MODULE III - CLASSIFICATION

Supervised Machine Learning

Supervised learning is the types of machine learning in which machines are trained using well "labelled" training data, and on basis of that data, machines predict the output. The labelled data means some input data is already tagged with the correct output.

In supervised learning, the training data provided to the machines work as the supervisor that teaches the machines to predict the output correctly. It applies the same concept as a student learns in the supervision of the teacher.

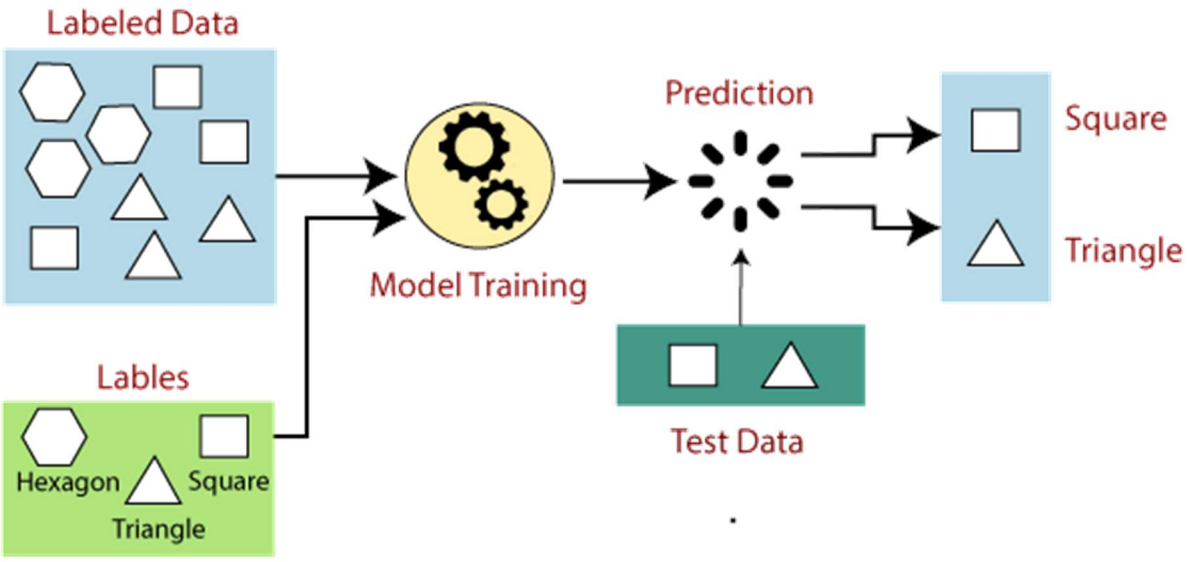
Supervised learning is a process of providing input data as well as correct output data to the machine learning model. The aim of a supervised learning algorithm is to **find a mapping function to map the input variable(x) with the output variable(y)**.

In the real-world, supervised learning can be used for **Risk Assessment, Image classification, Fraud Detection, spam filtering**, etc.

How Supervised Learning Works?

In supervised learning, models are trained using labelled dataset, where the model learns about each type of data. Once the training process is completed, the model is tested on the basis of test data (a subset of the training set), and then it predicts the output.

The working of Supervised learning can be easily understood by the below example and diagram:



Suppose we have a dataset of different types of shapes which includes square, rectangle, triangle, and Polygon. Now the first step is that we need to train the model for each shape.

- If the given shape has four sides, and all the sides are equal, then it will be labelled as a **Square**.
- If the given shape has three sides, then it will be labelled as a **triangle**.
- If the given shape has six equal sides then it will be labelled as **hexagon**.

Now, after training, we test our model using the test set, and the task of the model is to identify the shape.

The machine is already trained on all types of shapes, and when it finds a new shape, it classifies the shape on the bases of a number of sides, and predicts the output.

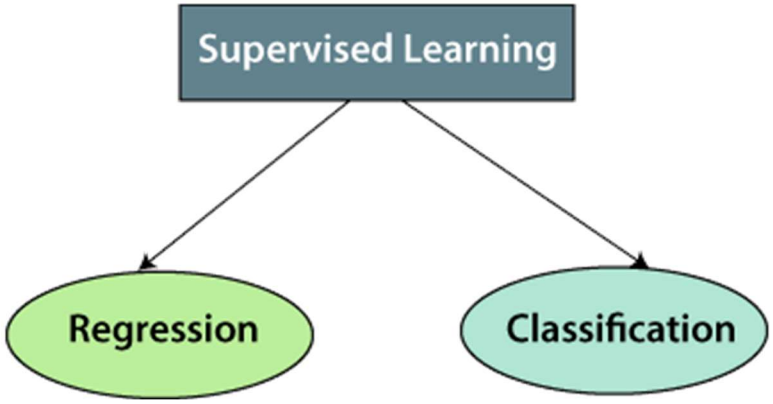
Steps Involved in Supervised Learning:

- First Determine the type of training dataset
- Collect/Gather the labelled training data.
- Split the training dataset into training **dataset, test dataset, and validation dataset**.
- Determine the input features of the training dataset, which should have enough knowledge so that the model can accurately predict the output.

- Determine the suitable algorithm for the model, such as support vector machine, decision tree, etc.
- Execute the algorithm on the training dataset. Sometimes we need validation sets as the control parameters, which are the subset of training datasets.
- Evaluate the accuracy of the model by providing the test set. If the model predicts the correct output, which means our model is accurate.

Types of supervised Machine learning Algorithms:

Supervised learning can be further divided into two types of problems:



1. Regression

Regression algorithms are used if there is a relationship between the input variable and the output variable. It is used for the prediction of continuous variables, such as Weather forecasting, Market Trends, etc. Below are some popular Regression algorithms which come under supervised learning:

- Linear Regression
- Regression Trees
- Non-Linear Regression
- Bayesian Linear Regression
- Polynomial Regression

2. Classification

Classification algorithms are used when the output variable is categorical, which means there are two classes such as Yes-No, Male-Female, True-false, etc.

Spam Filtering,

- Random Forest
- Decision Trees
- Logistic Regression
- Support vector Machines

Note: We will discuss these algorithms in detail in later chapters.

Advantages of Supervised learning:

- With the help of supervised learning, the model can predict the output on the basis of prior experiences.
- In supervised learning, we can have an exact idea about the classes of objects.
- Supervised learning model helps us to solve various real-world problems such as **fraud detection, spam filtering**, etc.

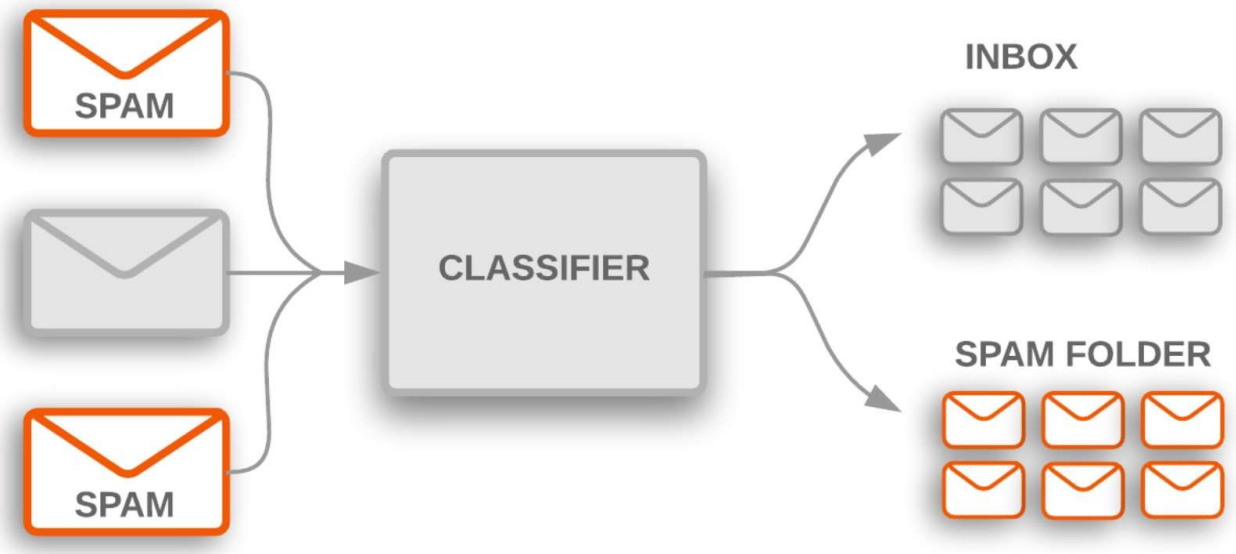
Disadvantages of supervised learning:

- Supervised learning models are not suitable for handling the complex tasks.
- Supervised learning cannot predict the correct output if the test data is different from the training dataset.
- Training required lots of computation times.
- In supervised learning, we need enough knowledge about the classes of object.

The Problem of classification

In machine learning, classification is a predictive modeling problem where the class label is anticipated for a specific example of input data. For example, in determining handwriting characters, identifying spam, and so on, the classification requires training data with a large number of datasets of input and output.

Example of Classification Problem



Classification Algorithm in Machine Learning

As we know, the Supervised Machine Learning algorithm can be broadly classified into Regression and Classification Algorithms. In Regression algorithms, we have predicted the output for continuous values, but to predict the categorical values, we need Classification algorithms.

What is the Classification Algorithm?

The Classification algorithm is a Supervised Learning technique that is used to identify the category of new observations on the basis of training data. In Classification, a program

learns from the given dataset or observations and then classifies new observation into a number of classes or groups. Such as, **Yes or No, 0 or 1, Spam or Not Spam, cat or dog,** etc. Classes can be called as targets/labels or categories.

Unlike regression, the output variable of Classification is a category, not a value, such as "Green or Blue", "fruit or animal", etc. Since the Classification algorithm is a Supervised learning technique, hence it takes labeled input data, which means it contains input with the corresponding output.

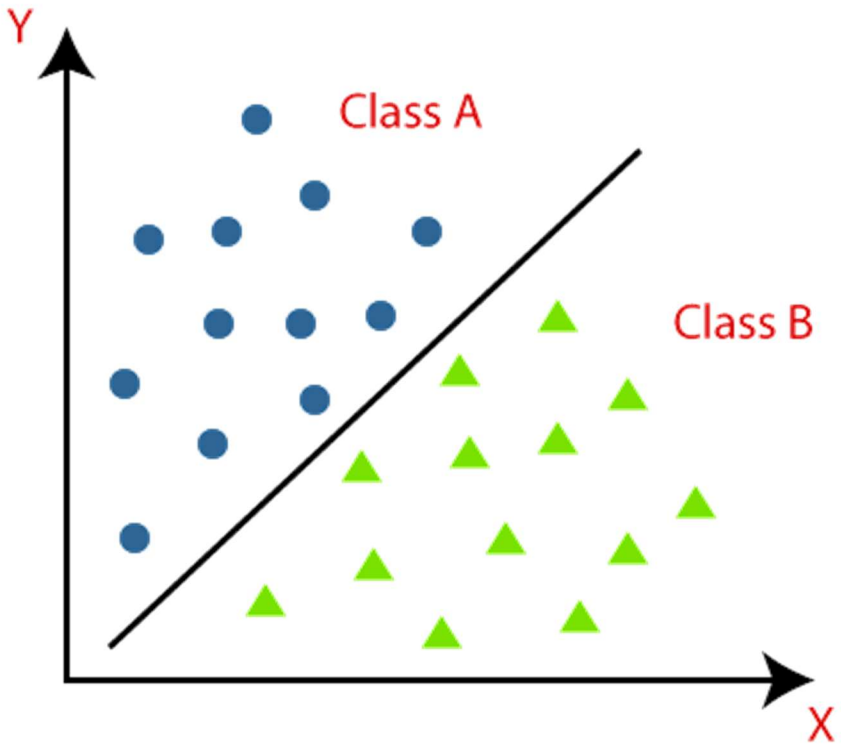
In classification algorithm, a discrete output function(y) is mapped to input variable(x).

1. y=f(x), where y = categorical output

The best example of an ML classification algorithm is **Email Spam Detector**.

The main goal of the Classification algorithm is to identify the category of a given dataset, and these algorithms are mainly used to predict the output for the categorical data.

Classification algorithms can be better understood using the below diagram. In the below diagram, there are two classes, class A and Class B. These classes have features that are similar to each other and dissimilar to other classes.



The algorithm which implements the classification on a dataset is known as a classifier. There are two types of Classifications:

- **Binary Classifier:** If the classification problem has only two possible outcomes, then it is called as Binary Classifier. **Examples:** YES or NO, MALE or FEMALE, SPAM or NOT SPAM, CAT or DOG, etc.
- **Multi-class Classifier:** If a classification problem has more than two outcomes, then it is called as Multi-class Classifier. **Example:** Classifications of types of crops, Classification of types of music.

Learners in Classification Problems:

In the classification problems, there are two types of learners:

1. **Lazy Learners:** Lazy Learner firstly stores the training dataset and wait until it receives the test dataset. In Lazy learner case, classification is done on the basis of the most related data stored in the training dataset. It takes less time in training but more time for predictions. **Example:** K-NN algorithm, Case-based reasoning
2. **Eager Learners:**Eager Learners develop a classification model based on a training dataset before receiving a test dataset. Opposite to Lazy learners, Eager Learner takes more time in learning, and less time in prediction. **Example:** Decision Trees, Naïve Bayes, ANN.

Types of ML Classification Algorithms:

Classification Algorithms can be further divided into the Mainly two category:

- **Linear Models**
  - Logistic Regression
  - Support Vector Machines
- **Non-linear Models**
  - K-Nearest Neighbours
  - Kernel SVM
  - Naïve Bayes

- Decision Tree Classification
- Random Forest Classification

Note: We will learn the above algorithms in later chapters.

Evaluating a Classification model:

Once our model is completed, it is necessary to evaluate its performance; either it is a Classification or Regression model. So for evaluating a Classification model, we have the following ways:

1. Log Loss or Cross-Entropy Loss:

- It is used for evaluating the performance of a classifier, whose output is a probability value between the 0 and 1.
- For a good binary Classification model, the value of log loss should be near to 0.
- The value of log loss increases if the predicted value deviates from the actual value.
- The lower log loss represents the higher accuracy of the model.
- For Binary classification, cross-entropy can be calculated as:

1. ?(ylog(p)+(1?y)log(1?p))

Where y= Actual output, p= predicted output.

2. Confusion Matrix:

- The confusion matrix provides us a matrix/table as output and describes the performance of the model.
- It is also known as the error matrix.
- The matrix consists of predictions result in a summarized form, which has a total number of correct predictions and incorrect predictions. The matrix looks like as below table:

	Actual Positive	Actual Negative

Predicted Positive	True Positive	False Positive
Predicted Negative	False Negative	True Negative

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{Total Population}}$$

3. AUC-ROC curve:

- ROC curve stands for **Receiver Operating Characteristics Curve** and AUC stands for **Area Under the Curve**.
- It is a graph that shows the performance of the classification model at different thresholds.
- To visualize the performance of the multi-class classification model, we use the AUC-ROC Curve.
- The ROC curve is plotted with TPR and FPR, where TPR (True Positive Rate) on Y-axis and FPR(False Positive Rate) on X-axis.

Use cases of Classification Algorithms

Classification algorithms can be used in different places. Below are some popular use cases of Classification Algorithms:

- Email Spam Detection
- Speech Recognition
- Identifications of Cancer tumor cells.
- Drugs Classification
- Biometric Identification, etc.

Training and testing classifiers models

The main difference between training data and testing data is that training data is the subset of original data that is used to train the machine learning model, whereas testing data is used to check the accuracy of the model. The training dataset is generally larger in size compared to the testing dataset.

Train and Test datasets in Machine Learning

Machine Learning is one of the booming technologies across the world that enables computers/machines to turn a huge amount of data into predictions. However, these predictions highly depend on the quality of the data, and if we are not using the right data for our model, then it will not generate the expected result. In machine learning projects, we generally divide the original dataset into training data and test data. We train our model over a subset of the original dataset, i.e., the training dataset, and then evaluate whether it can generalize well to the new or unseen dataset or test set. ***Therefore, train and test datasets are the two key concepts of machine learning, where the training dataset is used to fit the model, and the test dataset is used to evaluate the model***.

In this topic, we are going to discuss train and test datasets along with the difference between both of them. So, let's start with the introduction of the training dataset and test dataset in Machine Learning.

What is Training Dataset?

The ***training data is the biggest (in -size) subset of the original dataset, which is used to train or fit the machine learning model***. Firstly, the training data is fed to the ML algorithms, which lets them learn how to make predictions for the given task.

For example, for training a sentiment analysis model, the training data could be as below:

Input	Output (Labels)
The New UI is Great	Positive

Update is really Slow	Negative

The training data varies depending on whether we are using Supervised Learning or Unsupervised Learning Algorithms.

For **Unsupervised learning**, the training data contains unlabeled data points, i.e., inputs are not tagged with the corresponding outputs. Models are required to find the patterns from the given training datasets in order to make predictions.

On the other hand, for supervised learning, the training data contains labels in order to train the model and make predictions.

The type of training data that we provide to the model is highly responsible for the model's accuracy and prediction ability. It means that the better the quality of the training data, the better will be the performance of the model. Training data is approximately more than or equal to 60% of the total data for an ML project.

What is Test Dataset?

Once we train the model with the training dataset, it's time to test the model with the test dataset. This dataset evaluates the performance of the model and ensures that the model can generalize well with the new or unseen dataset. ***The test dataset is another subset of original data, which is independent of the training dataset***. However, it has some similar types of features and class probability distribution and uses it as a benchmark for model evaluation once the model training is completed. Test data is a well-organized dataset that contains data for each type of scenario for a given problem that the model would be facing when used in the real world. Usually, the test dataset is approximately 20-25% of the total original data for an ML project.

At this stage, we can also check and compare the testing accuracy with the training accuracy, which means how accurate our model is with the test dataset against the training dataset. If the accuracy of the model on training data is greater than that on testing data, then the model is said to have overfitting.

The testing data should:

- Represent or part of the original dataset.
- It should be large enough to give meaningful predictions.

Need of Splitting dataset into Train and Test set

Splitting the dataset into train and test sets is one of the important parts of data pre-processing, as by doing so, we can improve the performance of our model and hence give better predictability.

We can understand it as if we train our model with a training set and then test it with a completely different test dataset, and then our model will not be able to understand the correlations between the features.

Therefore, if we train and test the model with two different datasets, then it will decrease the performance of the model. Hence it is important to split a dataset into two parts, i.e., train and test set.

In this way, we can easily evaluate the performance of our model. Such as, if it performs well with the training data, but does not perform well with the test dataset, then it is estimated that the model may be overfitted.

For splitting the dataset, we can use the **train_test_split** function of **scikit-learn.**

The bellow line of code can be used to split dataset:

```
1. from sklearn.model_selection import train_test_split
2. x_train, x_test, y_train, y_test= train_test_split(x, y, test_size= 0.2, random_state=0)
```

Explanation:

In the first line of the above code, we have imported the train_test_split function from the **sklearn** library.

In the second line, we have used four variables, which are

- x_train: It is used to represent features for the training data
- x_test: It is used to represent features for testing data
- y_train: It is used to represent dependent variables for training data
- y_test: It is used to represent independent variable for testing data

- In the train_test_split() function, we have passed four parameters. Which first two are for arrays of data, and test_size is for specifying the size of the test set. The test_size may be .5, .3, or .2, which tells the dividing ratio of training and testing sets.
- The last parameter, random_state, is used to set a seed for a random generator so that you always get the same result, and the most used value for this is 42.

Overfitting and Underfitting issues

Overfitting and underfitting are the most common problems that occur in the Machine Learning model.

A model can be said as ***overfitted*** *when it performs quite well with the training dataset but does not generalize well with the new or unseen dataset*. The issue of overfitting occurs when the model tries to cover all the data points and hence starts caching noises present in the data. Due to this, it can't generalize well to the new dataset. Because of these issues, the accuracy and efficiency of the model degrade. Generally, the complex model has a high chance of overfitting. There are various ways by which we can avoid overfitting in the model, such as Using the **Cross-Validation method, early stopping the training, or by regularization**, etc.

On the other hand, the ***model is said to be under-fitted when it is not able to capture the underlying trend of the data***. It means the model shows poor performance even with the training dataset. In most cases, underfitting issues occur when the model is not perfectly suitable for the problem that we are trying to solve. To avoid the overfitting issue, we can either increase the training time of the model or increase the number of features in the dataset.

Training data vs. Testing Data

- The main difference between training data and testing data is that training data is the subset of original data that is used to train the machine learning model, whereas testing data is used to check the accuracy of the model.
- The training dataset is generally larger in size compared to the testing dataset. The general ratios of splitting train and test datasets are **80:20, 70:30, or 90:10.**
- Training data is well known to the model as it is used to train the model, whereas testing data is like unseen/new data to the model.

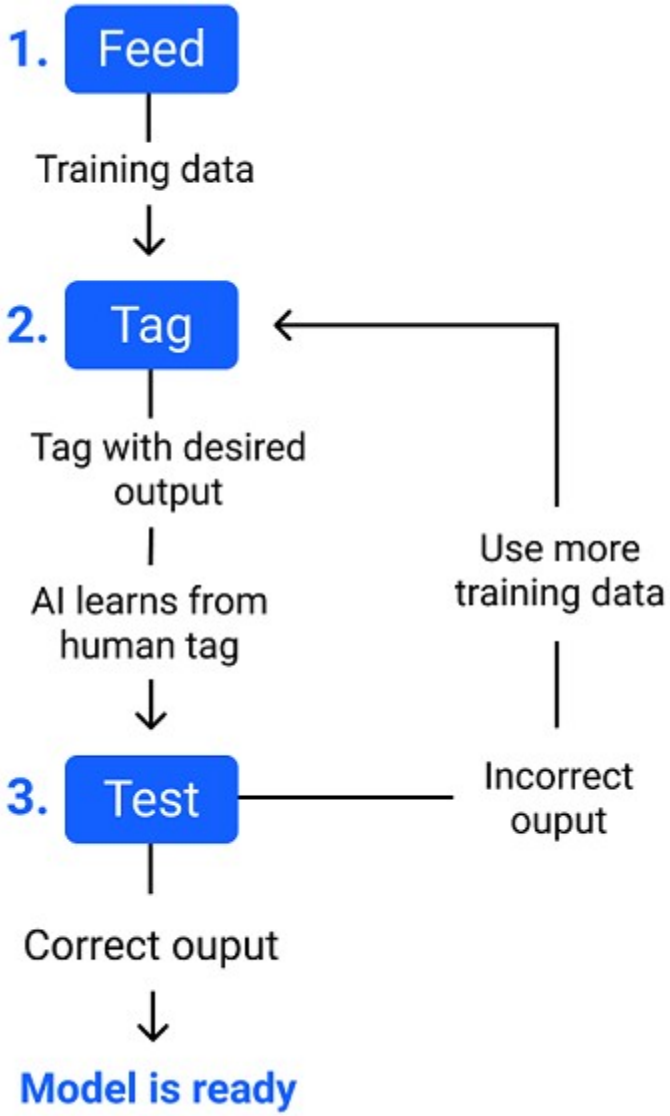
How do training and testing data work in Machine Learning?

Machine Learning algorithms enable the machines to make predictions and solve problems on the basis of past observations or experiences. These experiences or observations an algorithm can take from the training data, which is fed to it. Further, one of the great things about ML algorithms is that they can learn and improve over time on their own, as they are trained with the relevant training data.

Once the model is trained enough with the relevant training data, it is tested with the test data. We can understand the whole process of training and testing in three steps, which are as follows:

1. **Feed:** Firstly, we need to train the model by feeding it with training input data.
2. **Define:** Now, training data is tagged with the corresponding outputs (in Supervised Learning), and the model transforms the training data into text vectors or a number of data features.
3. **Test:** In the last step, we test the model by feeding it with the test data/unseen dataset. This step ensures that the model is trained efficiently and can generalize well.

The above process is explained using a flowchart given below:



Traits of Quality training data

As the ability to the prediction of an ML model highly depends on how it has been trained, therefore it is important to train the model with quality data. Further, ML works on the concept of "Garbage In, Garbage Out." It means that whatever type of data we will input into our model, it will make the predictions accordingly. For a quality training data, the below points should be considered:

1. Relevant

The very first quality of training data should be relevant to the problem that you are going to solve. It means that whatever data you are using should be relevant to the current problem. For

example, if you are building a model to analyze social media data, then data should be taken from different social sites such as Twitter, Facebook, Instagram, etc.

2. Uniform:

There should always be uniformity among the features of a dataset. It means all data for a particular problem should be taken from the same source with the same attributes.

3. Consistency: In the dataset, the similar attributes must always correspond to the similar label in order to ensure uniformity in the dataset.

4. Comprehensive: The training data must be large enough to represent sufficient features that you need to train the model in a better way. With a comprehensive dataset, the model will be able to learn all the edge cases.

Conclusion

Good training data is the backbone of machine learning. It is crucial to understand the importance of good training data in Machine Learning, as it ensures that you have data with the right quality and quantity to train your model.

Cross-Validation in Machine Learning

Cross-validation is a technique for validating the model efficiency by training it on the subset of input data and testing on previously unseen subset of the input data. ***We can also say that it is a technique to check how a statistical model generalizes to an independent dataset***.

In machine learning, there is always the need to test the stability of the model. It means based only on the training dataset; we can't fit our model on the training dataset. For this purpose, we reserve a particular sample of the dataset, which was not part of the training dataset. After that, we test our model on that sample before deployment, and this

complete process comes under cross-validation. This is something different from the general train-test split.

Hence the basic steps of cross-validations are:

- Reserve a subset of the dataset as a validation set.
- Provide the training to the model using the training dataset.
- Now, evaluate model performance using the validation set. If the model performs well with the validation set, perform the further step, else check for the issues.

Methods used for Cross-Validation

There are some common methods that are used for cross-validation. These methods are given below:

1. **Validation Set Approach**
2. **Leave-P-out cross-validation**
3. **Leave one out cross-validation**
4. **K-fold cross-validation**
5. **Stratified k-fold cross-validation**

Validation Set Approach

We divide our input dataset into a training set and test or validation set in the validation set approach. Both the subsets are given 50% of the dataset.

But it has one of the big disadvantages that we are just using a 50% dataset to train our model, so the model may miss out to capture important information of the dataset. It also tends to give the underfitted model.

Leave-P-out cross-validation

In this approach, the p datasets are left out of the training data. It means, if there are total n datapoints in the original input dataset, then n-p data points will be used as the training dataset and the p data points as the validation set. This complete process is repeated for all the samples, and the average error is calculated to know the effectiveness of the model.

There is a disadvantage of this technique; that is, it can be computationally difficult for the large p.

Leave one out cross-validation

This method is similar to the leave-p-out cross-validation, but instead of p, we need to take 1 dataset out of training. It means, in this approach, for each learning set, only one datapoint is reserved, and the remaining dataset is used to train the model. This process repeats for each datapoint. Hence for n samples, we get n different training set and n test set. It has the following features:

- In this approach, the bias is minimum as all the data points are used.
- The process is executed for n times; hence execution time is high.
- This approach leads to high variation in testing the effectiveness of the model as we iteratively check against one data point.

K-Fold Cross-Validation

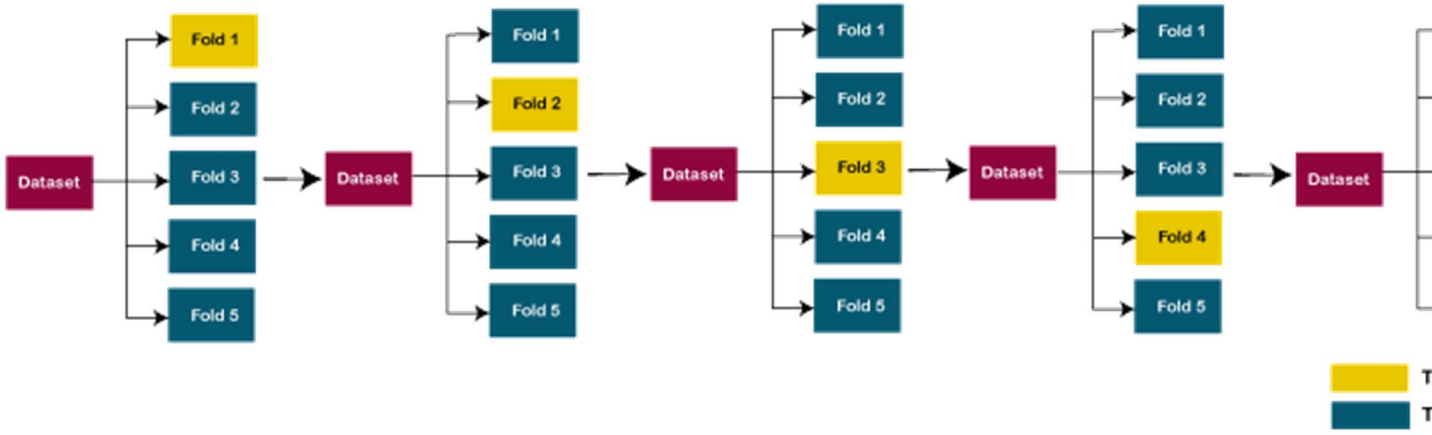
K-fold cross-validation approach divides the input dataset into K groups of samples of equal sizes. These samples are called **folds**. For each learning set, the prediction function uses k-1 folds, and the rest of the folds are used for the test set. This approach is a very popular CV approach because it is easy to understand, and the output is less biased than other methods.

The steps for k-fold cross-validation are:

- Split the input dataset into K groups
- For each group:
    - Take one group as the reserve or test data set.
    - Use remaining groups as the training dataset
    - Fit the model on the training set and evaluate the performance of the model using the test set.

Let's take an example of 5-folds cross-validation. So, the dataset is grouped into 5 folds. On 1^{st} iteration, the first fold is reserved for test the model, and rest are used to train the model. On 2^{nd} iteration, the second fold is used to test the model, and rest are used to train the model. This process will continue until each fold is not used for the test fold.

Consider the below diagram:



Stratified k-fold cross-validation

This technique is similar to k-fold cross-validation with some little changes. This approach works on stratification concept, it is a process of rearranging the data to ensure that each fold or group is a good representative of the complete dataset. To deal with the bias and variance, it is one of the best approaches.

It can be understood with an example of housing prices, such that the price of some houses can be much high than other houses. To tackle such situations, a stratified k-fold cross-validation technique is useful.

Holdout Method

This method is the simplest cross-validation technique among all. In this method, we need to remove a subset of the training data and use it to get prediction results by training it on the rest part of the dataset.

The error that occurs in this process tells how well our model will perform with the unknown dataset. Although this approach is simple to perform, it still faces the issue of high variance, and it also produces misleading results sometimes.

Comparison of Cross-validation to train/test split in Machine Learning

- **Train/test split:** The input data is divided into two parts, that are training set and test set on a ratio of 70:30, 80:20, etc. It provides a high variance, which is one of the biggest disadvantages.
    - **Training Data:** The training data is used to train the model, and the dependent variable is known.
    - **Test Data:** The test data is used to make the predictions from the model that is already trained on the training data. This has the same features as training data but not the part of that.
- **Cross-Validation dataset:** It is used to overcome the disadvantage of train/test split by splitting the dataset into groups of train/test splits, and averaging the result. It can be used if we want to optimize our model that has been trained on the training dataset for the best performance. It is more efficient as compared to train/test split as every observation is used for the training and testing both.

Limitations of Cross-Validation

There are some limitations of the cross-validation technique, which are given below:

- For the ideal conditions, it provides the optimum output. But for the inconsistent data, it may produce a drastic result. So, it is one of the big disadvantages of cross-validation, as there is no certainty of the type of data in machine learning.
- In predictive modeling, the data evolves over a period, due to which, it may face the differences between the training set and validation sets. Such as if we create a model for the prediction of stock market values, and the data is trained on the previous 5 years stock values, but the realistic future values for the next 5 years may drastically different, so it is difficult to expect the correct output for such situations.

Applications of Cross-Validation

- This technique can be used to compare the performance of different predictive modeling methods.
- It has great scope in the medical research field.

- It can also be used for the meta-analysis, as it is already being used by the data scientists in the field of medical statistics.

Model Evaluation

Precision and Recall in Machine Learning

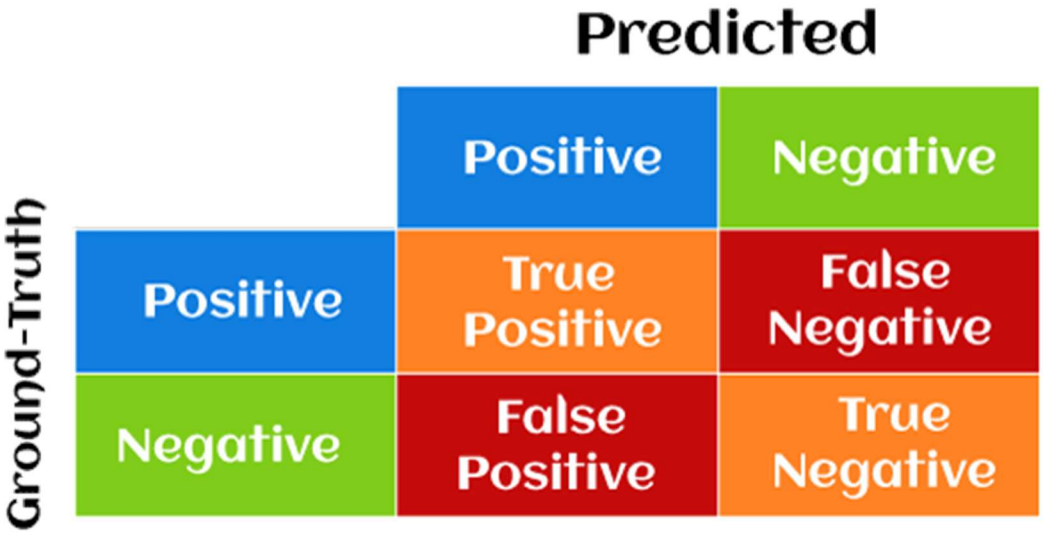
While building any machine learning model, the first thing that comes to our mind is how we can build an accurate & 'good fit' model and what the challenges are that will come during the entire procedure. Precision and Recall are the two most important but confusing concepts in Machine Learning. ***Precision and recall are performance metrics used for pattern recognition and classification in machine learning.*** These concepts are essential to build a perfect machine learning model which gives more precise and accurate results. Some of the models in machine learning require more precision and some model requires more recall. So, it is important to know the balance between Precision and recall or, simply, precision-recall trade-off.

In this article, we will understand Precision and recall, the most confusing but important concepts in machine learning that lots of professionals face during their entire data science & machine learning career. But before starting, first, we need to understand the **confusion matrix** concept. So, let's start with the quick introduction of Confusion Matrix in Machine Learning.

Confusion Matrix in Machine Learning

Confusion Matrix helps us to display the performance of a model or how a model has made its prediction in Machine Learning.

Confusion Matrix helps us to visualize the point where our model gets confused in discriminating two classes. It can be understood well through a 2×2 matrix where the row represents the **actual truth labels**, and the column represents **the predicted labels.**



This matrix consists of 4 main elements that show different metrics to count a number of correct and incorrect predictions. Each element has two words either as follows:

- True or False
- Positive or Negative

If the predicted and truth labels match, then the prediction is said to be correct, but when the predicted and truth labels are mismatched, then the prediction is said to be incorrect. Further, positive and negative represents the predicted labels in the matrix.

There are four metrics combinations in the confusion matrix, which are as follows:

- **True Positive:** This combination tells us how many times a model correctly classifies a positive sample as Positive?
- **False Negative:** This combination tells us how many times a model incorrectly classifies a positive sample as Negative?
- **False Positive:** This combination tells us how many times a model incorrectly classifies a negative sample as Positive?
- **True Negative:** This combination tells us how many times a model correctly classifies a negative sample as Negative?

Hence, we can calculate the total of 7 predictions in binary classification problems using a confusion matrix.

Now we can understand the concepts of Precision and Recall.

What is Precision?

Precision is defined as the *ratio of correctly classified positive samples (True Positive) to a total number of classified positive samples* (either correctly or incorrectly).

1. Precision = True Positive/True Positive + False Positive
2. Precision = TP/TP+FP

- TP- True Positive
- FP- False Positive

- The precision of a machine learning model will be low when the value of;

1. TP+FP (denominator) > TP (Numerator)

- The precision of the machine learning model will be high when Value of;

1. TP (Numerator) > TP+FP (denominator)

Hence, **precision helps us to visualize the reliability of the machine learning model in classifying the model as positive**.

Examples to calculate the Precision in the machine learning model

Below are some examples for calculating Precision in Machine Learning:

Case 1- In the below-mentioned scenario, the model correctly classified two positive samples while incorrectly classified one negative sample as positive. Hence, according to precision formula;

Precision = TP/TP+FP

Precision = 2/2+1 = 2/3 = 0.667

Case 2- In this scenario, we have three Positive samples that are correctly classified, and one Negative sample is incorrectly classified.

Put TP =3 and FP =1 in the precision formula, we get;

Precision = TP/TP+FP

Precision = 3/3+1 = 3/4 = 0.75

Case 3- In this scenario, we have three Positive samples that are correctly classified but no Negative sample which is incorrectly classified.

Put TP =3 and FP =0 in precision formula, we get;

Precision = TP/TP+FP

Precision = 3/3+0 = 3/3 = 1

Hence, in the last scenario, we have a precision value of 1 or 100% when all positive samples are classified as positive, and there is no any Negative sample that is incorrectly classified.

What is Recall?

The recall is calculated as the ratio between the numbers of Positive samples correctly classified as Positive to the total number of Positive samples. The ***recall measures the***

model's ability to detect positive samples. The higher the recall, the more positive samples detected.

1. Recall = True Positive/True Positive + False Negative
2. Recall = TP/TP+FN

- TP- True Positive
- FN- False Negative

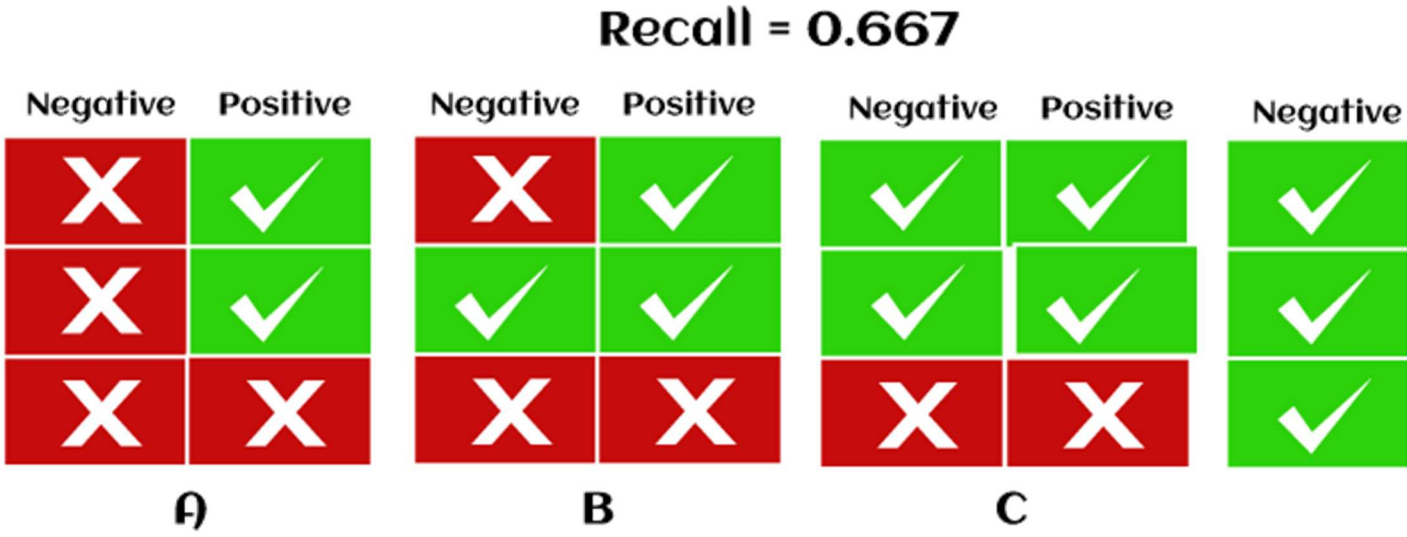
- Recall of a machine learning model will be low when the value of; TP+FN (denominator) > TP (Numerator)
- Recall of machine learning model will be high when Value of; TP (Numerator) > TP+FN (denominator)

Unlike Precision, Recall is independent of the number of negative sample classifications. Further, if the model classifies all positive samples as positive, then Recall will be 1.

Examples to calculate the Recall in the machine learning model

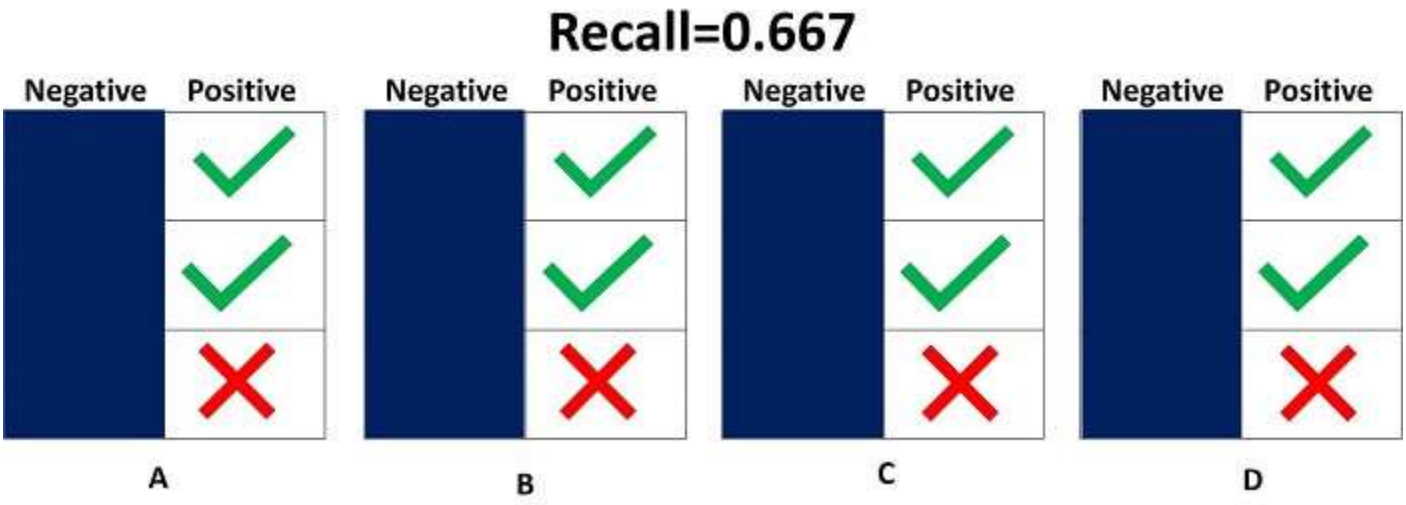
Below are some examples for calculating Recall in machine learning as follows

Example 1- Let's understand the calculation of Recall with four different cases where each case has the same Recall as 0.667 but differs in the classification of negative samples. See how:



In this scenario, the classification of the negative sample is different in each case. Case A has two negative samples classified as negative, and case B have two negative samples classified as negative; case c has only one negative sample classified as negative, while case d does not classify any negative sample as negative.

However, recall is independent of how the negative samples are classified in the model; hence, we can neglect negative samples and only calculate all samples that are classified as positive.



In the above image, we have only two positive samples that are correctly classified as positive while only 1 negative sample that is correctly classified as negative.

Hence, true positivity rate is 2 and while false negativity rate is 1. Then recall will be:

1. Recall = True Positive/True Positive + False Negative

Recall = TP/TP+FN

=2/(2+1)

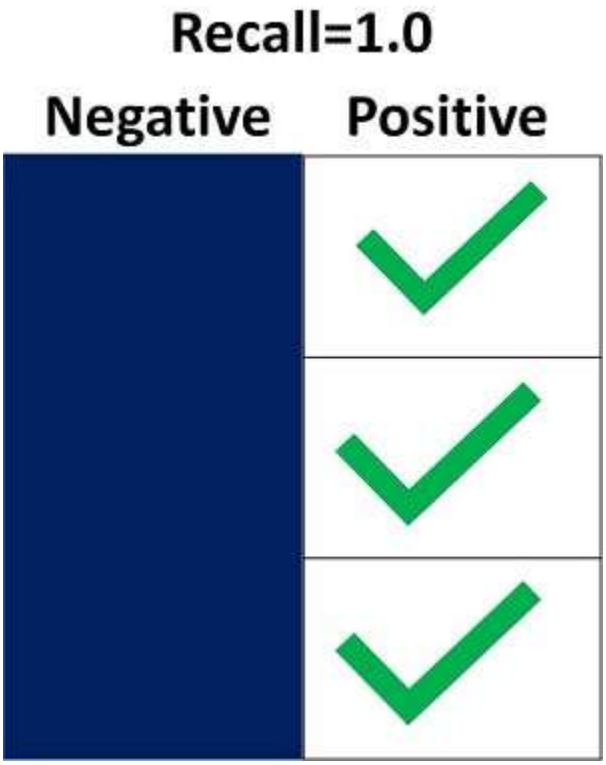
=2/3

=0.667

Note: This means the model has correctly classified only 0.667% of Positive Samples

Example-2

Now, we have another scenario where all positive samples are classified correctly as positive. Hence, the True Positive rate is 3 while the False Negative rate is 0.



Recall = TP/TP+FN = 3/(3+0) =3/3 =1

If the recall is 100%, then it tells us the model has detected all positive samples as positive and neglects how all negative samples are classified in the model. However, the model could still have so many samples that are classified as negative but recall just neglect those samples, which results in a high False Positive rate in the model.

Note: This means the model has correctly classified 100% of Positive Samples.

Example-3

In this scenario, the model does not identify any positive sample that is classified as positive. All positive samples are incorrectly classified as Negative. Hence, the true positive rate is 0, and the False Negative rate is 3. Then Recall will be:

Recall = TP/TP+FN = 0/(0+3) =0/3 =0

This means the model has not correctly classified any Positive Samples.

Difference between Precision and Recall in Machine Learning

Precision	Recall
It helps us to measure the ability to classify positive samples in the model.	It helps us to measure how many positive samples were correctly classified by the ML model.
While calculating the Precision of a model, we should consider both Positive as well as Negative samples that are classified.	While calculating the Recall of a model, we only need all positive samples while all negative samples will be neglected.
When a model classifies most of the positive samples correctly as well as many false-positive samples, then the model is said to be a high recall and low precision model.	When a model classifies a sample as Positive, but it can only classify a few positive samples, then the model is said to be high accuracy, high precision, and low recall model.
The precision of a machine learning model is dependent on both the negative and positive samples.	Recall of a machine learning model is dependent on positive samples and independent of negative samples.
In Precision, we should consider all positive samples that are classified as positive either correctly or incorrectly.	The recall cares about correctly classifying all positive samples. It does not consider if any negative sample is classified as positive.

Why use Precision and Recall in Machine Learning models?

This question is very common among all machine learning engineers and data researchers. The use of Precision and Recall varies according to the type of problem being solved.

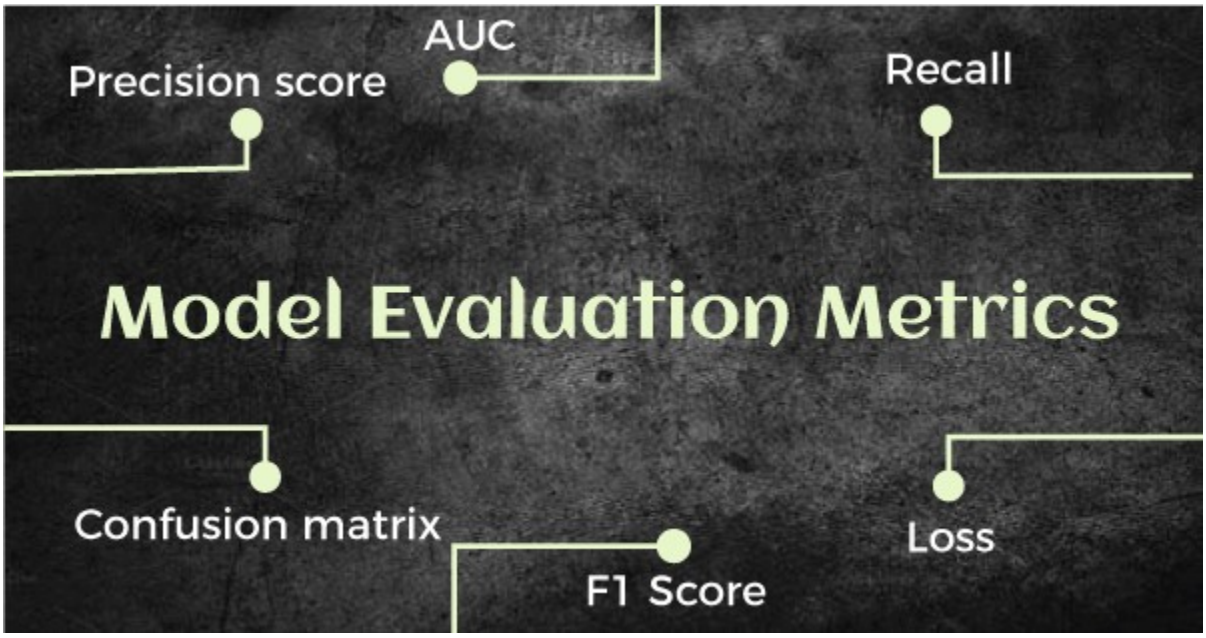
- If there is a requirement of classifying all positive as well as Negative samples as Positive, whether they are classified correctly or incorrectly, then use Precision.
- Further, on the other end, if our goal is to detect only all positive samples, then use Recall. Here, we should not care how negative samples are correctly or incorrectly classified the samples.

Conclusion:

In this tutorial, we have discussed various performance metrics such as confusion matrix, Precision, and Recall for binary classification problems of a machine learning model. Also, we have seen various examples to calculate Precision and Recall of a machine learning model and when we should use precision, and when to use Recall.

Performance Metrics in Machine Learning

Evaluating the performance of a Machine learning model is one of the important steps while building an effective ML model. ***To evaluate the performance or quality of the model, different metrics are used, and these metrics are known as performance metrics or evaluation metrics.*** These performance metrics help us understand how well our model has performed for the given data. In this way, we can improve the model's performance by tuning the hyper-parameters. Each ML model aims to generalize well on unseen/new data, and performance metrics help determine how well the model generalizes on the new dataset.



In machine learning, each task or problem is divided into **classification** and **Regression**. Not all metrics can be used for all types of problems; hence, it is important to know and

understand which metrics should be used. Different evaluation metrics are used for both Regression and Classification tasks. In this topic, we will discuss metrics used for classification and regression tasks.

1. Performance Metrics for Classification

In a classification problem, the category or classes of data is identified based on training data. The model learns from the given dataset and then classifies the new data into classes or groups based on the training. It predicts class labels as the output, such as *Yes or No, 0 or 1, Spam or Not Spam,* etc. To evaluate the performance of a classification model, different metrics are used, and some of them are as follows:

- **Accuracy**
- **Confusion Matrix**
- **Precision**
- **Recall**
- **F-Score**
- **AUC(Area Under the Curve)-ROC**

I. Accuracy

The accuracy metric is one of the simplest Classification metrics to implement, and it can be determined as the number of correct predictions to the total number of predictions.

It can be formulated as:

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ number\ of\ predictions}$$

To implement an accuracy metric, we can compare ground truth and predicted values in a loop, or we can also use the scikit-learn module for this.

Firstly, we need to import the *accuracy_score* function of the scikit-learn library as follows:

```
1. from sklearn.metrics import accuracy_score
2.
3. Here, metrics is a class of sklearn.
```

4.
5. Then we need to pass the ground truth and predicted values in the function to ca lculate the accuracy.
6.
7. print(f'Accuracy Score is {accuracy_score(y_test,y_hat)}')

Although it is simple to use and implement, it is suitable only for cases where an equal number of samples belong to each class.

When to Use Accuracy?

It is good to use the Accuracy metric when the target variable classes in data are approximately balanced. For example, if 60% of classes in a fruit image dataset are of Apple, 40% are Mango. In this case, if the model is asked to predict whether the image is of Apple or Mango, it will give a prediction with 97% of accuracy.

When not to use Accuracy?

It is recommended not to use the Accuracy measure when the target variable majorly belongs to one class. For example, Suppose there is a model for a disease prediction in which, out of 100 people, only five people have a disease, and 95 people don't have one. In this case, if our model predicts every person with no disease (which means a bad prediction), the Accuracy measure will be 95%, which is not correct.

II. Confusion Matrix

A confusion matrix is a tabular representation of prediction outcomes of any binary classifier, which is used to describe the performance of the classification model on a set of test data when true values are known.

The confusion matrix is simple to implement, but the terminologies used in this matrix might be confusing for beginners.

A typical confusion matrix for a binary classifier looks like the below image(However, it can be extended to use for classifiers with more than two classes).

n=165	Predicted: NO	Predicted: YES
Actual: NO	50	10
Actual: YES	5	100

We can determine the following from the above matrix:

- In the matrix, columns are for the prediction values, and rows specify the Actual values. Here Actual and prediction give two possible classes, Yes or No. So, if we are predicting the presence of a disease in a patient, the Prediction column with Yes means, Patient has the disease, and for NO, the Patient doesn't have the disease.
- In this example, the total number of predictions are 165, out of which 110 time predicted yes, whereas 55 times predicted No.
- However, in reality, 60 cases in which patients don't have the disease, whereas 105 cases in which patients have the disease.

In general, the table is divided into four terminologies, which are as follows:

1. **True Positive(TP):** In this case, the prediction outcome is true, and it is true in reality, also.
2. True Negative(TN): in this case, the prediction outcome is false, and it is false in reality, also.
3. False Positive(FP): In this case, prediction outcomes are true, but they are false in actuality.
4. False Negative(FN): In this case, predictions are false, and they are true in actuality.

III. Precision

The precision metric is used to overcome the limitation of Accuracy. The precision determines the proportion of positive prediction that was actually correct. It can be calculated as the True Positive or predictions that are actually true to the total positive predictions (True Positive and False Positive).

$$Precision = \frac{TP}{(TP + FP)}$$

IV. Recall or Sensitivity

It is also similar to the Precision metric; however, it aims to calculate the proportion of actual positive that was identified incorrectly. It can be calculated as True Positive or predictions that are actually true to the total number of positives, either correctly predicted as positive or incorrectly predicted as negative (true Positive and false negative).

The formula for calculating Recall is given below:

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

When to use Precision and Recall?

From the above definitions of Precision and Recall, we can say that recall determines the performance of a classifier with respect to a false negative, whereas precision gives information about the performance of a classifier with respect to a false positive.

So, if we want to minimize the false negative, then, Recall should be as near to 100%, and if we want to minimize the false positive, then precision should be close to 100% as possible.

In simple words, *if we maximize precision, it will minimize the FP errors, and if we maximize recall, it will minimize the FN error.*

V. F-Scores

F-score or F1 Score is a metric to evaluate a binary classification model on the basis of predictions that are made for the positive class. It is calculated with the help of Precision

and Recall. It is a type of single score that represents both Precision and Recall. So, ***the F1 Score can be calculated as the harmonic mean of both precision and Recall, assigning equal weight to each of them.***

The formula for calculating the F1 score is given below:

$$F1 - score = 2 * \frac{precision * recall}{precision + recall}$$

When to use F-Score?

As F-score make use of both precision and recall, so it should be used if both of them are important for evaluation, but one (precision or recall) is slightly more important to consider than the other. For example, when False negatives are comparatively more important than false positives, or vice versa.

VI. AUC-ROC

Sometimes we need to visualize the performance of the classification model on charts; then, we can use the AUC-ROC curve. It is one of the popular and important metrics for evaluating the performance of the classification model.

Firstly, let's understand ROC (Receiver Operating Characteristic curve) curve. ***ROC represents a graph to show the performance of a classification model at different threshold levels***. The curve is plotted between two parameters, which are:

- **True Positive Rate**
- **False Positive Rate**

TPR or true Positive rate is a synonym for Recall, hence can be calculated as:

$$TPR = \frac{TP}{TP + FN}$$

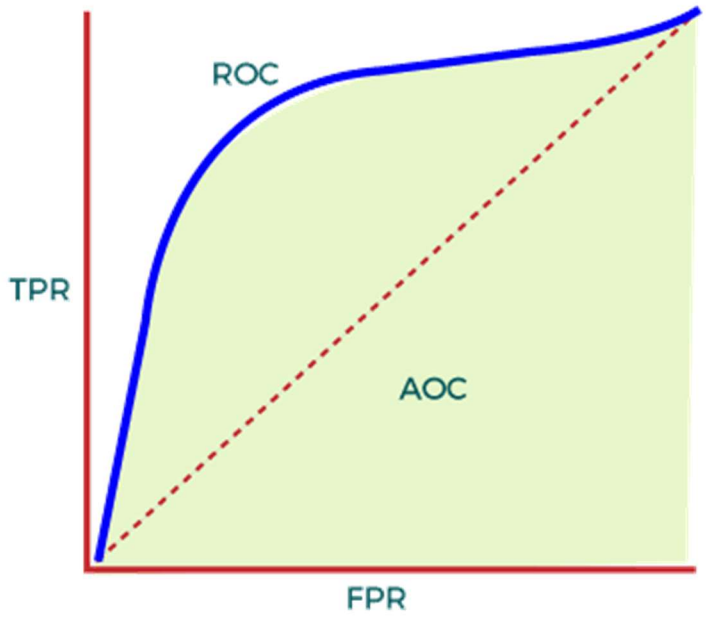
FPR or False Positive Rate can be calculated as:

$$TPR = \frac{FP}{FP + TN}$$

To calculate value at any point in a ROC curve, we can evaluate a logistic regression model multiple times with different classification thresholds, but this would not be much efficient. So, for this, one efficient method is used, which is known as AUC.

AUC: Area Under the ROC curve

AUC is known for **Area Under the ROC curve**. As its name suggests, AUC calculates the two-dimensional area under the entire ROC curve, as shown below image:



AUC calculates the performance across all the thresholds and provides an aggregate measure. The value of AUC ranges from 0 to 1. It means a model with 100% wrong prediction will have an AUC of 0.0, whereas models with 100% correct predictions will have an AUC of 1.0.

When to Use AUC

AUC should be used to measure how well the predictions are ranked rather than their absolute values. Moreover, it measures the quality of predictions of the model without considering the classification threshold.

When not to use AUC

As AUC is scale-invariant, which is not always desirable, and we need calibrating probability outputs, then AUC is not preferable.

Further, AUC is not a useful metric when there are wide disparities in the cost of false negatives vs. false positives, and it is difficult to minimize one type of classification error.

2. Performance Metrics for Regression

Regression is a supervised learning technique that aims to find the relationships between the dependent and independent variables. A predictive regression model predicts a numeric or discrete value. The metrics used for regression are different from the classification metrics. It means we cannot use the Accuracy metric (explained above) to evaluate a regression model; instead, the performance of a Regression model is reported as errors in the prediction. Following are the popular metrics that are used to evaluate the performance of Regression models.

- **Mean Absolute Error**
- **Mean Squared Error**
- **R2 Score**
- **Adjusted R2**

I. Mean Absolute Error (MAE)

Mean Absolute Error or MAE is one of the simplest metrics, which measures the absolute difference between actual and predicted values, where absolute means taking a number as Positive.

To understand MAE, let's take an example of Linear Regression, where the model draws a best fit line between dependent and independent variables. To measure the MAE or error in prediction, we need to calculate the difference between actual values and predicted values. But in order to find the absolute error for the complete dataset, we need to find the mean absolute of the complete dataset.

The below formula is used to calculate MAE:

$$MAE = 1/N \sum |Y - Y'|$$

Here,

Y is the Actual outcome, Y' is the predicted outcome, and N is the total number of data points.

MAE is much more robust for the outliers. One of the limitations of MAE is that it is not differentiable, so for this, we need to apply different optimizers such as Gradient Descent. However, to overcome this limitation, another metric can be used, which is Mean Squared Error or MSE.

II. Mean Squared Error

Mean Squared error or MSE is one of the most suitable metrics for Regression evaluation. It measures the average of the Squared difference between predicted values and the actual value given by the model.

Since in MSE, errors are squared, therefore it only assumes non-negative values, and it is usually positive and non-zero.

Moreover, due to squared differences, it penalizes small errors also, and hence it leads to over-estimation of how bad the model is.

MSE is a much-preferred metric compared to other regression metrics as it is differentiable and hence optimized better.

The formula for calculating MSE is given below:

$$MSE = 1/N \sum (Y - Y')^2$$

Here,

Y is the Actual outcome, Y' is the predicted outcome, and N is the total number of data points.

III. R Squared Score

R squared error is also known as Coefficient of Determination, which is another popular metric used for Regression model evaluation. The R-squared metric enables us to compare our model with a constant baseline to determine the performance of the model. To select the constant baseline, we need to take the mean of the data and draw the line at the mean.

The R squared score will always be less than or equal to 1 without concerning if the values are too large or small.

$$R^2 = 1 - \frac{MSE(Model)}{MSE(Baseline)}$$

IV. Adjusted R Squared

Adjusted R squared, as the name suggests, is the improved version of R squared error. R square has a limitation of improvement of a score on increasing the terms, even though the model is not improving, and it may mislead the data scientists.

To overcome the issue of R square, adjusted R squared is used, which will always show a lower value than R^2. It is because it adjusts the values of increasing predictors and only shows improvement if there is a real improvement.

We can calculate the adjusted R squared as follows:

$$R_a^2 = 1-\left[\left(\frac{n-1}{n-k-1}\right) \times \left(1 - R^2\right)\right]$$

Here,

n is the number of observations

k denotes the number of independent variables

and R_a^2 denotes the adjusted R^2

Linear Discriminant Analysis (LDA) in Machine Learning

Linear Discriminant Analysis (LDA) is one of the commonly used dimensionality reduction techniques in machine learning to solve more than two-class classification problems. It is also known as Normal Discriminant Analysis (NDA) or Discriminant Function Analysis (DFA).

This can be used to project the features of higher dimensional space into lower-dimensional space in order to reduce resources and dimensional costs. In this topic, "**Linear Discriminant Analysis (LDA) in machine learning"**, we will discuss the LDA algorithm for classification predictive modeling problems, limitation of logistic regression, representation of linear Discriminant analysis model, how to make a prediction using LDA, how to prepare data for LDA, extensions to LDA and much more. So, let's start with a quick introduction to Linear Discriminant Analysis (LDA) in machine learning.

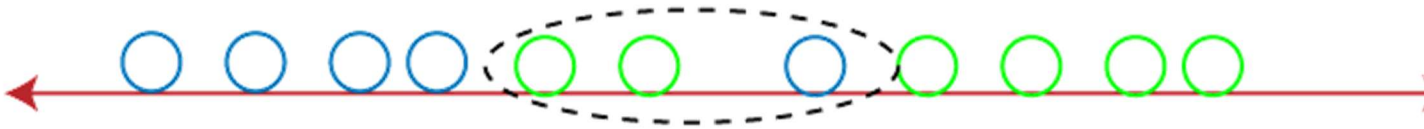
Note: Before starting this topic, it is recommended to learn the basics of Logistic Regression algorithms and a basic understanding of classification problems in machine learning as a prerequisite

What is Linear Discriminant Analysis (LDA)?

Although the logistic regression algorithm is limited to only two-class, linear Discriminant analysis is applicable for more than two classes of classification problems.

Linear Discriminant analysis is one of the most popular dimensionality reduction techniques used for supervised classification problems in machine learning. It is also considered a pre-processing step for modeling differences in ML and applications of pattern classification.

Whenever there is a requirement to separate two or more classes having multiple features efficiently, the Linear Discriminant Analysis model is considered the most common technique to solve such classification problems. For e.g., if we have two classes with multiple features and need to separate them efficiently. When we classify them using a single feature, then it may show overlapping.

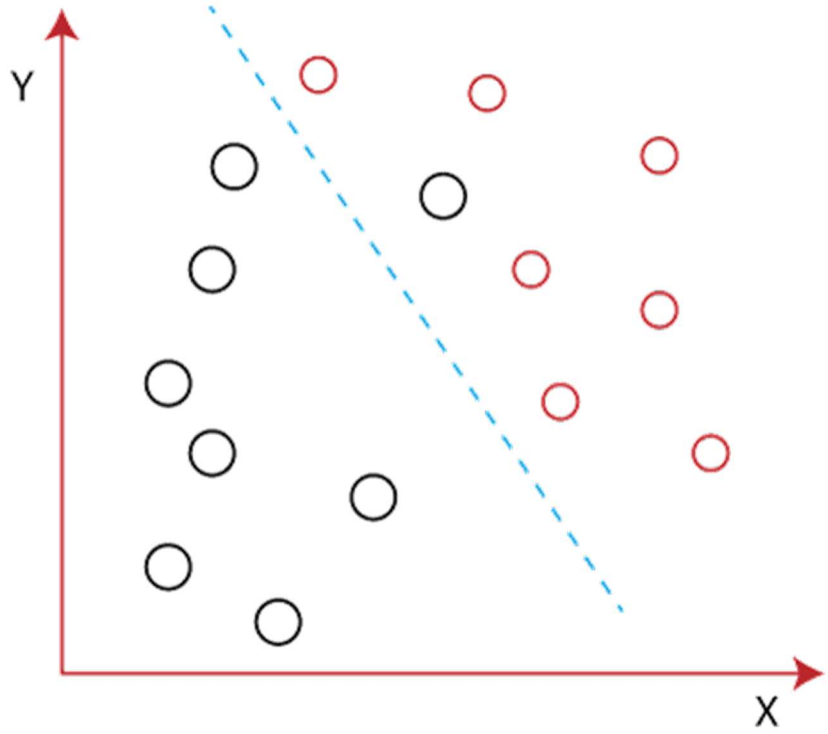


Overlapping

To overcome the overlapping issue in the classification process, we must increase the number of features regularly.

Example:

Let's assume we have to classify two different classes having two sets of data points in a 2-dimensional plane as shown below image:



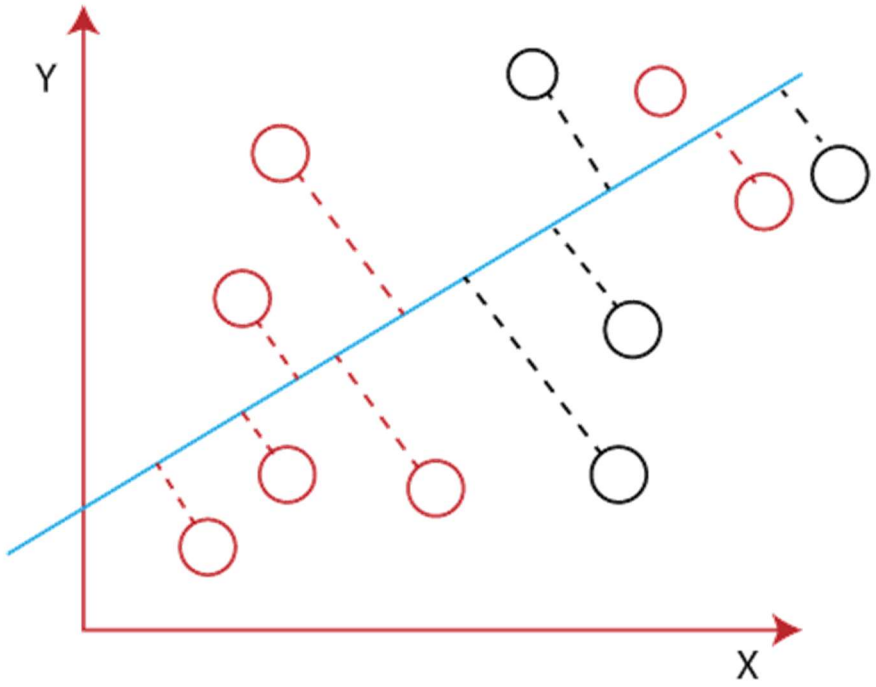
However, it is impossible to draw a straight line in a 2-d plane that can separate these data points efficiently but using linear Discriminant analysis; we can dimensionally reduce the 2-D plane into the 1-D plane. Using this technique, we can also maximize the separability between multiple classes.

How Linear Discriminant Analysis (LDA) works?

Linear Discriminant analysis is used as a dimensionality reduction technique in machine learning, using which we can easily transform a 2-D and 3-D graph into a 1-dimensional plane.

Let's consider an example where we have two classes in a 2-D plane having an X-Y axis, and we need to classify them efficiently. As we have already seen in the above example that LDA enables us to draw a straight line that can completely separate the two classes of the data points. Here, LDA uses an X-Y axis to create a new axis by separating them using a straight line and projecting data onto a new axis.

Hence, we can maximize the separation between these classes and reduce the 2-D plane into 1-D.



To create a new axis, Linear Discriminant Analysis uses the following criteria:

- It maximizes the distance between means of two classes.
- It minimizes the variance within the individual class.

Using the above two conditions, LDA generates a new axis in such a way that it can maximize the distance between the means of the two classes and minimizes the variation within each class.

In other words, we can say that the new axis will increase the separation between the data points of the two classes and plot them onto the new axis.

Why LDA?

- Logistic Regression is one of the most popular classification algorithms that perform well for binary classification but falls short in the case of multiple classification problems with well-separated classes. At the same time, LDA handles these quite efficiently.

- LDA can also be used in data pre-processing to reduce the number of features, just as PCA, which reduces the computing cost significantly.
- LDA is also used in face detection algorithms. In Fisherfaces, LDA is used to extract useful data from different faces. Coupled with eigenfaces, it produces effective results.

Drawbacks of Linear Discriminant Analysis (LDA)

Although, LDA is specifically used to solve supervised classification problems for two or more classes which are not possible using logistic regression in machine learning. But LDA also fails in some cases where the Mean of the distributions is shared. In this case, LDA fails to create a new axis that makes both the classes linearly separable.

To overcome such problems, we use **non-linear Discriminant analysis** in machine learning.

Extension to Linear Discriminant Analysis (LDA)

Linear Discriminant analysis is one of the most simple and effective methods to solve classification problems in machine learning. It has so many extensions and variations as follows:

1. **Quadratic Discriminant Analysis (QDA):** For multiple input variables, each class deploys its own estimate of variance.
2. **Flexible Discriminant Analysis (FDA):** it is used when there are non-linear groups of inputs are used, such as splines.
3. **Flexible Discriminant Analysis (FDA):** This uses regularization in the estimate of the variance (actually covariance) and hence moderates the influence of different variables on LDA.

Real-world Applications of LDA

Some of the common real-world applications of Linear discriminant Analysis are given below:

- **Face Recognition**
  Face recognition is the popular application of computer vision, where each face is

represented as the combination of a number of pixel values. In this case, LDA is used to minimize the number of features to a manageable number before going through the classification process. It generates a new template in which each dimension consists of a linear combination of pixel values. If a linear combination is generated using Fisher's linear discriminant, then it is called Fisher's face.

- **Medical**
  In the medical field, LDA has a great application in classifying the patient disease on the basis of various parameters of patient health and the medical treatment which is going on. On such parameters, it classifies disease as mild, moderate, or severe. This classification helps the doctors in either increasing or decreasing the pace of the treatment.
- **Customer Identification**
  In customer identification, LDA is currently being applied. It means with the help of LDA; we can easily identify and select the features that can specify the group of customers who are likely to purchase a specific product in a shopping mall. This can be helpful when we want to identify a group of customers who mostly purchase a product in a shopping mall.
- **For Predictions**
  LDA can also be used for making predictions and so in decision making. For example, "will you buy this product" will give a predicted result of either one or two possible classes as a buying or not.
- **In Learning**
  Nowadays, robots are being trained for learning and talking to simulate human work, and it can also be considered a classification problem. In this case, LDA builds similar groups on the basis of different parameters, including pitches, frequencies, sound, tunes, etc.

Difference between Linear Discriminant Analysis and PCA

Below are some basic differences between LDA and PCA:

- PCA is an unsupervised algorithm that does not care about classes and labels and only aims to find the principal components to maximize the variance in the given

dataset. At the same time, LDA is a supervised algorithm that aims to find the linear discriminants to represent the axes that maximize separation between different classes of data.

- LDA is much more suitable for multi-class classification tasks compared to PCA. However, PCA is assumed to be an as good performer for a comparatively small sample size.
- Both LDA and PCA are used as dimensionality reduction techniques, where PCA is first followed by LDA.

How to Prepare Data for LDA

Below are some suggestions that one should always consider while preparing the data to build the LDA model:

- **Classification Problems:** LDA is mainly applied for classification problems to classify the categorical output variable. It is suitable for both binary and multi-class classification problems.
- **Gaussian Distribution:** The standard LDA model applies the Gaussian Distribution of the input variables. One should review the univariate distribution of each attribute and transform them into more Gaussian-looking distributions. For e.g., use log and root for exponential distributions and Box-Cox for skewed distributions.
- **Remove Outliers:** It is good to firstly remove the outliers from your data because these outliers can skew the basic statistics used to separate classes in LDA, such as the mean and the standard deviation.
- **Same Variance:** As LDA always assumes that all the input variables have the same variance, hence it is always a better way to firstly standardize the data before implementing an LDA model. By this, the Mean will be 0, and it will have a standard deviation of 1.

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.

Python Implementation of the Naïve Bayes algorithm:

Now we will implement a Naive Bayes Algorithm using Python. So for this, we will use the "**user_data**" **dataset**, which we have used in our other classification model. Therefore we can easily compare the Naive Bayes model with the other models.

Steps to implement:

- Data Pre-processing step
- Fitting Naive Bayes to the Training set
- Predicting the test result
- Test accuracy of the result(Creation of Confusion matrix)
- Visualizing the test set result.

1) Data Pre-processing step:

In this step, we will pre-process/prepare the data so that we can use it efficiently in our code. It is similar as we did in data-pre-processing. The code for this is given below:

1. Importing the libraries
2. **import** numpy as nm
3. **import** matplotlib.pyplot as mtp

```
4. import pandas as pd
5.
6. # Importing the dataset
7. dataset = pd.read_csv('user_data.csv')
8. x = dataset.iloc[:, [2, 3]].values
9. y = dataset.iloc[:, 4].values
10.
11. # Splitting the dataset into the Training set and Test set
12. from sklearn.model_selection import train_test_split
13. x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25, random_state
    = 0)
14.
15. # Feature Scaling
16. from sklearn.preprocessing import StandardScaler
17. sc = StandardScaler()
18. x_train = sc.fit_transform(x_train)
19. x_test = sc.transform(x_test)
```

In the above code, we have loaded the dataset into our program using "**dataset = pd.read_csv('user_data.csv')**. The loaded dataset is divided into training and test set, and then we have scaled the feature variable.

The output for the dataset is given as:

dataset - DataFrame

Index	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0
5	15728773	Male	27	58000	0
6	15598044	Female	27	84000	0
7	15694829	Female	32	150000	1
8	15600575	Male	25	33000	0
9	15727311	Female	35	65000	0
10	15570769	Female	26	80000	0
11	15606274	Female	26	52000	0
12	15746139	Male	20	86000	0
13	15704987	Male	32	18000	0
14	15628972	Male	18	82000	0
15	15697686	Male	29	80000	0
16	15733883	Male	47	25000	1
17	15617482	Male	45	26000	1
18	15704583	Male	46	28000	1
19	15621083	Female	48	29000	1

2) Fitting Naive Bayes to the Training Set:

After the pre-processing step, now we will fit the Naive Bayes model to the Training set. Below is the code for it:

```
1. # Fitting Naive Bayes to the Training set
2. from sklearn.naive_bayes import GaussianNB
3. classifier = GaussianNB()
4. classifier.fit(x_train, y_train)
```

In the above code, we have used the **GaussianNB classifier** to fit it to the training dataset. We can also use other classifiers as per our requirement.

Output:

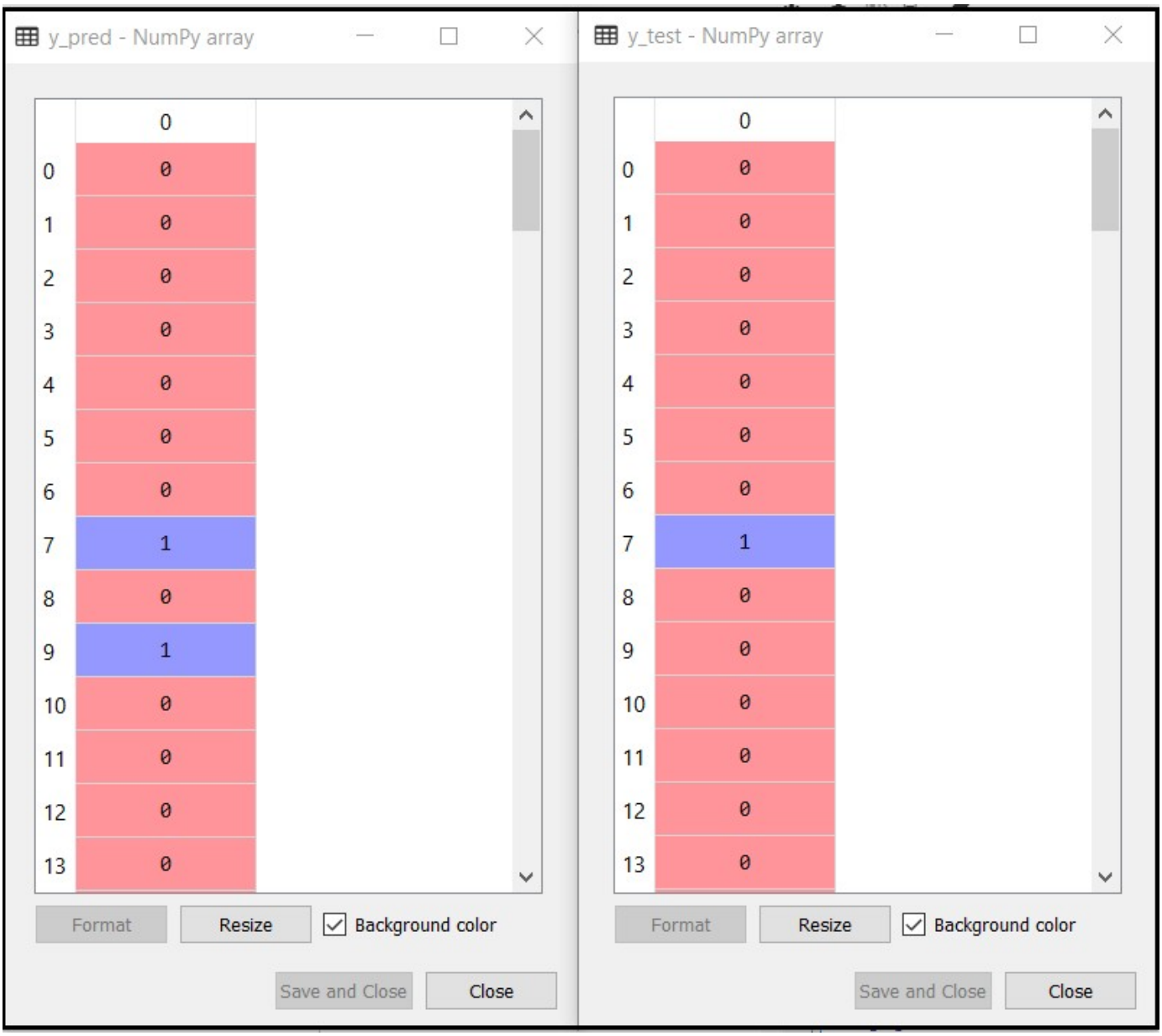
```
Out[6]: GaussianNB(priors=None, var_smoothing=1e-09)
```

3) Prediction of the test set result:

Now we will predict the test set result. For this, we will create a new predictor variable **y_pred**, and will use the predict function to make the predictions.

```
1. # Predicting the Test set results
2. y_pred = classifier.predict(x_test)
```

Output:



The above output shows the result for prediction vector **y_pred** and real vector y_test. We can see that some predications are different from the real values, which are the incorrect predictions.

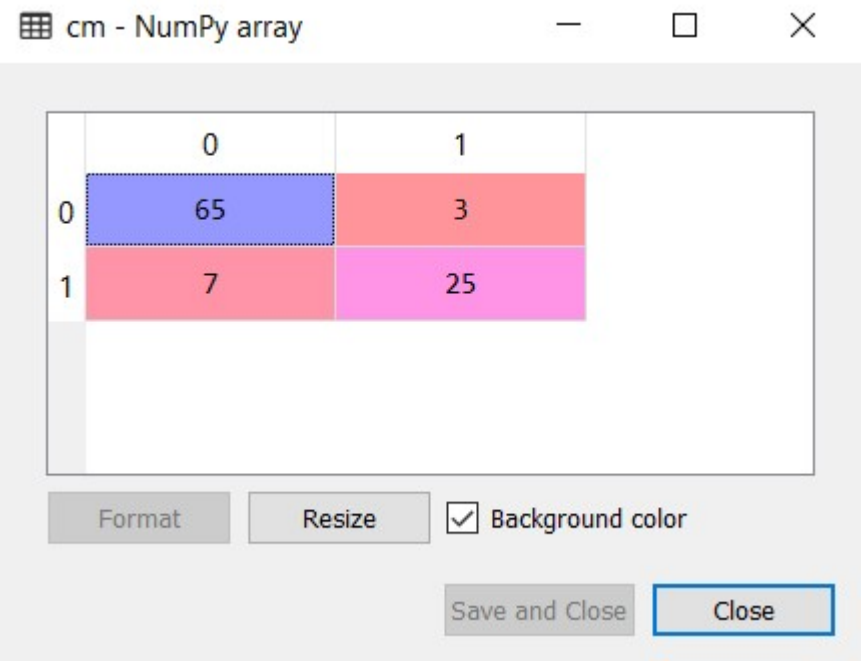
4) Creating Confusion Matrix:

Now we will check the accuracy of the Naive Bayes classifier using the Confusion matrix. Below is the code for it:

1. # Making the Confusion Matrix

```
2. from sklearn.metrics import confusion_matrix
3. cm = confusion_matrix(y_test, y_pred)
```

Output:



As we can see in the above confusion matrix output, there are 7+3= 10 incorrect predictions, and 65+25=90 correct predictions.

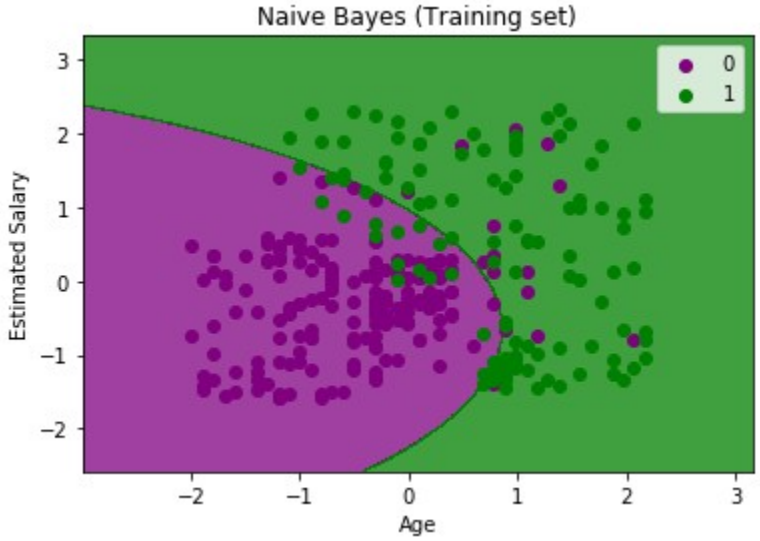
5) Visualizing the training set result:

Next we will visualize the training set result using Naïve Bayes Classifier. Below is the code for it:

```
1. # Visualising the Training set results
2. from matplotlib.colors import ListedColormap
3. x_set, y_set = x_train, y_train
4. X1, X2 = nm.meshgrid(nm.arange(start = x_set[:, 0].min() - 1, stop = x_set[:, 0].max
   () + 1, step = 0.01),
5.                      nm.arange(start = x_set[:, 1].min() - 1, stop = x_set[:, 1].max() + 1, ste
   p = 0.01))
6. mtp.contourf(X1, X2, classifier.predict(nm.array([X1.ravel(), X2.ravel()]).T).reshape(X
   1.shape),
```

```
                alpha = 0.75, cmap = ListedColormap(('purple', 'green')))
mtp.xlim(X1.min(), X1.max())
mtp.ylim(X2.min(), X2.max())
for i, j in enumerate(nm.unique(y_set)):
    mtp.scatter(x_set[y_set == j, 0], x_set[y_set == j, 1],
                c = ListedColormap(('purple', 'green'))(i), label = j)
mtp.title('Naive Bayes (Training set)')
mtp.xlabel('Age')
mtp.ylabel('Estimated Salary')
mtp.legend()
mtp.show()
```

Output:



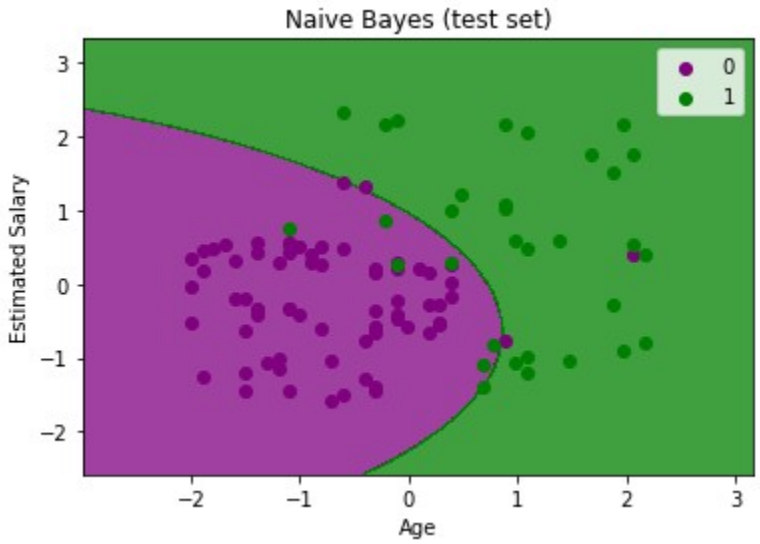
In the above output we can see that the Naïve Bayes classifier has segregated the data points with the fine boundary. It is Gaussian curve as we have used **GaussianNB** classifier in our code.

6) Visualizing the Test set result:

```
# Visualising the Test set results
from matplotlib.colors import ListedColormap
x_set, y_set = x_test, y_test
```

```
X1, X2 = nm.meshgrid(nm.arange(start = x_set[:, 0].min() - 1, stop = x_set[:, 0].max() + 1, step = 0.01),
                     nm.arange(start = x_set[:, 1].min() - 1, stop = x_set[:, 1].max() + 1, step = 0.01))
mtp.contourf(X1, X2, classifier.predict(nm.array([X1.ravel(), X2.ravel()]).T).reshape(X1.shape),
             alpha = 0.75, cmap = ListedColormap(('purple', 'green')))
mtp.xlim(X1.min(), X1.max())
mtp.ylim(X2.min(), X2.max())
for i, j in enumerate(nm.unique(y_set)):
    mtp.scatter(x_set[y_set == j, 0], x_set[y_set == j, 1],
                c = ListedColormap(('purple', 'green'))(i), label = j)
mtp.title('Naive Bayes (test set)')
mtp.xlabel('Age')
mtp.ylabel('Estimated Salary')
mtp.legend()
mtp.show()
```

Output:



The above output is final output for test set data. As we can see the classifier has created a Gaussian curve to divide the "purchased" and "not purchased" variables. There are some

wrong predictions which we have calculated in Confusion matrix. But still it is pretty good classifier.

Bayesian Belief Network

Bayesian belief network is key computer technology for dealing with probabilistic events and to solve a problem which has uncertainty. We can define a Bayesian network as:

"A Bayesian network is a probabilistic graphical model which represents a set of variables and their conditional dependencies using a directed acyclic graph."

It is also called a **Bayes network, belief network, decision network**, or **Bayesian model**.

Bayesian networks are probabilistic, because these networks are built from a **probability distribution**, and also use probability theory for prediction and anomaly detection.

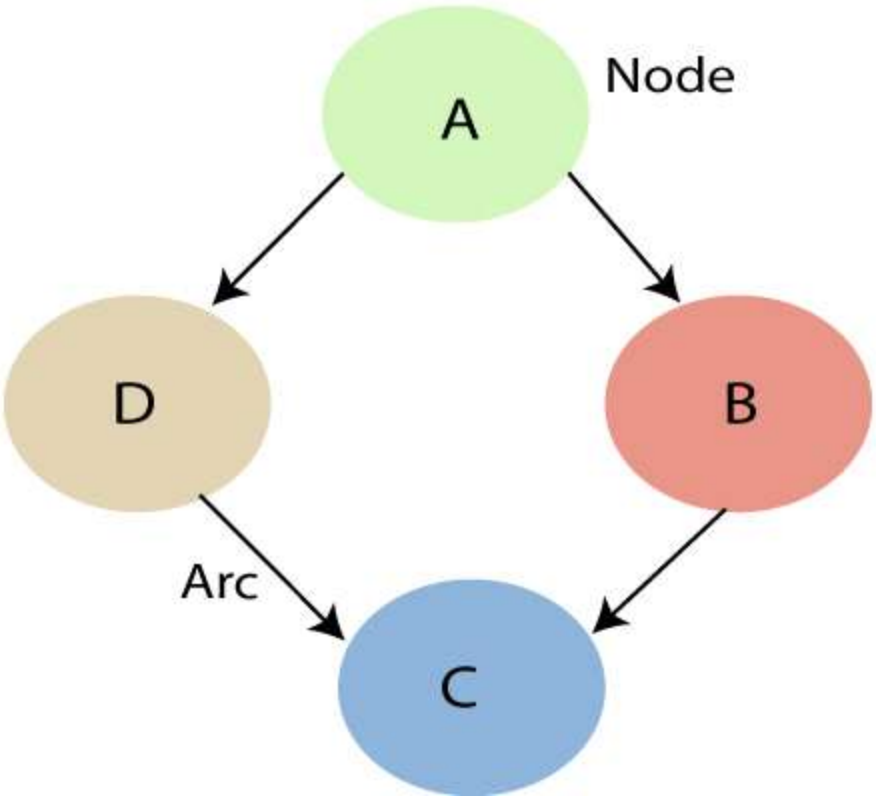
Real world applications are probabilistic in nature, and to represent the relationship between multiple events, we need a Bayesian network. It can also be used in various tasks including **prediction, anomaly detection, diagnostics, automated insight, reasoning, time series prediction**, and **decision making under uncertainty**.

Bayesian Network can be used for building models from data and experts opinions, and it consists of two parts:

- **Directed Acyclic Graph**
- **Table of conditional probabilities.**

The generalized form of Bayesian network that represents and solve decision problems under uncertain knowledge is known as an **Influence diagram**.

A Bayesian network graph is made up of nodes and Arcs (directed links), where:



- Each **node** corresponds to the random variables, and a variable can be **continuous** or **discrete**.
- **Arc or directed arrows** represent the causal relationship or conditional probabilities between random variables. These directed links or arrows connect the pair of nodes in the graph.
  These links represent that one node directly influence the other node, and if there is no directed link that means that nodes are independent with each other
  - **In the above diagram, A, B, C, and D are random variables represented by the nodes of the network graph.**
  - **If we are considering node B, which is connected with node A by a directed arrow, then node A is called the parent of Node B.**
  - **Node C is independent of node A.**

Note: The Bayesian network graph does not contain any cyclic graph. Hence, it is known as a **directed acyclic graph or DAG**.

The Bayesian network has mainly two components:

- **Causal Component**

- **Actual numbers**

Each node in the Bayesian network has condition probability distribution **$P(X_i \mid Parent(X_i))$**, which determines the effect of the parent on that node.

Bayesian network is based on Joint probability distribution and conditional probability. So let's first understand the joint probability distribution:

Joint probability distribution:

If we have variables x1, x2, x3,....., xn, then the probabilities of a different combination of x1, x2, x3.. xn, are known as Joint probability distribution.

$P[x_1, x_2, x_3, ..., x_n]$, it can be written as the following way in terms of the joint probability distribution.

$= P[x_1 \mid x_2, x_3, ..., x_n]P[x_2, x_3, ..., x_n]$

$= P[x_1 \mid x_2, x_3, ..., x_n]P[x_2 \mid x_3, ..., x_n]....P[x_{n-1} \mid x_n]P[x_n].$

In general for each variable Xi, we can write the equation as:

$$P(X_i \mid X_{i-1}, ..., X_1) = P(X_i \mid Parents(X_i))$$

Explanation of Bayesian network:

Let's understand the Bayesian network through an example by creating a directed acyclic graph:

Example: Harry installed a new burglar alarm at his home to detect burglary. The alarm reliably responds at detecting a burglary but also responds for minor earthquakes. Harry has two neighbors David and Sophia, who have taken a responsibility to inform Harry at work when they hear the alarm. David always calls Harry when he hears the alarm, but sometimes he got confused with the phone ringing and calls at that time too. On the other hand, Sophia likes to listen to high music, so sometimes she misses to hear the alarm. Here we would like to compute the probability of Burglary Alarm.

Problem:

Calculate the probability that alarm has sounded, but there is neither a burglary, nor an earthquake occurred, and David and Sophia both called the Harry.

Solution:

- The Bayesian network for the above problem is given below. The network structure is showing that burglary and earthquake is the parent node of the alarm and directly affecting the probability of alarm's going off, but David and Sophia's calls depend on alarm probability.
- The network is representing that our assumptions do not directly perceive the burglary and also do not notice the minor earthquake, and they also not confer before calling.
- The conditional distributions for each node are given as conditional probabilities table or CPT.
- Each row in the CPT must be sum to 1 because all the entries in the table represent an exhaustive set of cases for the variable.
- In CPT, a boolean variable with k boolean parents contains 2^K probabilities. Hence, if there are two parents, then CPT will contain 4 probability values

List of all events occurring in this network:

- **Burglary (B)**
- **Earthquake(E)**
- **Alarm(A)**
- **David Calls(D)**
- **Sophia calls(S)**

We can write the events of problem statement in the form of probability: **P[D, S, A, B, E]**, can rewrite the above probability statement using joint probability distribution:

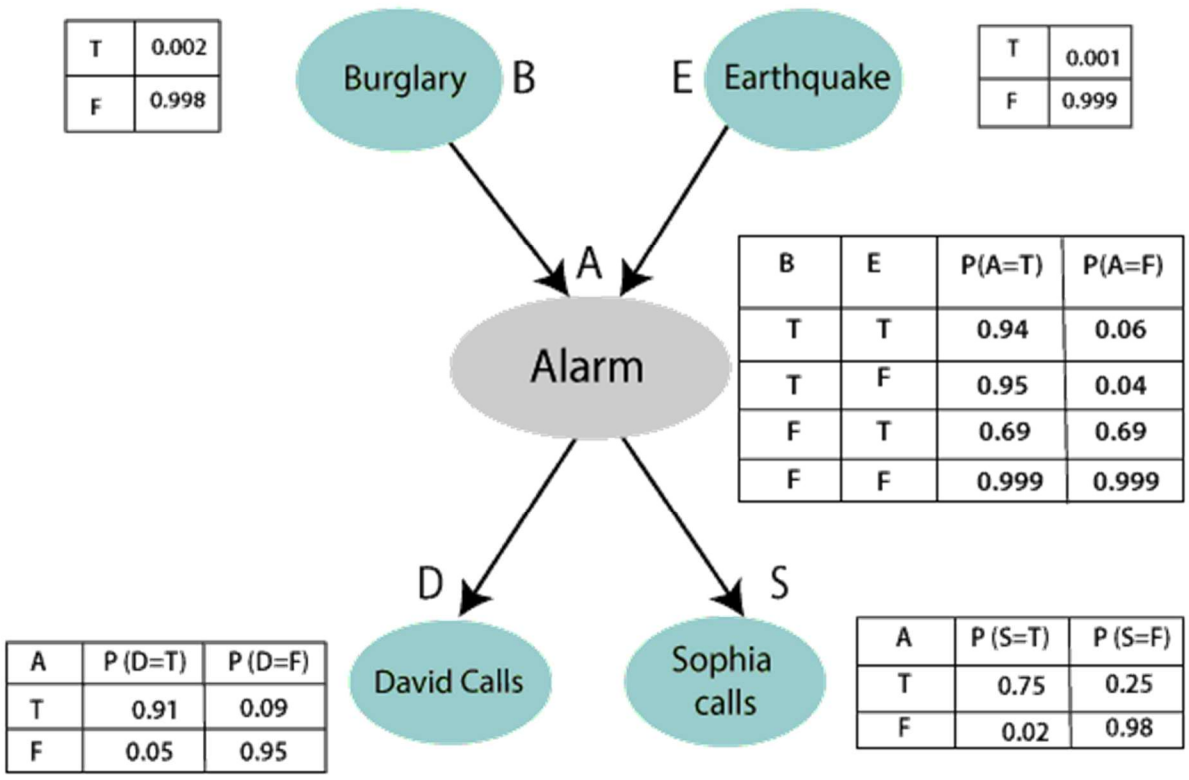
P[D, S, A, B, E]= P[D | S, A, B, E]. P[S, A, B, E]

=P[D | S, A, B, E]. P[S | A, B, E]. P[A, B, E]

= P [D| A]. P [S| A, B, E]. P[A, B, E]

= P[D | A]. P[S | A]. P[A| B, E]. P[B, E]

= P[D | A]. P[S | A]. P[A| B, E]. P[B |E]. P[E]



T	0.002
F	0.998

T	0.001
F	0.999

B	E	P(A=T)	P(A=F)
T	T	0.94	0.06
T	F	0.95	0.04
F	T	0.69	0.69
F	F	0.999	0.999

A	P (D=T)	P (D=F)
T	0.91	0.09
F	0.05	0.95

A	P (S=T)	P (S=F)
T	0.75	0.25
F	0.02	0.98

Let's take the observed probability for the Burglary and earthquake component:

P(B= True) = 0.002, which is the probability of burglary.

P(B= False)= 0.998, which is the probability of no burglary.

P(E= True)= 0.001, which is the probability of a minor earthquake

P(E= False)= 0.999, Which is the probability that an earthquake not occurred.

We can provide the conditional probabilities as per the below tables:

Conditional probability table for Alarm A:

The Conditional probability of Alarm A depends on Burglar and earthquake:

B	E	P(A= True)	P(A= False)
True	True	0.94	0.06
True	False	0.95	0.04

False	True	0.31	0.69
False	False	0.001	0.999

Conditional probability table for David Calls:

The Conditional probability of David that he will call depends on the probability of Alarm.

A	P(D= True)	P(D= False)
True	0.91	0.09
False	0.05	0.95

Conditional probability table for Sophia Calls:

The Conditional probability of Sophia that she calls is depending on its Parent Node "Alarm."

A	P(S= True)	P(S= False)
True	0.75	0.25
False	0.02	0.98

From the formula of joint distribution, we can write the problem statement in the form of probability distribution:

P(S, D, A, ¬B, ¬E) = P (S|A) *P (D|A)*P (A|¬B ^ ¬E) *P (¬B) *P (¬E).

= 0.75* 0.91* 0.001* 0.998*0.999

= 0.00068045.

Hence, a Bayesian network can answer any query about the domain by using Joint distribution.

The semantics of Bayesian Network:

There are two ways to understand the semantics of the Bayesian network, which is given below:

1. To understand the network as the representation of the Joint probability distribution.

It is helpful to understand how to construct the network.

2. To understand the network as an encoding of a collection of conditional independence statements.

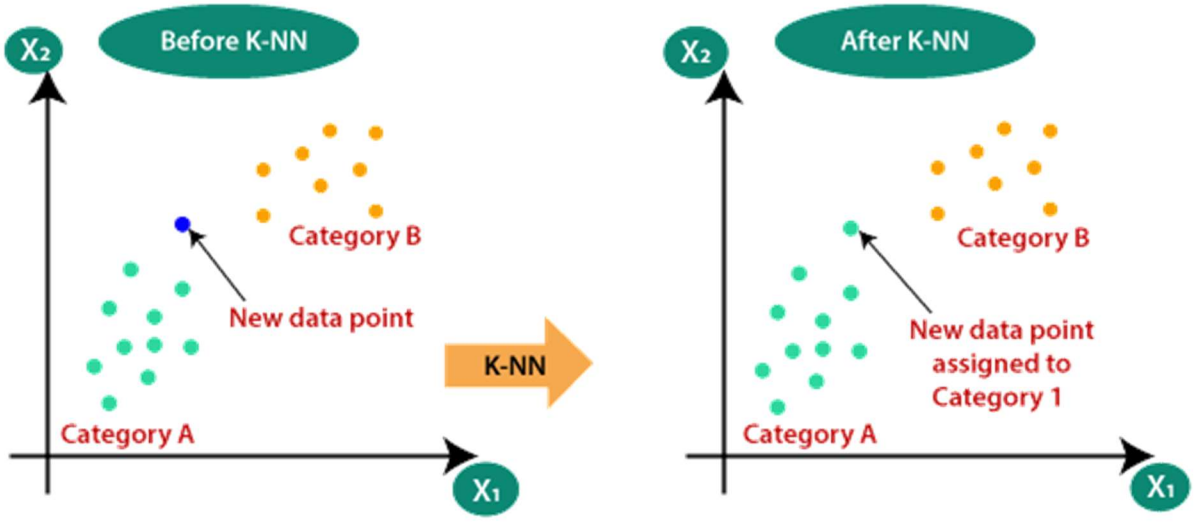
It is helpful in designing inference procedure.

K-Nearest Neighbor(KNN) Algorithm for Machine Learning

- K-Nearest Neighbour is one of the simplest Machine Learning algorithms based on Supervised Learning technique.
- K-NN algorithm assumes the similarity between the new case/data and available cases and put the new case into the category that is most similar to the available categories.
- K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm.
- K-NN algorithm can be used for Regression as well as for Classification but mostly it is used for the Classification problems.
- K-NN is a **non-parametric algorithm**, which means it does not make any assumption on underlying data.
- It is also called a **lazy learner algorithm** because it does not learn from the training set immediately instead it stores the dataset and at the time of classification, it performs an action on the dataset.
- KNN algorithm at the training phase just stores the dataset and when it gets new data, then it classifies that data into a category that is much similar to the new data.
- **Example:** Suppose, we have an image of a creature that looks similar to cat and dog, but we want to know either it is a cat or dog. So for this identification, we can use the KNN algorithm, as it works on a similarity measure. Our KNN model will find the similar features of the new data set to the cats and dogs images and based on the most similar features it will put it in either cat or dog category.

Why do we need a K-NN Algorithm?

Suppose there are two categories, i.e., Category A and Category B, and we have a new data point x1, so this data point will lie in which of these categories. To solve this type of problem, we need a K-NN algorithm. With the help of K-NN, we can easily identify the category or class of a particular dataset. Consider the below diagram:

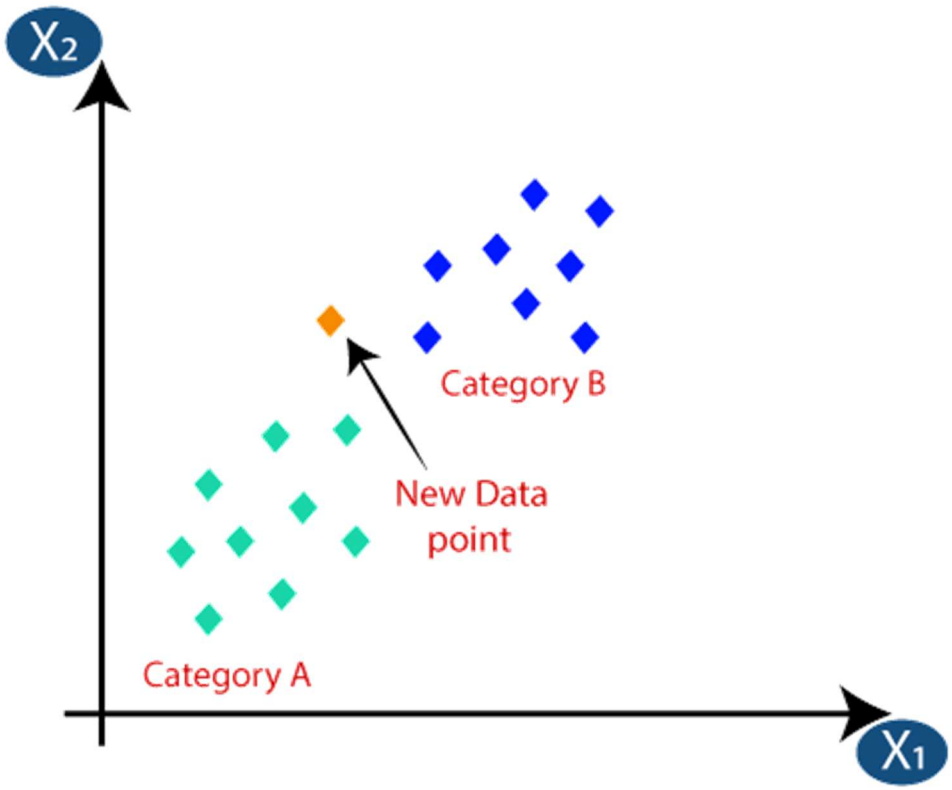


How does K-NN work?

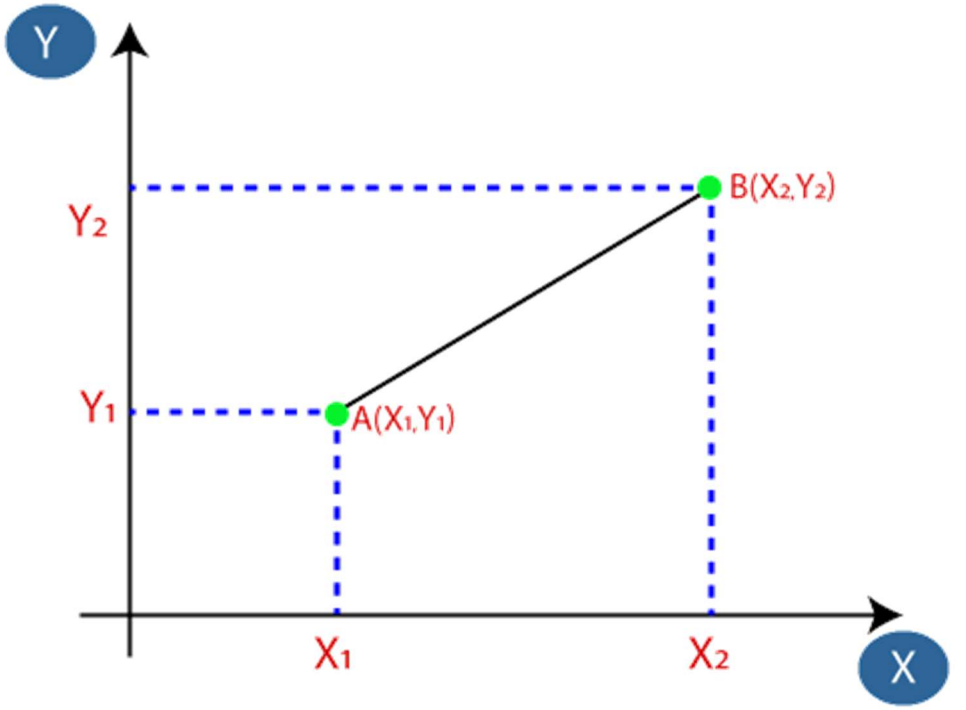
The K-NN working can be explained on the basis of the below algorithm:

- **Step-1:** Select the number K of the neighbors
- **Step-2:** Calculate the Euclidean distance of **K number of neighbors**
- **Step-3:** Take the K nearest neighbors as per the calculated Euclidean distance.
- **Step-4:** Among these k neighbors, count the number of the data points in each category.
- **Step-5:** Assign the new data points to that category for which the number of the neighbor is maximum.
- **Step-6:** Our model is ready.

Suppose we have a new data point and we need to put it in the required category. Consider the below image:



- Firstly, we will choose the number of neighbors, so we will choose the k=5.
- Next, we will calculate the **Euclidean distance** between the data points. The Euclidean distance is the distance between two points, which we have already studied in geometry. It can be calculated as:



Euclidean Distance between A_1 and B_2 = $\sqrt{(X_2-X_1)^2+(Y_2-Y_1)^2}$

- By calculating the Euclidean distance we got the nearest neighbors, as three nearest neighbors in category A and two nearest neighbors in category B. Consider the below image:

- As we can see the 3 nearest neighbors are from category A, hence this new data point must belong to category A.

How to select the value of K in the K-NN Algorithm?

Below are some points to remember while selecting the value of K in the K-NN algorithm:

- There is no particular way to determine the best value for "K", so we need to try some values to find the best out of them. The most preferred value for K is 5.
- A very low value for K such as K=1 or K=2, can be noisy and lead to the effects of outliers in the model.
- Large values for K are good, but it may find some difficulties.

Advantages of KNN Algorithm:

- It is simple to implement.
- It is robust to the noisy training data
- It can be more effective if the training data is large.

Disadvantages of KNN Algorithm:

- Always needs to determine the value of K which may be complex some time.
- The computation cost is high because of calculating the distance between the data points for all the training samples.

Python implementation of the KNN algorithm

To do the Python implementation of the K-NN algorithm, we will use the same problem and dataset which we have used in Logistic Regression. But here we will improve the performance of the model. Below is the problem description:

Problem for K-NN Algorithm: There is a Car manufacturer company that has manufactured a new SUV car. The company wants to give the ads to the users who are interested in buying that SUV. So for this problem, we have a dataset that contains multiple user's information through the social network. The dataset contains lots of information but the **Estimated Salary** and **Age** we will consider for the independent variable and the **Purchased variable** is for the dependent variable. Below is the dataset:

User ID	Gender	Age	EstimatedSalary	Purchased
15624510	Male	19	19000	0
15810944	Male	35	20000	0
15668575	Female	26	43000	0
15603246	Female	27	57000	0
15804002	Male	19	76000	0
15728773	Male	27	58000	0
15598044	Female	27	84000	0
15694829	Female	32	150000	1
15600575	Male	25	33000	0
15727311	Female	35	65000	0
15570769	Female	26	80000	0
15606274	Female	26	52000	0
15746139	Male	20	86000	0
15704987	Male	32	18000	0
15628972	Male	18	82000	0
15697686	Male	29	80000	0
15733883	Male	47	25000	1
15617482	Male	45	26000	1
15704583	Male	46	28000	1
15621083	Female	48	29000	1
15649487	Male	45	22000	1
15736760	Female	47	49000	1

Steps to implement the K-NN algorithm:

- Data Pre-processing step
- Fitting the K-NN algorithm to the Training set
- Predicting the test result
- Test accuracy of the result(Creation of Confusion matrix)
- Visualizing the test set result.

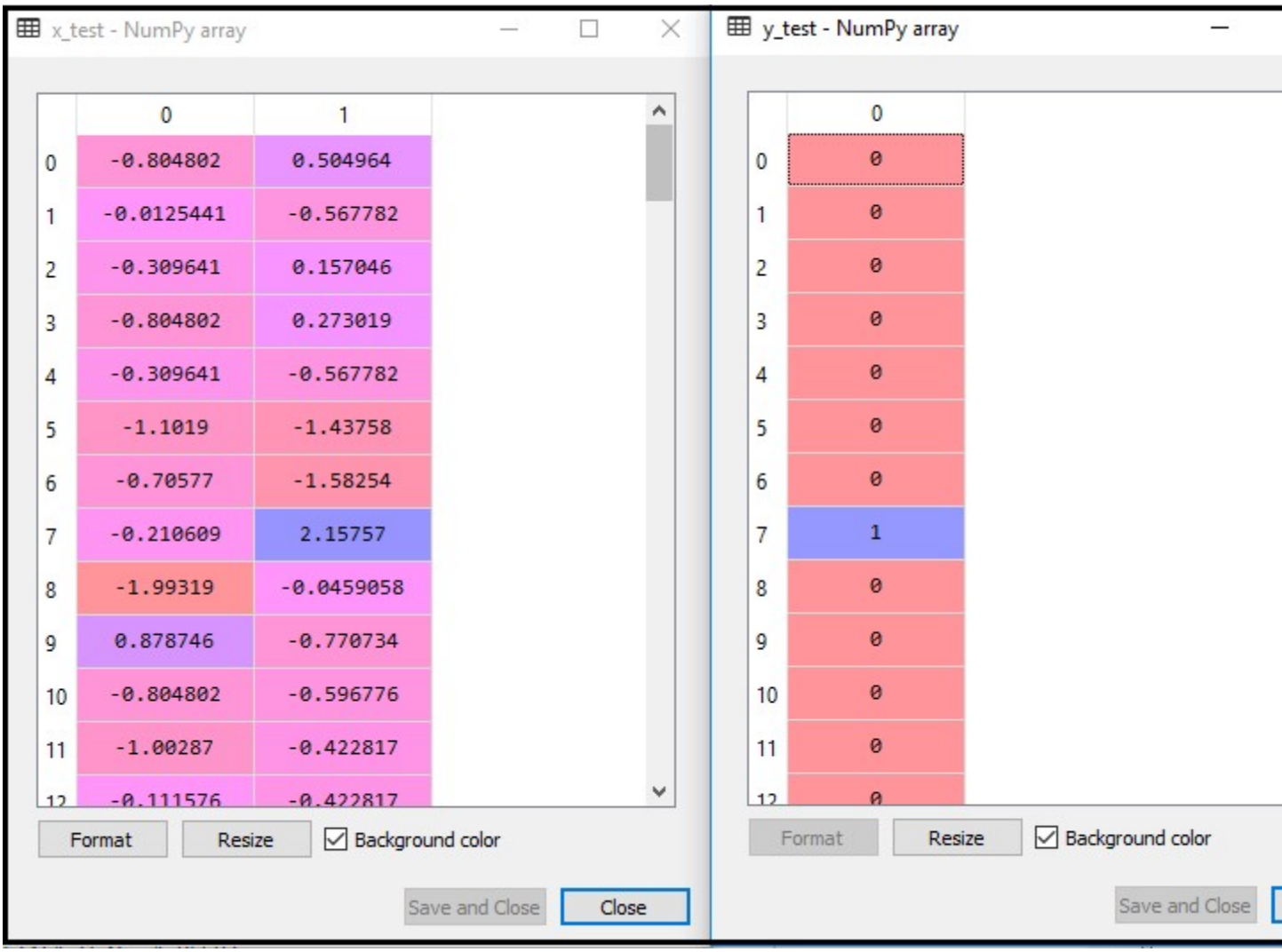
Data Pre-Processing Step:

The Data Pre-processing step will remain exactly the same as Logistic Regression. Below is the code for it:

```
# importing libraries
import numpy as nm
import matplotlib.pyplot as mtp
```

```
4. import pandas as pd
5.
6. #importing datasets
7. data_set= pd.read_csv('user_data.csv')
8.
9. #Extracting Independent and dependent Variable
10. x= data_set.iloc[:, [2,3]].values
11. y= data_set.iloc[:, 4].values
12.
13. # Splitting the dataset into training and test set.
14. from sklearn.model_selection import train_test_split
15. x_train, x_test, y_train, y_test= train_test_split(x, y, test_size= 0.25, random_state=0
    )
16.
17. #feature Scaling
18. from sklearn.preprocessing import StandardScaler
19. st_x= StandardScaler()
20. x_train= st_x.fit_transform(x_train)
21. x_test= st_x.transform(x_test)
```

By executing the above code, our dataset is imported to our program and well pre-processed. After feature scaling our test dataset will look like:



From the above output image, we can see that our data is successfully scaled.

- **Fitting K-NN classifier to the Training data:**
  Now we will fit the K-NN classifier to the training data. To do this we will import the **KNeighborsClassifier** class of **Sklearn Neighbors** library. After importing the class, we will create the **Classifier** object of the class. The Parameter of this class will be
  - **n_neighbors:** To define the required neighbors of the algorithm. Usually, it takes 5.
  - **metric='minkowski':** This is the default parameter and it decides the distance between the points.
  - **p=2:** It is equivalent to the standard Euclidean metric.

And then we will fit the classifier to the training data. Below is the code for it:

```
#Fitting K-NN classifier to the training set
from sklearn.neighbors import KNeighborsClassifier
classifier= KNeighborsClassifier(n_neighbors=5, metric='minkowski', p=2 )
classifier.fit(x_train, y_train)
```

Output: By executing the above code, we will get the output as:

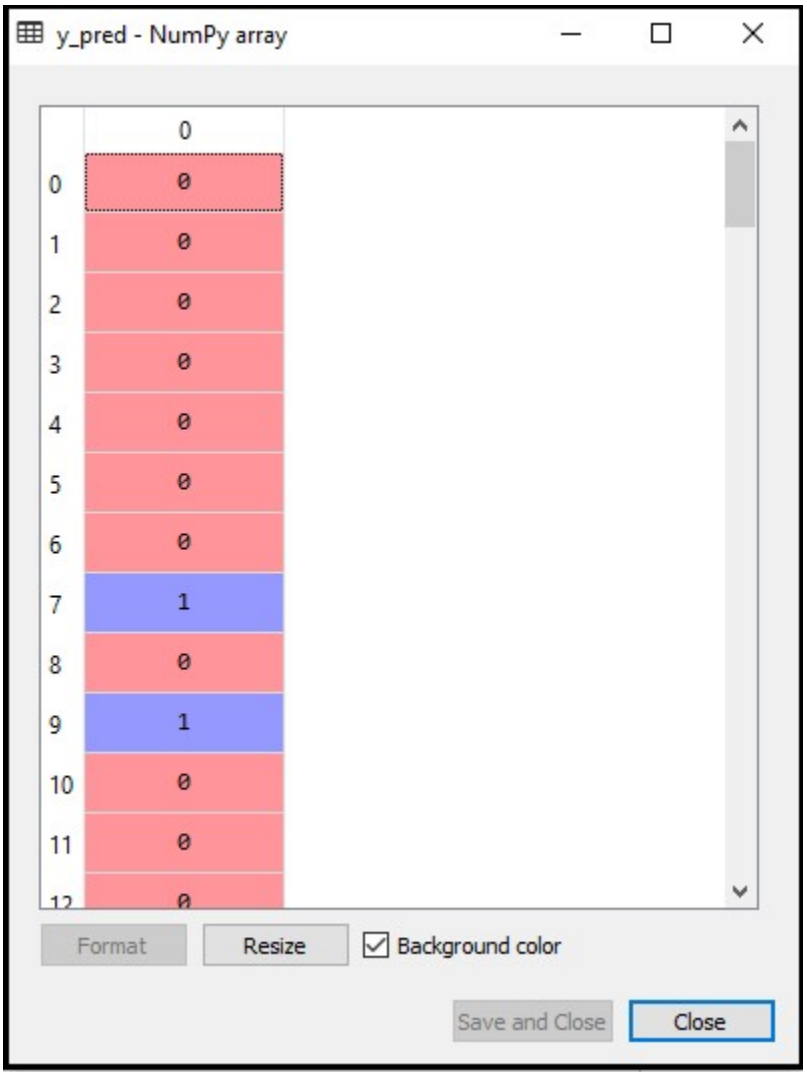
```
Out[10]:
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                     weights='uniform')
```

- **Predicting the Test Result:** To predict the test set result, we will create a **y_pred** vector as we did in Logistic Regression. Below is the code for it:

```
#Predicting the test set result
y_pred= classifier.predict(x_test)
```

Output:

The output for the above code will be:



- **Creating the Confusion Matrix:**
  Now we will create the Confusion Matrix for our K-NN model to see the accuracy of the classifier. Below is the code for it:

```
1. #Creating the Confusion matrix
2.     from sklearn.metrics import confusion_matrix
3.     cm= confusion_matrix(y_test, y_pred)
```

In above code, we have imported the confusion_matrix function and called it using the variable cm.

Output: By executing the above code, we will get the matrix as below:

In the above image, we can see there are 64+29= 93 correct predictions and 3+4= 7 incorrect predictions, whereas, in Logistic Regression, there were 11 incorrect predictions. So we can say that the performance of the model is improved by using the K-NN algorithm.

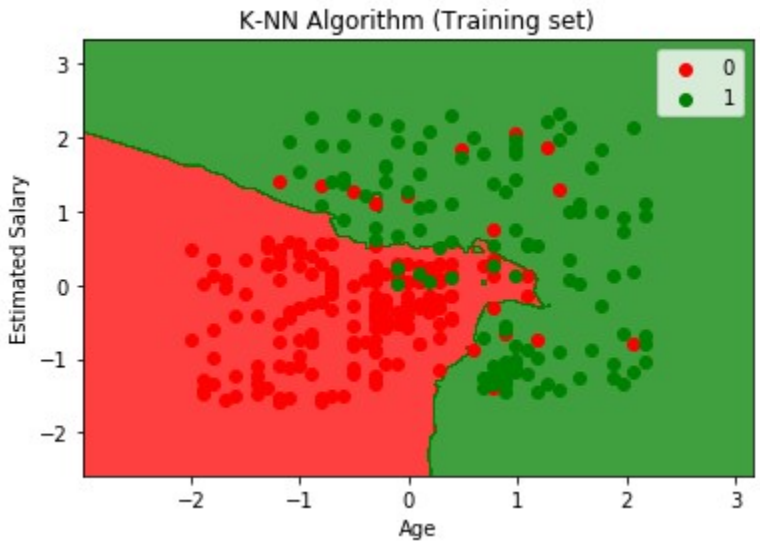
- **Visualizing the Training set result:**
  Now, we will visualize the training set result for K-NN model. The code will remain same as we did in Logistic Regression, except the name of the graph. Below is the code for it:

```
1. #Visulaizing the trianing set result
2. from matplotlib.colors import ListedColormap
3. x_set, y_set = x_train, y_train
4. x1, x2 = nm.meshgrid(nm.arange(start = x_set[:, 0].min() - 1, stop = x_set[:, 0].max(
   ) + 1, step  =0.01),
5. nm.arange(start = x_set[:, 1].min() - 1, stop = x_set[:, 1].max() + 1, step = 0.01))
6. mtp.contourf(x1, x2, classifier.predict(nm.array([x1.ravel(), x2.ravel()]).T).reshape(x1
   .shape),
7. alpha = 0.75, cmap = ListedColormap(('red','green' )))
8. mtp.xlim(x1.min(), x1.max())
9. mtp.ylim(x2.min(), x2.max())
```

```
for i, j in enumerate(nm.unique(y_set)):
    mtp.scatter(x_set[y_set == j, 0], x_set[y_set == j, 1],
        c = ListedColormap(('red', 'green'))(i), label = j)
mtp.title('K-NN Algorithm (Training set)')
mtp.xlabel('Age')
mtp.ylabel('Estimated Salary')
mtp.legend()
mtp.show()
```

Output:

By executing the above code, we will get the below graph:



The output graph is different from the graph which we have occurred in Logistic Regression. It can be understood in the below points:

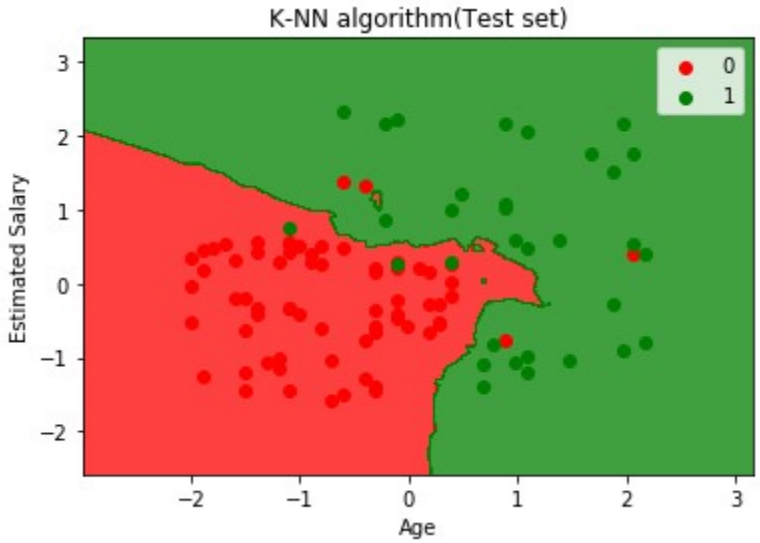
- As we can see the graph is showing the red point and green points. The green points are for Purchased(1) and Red Points for not Purchased(0) variable.
- The graph is showing an irregular boundary instead of showing any straight line or any curve because it is a K-NN algorithm, i.e., finding the nearest neighbor.

- The graph has classified users in the correct categories as most of the users who didn't buy the SUV are in the red region and users who bought the SUV are in the green region.
- The graph is showing good result but still, there are some green points in the red region and red points in the green region. But this is no big issue as by doing this model is prevented from overfitting issues.
- Hence our model is well trained.

- **Visualizing the Test set result:** After the training of the model, we will now test the result by putting a new dataset, i.e., Test dataset. Code remains the same except some minor changes: such as **x_train and y_train** will be replaced by **x_test and y_test**. Below is the code for it:

```
#Visualizing the test set result
from matplotlib.colors import ListedColormap
x_set, y_set = x_test, y_test
x1, x2 = nm.meshgrid(nm.arange(start = x_set[:, 0].min() - 1, stop = x_set[:, 0].max(
) + 1, step  =0.01),
nm.arange(start = x_set[:, 1].min() - 1, stop = x_set[:, 1].max() + 1, step = 0.01))
mtp.contourf(x1, x2, classifier.predict(nm.array([x1.ravel(), x2.ravel()]).T).reshape(x1
.shape),
alpha = 0.75, cmap = ListedColormap(('red','green' )))
mtp.xlim(x1.min(), x1.max())
mtp.ylim(x2.min(), x2.max())
for i, j in enumerate(nm.unique(y_set)):
    mtp.scatter(x_set[y_set == j, 0], x_set[y_set == j, 1],
        c = ListedColormap(('red', 'green'))(i), label = j)
mtp.title('K-NN algorithm(Test set)')
mtp.xlabel('Age')
mtp.ylabel('Estimated Salary')
mtp.legend()
mtp.show()
```

Output:



The above graph is showing the output for the test data set. As we can see in the graph, the predicted output is well good as most of the red points are in the red region and most of the green points are in the green region.

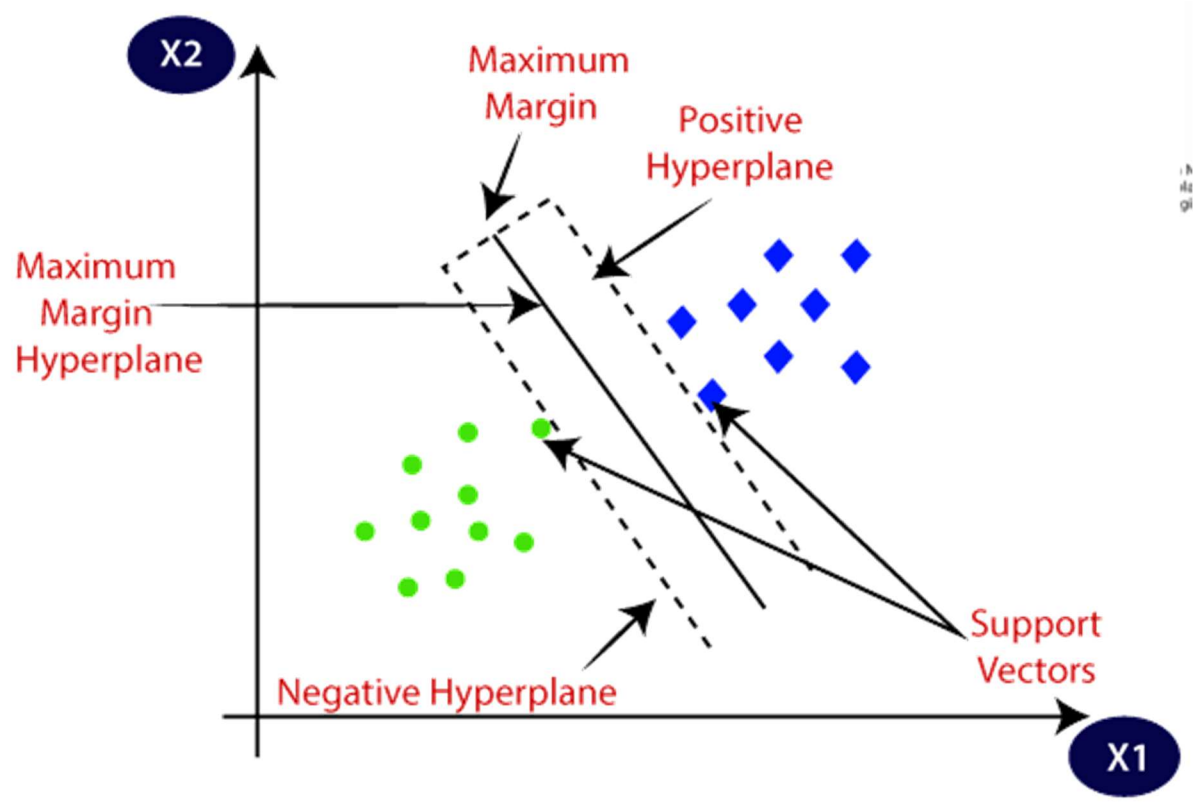
However, there are few green points in the red region and a few red points in the green region. So these are the incorrect observations that we have observed in the confusion matrix(7 Incorrect output).

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.

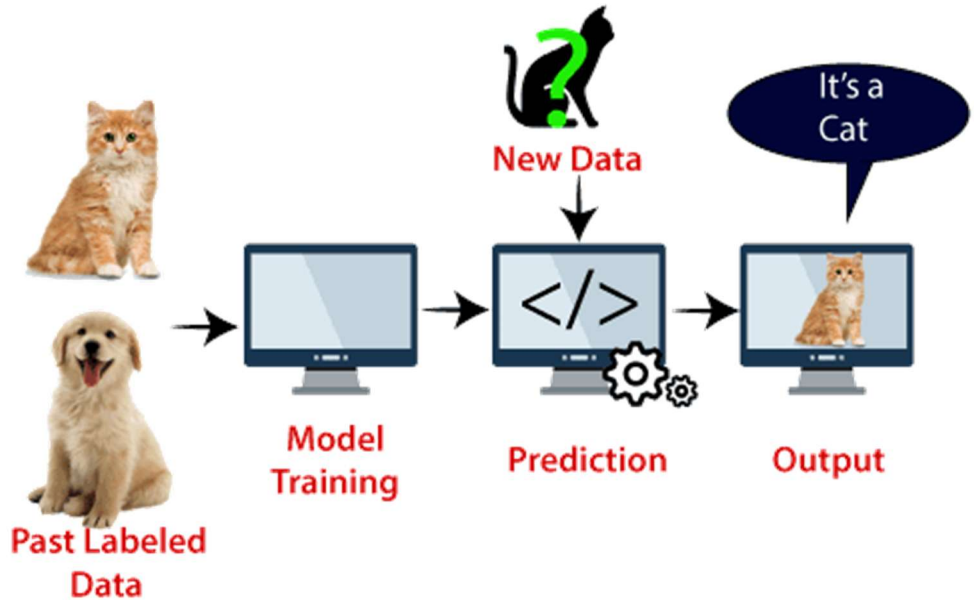
The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

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.

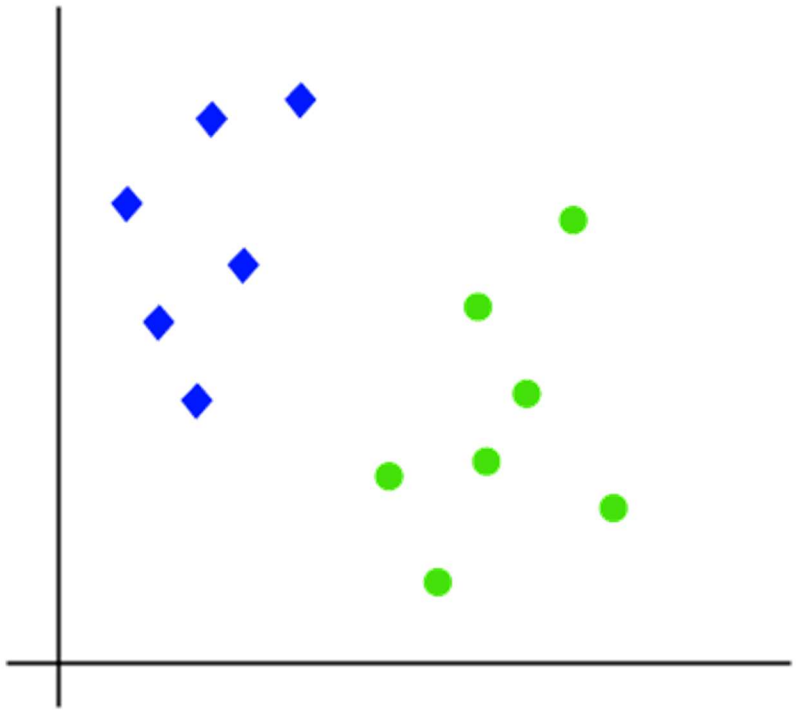
Support Vectors:

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.

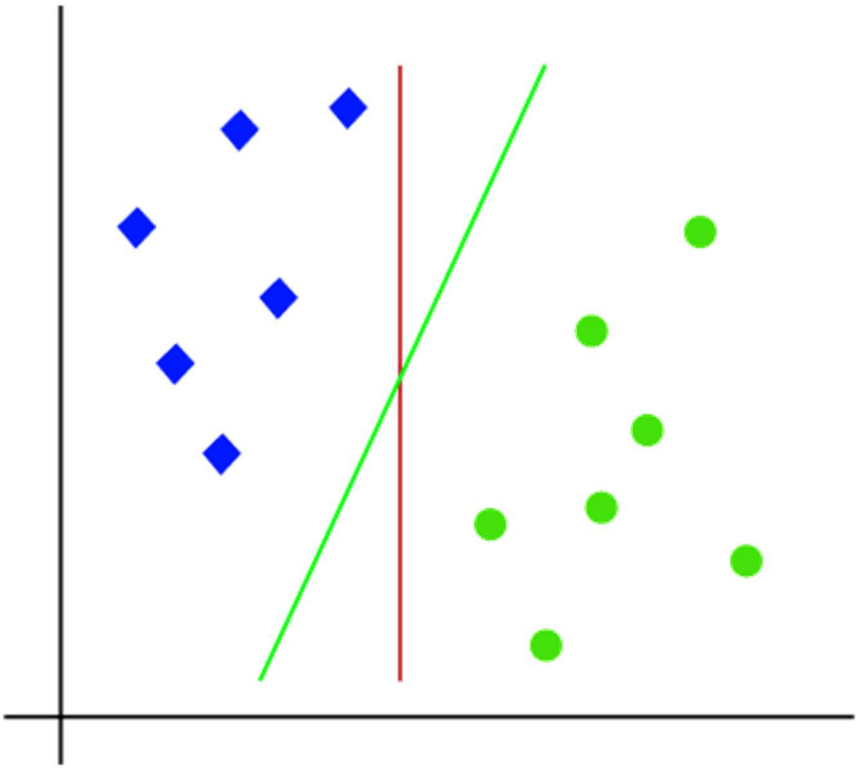
How does SVM works?

Linear SVM:

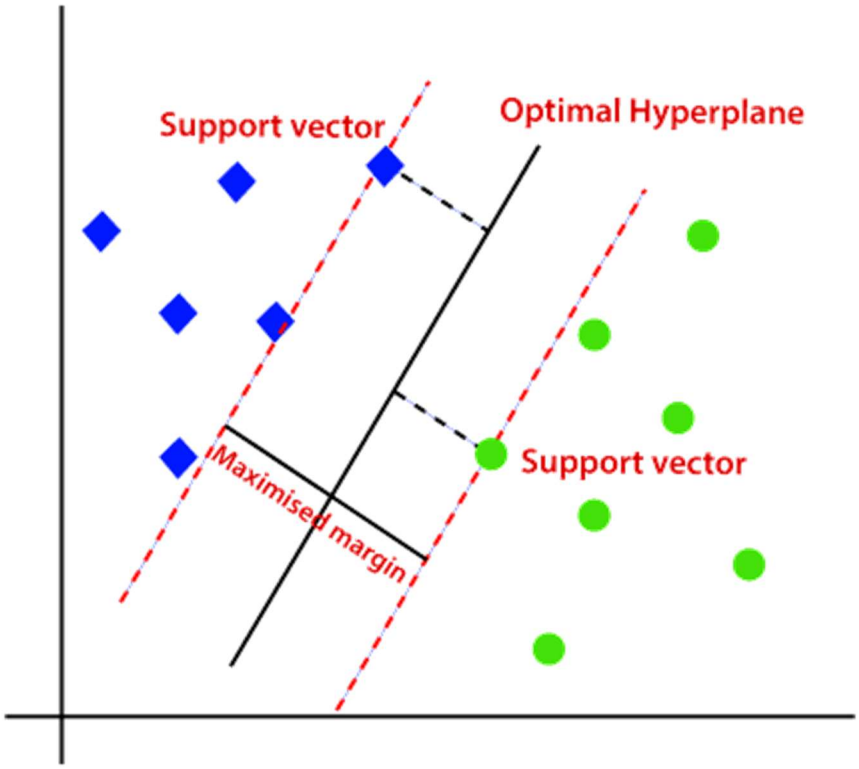
The working of the SVM algorithm can be understood by using an example. Suppose we have a dataset that has two tags (green and blue), and the dataset has two features x1 and x2. We want a classifier that can classify the pair(x1, x2) of coordinates in either green or blue. Consider the below image:



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:

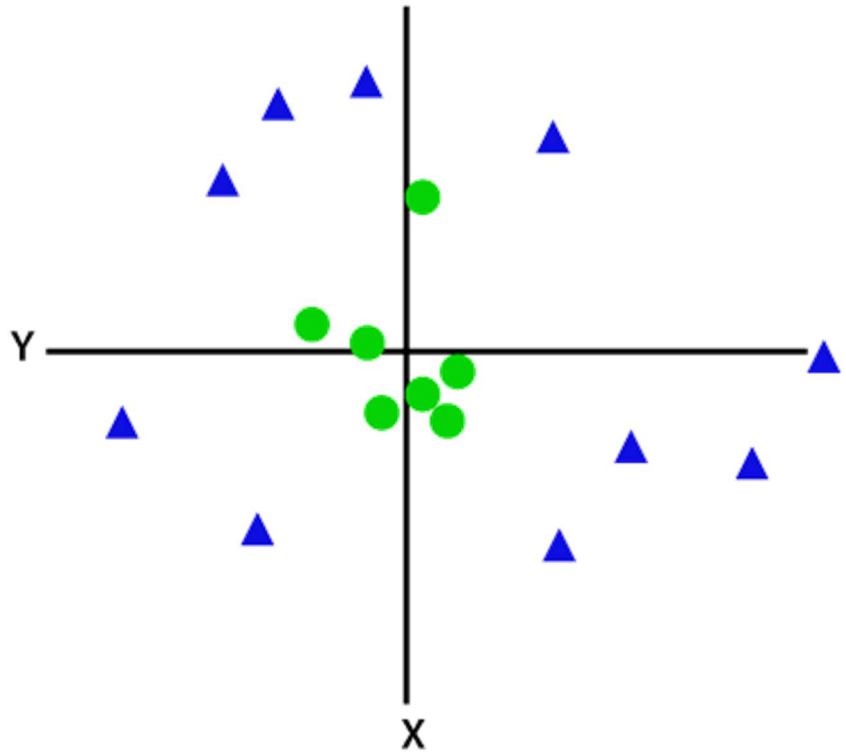


Hence, the SVM algorithm helps to find the best line or decision boundary; this best boundary or region is called as a **hyperplane**. SVM algorithm finds the closest point of the lines from both the classes. These points are called support vectors. The distance between the vectors and the hyperplane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

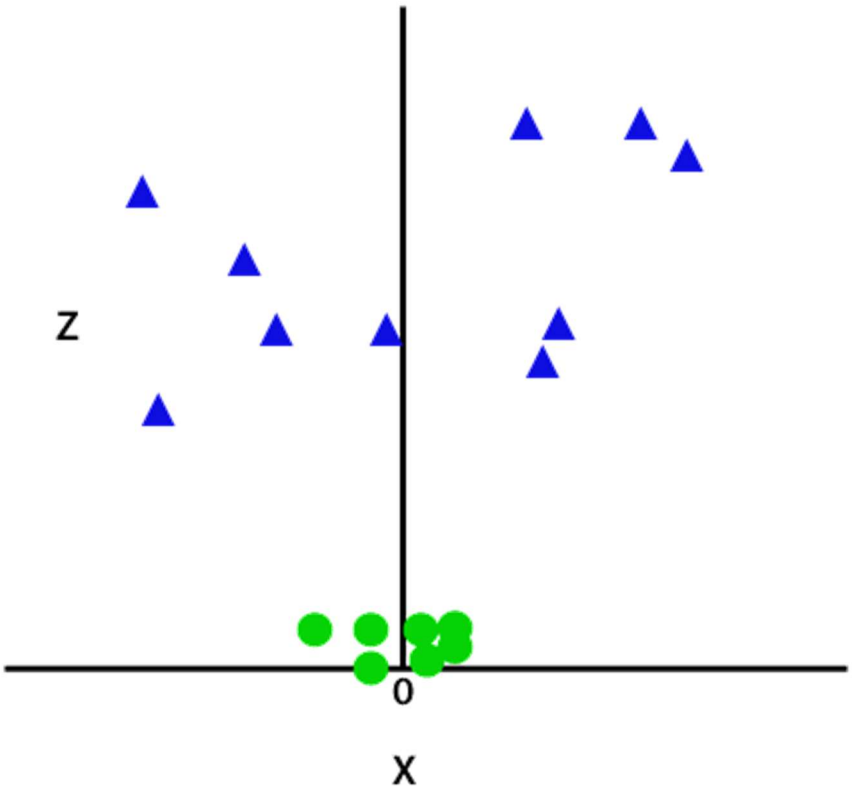
If data is linearly arranged, then we can separate it by using a straight line, but for non-linear data, we cannot draw a single straight line. Consider the below image:



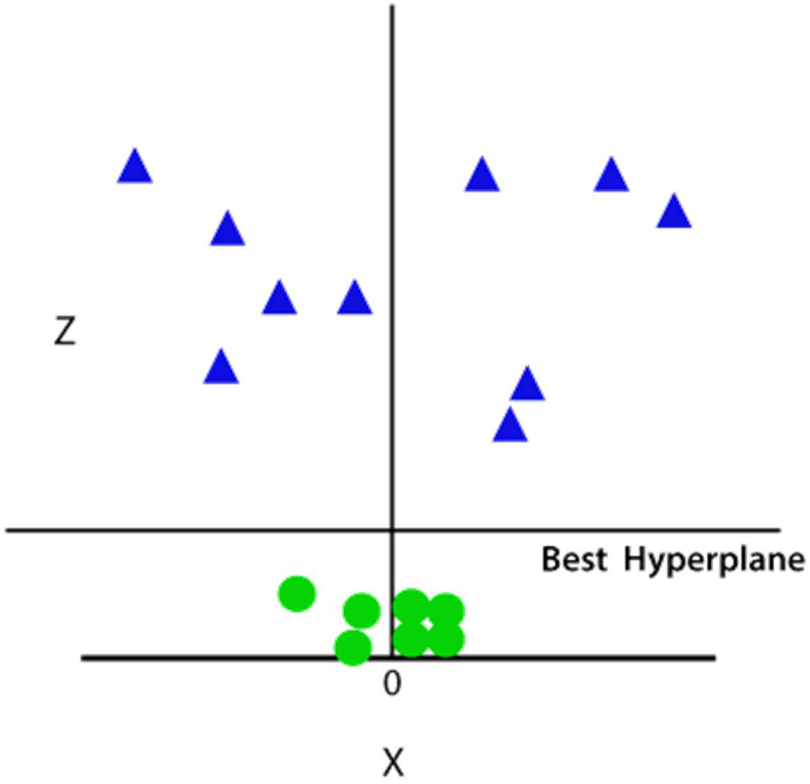
So to separate these data points, we need to add one more dimension. For linear data, we have used two dimensions x and y, so for non-linear data, we will add a third dimension z. It can be calculated as:

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

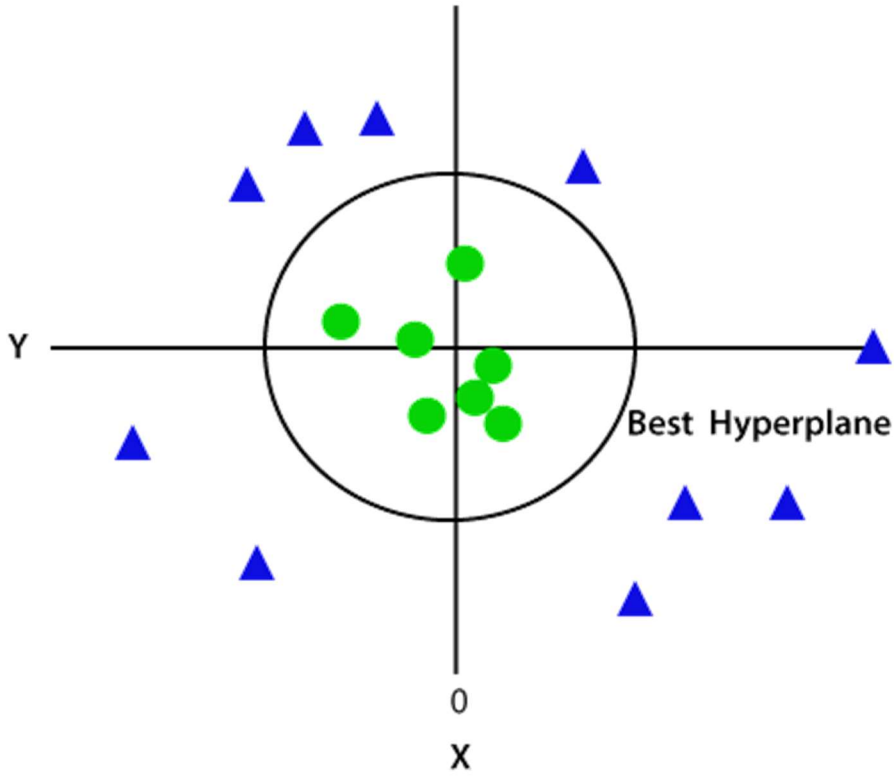
By adding the third dimension, the sample space will become as below image:



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.

Python Implementation of Support Vector Machine

Now we will implement the SVM algorithm using Python. Here we will use the same dataset **user_data**, which we have used in Logistic regression and KNN classification.

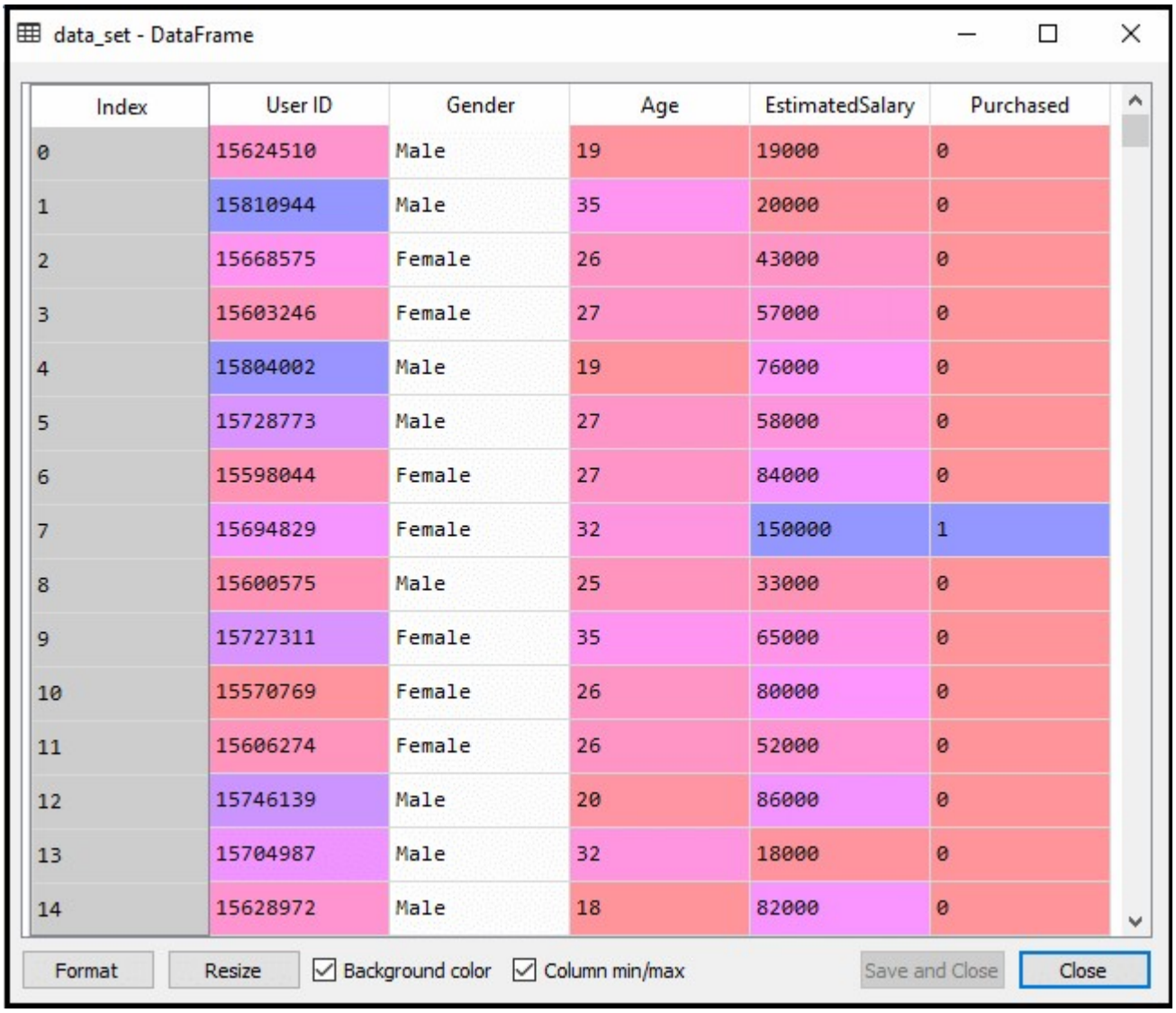
- **Data Pre-processing step**

Till the Data pre-processing step, the code will remain the same. Below is the code:

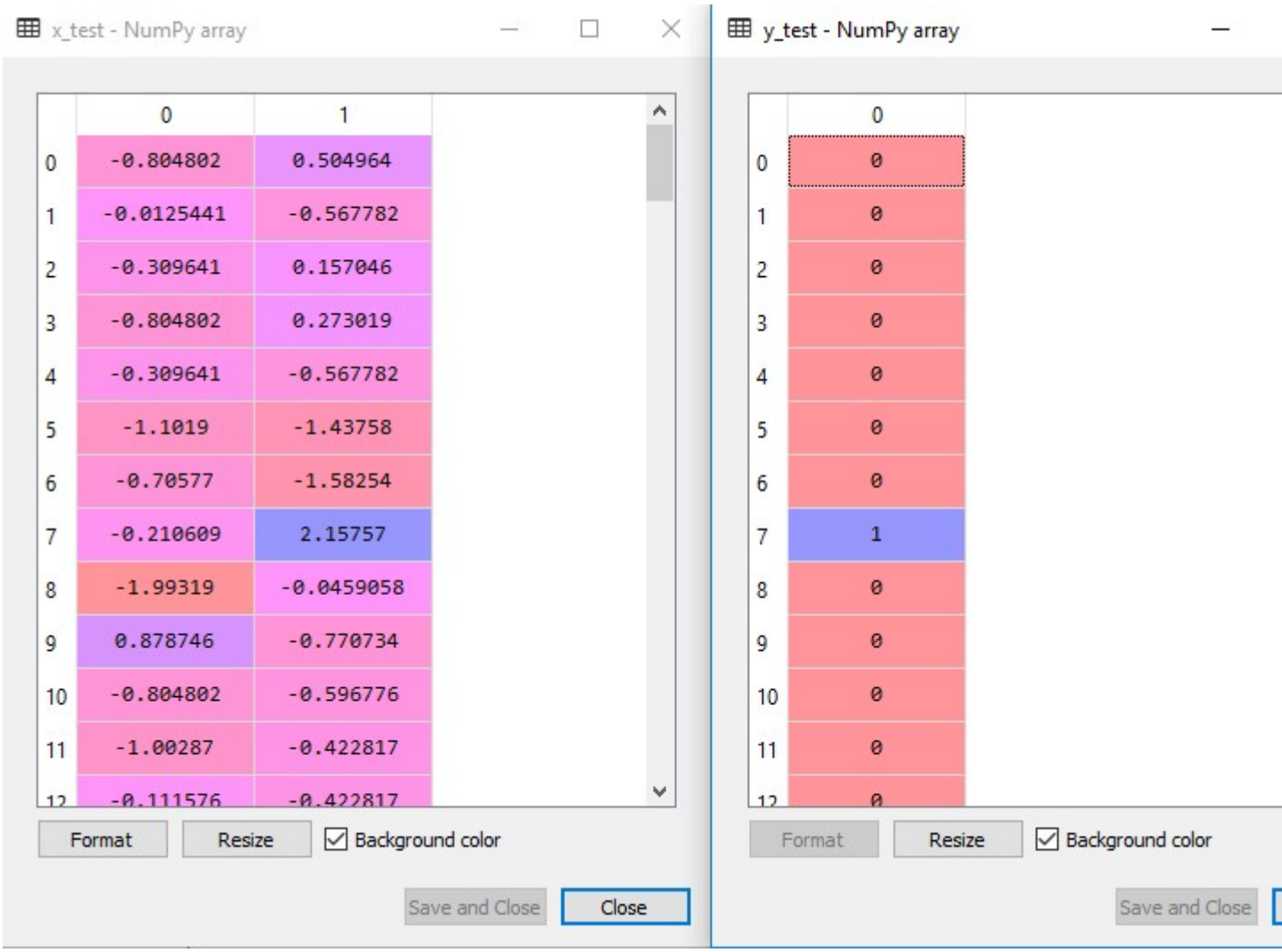
```
1. #Data Pre-processing Step
2. # importing libraries
3. import numpy as nm
4. import matplotlib.pyplot as mtp
5. import pandas as pd
6.
7. #importing datasets
8. data_set= pd.read_csv('user_data.csv')
```

```
9.
10. #Extracting Independent and dependent Variable
11. x= data_set.iloc[:, [2,3]].values
12. y= data_set.iloc[:, 4].values
13.
14. # Splitting the dataset into training and test set.
15. from sklearn.model_selection import train_test_split
16. x_train, x_test, y_train, y_test= train_test_split(x, y, test_size= 0.25, random_state=0
    )
17. #feature Scaling
18. from sklearn.preprocessing import StandardScaler
19. st_x= StandardScaler()
20. x_train= st_x.fit_transform(x_train)
21. x_test= st_x.transform(x_test)
```

After executing the above code, we will pre-process the data. The code will give the dataset as:



The scaled output for the test set will be:



Fitting the SVM classifier to the training set:

Now the training set will be fitted to the SVM classifier. To create the SVM classifier, we will import **SVC** class from **Sklearn.svm** library. Below is the code for it:

```
1. from sklearn.svm import SVC # "Support vector classifier"
2. classifier = SVC(kernel='linear', random_state=0)
3. classifier.fit(x_train, y_train)
```

In the above code, we have used **kernel='linear'**, as here we are creating SVM for linearly separable data. However, we can change it for non-linear data. And then we fitted the classifier to the training dataset(x_train, y_train)

Output:

```
Out[8]:
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
    kernel='linear', max_iter=-1, probability=False, random_state=0,
    shrinking=True, tol=0.001, verbose=False)
```

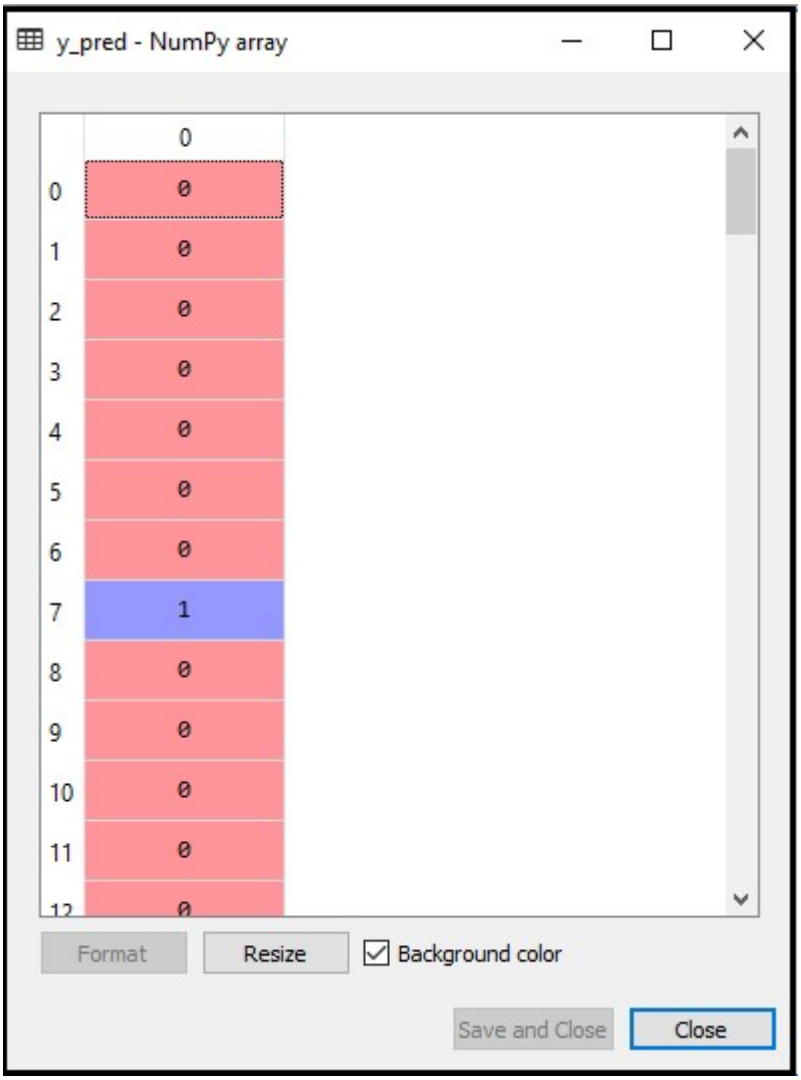
The model performance can be altered by changing the value of **C(Regularization factor), gamma, and kernel**.

- **Predicting the test set result:**
  Now, we will predict the output for test set. For this, we will create a new vector y_pred. Below is the code for it:

```
1. #Predicting the test set result
2. y_pred= classifier.predict(x_test)
```

After getting the y_pred vector, we can compare the result of **y_pred** and **y_test** to check the difference between the actual value and predicted value.

Output: Below is the output for the prediction of the test set:



- **Creating the confusion matrix:**
  Now we will see the performance of the SVM classifier that how many incorrect predictions are there as compared to the Logistic regression classifier. To create the confusion matrix, we need to import the **confusion_matrix** function of the sklearn library. After importing the function, we will call it using a new variable **cm**. The function takes two parameters, mainly **y_true**(the actual values) and **y_pred** (the targeted value return by the classifier). Below is the code for it:

```
1. #Creating the Confusion matrix
2. from sklearn.metrics import confusion_matrix
3. cm= confusion_matrix(y_test, y_pred)
```

Output:

As we can see in the above output image, there are 66+24= 90 correct predictions and 8+2= 10 correct predictions. Therefore we can say that our SVM model improved as compared to the Logistic regression model.

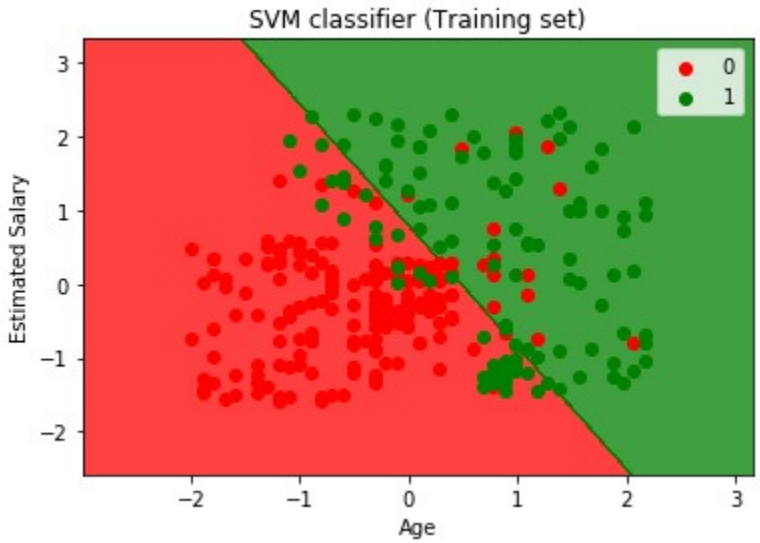
- **Visualizing the training set result:**
  Now we will visualize the training set result, below is the code for it:

```
1. from matplotlib.colors import ListedColormap
2. x_set, y_set = x_train, y_train
3. x1, x2 = nm.meshgrid(nm.arange(start = x_set[:, 0].min() - 1, stop = x_set[:, 0].max(
   ) + 1, step  =0.01),
4. nm.arange(start = x_set[:, 1].min() - 1, stop = x_set[:, 1].max() + 1, step = 0.01))
5. mtp.contourf(x1, x2, classifier.predict(nm.array([x1.ravel(), x2.ravel()]).T).reshape(x1
   .shape),
6. alpha = 0.75, cmap = ListedColormap(('red', 'green')))
7. mtp.xlim(x1.min(), x1.max())
8. mtp.ylim(x2.min(), x2.max())
9. for i, j in enumerate(nm.unique(y_set)):
10.     mtp.scatter(x_set[y_set == j, 0], x_set[y_set == j, 1],
11.         c = ListedColormap(('red', 'green'))(i), label = j)
12. mtp.title('SVM classifier (Training set)')
```

13. mtp.xlabel('Age')
14. mtp.ylabel('Estimated Salary')
15. mtp.legend()
16. mtp.show()

Output:

By executing the above code, we will get the output as:



As we can see, the above output is appearing similar to the Logistic regression output. In the output, we got the straight line as hyperplane because we have **used a linear kernel in the classifier**. And we have also discussed above that for the 2d space, the hyperplane in SVM is a straight line.

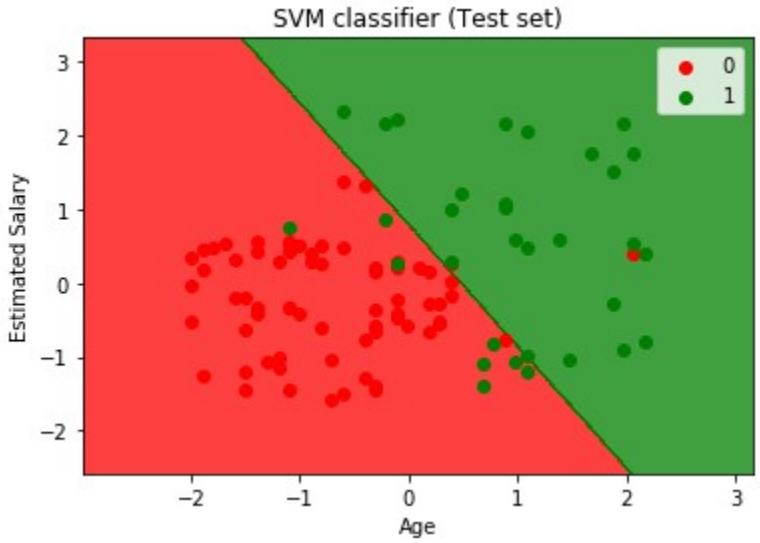
- **Visualizing the test set result:**

1. #Visulaizing the test set result
2. from matplotlib.colors **import** ListedColormap
3. x_set, y_set = x_test, y_test
4. x1, x2 = nm.meshgrid(nm.arange(start = x_set[:, 0].min() - 1, stop = x_set[:, 0].max( ) + 1, step =0.01),
5. nm.arange(start = x_set[:, 1].min() - 1, stop = x_set[:, 1].max() + 1, step = 0.01))
6. mtp.contourf(x1, x2, classifier.predict(nm.array([x1.ravel(), x2.ravel()]).T).reshape(x1 .shape),

```
    alpha = 0.75, cmap = ListedColormap(('red','green' )))
    mtp.xlim(x1.min(), x1.max())
    mtp.ylim(x2.min(), x2.max())
    for i, j in enumerate(nm.unique(y_set)):
        mtp.scatter(x_set[y_set == j, 0], x_set[y_set == j, 1],
            c = ListedColormap(('red', 'green'))(i), label = j)
    mtp.title('SVM classifier (Test set)')
    mtp.xlabel('Age')
    mtp.ylabel('Estimated Salary')
    mtp.legend()
    mtp.show()
```

Output:

By executing the above code, we will get the output as:

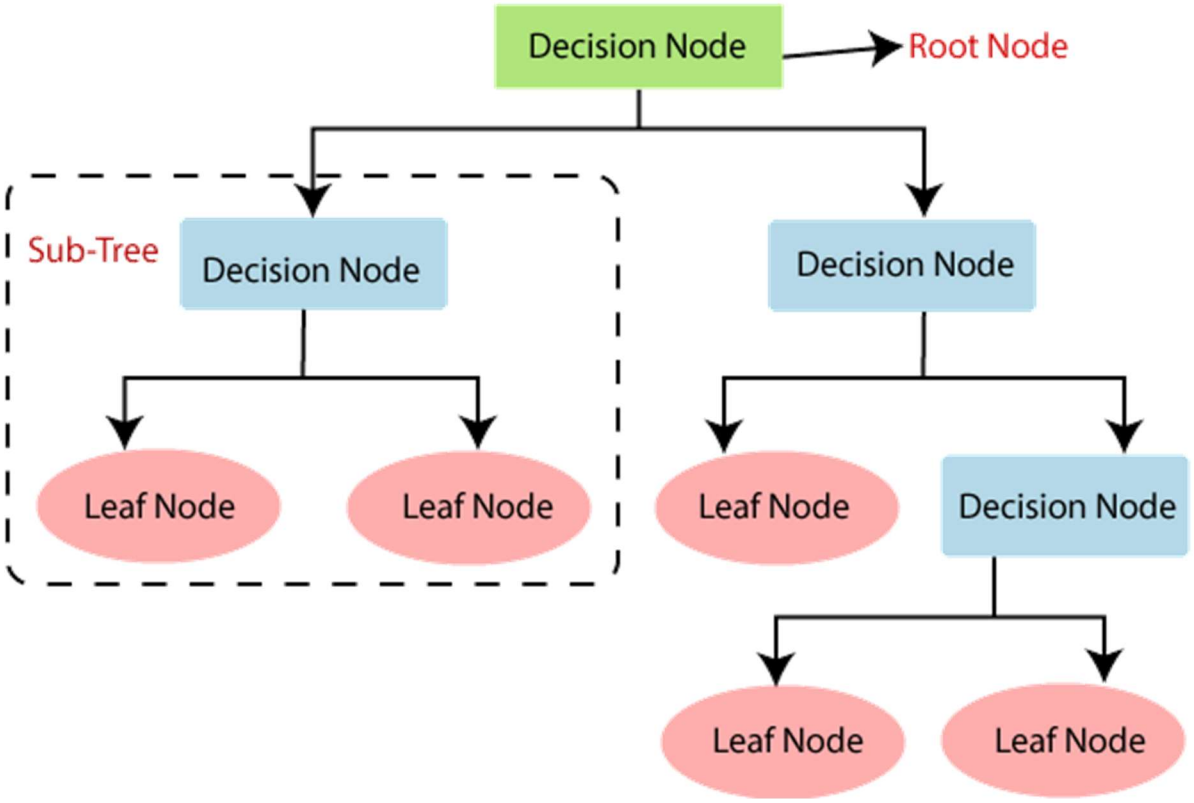


As we can see in the above output image, the SVM classifier has divided the users into two regions (Purchased or Not purchased). Users who purchased the SUV are in the red region with the red scatter points. And users who did not purchase the SUV are in the green region with green scatter points. The hyperplane has divided the two classes into Purchased and not purchased variable.

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.

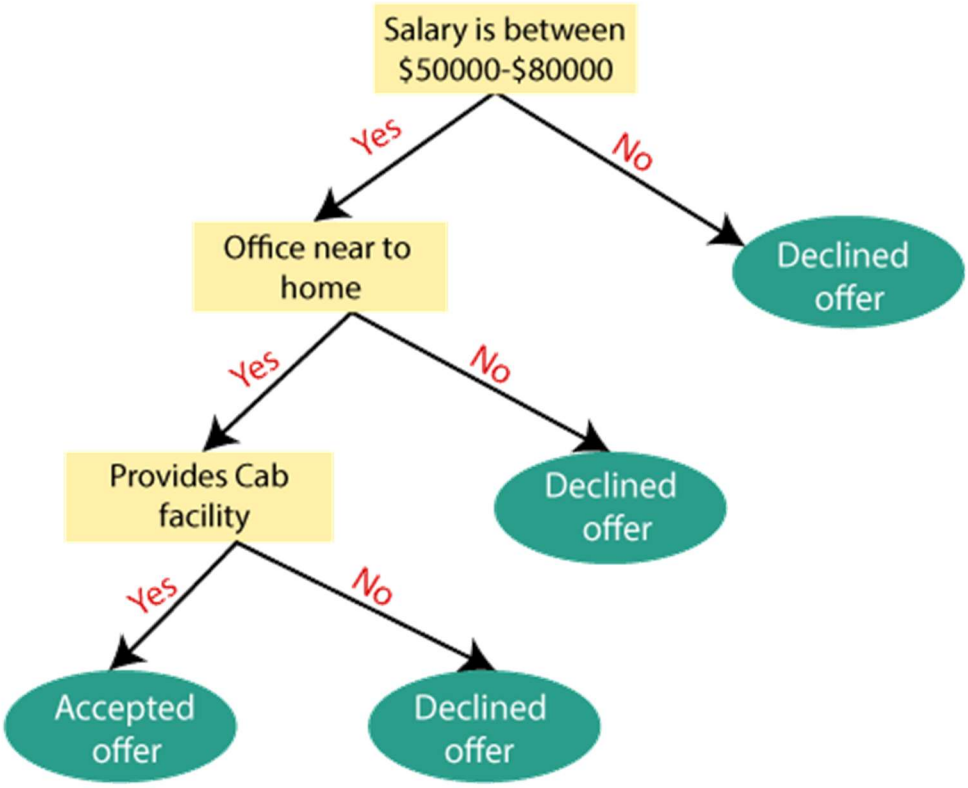
How does the Decision Tree algorithm Work?

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.

Python Implementation of Decision Tree

Now we will implement the Decision tree using Python. For this, we will use the dataset "**user_data.csv**," which we have used in previous classification models. By using the same dataset, we can compare the Decision tree classifier with other classification models such as KNN SVM, LogisticRegression, etc.

Steps will also remain the same, which are given below:

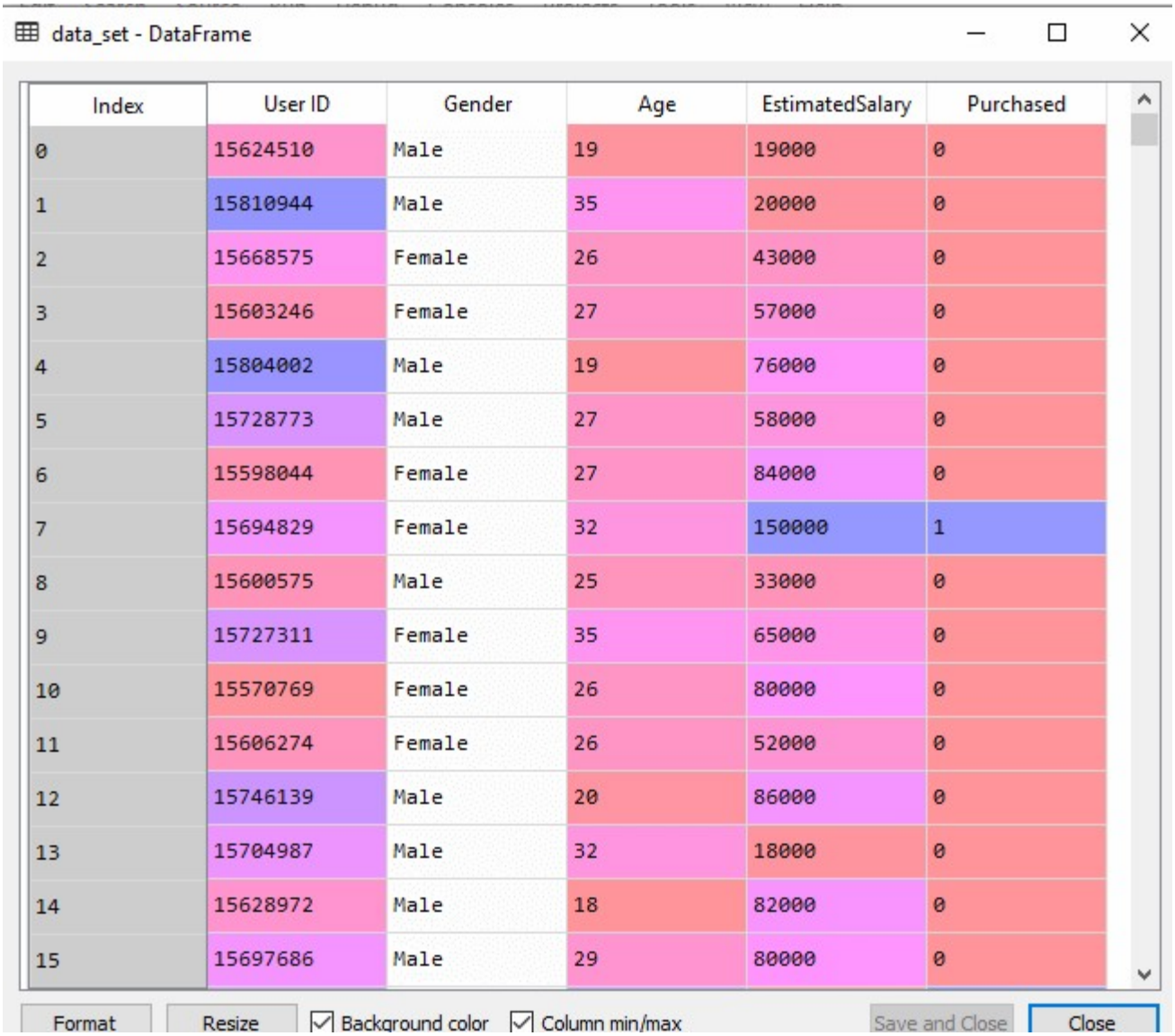
- **Data Pre-processing step**
- **Fitting a Decision-Tree algorithm to the Training set**
- **Predicting the test result**
- **Test accuracy of the result(Creation of Confusion matrix)**
- **Visualizing the test set result.**

1. Data Pre-Processing Step:

Below is the code for the pre-processing step:

```
1. # importing libraries
2. import numpy as nm
3. import matplotlib.pyplot as mtp
4. import pandas as pd
5.
6. #importing datasets
7. data_set= pd.read_csv('user_data.csv')
8.
9. #Extracting Independent and dependent Variable
10. x= data_set.iloc[:, [2,3]].values
11. y= data_set.iloc[:, 4].values
12.
13. # Splitting the dataset into training and test set.
14. from sklearn.model_selection import train_test_split
15. x_train, x_test, y_train, y_test= train_test_split(x, y, test_size= 0.25, random_state=0
    )
16.
17. #feature Scaling
18. from sklearn.preprocessing import StandardScaler
19. st_x= StandardScaler()
20. x_train= st_x.fit_transform(x_train)
21. x_test= st_x.transform(x_test)
```

In the above code, we have pre-processed the data. Where we have loaded the dataset, which is given as:



Index	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0
5	15728773	Male	27	58000	0
6	15598044	Female	27	84000	0
7	15694829	Female	32	150000	1
8	15600575	Male	25	33000	0
9	15727311	Female	35	65000	0
10	15570769	Female	26	80000	0
11	15606274	Female	26	52000	0
12	15746139	Male	20	86000	0
13	15704987	Male	32	18000	0
14	15628972	Male	18	82000	0
15	15697686	Male	29	80000	0

2. Fitting a Decision-Tree algorithm to the Training set

Now we will fit the model to the training set. For this, we will import the **DecisionTreeClassifier** class from **sklearn.tree** library. Below is the code for it:

```
1. #Fitting Decision Tree classifier to the training set
2. From sklearn.tree import DecisionTreeClassifier
3. classifier= DecisionTreeClassifier(criterion='entropy', random_state=0)
4. classifier.fit(x_train, y_train)
```

In the above code, we have created a classifier object, in which we have passed two main parameters;

- **"criterion='entropy':** Criterion is used to measure the quality of split, which is calculated by information gain given by entropy.
- **random_state=0":** For generating the random states.

Below is the output for this:

```
Out[8]:
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=None,
max_features=None, max_leaf_nodes=None,
min_impurity_decrease=0.0, min_impurity_split=None,
min_samples_leaf=1, min_samples_split=2,
min_weight_fraction_leaf=0.0, presort=False,
                       random_state=0, splitter='best')
```

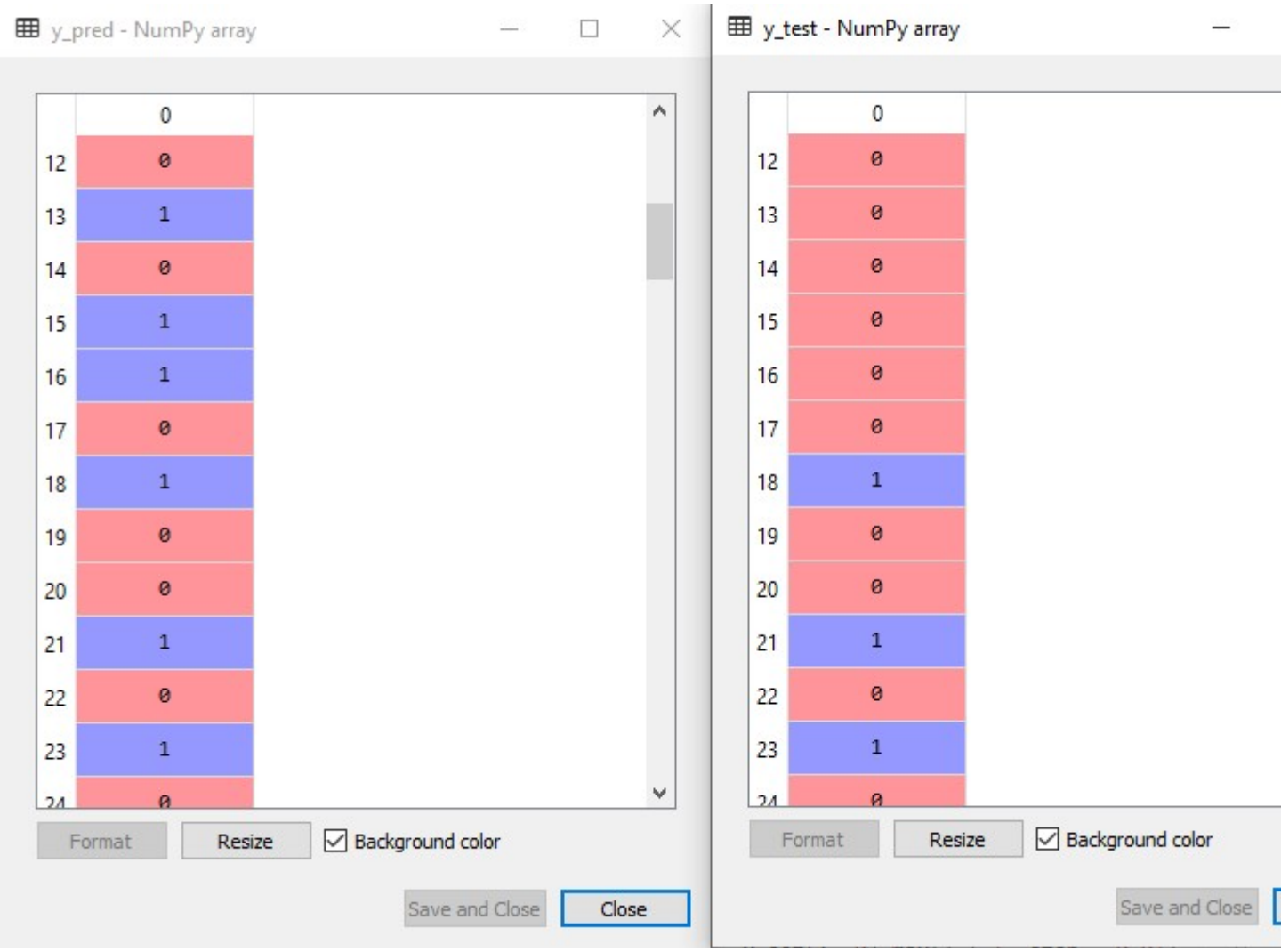
3. Predicting the test result

Now we will predict the test set result. We will create a new prediction vector **y_pred.** Below is the code for it:

```
1. #Predicting the test set result
2. y_pred= classifier.predict(x_test)
```

Output:

In the below output image, the predicted output and real test output are given. We can clearly see that there are some values in the prediction vector, which are different from the real vector values. These are prediction errors.

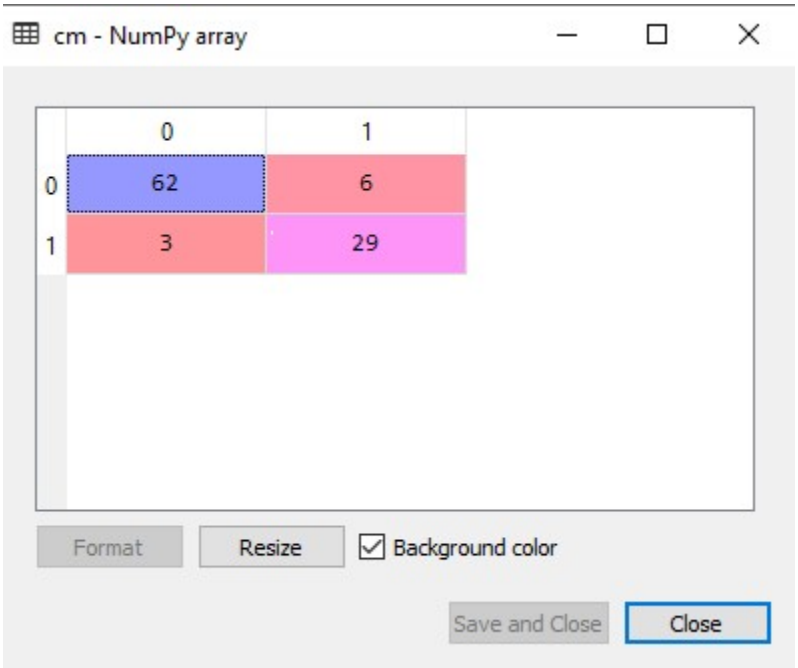


4. Test accuracy of the result (Creation of Confusion matrix)

In the above output, we have seen that there were some incorrect predictions, so if we want to know the number of correct and incorrect predictions, we need to use the confusion matrix. Below is the code for it:

```
1. #Creating the Confusion matrix
2. from sklearn.metrics import confusion_matrix
3. cm= confusion_matrix(y_test, y_pred)
```

Output:



In the above output image, we can see the confusion matrix, which has **6+3= 9 incorrect predictions** and**62+29=91 correct predictions. Therefore, we can say that compared to other classification models, the Decision Tree classifier made a good prediction.**

5. Visualizing the training set result:

Here we will visualize the training set result. To visualize the training set result we will plot a graph for the decision tree classifier. The classifier will predict yes or No for the users who have either Purchased or Not purchased the SUV car as we did in Logistic Regression. Below is the code for it:

```
#Visulaizing the trianing set result
from matplotlib.colors import ListedColormap
x_set, y_set = x_train, y_train
x1, x2 = nm.meshgrid(nm.arange(start = x_set[:, 0].min() - 1, stop = x_set[:, 0].max() ) + 1, step  =0.01),
nm.arange(start = x_set[:, 1].min() - 1, stop = x_set[:, 1].max() + 1, step = 0.01))
mtp.contourf(x1, x2, classifier.predict(nm.array([x1.ravel(), x2.ravel()]).T).reshape(x1 .shape),
alpha = 0.75, cmap = ListedColormap(('purple','green' )))
mtp.xlim(x1.min(), x1.max())
mtp.ylim(x2.min(), x2.max())
```

```
10. fori, j in enumerate(nm.unique(y_set)):
11. mtp.scatter(x_set[y_set == j, 0], x_set[y_set == j, 1],
12.         c = ListedColormap(('purple', 'green'))(i), label = j)
13. mtp.title('Decision Tree Algorithm (Training set)')
14. mtp.xlabel('Age')
15. mtp.ylabel('Estimated Salary')
16. mtp.legend()
17. mtp.show()
```

Output:

The above output is completely different from the rest classification models. It has both vertical and horizontal lines that are splitting the dataset according to the age and estimated salary variable.

As we can see, the tree is trying to capture each dataset, which is the case of overfitting.

6. Visualizing the test set result:

Visualization of test set result will be similar to the visualization of the training set except that the training set will be replaced with the test set.

```
1. #Visulaizing the test set result
2. from matplotlib.colors import ListedColormap
3. x_set, y_set = x_test, y_test
```

```
4. x1, x2 = nm.meshgrid(nm.arange(start = x_set[:, 0].min() - 1, stop = x_set[:, 0].max(
   ) + 1, step  =0.01),
5. nm.arange(start = x_set[:, 1].min() - 1, stop = x_set[:, 1].max() + 1, step = 0.01))
6. mtp.contourf(x1, x2, classifier.predict(nm.array([x1.ravel(), x2.ravel()]).T).reshape(x1
   .shape),
7. alpha = 0.75, cmap = ListedColormap(('purple','green' )))
8. mtp.xlim(x1.min(), x1.max())
9. mtp.ylim(x2.min(), x2.max())
10. fori, j in enumerate(nm.unique(y_set)):
11. mtp.scatter(x_set[y_set == j, 0], x_set[y_set == j, 1],
12.         c = ListedColormap(('purple', 'green'))(i), label = j)
13. mtp.title('Decision Tree Algorithm(Test set)')
14. mtp.xlabel('Age')
15. mtp.ylabel('Estimated Salary')
16. mtp.legend()
17. mtp.show()
```

Output:

As we can see in the above image that there are some green data points within the purple region and vice versa. So, these are the incorrect predictions which we have discussed in the confusion matrix.

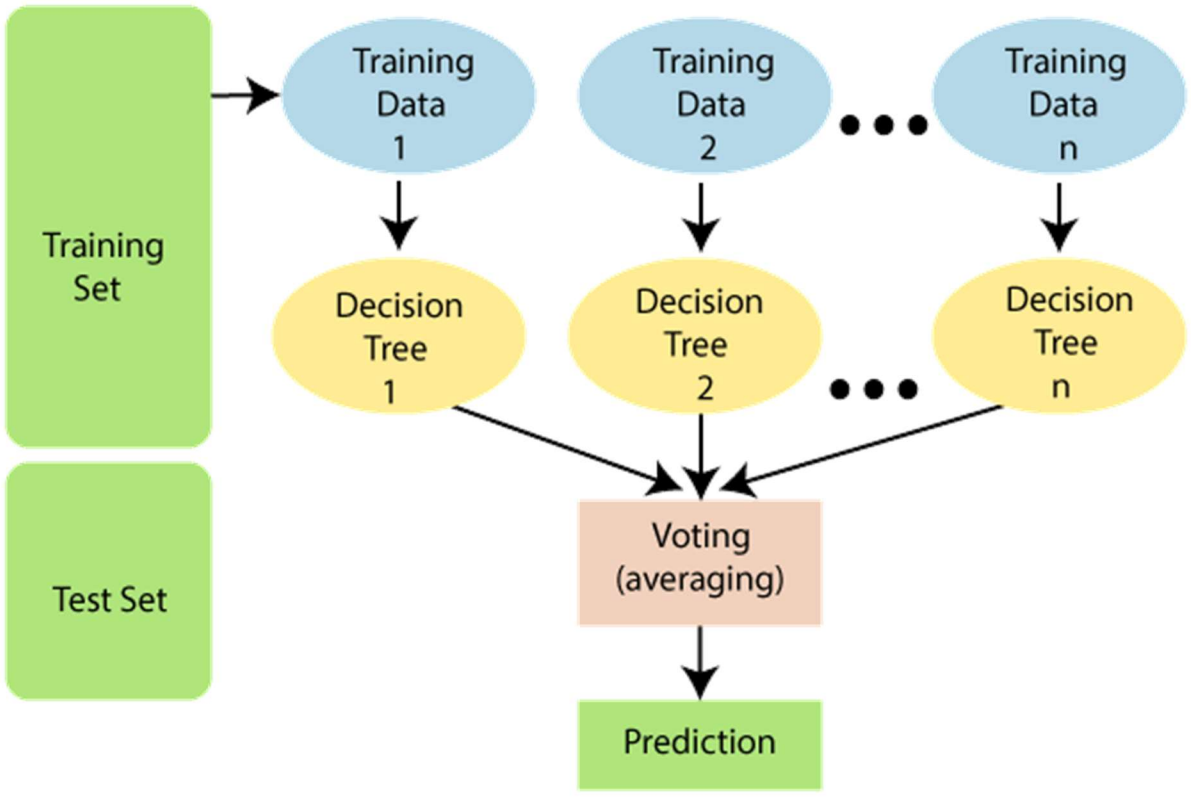
Random Forest Algorithm

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:

<=”” |i=””>

- 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).

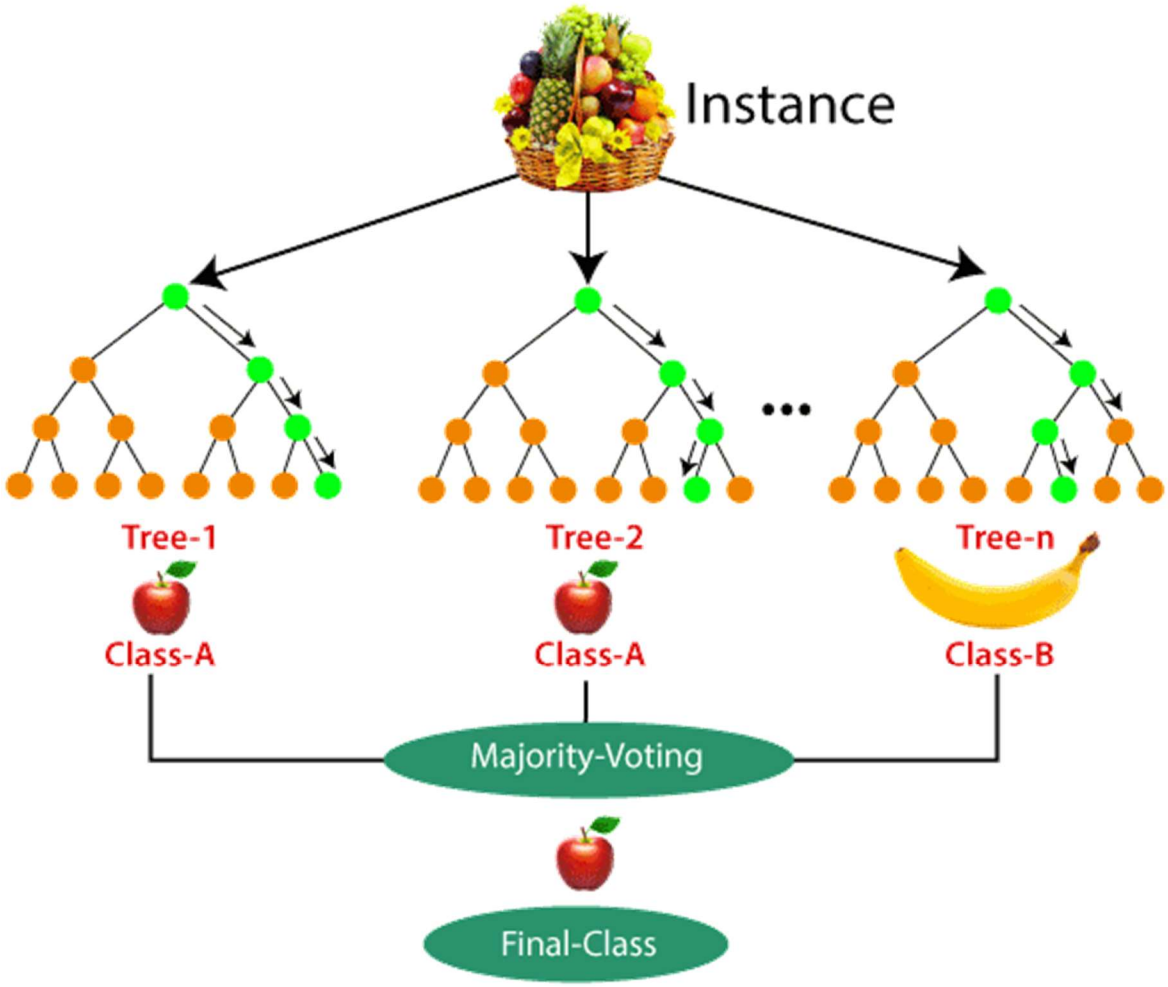
Step-3: Choose the number N for decision trees that you want to build.

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.

Python Implementation of Random Forest Algorithm

Now we will implement the Random Forest Algorithm tree using Python. For this, we will use the same dataset "user_data.csv", which we have used in previous classification models. By using the same dataset, we can compare the Random Forest classifier with other classification models such as Decision tree Classifier, KNN, SVM, Logistic Regression, etc.

Implementation Steps are given below:

- Data Pre-processing step
- Fitting the Random forest algorithm to the Training set
- Predicting the test result
- Test accuracy of the result (Creation of Confusion matrix)
- Visualizing the test set result.

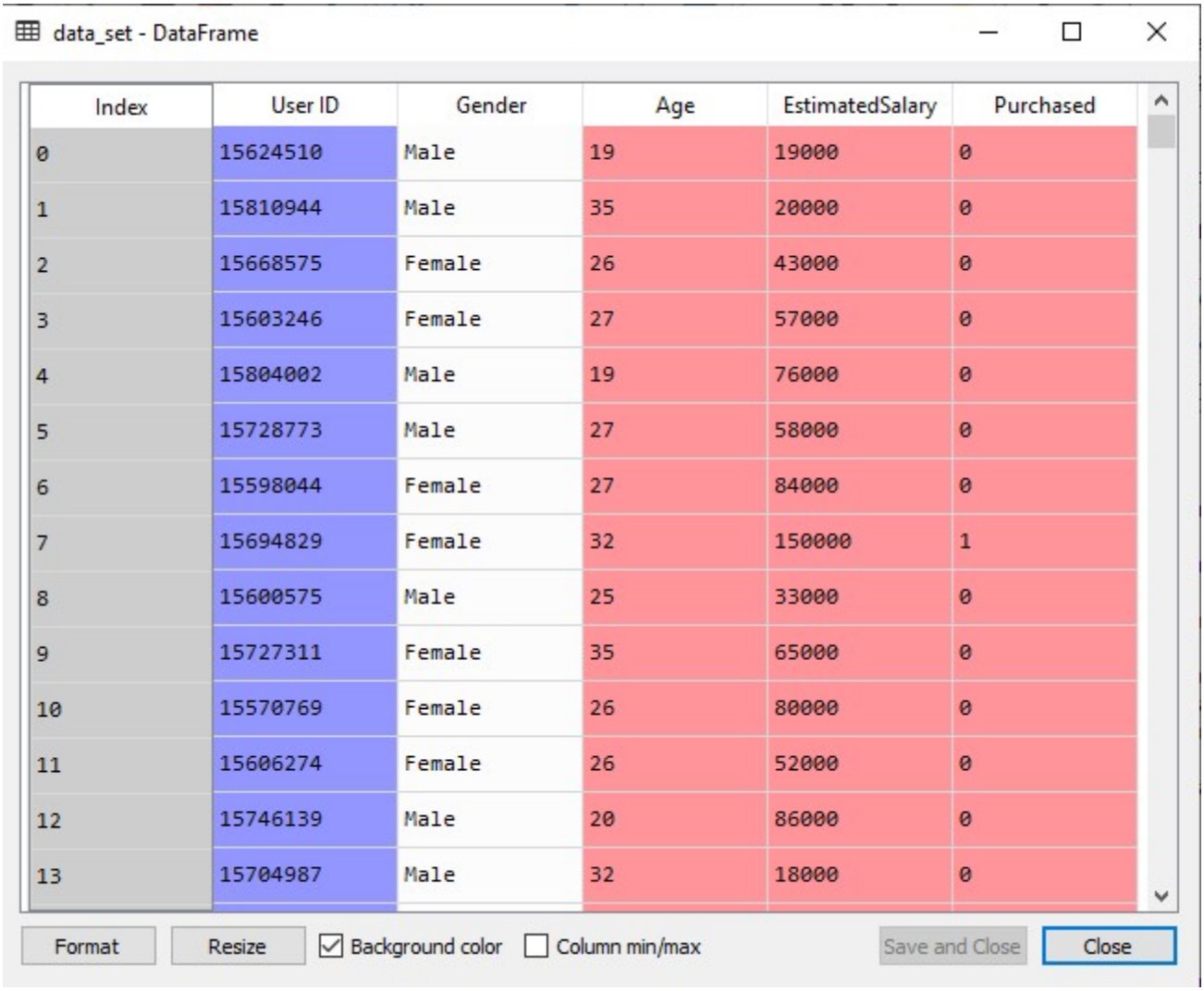
1.Data Pre-Processing Step:

Below is the code for the pre-processing step:

```
1. # importing libraries
2. import numpy as nm
```

```
3. import matplotlib.pyplot as mtp
4. import pandas as pd
5.
6. #importing datasets
7. data_set= pd.read_csv('user_data.csv')
8.
9. #Extracting Independent and dependent Variable
10. x= data_set.iloc[:, [2,3]].values
11. y= data_set.iloc[:, 4].values
12.
13. # Splitting the dataset into training and test set.
14. from sklearn.model_selection import train_test_split
15. x_train, x_test, y_train, y_test= train_test_split(x, y, test_size= 0.25, random_state=0
    )
16.
17. #feature Scaling
18. from sklearn.preprocessing import StandardScaler
19. st_x= StandardScaler()
20. x_train= st_x.fit_transform(x_train)
21. x_test= st_x.transform(x_test)
```

In the above code, we have pre-processed the data. Where we have loaded the dataset, which is given as:



Index	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0
5	15728773	Male	27	58000	0
6	15598044	Female	27	84000	0
7	15694829	Female	32	150000	1
8	15600575	Male	25	33000	0
9	15727311	Female	35	65000	0
10	15570769	Female	26	80000	0
11	15606274	Female	26	52000	0
12	15746139	Male	20	86000	0
13	15704987	Male	32	18000	0

2. Fitting the Random Forest algorithm to the training set:

Now we will fit the Random forest algorithm to the training set. To fit it, we will import the **RandomForestClassifier** class from the **sklearn.ensemble** library. The code is given below:

```
1. #Fitting Decision Tree classifier to the training set
2. from sklearn.ensemble import RandomForestClassifier
3. classifier= RandomForestClassifier(n_estimators= 10, criterion="entropy")
4. classifier.fit(x_train, y_train)
```

In the above code, the classifier object takes below parameters:

- **n_estimators=** The required number of trees in the Random Forest. The default value is 10. We can choose any number but need to take care of the overfitting issue.
- **criterion=** It is a function to analyze the accuracy of the split. Here we have taken "entropy" for the information gain.

Output:

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='entropy',
                       max_depth=None,                    max_features='auto',
max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=10,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

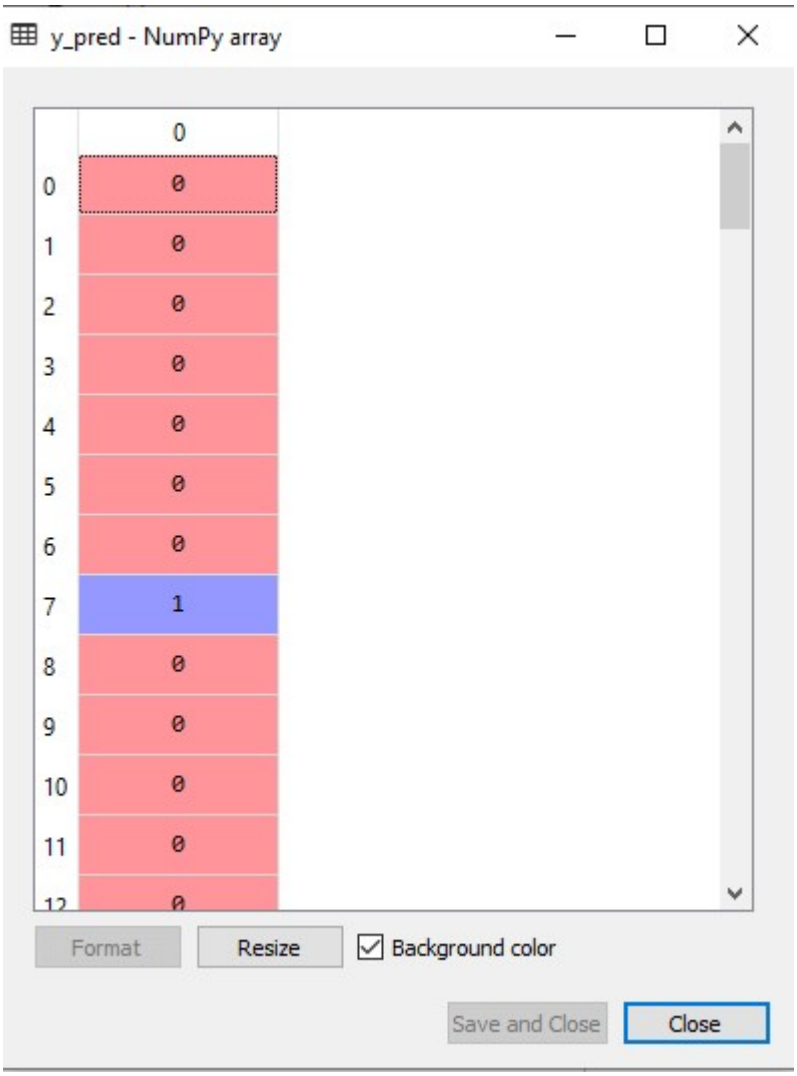
3. Predicting the Test Set result

Since our model is fitted to the training set, so now we can predict the test result. For prediction, we will create a new prediction vector y_pred. Below is the code for it:

1. #Predicting the test set result
2. y_pred= classifier.predict(x_test)

Output:

The prediction vector is given as:



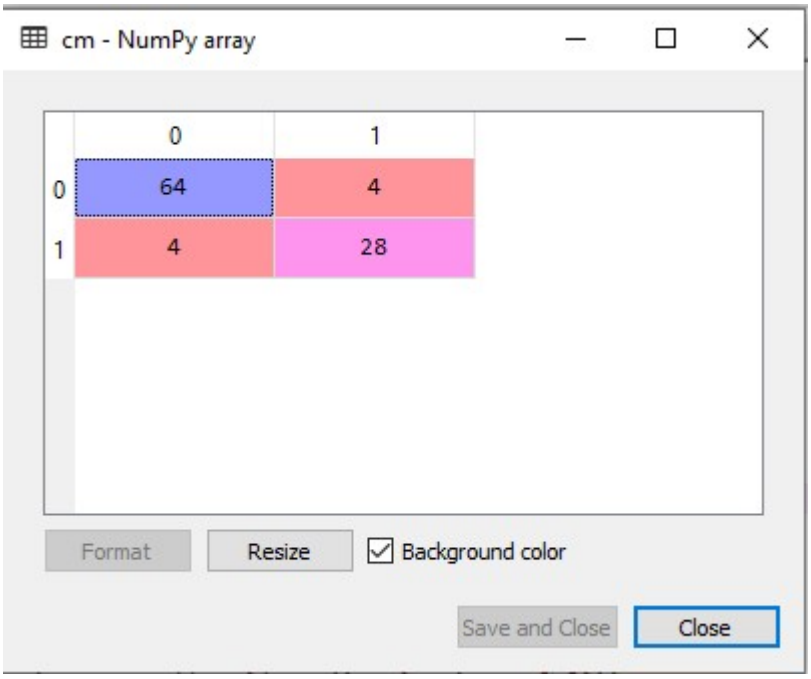
By checking the above prediction vector and test set real vector, we can determine the incorrect predictions done by the classifier.

4. Creating the Confusion Matrix

Now we will create the confusion matrix to determine the correct and incorrect predictions. Below is the code for it:

```
1. #Creating the Confusion matrix
2. from sklearn.metrics import confusion_matrix
3. cm= confusion_matrix(y_test, y_pred)
```

Output:



As we can see in the above matrix, there are **4+4= 8 incorrect predictions** and **64+28= 92 correct predictions.**

5. Visualizing the training Set result

Here we will visualize the training set result. To visualize the training set result we will plot a graph for the Random forest classifier. The classifier will predict yes or No for the users who have either Purchased or Not purchased the SUV car as we did in Logistic Regression. Below is the code for it:

```
1. from matplotlib.colors import ListedColormap
2. x_set, y_set = x_train, y_train
3. x1, x2 = nm.meshgrid(nm.arange(start = x_set[:, 0].min() - 1, stop = x_set[:, 0].max(
   ) + 1, step  =0.01),
4. nm.arange(start = x_set[:, 1].min() - 1, stop = x_set[:, 1].max() + 1, step = 0.01))
5. mtp.contourf(x1, x2, classifier.predict(nm.array([x1.ravel(), x2.ravel()]).T).reshape(x1
   .shape),
6. alpha = 0.75, cmap = ListedColormap(('purple','green' )))
7. mtp.xlim(x1.min(), x1.max())
8. mtp.ylim(x2.min(), x2.max())
9. for i, j in enumerate(nm.unique(y_set)):
10.     mtp.scatter(x_set[y_set == j, 0], x_set[y_set == j, 1],
```

```
        c = ListedColormap(('purple', 'green'))(i), label = j)
mtp.title('Random Forest Algorithm (Training set)')
mtp.xlabel('Age')
mtp.ylabel('Estimated Salary')
mtp.legend()
mtp.show()
```

Output:

The above image is the visualization result for the Random Forest classifier working with the training set result. It is very much similar to the Decision tree classifier. Each data point corresponds to each user of the user_data, and the purple and green regions are the prediction regions. The purple region is classified for the users who did not purchase the SUV car, and the green region is for the users who purchased the SUV.

So, in the Random Forest classifier, we have taken 10 trees that have predicted Yes or NO for the Purchased variable. The classifier took the majority of the predictions and provided the result.

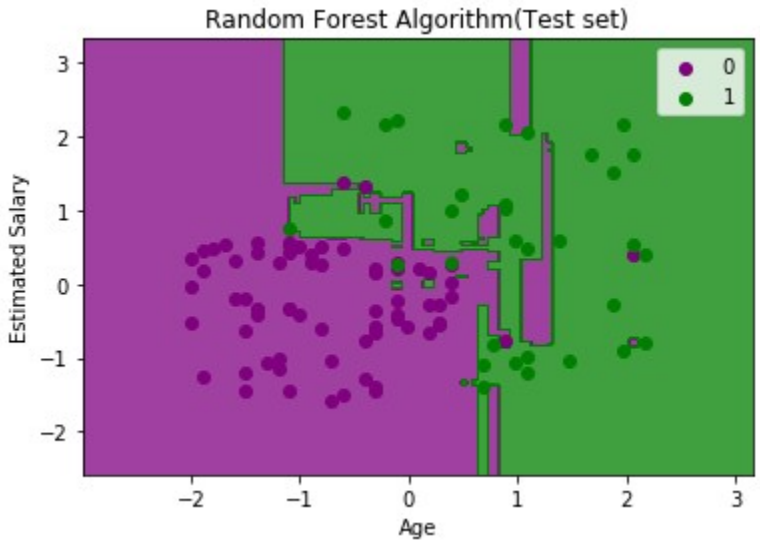
6. Visualizing the test set result

Now we will visualize the test set result. Below is the code for it:

```
#Visulaizing the test set result
from matplotlib.colors import ListedColormap
```

```
x_set, y_set = x_test, y_test
x1, x2 = nm.meshgrid(nm.arange(start = x_set[:, 0].min() - 1, stop = x_set[:, 0].max(
) + 1, step  =0.01),
nm.arange(start = x_set[:, 1].min() - 1, stop = x_set[:, 1].max() + 1, step = 0.01))
mtp.contourf(x1, x2, classifier.predict(nm.array([x1.ravel(), x2.ravel()]).T).reshape(x1
.shape),
alpha = 0.75, cmap = ListedColormap(('purple','green' )))
mtp.xlim(x1.min(), x1.max())
mtp.ylim(x2.min(), x2.max())
for i, j in enumerate(nm.unique(y_set)):
    mtp.scatter(x_set[y_set == j, 0], x_set[y_set == j, 1],
        c = ListedColormap(('purple', 'green'))(i), label = j)
mtp.title('Random Forest Algorithm(Test set)')
mtp.xlabel('Age')
mtp.ylabel('Estimated Salary')
mtp.legend()
mtp.show()
```

Output:



The above image is the visualization result for the test set. We can check that there is a minimum number of incorrect predictions (8) without the Overfitting issue. We will get different results by changing the number of trees in the classifier.