ESCOLA SUPERIOR DE TECNOLOGIA IPCA

Learning from examples

Fundamentals of Artificial Intelligence

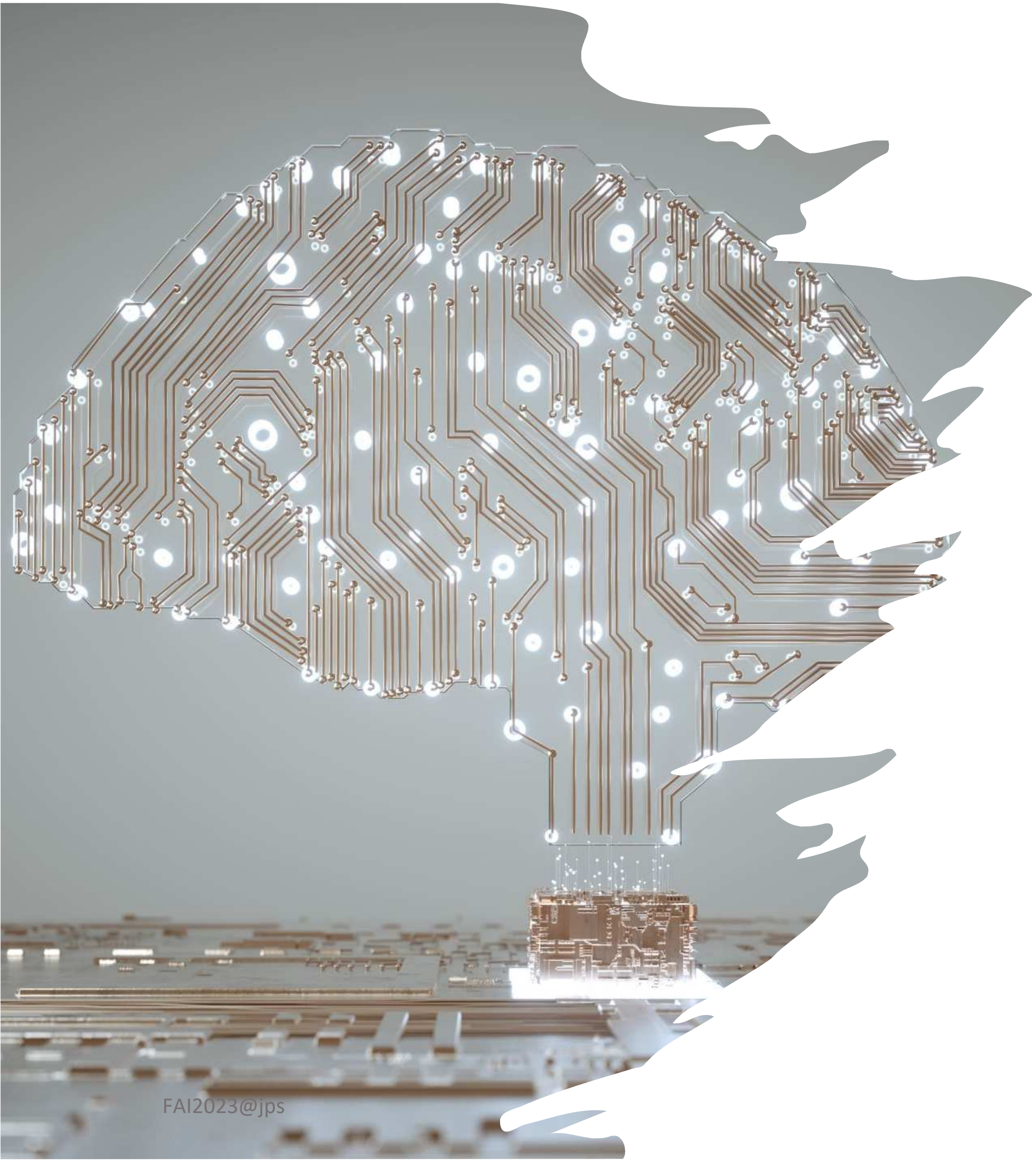
MSc in Applied Artificial Intelligence, 2023-24

Contents

- Topics included
  - Machine learning
  - Machine Learning Types
  - Model performance
  - Overfitting & Underfitting

- These slides were based essentially on the following bibliography:
  - Norvig, P, Russell, S. (2021). Artificial Intelligence: A Modern Approach, 4th Edition. Pearson, ISBN-13: 978-1292401133
  - Most of the slides are authored by Prof. Joaquim Gonçalves

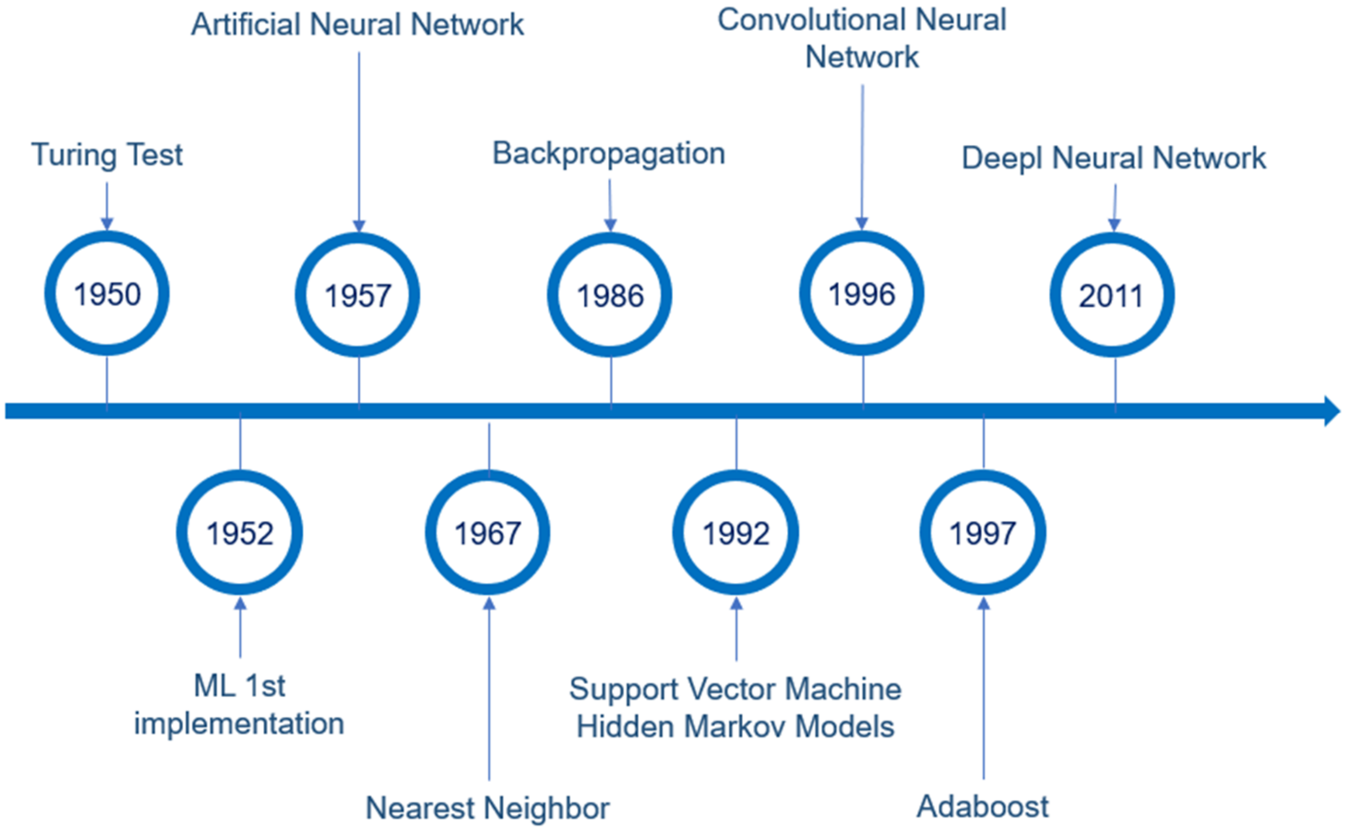
Machine learning



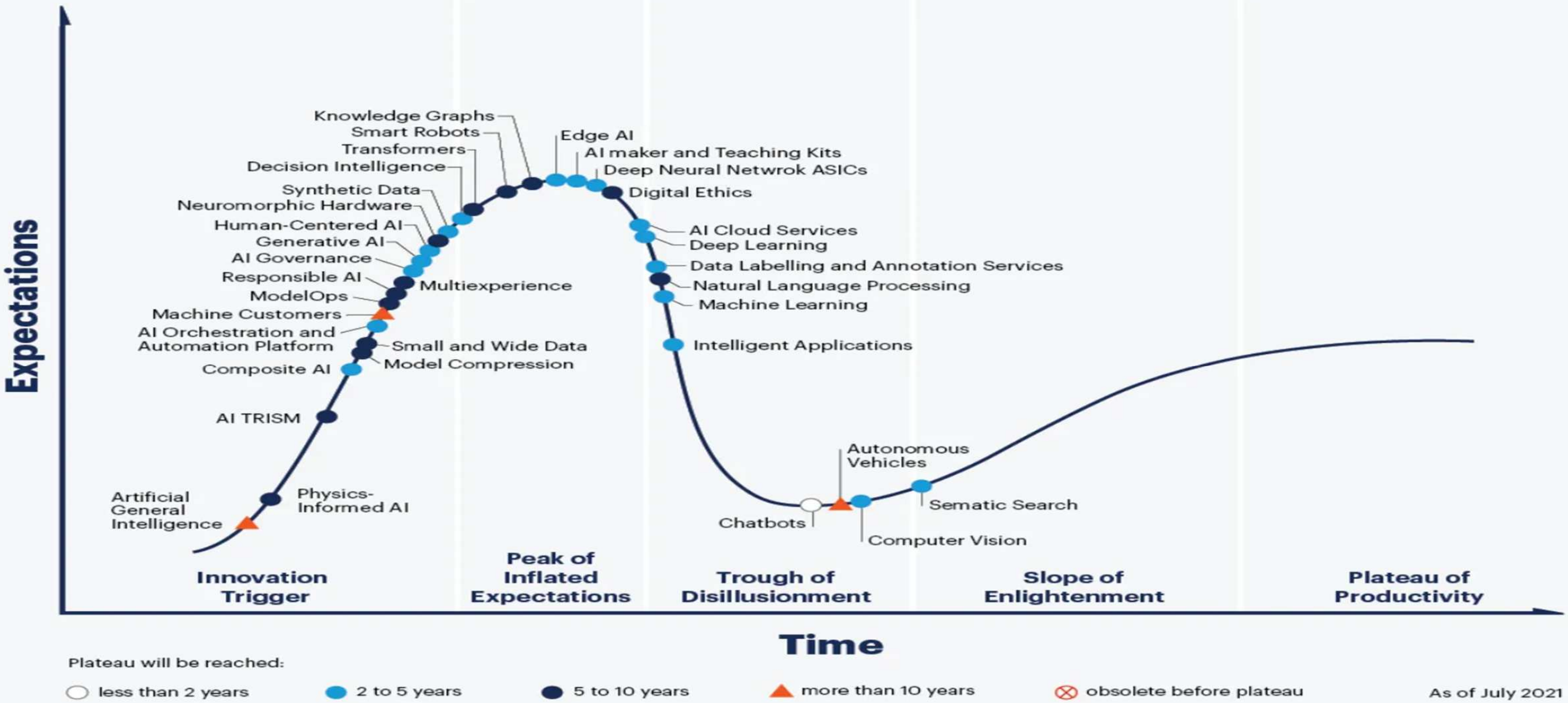
Machine Learning

- ... is a type of Artificial Intelligence that allows machines to learn, acquiring and integrating knowledge autonomously
- Learning occurs through algorithms that use stored data
- Although algorithms influence the ability to learn, learning does not depend on the algorithm, but on the data that feeds it
- The learning outcome is a predictive or classification model

Machine Learning Milestones



Hype Cycle for Artificial Intelligence, 2021

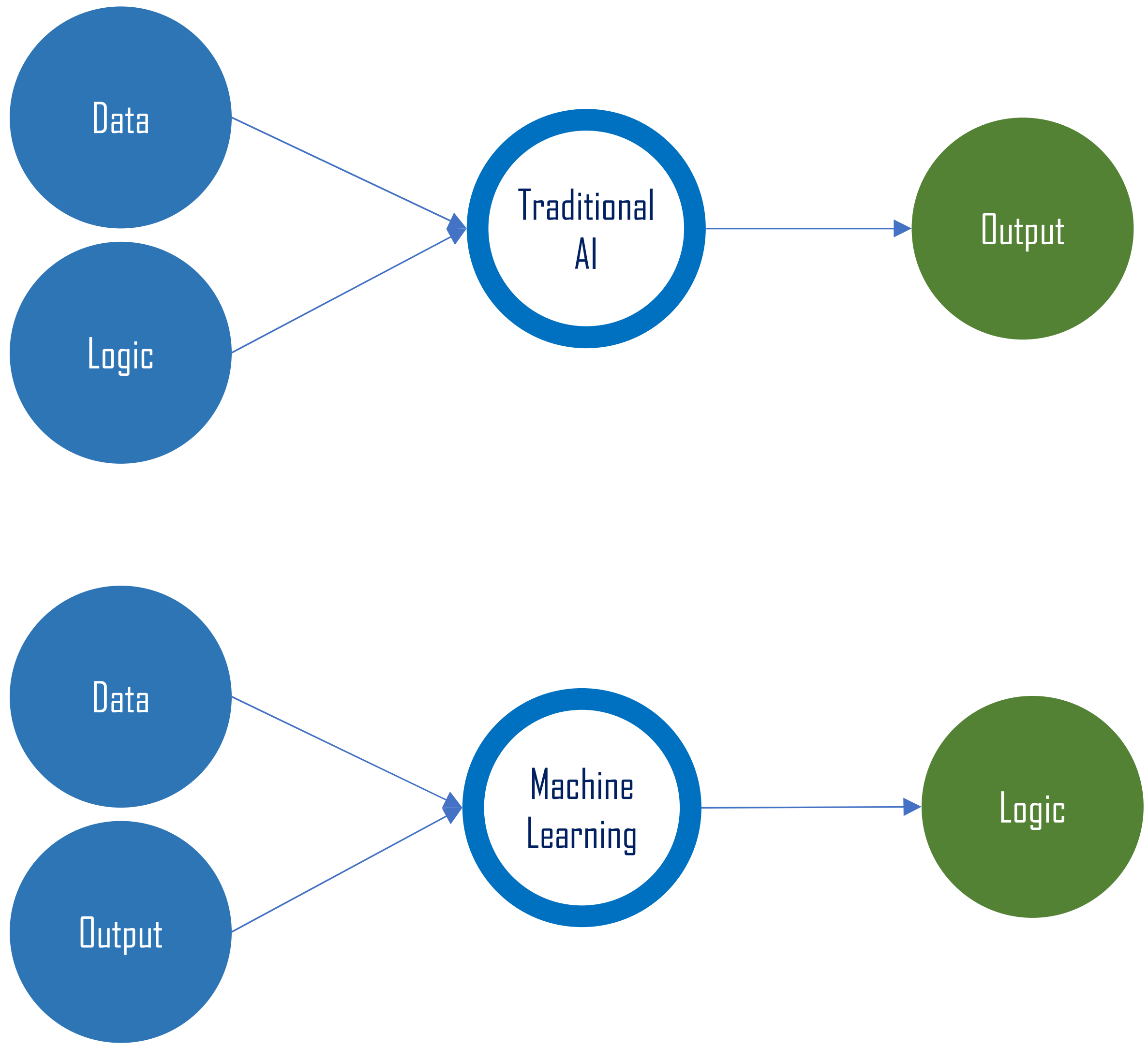


gartner.com

Source: Gartner

Gartner

Traditional AI *versus* Machine Learning



Machine Learning

What do you need to do ?

Questions	Data Input	Data Output	Model
About problem	To answer questions	What do you want to get	To best fit

Machine Learning

What is intended ?

Be Useful
(in the future)

Efficient

Accurate

Generalizable

Interpretable

Reliable

A lot work to do

Machine Learning

Besides what is important ?

Data Quality

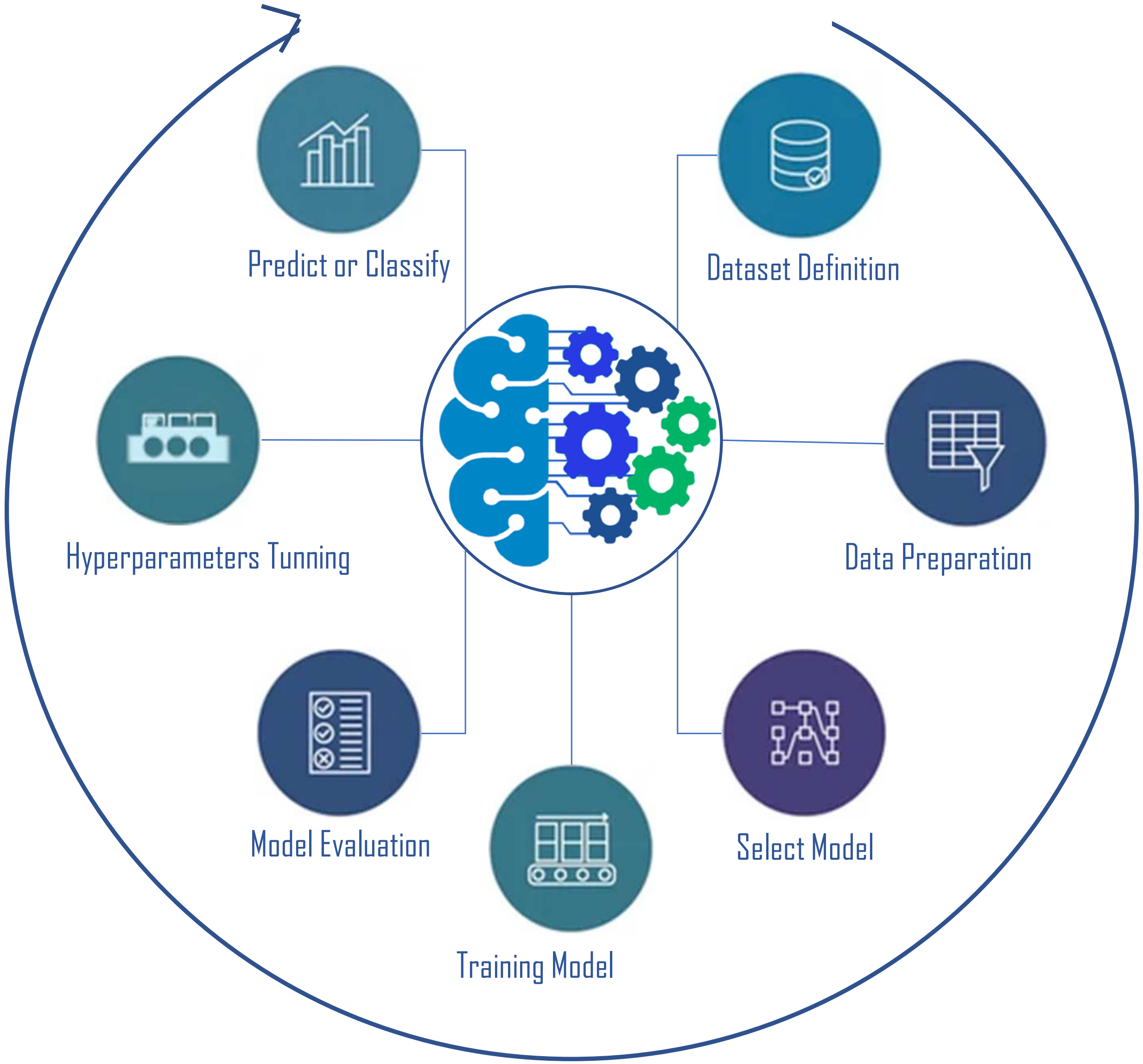
Sample Dimension

Dataset Structure

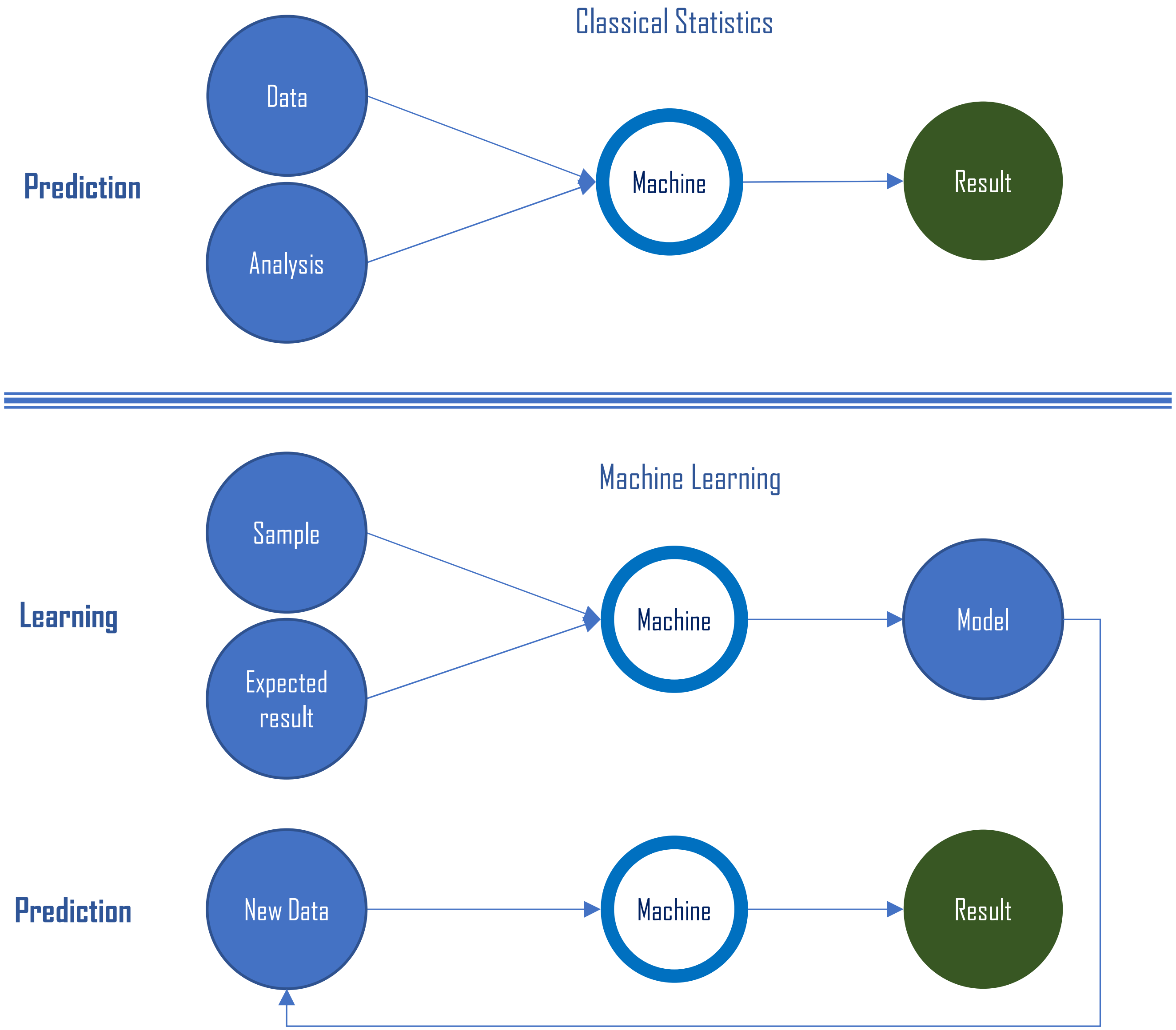
Applications

Financial	Customer Segmentation	Credit Evaluation	Risk Analysis	…
Manufactoring	Predictive Maintenance	Demand Forecasting	Alert System	…
Health	CollaborativeDiagnosis	Predictive Management	Sentiment Analysis	…
Security	Tax Fraud Surveillance	Data Protection	Server Attacks	…
Services	Autonomous Driving	Weather Forecast	Writing Predictor	…
Education	Adaptive Learning	Grading Assignments	Contents Selection	…
…				

Machine Learning Steps

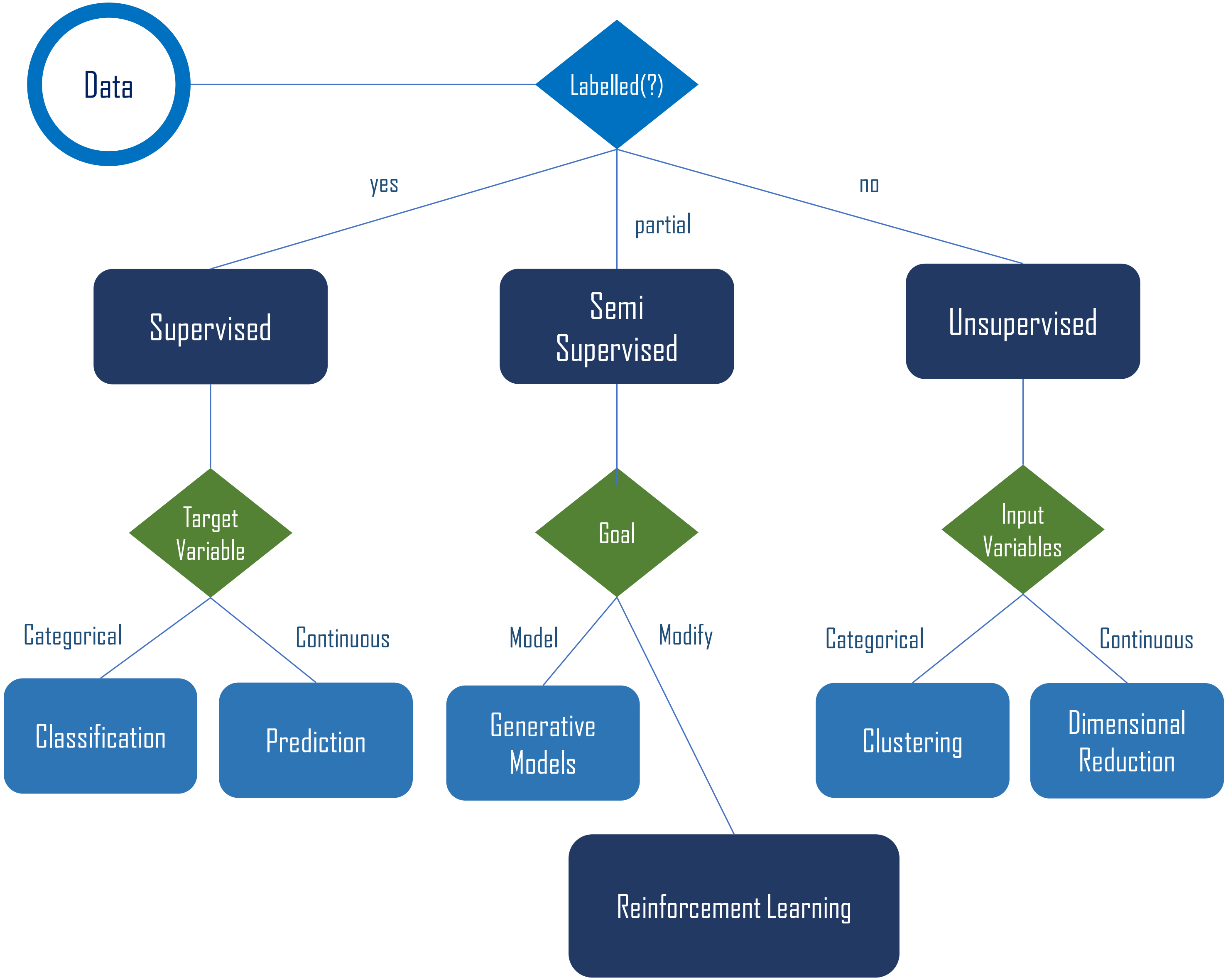


Prediction Process

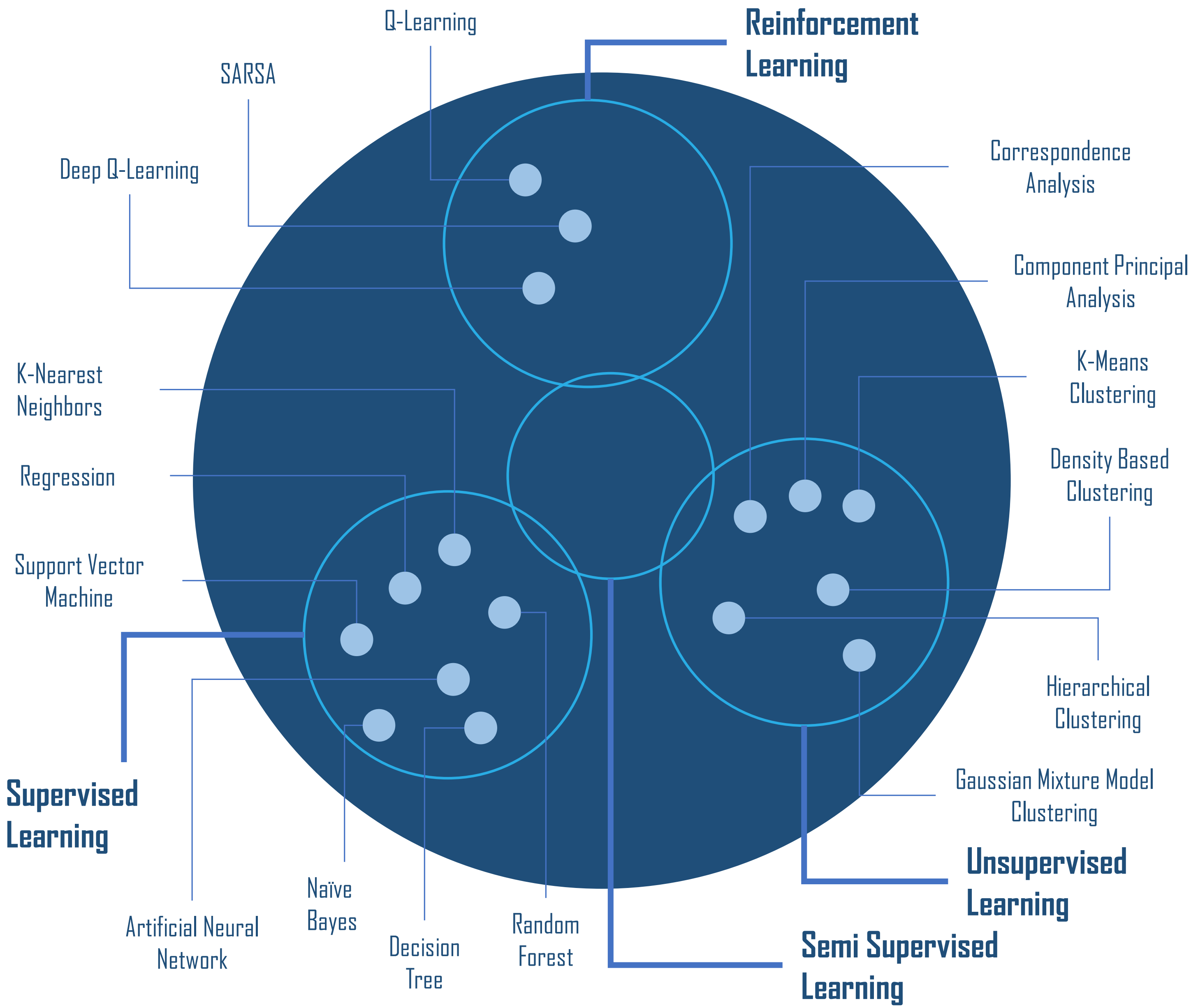


Machine Learning Types

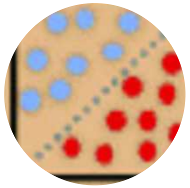
Machine Learning Types



Learning Types



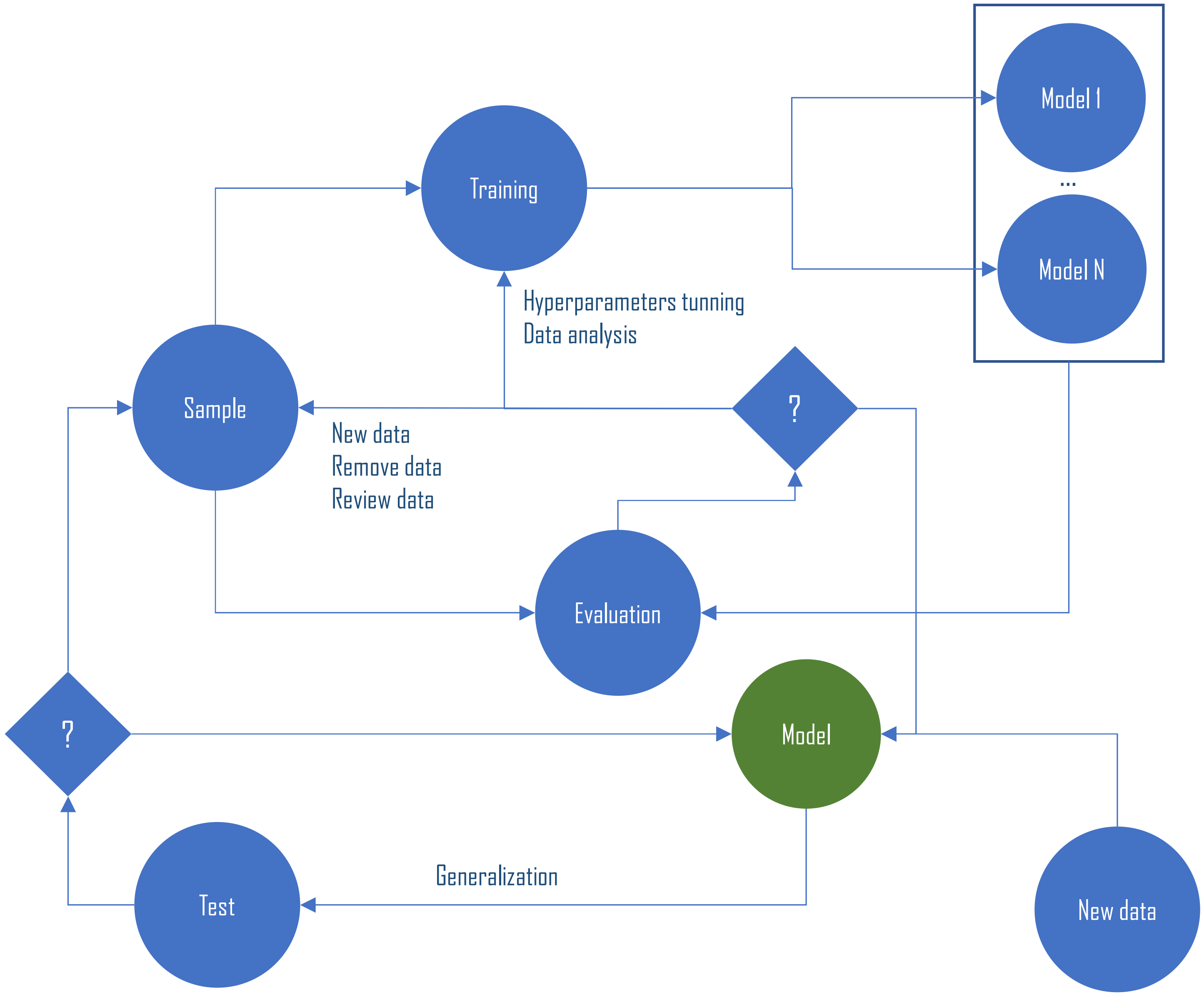
Supervised Learning



Machine learning technic where it have several input variables and an **output variable (Y)** and an algorithm is used to learn the mapping function from the input to the output.

The goal of supervised technic is, through a set of iterations, improve the mapping function until that a stop condition be satisfied

Supervised Learning Process



Supervised Learning

- Weather forecast
- Identification of license plates
- Imaging analysis for disease detection
- Fraud detection
- Spam filtering

Semi Supervised Learning

Machine learning technic that **combines labelled data with non labelled data**

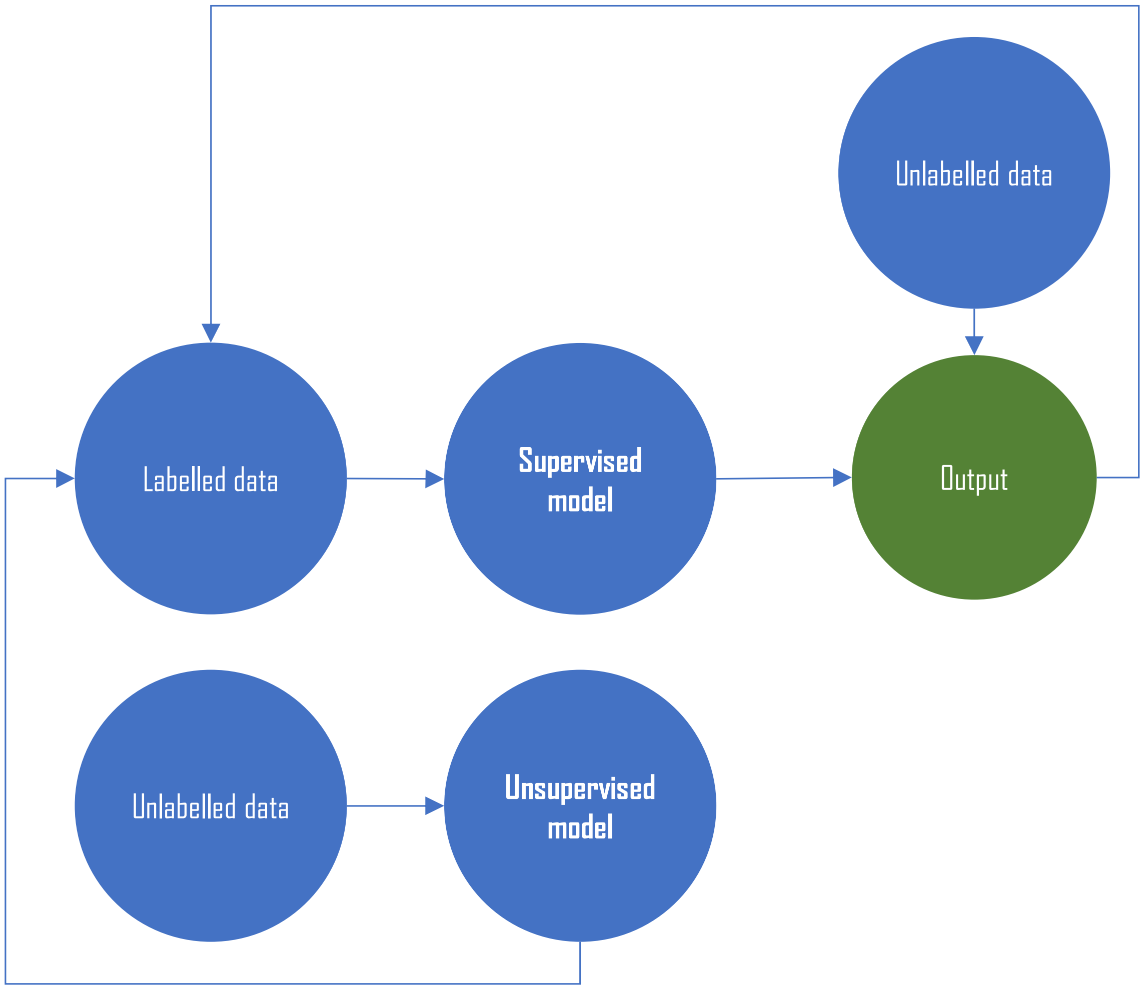
The labelled data is used to produce a model that's allow classify some of non labelled data.

This new labelled data are used to improve the model

The process is iterative

Unsupervised models can be used to label unlabelled data

Semi Supervised Learning



Semi Supervised Learning

Web content classification

Speech analysis

Image classification

Unsupervised learning

In unsupervised learning, the algorithm learns patterns from untagged data

In supervised learning the data is tagged by humans

Unsupervised algorithms discover hidden patterns without the need for human intervention.

Unsupervised algorithms aim to capture patterns that are potentially useful

Ability to discover similarities and differences in information

Used in exploratory data analysis, cross-selling strategies, customer segmentation, and image recognition

Some of the most used techniques are clustering, association rules, and dimensionality reduction

Unsupervised learning most common applications

Customer personas (generic profiles)

Recommendation Engines

Anomaly detection

Computer vision

Interesting / relevant patterns

A pattern is considered interesting when it is ...

potentially useful and valid for new data

readily understood by humans

previously unknown

of adequate degree of confidence for the implementation in view.

ML can generate billions or millions of patterns

Most of them without any interest

Objective measures of interest (statistics): support and trust

Subjective measures of interest: the novelty of the standard or its applicability

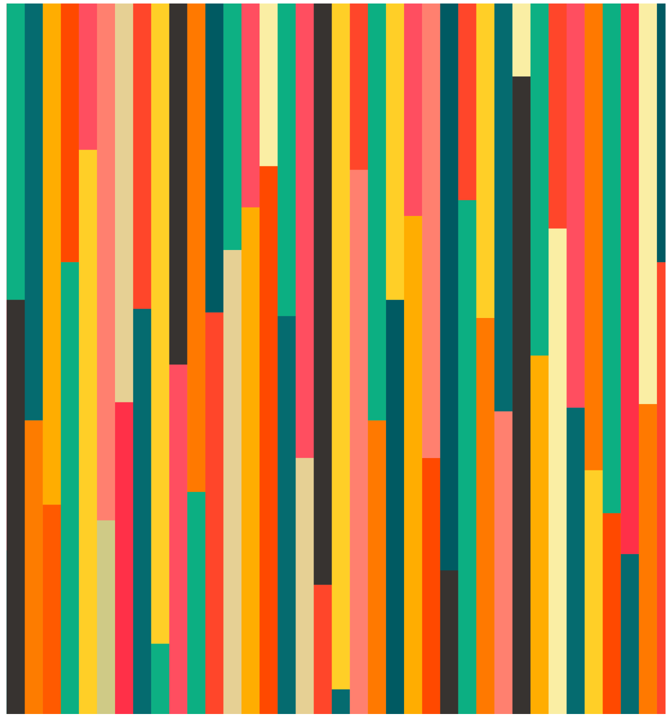
Strong human intervention in the ML process

The process is, by nature, iterative

Find all patterns or just the interesting ones?

Two possible approaches

- Consider **all standards**
  - It is exhaustive
  - Generates nK standards
  - We ne filter interesting
- Consider **only those interesting** ...
  - Generates the interesting
  - set threshold
  - Use of heuristics ...



Reinforcement Learning

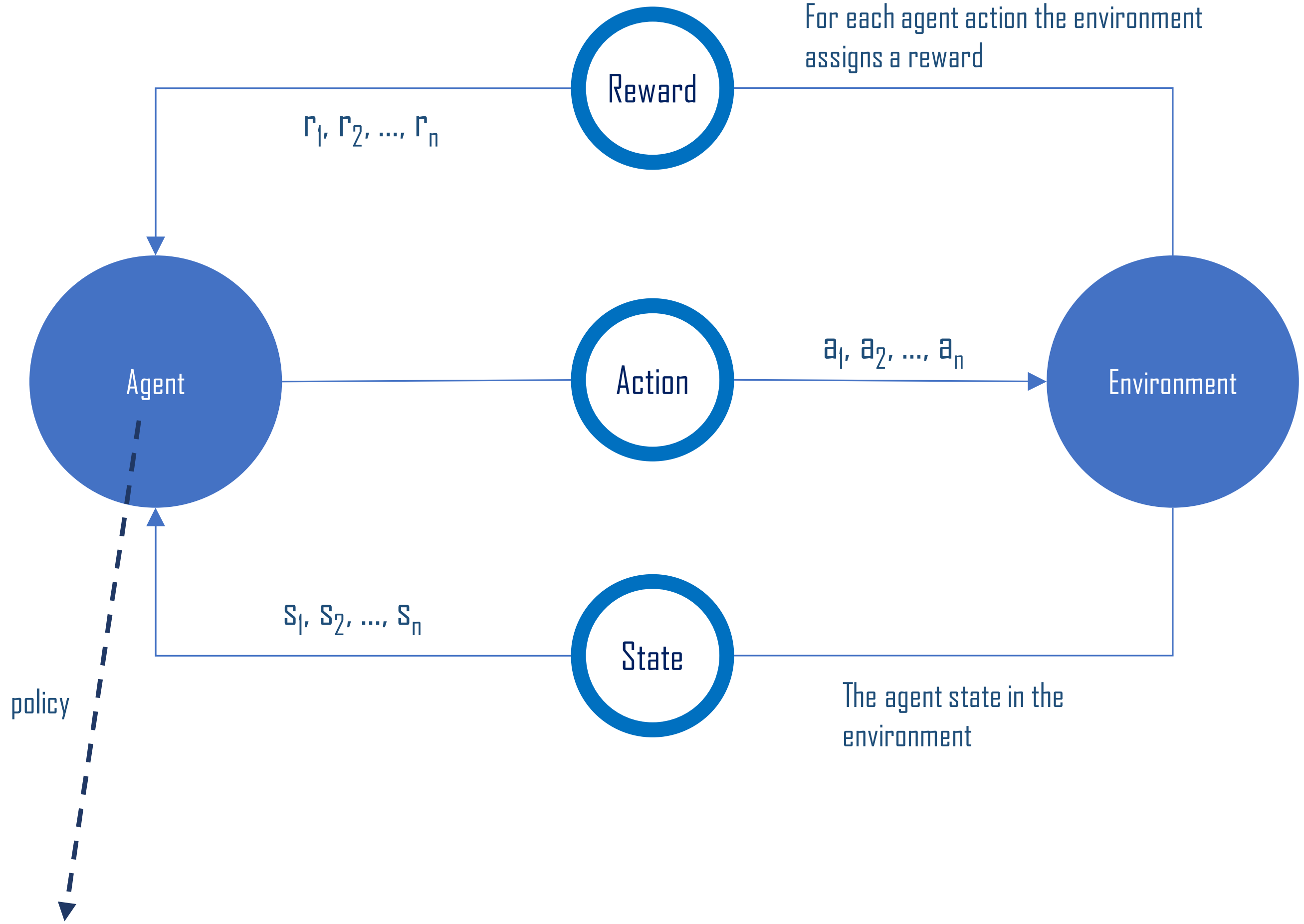
Inspired by the psychology of behaviour, reinforcement learning idea is learning by doing.

A machine can determine an ideal outcome by trial and error.

Over time, it learns to choose certain actions that result in the desirable outcome.

This type of learning is often used in applications such as gaming, navigation, and more.

Reinforcement Learning



$\boldsymbol{\pi(s, a)}$: *is a set of rules that determine the actions that the agent must perform, in the environment, to maximize future rewards.*

Reinforcement Learning

Policy

$$\pi(s, a) = P(a = a|s = S)$$

for each state

Value

$$V_{\pi}(s) = \mathbb{E}\left(\sum_{n} \gamma_t r_t | s_0 = s\right)$$

discount rate
depreciation

Reinforcement Learning Types

Model Based

Uses the experience indirectly to construct an internal model of the transitions and immediate outcomes in the environment.
Implies the construction of the model

Model Free

Uses the experience directly in the form of a reward prediction error.
Learn to define the best action to goal a determinate state.

Reinforcement Learning Types

EXAMPLE

Visit an unknown city for which there is no map.
The general direction from where you are to certain points is known, but there are a large number of different possible routes and some should be avoided.

Model Based

Keep all the routes taken with information from the different streets and landmarks that make up these routes to start creating a map of the area.

Model Free

Keeping route of the different places visited and the actions taken (direction taken) ignoring details of the routes themselves. Starting from a visited place, the directional choice is privileged, which led to a good result.

Type Variables & Technics

	Supervised	Unsupervised	Reinforcement
Continuos	Linear Regression Non Linear Regression		
All	Decision Tree Random Forest ANN SVM K-NN	K-Means PCA	Q-Learning MPD
Categorical	Logistic Regression Naïve Bayes	Correspondence Analysis	

Summary

	Target Variable Type	Model Type
Supervised	Categorical	Classification
	Continuous	Regression
Unsupervised	No Target	Association
		Clustering
Semi Supervised	Categorical	Classification
		Clustering
Reinforcement	Categorical	Classification
	No Target	Control

Model performance

Model Performance

Machine Learning models can be evaluated using a variety of metrics

The metrics for evaluating models in which the target variable is continuous are distinct from the metrics used in models whose target variable is categorical

Some metrics are used only by supervised models

Model Performance

Continuous Target variable

Metrics

Non-Normalized Measures

Mean Squared Error (MSE)

Mean Absolute Error (MAE)

Root Mean Absolute Error (RMSE)

Normalized Measures

Mean Absolute Percentage Error (MAPE)

Root Mean Squared Relative Error (RMSRE)

Model Performance

Continuous Target variable

Metrics

MSE

$$\frac{1}{N}\sum_{i=1}^{N}\left(y_i - h(x_i)\right)^2$$

MAE

$$\frac{1}{N}\sum_{i=1}^{N}\left|y_i - h(x_i)\right|$$

RMSE

$$\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - h(x_i)\right)^2}$$

MAPE

$$\frac{1}{N}\sum_{i=1}^{N}\frac{\left|y_i - h(x_i)\right|}{y_i}$$

RMSRE

$$\sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{\left(y_i - h(x_i)\right)^2}{y_i}}$$

Model Performance

Categorical Target Variable

Consistency

Measures the classifier's ability to classify correctly

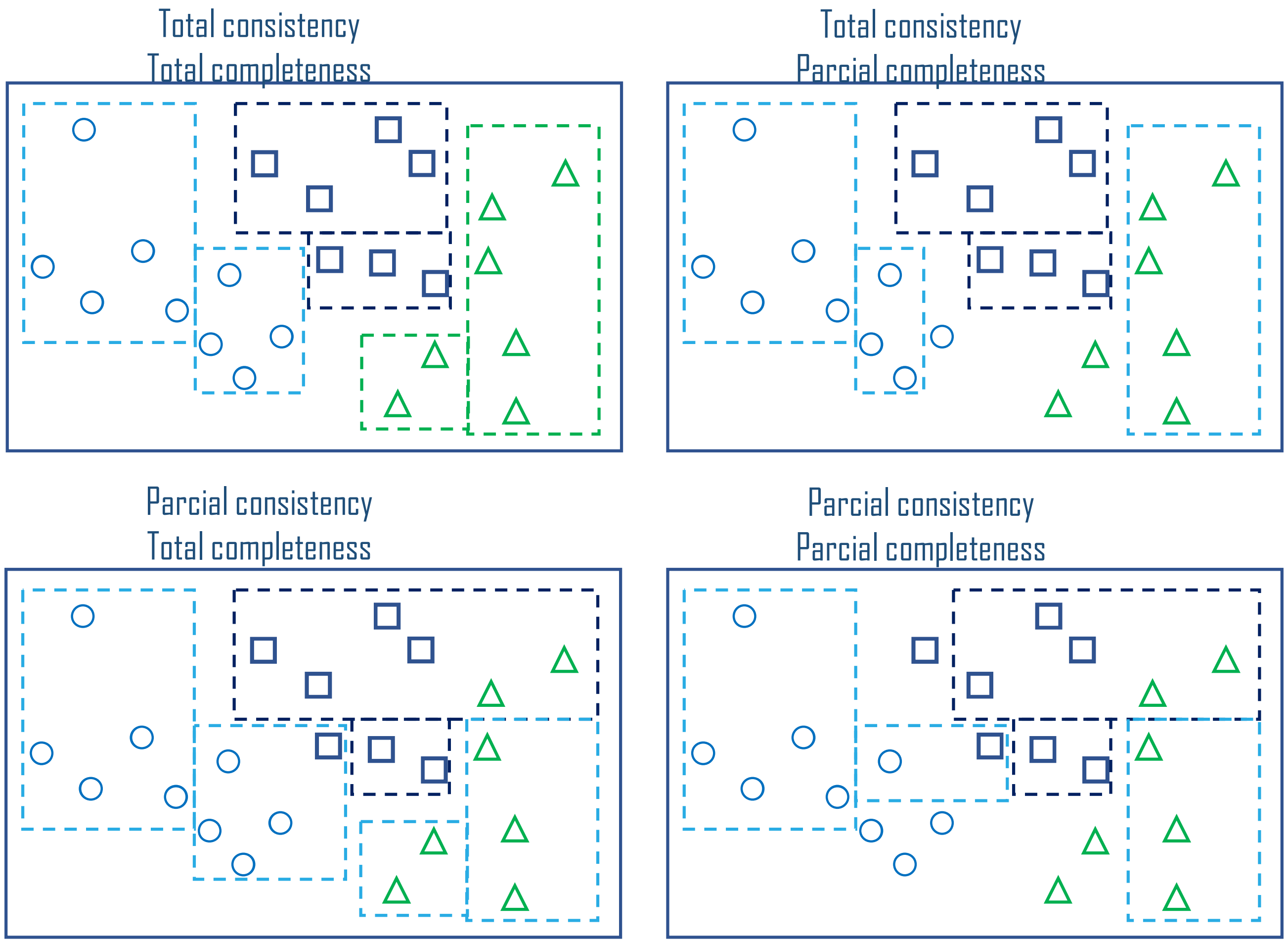
Completeness

Indicates the proportion of elements classified (correctly or not)

Model Performance

Categorical Target Variable

Consistency & Completeness



Model Performance

Categorical Target Variable

Confusion Matrix

Is a table (NxN) that allows you to view and summarize the performance of the classification algorithm

N is the number of categories of the target variable

Model Performance

Categorical Target Variable

Confusion matrix for two classes

		Predict	
		C_+	C_-
True	C_+	True Positive (TP)	False Negative (FN)
	C_-	False Positive (FP)	True Negative (TN)

Relative Error for C_-

$$\frac{FP}{TN + FP}$$

Relative Total Error

$$\frac{FN + FP}{N}$$

Relative Error for C_+

$$\frac{FN}{TP + FN}$$

Accuracy (ACC)

$$\frac{TP + TN}{N}$$

Model Performance

Categorical Target Variable

Confusion matrix for two classes

Precision (P)

$$\frac{TP}{TP + FP}$$

Precision measures how many detected items are **truly relevant**

	C_+	C_-
C_+	TP	FN
C_-	FP	TN

Sensitivity (Recall) (R)

$$\frac{TP}{TP + FN}$$

Recall measures how many relevant elements were detected

Model Performance

Categorical Target Variable

Confusion matrix for two classes

F1 score is the harmonic mean of precision and recall

$$\frac{2}{P^{-1} + R^{-1}}$$

simplifying

F1 score

$$2 \times \frac{P \times R}{P + R}$$

Accuracy is better when the distribution of sample elements by classes is homogeneous

F1-Score is better when the distribution of sample elements by classes is unbalanced

Model Performance

Categorical Target Variable

Confusion matrix for two classes

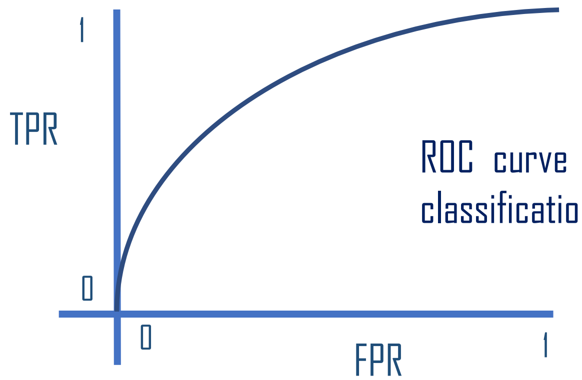
True Positive Rate (TPR)

$$\frac{TP}{TP + FN}$$

False Positive Rate (FPR)

$$\frac{FP}{FP + TN}$$

Receiver Operating Characteristic Curve (ROC curve)

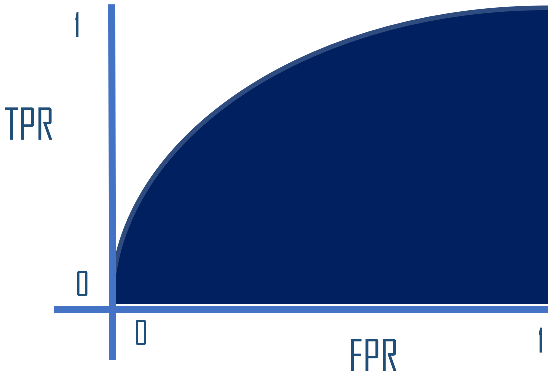


ROC curve related TPR with FPR through different classification thresholds

Model Performance

Categorical Target Variable

Confusion matrix for two classes



AUC – Area Under ROC curve

AUC provides an aggregate measure of performance across all possible classification thresholds

Model Performance

Categorical Target Variable

Confusion matrix for more than two classes

Predict

True

	C_1	C_2	...	C_n
C_1	T	F	F	F
C_2	F	T	F	F
...	F	F	T	F
C_n	F	F	F	T

Model Performance

Categorical Target Variable

Confusion matrix for more than two classes

Predict

True	C_1	C_2	...	C_n
C_1	T	F	F	F
C_2	F	T	F	F
...	F	F	T	F
C_n	F	F	F	T

For each class

Predict

True	C_+	C_-
C_+	TP	FN
C_-	FP	TN

$$TP = C_{i,i}$$

$$FP = \sum_{j=1}^{N} C_{j,i} - C_{i,i}$$

$$FN = \sum_{j=1}^{N} C_{i,j} - C_{i,i}$$

$$TN = \sum_{j=1}^{N} C_{j,i} - TP - FN - FP$$

Overfitting & Underfitting

Fitting

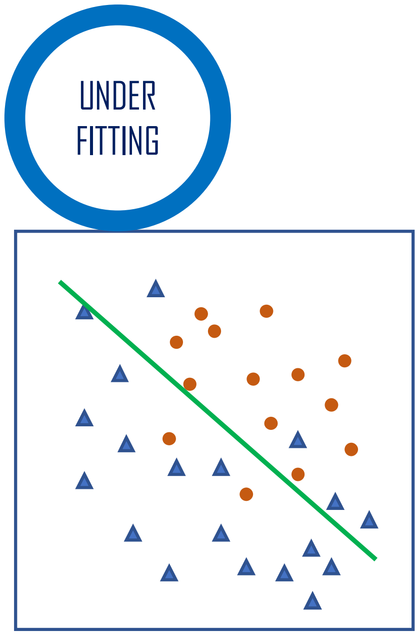
The basis of machine learning is the adjustment of the model to the input data

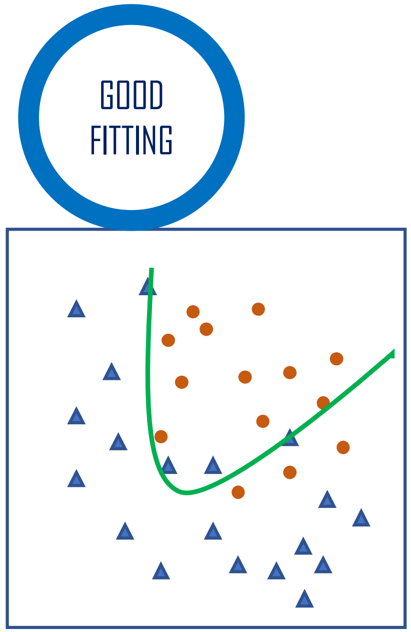
In a properly adjusted model, the relationships between independent variables and the target (dependent) variable are captured, which allow a classification or prediction with high accuracy

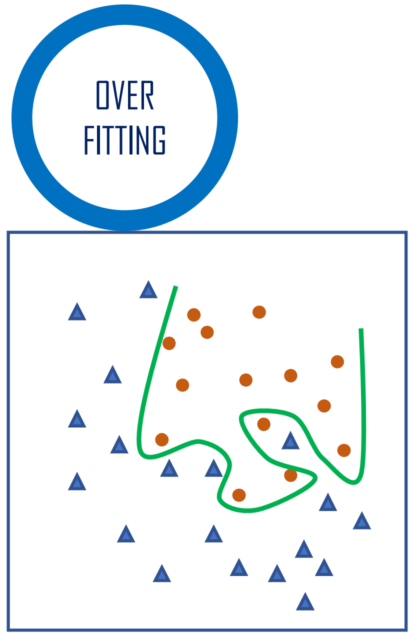
A model is considered good if it generalizes any new input data from the problem domain adequately

Overfitting & Underfitting

Are majorly responsible for the poor performances of the machine learning algorithms







Bias & Variance

Bias

Biases are the underlying assumptions made by models from the data in order to simplify the process of determining the function

Bias helps us to better generalize the data and make the model less sensitive to isolated data

Examples of high-bias algorithms include linear regression and logistic regression

Variance

Variance occurs due to a model's sensitivity to small fluctuations in the data set

The high variance would cause an algorithm to model outliers or noise in the training set

The model learns all data points and does not provide a good prediction when tested on a new dataset

Examples of high variance algorithms include decision tree, KNN, etc.

Underfitting

The model fails to capture the underlying trend of the data and therefore does not fit the data well

It usually happens when there are few or unfit data for the problem

The model fits the data easily, because they are few, but it will be inaccurate with other data

High bias and low variance

Overfitting

The model fails because it has too much data and manages to adjust itself to the noise itself, that is, the model incorporates the noise into the logic it encounters

New data is not categorized correctly because it does not have the same detail and noise

Non-parametric and non-linear methods are more vulnerable to overfitting because they have more freedom in model construction and can build unrealistic models

High variance and low bias

Overfitting & Underfitting

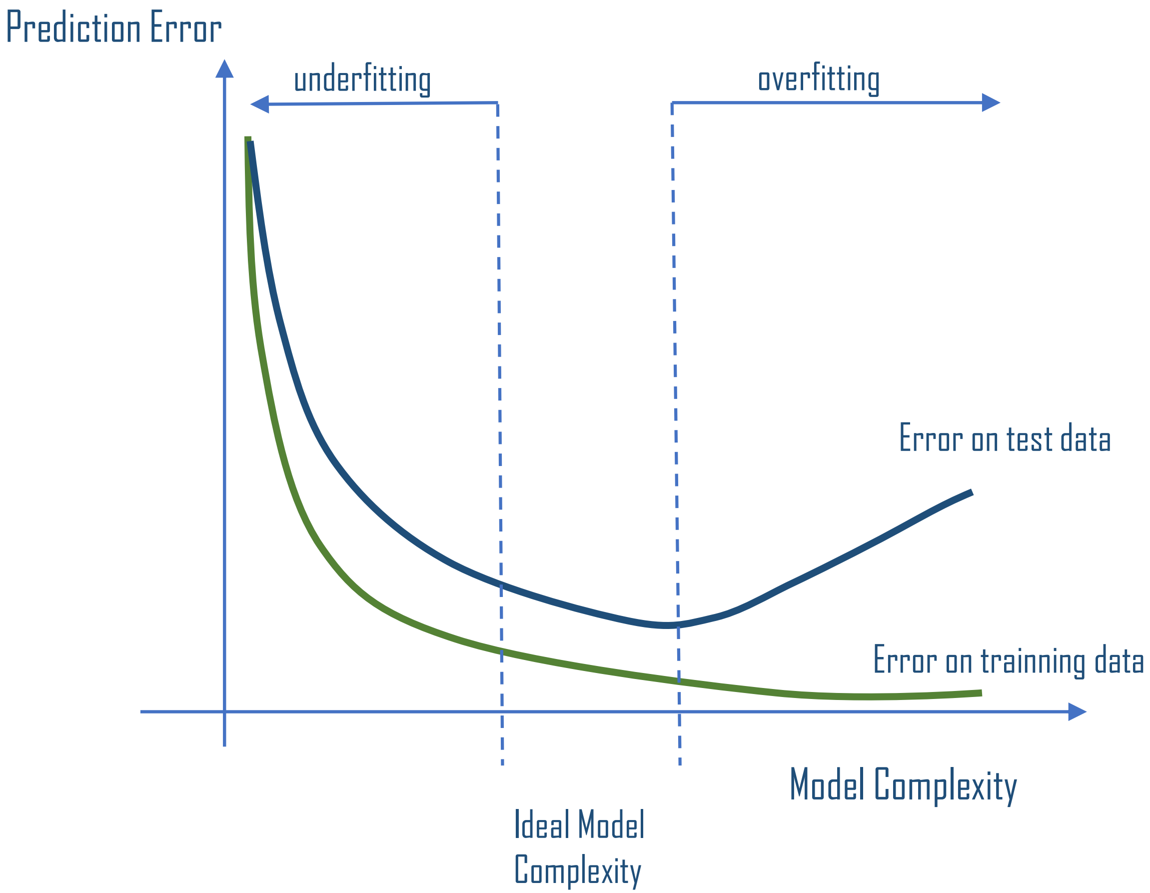
REDUCE UNDERFITTING TECHNICS

- Increase model complexity
- Increase the number of features
- Performing feature engineering
- Decrease hyperparameter regularization
- Remove noise from the data.
- Increase the number of epochs
- Increase the duration of training

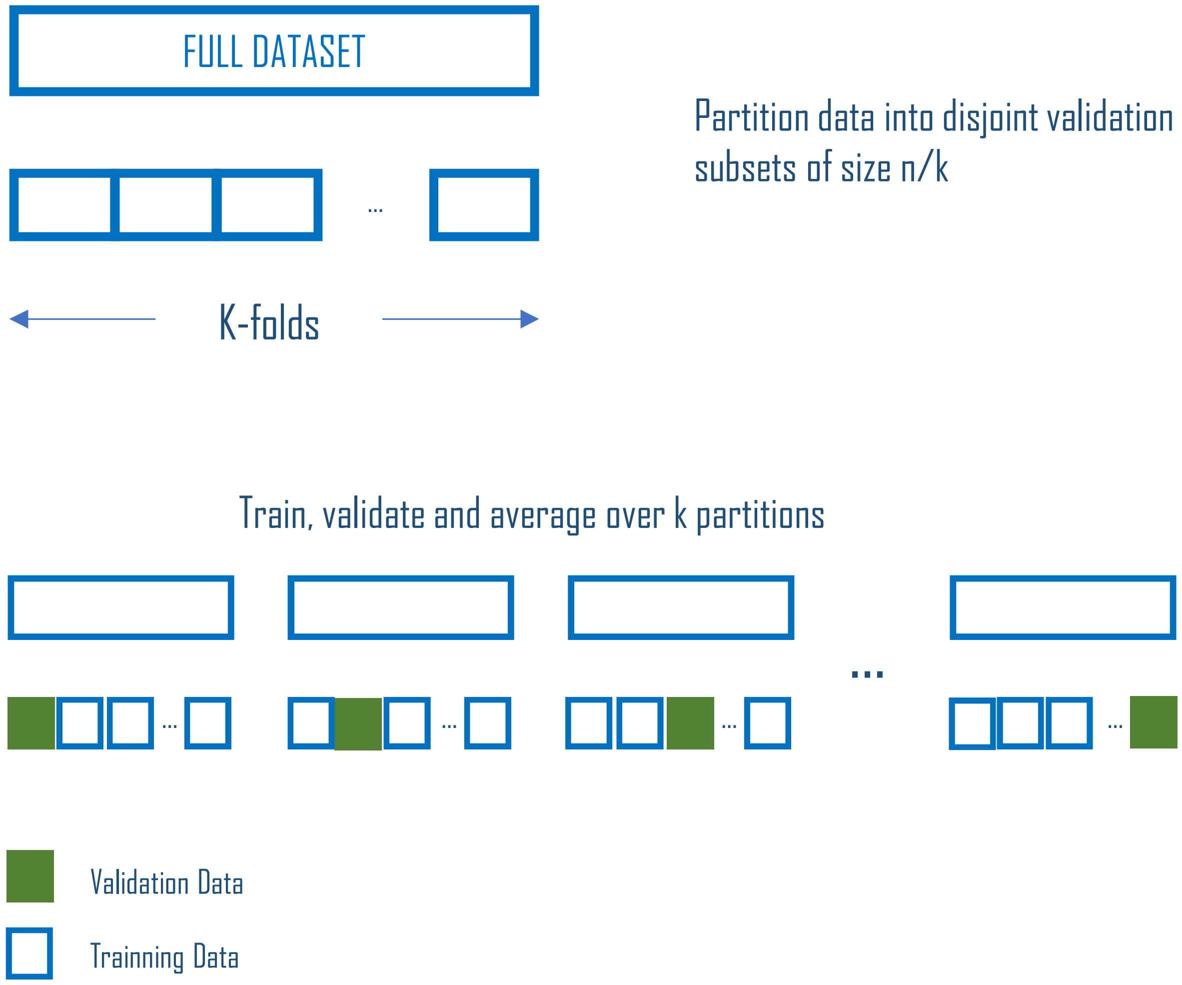
REDUCE OVERFITTING TECHNICS

- Increase training data
- Reduce model complexity.
- Early stopping the training phase
- Increase hyperparameter regularization
- Ridge Regularization
- Lasso Regularization
- Dropout Regularization (ANN)

Overfitting & Underfitting



Supervised Learning
K-Cross Validation



Thank you!