What is Classification and its Use Cases in Machine Learning?

Classification is the process of dividing a set of data into categories. It can be done on both structured and unstructured data. Predicting the class of provided data points is the first step in the procedure. Target, label, and categories are all terms used to describe the classes.

The task of approximating the mapping function from discrete input variables to discrete output variables is classified as predictive modeling. The basic goal is to figure out which category or class the new data belongs to. Let's have a look at a basic example to help us comprehend.

The type of content of an online article can be classified using Machine Learning Classification algorithms. In this situation, the classifier requires training data in order to comprehend how the input variables are related to the class. Once the classifier has been properly trained, it can be used to determine if an article's content is of type – sports or automotive, or science. There are a total of three types of classification tasks –

1. **Binary Classification –** Classification problems with two class labels are referred to as binary classification. Example – Email Spam Classification (spam or not spam).
2. **Multi-class Classification –** Classification jobs with more than two class labels are referred to as multi-class classification. Example – Classification of types of music.
3. **Multi-label Classification –** Classification tasks with two or more class labels, where one or more class labels can be anticipated for each case, are referred to as multi-label classification. Consider object detection, where an image may contain numerous things, and a model can predict the existence of multiple known objects in the scene, such as "bicycle," "apple," "person," and so on.

Use Cases of Classification in Machine Learning-

- **Predicting customer behavior –** Customers can be split into groups based on their shopping habits, browsing habits in online stores, and other characteristics. For example, classification models can be used to determine whether or not a customer is likely to purchase additional items. If the categorization model indicates that they will make more purchases, you may want to make special offers and discounts available to them. Alternatively, if it has been determined that they are likely to forsake their buying habits in the near future, you may choose to store their information for further use.
- **Document classification –** A multinomial classification model can be used to divide documents into distinct categories.
- **Image classification –** A multinomial classification model can be used to divide photos into various categories.
- **Product categorization –** A multinomial classification can be used to categorize products sold by multiple shops in the same categories, regardless of the categories assigned to them by the individual merchants. This use case can help eCommerce aggregators.
- **Malware classification –** Malware can be classified using a multinomial classification system based on similar malware features. Malware classification is incredibly useful in choosing the best line of action for combating and preventing malware for security experts.

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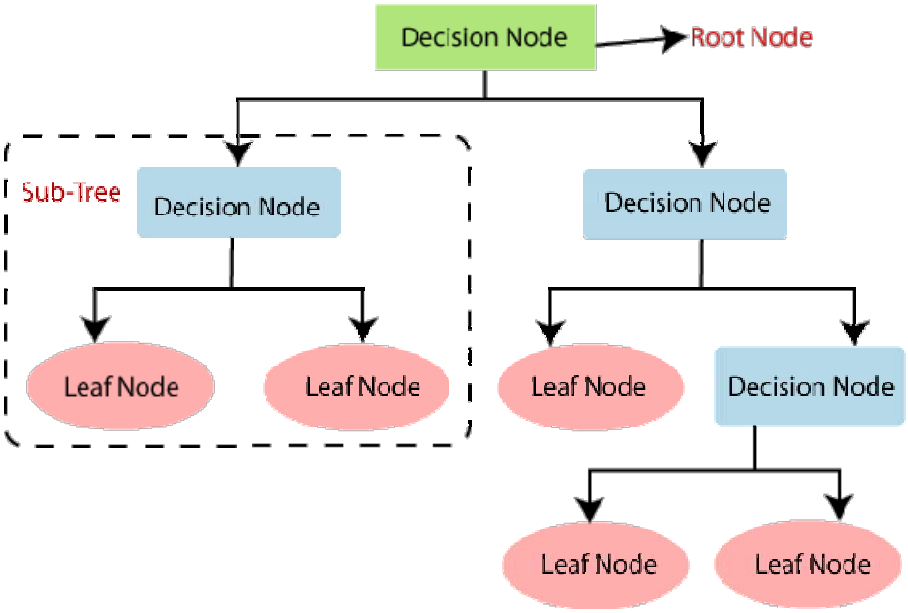
Decision Tree Classification Algorithm

- 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:
- note: A decision tree can contain categorical data (YES/NO) as well as numeric data.



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.

How does the Decision Tree algorithm Work?

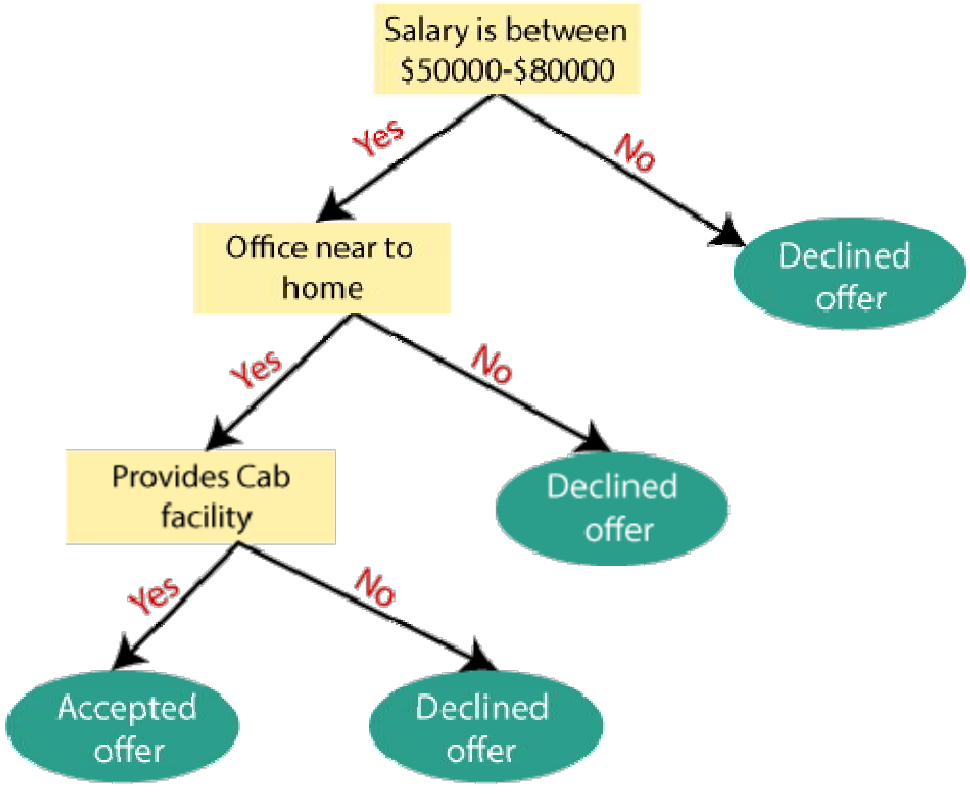
In a decision tree, for predicting the class of the given dataset, the algorithm starts from the root node of the tree. This algorithm compares the values of root attribute with the record (real dataset) attribute and, based on the comparison, follows the branch and jumps to the next node.

For the next node, the algorithm again compares the attribute value with the other sub-nodes and move further. It continues the process until it reaches the leaf node of the tree. The complete process can be better understood using the below algorithm:

- **Step-1:** Begin the tree with the root node, says S, which contains the complete dataset.

- **Step-2:** Find the best attribute in the dataset using **Attribute Selection Measure (ASM).**
- **Step-3:** Divide the S into subsets that contains possible values for the best attributes.
- **Step-4:** Generate the decision tree node, which contains the best attribute.
- **Step-5:** Recursively make new decision trees using the subsets of the dataset created in step -3. Continue this process until a stage is reached where you cannot further classify the nodes and called the final node as a leaf node.

Example: Suppose there is a candidate who has a job offer and wants to decide whether he should accept the offer or Not. So, to solve this problem, the decision tree starts with the root node (Salary attribute by ASM). The root node splits further into the next decision node (distance from the office) and one leaf node based on the corresponding labels. The next decision node further gets split into one decision node (Cab facility) and one leaf node. Finally, the decision node splits into two leaf nodes (Accepted offers and Declined offer). Consider the below diagram:



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:

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

Pruning: Getting an Optimal Decision tree

Pruning is a process of deleting the unnecessary nodes from a tree in order to get the optimal decision tree.

A too-large tree increases the risk of overfitting, and a small tree may not capture all the important features of the dataset. Therefore, a technique that decreases the size of the learning tree without reducing accuracy is known as Pruning. There are mainly two types of tree **pruning** technology used:

- **Cost Complexity Pruning**
- **Reduced Error Pruning.**

Advantages of the Decision Tree

- It is simple to understand as it follows the same process which a human follow while making any decision in real-life.
- It can be very useful for solving decision-related problems.
- It helps to think about all the possible outcomes for a problem.
- There is less requirement of data cleaning compared to other algorithms.

Disadvantages of the Decision Tree

- The decision tree contains lots of layers, which makes it complex.
- It may have an overfitting issue, which can be resolved using the **Random Forest algorithm.**
- For more class labels, the computational complexity of the decision tree may increase.

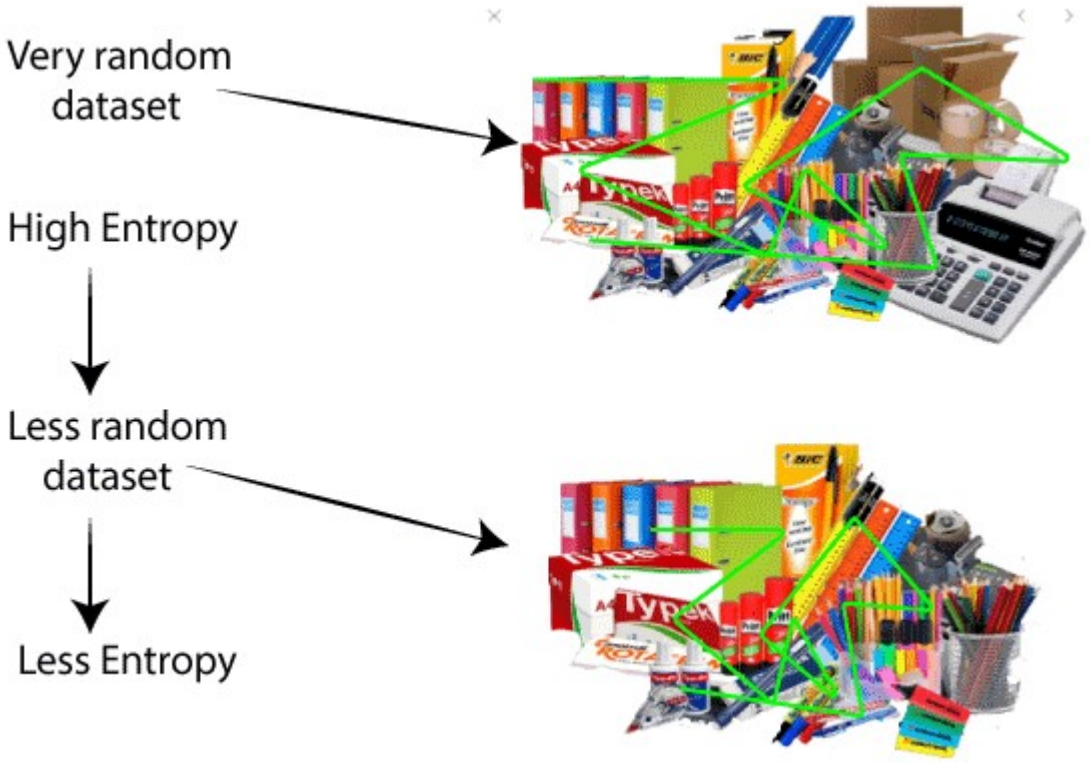
Decision Tree Induction

Decision Tree is a supervised learning method used in data mining for classification and regression methods. It is a tree that helps us in decision-making purposes. The decision tree creates classification or regression models as a tree structure. It separates a data set into smaller subsets, and at the same time, the decision tree is steadily developed. The final tree is a tree with the decision nodes and leaf nodes. A decision node has at least two branches. The leaf nodes show a classification or decision. We can't accomplish more split on leaf nodes-The uppermost decision node in a tree that relates to the best predictor called the root node. Decision trees can deal with both categorical and numerical data.

Key factors:

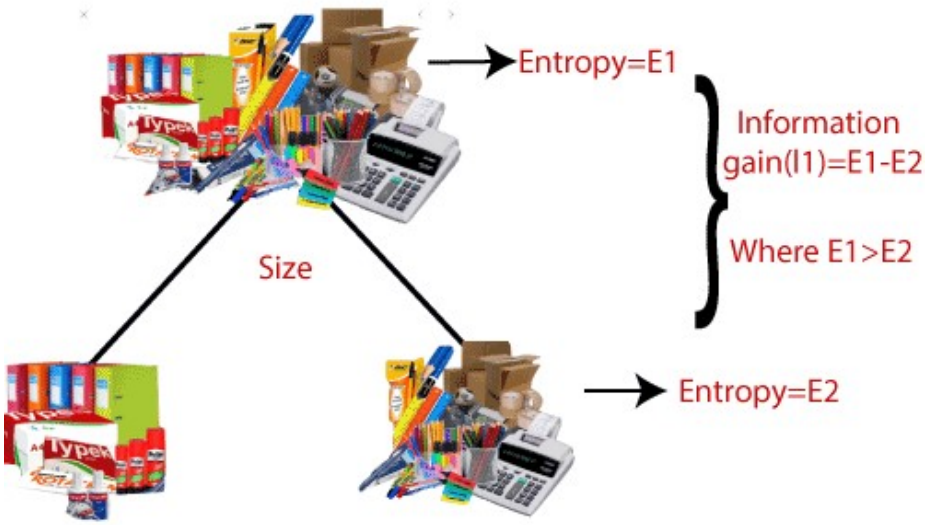
Entropy:

Entropy refers to a common way to measure impurity. In the decision tree, it measures the randomness or impurity in data sets.



Information Gain:

Information Gain refers to the decline in entropy after the dataset is split. It is also called **Entropy Reduction**. Building a decision tree is all about discovering attributes that return the highest data gain.



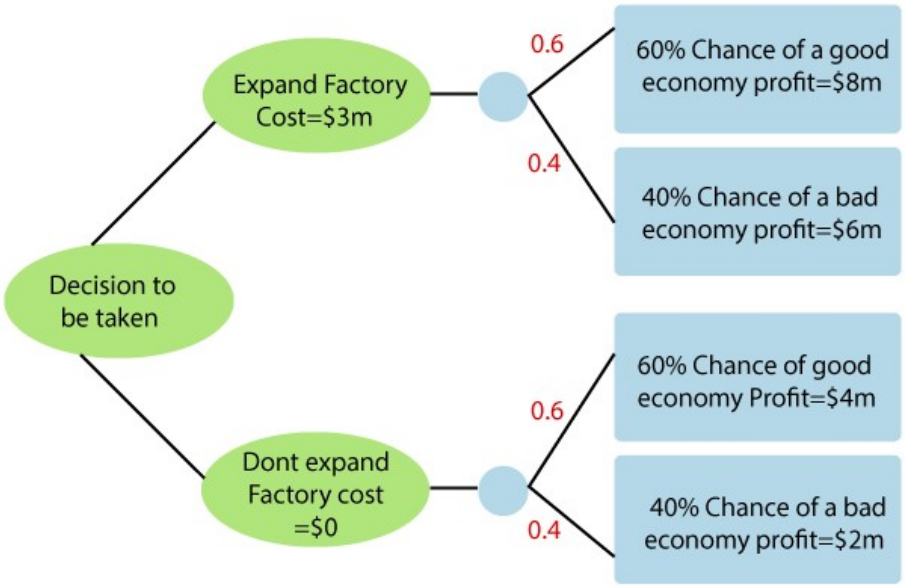
In short, a decision tree is just like a flow chart diagram with the terminal nodes showing decisions. Starting with the dataset, we can measure the entropy to find a way to segment the set until the data belongs to the same class.

Why are decision trees useful?

It enables us to analyze the possible consequences of a decision thoroughly.
It provides us a framework to measure the values of outcomes and the probability of accomplishing them.
It helps us to make the best decisions based on existing data and best speculations.

In other words, we can say that a decision tree is a hierarchical tree structure that can be used to split an extensive collection of records into smaller sets of the class by implementing a sequence of simple decision rules. A decision tree model comprises a set of rules for portioning a huge heterogeneous population into smaller, more homogeneous, or mutually exclusive classes. The attributes of the classes can be any variables from nominal, ordinal, binary, and quantitative values, in contrast, the classes must be a qualitative type, such as categorical or ordinal or binary. In brief, the given data of attributes together with its class, a decision tree creates a set of rules that can be used to identify the class. One rule is implemented after another, resulting in a hierarchy of segments within a segment. The hierarchy is known as the **tree**, and each segment is called a **node**. With each progressive division, the members from the subsequent sets become more and more similar to each other. Hence, the algorithm used to build a decision tree is referred to as recursive partitioning. The algorithm is known as **CART** (Classification and Regression Trees)

Consider the given example of a factory where



Expanding factor costs $3 million, the probability of a good economy is 0.6 (60%), which leads to $8 million profit, and the probability of a bad economy is 0.4 (40%), which leads to $6 million profit.
Not expanding factor with 0$ cost, the probability of a good economy is 0.6(60%), which leads to $4 million profit, and the probability of a bad economy is 0.4, which leads to $2 million profit.
The management teams need to take a data-driven decision to expand or not based on the given data.
Net Expand = (0.6 *8 + 0.4*6) - 3 = $4.2M
Net Not Expand = (0.6*4 + 0.4*2) - 0 = $3M
$4.2M > $3M,therefore the factory should be expanded.

Decision tree Algorithm: **The decision tree algorithm may appear long, but it is quite simply the basis algorithm techniques is as follows:**

The **algorithm** is based on three parameters**: D, attribute_list, and Attribute _selection_method.**
Generally, we refer to **D** as a **data partition.**
Initially, **D** is the entire set of **training tuples** and their related **class levels** (input training data).
The parameter **attribute_list** is a set of **attributes** defining the tuples.

Attribute_selection_method specifies a **heuristic process** for choosing the attribute that "best" discriminates the given tuples according to **class**.

Attribute_selection_method process applies an **attribute selection measure**.

Confusion Matrix in Machine Learning

The confusion matrix is a matrix used to determine the performance of the classification models for a given set of test data. It can only be determined if the true values for test data are known. The matrix itself can be easily understood, but the related terminologies may be confusing. Since it shows the errors in the model performance in the form of a matrix, hence also known as an **error matrix**. Some features of Confusion matrix are given below:

- For the 2 prediction classes of classifiers, the matrix is of 2*2 table, for 3 classes, it is 3*3 table, and so on.
- The matrix is divided into two dimensions, that are **predicted values** and **actual values** along with the total number of predictions.
- Predicted values are those values, which are predicted by the model, and actual values are the true values for the given observations.
- It looks like the below table:

n = total predictions	Actual: No	Actual: Yes
Predicted: No	True Negative	False Positive
Predicted: Yes	False Negative	True Positive

The above table has the following cases:

- **True Negative:** Model has given prediction No, and the real or actual value was also No.
- **True Positive:** The model has predicted yes, and the actual value was also true.
- **False Negative:** The model has predicted no, but the actual value was Yes, it is also called as **Type-II error**.
- **False Positive:** The model has predicted Yes, but the actual value was No. It is also called a **Type-I error.**

Need for Confusion Matrix in Machine learning

- It evaluates the performance of the classification models, when they make predictions on test data, and tells how good our classification model is.

- It not only tells the error made by the classifiers but also the type of errors such as it is either type-I or type-II error.
- With the help of the confusion matrix, we can calculate the different parameters for the model, such as accuracy, precision, etc.

Example: We can understand the confusion matrix using an example.

Suppose we are trying to create a model that can predict the result for the disease that is either a person has that disease or not. So, the confusion matrix for this is given as:

n = 100	Actual: No	Actual: Yes	
Predicted: No	TN: 65	FP: 3	68
Predicted: Yes	FN: 8	TP: 24	32
	73	27	

From the above example, we can conclude that:

- The table is given for the two-class classifier, which has two predictions "Yes" and "NO." Here, Yes defines that patient has the disease, and No defines that patient does not has that disease.
- The classifier has made a total of **100 predictions**. Out of 100 predictions, **89 are true predictions**, and **11 are incorrect predictions**.
- The model has given prediction "yes" for 32 times, and "No" for 68 times. Whereas the actual "Yes" was 27, and actual "No" was 73 times.

Calculations using Confusion Matrix:

We can perform various calculations for the model, such as the model's accuracy, using this matrix. These calculations are given below:

- **Classification Accuracy:** It is one of the important parameters to determine the accuracy of the classification problems. It defines how often the model predicts the correct output.

It can be calculated as the ratio of the number of correct predictions made by the classifier to all number of predictions made by the classifiers. The formula is given below:

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

- **Misclassification rate:** It is also termed as Error rate, and it defines how often the model gives the wrong predictions. The value of error rate can be calculated as the number of incorrect predictions to all number of the predictions made by the classifier. The formula is given below:

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

- **Precision:** It can be defined as the number of correct outputs provided by the model or out of all positive classes that have predicted correctly by the model, how many of them were actually true. It can be calculated using the below formula:

$$\text{Precision}=\frac{TP}{TP+FP}$$

- **Recall:** It is defined as the out of total positive classes, how our model predicted correctly. The recall must be as high as possible.

$$\text{Recall}=\frac{TP}{TP+FN}$$

- **F-measure:** If two models have low precision and high recall or vice versa, it is difficult to compare these models. So, for this purpose, we can use F-score. This score helps us to evaluate the recall and precision at the same time. The F-score is maximum if the recall is equal to the precision. It can be calculated using the below formula:

$$\text{F-measure}=\frac{2*Recall*Precision}{Recall+Precision}$$

Random Forest Algorithm

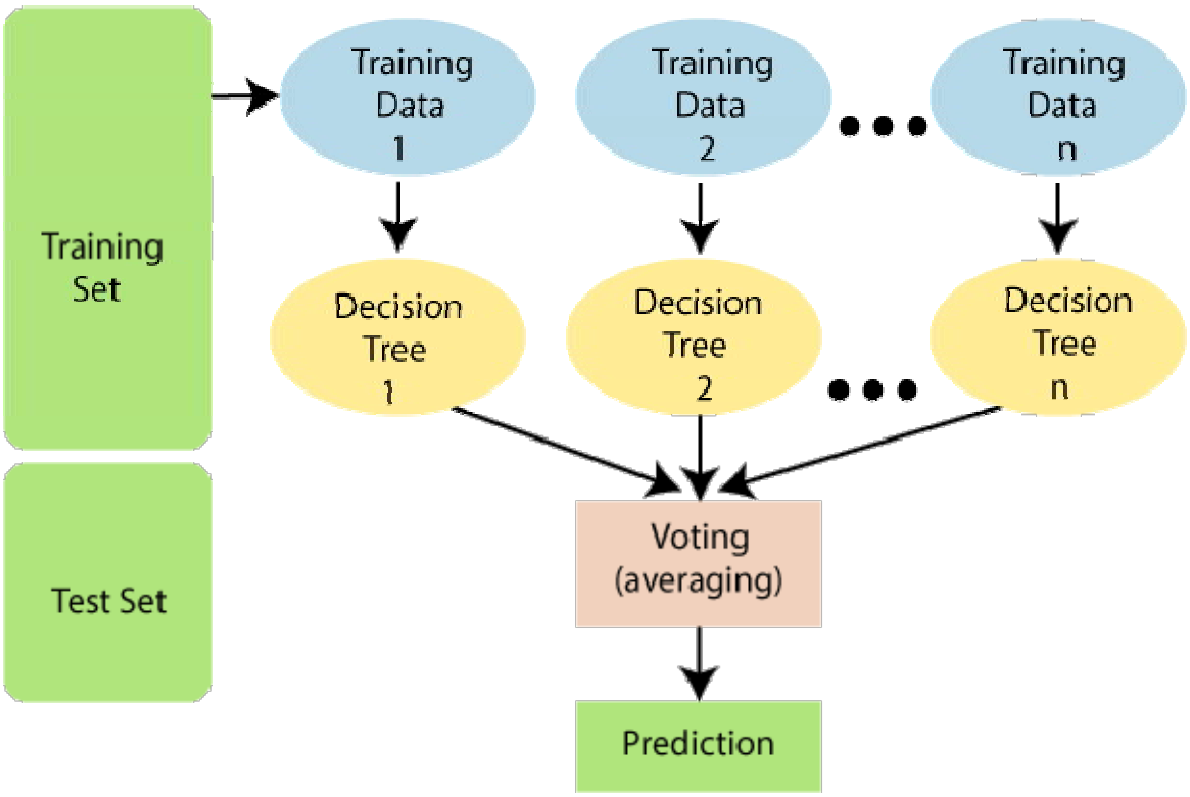
Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of **ensemble learning,** which is a process of *combining multiple classifiers to solve a complex 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).

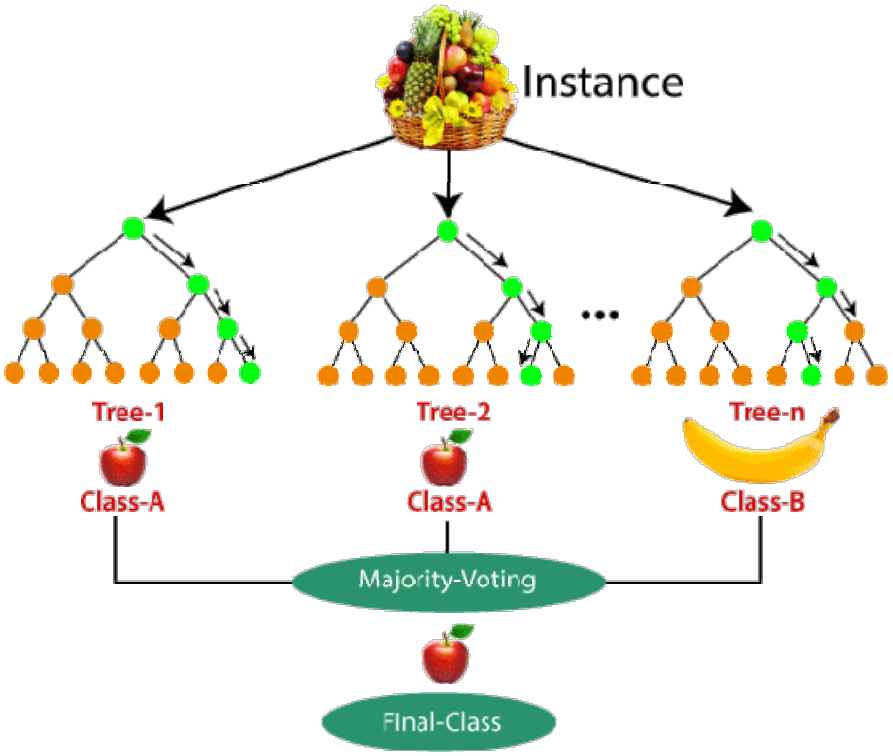
Step-3: Choose the number N for decision trees that you want to build.

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.

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.

Problem: If the weather is sunny, then the Player should play or not?

Solution: To solve this, first consider the below dataset:

	Outlook	Play
0	Rainy	Yes
1	Sunny	Yes
2	Overcast	Yes
3	Overcast	Yes

4	Sunny	No
5	Rainy	Yes
6	Sunny	Yes
7	Overcast	Yes
8	Rainy	No
9	Sunny	No
10	Sunny	Yes
11	Rainy	No
12	Overcast	Yes
13	Overcast	Yes

Frequency table for the Weather Conditions:

Weather	Yes	No
Overcast	5	0
Rainy	2	2
Sunny	3	2
Total	10	5

Likelihood table weather condition:

Weather	No	Yes	
Overcast	0	5	5/14= 0.35
Rainy	2	2	4/14=0.29
Sunny	2	3	5/14=0.35
All	4/14=0.29	10/14=0.71	

Applying Bayes'theorem:

P(Yes|Sunny)= P(Sunny|Yes)*P(Yes)/P(Sunny)

P(Sunny|Yes)= 3/10= 0.3

P(Sunny)= 0.35

P(Yes)=0.71

So P(Yes|Sunny) = 0.3*0.71/0.35= **0.60**

P(No|Sunny)= P(Sunny|No)*P(No)/P(Sunny)

P(Sunny|NO)= 2/4=0.5

P(No)= 0.29

P(Sunny)= 0.35

So P(No|Sunny)= 0.5*0.29/0.35 = **0.41**

So as we can see from the above calculation that **P(Yes|Sunny)>P(No|Sunny)**

Hence on a Sunny day, Player can play the game.

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:

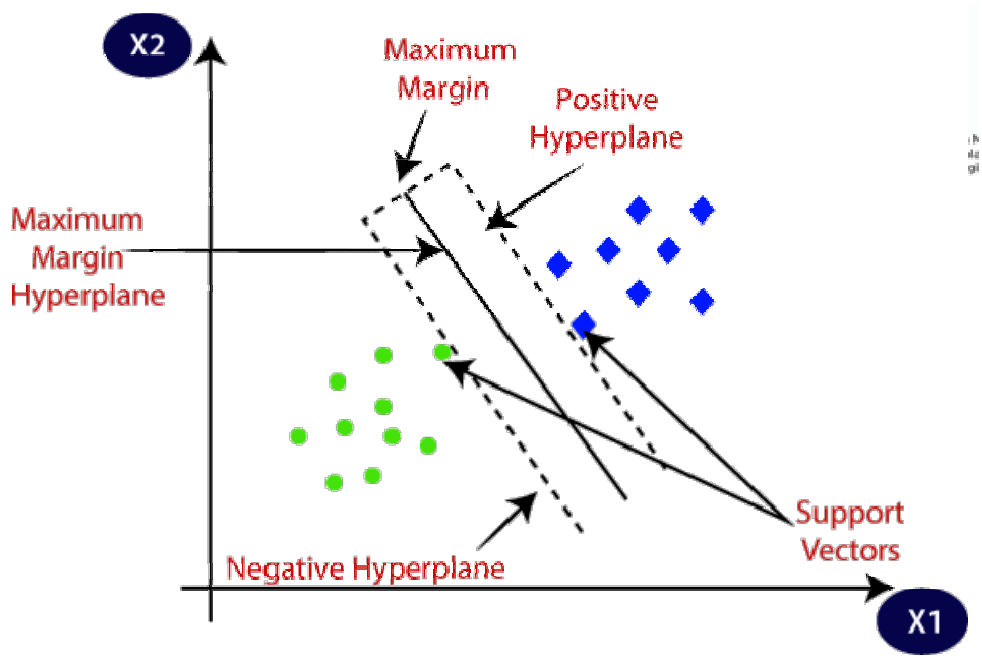
- **Gaussian**: The Gaussian model assumes that features follow a normal distribution. This means if predictors take continuous values instead of discrete, then the model assumes that these values are sampled from the Gaussian distribution.
- **Multinomial**: The Multinomial Naïve Bayes classifier is 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.

Support Vector Machine Algorithm

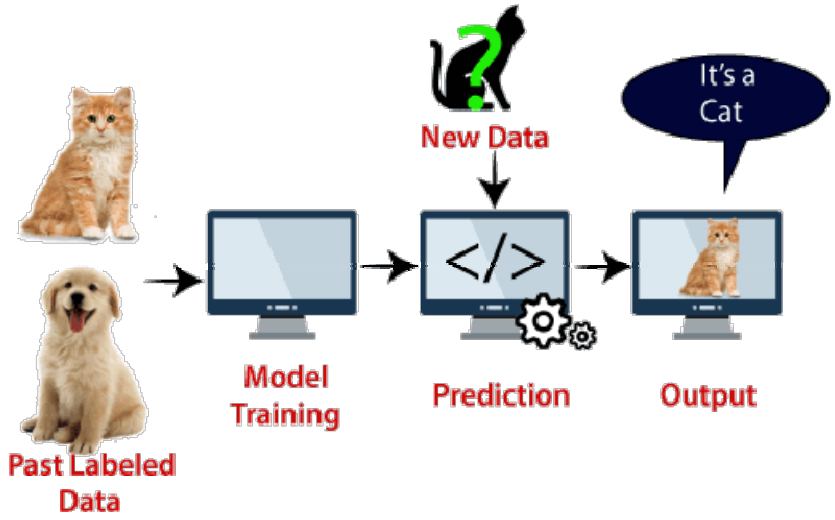
Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning.

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:



Example: SVM can be understood with the example that we have used in the KNN classifier. Suppose we see a strange cat that also has some features of dogs, so if we want a model that can accurately identify whether it is a cat or dog, so such a model can be created by using the SVM algorithm. We will first train our model with lots of images of cats and dogs so that it can learn about different features of cats and dogs, and then we test it with this strange creature. So as support vector creates a decision boundary between these two data (cat and dog) and choose extreme cases (support vectors), it will see the extreme case of cat and dog. On the basis of the support vectors, it will classify it as a cat. Consider the below diagram:



SVM algorithm can be used for **Face detection, image classification, text categorization,** etc.

Types of SVM

SVM can be of two types:

- **Linear SVM:** Linear SVM is used for linearly separable data, which means if a dataset can be classified into two classes by using a single straight line, then such data is termed as linearly separable data, and classifier is used called as Linear SVM classifier.
- **Non-linear SVM:** Non-Linear SVM is used for non-linearly separated data, which means if a dataset cannot be classified by using a straight line, then such data is termed as non-linear data and classifier used is called as Non-linear SVM classifier.

Hyperplane and Support Vectors in the SVM algorithm:

Hyperplane: There can be multiple lines/decision boundaries to segregate the classes in n-dimensional space, but we need to find out the best decision boundary that helps to classify the data points. This best boundary is known as the hyperplane of SVM.

The dimensions of the hyperplane depend on the features present in the dataset, which means if there are 2 features (as shown in image), then hyperplane will be a straight line. And if there are 3 features, then hyperplane will be a 2-dimension plane.

We always create a hyperplane that has a maximum margin, which means the maximum distance between the data points.

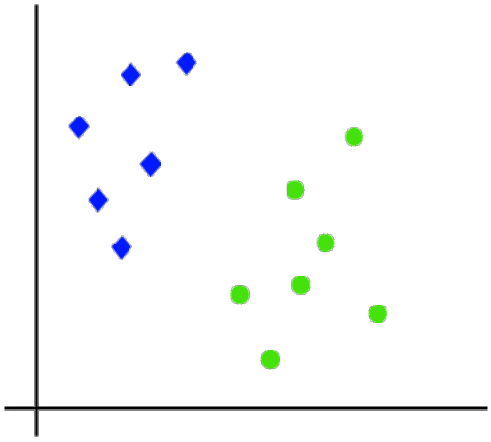
Support Vectors:

The data points or vectors that are the closest to the hyperplane and which affect the position of the hyperplane are termed as Support Vector. Since these vectors support the hyperplane, hence called a Support vector.

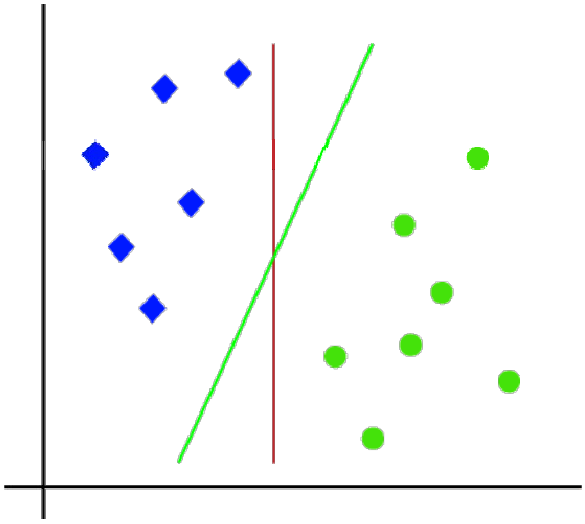
How does SVM works?

Linear SVM:

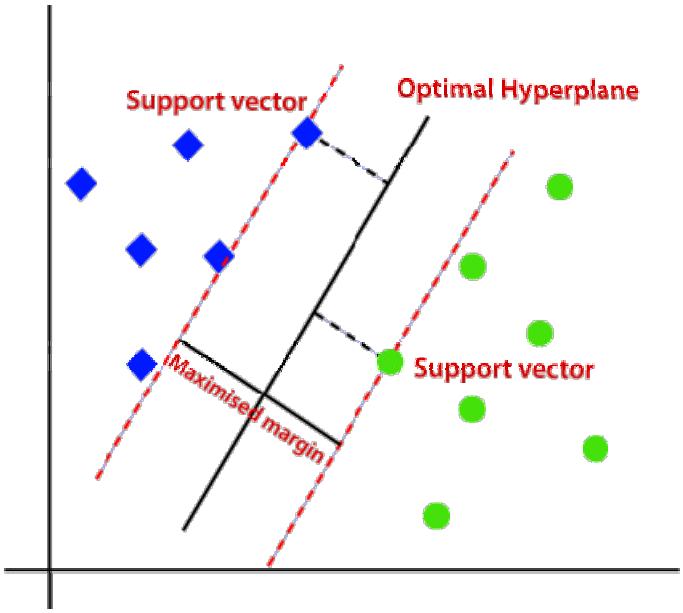
The working of the SVM algorithm can be understood by using an example. Suppose we have a dataset that has two tags (green and blue), and the dataset has two features x1 and x2. We want a classifier that can classify the pair(x1, x2) of coordinates in either green or blue. Consider the below image:



So as it is 2-d space so by just using a straight line, we can easily separate these two classes. But there can be multiple lines that can separate these classes. Consider the below image:

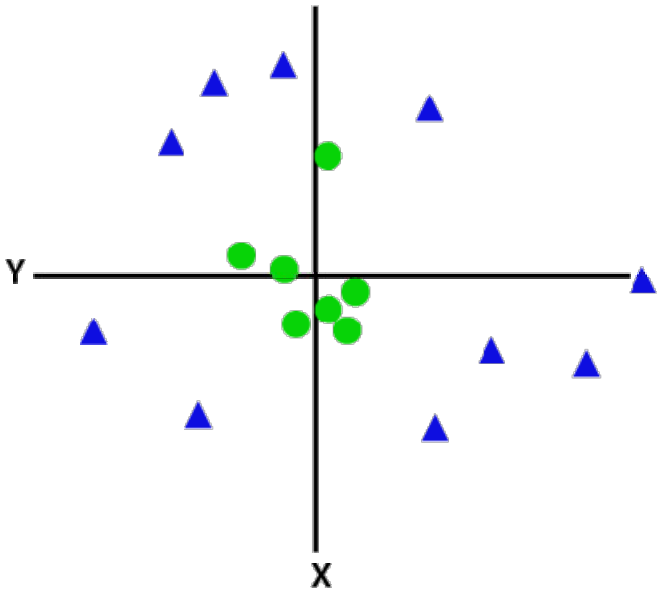


Hence, the SVM algorithm helps to find the best line or decision boundary; this best boundary or region is called as a **hyperplane**. SVM algorithm finds the closest point of the lines from both the classes. These points are called support vectors. The distance between the vectors and the hyperplane is called as **margin**. And the goal of SVM is to maximize this margin. The **hyperplane** with maximum margin is called the **optimal hyperplane**.



Non-Linear SVM:

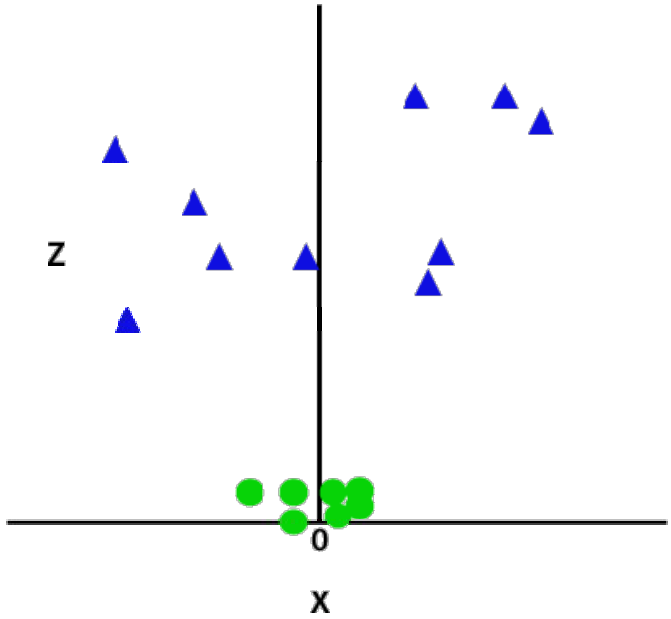
If data is linearly arranged, then we can separate it by using a straight line, but for non-linear data, we cannot draw a single straight line. Consider the below image:



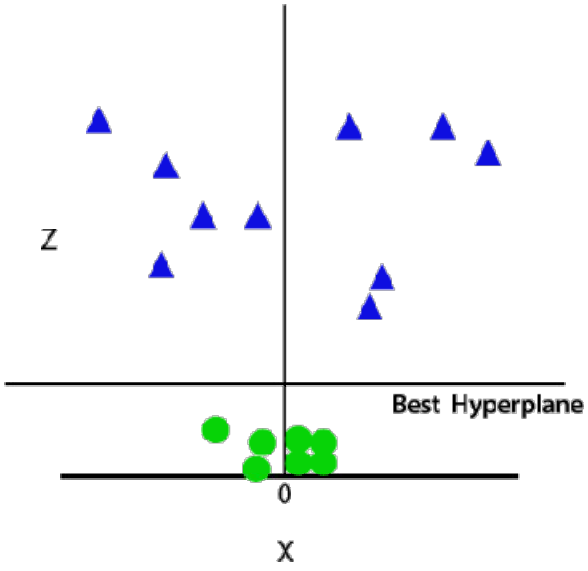
So to separate these data points, we need to add one more dimension. For linear data, we have used two dimensions x and y, so for non-linear data, we will add a third dimension z. It can be calculated as:

$$z=x^2 +y^2$$

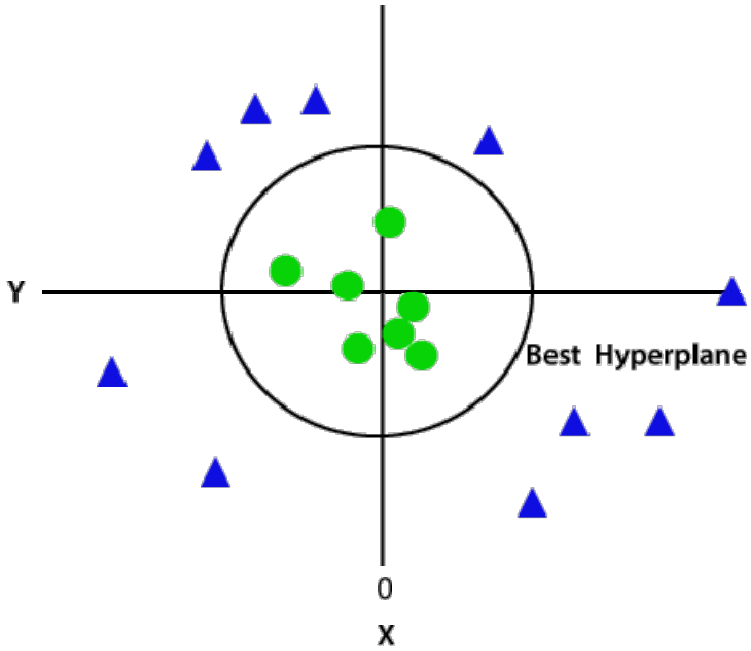
By adding the third dimension, the sample space will become as below image:



So now, SVM will divide the datasets into classes in the following way. Consider the below image:



Since we are in 3-d Space, hence it is looking like a plane parallel to the x-axis. If we convert it in 2d space with z=1, then it will become as:



Hence we get a circumference of radius 1 in case of non-linear data.

What are hyperparameters?

In Machine Learning/Deep Learning, a model is represented by its parameters. In contrast, a training process involves selecting the best/optimal hyperparameters that are used by learning algorithms to provide the best result. So, what are these hyperparameters? The answer is, "***Hyperparameters are defined as the parameters that are explicitly defined by the user to control the learning process.***"

Here the prefix "hyper" suggests that the parameters are top-level parameters that are used in controlling the learning process. The value of the Hyperparameter is selected and set by the machine learning engineer before the learning algorithm begins training the model. **Hence, these are external to the model, and their values cannot be changed during the training process**.

Some examples of Hyperparameters in Machine Learning

- Learning rate for training a neural network
- Train-test split ratio
- Batch Size
- Branches in Decision Tree
- Number of clusters in Clustering Algorithm

Difference between Parameter and Hyperparameter?

There is always a big confusion between Parameters and hyperparameters or model hyperparameters. So, in order to clear this confusion, let's understand the difference between both of them and how they are related to each other.

Model Parameters:

Model parameters are configuration variables that are internal to the model, and a model learns them on its own. For example**, W Weights or Coefficients of independent variables in the Linear regression model**. or **Weights or Coefficients of independent variables in SVM, weight, and biases of a neural network, cluster centroid in clustering.** Some key points for model parameters are as follows:

- They are used by the model for making predictions.
- They are learned by the model from the data itself
- These are usually not set manually.
- These are the part of the model and key to a machine learning Algorithm.

Model Hyperparameters:

Hyperparameters are those parameters that are explicitly defined by the user to control the learning process. Some key points for model parameters are as follows:

- These are usually defined manually by the machine learning engineer.

- One cannot know the exact best value for hyperparameters for the given problem. The best value can be determined either by the rule of thumb or by trial and error.
- Some examples of Hyperparameters are **the learning rate for training a neural network, K in the KNN algorithm,**

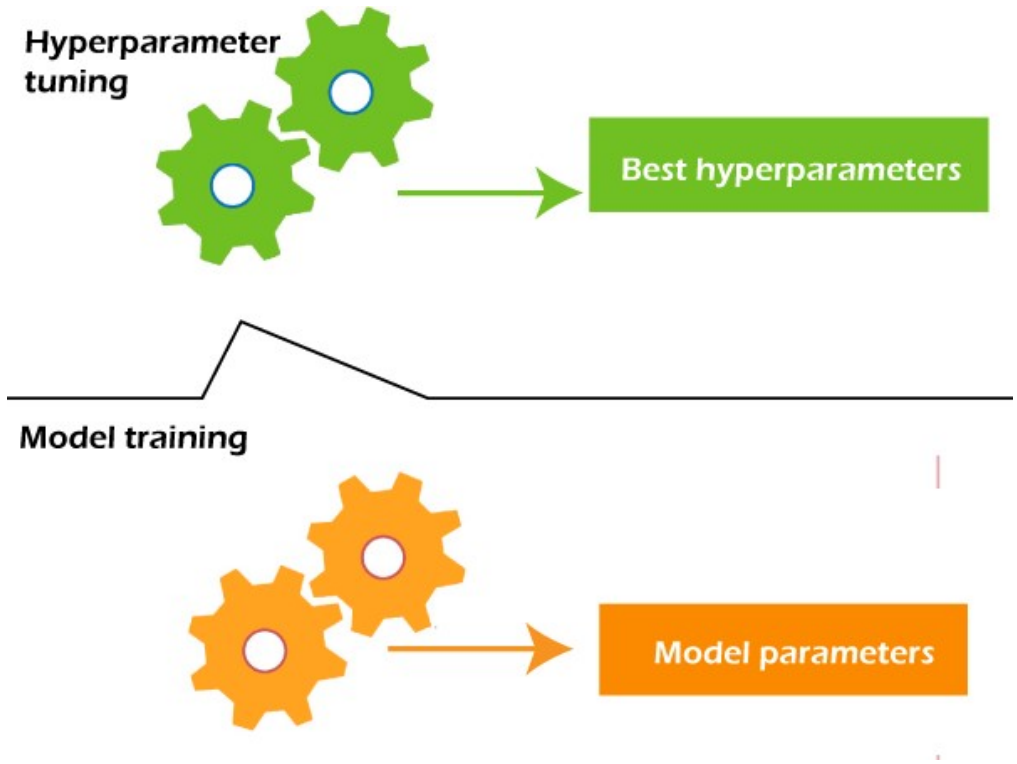
Categories of Hyperparameters

Broadly hyperparameters can be divided into two categories, which are given below:

1. **Hyperparameter for Optimization**
2. **Hyperparameter for Specific Models**

Hyperparameter for Optimization

The process of selecting the best hyperparameters to use is known as hyperparameter tuning, and the tuning process is also known as hyperparameter optimization. Optimization parameters are used for optimizing the model.



Some of the popular optimization parameters are given below:

- **Learning Rate:** The learning rate is the hyperparameter in optimization algorithms that controls how much the model needs to change in response to the estimated error for each time when the model's weights are updated. It is one of the crucial parameters

while building a neural network, and also it determines the frequency of cross-checking with model parameters. Selecting the optimized learning rate is a challenging task because if the learning rate is very less, then it may slow down the training process. On the other hand, if the learning rate is too large, then it may not optimize the model properly.

- **Batch Size:** To enhance the speed of the learning process, the training set is divided into different subsets, which are known as a batch. **Number of Epochs:** An epoch can be defined as the complete cycle for training the machine learning model. Epoch represents an iterative learning process. The number of epochs varies from model to model, and various models are created with more than one epoch. To determine the right number of epochs, a validation error is taken into account. The number of epochs is increased until there is a reduction in a validation error. If there is no improvement in reduction error for the consecutive epochs, then it indicates to stop increasing the number of epochs.

Hyperparameter for Specific Models

Hyperparameters that are involved in the structure of the model are known as hyperparameters for specific models. These are given below:

- **A number of Hidden Units:** Hidden units are part of neural networks, which refer to the components comprising the layers of processors between input and output units in a neural network.

It is important to specify the number of hidden units hyperparameter for the neural network. It should be between the size of the input layer and the size of the output layer. More specifically, the number of hidden units should be 2/3 of the size of the input layer, plus the size of the output layer.

For complex functions, it is necessary to specify the number of hidden units, but it should not overfit the model.

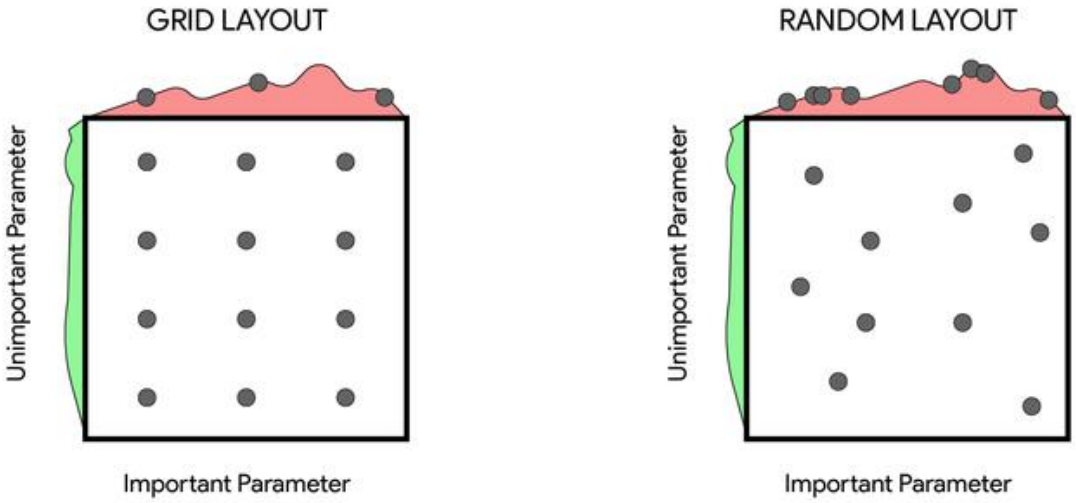
- **Number of Layers:** A neural network is made up of vertically arranged components, which are called layers. There are mainly **input layers, hidden layers, and output layers**. A 3-layered neural network gives a better performance than a 2-layered network. For a Convolutional Neural network, a greater number of layers make a better model.

Hyperparameters Optimization Technique

Exhaustive Search Methods

Let's first discuss some Exhaustive Search Methods to optimize the hyperparameter.

- **Grid Search:** In Grid Search, the possible values of hyperparameters are defined in the set. Then these sets of possible values of hyperparameters are combined by using Cartesian product and form a multidimensional grid. Then we try all the parameters in the grid and select the hyperparameter setting with the best result.
- **Random Search:** This is another variant of Grid Search in which instead of trying all the points in the grid we try random points. This solves a couple of problems that are in Grid Search such as we don't need to expand our search space exponentially every time add a new hyperparameter



Drawback:

Random Search and Grid Search are easy to implement and can run in parallel but here are few drawbacks of these algorithm:

- If the hyperparameter search space is large, it takes a lot of time and computational power to optimize the hyperparameter.
- There is no guarantee that these algorithms find local maxima if the sample is not meticulously done.