Savitribai Phule Pune University

MACHINE LEARNING

LAB MANUAL

(T.E. IT)

Prepared By

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Prerequisites:

1. **Python programming language**

Course Objectives:

1. **The objective of this course is to provide students with the fundamental elements of machine**

learning for classification, regression, clustering.

2. **Design and evaluate the performance of a different machine learning models.**

Course Outcomes:

On completion of the course,students will be able to–

CO1: Implement different supervised and unsupervised learning algorithms.

CO2: Evaluate performance of machine learning algorithms for real-world applications.

Assignment 1: ***Data Preparation***

AIM:

Download 'Heart' data from below link. https://www.kaggle.com/datasets/zhaoyingzhu/heartcsv

Perform following operations on given dataset

a) Find shape of Data
b) Find Missing Values
c) Find Data type of each column
d) Finding out zero's
e) Find mean age of patients
f) Now extract only age, Sex, ChestPain, RestBP, Chol, Randomly divide dataset in training (75%) and testing (25%)

Through the diagnosis test I predicted 100 report as COVID positive, but only 45 of those were actually positive. Total 50 people in my sample were actually COVID positive. I have total 500 samples.

Create Confusion Matrix based on above data to find

a) Accuracy
b) Precision
c) Recall
d) F-1 Score

Theory:

What is Data Preparation?

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

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

Data preparation is particular to data, the objectives of the projects, and the algorithms that will be used in data modeling techniques.

Prerequisites for Data Preparation

Everyone must explore a few essential tasks when working with data in the data preparation step. These are as follows:

Data cleaning: This task includes the identification of errors and making corrections or improvements to those errors.

Feature Selection: We need to identify the most important or relevant input data variables for the model.

Data Transforms: Data transformation involves converting raw data into a well-suitable format for the model.

Feature Engineering: Feature engineering involves deriving new variables from the available dataset.

Dimensionality Reduction: The dimensionality reduction process involves converting higher dimensions into lower dimension features without changing the information.

Data Preparation in Machine Learning

Data Preparation is the process of cleaning and transforming raw data to make predictions accurately through using ML algorithms. Although data preparation is considered the most complicated stage in ML, it reduces process complexity later in real-time projects. Various issues have been reported during the data preparation step in machine learning as follows:

Missing data: Missing data or incomplete records is a prevalent issue found in most datasets. Instead of appropriate data, sometimes records contain empty cells, values (e.g., NULL or N/A), or a specific character, such as a question mark, etc.

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

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

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

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

Why is Data Preparation important?

Each machine learning project requires a specific data format. To do so, datasets need to be prepared well before applying it to the projects. Sometimes, data in data sets have missing or incomplete information, which leads to less accurate or incorrect predictions. Further, sometimes data sets are clean but not adequately shaped, such as aggregated or pivoted, and some have less business context. Hence, after collecting data from various data sources, data preparation needs to transform raw data. Below are a few significant advantages of data preparation in machine learning as follows:

It helps to provide reliable prediction outcomes in various analytics operations.

It helps identify data issues or errors and significantly reduces the chances of errors.

It increases decision-making capability.

It reduces overall project cost (data management and analytic cost).

It helps to remove duplicate content to make it worthwhile for different applications. It increases model performance.

In [1]:
```python
import os
os.getcwd()
```

Out[1]:
```
'C:\\Users\\kapil\\Documents'
```

In [2]:
```python
import pandas as pd
```

In [4]:
```python
# import the dataset
df = pd.read_csv('Heart.csv')
```

In [5]:
```python
df.head()
```

Out[5]:

	Unnamed: 0	Age	Sex	ChestPain	RestBP	Chol	Fbs	RestECG	MaxHR	ExAng	Oldpeak	Sl
0	1	63	1	typical	145	233	1	2	150	0	2.3	
1	2	67	1	asymptomatic	160	286	0	2	108	1	1.5	
2	3	67	1	asymptomatic	120	229	0	2	129	1	2.6	
3	4	37	1	nonanginal	130	250	0	0	187	0	3.5	
4	5	41	0	nontypical	130	204	0	2	172	0	1.4	

In [6]:
```python
# a)Shape of data
```

In [8]:
```python
df.shape
```

Out[8]:
```
(303, 15)
```

In [9]:
```python
#To find the null values/missing values in dataset
df.isnull()
```

Out[9]:

	Unnamed: 0	Age	Sex	ChestPain	RestBP	Chol	Fbs	RestECG	MaxHR	ExAng	Oldpeak
0	False	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...	...
298	False	False	False	False	False	False	False	False	False	False	False
299	False	False	False	False	False	False	False	False	False	False	False
300	False	False	False	False	False	False	False	False	False	False	False
301	False	False	False	False	False	False	False	False	False	False	False
302	False	False	False	False	False	False	False	False	False	False	False

303 rows × 15 columns

In [10]:
```
# To find how many null values
```

In [11]:
```
df.isnull().sum()
```

Out[11]:
```
Unnamed: 0    0
Age           0
Sex           0
ChestPain     0
RestBP        0
Chol          0
Fbs           0
RestECG       0
MaxHR         0
ExAng         0
Oldpeak       0
Slope         0
Ca            4
Thal          2
AHD           0
dtype: int64
```

In [12]:
```
# Another way
df.count()
```

Out[12]:
```
Unnamed: 0    303
Age           303
Sex           303
ChestPain     303
RestBP        303
Chol          303
Fbs           303
RestECG       303
MaxHR         303
ExAng         303
Oldpeak       303
Slope         303
Ca            299
Thal          301
AHD           303
dtype: int64
```

In [13]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 15 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Unnamed: 0  303 non-null    int64  
 1   Age         303 non-null    int64  
 2   Sex         303 non-null    int64  
 3   ChestPain   303 non-null    object 
 4   RestBP      303 non-null    int64  
 5   Chol        303 non-null    int64  
 6   Fbs         303 non-null    int64  
 7   RestECG     303 non-null    int64  
 8   MaxHR       303 non-null    int64  
 9   ExAng       303 non-null    int64  
 10  Oldpeak     303 non-null    float64
 11  Slope       303 non-null    int64  
 12  Ca          299 non-null    float64
 13  Thal        301 non-null    object 
 14  AHD         303 non-null    object 
dtypes: float64(2), int64(10), object(3)
memory usage: 35.6+ KB
```

In [14]:
```
# Find the datatypes
```

In [15]:
```
df.dtypes
```

Out[15]:
```
Unnamed: 0      int64
Age             int64
Sex             int64
ChestPain      object
RestBP          int64
Chol            int64
Fbs             int64
RestECG         int64
MaxHR           int64
ExAng           int64
Oldpeak       float64
Slope           int64
Ca            float64
Thal           object
AHD            object
dtype: object
```

In [16]:
```
#Finding out zeros where there is true written are 0 values
df == 0
```

Out[16]:

	Unnamed: 0	Age	Sex	ChestPain	RestBP	Chol	Fbs	RestECG	MaxHR	ExAng	Oldpeak
0	False	False	False	False	False	False	False	False	False	True	False
1	False	False	False	False	False	False	True	False	False	False	False
2	False	False	False	False	False	False	True	False	False	False	False
3	False	False	False	False	False	False	True	True	False	True	False
4	False	False	True	False	False	False	True	False	False	True	False
...	...	...	...	...	...	...	...	...	...	...	...
298	False	False	False	False	False	False	True	True	False	True	False
299	False	False	False	False	False	False	False	True	False	True	False
300	False	False	False	False	False	False	True	True	False	False	False
301	False	False	True	False	False	False	True	False	False	True	True
302	False	False	False	False	False	False	True	True	False	True	True

303 rows × 15 columns

In [17]:

```
#To see 0 values directly
df[df==0]
```

Out[17]:

	Unnamed: 0	Age	Sex	ChestPain	RestBP	Chol	Fbs	RestECG	MaxHR	ExAng	Oldpeak	S
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.0	NaN	
1	NaN	NaN	NaN	NaN	NaN	NaN	0.0	NaN	NaN	NaN	NaN	
2	NaN	NaN	NaN	NaN	NaN	NaN	0.0	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	NaN	NaN	0.0	0.0	NaN	0.0	NaN	
4	NaN	NaN	0.0	NaN	NaN	NaN	0.0	NaN	NaN	0.0	NaN	
...	...	...	...	...	...	...	...	...	...	...	...	
298	NaN	NaN	NaN	NaN	NaN	NaN	0.0	0.0	NaN	0.0	NaN	
299	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.0	NaN	0.0	NaN	
300	NaN	NaN	NaN	NaN	NaN	NaN	0.0	0.0	NaN	NaN	NaN	
301	NaN	NaN	0.0	NaN	NaN	NaN	0.0	NaN	NaN	0.0	0.0	
302	NaN	NaN	NaN	NaN	NaN	NaN	0.0	0.0	NaN	0.0	0.0	

303 rows × 15 columns

In [18]:

```
# Finding mean age of patient
df.columns
```

Out[18]:

```
Index(['Unnamed: 0', 'Age', 'Sex', 'ChestPain', 'RestBP', 'Chol', 'Fbs',
       'RestECG', 'MaxHR', 'ExAng', 'Oldpeak', 'Slope', 'Ca', 'Thal', 'AHD'],
      dtype='object')
```

In [19]:

```
df['Age']
```

Out[19]:
```
0      63
1      67
2      67
3      37
4      41
       ..
298    45
299    68
300    57
301    57
302    38
Name: Age, Length: 303, dtype: int64
```

In [20]:
```
# Find the mean age
df['Age'].mean()
```

Out[20]:
```
54.43894389438944
```

In [22]:
```
# Extract the only Age, Sex, ChestPain, RestBP,Chol,Randomly divide dataset in trai
newdf = df[['Age','Sex','ChestPain','RestBP','Chol']]
```

In [23]:
```
newdf
```

Out[23]:

	Age	Sex	ChestPain	RestBP	Chol
0	63	1	typical	145	233
1	67	1	asymptomatic	160	286
2	67	1	asymptomatic	120	229
3	37	1	nonanginal	130	250
4	41	0	nontypical	130	204
...	...	...	...	...	...
298	45	1	typical	110	264
299	68	1	asymptomatic	144	193
300	57	1	asymptomatic	130	131
301	57	0	nontypical	130	236
302	38	1	nonanginal	138	175

303 rows × 5 columns

In [24]:
```
# Cross Validation
from sklearn.model_selection import train_test_split
```

In [25]:
```
train,test = train_test_split(df,random_state=0,test_size=0.25)
```

In [26]:
```
train.shape
```

Out[26]:
```
(227, 15)
```

In [27]:
```
test.shape
```

Out[27]:
```
(76, 15)
```

In [28]:
```
# Through the diagnosis test I predicted 100 report as COVID posiive, but only 45 c
# Total 50 people in my sample were actully COVID positive. I have total 500 sample
# Create confusion matrix based on above data and find
# 1. Accuracy 2. Precision  3. Recall  4. F-1 Score
```

In [29]:
```
import numpy as np
```

In [30]:
```
actual = list(np.ones(45)) + list(np.zeros(55))
```

In [31]:
```
np.array(actual)
```

Out[31]:
```
array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1.,
       1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1.,
       1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.])
```

In [32]:
```
predicted = list(np.ones(40)) + list(np.zeros(52)) + list(np.ones(8))
```

In [33]:
```
np.array(predicted)
```

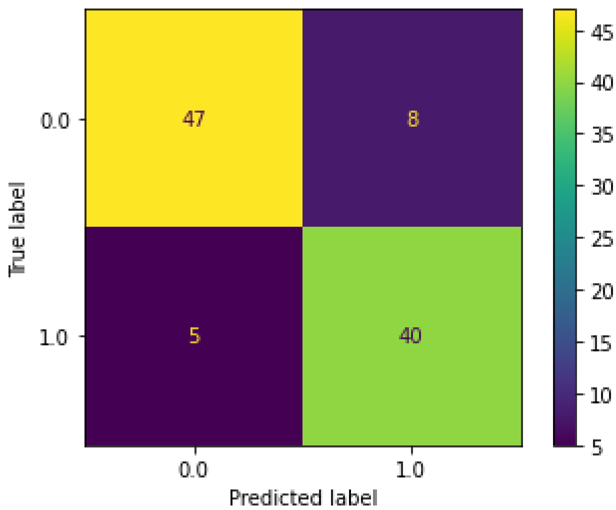
Out[33]:
```
array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1.,
       1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1.,
       1., 1., 1., 1., 1., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 1., 1., 1., 1., 1., 1., 1., 1.])
```

In [34]:
```
# Now if we match the above actual values with predicted values sequentially one by
# we will find that 1 mapped with 1, 1 mapped with 0, 0 mapped with 0 and 0 mapped
# To draw the matrix of it is called confusion matrix
```

In [35]:
```
from sklearn.metrics import ConfusionMatrixDisplay
```

In [36]:
```
ConfusionMatrixDisplay.from_predictions(actual,predicted)
```

Out[36]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2b318dc5cd0>
```



In [37]:
```
# in above matrics actual 1's matching with predicted 1's = 40
#                  actual 0's matching with predicted 1's = 8
#                  actual 1's matching with predicted 0's = 5
#                  actual 0's matching with predicted 0's = 47
```

In [38]:
```python
from sklearn.metrics import classification_report
```

In [39]:
```python
print(classification_report(actual,predicted))
```

```
              precision    recall  f1-score   support

         0.0       0.90      0.85      0.88        55
         1.0       0.83      0.89      0.86        45

    accuracy                           0.87       100
   macro avg       0.87      0.87      0.87       100
weighted avg       0.87      0.87      0.87       100
```

In [40]:
```python
# Recall means individual class accuracy
#47 matching out of 55
# so 47/55 = 0.85
# and 40/45 = 0.89
# precision is check columnwise matrix
# so first column 47+5 =52   i.e  47/52 = 0.90
# and second column 40/48 = 0.83
# f-1 score is harmonic mean of precision and recall
# (0.90+0.85)/2 = 0.875 = 0.88
# (0.83+0.89)/2= 0.86
```

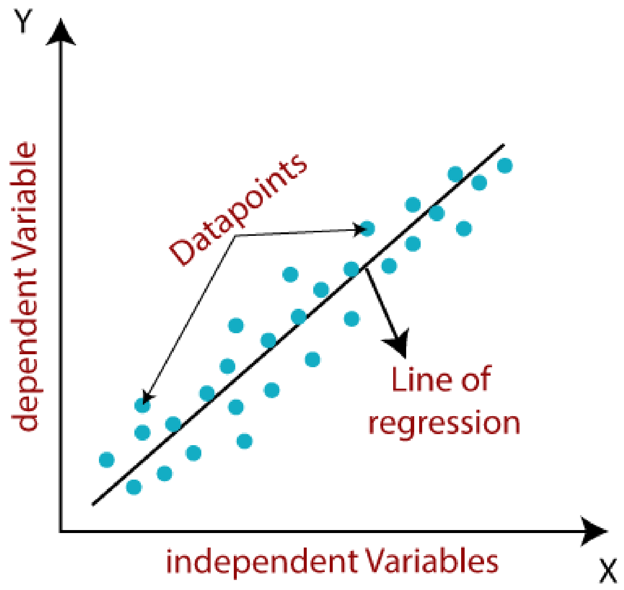
In [ ]:
```python

```

Assignment 2: ***<u>Assignment on Regression technique</u>***

AIM:
Download temperature data from below link. https://www.kaggle.com/venky73/temperaturesof-india?select=temperatures.csv

This data consists of temperatures of INDIA averaging the temperatures of all places month wise. Temperatures values are recorded in CELSIUS A. Apply Linear Regression using suitable library function and predict the Month-wise temperature. B. Assessthe performance of regression models using MSE, MAE and R-Square metrics C. Visualize simple regression model.

Theory:
Linear regression is one of the easiest and most popular Machine Learning algorithms. It is a statistical method that is used for predictive analysis. Linear regression makes predictions for continuous/real or numeric variables such as **sales, salary, age, product price,** etc.
Linear regression algorithm shows a linear relationship between a dependent (y) and one or more independent (y) variables, hence called as linear regression. Since linear regression shows the linear relationship, which means it finds how the value of the dependent variable is changing according to the value of the independent variable.
The linear regression model provides a sloped straight line representing the relationship between the variables. Consider the below image:



Mathematically, we can represent a linear regression as:

$y = a0 + a1x + \varepsilon$

Y= Dependent Variable (Target Variable)
X= Independent Variable (predictor Variable)
a0= intercept of the line (Gives an additional degree of freedom)
a1 = Linear regression coefficient (scale factor to each input value).
ε = random error
The values for x and y variables are training datasets for Linear Regression model representation.

Types of Linear Regression
Linear regression can be further divided into two types of the algorithm:

Simple Linear Regression:
If a single independent variable is used to predict the value of a numerical dependent variable, then such a Linear Regression algorithm is called Simple Linear Regression.
Multiple Linear regression:
If more than one independent variable is used to predict the value of a numerical dependent variable, then such a Linear Regression algorithm is called Multiple Linear Regression.

In [1]:
```python
#Download Temperatures of INDIA dataset from kaggle.com
# Apply Linear Regression using suitable library function and
# predict the Month-wise temperature
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
Matplotlib is building the font cache; this may take a moment.
```

In [2]:
```python
df = pd.read_csv('temperatures.csv')
```

In [3]:
```python
df
```

Out[3]:

	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUA
0	1901	22.40	24.14	29.07	31.91	33.41	33.18	31.21	30.39	30.47	29.97	27.31	24.49	28.9
1	1902	24.93	26.58	29.77	31.78	33.73	32.91	30.92	30.73	29.80	29.12	26.31	24.04	29.2
2	1903	23.44	25.03	27.83	31.39	32.91	33.00	31.34	29.98	29.85	29.04	26.08	23.65	28.4
3	1904	22.50	24.73	28.21	32.02	32.64	32.07	30.36	30.09	30.04	29.20	26.36	23.63	28.4
4	1905	22.00	22.83	26.68	30.01	33.32	33.25	31.44	30.68	30.12	30.67	27.52	23.82	28.3
...	...	...	...	...	...	...	...	...	...	...	...	...	...	..
112	2013	24.56	26.59	30.62	32.66	34.46	32.44	31.07	30.76	31.04	30.27	27.83	25.37	29.8
113	2014	23.83	25.97	28.95	32.74	33.77	34.15	31.85	31.32	30.68	30.29	28.05	25.08	29.7
114	2015	24.58	26.89	29.07	31.87	34.09	32.48	31.88	31.52	31.55	31.04	28.10	25.67	29.9
115	2016	26.94	29.72	32.62	35.38	35.72	34.03	31.64	31.79	31.66	31.98	30.11	28.01	31.6
116	2017	26.45	29.46	31.60	34.95	35.84	33.82	31.88	31.72	32.22	32.29	29.60	27.18	31.4

117 rows × 18 columns

In [4]:
```python
df.head()
```

Out[4]:

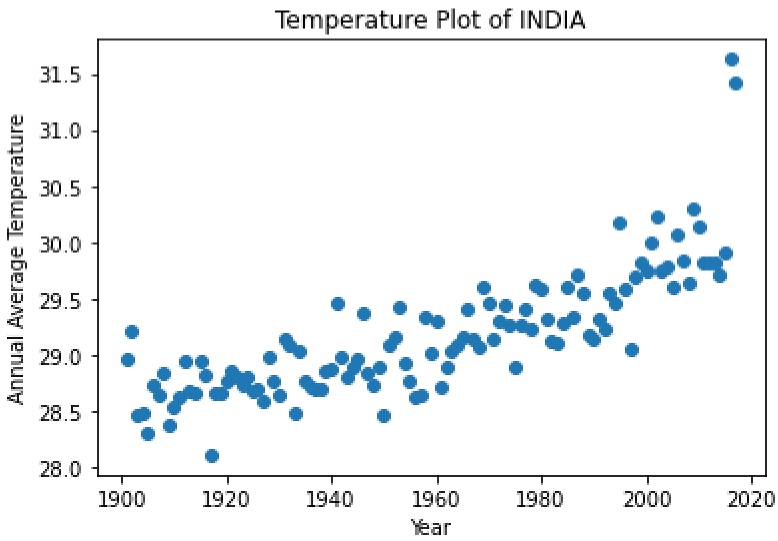
	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL
0	1901	22.40	24.14	29.07	31.91	33.41	33.18	31.21	30.39	30.47	29.97	27.31	24.49	28.96
1	1902	24.93	26.58	29.77	31.78	33.73	32.91	30.92	30.73	29.80	29.12	26.31	24.04	29.22
2	1903	23.44	25.03	27.83	31.39	32.91	33.00	31.34	29.98	29.85	29.04	26.08	23.65	28.47
3	1904	22.50	24.73	28.21	32.02	32.64	32.07	30.36	30.09	30.04	29.20	26.36	23.63	28.49
4	1905	22.00	22.83	26.68	30.01	33.32	33.25	31.44	30.68	30.12	30.67	27.52	23.82	28.30

In [5]:
```python
x = df['YEAR']
```

In [6]:
```
y = df['ANNUAL']
```

In [8]:
```
#plt.figure(figsize=(16,9))
plt.title('Temperature Plot of INDIA')
plt.xlabel('Year')
plt.ylabel('Annual Average Temperature')
plt.scatter(x,y)
```

Out[8]:
```
<matplotlib.collections.PathCollection at 0x14c7bb7fdc0>
```



In [10]:
```
x = x.values
```

In [11]:
```
x = x.reshape(117,1)
```

In [12]:
```
x.shape
```

Out[12]:
```
(117, 1)
```

In [17]:
```
from sklearn.linear_model import LinearRegression
```

In [18]:
```
#Now we are going to train regression model of M/c Learning
regressor = LinearRegression()
```

In [19]:
```
regressor.fit(x,y)
#Model done
```

Out[19]:
```
LinearRegression()
```

In [20]:
```
#Now we will find 'm' value from y = mx + c
regressor.coef_
```

Out[20]:
```
array([0.01312158])
```

In [21]:

```
#Now we will find 'c' value from y = mx + c
regressor.intercept_
```

Out[21]:

```
3.4761897126187016
```

In [25]:

```
regressor.predict([[2120]])
```

Out[25]:

```
array([31.29394211])
```

In [30]:

```
# Assess the performance of regression models using MSE, MAE and R-Square metrics
predicted = regressor.predict(x)
```

In [27]:

```
predicted
```

Out[27]:

```
array([28.4203158 , 28.43343739, 28.44655897, 28.45968055, 28.47280213,
       28.48592371, 28.49904529, 28.51216687, 28.52528846, 28.53841004,
       28.55153162, 28.5646532 , 28.57777478, 28.59089636, 28.60401794,
       28.61713952, 28.63026111, 28.64338269, 28.65650427, 28.66962585,
       28.68274743, 28.69586901, 28.70899059, 28.72211218, 28.73523376,
       28.74835534, 28.76147692, 28.7745985 , 28.78772008, 28.80084166,
       28.81396324, 28.82708483, 28.84020641, 28.85332799, 28.86644957,
       28.87957115, 28.89269273, 28.90581431, 28.91893589, 28.93205748,
       28.94517906, 28.95830064, 28.97142222, 28.9845438 , 28.99766538,
       29.01078696, 29.02390855, 29.03703013, 29.05015171, 29.06327329,
       29.07639487, 29.08951645, 29.10263803, 29.11575961, 29.1288812 ,
       29.14200278, 29.15512436, 29.16824594, 29.18136752, 29.1944891 ,
       29.20761068, 29.22073227, 29.23385385, 29.24697543, 29.26009701,
       29.27321859, 29.28634017, 29.29946175, 29.31258333, 29.32570492,
       29.3388265 , 29.35194808, 29.36506966, 29.37819124, 29.39131282,
       29.4044344 , 29.41755599, 29.43067757, 29.44379915, 29.45692073,
       29.47004231, 29.48316389, 29.49628547, 29.50940705, 29.52252864,
       29.53565022, 29.5487718 , 29.56189338, 29.57501496, 29.58813654,
       29.60125812, 29.6143797 , 29.62750129, 29.64062287, 29.65374445,
       29.66686603, 29.67998761, 29.69310919, 29.70623077, 29.71935236,
       29.73247394, 29.74559552, 29.7587171 , 29.77183868, 29.78496026,
       29.79808184, 29.81120342, 29.82432501, 29.83744659, 29.85056817,
       29.86368975, 29.87681133, 29.88993291, 29.90305449, 29.91617608,
       29.92929766, 29.94241924])
```

In [28]:

```
y
```

Out[28]:

```
0      28.96
1      29.22
2      28.47
3      28.49
4      28.30
       ...
112    29.81
113    29.72
114    29.90
115    31.63
116    31.42
Name: ANNUAL, Length: 117, dtype: float64
```

In [32]:

```
# Mean Absolute Error
import numpy as np
```

```
np.mean(abs(y - predicted))
```

Out[32]: 0.22535284978630413

In [33]:
```
from sklearn.metrics import mean_absolute_error
mean_absolute_error(y,predicted)
```

Out[33]: 0.22535284978630413

In [34]:
```
# Mean Squared Error
np.mean((y - predicted) ** 2)
```

Out[34]: 0.10960795229110352

In [35]:
```
from sklearn.metrics import mean_squared_error
mean_squared_error(y,predicted)
```

Out[35]: 0.10960795229110352

In [36]:
```
# R-Square Error : How much linearity in this model?
from sklearn.metrics import r2_score
r2_score(y,predicted)
```

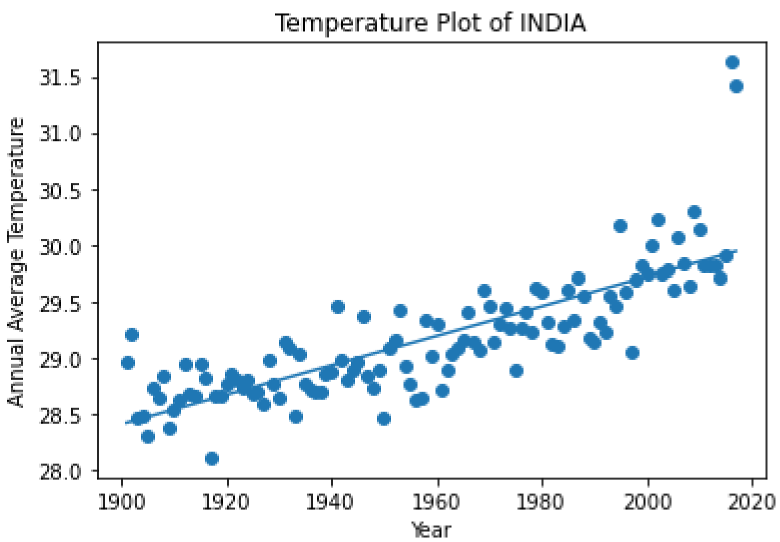
Out[36]: 0.6418078912783682

In [37]:
```
regressor.score(x,y)
```

Out[37]: 0.6418078912783682

In [38]:
```
# Visualize the regression model
plt.title('Temperature Plot of INDIA')
plt.xlabel('Year')
plt.ylabel('Annual Average Temperature')
plt.scatter(x,y,label = 'actual')
plt.plot(x,predicted, label = 'predicted')
```

Out[38]: [<matplotlib.lines.Line2D at 0x14c7c28f6a0>]



In [ ]:

Assignment 3: *Assignment on Classification technique*

AIM:

Every year many students give the GRE exam to get admission in foreign Universities. The data set contains GRE Scores (out of 340), TOEFL Scores (out of 120), University Rating (out of 5), Statement of Purpose strength (out of 5), Letter of Recommendation strength (out of 5), Undergraduate GPA (out of 10), Research Experience (0=no, 1=yes), Admitted (0=no, 1=yes). Admitted is the target variable. Data Set Available on kaggle (The last column of the dataset needs to be changed to 0 or 1)Data Set : https://www.kaggle.com/mohansacharya/graduate-admissions The counselor of the firm is supposed check whether the student will get an admission or not based on his/her GRE score and Academic Score. So to help the counselor to take appropriate decisions build a machine learning model classifier using Decision tree to predict whether a student will get admission or not.

a) Apply Data pre-processing (Label Encoding, Data Transformation….) techniques if necessary.
b) Perform data-preparation (Train-Test Split)
c) Apply Machine Learning Algorithm
d) Evaluate Model.

Theory:

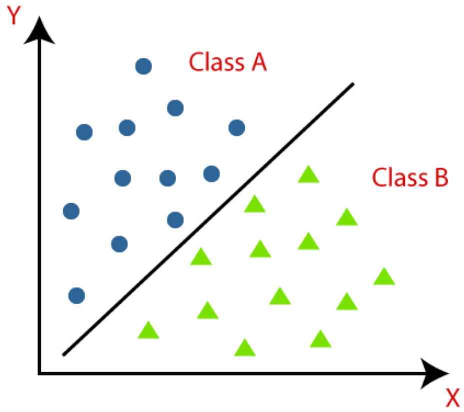
What is the Classification Algorithm?

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
2. The best example of an ML classification algorithm is **Email Spam Detector**.
3. 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.
4. 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.

n [2]:

```
import pandas as pd
import seaborn as sns
```

n [3]:

```
df = pd.read_csv('Admission_Predict.csv')
```

n [4]:

```
df.head()
```

ut[4]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	1	337	118	4	4.5	4.5	9.65	1	0.92
1	2	324	107	4	4.0	4.5	8.87	1	0.76
2	3	316	104	3	3.0	3.5	8.00	1	0.72
3	4	322	110	3	3.5	2.5	8.67	1	0.80
4	5	314	103	2	2.0	3.0	8.21	0	0.65

n [5]:

```
df.shape
```

ut[5]:

```
(500, 9)
```

n [6]:

```
from sklearn.preprocessing import Binarizer
```

n [7]:

```
bi = Binarizer(threshold=0.75)
df['Chance of Admit '] = bi.fit_transform(df[['Chance of Admit ']])
```

n [8]:

```
df.head()
```

ut[8]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	1	337	118	4	4.5	4.5	9.65	1	1.0
1	2	324	107	4	4.0	4.5	8.87	1	1.0
2	3	316	104	3	3.0	3.5	8.00	1	0.0
3	4	322	110	3	3.5	2.5	8.67	1	1.0
4	5	314	103	2	2.0	3.0	8.21	0	0.0

n [9]:

```
x = df.drop('Chance of Admit ', axis =1)
y = df['Chance of Admit ']
```

n [10]:

```
x
```

ut[10]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research
0	1	337	118	4	4.5	4.5	9.65	1

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research
1	2	324	107	4	4.0	4.5	8.87	1
2	3	316	104	3	3.0	3.5	8.00	1
3	4	322	110	3	3.5	2.5	8.67	1
4	5	314	103	2	2.0	3.0	8.21	0
...	...	...	...	...	...	...	...	...
495	496	332	108	5	4.5	4.0	9.02	1
496	497	337	117	5	5.0	5.0	9.87	1
497	498	330	120	5	4.5	5.0	9.56	1
498	499	312	103	4	4.0	5.0	8.43	0
499	500	327	113	4	4.5	4.5	9.04	0

500 rows × 8 columns

n [11]:

```
y= y.astype('int')
```

n [12]:

```
y
```

ut[12]:

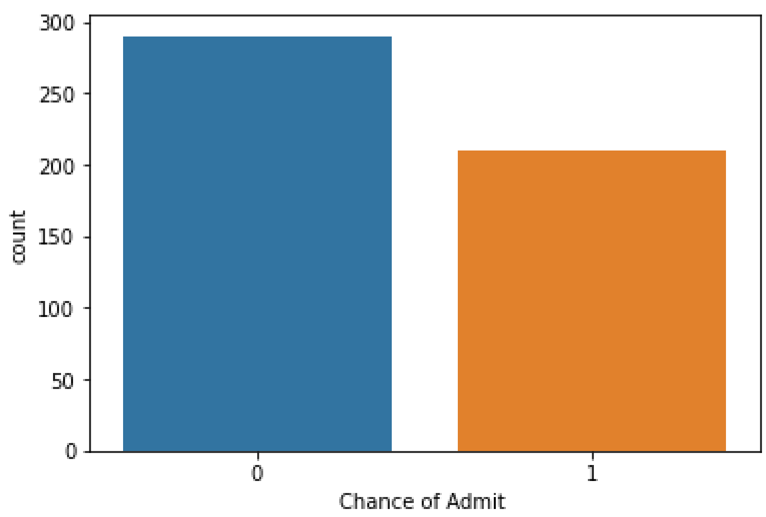
```
0      1
1      1
2      0
3      1
4      0
      ..
495    1
496    1
497    1
498    0
499    1
Name: Chance of Admit , Length: 500, dtype: int32
```

n [13]:

```
sns.countplot(x=y)
```

ut[13]:

```
<AxesSubplot:xlabel='Chance of Admit ', ylabel='count'>
```



n [31]:

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

n [15]:

```
x_train.shape
```

ut[15]:

```
(375, 8)
```

n [16]:

```
x_test.shape
```

ut[16]:

```
(125, 8)
```

n [17]:

```
y_train.shape
```

ut[17]:

```
(375,)
```

n [18]:

```
y_test.shape
```

ut[18]:

```
(125,)
```

n [32]:

```
from sklearn.tree import DecisionTreeClassifier
```

n [33]:

```
classifier = DecisionTreeClassifier(random_state=0)
```

n [34]:

```
classifier.fit(x_train,y_train)
```

ut[34]:

```
DecisionTreeClassifier(random_state=0)
```

n [35]:

```
y_pred = classifier.predict(x_test)
```

n [36]:

```
result = pd.DataFrame({'actual' : y_test,'predicted':y_pred})
```

n [37]:

```
result
```

ut[37]:

	actual	predicted
90	0	0
254	1	1
283	1	1
445	1	1
461	0	0
...	...	...
430	0	0
49	1	0

	actual	predicted
134	1	1
365	1	1
413	0	0

125 rows × 2 columns

n [44]:

```
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
C:\Users\OSLAB~1\AppData\Local\Temp/ipykernel_3204/1472053813.py in <module>
----> 1 cm = confusion_matrix(y_test, predictions, labels=classifier.classes_)

NameError: name 'confusion_matrix' is not defined
```

n [42]:

```
from sklearn.metrics import ConfusionMatrixDisplay, accuracy_score
```

n [39]:

```
from sklearn.metrics import classification_report
```

n [ ]:

```
```

n [43]:

```
accuracy_score(y_test,y_pred)
```

ut[43]:

```
0.96
```

n [50]:

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred,labels = classifier.classes_)
```

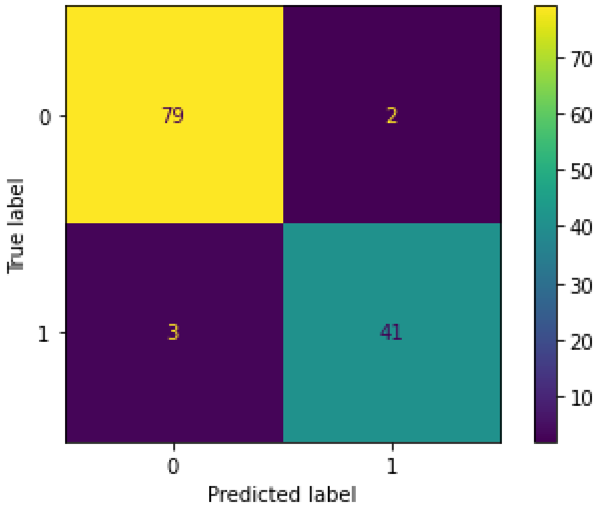
n [51]:

```
disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels = classifier.classe
```

n [52]:

```
disp.plot()
```

ut[52]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1c7f4a76c70>



n [54]:

```
accuracy_score(y_test, y_pred)
```

ut[54]: 0.96

n [55]:

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.96      0.98      0.97        81
           1       0.95      0.93      0.94        44

    accuracy                           0.96       125
   macro avg       0.96      0.95      0.96       125
weighted avg       0.96      0.96      0.96       125
```

n [68]:

```
new = [[140,300,110,5,4.5,4.5,9.2,1]]
```

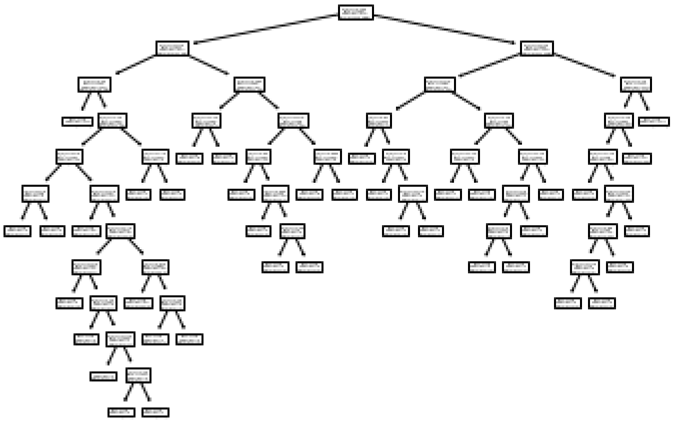
n [69]:

```
classifier.predict(new)[0]
```

ut[69]: 1

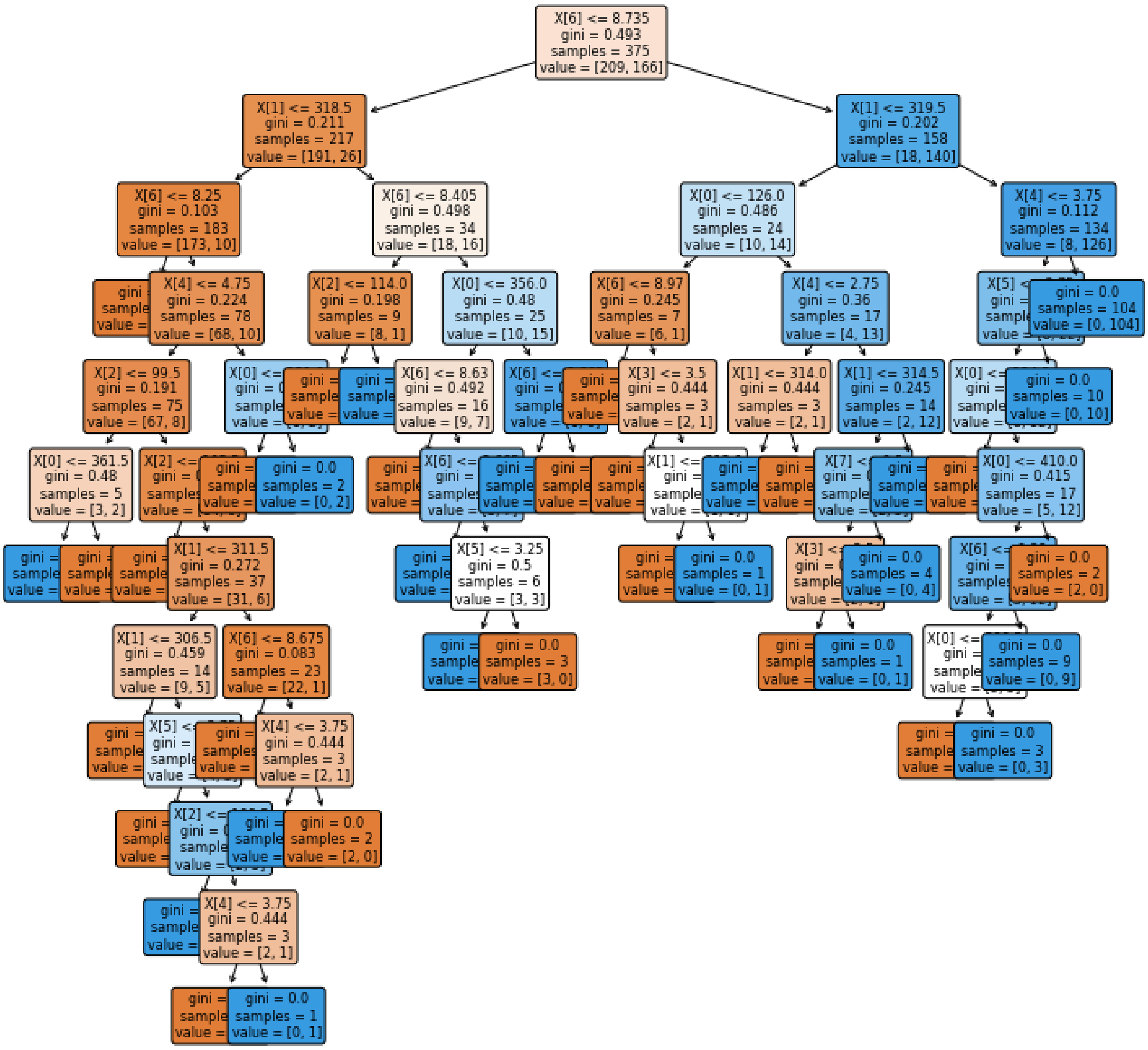
n [70]:

```
from sklearn.tree import plot_tree
plot_tree(classifier, );
```



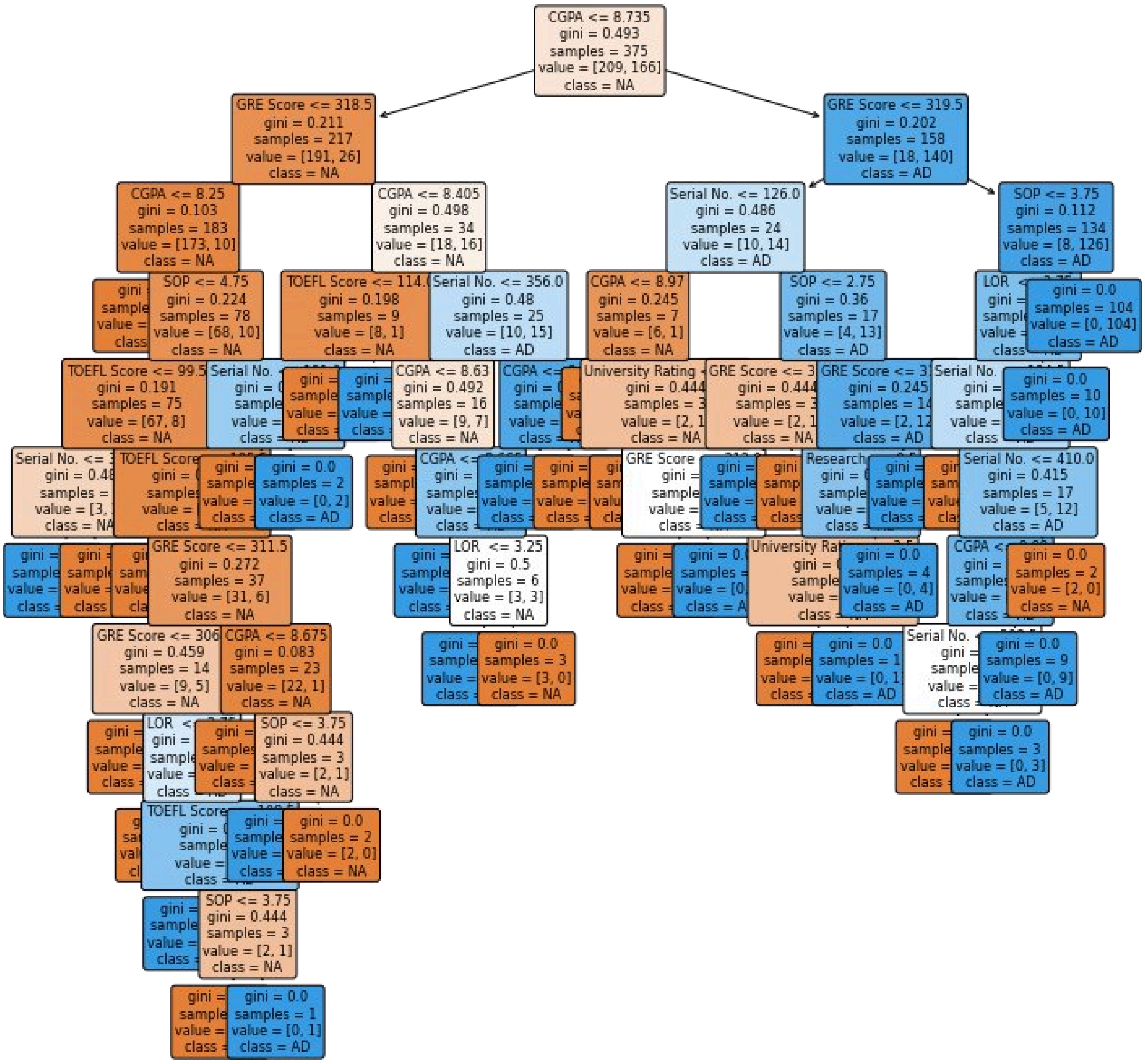
n [73]:

```
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt
plt.figure(figsize=(12,12))
plot_tree(classifier, fontsize=8, filled=True, rounded = True);
```



n [74]:

```
plt.figure(figsize=(12,12))
plot_tree(classifier, fontsize=8, filled=True, rounded = True, feature_names=x.colum
```


CGPA <= 8.735
gini = 0.493
samples = 375
value = [209, 166]
class = NA
GRE Score <= 318.5
gini = 0.211
samples = 217
value = [191, 26]
class = NA
GRE Score <= 319.5
gini = 0.202
samples = 158
value = [18, 140]
class = AD
CGPA <= 8.25
gini = 0.103
samples = 183
value = [173, 10]
class = NA
CGPA <= 8.405
gini = 0.498
samples = 34
value = [18, 16]
class = NA
Serial No. <= 126.0
gini = 0.486
samples = 24
value = [10, 14]
class = AD
SOP <= 3.75
gini = 0.112
samples = 134
value = [8, 126]
class = AD
SOP <= 4.75
gini = 0.224
samples = 78
value = [68, 10]
class = NA
Serial No. <= 356.0
gini = 0.48
samples = 25
value = [10, 15]
class = AD
CGPA <= 8.97
gini = 0.245
samples = 7
value = [6, 1]
class = NA
SOP <= 2.75
gini = 0.36
samples = 17
value = [4, 13]
class = AD
gini = 0.0
samples = 104
value = [0, 104]
class = AD
TOEFL Score <= 99.5
gini = 0.191
samples = 75
value = [67, 8]
class = NA
CGPA <= 8.63
gini = 0.492
samples = 16
value = [9, 7]
class = NA
gini = 0.0
samples = 10
value = [0, 10]
class = AD
gini = 0.0
samples = 2
value = [0, 2]
class = AD
Serial No. <= 410.0
gini = 0.415
samples = 17
value = [5, 12]
class = AD
GRE Score <= 311.5
gini = 0.272
samples = 37
value = [31, 6]
class = NA
LOR <= 3.25
gini = 0.5
samples = 6
value = [3, 3]
class = NA
gini = 0.0
samples = 4
value = [0, 4]
class = AD
gini = 0.0
samples = 2
value = [2, 0]
class = NA
GRE Score <= 306
gini = 0.459
samples = 14
value = [9, 5]
class = NA
CGPA <= 8.675
gini = 0.083
samples = 23
value = [22, 1]
class = NA
gini = 0.0
samples = 3
value = [3, 0]
class = NA
gini = 0.0
samples = 9
value = [0, 9]
class = AD
SOP <= 3.75
gini = 0.444
samples = 3
value = [2, 1]
class = NA
gini = 0.0
samples = 3
value = [0, 3]
class = AD
gini = 0.0
samples = 2
value = [2, 0]
class = NA
SOP <= 3.75
gini = 0.444
samples = 3
value = [2, 1]
class = NA
gini = 0.0
samples = 1
value = [0, 1]
class = AD

n [ ]:

Assignment 4: ***Assignment on Improving Performance of Classifier Models***

AIM:

A SMS unsolicited mail (every now and then known as cell smartphone junk mail) is any junk message brought to a cellular phone as textual content messaging via the Short Message Service (SMS). Use probabilistic approach (Naive Bayes Classifier / Bayesian Network) to implement SMS Spam Filtering system. SMS messages are categorized as SPAM or HAM using features like length of message, word depend, unique keywords etc. Download Data -Set from:

http://archive.ics.uci.edu/ml/datasets/sms+spam+collection

This dataset is composed by just one text file, where each line has the correct class followed by the raw message.

A. Apply Data pre-processing (Label Encoding, Data Transformation….) techniques if necessary

B. Perform data-preparation (Train-Test Split)

C. Apply at least two Machine Learning Algorithms and Evaluate Models

D. Apply Cross-Validation and Evaluate Models and compare performance.

E. Apply Hyper parameter tuning and evaluate models and compare performance.

Theory:

Machine learning largely relies on classification models, and the accuracy of these models is a key performance indicator. It can be difficult to increase a classification model's accuracy since it depends on a number of variables, including data quality, model complexity, hyperparameters, and others.

Data Preprocessing

Each machine learning project must include data preprocessing since the model's performance may be greatly impacted by the quality of the training data. There are various processes in preprocessing, like cleaning, normalization, and feature engineering. Here are some recommendations for preparing data to increase a classification model's accuracy:

Cleansing Data Remove missing values, outliers, and duplicate data points to clean up the data. Techniques like mean imputation, median imputation, or eliminating rows or columns with missing data can all be used to accomplish this.

To make sure that all characteristics are scaled equally, normalize the data. Techniques like min−max normalization, z−score normalization, or log transformation can be used for this.

Feature engineering is the process of building new features from already existing ones in order to more accurately reflect the underlying data. Techniques like polynomial features, interaction features, or feature selection can be used for this.

Feature Selection

The process of choosing the most pertinent characteristics from a dataset that might aid in classification is known as feature selection. The complexity of the model may be reduced and overfitting can be avoided with the use of feature selection. Feature selection methods include the following:

Analysis of Correlation: The correlation between each characteristic and the target variable is determined during a correlation analysis. High correlation features may be used for the model.

Sorting features according to their significance in the classification process is known as "feature importance ranking." Techniques like decision treebased feature importance or permutation importance can be used for this.

Dimensionality Reduction: It is possible to decrease the number of features in a dataset while keeping the majority of the data by using dimensionality reduction techniques like PCA.

Model Selection

The accuracy of the model can be considerably impacted by the classification algorithm selection. Various data kinds or categorization jobs may lend themselves to different algorithms performing better. These are a few typical categorization methods:

Logistic Regression: A linear model that may be applied to binary classification is logistic regression. It operates by calculating the likelihood of a binary result depending on the properties of the input.

Decision Trees: Decision trees are non−linear models that may be applied to multi−class classification as well as binary classification. Based on the input characteristics, they divide the input space into more manageable chunks.

Support Vector Machines (SVM): SVM is a non−linear model that may be applied to multi−class classification as well as binary classification. The method finds a hyperplane based on the input characteristics that maximum isolates the input data.

Random Forest: To increase the model's accuracy, random forest is an ensemble approach that mixes different decision trees. It operates by combining the forecasts from many decision trees.

Hyperparameter Tuning

Options for model configuration known as hyperparameters cannot be inferred from data. The hyperparameters are tweaked to enhance the model's performance. Listed below are numerous approaches to hyperparameter tuning:

Grid Search: In grid search, a grid of hyperparameter values are used to evaluate the model's performance for each conceivable combination.

Random Search: In random search, values for the model's hyperparameters are selected at random from a distribution, and the model's performance is evaluated for each set of hyperparameters.

Bayesian optimization involves using a probabilistic model to predict how the model will perform given different values for its hyperparameters in order to select the hyperparameters that will maximize the performance of the model.

Cross−Validation

Cross−validation is a method for assessing the effectiveness of the model and preventing overfitting. When a model performs well on training data but badly on test data, this is known as overfitting. In cross−validation, the model is tested on various subsets of the data after being divided into training and validation sets. Here are a few typical cross−validation methods:

K−Fold K−fold cross−validation In cross−validation, the data are split into k equal−sized subsets, the model is trained on k−1 subsets, and then the model is tested on the remaining subset. Each subset is utilized as the validation set once throughout this procedure, which is repeated k times.

Stratified cross−validation entails making sure that each fold has a target variable distribution that is comparable to the distribution throughout the whole dataset. When the target variable is unbalanced, this might be helpful.

Leave−One−Out Cross−Validation: In leave−one−out cross−validation, the model is trained on all data points except for one and tested on the remaining data points. Each data point undergoes this procedure once, resulting in n distinct models, where n is the total number of data points.

In [118…

```python
import pandas as pd
```

In [119…

```python
df = pd.read_csv('SMSSpamCollection', sep = '\t', names = ['label','text'])
```

In [120…

```python
df
```

Out[120…

	label	text
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...
...	...	...
5567	spam	This is the 2nd time we have tried 2 contact u...
5568	ham	Will ü b going to esplanade fr home?
5569	ham	Pity, * was in mood for that. So...any other s...
5570	ham	The guy did some bitching but I acted like i'd...
5571	ham	Rofl. Its true to its name

5572 rows × 2 columns

In [121…

```python
df.shape
```

Out[121…

```
(5572, 2)
```

In [13]:

```python
#Now our data should be in number format
#our data is in text format we need to convert
```

```
#before that we need to use some NLP methods here
#we need to delete some unnecessory things from the data means data cleaning
#like punctuation, stopwords like was, the, I , Any, for, he , then etc
# we need to do stemming as well like remove ed from trusted etc
```

In [122…

```
#install nltk natural language tool kit
!pip install nltk
```

```
Requirement already satisfied: nltk in c:\programdata\anaconda3\lib\site-packages (3.6.5)
Requirement already satisfied: click in c:\programdata\anaconda3\lib\site-packages (from nltk) (8.0.3)
Requirement already satisfied: joblib in c:\programdata\anaconda3\lib\site-packages (from nltk) (1.1.0)
Requirement already satisfied: regex>=2021.8.3 in c:\programdata\anaconda3\lib\site-packages (from nltk) (2021.8.3)
Requirement already satisfied: tqdm in c:\programdata\anaconda3\lib\site-packages (from nltk) (4.62.3)
Requirement already satisfied: colorama in c:\programdata\anaconda3\lib\site-packages (from click->nltk) (0.4.4)
```

In [123…

```
import nltk
```

In [124…

```
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to C:\Users\OS
[nltk_data]     LAB\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Out[124…

```
True
```

In [125…

```
sent = 'Hello friends! How are you?'
```

In [19]:

```
#first process is tokenization i.e. symbols separation
```

In [126…

```
from nltk import word_tokenize
```

In [127…

```
nltk.download('punkt')
```

```
[nltk_data] Downloading package punkt to C:\Users\OS
[nltk_data]     LAB\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

Out[127…

```
True
```

In [128…

```
nltk.word_tokenize(sent)
```

Out[128…

```
['Hello', 'friends', '!', 'How', 'are', 'you', '?']
```

In [129…

```
from nltk.corpus import stopwords
swords = stopwords.words('english')
```

In [11]:

```
swords
```

Out[11]:

```
['i',
 'me',
 'my',
 'myself',
 'we',
 'our',
 'ours',
 'ourselves',
 'you',
 "you're",
 "you've",
 "you'll",
 "you'd",
 'your',
 'yours',
 'yourself',
 'yourselves',
 'he',
 'him',
 'his',
 'himself',
 'she',
 "she's",
 'her',
 'hers',
 'herself',
 'it',
 "it's",
 'its',
```

```
 'mightn',
 "mightn't",
 'mustn',
 "mustn't",
 'needn',
 "needn't",
 'shan',
 "shan't",
 'shouldn',
 "shouldn't",
 'wasn',
 "wasn't",
 'weren',
 "weren't",
 'won',
 "won't",
 'wouldn',
 "wouldn't"]
```

In [130…

```
clean = [word for word in word_tokenize(sent) if word not in swords]
```

In [131…

```
clean
```

Out[131…

```
['Hello', 'friends', '!', 'How', '?']
```

In [14]:

```
#Stemming
```

In [132…

```
from nltk.stem import PorterStemmer
```

In [133…

```
ps = PorterStemmer()
```

In [134…

```
clean = [ps.stem(word) for word in word_tokenize(sent) if word not in swords]
```

In [135…

```
clean
```

Out[135…

```
['hello', 'friend', '!', 'how', '?']
```

In [21]:

```
sent1 = 'Hello friends! How are you? We will be learning Python today.'
```

In [136…

```
def clean_text(sent):
    tokens = word_tokenize(sent)
    clean = [word for word in tokens if word.isdigit() or word.isalpha()]
    clean = [ps.stem(word) for word in clean if word not in swords]
    return clean
```

In [137…

```
clean_text(sent1)
```

Out[137…

```
['hello', 'friend', 'how', 'we', 'learn', 'python', 'today']
```

In [27]:

```
#Above we Learned the Preprocessing
```

In [30]:

```
# preprocessing method to use text data is TF*IDF vectorizer
```

In [31]:

```
#TF*IDF algo is used to weigh a keyword in any document and assign the importance to that
# keyword based on the number of times it appears in the document
# Put simply, the higher the TF*IDF score (weight), the rarer and more importan the term, and vice versa
# Each word or term has its respective TF and IDF score.
#The product of the TF and IDF scores of a term is called the TF*IDF weight of that term.
#The TF(Term Frequency) of a word is the number of times it appears in a doc.
#You can understand that you are using a term too often or too infrequently.
# TF(t) = (Number of times term t appears in a doc)/(Total number of terms in the doc)

# The IDF (Inverse Doc Frequency) of a word is the measure of how significant that term is in
#the whole corpus.

# IDF(t) = Log_e(Total number of documents/Number of documents with term t in it)
```

In [138…

```
# PreProcessing
from sklearn.feature_extraction.text import TfidfVectorizer
```

In [139…

```
tfidf = TfidfVectorizer(analyzer = clean_text)
```

In [140…

```
x = df['text']
y = df['label']
```

In [141…

```
#tranform into numbers
x_new = tfidf.fit_transform(x)
```

In [142…

```
x.shape
```

Out[142…

```
(5572,)
```

In [143…

```
x_new.shape
```

Out[143…

```
(5572, 6513)
```

In [144…

```
x_new
```

Out[144…

```
<5572x6513 sparse matrix of type '<class 'numpy.float64'>'
	with 52573 stored elements in Compressed Sparse Row format>
```

In [ ]:

```
#We have done vectorization after cleaning
```

In [145…

```
tfidf.get_feature_names()
```

Out[145…

```
['0',
 '008704050406',
 '0089',
 '0121',
```

```
'01223585236',
'01223585334',
'0125698789',
'02',
'0207',
'02072069400',
'02073162414',
'02085076972',
'021',
'050703',
'0578',
'06',
'07008009200',
'07046744435',
'07090201529',
'07090298926',
'07099833605',
'07123456789',
'0721072',
'07732584351',
'07734396839',
'07742676969',
'07753741225',
'07786200117',
'078',
'07801543489',
'07808',
'07808247860',
'07808726822',
'07815296484',
'07821230901',
'078498',
'07973788240',
'0800',
'08000407165',
'08000776320',
'08000839402',
'08000930705',
'08000938767',
'08001950382',
'08002888812',
'08002986030',
'08002986906',
'08002988890',
```

```
 'bbq',
 'bc',
 'bcaz',
 'bck',
 'bcm',
 'bcoz',
 'bcum',
 'bcz',
 'bday',
 'be',
 'beach',
 'bead',
 'bear',
 'beat',
 'beauti',
 'bec',
 'becau',
 'becaus',
 'becausethey',
 'becom',
 'becoz',
 'becz',
 'bed',
 'bedbut',
 'bedreal',
 'bedrm',
 'bedroom',
 'beeen',
 ...]
```

In [66]:
```
# Cross Validation
```

In [146…
```
y.value_counts()
```

Out[146…
```
ham     4825
spam     747
Name: label, dtype: int64
```

In [147…
```
from sklearn.model_selection import train_test_split
```

In [148…

```
x_train, x_test, y_train, y_test = train_test_split(x_new, y, random_state=0, test_size=0.25)
```

In [150…

```
x_train.shape
```

Out[150…

```
(4179, 6513)
```

In [151…

```
x_test.shape
```

Out[151…

```
(1393, 6513)
```

In [152…

```
from sklearn.naive_bayes import GaussianNB
```

In [153…

```
nb = GaussianNB()
```

In [154…

```
nb.fit(x_train.toarray(), y_train)
```

Out[154…

```
GaussianNB()
```

In [155…

```
y_pred = nb.predict(x_test.toarray())
```

In [156…

```
y_test.value_counts()
```

Out[156…

```
ham     1208
spam     185
Name: label, dtype: int64
```

In [157…

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

In [ ]:

```

```

In [158…

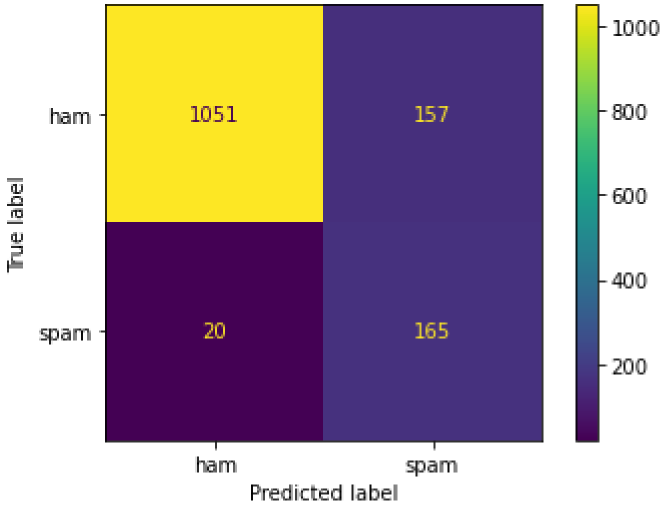
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred,labels = nb.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels = nb.classes_)
```

In [159…

```
disp.plot()
```

Out[159…

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x213d539bdc0>
```



In [160…

```
from sklearn.metrics import classification_report, accuracy_score
```

In [161…

```
accuracy_score(y_test, y_pred)
```

Out[161…

```
0.8729361091170137
```

In [162…

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

         ham       0.98      0.87      0.92      1208
        spam       0.51      0.89      0.65       185
```

```
    accuracy                           0.87      1393
   macro avg       0.75      0.88      0.79      1393
weighted avg       0.92      0.87      0.89      1393
```

In [163…
```python
from sklearn.ensemble import RandomForestClassifier
```

In [164…
```python
rf = RandomForestClassifier(random_state=0)
```

In [165…
```python
rf.fit(x_train, y_train)
```

Out[165…
```
RandomForestClassifier(random_state=0)
```

In [167…
```python
y_pred = rf.predict(x_test)
```

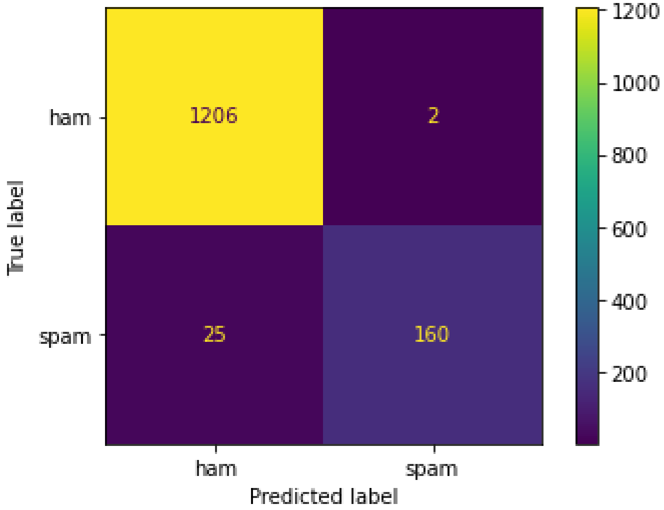
In [168…
```python
ConfusionMatrixDisplay.from_predictions(y_test,y_pred);
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
C:\Users\OSLAB~1\AppData\Local\Temp/ipykernel_17028/394578003.py in <module>
----> 1 ConfusionMatrixDisplay.from_predictions(y_test,y_pred);

AttributeError: type object 'ConfusionMatrixDisplay' has no attribute 'from_predictions'
```

In [169…
```python
cm = confusion_matrix(y_test, y_pred,labels = rf.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels = rf.classes_)
```

In [170…
```python
disp.plot()
```

Out[170…
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x213d8b68fa0>
```



In [171…

```
accuracy_score(y_test, y_pred)
```

Out[171…

```
0.9806173725771715
```

In [172…

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

         ham       0.98      1.00      0.99      1208
        spam       0.99      0.86      0.92       185

    accuracy                           0.98      1393
   macro avg       0.98      0.93      0.96      1393
weighted avg       0.98      0.98      0.98      1393
```

In [173…

```
from sklearn.linear_model import LogisticRegression
log = LogisticRegression()
log.fit(x_train, y_train)
y_pred = log.predict(x_test)
accuracy_score(y_test, y_pred)
```

Out[173… 0.9641062455132807

In [117…
```
# RandomForest accuracy looks good
```

In [ ]:
```
# hyperparameter tuning and evaluate the model
# any algorithm we passing parameters that parameters we need to decide ideally
```

In [174…
```
from sklearn.model_selection import GridSearchCV
```

In [ ]:
```
#Gridsearch is a class of cross validation
# we need to create object of that class first
```

In [ ]:
```
#https://scikit-learn.org/stable/modules/generated/
#sklearn.ensemble.RandomForestClassifier.html#randomforestclassifier
# see two parameters gini and entropy
```

In [179…
```
params= {
    'criterion': ['gini','entropy'],
    'max_features': ['sqrt','log2'],
    'random_state': [0,1,2,3,4],
    'class_weight': ['balanced','balanced_subsample']
}
```

In [180…
```
grid = GridSearchCV(rf,param_grid=params, cv = 5,scoring='accuracy')
```

In [181…
```
# GridSearch cross validation will search the ideal values
#for the parameters given in params above
```

In [182…
```
grid.fit(x_train, y_train)
```

Out[182…
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(random_state=0),
             param_grid={'class_weight': ['balanced', 'balanced_subsample'],
```

```
                              'criterion': ['gini', 'entropy'],
                              'max_features': ['sqrt', 'log2'],
                              'random_state': [0, 1, 2, 3, 4]},
                  scoring='accuracy')
```

In [183…

```
# Above may take 5 to 10 minutes
```

In [186…

```
grid.best_estimator_
```

Out[186…

```
RandomForestClassifier(class_weight='balanced_subsample', max_features='sqrt',
                       random_state=1)
```

In [ ]:

```
#Above you can see estimated parameters
```

In [187…

```
rf = grid.best_estimator_
```

In [188…

```
y_pred = rf.predict(x_test)
```

In [190…

```
accuracy_score(y_test,y_pred)
```

Out[190…

```
0.9770279971284996
```

In [ ]:

```
# so using hyper parameter tuning we can find the accuracy of the algorithm
# as well as model performance and finding ideal values for parameters
```

Assignment 5: *Assignment on Clustering Techniques*

AIM:

Download the following customer dataset from below link: Data Set: https://www.kaggle.com/shwetabh123/mall-customers This dataset gives the data of Income and money spent by the customers visiting a Shopping Mall. The data set contains Customer ID, Gender, Age, Annual Income, Spending Score. Therefore, as a mall owner you need to find the group of people who are the profitable customers for the mall owner. Apply at least two clustering algorithms (based on Spending Score) to find the group of customers.

A. Apply Data pre-processing (Label Encoding , Data Transformation….) techniques if necessary.
B. Perform data-preparation(Train-Test Split)
C. Apply Machine Learning Algorithm
D. Evaluate Model.
E. Apply Cross-Validation and Evaluate Model

Theory:

Clustering in Machine Learning

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

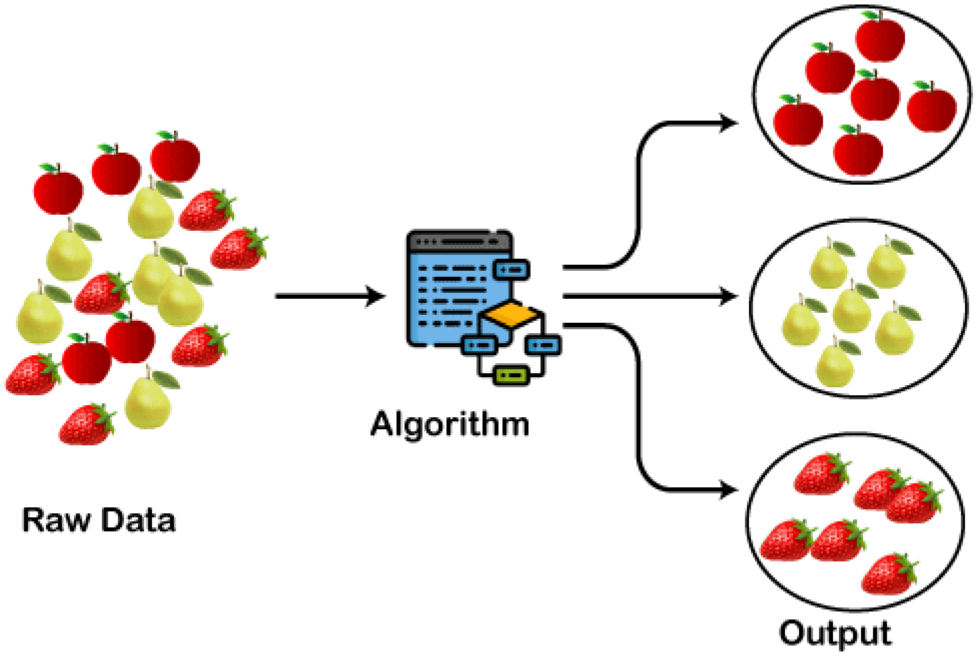
It does it by finding some similar patterns in the unlabelled dataset such as shape, size, color, behavior, etc., and divides them as per the presence and absence of those similar patterns.

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

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

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

The clustering technique can be widely used in various tasks. Some most common uses of this technique are:
Market Segmentation
Statistical data analysis
Social network analysis
Image segmentation
Anomaly detection, etc.
Apart from these general usages, it is used by the **Amazon** in its recommendation system to provide the recommendations as per the past search of products. **Netflix** also uses this technique to recommend the movies and web-series to its users as per the watch history.
The below diagram explains the working of the clustering algorithm. We can see the different fruits are divided into several groups with similar properties.



Types of Clustering Methods
The clustering methods are broadly divided into **Hard clustering** (datapoint belongs to only one group) and **Soft Clustering** (data points can belong to another group also). But there are also other various approaches of Clustering exist. Below are the main clustering methods used in Machine learning:
Partitioning Clustering
It is a type of clustering that divides the data into non-hierarchical groups. It is also known as the **centroid-based method**. The most common example of partitioning clustering is the K-Means Clustering algorithm.
In this type, the dataset is divided into a set of k groups, where K is used to define the number of pre-defined groups. The cluster center is created in such a way that the distance between the data points of one cluster is minimum as compared to another cluster centroid.
Density-Based Clustering

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

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

Distribution Model-Based Clustering

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

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

Hierarchical Clustering

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

Fuzzy Clustering

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