MODULE - 1

CHAPTER-01: Introduction to Machine Learning

Machine Learning (ML) is a promising and flourishing field.

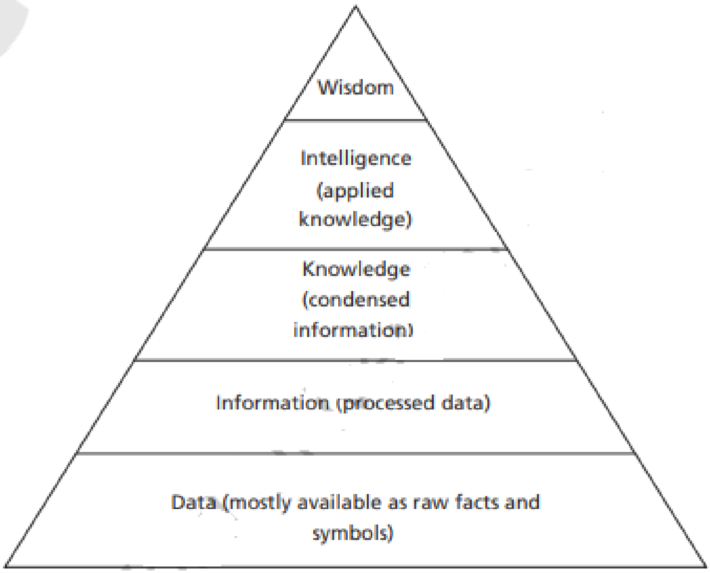
It can enable top management of an organization to extract the knowledge from the data stored in various archives of the business organizations to facilitate decision making.

Such decisions can be useful for organizations to design new products, improve business processes, and to develop decision support systems.

NEED FOR MACHINE LEARNING

- Business organizations use huge amount of data for their daily activities.
- Earlier, the full potential of this data was not utilized due to two reasons.
- One reason was data being scattered across different archive systems and organizations not being able to integrate these sources fully.
- Secondly, the lack of awareness about software tools that could help to unearth the useful information from data.
- But nowadays business organizations have now started to use the latest technology, machine learning, for this purpose.
- Machine learning has become so popular because of three reasons:
    1. **High volume of available data to manage:** Big companies such as Facebook, Twitter, and YouTube generate huge amount of data that grows at a phenomenal rate. It is estimated that the data approximately gets doubled every year.
    2. Second reason is that the **cost of storage has reduced**. The hardware cost has also dropped. Therefore, it is easier now to capture, process, store, distribute, and transmit the digital information.
    3. Third reason for popularity of machine learning is the **availability of complex algorithms** now. Especially with the advent of deep learning, many algorithms are available for machine learning.

With the popularity and ready adaption of machine learning by business organizations, it has become a dominant technology trend now. A knowledge pyramid is shown in Figure.


Wisdom
Intelligence (applied knowledge)
Knowledge (condensed information)
Information (processed data)
Data (mostly available as raw facts and symbols)

Data: All facts are data. Data can be numbers or text that can be processed by a computer. Today, organizations are accumulating vast and growing amounts of data with data sources such as flat files, databases, or data warehouses in different storage formats.

Information: Processed data is called information. This includes patterns, associations, or relationships among data.

Knowledge: Condensed information is called knowledge. Unless knowledge is extracted, data is of no use. Similarly, knowledge is not useful unless it is put into action.

Intelligence is the applied knowledge for actions. An actionable form of knowledge is called intelligence. Computer systems have been successful till this stage.

The ultimate objective of knowledge pyramid is **wisdom** that represents the maturity of mind that is, so far, exhibited only by humans.

MACHINE LEARNING EXPLAINED

- Machine learning is an important sub-branch of Artificial Intelligence (AI).
- A frequently quoted definition of machine learning was by Arthur Samuel, one of the pioneers of Artificial Intelligence.
- **Arthur Samuel** stated that "**Machine learning is the field of study that gives the computers ability to learn without being explicitly programmed.**"
- In conventional programming, after understanding the problem, a detailed design of the program such as a flowchart or an algorithm needs to be created and converted into programs using a suitable programming language. This approach could be difficult for many real-world problems such as puzzles, games, and complex image recognition applications.
- Initially, artificial intelligence aims to understand these problems and develop general purpose rules manually. Then, these rules are formulated into logic and implemented in a program to create intelligent systems.
- This idea of developing intelligent systems by using logic and reasoning by converting an expert's knowledge into a set of rules and programs is called an expert system.
- The expert system approach was impractical in many domains as programs still depended on human expertise and hence did not truly exhibit intelligence.
- The focus of AI is to develop intelligent systems by using data-driven approach, where data is used as an input to develop intelligent models.
- The models can then be used to predict new inputs. Thus, the aim of machine learning is to learn a model or set of rules from the given dataset automatically so that it can predict the unknown data correctly.

- As humans take decisions based on an experience, computers make models based on extracted patterns in the input data and then use these data-filled models for prediction and to take decisions. For computers, the learnt model is equivalent to human experience.

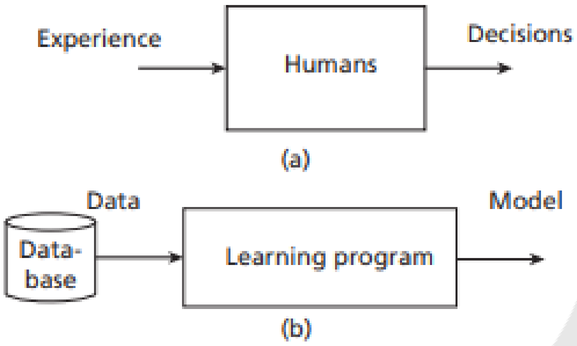


Figure 1.2: (a) A Learning System for Humans (b) A Learning System for Machine Learning

- Often, the quality of data determines the quality of experience and, therefore, the quality of the learning system. In statistical learning, the relationship between the input x and output y is modelled as a function in the form y = f(x). Here, f is the learning function that maps the input x to output y.
- A model can be a formula, procedure or representation that can generate data decisions. The difference between pattern and model is that the former is local and applicable only to certain attributes but the latter is global and fits the entire dataset.
- Another pioneer of AI, **Tom Mitchell's** definition of machine learning states that, "**A computer program is said to learn from experience E, with respect to task T and some performance measure P, if its performance on T measured by P improves with experience E.**" The important components of this definition are experience E, task T, and performance measure P.
- Models of computer systems are equivalent to human experience.
- Once the knowledge is gained, when a new problem is encountered, humans search for similar past situations and then formulate the heuristics and use that for prediction.
- But, in systems, experience is gathered by these steps:
  1. Collection of data
  2. Once data is gathered, abstract concepts are formed out of that data. Abstraction is used to generate concepts..
  3. Generalization converts the abstraction into an actionable form of intelligence. It can be viewed as ordering of all possible concepts.
  4. Heuristics normally works! But, occasionally, it may fail too. It is not the fault of heuristics as it is just a 'rule of thumb′. The course correction is done by taking evaluation measures.

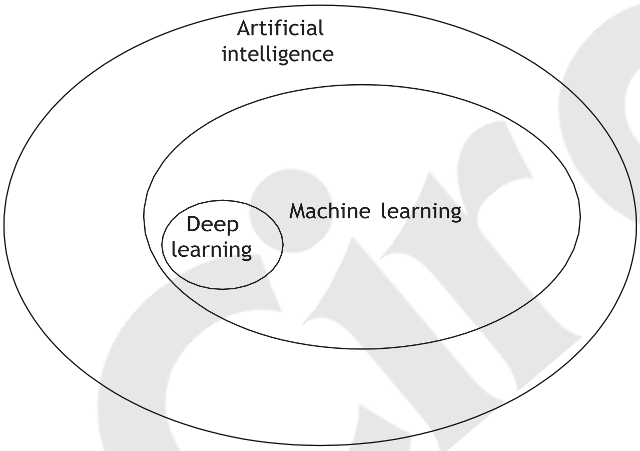
Evaluation checks the thoroughness of the models and to-do course correction, if necessary, to generate better formulations.

MACHINE LEARNING IN RELATION TO OTHER FIELDS

Machine learning uses the concepts of Artificial Intelligence, Data Science, and Statistics primarily. It is the resultant of combined ideas of diverse fields.

Machine Learning and Artificial Intelligence

Machine learning is an important branch of AI, which is a much broader subject. The aim of AI is to develop intelligent agents. An agent can be a robot, humans, or any autonomous systems. Initially, the idea of AI was ambitious, that is, to develop intelligent systems like human beings. The focus was on logic and logical inferences. It had seen many ups and downs. These down periods were called AI winters.



Deep learning is a subbranch of machine learning. In deep learning, the models are constructed using neural network technology. Neural networks are based on the human neuron models. Many neurons form a network connected with the activation functions that trigger further neurons to perform tasks.

Machine Learning, Data Science, Data Mining, and Data Analytics

Data science is an 'Umbrella' term that encompasses many fields. Machine learning starts with data. Therefore, data science and machine learning are interlinked. Machine learning is a branch of data science. Data science deals with gathering of data for analysis. It is a broad field that includes:

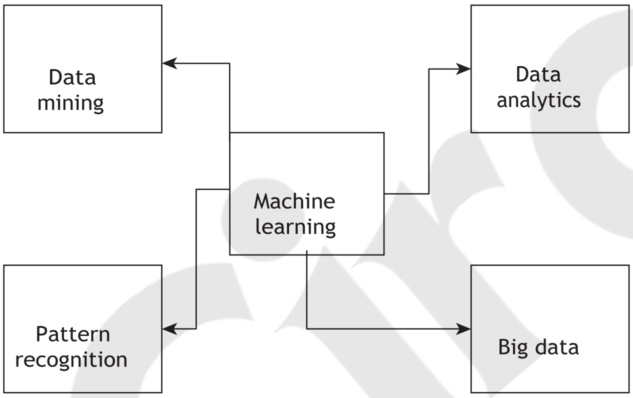
Big Data Data science concerns about collection of data. Big data is a field of data science that deals with data's following characteristics:

1. **Volume:** Huge amount of data is generated by big companies like Facebook, Twitter, YouTube.
2. **Variety:** Data is available in variety of forms like images, videos, and in different formats.
3. **Velocity:** It refers to the speed at which the data is generated and processed.

Data Mining Data mining's original genesis is in the business. Like while mining the earth one gets into precious resources, it is often believed that unearthing of the data produces hidden information that otherwise would have eluded the attention of the management. There is no difference between these fields except that data mining aims to extract the hidden patterns that are present in the data, whereas, machine learning aims to use it for prediction.

Data Analytics Another branch of data science is data analytics. It aims to extract useful knowledge from crude data. There are different types of analytics. Predictive data analytics is used for making predictions. Machine learning is closely related to this branch of analytics and shares almost all algorithms.

Pattern Recognition It is an engineering field. It uses machine learning algorithms to extract the features for pattern analysis and pattern classification. One can view pattern recognition as a specific application of machine learning.



Machine Learning and Statistics

Statistics is a branch of mathematics that has a solid theoretical foundation regarding statistical learning. Like machine learning (ML), it can learn from data. But the difference between statistics and ML is that statistical methods look for regularity in data called patterns. Initially, statistics sets a hypothesis and performs experiments to verify and validate the hypothesis in order to find relationships among data.

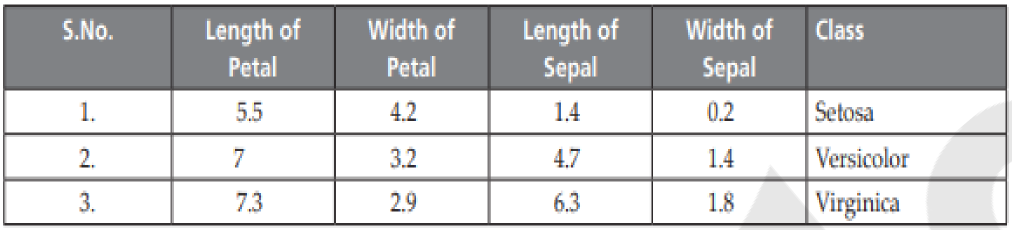
Statistics requires knowledge of the statistical procedures and the guidance of a good statistician. Machine learning, comparatively, has less assumptions and requires less statistical knowledge. But, it often requires interaction with various tools to automate the process of learning.

TYPES OF MACHINE LEARNING

- Data is a raw fact. Normally, data is represented in the form of a table. Data also can be referred to as a data point, sample, or an example. Each row of the table represents a data point.
- Features are attributes or characteristics of an object. Normally, the columns of the table are attributes.
- Out of all attributes, one attribute is important and is called a label. Label is the feature that we aim to predict.

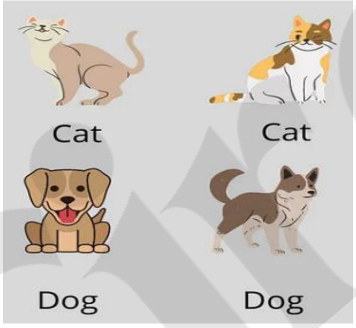
- Thus, there are two types of data – labelled and unlabelled.
- **Labeled data** is data that has some predefined tags such as name, type, or number.

  To illustrate labelled data, let us take one example dataset called Iris flower dataset. The dataset has 3 samples of Iris – with four attributes, length and width of sepals and petals. The **target variable** is called **class**. There are three classes – **Iris setosa, Iris virginica, and Iris versicolor**.

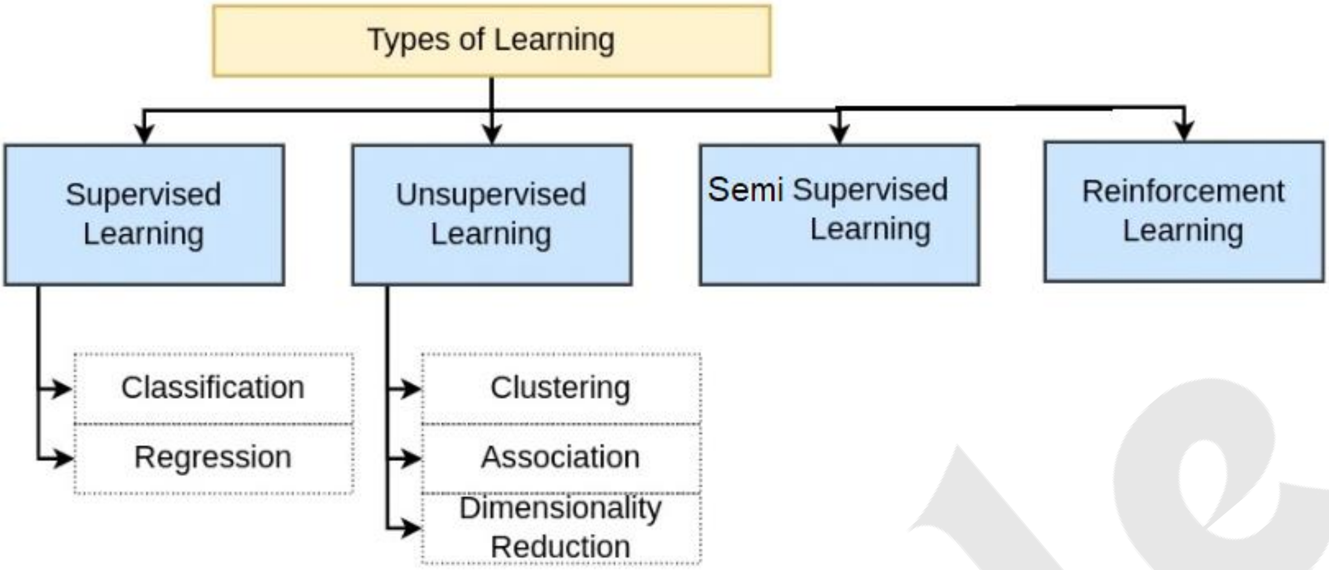


S.No.	Length of Petal	Width of Petal	Length of Sepal	Width of Sepal	Class
1.	5.5	4.2	1.4	0.2	Setosa
2.	7	3.2	4.7	1.4	Versicolor
3.	7.3	2.9	6.3	1.8	Virginica

A dataset need not be always numbers. It can be images or video frames. Deep neural networks can handle images with labels.

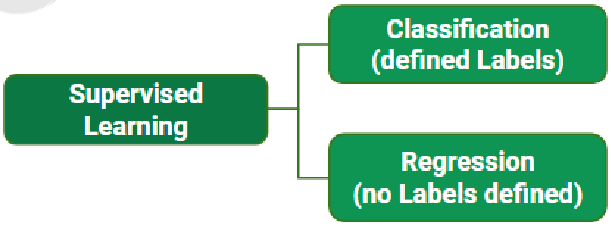


- **Unlabelled data**: Any data that does not have any labels specifying its characteristics, identity, classification, or properties can be considered unlabelled data. In unlabelled data, there are no labels in the dataset.



1. Supervised Learning

- Supervised algorithms use labelled dataset. There is a supervisor or teacher component in supervised learning.
- A supervisor provides labelled data so that the model is constructed and generates test data.
- In supervised learning algorithms, learning takes place in two stages.
  - ➢ **First stage**, the teacher communicates the information to the student that the student is supposed to master. The student receives the information and understands it. During this stage, the teacher has no knowledge of whether the information is grasped by the student.
  - ➢ In **Second stage** of learning, the teacher asks the student a set of questions to find out how much information has been grasped by the student. Based on these questions, the student is tested, and the teacher informs the student about his assessment. This kind of learning is typically called supervised learning.
- Supervised learning has two methods:


Supervised Learning
Classification (defined Labels)
Regression (no Labels defined)

i) Classification

Classification is a supervised learning method.

The input attributes of the classification algorithms are called **independent variables.**

The target attribute is called **label** or **dependent variable**.

The relationship between the input and target variable is represented in the form of a structure which is called a **classification model**.

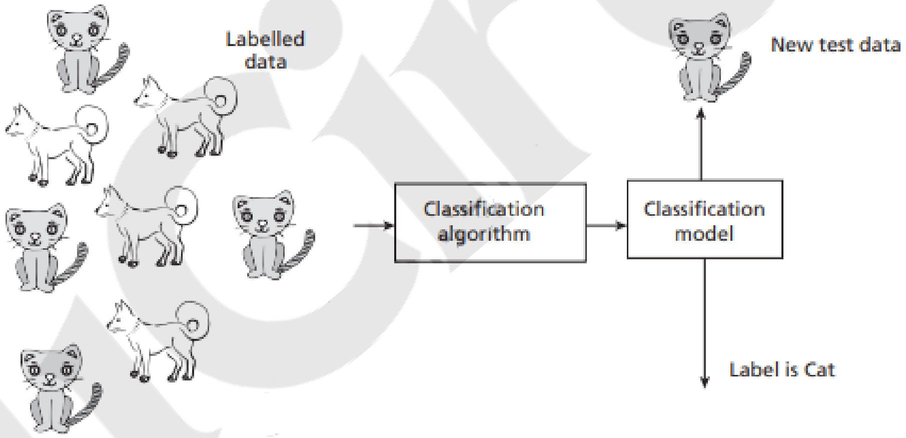
So, the focus of classification is to predict the ‘label’ that is in a discrete form (a value from the set of finite values).

An example were figure shows a classification algorithm takes a set of labelled data images such as dogs and cats to construct a model that can later be used to classify an unknown test image data.

In classification, learning takes place in two stages.

During the **first stage**, called training stage, the learning algorithm takes a labelled dataset and starts learning. After the training set, samples are processed and the model is generated. In the **second stage**, the constructed model is tested with test or unknown sample and assigned a label. This is the classification process.

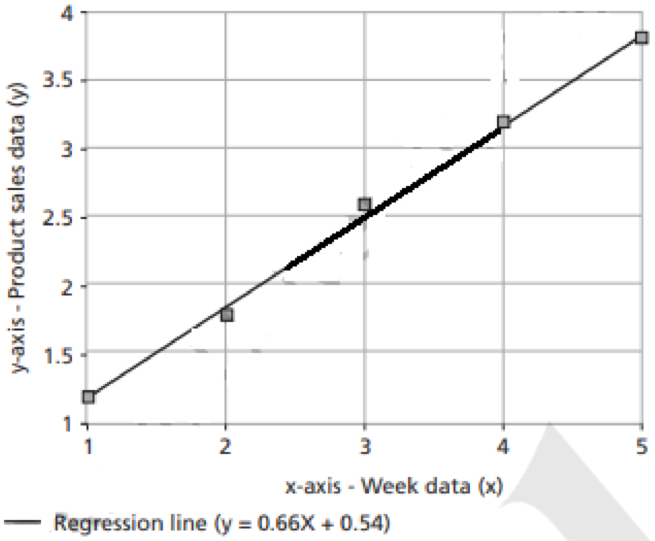
Some of the key algorithms of classification are **Decision Tree, Random Forest, Support Vector Machines, Naïve Bayes, Artificial Neural Network** and **Deep Learning networks like CNN.**



ii) Regression Models

Regression models, unlike classification algorithms, predict continuous variables like price. In other words, it is a number.

A fitted regression model is shown in Figure for a dataset that represent weeks input x and product sales y.



The regression model takes input x and generates a model in the form of a fitted line of the form y = f(x).

Here, x is the independent variable that may be one or more attributes and y is the dependent variable.

The advantage of this model is that prediction for product sales (y) can be made for unknown week data (x).

One of the most important regression algorithms is linear regression.

Difference between classification and Regression

Regression Algorithm	**Classification Algorithm**
In Regression, the output variable must be of continuous nature or real value.	In Classification, the output variable must be a discrete value.
The task of the regression algorithm is to map the input value (x) with the continuous output variable(y).	The task of the classification algorithm is to map the input value(x) with the discrete output variable(y).
Regression Algorithms are used with continuous data.	Classification Algorithms are used with discrete data.
In Regression, we try to find the best fit line, which can predict the output more accurately.	In Classification, we try to find the decision boundary, which can divide the dataset into different classes.
Regression algorithms can be used to solve the regression problems such as Weather Prediction, House price prediction, etc.	Classification Algorithms can be used to solve classification problems such as Identification of spam emails, Speech Recognition, Identification of cancer cells, etc.
The regression Algorithm can be further divided into Linear and Non-linear Regression.	The Classification algorithms can be divided into Binary Classifier and Multi-class Classifier.

2. Unsupervised Learning

- The second kind of learning is by self-instruction. As the name suggests, there are no supervisor or teacher components.
- In the absence of a supervisor or teacher, self-instruction is the most common kind of learning process.
- This process of self-instruction is based on the concept of trial and error. Here, the program is supplied with objects, but no labels are defined.
- The algorithm itself observes the examples and recognizes patterns based on the principles of grouping. Grouping is done in ways that similar objects form the same group.
- Cluster analysis and Dimensional reduction algorithms are examples of unsupervised algorithms.

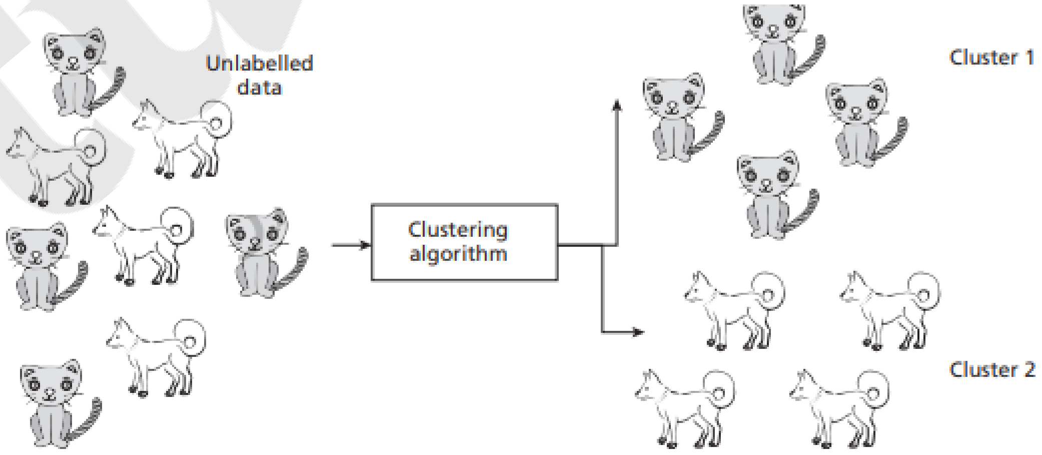
i) Cluster Analysis

Cluster analysis aims to group objects into disjoint clusters or groups. Cluster analysis clusters objects based on its attributes.

All the data objects of the partitions are similar in some aspect and vary from the data objects in the other partitions significantly.

Some of the examples of clustering processes are — segmentation of a region of interest in an image, detection of abnormal growth in a medical image, and determining clusters of signatures in a gene database.

Example: The clustering algorithm takes a set of dogs and cats images and groups it as two clusters-dogs and cats. It can be observed that the samples belonging to a cluster are similar and samples are different radically across clusters.



Some of the key clustering algorithms are: k-means algorithm , Hierarchical algorithms.

ii) Dimensionality Reduction

Dimensionality reduction algorithms are examples of unsupervised algorithms.

It takes a higher dimension data as input and outputs the data in lower dimension by taking advantage of the variance of the data.

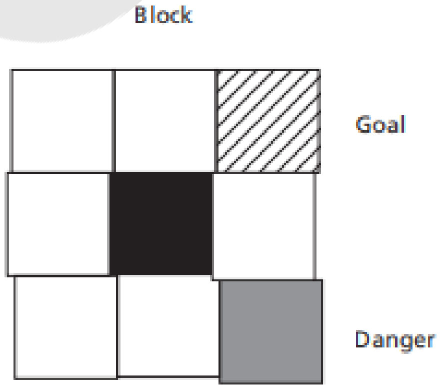
It is a task of reducing the dataset with few features without losing the generality.

3. Semi-supervised Learning

- There are circumstances where the dataset has a huge collection of unlabelled data and some labelled data.
- Labelling is a costly process and difficult to perform by the humans.
- Semi-supervised algorithms use unlabelled data by assigning a pseudo-label. Then, the labelled and pseudo-labelled dataset can be combined.

4. Reinforcement Learning

- Reinforcement learning mimics human beings. Like human beings use ears and eyes to perceive the world and take actions, reinforcement learning allows the agent to interact with the environment to get rewards.
- The agent can be human, animal, robot, or any independent program.
- The rewards enable the agent to gain experience. The agent aims to maximize the reward.
- The reward can be positive or negative (Punishment). When the rewards are more, the behavior gets reinforced and learning becomes possible.
- Consider the following example of a Grid game as shown



- In this grid game, the gray tile indicates the danger, black is a block, and the tile with diagonal lines is the goal. The aim is to start, say from bottom-left grid, using the actions left, right, top and bottom to reach the goal state.
- To solve this sort of problem, there is no data. The agent interacts with the environment to get experience.
- In the above case, the agent tries to create a model by simulating many paths and finding rewarding paths. This experience helps in constructing a model.

Difference between Supervised and unsupervised Learning

Supervised Learning	Unsupervised Learning
Supervised learning algorithms are trained using labeled data.	Unsupervised learning algorithms are trained using unlabeled data.
Supervised learning model takes direct feedback to check if it is predicting correct output or not.	Unsupervised learning model does not take any feedback.
Supervised learning model predicts the output.	Unsupervised learning model finds the hidden patterns in data.
In supervised learning, input data is provided to the model along with the output.	In unsupervised learning, only input data is provided to the model.
The goal of supervised learning is to train the model so that it can predict the output when it is given new data.	The goal of unsupervised learning is to find the hidden patterns and useful insights from the unknown dataset.
Supervised learning needs supervision to train the model.	Unsupervised learning does not need any supervision to train the model.
Supervised learning can be categorized in **Classification** and **Regression** problems.	Unsupervised Learning can be classified in **Clustering** and **Associations** problems.
Supervised learning can be used for those cases where we know the input as well as corresponding outputs.	Unsupervised learning can be used for those cases where we have only input data and no corresponding output data.
Supervised learning model produces an accurate result.	Unsupervised learning model may give less accurate result as compared to supervised learning.
Supervised learning is not close to true Artificial intelligence as in this, we first train the model for each data, and then only it can predict the correct output.	Unsupervised learning is more close to the true Artificial Intelligence as it learns similarly as a child learns daily routine things by his experiences.
It includes various algorithms such as Linear Regression, Logistic Regression, Support Vector Machine, Multi-class Classification, Decision tree, Bayesian Logic, etc.	It includes various algorithms such as Clustering, KNN, and Apriori algorithm.

CHALLENGES OF MACHINE LEARNING

Computers are better than humans in performing tasks like computation. For example, while calculating the square root of large numbers, an average human may blink but computers can display the result in seconds.

Computers can play games like chess, GO, and even beat professional players of that game.

However, humans are better than computers in many aspects like recognition. But, deep learning systems challenge human beings in this aspect as well. Machines can recognize human faces in a second.

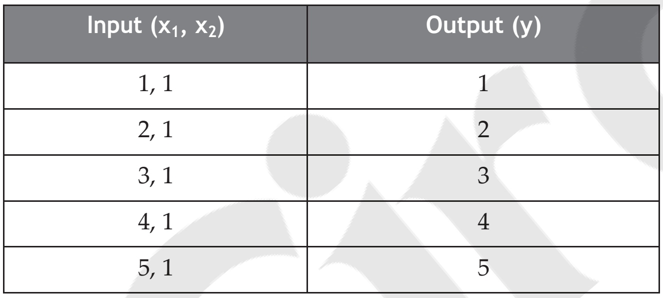
Still, there are tasks where humans are better as machine learning systems still require quality data for model construction.

The quality of a learning system depends on the quality of data. This is a challenge.

Some of the challenges are listed below:

1. **Problems** – Machine learning can deal with the 'well-posed' problems where specifications are complete and available. Computers cannot solve 'ill-posed' problems.

Consider one simple example



Input (x_1, x_2)	Output (y)
1, 1	1
2, 1	2
3, 1	3
4, 1	4
5, 1	5

Can a model for this test data be multiplication? That is, y = x1 × x2. . Well! It is true! But, this is equally true that y may be y = x1 ÷ x2 , or y = x1 x2. So, there are three functions that fit the data.

This means that the problem is ill-posed. To solve this problem, one needs more example to check the model.

2**. Huge data** – This is a primary requirement of machine learning. Availability of a quality data is a challenge. A quality data means it should be large and should not have data problems such as missing data or incorrect data.

3. **High computation power** – With the availability of Big Data, the computational resource requirement has also increased. Systems with Graphics Processing Unit (GPU) or even Tensor Processing Unit (TPU) are required to execute machine learning algorithms. Also, machine learning tasks have become complex and hence time complexity has increased, and that can be solved only with high computing power.

4. **Complexity of the algorithms** – The selection of algorithms, describing the algorithms, application of algorithms to solve machine learning task, and comparison of algorithms have become necessary for machine learning or data scientists now.

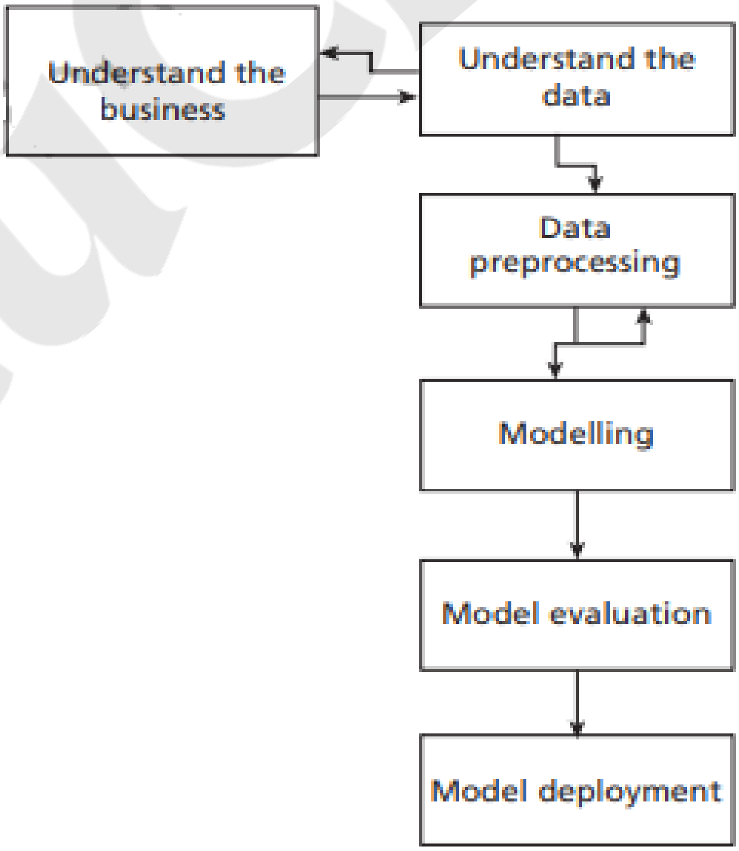
5. **Bias/Variance** – Variance is the error of the model. This leads to a problem called bias/ variance tradeoff. A model that fits the training data correctly but fails for test data, in general lacks

generalization, is called **overfitting**. The reverse problem is called **underfitting** where the model fails for training data but has good generalization.

MACHINE LEARNING PROCESS

The emerging process model for the data mining solutions for business organizations is CRISP-DM. This process involves six steps. The steps are listed below

1. **Understanding the business** – This step involves understanding the objectives and requirements of the business organization. Generally, a single data mining algorithm is enough for giving the solution. This step also involves the formulation of the problem statement for the data mining process.
2. **Understanding the data** – It involves the steps like data collection, study of the characteristics of the data, formulation of hypothesis, and matching of patterns to the selected hypothesis.
3. **Preparation of data** – This step involves producing the final dataset by cleaning the raw data and preparation of data for the data mining process. The missing values may cause problems during both training and testing phases. Missing data forces classifiers to produce inaccurate results.
4. **Modelling** – This step plays a role in the application of data mining algorithm for the data to obtain a model or pattern.



5. **Evaluate** – This step involves the evaluation of the data mining results using statistical analysis and visualization methods. The performance of the classifier is determined by evaluating the accuracy of the classifier. The process of classification is a fuzzy issue.
6. **Deployment** – This step involves the deployment of results of the data mining algorithm to improve the existing process or for a new situation.

MACHINE LEARNING APPLICATIONS

Machine Learning technologies are used widely now in different domains One encounters many machine learning applications in the day-to-day life. Some applications are listed below:

1. **Sentiment analysis** – This is an application of natural language processing (NLP) where the words of documents are converted to sentiments like happy, sad, and angry which are captured by emoticons effectively. For movie reviews or product reviews, five stars or one star are automatically attached using sentiment analysis programs.

2. **Recommendation systems** – These are systems that make personalized purchases possible. For example, Amazon recommends users to find related books or books bought by people who have the same taste like you, and Netflix suggests shows or related movies of your taste. The recommendation systems are based on machine learning.

3. **Voice assistants** – Products like Amazon Alexa, Microsoft Cortana, Apple Siri, and Google Assistant are all examples of voice assistants. They take speech commands and perform tasks. These chatbots are the result of machine learning technologies.

4. **Technologies** like Google Maps and those used by Uber are all examples of machine learning which offer to locate and navigate shortest paths to reduce time.

The machine learning applications are enormous. The following Table summarizes some of the machine learning applications.

S.No.	Problem Domain	Applications
1.	Business	Predicting the bankruptcy of a business firm
2.	Banking	Prediction of bank loan defaulters and detecting credit card frauds
3.	Image Processing	Image search engines, object identification, image classification, and generating synthetic images
4.	Audio/Voice	Chatbots like Alexa, Microsoft Cortana. Developing chatbots forcustomer support, speech to text, and text to voice

5.	Telecommunication	Trend analysis and identification of bogus calls, fraudulent calls and its callers, churn analysis
6.	Marketing	Retail sales analysis, market basket analysis, product performance analysis, market segmentation analysis, and study of travel patterns of customers for marketing tours
7.	Games	Game programs for Chess, GO, and Atari video games
8.	Natural Language Translation	Google Translate, Text summarization, and sentiment analysis
9.	Web Analysis and Services	Identification of access patterns, detection of e-mail spams, viruses, personalized web services, search engines like Google, detection of promotion of user websites, and finding loyalty of users after web page layout modification
10.	Medicine	Prediction of diseases, given disease symptoms as cancer or diabetes. Prediction of effectiveness of the treatment using patient history and Chatbots to interact with patients like IBM Watson uses machine learning technologies.
11.	Multimedia and Security	Face recognition/identification, biometric projects like identification of a person from a large image or video database, and applications involving multimedia retrieval
12.	Scientific Domain	Discovery of new galaxies, identification of groups of houses based on house type/geographical location, identification of earthquake epicenters, and identification of similar land use

KEY TERMS:

- **Machine Learning** – A branch of AI that concerns about machines to learn automatically without being explicitly programmed.
- **Data** – A raw fact.
- **Model** – An explicit description of patterns in a data.
- **Experience** – A collection of knowledge and heuristics in humans and historical training data in case of machines.
- **Predictive Modelling** – A technique of developing models and making a prediction of unseen data.
- **Deep Learning** – A branch of machine learning that deals with constructing models using neural networks.
- **Data Science** – A field of study that encompasses capturing of data to its analysis covering all stages of data management.
- **Data Analytics** – A field of study that deals with analysis of data.
- **Big Data** – A study of data that has characteristics of volume, variety, and velocity.
- **Statistics** – A branch of mathematics that deals with learning from data using statistical methods.
- **Hypothesis** – An initial assumption of an experiment.

- **Learning** – Adapting to the environment that happens because of interaction of an agent with the environment.
- **Label** – A target attribute.
- **Labelled Data** – A data that is associated with a label.
- **Unlabelled Data** – A data without labels.
- **Supervised Learning** – A type of machine learning that uses labelled data and learns with the help of a supervisor or teacher component.
- **Classification Program** – A supervisory learning method that takes an unknown input and assigns a label for it. In simple words, finds the category of class of the input attributes.
- **Regression Analysis** – A supervisory method that predicts the continuous variables based on the input variables.
- **Unsupervised Learning** – A type of machine leaning that uses unlabelled data and groups the attributes to clusters using a trial and error approach.
- **Cluster Analysis** – A type of unsupervised approach that groups the objects based on attributes so that similar objects or data points form a cluster.
- **Semi-supervised Learning** – A type of machine learning that uses limited labelled and large unlabeled data. It first labels unlabelled data using labelled data and combines it for learning purposes.
- **Reinforcement Learning** – A type of machine learning that uses agents and environment interaction for creating labelled data for learning.
- **Well-posed Problem** – A problem that has well-defined specifications. Otherwise, the problem is called ill-posed.
- **Bias/Variance** – The inability of the machine learning algorithm to predict correctly due to lack of generalization is called bias. Variance is the error of the model for training data. This leads to problems called overfitting and underfitting.
- **Model Deployment** – A method of deploying machine learning algorithms to improve the existing business processes for a new situation.

CHAPTER-02: Understanding Data

WHAT IS DATA?

- All facts are data. In computer systems, bits encode facts present in numbers, text, images, audio, and video.
- Data such as numbers or texts can be directly human interpretable or diffused data such as images or video that can be interpreted only by a computer.
- Data is available in different data sources like flat files, databases, or data warehouses. It can either be an operational data or a non-operational data.
- **Operational data** is the one that is encountered in normal business procedures and processes. For example, daily sales data is operational data.
- **Non-operational data** is the kind of data that is used for decision making.
- Data by itself is meaningless. It has to be processed to generate any information. A string of bytes is meaningless. Only when a label is attached, the data becomes meaningful.
- Processed data is called information that includes patterns, associations, or relationships among data.
- Data whose volume is less and can be stored and processed by a small-scale computer is called 'small data'. These data are collected from several sources, and integrated and processed by a small-scale computer.
- Big data, on the other hand, is a larger data whose volume is much larger than 'small data' and is characterized as follows:

  1. Volume – Since there is a reduction in the cost of storing devices, there has been a tremendous growth of data. Small traditional data is measured in terms of gigabytes (GB) and terabytes (TB), but Big Data is measured in terms of petabytes (PB) and exabytes (EB). One exabyte is 1 million terabytes.

  2. Velocity – The fast arrival speed of data and its increase in data volume is noted as velocity. The availability of IoT devices and Internet power ensures that the data is arriving at a faster rate. Velocity helps to understand the relative growth of big data and its accessibility by users, systems and applications.

  3. Variety – The variety of Big Data includes:

  Form – There are many forms of data. Data types range from text, graph, audio, video, to maps. There can be composite data too, where one media can have many other sources of data, for example, a video can have an audio song.

  Function – These are data from various sources like human conversations, transaction records, and old archive data.

Source of data – This is the third aspect of variety. There are many sources of data. Broadly, the data source can be classified as open/public data, social media data and multimodal data.

Some of the other forms of Vs that are often quoted in the literature as characteristics of Big data are:

Veracity of data – Veracity of data deals with aspects like conformity to the facts, truthfulness, believablity, and confidence in data. There may be many sources of error such as technical errors, typographical errors, and human errors. So, veracity is one of the most important aspects of data.

Validity – Validity is the accuracy of the data for taking decisions or for any other goals that are needed by the given problem.

Value – Value is the characteristic of big data that indicates the value of the information that is extracted from the data and its influence on the decisions that are taken based on it. Thus, these 6 Vs are helpful to characterize the big data.

- The data quality of the numeric attributes is determined by factors like precision, bias, and accuracy. Precision is defined as the closeness of repeated measurements. Often, standard deviation is used to measure the precision.
- Bias is a systematic result due to erroneous assumptions of the algorithms or procedures.
- Accuracy is the degree of measurement of errors that refers to the closeness of measurements to the true value of the quantity. Normally, the significant digits used to store and manipulate indicate the accuracy of the measurement.

TYPES OF DATA

In Big Data, there are three kinds of data. They are structured data, unstructured data, and semistructured data.

Structured Data:

In structured data, data is stored in an organized manner such as a database where it is available in the form of a table. The data can also be retrieved in an organized manner using tools like SQL. The structured data frequently encountered in machine learning are listed below:

- **Record Data** A dataset is a collection of measurements taken from a process. We have a collection of objects in a dataset and each object has a set of measurements. The measurements can be arranged in the form of a matrix. Rows in the matrix represent an object and can be called as entities, cases, or records. The columns of the dataset are called attributes, features, or fields. The table is filled with observed data. Also, it is better to note the general jargons that are associated with the dataset. Label is the term that is used to describe the individual observations.

- **Data Matrix** It is a variation of the record type because it consists of numeric attributes. The standard matrix operations can be applied on these data. The data is thought of as points or vectors in the multidimensional space where every attribute is a dimension describing the object.
- **Graph Data** It involves the relationships among objects. For example, a web page can refer to another web page. This can be modeled as a graph. The modes are web pages and the hyperlink is an edge that connects the nodes.
- **Ordered Data** Ordered data objects involve attributes that have an implicit order among them. The examples of ordered data are:
  - ❖ **Temporal data** – It is the data whose attributes are associated with time. For example, the customer purchasing patterns during festival time is sequential data. Time series data is a special type of sequence data where the data is a series of measurements over time.
  - ❖ **Sequence data** – It is like sequential data but does not have time stamps. This data involves the sequence of words or letters. For example, DNA data is a sequence of four characters – A T G C.
  - ❖ **Spatial data** – It has attributes such as positions or areas. For example, maps are spatial data where the points are related by location.

Unstructured Data

Unstructured data includes video, image, and audio. It also includes textual documents, programs, and blog data. It is estimated that 80% of the data are unstructured data.

Semi-Structured Data

Semi-structured data are partially structured and partially unstructured. These include data like XML/JSON data, RSS feeds, and hierarchical data.

DATA STORAGE AND REPRESENTATION

Once the dataset is assembled, it must be stored in a structure that is suitable for data analysis.

The goal of data storage management is to make data available for analysis. There are different approaches to organize and manage data in storage files and systems from flat file to data warehouses.

Some of them are listed below:

Flat Files These are the simplest and most commonly available data source. It is also the cheapest way of organizing the data. These flat files are the files where data is stored in plain ASCII or EBCDIC format. Minor changes of data in flat files affect the results of the data mining algorithms.

Hence, flat file is suitable only for storing small dataset and not desirable if the dataset becomes larger.

Some of the popular spreadsheet formats are listed below:

- **CSV files** – CSV stands for comma-separated value files where the values are separated by commas. These are used by spreadsheet and database applications. The first row may have attributes and the rest of the rows represent the data.

- **TSV files** – TSV stands for Tab separated values files where values are separated by Tab. Both CSV and TSV files are generic in nature and can be shared. There are many tools like Google Sheets and Microsoft Excel to process these files.

Database System It normally consists of database files and a database management system (DBMS). Database files contain original data and metadata.

DBMS aims to manage data and improve operator performance by including various tools like database administrator, query processing, and transaction manager.

A relational database consists of sets of tables. The tables have rows and columns. The columns represent the attributes and rows represent tuples.

A tuple corresponds to either an object or a relationship between objects. A user can access and manipulate the data in the database using SQL.

Different types of databases are listed below:

- **Transactional database** is a collection of transactional records. Each record is a transaction. A transaction may have a time stamp, identifier and a set of items, which may have links to other tables. Normally, transaction databases are created for performing associational analysis that indicates the correlation among the items.
- **Time-series database** stores time related information like log files where data is associated with a time stamp. This data represents the sequences of data, which represent values or events obtained over a period (for example, hourly, weekly or yearly) or repeated time span. Observing sales of product continuously may yield a time-series data.
- **Spatial databases** contain spatial information in a raster or vector format. Raster formats are either bitmaps or pixel maps. For example, images can be stored as a raster data. On the other hand, the vector format can be used to store maps as maps use basic geometric primitives like points, lines, polygons and so forth.
- **World Wide Web (WWW)** It provides a diverse, worldwide online information source. The objective of data mining algorithms is to mine interesting patterns of information present in WWW.
- **XML (eXtensible Markup Language)** It is both human and machine interpretable data format that can be used to represent data that needs to be shared across the platforms.
- **Data Stream** It is dynamic data, which flows in and out of the observing environment. Typical characteristics of data stream are huge volume of data, dynamic, fixed order movement, and realtime constraints.
- **RSS (Really Simple Syndication)** It is a format for sharing instant feeds across services.
- **JSON (JavaScript Object Notation)** It is another useful data interchange format that is often used for many machine learning algorithms.

BIG DATA ANALYTICS AND TYPES OF ANALYTICS

- The primary aim of data analysis is to assist business organizations to take decisions.
- For example, a business organization may want to know which is the fastest selling product, in order for them to market activities.
- Data analysis is an activity that takes the data and generates useful information and insights for assisting the organizations.
- Data analysis and data analytics are terms that are used interchangeably to refer to the same concept.
- Data analytics is a general term and data analysis is a part of it. Data analytics refers to the process of data collection, pre-processing and analysis.
- It deals with the complete cycle of data management.
- **Data analysis** is just analysis and is a part of data analytics. It takes historical data and does the analysis. **Data analytics**, instead, concentrates more on future and helps in prediction.
- There are four types of data analytics:
  1. Descriptive analytics
  2. Diagnostic analytics
  3. Predictive analytics
  4. Prescriptive analytics

1. Descriptive Analytics: It is about describing the main features of the data.

- After data collection is done, descriptive analytics deals with the collected data and quantifies it.
- It is often stated that analytics is essentially statistics.
- There are two aspects of statistics – Descriptive and Inference.
- Descriptive analytics only focuses on the description part of the data and not the inference part.

2. Diagnostic Analytics

- It deals with the question – ‘Why?’.
- This is also known as causal analysis, as it aims to find out the cause and effect of the events. There may be multiple reasons and associated effects are analyzed as part of it.

3. Predictive Analytics

- It deals with the future.
- It deals with the question – ‘What will happen in future given this data?’.
- This involves the application of algorithms to identify the patterns to predict the future.

4. Prescriptive Analytics

- It is about the finding the best course of action for the business organizations.
- Prescriptive analytics goes beyond prediction and helps in decision making by giving a set of actions.

- It helps the organizations to plan better for the future and to mitigate the risks that are involved.

BIG DATA ANALYSIS FRAMEWORK

- For performing data analytics, many frameworks are proposed.
- All proposed analytics frameworks have some common factors. Big data framework is a layered architecture.
- Such an architecture has many advantages such as genericness. A 4-layer architecture has the following layers:
  1. Data connection layer
  2. Data management layer
  3. Data analytics later
  4. Presentation layer

1. Data Connection Layer:

- It has data ingestion mechanisms and data connectors.
- Data ingestion means taking raw data and importing it into appropriate data structures.
- It performs the tasks of ETL process. By ETL, it means **extract, transform** and **load** operations.

2. Data Management Layer

- It performs preprocessing of data.
- The purpose of this layer is to allow parallel execution of queries, and read, write and data management tasks. There may be many schemes that can be implemented by this layer such as data-in-place, where the data is not moved at all, or constructing data repositories such as data warehouses and pull data on-demand mechanisms.

3. Data Analytic Layer

- It has many functionalities such as statistical tests, machine learning algorithms to
- understand, and construction of machine learning models.
- This layer implements many model validation mechanisms too.

4. Presentation Layer

- It has mechanisms such as dashboards, and applications that display the results of analytical engines and machine learning algorithms.
- Thus, the Big Data processing cycle involves data management that consists of the following steps.
  1. Data collection
  2. Data preprocessing
  3. Applications of machine learning algorithm
  4. Interpretation of results and visualization of machine learning algorithm.

DATA COLLECTION

- The first task of gathering datasets are the collection of data.
- It is often estimated that most of the time is spent
- for collection of good quality data. A good quality data yields a better result.
- It is often difficult to characterize a ‘Good data’. ‘Good data’ is one that has the following properties:

1. **Timeliness** – The data should be relevant and not stale or obsolete data.
2. **Relevancy** – The data should be relevant and ready for the machine learning or data mining algorithms. All the necessary information should be available and there should be no bias in the data.
3. **Knowledge about the data** – The data should be understandable and interpretable, and should be selfsufficient for the required application as desired by the domain knowledge engineer.

- Broadly, the data source can be classified as open/public data, social media data and multimodal data.
  - ❖ **Open or public data source** – It is a data source that does not have any stringent copyright rules or restrictions. Its data can be primarily used for many purposes. Government census data are good examples of open data
  - ❖ **Digital libraries** that have huge amount of text data as well as document images • Scientific domains with a huge collection of experimental data like genomic data and biological data. Healthcare systems that use extensive databases like patient databases, health insurance data, doctors’ information, and bioinformatics information
  - ❖ **Social media** – It is the data that is generated by various social media platforms like Twitter, Facebook, YouTube, and Instagram. An enormous amount of data is generated by these platforms.
  - ❖ **Multimodal data** – It includes data that involves many modes such as text, video, audio and mixed types. Some of them are listed below:
    - ♦ Image archives contain larger image databases along with numeric and text data.
    - ♦ The World Wide Web (WWW) has huge amount of data that is distributed on the Internet. These data are heterogeneous in nature.

DATA PREPROCESSING

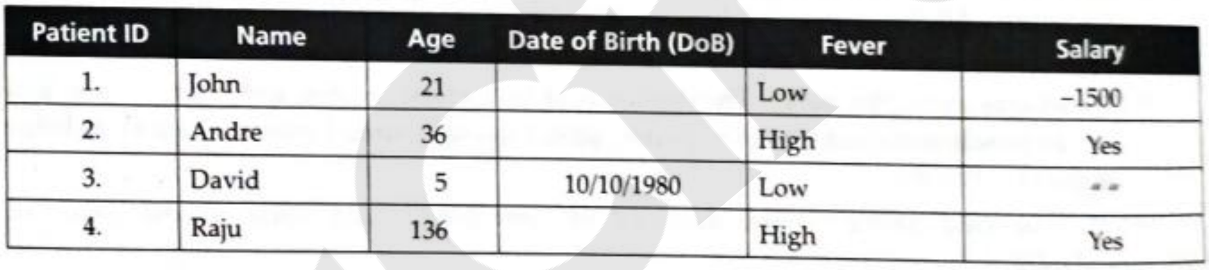
In real world, the available data is ’dirty’. By this word ’dirty’, it means:

- ❖ Incomplete data
- ❖ Inaccurate data
- ❖ Outlier data
- ❖ Data with missing values

- ❖ Data with inconsistent values
- ❖ Duplicate data

- Data preprocessing improves the quality of the data mining techniques. The raw data must be preprocessed to give accurate results.
- The process of detection and removal of errors in data is called data cleaning.
- Datawrangling means making the data processable for machine learning algorithms.
- Some of the data errors include human errors such as typographical errors or incorrect measurement and structural errors like improper data formats.
- Data errors can also arise from omission and duplication of attributes. Noise is a random component and involves distortion of a value or introduction of spurious objects. Often, the noise is used if the data is a spatial or temporal component.
- Certain deterministic distortions in the form of a streak are known as artifacts.
- Consider, for example

Table : Illustration of 'Bad' Data



Patient ID	Name	Age	Date of Birth (DoB)	Fever	Salary
1.	John	21		Low	−1500
2.	Andre	36		High	Yes
3.	David	5	10/10/1980	Low	' '
4.	Raju	136		High	Yes

- It can be observed that data like Salary = ' ' is incomplete data. The DoB of patients, John, Andre, and Raju, is the missing data. The age of David is recorded as '5' but his DoB indicates it is 10/10/1980. This is called inconsistent data.
- Inconsistent data occurs due to problems in conversions, inconsistent formats, and difference in units. Salary for John is -1500. It cannot be less than '0'.
- It is an instance of noisy data. Outliers are data that exhibit the characteristics that are different from other data and have very unusual values. The age of Raju cannot be 136. It might be a typographical error. It is often required to distinguish between noise and outlier data.

MISSING DATA ANALYSIS

The primary data cleaning process is missing data analysis. Data cleaning routines attempt to fill up the missing values, smoothen the noise while identifying the outliers and correct the inconsistencies of the data.

This enables data mining to avoid overfitting of the models.

The procedures that are given below can solve the problem of missing data:

1. **Ignore the tuple** – A tuple with missing data, especially the class label, is ignored. This method is not effective when the percentage of the missing values increases.

2. **Fill in the values manually** – Here, the domain expert can analyse the data tables and carry out the analysis and fill in the values manually. But, this is time consuming and may not be feasible for larger sets.

3. **A global constant** can be used to fill in the missing attributes. The missing values may be 'Unknown' or be 'Infinity'. But, some data mining results may give spurious results by analysing these labels.

4. The **attribute value may be filled by the attribute value**. Say, the average income can replace a missing value.

5. Use the **attribute mean** for all samples belonging to the same class. Here, the average value replaces the missing values of all tuples that fall in this group.

REMOVAL OF NOISY OR OUTLIER DATA

Noise is a random error or variance in a measured value. It can be removed by using binning, which is a method where the given data values are sorted and distributed into equal frequency bins.

The bins are also called as buckets. The binning method then uses the neighbor values to smooth the noisy data.

Some of the techniques commonly used are 'smoothing by means' where the mean of the bin removes the values of the bins , 'smoothing by bin medians' where the bin median replaces the bin values, and 'smoothing by bin boundaries' where the bin value is replaced by the closest bin boundary.

The maximum and minimum values are called bin boundaries. Binning methods may be used as a discretization technique.

Example:

Consider the following set: S = {12, 14, 19, 22, 24, 26, 28, 31, 34}. Apply various binning techniques and show the result.

Solution: By equal-frequency bin method, the data should be distributed across bins. Let us assume the bins of size 3, then the above data is distributed across the bins as shown below:

Bin 1 : 12 , 14, 19

Bin 2 : 22, 24, 26

Bin 3 : 28, 31, 32

By smoothing bins method, the bins are replaced by the bin means. This method results in:

Bin 1 : 15, 15, 15

Bin 2 : 24, 24, 24

Bin 3 : 30.3, 30.3, 30.3

Using smoothing by bin boundaries method, the bins' values would be like:

Bin 1 : 12, 12, 19

Bin 2 : 22, 22, 26

Bin 3 : 28, 32, 32

As per the method, the minimum and maximum values of the bin are determined, and it serves as bin boundary and does not change.

DATA INTEGRATION AND DATA TRANSFORMATIONS

- Data integration involves routines that merge data from multiple sources into a single data source. So, this may lead to redundant data.
- The main goal of data integration is to detect and remove redundancies that arise from integration. Data transformation routines perform operations like normalization to improve the performance of the data mining algorithms. It is necessary to transform data so that it can be processed.
- This can be considered as a preliminary stage of data conditioning. Normalization is one such technique. In normalization, the attribute values are scaled to fit in a range (say 0-1) to improve the performance of the data mining algorithm.
- Often, in neural networks, these techniques are used. Some of the normalization procedures used are:
    - Min-Max
    - z-Score

1. **Min-Max Procedure**: It is a normalization technique where each variable V is normalized by its difference with the minimum value divided by the range to a new range, say 0–1. Often, neural networks require this kind of normalization. The formula to implement this normalization is given as:

$$\textbf{min-max}=\frac{\boldsymbol{V-min}}{\boldsymbol{max-min}} \ast\textbf{(new max-new min)+new min}$$

Here max-min is the range. Min and max are the minimum and maximum of the given data, new max and new min are the minimum and maximum of the target range, say 0 and 1.

Example:

Consider the set: V = {88, 90, 92, 94}. Apply Min-Max procedure and map the marks to a new range 0–1.

Solution: The minimum of the list V is 88 and maximum is 94. The new min and new max are 0 and 1, respectively.

For marks 88

$$\text{min-max}=\frac{88-88}{94-88} \ast(1 - 0) + 0 \ = 0$$

For marks 90

$$\text{min-max}=\frac{90-88}{94-88} \ast(1 - 0) + 0 \ = 0.33$$

For marks 92

$$\text{min-max}=\frac{92-88}{94-88}*(1 - 0) + 0 \ = 0.66$$

For marks 94

$$\text{min-max}=\frac{94-88}{94-88}*(1 - 0) + 0 \ = 1$$

So, it can be observed that the marks {88, 90, 92, 94} are mapped to the new range {0, 0.33, 0.66, 1}. Thus, the Min-Max normalization range is between 0 and 1.

2. **z-Score Normalization:** This procedure works by taking the difference between the field value and mean value, and by scaling this difference by standard deviation of the attribute.

$$V^{*}=\frac{V-\mu}{\sigma}$$

Here, s is the standard deviation of the list V and m is the mean of the list V.

Example :

Consider the mark list V = {10, 20, 30}, convert the marks to z-score.

Solution: The mean and Sample Standard deviation (s) values of the list V are 20 and 10, respectively. So the z-scores of these marks are calculated using above Equation as:

$$z\ Score\ of\ 10=\frac{10-20}{10} = -1$$

$$z\ Score\ of\ 20=\frac{20-20}{10} = 0$$

$$z\ Score\ of\ 30=\frac{30-20}{10} = 1$$

Hence, the z-score of the marks 10, 20, 30 are -1, 0 and 1, respectively.

DATA REDUCTION

- Data reduction reduces data size but produces the same results.
- There are different ways in which data reduction can be carried out such as data aggregation, feature selection, and dimensionality reduction.

DESCRIPTIVE STATISTICS

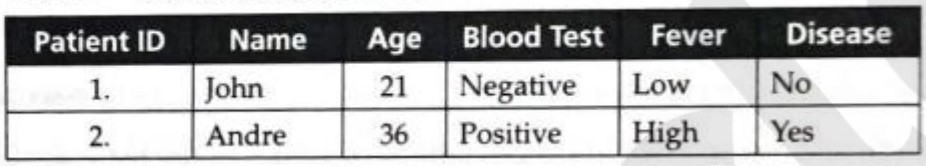
- Descriptive statistics is a branch of statistics that does dataset summarization.
- It is used to summarize and describe data. Descriptive statistics are just descriptive and do not go beyond that.

- In other words, descriptive statistics do not bother too much about machine learning algorithms and its functioning.
- Descriptive statistics with the fundamental concepts of data types.

❖ **Dataset and Data Types**

- A dataset can be assumed to be a collection of data objects. The data objects may be records, points, vectors, patterns, events, cases, samples or observations.
- These records contain many attributes. An attribute can be defined as the property or characteristics of an object.

Table Sample Patient Table



Patient ID	Name	Age	Blood Test	Fever	Disease
1.	John	21	Negative	Low	No
2.	Andre	36	Positive	High	Yes

- Every attribute should be associated with a value. This process is called measurement. The type of attribute determines the data types, often referred to as measurement scale types.

  Broadly, data can be classified into two types:

1. ***<u>Categorical or qualitative data</u>***

   The categorical data can be divided into two types. They are nominal type and ordinal type.

   Nominal Data:

   Nominal data are symbols and cannot be processed like a number. For example, the average of a patient ID does not make any statistical sense.

   Nominal data type provides only information but has no ordering among data. Only operations like (=, ≠) are meaningful for these data.

   Ordinal Data:

   It provides enough information and has natural order. For example, Fever = {Low, Medium, High} is an ordinal data. Certainly, low is less than medium and medium is less than high, irrespective of the value. Any transformation can be applied to these data to get a new value.

2. ***<u>Numerical or quantitative data</u>***

   It can be divided into two categories. They are interval type and ratio type.

   Interval Data:

   Interval data is a numeric data for which the differences between values are meaningful. For example, there is a difference between 30 degree and 40 degree. Only the permissible operations are + and -.

   Ratio Data:

For ratio data, both differences and ratio are meaningful. The difference between the ratio and interval data is the position of zero in the scale. For example, take the Centigrade Fahrenheit conversion. The zeroes of both scales do not match. Hence, these are interval data.

- Another way of classifying the data is to classify it as:
    1. Discrete value data
    2. Continuous data
- **Discrete Data** This kind of data is recorded as integers. For example, the responses of the survey can bediscrete data. Employee identification number such as 10001 is discrete data.
- **Continuous Data** It can be fitted into a range and includes decimal point. For example, age is a continuous data. Though age appears to be discrete data, one may be 12.5 years old and it makes sense. Patient height and weight are all continuous data.
- Third way of classifying the data is based on the number of variables used in the dataset. Based on that, thedata can be classified as univariate data, bivariate data, and multivariate data.

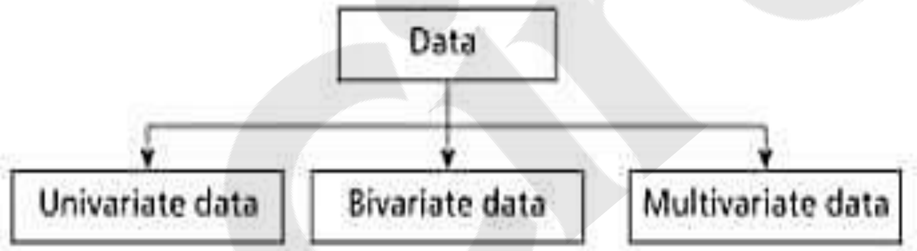


Figure 2.2: Types of Data Based on Variables

UNIVARIATE DATA ANALYSIS AND VISUALIZATION

- Univariate analysis is the simplest form of statistical analysis. As the name indicates, the dataset has only one variable. A variable can be called as a category.
- Univariate does not deal with cause or relationships. The aim of univariate analysis is to describe data and find patterns.
- Univariate data description involves finding the frequency distributions, central tendency measures, dispersion or variation, and shape of the data.

Data Visualization

- To understand data graph visualization is must.
- Data visualization helps to understand data it helps to present information and data to customers.
- Some of the graphs that are used in unvaried data analysis are bar chart histogram frequency

polygon and pie chart.

Bar Chart: A Bar chart (or Bar graph) is used to display the frequency distribution for variables. Bar charts are used to illustrate discrete data. The charts can also help to explain the counts of nominal data. It also helps in comparing the frequency of different groups.

The bar chart for students' marks {45, 60, 60, 80, 85} with Student ID = {1, 2, 3, 4, 5} is shown below in Figure.

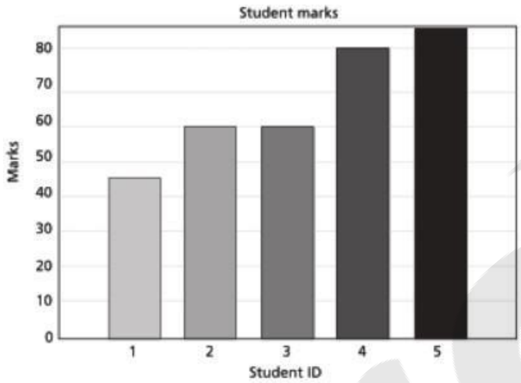


Figure 2.3: Bar Chart

Pie Chart These are equally helpful in illustrating the univariate data. The percentage frequency distribution ofstudents' marks {22, 22, 40, 40, 70, 70, 70, 85, 90, 90} is below in Figure.

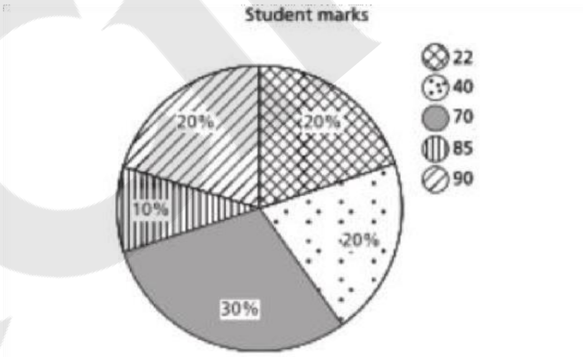


Figure 2.4: Pie Chart

It can be observed that the number of students with 22 marks are 2. The total number of students are 10. So, 2/10 × 100 = 20% space in a pie of 100% is allotted for marks 22 in Figure.

Histogram It plays an important role in data mining for showing frequency distributions. The histogram for students’ marks {45, 60, 60, 80, 85} in the group range of 0-25, 26-50, 51-75, 76-100 is givenbelow in

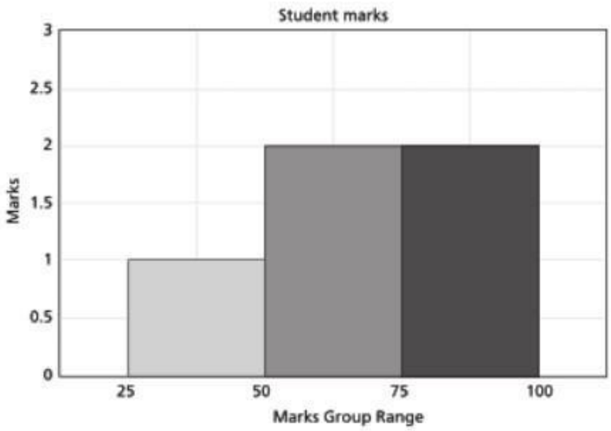


Figure 2.5: Sample Histogram of English Marks

Histogram conveys useful information like nature of data and its mode. Mode indicates the peak of dataset. In other words, histograms can be used as charts to show frequency, skewness present in the data, and shape.

Dot Plots These are similar to bar charts. They are less clustered as compared to bar charts, as they illustrate the bars only with single points. The dot plot of English marks for five students with ID as {1, 2, 3, 4, 5} and marks {45, 60, 60, 80, 85} is given in Figure. The advantage is that by visual inspection one can find out who got more marks.

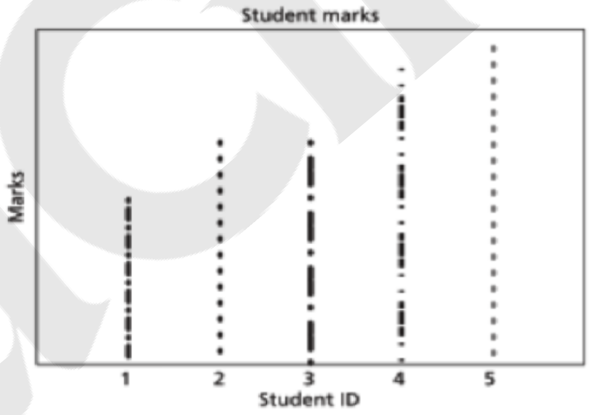


Figure 2.6: Dot Plots

Central Tendency

A condensation or summary of the data is necessary. This makes the data analysis easy and simple. One such summary is called central tendency.

Thus, central tendency can explain the characteristics of data and that further helps in comparison.

Mass data have tendency to concentrate at certain values, normally in the central location.

It is called measure of central tendency (or averages). Popular measures are mean, median and mode.

1. **Mean** – Arithmetic average (or mean) is a measure of central tendency that represents the 'center' of the dataset. Mathematically, the average of all the values in the sample (population) is denoted as x. Let x1, x2, … , xN be a set of 'N' values or observations, then the arithmetic mean is given as:

$$\bar{x} = \frac{x_1 + x_2 + \cdots + x_N}{N} = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad (2.3)$$

Weighted mean – Unlike arithmetic mean that gives the weightage of all items equally, weighted mean gives different importance to all items as the item importance varies.

Hence, different weightage can be given to items. In case of frequency distribution, mid values of the range are taken for computation.

Geometric mean – Let x1, x2, … , xN be a set of 'N' values or observations. Geometric mean is the Nth root of the product of N items. The formula for computing geometric mean is given as follows:

$$\text{Geometric mean} = \left(\prod_{i=1}^{n} x_i\right)^{\frac{1}{N}} = \sqrt[N]{x_1 \times x_2 \times \cdots \times x_N} \qquad (2.4)$$

Here, n is the number of items and xi are values.

2. Median – The middle value in the distribution is called median. If the total number of items in the distribution is odd, then the middle value is called median. A median class is that class where (N/2)th item ispresent. continuous case, the median is given by the formula:

In the continuous case, the median is given by the formula:

$$\text{Median} = L_1 + \frac{\frac{N}{2} - cf}{f} \times i \qquad (2.7)$$

Median class is that class where N/2th item is present. Here, i is the class interval of the median class and L1 is the lower limit of median class, f is the frequency of the median class, and cf is the cumulative frequency ofall classes preceding median.

3. Mode – Mode is the value that occurs more frequently in the dataset. In other words, the value that has the highest frequency is called mode.

Dispersion

The spreadout of a set of data around the central tendency (mean, median or mode) is called dispersion. Dispersion is represented by various ways such as range, variance, standard deviation, and standard error. These are second order measures. The most common measures of the dispersion data are listed below:

Range Range is the difference between the maximum and minimum of values of the given list of data.

Standard Deviation The mean does not convey much more than a middle point. For example, the following datasets {10, 20, 30} and {10, 50, 0} both have a mean of 20. The difference between these two sets is the spread of data. Standard deviation is the average distance from the mean of the dataset to each point.

The formula for sample standard deviation is given by:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N-1}} \qquad (2.8)$$

Here, N is the size of the population, xi is observation or value from the population and m is the populationmean. Often, N – 1 is used instead of N in the denominator of Eq. (2.8).

Quartiles and Inter Quartile Range

It is sometimes convenient to subdivide the dataset using coordinates. Percentiles are about data that are less than the coordinates by some percentage of the total value. Kth percentile is the property that the k% of the data lies at or below Xi. The 25th percentile is called first quartile (Q1) and the 75th percentile is called third quartile (Q3).

Another measure that is useful to measure dispersion is Inter Quartile Range (IQR). The IQR is the difference between Q3 and Q1. Interquartile percentile = Q3 – Q1

Outliers are normally the values falling apart at least by the amount 1.5 × IQR above the third quartile or below the first quartile. Interquartile is defined by Q0.75 – Q0.25.

Example: A teacher recorded the test scores of 12 students in a math exam {45, 50, 55, 60, 62, 65, 68, 70, 72, 75, 80, 85}

Solution:

Step 1: Arrange the Data in Ascending Order

The given scores are: 45,50,55,60,62,65,68,70,72,75,80,85
This data is already sorted.

Step 2: Find Quartiles (Q1, Q2, Q3)

Finding the Median (Q2)

The median (Q2) is the middle value. Since we have **12 values (even number),** the median is the average of the **6th** and **7th** values.
Q2=65+68/ 2 = 133/ 2 = **66.5**

Finding the First Quartile (Q1)

Q1 is the **median of the lower half** of the data:
45, 50, 55, 60, 62, 65
The median of these six numbers is the average of the **3rd** and **4th** values:
Q1=55+60/ 2=115/ 2=**57.5**

Finding the Third Quartile (Q3)

Q3 is the **median of the upper half** of the data:

68, 70, 72, 75, 80, 85

The median of these six numbers is the average of the **3rd** and **4th** values:

Q3=72+75/2 = 147/2 = **73.5**

Step 3: Compute the Interquartile Range (IQR)

The **IQR** is the difference between Q3 and Q1:

IQR = Q3−Q1 = 73.5−57.5 = 16

Step 4: Find Outliers

A data point is an **outlier** if it lies **outside** the range:

Lower Bound = Q1−1.5×IQR = 57.5 − (1.5×16) = 57.5−24 = **33.5**
Upper Bound = Q3+1.5×IQR = 73.5 + (1.5×16) = 73.5+24 = **97.5**

Any values **below 33.5** or **above 97.5** are outliers.

Semi IQR = IQR/2 = 16 /2 = **8**

Five-point Summary and Box Plot:

The median, quartiles Q1 and Q3, and minimum and maximum written in the order < Minimum, Q1, Median, Q3, Maximum > is known as five-point summary.

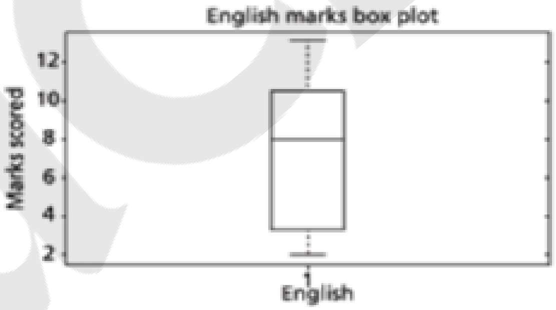


Figure 2.7: Box Plot for English Marks

Shape

Skewness and Kurtosis (called moments) indicate the symmetry/asymmetry and peak location of the dataset.

Skewness

The measures of direction and degree of symmetry are called measures of third order. Ideally, skewness should be zero as in ideal normal distribution. More often, the given dataset may not have perfect symmetry(consider the following Figure 2.8).

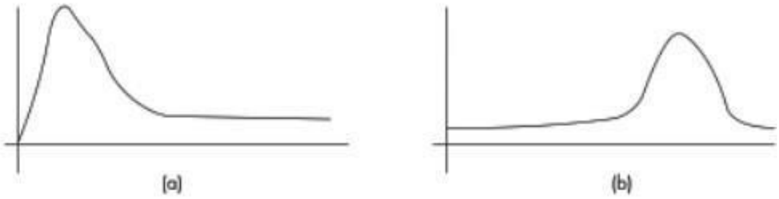


Figure 2.8: (a) Positive Skewed and (b) Negative Skewed Data

Generally, for negatively skewed distribution, the median is more than the mean. The relationship between skew and the relative size of the mean and median can be summarized by a convenient numerical skew indexknown as Pearson 2 skewness coefficient.

$$\frac{3 \times (\mu - median)}{\sigma} \qquad (2.12)$$

Also, the following measure is more commonly used to measure skewness. Let X1, X2, …, XN be a set of 'N' values or observations then the skewness can be given as:

$$\frac{1}{N} \times \sum_{i=1}^{N} \frac{(x_i - \mu)^3}{\sigma^3} \qquad (2.13)$$

Here, m is the population mean and s is the population standard deviation of the univariate data. Sometimes, for bias correction instead of N, N - 1 is used.

Kurtosis

Kurtosis also indicates the peaks of data. If the data is high peak, then it indicates higher kurtosis and viceversa. Kurtosis is measured using the formula given below:

$$\frac{\sum_{i=1}^{N}(x_i - \bar{x})^4 / N}{\sigma^4} \qquad (2.14)$$

It can be observed that N - 1 is used instead of N in the numerator of Eq. (2.14) for bias correction. Here, x and s are the mean and standard deviation of the univariate data, respectively. Some of the other useful measures for finding the shape of the univariate dataset are mean absolute deviation (MAD) and coefficient of variation (CV).