SEMINAR PRESENTATION ON MACHINE LEARNING

By:
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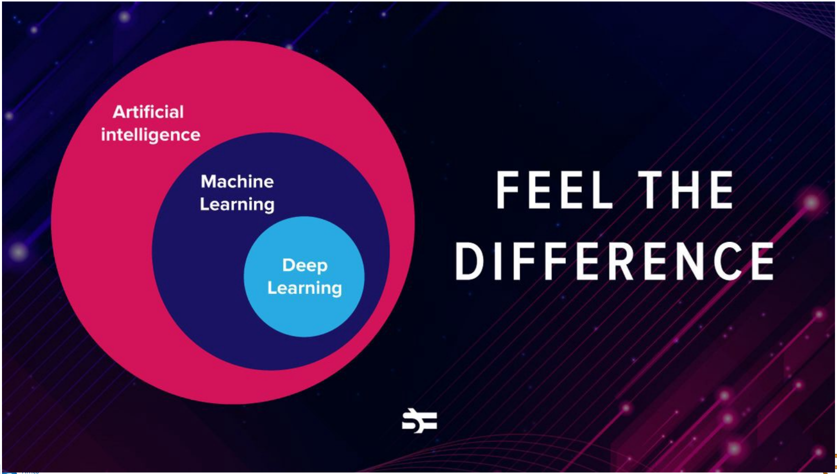
ECOLE POLYTECHNIQUE DE THIES

September 12, 2020

Outline

Machine Learning vs Deep Learning vs AI.



Introduction

What is Learning?

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"Herbert Simon"

Machine Learning vs Deep Learning vs AI ?

Artificial Intelligence

Machine Learning vs Deep Learning vs AI ?

Artificial Intelligence

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Machine Learning vs Deep Learning vs AI ?

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Machine Learning

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Machine Learning

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Goal

The goal of machine learning generally is to understand the structure of data and fit that data into models that can be understood and utilized by people.

Africa Digital Native

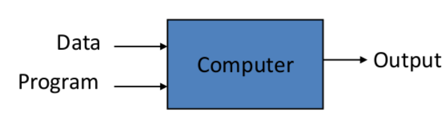
Sagesse Devoir Ecole Polytechnique Thiès

Historically

Traditional Programming

Historically

Traditional Programming



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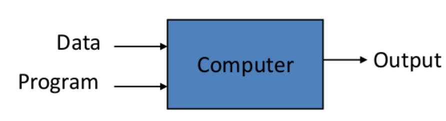

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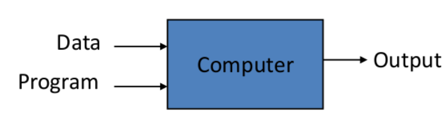
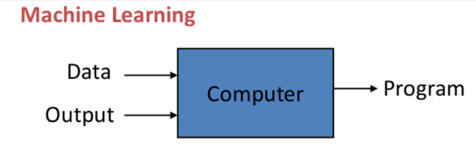


Machine Learning



When Do We Use Machine Learning?

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- Models are based on huge amounts of data (Genomics)

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Application of Machine Learning

Health Care

Application of Machine Learning

Health Care

- Identification of Diseases and Diagnosis

Application of Machine Learning

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- Identification of Diseases and Diagnosis
- Drug Discovery and Manufacturing

Application of Machine Learning

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- Identification of Diseases and Diagnosis
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- Medical Imaging

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Retail

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- Market Basket Analysis

Retail

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- Customer Relation Management(CRM)

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- Customer Relation Management(CRM)

Finance

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- Credit Scoring

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Manufacturing

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- Optimization

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- Optimization
- Troubleshooting

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Bioinformatics

Manufacturing

- Optimization
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Bioinformatics

- Motifs

Manufacturing

- Optimization
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Bioinformatics

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- Alignment

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Web Mining

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Education

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- Accurately Grading Assignments

Education

- Accurately Grading Assignments
- Learning Analytic

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- Accurately Grading Assignments
- Learning Analytic
- Adaptive Learning

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- Accurately Grading Assignments
- Learning Analytic
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- Predictive Analytics

Agriculture

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- Species Recognition

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Telecommunication

- Quality of Service Optimization.

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Machine Learning Groupings

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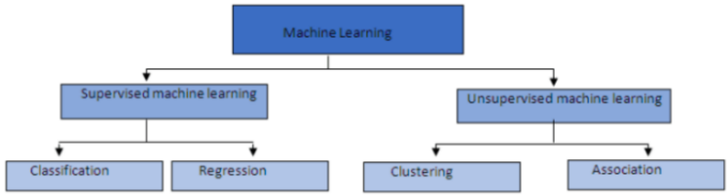

Figure: Machine Learning Groupings

Supervised Learning

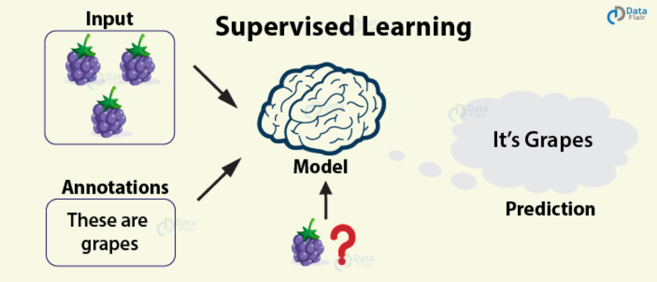

Figure: Supervised learning.

Supervised Learning

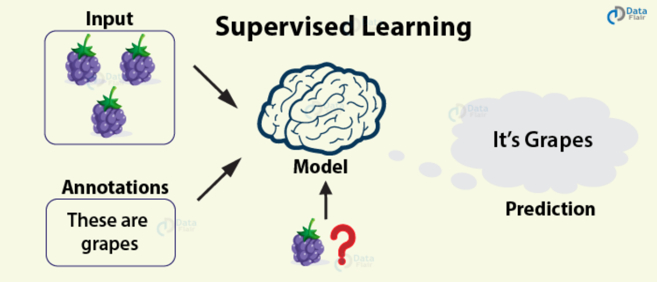

Figure: Supervised learning.

Supervised Learning is is a type of learning where the input data is labeled/already known.

Classification

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Classifier:
An algorithm that maps the input data to a specific category.

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- Logistics regression

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- Logistics regression
- Support vector machine(SVM)

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- Random Forest

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Implementation

Examples of Classification Algorithms

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Implementation

- **Initialize** The classifier to be used.

Examples of Classification Algorithms

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Implementation

- **Initialize** The classifier to be used.
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- **Predict the target.**

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Examples of Classification Problems

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- Fraud Detection

Examples of Classification Problems

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- Fraud Detection
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Examples of Classification Problems

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- Medical Diagnostics

Examples of Classification Problems

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Examples of Classification Problems

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Regression

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It is a supervised machine learning algorithm that predict or forecast numerical values.

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Regression Algorithms

- Linear regression

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Examples of Regression Problems

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Examples of Regression Problems

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- Sales Predictions

Examples of Regression Problems

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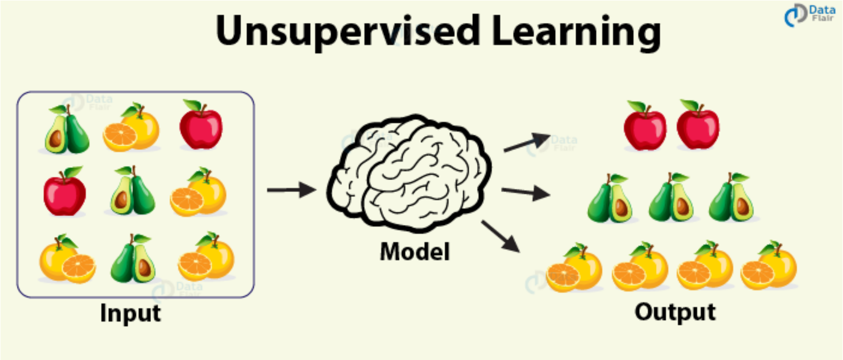
Unsupervised Learning Introduction



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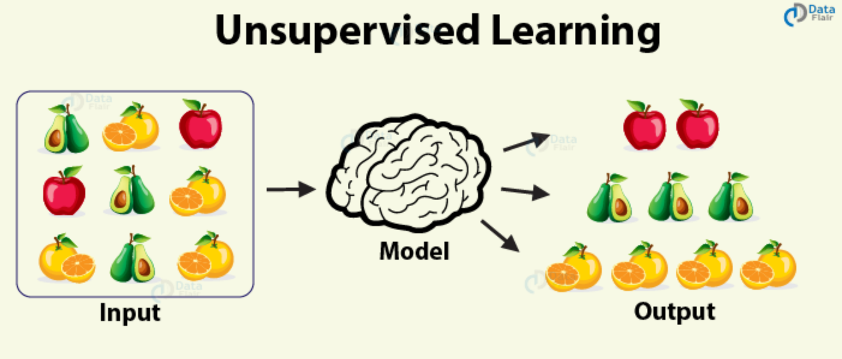

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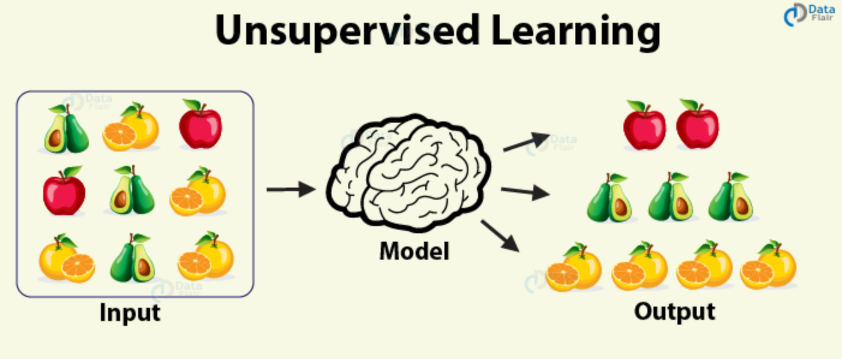

Unsupervised Learning

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Dimensional Reduction

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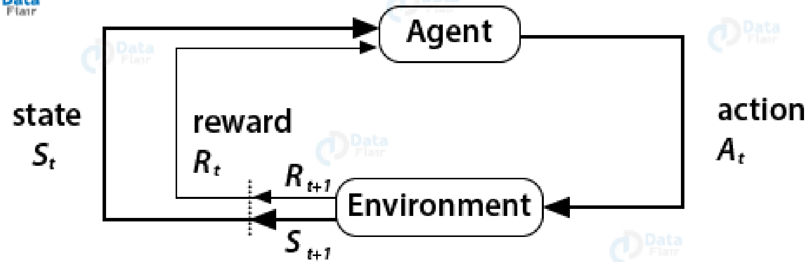
Reinforcement Learning Introduction



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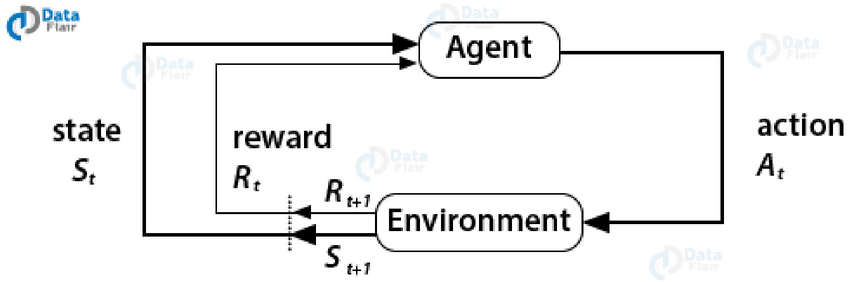

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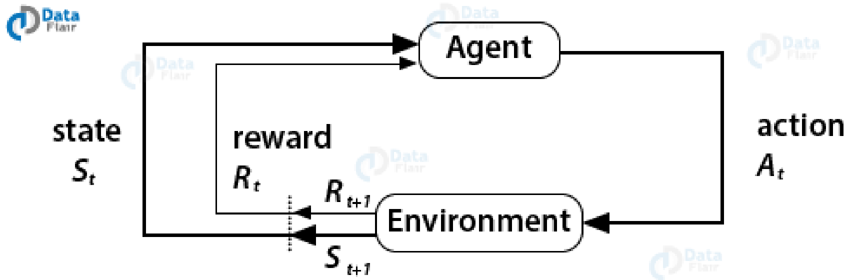

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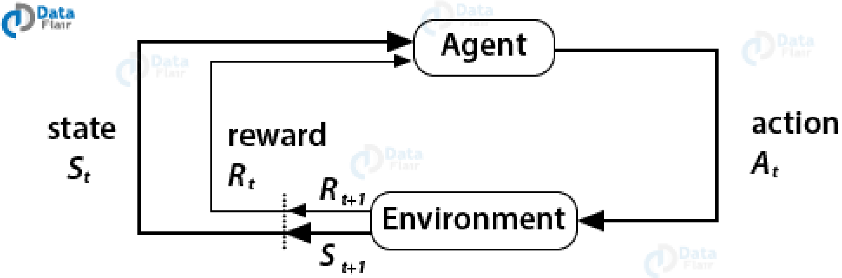

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Reinforcement Learning Algorithms

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- Q-Learning

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Reinforcement Learning Algorithms

- Q-Learning
- Temporal Difference (TD)
- Monte-Carlo Tree Search (MCTS)

Reinforcement Learning Algorithms

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- Asynchronous Actor-Critic Agents (A3C)

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Reinforcement Learning Problems

Reinforcement Learning Problems

- Gaming

Reinforcement Learning Problems

- Gaming
- Finance Sector

Reinforcement Learning Problems

- Gaming
- Finance Sector
- Manufacturing

Reinforcement Learning Problems

- Gaming
- Finance Sector
- Manufacturing
- Inventory Management

Reinforcement Learning Problems

- Gaming
- Finance Sector
- Manufacturing
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- Robot Navigation

Reinforcement Learning Problems

- Gaming
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Data Science

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Data Science Is OSEMN

1. Obtaining data.

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Data Science Is OSEMN

1. Obtaining data.
2. Scrubbing data.

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Data Science Is OSEMN

1. Obtaining data.
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3. Exploring data.

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Data Science Is OSEMN

1. Obtaining data.
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3. Exploring data.
4. Modeling data and
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Data Science Work Flow

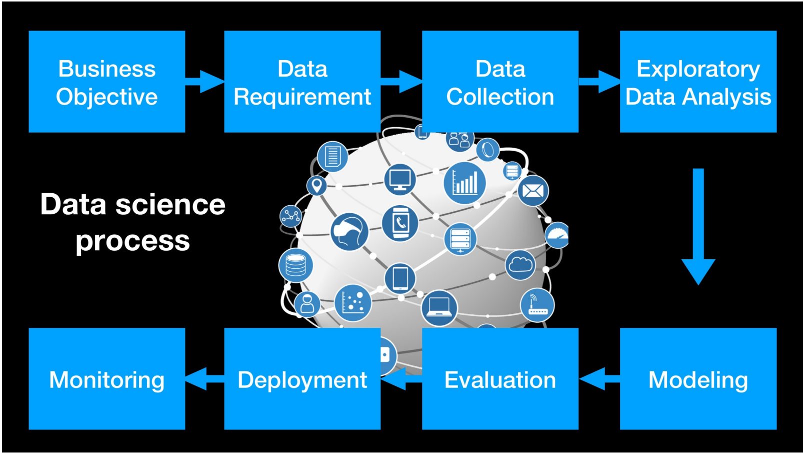

Figure: Data Science Workflow

Performance Metric

The metrics that you choose to evaluate your machine learning algorithms are very important.

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Choice of metric influences how the performance of machine learning algorithms is measured and compared.

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Performance Metric Cont..

Performance Metric Cont..

Classification Metric

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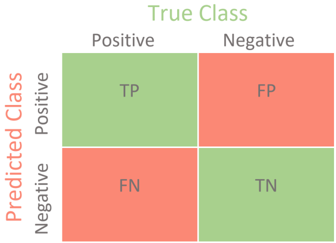

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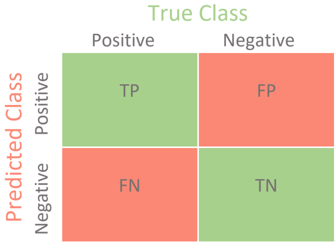

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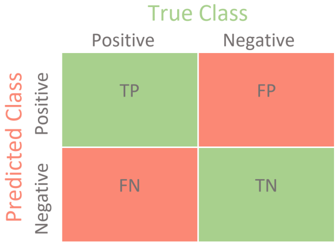

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1. True Positives(TP): These are cases in which we predicted Yes and its actually Yes.

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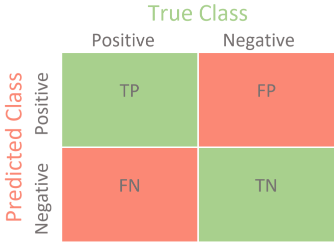

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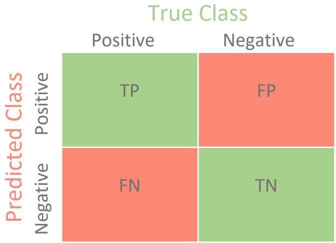

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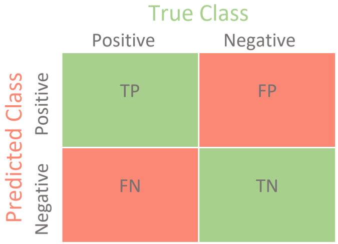

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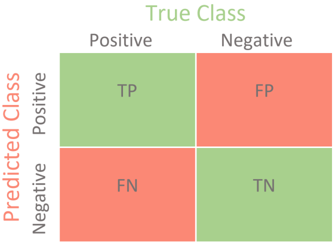

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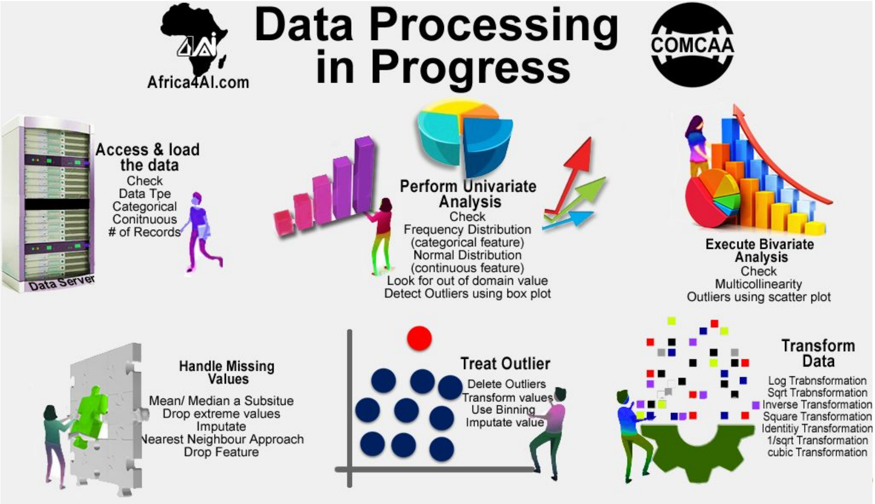

Univariate plots

- Histogram
- Density Plots

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Implementation

Implementation Steps

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1. Prepare Problem

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Digital Native

Sagesse Devoir
Ecole Polytechnique Thiès

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4. https://machinelearningmastery.com/machine-learning-with-python/
5. www.africa4ai.com

Conclusion


THANK
YOU
GRACIAS
ARIGATO
SHUKURIA
DANKSCHEEN
TASHAKKUR ATU
SUKSAMA
BIYAN
SHUKRIA
GRAZIE
MEHRBANI
BOLZIN
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