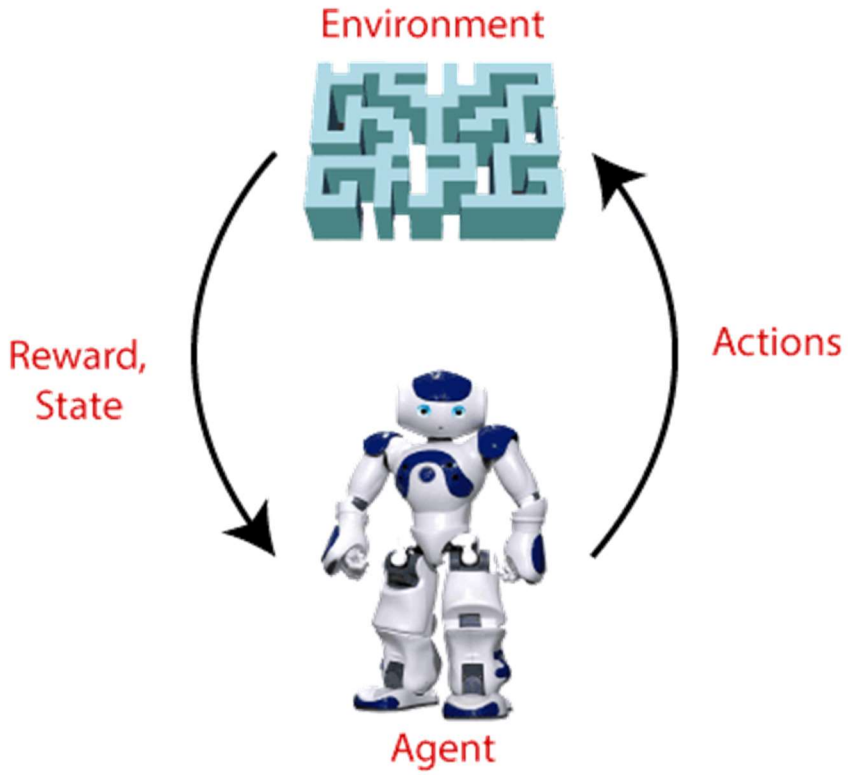
[1]What is Reinforcement Learning?

- Reinforcement Learning is a feedback-based Machine learning technique in which an agent learns to behave in an environment by performing the actions and seeing the results of actions. For each good action, the agent gets positive feedback, and for each bad action, the agent gets negative feedback or penalty.
- In Reinforcement Learning, the agent learns automatically using feedbacks without any labeled data, unlike supervised learning.
- Since there is no labeled data, so the agent is bound to learn by its experience only.
- RL solves a specific type of problem where decision making is sequential, and the goal is long-term, such as **game-playing, robotics**, etc.
- The agent interacts with the environment and explores it by itself. The primary goal of an agent in reinforcement learning is to improve the performance by getting the maximum positive rewards.
- The agent learns with the process of hit and trial, and based on the experience, it learns to perform the task in a better way. Hence, we can say that **"*Reinforcement learning is a type of machine learning method where an intelligent agent (computer program) interacts with the environment and learns to act within that.*"** How a Robotic dog learns the movement of his arms is an example of Reinforcement learning.
- It is a core part of Artificial intelligence, and all AI agent works on the concept of reinforcement learning. Here we do not need to pre-program the agent, as it learns from its own experience without any human intervention.
- **Example:** Suppose there is an AI agent present within a maze environment, and his goal is to find the diamond. The agent interacts with the environment by performing some actions, and based on those actions, the state of the agent gets changed, and it also receives a reward or penalty as feedback.
- The agent continues doing these three things (**take action, change state/remain in the same state, and get feedback**), and by doing these actions, he learns and explores the environment.
- The agent learns that what actions lead to positive feedback or rewards and what actions lead to negative feedback penalty. As a positive reward, the agent gets a positive point, and as a penalty, it gets a negative point.



Terms used in Reinforcement Learning

- **Agent():** An entity that can perceive/explore the environment and act upon it.
- **Environment():** A situation in which an agent is present or surrounded by. In RL, we assume the stochastic environment, which means it is random in nature.
- **Action():** Actions are the moves taken by an agent within the environment.
- **State():** State is a situation returned by the environment after each action taken by the agent.
- **Reward():** A feedback returned to the agent from the environment to evaluate the action of the agent.
- **Policy():** Policy is a strategy applied by the agent for the next action based on the current state.
- **Value():** It is expected long-term retuned with the discount factor and opposite to the short-term reward.
- **Q-value():** It is mostly similar to the value, but it takes one additional parameter as a current action (a).

Key Features of Reinforcement Learning

- In RL, the agent is not instructed about the environment and what actions need to be taken.
- It is based on the hit and trial process.
- The agent takes the next action and changes states according to the feedback of the previous action.
- The agent may get a delayed reward.
- The environment is stochastic, and the agent needs to explore it to reach to get the maximum positive rewards.

Types of Reinforcement learning

There are mainly two types of reinforcement learning, which are:

- **Positive Reinforcement**
- **Negative Reinforcement**

Positive Reinforcement:

The positive reinforcement learning means adding something to increase the tendency that expected behavior would occur again. It impacts positively on the behavior of the agent and increases the strength of the behavior.

This type of reinforcement can sustain the changes for a long time, but too much positive reinforcement may lead to an overload of states that can reduce the consequences.

Negative Reinforcement:

The negative reinforcement learning is opposite to the positive reinforcement as it increases the tendency that the specific behavior will occur again by avoiding the negative condition.

It can be more effective than the positive reinforcement depending on situation and behavior, but it provides reinforcement only to meet minimum behavior.

[2]Naïve Bayes Classifier Algorithm

- Naïve Bayes algorithm is a supervised learning algorithm, which is based on **Bayes theorem** and used for solving classification problems.
- It is mainly used in *text classification* that includes a high-dimensional training dataset.
- Naïve Bayes Classifier is one of the simple and most effective Classification algorithms which helps in building the fast machine learning models that can make quick predictions.
- **It is a probabilistic classifier, which means it predicts on the basis of the probability of an object**.
- Some popular examples of Naïve Bayes Algorithm are **spam filtration, Sentimental analysis, and classifying articles**.

Why is it called Naïve Bayes?

The Naïve Bayes algorithm is comprised of two words Naïve and Bayes, Which can be described as:

- **Naïve**: It is called Naïve because it assumes that the occurrence of a certain feature is independent of the occurrence of other features. Such as if the fruit is identified on the bases of color, shape, and taste, then red, spherical, and sweet fruit is recognized as an apple. Hence each feature individually contributes to identify that it is an apple without depending on each other.
- **Bayes**: It is called Bayes because it depends on the principle of Bayes' Theorem.

Bayes' Theorem:

- Bayes' theorem is also known as **Bayes' Rule** or **Bayes' law**, which is used to determine the probability of a hypothesis with prior knowledge. It depends on the conditional probability.
- The formula for Bayes' theorem is given as:

$$P(A|B)= \frac{P(B|A)P(A)}{P(B)}$$

Where,

P(A|B) is Posterior probability: Probability of hypothesis A on the observed event B.

P(B|A) is Likelihood probability: Probability of the evidence given that the probability of a hypothesis is true.

P(A) is Prior Probability: Probability of hypothesis before observing the evidence.

P(B) is Marginal Probability: Probability of Evidence.

Working of Naïve Bayes' Classifier:

Working of Naïve Bayes' Classifier can be understood with the help of the below example:

Suppose we have a dataset of **weather conditions** and corresponding target variable "**Play**". So using this dataset we need to decide that whether we should play or not on a particular day according to the weather conditions. So to solve this problem, we need to follow the below steps:

1. Convert the given dataset into frequency tables.
2. Generate Likelihood table by finding the probabilities of given features.
3. Now, use Bayes theorem to calculate the posterior probability.

Advantages of Naïve Bayes Classifier:

- Naïve Bayes is one of the fast and easy ML algorithms to predict a class of datasets.
- It can be used for Binary as well as Multi-class Classifications.
- It performs well in Multi-class predictions as compared to the other Algorithms.
- It is the most popular choice for **text classification problems**.

Disadvantages of Naïve Bayes Classifier:

- Naive Bayes assumes that all features are independent or unrelated, so it cannot learn the relationship between features.

Applications of Naïve Bayes Classifier:

- It is used for **Credit Scoring**.
- It is used in **medical data classification**.
- It can be used in **real-time predictions** because Naïve Bayes Classifier is an eager learner.
- It is used in Text classification such as **Spam filtering** and **Sentiment analysis**.

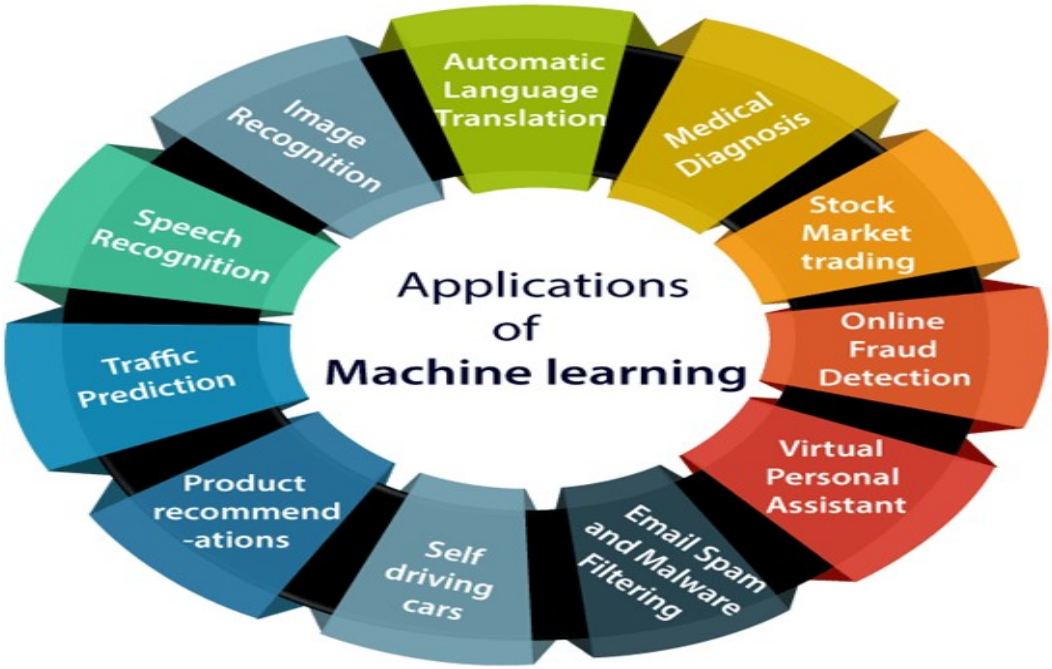
Types of Naïve Bayes Model:

There are three types of Naive Bayes Model, which are given below:

- **Gaussian**: The Gaussian model assumes that features follow a normal distribution. This means if predictors take continuous values instead of discrete, then the model assumes that these values are sampled from the Gaussian distribution.
- **Multinomial**: The Multinomial Naïve Bayes classifier is used when the data is multinomial distributed. It is primarily used for document classification problems, it means a particular document belongs to which category such as Sports, Politics, education,etc..The classifier uses the frequency of words for the predictors.
- **Bernoulli**: The Bernoulli classifier works similar to the Multinomial classifier, but the predictor variables are the independent Booleans variables. Such as if a particular word is present or not in a document. This model is also famous for document classification tasks.

Applications of Machine learning

Machine learning is a buzzword for today's technology, and it is growing very rapidly day by day. We are using machine learning in our daily life even without knowing it such as Google Maps, Google assistant, Alexa, etc. Below are some most trending real-world applications of Machine Learning:



1. Image Recognition:

Image recognition is one of the most common applications of machine learning. It is used to identify objects, persons, places, digital images, etc. The popular use case of image recognition and face detection is, **Automatic friend tagging suggestion**:

Facebook provides us a feature of auto friend tagging suggestion. Whenever we upload a photo with our Facebook friends, then we automatically get a tagging suggestion with name, and the technology behind this is machine learning's **face detection** and **recognition algorithm**.

It is based on the Facebook project named "**Deep Face**," which is responsible for face recognition and person identification in the picture.

2. Speech Recognition

While using Google, we get an option of "**Search by voice**," it comes under speech recognition, and it's a popular application of machine learning.

Speech recognition is a process of converting voice instructions into text, and it is also known as "**Speech to text**", or "**Computer speech recognition**." At present, machine learning algorithms are widely used by various applications of speech recognition. **Google assistant**, **Siri**, **Cortana**, and **Alexa** are using speech recognition technology to follow the voice instructions.

3. Traffic prediction:

If we want to visit a new place, we take help of Google Maps, which shows us the correct path with the shortest route and predicts the traffic conditions.

It predicts the traffic conditions such as whether traffic is cleared, slow-moving, or heavily congested with the help of two ways:

- **Real Time location** of the vehicle form Google Map app and sensors
- **Average time has taken** on past days at the same time.

Everyone who is using Google Map is helping this app to make it better. It takes information from the user and sends back to its database to improve the performance.

4. Product recommendations:

Machine learning is widely used by various e-commerce and entertainment companies such as **Amazon**, **Netflix**, etc., for product recommendation to the user. Whenever we search for some product on Amazon, then we started getting an advertisement for the

same product while internet surfing on the same browser and this is because of machine learning.

Google understands the user interest using various machine learning algorithms and suggests the product as per customer interest.

As similar, when we use Netflix, we find some recommendations for entertainment series, movies, etc., and this is also done with the help of machine learning.

5. Self-driving cars:

One of the most exciting applications of machine learning is self-driving cars. Machine learning plays a significant role in self-driving cars. Tesla, the most popular car manufacturing company is working on self-driving car. It is using unsupervised learning method to train the car models to detect people and objects while driving.

6. Email Spam and Malware Filtering:

Whenever we receive a new email, it is filtered automatically as important, normal, and spam. We always receive an important mail in our inbox with the important symbol and spam emails in our spam box, and the technology behind this is Machine learning. Below are some spam filters used by Gmail:

- Content Filter
- Header filter
- General blacklists filter
- Rules-based filters
- Permission filters

Some machine learning algorithms such as **Multi-Layer Perceptron**, **Decision tree**, and **Naïve Bayes classifier** are used for email spam filtering and malware detection.

7. Virtual Personal Assistant:

We have various virtual personal assistants such as **Google assistant**, **Alexa**, **Cortana**, **Siri**. As the name suggests, they help us in finding the information using our voice instruction. These assistants can help us in various ways just by our voice instructions such as Play music, call someone, Open an email, Scheduling an appointment, etc.

These virtual assistants use machine learning algorithms as an important part.

These assistant record our voice instructions, send it over the server on a cloud, and decode it using ML algorithms and act accordingly.

8. Online Fraud Detection:

Machine learning is making our online transaction safe and secure by detecting fraud transaction. Whenever we perform some online transaction, there may be various ways that a fraudulent transaction can take place such as **fake accounts**, **fake ids**, and **steal money** in the middle of a transaction. So to detect this, **Feed Forward Neural network** helps us by checking whether it is a genuine transaction or a fraud transaction.

For each genuine transaction, the output is converted into some hash values, and these values become the input for the next round. For each genuine transaction, there is a specific pattern which gets change for the fraud transaction hence, it detects it and makes our online transactions more secure.

9. Stock Market trading:

Machine learning is widely used in stock market trading. In the stock market, there is always a risk of up and downs in shares, so for this machine learning's **long short term memory neural network** is used for the prediction of stock market trends.

10. Medical Diagnosis:

In medical science, machine learning is used for diseases diagnoses. With this, medical technology is growing very fast and able to build 3D models that can predict the exact position of lesions in the brain.

It helps in finding brain tumors and other brain-related diseases easily.

11. Automatic Language Translation:

Nowadays, if we visit a new place and we are not aware of the language then it is not a problem at all, as for this also machine learning helps us by converting the text into our known languages. Google's GNMT (Google Neural Machine Translation) provide this feature, which is a Neural Machine Learning that translates the text into our familiar language, and it called as automatic translation.

The technology behind the automatic translation is a sequence to sequence learning algorithm, which is used with image recognition and translates the text from one language to another language.

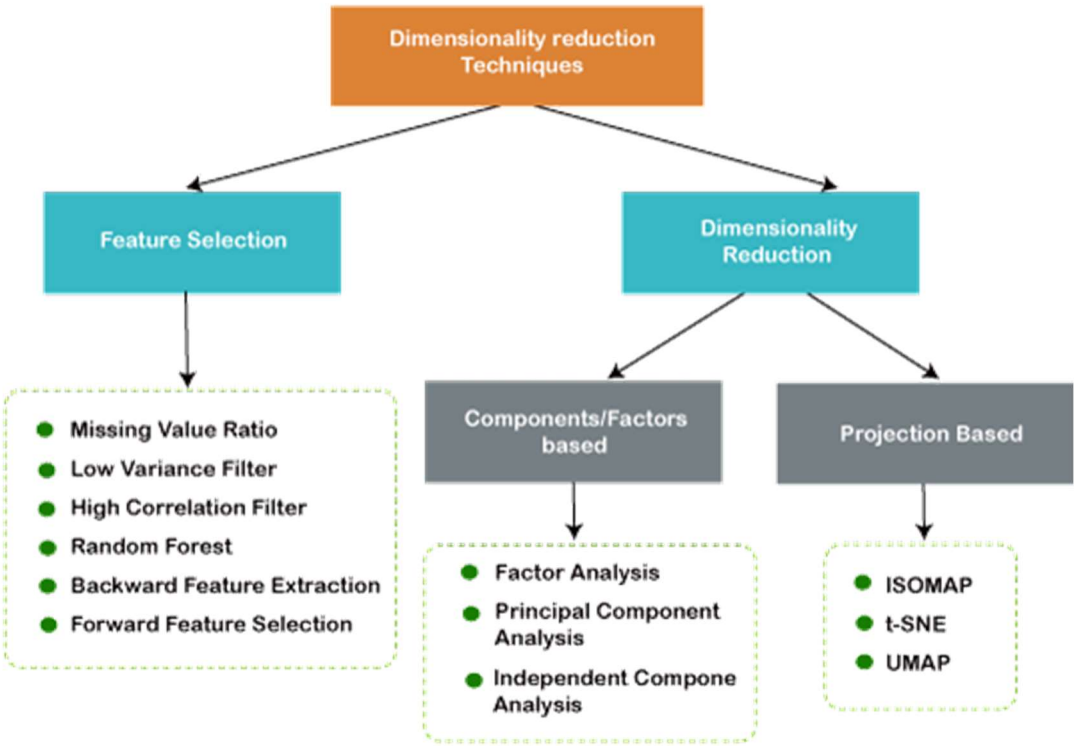
[3]What is Dimensionality Reduction?

The number of input features, variables, or columns present in a given dataset is known as dimensionality, and the process to reduce these features is called dimensionality reduction.

A dataset contains a huge number of input features in various cases, which makes the predictive modeling task more complicated. Because it is very difficult to visualize or make predictions for the training dataset with a high number of features, for such cases, dimensionality reduction techniques are required to use.

Dimensionality reduction technique can be defined as, ***"It is a way of converting the higher dimensions dataset into lesser dimensions dataset ensuring that it provides similar information."*** These techniques are widely used in machine learning for obtaining a better fit predictive model while solving the classification and regression problems.

It is commonly used in the fields that deal with high-dimensional data, such as **speech recognition, signal processing, bioinformatics, etc. It can also be used for data visualization, noise reduction, cluster analysis**, etc.



The Curse of Dimensionality

Handling the high-dimensional data is very difficult in practice, commonly known as the *curse of dimensionality*. If the dimensionality of the input dataset increases, any

machine learning algorithm and model becomes more complex. As the number of features increases, the number of samples also gets increased proportionally, and the chance of overfitting also increases. If the machine learning model is trained on high-dimensional data, it becomes overfitted and results in poor performance.

Hence, it is often required to reduce the number of features, which can be done with dimensionality reduction.

Benefits of applying Dimensionality Reduction

Some benefits of applying dimensionality reduction technique to the given dataset are given below:

- By reducing the dimensions of the features, the space required to store the dataset also gets reduced.
- Less Computation training time is required for reduced dimensions of features.
- Reduced dimensions of features of the dataset help in visualizing the data quickly.
- **I**t removes the redundant features (if present) by taking care of multicollinearity.

Disadvantages of dimensionality Reduction

There are also some disadvantages of applying the dimensionality reduction, which are given below:

- Some data may be lost due to dimensionality reduction.
- In the PCA dimensionality reduction technique, sometimes the principal components required to consider are unknown.

Common techniques of Dimensionality Reduction

a. **Principal Component Analysis**

b. **Backward Elimination**

c. **Forward Selection**

d. **Score comparison**

e. **Missing Value Ratio**

f. **Low Variance Filter**

g. **High Correlation Filter**

h. **Random Forest**

i. **Factor Analysis**

j. **Auto-Encoder**

[4]Common issues in Machine Learning

Although machine learning is being used in every industry and helps organizations make more informed and data-driven choices that are more effective than classical methodologies, it still has so many problems that cannot be ignored. Here are some common issues in Machine Learning that professionals face to inculcate ML skills and create an application from scratch.

1. Inadequate Training Data

The major issue that comes while using machine learning algorithms is the lack of quality as well as quantity of data. Although data plays a vital role in the processing of machine learning algorithms, many data scientists claim that inadequate data, noisy data, and unclean data are extremely exhausting the machine learning algorithms. For example, a simple task requires thousands of sample data, and an advanced task such as speech or image recognition needs millions of sample data examples. Further, data quality is also important for the algorithms to work ideally, but the absence of data quality is also found in Machine Learning applications. Data quality can be affected by some factors as follows:

- **Noisy Data-** It is responsible for an inaccurate prediction that affects the decision as well as accuracy in classification tasks.
- **Incorrect data-** It is also responsible for faulty programming and results obtained in machine learning models. Hence, incorrect data may affect the accuracy of the results also.
- **Generalizing of output data-** Sometimes, it is also found that generalizing output data becomes complex, which results in comparatively poor future actions.

2. Poor quality of data

As we have discussed above, data plays a significant role in machine learning, and it must be of good quality as well. Noisy data, incomplete data, inaccurate data, and unclean data lead to less accuracy in classification and low-quality results. Hence, data quality can also be considered as a major common problem while processing machine learning algorithms.

3. Non-representative training data

To make sure our training model is generalized well or not, we have to ensure that sample training data must be representative of new cases that we need to generalize. The training data must cover all cases that are already occurred as well as occurring.

Further, if we are using non-representative training data in the model, it results in less accurate predictions. A machine learning model is said to be ideal if it predicts well for generalized cases and provides accurate decisions. If there is less training data, then there will be a sampling noise in the model, called the non-representative training set. It won't be accurate in predictions. To overcome this, it will be biased against one class or a group.

Hence, we should use representative data in training to protect against being biased and make accurate predictions without any drift.

4. Overfitting and Underfitting

Overfitting:

Overfitting is one of the most common issues faced by Machine Learning engineers and data scientists. Whenever a machine learning model is trained with a huge amount of data, it starts capturing noise and inaccurate data into the training data set. It negatively affects the performance of the model. Let's understand with a simple example where we have a few training data sets such as 1000 mangoes, 1000 apples, 1000 bananas, and 5000 papayas. Then there is a considerable probability of identification of an apple as papaya because we have a massive amount of biased data in the training data set; hence prediction got negatively affected. The main reason behind overfitting is using non-linear methods used in machine learning algorithms as they build non-realistic data models. We can overcome overfitting by using linear and parametric algorithms in the machine learning models.

Methods to reduce overfitting:

- Increase training data in a dataset.
- Reduce model complexity by simplifying the model by selecting one with fewer parameters
- Ridge Regularization and Lasso Regularization
- Early stopping during the training phase
- Reduce the noise
- Reduce the number of attributes in training data.

- Constraining the model.

Underfitting:

Underfitting is just the opposite of overfitting. Whenever a machine learning model is trained with fewer amounts of data, and as a result, it provides incomplete and inaccurate data and destroys the accuracy of the machine learning model.

Underfitting occurs when our model is too simple to understand the base structure of the data, just like an undersized pant. This generally happens when we have limited data into the data set, and we try to build a linear model with non-linear data. In such scenarios, the complexity of the model destroys, and rules of the machine learning model become too easy to be applied on this data set, and the model starts doing wrong predictions as well.

Methods to reduce Underfitting:

- Increase model complexity
- Remove noise from the data
- Trained on increased and better features
- Reduce the constraints
- Increase the number of epochs to get better results.

5. Monitoring and maintenance

As we know that generalized output data is mandatory for any machine learning model; hence, regular monitoring and maintenance become compulsory for the same. Different results for different actions require data change; hence editing of codes as well as resources for monitoring them also become necessary.

6. Getting bad recommendations

A machine learning model operates under a specific context which results in bad recommendations and concept drift in the model. Let's understand with an example where at a specific time customer is looking for some gadgets, but now customer requirement changed over time but still machine learning model showing same recommendations to the customer while customer expectation has been changed. This incident is called a Data Drift. It generally occurs when new data is introduced or interpretation of data changes. However, we can overcome this by regularly updating and monitoring data according to the expectations.

7. Lack of skilled resources

Although Machine Learning and Artificial Intelligence are continuously growing in the market, still these industries are fresher in comparison to others. The absence of skilled resources in the form of manpower is also an issue. Hence, we need manpower having in-depth knowledge of mathematics, science, and technologies for developing and managing scientific substances for machine learning.

8. Customer Segmentation

Customer segmentation is also an important issue while developing a machine learning algorithm. To identify the customers who paid for the recommendations shown by the model and who don't even check them. Hence, an algorithm is necessary to recognize the customer behavior and trigger a relevant recommendation for the user based on past experience.

9. Process Complexity of Machine Learning

The machine learning process is very complex, which is also another major issue faced by machine learning engineers and data scientists. However, Machine Learning and Artificial Intelligence are very new technologies but are still in an experimental phase and continuously being changing over time. There is the majority of hits and trial experiments; hence the probability of error is higher than expected. Further, it also includes analyzing the data, removing data bias, training data, applying complex mathematical calculations, etc., making the procedure more complicated and quite tedious.

10. Data Bias

Data Biasing is also found a big challenge in Machine Learning. These errors exist when certain elements of the dataset are heavily weighted or need more importance than others. Biased data leads to inaccurate results, skewed outcomes, and other analytical errors. However, we can resolve this error by determining where data is actually biased in the dataset. Further, take necessary steps to reduce it.

Methods to remove Data Bias:

- Research more for customer segmentation.
- Be aware of your general use cases and potential outliers.
- Combine inputs from multiple sources to ensure data diversity.
- Include bias testing in the development process.
- Analyze data regularly and keep tracking errors to resolve them easily.

- Review the collected and annotated data.
- Use multi-pass annotation such as sentiment analysis, content moderation, and intent recognition.

11. Lack of Explainability

This basically means the outputs cannot be easily comprehended as it is programmed in specific ways to deliver for certain conditions. Hence, a lack of explainability is also found in machine learning algorithms which reduce the credibility of the algorithms.

12. Slow implementations and results

This issue is also very commonly seen in machine learning models. However, machine learning models are highly efficient in producing accurate results but are time-consuming. Slow programming, excessive requirements' and overloaded data take more time to provide accurate results than expected. This needs continuous maintenance and monitoring of the model for delivering accurate results.

13. Irrelevant features

Although machine learning models are intended to give the best possible outcome, if we feed garbage data as input, then the result will also be garbage. Hence, we should use relevant features in our training sample. A machine learning model is said to be good if training data has a good set of features or less to no irrelevant features.

[5]Risks of Machine Learning

Nowadays, Machine Learning is playing a big role in helping organizations in different aspects such as analyzing structured and unstructured data, detecting risks, automating manuals tasks, making data-driven decisions for business growth, etc. It is capable of replacing the huge amount of human labour by applying automation and providing insights to make better decisions for assessing, monitoring, and reducing the risks for an organization.

Although machine learning can be used as a risk management tool, it also contains many risks itself. While 49% of companies are exploring or planning to use machine learning, only a small minority recognize the risks it poses. In which, only 41% of organizations in a global McKinsey survey say they can comprehensively identify and prioritize machine learning risks. Hence, it is necessary to be aware of some of the risks of machine learning-and how they can be adequately evaluated and managed.

Below are a few risks associated with Machine Learning:

1. Poor Data

As we know, a machine learning model only works on the data that we provide to it, or we can say it completely depends on human-given training data to work. What we will be input that we will get as an output, so if we will enter the poor data, the ML model will generate abrupt output. Poor data or dirty data includes errors in training data, outliers, and unstructured data, which cannot be adequately interpreted by the model.

2. Overfitting

Overfitting is commonly found in non-parametric and non-linear models that are more flexible to learn target function.

An overfitted model fits the training data so perfectly that it becomes unable to learn the variability for the algorithm. It means it won't be able to generalize well when it comes to testing real data.

3. Biased data

Biased data means that human biases can creep into your datasets and spoil outcomes. For instance, the popular selfie editor FaceApp was initially inadvertently trained to make faces "hotter" by lightening the skin tone-a result of having been fed a much larger quantity of photos of people with lighter skin tones.

4. Lack of strategy and experience:

Machine learning is a very new technology in the IT sector; hence, less availability of trained and skilled resources is a very big issue for the industries. Further, lack of strategy and experience due to fewer resources leads to wastage of time and money as well as negatively affect the organization's production and revenue. According to a survey of over 2000 people, 860 reported to lack of clear strategy and 840 were reported to lack of talent with appropriate skill sets. This survey shows how lack of strategy and relevant experience creates a barrier in the development of machine learning for organizations.

5. Security Risks

Security of data is one of the major issues for the IT world. Security also affects the production and revenue of organizations. When it comes to machine learning, there are various types of security risks exist that can compromise machine learning algorithms and systems. Data scientists and machine learning experts have reported 3 types of attacks, primarily for machine learning models. These are as follows:

- **Evasion attacks:**These attacks are commonly arisen due to adversarial input introduced in the models; hence they are also known as adversarial attacks. An evasion attack happens when the network uses adversarial examples as input which can influence the classifiers, i.e., disrupting ML models. When a security violation involves supplying malicious data that gets classified as genuine. A targeted attack attempts to allow a specific intrusion or disruption, or alternatively to create general mayhem.

  Evasion attacks are the most dominant type of attack, where data is modified in a way that it seems as genuine data. Evasion doesn't involve influence over the data used to train a model, but it is comparable to the way spammers and hackers obfuscate the content of spam emails and malware.

- **Data Poisoning attacks:**

  In data poisoning attacks, the source of raw data is known, which is used to train the ML models. Further, it strives to bias or "poison" the data to compromise the resulting machine learning model's accuracy. The effects of these attacks can be overcome by prevention and detection. Through proper monitoring, we can prevent ML models from data poisoning.

  Model skewing is one the most common type of data poisoning attacks in which spammers categorise the classifiers with bad input as good.

- **Model Stealing:**

  Model stealing is one of the most important security risks in machine learning. Model stealing techniques are used to create a clone model based on information or data used in the training of a base model. Why we are saying model stealing is a major concern for ML experts because ML models are the valuable intellectual property of organizations that consist of sensitive data of users such as account details, transactions, financial information, etc. The attackers use public API and sample data of the original model and reconstruct another model having a similar look and feel.

6. Data privacy and confidentiality

Data is one of the main key players in developing Machine learning models. We know machine learning requires a huge amount of structured and unstructured data for training models so they can predict accurately in future. Hence, to achieve good results, we need to secure data by defining some privacy terms and conditions as well as making it confidential. Hackers can launch data extraction attacks that can fly under the radar, which can put your entire machine learning system at risk.

7. Third-party risks

These types of security risks are not so famous in industries as there are very minimal chances of these risks in industries. Third-party risks generally exist when someone outsources their business to third-party service providers who may fail to properly govern a machine learning solution. This leads to various types of data breaches in the ML industry.

8. Regulatory challenges

Regulatory challenges occur whenever a knowledge gap is found in an organization, such as teammates do not aware of how ML algorithms work and create decisions. Hence, a lack of knowledge to justify decisions to regulators can also be a major security risk for industries.

[6]Clustering in Machine Learning

Clustering or cluster analysis is a machine learning technique, which groups the unlabelled dataset. It can be defined as ***"A way of grouping the data points into different clusters, consisting of similar data points. The objects with the possible similarities remain in a group that has less or no similarities with another group."***

It does it by finding some similar patterns in the unlabelled dataset such as shape, size, color, behavior, etc., and divides them as per the presence and absence of those similar patterns.

It is an unsupervised learning method, hence no supervision is provided to the algorithm, and it deals with the unlabeled dataset.

After applying this clustering technique, each cluster or group is provided with a cluster-ID. ML system can use this id to simplify the processing of large and complex datasets.

The clustering technique is commonly used for **statistical data analysis.**

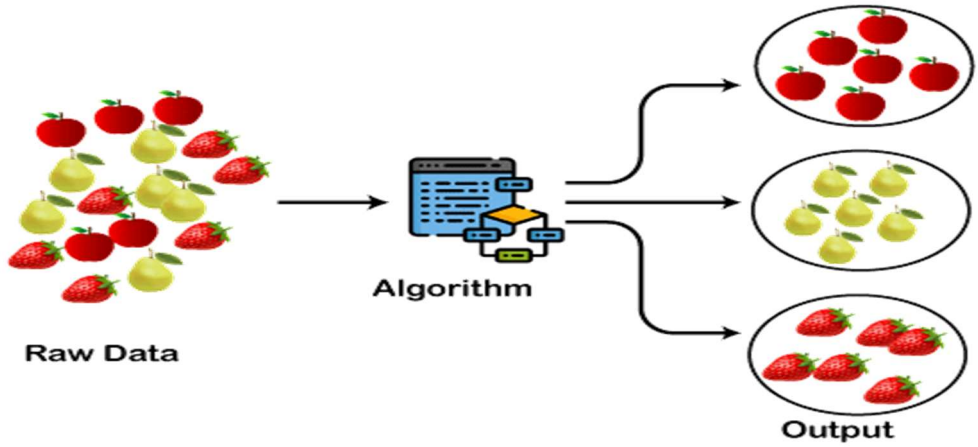
Example: Let's understand the clustering technique with the real-world example of Mall: When we visit any shopping mall, we can observe that the things with similar usage are grouped together. Such as the t-shirts are grouped in one section, and trousers are at other sections, similarly, at vegetable sections, apples, bananas, Mangoes, etc., are grouped in separate sections, so that we can easily find out the things. The clustering technique also works in the same way. Other examples of clustering are grouping documents according to the topic.

The clustering technique can be widely used in various tasks. Some most common uses of this technique are:

- Market Segmentation
- Statistical data analysis
- Social network analysis
- Image segmentation
- Anomaly detection, etc.

Apart from these general usages, it is used by the **Amazon** in its recommendation system to provide the recommendations as per the past search of products. **Netflix** also uses this technique to recommend the movies and web-series to its users as per the watch history.

The below diagram explains the working of the clustering algorithm. We can see the different fruits are divided into several groups with similar properties.



Types of Clustering Methods

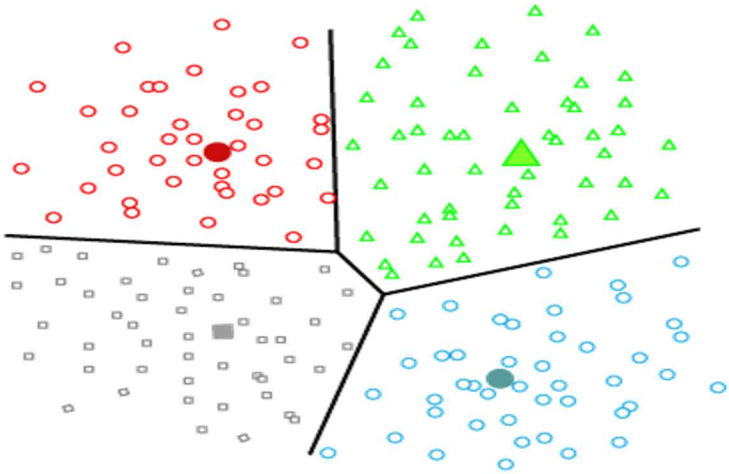
The clustering methods are broadly divided into **Hard clustering** (datapoint belongs to only one group) and **Soft Clustering** (data points can belong to another group also). But there are also other various approaches of Clustering exist. Below are the main clustering methods used in Machine learning:

1. **Partitioning Clustering**
2. **Density-Based Clustering**
3. **Distribution Model-Based Clustering**
4. **Hierarchical Clustering**
5. **Fuzzy Clustering**

Partitioning Clustering

It is a type of clustering that divides the data into non-hierarchical groups. It is also known as the **centroid-based method**. The most common example of partitioning clustering is the **K-Means Clustering algorithm**.

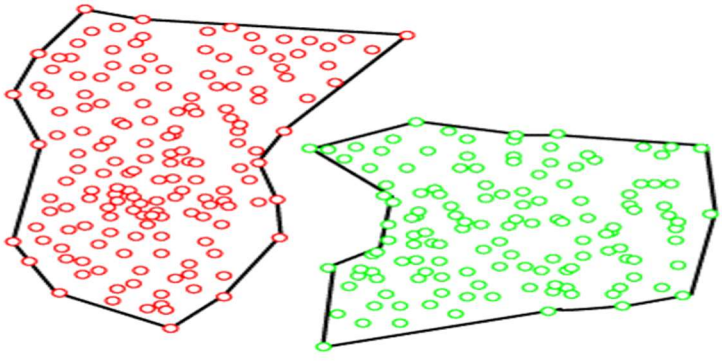
In this type, the dataset is divided into a set of k groups, where K is used to define the number of pre-defined groups. The cluster center is created in such a way that the distance between the data points of one cluster is minimum as compared to another cluster centroid.



Density-Based Clustering

The density-based clustering method connects the highly-dense areas into clusters, and the arbitrarily shaped distributions are formed as long as the dense region can be connected. This algorithm does it by identifying different clusters in the dataset and connects the areas of high densities into clusters. The dense areas in data space are divided from each other by sparser areas.

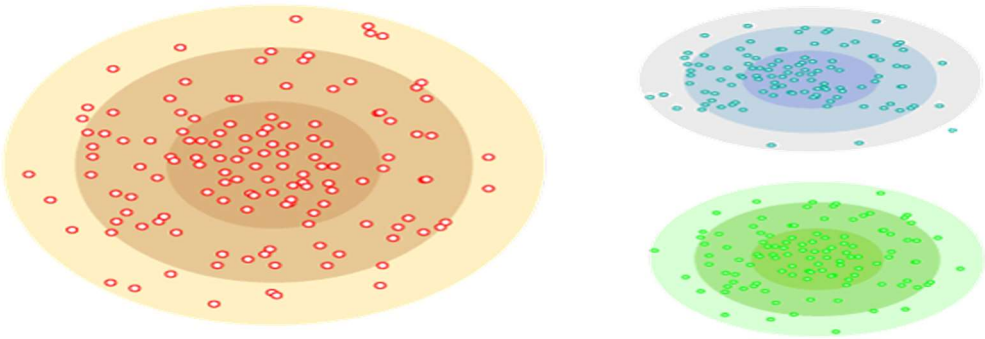
These algorithms can face difficulty in clustering the data points if the dataset has varying densities and high dimensions.



Distribution Model-Based Clustering

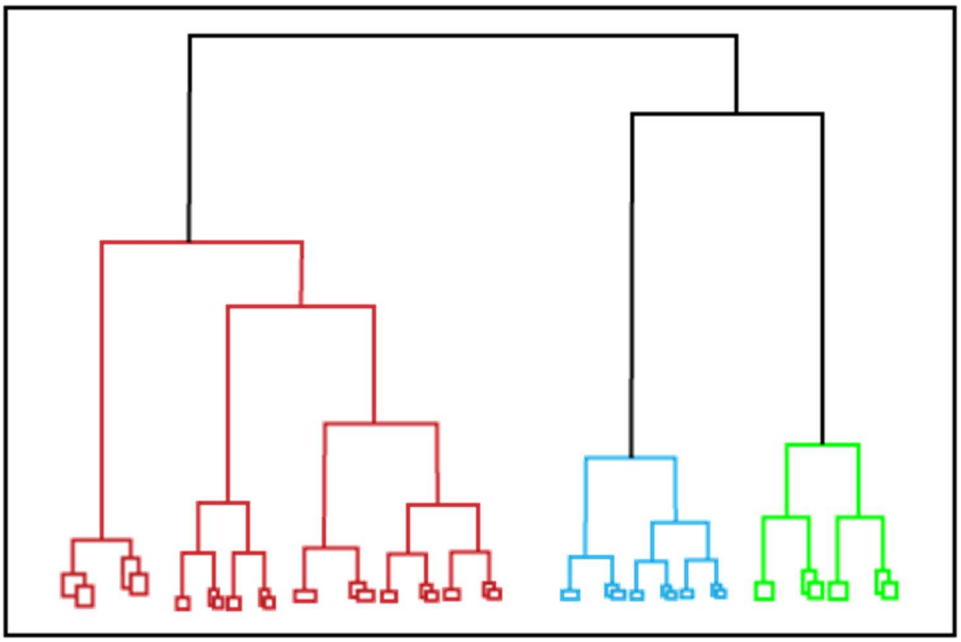
In the distribution model-based clustering method, the data is divided based on the probability of how a dataset belongs to a particular distribution. The grouping is done by assuming some distributions commonly **Gaussian Distribution**.

The example of this type is the **Expectation-Maximization Clustering algorithm** that uses Gaussian Mixture Models (GMM).



Hierarchical Clustering

Hierarchical clustering can be used as an alternative for the partitioned clustering as there is no requirement of pre-specifying the number of clusters to be created. In this technique, the dataset is divided into clusters to create a tree-like structure, which is also called a **dendrogram**. The observations or any number of clusters can be selected by cutting the tree at the correct level. The most common example of this method is the **Agglomerative Hierarchical algorithm**.



Fuzzy Clustering

Fuzzy clustering is a type of soft method in which a data object may belong to more than one group or cluster. Each dataset has a set of membership coefficients, which depend on the degree of membership to be in a cluster. **Fuzzy C-means algorithm** is the example of this type of clustering; it is sometimes also known as the Fuzzy k-means algorithm.

Clustering Algorithms

The Clustering algorithms can be divided based on their models that are explained above. There are different types of clustering algorithms published, but only a few are commonly used. The clustering algorithm is based on the kind of data that we are using. Such as, some algorithms need to guess the number of clusters in the given dataset, whereas some are required to find the minimum distance between the observation of the dataset.

Here we are discussing mainly popular Clustering algorithms that are widely used in machine learning:

1. **K-Means algorithm:** The k-means algorithm is one of the most popular clustering algorithms. It classifies the dataset by dividing the samples into different clusters of equal variances. The number of clusters must be specified in this algorithm. It is fast with fewer computations required, with the linear complexity of **O(n).**
2. **Mean-shift algorithm:** Mean-shift algorithm tries to find the dense areas in the smooth density of data points. It is an example of a centroid-based model, that works on updating the candidates for centroid to be the center of the points within a given region.
3. **DBSCAN Algorithm:** It stands **for Density-Based Spatial Clustering of Applications with Noise**. It is an example of a density-based model similar to the mean-shift, but with some remarkable advantages. In this algorithm, the areas of high density are separated by the areas of low density. Because of this, the clusters can be found in any arbitrary shape.
4. **Expectation-Maximization Clustering using GMM:** This algorithm can be used as an alternative for the k-means algorithm or for those cases where K-means can be failed. In GMM, it is assumed that the data points are Gaussian distributed.
5. **Agglomerative Hierarchical algorithm:** The Agglomerative hierarchical algorithm performs the bottom-up hierarchical clustering. In this, each data point is treated as a

single cluster at the outset and then successively merged. The cluster hierarchy can be represented as a tree-structure.

6. **Affinity Propagation:** It is different from other clustering algorithms as it does not require to specify the number of clusters. In this, each data point sends a message between the pair of data points until convergence. It has $O(N^2T)$ time complexity, which is the main drawback of this algorithm.

[7]What is Cost Function?

A cost function is an important parameter that determines how well a machine learning model performs for a given dataset. It calculates the difference between the expected value and predicted value and represents it as a single real number.

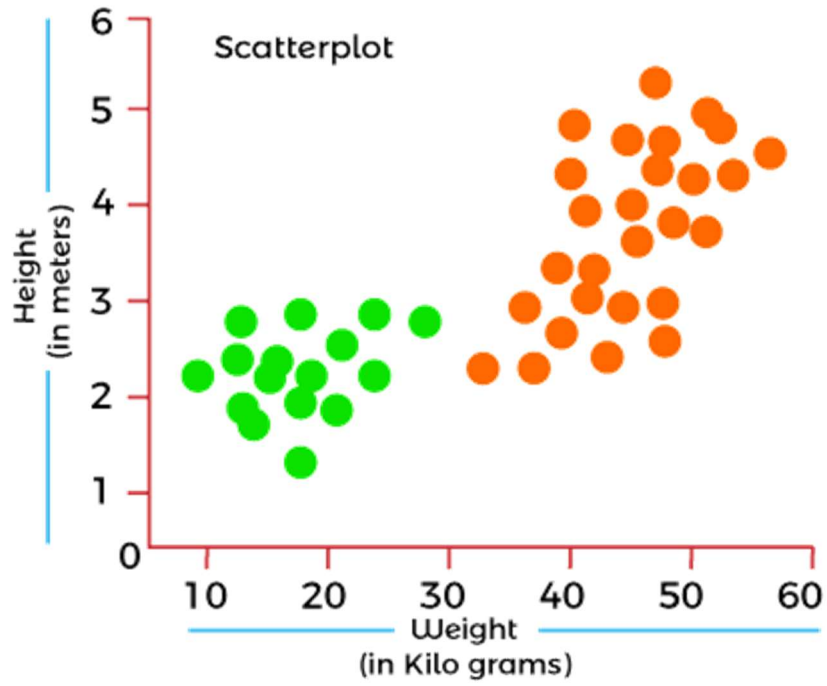
In machine learning, once we train our model, then we want to see how well our model is performing. Although there are various accuracy functions that tell you how your model is performing, but will not give insights to improve them. So, we need a function that can find when the model is most accurate by finding the spot between the undertrained and overtrained model.

In simple, "***Cost function is a measure of how wrong the model is in estimating the relationship between X(input) and Y(output) Parameter***." A cost function is sometimes also referred to as Loss function, and it can be estimated by iteratively running the model to compare estimated predictions against the known values of Y.

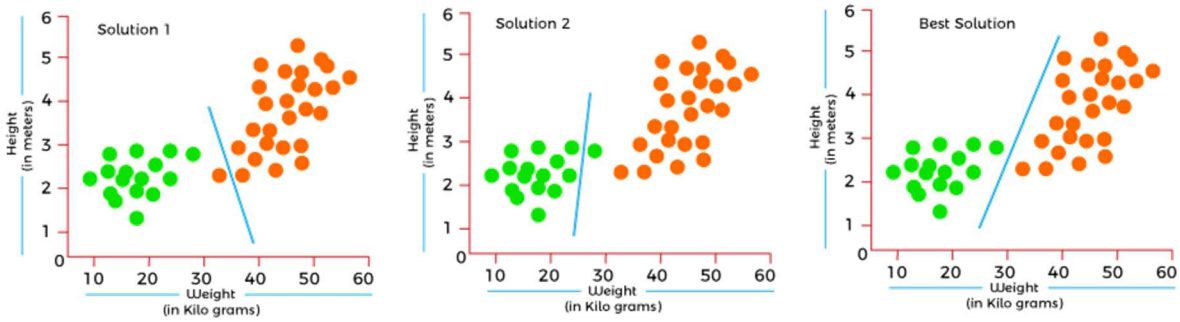
The main aim of each ML model is to determine parameters or weights that can minimize the cost function.

Why use Cost Function?

While there are different accuracy parameters, then why do we need a Cost function for the Machine learning model. So, we can understand it with an example of the classification of data. Suppose we have a dataset that contains the height and weights of cats & dogs, and we need to classify them accordingly. If we plot the records using these two features, we will get a scatter plot as below:



In the above image, the green dots are cats, and the yellow dots are dogs. Below are the three possible solutions for this classification problem.



In the above solutions, all three classifiers have high accuracy, but the third solution is the best because it correctly classifies each datapoint. The reason behind the best classification is that it is in mid between both the classes, not close or not far to any of them.

To get such results, we need a Cost function. It means for getting the optimal solution; we need a Cost function. It calculated the difference between the actual values and predicted values and measured how wrong was our model in the prediction. By minimizing the value of the cost function, we can get the optimal solution.

[8]Random Forest Algorithm

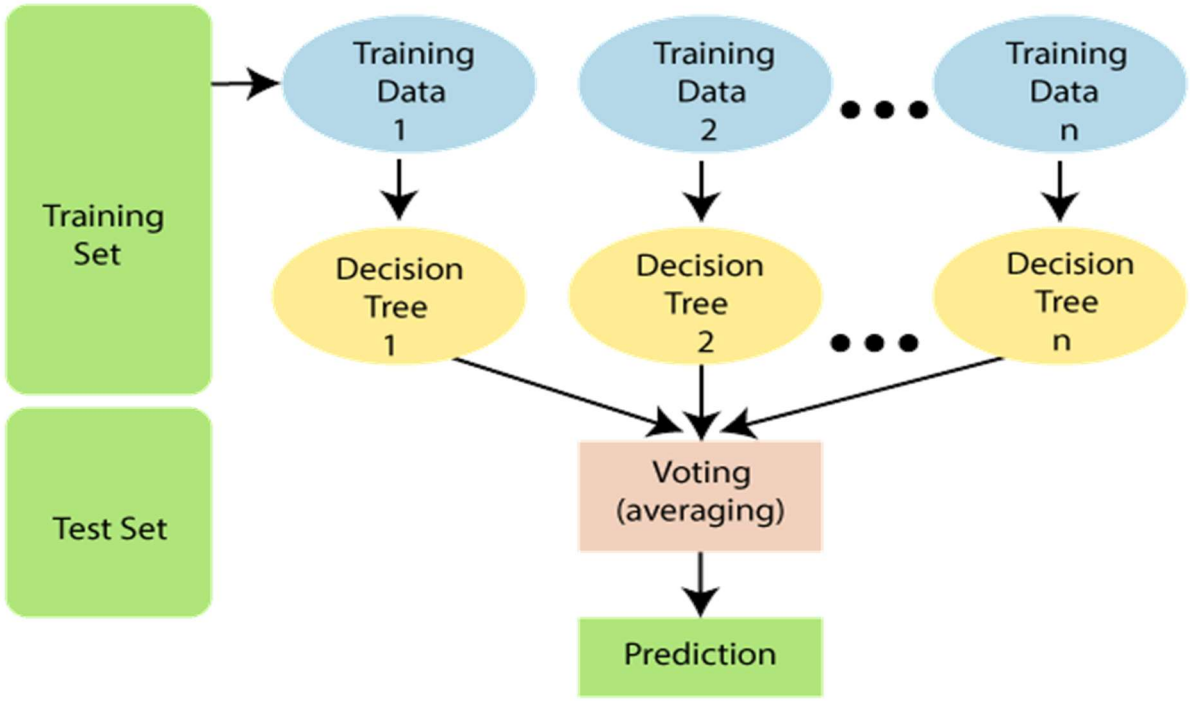
Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in

ML. It is based on the concept of **ensemble learning,** which is a process of *combining multiple classifiers to solve a complex problem and to improve the performance of the model.*

As the name suggests, **"*Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset.*"** Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

The below diagram explains the working of the Random Forest algorithm:



Note: To better understand the Random Forest Algorithm, you should have knowledge of the Decision Tree Algorithm.

Assumptions for Random Forest

Since the random forest combines multiple trees to predict the class of the dataset, it is possible that some decision trees may predict the correct output, while others may not. But together, all the trees predict the correct output. Therefore, below are two assumptions for a better Random forest classifier:

- There should be some actual values in the feature variable of the dataset so that the classifier can predict accurate results rather than a guessed result.
- The predictions from each tree must have very low correlations.

Why use Random Forest?

Below are some points that explain why we should use the Random Forest algorithm:

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- It takes less training time as compared to other algorithms.
- It predicts output with high accuracy, even for the large dataset it runs efficiently.
- It can also maintain accuracy when a large proportion of data is missing.

How does Random Forest algorithm work?

Random Forest works in two-phase first is to create the random forest by combining N decision tree, and second is to make predictions for each tree created in the first phase.

The Working process can be explained in the below steps and diagram:

Step-1: Select random K data points from the training set.

Step-2: Build the decision trees associated with the selected data points (Subsets).

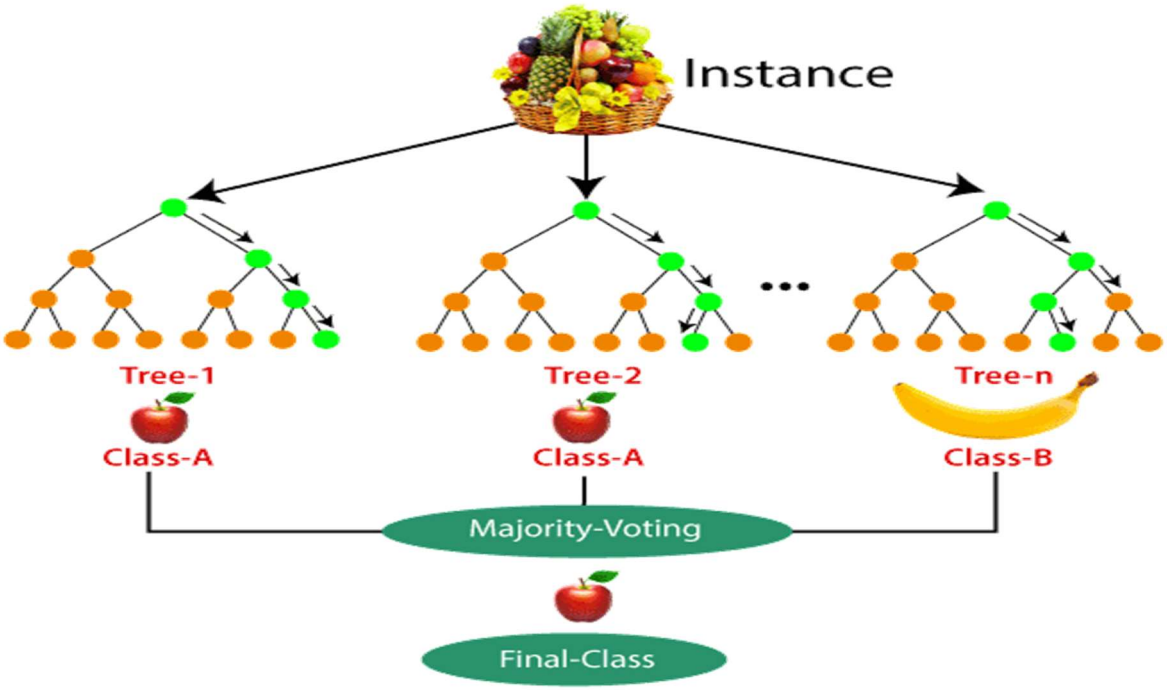
Step-3: Choose the number N for decision trees that you want to build.

Step-4: Repeat Step 1 & 2.

Step-5: For new data points, find the predictions of each decision tree, and assign the new data points to the category that wins the majority votes.

The working of the algorithm can be better understood by the below example:

Example: Suppose there is a dataset that contains multiple fruit images. So, this dataset is given to the Random forest classifier. The dataset is divided into subsets and given to each decision tree. During the training phase, each decision tree produces a prediction result, and when a new data point occurs, then based on the majority of results, the Random Forest classifier predicts the final decision. Consider the below image:



Applications of Random Forest

There are mainly four sectors where Random forest mostly used:

1. **Banking:** Banking sector mostly uses this algorithm for the identification of loan risk.
2. **Medicine:** With the help of this algorithm, disease trends and risks of the disease can be identified.
3. **Land Use:** We can identify the areas of similar land use by this algorithm.
4. **Marketing:** Marketing trends can be identified using this algorithm.

Advantages of Random Forest

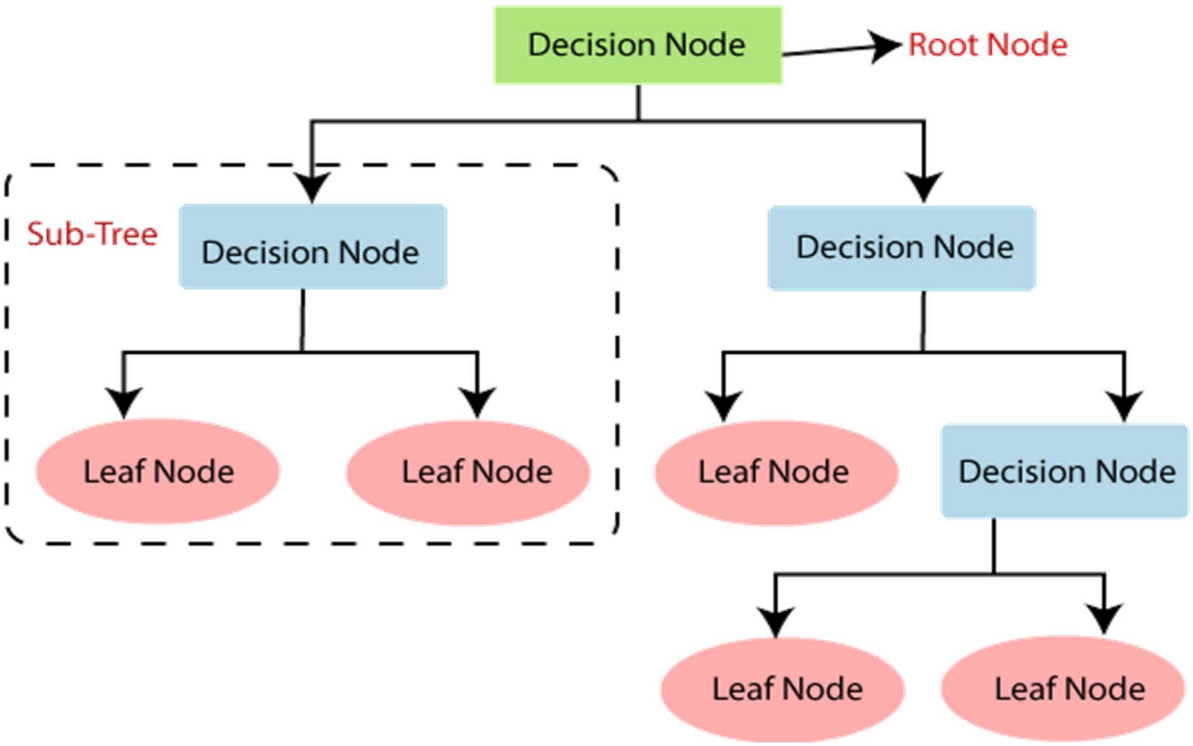
- Random Forest is capable of performing both Classification and Regression tasks.
- It is capable of handling large datasets with high dimensionality.
- It enhances the accuracy of the model and prevents the overfitting issue.

Disadvantages of Random Forest

- Although random forest can be used for both classification and regression tasks, it is not more suitable for Regression tasks.

[9]Decision Tree Classification Algorithm

- Decision Tree is a **Supervised learning technique** that can be used for both classification and Regression problems, but mostly it is preferred for solving Classification problems. It is a tree-structured classifier, where **internal nodes represent the features of a dataset, branches represent the decision rules** and **each leaf node represents the outcome.**
- In a Decision tree, there are two nodes, which are the **Decision Node** and **Leaf Node.** Decision nodes are used to make any decision and have multiple branches, whereas Leaf nodes are the output of those decisions and do not contain any further branches.
- The decisions or the test are performed on the basis of features of the given dataset.
- ***It is a graphical representation for getting all the possible solutions to a problem/decision based on given conditions.***
- It is called a decision tree because, similar to a tree, it starts with the root node, which expands on further branches and constructs a tree-like structure.
- In order to build a tree, we use the **CART algorithm,** which stands for **Classification and Regression Tree algorithm.**
- A decision tree simply asks a question, and based on the answer (Yes/No), it further split the tree into subtrees.
- Below diagram explains the general structure of a decision tree:



Why use Decision Trees?

There are various algorithms in Machine learning, so choosing the best algorithm for the given dataset and problem is the main point to remember while creating a machine learning model. Below are the two reasons for using the Decision tree:

- Decision Trees usually mimic human thinking ability while making a decision, so it is easy to understand.
- The logic behind the decision tree can be easily understood because it shows a tree-like structure.

Decision Tree Terminologies

- **Root Node:** Root node is from where the decision tree starts. It represents the entire dataset, which further gets divided into two or more homogeneous sets.
- **Leaf Node:** Leaf nodes are the final output node, and the tree cannot be segregated further after getting a leaf node.
- **Splitting:** Splitting is the process of dividing the decision node/root node into sub-nodes according to the given conditions.
- **Branch/Sub Tree:** A tree formed by splitting the tree.
- **Pruning:** Pruning is the process of removing the unwanted branches from the tree.
- **Parent/Child node:** The root node of the tree is called the parent node, and other nodes are called the child nodes.

Attribute Selection Measures

While implementing a Decision tree, the main issue arises that how to select the best attribute for the root node and for sub-nodes. So, to solve such problems there is a technique which is called as **Attribute selection measure or ASM.** By this measurement, we can easily select the best attribute for the nodes of the tree. There are two popular techniques for ASM, which are:

- **Information Gain**
- **Gini Index**

1. Information Gain:

- Information gain is the measurement of changes in entropy after the segmentation of a dataset based on an attribute.
- It calculates how much information a feature provides us about a class.

- According to the value of information gain, we split the node and build the decision tree.
- A decision tree algorithm always tries to maximize the value of information gain, and a node/attribute having the highest information gain is split first. It can be calculated using the below formula:

1. Information Gain= Entropy(S)- [(Weighted Avg) *Entropy(each feature)

Entropy: Entropy is a metric to measure the impurity in a given attribute. It specifies randomness in data. Entropy can be calculated as:

```
Entropy(s)= -P(yes)log2 P(yes)- P(no) log2 P(no)
```

Where,

- **S= Total number of samples**
- **P(yes)= probability of yes**
- **P(no)= probability of no**

2. Gini Index:

- Gini index is a measure of impurity or purity used while creating a decision tree in the CART(Classification and Regression Tree) algorithm.
- An attribute with the low Gini index should be preferred as compared to the high Gini index.
- It only creates binary splits, and the CART algorithm uses the Gini index to create binary splits.
- Gini index can be calculated using the below formula:

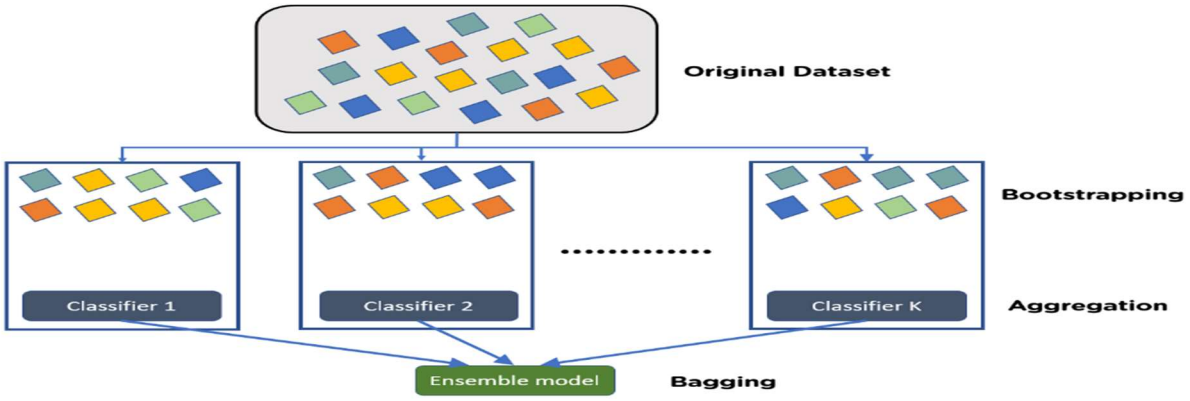
$$\text{Gini Index} = 1 - \sum_j P_j^2$$

[10]What Is Ensemble Learning?

Ensemble learning is a widely-used and preferred machine learning technique in which multiple individual models, often called base models, are combined to produce an effective optimal prediction model. The Random Forest algorithm is an example of ensemble learning.

What Is Bagging in Machine Learning?

Bagging, also known as Bootstrap aggregating, is an ensemble learning technique that helps to improve the performance and accuracy of machine learning algorithms. It is used to deal with bias-variance trade-offs and reduces the variance of a prediction model. Bagging avoids overfitting of data and is used for both regression and classification models, specifically for decision tree algorithms.



Steps to Perform Bagging

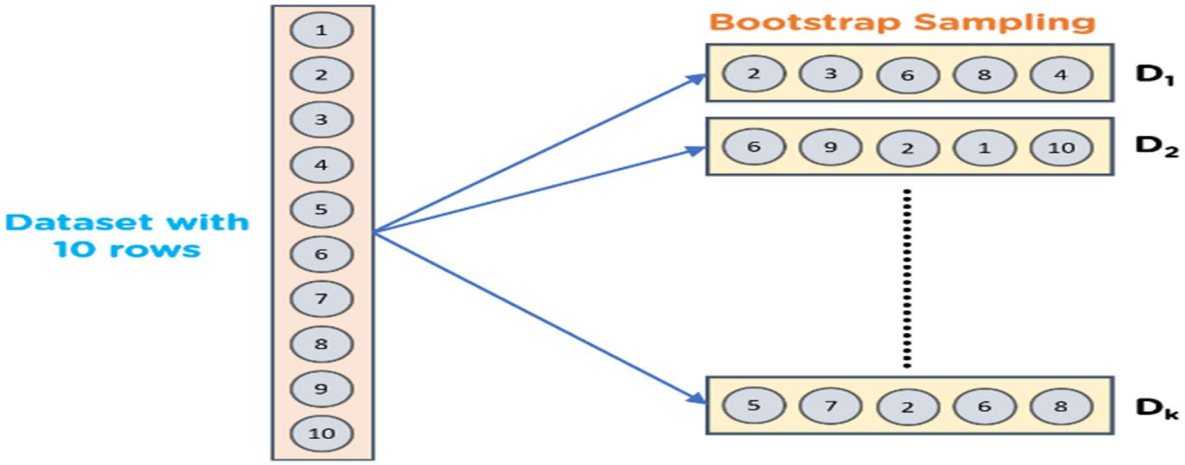
- Consider there are n observations and m features in the training set. You need to select a random sample from the training dataset without replacement
- A subset of m features is chosen randomly to create a model using sample observations
- The feature offering the best split out of the lot is used to split the nodes
- The tree is grown, so you have the best root nodes
- The above steps are repeated n times. It aggregates the output of individual decision trees to give the best prediction

Advantages of Bagging in Machine Learning

- Bagging minimizes the overfitting of data
- It improves the model's accuracy
- It deals with higher dimensional data efficiently

What Is Bootstrapping?

Bootstrapping is the method of randomly creating samples of data out of a population with replacement to estimate a population parameter.



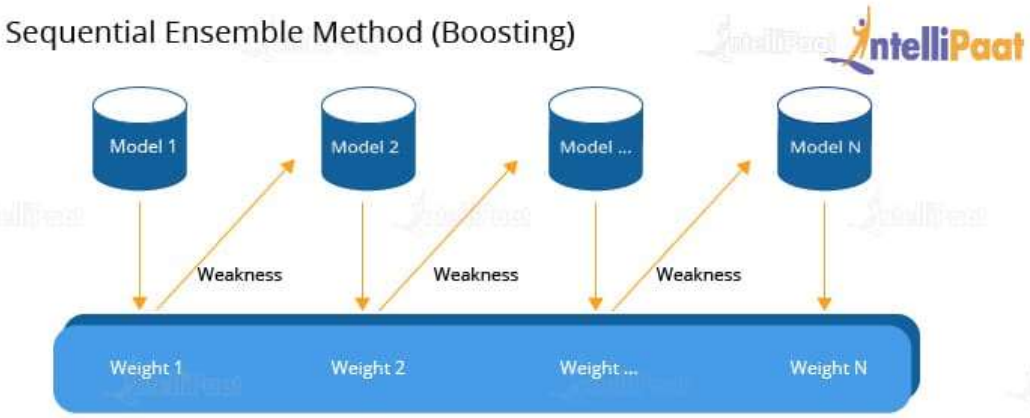
What is Boosting?

Boosting is a technique to combine weak learners and convert them into strong ones with the help of Machine Learning algorithms. It uses ensemble learning to boost the accuracy of a model. Ensemble learning is a technique to improve the accuracy of Machine Learning models. There are two types of ensemble learning:

1. Sequential Ensemble Learning

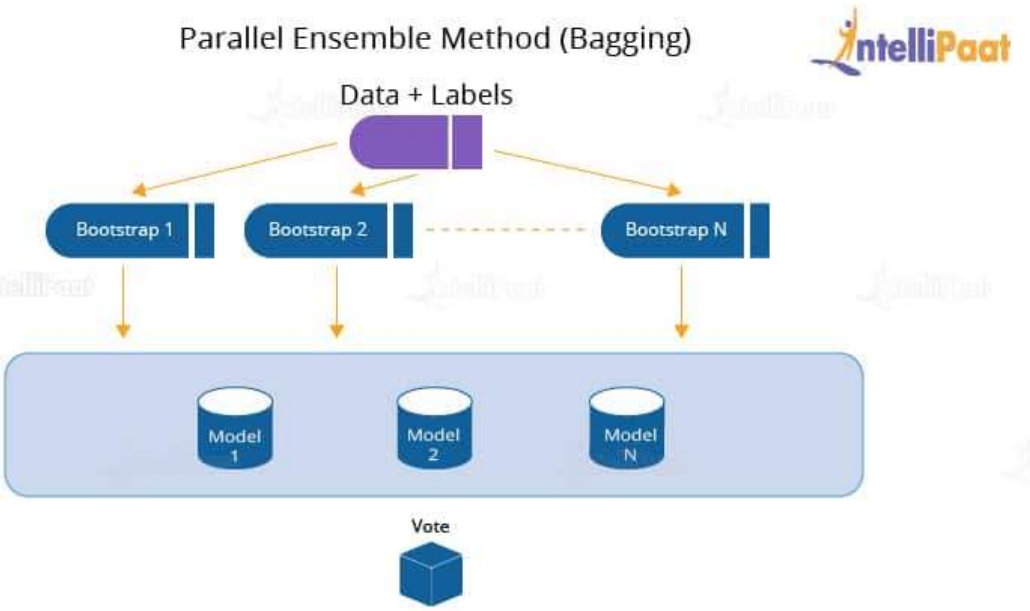
It is a boosting technique where the outputs from individual weak learners associate sequentially during the training phase. The performance of the model is boosted by assigning higher weights to the samples that are incorrectly

classified. AdaBoost algorithm is an example of sequential learning that we will learn later in this blog.



2. Parallel Ensemble Learning

It is a bagging technique where the outputs from the weak learners are generated parallelly. It reduces errors by averaging the outputs from all weak learners. The random forest algorithm is an example of parallel ensemble learning.



Mechanism of Boosting Algorithms

Boosting is creating a generic algorithm by considering the prediction of the majority of weak learners. It helps in increasing the prediction power of the Machine Learning model. This is done by training a series of weak models.

Below are the steps that show the mechanism of the boosting algorithm:

1. Reading data

2. Assigning weights to observations

3. Identification of misinterpretation (false prediction)

4. Assigning the false prediction, along with a higher weightage, to the next learner

5. Finally, iterating Step 2 until we get the correctly classified output

Types of Boosting Algorithms

Basically, there are three types of boosting algorithms discussed as below:

1. Adaptive Boosting (AdaBoost)

Adaptive boosting is a technique used for binary classification. For implementing AdaBoost, we use short decision trees as weak learners.

Steps for implementing AdaBoost:

1. Train the base model using the weighted training data

2. Then, add weak learners sequentially to make it a strong learner

3. Each weak learner consists of a decision tree; analyze the output of each decision tree and assign higher weights to the misclassified results. This gives more significance to the prediction with higher weights.

4. Continue the process until the model becomes capable of predicting the accurate result

2. Gradient Boosting

In Machine Learning, we use gradient boosting to solve **classification** and regression problems. It is a sequential ensemble learning technique where the performance of the model improves over iterations. This method creates the model in a stage-wise fashion. It infers the model by enabling the optimization of an absolute differentiable loss function. As we add each weak learner, a new model is created that gives a more precise estimation of the response variable.

The gradient boosting algorithm requires the below components to function:

1. **Loss function**: To reduce errors in prediction, we need to optimize the loss function. Unlike in AdaBoost, the incorrect result is not given a higher weightage in gradient boosting. It tries to reduce the loss function by averaging the outputs from weak learners.

2. **Weak learner**: In gradient boosting, we require weak learners to make predictions. To get real values as output, we use regression trees. To get the most suitable split point, we create trees in a greedy manner, due to this the model overfits the dataset.

3. **Additive model**: In gradient boosting, we try to reduce the loss by adding decision trees. Also, we can minimize the error rate by cutting down the parameters. So, in this case, we design the model in such a way that the addition of a tree does not change the existing tree.

Finally, we update the weights to minimize the error that is being calculated.