

Issy-les-Moulineaux
26/02/2024

Le deep learning et l'analyse prédictive



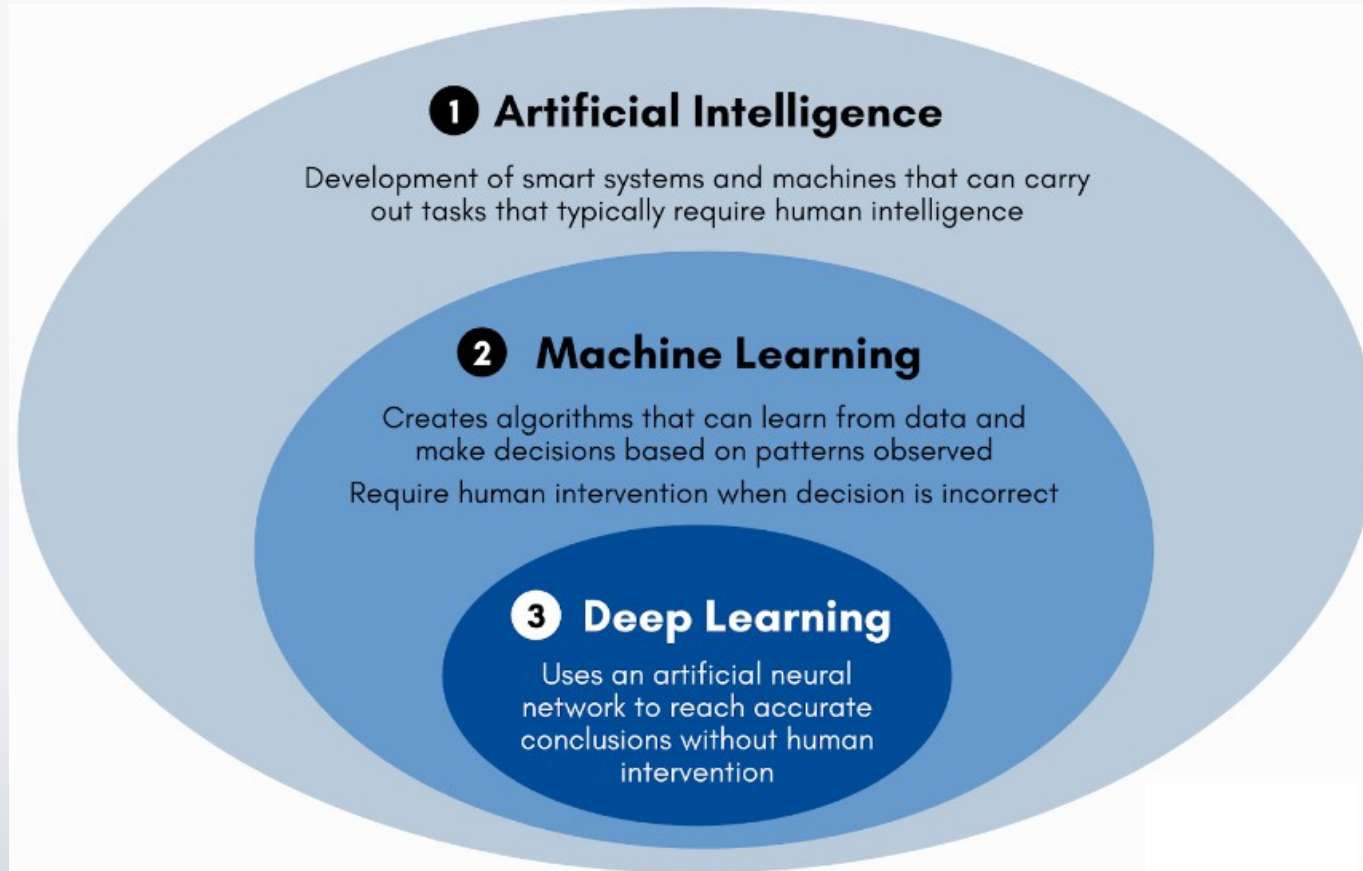
Lotfi Hocini

Table of Content

1. Introduction to ML and DS in Python
2. Deep Learning with Tensorflow
3. Containerized Machine Learning
4. Azure IA
5. Dataiku
6. Assessment

1. Introduction to ML and DS in Python

AI vs ML vs DL



Some AI Applications

01



Identification of
Spam



02



Recommending
Products



03



Customer
Segmentation



04



Image and Video
Recognition



05



Fraudulent
Transactions



06



Demand
Forecasting



07



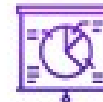
Virtual Personal
Assistant



08



Sentiment
Analysis



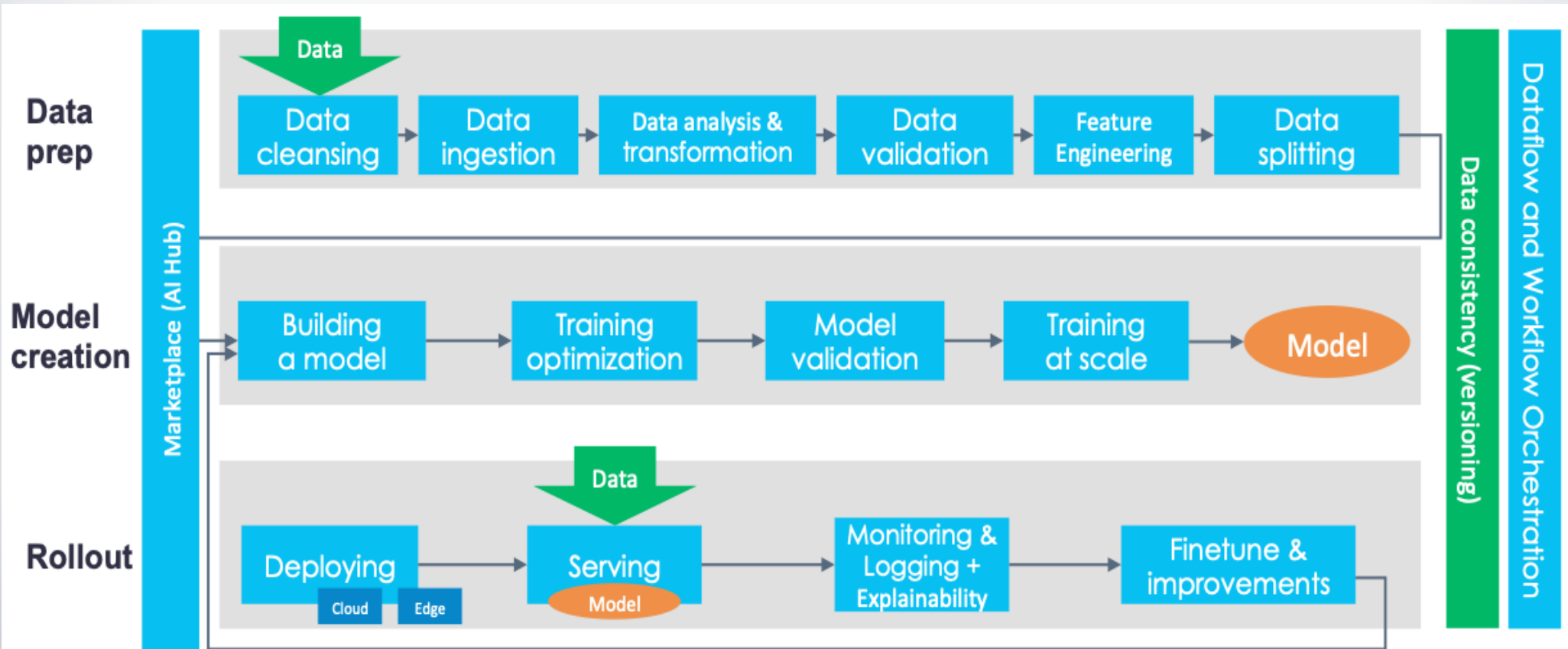
09



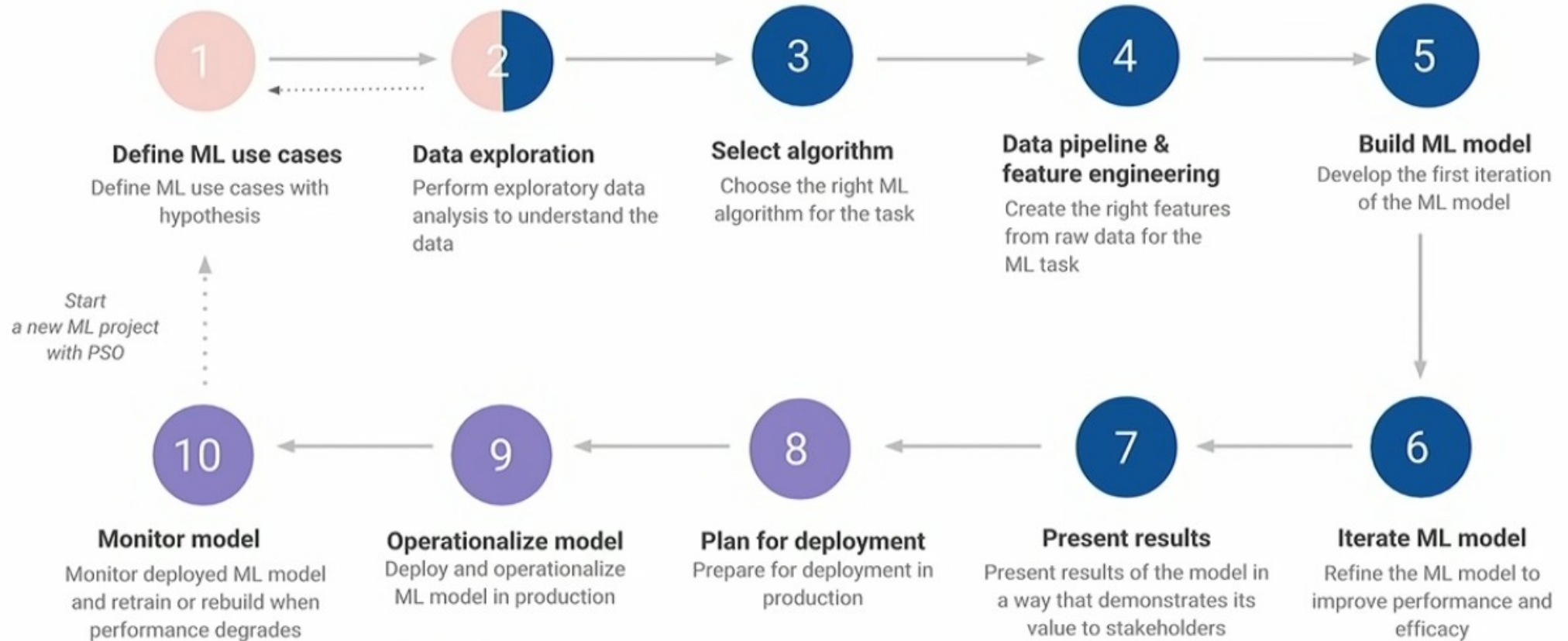
Customer Service
Automation



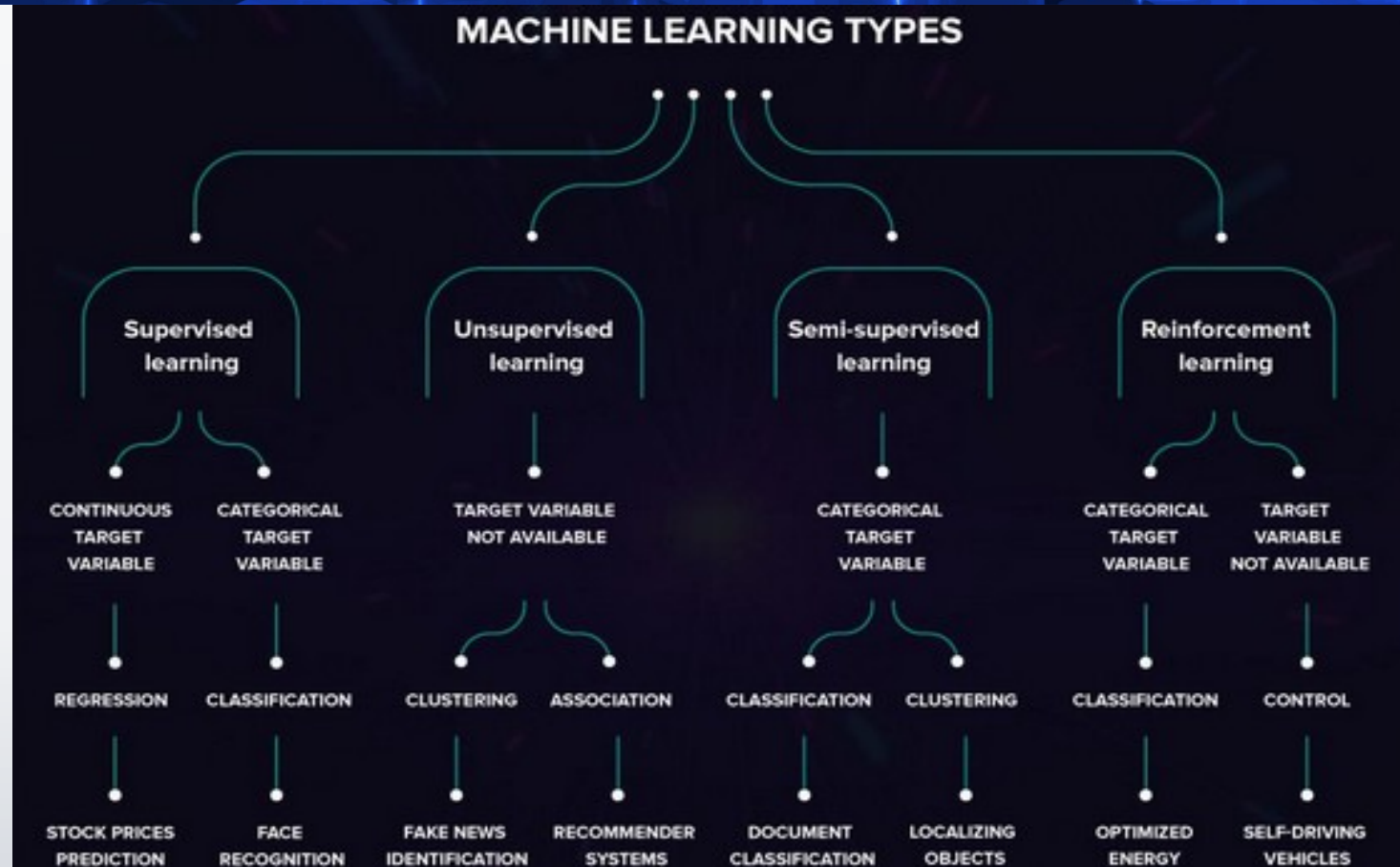
AI-ML Pipelines



AI-ML Pipelines



Some ML Approaches



Supervised vs Unsupervised ML

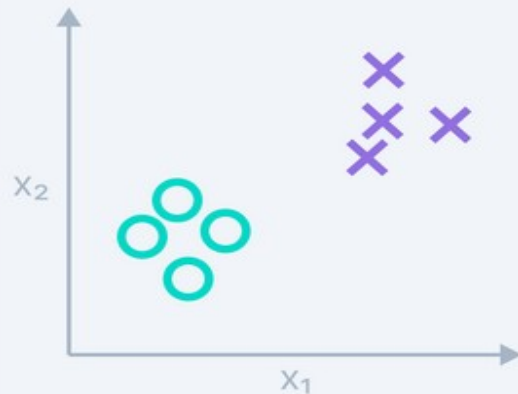
Supervised learning	Unsupervised learning
Input data is labeled	Input data is unlabeled
Has a feedback mechanism	Has no feedback mechanism
Data is classified based on the training dataset	Assigns properties of given data to classify it
Divided into Regression & Classification	Divided into Clustering & Association
Used for prediction	Used for analysis

Supervised vs Unsupervised ML

Supervised learning

Algorithms include: decision trees, logistic regressions, support vector machine

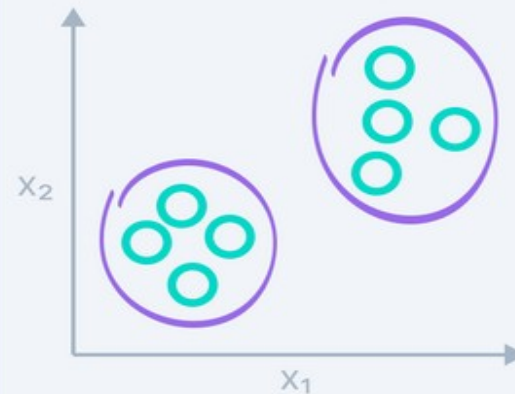
A known number of classes



Unsupervised learning

Algorithms include: k-means clustering, hierarchical clustering, apriori algorithm

A unknown number of classes



Some Metrics - Regression -

1.3 Minimizing the MSE

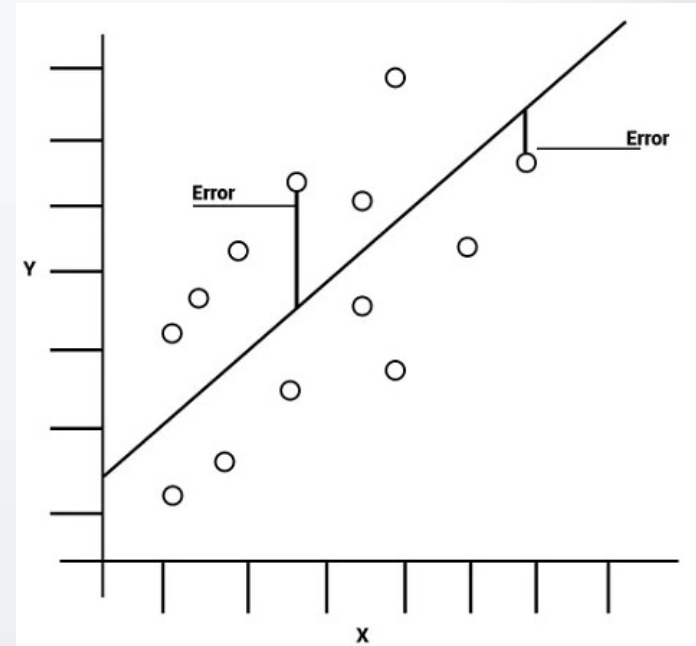
First, we find the gradient of the MSE with respect to β :

$$\begin{aligned}\nabla MSE(\beta) &= \frac{1}{n} (\nabla \mathbf{y}^T \mathbf{y} - 2\nabla \beta^T \mathbf{x}^T \mathbf{y} + \nabla \beta^T \mathbf{x}^T \mathbf{x} \beta) \\ &= \frac{1}{n} (0 - 2\mathbf{x}^T \mathbf{y} + 2\mathbf{x}^T \mathbf{x} \beta) \\ &= \frac{2}{n} (\mathbf{x}^T \mathbf{x} \beta - \mathbf{x}^T \mathbf{y})\end{aligned}$$

We now set this to zero at the optimum, $\hat{\beta}$:

$$\mathbf{x}^T \mathbf{x} \hat{\beta} - \mathbf{x}^T \mathbf{y} = 0$$

$$\hat{\beta} = (\mathbf{x}^T \mathbf{x})^{-1} \mathbf{x}^T \mathbf{y}$$



Some Metrics

- Binary Classification -

		Predicted		
		0	1	
Actual	0	TN	FP Type I error	Specificity = $TN/(TN+FP)$
	1	FN Type II error	TP	Recall or Sensitivity = $TP/(TP+FN)$
		Negative Rate = $TN/(FN+TN)$	Precision = $TP/(TP+FP)$	

Confusion Matrix

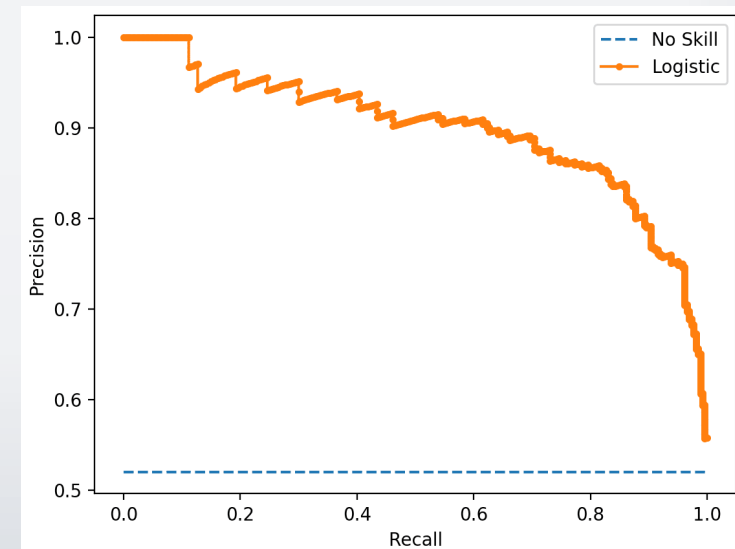
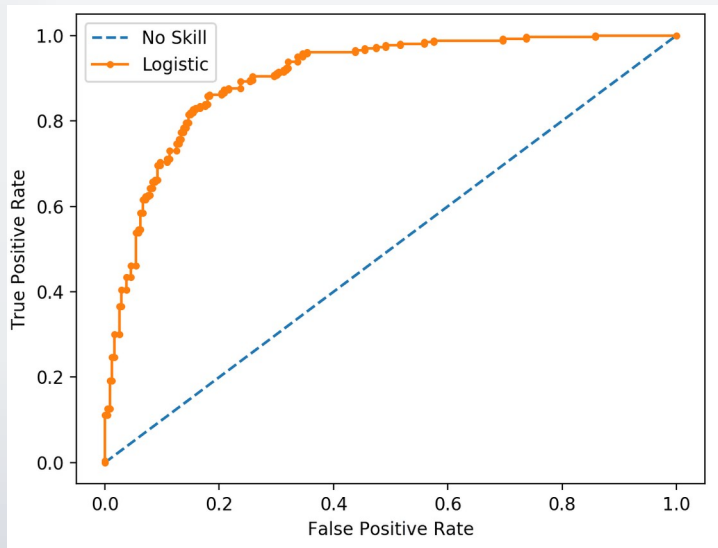
$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN}$$

$$\text{F1 - Score} = \frac{2 * \text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}}$$

Some Metrics

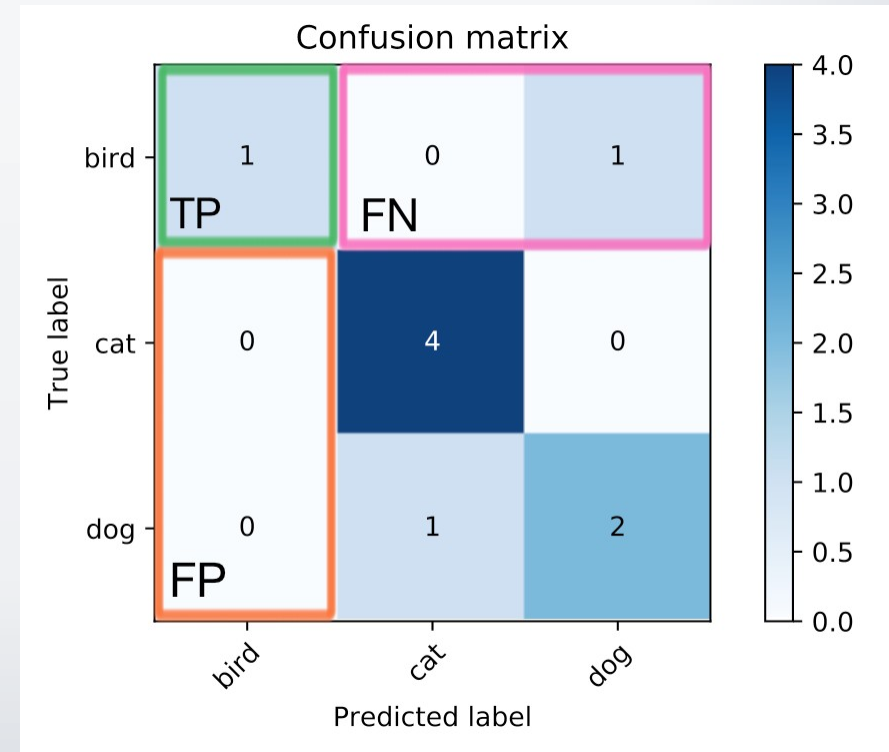
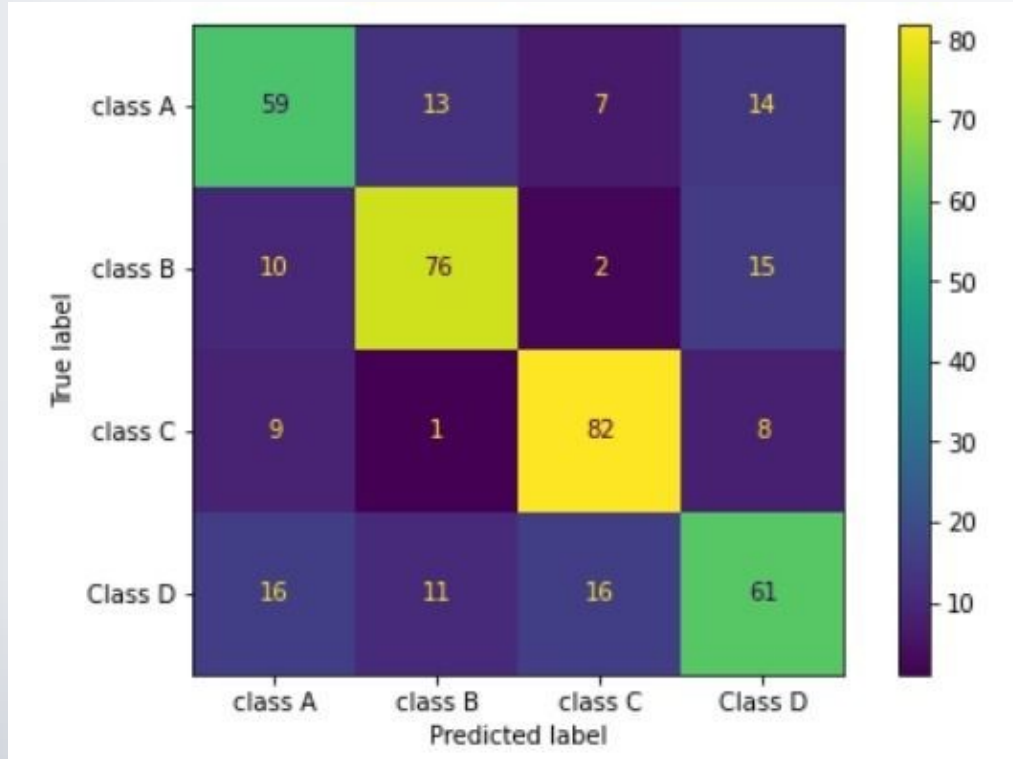
- Binary Classification -

- **ROC curves** should be used when there are roughly equal numbers of observations for each class.
- **Precision-Recall** curves should be used when there is a moderate to large class imbalance.



Some Metrics

- Multi-Class Classification -



Some Metrics

- Multi Class Classification -

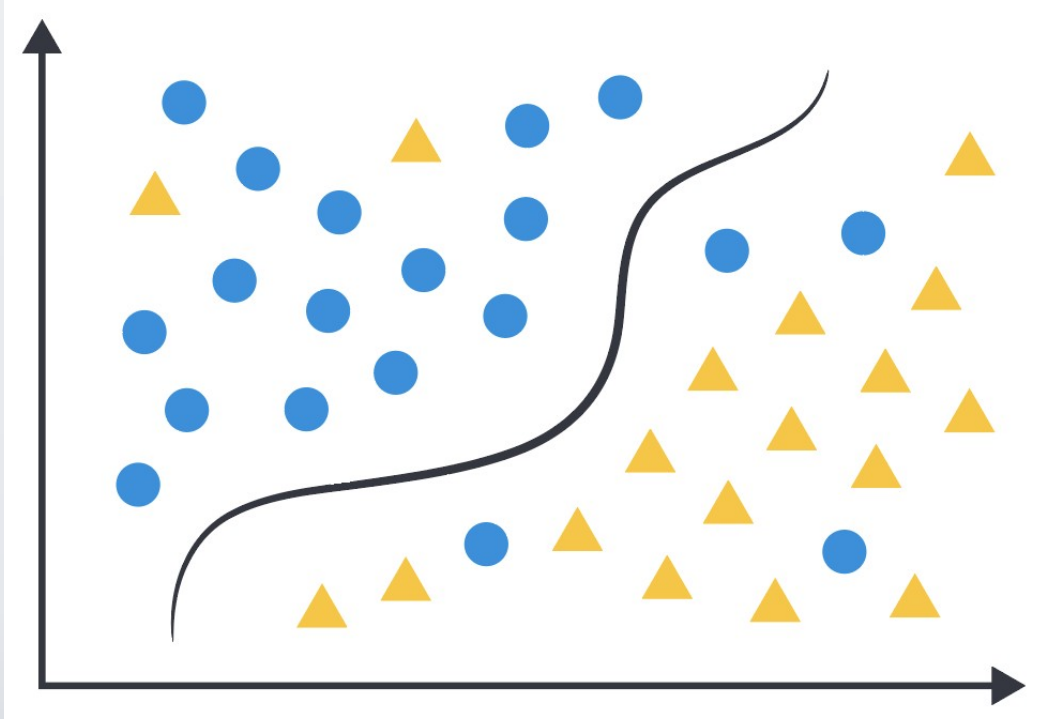
► Micro average method

- Sum up individual tp, fp.
- Micro precision = $\frac{tp_1 + tp_2 + \dots + tp_n}{tp_1 + tp_2 + \dots + tp_n + fp_1 + fp_2 + \dots + fp_n}$
- Micro recall = $\frac{tp_1 + tp_2 + \dots + tp_n}{tp_1 + tp_2 + \dots + tp_n + fn_1 + fn_2 + \dots + fn_n}$

► Macro average method

- Compute metric independently for each class and then take average

Exercise 1



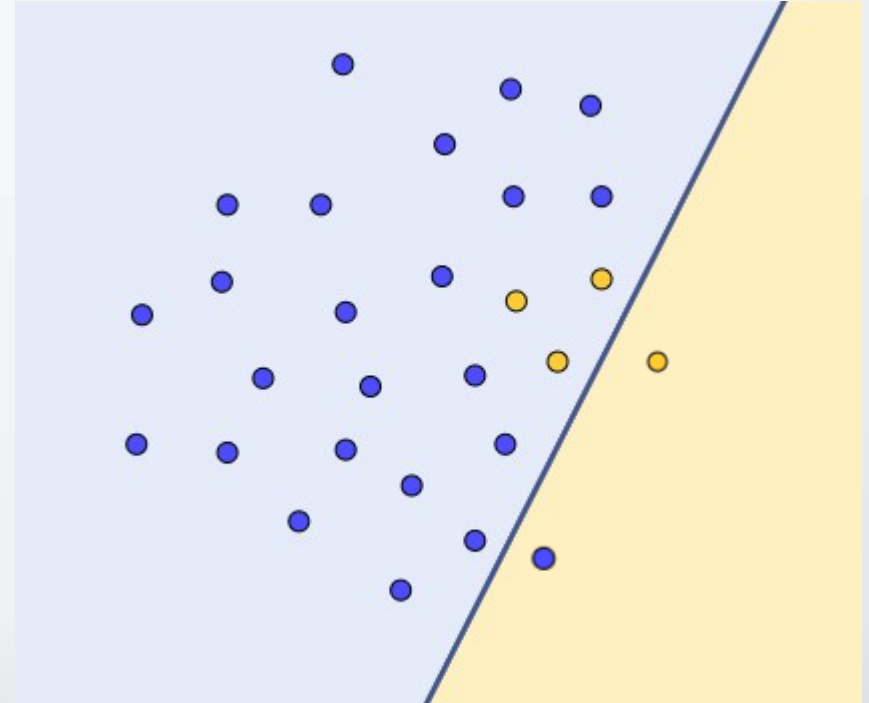
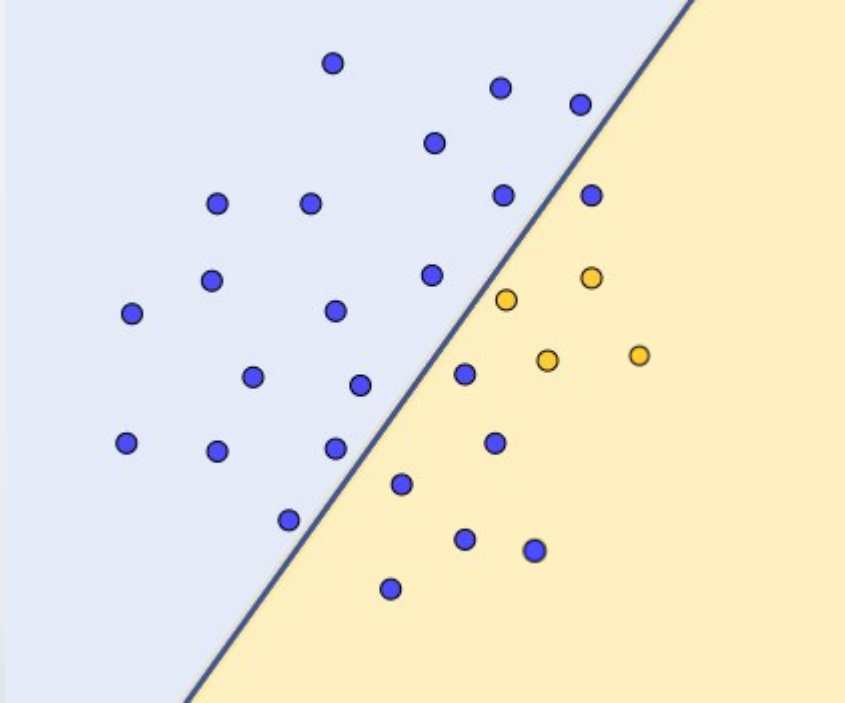
- Calculate the classification metrics

		Predicted		
		0	1	
Actual	0	TN	FP Type I error	Specificity = $TN/(TN+FP)$
	1	FN Type II error	TP	Recall or Sensitivity = $TP/(TP+FN)$
		Negative Rate = $TN/(FN+TN)$	Precision = $TP/(TP+FP)$	

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

$$\text{F1 - Score} = \frac{2 * \text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}}$$

Exercise 2



- Calculate the classification metrics
- Derive insights

Configure VSCode

- Install Data Science Profil
- Install Additional extenstions

Python - Advanced

<https://www.geeksforgeeks.org/python-programming-language/?ref=lbp>



Python - Virtual environment

<https://packaging.python.org/en/latest/guides/installing-using-pip-and-virtual-environments/>



Python - FastApi

<https://fastapi.tiangolo.com/tutorial/>



ML Practice

- **Topics:** Data Preparation, Missing Data, Imbalanced data, Split Datasets, Metrics, Visualization, model selection, saving ...
- **Database:** '**data**' Folder

To install :

- pip install virtualenv, then create virtual environment **and** activate it
- pip install ipykernel
- pip install pandas
- Pip install numpy
- pip install matplotlib
- pip install seaborn
- pip install scikit-learn

Next Sesssion

2. Deep Learning with Tensorflow