires more ressources
- Makes interpretation more difficult

Evaluating a classification algorithm



Confusion matrices allow you to analyse how well each class is handled

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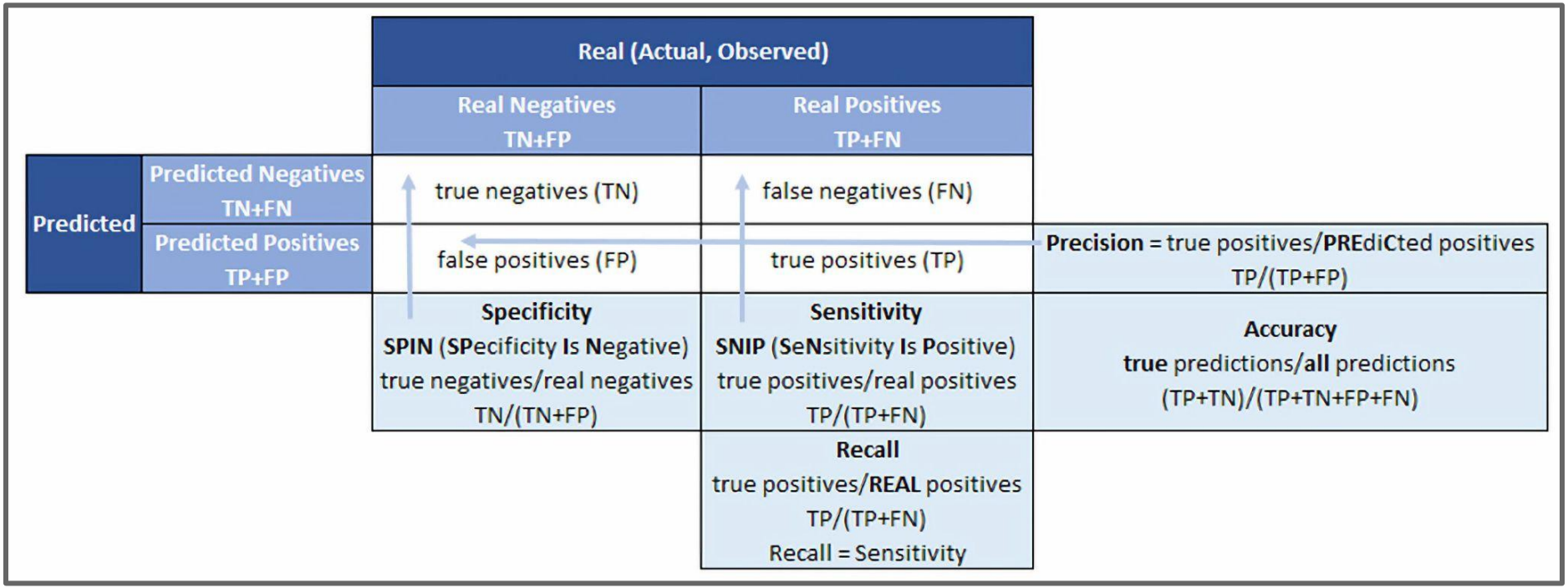
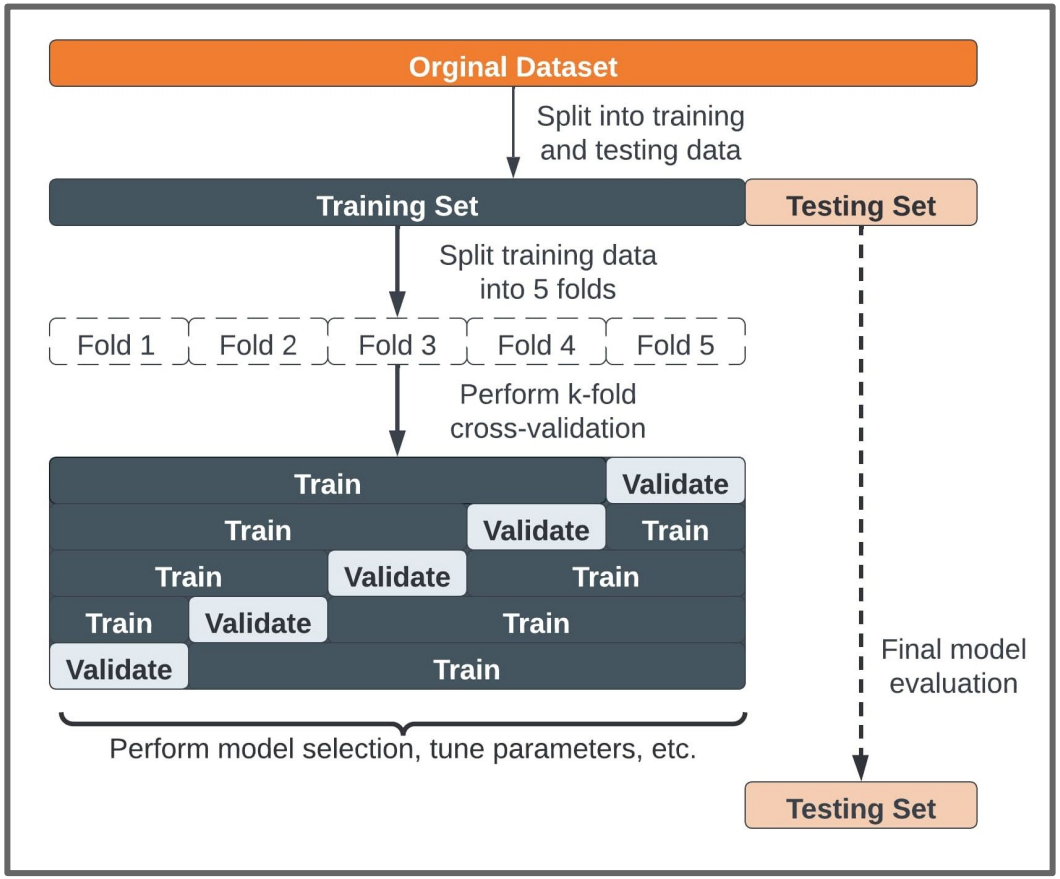


Several performance indicators can be computed from the confusion matrix

Image source

$$\text{F1 Score} = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

F1-Score is a synthesis of the previous metrics and can be more meaningful than accuracy



Cross-validation can allows for a better estimation of the model's performance

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Practical work

The notebook contains all the necessary instructions

Debrief

Debrief

What did we learn today?

What could we have done better?

What are we doing next time?

Machine Learning

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