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Dr. Vishwanath Karad

MIT WORLD PEACE UNIVERSITY | PUNE

TECHNOLOGY, RESEARCH, SOCIAL INNOVATION & PARTNERSHIPS

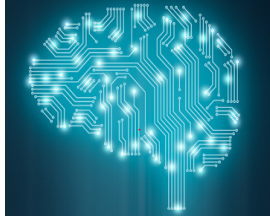
MACHINE LEARNING

Professional Core(CET3006B)

T. Y. B.Tech AIDS Sem-V

2024-2025

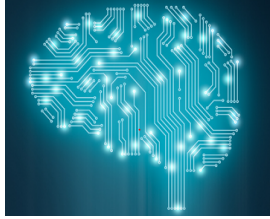
SoCSE – Dept. of Computer Engineering & Technology



MACHINE LEARNING

- **Credits :** 3+1 (Four)
- **Examination scheme:** Total Marks-100

  - 30 Marks CCA
  - 30 Marks LCA
  - 40 Marks End Term Examination



MACHINE LEARNING

Course Objectives:

1.Knowledge:

i. To learn data preparation techniques for Machine Learning methods

ii. To understand advance supervised and unsupervised Learning methods

2.Skills:

i. To apply suitable pre-processing techniques on various datasets for Machine Learning applications.

ii. To design and implement various advanced supervised and unsupervised learning methods

3.Attitude:

i. To be able to choose and apply suitable ML techniques to solve the problem

ii. To compare & analyze various advanced supervised and unsupervised learning methods.

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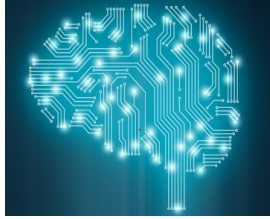

ADVANCES IN MACHINE LEARNING

Course Outcomes:

After completion of the course the students will be able to:

1. Analyze and apply different data preparation techniques for Machine Learning applications

2. Identify, Analyze and compare appropriate supervised learning algorithm for given problem

3. Identify, Analyze and Compare Unsupervised and semi supervised algorithms

4. Design and implement Machine Learning techniques for real-time applications

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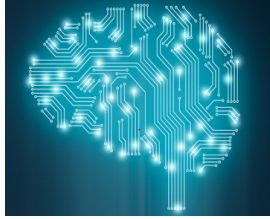

Course Contents:

Unit 1. Introduction to ML

Unit 2. Supervised Learning: Classification

Unit 3. Unsupervised Learning: Clustering

Unit 4. Advanced Machine Learning Models

Unit 5. Trends in ML

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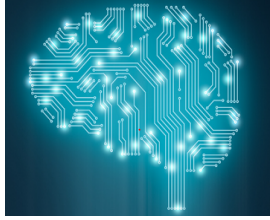
Course Contents:



Laboratory Exercises:

1. Implement various Pre-processing techniques on given dataset.
2. Implement KNN classifier for given dataset.
3. Implementation of Tree based Classifiers.
4. Implementation of SVM, Comparison with Tree Based Classifier
5. Implementation of Ensemble, Random Forests. Analyze the Performance.
6. Implementation and Comparison of various clustering techniques such as Spectral & DBSCAN.
7. Implement Regression Technique & evaluate its performance.
8. Mini-Project based on suitable Machine Learning dataset

Course Contents:

Text Books:

1. E. Alpaydin, Introduction to Machine Learning, PHI, 2004.
2. Peter Flach: Machine Learning: The Art and Science of Algorithms that Make Sense of Data, Cambridge University Press, Edition 2012.
3. T. Mitchell, Machine Learning, McGraw-Hill, 1997.
4. Josh Patterson, Adam Gibson, "Deep Learning: A Practitioners Approach", O"REILLY, SPD, ISBN: 978-93-5213-604-9, 2017 Edition 1st

Reference Books:

1. C. M. Bishop: Pattern Recognition and Machine Learning, Springer 1st Edition-2013.
2. Ian H Witten, Eibe Frank, Mark A Hall: Data Mining, Practical Machine Learning Tools and Techniques, Elsevier, 3rd Edition.
3. Shaishalev-shwartz, Shai Ben-David: Understanding Machine Learning from Theory to algorithms, Cambridge University Press, ISBN-978-1-107-51282-5, 2014.

Course Contents:

Supplementary Reading:

1. AurelienGeron, “Hands-on Machine Learning with Scikit-learn and Tensor flow, O’Reilly Media

Web Resources:

1. Popular dataset resource for ML beginners: http://archive.ics.uci.edu/ml/index.php

Web links:

1. https://www.kaggle.com/datasets
2. http://deeplearning.net/datasets/

MOOCs:

1. https://swayam.gov.in/nd1_noc20_cs29/preview
2. https://swayam.gov.in/nd1_noc20_cs44/preview

Course Contents:

Assessment Scheme:

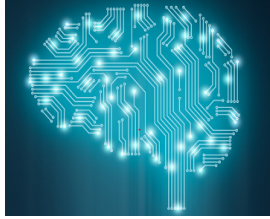
Class Continuous Assessment (CCA): 30 Marks

Mid Term	Component 1 (Active Learning)	Component 2
15 Marks	10 Marks	5 Marks

Laboratory Continuous Assessment (LCA): 30 Marks

Practical Performance	Active learning / Mini Project/Additional implementation/ On paper design	End term practical /oral examination
10 Marks	10 Marks	10 Marks

Term End Examination: 40 Marks



Syllabus-Unit 1

Introduction to ML:

Introduction, Data Preparation

Data Encoding Techniques

Data Pre-processing techniques for ML applications.

Feature Engineering:

Dimensionality Reduction using PCA

Exploratory Data Analysis

Feature Selection

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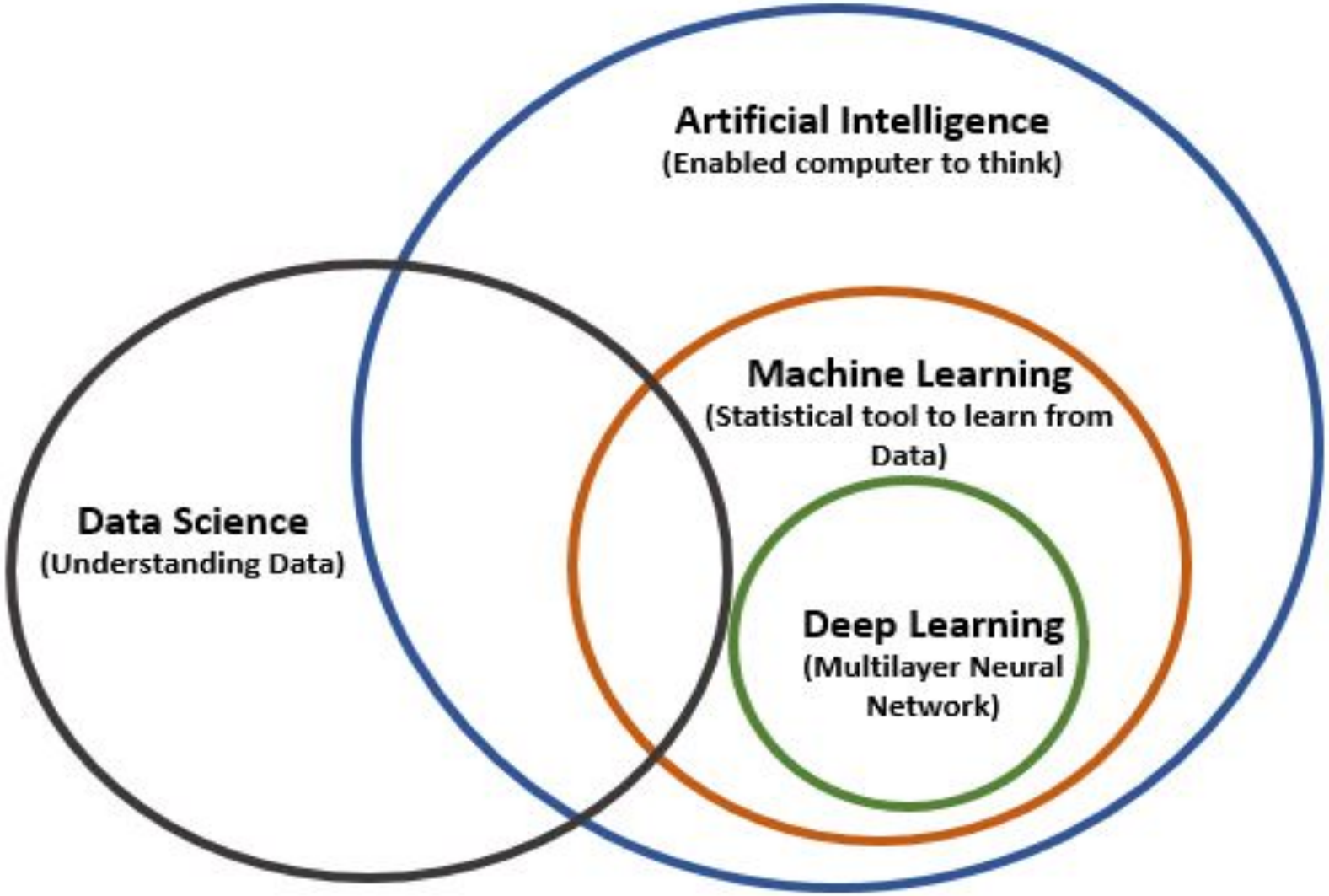
AI Vs. ML



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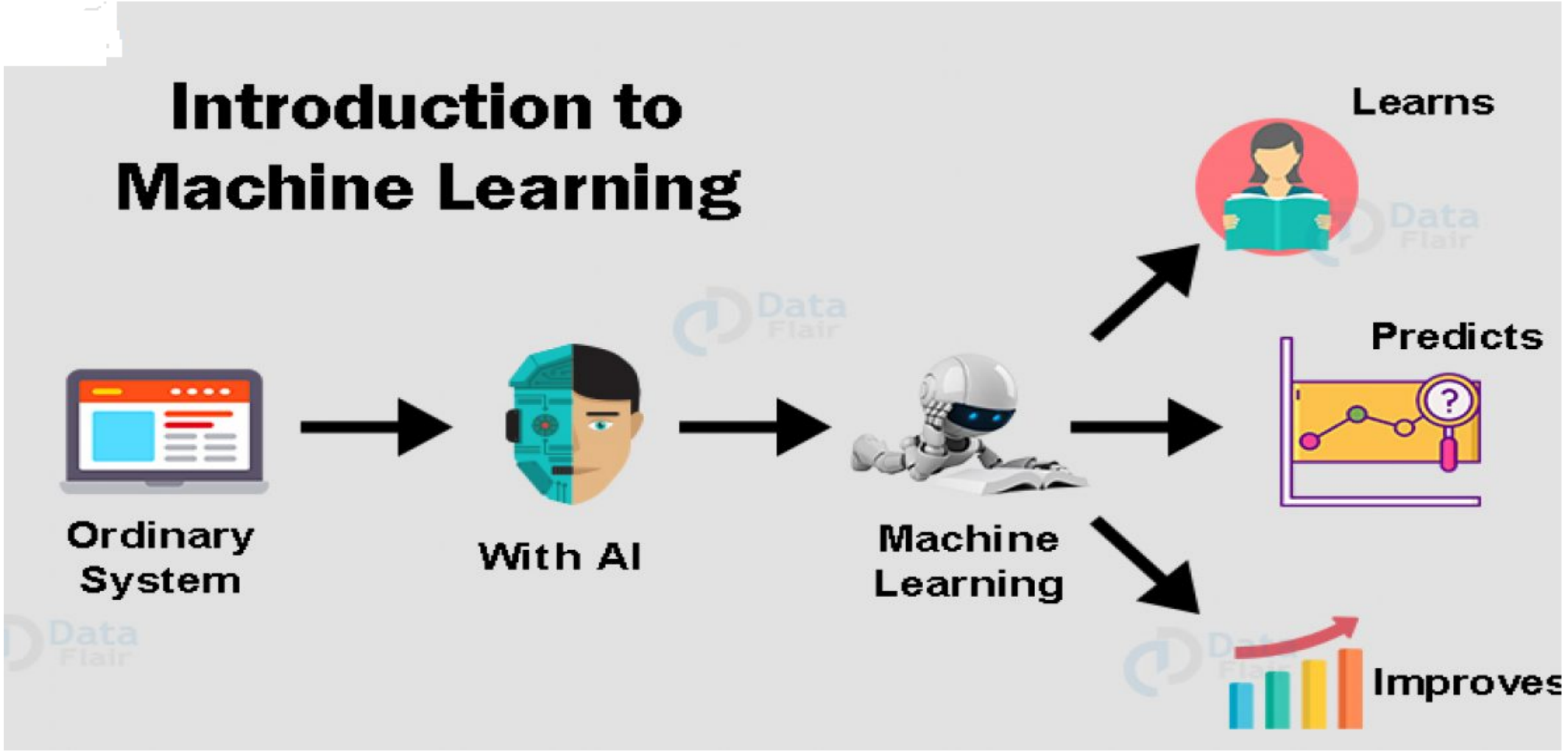
INTRODUCTION



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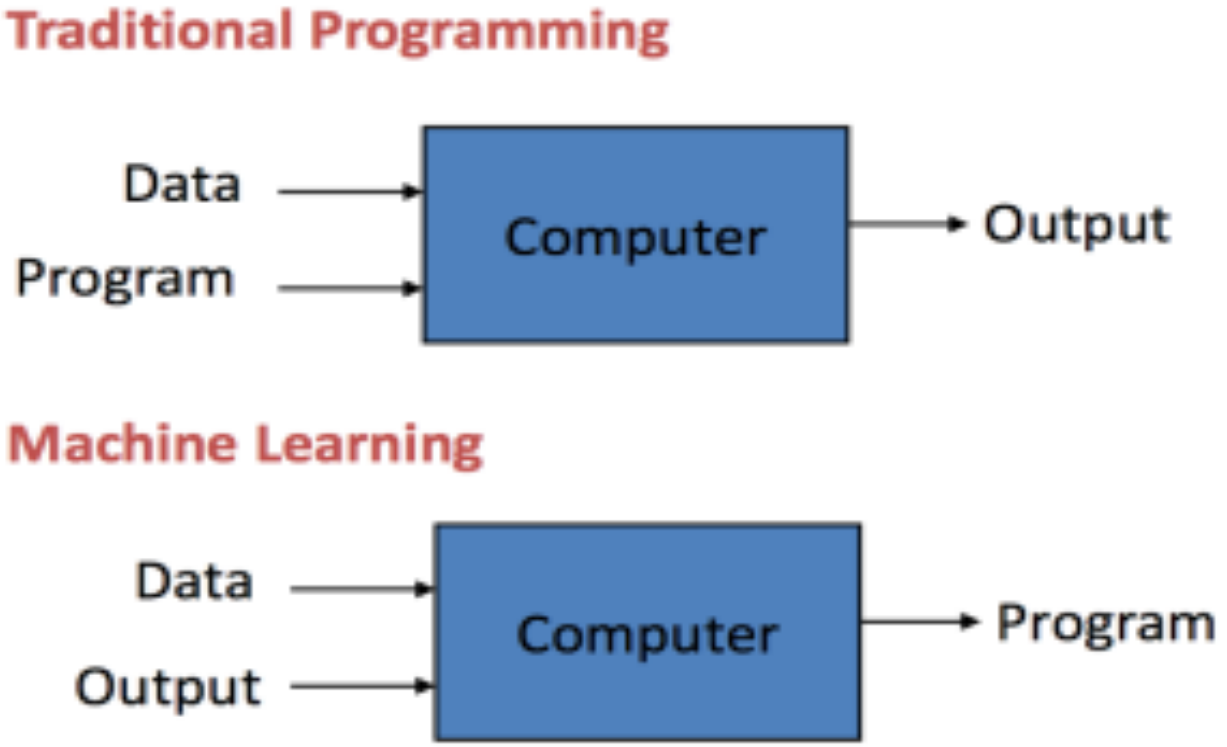

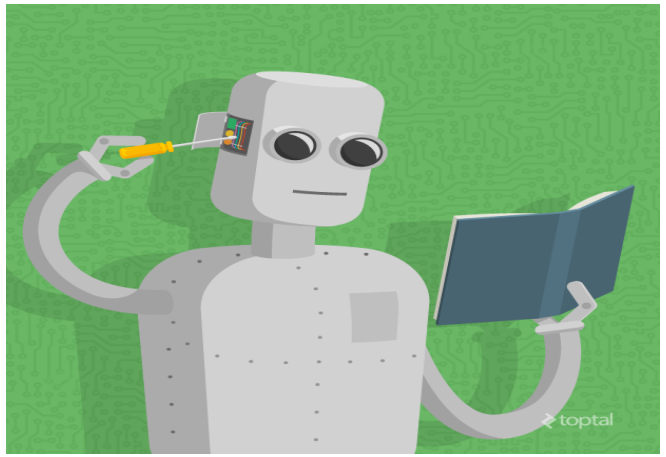

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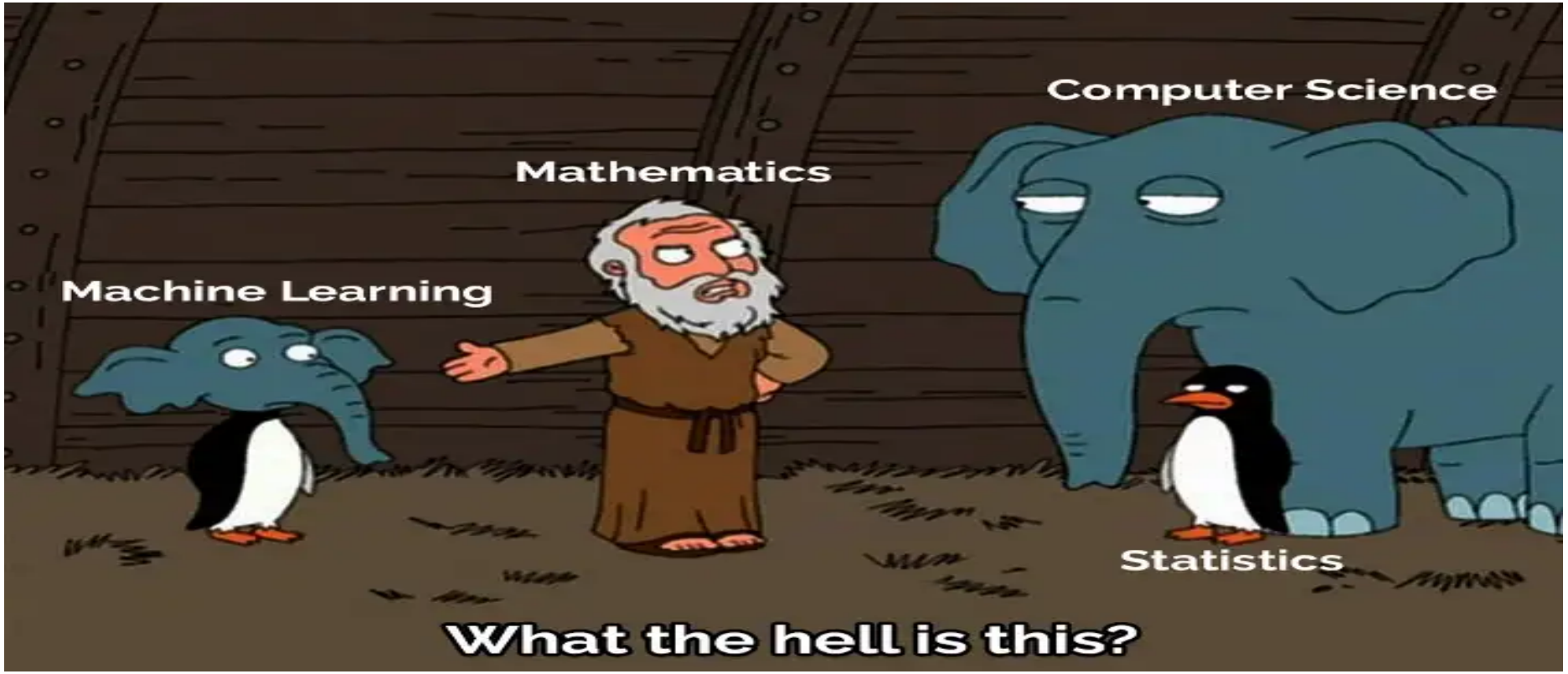

(source: https://medium.com/analytics-vidhya/introduction-to-machine-learning-e1b9c055039c)

- Machine learning is a "***Field of study*** *that gives computers* ***the ability to learn*** *without being explicitly programmed.*"
- In other words it is concerned with the question of *how to construct computer programs* that **automatically improve with the experience**. - According to Arthur Samuel(1959)

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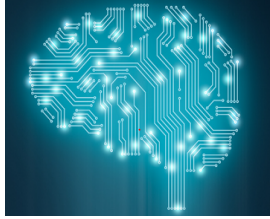
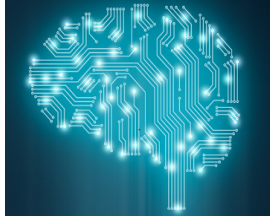


Cntd..

- A **computer program** is said to **learn** from **experience 'E'** with respect to some class of **task 'T'** and **performance measure 'P'** if its performance at task in 'T' as measured by 'P' **improves with experience** 'E' – Tom M Mitchell

- Machine learning is an application of artificial intelligence (AI) that provides systems the **ability to automatically learn** and **improve from experience** without being explicitly programmed.

- Machine learning focuses on the development of computer programs that can access data and use it learn for themselves.



Cntd..

Example 1

Classify Email as spam or not spam

- Task (T): Classify email as spam or not spam
- Experience(E): watching the user to mark/label the email as spam or not spam
- Performance (P): The number or fraction of email to be correctly classified as spam or not spam

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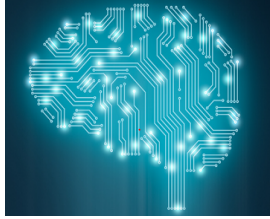

Cntd..

Example 2

Recognizing hand written digits/ characters

- Task(T): Recognizing hand written digit
- Experience (E): watching the user to mark/ label the hand written digit to 10 classes(0-9) & identify underling pattern
- Performance(P):The number of fractions of hand-written digits correctly classified

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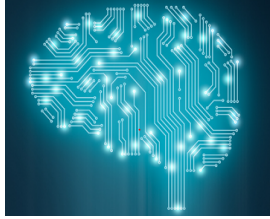
Why Machine Learning Important?.



- **Human expertise does not exist**

  Navigating on Mars

  industrial/manufacturing control

  mass spectrometer analysis, drug design, astronomic discovery

- **Black-box human expertise OR Some tasks cannot be defined well, except by examples**

  face/handwriting/speech recognition/ recognizing people

  driving a car, flying a plane

- **Relationships and correlations can be hidden within large amounts of data**

  (e.g., stock market analysis)

- **Environments change over time.**

  (e.g., routing on a computer network)

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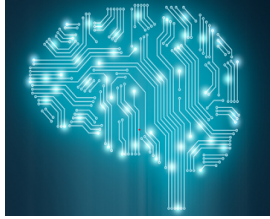

Cntd..

- **The amount of knowledge available about certain tasks might be too large for explicit encoding by humans**

  (e.g., medical diagnostic).

- **New knowledge about tasks is constantly being discovered by humans. It may be difficult to continuously re-design systems "by hand".**

- **Rapidly changing phenomena**

  credit scoring, financial modeling

  diagnosis, fraud detection

- **Need for customization/personalization**

  personalized news reader

  movie/book recommendation

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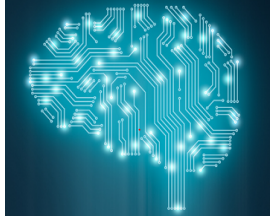

How does Machine Learning help us in daily life?

Social networking :

- Use of the appropriate emotions, suggestions about friend tags on Facebook, filtered on Instagram, content recommendations and suggested followers on social media platforms, etc., are examples of how machine learning helps us in social networking.

Personal finance and banking solutions

- Whether it's fraud prevention, credit decisions, or checking deposits on our smartphones machine learning does it all.

Commute estimation

- Identification of the route to our selected destination, estimation of the time required to reach that destination using different transportation modes, calculating traffic time, and so on are all made by machine learning.

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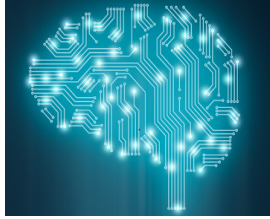
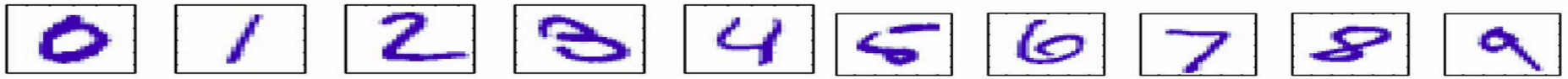


Applications of Machine Learning

- Face detection
- Stock prediction
- Spam Email Detection
- Machine Translation
- Self-parking Cars
- Airplane Navigation Systems
- Medicine
- Data Mining
- Speech recognition
- Hand-written digit recognition
- Computational Biology
- Recommender Systems
- Guiding robots
- Space Exploration
- Supermarket Chain

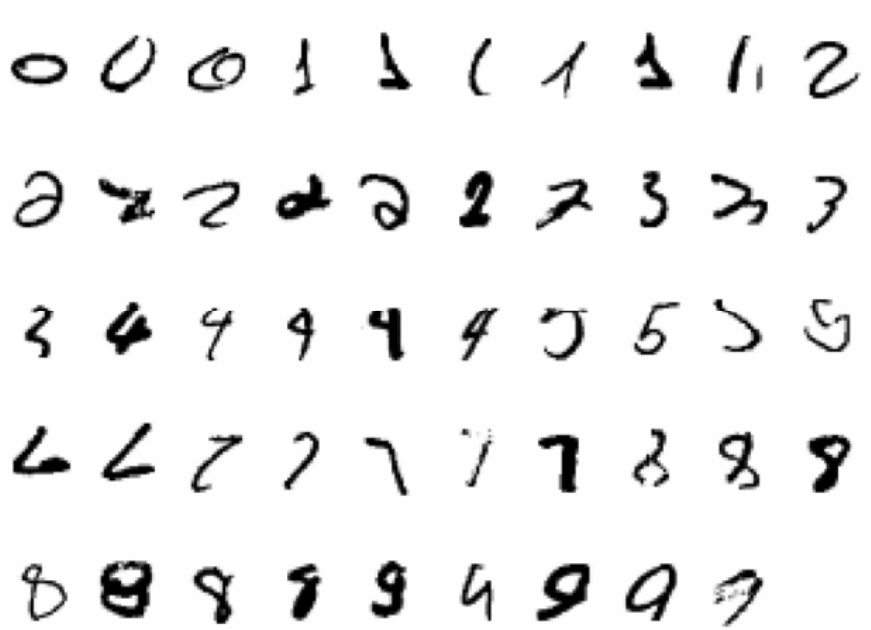
Examples…

~~Example 1: hand-written digit recognition:~~ Output



Learn a classifier f(x) such that, f : x → {0, 1, 2, 3, 4, 5, 6, 7, 8, 9}

Input training data : e.g. 500 samples

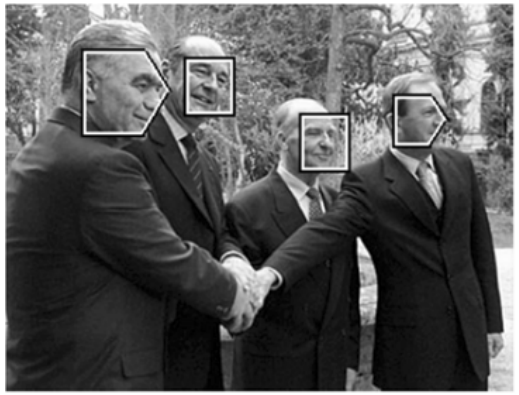


Example 2: Face detection

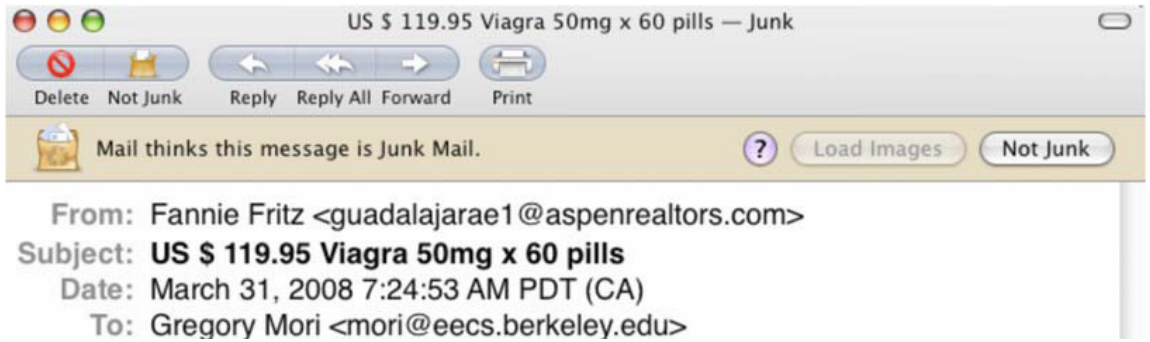
Input : an image, the classes are people to be recognized …

[non-face, frontal-face, profile-face] and the learning program should learn to associate the face images to identities.

This problem is more difficult because there are more classes, input image is larger, and a face is 3-dimensional and differences in pose and lighting cause significant changes in the image. There may also be occlusion (blockage)of certain inputs; e.g. glasses may hide the eyes and eyebrows, and a beard may hide the chin.

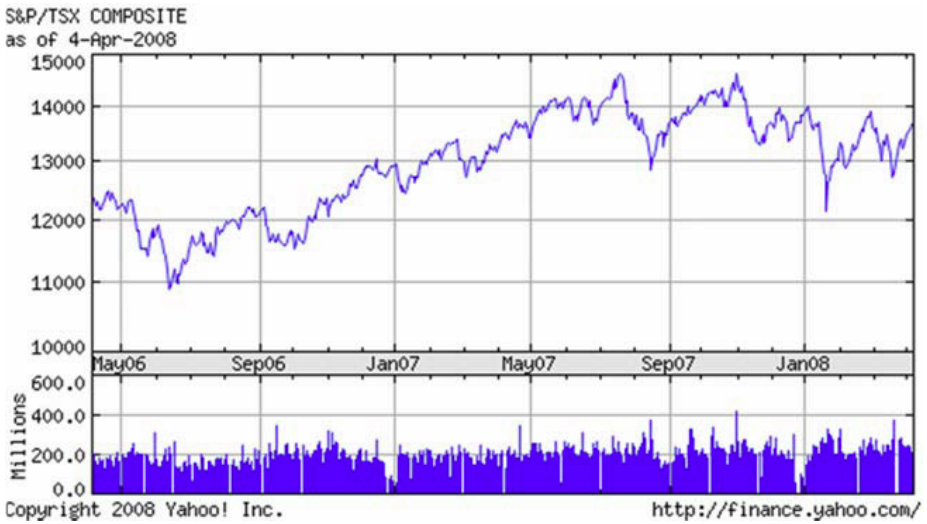


Example 3: Spam detection



- This is a classification problem
- Task is to classify email into spam/non-spam
- Requires a learning system as “enemy” keeps innovating

Example 4: Stock price prediction



- Task is to predict stock price at future date
- This is a regression task, as the output is continuous

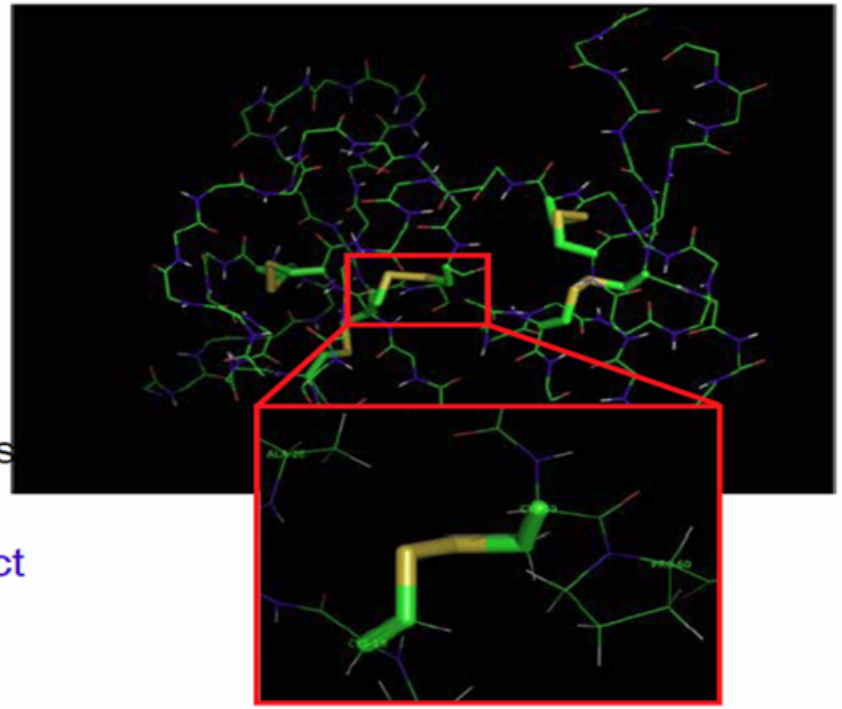
Example 5: Computational Biology

x

AVITGACERDLQCG
KGTCCAVSLWIKSV
RVCTPVGTSGEDCH
PASHKIPFSGQRMH
HTCPCAPNLACVQT
SPKKFKCLSK

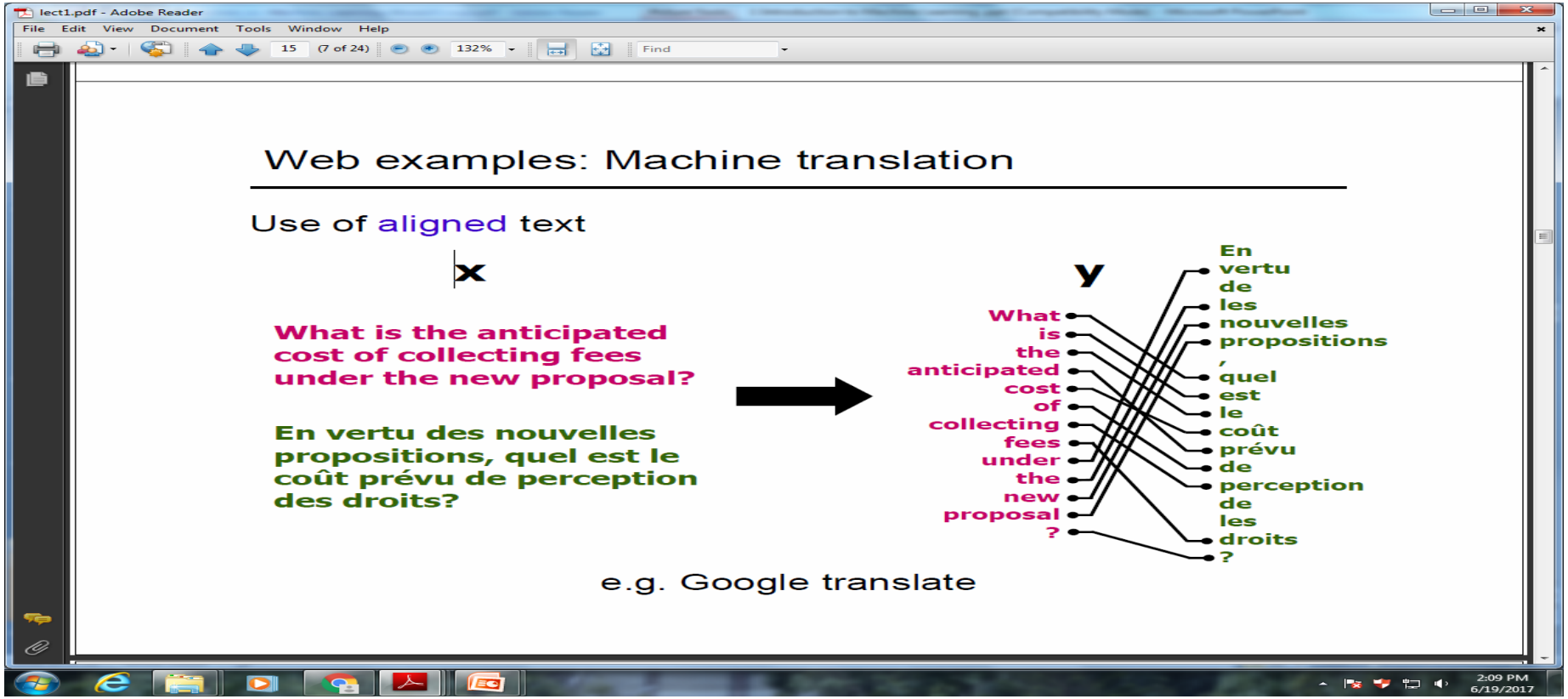
Protein Structure and Disulfide Bridges

y



Regression task: given sequence predict 3D structure

Protein: 1IMT


lect1.pdf - Adobe Reader
File Edit View Document Tools Window Help
Web examples: Machine translation
Use of aligned text
x
What is the anticipated cost of collecting fees under the new proposal?
En vertu des nouvelles propositions, quel est le coût prévu de perception des droits?
y
What is the anticipated cost of collecting fees under the new proposal ?
En vertu de les nouvelles propositions , quel est le coût prévu de perception de les droits ?
e.g. Google translate


Web Images Maps News Shopping Mail more ▾ Help
Google Translate BETA
Home Text and Web Translated Search Dictionary Tools
Translate text or webpage
Enter text or a webpage URL.
En vertu des nouvelles propositions, quel est le coût prévu de perception des droits?
Translation: French » English
Under the new proposals, what is the cost of collection of fees?
French > English swap Translate
Suggest a better translation

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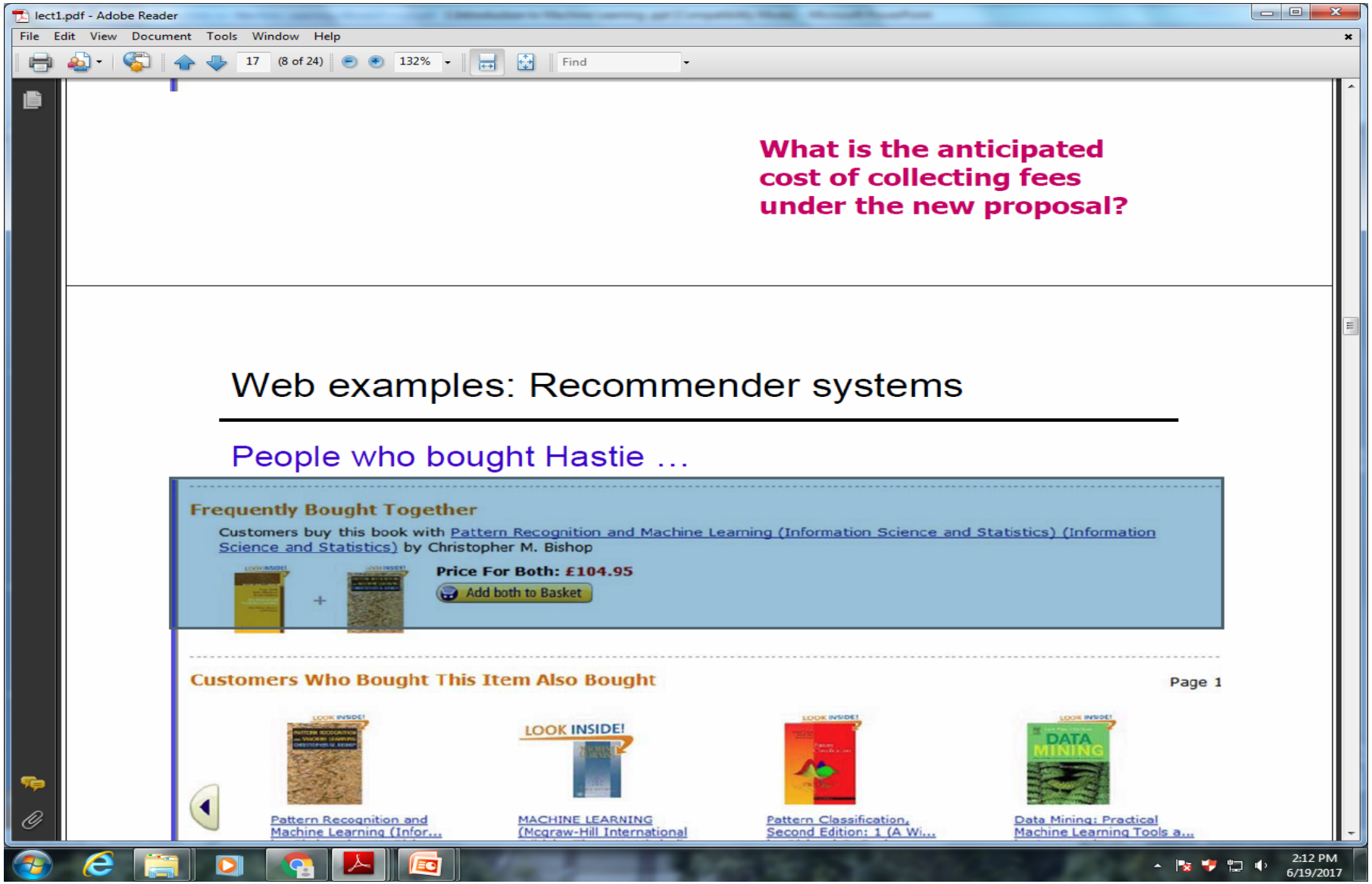

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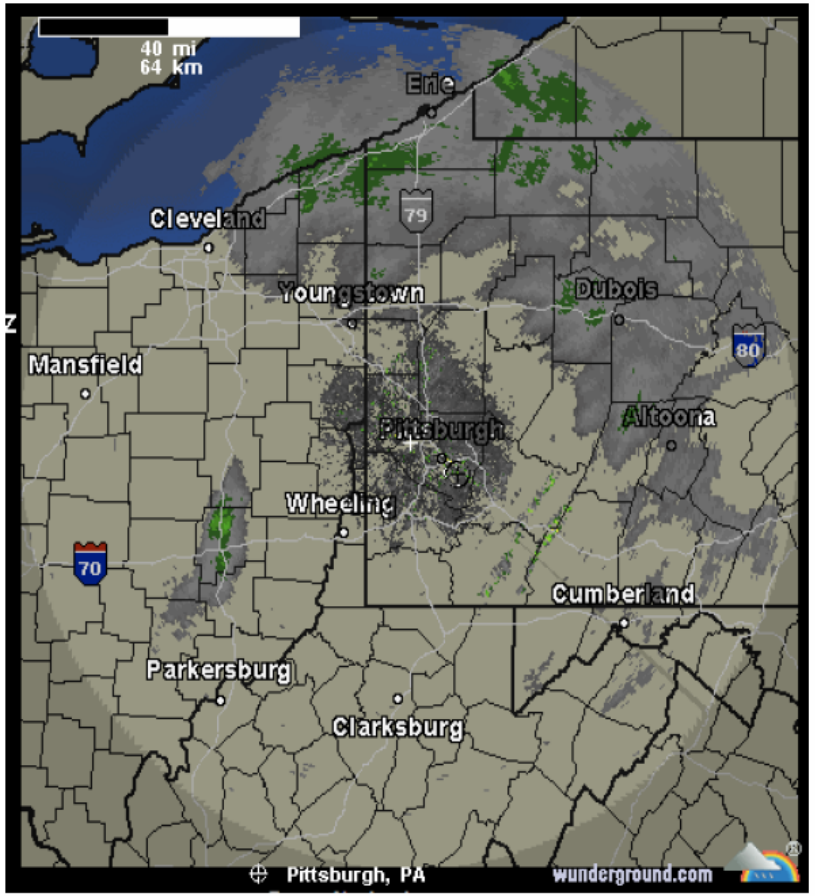
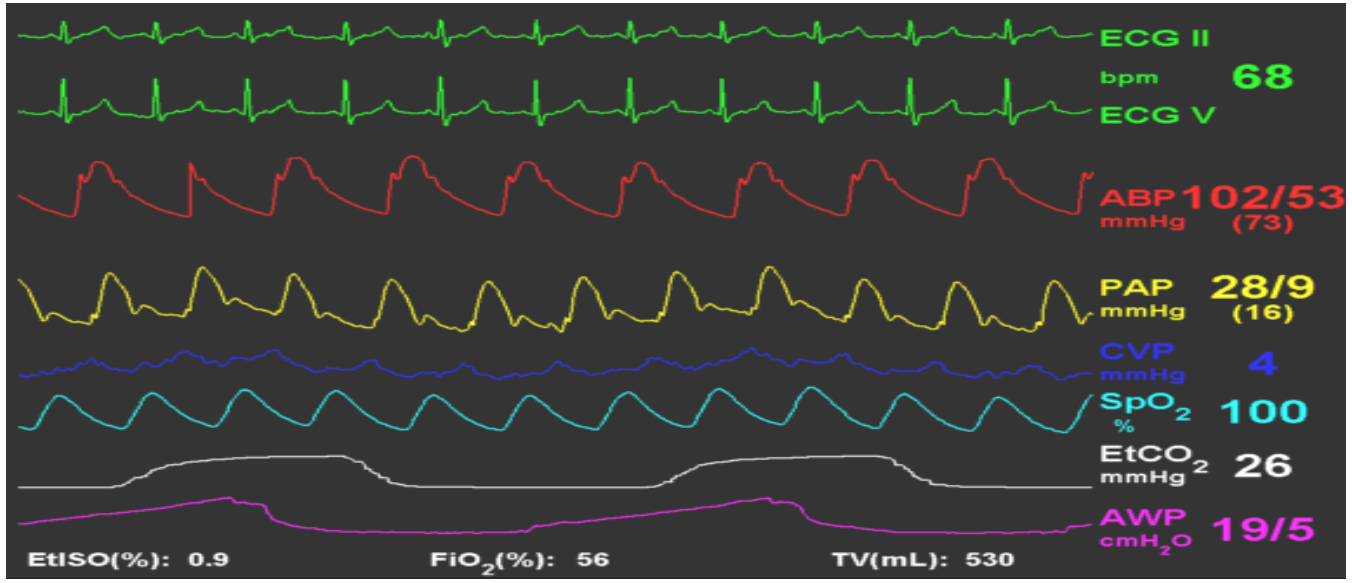
Example : Weather prediction



Example : Medical Diagnosis

- Inputs are the relevant information about the patient and the classes are the illnesses.
- The inputs contain the patient's age, gender, past medical history, and current symptoms.
- Some tests may not have been applied to the patient, and thus these inputs would be missing.
- Tests take time, may be costly, and may inconvience the patient so we do not want to apply them unless we believe that they will give us valuable information.
- In the case of a medical diagnosis, a wrong decision may lead to a wrong or no treatment, and in cases of doubt it is preferable that the classifier reject and defer decision to a human expert.



Example : Agriculture

A Crop Yield Prediction App in Senegal Using Satellite Imagery (Video Link)

https://www.youtube.com/watch?v=4OnBGkhA4jc&t=160s

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Data Preparation

Data Preparation Pipeline

Data Preparation

1. Clean Data
- a. do a preliminary exploration of data
- b. deal with spurious lines
- c. find and deal with missing data
- d. remove unwanted columns
- e. find and deal with bad numeric data
- f. find and deal with bad categorical data

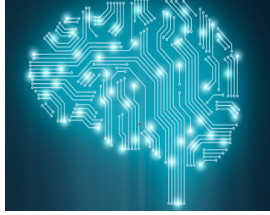
2. Normalize and Encode Data
- a. normalize numeric predictors
- b. encode categorical predictors
- c. encode categorical dependent variable

3. Split Data
- a. split data into train and test sets
- b. split train and test into train_x, train_y, test_x, test_y

Data Preparation

- Data preparation is defined as a **gathering**, **combining**, **cleaning**, and **transforming raw data** to make accurate predictions or uncover insights in Machine learning projects.

Why is Data Preparation important?



sometimes, data in data sets **have missing or incomplete information**, which leads to less accurate or incorrect predictions.

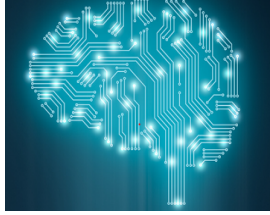
Further, sometimes data sets are clean but not adequately shaped, such as aggregated or pivoted, and some have less business context.

Hence, after collecting data from various data sources, **data preparation needs to transform raw data**.

Significant advantages of data preparation in machine learning as follows:

- It helps to provide reliable prediction outcomes in various analytics operations.
- It helps identify data issues or errors and significantly reduces the chances of errors.
- It increases decision-making capability.
- It reduces overall project cost (data management and analytic cost).
- It helps to remove duplicate content to make it worthwhile for different applications.
- It increases model performance.

Steps in Data Preparation Process



1. Understand the problem:

Understand the actual problem and try to solve it.

2.Data collection:

collect data from various potential sources. These data sources may be either within enterprise or third parties vendors.

Data collection is beneficial to reduce and mitigate biasing in the ML model.

So, before collecting data, always analyze it and also ensure that the data set was collected from diverse people, geographical areas, and perspectives.

3.Profiling and Data Exploration:

explore data such as trends, outliers, exceptions, incorrect, inconsistent, missing, or skewed information, etc.

Data exploration helps to determine problems such as **collinearity,** which means a situation when the Standardization of data sets and other data transformations are necessary.

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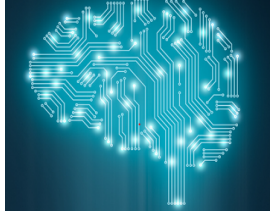
Steps in Data Preparation Process



4.Data Cleaning and Validation:

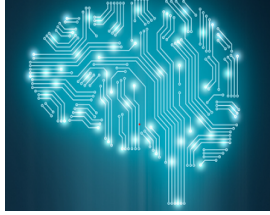
Data cleaning and validation techniques help determine and solve inconsistencies, outliers, anomalies, incomplete data, etc.

Clean data helps to find valuable patterns and information in data and ignores irrelevant data in the datasets.

5.Data Formatting:

After cleaning and validating data, the following approach is to ensure that the data is correctly formatted or not.

Steps in Data Preparation Process



6.Feature engineering and selection:

- Feature engineering is defined as the study of selecting, manipulating, and transforming raw data into valuable features

There are various feature engineering techniques used in Machine Learning as follows:

Imputation:

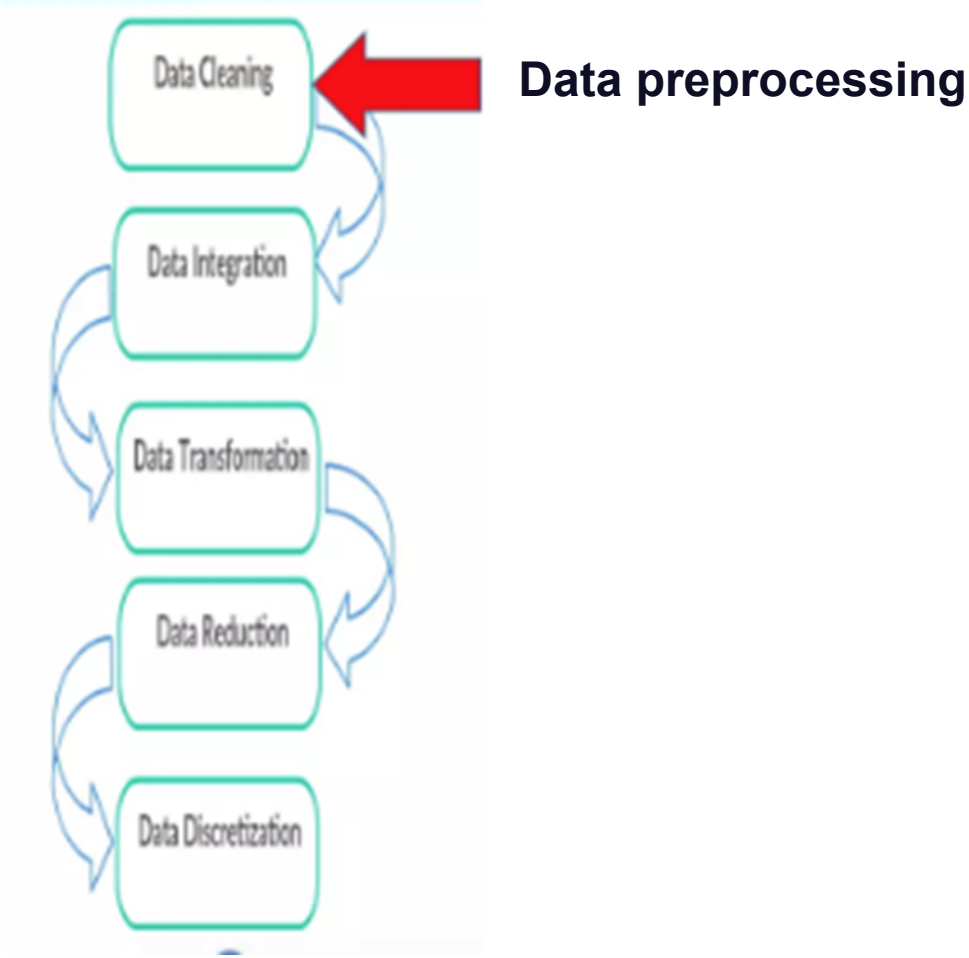
- Feature imputation is the technique to fill incomplete fields in the datasets.
- It is essential because most machine learning models don't work when there are missing data in the dataset.
- Although, the missing values problem can be reduced by using techniques such as single value imputation, multiple value imputation, K-Nearest neighbor, deleting the row, etc.

Encoding:

- Feature encoding is defined as the method to **convert string values into numeric form**.
- This is important as all ML models require all values in numeric format.
- Feature encoding includes label encoding and One Hot Encoding (also known as get_dummies).

Data Pre-Processing

1.Data cleaning
2.Data integration
3.Data transformation
4.Data reduction
5.Data Discretization



Cntd..

- Data preparation is also known as data "**pre-processing**," "**data wrangling**," "**data cleaning**," "**data pre-processing**," and "**feature engineering**."
- It is the later stage of the machine learning lifecycle, which comes after data collection..

The data preparation process can be complicated by issues such as:

1. **Missing or incomplete records:** Missing data sometimes appears as empty cells, values (e.g., NULL or N/A), or a particular character, such as a question mark

age	weight
[50-60)	?
[20-30)	[50-75)
[80-90)	?
[50-60)	?
[50-60)	?
[70-80)	?

Cntd..

- **Data is not always available**

E.g., while admission filling form by student at the time of admission, he might be don't known local guardian contact number.

- **Missing data may be due to**

✓equipment malfunction

✓inconsistent with other recorded data and thus deleted

✓data not entered due to misunderstanding

✓certain data may not be considered important at the time of entry

✓no register history or changes of the data

✓expansion of data schema

Cntd..

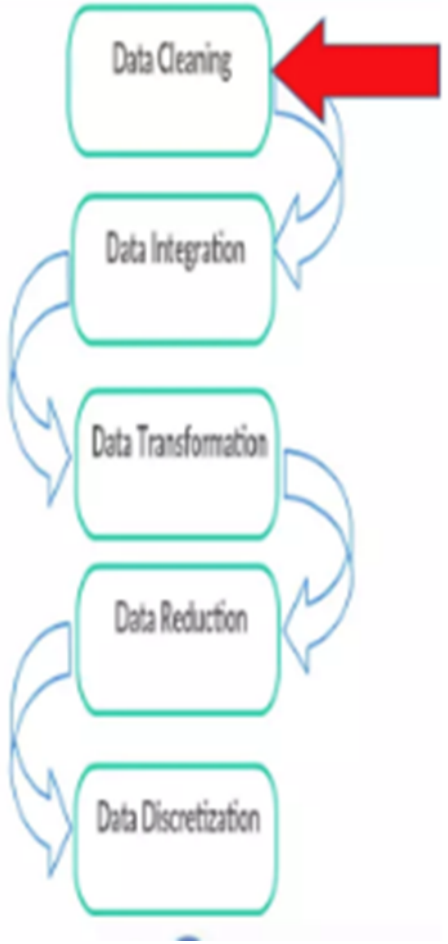
How to Handle Missing Data?

- Ignore the tuple (loss of information)
- Fill in missing values manually: tedious, infeasible?
- Fill in it automatically with

✓a global constant : e.g., unknown, a new class?!

✓**Imputation**: Use the attribute **mean** to fill in the missing value,

✓ Use the most **probable value** to fill in the missing value.



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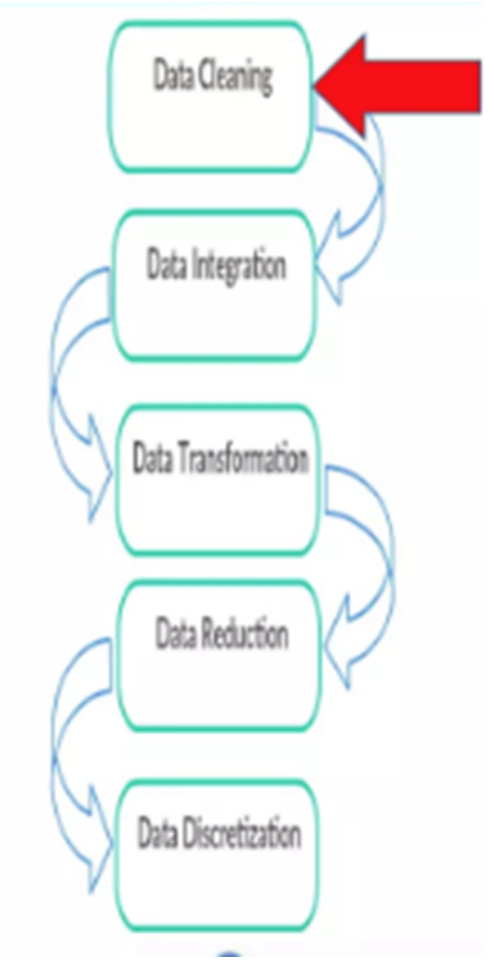
Noisy Data

- Noise: random **error** or variance in a measured variable
- Incorrect attribute values may due to
  - ✓ faulty data collection instruments
  - ✓ data entry problems
  - ✓ data transmission problems
  - ✓ technology limitation
  - ✓ inconsistency in naming convention
- Other data problems which requires data cleaning
  - ✓ duplicate records
  - ✓ incomplete data
  - ✓ inconsistent data



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How to handle noisy data?

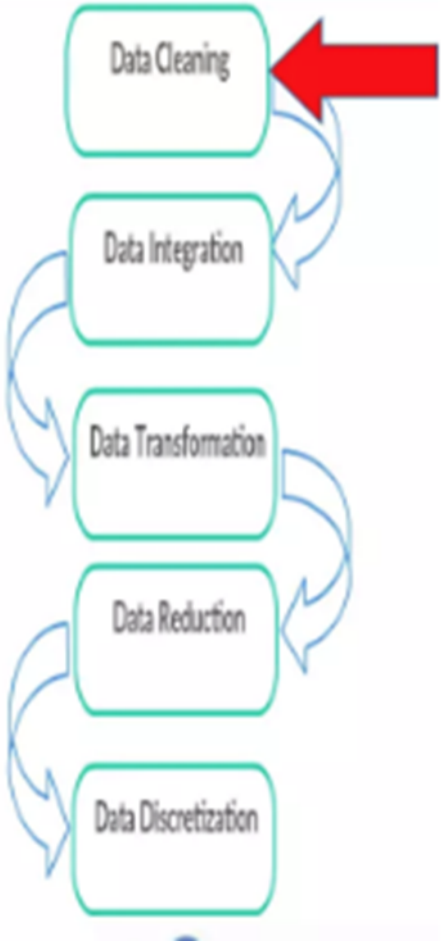
- **Binning method:**

✓first **sort data** and **partition** into (equi-depth) bins

✓then one can smooth by bin **means**, smooth by bin **median**, smooth by bin **boundaries**, etc.

- **Combined computer and human inspection**

✓detect suspicious values and check by human



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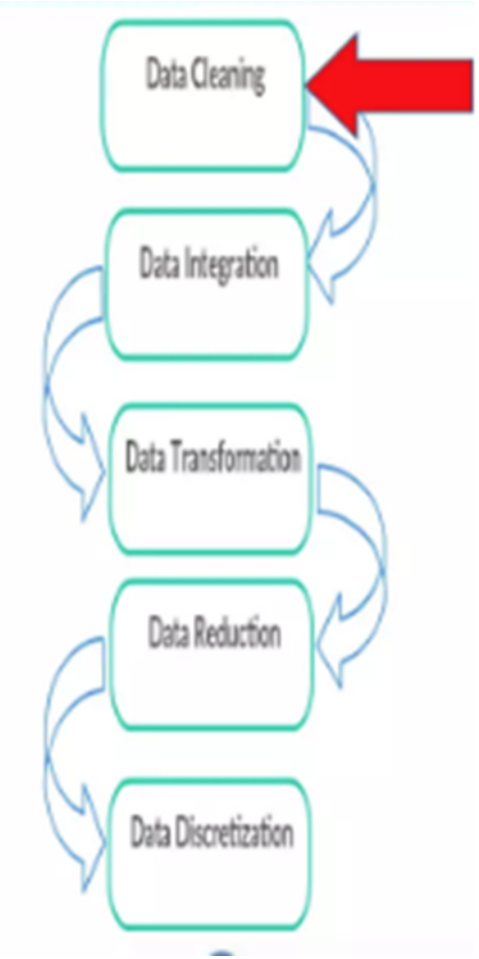
Binning Methods for Data Smoothing

- Sorted data for price (in dollars): 4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 34

* Partition into (equi-depth) bins:
  - -Bin 1: 4, 8, 9, 15
  - -Bin 2: 21, 21, 24, 25
  - -Bin 3: 26, 28, 29, 34
* Smoothing by bin means:
  - -Bin 1: 9, 9, 9, 9 (4+8+9+15/4) =9
  - -Bin 2: 23, 23, 23, 23 (21+21+24+25/4)=23
  - -Bin 3: 29, 29, 29, 29 (26+28+29+34/4) =29
* Smoothing by bin boundaries:
  - -Bin 1: 4, 4, 4, 15
  - -Bin 2: 21, 21, 25, 25
  - -Bin 3: 26, 26, 26, 34



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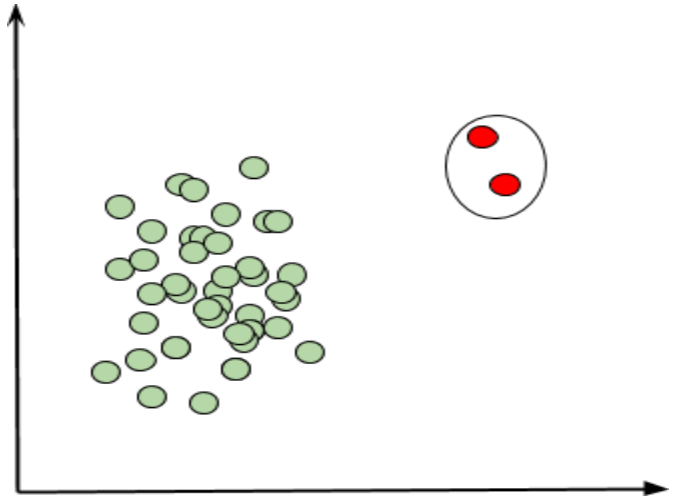
2. Outliers or anomalies: Unexpected values

- ML algorithms are sensitive to the range and distribution of values when data comes from unknown sources.
- These values can spoil the entire machine learning training system and the performance of the model.
- Hence, it is essential to detect these outliers or anomalies through techniques such as visualization technique.



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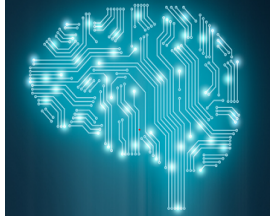

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3. Unstructured data format :

- Data comes from various sources and needs to be extracted into a different format.
- Hence, before deploying an ML project, always consult with domain experts or import data from known sources.

4. Limited or sparse features / attributes :

- Whenever data comes from a single source, it contains limited features,
- so it is necessary to import data from various sources for feature enrichment or build multiple features in datasets.

5. Understanding feature engineering:

- Features engineering helps develop additional content in the ML models, increasing model performance and accuracy in predictions.

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Data Integration

Data integration:

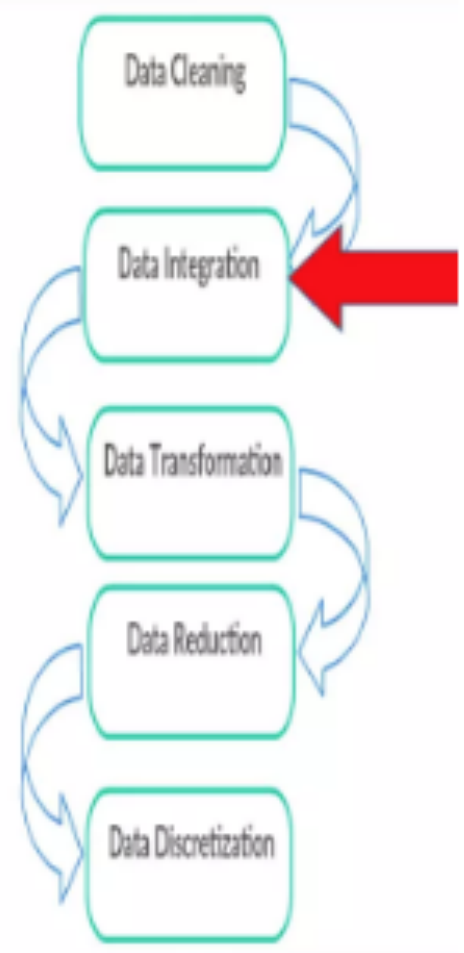
Its **combines data** from multiple sources

- **Schema integration**

Integrate metadata from different sources

Entity identification problem: identify real world entities from multiple data sources, e.g., A.cust-id ≡ B.cust-#

- **Detecting and resolving data value conflicts**
- for the same real world entity, attribute values from different sources are different, e.g., different scales, metric vs. British units
- **Removing duplicates and redundant data**



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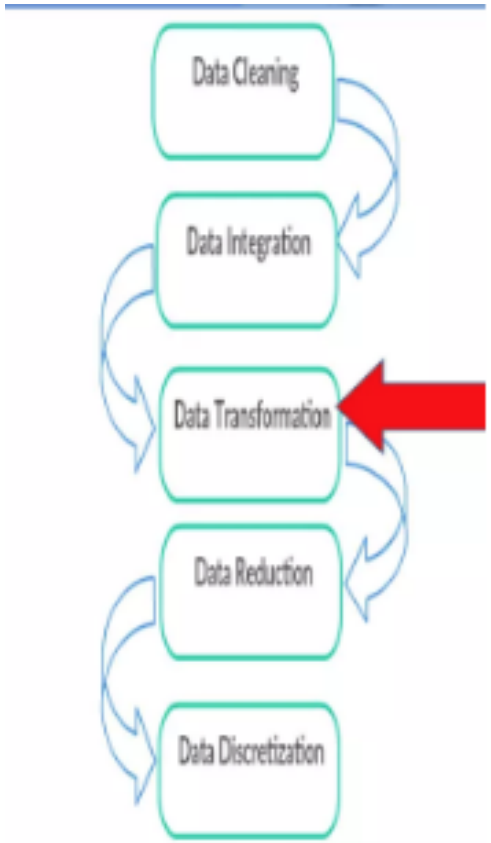
Data Transformation

Data Transformation

- Smoothing: **remove noise** from data
- **Normalization**: scaled to fall within a small, specified range
- Attribute/feature construction
  - ✓ New attributes constructed from the given ones
- **Aggregation**: summarization
  - ✓ Integrate data from different sources (tables)



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Data Reduction

- **Data is too big to work with**

✓ Too many instances

✓ too many features (attributes)

✓ **Data Reduction**

✓ Obtain a reduced representation of the data set that is much smaller in **volume** but yet produce the same (or almost the same) **analytical** results (easily said but difficult to do)

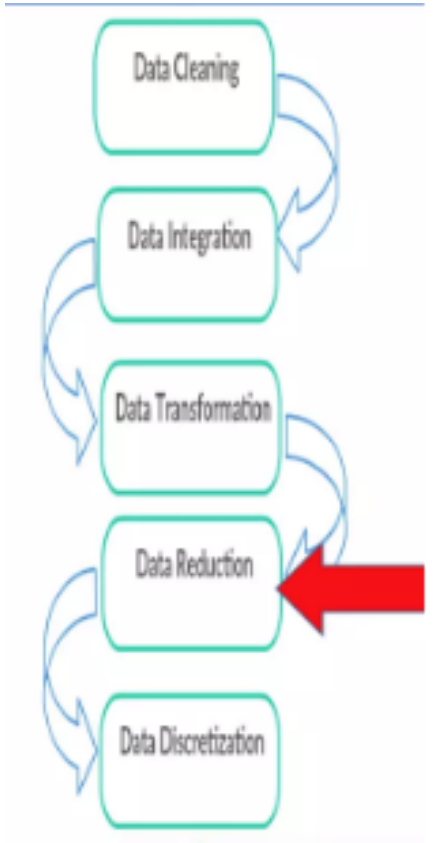
- **Data reduction strategies**

✓ Dimensionality reduction – remove unimportant attributes

✓ Aggregation and clustering –

✓ Remove redundant or close associated ones

✓ Sampling



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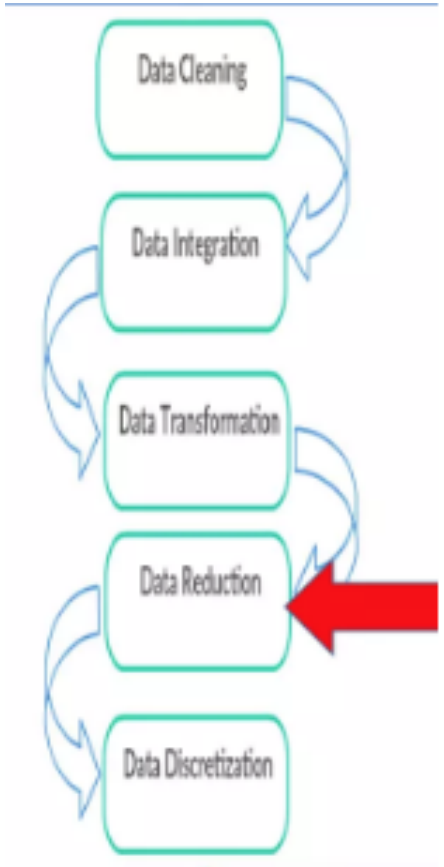
Data Reduction

Clustering

- Partition data set into **clusters**, and one can store cluster representation only.
- Can be very effective if data is clustered but not if data is **dirty**.
- There are many choices of clustering and clustering algorithms.



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Data Reduction

Sampling

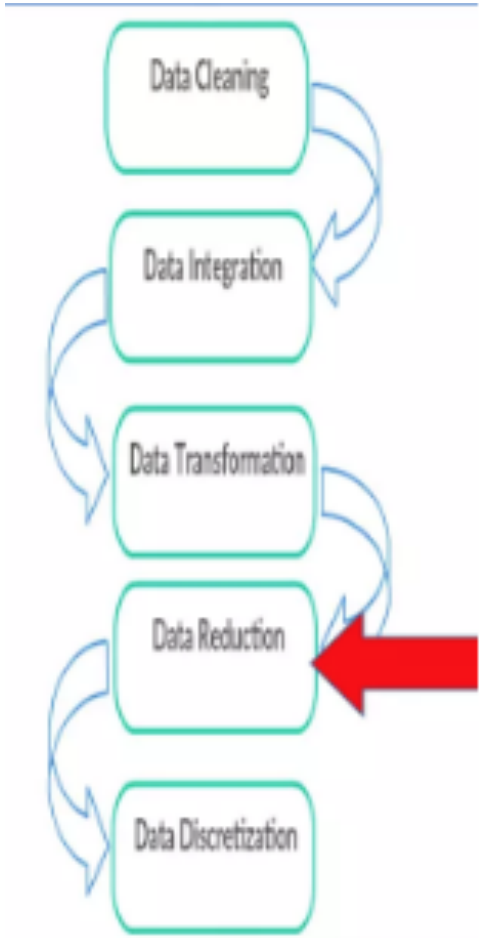
- **Choose a representative subset of the data**

✓ Simply selecting random **sampling** may have improve performance in the presence of scenario .

- **Develop adaptive sampling methods**

✓ Stratified sampling:

➢ Approximate the percentage of each class (or subpopulation of interest) in the overall database



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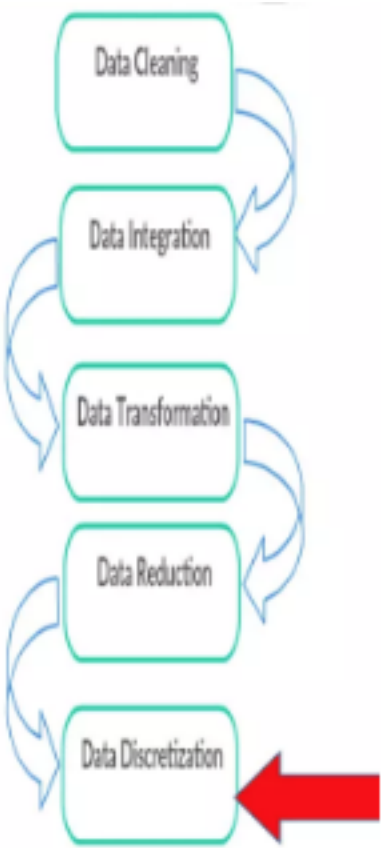
Data Discretization

- Discretization is a process that transforms **quantitative** data into **qualitative** data.
- It significantly improve the quality of **discovering knowledge.**
- It **reduces** the running time of various machine learning tasks such as association rule discovery, classification, clustering and prediction.
- It reduce the number of values for a given continuous attribute by dividing the range of the attribute into **intervals**.
- Interval labels can then be used to **replace** actual data values



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Data Discretization

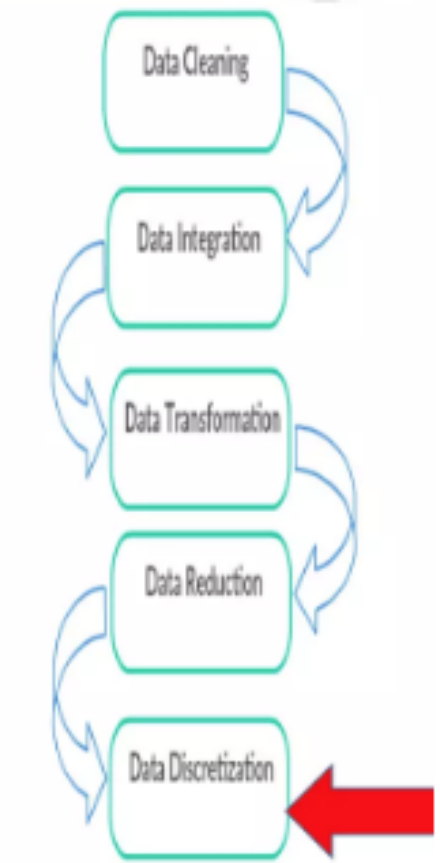
Discretization - Example

- **Example: discretizing the "Humidity" attribute using 3 bins.**

Humidity
85
90
78
96
80
70
65
95
70
80
70
90
75
80

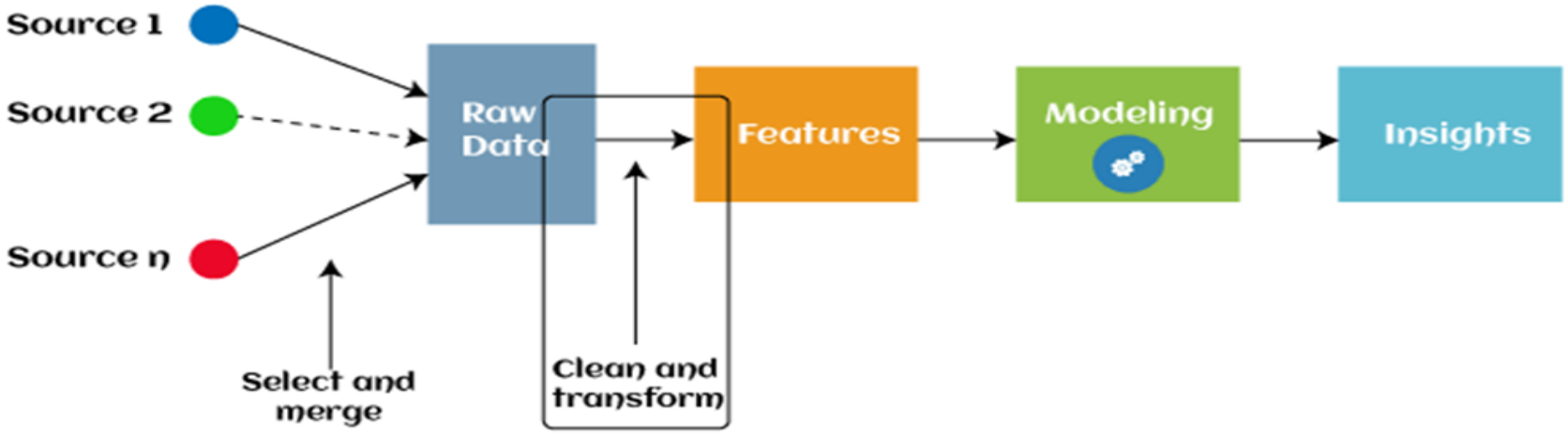
Low = 60-69
Normal = 70-79
High = 80+

Humidity
High
High
Normal
High
High
Normal
Low
High
Normal
High
Normal
High
Normal
High



Feature Engineering

Feature engineering is the pre-processing step of machine learning, which is used to **transform raw data into features** that can be used for creating a predictive model using Machine learning or statistical Modelling.



Feature engineering is the pre-processing step of machine learning, which extracts features from raw data.

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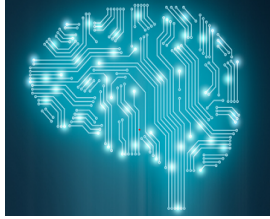


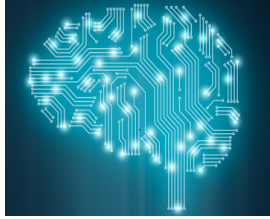
Feature Engineering

What is a feature?

- Generally, all machine learning algorithms take input data to generate the output.
- The input data remains in a tabular form consisting of rows (instances or observations) and columns (variable or attributes), and these attributes are often known as **features**.

Feature Engineering processes:

1. **Feature Creation**: Feature creation is **finding the most useful variables** to be used in a predictive model.
2. **Transformations**: The transformation step of feature engineering involves adjusting the predictor variable to improve the accuracy and performance of the model.



Feature Engineering

3.Feature Extraction: Feature extraction is an automated feature engineering process that **generates new variables by extracting them from the raw data.**

The main aim of this step is to reduce the volume of data so that it can be easily used and managed for data modelling.

Feature extraction methods include **cluster analysis, text analytics, edge detection algorithms, and principal components analysis (PCA)**.

4. **Feature Selection:** *Feature selection is a way of selecting the subset of the most relevant features from the original features set by* ***removing the redundant, irrelevant, or noisy features."***

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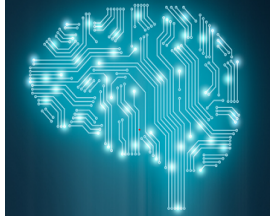
Feature Engineering



Steps in Feature Engineering

Data Preparation:

- In this step, raw data acquired from different resources are prepared to make it in a suitable format so that it can be use in the ML model.
- The data preparation may contain cleaning of data, delivery, data augmentation, fusion, ingestion, or loading.

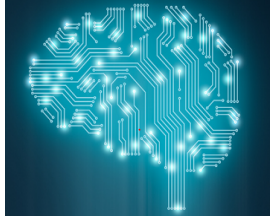
Exploratory Analysis:

- This step involves analysis, investing data set, and summarization of the main characteristics of data.
- Different **data visualization techniques** are used to better understand the manipulation of data sources, to find the mo appropriate statistical technique for data analysis & to select the best features for the data.

Benchmark:

- Benchmarking is a process of **setting a standard baseline** for accuracy to compare all the variables from this baseline
- The benchmarking process is used to **improve the predictability of the model and reduce the error rate**.

Feature Engineering



Feature Engineering Techniques:

1. **Imputation**:

Imputation is responsible for handling irregularities within the dataset.

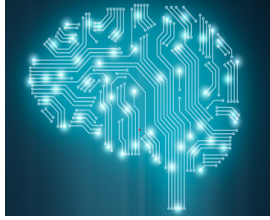
- For numerical data imputation, a **default value** can be imputed in a column, and missing values can be filled with **means or medians** of the columns.
- For categorical data imputation, missing values can be interchanged with the maximum occurred value in a column.

2. **Handling Outliers**:

This technique first identifies the outliers and then remove them out.

- Standard deviation can be used to identify the outliers
- Z-score can also be used to detect outliers.

Feature Engineering



Feature Engineering Techniques:

3. **Log transform**:

Log transform helps in handling the skewed data, and it makes the distribution more approximate to normal after transformation.

4. **Binning**:

can be used to normalize the noisy data. This process involves segmenting different features into bins.

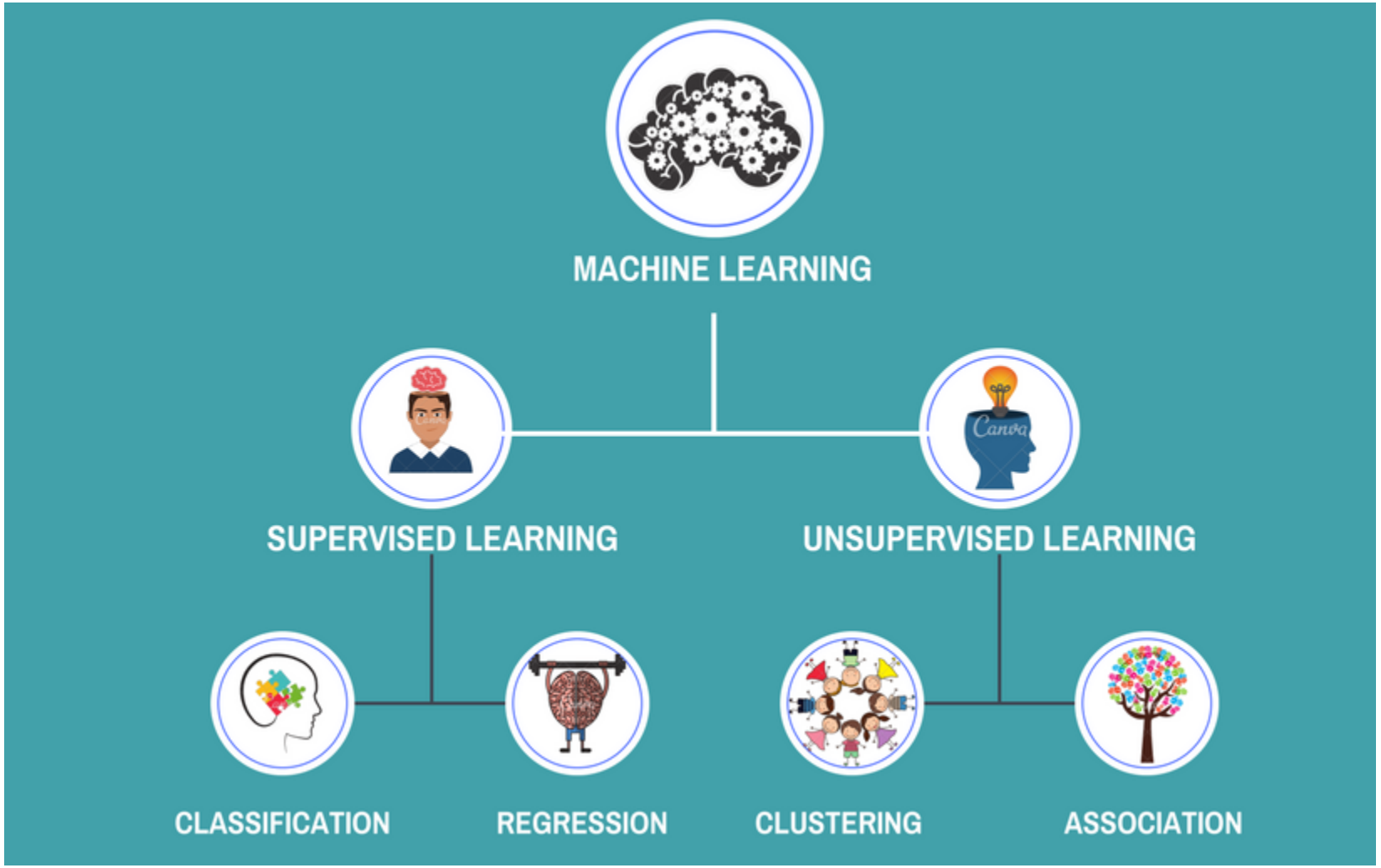
5. **Feature Split**:

is the process of splitting features intimately into two or more parts and performing to make new features.

6. **One hot encoding**:

It is a technique that converts the categorical data in a form so that they can be easily understood by machine learning algorithms and hence can make a good prediction.

Types of Machine Learning



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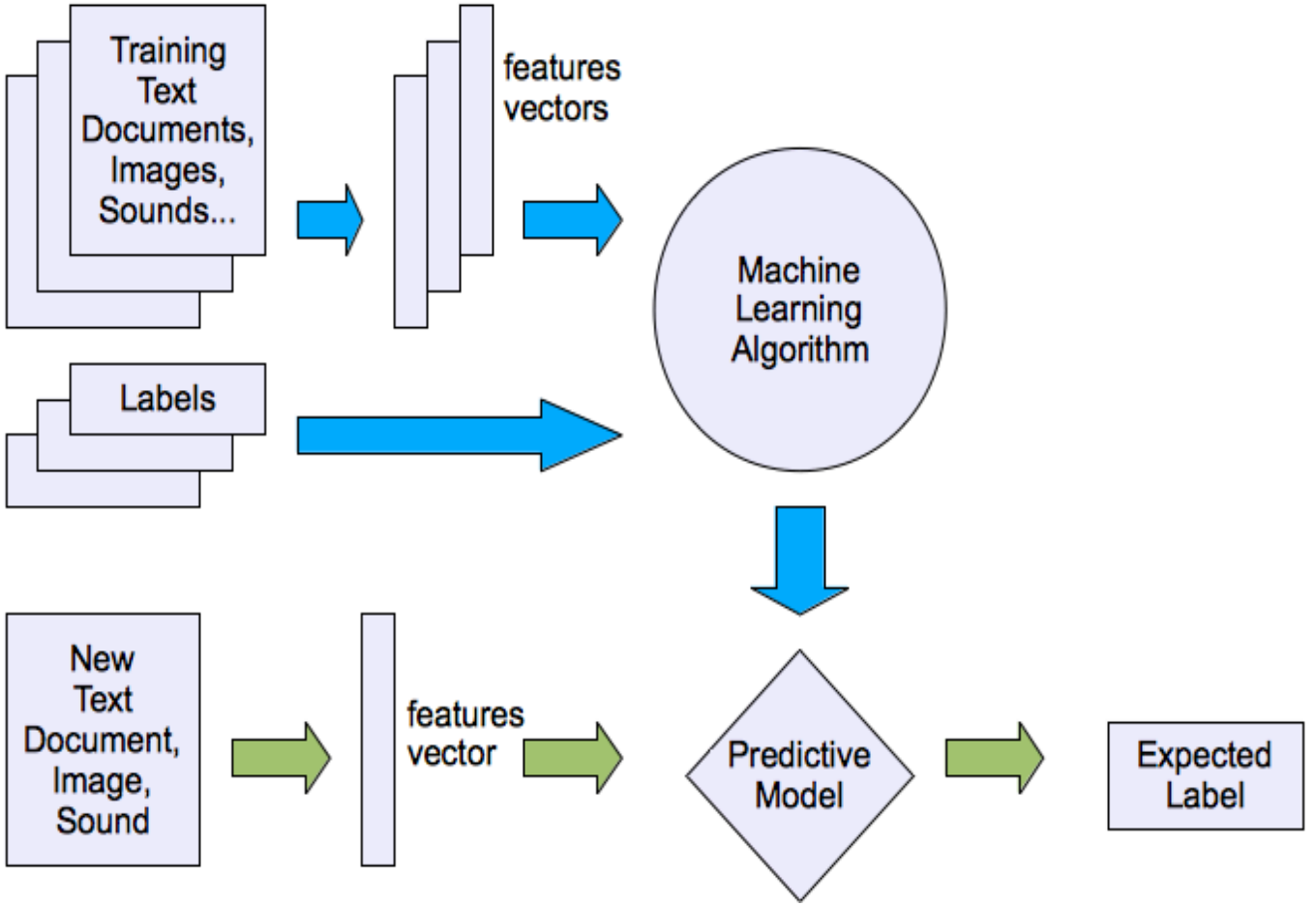
Types of Learning

- Supervised learning



Types of Learning

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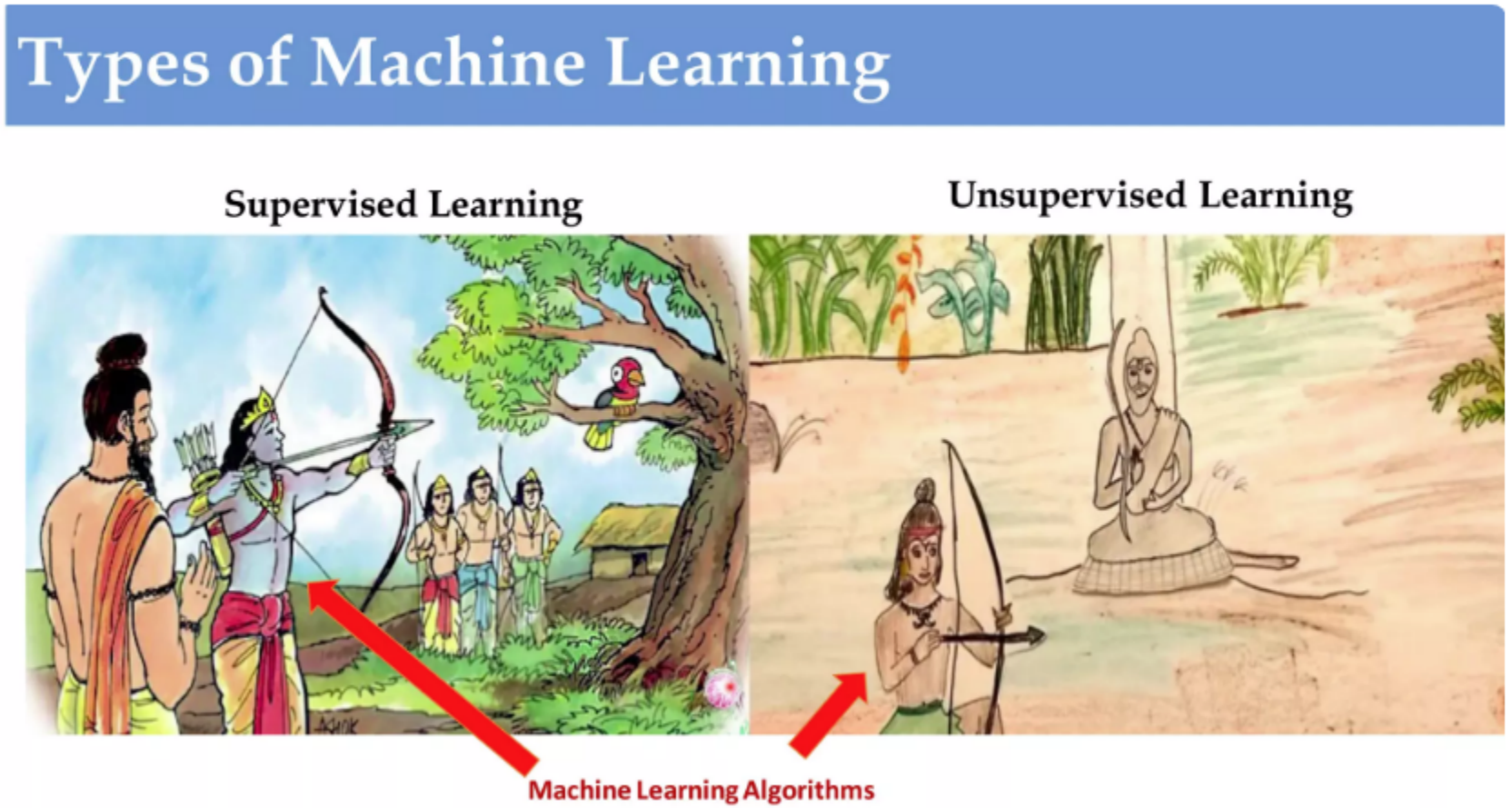
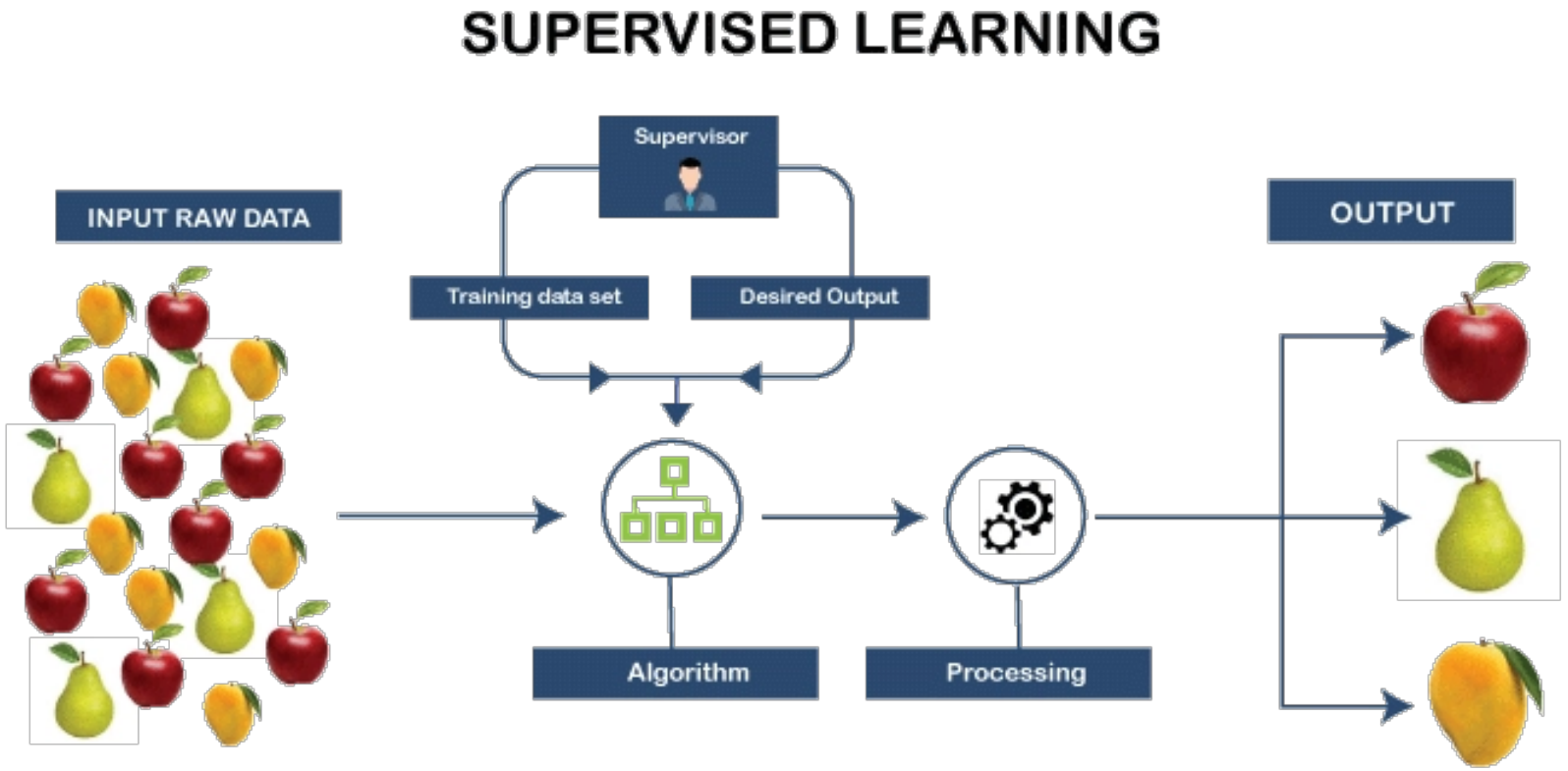
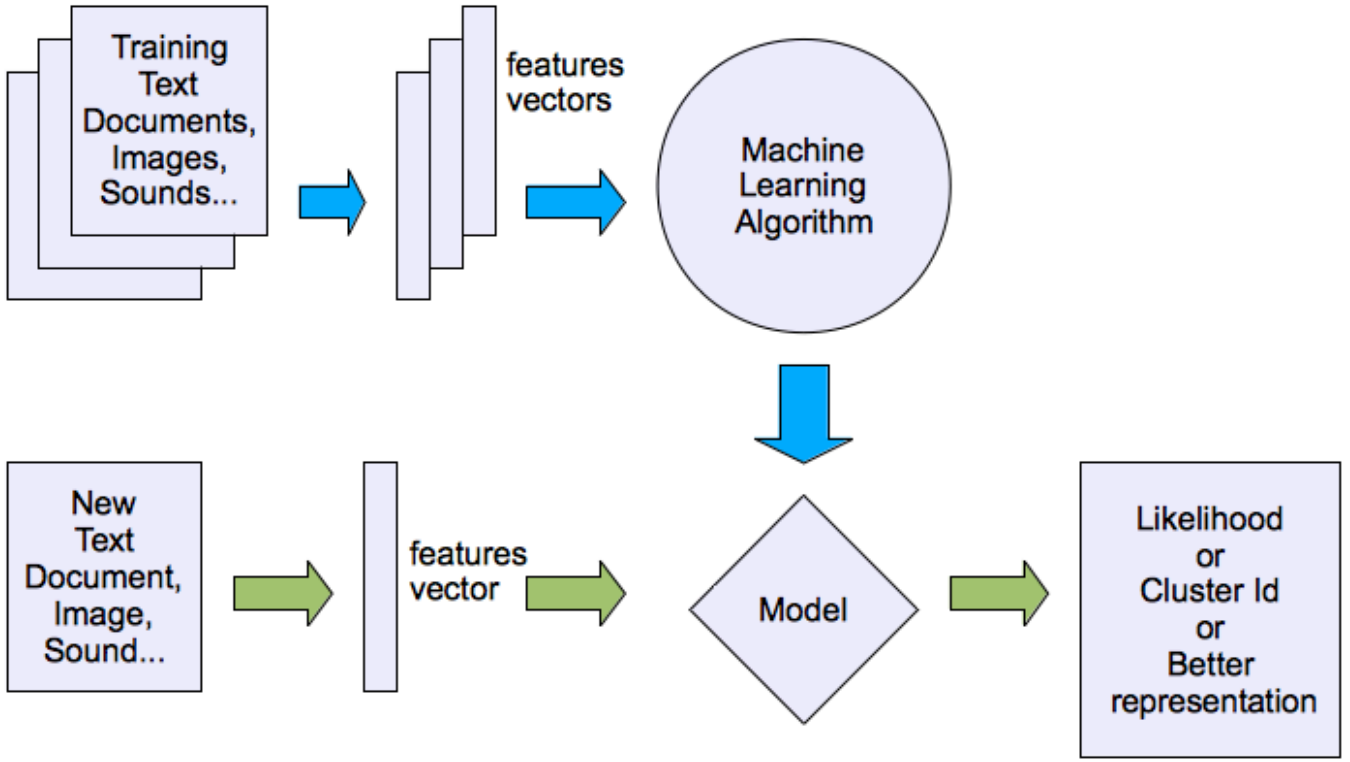


Types of Learning



Unsupervised Learning

- Unsupervised learning



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Example of Unsupervised learning

- Clustering
- Association

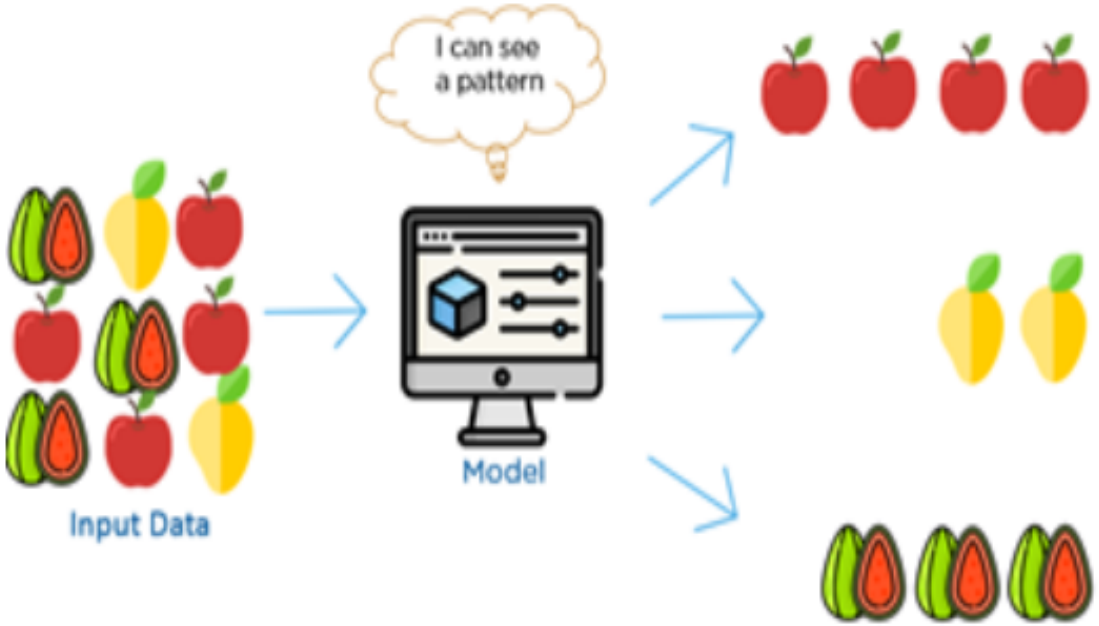
Clustering

sample

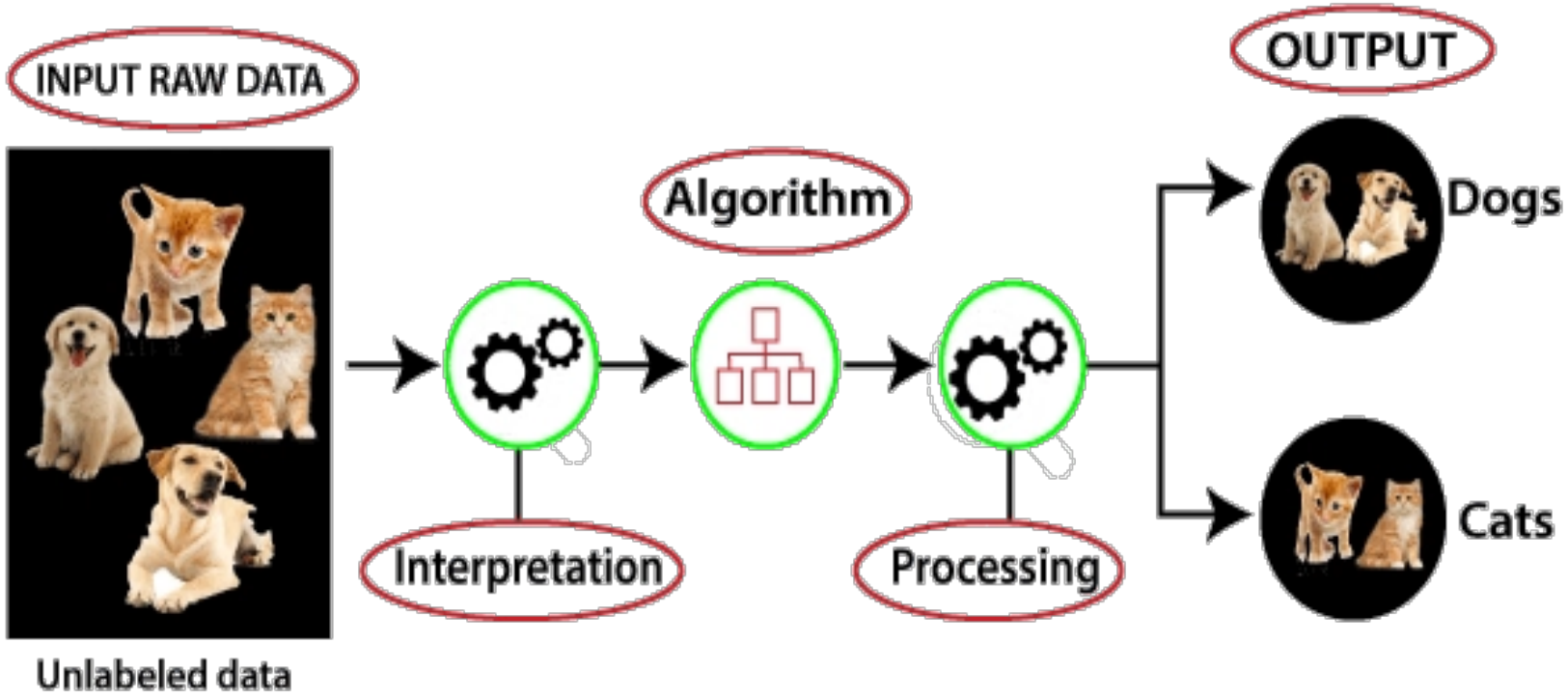
Cluster/group

Example of Unsupervised learning

- Clustering
- Association



Example of Unsupervised learning



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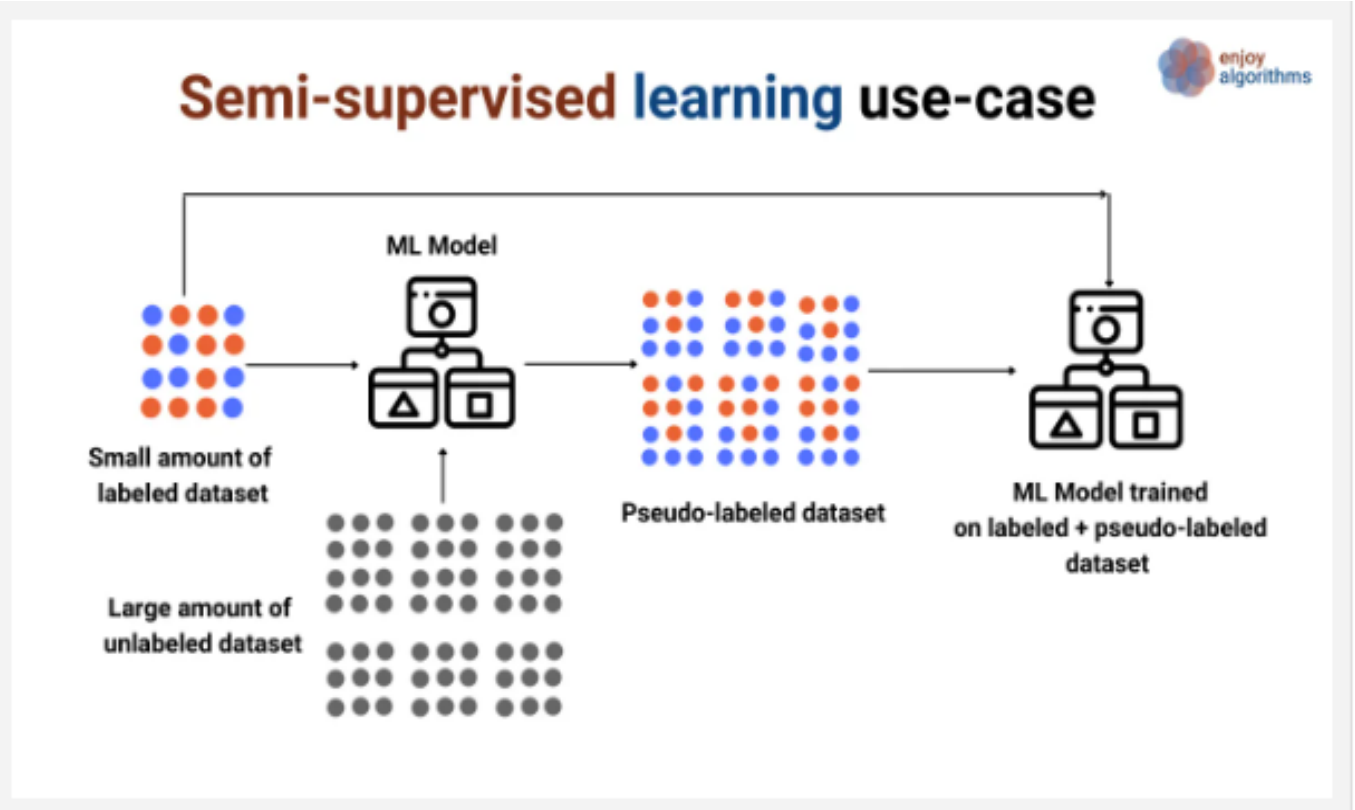
Example of Semi-supervised learning



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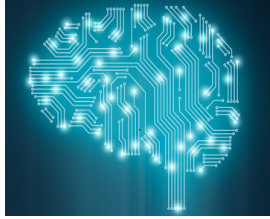

Reinforcement Learning

- learning from mistakes
- Place a reinforcement learning algorithm into any environment and it will make a **lot of mistakes in the beginning**
- As we provide some sort of signal to the algorithm that associates **good behaviors with a positive signal** and **bad behaviors with a negative one**
- we can **reinforce our algorithm to prefer good behaviors** over bad ones.
- Over time, our learning algorithm learns to make less mistakes than it used to.

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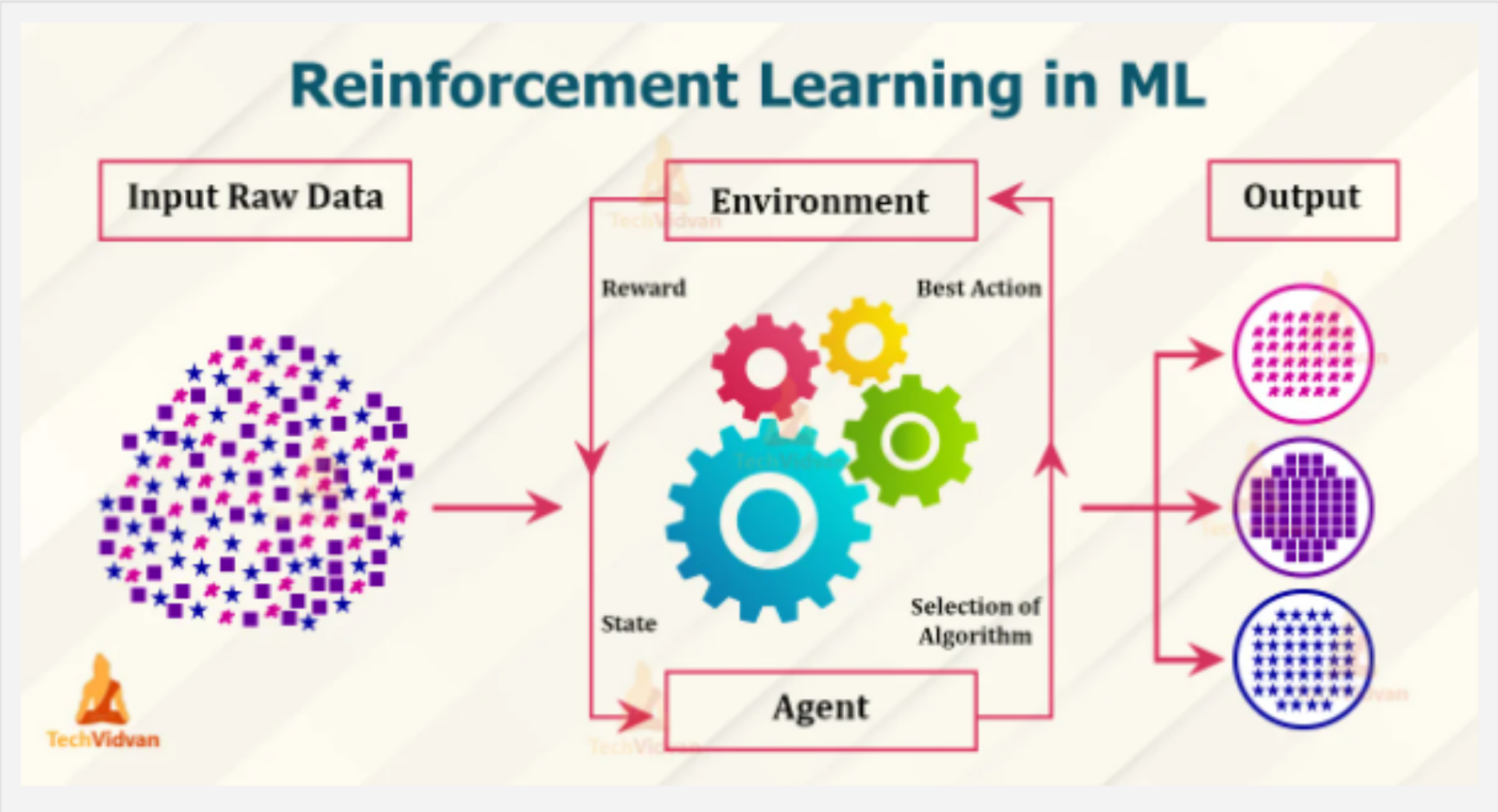
Reinforcement Learning



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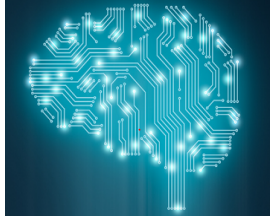
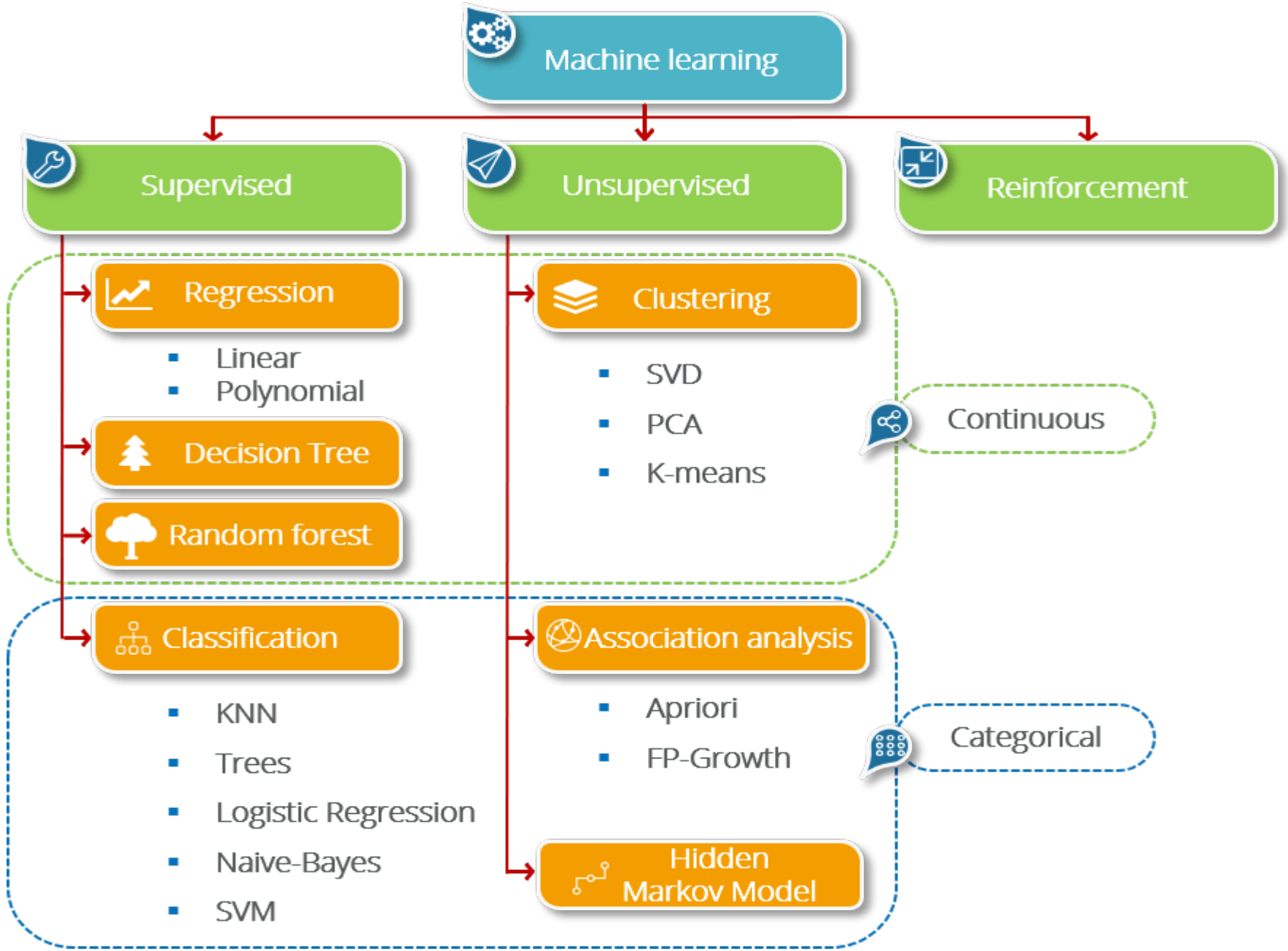
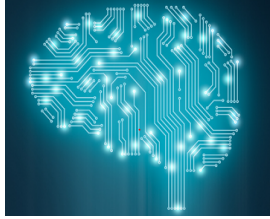


Reinforcement Learning

Where is reinforcement learning in the real world?

- **Video Games**
- **Industrial Simulation**:
- **Resource Management**


Machine learning
Supervised
Unsupervised
Reinforcement
Regression
Linear
Polynomial
Decision Tree
Random forest
Clustering
SVD
PCA
K-means
Continuous
Classification
KNN
Trees
Logistic Regression
Naive-Bayes
SVM
Association analysis
Apriori
FP-Growth
Categorical
Hidden Markov Model



Aspects of developing a learning system:

For training and testing purpose of our model we need to split the dataset in to three distinct dataset, **training set, validation set and testing set**

Training set:-

- A set of data used **to train the model**
- It is used **to fit the model**
- The model sees and **learn from this data**
- **Later on the trained model** can be deployed and used to accurately predict on new data that it has not seen before
- **Labeled data is used**

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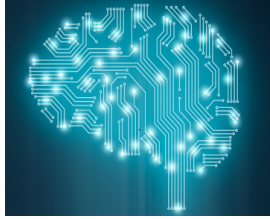
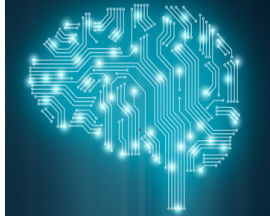


Validation set

- Validation set is the set of **data separate from the training data**
- It is used to **validate our model** during training
- It **gives information** which is used for tuning model hyper parameter
- It **ensures** that **our model is not over fitting** to the data in the training set
- Labeled data is used



Test Set

- A set of data use to **test the model**
- The test set is **separated from both the train set and validation set**
- Once the model is train and validated using the training data and validation sets then the **model is used to predict the output** for the data in the test set
- **Unlabeled data is used**

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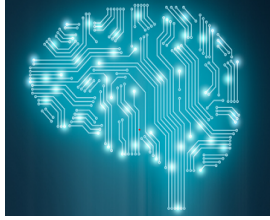


Data Split

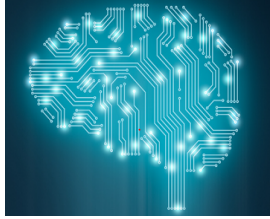
- Rules for performing data split operation
- In order to avoid a correlation between the original dataset must be **randomly shuffled** before applying the split phase
- All the split must represent the original distribution
- The percentage of splitting is mostly **60%** for training **20%** for validation and **20%** for testing
- With scikit-learn this can be done using **train_test_split() function**

Exploratory Data 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.**

Importance of EDA

- Identifying the most **important variables/features** in your dataset.
- Testing a **hypothesis** or checking assumptions related to the dataset.
- To check the **quality of data** for further processing and cleaning.
- Deliver **data-driven insights** to business stakeholders.
- Verify expected **relationships** actually exist in the data.
- To find **unexpected structure** or insights in the data.



Exploratory Data Analysis

Typical graphical techniques used in EDA are:

- Box plot
- Histogram
- Multi-vari chart
- Run chart
- Pareto chart
- Scatter plot
- Stem-and-leaf plot
- Stem-and-leaf plot
- Parallel coordinates
- Odds ratio
- Targeted projection pursuit

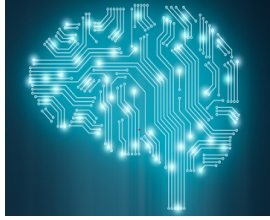
EDA Example

- Wine quality data set from UCI ML repository
- imported necessary libraries (for this example pandas, numpy, matplotlib and seaborn) and loaded the data set.

```
In [2]: df = pd.read_csv('winequality-white.csv',sep=';')
        df.head()
```

Out[2]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.0010	3.00	0.45	8.8	6
1	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.9940	3.30	0.49	9.5	6
2	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.9951	3.26	0.44	10.1	6
3	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40	9.9	6
4	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40	9.9	6

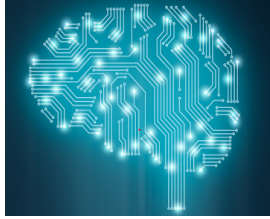


EDA Techniques

```
In [3]: df.shape

Out[3]: (4898, 12)
```

- found out the total number of rows and columns in the data set using ".shape"
- Dataset comprises of 4898 observations and 12 characteristics.
- Out of which one is dependent variable and rest 11 are independent variables — physico-chemical characteristics.
- It is also a good practice to know the columns and their corresponding data types,along with finding whether they contain null values or not.



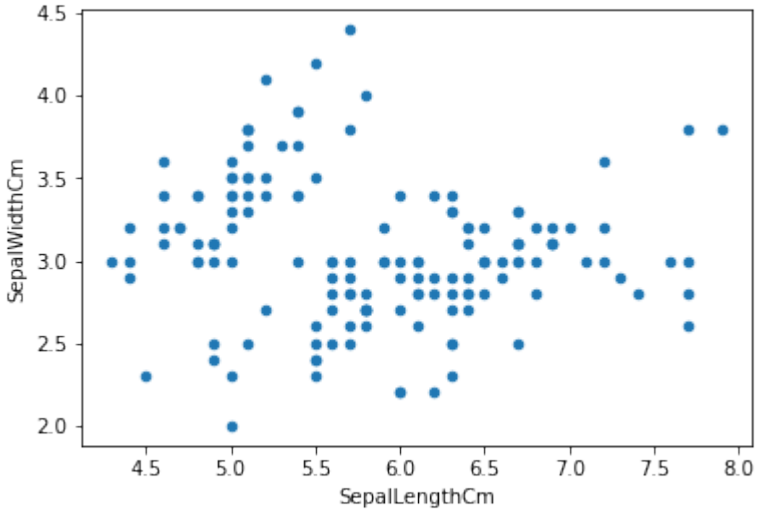
EDA: Exploratory Data Analysis

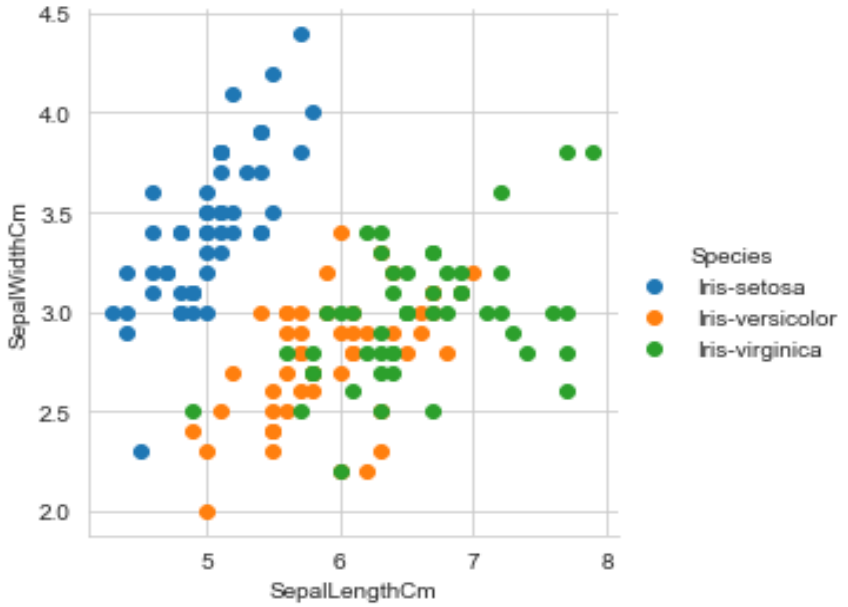
Plotting using matplotlib

```
import pandas as pd
import matplotlib.pyplot as plt
iris = pd.read_csv("iris.csv")
iris.head(5)
iris.plot(kind='scatter', x='sepal_length', y='sepal_width') ;
plt.show()
```

import seaborn as sns

```
# 2-D Scatter plot with color-coding for each flower type/ class.
# Here 'sns' corresponds to seaborn.
sns.set_style("whitegrid");
sns.FacetGrid(iris, hue="species", size=4) \
   .map(plt.scatter, "sepal_length", "sepal_width") \
   .add_legend();
plt.show();
```


SepalWidthCm
SepalLengthCm
4.5
4.0
3.5
3.0
2.5
2.0
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0


SepalWidthCm
SepalLengthCm
4.5
4.0
3.5
3.0
2.5
2.0
5
6
7
8
Species
Iris-setosa
Iris-versicolor
Iris-virginica

EDA: Exploratory Data Analysis

3D scatter plot https://plot.ly/pandas/3d-scatter-plots/

```
import plotly

import plotly.express as px

iris = px.data.iris()

fig = px.scatter_3d(iris, x='sepal_length',
y='sepal_width', z='petal_width',

            color='species')

fig.show()
```

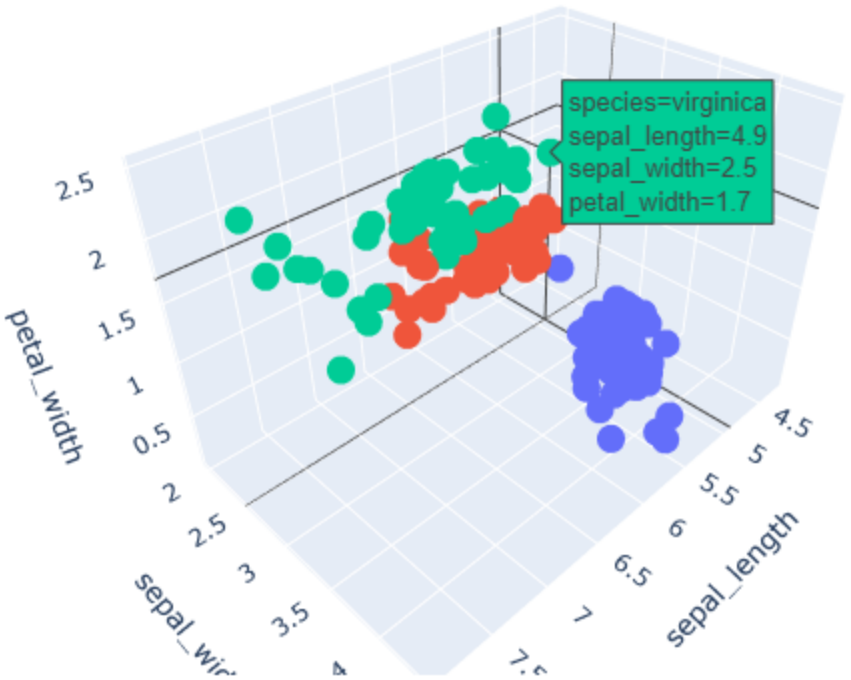
What about 4-D, 5-D or n-D scatter plot?

Pair-plot

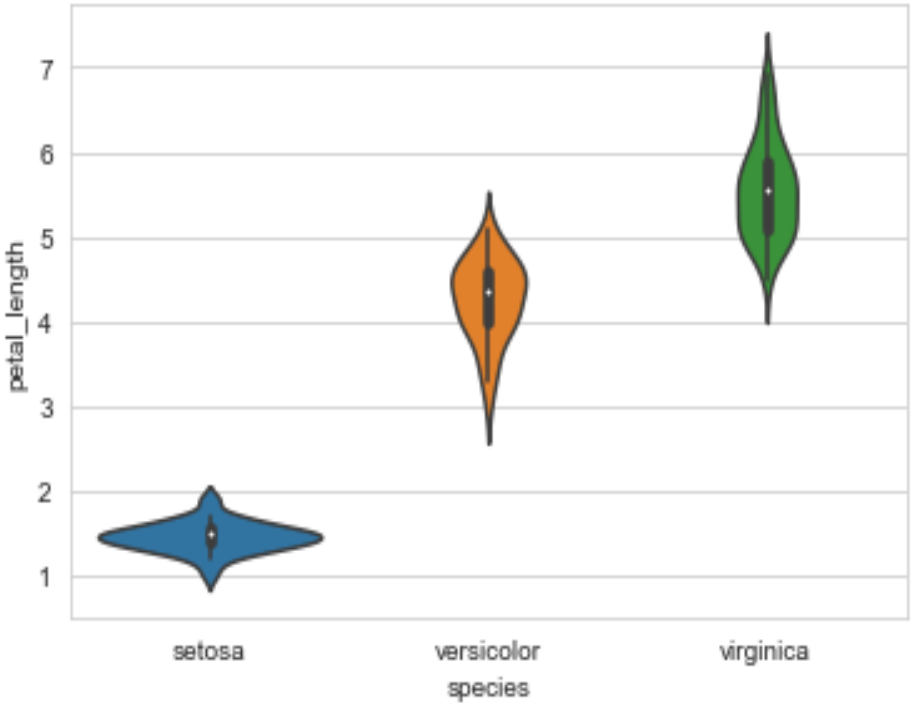
```
#Only possible to view 2D patterns.
plt.close();
sns.set_style("whitegrid");
sns.pairplot(iris, hue="species", size=3);
plt.show()
```

VIOLIN PLOT

```
sns.violinplot(x="species", y="petal_length", data=iris,
size=8)
plt.show()
```


species=virginica
sepal_length=4.9
sepal_width=2.5
petal_width=1.7
petal_width
2.5
2
1.5
1
0.5
sepal_length
4.5
5
5.5
6
6.5
7
sepal_width
2
2.5
3
3.5
species
setosa
versicolor
virginica


sepal_length
sepal_width
petal_length
petal_width
species_id
species
setosa
versicolor
virginica

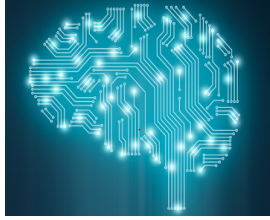

7
6
5
4
3
2
1
petal_length
setosa
versicolor
virginica
species

Progressive Data Analysis

- Data has only **float and integer values.**
- **No** variable column **has null/missing values.**

```
In [5]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4898 entries, 0 to 4897
Data columns (total 12 columns):
fixed acidity           4898 non-null float64
volatile acidity        4898 non-null float64
citric acid             4898 non-null float64
residual sugar          4898 non-null float64
chlorides               4898 non-null float64
free sulfur dioxide     4898 non-null float64
total sulfur dioxide    4898 non-null float64
density                 4898 non-null float64
pH                      4898 non-null float64
sulphates               4898 non-null float64
alcohol                 4898 non-null float64
quality                 4898 non-null int64
dtypes: float64(11), int64(1)
memory usage: 459.3 KB
```



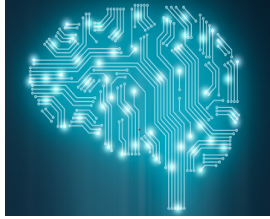
PDA Techniques

```
In [6]: df.describe()
```

Out[6]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol
count	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000
mean	6.854788	0.278241	0.334192	6.391415	0.045772	35.308085	138.360657	0.994027	3.188267	0.489847	10.514267
std	0.843868	0.100795	0.121020	5.072058	0.021848	17.007137	42.498065	0.002991	0.151001	0.114126	1.230621
min	3.800000	0.080000	0.000000	0.600000	0.009000	2.000000	9.000000	0.987110	2.720000	0.220000	8.000000
25%	6.300000	0.210000	0.270000	1.700000	0.036000	23.000000	108.000000	0.991723	3.090000	0.410000	9.500000
50%	6.800000	0.260000	0.320000	5.200000	0.043000	34.000000	134.000000	0.993740	3.180000	0.470000	10.400000
75%	7.300000	0.320000	0.390000	9.900000	0.050000	46.000000	167.000000	0.996100	3.280000	0.550000	11.400000
max	14.200000	1.100000	1.660000	65.800000	0.346000	289.000000	440.000000	1.038980	3.820000	1.080000	14.200000

- The describe() function in pandas is very handy in getting various summary statistics.
- This function returns the **count, mean, standard deviation, minimum and maximum values and the quantiles** of the data.



Data Preparation: Types of Data

- Here as you can notice mean value is larger than median value of each column which is represented by 50%(50th percentile) in index column.
- There is notably a large difference between 75th %tile and max values of predictors “residualsugar”, ”freesulfurdioxide”, ”totalsulfur dioxide”.
- Thus observations 1 and 2 suggests that there are extreme values-Outliers in our data set.

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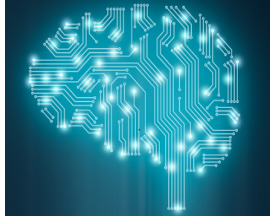
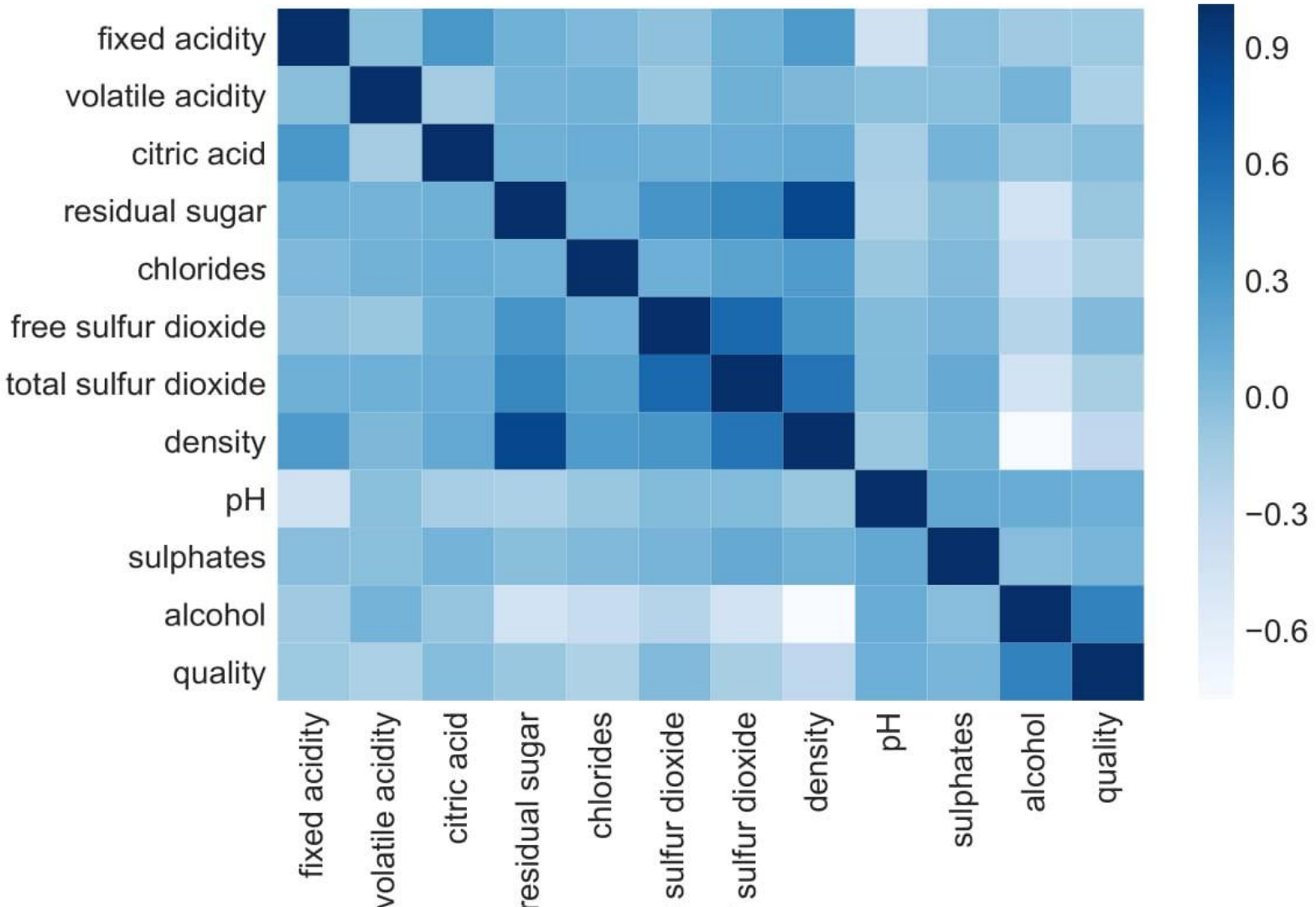
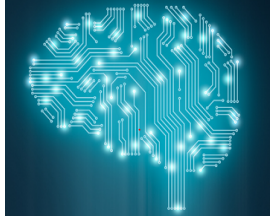


Graph Visualisation Techniques

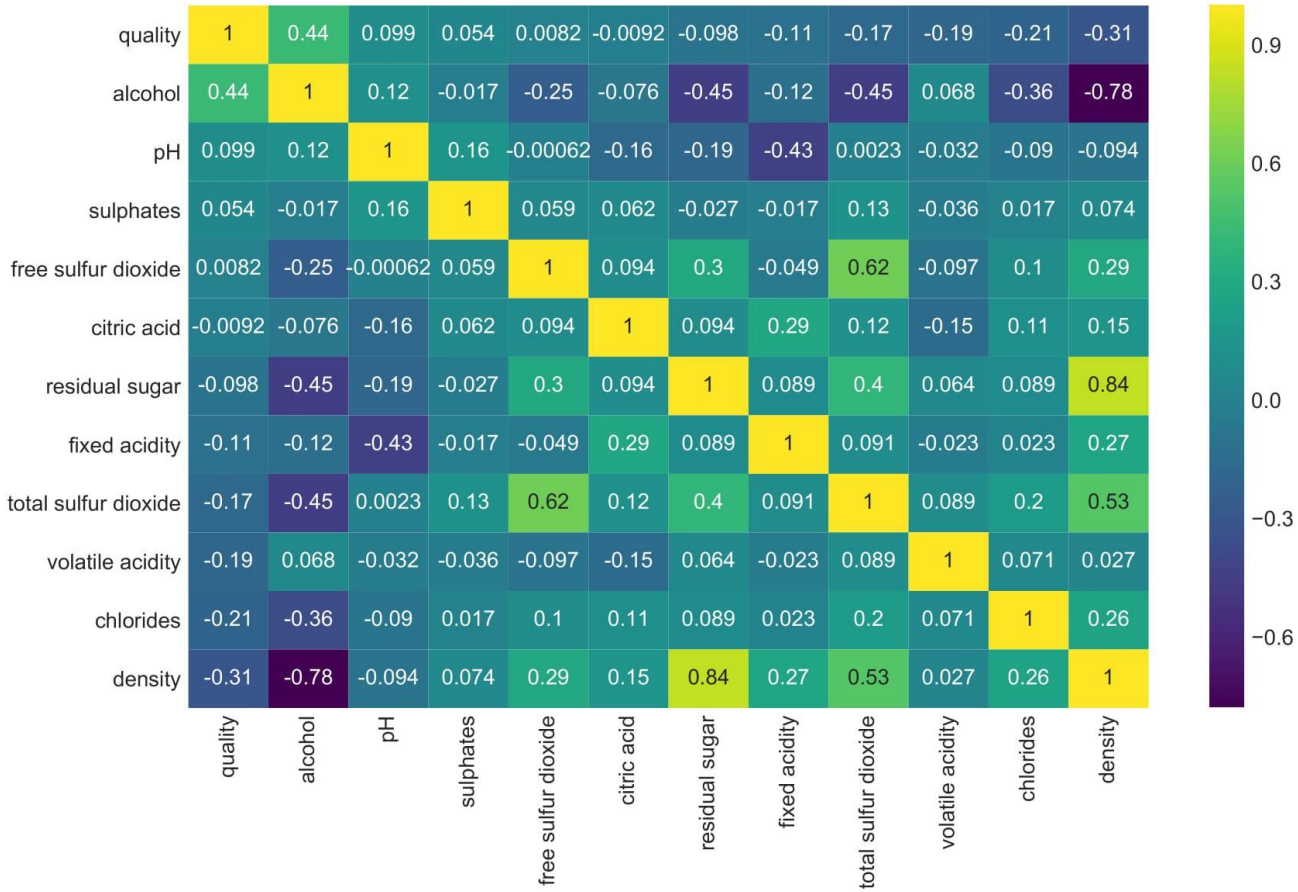
- Let's now explore data with beautiful graphs. Python has a visualization library , Seaborn which build on top of matplotlib.
- It provides very attractive statistical graphs in order to perform both Univariate and Multivariate analysis.
- To use linear regression for modelling, Its **necessary to remove correlated variables to improve your model.**
- One can find correlations using pandas **".corr()" function** and can visualize the correlation matrix using a **heatmap in seaborn**.

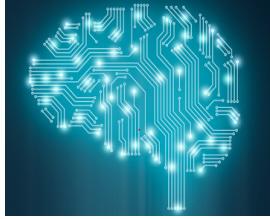

fixed acidity
volatile acidity
citric acid
residual sugar
chlorides
free sulfur dioxide
total sulfur dioxide
density
pH
sulphates
alcohol
quality
0.9
0.6
0.3
0.0
−0.3
−0.6

Data Pre-processing techniques for ML applications



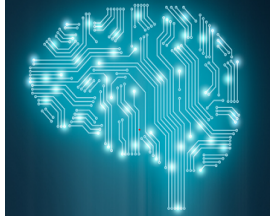
- Dark shades represents **positive correlation** while lighter shades represents **negative correlation**.
- If you set annot=True, you'll get values by which features are correlated to each other in grid-cells.


quality 1 0.44 0.099 0.054 0.0082 -0.0092 -0.098 -0.11 -0.17 -0.19 -0.21 -0.31
alcohol 0.44 1 0.12 -0.017 -0.25 -0.076 -0.45 -0.12 -0.45 0.068 -0.36 -0.78
pH 0.099 0.12 1 0.16 -0.00062 -0.16 -0.19 -0.43 0.0023 -0.032 -0.09 -0.094
sulphates 0.054 -0.017 0.16 1 0.059 0.062 -0.027 -0.017 0.13 -0.036 0.017 0.074
free sulfur dioxide 0.0082 -0.25 -0.00062 0.059 1 0.094 0.3 -0.049 0.62 -0.097 0.1 0.29
citric acid -0.0092 -0.076 -0.16 0.062 0.094 1 0.094 0.29 0.12 -0.15 0.11 0.15
residual sugar -0.098 -0.45 -0.19 -0.027 0.3 0.094 1 0.089 0.4 0.064 0.089 0.84
fixed acidity -0.11 -0.12 -0.43 -0.017 -0.049 0.29 0.089 1 0.091 -0.023 0.023 0.27
total sulfur dioxide -0.17 -0.45 0.0023 0.13 0.62 0.12 0.4 0.091 1 0.089 0.2 0.53
volatile acidity -0.19 0.068 -0.032 -0.036 -0.097 -0.15 0.064 -0.023 0.089 1 0.071 0.027
chlorides -0.21 -0.36 -0.09 0.017 0.1 0.11 0.089 0.023 0.2 0.071 1 0.26
density -0.31 -0.78 -0.094 0.074 0.29 0.15 0.84 0.27 0.53 0.027 0.26 1
quality
alcohol
pH
sulphates
free sulfur dioxide
citric acid
residual sugar
fixed acidity
total sulfur dioxide
volatile acidity
chlorides
density
0.9
0.6
0.3
0.0
−0.3
−0.6

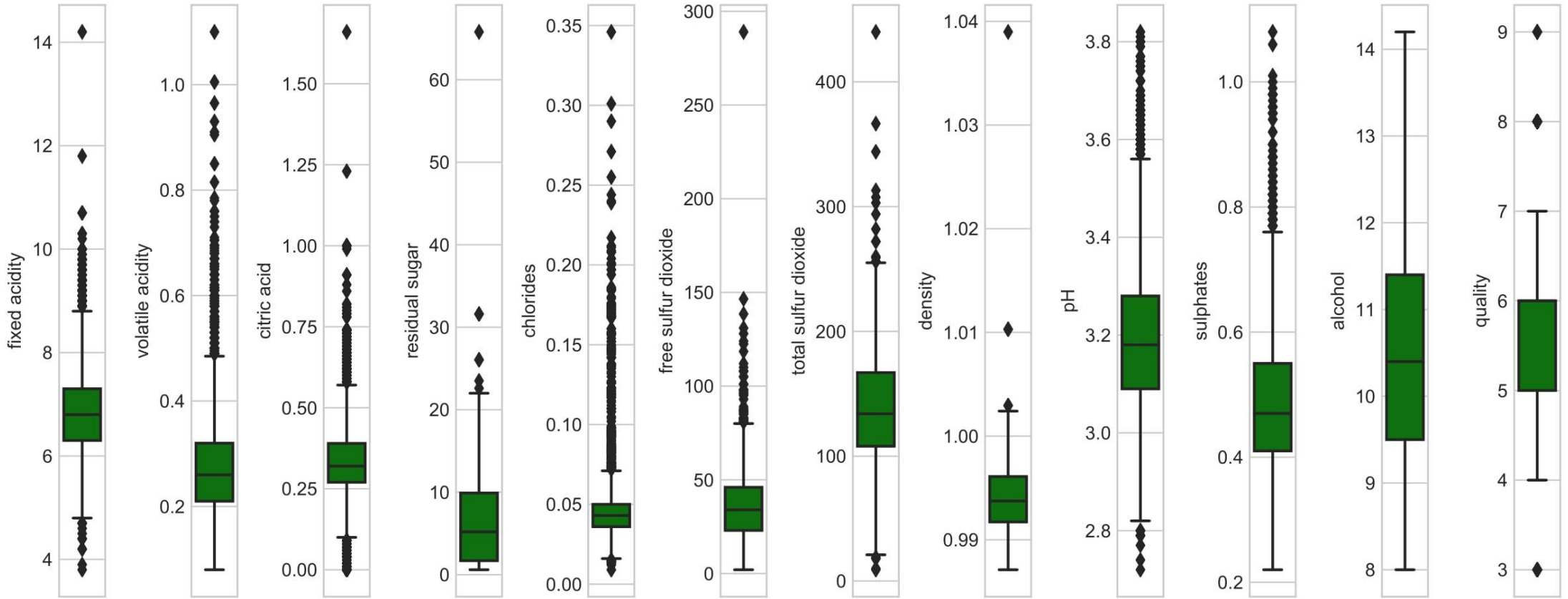


Box Plot

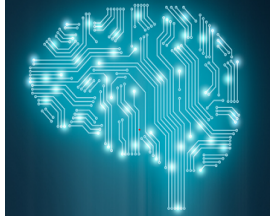
- A box plot (or box-and-whisker plot) shows **the distribution of quantitative data** in a way that facilitates comparisons between variables.
- The **box shows** the **quartiles of the dataset** while the whiskers extend to show the rest of the distribution.
- The box plot (a.k.a. box and whisker diagram) is a standardized way of displaying the distribution of data based on the five number summary



- Minimum
- First quartile
- Median
- Third quartile
- Maximum.
- In the simplest box plot the central rectangle spans the first quartile to the third quartile (the interquartile range or IQR).


fixed acidity
volatile acidity
citric acid
residual sugar
chlorides
free sulfur dioxide
total sulfur dioxide
density
pH
sulphates
alcohol
quality

Feature Engineering: Feature selection



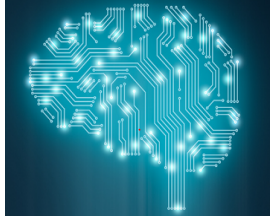
Feature Selection

In statistics and Machine learning, feature selection (also known as variable selection, attribute selection, or variable subset selection) is the practice of choosing a subset of relevant features (predictors and variables) for use in a model construction. It is the automatic selection of attributes present in the data (such as columns in tabular data) that are most significant and appropriate to the predictive modeling problem that one is working on.

Feature Selection and Dimensionality Reduction

Feature selection is different from dimensionality reduction. Both methods work to decrease the number of attributes in the dataset; however, dimensionality reduction works by creating new groupings of attributes, whereas feature selection methods include and remove attributes available in the data without modifying the attributes. Examples of dimensionality reduction methods are principal component analysis, singular value decomposition, and sammon's mapping.

Feature Engineering: Feature selection



Objective of Feature Selection

The objective of feature selection in ML is to identify the best set of features that enable one to build useful and constructive models of the subject one is trying to study. The methods for feature selection in Machine Learning can be classified into the following categories:

- **Supervised methods**: These methods are used for labeled data, and are also used to classify the relevant features for increasing the efficiency of supervised models, such as classification and regression.
- **Unsupervised methods**: These methods are used for unlabelled data.

The advantages of feature selection can be summed up as:

- **Decreases over-fitting**: Less redundant data means less chances of making decisions based on noise.
- **Reduces training time**: Less data means that the algorithms train sooner.
- **Improved accuracy**: Less ambiguous data means improvement of modeling accuracy.

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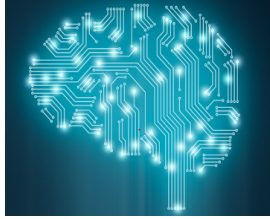
Feature Engineering: Feature selection



From a taxonomic point of view these methods can be classified under:

- **Filter methods**: These methods collect the fundamental properties of the features that are measured through univariate statistics instead of using cross-validation performance. These methods are quicker and less expensive computationally than wrapper methods. While dealing with high-dimensional data, it is computationally cheaper to use filter methods.
- **Wrapper methods**: Wrappers necessitate a method to search the space of all possible subsets of features, assessing a classifier with that feature subset, and evaluating their quality by learning. The feature selection process is based on a particular ML algorithm that one tries to fit on a given dataset. The wrapper methods usually provide a better predictive accuracy than filter methods.
- **Embedded methods**: These methods cover the advantages of both filter and wrapper methods by not only comprising interactions of features but also by retaining a reasonable computational cost.

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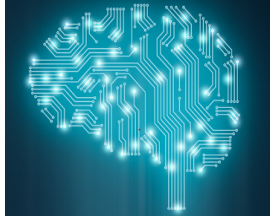


Principal Component Analysis (PCA)

Principal Component Analysis Steps

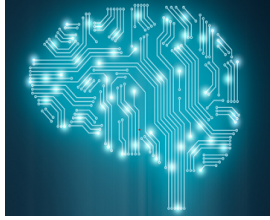
01 Perform standardization on the initial set of continuous variables

02 Find out the covariance matrix

03 Calculate the eigenvectors and eigenvalues of the covariance matrix to arrive at the PCs

04 Figure out which PCs to retain

05 Replot the data on your original axes



Principal Component Analysis (PCA)

1.Standardization of the data

- missing out on standardization will probably result in a biased outcome.
- Standardization is all about scaling your data in such a way that all the variables and their values lie within a similar range
- E.g let's say that we have 2 variables in our data set, one has values ranging between 10-100 and the other has values between 1000-5000.
- In such a scenario, it is obvious that the output calculated by using these predictor variables is going to be biased
- standardizing the data into a comparable range is very important.

$$Z = \frac{Variable\ value - mean}{Standard\ deviation}$$

Principal Component Analysis (PCA)

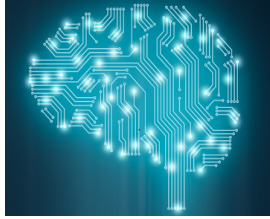
2 Computing the covariance matrix

- A covariance matrix expresses the **correlation between the different variables in the data set**.
- It is essential to identify **heavily dependent variables** because they contain biased and redundant information which reduces the overall performance of the model.
- a covariance matrix is a p × p matrix, where p represents the dimensions of the data set.
- 2-Dimensional data set with **variables a and b**, the covariance matrix is a 2×2 matrix as shown below

$$\begin{bmatrix} Cov(a, a) & Cov(a, b) \\ Cov(b, a) & Cov(b, b) \end{bmatrix}$$

- If the covariance value is negative, it denotes the respective variables are indirectly proportional to each other
- A positive covariance denotes that the respective variables are directly proportional to each other

Principal Component Analysis (PCA)

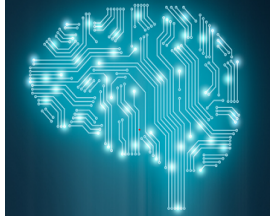


3. Calculating the Eigenvectors and Eigenvalues

Eigenvectors and eigenvalues are computed **from the covariance matrix** in order to determine the principal components of the data set.

What are Principal Components?

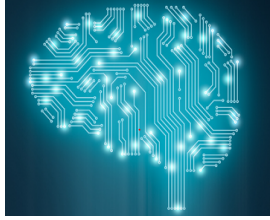
- Principal components are the new set of variables that are obtained from the initial set of variables.
- The principal components are computed in such a manner that newly obtained variables are highly significant and independent of each other.
- The principal components compress and possess most of the useful information that was scattered among the initial variables.
- E.g data set is of 5 dimensions, then 5 principal components are computed, such that, the first principal component stores the maximum possible information and the second one stores the remaining maximum info and so on



Principal Component Analysis (PCA)

4. Computing the Principal Components

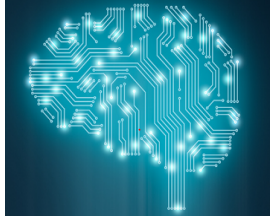
- Eigenvectors and eigenvalues placed in the descending order
- where the **eigenvector with the highest eigenvalue is the most significant** and thus forms the **first principal component**.
- The principal components of **lesser significances can thus be removed** in order to reduce the dimensions of the data.
- The final step in computing the Principal Components is to form a matrix known as **the feature matrix** that contains all the significant data variables that possess maximum information about the data.



Principal Component Analysis (PCA)

5. Reducing the dimensions of the data set

- performing PCA is to **re-arrange the original data** with the final principal components which represent the maximum and the most significant information of the data set.
- In order to **replace the original data axis with the newly formed Principal Components**, you simply multiply the transpose of the original data set by the transpose of the obtained feature vector.
- For iris https://towardsdatascience.com/pca-using-python-scikit-learn-e653f8989e60



T-SNE

https://distill.pub/2016/misread-tsne/

https://colah.github.io/posts/2014-10-Visualizing-MNIST/

t-SNE is t- distributed stochastic neighborhood embedding

- Used dimensionality reduction
- Best technique for visualization
- PCA and t-SNE used in industry
- PCA preserve global structure whereas t-SNE preserve local structure

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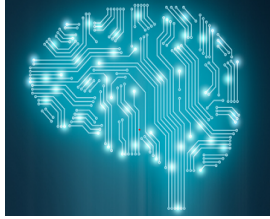

T-SNE.

Neighborhood and Embedding

- Points are geometrically together…….Neighborhood
- Embedding….For every points in high-dim space finding its corresponding points in low dimension

Stochastic …….probabilistic

Geometric intuition…preserving distances of points in neighborhood

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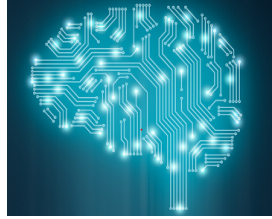
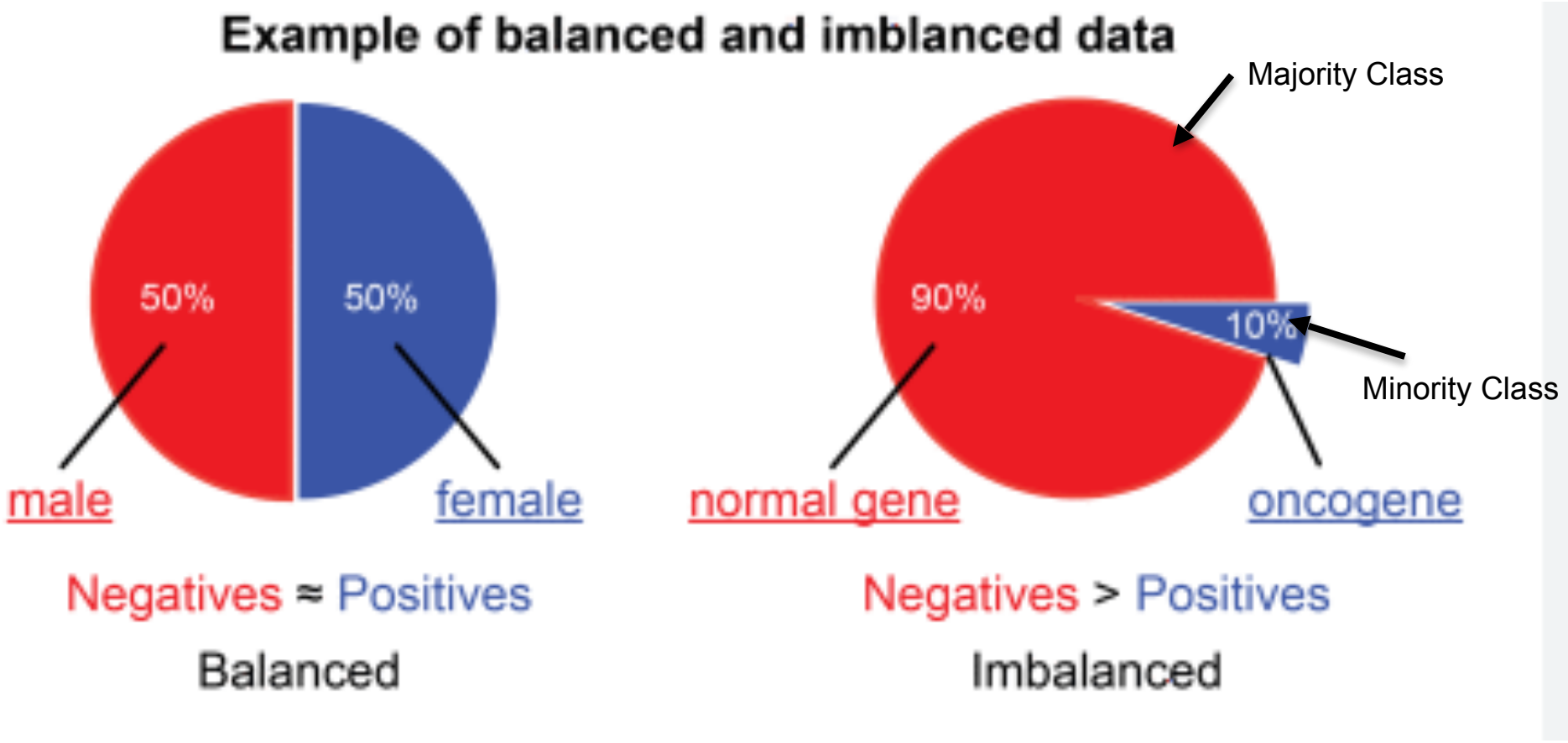
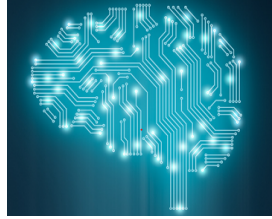
Class Imbalance Problem

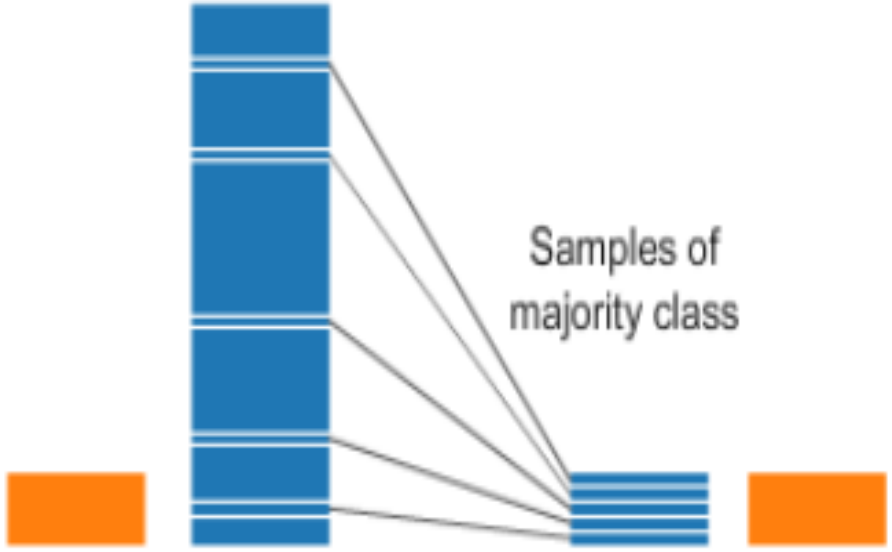
- Problem
  - Class Imbalance: examples in training data belonging to one class heavily outnumber the examples in the other class.
  - Most learning systems assume the training sets to be balanced.
- Result:
  - influence the performance achieved by existing learning systems.
  - The learning system may have difficulties to learn the concept related to the minority class.




Example of balanced and imblanced data
50%
50%
male
female
Negatives ≈ Positives
Balanced
Majority Class
90%
10%
Minority Class
normal gene
oncogene
Negatives > Positives
Imbalanced

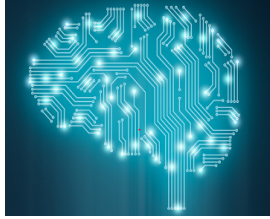


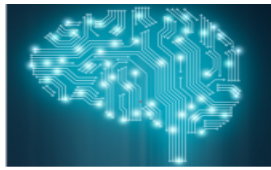
Undersampling



Oversampling

SMOTE(Oversampling)





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SMOTE

Synthetic Minority Over-sampling Technique (SMOTE), is a preprocessing technique used to address a class imbalance in a dataset.

- To form new minority class examples by interpolating between several minority class examples that lie together.
- in ``feature space'' rather than ``data space''
- Algorithm: For each minority class example, introduce synthetic examples along the line segments joining any/all of the k minority class nearest neighbors.
- Note: Depending upon the amount of over-sampling required, neighbors from the *k* nearest neighbors are randomly chosen.

SMOTE

- Synthetic samples are generated in the following way:
  - Take the difference between the feature vector (sample) under consideration and its nearest neighbor.
  - Multiply this difference by a random number between 0 and 1
  - Add it to the feature vector under consideration.

Consider a sample (6,4) and let (4,3) be its nearest neighbor.
(6,4) is the sample for which k-nearest neighbors are being identified
(4,3) is one of its k-nearest neighbors.
Let:
f1_1 = 6 f2_1 = 4 f2_1 - f1_1 = -2
f1_2 = 4 f2_2 = 3 f2_2 - f1_2 = -1
The new samples will be generated as
(f1',f2') = (6,4) + rand(0-1) * (-2,-1)
rand(0-1) generates a random number between 0 and 1.


Thank you