



Machine Learning



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Agenda

Machine Learning process

Types of Machine Learning

Algorithms

Trends and Challenges of ML

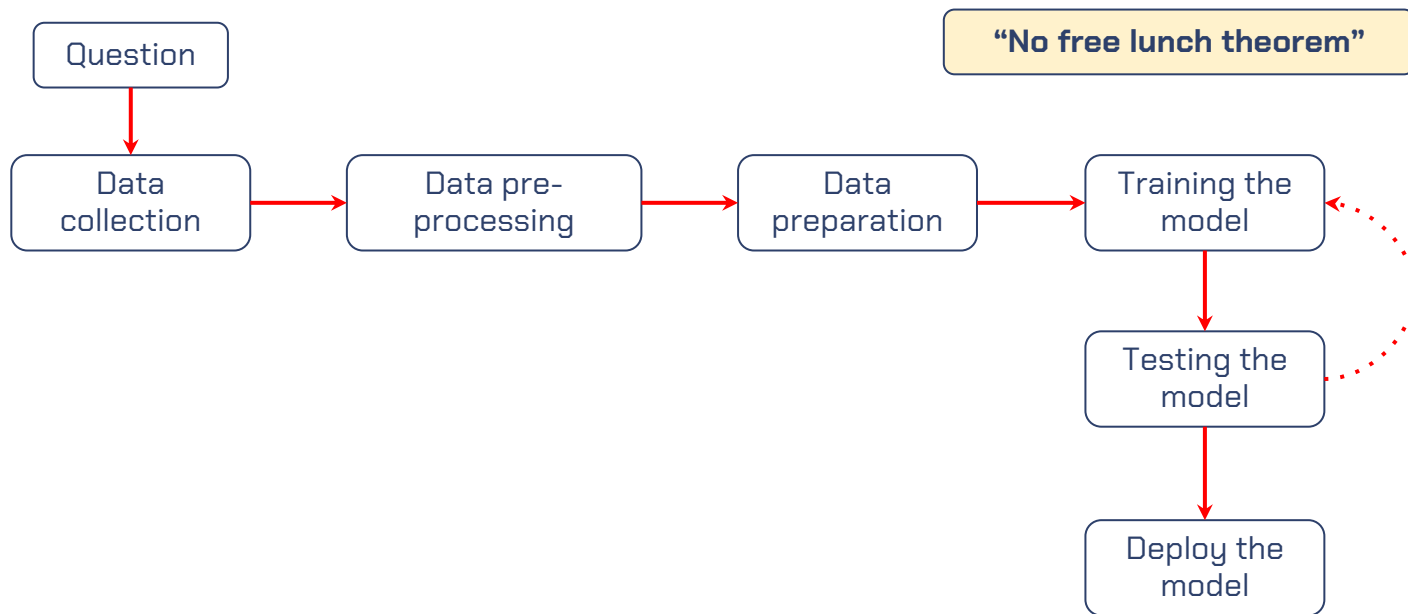


Topic 1

Machine Learning Process



Machine Learning process

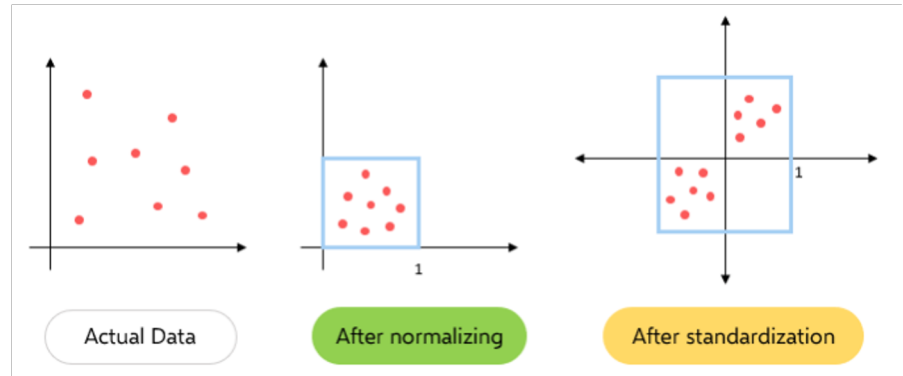


Data pre-processing

Duplicates, Errors & Missing values

Reclassifying labels

Standardization and normalization



Exploratory analysis

Exploratory Data Analysis refers to the critical process of performing initial investigations on data so as to **discover patterns**, to **spot anomalies**, to **test hypothesis** and to **check assumptions** with the help of summary statistics and graphical representations.

Methods of central tendency and deviation

Correlation

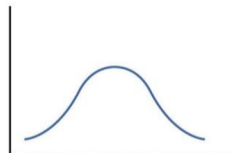
→ remove correlated variables to improve your model

Outliers

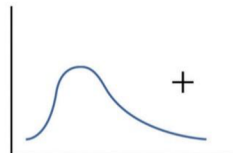
→ Box plot, histogram, scatter plot

Skewness

→ Distribution



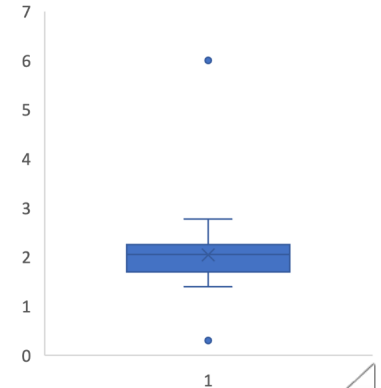
Normal Curve



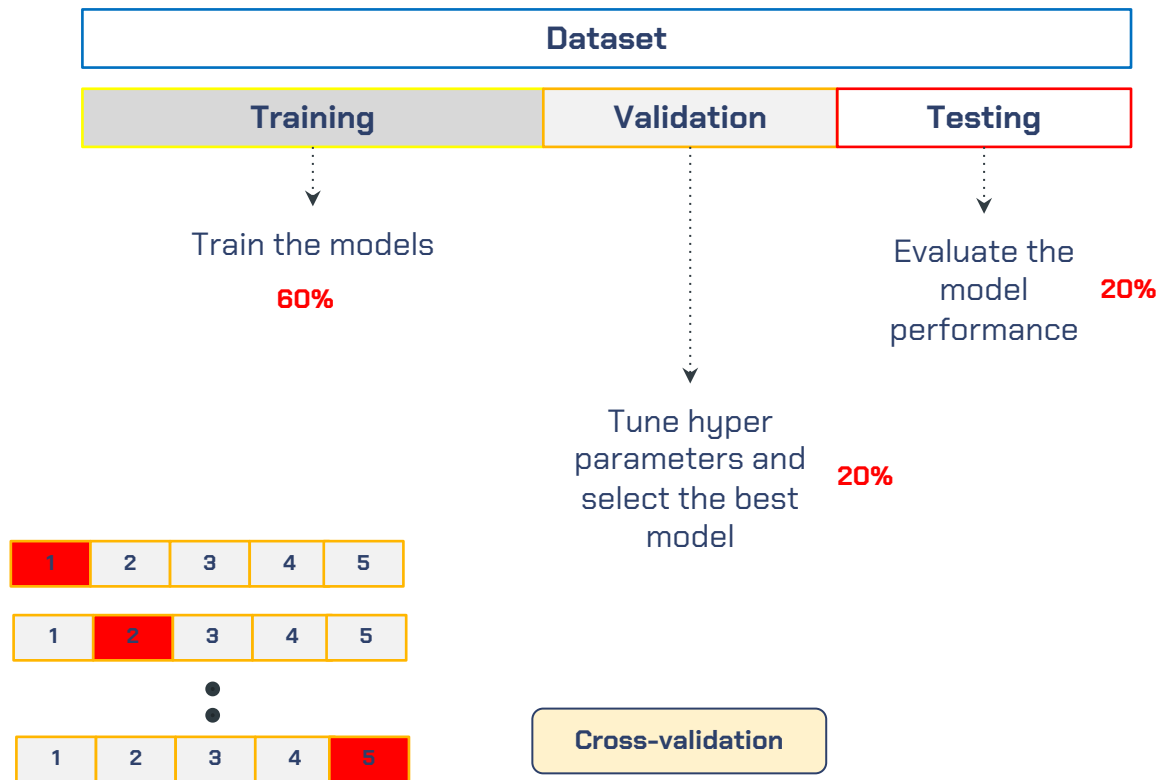
Positive Skew



Negative Skew



Data preparation



If the model performance is significantly better on the validation set than the testing data → **model is overfitting**

Optimal model

Underfitting

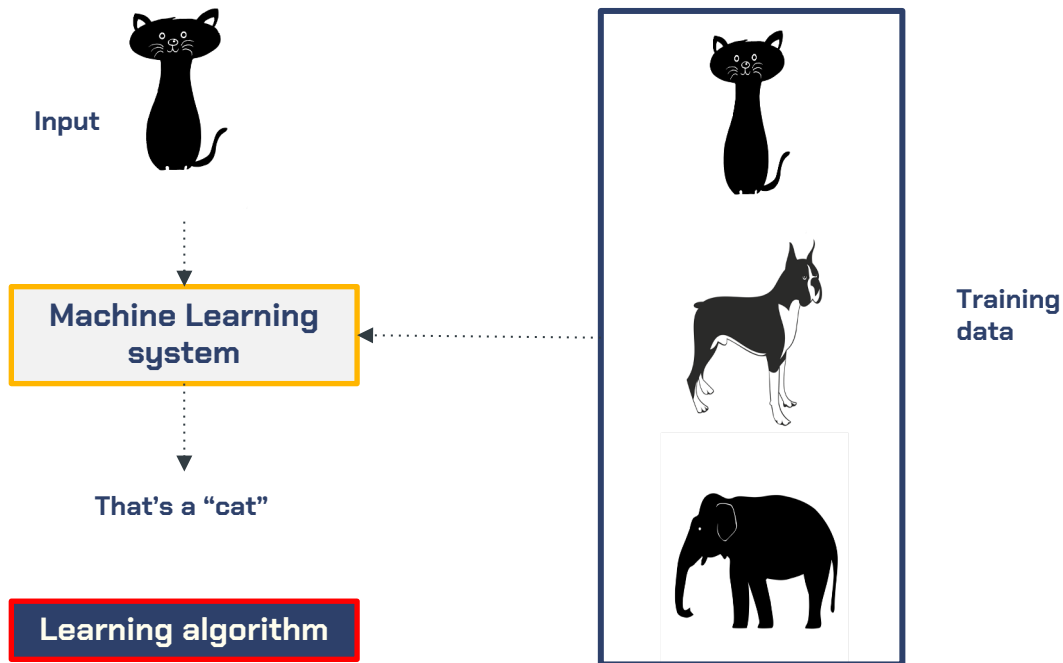
Overfitting

Topic 2

What is Machine Learning?



Machine Learning



Types of learning

Supervised learning

Unsupervised learning

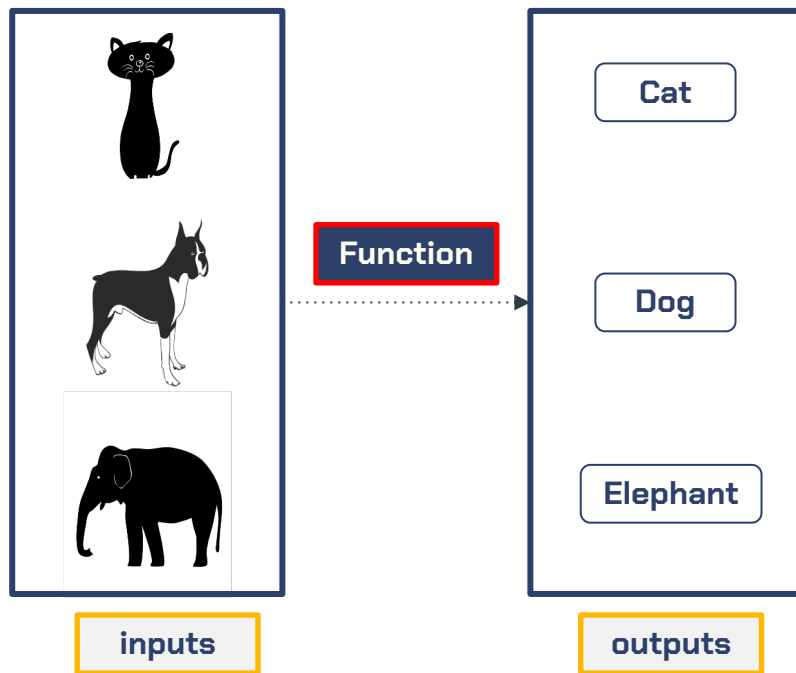
Semi-supervised learning

Reinforcement learning

Transfer learning



Supervised learning



Logistic Regression

Support vector Machine

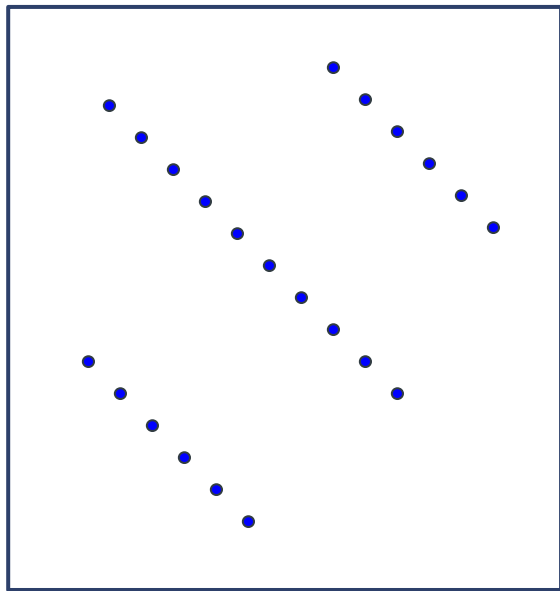
Random Forest

Neural Network

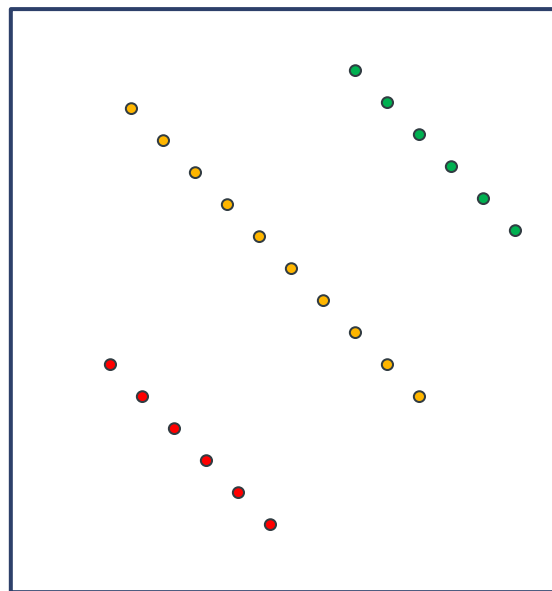
And many more..



Unsupervised learning



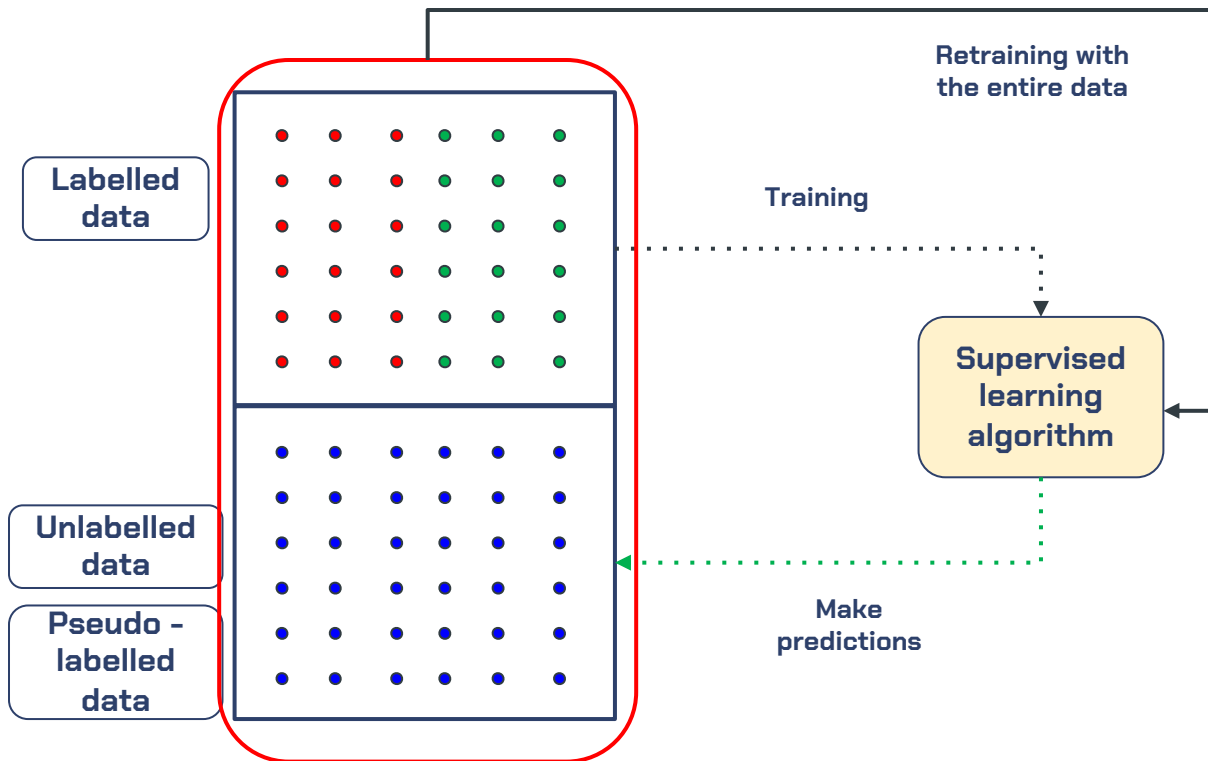
No labels



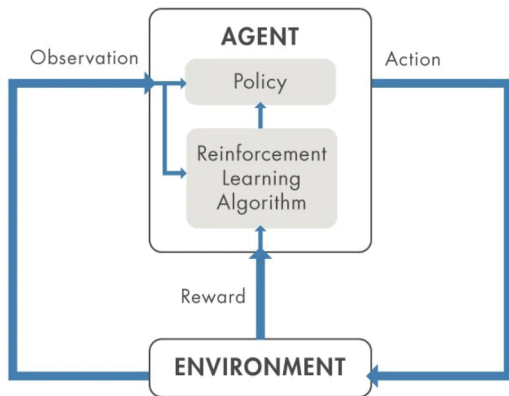
Clustering



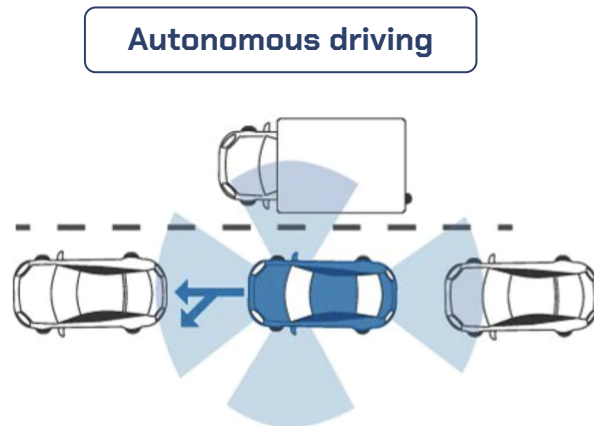
Semi-supervised learning



Reinforcement learning

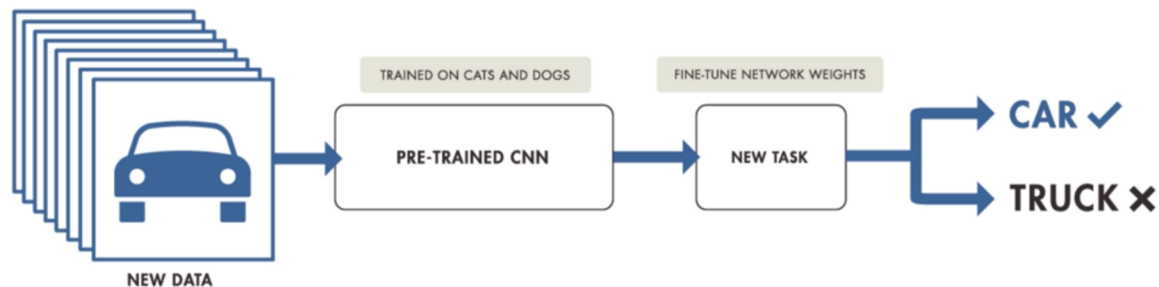


- **Observe**
- **Select a policy**
- **Action**
- **Get reward**
- **Update policy**
- **Iterate until optimal policy is found**



Deep neural networks

Transfer learning



Saves times - no need to build models from scratch.

Eliminates the need for **huge training dataset**

Improves **generalizability**

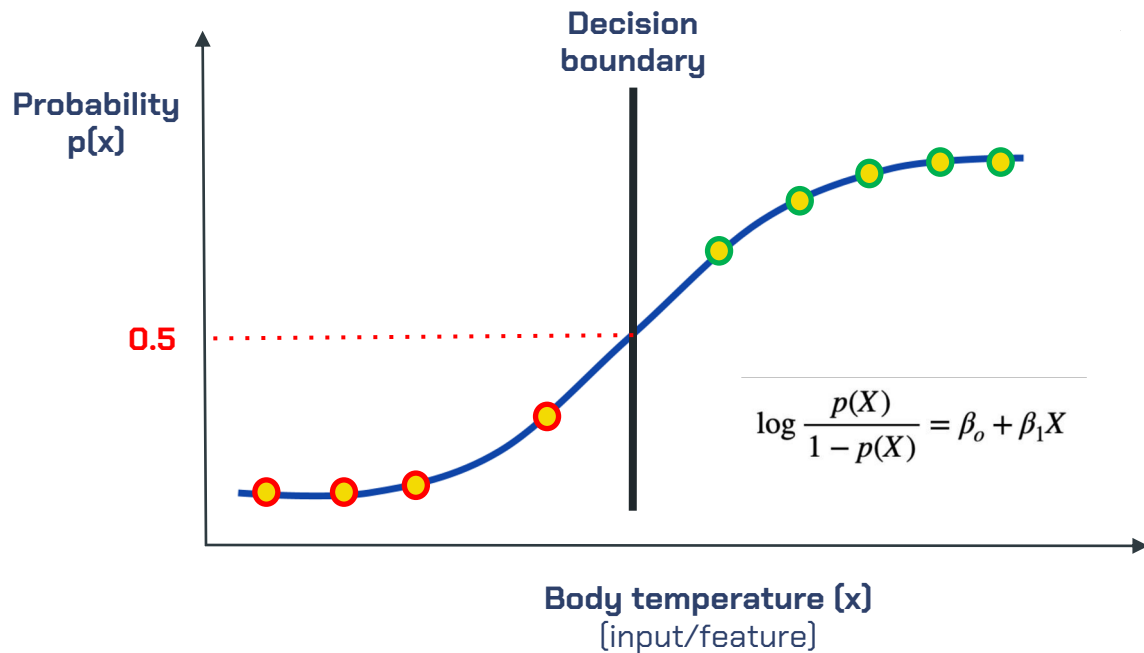


Topic 3

Logistic Regression

Logistic Regression

Binomial classification

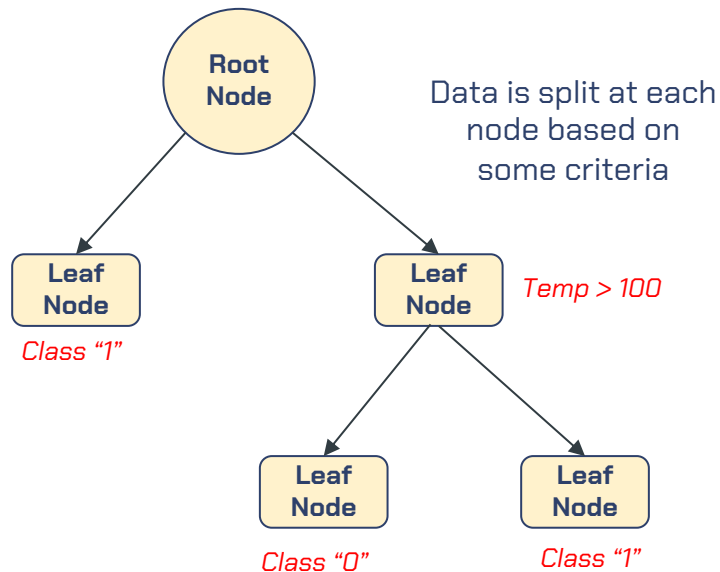


Topic 4

Random forest

Random forest

Objective - minimize dissimilarity in terminal nodes

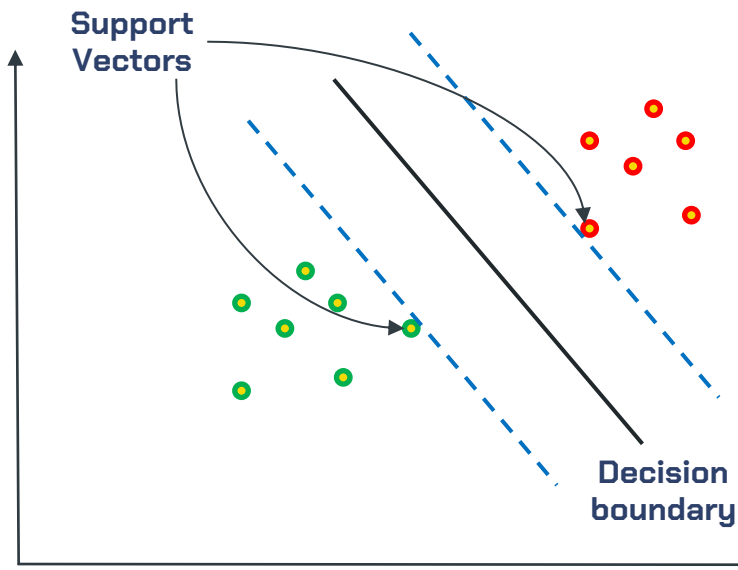


Topic 5

Support Vector Machine

Support Vector Machine

A linear SVM classifier fits the “*widest possible street*” between the classes.



The decision boundary separates the two classes, but also stays as far away from the closest training example as possible.

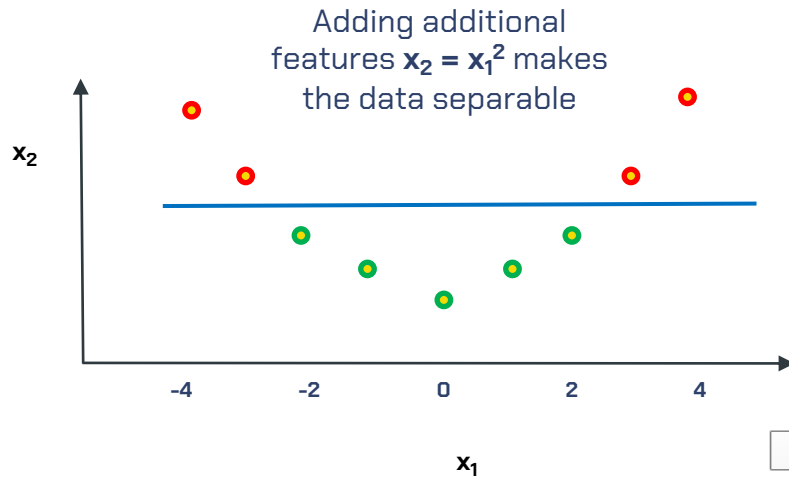
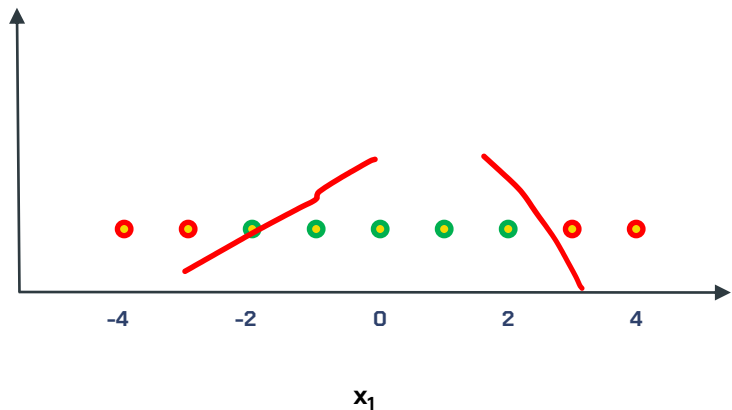


Non-linear Support Vector Machine

Many datasets are not linearly separable.

Adding additional features can make it linearly separable.

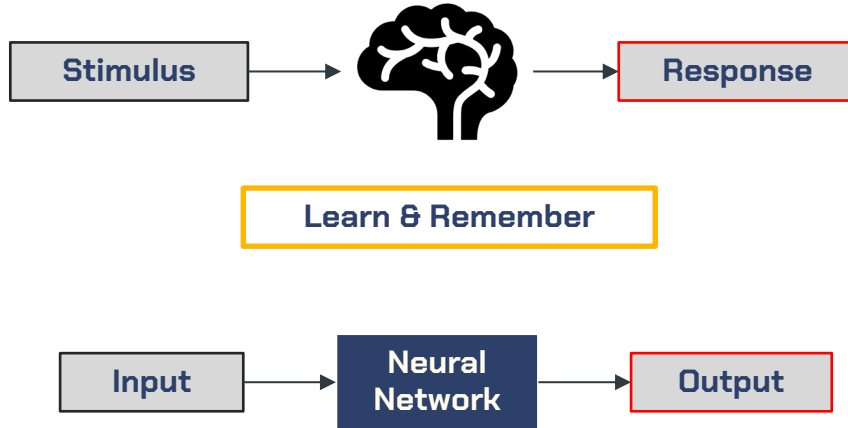
Kernel trick



Topic 6

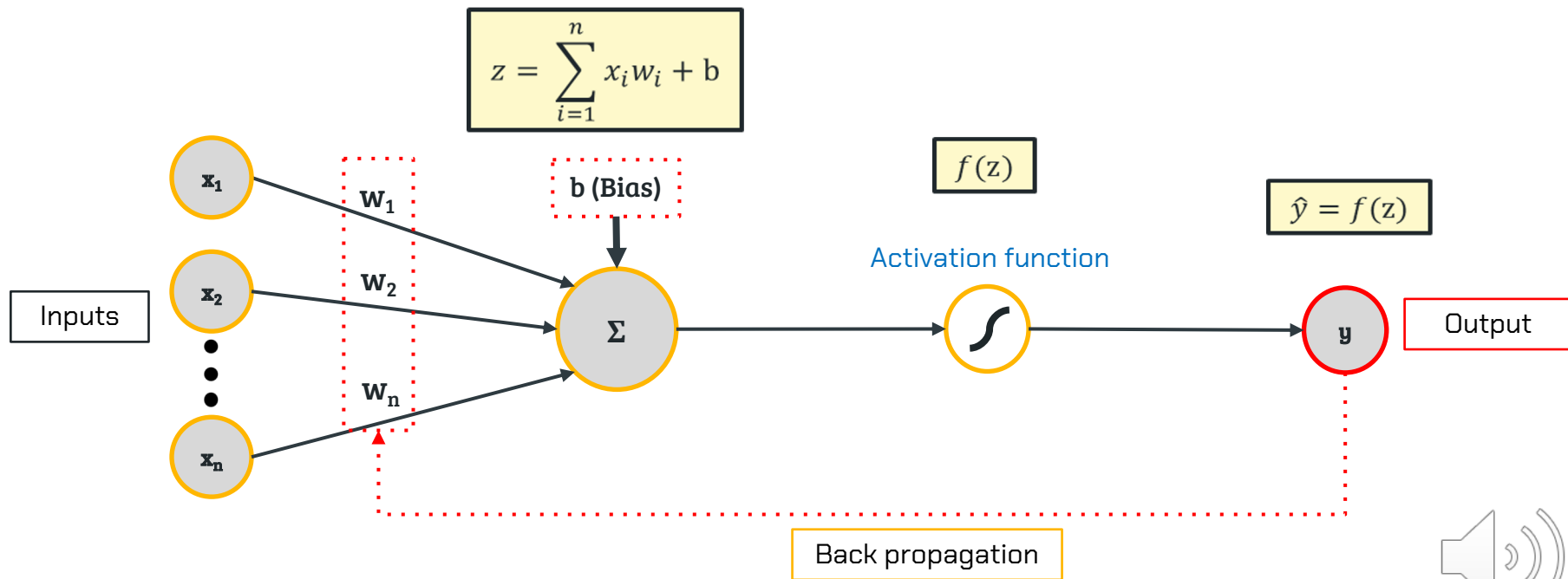
Artificial Neural Network

Artificial Neural Network



- **Neuron** - receive and transmit signals
- **Network** - Group of things connected to each other
- **Artificial Neural Network**
 - Group of connected neurons
 - Replicate the behavior of brain - training

Training a Neuron



Backpropagation

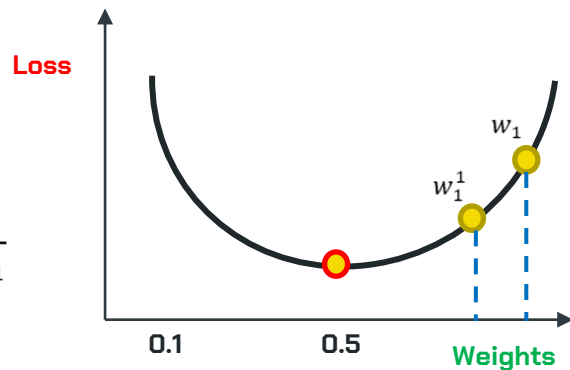
- **Step 1** - How off is the prediction?

Errors

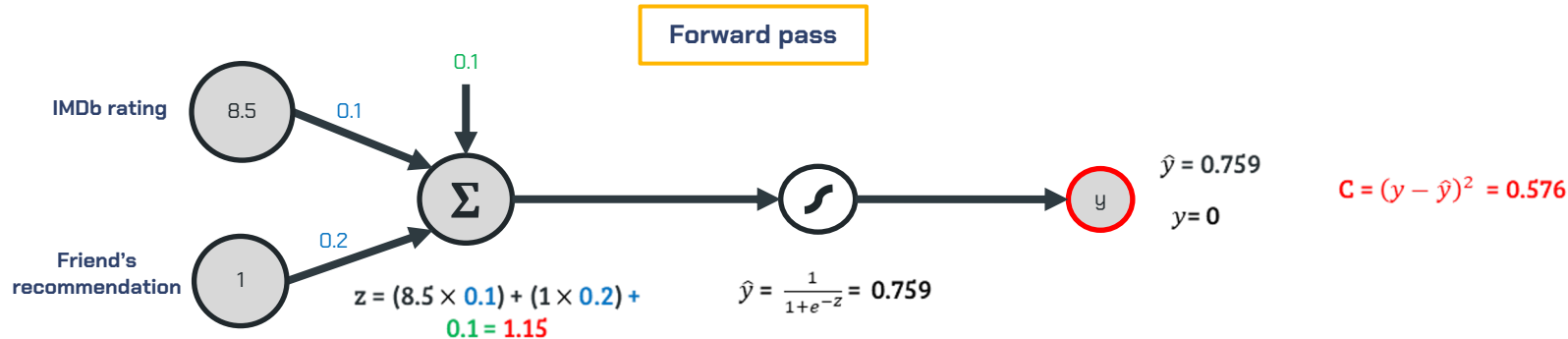
- **Step 2** - How much to correct

Minimize "C"

$$\text{new weight}(w_1^1) = \text{old weight}(w_1) - \text{learning rate}(\alpha) \times \frac{\partial C}{\partial w_1}$$



To watch or not to watch, that is the question..



$$\frac{\partial C}{\partial \hat{y}} = -2(y - \hat{y}) = -2(0 - 0.759) = 1.518$$

$$\frac{\partial \hat{y}}{\partial z} = \hat{y}(1 - \hat{y}) = 0.759 \times 0.241 = 0.183$$

$$\frac{\partial z}{\partial w_1} = x_1 = 8.5 \quad (z = w_1 x_1 + w_2 x_2 + b)$$

$$\frac{\partial C}{\partial w_1} = 2.36$$

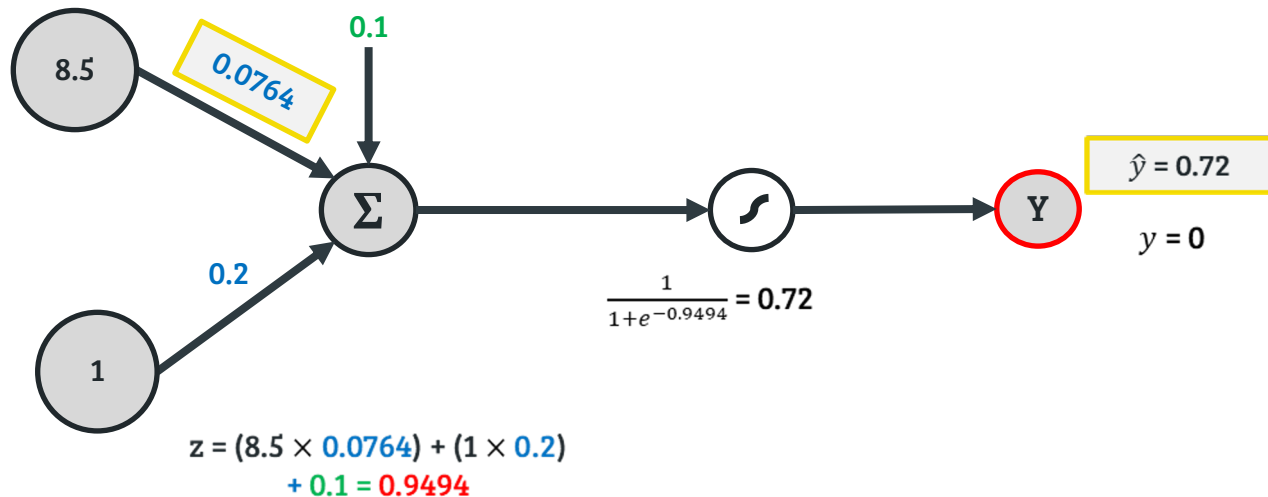
$$\frac{\partial C}{\partial w_i} = \frac{\partial C}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial z}{\partial w_i}$$

Learning rate (α) = 0.01

$$\text{New weight, } w_1^1 = w_1 - \alpha \times \frac{\partial C}{\partial w_1} = 0.0764$$



Updating weights → Learning



Topic 7

Evaluating Classification performance

Classification - performance measures

Confusion matrix

Predicted values	Actual values	
	Positive [1]	Negative [0]
Positive [1]	100 (TP)	30 (FP)
Negative [0]	50 (FN)	120 (TN)

$$\text{Sensitivity} = \text{TP} / (\text{TP} + \text{FN})$$

$$100 / (100 + 50) = \mathbf{0.667}$$

$$\text{Specificity} = \text{TN} / (\text{TN} + \text{FP})$$

$$120 / (120 + 30) = \mathbf{0.80}$$

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

$$100 / (100 + 30) = \mathbf{0.769}$$

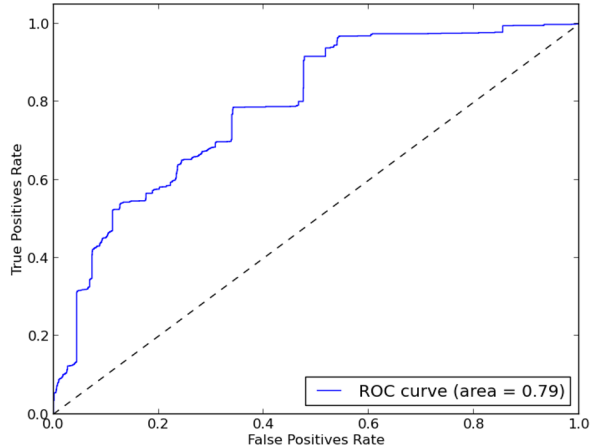
$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{TN} + \text{FP}}$$

$$(100 + 120) / 300 = \mathbf{0.733}$$



Classification - performance measures

Receiver Operator Characteristic



- True positive rate (Sensitivity)
- False positive rate (1-Specificity)

Plot → Sensitivity vs. (1 – Specificity)

Best operating point

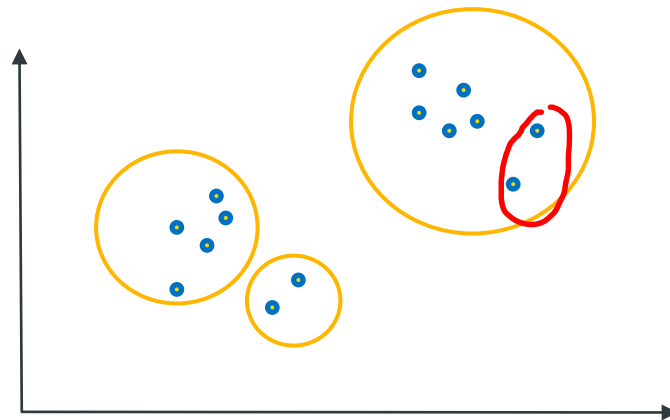
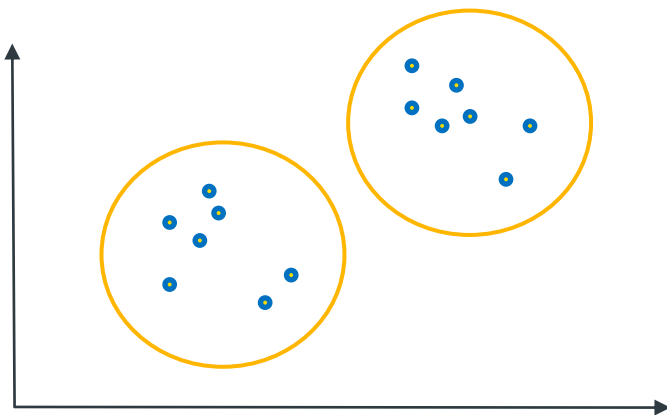
Topic 8

Clustering

Clustering

Unlabelled data

Example: Given a set of restaurants, group them into **good**, **average** and **bad**.



K-means clustering

Dataset, $D = \{\mathbf{x}_1, \dots, \mathbf{x}_m\}$

Clusters, $\mathcal{C} = \{C_1, \dots, C_k\}$

Objective: Minimize $\rightarrow E = \sum_{i=1}^k \sum_{\mathbf{x} \in C_i} \|\mathbf{x} - \boldsymbol{\mu}_i\|_2^2$ where, $\boldsymbol{\mu}_i = \frac{1}{|C_i|} \sum_{\mathbf{x} \in C_i} \mathbf{x}$

Steps:

Given a value of k , the k -means algorithm randomly assigns each observation to one of the k clusters.

After all observations have been assigned to a cluster, the resulting cluster centroids are calculated.

Using the cluster centroids, all observations are reassigned to the cluster with the closest centroid.



Topic 9

Discussion

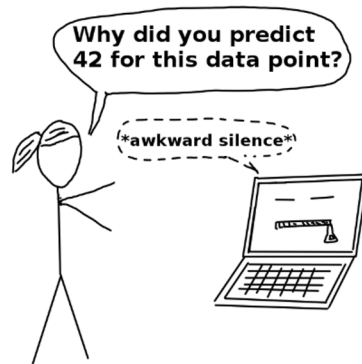
Advanced Machine Learning

Deep learning

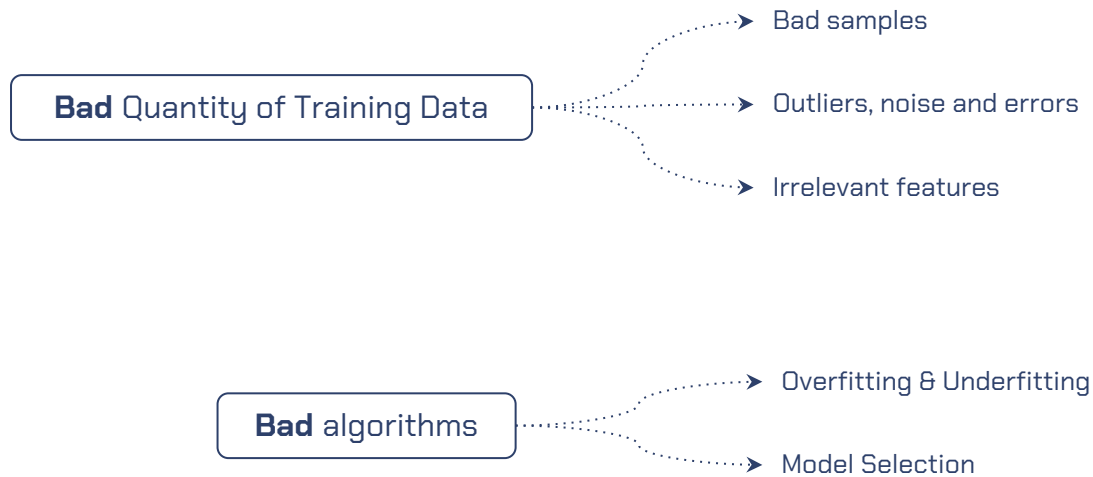
Interpretable machine learning

Attention and transformers

Generative Adversarial Networks (GAN)



Challenges of Machine Learning





Errors are Okay!

Any questions?