MADRAS INSTITUTE OF TECHNOLOGY

ANNA UNIVERSITY

DEPARTMENT OF INFORMATION TECHNOLOGY

IT5612- DATA ANALYTICS AND CLOUD COMPUTING LABORATORY

RECORD

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BONAFIDE CERTIFICATE

Certified that the bonafide record of the practical work done by Mr. Rozen Berg D Register Number (2019506076) of **Sixth** Semester, **B.Tech Information Technology** in the **IT5612-Data Analytics and Cloud Computing Laboratory** during the academic period from **March 2022 to June 2022**

Submitted for Practical Examination held on _____

Date: Course Instructor

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Internal Examiner External Examiner

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Exp.No : 1A **Date:** 08/03/22

STUDY ON NUMPY, SCIPY , STATSMODELS AND PANDAS PACKAGES

Aim:

To explore the functions in Numpy , SciPy , Statsmodels and pandas packages and prepare a study with an example for each function

NumPy:

S.No.	Function	Description	Example
1	array()	Used to create a Numpy array object	arr=np.array([1,2,3,4,5] print(arr) Output: [1 2 3 4 5]
2	name[index]	It is used to access array element at specific index	arr=np.array([1,2,3,4,5] print(arr[0]) Output: 1
3	dtype	Returns data type of the array	arr=np.array([1,2,3,4,5] print(arr.dtype) Output: int64
4	copy()	Makes a copy of original array	arr=np.array([1,2,3,4,5]) x=arr.copy() arr[0]=4 print(arr) print(x) Output: [4 2 3 4 5] [1 2 3 4 5]
5	tan()	Helps calculate trigonometric tangent for all parameter	np.tan(np.array([pi,pi/2,pi])) Output: array([1.22e-16,1.63e+16,-1.22e-16])

SciPy:

Scipy is a scientific computation library that uses Numpy underneath

SciPy Constants:

from scipy import constants

print(constants.pi)

Output

3.141592653589793

SciPy Optimizers:

Optimize.root helps us to find the root of the equation

Example:

```
from scipy.optimize import root
from math import os
def eqn(x) :
    return x+cos(x)
myroot=root(eqn,0)
```

Output:

```
[-0.73908513]
```

SciPy Sparse Data:

Sparse data is data that has unused elements

Example:

```
import numpy as np
from scipy.sparse import csr_matrix
arr=np.array([0,0,0,0,0,1,1,0,2])
print(csr_matrix(arr))
```

Output:

```
(0,5)  1
(0,6)  1
(0,8)  2
```

Statsmodels:

Statsmodel is a python module that provides classes and functions for the estimation of many different statistical models, as well as for conducting statistical tests and statistical data exploration. An extensive list of result statistics is available for each estimator. The results are tested against existing statistical packages to ensure that they are correct.

OLS() – It is used to estimate by ordinary least squares

OLS() function can be used for

a) Regression models
b) Linear models
c) Time Series Analysis
d) Contingency tables

Pandas:

Pandas is a Python library used for working with data sets. It has functions for analyzing, cleaning , exploring and manipulating data.

Pandas DataFrame

Pandas DataFrame is a 2D data structure

Example

```
import pandas as pd
data = {
    "calories" : [420],
    "duration" : [50]
}
df=pd.dataframe(data)
print(df)
```

Output:

```
0   calories  duration
    420       50
```

Read and Analyse:

read_csv() - It is used to read CSV files

read_json() - It is used to read JSON files

head() - We can view first rows of data frame

tail() - We can view last rows of data frame

Result:

Study of basic Python packages have been done successfully.

Exp.No : 1B **Date:** 08/03/22

READ DATA/DATASET

Aim:

To use inbuilt packages to read data from text file, excel and the web

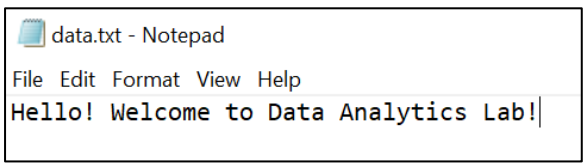
Code:

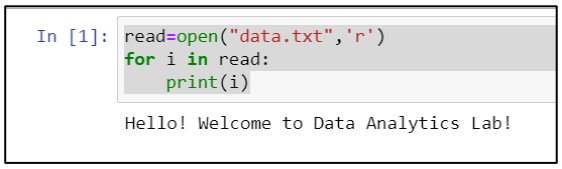
1)a)**Read data from text file:**

```
read=open("data.txt",'r')
for i in read:
    print(i)
```

Output:

Contents of data.txt and reading:

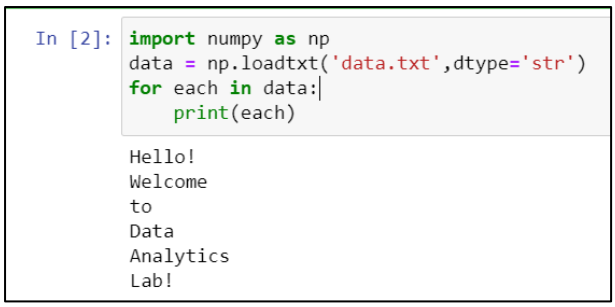




b)**Read data using numpy:**

```
import numpy as np
data = np.loadtxt('data.txt',dtype='str')
for each in data:
    print(each)
```

Output:



2)**Read from web:**

```
import urllib.request
url=”https://google.com”
req=urllib.request.Request(url)
res=p=urllib.request.urlopen(req)
```

data=res.read()

print(data)

Output:

```
b'<!doctype html><html itemscope="" itemtype="http://schema.org/WebPage" lang="en-IN"><head><meta content="text/html; charset
=UTF-8" http-equiv="Content-Type"><meta content="/images/branding/googleg/1x/googleg_standard_color_128dp.png" itemprop="imag
e"><title>Google</title><script nonce="c+GPJEk5/uiaYGMx/839Wg==">(function(){window.google={kEI:\'DkcwYvCSCJDe2roPnLyB4Ac\',k
EXPI:\'0,1302536,56873,1709,4349,207,2415,2389,2316,383,246,5,1354,4013,1238,2944,1119571,1197752,670,16,380053,16114,28684,1
7572,4858,1362,9291,3027,4746,12835,4020,978,13228,8039,6430,7432,15309,261,649,5764,1279,2742,149,1103,840,2196,4101,3514,60
6,2023,1777,520,14670,3228,2844,8,4810,12639,7540,4085,4143,552,8248,9359,3,346,230,1014,1,5444,149,11323,2652,4,1253,275,65
5,1649,7039,22023,3050,2658,7356,31,18065,9358,7428,651,5146,2560,4094,17,4035,3,3541,1,16807,38,25309,2,14022,1931,784,255,4
550,744,5852,9868,595,1160,5679,1020,2381,2719,18242,2,2,5,7772,4568,6252,17116,6308,1252,5835,11862,3106,1542,2790,8,2269,24
00,1412,1395,445,2,2,1,6394,566,3829,3051,9909,34,44,703,248,1407,10,1,8591,113,2453,2600,5,466,945,798,1,2,460,2,2579,3550,3
878,421,2769,83,936,255,753,883,5450,14,2201,583,420,68,117,2,2,5,1209,1450,2,1,466,140,203,1937,3083,109,1,341,598,321,1295,
408,2,1168,238,3,897,1090,719,478,756,329,498,171,303,761,1105,1095,298,666,610,49,2,72,681,33,524,343,46,230,601,473,173,121
2,1252,5462973,859,5996732,2800420,882,444,3,1877,1,2562,1,748,141,795,563,1,4265,1,1,2,1331,4142,2609,155,17,13,72,139,4,2,2
0,2,169,13,19,46,5,39,96,548,29,2,2,1,2,1,2,2,7,4,1,2,2,2,2,2,2,353,513,186,1,1,158,3,2,2,2,2,2,4,2,3,3,269,1601,141,577,425,
32,19,29,1,74,21,2,23951801,4041689,3,450,1964,1008,483,9,1435,159,1358,4726,3,923,32,3,1215,489,1803,1532,2442,769966\',kB
L:\'skq8\'};google.sn=\'webhp\';google.kHL=\'en-IN\';})();(function(){\nvar f=this||self;var h,k=[];function l(a){for(var b;a
&&(!a.getAttribute||!(b=a.getAttribute("eid")));)a=a.parentNode;return b||h}function m(a){for(var b=null;a&&(!a.getAttribute|
|!(b=a.getAttribute("leid")));)a=a.parentNode;return b}\nfunction n(a,b,c,d,g){var e="";c||-1!==b.search("&ei=")||(e="&ei="+l
(d),-1===b.search("&lei=")&&(d=m(d))&&(e+="&lei="+d));d="";!c&&f._cshid&&-1===b.search("&cshid=")&&"slh"!==a&&(d="&cshid="+f.
_cshid);c=c||"/"+(g||"gen_204")+"?atyp=i&ct="+a+"&cad="+b+e+"&zx="+Date.now()+d;/^http:/i.test(c)&&"https:"===window.locatio
```

3)**Read from excel:**

import pandas as pd

data1=pd.read_excel(‘dow_jones_index.xlsx’)

print(data1)

Output:

	quarter	stock	date	open	high	low	close	volume
0	1	AA	1/7/2011	$15.82	$16.72	$15.78	$16.42	239655616
1	1	AA	1/14/2011	$16.71	$16.71	$15.64	$15.97	242963398
2	1	AA	1/21/2011	$16.19	$16.38	$15.60	$15.79	138428495
3	1	AA	1/28/2011	$15.87	$16.63	$15.82	$16.13	151379173
4	1	AA	2/4/2011	$16.18	$17.39	$16.18	$17.14	154387761
..	...	...	...	...	...	...	...	...
745	2	XOM	5/27/2011	$80.22	$82.63	$80.07	$82.63	68230855
746	2	XOM	6/3/2011	$83.28	$83.75	$80.18	$81.18	78616295
747	2	XOM	6/10/2011	$80.93	$81.87	$79.72	$79.78	92380844
748	2	XOM	6/17/2011	$80.00	$80.82	$78.33	$79.02	100521400
749	2	XOM	6/24/2011	$78.65	$81.12	$76.78	$76.78	118679791

Result:

Reading data using inbuilt packages have been done successfully and the results are verified.

Exp.No : 2 **Date:** 15/03/22

DESCRIPTIVE ANALYTICS

1)Aim:

To use Iris Dataset for exploring various commands for doing descriptive analytics

Code & Output:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
data = pd.read_csv("iris.csv")
data
```

Output:

Out[5]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 5 columns

```
data.info()
```

Output:

```
In [6]: data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 non-null    float64
 3   petal_width   150 non-null    float64
 4   species       150 non-null    object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

data.describe()

Output:

```
In [7]: data.describe()
```

Out[7]:

	sepal_length	sepal_width	petal_length	petal_width
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.054000	3.758667	1.198667
std	0.828066	0.433594	1.764420	0.763161
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

data[data.duplicated()]

Output:

```
In [8]: data[data.duplicated()]
```

Out[8]:

	sepal_length	sepal_width	petal_length	petal_width	species
34	4.9	3.1	1.5	0.1	Iris-setosa
37	4.9	3.1	1.5	0.1	Iris-setosa
142	5.8	2.7	5.1	1.9	Iris-virginica

data['species'].value_counts()

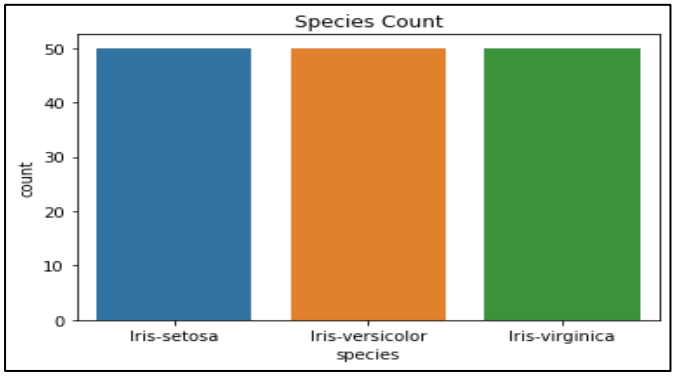
Output:

```
In [9]: data['species'].value_counts()
Out[9]: Iris-setosa        50
        Iris-versicolor    50
        Iris-virginica     50
        Name: species, dtype: int64
```

plt.title("Species Count")

sns.countplot(data['species'])

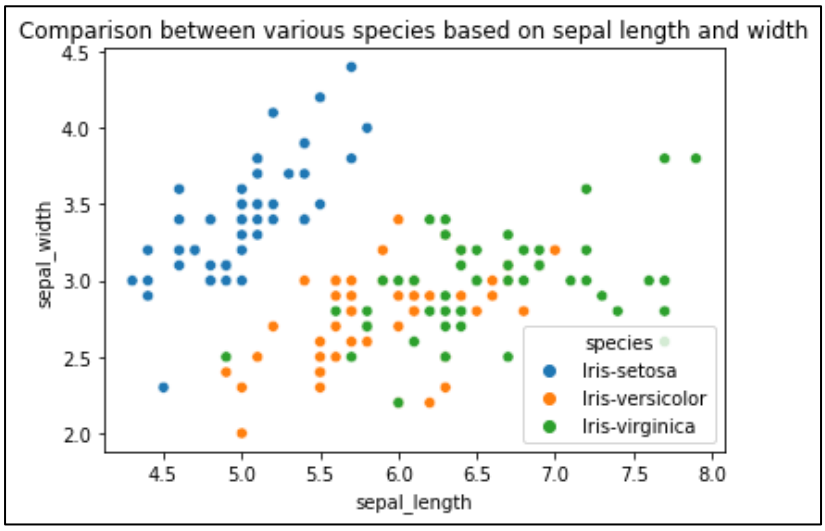
Output:



plt.title("Comparison between various species based on sepal length and width")

sns.scatterplot(data['sepal_length'],data['sepal_width'],hue=data['species'])

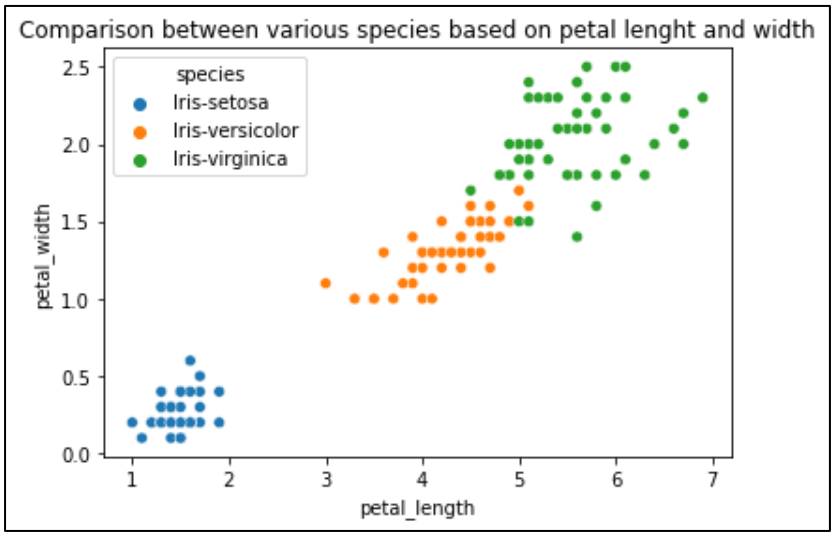
Output:



plt.title("Comparison between various species based on petal lenght and width")

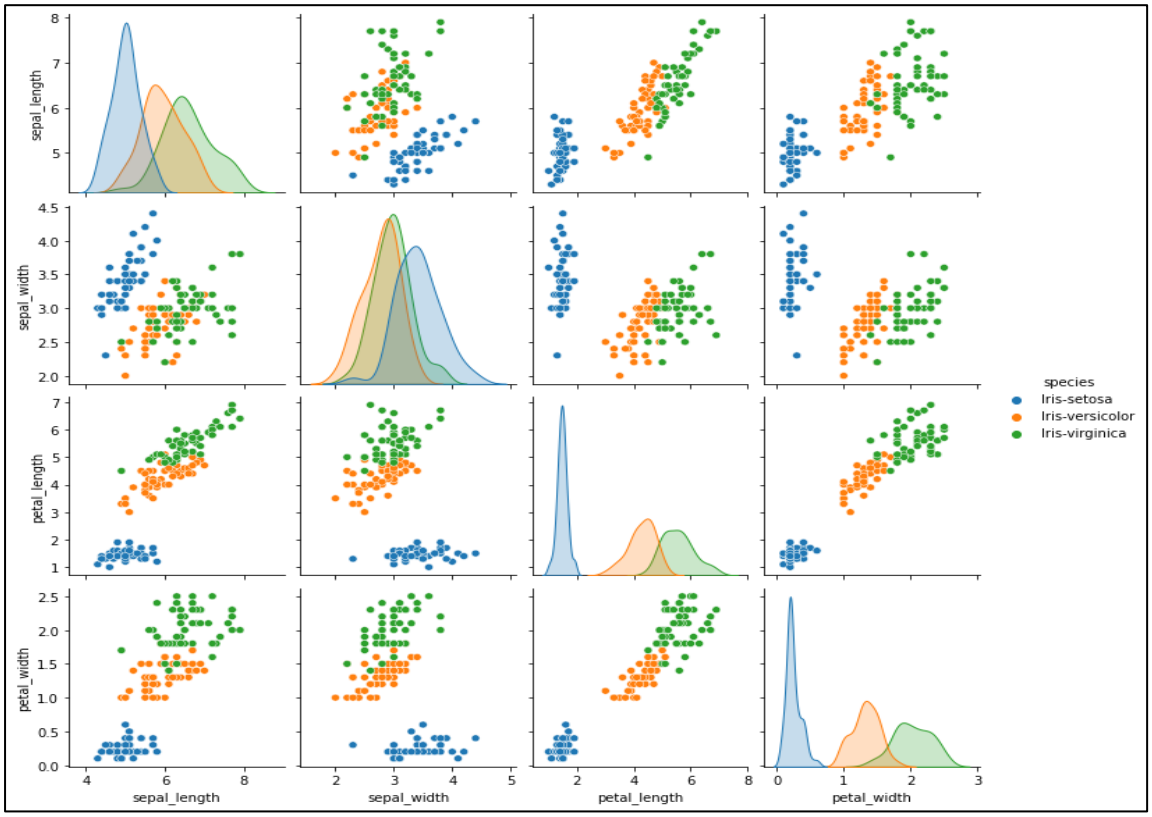
sns.scatterplot(data['petal_length'],data['petal_width'],hue=data['species'])

Output:



sns.pairplot(data,hue="species")

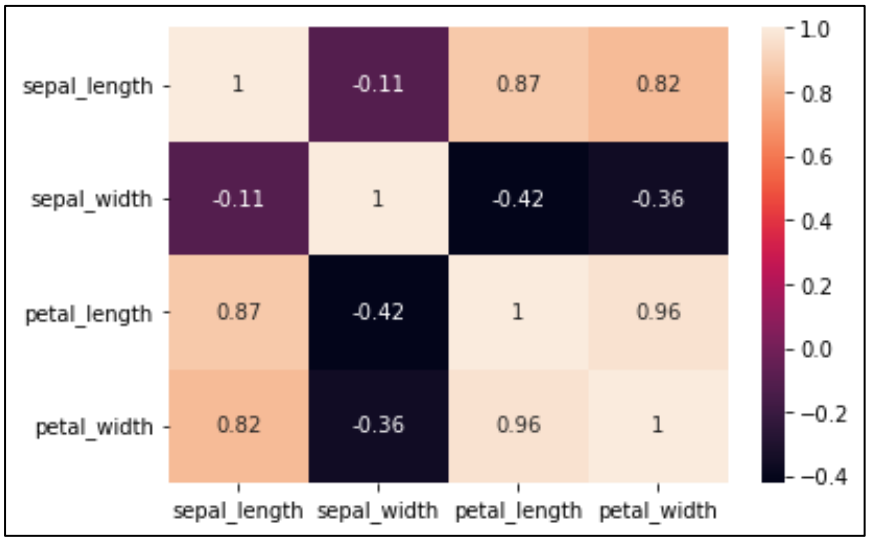
Output:



sns.heatmap(data.corr(),annot=True)

plt.plot()

Output:



data.groupby('species').agg(['mean','median'])

Output:

```
In [19]: data.groupby('species').agg(['mean','median'])
```

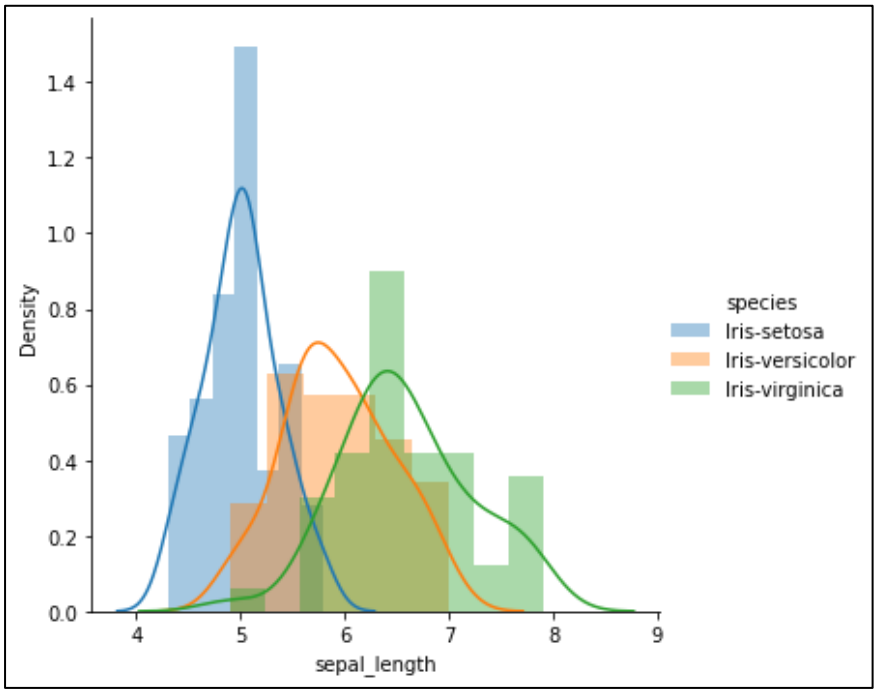
Out[19]:

	sepal_length		sepal_width		petal_length		petal_width	
	mean	median	mean	median	mean	median	mean	median
species								
Iris-setosa	5.006	5.0	3.418	3.4	1.464	1.50	0.244	0.2
Iris-versicolor	5.936	5.9	2.770	2.8	4.260	4.35	1.326	1.3
Iris-virginica	6.588	6.5	2.974	3.0	5.552	5.55	2.026	2.0

sns.FacetGrid(data, hue="species",height=5).map(sns.distplot, "sepal_length").add_legend()

plt.show()

Output:



Result:

Iris Dataset has been successfully used for exploring various commands to do descriptive analytics and the results are verified.

2)**Aim:**

To use personal (Dow Jones Index) dataset for exploring various commands for doing descriptive analytics

Code & Output:

```
import pandas as pd

import seaborn as sns

import numpy as np

import matplotlib.pyplot as plt


data=pd.read_csv("dow_jones_index.csv")

data
```

Output:

Out[2]:

	quarter	stock	date	open	high	low	close	volume	percent_change_price	percent_change_volume_over_last_wk	pr
0	1	AA	1/7/2011	$15.82	$16.72	$15.78	$16.42	239655616	3.79267	NaN	
1	1	AA	1/14/2011	$16.71	$16.71	$15.64	$15.97	242963398	-4.42849	1.380223	
2	1	AA	1/21/2011	$16.19	$16.38	$15.60	$15.79	138428495	-2.47066	-43.024959	
3	1	AA	1/28/2011	$15.87	$16.63	$15.82	$16.13	151379173	1.63831	9.355500	
4	1	AA	2/4/2011	$16.18	$17.39	$16.18	$17.14	154387761	5.93325	1.987452	
...	...	...	...	...	...	...	...	...	...	...	
745	2	XOM	5/27/2011	$80.22	$82.63	$80.07	$82.63	68230855	3.00424	-21.355713	
746	2	XOM	6/3/2011	$83.28	$83.75	$80.18	$81.18	78616295	-2.52161	15.221032	
747	2	XOM	6/10/2011	$80.93	$81.87	$79.72	$79.78	92380844	-1.42098	17.508519	
748	2	XOM	6/17/2011	$80.00	$80.82	$78.33	$79.02	100521400	-1.22500	8.811952	
749	2	XOM	6/24/2011	$78.65	$81.12	$76.78	$76.78	118679791	-2.37762	18.064204	

```
data['high'] = data['high'].str.replace('$', '')

data['open'] = data['open'].str.replace('$', '')

data['low'] = data['low'].str.replace('$', '')

data['close'] = data['close'].str.replace('$', '')

data['next_weeks_open'] = data['next_weeks_open'].str.replace('$', '')

data['next_weeks_close'] = data['next_weeks_close'].str.replace('$', '')

data
```

Output:

	quarter	stock	date	open	high	low	close	volume	percent_change_price	percent_change_volume_over_last_wk	previous_weeks_volume	
0	1	AA	1/7/2011	15.82	16.72	15.78	16.42	239655616	3.79267	NaN	NaN	
1	1	AA	1/14/2011	16.71	16.71	15.64	15.97	242963398	-4.42849	1.380223	239655616.0	
2	1	AA	1/21/2011	16.19	16.38	15.60	15.79	138428495	-2.47066	-43.024959	242963398.0	
3	1	AA	1/28/2011	15.87	16.63	15.82	16.13	151379173	1.63831	9.355500	138428495.0	
4	1	AA	2/4/2011	16.18	17.39	16.18	17.14	154387761	5.93325	1.987452	151379173.0	
...	...	...	...	...	...	...	...	...	...	...	...	
745	2	XOM	5/27/2011	80.22	82.63	80.07	82.63	68230855	3.00424	-21.355713	86758820.0	
746	2	XOM	6/3/2011	83.28	83.75	80.18	81.18	78616295	-2.52161	15.221032	68230855.0	
747	2	XOM	6/10/2011	80.93	81.87	79.72	79.78	92380844	-1.42098	17.508519	78616295.0	
748	2	XOM	6/17/2011	80.00	80.82	78.33	79.02	100521400	-1.22500	8.811952	92380844.0	
749	2	XOM	6/24/2011	78.65	81.12	76.78	76.78	118679791	-2.37762	18.064204	100521400.0	

data.info()

Output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 750 entries, 0 to 749
Data columns (total 16 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   quarter                           750 non-null    int64
 1   stock                             750 non-null    object
 2   date                              750 non-null    object
 3   open                              750 non-null    object
 4   high                              750 non-null    object
 5   low                               750 non-null    object
 6   close                             750 non-null    object
 7   volume                            750 non-null    int64
 8   percent_change_price              750 non-null    float64
 9   percent_change_volume_over_last_wk  720 non-null    float64
 10  previous_weeks_volume             720 non-null    float64
 11  next_weeks_open                   750 non-null    object
 12  next_weeks_close                  750 non-null    object
 13  percent_change_next_weeks_price   750 non-null    float64
 14  days_to_next_dividend             750 non-null    int64
 15  percent_return_next_dividend      750 non-null    float64
dtypes: float64(5), int64(3), object(8)
memory usage: 93.9+ KB
```

data.shape

Output:

```
In [5]: data.shape
Out[5]: (750, 16)
```

data.describe()

Output:

```
In [6]: data.describe()
```

Out[6]:

	quarter	volume	percent_change_price	percent_change_volume_over_last_wk	previous_weeks_volume	percent_change_next_weeks_price
count	750.000000	7.500000e+02	750.000000	720.000000	7.200000e+02	750.000000
mean	1.520000	1.175478e+08	0.050262	5.593627	1.173876e+08	0.238468
std	0.499933	1.584381e+08	2.517809	40.543478	1.592322e+08	2.679538
min	1.000000	9.718851e+06	-15.422900	-61.433175	9.718851e+06	-15.422900
25%	1.000000	3.086624e+07	-1.288053	-19.804284	3.067832e+07	-1.222068
50%	2.000000	5.306088e+07	0.000000	0.512586	5.294556e+07	0.101193
75%	2.000000	1.327218e+08	1.650888	21.800622	1.333230e+08	1.845562
max	2.000000	1.453439e+09	9.882230	327.408924	1.453439e+09	9.882230

data['stock'].value_counts()

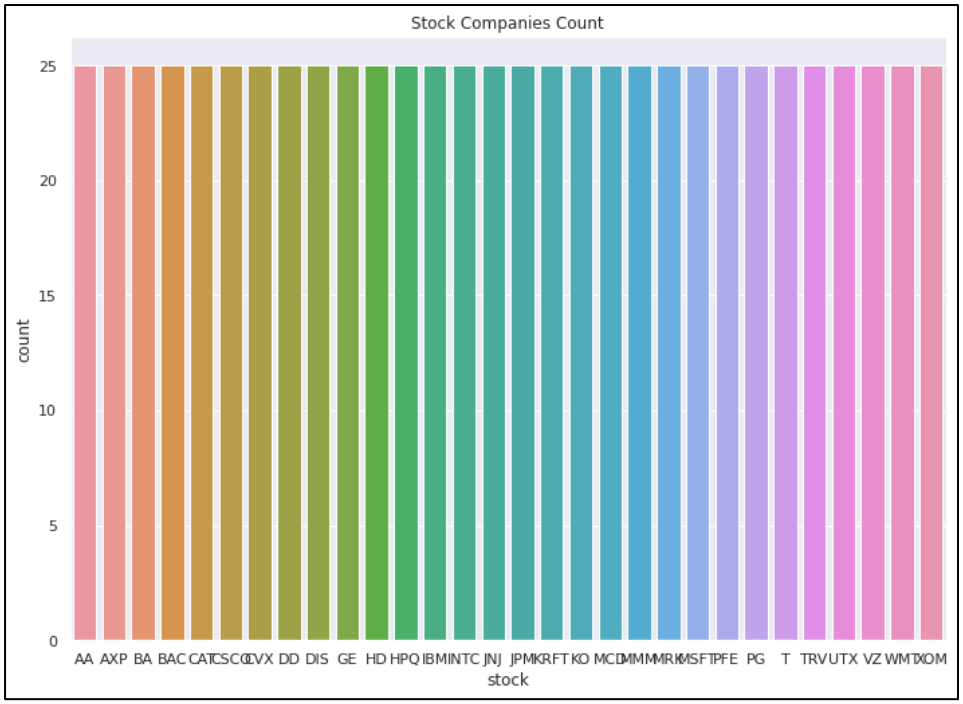
Output:

```
In [12]: data['stock'].value_counts()
Out[12]: AA      25
         AXP     25
         WMT     25
         VZ      25
         UTX     25
         TRV     25
         T       25
         PG      25
         PFE     25
         MSFT    25
         MRK     25
         MMM     25
         MCD     25
         KO      25
         KRFT    25
         JPM     25
         JNJ     25
         INTC    25
         IBM     25
         HPQ     25
         HD      25
         GE      25
         DIS     25
         DD      25
         CVX     25
         CSCO    25
         CAT     25
         BAC     25
         BA      25
         XOM     25
         Name: stock, dtype: int64
```

plt.title('Stock Companies Count')

sns.countplot(data['stock'])

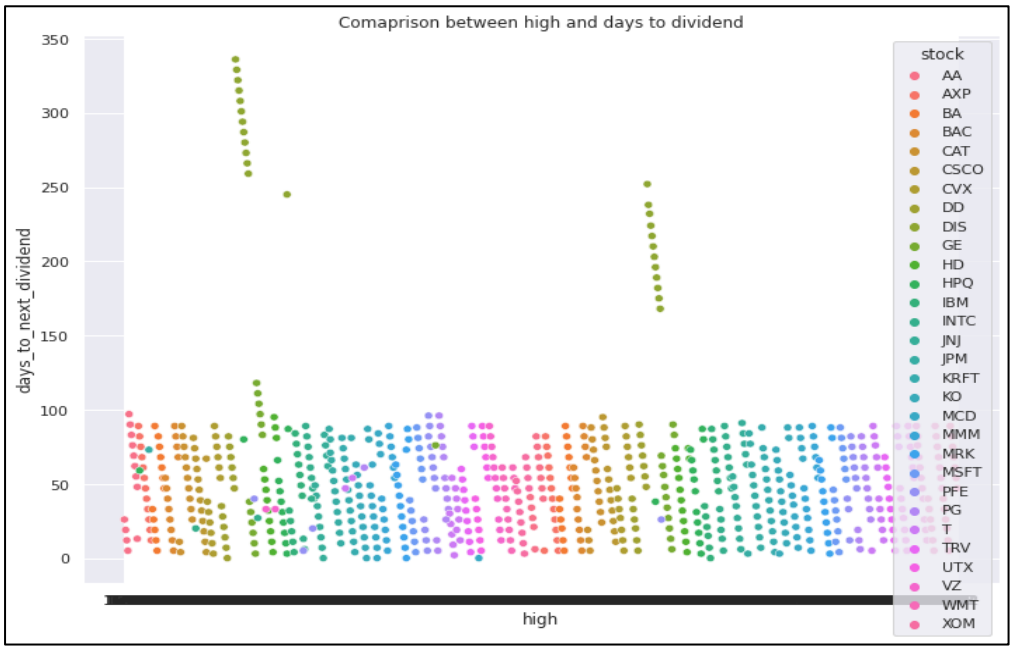
Output:



plt.title("Comaprison between high and days to dividend")

sns.scatterplot(data['high'],data['days_to_next_dividend'],hue=data['stock'])

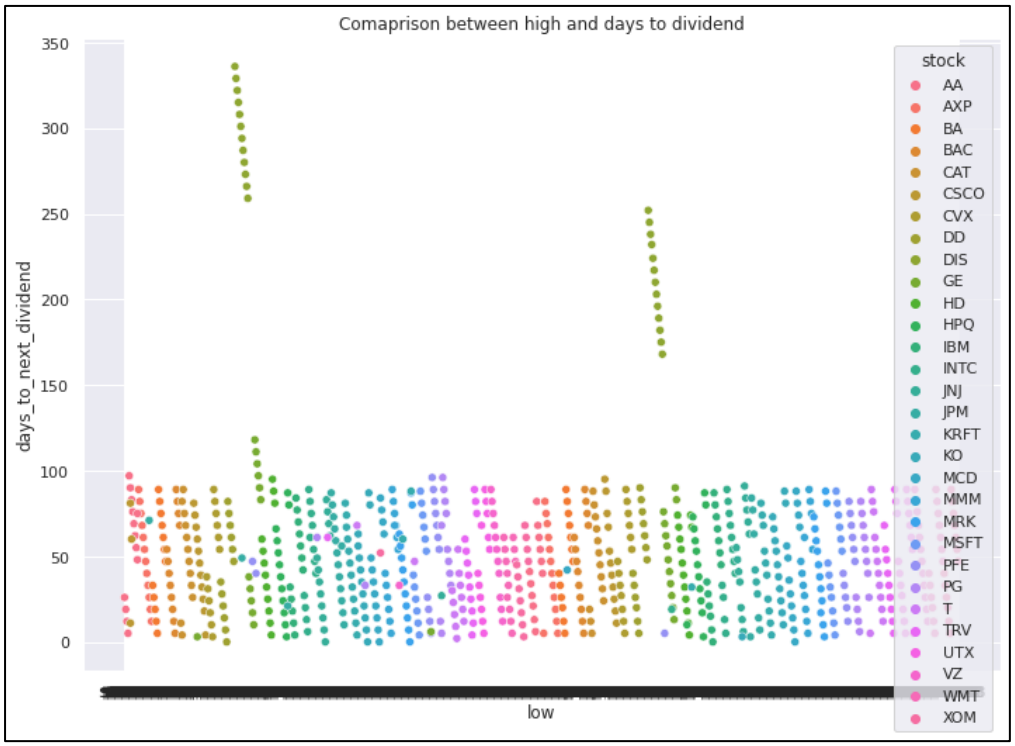
Output:



plt.title("Comaprison between high and days to dividend")

sns.scatterplot(data['low'],data['days_to_next_dividend'],hue=data['stock'])

Output:



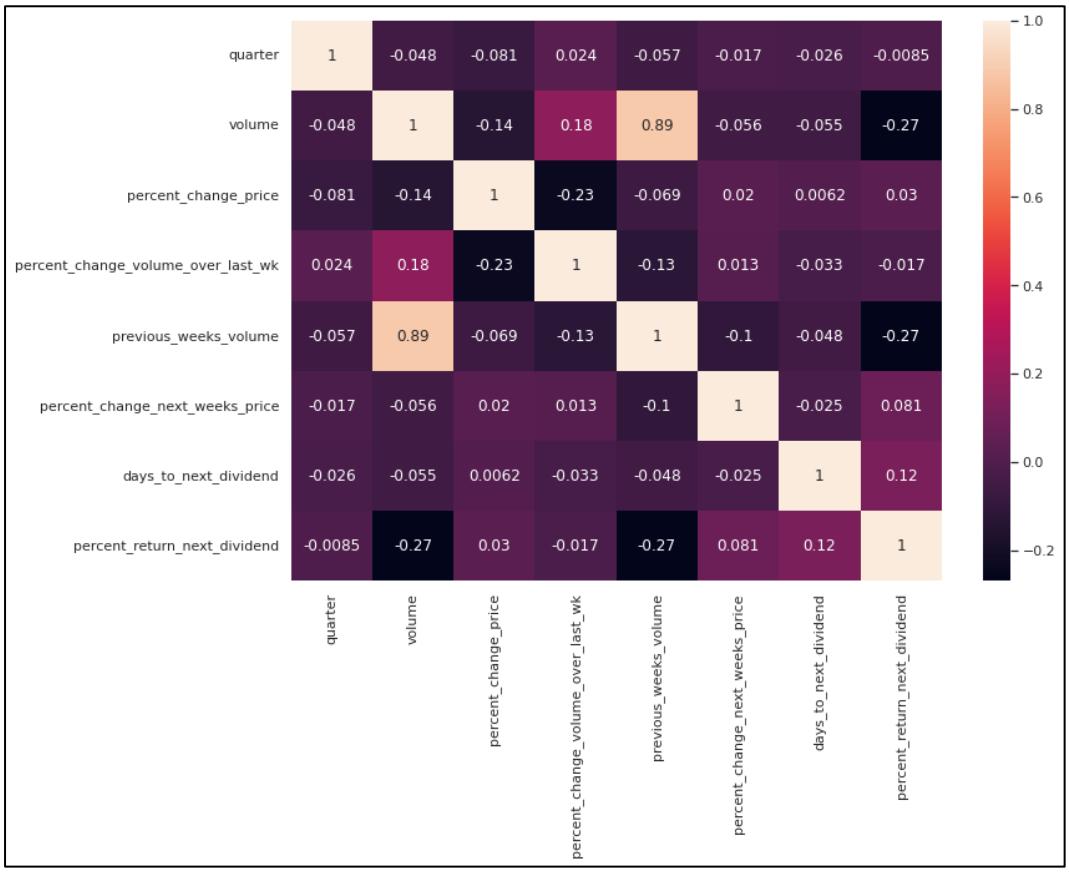
sns.pairplot(data,hue="stock")

Output:

sns.heatmap(data.corr(),annot=True)

plt.plot()

Output:



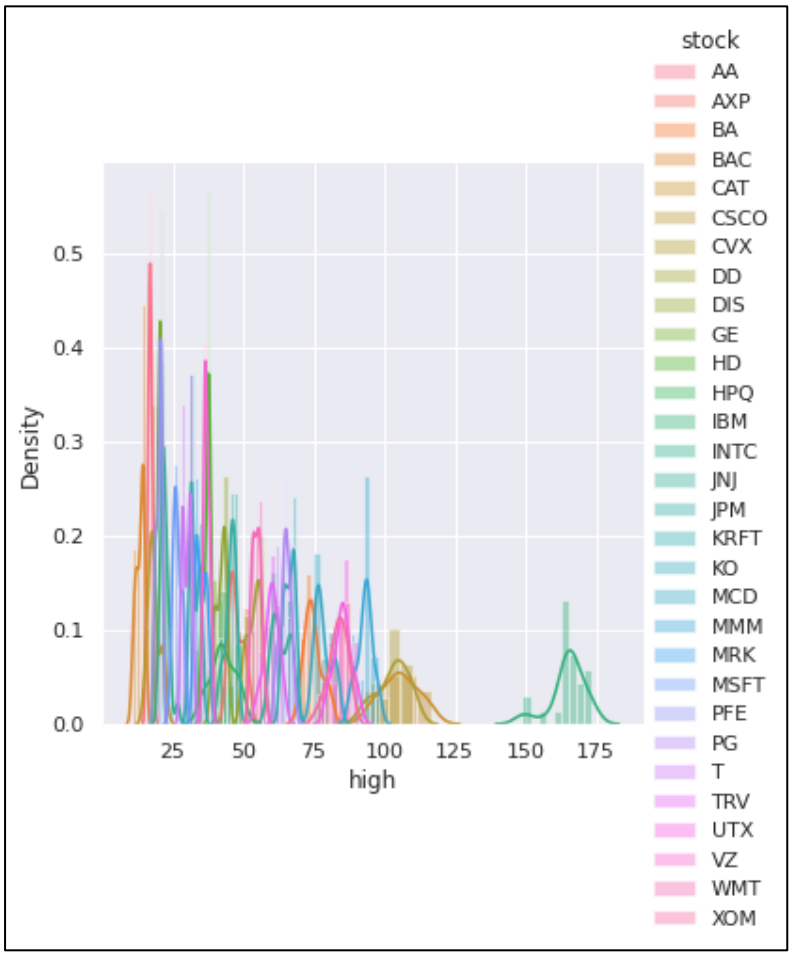
data.groupby('stock').agg(['mean','median'])

Output:

	quarter		volume		percent_change_price		percent_change_volume_over_last_wk		previous_weeks_volume		percent_change_next
	mean	median	mean	median	mean	median	mean	median	mean	median	mean
stock											
AA	1.52	2.0	1.296388e+08	114332562.0	-0.302084	-0.349650	4.032988	3.203676	1.308978e+08	114511920.5	-0.167325
AXP	1.52	2.0	3.520848e+07	35427164.0	0.521029	0.706794	2.149548	-2.602828	3.522226e+07	35996388.0	0.740698
BA	1.52	2.0	2.378142e+07	22770062.0	0.253427	0.122649	3.571908	-0.580803	2.349417e+07	22289736.5	0.216568
BAC	1.52	2.0	7.229991e+08	699671790.0	-0.976965	-1.051160	-0.143670	-1.505000	7.279950e+08	706064273.5	-0.875759
CAT	1.52	2.0	3.373112e+07	31169285.0	0.152660	0.311526	6.578793	6.373469	3.331479e+07	30933587.0	0.526747
CSCO	1.52	2.0	3.586616e+08	308644641.0	-1.178297	-0.480513	16.967192	4.468062	3.557004e+08	306095259.5	-1.033689
CVX	1.52	2.0	3.857983e+07	39606692.0	0.340060	0.903809	6.117655	-4.519508	3.841169e+07	39222643.5	0.611745
DD	1.52	2.0	2.911666e+07	27511651.0	0.362452	-0.180180	4.989947	-0.076329	2.887994e+07	27505269.0	0.587751
DIS	1.52	2.0	4.744367e+07	42131642.0	0.175203	0.280177	6.859223	7.773932	4.732010e+07	41680515.0	0.217249
GE	1.52	2.0	2.639381e+08	246591055.0	-0.240471	-0.287356	6.513043	-1.148899	2.626030e+08	242604845.5	0.039176
HD	1.52	2.0	4.820505e+07	47021433.0	0.108416	0.216626	6.970308	-8.902819	4.748789e+07	46314048.0	0.395717
HPQ	1.52	2.0	9.485843e+07	84066350.0	-0.472149	0.024207	18.604938	-10.509219	9.452860e+07	83344901.5	-0.515813
IBM	1.52	2.0	2.473918e+07	23505533.0	0.587680	0.489097	5.512527	1.683035	2.481229e+07	23584077.0	0.780497
INTC	1.52	2.0	2.990224e+08	289874871.0	0.188712	-0.410023	2.555824	5.484880	2.986054e+08	288109410.5	0.512314
JNJ	1.52	2.0	5.600611e+07	53844149.0	0.270470	0.333991	3.465652	-2.778951	5.598406e+07	53614623.0	0.401220
JPM	1.52	2.0	1.511090e+08	140414285.0	-0.070105	0.372353	2.027203	0.314943	1.504223e+08	139977205.0	0.091680
KO	1.52	2.0	3.855617e+07	34863226.0	0.081142	0.293686	6.647356	4.548834	3.808740e+07	34405394.0	0.460708

```
sns.FacetGrid(data,hue='stock',height=5).map(sns.distplot,'high').add_legend()
plt.show()
```

Output:



Result:

Dow Jones Index Dataset has been successfully used for exploring various commands to do descriptive analytics and the results are verified.

3)**Aim:**

To use personal (Dow Jones Index) dataset and do the following :

a)Find correlation between features and visualize it b)Fill missing data c) Data Partitioning

d) Perform statistical tests for the dataset

- Normality test
- Corelation test
- Parametric statistical Hypothesis test
- Nonparametric statistical Hypothesis test

Code & Output:

```
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt

data=pd.read_csv("dow_jones_index.csv")
#data partitioning
data['high'] = data['high'].str.replace('$', '')
data['open'] = data['open'].str.replace('$', '')
data['low'] = data['low'].str.replace('$', '')
data['close'] = data['close'].str.replace('$', '')
data['next_weeks_open'] = data['next_weeks_open'].str.replace('$', '')
data['next_weeks_close'] = data['next_weeks_close'].str.replace('$', '')

data['high']=pd.to_numeric(data['high'])
data['open']=pd.to_numeric(data['open'])
data['low']=pd.to_numeric(data['low'])
data['close']=pd.to_numeric(data['close'])
data['next_weeks_open']=pd.to_numeric(data['next_weeks_open'])
data['next_weeks_close']=pd.to_numeric(data['next_weeks_close'])
```

#fill missing data

data['percent_change_volume_over_last_wk'].fillna(value=0,inplace=True)

data['previous_weeks_volume'].fillna(value=0,inplace=True)

data

Output:

In [6]: data

Out[6]:

	quarter	stock	date	open	high	low	close	volume	percent_change_price	percent_change_volume_over_last_wk	previous_weeks_volume	ne
0	1	AA	1/7/2011	15.82	16.72	15.78	16.42	239655616	3.79267	0.000000	0.0	
1	1	AA	1/14/2011	16.71	16.71	15.64	15.97	242963398	-4.42849	1.380223	239655616.0	
2	1	AA	1/21/2011	16.19	16.38	15.60	15.79	138428495	-2.47066	-43.024959	242963398.0	
3	1	AA	1/28/2011	15.87	16.63	15.82	16.13	151379173	1.63831	9.355500	138428495.0	
4	1	AA	2/4/2011	16.18	17.39	16.18	17.14	154387761	5.93325	1.987452	151379173.0	
...	...	...	...	...	...	...	...	...	...	...	...	
745	2	XOM	5/27/2011	80.22	82.63	80.07	82.63	68230855	3.00424	-21.355713	86758820.0	
746	2	XOM	6/3/2011	83.28	83.75	80.18	81.18	78616295	-2.52161	15.221032	68230855.0	
747	2	XOM	6/10/2011	80.93	81.87	79.72	79.78	92380844	-1.42098	17.508519	78616295.0	
748	2	XOM	6/17/2011	80.00	80.82	78.33	79.02	100521400	-1.22500	8.811952	92380844.0	
749	2	XOM	6/24/2011	78.65	81.12	76.78	76.78	118679791	-2.37762	18.064204	100521400.0	

750 rows × 16 columns

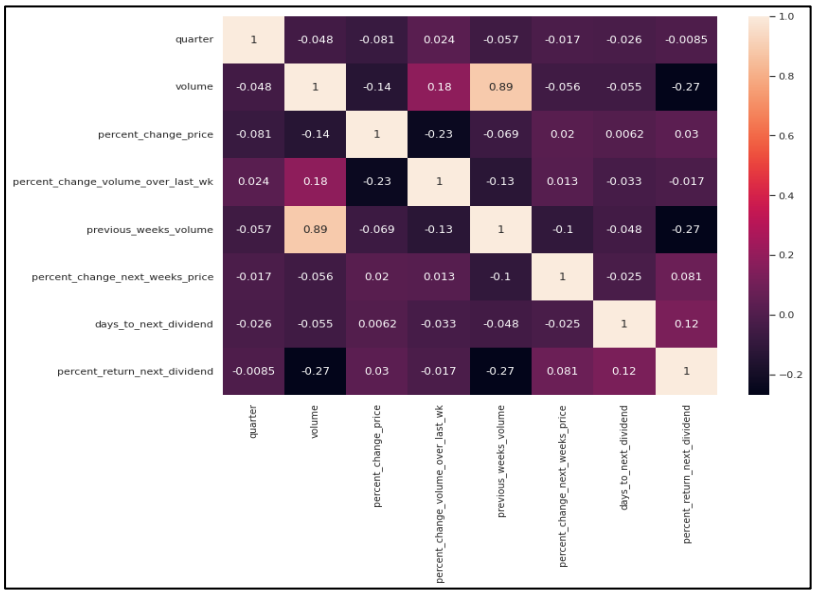
previous_weeks_volume	next_weeks_open	next_weeks_close	percent_change_next_weeks_price	days_to_next_dividend	percent_return_next_dividend
0.0	16.71	15.97	-4.428490	26	0.182704
239655616.0	16.19	15.79	-2.470660	19	0.187852
242963398.0	15.87	16.13	1.638310	12	0.189994
138428495.0	16.18	17.14	5.933250	5	0.185989
151379173.0	17.33	17.37	0.230814	97	0.175029
...	...	...	...	...	...
86758820.0	83.28	81.18	-2.521610	75	0.568801
68230855.0	80.93	79.78	-1.420980	68	0.578960
78616295.0	80.00	79.02	-1.225000	61	0.589120
92380844.0	78.65	76.78	-2.377620	54	0.594786
100521400.0	76.88	82.01	6.672740	47	0.612139

#corelation

sns.heatmap(data.corr(),annot=True)

plt.plot()

Output:



#normality test

```
from scipy import stats
z=[data['high'],data['low']]
for i in z:
    print([i])
    a,b=stats.normaltest(data['high'])
    print(a,b)
    alpha = 0.05
    if b<alpha :
        print('null hypothesis rejected')
    else:
        print('null hypothesis cannot be rejected')
```

Output:

```
[0      16.72
1      16.71
2      16.38
3      16.63
4      17.39
       ...
745    82.63
746    83.75
747    81.87
748    80.82
749    81.12
Name: high, Length: 750, dtype: float64]
165.8155807197986 9.85380899939066e-37
null hypothesis rejected
[0      15.78
1      15.64
2      15.60
3      15.82
4      16.18
       ...
745    80.07
746    80.18
747    79.72
748    78.33
749    76.78
Name: low, Length: 750, dtype: float64]
165.8155807197986 9.85380899939066e-37
null hypothesis rejected
```

#correlation test

```
from scipy.stats import pearsonr
data['high']= pd.to_numeric(data['high'])
data['low']= pd.to_numeric(data['low'])
list1 = data['high']
```

```
list2 = data['low']
corr,_= pearsonr(list1, list2)
print('Pearsons correlation: %.3f'% corr)
```

Output:

```
Pearsons correlation: 0.999
```

#Parametric statistical Hypothesis test

```
from scipy.stats import ttest_ind
z=[data['high'],data['low']]
for i in z:
    print([i])
    a,b=ttest_ind(data['high'],data['low'])
    print(a,b)
    alpha = 0.05
    if b>alpha :
        print('Same distributions')
    else:
        print('Different distributions')
```

Output:

```
[0      16.72
1      16.71
2      16.38
3      16.63
4      17.39
       ...
745    82.63
746    83.75
747    81.87
748    80.82
749    81.12
Name: high, Length: 750, dtype: float64]
1.2030833315757794 0.22913417910648973
Same distributions
[0      15.78
1      15.64
2      15.60
3      15.82
4      16.18
       ...
745    80.07
746    80.18
747    79.72
748    78.33
749    76.78
Name: low, Length: 750, dtype: float64]
1.2030833315757794 0.22913417910648973
Same distributions
```

#Non Parametric statistical Hypothesis test

```
from scipy.stats import mannwhitneyu
z=[data['high'],data['low']]
for i in z:
    print([i])
    a,b=mannwhitneyu(data['high'],data['low'])
    print(a,b)
    alpha = 0.05
    if b>alpha :
        print('Same distributions')
    else:
        print('Different distributions')
```

Output:

```
[0      16.72
1      16.71
2      16.38
3      16.63
4      17.39
       ...
745    82.63
746    83.75
747    81.87
748    80.82
749    81.12
Name: high, Length: 750, dtype: float64]
292745.5 0.17056138472040383
Same distributions
[0      15.78
1      15.64
2      15.60
3      15.82
4      16.18
       ...
745    80.07
746    80.18
747    79.72
748    78.33
749    76.78
Name: low, Length: 750, dtype: float64]
292745.5 0.17056138472040383
Same distributions
```

Result:

Dow Jones Index Dataset has been successfully used for exploring various commands to do descriptive analytics and the results are verified.

Exp.No : 2A **Date:**22/03/22

UNIVARIATE ANALYSIS

1)Aim:

To use the diabetes data set from UCI and Pima Indians Diabetes data set and perform the following: Univariate analysis,Frequency, Mean, Median, Mode, Variance, Standard Deviation, Skewness and Kurtosis.

Code & Output:

```
import pandas as pd

import numpy as np

import seaborn as sns

import matplotlib.pyplot as plt

data = pd.read_csv("diabetes.csv")

data
```

Output:

```
In [3]: data = pd.read_csv("diabetes.csv")
        data
```

Out[3]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
...	...	...	...	...	...	...	...	...	...
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

768 rows × 9 columns

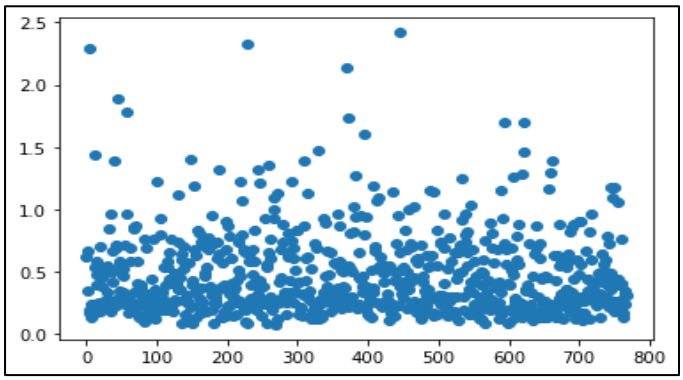
data.dtypes

Output:

```
In [5]: data.dtypes

Out[5]: Pregnancies                 int64
        Glucose                     int64
        BloodPressure               int64
        SkinThickness               int64
        Insulin                     int64
        BMI                       float64
        DiabetesPedigreeFunction  float64
        Age                         int64
        Outcome                     int64
        dtype: object
```

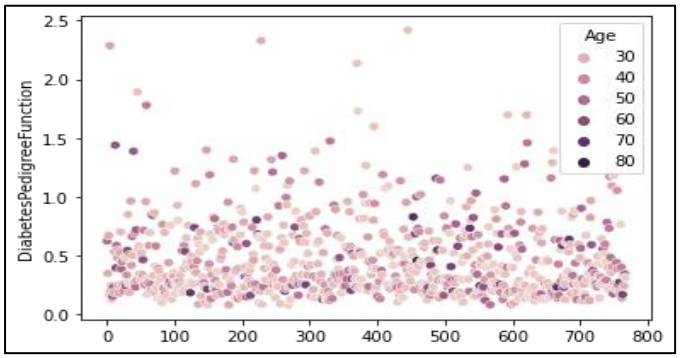
```
plt.scatter(data.index,data['DiabetesPedigreeFunction'])
plt.show()
```

Output:



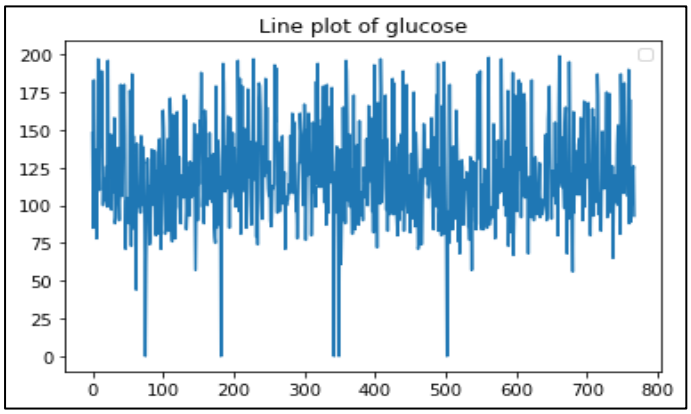

```
sns.scatterplot(x=data.index,y=data['DiabetesPedigreeFunction'],hue=data['Age'])
```

Output:



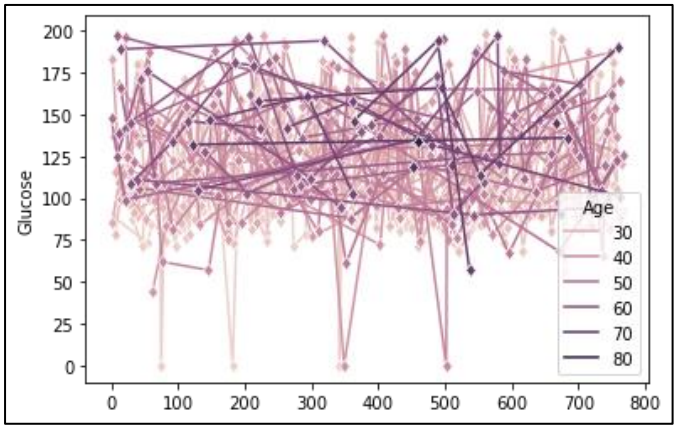

```
plt.title('Line plot of glucose')
plt.plot(data.index,data['Glucose'])
plt.legend()
plt.show()
```

Output:



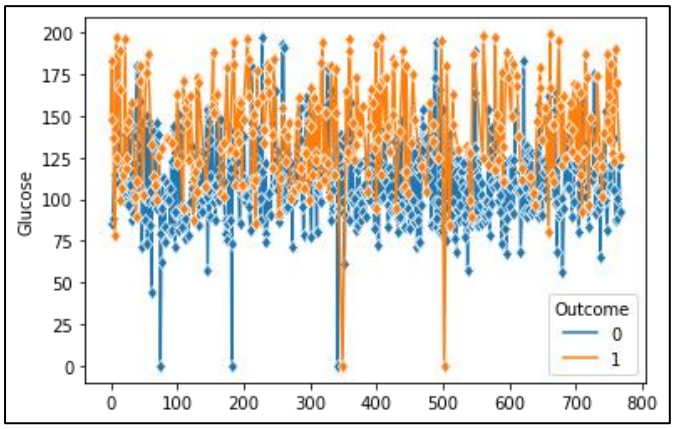
fig=sns.lineplot(x=data.index,y=data['Glucose'],markevery=1,marker='d',data=data,hue=data['Age'])

Output:



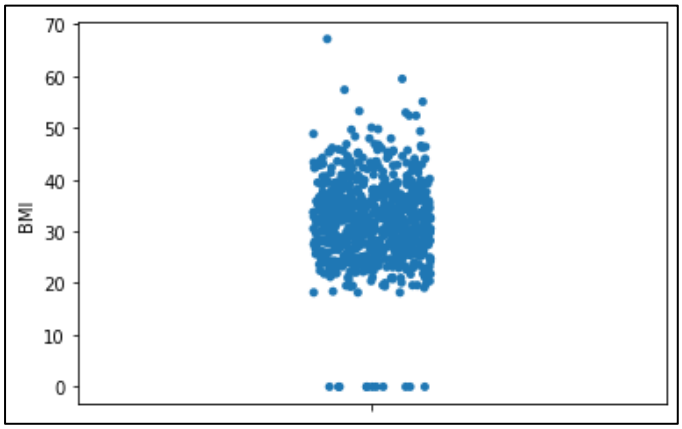
fig=sns.lineplot(x=data.index,y=data['Glucose'],markevery=1,marker='d',data=data,hue=data['Outcome'])

Output:



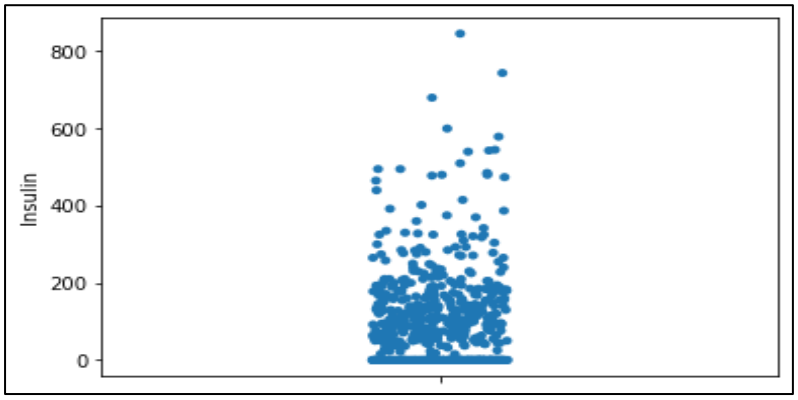
sns.stripplot(y=data['BMI'])

Output:



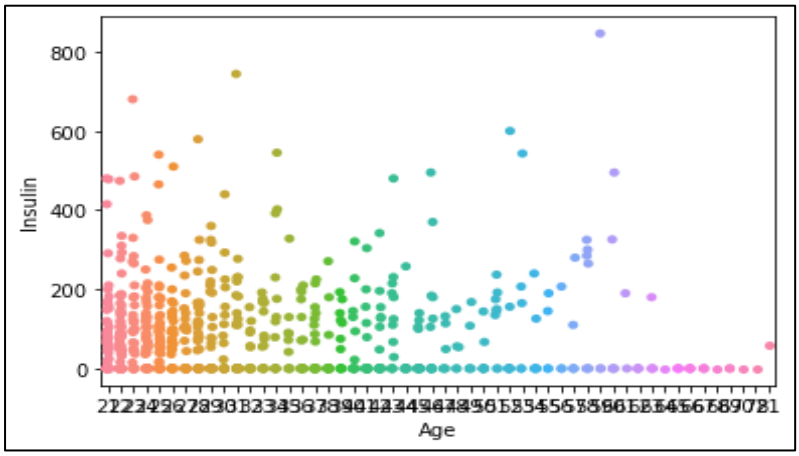
sns.stripplot(y=data['Insulin'])

Output:



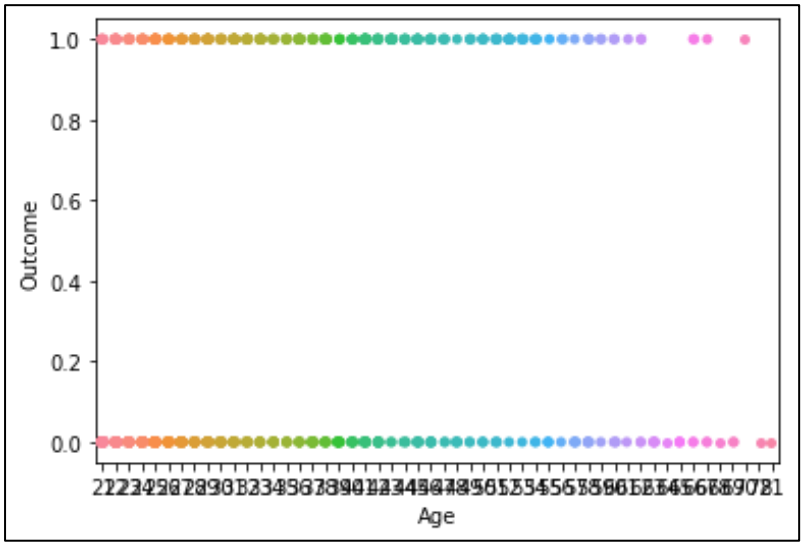
sns.stripplot(x=data['Age'],y=data['Insulin'])

Output:



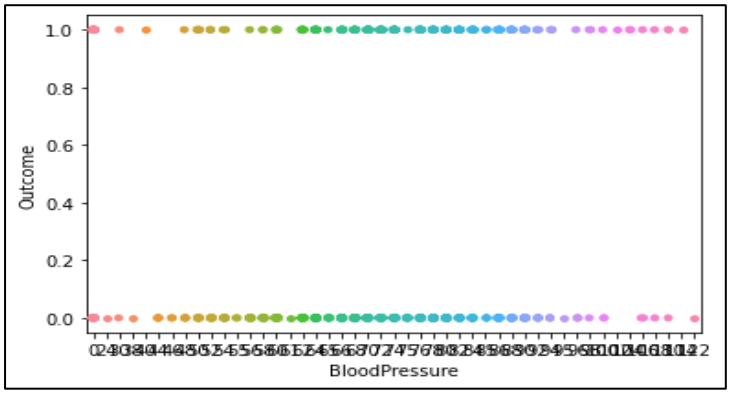
sns.stripplot(x=data['Age'],y=data['Outcome'])

Output:



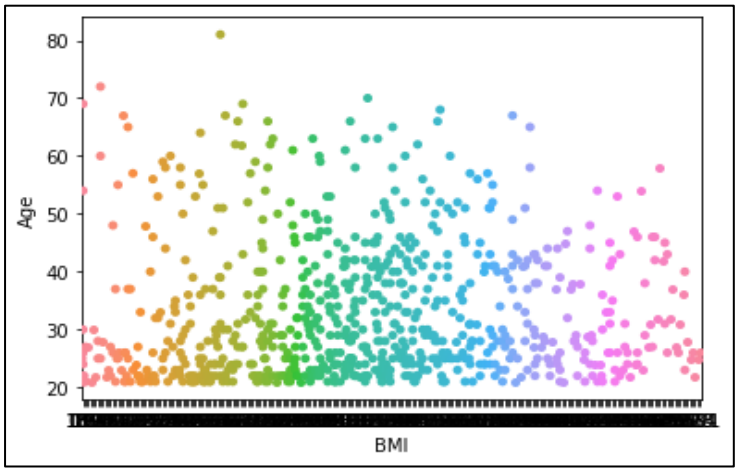
sns.stripplot(x=data['BloodPressure'],y=data['Outcome'])

Output:



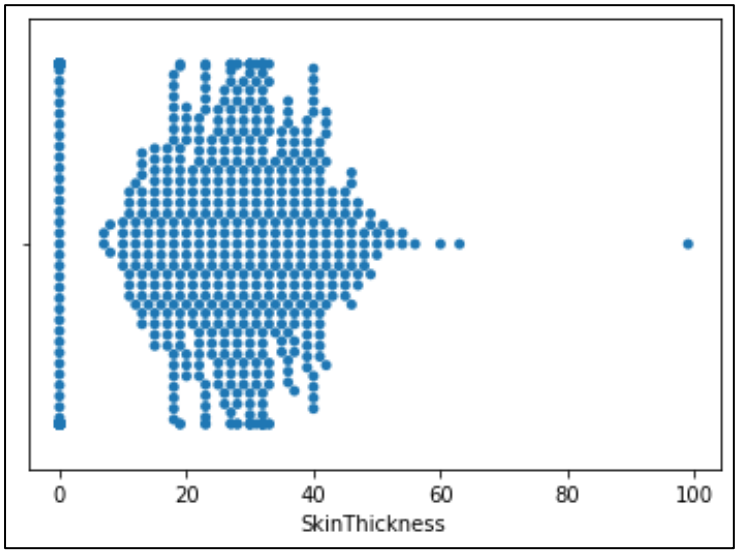
sns.swarmplot(x=data['BMI'],y=data['Age'])

Output:



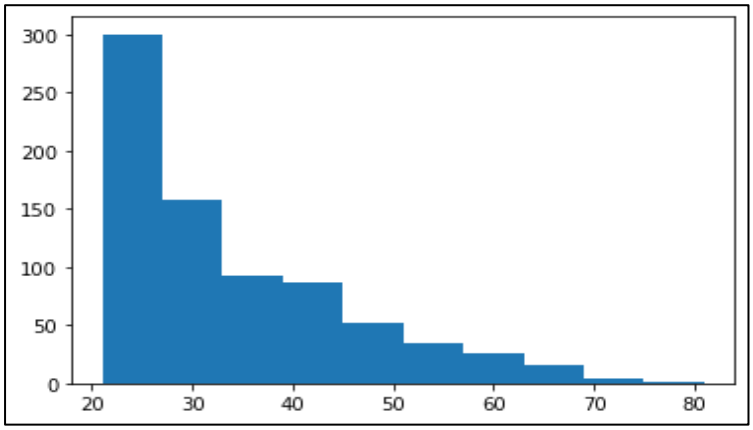
sns.swarmplot(x=data['SkinThickness'])

Output:



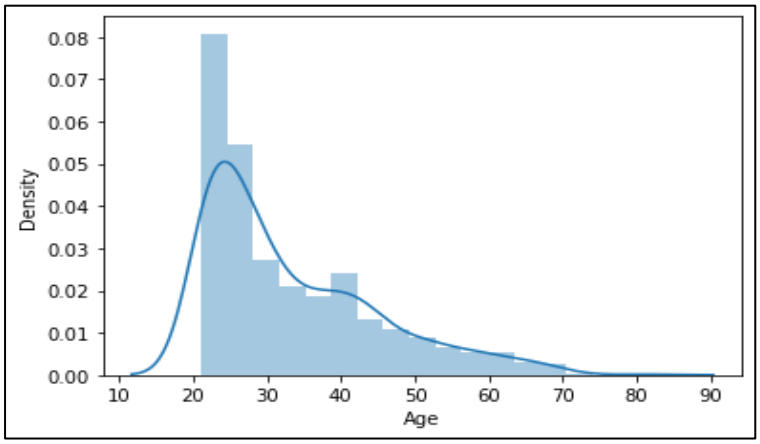
plt.hist(data['Age'])

Output:



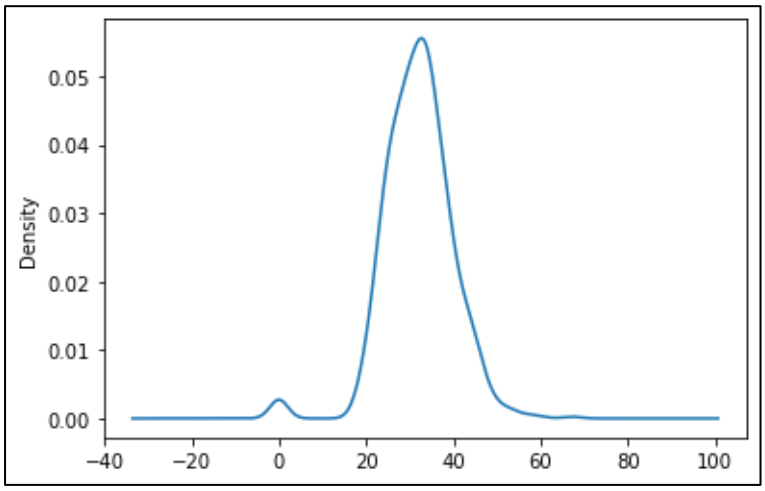
sns.distplot(data['Age'])

Output:



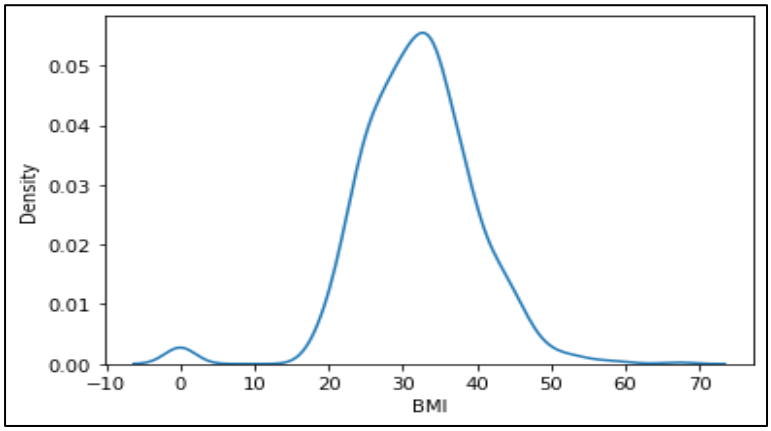
data['BMI'].plot(kind='density')

Output:



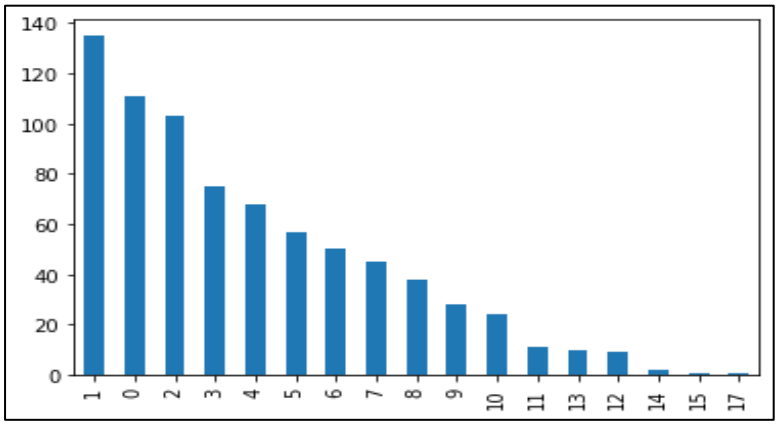
sns.kdeplot(data['BMI'])

Output:



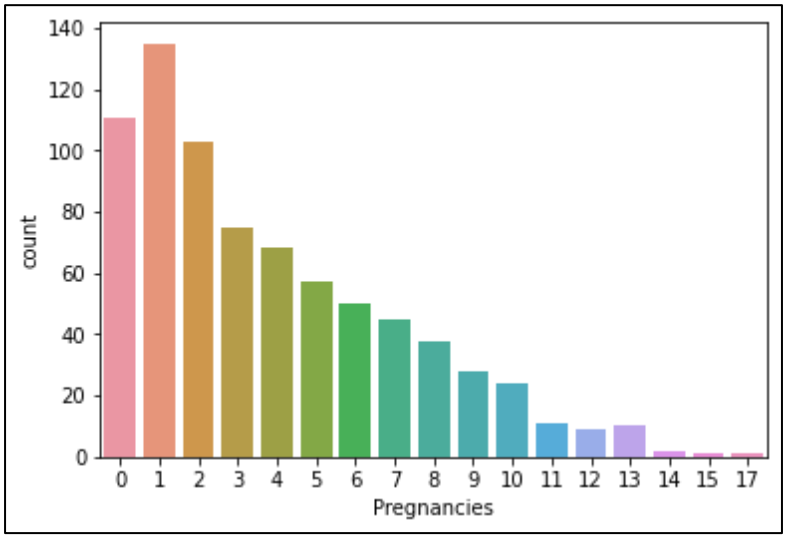
data['Pregnancies'].value_counts().plot.bar()

Output:



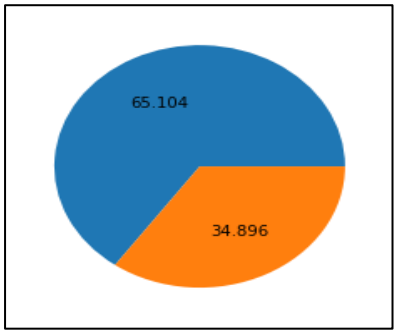
sns.countplot(data['Pregnancies'])

Output:



plt.pie(data['Outcome'].value_counts(),autopct='%.3f')

Output:



data['BMI'].mean()

Output:

```
In [32]: data['BMI'].mean()
Out[32]: 31.992578124999977
```

data['BMI'].mode()

Output:

```
In [33]: data['BMI'].mode()
Out[33]: 0    32.0
         Name: BMI, dtype: float64
```

data['BMI'].median()

Output:

```
In [34]: data['BMI'].median()
Out[34]: 32.0
```

data.mean()

Output:

```
In [35]: data.mean()
Out[35]: Pregnancies                 3.845052
         Glucose                   120.894531
         BloodPressure              69.105469
         SkinThickness              20.536458
         Insulin                    79.799479
         BMI                        31.992578
         DiabetesPedigreeFunction    0.471876
         Age                        33.240885
         Outcome                     0.348958
         dtype: float64
```

data.mode()

Output:

```
In [36]: data.mode()
```

Out[36]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	1.0	99	70.0	0.0	0.0	32.0	0.254	22.0	0.0
1	NaN	100	NaN	NaN	NaN	NaN	0.258	NaN	NaN

data.median()

Output:

```
In [37]: data.median()

Out[37]: Pregnancies                 3.0000
         Glucose                   117.0000
         BloodPressure              72.0000
         SkinThickness              23.0000
         Insulin                    30.5000
         BMI                        32.0000
         DiabetesPedigreeFunction    0.3725
         Age                        29.0000
         Outcome                     0.0000
         dtype: float64
```

data.var()

Output:

```
In [38]: data.var()

Out[38]: Pregnancies                 11.354056
         Glucose                   1022.248314
         BloodPressure              374.647271
         SkinThickness              254.473245
         Insulin                  13281.180078
         BMI                         62.159984
         DiabetesPedigreeFunction     0.109779
         Age                        138.303046
         Outcome                      0.227483
         dtype: float64
```

data.std()

Output:

```
In [39]: data.std()

Out[39]: Pregnancies                 3.369578
         Glucose                    31.972618
         BloodPressure              19.355807
         SkinThickness              15.952218
         Insulin                   115.244002
         BMI                         7.884160
         DiabetesPedigreeFunction    0.331329
         Age                        11.760232
         Outcome                     0.476951
         dtype: float64
```

data.skew()

Output:

```
In [40]: data.skew()

Out[40]: Pregnancies                 0.901674
         Glucose                     0.173754
         BloodPressure              -1.843608
         SkinThickness               0.109372
         Insulin                     2.272251
         BMI                        -0.428982
         DiabetesPedigreeFunction    1.919911
         Age                         1.129597
         Outcome                     0.635017
         dtype: float64
```

data.kurt()

Output:

```
In [41]: data.kurt()

Out[41]: Pregnancies                 0.159220
         Glucose                     0.640780
         BloodPressure               5.180157
         SkinThickness              -0.520072
         Insulin                     7.214260
         BMI                         3.290443
         DiabetesPedigreeFunction    5.594954
         Age                         0.643159
         Outcome                    -1.600930
         dtype: float64
```

Result:

Univariate analysis has been successfully done for Diabetes dataset and the results are verified.

2)**Aim:**

To use dow jones index data set and perform the following: Univariate analysis,Frequency, Mean, Median, Mode, Variance, Standard Deviation, Skewness and Kurtosis.

Code & Output:

```
import pandas as pd

import numpy as np

import seaborn as sns

import matplotlib.pyplot as plt


data = pd.read_csv('dow_jones_index.csv')

data['high'] = data['high'].str.replace('$', '')

data['open'] = data['open'].str.replace('$', '')

data['low'] = data['low'].str.replace('$', '')

data['close'] = data['close'].str.replace('$', '')

data['next_weeks_open'] = data['next_weeks_open'].str.replace('$', '')

data['next_weeks_close'] = data['next_weeks_close'].str.replace('$', '')

data
```

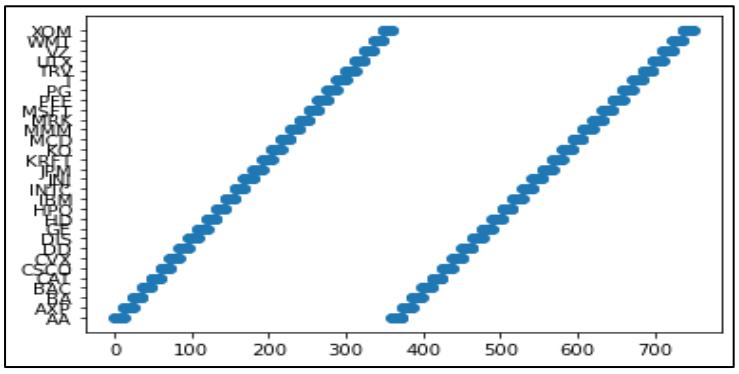
Output:

	quarter	stock	date	open	high	low	close	volume	percent_change_price	percent_change_volume_over_last_wk	previous_weeks_volume
0	1	AA	1/7/2011	15.82	16.72	15.78	16.42	239655616	3.79267	NaN	NaN
1	1	AA	1/14/2011	16.71	16.71	15.64	15.97	242963398	-4.42849	1.380223	239655616.0
2	1	AA	1/21/2011	16.19	16.38	15.60	15.79	138428495	-2.47066	-43.024959	242963398.0
3	1	AA	1/28/2011	15.87	16.63	15.82	16.13	151379173	1.63831	9.355500	138428495.0
4	1	AA	2/4/2011	16.18	17.39	16.18	17.14	154387761	5.93325	1.987452	151379173.0
...	...	...	...	...	...	...	...	...	...	...	...
745	2	XOM	5/27/2011	80.22	82.63	80.07	82.63	68230855	3.00424	-21.355713	86758820.0
746	2	XOM	6/3/2011	83.28	83.75	80.18	81.18	78616295	-2.52161	15.221032	68230855.0
747	2	XOM	6/10/2011	80.93	81.87	79.72	79.78	92380844	-1.42098	17.508519	78616295.0
748	2	XOM	6/17/2011	80.00	80.82	78.33	79.02	100521400	-1.22500	8.811952	92380844.0
749	2	XOM	6/24/2011	78.65	81.12	76.78	76.78	118679791	-2.37762	18.064204	100521400.0

750 rows × 16 columns

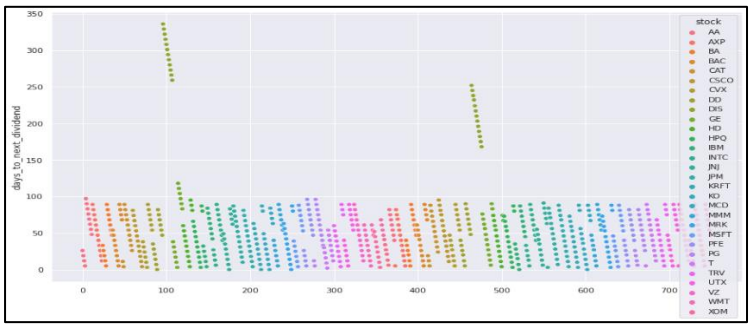
```
plt.scatter(data.index,data['stock'])
plt.show()
```

Output:



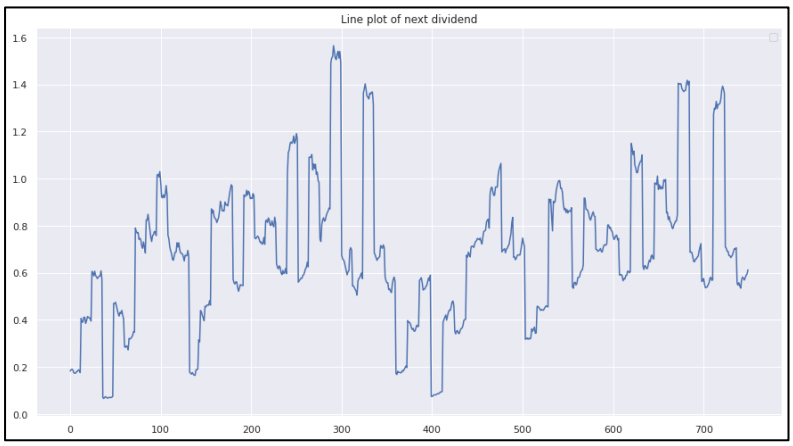

```
sns.set(rc={'figure.figsize':(15,8)})
sns.scatterplot(x=data.index,y=data['days_to_next_dividend'],hue=data['stock'])
```

Output:



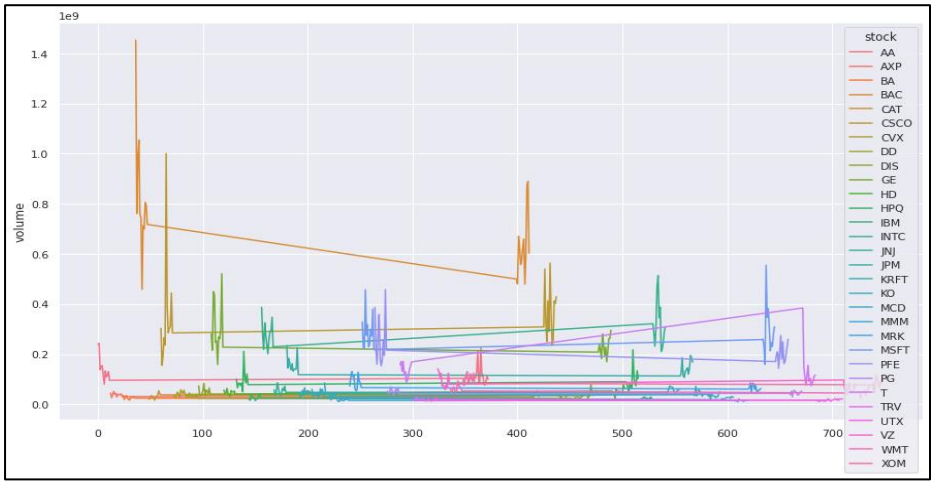

```
plt.title("Line plot of next dividend")
plt.plot(data.index,data['percent_return_next_dividend'])
plt.legend()
plt.show()
```

Output:



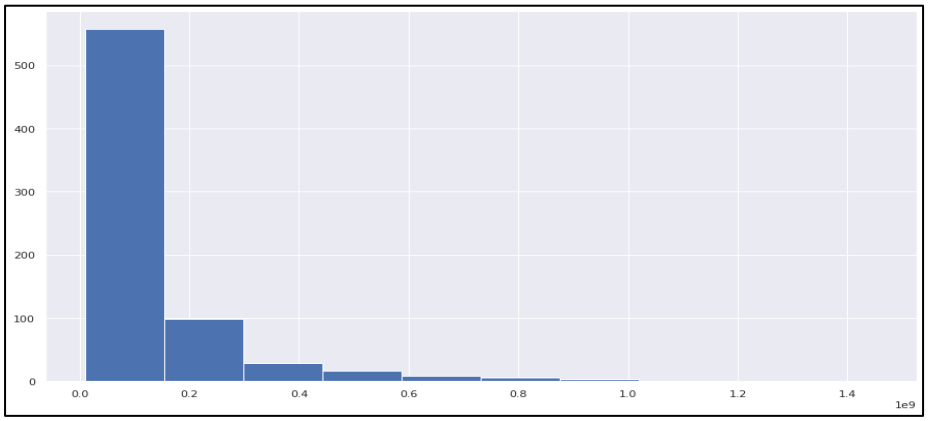
fig=sns.lineplot(x=data.index,y=data['volume'],hue=data['stock'])

Output:



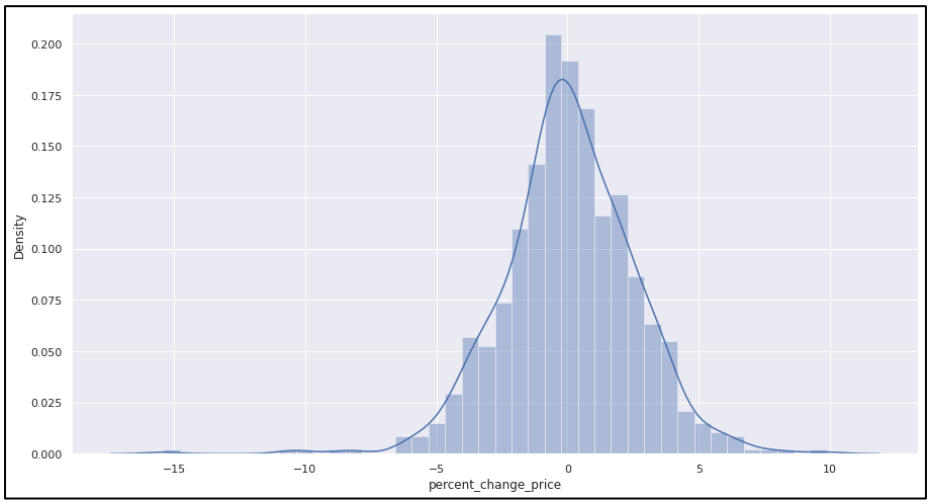
plt.hist(data['previous_weeks_volume'])

Output:



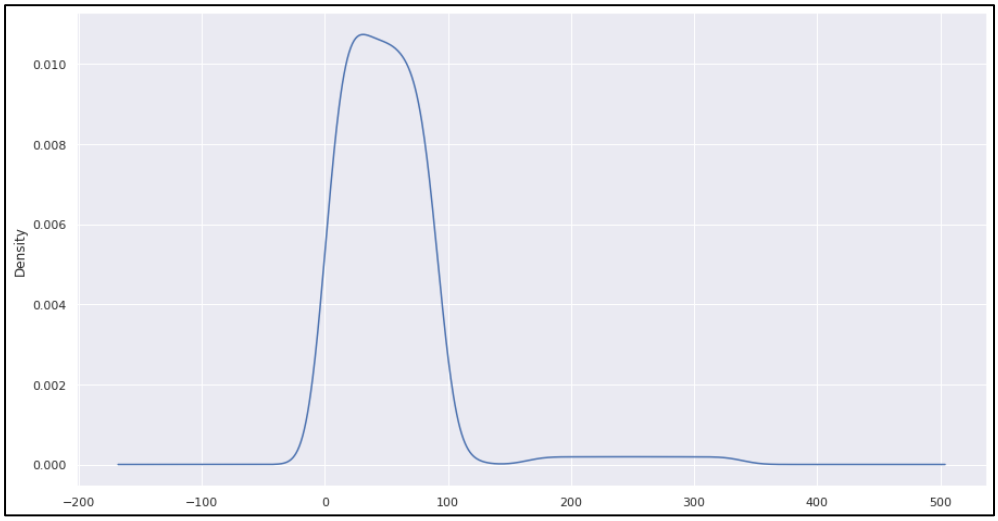
sns.distplot(data['percent_change_price'])

Output:



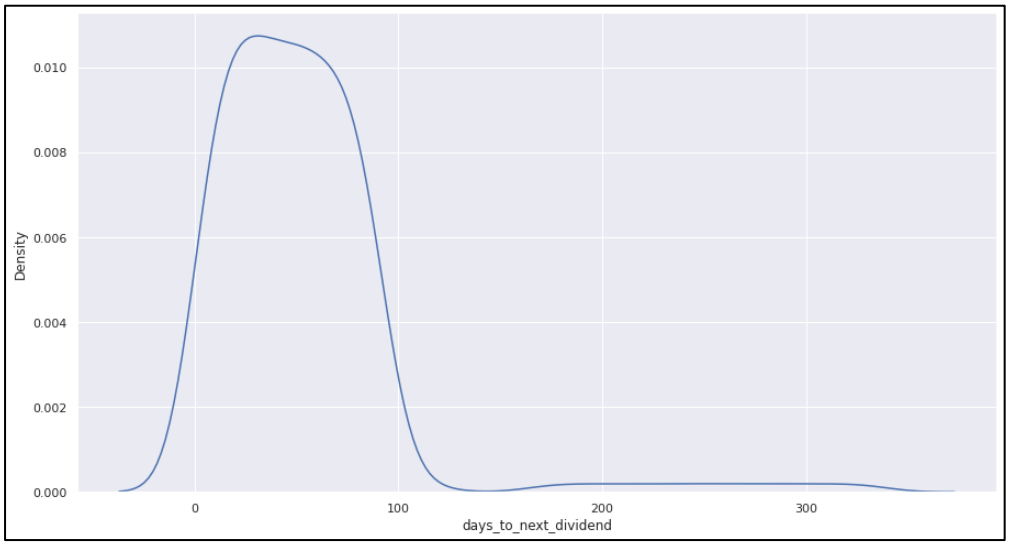
data['days_to_next_dividend'].plot(kind='density')

Output:



sns.kdeplot(data['days_to_next_dividend'])

Output:



data.var()

Output:

```
Out[28]: quarter                            2.499332e-01
         volume                             2.510263e+16
         percent_change_price               6.339363e+00
         percent_change_volume_over_last_wk 1.643774e+03
         previous_weeks_volume              2.535490e+16
         percent_change_next_weeks_price    7.179926e+00
         days_to_next_dividend              2.146941e+03
         percent_return_next_dividend       9.331917e-02
         dtype: float64
```

data.mean()

Output:

```
Out[29]: quarter                                 1.520000e+00
         volume                                  1.175478e+08
         percent_change_price                    5.026241e-02
         percent_change_volume_over_last_wk      5.593627e+00
         previous_weeks_volume                   1.173876e+08
         percent_change_next_weeks_price         2.384681e-01
         days_to_next_dividend                   5.252533e+01
         percent_return_next_dividend            6.918256e-01
         dtype: float64
```

data.mode()

Output:

	quarter	stock	date	open	high	low	close	volume	percent_change_price	percent_change_volume_over_last_wk	previous_weeks_volume
0	2.0	AA	1/14/2011	37.26	12.60	16.97	33.07	9718851	0.0	-61.433175	9718851.0
1	NaN	AXP	1/21/2011	44.75	17.24	63.40	36.00	10135730	NaN	-60.988311	10135730.0
2	NaN	BA	1/28/2011	NaN	17.64	NaN	41.52	10705548	NaN	-59.994858	10705548.0
3	NaN	BAC	1/7/2011	NaN	19.39	NaN	46.25	11585909	NaN	-59.668839	11585909.0
4	NaN	CAT	2/11/2011	NaN	20.20	NaN	NaN	11690792	NaN	-57.488522	11690792.0
...	...	...	...	...	...	...	...	...	...	...	...
745	NaN	NaN	NaN	NaN	NaN	NaN	NaN	889460755	NaN	NaN	NaN
746	NaN	NaN	NaN	NaN	NaN	NaN	NaN	982445809	NaN	NaN	NaN
747	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1000362015	NaN	NaN	NaN
748	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1054415375	NaN	NaN	NaN
749	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1453438639	NaN	NaN	NaN

750 rows × 16 columns

data.median()

Output:

```
Out[31]: quarter                                 2.000000e+00
         open                                    4.597000e+01
         high                                    4.688500e+01
         low                                     4.480000e+01
         close                                   4.593000e+01
         volume                                  5.306088e+07
         percent_change_price                    0.000000e+00
         percent_change_volume_over_last_wk      5.125859e-01
         previous_weeks_volume                   5.294556e+07
         next_weeks_open                         4.601500e+01
         next_weeks_close                        4.612500e+01
         percent_change_next_weeks_price         1.011926e-01
         days_to_next_dividend                   4.700000e+01
         percent_return_next_dividend            6.810665e-01
         dtype: float64
```

data.skew()

Output:

```
Out[32]: quarter                                -0.080225
         open                                    1.269375
         high                                    1.269406
         low                                     1.279839
         close                                   1.274375
         volume                                  3.223405
         percent_change_price                   -0.380849
         percent_change_volume_over_last_wk      2.544001
         previous_weeks_volume                   3.256532
         next_weeks_open                         1.273419
         next_weeks_close                        1.278622
         percent_change_next_weeks_price        -0.172372
         days_to_next_dividend                   3.055018
         percent_return_next_dividend            0.394347
         dtype: float64
```

data.kurt()

Output:

```
Out[33]: quarter                                -1.998902
         open                                    2.007631
         high                                    1.991205
         low                                     2.079614
         close                                   2.028985
         volume                                 14.197635
         percent_change_price                    2.706643
         percent_change_volume_over_last_wk     13.900139
         previous_weeks_volume                  14.426624
         next_weeks_open                         2.018298
         next_weeks_close                        2.037552
         percent_change_next_weeks_price         2.268632
         days_to_next_dividend                  13.312999
         percent_return_next_dividend            0.389911
         dtype: float64
```

data.std()

Output:

```
ut[34]: quarter                                4.999332e-01
        volume                                 1.584381e+08
        percent_change_price                   2.517809e+00
        percent_change_volume_over_last_wk     4.054348e+01
        previous_weeks_volume                  1.592322e+08
        percent_change_next_weeks_price        2.679538e+00
        days_to_next_dividend                  4.633510e+01
        percent_return_next_dividend           3.054819e-01
        dtype: float64
```

df=data['stock'].value_counts()

df

Output:

```
Out[7]: AA      25
        AXP     25
        WMT     25
        VZ      25
        UTX     25
        TRV     25
        T       25
        PG      25
        PFE     25
        MSFT    25
        MRK     25
        MMM     25
        MCD     25
        KO      25
        KRFT    25
        JPM     25
```

```
        JNJ     25
        INTC    25
        IBM     25
        HPQ     25
        HD      25
        GE      25
        DIS     25
        DD      25
        CVX     25
        CSCO    25
        CAT     25
        BAC     25
        BA      25
        XOM     25
        Name: stock, dtype: int64
```

Result:

Univariate analysis has been successfully done for dow jones index dataset and the results are verified.

3)**Aim:**

To perform the following using dow jones index dataset a)Univariate Linear Regression b)Summary statistics c)Frequency table d)Charts e)univariate analysis for numerical and categorical attributes f)Univariate Function Optimization g) Perform Feature Extraction with Univariate Statistical Tests and summarize the selected features

Code & Output:

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns


data = pd.read_csv('dow_jones_index.csv')

#summary statistics

data.describe()
```

Output:

```
In [10]: data.describe()
```

Out[10]:

	quarter	volume	percent_change_price	percent_change_volume_over_last_wk	previous_weeks_volume	percent_change_next_weeks_price	da
count	750.000000	7.500000e+02	750.000000	720.000000	7.200000e+02	750.000000	
mean	1.520000	1.175478e+08	0.050262	5.593627	1.173876e+08	0.238468	
std	0.499933	1.584381e+08	2.517809	40.543478	1.592322e+08	2.679538	
min	1.000000	9.718851e+06	-15.422900	-61.433175	9.718851e+06	-15.422900	
25%	1.000000	3.086624e+07	-1.288053	-19.804284	3.067832e+07	-1.222068	
50%	2.000000	5.306088e+07	0.000000	0.512586	5.294556e+07	0.101193	
75%	2.000000	1.327218e+08	1.650888	21.800622	1.333230e+08	1.845562	
max	2.000000	1.453439e+09	9.882230	327.408924	1.453439e+09	9.882230	

```
data['volume'].value_counts()
```

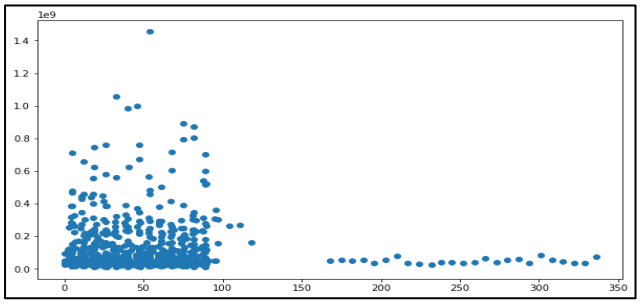
Output:

```
In [11]: data['volume'].value_counts()

Out[11]: 239655616    1
         90069975     1
         61019095     1
         52439439     1
         41391929     1
                     ..
         328646154    1
         227601331    1
         220040646    1
         457318851    1
         118679791    1
         Name: volume, Length: 750, dtype: int64
```

#charts

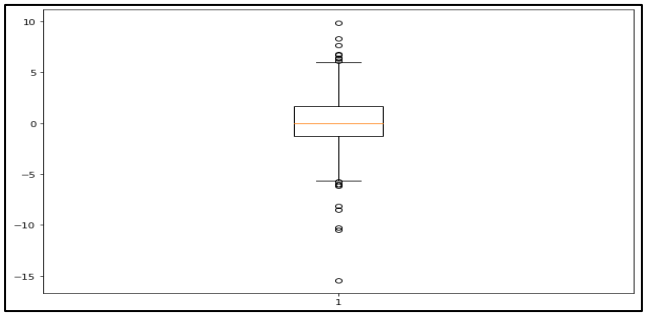
```
y=data['volume']
x=data['days_to_next_dividend']
plt.rcParams['figure.figsize']=(10,6)
plt.scatter(x,y)
```

Output:



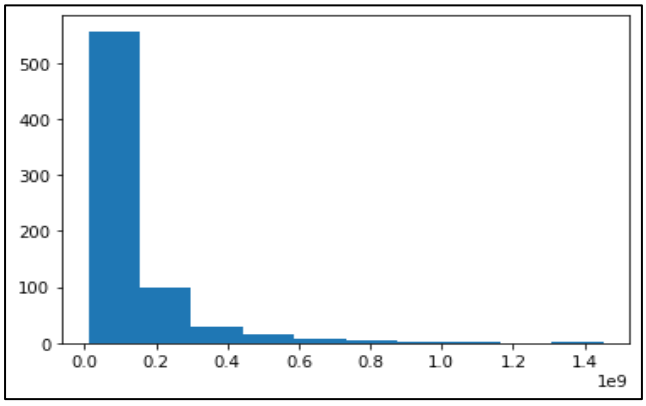

```
fig=plt.figure(figsize=(10,7))
plt.boxplot(data['percent_change_price'])
plt.show()
```

Output:



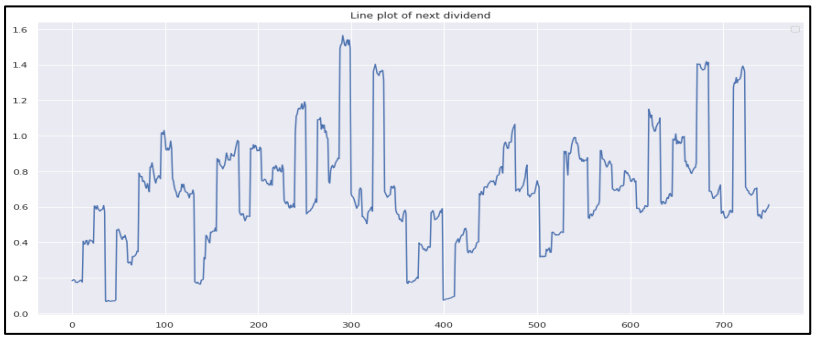

```
plt.hist(data['previous_weeks_volume'])
```

Output:



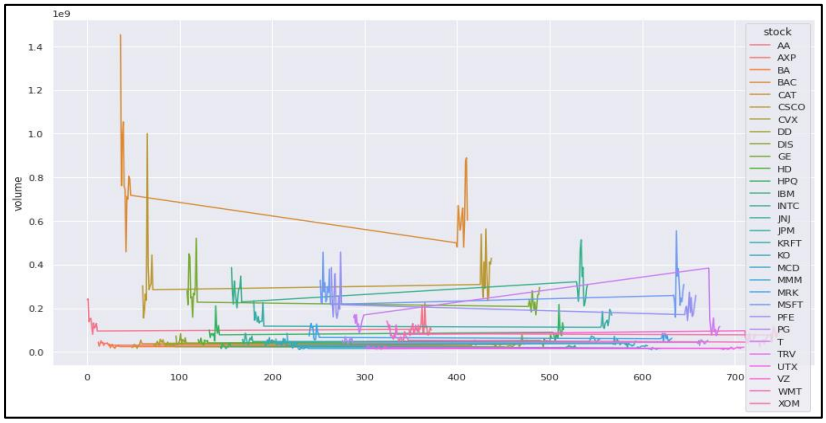
```
plt.title("Line plot of next dividend")
plt.plot(data.index,data['percent_return_next_dividend'])
plt.legend()
plt.show()
```

Output:



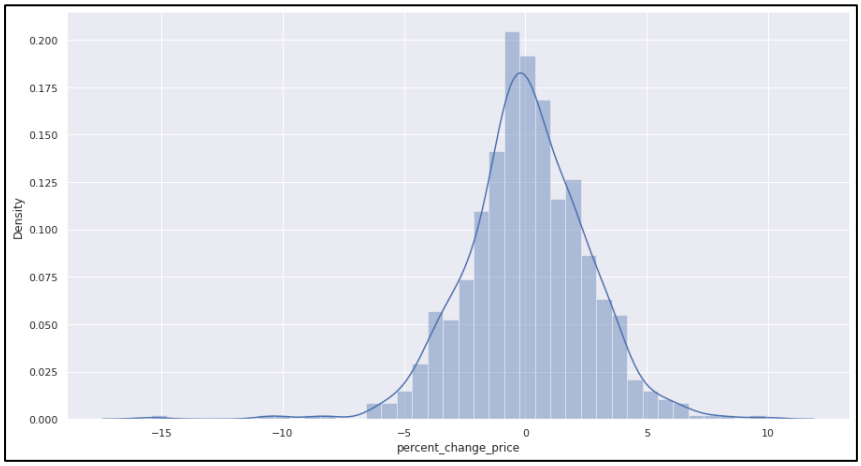

```
fig=sns.lineplot(x=data.index,y=data['volume'],hue=data['stock'])
```

Output:




```
sns.distplot(data['percent_change_price'])
```

Output:



#univariate linear regression

```
from sklearn.linear_model import LinearRegression
model = LinearRegression().fit(x,y)
r_sq=model.score(x,y)
print("R square value :",r_sq)
```

Output:

```
In [25]: from sklearn.linear_model import LinearRegression
         model = LinearRegression().fit(x,y)
         r_sq=model.score(x,y)
         print("R square value :",r_sq)

         R square value : 0.2623896707626756
```

#frequency table

```
data['stock'].value_counts()
```

Output:

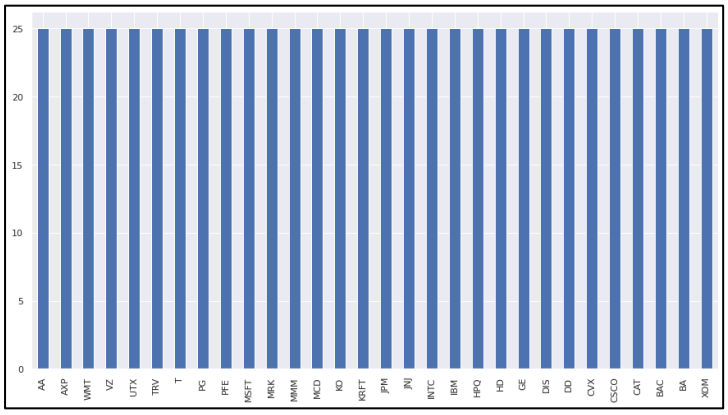
```
Out[12]: AA      25
         AXP     25
         WMT     25
         VZ      25
         UTX     25
         TRV     25
         T       25
         PG      25
         PFE     25
         MSFT    25
         MRK     25
         MMM     25
         MCD     25
         KO      25
         KRFT    25
         JPM     25
         JNJ     25
         INTC    25
```

```
INTC    25
IBM     25
HPQ     25
HD      25
GE      25
DIS     25
DD      25
CVX     25
CSCO    25
CAT     25
BAC     25
BA      25
XOM     25
Name: stock, dtype: int64
```

#univariate analysis numerical attributes

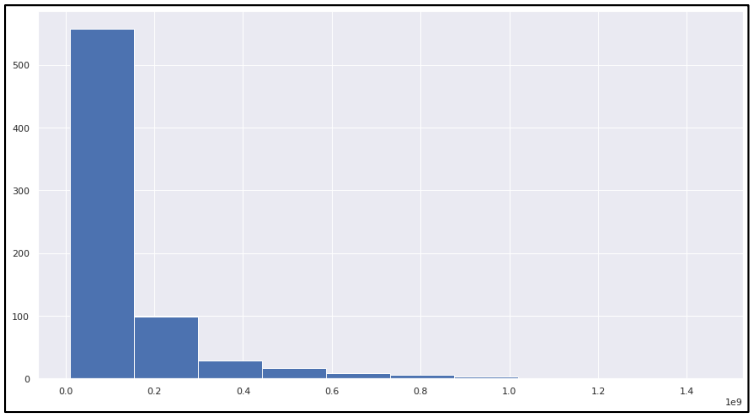
```
data['stock'].value_counts().plot.bar()
```

Output:



plt.hist(data['previous_weeks_volume'])

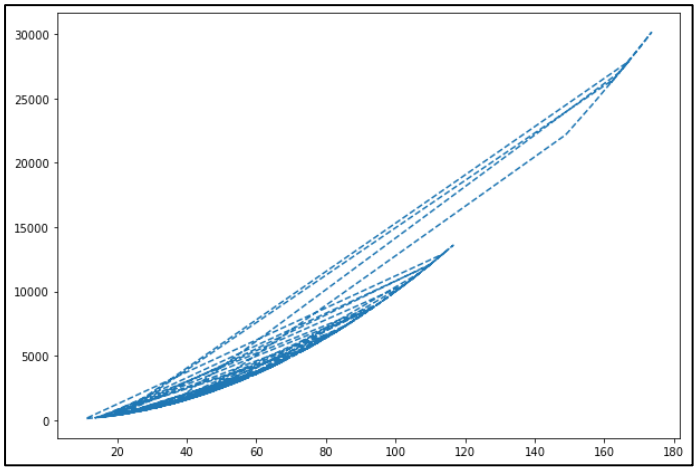
Output:



#function optimization

```
def objective(x):
    return (0.005 + x)**2
inputs = data['high']
targets = [objective(x) for x in inputs]
fig=plt.figure(figsize=(10,7))
plt.plot(inputs, targets,'--')
plt.show()
```

Output:



#univariate statistical tests

#correlation test

```
from scipy.stats import pearsonr
data['high']= pd.to_numeric(data['high'])
```

```
data['low']= pd.to_numeric(data['low'])
list1 = data['high']
list2 = data['low']
corr,_= pearsonr(list1, list2)
print('Pearsons correlation: %.3f'% corr)
```

Output:

```
Pearsons correlation: 0.999
```

```
#normality test
from scipy import stats
z=[data['high'],data['low']]
for i in z:
    print([i])
    a,b=stats.normaltest(data['high'])
    print(a,b)
    alpha = 0.05
    if b<alpha :
        print('null hypothesis rejected')
    else:
        print('null hypothesis cannot be rejected')
```

Output:

```
[0       16.72
1       16.71
2       16.38
3       16.63
4       17.39
        ...
745     82.63
746     83.75
747     81.87
748     80.82
749     81.12
Name: high, Length: 750, dtype: float64]
165.8155807197986 9.853808999390666e-37
null hypothesis rejected
[0       15.78
1       15.64
2       15.60
3       15.82
4       16.18
        ...
745     80.07
746     80.18
747     79.72
748     78.33
749     76.78
Name: low, Length: 750, dtype: float64]
165.8155807197986 9.853808999390666e-37
null hypothesis rejected
```

#parametric statistical hypothesis test

```
from scipy.stats import ttest_ind
z=[data['high'],data['low']]
for i in z:
    print([i])
    a,b=ttest_ind(data['high'],data['low'])
    print(a,b)
    alpha = 0.05
    if b>alpha :
        print('Same distributions')
    else:
        print('Different distributions')
```

Output:

```
[0      16.72
1      16.71
2      16.38
3      16.63
4      17.39
       ...
745    82.63
746    83.75
747    81.87
748    80.82
749    81.12
Name: high, Length: 750, dtype: float64]
1.2030833315757794 0.22913417910648973
Same distributions
[0      15.78
1      15.64
2      15.60
3      15.82
4      16.18
       ...
745    80.07
746    80.18
747    79.72
748    78.33
749    76.78
Name: low, Length: 750, dtype: float64]
1.2030833315757794 0.22913417910648973
Same distributions
```

#non parametric statistical hypothesis test

```
from scipy.stats import mannwhitneyu
z=[data['high'],data['low']]
for i in z:
    print([i])
    a,b=mannwhitneyu(data['high'],data['low'])
    print(a,b)
    alpha = 0.05
    if b>alpha :
        print('Same distributions')
    else:
        print('Different distributions')
```

Output:

```
[0      16.72
1       16.71
2       16.38
3       16.63
4       17.39
        ...
745     82.63
746     83.75
747     81.87
748     80.82
749     81.12
Name: high, Length: 750, dtype: float64]
292745.5 0.17056138472040383
Same distributions
[0      15.78
1       15.64
2       15.60
3       15.82
4       16.18
        ...
745     80.07
746     80.18
747     79.72
748     78.33
749     76.78
Name: low, Length: 750, dtype: float64]
292745.5 0.17056138472040383
Same distributions
```

Result:

Univariate analysis like linear regression , charts , analysis for numerical and categorical attributes , feature extraction has been done successfully and the results are verified.

Exp.No : 2B **Date:**29/03/22

UNIVARIATE TIME SERIES ANALYSIS

1)**Aim:**

To get a time series data set and perform the following: a)create time series features b)plot feature importance c)forecast and evaluate the data

Code & Output:

```
import pandas as pd
from pandas.plotting import autocorrelation_plot
from pandas import DataFrame
from pandas import concat
import numpy as np
from math import sqrt


from sklearn.metrics import mean_squared_error
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.stattools import acf
from statsmodels.tsa.stattools import pacf
from statsmodels.tsa.arima.model import ARIMA
from scipy.stats import boxcox
import seaborn as sns
sns.set_style("whitegrid")
import matplotlib.pyplot as plt
from matplotlib.pylab import rcParams
from matplotlib import colors
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')


col_names = ["date", "value"]
```

```
df = pd.read_csv("Electric_Production.csv",
                 names = col_names, header = 0, parse_dates = [0])
df['date'] = pd.to_datetime(df['date'],infer_datetime_format=True)
df = df.set_index(['date'])
df.head()
```

Output:

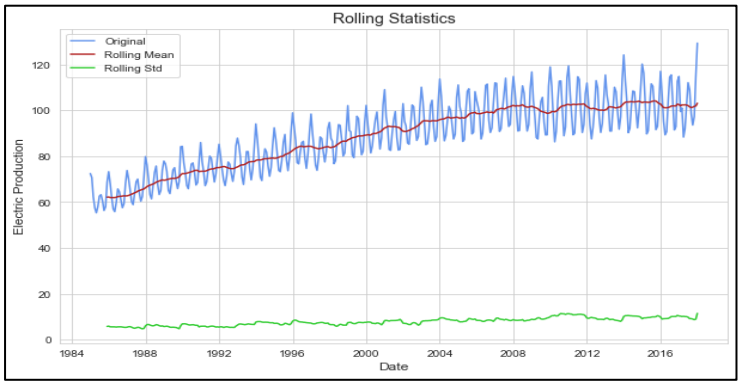
Out[2]:

date	value
1985-01-01	72.5052
1985-02-01	70.6720
1985-03-01	62.4502
1985-04-01	57.4714
1985-05-01	55.3151

#time series features

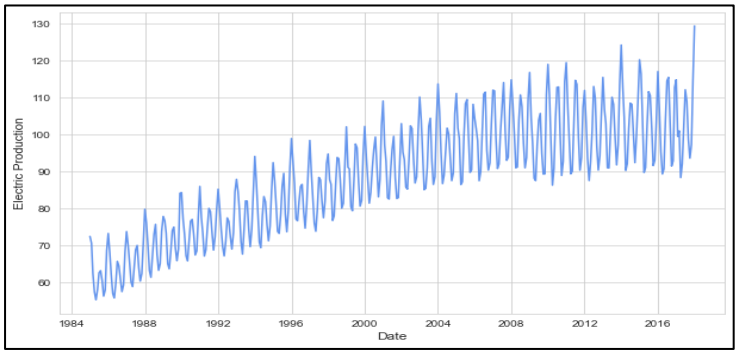
```
rolling_mean = df.rolling(window=12).mean()
rolling_std = df.rolling(window=12).std()
plt.figure(figsize = (10,6))
plt.plot(df, color='cornflowerblue', label='Original')
plt.plot(rolling_mean, color='firebrick', label='Rolling Mean')
plt.plot(rolling_std, color='limegreen', label='Rolling Std')
plt.xlabel('Date', size = 12)
plt.ylabel('Electric Production', size  = 12)
plt.legend(loc = 'upper left')
plt.title('Rolling Statistics', size = 14)
plt.show()
```

Output:



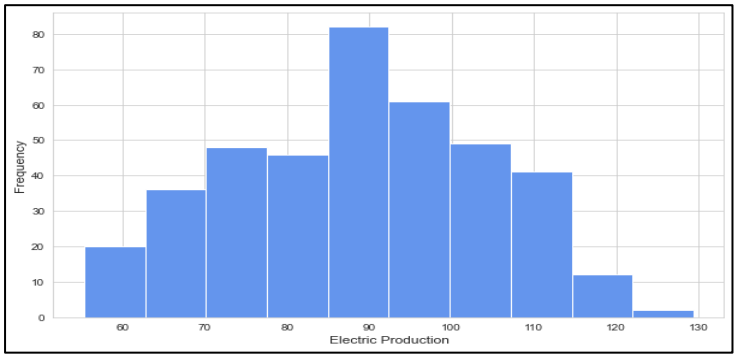
```
plt.figure(figsize = (10,6))
plt.plot(df['value'], color = 'cornflowerblue')
plt.xlabel('Date', size = 12)
plt.ylabel('Electric Production', size = 12)
plt.show()
```

Output:




```
plt.figure(figsize = (10,6))
plt.hist(df['value'], color = 'cornflowerblue')
plt.xlabel('Electric Production', size = 12)
plt.ylabel('Frequency', size = 12)
plt.show()
```

Output:




```
print("Data Shape: {}".format(df.shape))
value_1 = df[0:199]
value_2 = df[200:397]
```

Output:

```
Data Shape: (397, 1)
```

```
print("Mean of value_1: {}".format(round(value_1.mean()[0],3)))
print("Mean of value_2: {}".format(round(value_2.mean()[0],3)))
```

Output:

```
Mean of value_1: 77.497
Mean of value_2: 100.258
```

```
print("Variance of value_1: {}".format(round(value_1.var()[0],3)))
print("Variance of value_2: {}".format(round(value_2.var()[0],3)))
```

Output:

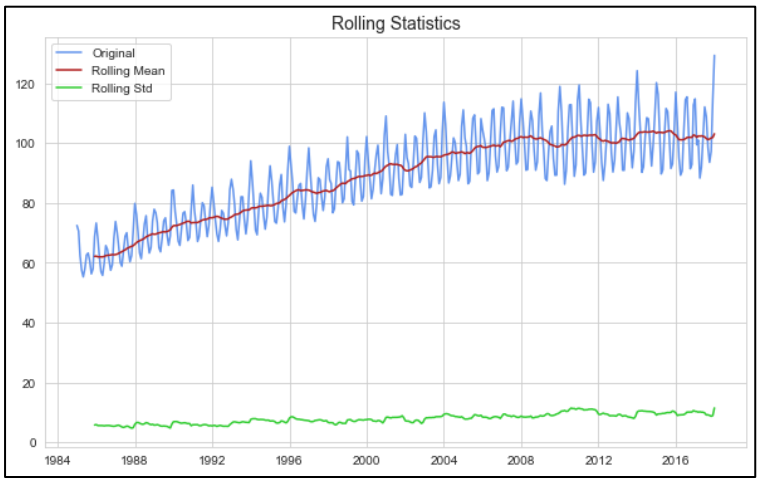
```
Variance of value_1: 123.226
Variance of value_2: 91.677
```

```
def adfuller_test(ts, window = 12):
    movingAverage = ts.rolling(window).mean()
    movingSTD = ts.rolling(window).std()
    plt.figure(figsize = (10,6))
    orig = plt.plot(ts, color='cornflowerblue',label='Original')
    mean = plt.plot(movingAverage, color='firebrick',label='Rolling Mean')
    std = plt.plot(movingSTD, color='limegreen',label='Rolling Std')
    plt.legend(loc = 'upper left')
    plt.title('Rolling Statistics', size = 14)
    plt.show(block=False)
    adf = adfuller(ts, autolag='AIC')
    print('ADF Statistic: {}'.format(round(adf[0],3)))
    print('p-value: {}'.format(round(adf[1],3)))
    print("###################################")
    print('Critical Values:')

    for key, ts in adf[4].items():
        print('{}: {}'.format(key, round(ts,3)))
    print("###################################")
```

```
    if adf[0] > adf[4]["5%"]:
        print("ADF > Critical Values")
        print ("Failed to reject null hypothesis, time series is non-stationary.")
    else:
        print("ADF < Critical Values")
        print ("Reject null hypothesis, time series is stationary.")
```

```
adfuller_test(df, window = 12)
```

Output:

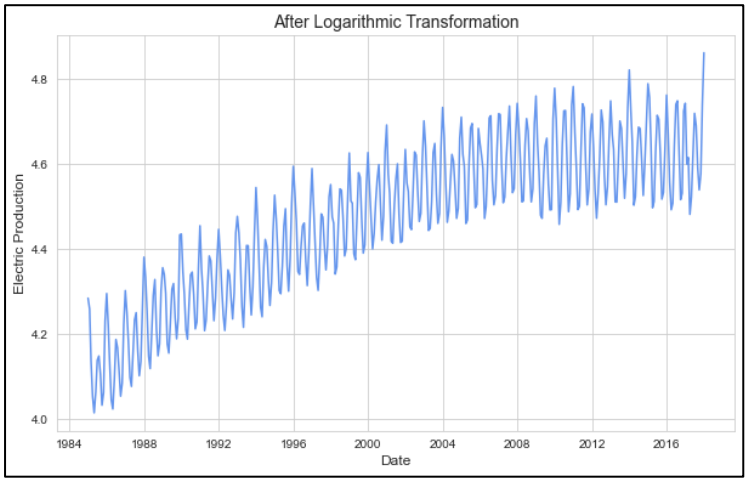



```
ADF Statistic: -2.257
p-value: 0.186
##################################
Critical Values:
1%: -3.448
5%: -2.869
10%: -2.571
##################################
ADF > Critical Values
Failed to reject null hypothesis, time series is non-stationary.
```

```
df_log_scaled = df
df_log_scaled['value'] = boxcox(df_log_scaled['value'], lmbda=0.0)
plt.figure(figsize = (10,6))
plt.plot(df_log_scaled, color = 'cornflowerblue')
plt.xlabel('Date', size = 12)
plt.ylabel('Electric Production', size = 12)
plt.title("After Logarithmic Transformation", size = 14)
```

plt.show()

Output:s



moving_avg = df_log_scaled.rolling(window=12).mean()

df_log_scaled_ma = df_log_scaled - moving_avg

df_log_scaled_ma.dropna(inplace=True)

plt.figure(figsize = (10,6))

plt.plot(df_log_scaled_ma, color = 'cornflowerblue')

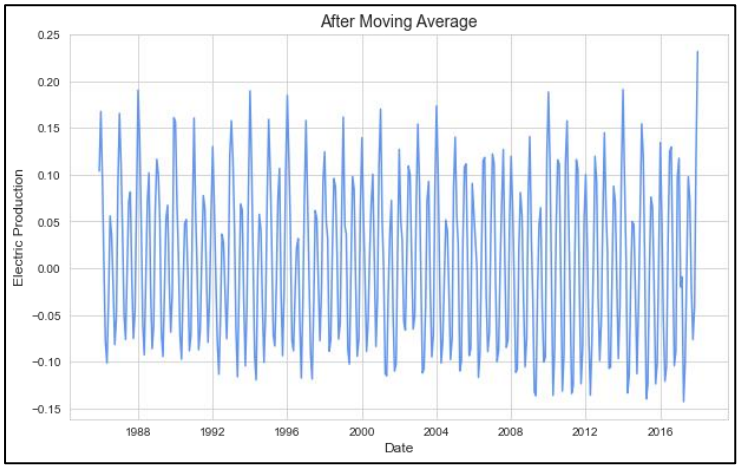
plt.xlabel('Date', size = 12)

plt.ylabel('Electric Production', size = 12)

plt.title("After Moving Average", size = 14)

plt.show()

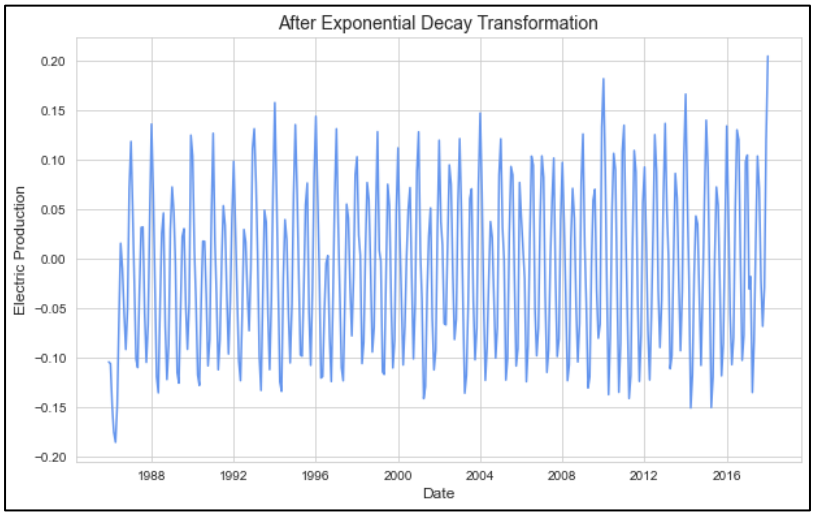
Output:



df_log_scaled_ma_ed = df_log_scaled_ma.ewm(halflife=12, min_periods=0, adjust=True).mean()

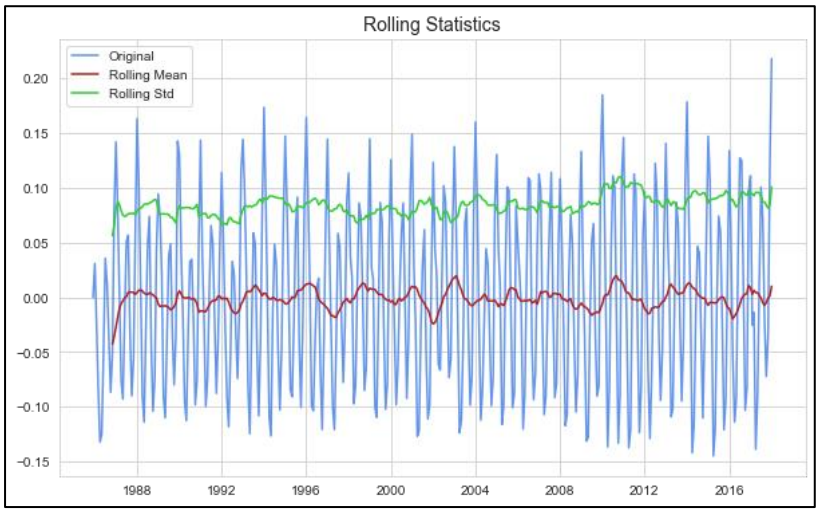
```
df_lsma_sub_df_lsma_ed = df_log_scaled_ma - df_log_scaled_ma_ed
plt.figure(figsize = (10,6))
plt.plot(df_lsma_sub_df_lsma_ed - df_log_scaled_ma_ed, color='cornflowerblue')
plt.xlabel('Date', size = 12)
plt.ylabel('Electric Production', size = 12)
plt.title("After Exponential Decay Transformation", size = 14)
plt.show()
```

Output:




```
adfuller_test(df_lsma_sub_df_lsma_ed, window = 12)
```

Output:



```
ADF Statistic: -7.213
p-value: 0.0
###################################
Critical Values:
1%: -3.448
5%: -2.869
10%: -2.571
###################################
ADF < Critical Values
Reject null hypothesis, time series is stationary.
```

rcParams['figure.figsize']=10,8

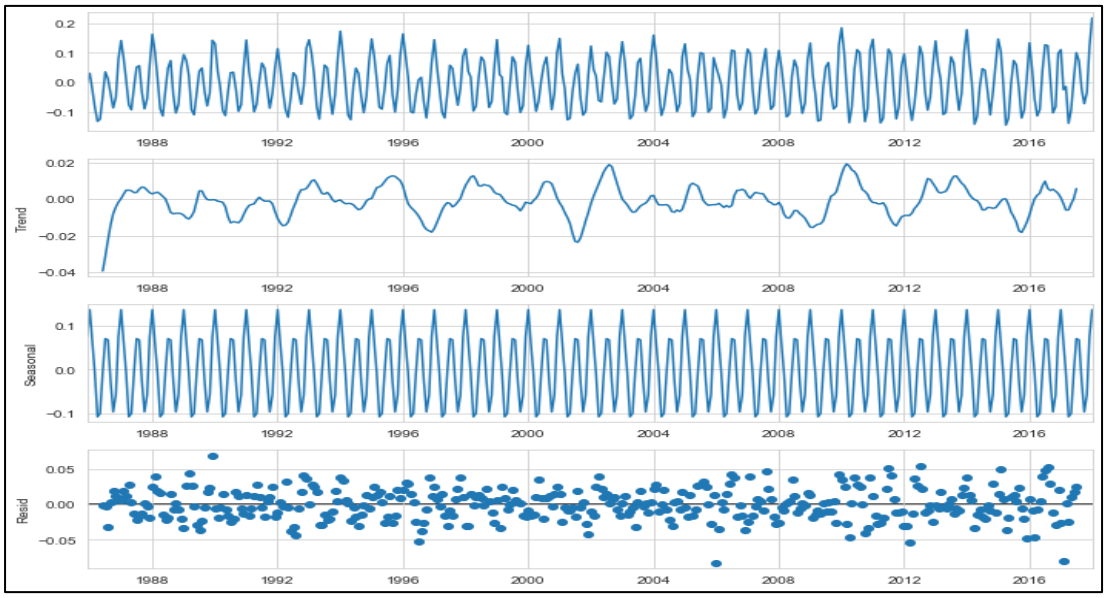
df_seasonal_decompose = seasonal_decompose(df_lsma_sub_df_lsma_ed,

model='duplicative')

df_seasonal_decompose.plot()

plt.show()

Output:



auto_c_f = acf(df_lsma_sub_df_lsma_ed, nlags=20)

partial_auto_c_f = pacf(df_lsma_sub_df_lsma_ed, nlags=20, method='ols')

fig, axs = plt.subplots(1, 2, figsize =(12,5))

plt.subplot(121)

plt.plot(auto_c_f)

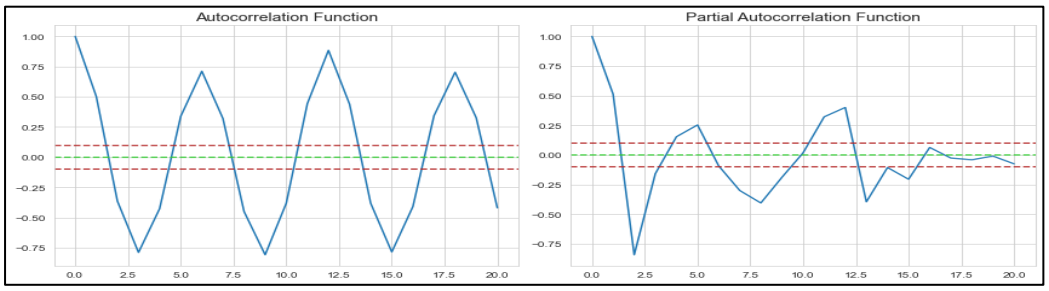
plt.axhline(y=0, linestyle='--', color='limegreen')

plt.axhline(y=-1.96/np.sqrt(len(df_lsma_sub_df_lsma_ed)),linestyle='--', color='firebrick')

plt.axhline(y=1.96/np.sqrt(len(df_lsma_sub_df_lsma_ed)),linestyle='--', color='firebrick')

```
plt.title('Autocorrelation Function', size = 14)
plt.subplot(122)
plt.plot(partial_auto_c_f)
plt.axhline(y=0, linestyle='--', color='limegreen')
plt.axhline(y=-1.96/np.sqrt(len(df_lsma_sub_df_lsma_ed)), linestyle='--', color='firebrick')
plt.axhline(y=1.96/np.sqrt(len(df_lsma_sub_df_lsma_ed)),linestyle='--', color='firebrick')
plt.title('Partial Autocorrelation Function', size = 14)
plt.tight_layout()
```

Output:




```
values = DataFrame(df_lsma_sub_df_lsma_ed.values)
persistence_df = concat([values.shift(1), values], axis=1)
persistence_df.columns = ['t-1', 't+1']
per_values = persistence_df.values
train = per_values[1:len(per_values)-10]
test = per_values[len(per_values)-10:]
X_train, y_train = train[:,0], train[:,1]
X_test, y_test = test[:,0], test[:,1]
def persistence(x):
    return x
predictions = []
for i in X_test:
    y_pred = persistence(i)
    predictions.append(y_pred)
persistence_score = mean_squared_error(y_test, predictions)
print('Persistence MSE: {}'.format(round(persistence_score,4)))
```

Output:

```
Persistence MSE: 0.0084
```

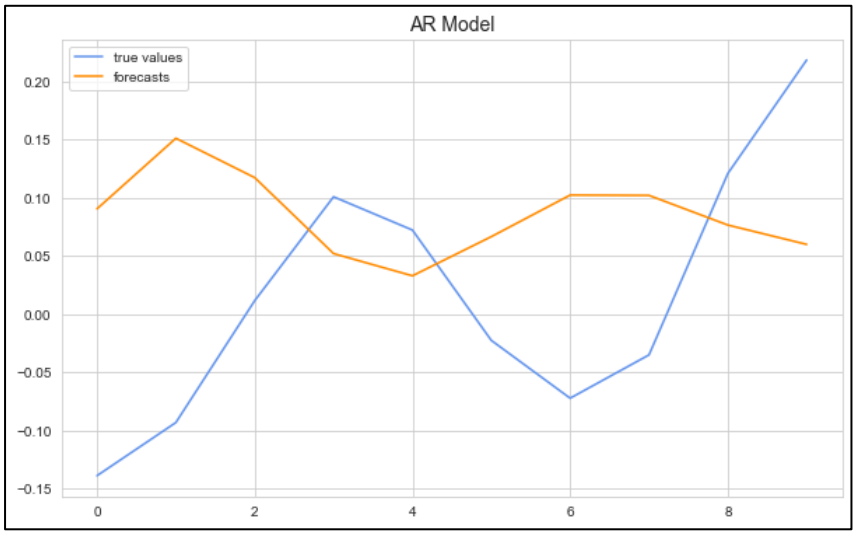
```
ar_values = df_lsma_sub_df_lsma_ed.values
train = ar_values[1:len(ar_values)-10]
test = ar_values[len(ar_values)-10:]
model = ARIMA(train, order=(2,1,0))
AR_model = model.fit()
predictions = AR_model.predict(start=len(train), end=len(train)+len(test)-1, dynamic=False)
ar_score = mean_squared_error(test, predictions)
print('AR MSE: {}'.format(round(ar_score,4)))
```

Output:

```
AR MSE: 0.0211
```

```
plt.figure(figsize = (10,6))
plt.plot(test, label = "true values", color = "cornflowerblue")
plt.plot(predictions,label = "forecasts", color='darkorange')
plt.title("AR Model", size = 14)
plt.legend(loc = 'upper left')
plt.show()
```

Output:



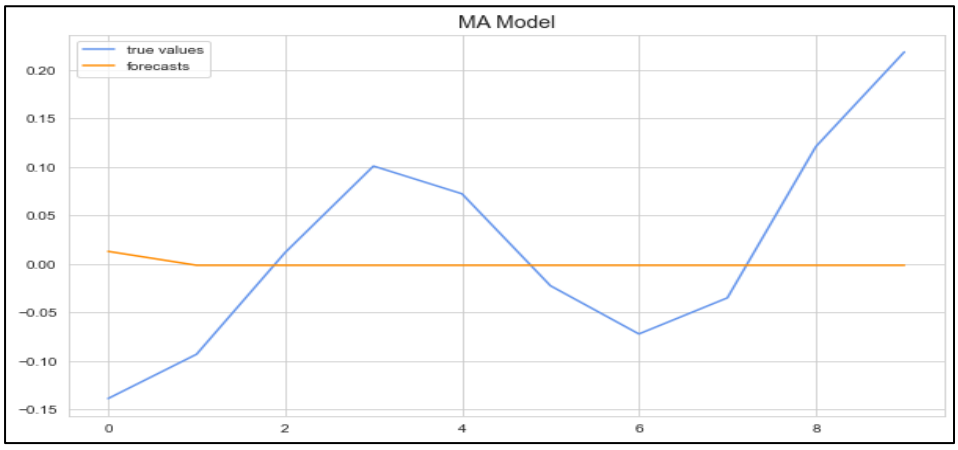
```
model = ARIMA(train, order=(0,1,2))
MA_model = model.fit()
predictions = MA_model.predict(start=len(train), end=len(train)+len(test)-1, dynamic=False)
ma_score = mean_squared_error(test, predictions)
print('MA MSE: {}'.format(round(ma_score,4)))
```

Output:

```
MA MSE: 0.0117
```

```
plt.figure(figsize = (10,6))
plt.plot(test, label = "true values", color = "cornflowerblue")
plt.plot(predictions,label = "forecasts", color='darkorange')
plt.title("MA Model", size = 14)
plt.legend(loc = 'upper left')
plt.show()
```

Output:



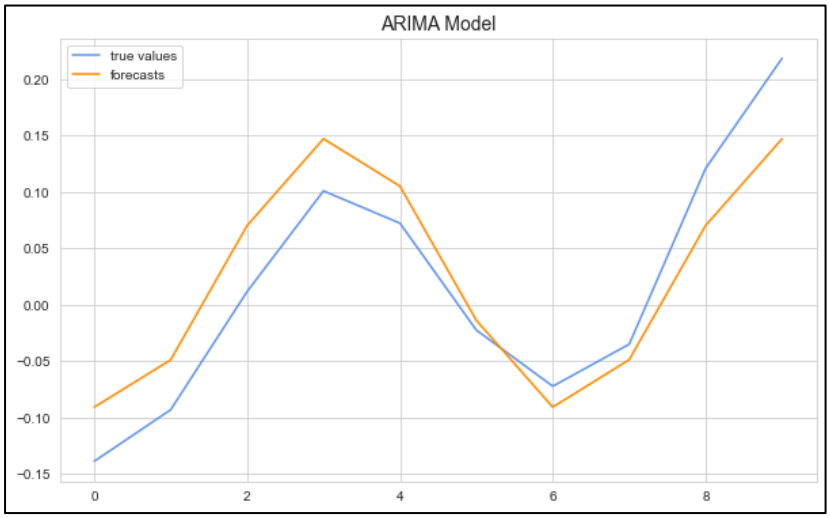

```
model = ARIMA(train, order=(2,1,2))
ARIMA_model = model.fit()
predictions = ARIMA_model.predict(start=len(train), end=len(train)+len(test)-1,
dynamic=False)
arima_score = mean_squared_error(test, predictions)
print('ARIMA MSE: {}'.format(round(arima_score,4)))
```

Output:

```
ARIMA MSE: 0.0019
```

```
plt.figure(figsize = (10,6))
plt.plot(test, label = "true values", color = "cornflowerblue")
plt.plot(predictions,label = "forecasts", color='darkorange')
plt.title("ARIMA Model", size = 14)
plt.legend(loc = 'upper left')
plt.show()
```

Output:




```
errors = pd.DataFrame()
errors["Model"] = ["Persistence", "Autoregression", "Moving Average", "ARIMA"]
errors["MSE"] = [persistence_score, ar_score, ma_score, arima_score]
errors = errors.sort_values("MSE", ascending = True, ignore_index = True)
errors.index = errors.Model
del errors["Model"]


def coloring_bg(s, min_, max_, cmap='Reds', low=0, high=0):
    color_range = max_ - min_
    norm = colors.Normalize(min_ - (color_range * low), max_ + (color_range * high))
    normed = norm(s.values)
    c = [colors.rgb2hex(x) for x in plt.cm.get_cmap(cmap)(normed)]
    return ['background-color: %s' % color for color in c]
```

```
errors.style.apply(coloring_bg,min_ =errors.min().min(),
        max_ = errors.max().max(), low = 0.1, high = 0.85)
```

Output:

Model	MSE
ARIMA	0.001913
Persistence	0.008401
Moving Average	0.011716
Autoregression	0.021126

Result:

Univariate time analysis has been done successfully and the results are verified.

Exp.No : 3 **Date:**29/03/22

OPENSTACK

1)Aim:

To understand openstack deployment, its implementation and its application.

Openstack:

Open stack is a free, open standard cloud computing platform. It is mostly deployed as Infrastructure as Service (Iaas) in both public and private clouds where virtual servers and other resource are made available to users. The software platform consists of inter related components that control diverse, multi-vendor hardware pools of processing, storage and networking resources throughout a data center.

Deployment Models:

1)Open stack based public cloud

A vendor provides a public cloud computing system based on the OpenStack project

2) On-premises distribution

In this model, a customer downloads and installs an OpenStack distribution in their internal network.

3) Hosted OpenStack Private Cloud

A vendor hosts an OpenStack-based private cloud: including the underlying hardware and the OpenStack software

4) OpenStack-as-a-Service

A vendor hosts OpenStack management software (without any hardware) as a service. Customers sign up for the service and pair it with their internal servers, storage and networks to get a fully operational private cloud

5) Appliance based OpenStack

Nebula was a vendor that sold appliances that could be plugged into a network which spawned an OpenStack deployment

Implementation:

1)We use Devstack to shell scrip the complete openstack development environment.

2)Install all components without clustering

3)Install Logical Volume Management (LVM). This process includes allocating disks , striping, mirroring and resizing logical volumes.

4)Install MaaS (Metal as a Service).

5)Install Trove (Redstack)

Applications:

a) Nova – It is the primary computing engine

b) Swift – It is the storage system. It is used to give unique ID to every users.

c) Cinder – It is a block storage component, is used to access data in a very high speed.

d) Newton – It is the networking control and helps the components of OpenStack to communicate with one another.

e) Glance – It allows images to be used as templates.

f) Heat – It allows developers to store all requirements of each cloud application in a single file.

g) Keystone – It provides with identity services and helps to map user's access methods

Result:

Openstack deployment, implementation and application's study has been done successfully.

Exp.No : 4A **Date:**05/04/22

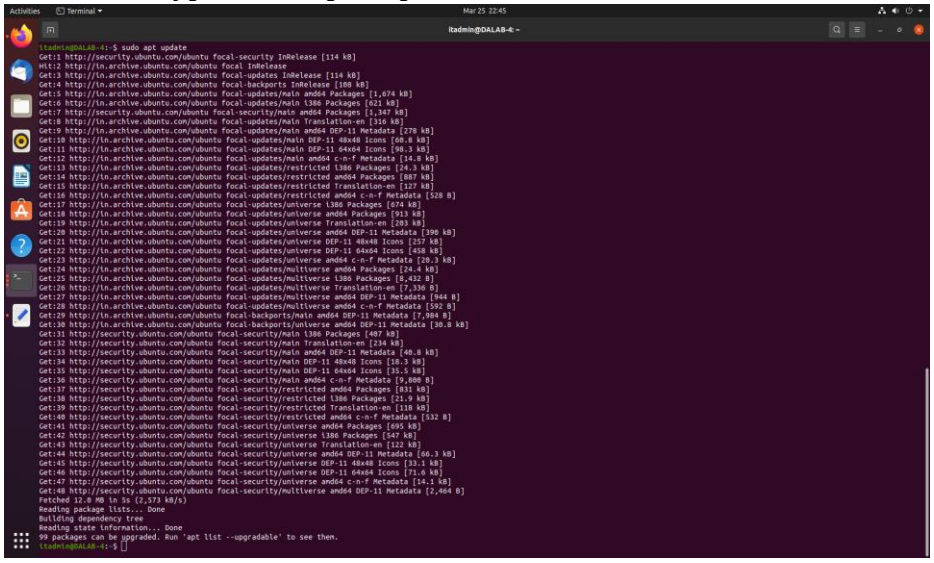
OPENSTACK INSTALLATION

1)Aim:

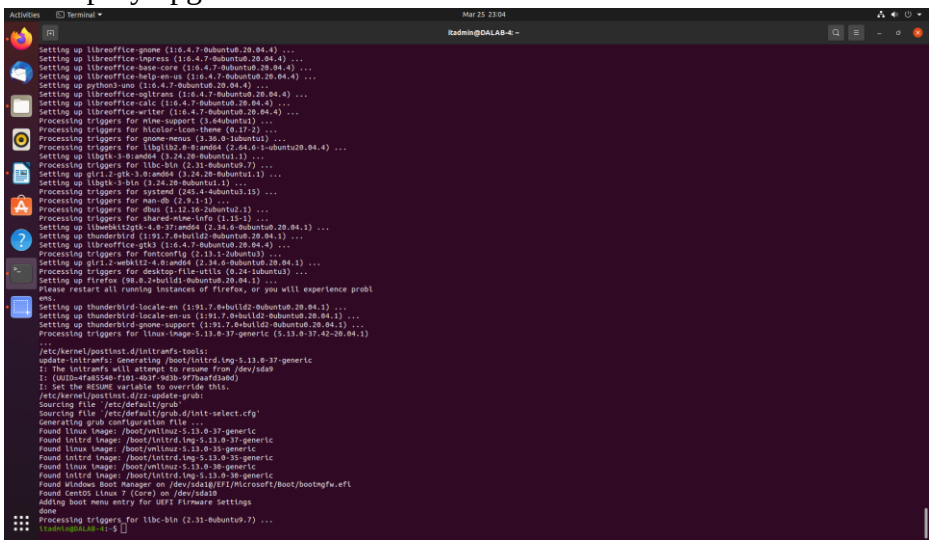
To implement infrastructure as service using Open Stack.

Installation:

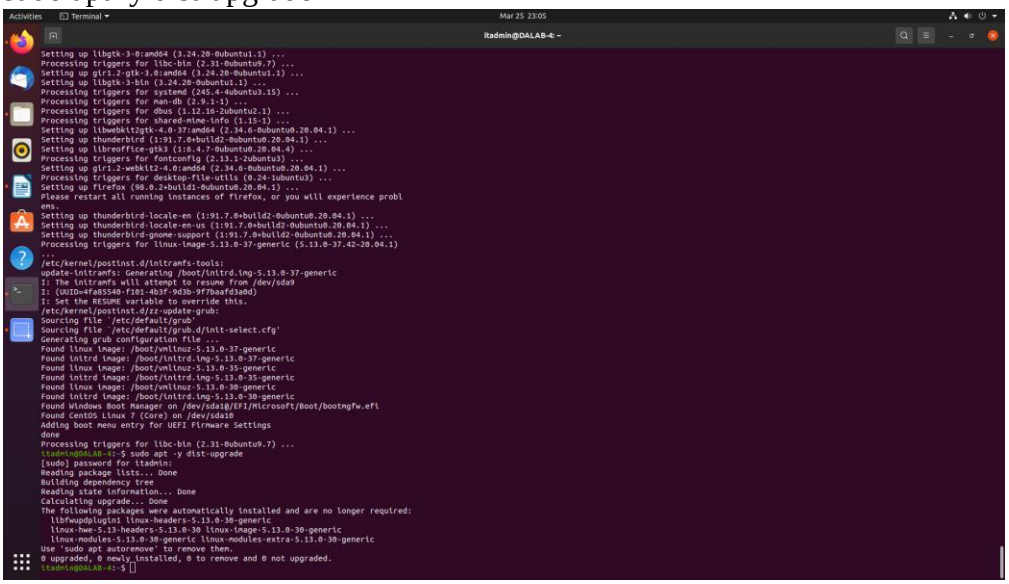
1. Login to sudo ("superuser do") user
2. Open Terminal
3. In Terminal type : sudo apt – update



4. sudo apt -y upgrade



5. sudo apt -y dist-upgrade



6. sudo useradd -s /bin/bash -d /opt/stack -m stack

```
(base) student@DALAB-4:~/Desktop$ sudo useradd -s /bin/bash -d /opt/stack -m stack
[sudo] password for student:
student is not in the sudoers file.  This incident will be reported.
(base) student@DALAB-4:~/Desktop$ su - itadmin
Password:
itadmin@DALAB-4:~$ sudo useradd -s /bin/bash -d /opt/stack -m stack
[sudo] password for itadmin:
itadmin@DALAB-4:~$
```

7. echo "stack ALL=(ALL) NOPASSWD: ALL" | sudo tee /etc/sudoers.d/stack

```
itadmin@DALAB-4:~$ echo "stack ALL=(ALL) NOPASSWD: ALL" | sudo tee /etc/sudoers.d/stack
stack ALL=(ALL) NOPASSWD: ALL
itadmin@DALAB-4:~$
```

8. sudo su - stack

```
itadmin@DALAB-4:~$ sudo su - stack
```

9. sudo apt -y install git

```
stack@DALAB-4:~$ sudo apt -y install git
Reading package lists... Done
Building dependency tree
Reading state information... Done
The following packages were automatically installed and are no longer required:
  libfwupdplugin1 linux-headers-5.13.0-30-generic
  linux-hwe-5.13-headers-5.13.0-30 linux-image-5.13.0-30-generic
  linux-modules-5.13.0-30-generic linux-modules-extra-5.13.0-30-generic
Use 'sudo apt autoremove' to remove them.
The following additional packages will be installed:
  git-man liberror-perl
Suggested packages:
  git-daemon-run | git-daemon-sysvinit git-doc git-el git-email git-gui gitk
  gitweb git-cvs git-mediawiki git-svn
The following NEW packages will be installed:
  git git-man liberror-perl
0 upgraded, 3 newly installed, 0 to remove and 0 not upgraded.
Need to get 5,465 kB of archives.
After this operation, 38.4 MB of additional disk space will be used.
Get:1 http://in.archive.ubuntu.com/ubuntu focal/main amd64 liberror-perl all 0.17029-1 [26.5 kB]
Get:2 http://in.archive.ubuntu.com/ubuntu focal-updates/main amd64 git-man all 1:2.25.1-1ubuntu3.2 [884 kB]
9% [2 git-man 114 kB/884 kB 13%]
pdates/main amd64 git amd64 1:2.25.1-1ubuntu3.2 [4,554 kB]
Fetched 5,465 kB in 4min 3s (22.5 kB/s)
Selecting previously unselected package liberror-perl.
(Reading database ... 213052 files and directories currently installed.)
Preparing to unpack .../liberror-perl_0.17029-1_all.deb ...
Unpacking liberror-perl (0.17029-1) ...
Selecting previously unselected package git-man.
Preparing to unpack .../git-man_1%3a2.25.1-1ubuntu3.2_all.deb ...
Unpacking git-man (1:2.25.1-1ubuntu3.2) ...
Selecting previously unselected package git.
Preparing to unpack .../git_1%3a2.25.1-1ubuntu3.2_amd64.deb ...
Unpacking git (1:2.25.1-1ubuntu3.2) ...
Setting up liberror-perl (0.17029-1) ...
Setting up git-man (1:2.25.1-1ubuntu3.2) ...
Setting up git (1:2.25.1-1ubuntu3.2) ...
Processing triggers for man-db (2.9.1-1) ...
```

10. git clone https://git.openstack.org/openstack-dev/devstack

```
stack@DALAB-4:~$ git clone https://github.com/openstack-dev/devstack.git
Cloning into 'devstack'...
remote: Enumerating objects: 48499, done.
remote: Counting objects: 100% (1725/1725), done.
remote: Compressing objects: 100% (686/686), done.
remote: Total 48499 (delta 1177), reused 1444 (delta 1033), pack-reused 46774
Receiving objects: 100% (48499/48499), 15.48 MiB | 4.31 MiB/s, done.
Resolving deltas: 100% (33808/33808), done.
```

11. cd devstack

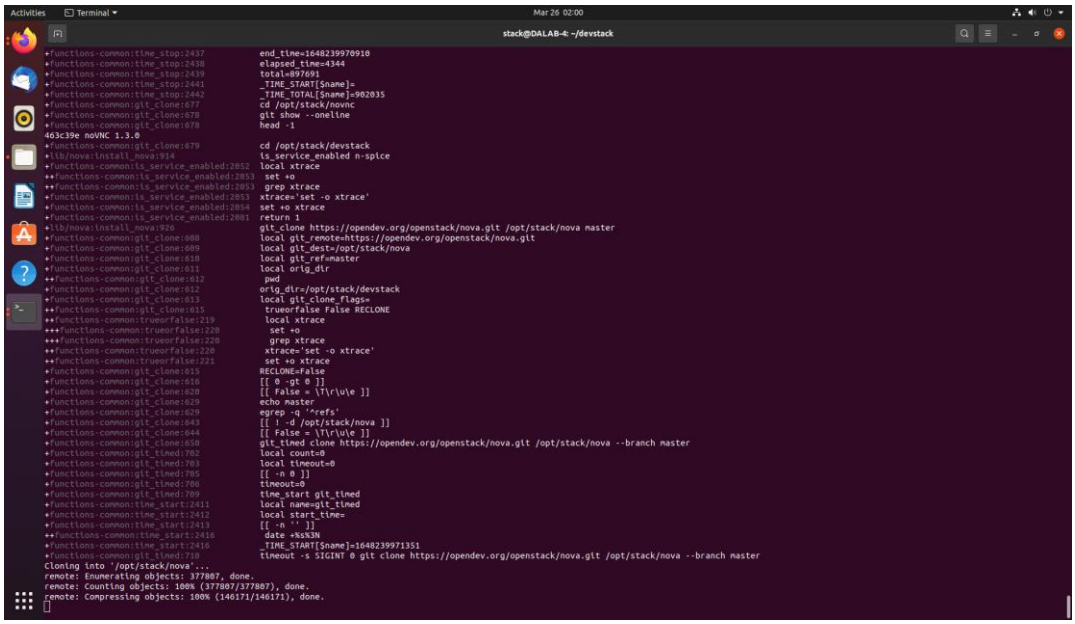
```
stack@DALAB-4:~$ cd devstack
stack@DALAB-4:~/devstack$
```

12. vi local.conf / nano local.conf

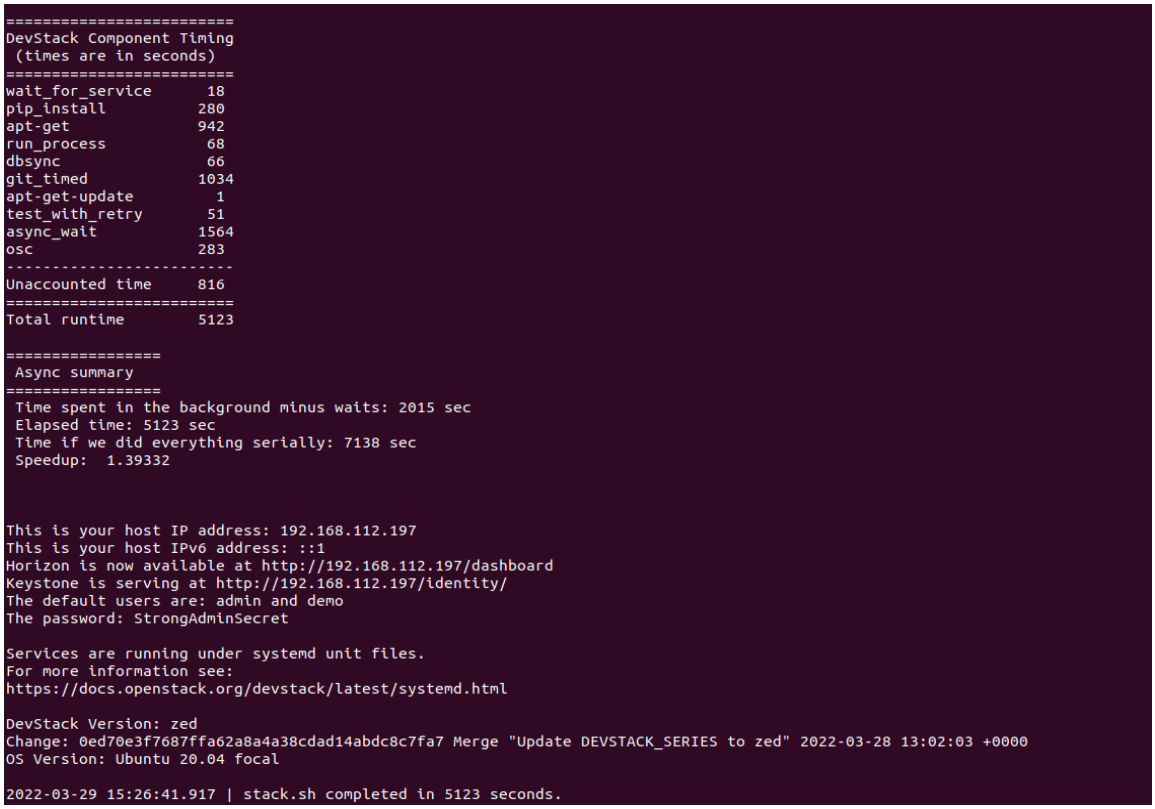
```
stack@DALAB-4:~$ cd devstack
stack@DALAB-4:~/devstack$ nano local.conf
stack@DALAB-4:~/devstack$ vi local.conf
```

13. We need to add the following in local.conf
    [[local|localrc]]
    ADMIN_PASSWORD=StrongAdminSecret
    DATABASE_PASSWORD=$ADMIN_PASSWORD
    RABBIT_PASSWORD=$ADMIN_PASSWORD
    SERVICE_PASSWORD=$ADMIN_PASSWORD

14. Run this script to setup OpenStack
    ./stack.sh



After Installation:



Result:

Openstack has been successfully installed and it has been verified.

Exp.No : 4 **Date:**09/04/22

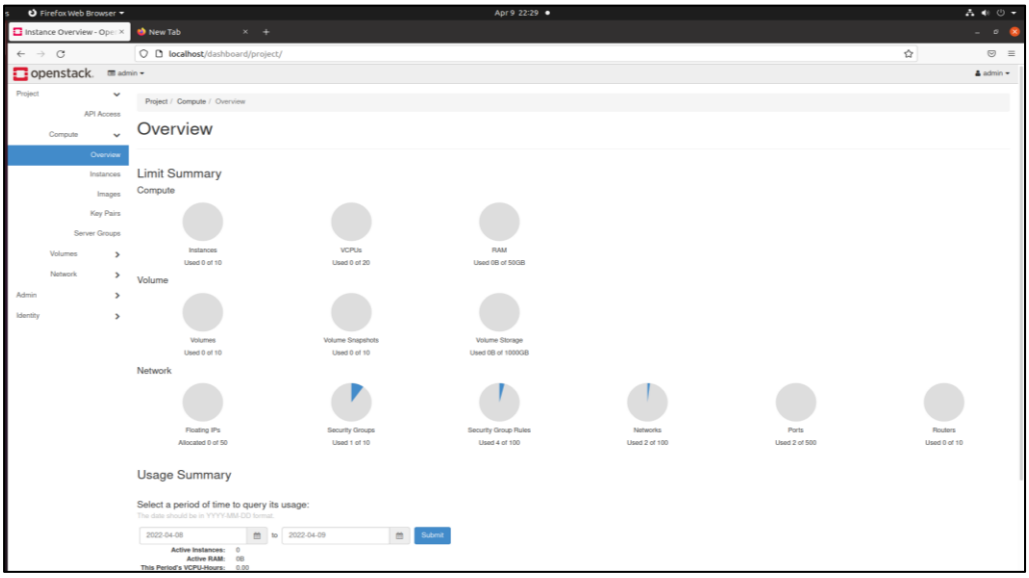
CREATION OF VMs IN OPENSTACK

1)Aim:

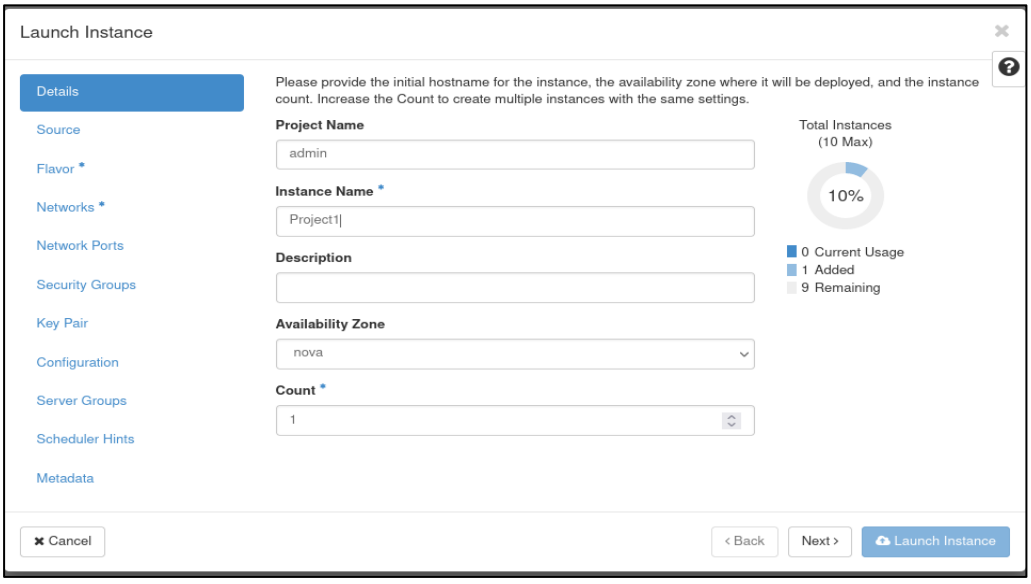
To create a VM in openstack and execution of simple application in openstack.

Steps to Deploy VM:

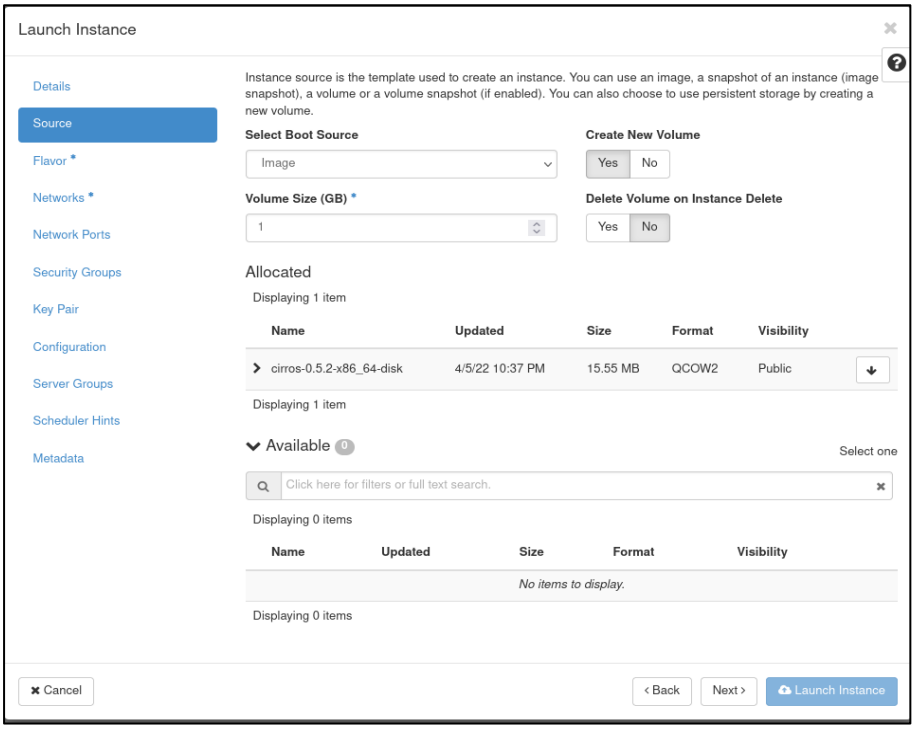
1. We need to launch openstack



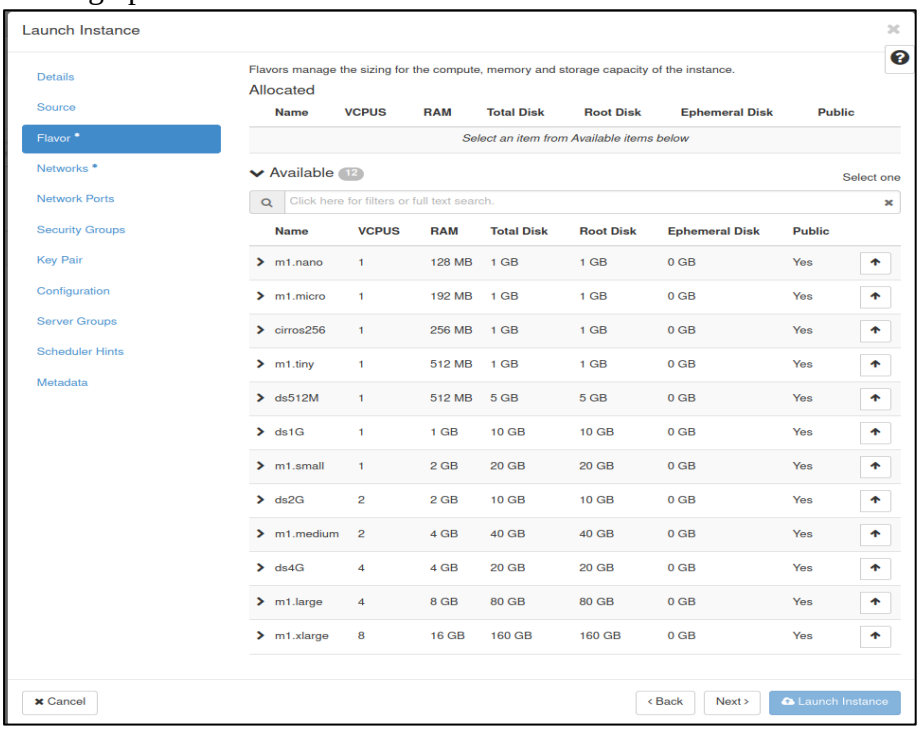
2. After clicking launch option we will get a popup window

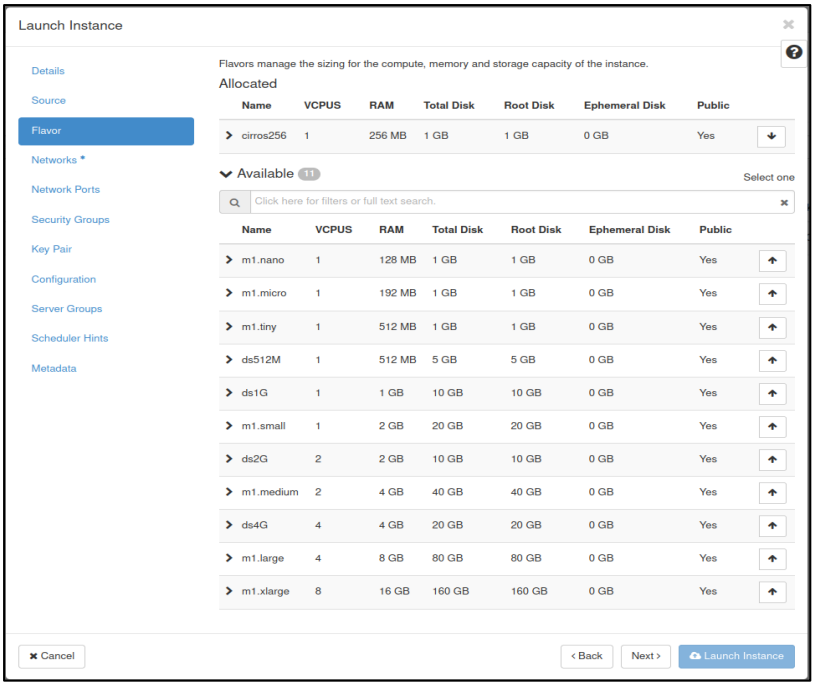


3. We need to give an instance name and leave all fields as default and click next
4. We will get a source tab in launch instance window where storage is created and click next

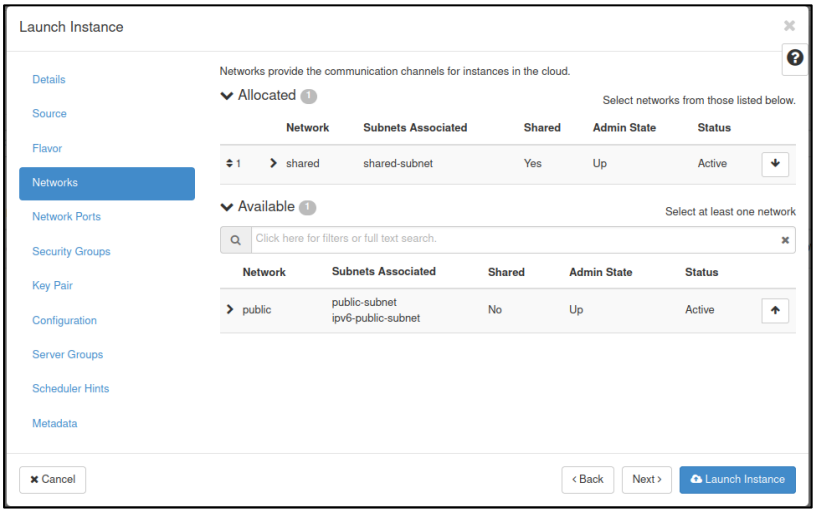


5. We need to allocate virtual machine resources by adding a flavor suited to our needs and click next
6. From available instance we need to add instance which we already launched by clicking upward arrow mark

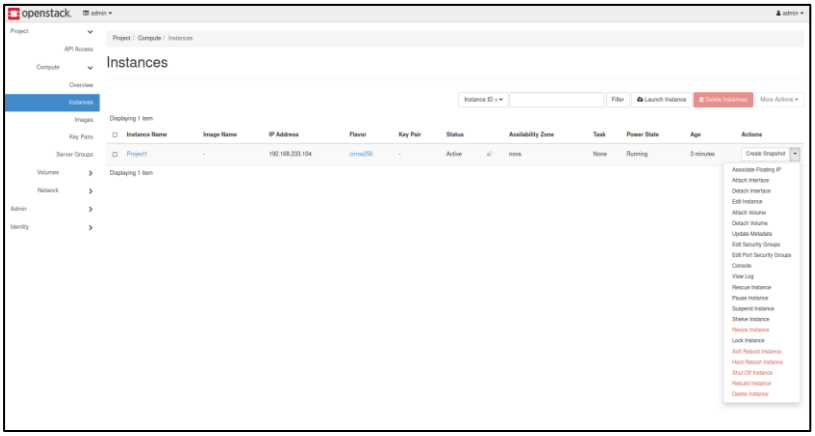




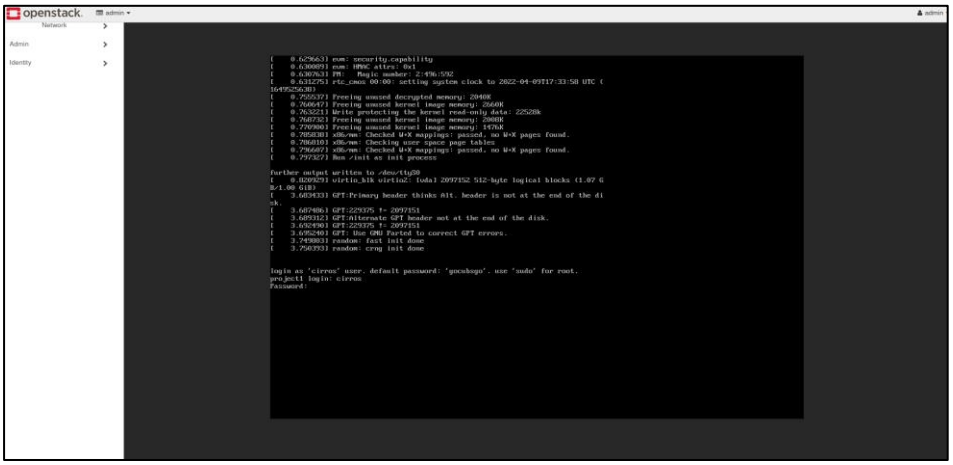
7. Finally, we add the shared network for available networks in openstack to our instance using the upward arrow mark button and hit on Launch Instance to start the virtual machine



8. We click the console

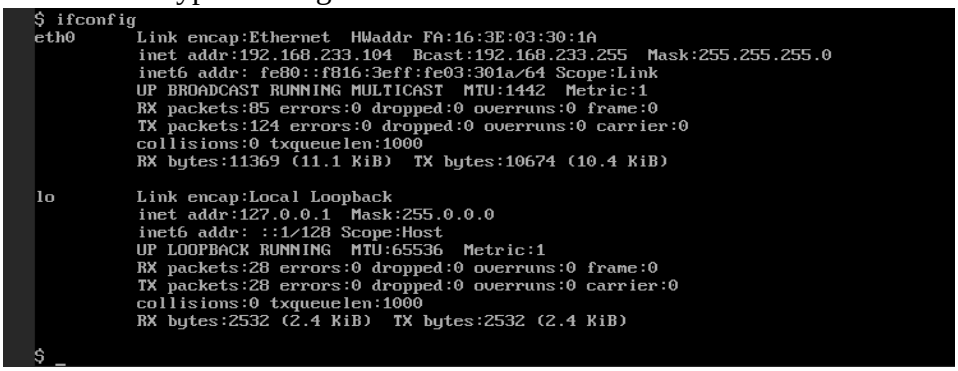


9. In console window , we create a text file. Eg. vi text.tst .



We dispay the contents using cat text.txt

We can also type ifconfig and execute the command



Result:

Creation of VM in openstack has been done successfully and execution of simple application using Open Stack has also been done successfully and the results are verified.

Exp.No : 5 **Date:**12/04/22

MONGODB BASICS

1)Aim:

To do a study on MongoDB.

MongoDB:

MongoDB is an open-source document database.It is a NOSQL database. MongoDB is written in C++. It is a highly scalable and performance-oriented database.

Features:

A) Documents

MongoDB stores data as JSON documents. The document data model maps naturally to objects in application code, making it simple for developers to learn and use. Documents can be nested to express hierarchical relationships and store structures as arrays.

B) Collections
In MongoDB, a collection is a group of documents. Each collection is associated with one MongoDB database.

C) Replica Sets
When we create a database in MongoDB, the system automatically creates at least two or more copies of data referred as a replica set It ensures high availability of data , offers redundancy and protection against downtime in face of system failure / maintenance.

D) Sharding
MongoDB shards data at collection level, distributing documents in a collection across the shards in a cluster. It is useful to handle massive data growth scaling.

E) Indexes

Indexes support the efficient execution of queries. MongoDB offers variety of different indexing strategies. Indexes speed up queries because queries scan the index instead of reading every document in the collection.

Result:

Study on MongoDB has been done successfully.

2)**Aim:**

To create a database and corresponding tables, populate the tables with data and apply insert /search operation

Code:

show dbs

Output:

```
> show dbs
admin   0.000GB
config  0.000GB
local   0.000GB
```

use sample

Output:

```
samlpe> use sample
switched to db sample
```

show tables

Output:

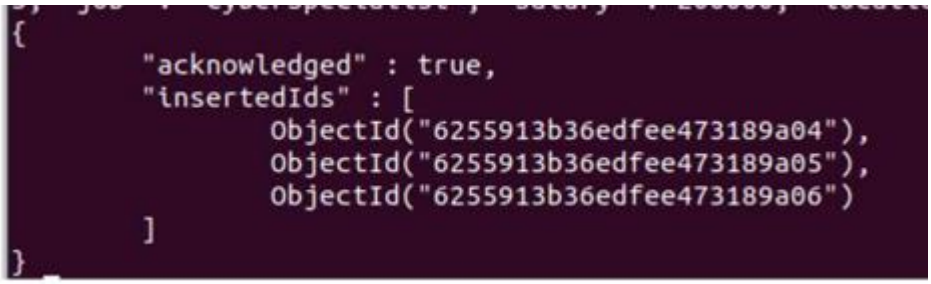
```
sample> show tables
faculty
student
subject
```

Insertion of data:

```
db.student.insertMany(
[
        {
                "name":"rozen",
                "reg":"1",
                "cgpa":"9.6"
        },
        {
                "name" : "raj",
                "reg":"2",
```

```
        "cgpa":"9.2"
    },
    {
        "name" : "raju",
        "reg":"3",
        "cgpa":"9.2"
    }
])
```

Output:




```
db.subject.insertMany(
[
    {
        "name":"maths",
        "code":"MA5501"
    },
    {
        "name" : "chemistry",
        "code":"CH5801"
    },
    {
        "name" : "physics",
        "code":"PH8801"
    }
])
db.student.find().pretty()
```

Output:

```
sample> db.student.find().pretty()
[
  {
    _id: ObjectId("6255d59d6f49f81bc99a1856"),
    name: 'rozen',
    reg: '1',
    cgpa: '9.6'
  },
  {
    _id: ObjectId("6255d59d6f49f81bc99a1857"),
    name: 'raj',
    reg: '2',
    cgpa: '9.2'
  },
  {
    _id: ObjectId("6255d59d6f49f81bc99a1858"),
    name: 'raju',
    reg: '3',
    cgpa: '9.2'
  }
]
sample>
```

db.faculty.insertMany(

[

{

name: “Dr.A”,

subject: ‘maths’

},

{

name: “Dr.B”,

subject: ‘chemistry’

},

{

name: “Dr.C”,

subject: ‘physics’

}

])

db.faculty.find().pretty()

Output:

```
sample> db.faculty.find().pretty()
[
  {
    _id: ObjectId("6255d93b6f49f81bc99a185c"),
    name: 'Dr.D',
    subject: 'maths'
  },
  {
    _id: ObjectId("6255d93b6f49f81bc99a185d"),
    name: 'Dr.B',
    subject: 'chemistry'
  },
  {
    _id: ObjectId("6255d93b6f49f81bc99a185e"),
    name: 'Dr.C',
    subject: 'physics'
  }
]
sample>
```

db.subject.insertMany(

[

{

"name":"dsa",

"code":"IT5603"

},

{

"name" : "cloud",

"code":"IT5602"

},

{

"name" : "embedded",

"code":"IT5601"

}

])

db.subject.find().pretty()

Output:

```
sample> db.subject.find().pretty()
[
  {
    _id: ObjectId("6255d68f6f49f81bc99a1859"),
    name: 'maths',
    code: 'MA5501'
  },
  {
    _id: ObjectId("6255d68f6f49f81bc99a185a"),
    name: 'chemistry',
    code: 'CH5801'
  },
  {
    _id: ObjectId("6255d68f6f49f81bc99a185b"),
    name: 'physics',
    code: 'PH8801'
  },
  {
    _id: ObjectId("6255dd376f49f81bc99a185f"),
    name: 'dsa',
    code: 'IT5603'
  },
  {
    _id: ObjectId("6255dd376f49f81bc99a1860"),
    name: 'cloud',
    code: 'IT5602'
  },
  {
    _id: ObjectId("6255dd376f49f81bc99a1861"),
    name: 'embedded',
    code: 'IT5601'
  }
]
sample>
```

use shopping

db.products.insertOne({"name":"abc","price":30,"color":"red"})

Output:

```
{
        "acknowledged" : true,
        "insertedId" : ObjectId("5c766be6d27187cc70d7666f")
}
```

db.products.find()

Output:

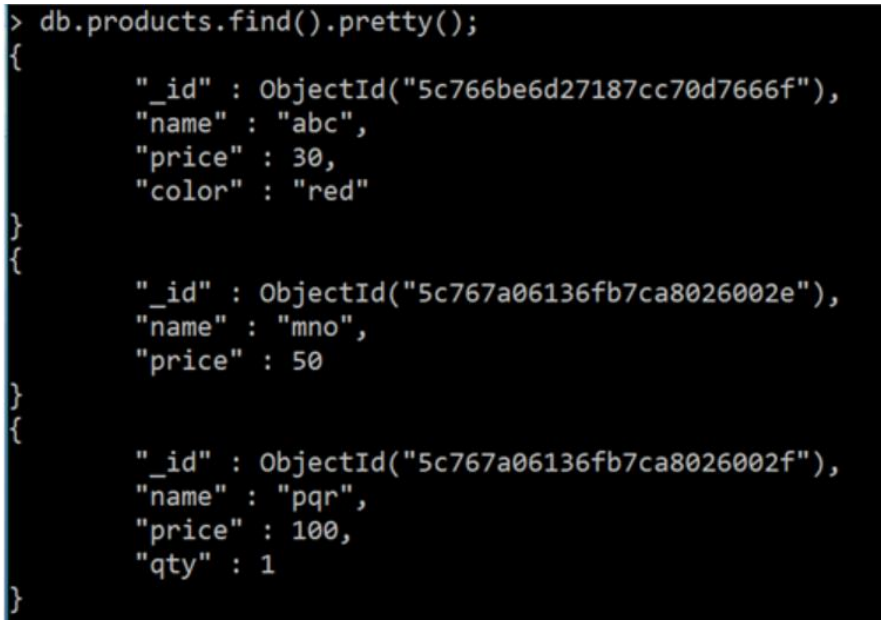
```
> db.products.find().pretty();
{
        "_id" : ObjectId("5c766be6d27187cc70d7666f"),
        "name" : "abc",
        "price" : 30,
        "color" : "red"
}
```

db.products.insertMany([{"name":"mno","price":50},{"name":"pqr","price":100,"qty":1}]);

Output:

db.products.find().pretty()

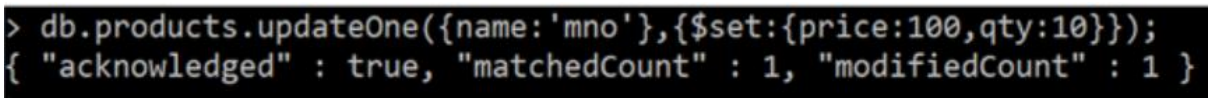
Output:



db.products.insertOne({"name":"abc",_id:"p01"})

db.products.updateOne({name:'mno'},{$set:{price:100,qty:10}})

Output:

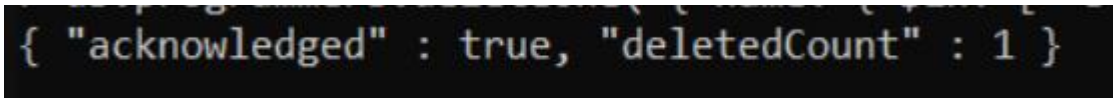


db.products.updateMany({name:'abc'},{$set:{ qty:150}})

Output:

db.products.deleteOne({_id:’p01’});

Output:



Result:

Database has been created, populated with data , insert/search operations are performed successfully and the results are verified.

Exp.No : 6 **Date:**19/04/22

BIVARIATE ANALYSIS

1)Aim:

To perform the following from the dow jones index dataset:

a)Pearson Correlation Coefficients and Interpretation b)Simple Linear Regression

c)Chi-square test d)T-test e)Analysis of Variance f)Scatterplots

Code:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

data['high'] = data['high'].str.replace('$', '')
data['open'] = data['open'].str.replace('$', '')
data['low'] = data['low'].str.replace('$', '')
data['close'] = data['close'].str.replace('$', '')

data['next_weeks_open'] = data['next_weeks_open'].str.replace('$', '')
data['next_weeks_close'] = data['next_weeks_close'].str.replace('$', '')

data['high']=pd.to_numeric(data['high'])
data['open']=pd.to_numeric(data['open'])
data['low']=pd.to_numeric(data['low'])
data['close']=pd.to_numeric(data['close'])
data['next_weeks_open']=pd.to_numeric(data['next_weeks_open'])
data['next_weeks_close']=pd.to_numeric(data['next_weeks_close'])


data['percent_change_volume_over_last_wk'].fillna(value=0,inplace=True)
data['previous_weeks_volume'].fillna(value=0,inplace=True)
```

data

Output:

	quarter	stock	date	open	high	low	close	volume	percent_change_price	percent_change_volume_over_last_wk	previous_weeks_volume	n
0	1	AA	1/7/2011	15.82	16.72	15.78	16.42	239655616	3.79267	0.000000	0.0	
1	1	AA	1/14/2011	16.71	16.71	15.64	15.97	242963398	-4.42849	1.380223	239655616.0	
2	1	AA	1/21/2011	16.19	16.38	15.60	15.79	138428495	-2.47066	-43.024959	242963398.0	
3	1	AA	1/28/2011	15.87	16.63	15.82	16.13	151379173	1.63831	9.355500	138428495.0	
4	1	AA	2/4/2011	16.18	17.39	16.18	17.14	154387761	5.93325	1.987452	151379173.0	
...	...	...	...	...	...	...	...	...	...	...	...	
745	2	XOM	5/27/2011	80.22	82.63	80.07	82.63	68230855	3.00424	-21.355713	86758820.0	
746	2	XOM	6/3/2011	83.28	83.75	80.18	81.18	78616295	-2.52161	15.221032	68230855.0	
747	2	XOM	6/10/2011	80.93	81.87	79.72	79.78	92380844	-1.42098	17.508519	78616295.0	
748	2	XOM	6/17/2011	80.00	80.82	78.33	79.02	100521400	-1.22500	8.811952	92380844.0	
749	2	XOM	6/24/2011	78.65	81.12	76.78	76.78	118679791	-2.37762	18.064204	100521400.0	

750 rows × 16 columns

#Pearson Correlation

```
import scipy.stats
corr,_=scipy.stats.pearsonr(data['high'],data['low'])
print(corr)
```

Output:

```
0.9994191540117697
```

```
corr,_=scipy.stats.pearsonr(data['volume'],data['open'])
print(corr)
```

Output:

```
-0.5134239596601641
```

```
corr,_=scipy.stats.pearsonr(data['days_to_next_dividend'],data['next_weeks_close'])
print(corr)
```

Output:

```
-0.06772514422301334
```

```
corr,_=scipy.stats.pearsonr(data['open'],data['close'])
print(corr)
```

Output:

```
0.999044034320146
```

corr,_=scipy.stats.pearsonr(data['percent_change_volume_over_last_wk'],data['percent_change_price'])

print(corr)

Output:

```
-0.22956755048417227
```

corr,_=scipy.stats.pearsonr(data['next_weeks_open'],data['next_weeks_close'])

print(corr)

Output:

```
0.9988798616255573
```

corr,_=scipy.stats.pearsonr(data['days_to_next_dividend'],data['percent_return_next_dividend'])

print(corr)

Output:

```
0.12174809745628305
```

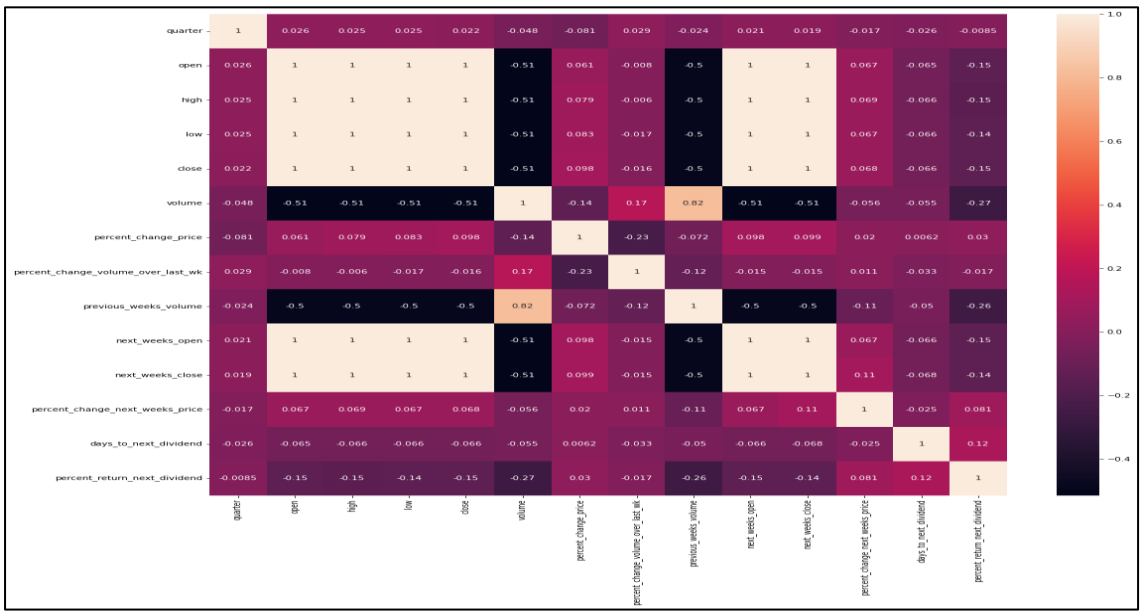
from matplotlib.pyplot import figure

figure(figsize=(18, 16))

sns.heatmap(data.corr(),annot=True)

plt.plot()

Output:



#Simple Linear Regression

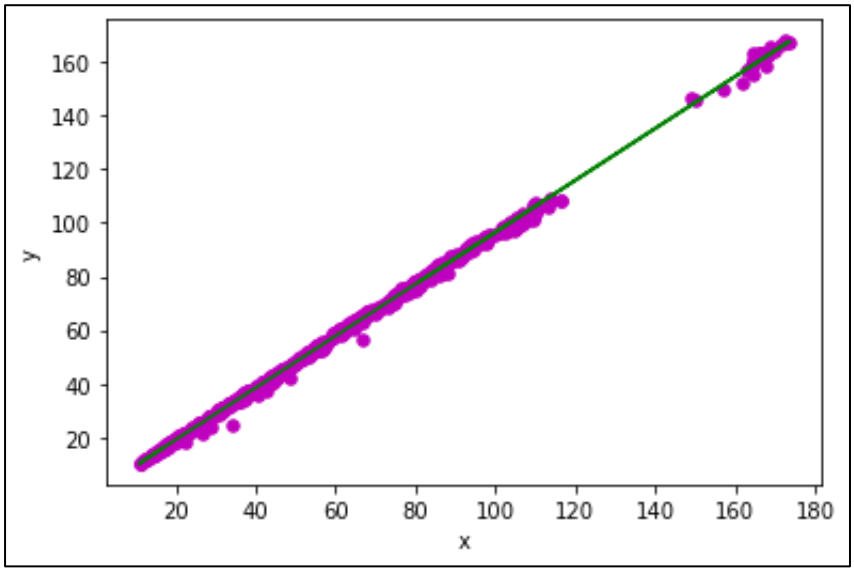
```
def estimate_coef(x, y):
    # number of observations/points
    n = np.size(x)
    # mean of x and y vector
    m_x = np.mean(x)
    m_y = np.mean(y)
    # calculating cross-deviation and deviation about x
    SS_xy = np.sum(y*x) - n*m_y*m_x
    SS_xx = np.sum(x*x) - n*m_x*m_x
    # calculating regression coefficients
    b_1 = SS_xy / SS_xx
    b_0 = m_y - b_1*m_x
    return (b_0, b_1)

def plot_regression_line(x, y, b):
    # plotting the actual points as scatter plot
    plt.scatter(x, y, color = "m",
            marker = "o", s = 30)
    # predicted response vector
    y_pred = b[0] + b[1]*x
    # plotting the regression line
    plt.plot(x, y_pred, color = "g")
    # putting labels
    plt.xlabel('x')
    plt.ylabel('y')
    # function to show plot
    plt.show()
def main():
    # observations / data
```

```
    x = np.array(data['high'])
    y = np.array(data['low'])
    # estimating coefficients
    b = estimate_coef(x, y)
    print("Estimated coefficients:\nc = {} \\nm = {}".format(b[0], b[1]))
    # plotting regression line
    plot_regression_line(x, y, b)

if __name__ == "__main__":
    main()
```

Output:

```
Estimated coefficients:
c = -0.19404242022824292
m = 0.9664206201909
```

#scatter plot



#chi square test

```
from scipy.stats import chi2_contingency
# defining the table
data_c = [data['low'],data['open'],data['high']]
stat, p, dof, expected = chi2_contingency(data_c)
```

```
# interpret p-value
alpha = 0.05
print("p value is " + str(p))
if p <= alpha:
        print('Dependent (reject H0)')
else:
        print('Independent (H0 holds true)')
```

Output:

```
p value is 1.0
Independent (H0 holds true)
```

#t test

```
from scipy.stats import ttest_ind
# defining the table
stat, p = ttest_ind(data['low'],data['open'])
# interpret p-value
alpha = 0.05
print("p value is " + str(p))
if p <= alpha:
        print('Dependent (reject H0)')
else:
        print('Independent (H0 holds true)')
```

Output:

```
p value is 0.5452473592620216
Independent (H0 holds true)
```

```
from scipy.stats import ttest_ind
# defining the table
stat, p = ttest_ind(data['high'],data['close'])
```

```
# interpret p-value
alpha = 0.05
print("p value is " + str(p))
if p <= alpha:
        print('Dependent (reject H0)')
else:
        print('Independent (H0 holds true)')
```

Output:

```
p value is 0.581045977109643
Independent (H0 holds true)
```

#Analysis of Variance

```
import scipy.stats as st
st.f_oneway(data['high'],data['low'],data['open'])
```

Output:

```
F_onewayResult(statistic=0.7242002902172524, pvalue=0.4848251428613093)
```

Result:

Operations related to bivariate analysis has been successfully executed and the results are verified.

Exp.No : 7 **Date:**26/04/22

LOGISTIC REGRESSION

1)**Aim:**

To perform the following from the dataset i)Binary ii)Multi-class or Multinominal iii)Ordinal

Code:

i)Binary

```
import pandas as pd

import seaborn as sns

import matplotlib.pyplot as plt


data=pd.read_csv("diabetes.csv")

data.info()
```

Output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               768 non-null    int64  
 1   Glucose                   768 non-null    int64  
 2   BloodPressure             768 non-null    int64  
 3   SkinThickness             768 non-null    int64  
 4   Insulin                   768 non-null    int64  
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
 8   Outcome                   768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

```
from sklearn.model_selection import train_test_split

train,test=train_test_split(data,test_size=0.20,random_state=42)


import statsmodels.api as sm

from statsmodels.formula.api import logit

formula=('Outcome ~ Pregnancies + Glucose + BloodPressure + SkinThickness + Insulin + BMI + DiabetesPedigreeFunction + Age')

model=logit(formula=formula,data=train).fit()
```

Output:

```
Optimization terminated successfully.
         Current function value: 0.467835
         Iterations 6
```

model.summary()

Output:

Logit Regression Results

Dep. Variable:	Outcome	**No. Observations:**	614
Model:	Logit	**Df Residuals:**	605
Method:	MLE	**Df Model:**	8
Date:	Sun, 15 May 2022	**Pseudo R-squ.:**	0.2752
Time:	21:05:52	**Log-Likelihood:**	-287.25
converged:	True	**LL-Null:**	-396.34
Covariance Type:	nonrobust	**LLR p-value:**	9.311e-43

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-9.0359	0.837	-10.802	0.000	-10.675	-7.396
Pregnancies	0.0645	0.036	1.791	0.073	-0.006	0.135
Glucose	0.0341	0.004	8.055	0.000	0.026	0.042
BloodPressure	-0.0139	0.006	-2.260	0.024	-0.026	-0.002
SkinThickness	0.0031	0.008	0.397	0.691	-0.012	0.019
Insulin	-0.0018	0.001	-1.782	0.075	-0.004	0.000
BMI	0.1026	0.017	5.948	0.000	0.069	0.136
DiabetesPedigreeFunction	0.6945	0.330	2.107	0.035	0.049	1.341
Age	0.0371	0.011	3.400	0.001	0.016	0.058

AME=model.get_margeff(at='overall',method='dydx')

AME.summary()

Output:

Logit Marginal Effects

Dep. Variable:	Outcome
Method:	dydx
At:	overall

	dy/dx	std err	z	P>|z|	[0.025	0.975]
Pregnancies	0.0098	0.005	1.807	0.071	-0.001	0.021
Glucose	0.0052	0.001	10.107	0.000	0.004	0.006
BloodPressure	-0.0021	0.001	-2.291	0.022	-0.004	-0.000
SkinThickness	0.0005	0.001	0.398	0.691	-0.002	0.003
Insulin	-0.0003	0.000	-1.797	0.072	-0.001	2.51e-05
BMI	0.0156	0.002	6.584	0.000	0.011	0.020
DiabetesPedigreeFunction	0.1059	0.050	2.132	0.033	0.009	0.203
Age	0.0057	0.002	3.514	0.000	0.003	0.009

```
import numpy as np

from sklearn.metrics import classification_report,accuracy_score,confusion_matrix

prediction = model.predict(exog=test)

cutoff=0.5

y_pred=np.where(prediction>cutoff ,1,0)

y_actual=test['Outcome']

conf_matrix=pd.crosstab(y_actual,y_pred,rownames=['Actual'],colnames=['Predicted'],margins=True)

conf_matrix
```

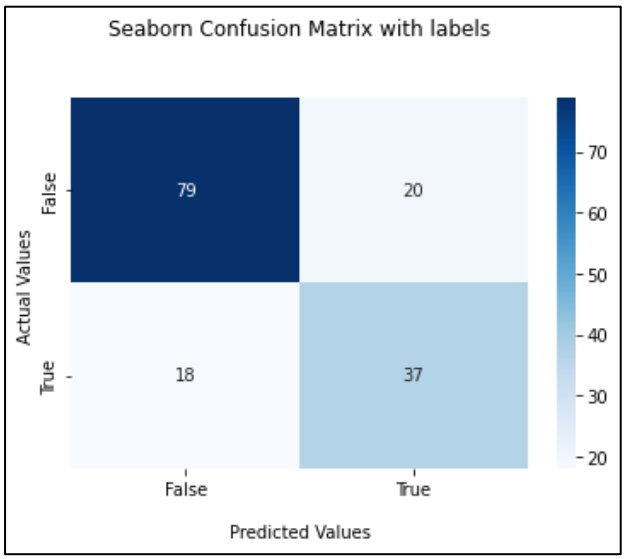
Output:

Predicted	0	1	All
Actual			
0	79	20	99
1	18	37	55
All	97	57	154

```
ax = sns.heatmap(confusion_matrix(y_actual,y_pred), annot=True, cmap='Blues')
```

```
ax.set_title('Seaborn Confusion Matrix with labels\n\n');
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ');
## Ticket labels - List must be in alphabetical order
ax.xaxis.set_ticklabels(['False','True'])
ax.yaxis.set_ticklabels(['False','True'])
## Display the visualization of the Confusion Matrix.
plt.show()
```

Output:




```
acc=accuracy_score(y_actual,y_pred)
acc
```

Output:

```
acc
0.7532467532467533
```

print(classification_report(y_actual,y_pred))

Output:

	precision	recall	f1-score	support
0	0.81	0.80	0.81	99
1	0.65	0.67	0.66	55
accuracy			0.75	154
macro avg	0.73	0.74	0.73	154
weighted avg	0.76	0.75	0.75	154

from sklearn.metrics import roc_curve

fpr,tpr,_=roc_curve(y_actual,y_pred)

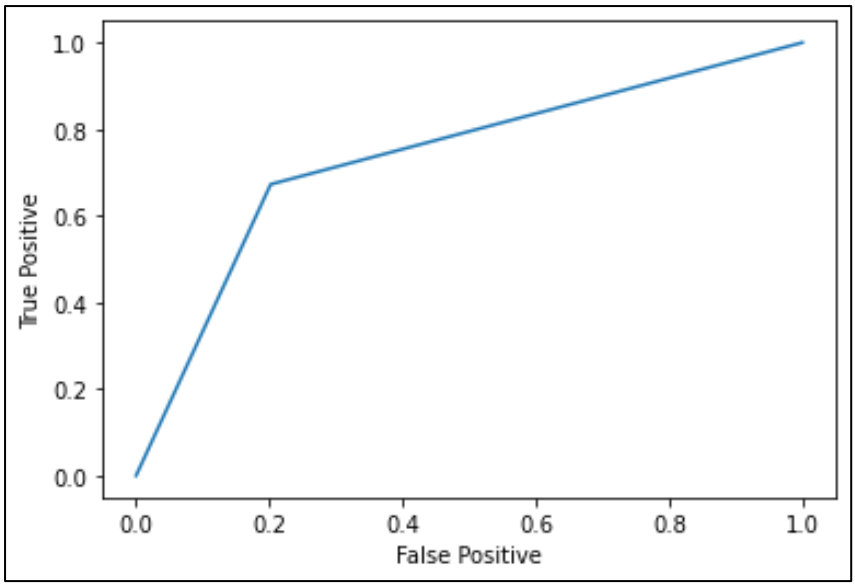
plt.plot(fpr,tpr)

plt.xlabel('False Positive')

plt.ylabel('True Positive')

plt.show()

Output:



ii)Multiclass or Multinomial

import pandas as pd

import numpy as np

import seaborn as sans

import matplotlib.pyplot as plt

```
data = pd.read_csv("dow_jones_index.csv")
data.corr()
```

Output:

	quarter	open	high	low	close	volume	percent_change_price
quarter	1.000000	0.025883	0.024727	0.024730	0.022102	-0.047599	-0.080959
open	0.025883	1.000000	0.999607	0.999344	0.999044	-0.513424	0.061485
high	0.024727	0.999607	1.000000	0.999419	0.999558	-0.512240	0.078656
low	0.024730	0.999344	0.999419	1.000000	0.999549	-0.514850	0.083170
close	0.022102	0.999044	0.999558	0.999549	1.000000	-0.514545	0.097980
volume	-0.047599	-0.513424	-0.512240	-0.514850	-0.514545	1.000000	-0.138924
percent_change_price	-0.080959	0.061485	0.078656	0.083170	0.097980	-0.138924	1.000000
percent_change_volume_over_last_wk	0.028977	-0.007966	-0.006020	-0.016874	-0.015809	0.169133	-0.229568
previous_weeks_volume	-0.024383	-0.495972	-0.495702	-0.495703	-0.495598	0.817078	-0.071942
next_weeks_open	0.021018	0.998942	0.999480	0.999430	0.999916	-0.514324	0.098270
next_weeks_close	0.019103	0.997787	0.998500	0.998326	0.998854	-0.513456	0.099243
percent_change_next_weeks_price	-0.017460	0.066603	0.069474	0.067320	0.067664	-0.056389	0.019955
days_to_next_dividend	-0.025641	-0.065228	-0.065516	-0.066270	-0.065975	-0.055486	0.006217
percent_return_next_dividend	-0.008505	-0.146001	-0.148343	-0.143838	-0.146417	-0.269735	0.029925

```
cols=['open','high','low','close','next_weeks_open','next_weeks_close']
X = data[cols]
Y = data['stock']
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size = 0.2, random_state=9)
from sklearn.linear_model import LogisticRegression
model=LogisticRegression(multi_class='multinomial', solver='lbfgs', penalty='none')
model.fit(X_train,y_train)
```

Output:

```
LogisticRegression(multi_class='multinomial', penalty='none')
```

```
pred=model.predict(X_test)
from sklearn.metrics import classification_report , accuracy_score
acc=accuracy_score(y_test,pred)
print(acc)
```

Output:

```
acc=accuracy_score(y_test,pred)
print(acc)

0.1
```

print(classification_report(y_test,pred))

Output:

	precision	recall	f1-score	support
AA	0.00	0.00	0.00	5
AXP	0.17	0.33	0.22	3
BA	0.00	0.00	0.00	5
BAC	0.33	0.20	0.25	10
CAT	0.33	0.17	0.22	6
CSCO	0.00	0.00	0.00	8
CVX	0.00	0.00	0.00	4
DD	0.50	0.12	0.20	8
DIS	0.00	0.00	0.00	5
GE	0.18	0.67	0.29	3
HD	0.00	0.00	0.00	7
HPQ	0.00	0.00	0.00	2
IBM	0.50	1.00	0.67	4
INTC	0.00	0.00	0.00	6
JNJ	0.00	0.00	0.00	8
JPM	0.00	0.00	0.00	4
KO	0.00	0.00	0.00	5

iii)Ordinal

import pandas as pd

data=pd.read_csv('diamonds.csv')

data

Output:

	Unnamed: 0	carat	cut	color	clarity	depth	table	price	x	y	z
0	1	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	2	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	3	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31
3	4	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
4	5	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75
...	...	...	...	...	...	...	...	...	...	...	...
53935	53936	0.72	Ideal	D	SI1	60.8	57.0	2757	5.75	5.76	3.50
53936	53937	0.72	Good	D	SI1	63.1	55.0	2757	5.69	5.75	3.61
53937	53938	0.70	Very Good	D	SI1	62.8	60.0	2757	5.66	5.68	3.56
53938	53939	0.86	Premium	H	SI2	61.0	58.0	2757	6.15	6.12	3.74
53939	53940	0.75	Ideal	D	SI2	62.2	55.0	2757	5.83	5.87	3.64

data.dtypes

Output:

```
Unnamed: 0      int64
carat         float64
cut            object
color          object
clarity        object
depth         float64
table         float64
price           int64
x             float64
y             float64
z             float64
dtype: object
```

data.info()

Output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53940 entries, 0 to 53939
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  53940 non-null  int64
 1   carat       53940 non-null  float64
 2   cut         53940 non-null  object
 3   color       53940 non-null  object
 4   clarity     53940 non-null  object
 5   depth       53940 non-null  float64
 6   table       53940 non-null  float64
 7   price       53940 non-null  int64
 8   x           53940 non-null  float64
 9   y           53940 non-null  float64
 10  z           53940 non-null  float64
dtypes: float64(6), int64(2), object(3)
memory usage: 4.5+ MB
```

from pandas.api.types import CategoricalDtype

cat_type = CategoricalDtype(categories=['Fair', 'Good', 'Ideal', 'Very Good', 'Premium'], ordered=True)

data["cut"] = data["cut"].astype(cat_type)

data['cut'].dtype

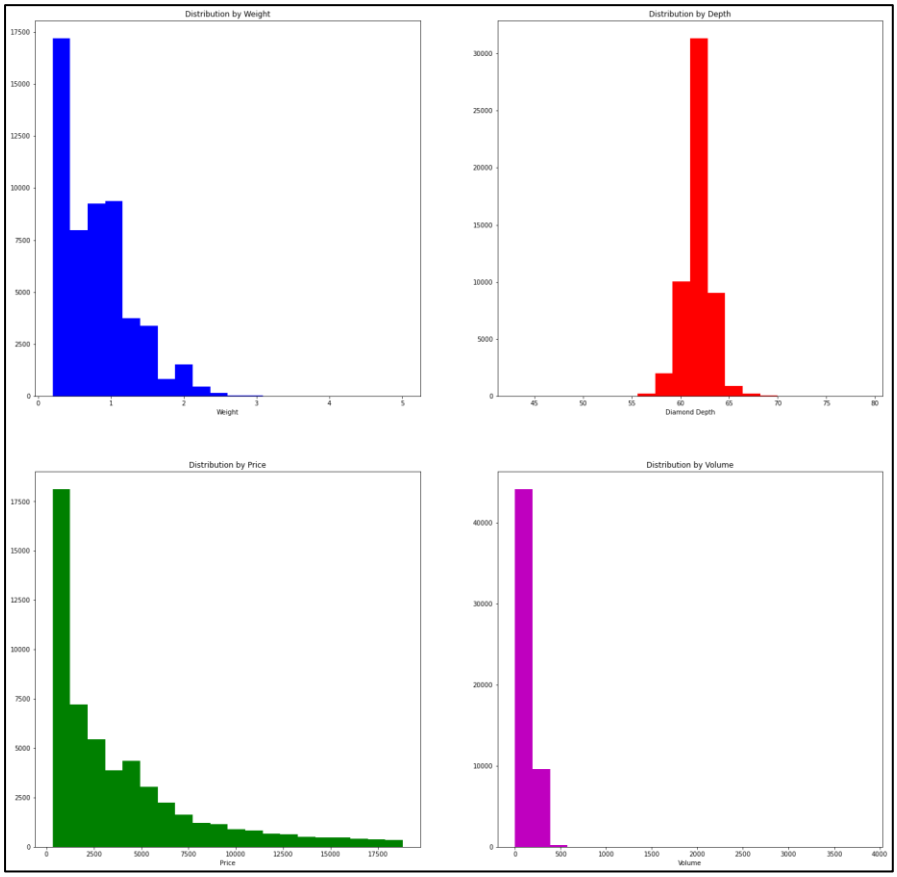
Output:

```
data['cut'].dtype
```

```
CategoricalDtype(categories=['Fair', 'Good', 'Ideal', 'Very Good', 'Premium'], ordered=True)
```

```
data['volume'] = data['x']*data['y']*data['z']
data.drop(['x','y','z'],axis=1,inplace=True)
import matplotlib.pyplot as plt
plt.figure(figsize=[24,24])

plt.subplot(221)
plt.hist(data['carat'],bins=20,color='b')
plt.xlabel('Weight')
plt.title('Distribution by Weight')

plt.subplot(222)
plt.hist(data['depth'],bins=20,color='r')
plt.xlabel('Diamond Depth')
plt.title('Distribution by Depth')

plt.subplot(223)
plt.hist(data['price'],bins=20,color='g')
plt.xlabel('Price')
plt.title('Distribution by Price')

plt.subplot(224)
plt.hist(data['volume'],bins=20,color='m')
plt.xlabel('Volume')
plt.title('Distribution by Volume')
```

Output:




```
from statsmodels.miscmodels.ordinal_model import OrderedModel
mod_prob = OrderedModel(data['cut'],data[['volume', 'price', 'carat']],distr='probit')

res_prob = mod_prob.fit(method='bfgs')
res_prob.summary()
```

Output:

```
Optimization terminated successfully.
         Current function value: 1.369122
         Iterations: 29
         Function evaluations: 35
         Gradient evaluations: 35
```

OrderedModel Results

Dep. Variable:	cut	**Log-Likelihood:**	-73850.
Model:	OrderedModel	**AIC:**	1.477e+05
Method:	Maximum Likelihood	**BIC:**	1.478e+05
Date:	Sun, 15 May 2022		
Time:	23:59:16		
No. Observations:	53940		
Df Residuals:	53933		
Df Model:	7		

#ordered logit

```
mod_prob = OrderedModel(data['cut'],data[['volume', 'price', 'carat']],distr='logit')

res_log = mod_prob.fit(method='bfgs')

res_log.summary()
```

Output:

```
Optimization terminated successfully.
         Current function value: 1.369215
         Iterations: 36
         Function evaluations: 42
         Gradient evaluations: 42
```

OrderedModel Results

Dep. Variable:	cut	**Log-Likelihood:**	-73855.
Model:	OrderedModel	**AIC:**	1.477e+05
Method:	Maximum Likelihood	**BIC:**	1.478e+05
Date:	Mon, 16 May 2022		
Time:	00:01:08		
No. Observations:	53940		
Df Residuals:	53933		
Df Model:	7		

Result:

Various types of logistic regression models have been tried successfully and the results are verified.

2)Aim:

To build a logistic regression model from the unique dataset and perform the following:

a.Data Understanding, Data cleaning, Exploratory Data Analysis-Relationship between target variable and other variables, Feature Engineering, Feature Normalization, Build and Train the model, Prediction, Perform Evaluation using standard metrics.

b.Build Model by Optimizing the Hyperparameters, Evaluate the model.

Code:

```
import numpy as np # linear algebra

import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

import matplotlib.pyplot as plt # data visualization

import seaborn as sns # statistical data visualization


import warnings

warnings.filterwarnings('ignore')

df=pd.read_csv('weatherAUS.csv')

col_names = df.columns

col_names
```

Output:

```
Index(['Date', 'Location', 'MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation',
       'Sunshine', 'WindGustDir', 'WindGustSpeed', 'WindDir9am', 'WindDir3pm',
       'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm',
       'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am',
       'Temp3pm', 'RainToday', 'RISK_MM', 'RainTomorrow'],
      dtype='object')
```

```
df.drop('RISK_MM',axis=1,inplace=True)

categorical = [var for var in df.columns if df[var].dtype=='O']

print('There are {} categorical variables\n'.format(len(categorical)))

print('The categorical variables are :', categorical)
```

Output:

```
There are 7 categorical variables

The categorical variables are : ['Date', 'Location', 'WindGustDir', 'WindDir9am', 'WindDir3pm', 'Rain
Today', 'RainTomorrow']
```

 # parse the dates, currently coded as strings, into datetime format

df['Date'] = pd.to_datetime(df['Date'])

 # drop the original Date variable

df.drop('Date', axis=1, inplace = True)

get k-1 dummy variables after One Hot Encoding

preview the dataset with head() method

pd.get_dummies(df.Location, drop_first=True).head()

preview the dataset with head() method

Output:

	Albany	Albury	AliceSprings	BadgerysCreek	Ballarat	Bendigo	Brisbane	Cairns	Canberra	Cobar
0	0	1	0	0	0	0	0	0	0	0
1	0	1	0	0	0	0	0	0	0	0
2	0	1	0	0	0	0	0	0	0	0
3	0	1	0	0	0	0	0	0	0	0
4	0	1	0	0	0	0	0	0	0	0

5 rows × 48 columns

pd.get_dummies(df.WindGustDir, drop_first=True, dummy_na=True).head()

Output:

	ENE	ESE	N	NE	NNE	NNW	NW	S	SE	SSE	SSW	SW	W	WNW	WSW	NaN
0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0

df[numerical].isnull().sum()

plt.figure(figsize=(15,10))

plt.subplot(2, 2, 1)

fig = df.boxplot(column='Rainfall')

fig.set_title('')

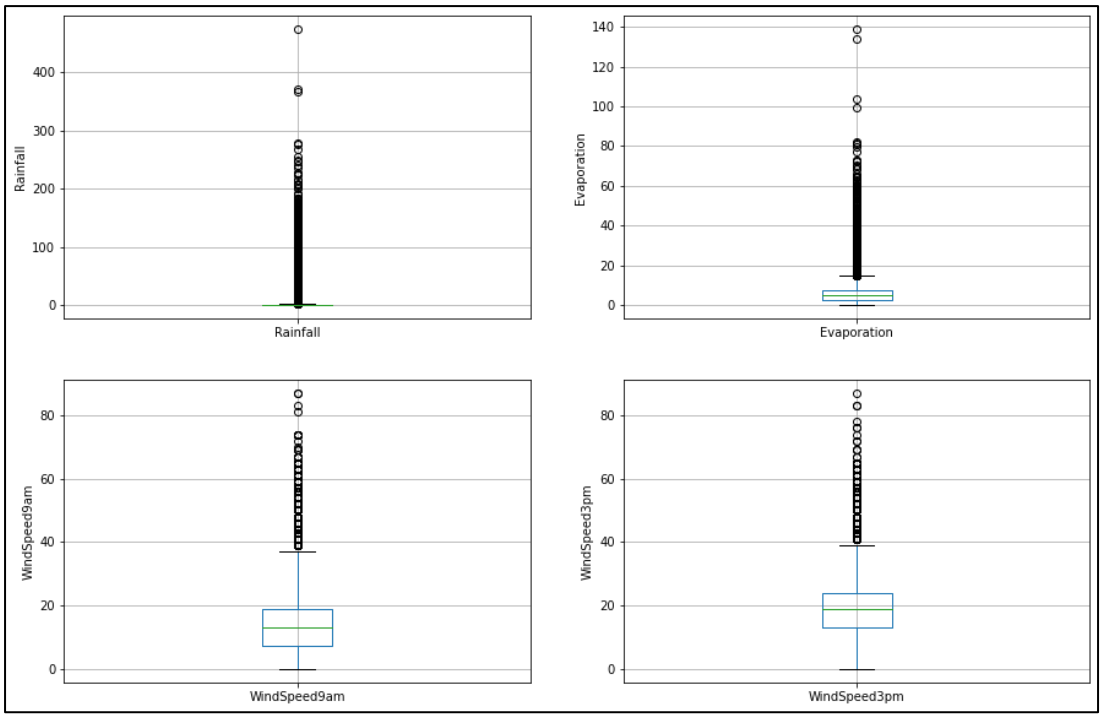
fig.set_ylabel('Rainfall')

plt.subplot(2, 2, 2)

fig = df.boxplot(column='Evaporation')

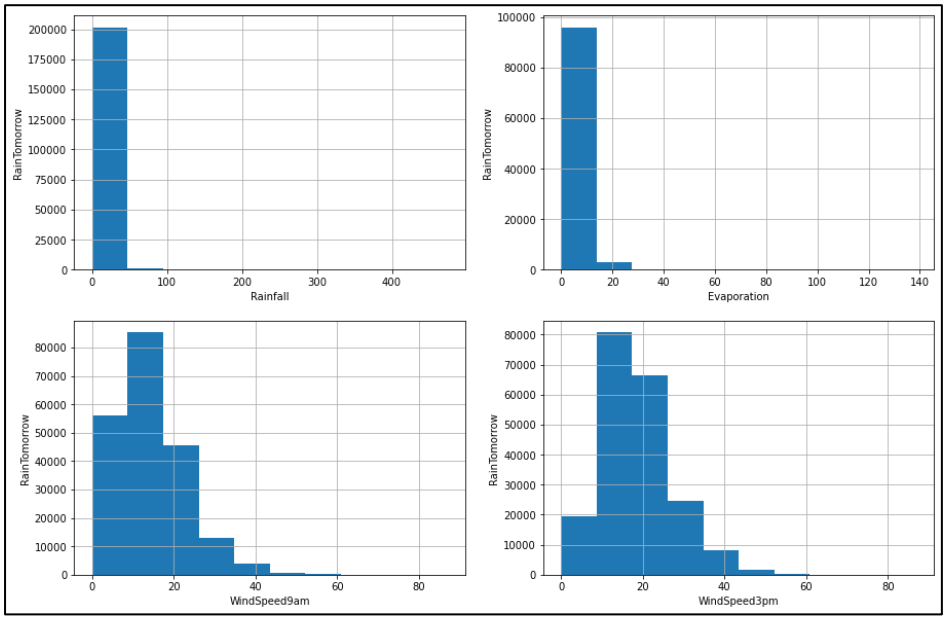
```
fig.set_title('')
fig.set_ylabel('Evaporation')


plt.subplot(2, 2, 3)
fig = df.boxplot(column='WindSpeed9am')
fig.set_title('')
fig.set_ylabel('WindSpeed9am')


plt.subplot(2, 2, 4)
fig = df.boxplot(column='WindSpeed3pm')
fig.set_title('')
fig.set_ylabel('WindSpeed3pm')
```

Output:



```
# plot histogram to check distribution
plt.figure(figsize=(15,10))

plt.subplot(2, 2, 1)
fig = df.Rainfall.hist(bins=10)
fig.set_xlabel('Rainfall')
fig.set_ylabel('RainTomorrow')

plt.subplot(2, 2, 2)
fig = df.Evaporation.hist(bins=10)
fig.set_xlabel('Evaporation')
fig.set_ylabel('RainTomorrow')

plt.subplot(2, 2, 3)
fig = df.WindSpeed9am.hist(bins=10)
fig.set_xlabel('WindSpeed9am')
fig.set_ylabel('RainTomorrow')

plt.subplot(2, 2, 4)
fig = df.WindSpeed3pm.hist(bins=10)
fig.set_xlabel('WindSpeed3pm')
fig.set_ylabel('RainTomorrow')
```

Output:



 # find outliers for Rainfall variable

IQR = df.Rainfall.quantile(0.75) - df.Rainfall.quantile(0.25)

Lower_fence = df.Rainfall.quantile(0.25) - (IQR * 3)

Upper_fence = df.Rainfall.quantile(0.75) + (IQR * 3)

print('Rainfall outliers are values < {lowerboundary} or > {upperboundary}'.format(lowerboundary=Lower_fence, upperboundary=Upper_fence))

Output:

```
Rainfall outliers are values < -1.7999999999999998 or > 2.4
```

X = df.drop(['RainTomorrow'], axis=1)

y = df['RainTomorrow']

 # split X and y into training and testing sets

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)

X_train.shape, X_test.shape

Output:

```
((166796, 24), (41699, 24))
```

```
categorical = [col for col in X_train.columns if X_train[col].dtypes == 'O']
categorical
```

Output:

```
['Location', 'WindGustDir', 'WindDir9am', 'WindDir3pm', 'RainToday']
```

```
X_test = pd.concat([X_test[numerical], X_test[['RainToday_0', 'RainToday_1']],
                    pd.get_dummies(X_test.Location),
                    pd.get_dummies(X_test.WindGustDir),
                    pd.get_dummies(X_test.WindDir9am),
                    pd.get_dummies(X_test.WindDir3pm)], axis=1)
from sklearn.preprocessing import MinMaxScaler


scaler = MinMaxScaler()


X_train = scaler.fit_transform(X_train)


X_test = scaler.transform(X_test)
X_train = pd.DataFrame(X_train, columns=[cols])
X_test = pd.DataFrame(X_test, columns=[cols])
X_train.describe()
```

Output:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am
count	166796.000000	166796.000000	166796.000000	166796.000000	166796.000000	166796.000000	166796.000000
mean	0.487908	0.513154	0.202868	0.234397	0.560815	0.285994	0.255518
std	0.149906	0.134568	0.364995	0.118438	0.173719	0.098076	0.160017
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.382629	0.413662	0.000000	0.220183	0.586207	0.218045	0.127273
50%	0.483568	0.502846	0.000000	0.220183	0.586207	0.278195	0.236364
75%	0.596244	0.607211	0.187500	0.220183	0.586207	0.330827	0.345455
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

```
y_train.fillna('Yes',inplace=True)
y_test.fillna('Yes',inplace=True)
```

 # train a logistic regression model on the training set

```
from sklearn.linear_model import LogisticRegression
```

 # instantiate the model

logreg = LogisticRegression(solver='liblinear', random_state=0)

 # fit the model

logreg.fit(X_train, y_train)

Output:

```
LogisticRegression(random_state=0, solver='liblinear')
```

y_pred_test = logreg.predict(X_test)

y_pred_test

Output:

```
array(['Yes', 'No', 'No', ..., 'No', 'Yes', 'No'], dtype=object)
```

probability of getting output as 0 - no rain

logreg.predict_proba(X_test)[:,0]

Output:

```
array([0.40401211, 0.94783797, 0.83423034, ..., 0.9788821 , 0.32928284,
       0.88280924])
```

probability of getting output as 1 - rain

logreg.predict_proba(X_test)[:,1]

Output:

```
array([0.59598789, 0.05216203, 0.16576966, ..., 0.0211179 , 0.67071716,
       0.11719076])
```

from sklearn.metrics import accuracy_score

print('Model accuracy score: {0:0.4f}'. format(accuracy_score(y_test, y_pred_test)))

Output:

```
Model accuracy score: 0.8329
```

```
y_pred_train = logreg.predict(X_train)

y_pred_train
```

Output:

```
array(['No', 'No', 'No', ..., 'Yes', 'No', 'No'], dtype=object)
```

```
print('Training-set accuracy score: {0:0.4f}'. format(accuracy_score(y_train, y_pred_train)))
```

Output:

```
Training-set accuracy score: 0.8349
```

```
# print the scores on training and test set

print('Training set score: {:.4f}'.format(logreg.score(X_train, y_train)))

print('Test set score: {:.4f}'.format(logreg.score(X_test, y_test)))
```

Output:

```
Training set score: 0.8349
Test set score: 0.8329
```

```
# check null accuracy score

null_accuracy = (31538/(31538+10161))

print('Null accuracy score: {0:0.4f}'. format(null_accuracy))
```

Output:

```
Null accuracy score: 0.7563
```

```
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, y_pred_test)

print('Confusion matrix\n\n', cm)

print('\nTrue Positives(TP) = ', cm[0,0])

print('\nTrue Negatives(TN) = ', cm[1,1])

print('\nFalse Positives(FP) = ', cm[0,1])

print('\nFalse Negatives(FN) = ', cm[1,0])
```

Output:

```
Confusion matrix

 [[29652  1886]
 [ 5081  5080]]

True Positives(TP) =  29652

True Negatives(TN) =  5080

False Positives(FP) =  1886

False Negatives(FN) =  5081
```

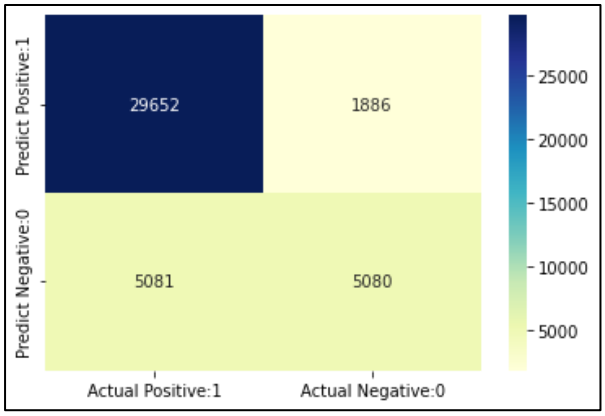
 # visualize confusion matrix with seaborn heatmap

cm_matrix = pd.DataFrame(data=cm, columns=['Actual Positive:1', 'Actual Negative:0'],

index=['Predict Positive:1', 'Predict Negative:0'])

sns.heatmap(cm_matrix, annot=True, fmt='d', cmap='YlGnBu')

Output:



from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred_test))

Output:

	precision	recall	f1-score	support
No	0.85	0.94	0.89	31538
Yes	0.73	0.50	0.59	10161
accuracy			0.83	41699
macro avg	0.79	0.72	0.74	41699
weighted avg	0.82	0.83	0.82	41699

```
TP = cm[0,0]

TN = cm[1,1]

FP = cm[0,1]

FN = cm[1,0]
```

 # print classification accuracy

```
classification_accuracy = (TP + TN) / float(TP + TN + FP + FN)

print('Classification accuracy : {0:0.4f}'.format(classification_accuracy))
```

Output:

```
Classification accuracy : 0.8329
```

 # print classification error

```
classification_error = (FP + FN) / float(TP + TN + FP + FN)

print('Classification error : {0:0.4f}'.format(classification_error))
```

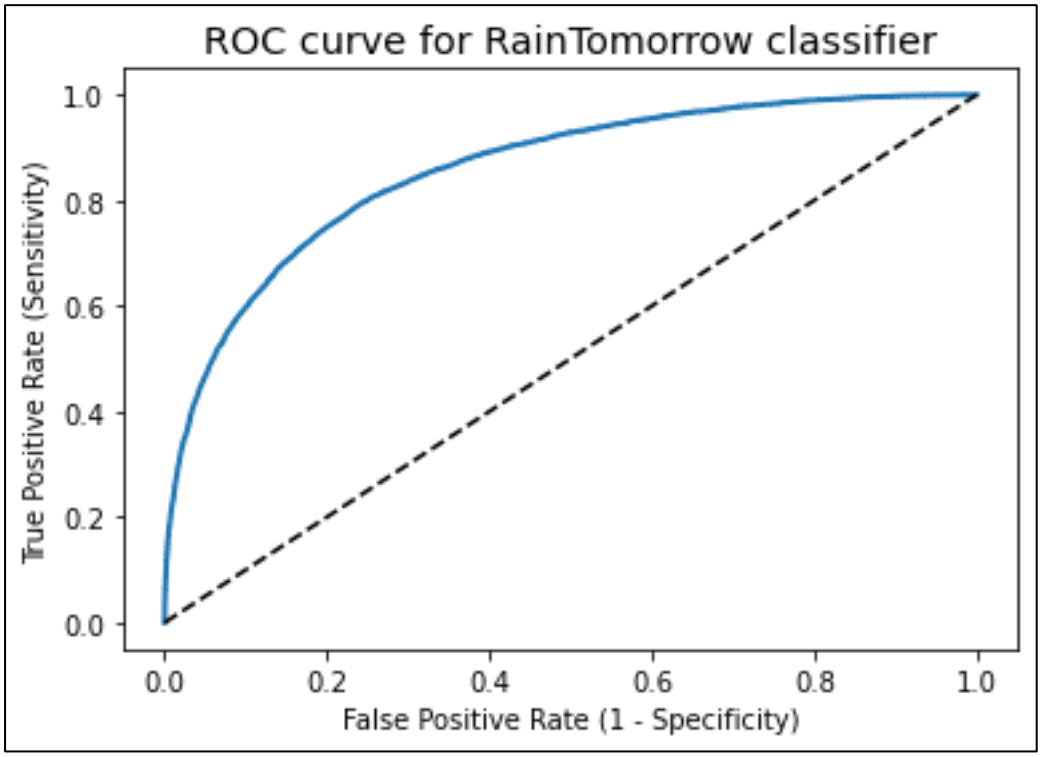
Output:

```
Classification error : 0.1671
```

 # plot ROC Curve

```
y_pred1 = logreg.predict_proba(X_test)[:,1]

y_pred1 = y_pred1.reshape(-1,1)

from sklearn.metrics import roc_curve

fpr, tpr, thresholds = roc_curve(y_test, y_pred1, pos_label = 'Yes')

plt.figure(figsize=(6,4))

plt.plot(fpr, tpr, linewidth=2)

plt.plot([0,1], [0,1], 'k--' )

plt.rcParams['font.size'] = 12

plt.title('ROC curve for RainTomorrow classifier')

plt.xlabel('False Positive Rate (1 - Specificity)')

plt.ylabel('True Positive Rate (Sensitivity)')

plt.show()
```

Output:




```
from sklearn.metrics import roc_auc_score

ROC_AUC = roc_auc_score(y_test, y_pred1)

print('ROC AUC : {:.4f}'.format(ROC_AUC))
```

Output:

```
ROC AUC : 0.8571
```

```
from sklearn.model_selection import cross_val_score

scores = cross_val_score(logreg, X_train, y_train, cv = 5, scoring='accuracy')

print('Cross-validation scores:{}'.format(scores))
```

Output:

```
Cross-validation scores:[0.83228417 0.83326838 0.83326838 0.83776492 0.83599628]
```

```
# compute Average cross-validation score

print('Average cross-validation score: {:.4f}'.format(scores.mean()))
```

Output:

```
Average cross-validation score: 0.8345
```

```
from sklearn.model_selection import GridSearchCV

parameters = [{'penalty':['l1','l2']}, {'C':[1, 10, 100, 1000]}]

grid_search = GridSearchCV(estimator = logreg, param_grid = parameters,scoring =
'accuracy', cv = 5,verbose=0)

grid_search.fit(X_train, y_train)
```

Output:

```
GridSearchCV(cv=5,
             estimator=LogisticRegression(random_state=0, solver='liblinear'),
             param_grid=[{'penalty': ['l1', 'l2']}, {'C': [1, 10, 100, 1000]}],
             scoring='accuracy')
```

```
# examine the best model

# best score achieved during the GridSearchCV

print('GridSearch CV best score : {:.4f}\n\n'.format(grid_search.best_score_))

# print parameters that give the best results

print('Parameters that give the best results :','\n\n', (grid_search.best_params_))

# print estimator that was chosen by the GridSearch

print('\n\nEstimator that was chosen by the search :','\n\n', (grid_search.best_estimator_))
```

Output:

```
GridSearch CV best score : 0.8347


Parameters that give the best results :

 {'C': 10}


Estimator that was chosen by the search :

 LogisticRegression(C=10, random_state=0, solver='liblinear')
```

```
# calculate GridSearch CV score on test set
print('GridSearch CV score on test set: {0:0.4f}'.format(grid_search.score(X_test, y_test)))
```

Output:

```
GridSearch CV score on test set: 0.8328
```

Result:

Logistic Regression model has been successfully built and the results are verified.

Exp.No : 8 **Date:**26/04/22

MULTIPLE REGRESSION ANALYSIS

1)**Aim:**

To build a multiple linear regression model

Code:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

data = pd.read_csv("dow_jones_index.csv")
data
```

Output:

	quarter	stock	date	open	high	low	close	volume	percent_change_price	percent_change_volume_over_last_wk	p
0	1	AA	1/7/2011	$15.82	$16.72	$15.78	$16.42	239655616	3.79267	NaN	
1	1	AA	1/14/2011	$16.71	$16.71	$15.64	$15.97	242963398	-4.42849	1.380223	
2	1	AA	1/21/2011	$16.19	$16.38	$15.60	$15.79	138428495	-2.47066	-43.024959	
3	1	AA	1/28/2011	$15.87	$16.63	$15.82	$16.13	151379173	1.63831	9.355500	
4	1	AA	2/4/2011	$16.18	$17.39	$16.18	$17.14	154387761	5.93325	1.987452	
...	...	...	...	...	...	...	...	...	...	...	
745	2	XOM	5/27/2011	$80.22	$82.63	$80.07	$82.63	68230855	3.00424	-21.355713	
746	2	XOM	6/3/2011	$83.28	$83.75	$80.18	$81.18	78616295	-2.52161	15.221032	
747	2	XOM	6/10/2011	$80.93	$81.87	$79.72	$79.78	92380844	-1.42098	17.508519	
748	2	XOM	6/17/2011	$80.00	$80.82	$78.33	$79.02	100521400	-1.22500	8.811952	
749	2	XOM	6/24/2011	$78.65	$81.12	$76.78	$76.78	118679791	-2.37762	18.064204	

```
data['high'] = data['high'].str.replace('$', '')
data['open'] = data['open'].str.replace('$', '')
data['low'] = data['low'].str.replace('$', '')
data['close'] = data['close'].str.replace('$', '')
data['next_weeks_open'] = data['next_weeks_open'].str.replace('$', '')
data['next_weeks_close'] = data['next_weeks_close'].str.replace('$', '')

data['high']=pd.to_numeric(data['high'])
data['open']=pd.to_numeric(data['open'])
```

```
data['low']=pd.to_numeric(data['low'])
data['close']=pd.to_numeric(data['close'])
data['next_weeks_open']=pd.to_numeric(data['next_weeks_open'])
data['next_weeks_close']=pd.to_numeric(data['next_weeks_close'])

data['percent_change_volume_over_last_wk'].fillna(value=0,inplace=True)
data['previous_weeks_volume'].fillna(value=0,inplace=True)
data
```

Output:

	quarter	stock	date	open	high	low	close	volume	percent_change_price	percent_change_volume_over_last_wk	pre
0	1	AA	1/7/2011	15.82	16.72	15.78	16.42	239655616	3.79267	0.000000	
1	1	AA	1/14/2011	16.71	16.71	15.64	15.97	242963398	-4.42849	1.380223	
2	1	AA	1/21/2011	16.19	16.38	15.60	15.79	138428495	-2.47066	-43.024959	
3	1	AA	1/28/2011	15.87	16.63	15.82	16.13	151379173	1.63831	9.355500	
4	1	AA	2/4/2011	16.18	17.39	16.18	17.14	154387761	5.93325	1.987452	
...	...	...	...	...	...	...	...	...	...	...	
745	2	XOM	5/27/2011	80.22	82.63	80.07	82.63	68230855	3.00424	-21.355713	
746	2	XOM	6/3/2011	83.28	83.75	80.18	81.18	78616295	-2.52161	15.221032	
747	2	XOM	6/10/2011	80.93	81.87	79.72	79.78	92380844	-1.42098	17.508519	
748	2	XOM	6/17/2011	80.00	80.82	78.33	79.02	100521400	-1.22500	8.811952	

```
data.info()
```

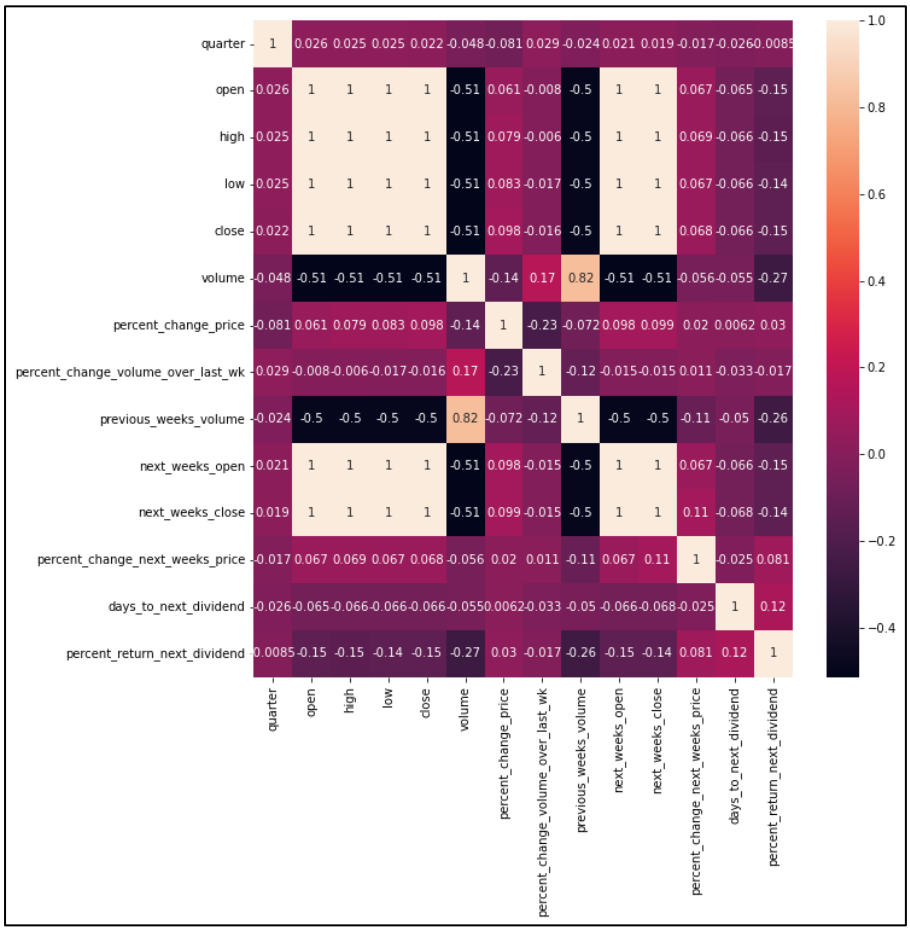
Output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 750 entries, 0 to 749
Data columns (total 16 columns):
 #   Column                             Non-Null Count  Dtype
---  ------                             --------------  -----
 0   quarter                            750 non-null    int64
 1   stock                              750 non-null    object
 2   date                               750 non-null    object
 3   open                               750 non-null    float64
 4   high                               750 non-null    float64
 5   low                                750 non-null    float64
 6   close                              750 non-null    float64
 7   volume                             750 non-null    int64
 8   percent_change_price               750 non-null    float64
 9   percent_change_volume_over_last_wk  750 non-null    float64
 10  previous_weeks_volume              750 non-null    float64
 11  next_weeks_open                    750 non-null    float64
 12  next_weeks_close                   750 non-null    float64
 13  percent_change_next_weeks_price    750 non-null    float64
 14  days_to_next_dividend              750 non-null    int64
 15  percent_return_next_dividend       750 non-null    float64
dtypes: float64(11), int64(3), object(2)
memory usage: 93.9+ KB
```

plt.figure(figsize=(10,10))

sns.heatmap(data.corr(),annot=True)

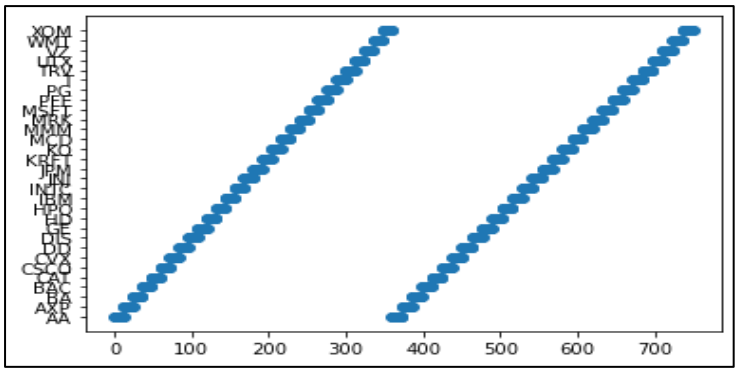
Output:



plt.scatter(data.index,data['stock'])

plt.show()

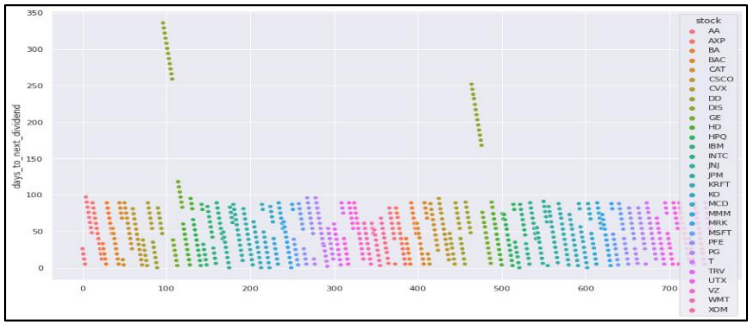
Output:



sns.set(rc={'figure.figsize':(15,8)})

sns.scatterplot(x=data.index,y=data['days_to_next_dividend'],hue=data['stock'])

Output:



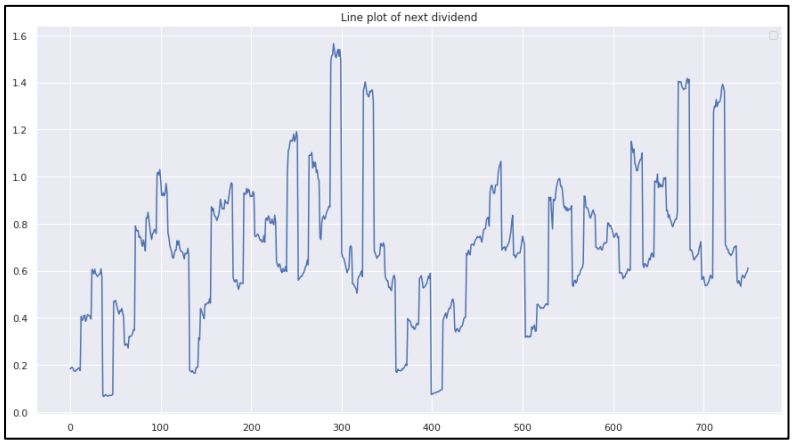
plt.title("Line plot of next dividend")

plt.plot(data.index,data['percent_return_next_dividend'])

plt.legend()

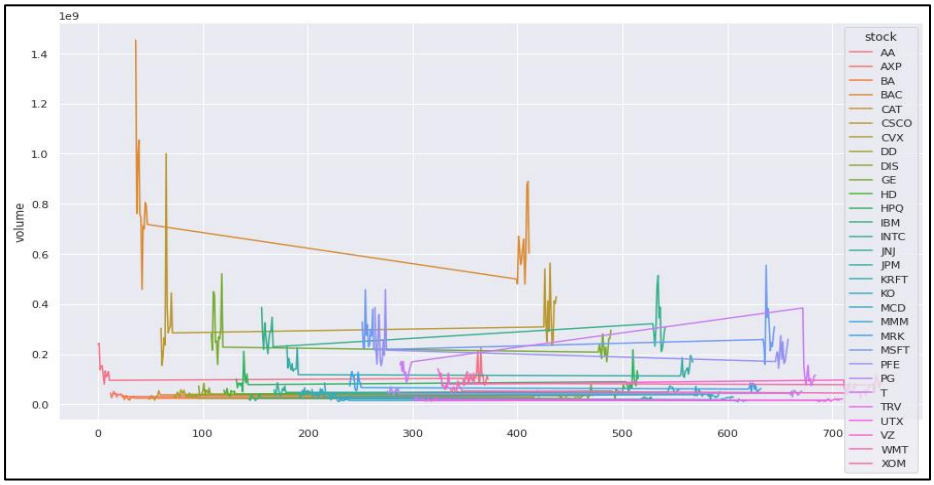
plt.show()

Output:



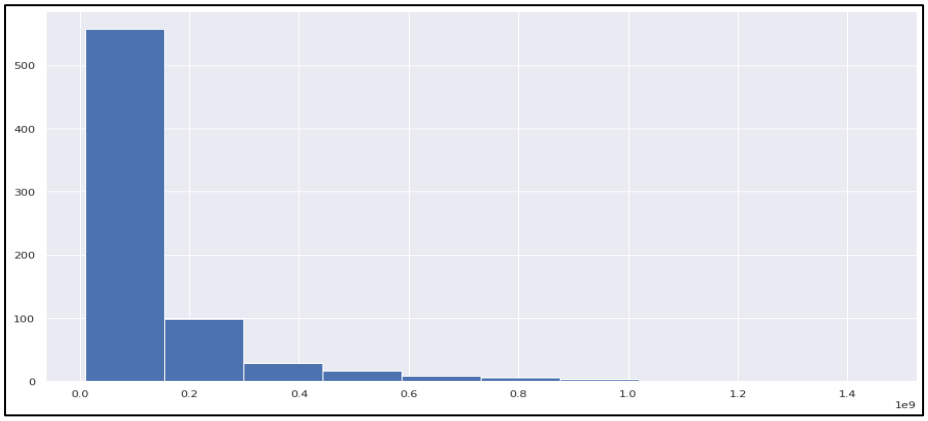
fig=sns.lineplot(x=data.index,y=data['volume'],hue=data['stock'])

Output:



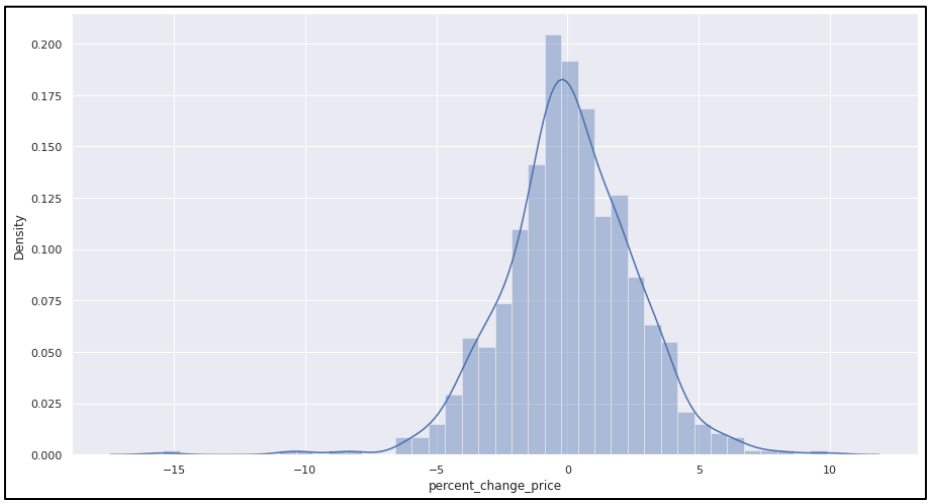
plt.hist(data['previous_weeks_volume'])

Output:



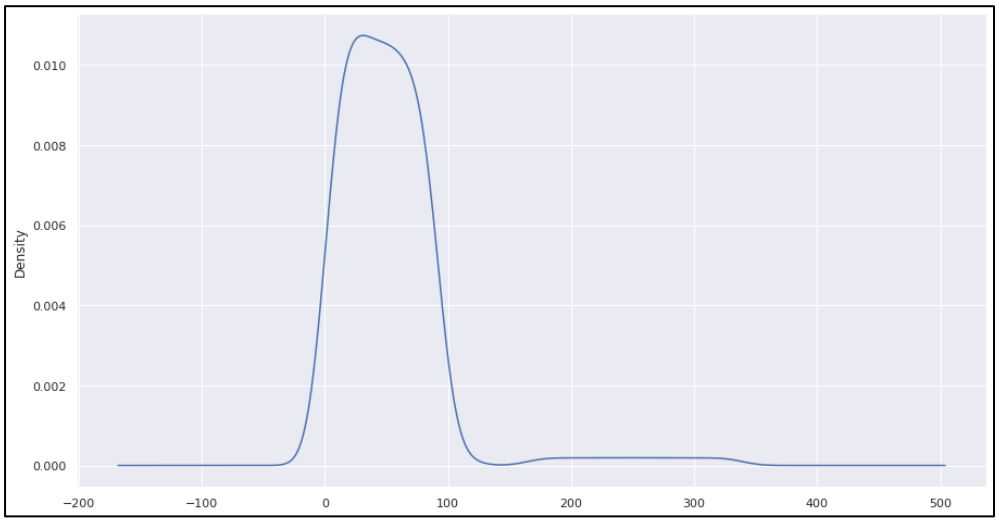
sns.distplot(data['percent_change_price'])

Output:



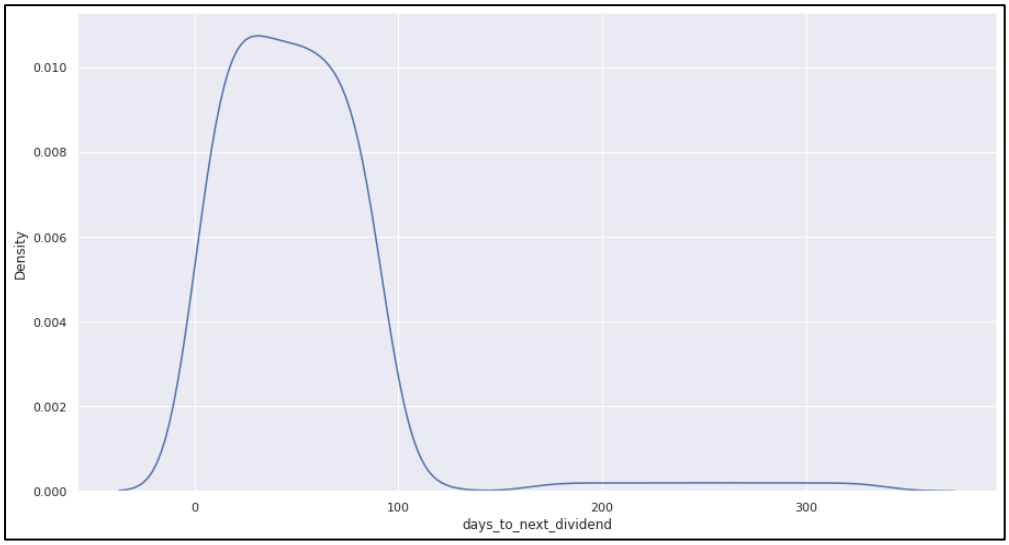
data['days_to_next_dividend'].plot(kind='density')

Output:



sns.kdeplot(data['days_to_next_dividend'])

Output:



data.var()

Output:

```
Out[28]: quarter                            2.499332e-01
         volume                             2.510263e+16
         percent_change_price               6.339363e+00
         percent_change_volume_over_last_wk 1.643774e+03
         previous_weeks_volume              2.535490e+16
         percent_change_next_weeks_price    7.179926e+00
         days_to_next_dividend              2.146941e+03
         percent_return_next_dividend       9.331917e-02
         dtype: float64
```

cols=['open','high','low','close','volume','percent_change_price','next_weeks_open','next_weeks_close','days_to_next_dividend' ,'percent_return_next_dividend']

X=data[cols]

y=data['quarter']

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state=9)

from sklearn.linear_model import LinearRegression

model=LinearRegression()

model.fit(X_train,y_train)

Output:

```
model.fit(X_train,y_train)

LinearRegression()
```

pred=model.predict(X_test)

pred

Output:

```
array([1.54913074, 1.54813425, 1.49749033, 1.54832875, 1.57205104,
       1.57517716, 1.52709849, 1.52365576, 1.49634746, 1.46801631,
       1.55007912, 1.50031549, 1.52780842, 1.48809572, 1.49257709,
       1.42785859, 1.4869727 , 1.49517245, 1.5455281 , 1.6338926 ,
       1.49020232, 1.42692687, 1.52580381, 1.52978727, 1.52162128,
       1.48612595, 1.50104161, 1.55947532, 1.58657317, 1.45367538,
       1.4444433 , 1.44392882, 1.54155301, 1.56212753, 1.59859272,
       1.53719739, 1.45900454, 1.6713445 , 1.46808814, 1.33376232,
       1.48355797, 1.48292294, 1.5028681 , 1.54954379, 1.55624776,
       1.59012436, 1.75127226, 1.56747024, 1.46323332, 1.43074352,
       1.4686594 , 1.45738999, 1.44713124, 1.61041957, 1.52232834,
       1.46044442, 1.50823302, 1.51220186, 1.52237218, 1.51761204,
       1.58537606, 1.53079649, 1.63827155, 1.63449266, 1.59079475,
       1.65187618, 1.47724958, 1.4886941 , 1.59469714, 1.47597925,
       1.64065202, 1.50897175, 1.63079161, 1.5126231 , 1.51115985,
       1.63870211, 1.47376849, 1.49901546, 1.54872444, 1.47210942,
       1.56179107, 1.53450276, 1.57096706, 1.50328843, 1.64137974,
       1.56695183, 1.53711204, 1.51617007, 1.49040867, 1.52103114,
       1.38263396, 1.58400605, 1.53274877, 1.60790847, 1.51426924,
       1.47758578, 1.53083506, 1.49721352, 1.6319571 , 1.51986792
```

print('Coefficients: ', model.coef_)

Output:

```
Coefficients:  [ 1.21559843e-03  1.68935129e-02  1.32063229e-02  9.71230820e-02
 -6.90544664e-11 -7.60770675e-03 -1.14063908e-01 -1.42938759e-02
 -1.34534545e-04 -4.45672353e-02]
```

print('Variance score: {}'.format(model.score(X_test, y_test)))

Output:

```
Variance score: 0.012848113274527173
```

plt.scatter(model.predict(X_train), model.predict(X_train) - y_train,

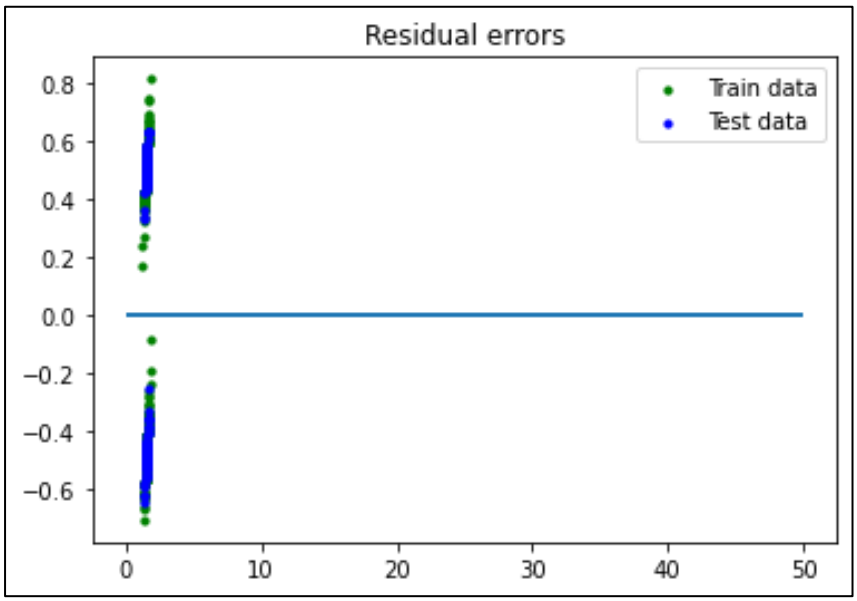
color = "green", s = 10, label = 'Train data')

plotting residual errors in test data

plt.scatter(model.predict(X_test), model.predict(X_test) - y_test,

```
        color = "blue", s = 10, label = 'Test data')
## plotting line for zero residual error
plt.hlines(y = 0, xmin = 0, xmax = 50, linewidth = 2)
## plotting legend
plt.legend(loc = 'upper right')
## plot title
plt.title("Residual errors")
## method call for showing the plot
plt.show()
```

Output:



Result:

Multivariate Linear Regression model has been successfully built and the results are verified.

Exp.No : 9 **Date:**17/05/22

Classification –NaïveBayes

1)**Aim:**

To build a model to perform Naïve Bayes classifier with following specifications :

a. Exploratory data analysis b. Identify Numerical and Categorical variables c. Identify the missing values d. Apply feature engineering and apply feature scaling e. Train the model d. Test the model and display the results e. Check accuracy score f. Check for overfitting and underfitting g. Summarize the performance of model using confusion matrix h. Evaluate the model performance with classification report i. Analyze the model performance visually.

Code:

i)Iris Dataset

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
dataset = pd.read_csv('iris.csv')
from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()
dataset['species']= label_encoder.fit_transform(dataset['species'])
dataset['species'].unique()
```

Output:

```
array([0, 1, 2])
```

```
X = dataset.iloc[:,:4].values
y = dataset['species'].values
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
```

classifier.fit(X_train, y_train)

Output:

```
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)
```

```
GaussianNB()
```

y_pred = classifier.predict(X_test)

y_pred

Output:

```
array([2, 2, 1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 2, 2, 1, 0, 1, 0, 2, 0, 0, 2,
       0, 1, 1, 0, 2, 0, 1, 2])
```

from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, y_pred)

from sklearn.metrics import accuracy_score

print ("Accuracy : ", accuracy_score(y_test, y_pred))

cm

Output:

```
Accuracy :  0.9333333333333333

array([[11,  0,  0],
       [ 0,  9,  0],
       [ 0,  2,  8]])
```

from sklearn.metrics import classification_report

print(classification_report(y_test,y_pred))

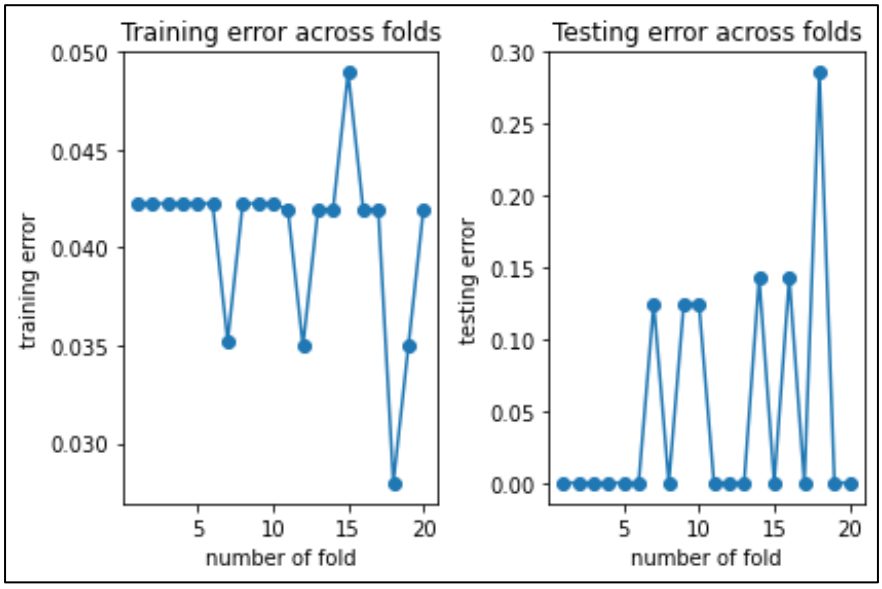
Output:

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        11
           1       0.82      1.00      0.90         9
           2       1.00      0.80      0.89        10

    accuracy                           0.93        30
   macro avg       0.94      0.93      0.93        30
weighted avg       0.95      0.93      0.93        30
```

```
from sklearn.model_selection import KFold
from sklearn.metrics import mean_absolute_error
kf = KFold(n_splits=20)
list_training_error = []
list_testing_error = []
for train_index, test_index in kf.split(X):
    X_train, X_test = X[train_index], X[test_index]
    y_train, y_test = y[train_index], y[test_index]
    model = GaussianNB()
    model.fit(X_train, y_train)
    y_train_data_pred = model.predict(X_train)
    y_test_data_pred = model.predict(X_test)
    fold_training_error = mean_absolute_error(y_train, y_train_data_pred)
    fold_testing_error = mean_absolute_error(y_test, y_test_data_pred)
    list_training_error.append(fold_training_error)
    list_testing_error.append(fold_testing_error)

plt.subplot(1,2,1)
plt.plot(range(1, kf.get_n_splits() + 1), np.array(list_training_error).ravel(), 'o-')
plt.xlabel('number of fold')
plt.ylabel('training error')
plt.title('Training error across folds')
plt.tight_layout()
plt.subplot(1,2,2)

plt.plot(range(1, kf.get_n_splits() + 1), np.array(list_testing_error).ravel(), 'o-')
plt.xlabel('number of fold')
plt.ylabel('testing error')
plt.title('Testing error across folds')
plt.tight_layout()
```

plt.show()

Output:



ii)Diabetes.csv

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
from sklearn.metrics import accuracy_score
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.feature_selection import VarianceThreshold
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
dataset = pd.read_csv('diabetes.csv')


print(dataset.describe())
```

X = dataset.iloc[:, 0:8]

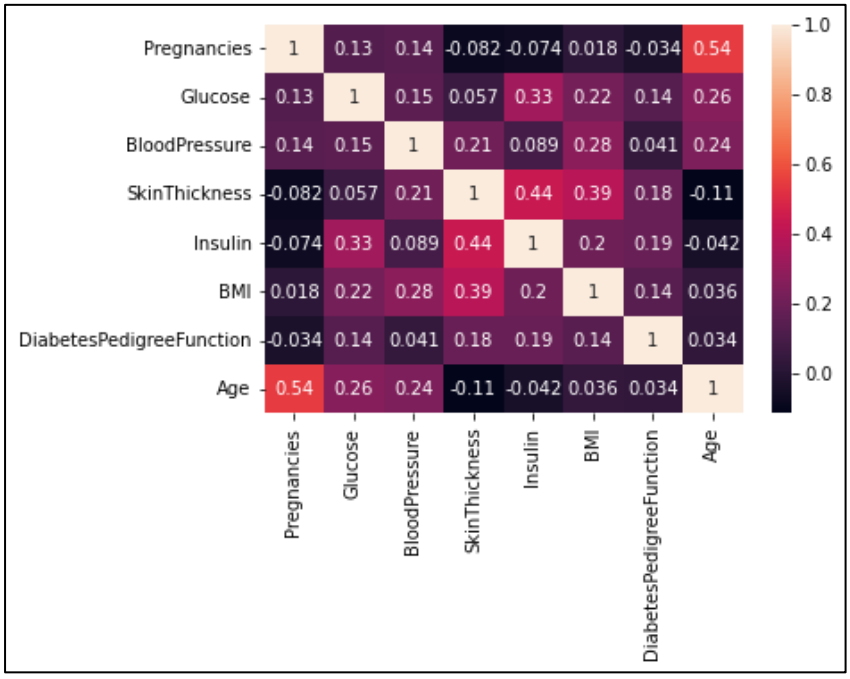
y = dataset.iloc[:, 8]

Output:

```
       Pregnancies     Glucose  BloodPressure  SkinThickness     Insulin  \
count   768.000000  768.000000     768.000000     768.000000  768.000000
mean      3.845052  120.894531      69.105469      20.536458   79.799479
std       3.369578   31.972618      19.355807      15.952218  115.244002
min       0.000000    0.000000       0.000000       0.000000    0.000000
25%       1.000000   99.000000      62.000000       0.000000    0.000000
50%       3.000000  117.000000      72.000000      23.000000   30.500000
75%       6.000000  140.250000      80.000000      32.000000  127.250000
max      17.000000  199.000000     122.000000      99.000000  846.000000

              BMI  DiabetesPedigreeFunction         Age     Outcome
count  768.000000                768.000000  768.000000  768.000000
mean    31.992578                  0.471876   33.240885    0.348958
std      7.884160                  0.331329   11.760232    0.476951
min      0.000000                  0.078000   21.000000    0.000000
25%     27.300000                  0.243750   24.000000    0.000000
50%     32.000000                  0.372500   29.000000    0.000000
75%     36.600000                  0.626250   41.000000    1.000000
max     67.100000                  2.420000   81.000000    1.000000
```

sns.heatmap(X.corr(), annot = True)

Output:



zero_not_accepted = ['Glucose', 'BloodPressure', 'SkinThickness', 'BMI', 'Insulin']

for column in zero_not_accepted:

    X[column] = X[column].replace(0,np.NaN)

    mean = int(X[column].mean(skipna=True))

    X[column] = X[column].replace(np.NaN, mean)

```
sel = VarianceThreshold(threshold=(.8 * (1 - .8)))
X_filtered = sel.fit_transform(X)
print(X.head(1))
print(X_filtered[0])
```

#DiabetesPedigreeFunction was dropped

```
X = X.drop('DiabetesPedigreeFunction', axis=1)
top_4_features = SelectKBest(score_func=chi2, k=4)
X_top_4_features = top_4_features.fit_transform(X, y)
print(X.head())
print(X_top_4_features)
X = X.drop(['Pregnancies', 'BloodPressure', 'SkinThickness'], axis=1)
```

Output:

```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35       79  33.6

   DiabetesPedigreeFunction  Age
0                     0.627   50
[  6.  148.   72.   35.   79.   33.6  50. ]
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  Age
0            6      148             72             35       79  33.6   50
1            1       85             66             29       79  26.6   31
2            8      183             64             20       79  23.3   32
3            1       89             66             23       94  28.1   21
4            0      137             40             35      168  43.1   33
[[  6. 148.  79.  50.]
 [  1.  85.  79.  31.]
 [  8. 183.  79.  32.]
 ...
 [  5. 121. 112.  30.]
 [  1. 126.  79.  47.]
 [  1.  93.  79.  23.]]
```

```
X_train, X_test, y_train, y_test = train_test_split(X.values, y.values, random_state=0, test_size=0.20)
sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)
classifier = GaussianNB()
classifier.fit(X_train, y_train)
```

Output:

```
GaussianNB()
```

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

```
cm = confusion_matrix(y_test, y_pred)
print (cm)
print(f1_score(y_test, y_pred))
print(accuracy_score(y_test, y_pred))
```

Output:

```
[[96 11]
 [20 27]]
0.6352941176470589
0.7987012987012987
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test,y_pred))
```

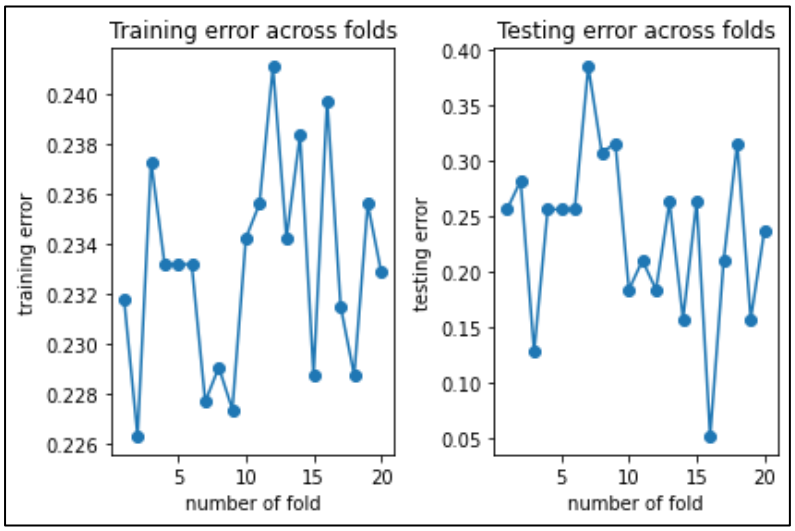
Output:

	precision	recall	f1-score	support
0	0.83	0.90	0.86	107
1	0.71	0.57	0.64	47
accuracy			0.80	154
macro avg	0.77	0.74	0.75	154
weighted avg	0.79	0.80	0.79	154

```
from sklearn.model_selection import KFold
from sklearn.metrics import mean_absolute_error
kf = KFold(n_splits=20)
list_training_error = []
list_testing_error = []
X=X.values
y=y.values
for train_index, test_index in kf.split(X):
    X_train, X_test = X[train_index], X[test_index]
    y_train, y_test = y[train_index], y[test_index]
    model = GaussianNB()
    model.fit(X_train, y_train)
```

```
    y_train_data_pred = model.predict(X_train)
    y_test_data_pred = model.predict(X_test)
    fold_training_error = mean_absolute_error(y_train, y_train_data_pred)
    fold_testing_error = mean_absolute_error(y_test, y_test_data_pred)
    list_training_error.append(fold_training_error)
    list_testing_error.append(fold_testing_error)


plt.subplot(1,2,1)
plt.plot(range(1, kf.get_n_splits() + 1), np.array(list_training_error).ravel(), 'o-')
plt.xlabel('number of fold')
plt.ylabel('training error')
plt.title('Training error across folds')
plt.tight_layout()
plt.subplot(1,2,2)
plt.plot(range(1, kf.get_n_splits() + 1), np.array(list_testing_error).ravel(), 'o-')
plt.xlabel('number of fold')
plt.ylabel('testing error')
plt.title('Testing error across folds')
plt.tight_layout()
plt.show()
```

Output:



iii) dow_jones_index

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
data = pd.read_csv('dow_jones_index.csv')
from sklearn.preprocessing import LabelEncoder
encoder=LabelEncoder()
data['stock']=encoder.fit_transform(data['stock'])
data['stock'].unique()
```

Output:

```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 17,
       16, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29])
```

```
categorical = [cols for cols in data.columns if data[cols].dtype=='O']
categorical
```

Output:

```
['date']
```

```
numerical = [cols for cols in data.columns if data[cols].dtype!='O']
numerical
```

Output:

```
['quarter',
 'stock',
 'open',
 'high',
 'low',
 'close',
 'volume',
 'percent_change_price',
 'percent_change_volume_over_last_wk',
 'previous_weeks_volume',
 'next_weeks_open',
 'next_weeks_close',
 'percent_change_next_weeks_price',
 'days_to_next_dividend',
 'percent_return_next_dividend']
```

```
cols=['open','high','low','volume','close','percent_change_price','percent_change_volume_over
_last_wk','previous_weeks_volume','next_weeks_open','next_weeks_close','percent_change_
next_weeks_price','days_to_next_dividend','percent_return_next_dividend']

X=data[cols]

y=data['stock']

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)

from sklearn.preprocessing import StandardScaler

sc = StandardScaler()

X_train = sc.fit_transform(X_train)

X_test = sc.transform(X_test)

from sklearn.naive_bayes import GaussianNB

classifier = GaussianNB()

classifier.fit(X_train, y_train)
```

Output:

```
GaussianNB()
```

```
y_pred = classifier.predict(X_test)

y_pred
```

Output:

```
array([19, 19,  2, 22, 23, 10,  5, 14, 21,  2, 16,  1, 24, 12, 11, 19, 19,
       17, 23, 19,  9, 18, 19, 18, 12,  7, 18, 25,  7,  0,  0, 27, 25,  6,
       27, 20, 23,  7,  7,  9, 13,  4,  9, 24,  0, 17, 24, 19,  2, 20, 23,
       16, 12, 15,  2, 11, 17, 24, 17,  7, 28,  6, 10, 29, 18,  9,  4, 27,
       23,  6, 21,  7, 16,  5,  6,  2, 27, 27,  3, 19, 20, 11, 18,  4, 15,
       28, 12,  2, 29,  5, 26, 20, 19, 26, 13, 17, 13, 14, 15,  3, 19, 28,
       21,  2, 13, 17, 24,  5, 24,  9,  6,  0, 26, 18, 28, 18,  8,  4,  9,
        6, 27, 28,  7, 24, 13, 25,  5, 24, 26,  6,  7,  3,  6, 18, 13, 22,
       16, 12,  9, 28, 29, 23,  6, 13,  3,  3,  7, 10, 21, 27])
```

```
from sklearn.metrics import accuracy_score

print ("Accuracy : ", accuracy_score(y_test, y_pred))
```

Output:

```
Accuracy :  0.96
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test,y_pred))
```

Output:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	4
1	1.00	1.00	1.00	1
2	1.00	1.00	1.00	7
3	1.00	1.00	1.00	5
4	1.00	1.00	1.00	4
5	1.00	1.00	1.00	5
6	1.00	1.00	1.00	9
7	0.89	1.00	0.94	8
8	1.00	1.00	1.00	1
9	1.00	1.00	1.00	7
10	1.00	1.00	1.00	3

accuracy			0.96	150
macro avg	0.97	0.95	0.95	150
weighted avg	0.97	0.96	0.96	150

```
from sklearn.model_selection import KFold
from sklearn.metrics import mean_absolute_error
kf = KFold(n_splits=20)
list_training_error = []
list_testing_error = []

for train_index, test_index in kf.split(X):
    X_train, X_test = X[train_index], X[test_index]
    y_train, y_test = y[train_index], y[test_index]
    model = GaussianNB()
    model.fit(X_train, y_train)
    y_train_data_pred = model.predict(X_train)
    y_test_data_pred = model.predict(X_test)
    fold_training_error = mean_absolute_error(y_train, y_train_data_pred)
    fold_testing_error = mean_absolute_error(y_test, y_test_data_pred)
```

```
    list_training_error.append(fold_training_error)
    list_testing_error.append(fold_testing_error)

plt.subplot(1,2,1)
plt.plot(range(1, kf.get_n_splits() + 1), np.array(list_training_error).ravel(), 'o-')
plt.xlabel('number of fold')
plt.ylabel('training error')
plt.title('Training error across folds')
plt.tight_layout()
plt.subplot(1,2,2)

plt.plot(range(1, kf.get_n_splits() + 1), np.array(list_testing_error).ravel(), 'o-')
plt.xlabel('number of fold')
plt.ylabel('testing error')
plt.title('Testing error across folds')
plt.tight_layout()
plt.show()
```

Output:

iv)Multinomial dow_jones_index

```
import numpy as np
import matplotlib.pyplot as plt
```

```
import pandas as pd


data = pd.read_csv('dow_jones_index.csv')

cols=['open','high','low','close','volume','percent_change_price','percent_change_volume_over_last_wk','previous_weeks_volume','next_weeks_open','next_weeks_close','percent_change_next_weeks_price','days_to_next_dividend','percent_return_next_dividend']

X=data[cols]

y=data['quarter']

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)

from sklearn.preprocessing import StandardScaler

sc = StandardScaler()

X_train = sc.fit_transform(X_train)

X_test = sc.transform(X_test)

from sklearn.naive_bayes import MultinomialNB

from sklearn.preprocessing import MinMaxScaler

from sklearn.pipeline import Pipeline

p = Pipeline([('Normalizing',MinMaxScaler()),('MultinomialNB',MultinomialNB())])

p.fit(X_train,y_train)
```

<u>Output:</u>

```
Pipeline(steps=[('Normalizing', MinMaxScaler()),
                ('MultinomialNB', MultinomialNB())])
```

```
y_pred = p.predict(X_test)

y_pred
```

<u>Output:</u>

```
array([2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

```
from sklearn.metrics import accuracy_score
```

print ("Accuracy : ", accuracy_score(y_test, y_pred))

Output:

```
Accuracy :  0.5266666666666666
```

from sklearn.metrics import classification_report

print(classification_report(y_test,y_pred))

Output:

	precision	recall	f1-score	support
1	0.00	0.00	0.00	71
2	0.53	1.00	0.69	79
accuracy			0.53	150
macro avg	0.26	0.50	0.34	150
weighted avg	0.28	0.53	0.36	150

Result:

The Naïve Bayes model has been successfully executed and the results are verified.

Exp.No : 10 **Date:**17/05/22

Visualization Tools in Python

1)**Aim:**

To explore the following plotting/visualization tools in python:

- Matplotlib
- Diagram
- Mayai
- Seaborn
- VisPy
- PyQtGraph
- Chartify

Matplotlib:

1)pyplot() – It is a state based interface to a matplotlib module which provides a MATLAB like interface

2)figure() – creates a new figure

3)hist() – Plot a histogram

4)pie() – Display a figure

5)show() – Display a figure

6)spy() – Plot the sparsity pattern of a 2D array

7)bar() – Plot bar graphs

Diagram:

1)aws() – node classes list of aws provider

2)azure() – node classes list of azure provider

3)gcp() – node classes list of gcp provider

4)programming – node classes list of programming provider

5)saas() – node classes list of saas provider

6)ibm() – node classes list of ibm provider

7)kbs() – node classes list of kbs provider

Maya:

1)now() – present datetime

2)when() – required datetime

3)datetime() – show database info

4)slang_date() – print date

5)slang_time() – print time

6)from_iso8601() – print time from iso 8601

7)from_rfc2822 – print time from rfc 2822

Seaborn:

1)set_theme() – Apply the default theme

2)load_dataset() – Load an dataset

3)replot() – visualizes relation b/w variables

4)lmplot() – plot linear regression model

5)displot() – plot distributed function of data

6)catplot() – plot scatter plot

7)jointplot() – plot a joint plot

VisPy:

1)app() – integrates event system and offers united interface

2)gloo() – object oriented interface to openGL

3)plot() – high level plotting interfaces

4)visual() – graphical abstractions

5)transform() – implement 2D/3D transforms

6)shaden() – implements shader composition

7)scene() – system for underlying high level visualization interfaces

PyQtGraph:

1)mtQApp() – build a Q application

2)setConfiguration() – set up a configuration

3)plot() – plot with colours

4)GLGridItem() – create grids

5)rotate() – rotate x and y grids

6)scale() – scale each grid

7)export() – export the file

Chartify:

1)_core_plot.PlotCategoricalXY() – Plot functions for categorical X & Y

2)PlotNumericXY() – plot functions for numerical X,Y

3)PlotNumericDensityXY() – plot single density

4)PlotDensityXY() – plot density X&Y

5)PlotMixedTypeXY() – plot mixed type

6)lollipop() – Lollipop chart

7)parallel() – Parallel coordinate plot

Result:

Visualization tools have been explored successfully in Python

Exp.No : 11 **Date:**24/05/22

Hadoop Installation

1)**Aim:**

To study on Hadoop architecture and its components

Hadoop:

Hadoop is a framework written in Java that utilizes a large cluster of commodity hardware to maintain and store big size data. Hadoop works on MapReduce Programming algorithm that was introduced by Google. The Hadoop architecture mainly consists of four components:

- MapReduce
- HDFS
- YARN
- Common Utilities

MapReduce

It is an algorithm based on the YARN framework.It performs the distributed processing in parallel in a Hadoop cluster. This makes Hadoop work faster.

HDFS:

Hadoop Distrubuted File System is utilized for storage permission in a Hadoop cluster. It is mainly designed for working on commodity Hardware. HDFS provides fault-tolerance and high availability to the storage layer.

YARN:

Yet Another Resource Navigator (YARN) is a framework on which MapReduce works. YARN performs two operations that are Job Scheduling and Resource Management. Features of YARN:

- Multi-tenancy
- Scalability
- Cluster-utilization
- Compatibility

Common Utilities:

Common Utilities are JAVA files we need for all other components present in a Hadoop cluster. These utilities are used by HDFS, YARN and MapReduce for running the Hadoop cluster.

Result:

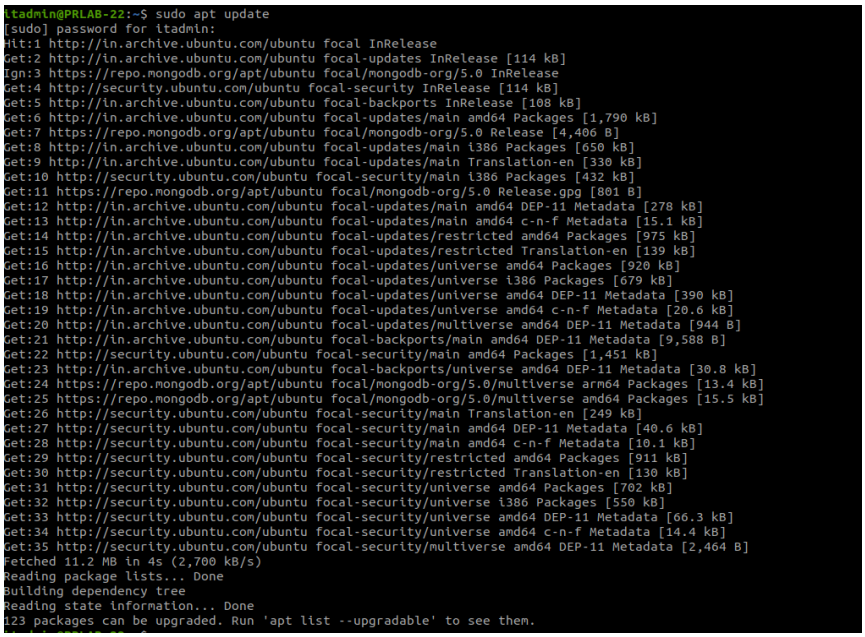
Study on Hadoop architecture and its components have been done successfully.

2)Aim:

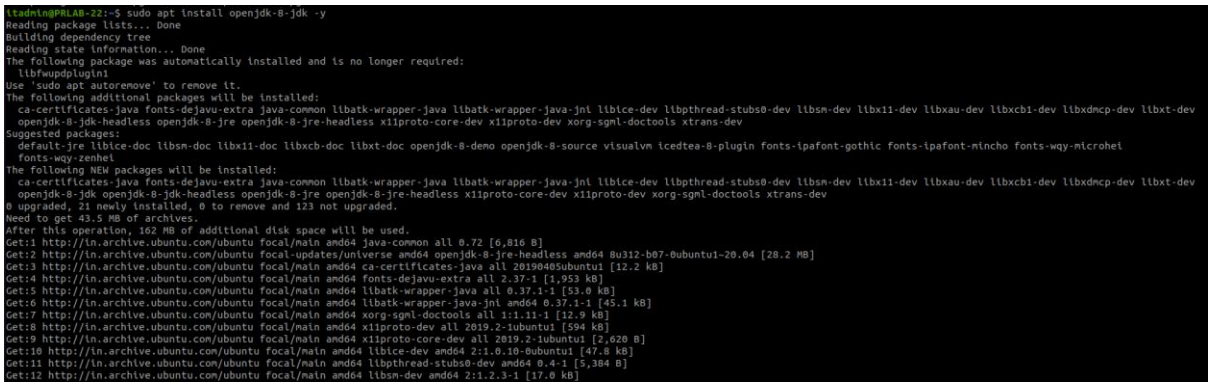
To install and configure Hadoop

Steps for Installation:

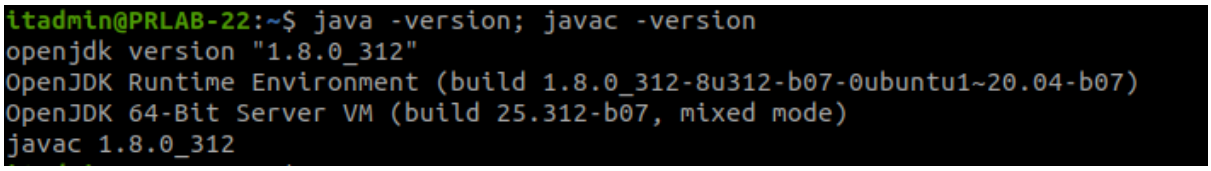
Step-1 sudo apt update



Step-2 : sudo apt install openjdk-8-jdk -y



Step-3 java -version; javac -version



Step-4 sudo apt install openssh-server openssh-client -y

```
itadmin@PRLAB-22:~$ sudo apt install openssh-server openssh-client -y
Reading package lists... Done
Building dependency tree
Reading state information... Done
The following package was automatically installed and is no longer required:
  libfwupdplugin1
Use 'sudo apt autoremove' to remove it.
The following additional packages will be installed:
  openssh-sftp-server
Suggested packages:
  keychain libpam-ssh monkeysphere ssh-askpass molly-guard
The following packages will be upgraded:
  openssh-client openssh-server openssh-sftp-server
3 upgraded, 0 newly installed, 0 to remove and 120 not upgraded.
Need to get 1,099 kB of archives.
After this operation, 0 B of additional disk space will be used.
Get:1 http://in.archive.ubuntu.com/ubuntu focal-updates/main amd64 openssh-sftp-server amd64 1:8.2p1-4ubuntu0.5 [51.5 kB]
Get:2 http://in.archive.ubuntu.com/ubuntu focal-updates/main amd64 openssh-server amd64 1:8.2p1-4ubuntu0.5 [377 kB]
Get:3 http://in.archive.ubuntu.com/ubuntu focal-updates/main amd64 openssh-client amd64 1:8.2p1-4ubuntu0.5 [671 kB]
Fetched 1,099 kB in 0s (2,271 kB/s)
Preconfiguring packages ...
(Reading database ... 213340 files and directories currently installed.)
Preparing to unpack .../openssh-sftp-server_1%3a8.2p1-4ubuntu0.5_amd64.deb ...
Unpacking openssh-sftp-server (1:8.2p1-4ubuntu0.5) over (1:8.2p1-4ubuntu0.4) ...
Preparing to unpack .../openssh-server_1%3a8.2p1-4ubuntu0.5_amd64.deb ...
Unpacking openssh-server (1:8.2p1-4ubuntu0.5) over (1:8.2p1-4ubuntu0.4) ...
Preparing to unpack .../openssh-client_1%3a8.2p1-4ubuntu0.5_amd64.deb ...
Unpacking openssh-client (1:8.2p1-4ubuntu0.5) over (1:8.2p1-4ubuntu0.4) ...
Setting up openssh-client (1:8.2p1-4ubuntu0.5) ...
Setting up openssh-sftp-server (1:8.2p1-4ubuntu0.5) ...
Setting up openssh-server (1:8.2p1-4ubuntu0.5) ...
rescue-ssh.target is a disabled or a static unit, not starting it.
Processing triggers for systemd (245.4-4ubuntu3.15) ...
Processing triggers for man-db (2.9.1-1) ...
Processing triggers for ufw (0.36-6ubuntu1) ...
```

Step-5 sudo adduser hdoop

```
itadmin@PRLAB-22:~$ sudo adduser hdoop
Adding user `hdoop' ...
Adding new group `hdoop' (1002) ...
Adding new user `hdoop' (1002) with group `hdoop' ...
Creating home directory `/home/hdoop' ...
Copying files from `/etc/skel' ...
New password:
Retype new password:
passwd: password updated successfully
Changing the user information for hdoop
Enter the new value, or press ENTER for the default
        Full Name []:
        Room Number []:
        Work Phone []:
        Home Phone []:
        Other []:
Is the information correct? [Y/n] y
```

Step-6 : su – hdoop

```
itadmin@PRLAB-22:~$ su - hdoop
Password:
hdoop@PRLAB-22:~$
```

Step-7 ssh-keygen -t rsa -P " -f ~/.ssh/id_rsa

```
hdoop@PRLAB-22:~$ ssh-keygen -t rsa -P '' -f ~/.ssh/id_rsa
Generating public/private rsa key pair.
Created directory '/home/hdoop/.ssh'.
Your identification has been saved in /home/hdoop/.ssh/id_rsa
Your public key has been saved in /home/hdoop/.ssh/id_rsa.pub
The key fingerprint is:
SHA256:ML0nTmQKjrrLU8f7Y+ogsbBvRvyK8hur4xvz6CTYUA4 hdoop@PRLAB-22
The key's randomart image is:
+---[RSA 3072]----+
|                 |
|       .         |
|E . . o +        |
| + o . * .       |
|ooo o . S .      |
|o==. o o o       |
|=B+o. . .        |
|*=Ooo. o         |
|O&O+.o+..        |
+----[SHA256]-----+
```

Step-8: cat ~/.ssh/id_rsa.pub >> ~/.ssh/authorized_keys

Step-9 chmod 0600 ~/.ssh/authorized_keys

```
hdoop@PRLAB-22:~$ cat ~/.ssh/id_rsa.pub >> ~/.ssh/authorized_keys
hdoop@PRLAB-22:~$ chmod 0600 ~/.ssh/authorized_keys
```

Step-10 ssh localhost

```
hdoop@PRLAB-22:~$ ssh localhost
The authenticity of host 'localhost (127.0.0.1)' can't be established.
ECDSA key fingerprint is SHA256:SaTAp+60cPT8NCkg14kfRqJ8pzcBqlN5mV2T5rgLflE.
Are you sure you want to continue connecting (yes/no/[fingerprint])? yes
Warning: Permanently added 'localhost' (ECDSA) to the list of known hosts.
Welcome to Ubuntu 20.04.4 LTS (GNU/Linux 5.13.0-39-generic x86_64)

 * Documentation:  https://help.ubuntu.com
 * Management:     https://landscape.canonical.com
 * Support:        https://ubuntu.com/advantage

118 updates can be applied immediately.
67 of these updates are standard security updates.
To see these additional updates run: apt list --upgradable

Your Hardware Enablement Stack (HWE) is supported until April 2025.

The programs included with the Ubuntu system are free software;
the exact distribution terms for each program are described in the
individual files in /usr/share/doc/*/copyright.

Ubuntu comes with ABSOLUTELY NO WARRANTY, to the extent permitted by
applicable law.
```

Step-11

- Visit the official Apache Hadoop project page, and select the version of Hadoop you want to implement

  https://hadoop.apache.org/releases.html

Download

Hadoop is released as source code tarballs with corresponding binary tarballs for convenience. The downloads are distributed via mirror sites and should be checked for tampering using GPG or SHA-512.

Version	Release date	Source download	Binary download	Release notes
3.2.3	2022 Mar 28	source (checksum signature)	binary (checksum signature)	Announcement
3.3.2	2022 Mar 3	source (checksum signature)	binary (checksum signature) binary-aarch64 (checksum signature)	Announcement
2.10.1	2020 Sep 21	source (checksum signature)	binary (checksum signature)	Announcement

- Click recent version 3.2.3 binary

We suggest the following site for your download:

https://dlcdn.apache.org/hadoop/common/hadoop-3.2.3/hadoop-3.2.3.tar.gz

Alternate download locations are suggested below.

It is essential that you verify the integrity of the downloaded file using the PGP signature (.asc file) or a hash (.md5 or .sha* file).

- Click the link to download locally in a machine

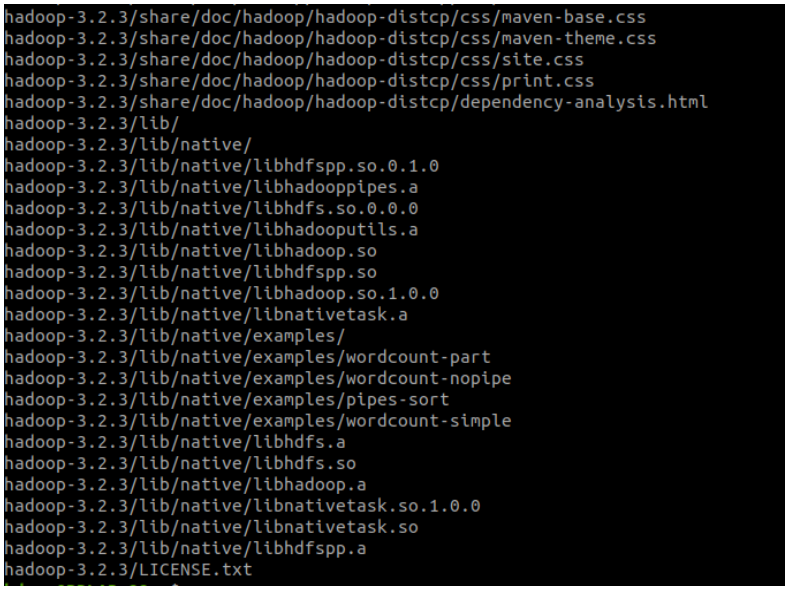
  Or type

- Wget https://dlcdn.apache.org/hadoop/common/hadoop-3.2.3/hadoop-3.2.3.tar.gz

  Once the download is complete, extract the files to initiate the Hadoop installation:

  -x : Extract the archive ,-v : Displays Verbose Information, -z : zip, tells tar command that creates tar file using gzip , -f : creates archive with given filename

- tar xvzf hadoop-3.2.3.tar.gz



Step-12 mv hadoop-3.2.3 hadoop

Step-13 dirname $(dirname $(readlink -f $(which java)))

Step-14 Vi .bashrc

Define the Hadoop environment variables by adding the following content to the end of the file:

#Hadoop Related Options

export JAVA_HOME=/usr/lib/jvm/java-8-openjdk-amd64

export HADOOP_HOME=/home/hdoop/hadoop

export HADOOP_INSTALL=$HADOOP_HOME

export HADOOP_MAPRED_HOME=$HADOOP_HOME

export HADOOP_COMMON_HOME=$HADOOP_HOME

export HADOOP_HDFS_HOME=$HADOOP_HOME

export YARN_HOME=$HADOOP_HOME

export HADOOP_COMMON_LIB_NATIVE_DIR=$HADOOP_HOME/lib/native

export PATH=$PATH:$HADOOP_HOME/sbin:$HADOOP_HOME/bin

export HADOOP_OPTS="-Djava.library.path=$HADOOP_HOME/lib/native"

Step-15 source ~/.bashrc

Step-16 Vi $HADOOP_HOME/etc/hadoop/hadoop-env.sh

Uncomment the $JAVA_HOME variable (i.e., remove the # sign) and add the full path to the OpenJDK installation on your system.

export JAVA_HOME=/usr/lib/jvm/java-8-openjdk-amd64

```
hdoop@PRLAB-22:~$ ls
hadoop  hadoop-3.2.3.tar.gz  test.txt
hdoop@PRLAB-22:~$ cd hadoop
hdoop@PRLAB-22:~/hadoop$ ls
bin  include  libexec      NOTICE.txt  sbin
etc  lib      LICENSE.txt  README.txt  share
hdoop@PRLAB-22:~/hadoop$ cd etc
hdoop@PRLAB-22:~/hadoop/etc$ ls
hadoop
hdoop@PRLAB-22:~/hadoop/etc$ cd hadoop
hdoop@PRLAB-22:~/hadoop/etc/hadoop$ ls
capacity-scheduler.xml            kms-log4j.properties
configuration.xsl                 kms-site.xml
container-executor.cfg            log4j.properties
core-site.xml                     mapred-env.cmd
hadoop-env.cmd                    mapred-env.sh
hadoop-env.sh                     mapred-queues.xml.template
hadoop-metrics2.properties        mapred-site.xml
hadoop-policy.xml                 shellprofile.d
hadoop-user-functions.sh.example  ssl-client.xml.example
hdfs-site.xml                     ssl-server.xml.example
httpfs-env.sh                     user_ec_policies.xml.template
httpfs-log4j.properties           workers
httpfs-signature.secret           yarn-env.cmd
httpfs-site.xml                   yarn-env.sh
kms-acls.xml                      yarnservice-log4j.properties
kms-env.sh                        yarn-site.xml
hdoop@PRLAB-22:~/hadoop/etc/hadoop$ vi hadoop-env.sh
hdoop@PRLAB-22:~/hadoop/etc/hadoop$
```

Step 17- configure Apache Hadoop on the Ubuntu system. For this, the step is to create two directories: datanode and namenode, inside the home directory of Hadoop:

mkdir -p ~/dfsdata/namenode

mkdir -p ~/dfsdata/datanode

Step-18 Vi $HADOOP_HOME/etc/hadoop/core-site.xml

Add the following configuration to override the default values for the temporary directory and add your HDFS URL to replace the default local file system setting:

<property>

<name>hadoop.tmp.dir</name>

<value>/home/hdoop/tmpdata</value>

</property>

<property>

<name>fs.default.name</name>

<value>hdfs://127.0.0.1:9000</value>

</property>

Step-19 Vi $HADOOP_HOME/etc/hadoop/hdfs-site.xml

Add the following configuration to the file and, if needed, adjust the NameNode and DataNode directories to your custom locations:

<configuration>

<property>

<name>dfs.data.dir</name>

<value>/home/hdoop/dfsdata/namenode</value>

</property>

<property>

<name>dfs.data.dir</name>

<value>/home/hdoop/dfsdata/datanode</value>

</property>

<property>

<name>dfs.replication</name>

<value>1</value>

</property>

</configuration>

```
<configuration>

<property>
  <name>dfs.data.dir</name>
  <value>/home/hdoop/dfsdata/namenode</value>
</property>
<property>
  <name>dfs.data.dir</name>
  <value>/home/hdoop/dfsdata/datanode</value>
</property>
<property>
  <name>dfs.replication</name>
  <value>1</value>
</property></configuration>
```

Step 20 Vi $HADOOP_HOME/etc/hadoop/mapred-site.xml

Add the following configuration to change the default MapReduce framework name value to yarn:

<configuration>

<property>

<name>mapreduce.framework.name</name>

<value>yarn</value>

</property>

</configuration>

```
<configuration>

<property>
  <name>mapreduce.framework.name</name>
  <value>yarn</value>
</property> </configuration>
```

Step 21 Vi $HADOOP_HOME/etc/hadoop/yarn-site.xml

Append the following configuration to the file:

<configuration>

<property>

<name>yarn.nodemanager.aux-services</name>

<value>mapreduce_shuffle</value>

</property>

<property>

<name>yarn.nodemanager.aux-services.mapreduce.shuffle.class</name>

<value>org.apache.hadoop.mapred.ShuffleHandler</value>

</property>

<property>

<name>yarn.resourcemanager.hostname</name>

<value>127.0.0.1</value>

</property>

<property>

<name>yarn.acl.enable</name>

<value>0</value>

</property>

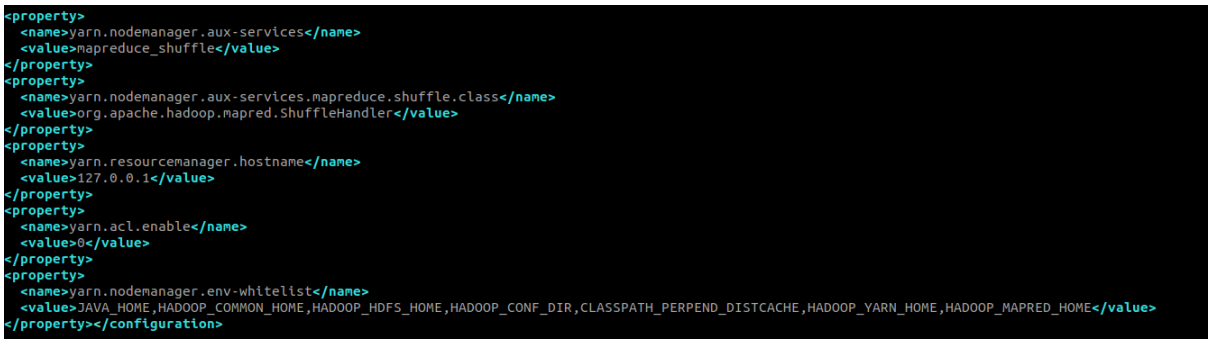
<property>

<name>yarn.nodemanager.env-whitelist</name>

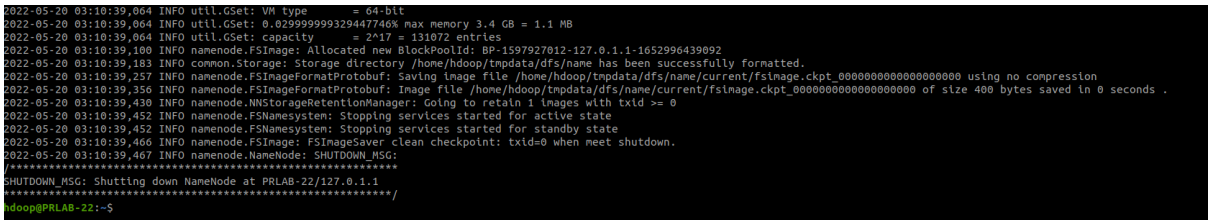
<value>JAVA_HOME,HADOOP_COMMON_HOME,HADOOP_HDFS_HOME,HADOOP_CONF_DIR,CLASSPATH_PERPEND_DISTCACHE,HADOOP_YARN_HOME,HADOOP_MAPRED_HOME</value>

</property>

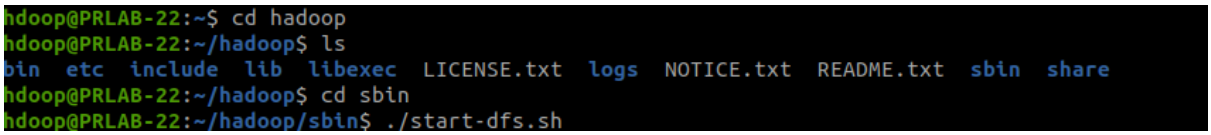
</configuration>

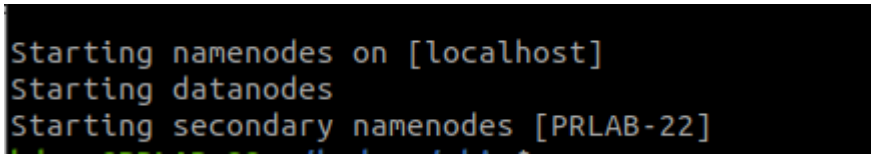


Step 22 hdfs namenode -format

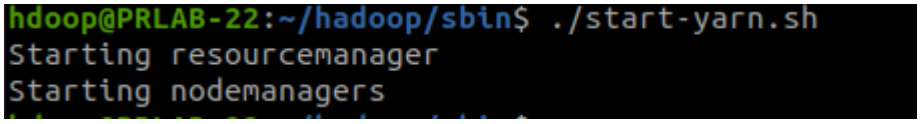


Step-23 ./start-dfs.sh

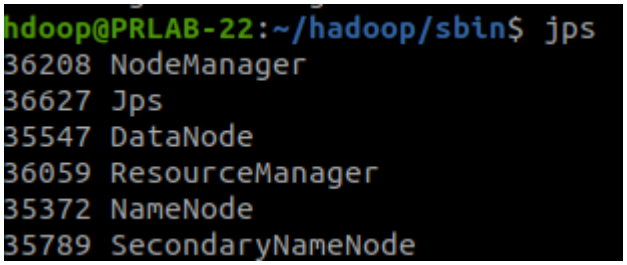




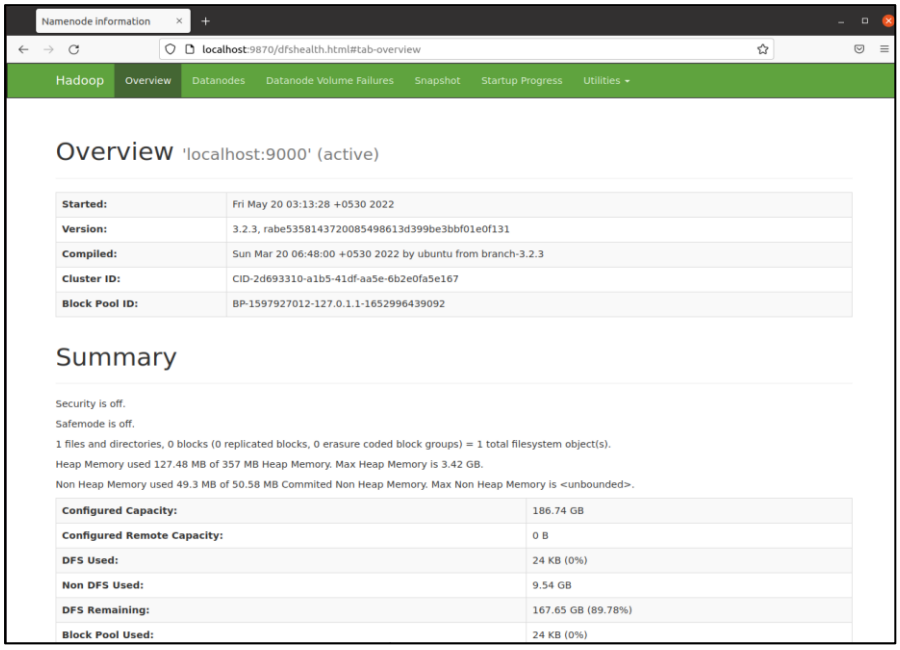
Step-24 ./start-yarn.sh



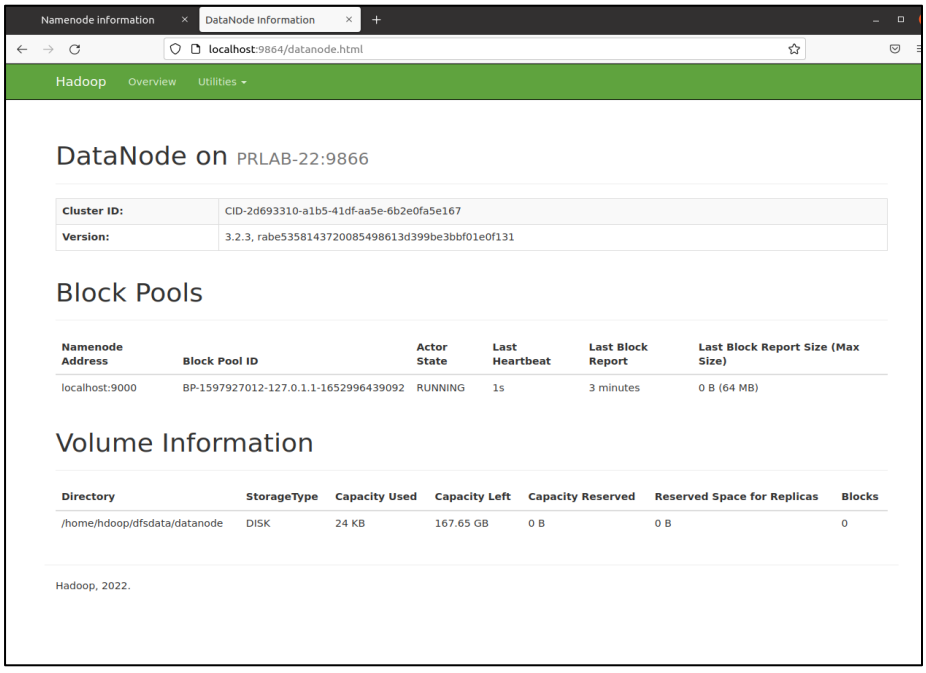
Step 25 jps



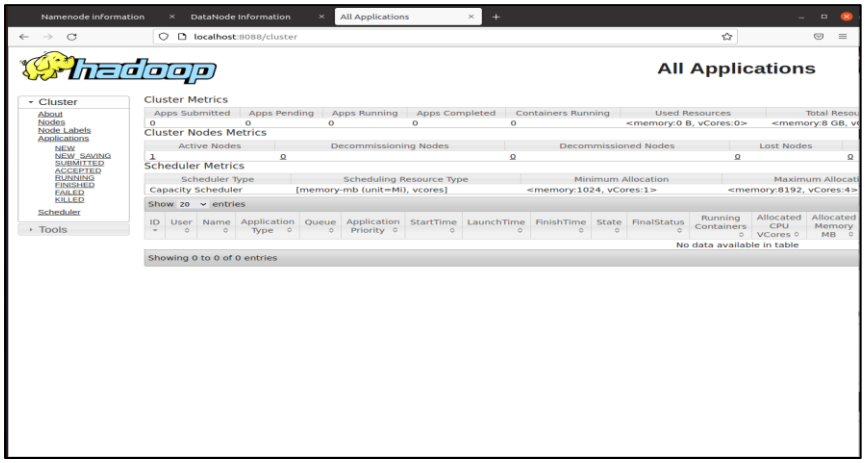
Step 26 http://localhost:9870



Step-27 http://localhost:9864



Step 28 http://localhost:8088



Step 29 To Stop namenode , datanode and yarn

```
hdoop@PRLAB-22:~/hadoop/sbin$ ./stop-yarn.sh
Stopping nodemanagers
Stopping resourcemanager
hdoop@PRLAB-22:~/hadoop/sbin$ ./stop-dfs.sh
Stopping namenodes on [localhost]
Stopping datanodes
Stopping secondary namenodes [PRLAB-22]
hdoop@PRLAB-22:~/hadoop/sbin$ jps
37827 Jps
```

Result:

Hadoop has been successfully installed in the system.

Exp.No : 12 **Date:**24/05/22

FILE MANAGEMENT IN HADOOP

1)**Aim:**

To implement the following task in Hadoop: a.Adding Directories. b.Adding Files. c.Retrieving files and its content.d.Deleting files.

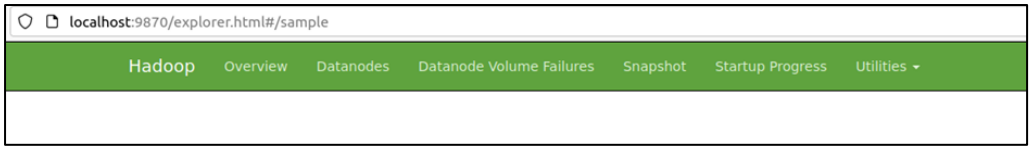
Adding Directory

hadoop fs -mkdir /sample

```
hdoop@PRLAB-22:~$ hadoop fs -mkdir /sample
```

Now login in web browser:

http://localhost:9870



Under Utilities → click (Browse the file system option)

Adding file:

In terminal create new file

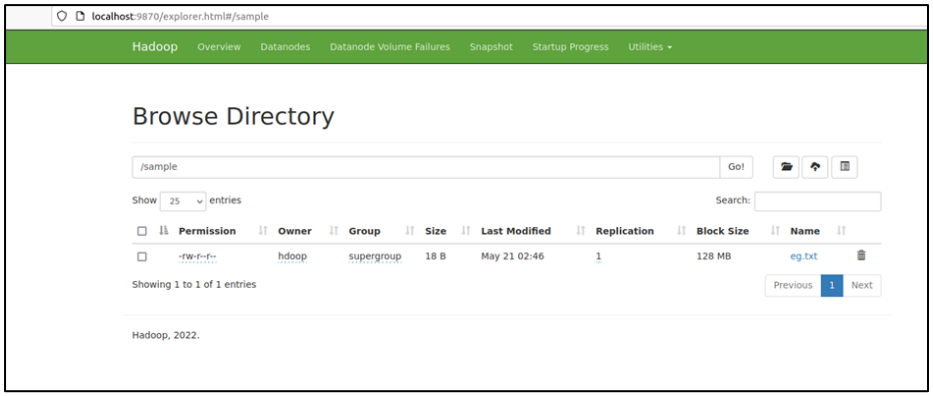
vi eg.txt

```
hdoop@PRLAB-22:~$ vi eg.txt
```

Move the file to the newly created directory

hadoop fs -put eg.txt /sample

```
hdoop@PRLAB-22:~$ hadoop fs -put eg.txt /sample
```



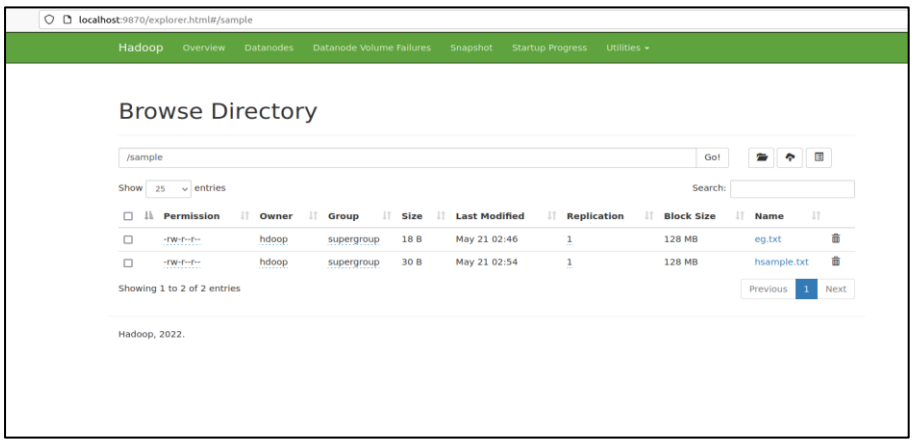
Retrieve a file:

hadoop fs -cat /sample/eg.txt

```
hdoop@PRLAB-22:~$ hadoop fs -cat /sample/eg.txt
welcome to hadoop
```

Delete a file:

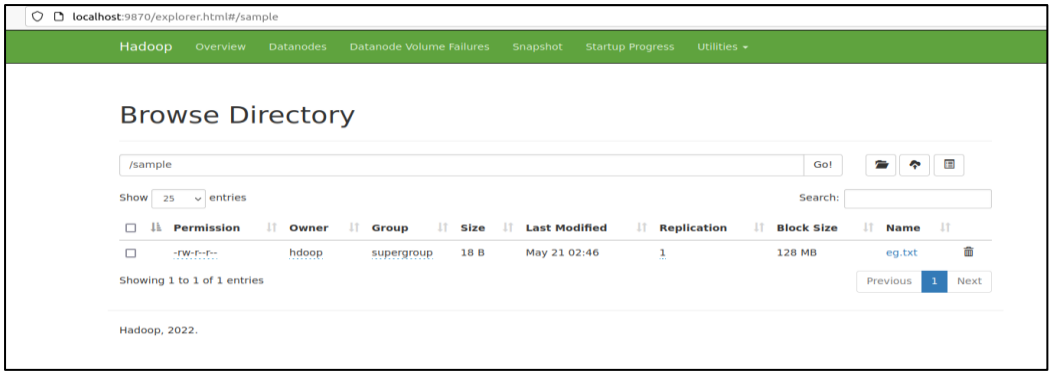
Existing files



hadoop fs -rm /sample/hsample.txt

```
hdoop@PRLAB-22:~$ hadoop fs -rm /sample/hsample.txt
Deleted /sample/hsample.txt
```

After deletion



Result:

File Management in Hadoop has been done successfully and the results are verified.

Exp.No : 13 **Date:**31/05/22

MongoDB-Data Replication

1)**Aim:**

To perform data replication using Mongo DB

Steps:

Step 1: Creating a node in port 27021

Step 2:

mkdir -p $HOME/mongo/data/db01

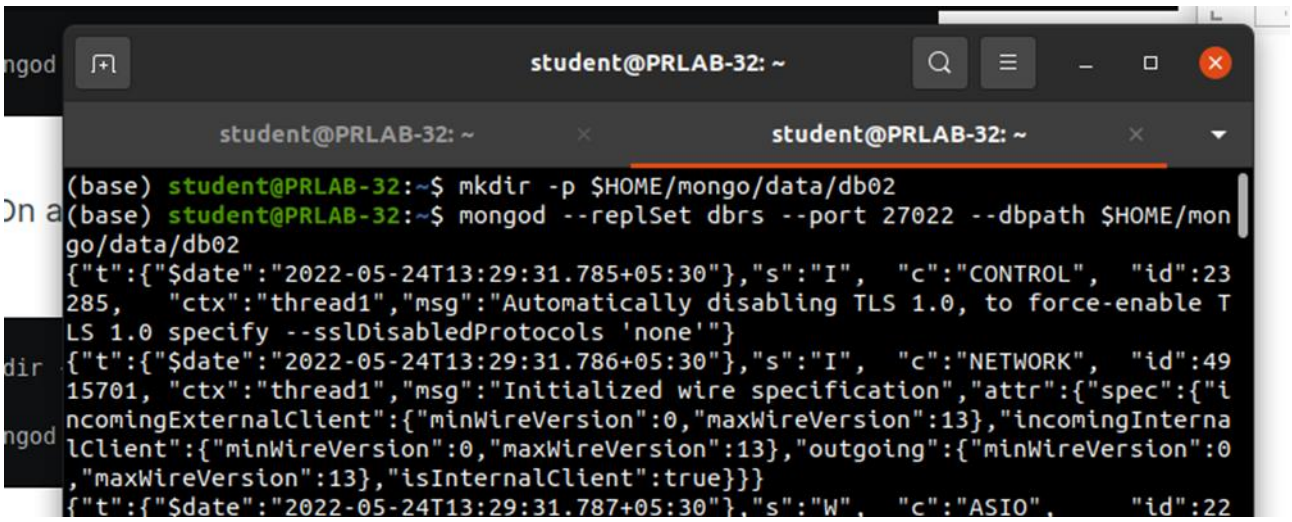
mongod --replSet dbrs --port 27021 --dbpath $HOME/mongo/data/db01

Step 3: Open another terminal

mkdir -p $HOME/mongo/data/db02

mongod --replSet dbrs --port 27022 --dbpath $HOME/mongo/data/db02

Output:



Step 4: Third Terminal

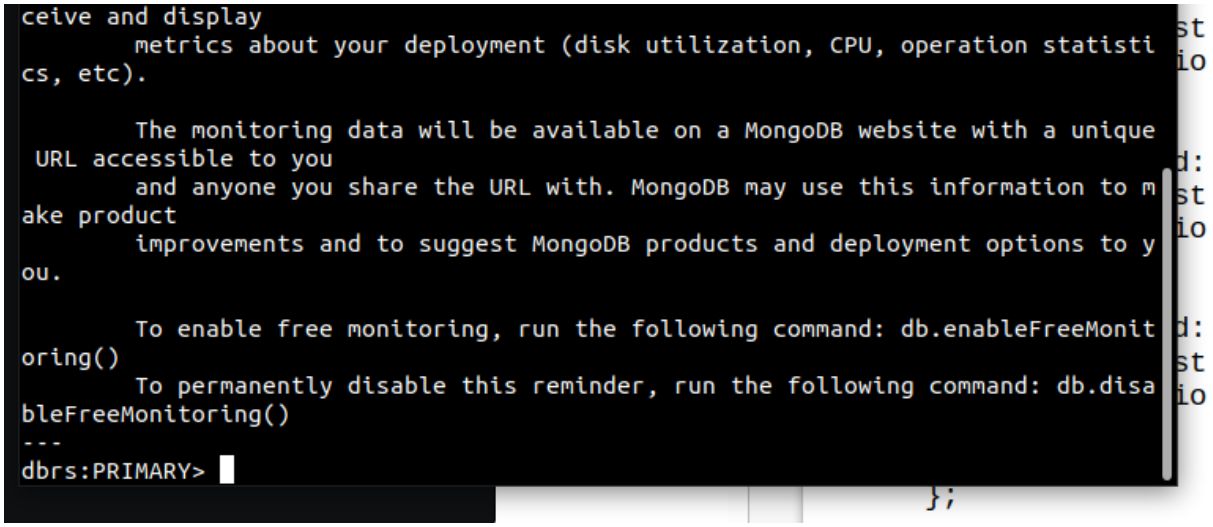
mkdir -p $HOME/mongo/data/db03

mongod --replSet dbrs --port 27023 --dbpath $HOME/mongo/data/db03

Step 5: Connect to any one of the mongo daemon

mongo --port 27021

Output:



Step 6: rsconf = {

_id: "dbrs",

members: [

{

_id: 0,

host: "127.0.0.1:27021",

priority: 3

},

{

_id: 1,

host: "127.0.0.1:27022",

priority: 1,

},

{

_id: 2,

host: "127.0.0.1:27023",

priority: 2

}

]

};

db.getMongo().setReadPref('secondary')

Output:

Result:

Data replication using MongoDB has been successfully done and the results are verified.

Exp.No : 14 **Date:**31/05/22

Classification-SVM

1)**Aim:**

To build a SVM classification model and perform the following a. Exploratory data analysis b. Explore missing values in variables c. Handle outliers d .Check the distribution of variables e. Declare feature vector and target variable f. Split data into separate training and test set g. Perform Feature Scaling h. Run SVM with default Hyperparameters i. Run SVM with RBF kernel j. Run SVM with Linear kernel k. Run SVM with polynomial kernel l. Run SVM with sigmoid kernel m. Compare the train-set and test-set accuracy n. Check for overfitting and underfitting o. Summarize the performance of model using confusion matrix p. Evaluate the model performance with classification report q. Analyze the model performance visually.

Code:

```
import numpy as np

import matplotlib.pyplot as plt

import pandas as pd

import seaborn as sns


data = pd.read_csv('dow_jones_index.csv')

data['high'] = data['high'].str.replace('$', '')

data['open'] = data['open'].str.replace('$', '')

data['low'] = data['low'].str.replace('$', '')

data['close'] = data['close'].str.replace('$', '')

data['next_weeks_open'] = data['next_weeks_open'].str.replace('$', '')

data['next_weeks_close'] = data['next_weeks_close'].str.replace('$', '')


data['high']=pd.to_numeric(data['high'])

data['open']=pd.to_numeric(data['open'])

data['low']=pd.to_numeric(data['low'])

data['close']=pd.to_numeric(data['close'])

data['next_weeks_open']=pd.to_numeric(data['next_weeks_open'])

data['next_weeks_close']=pd.to_numeric(data['next_weeks_close'])
```

data['percent_change_volume_over_last_wk'].fillna(value=0,inplace=True)

data['previous_weeks_volume'].fillna(value=0,inplace=True)

data.shape

Output:

```
data.shape

(750, 16)
```

data.info()

Output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 750 entries, 0 to 749
Data columns (total 16 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   quarter                           750 non-null    int64
 1   stock                             750 non-null    object
 2   date                              750 non-null    object
 3   open                              750 non-null    float64
 4   high                              750 non-null    float64
 5   low                               750 non-null    float64
 6   close                             750 non-null    float64
 7   volume                            750 non-null    int64
 8   percent_change_price              750 non-null    float64
 9   percent_change_volume_over_last_wk  720 non-null    float64
 10  previous_weeks_volume             720 non-null    float64
 11  next_weeks_open                   750 non-null    float64
 12  next_weeks_close                  750 non-null    float64
 13  percent_change_next_weeks_price   750 non-null    float64
 14  days_to_next_dividend             750 non-null    int64
 15  percent_return_next_dividend      750 non-null    float64
dtypes: float64(11), int64(3), object(2)
memory usage: 93.9+ KB
```

data.describe()

Output:

	quarter	open	high	low	close	volume	percent_change_price	percent_change_volume_over_last_wk	p
count	750.000000	750.000000	750.000000	750.000000	750.000000	7.500000e+02	750.000000	720.000000	
mean	1.520000	53.651840	54.669987	52.640160	53.729267	1.175478e+08	0.050262	5.593627	
std	0.499933	32.638852	33.215994	32.119277	32.788787	1.584381e+08	2.517809	40.543478	
min	1.000000	10.590000	10.940000	10.400000	10.520000	9.718851e+06	-15.422900	-61.433175	
25%	1.000000	29.830000	30.627500	28.720000	30.365000	3.086624e+07	-1.288053	-19.804284	
50%	2.000000	45.970000	46.885000	44.800000	45.930000	5.306088e+07	0.000000	0.512586	
75%	2.000000	72.715000	74.287500	71.037500	72.667500	1.327218e+08	1.650888	21.800622	
max	2.000000	172.110000	173.540000	167.820000	170.580000	1.453439e+09	9.882230	327.408924	

percent_change_volume_over_last_wk	previous_weeks_volume	next_weeks_open	next_weeks_close	percent_change_next_weeks_price	days_to_next_dividend
720.000000	7.200000e+02	750.000000	750.000000	750.000000	750.000000
5.593627	1.173876e+08	53.702440	53.889080	0.238468	52.525333
40.543478	1.592322e+08	32.778111	33.016677	2.679538	46.335098
-61.433175	9.718851e+06	10.520000	10.520000	-15.422900	0.000000
-19.804284	3.067832e+07	30.315000	30.462500	-1.222068	24.000000
0.512586	5.294556e+07	46.015000	46.125000	0.101193	47.000000
21.800622	1.333230e+08	72.715000	72.915000	1.845562	69.000000
327.408924	1.453439e+09	172.110000	174.540000	9.882230	336.000000

cols=['open','high','low','close','volume','next_weeks_open','next_weeks_close','percent_change_next_weeks_price']

X=data[cols]

y=data['quarter']

 # split X and y into training and testing sets

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)

 # check the shape of X_train and X_test

X_train.shape, X_test.shape

Output:

```
# check the shape of X_train and X_test

X_train.shape, X_test.shape

((600, 8), (150, 8))
```

cols = X_train.columns

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)

X_test = scaler.transform(X_test)

X_train = pd.DataFrame(X_train, columns=[cols])

X_test = pd.DataFrame(X_test, columns=[cols])

X_train.describe()

Output:

	open	high	low	close	volume	next_weeks_open	next_weeks_close	percent_change_next_weeks_price
count	6.000000e+02	6.000000e+02	6.000000e+02	6.000000e+02	6.000000e+02	6.000000e+02	6.000000e+02	6.000000e+02
mean	-2.035409e-18	-5.939693e-17	-2.096471e-16	8.252658e-17	-3.044873e-17	1.789309e-16	2.942091e-17	4.847974e-17
std	1.000834e+00	1.000834e+00	1.000834e+00	1.000834e+00	1.000834e+00	1.000834e+00	1.000834e+00	1.000834e+00
min	-1.327585e+00	-1.322818e+00	-1.323036e+00	-1.324817e+00	-6.656439e-01	-1.323918e+00	-1.321378e+00	-4.059979e+00
25%	-7.113305e-01	-7.140684e-01	-7.073728e-01	-7.108043e-01	-5.316059e-01	-7.101924e-01	-7.060590e-01	-5.750435e-01
50%	-2.460951e-01	-2.421160e-01	-2.535420e-01	-2.500281e-01	-3.982804e-01	-2.441872e-01	-2.396332e-01	-2.436433e-02
75%	5.751698e-01	5.639386e-01	5.608326e-01	5.671071e-01	9.044814e-02	5.701036e-01	5.695192e-01	6.376863e-01
max	3.620221e+00	3.565823e+00	3.566168e+00	3.551337e+00	8.305524e+00	3.597767e+00	3.642331e+00	3.616121e+00

 # import SVC classifier

```
from sklearn.svm import SVC

from sklearn.metrics import accuracy_score
```

 # instantiate classifier with default hyperparameters

```
svc=SVC()

svc.fit(X_train,y_train)

y_pred=svc.predict(X_test)

print('Model accuracy score with default hyperparameters: {0:0.4f}'.
format(accuracy_score(y_test, y_pred)))
```

Output:

```
Model accuracy score with default hyperparameters: 0.4733
```

 # instantiate classifier with rbf kernel and C=100

```
svc=SVC(C=100.0)

svc.fit(X_train,y_train)

y_pred=svc.predict(X_test)

print('Model accuracy score with rbf kernel and C=100.0 : {0:0.4f}'.
format(accuracy_score(y_test, y_pred)))
```

Output:

```
Model accuracy score with rbf kernel and C=100.0 : 0.5333
```

 # instantiate classifier with rbf kernel and C=1000

```
svc=SVC(C=1000.0)

svc.fit(X_train,y_train)

y_pred=svc.predict(X_test)
```

```
print('Model accuracy score with rbf kernel and C=1000.0 : {0:0.4f}'.
format(accuracy_score(y_test, y_pred)))
```

Output:

```
Model accuracy score with rbf kernel and C=1000.0 : 0.5733
```

 # instantiate classifier with linear kernel and C=1.0

```
linear_svc=SVC(kernel='linear', C=1.0)

linear_svc.fit(X_train,y_train)

y_pred_test=linear_svc.predict(X_test)

print('Model accuracy score with linear kernel and C=1.0 : {0:0.4f}'.
format(accuracy_score(y_test, y_pred_test)))
```

Output:

```
Model accuracy score with linear kernel and C=1.0 : 0.5333
```

 # instantiate classifier with linear kernel and C=100.0

```
linear_svc100=SVC(kernel='linear', C=100.0)

linear_svc100.fit(X_train, y_train)

y_pred=linear_svc100.predict(X_test)

print('Model accuracy score with linear kernel and C=100.0 : {0:0.4f}'.
format(accuracy_score(y_test, y_pred)))
```

Output:

```
Model accuracy score with linear kernel and C=100.0 : 0.5200
```

 # instantiate classifier with linear kernel and C=1000.0

```
linear_svc1000=SVC(kernel='linear', C=1000.0)

linear_svc1000.fit(X_train, y_train)

y_pred=linear_svc1000.predict(X_test)

print('Model accuracy score with linear kernel and C=1000.0 : {0:0.4f}'.
format(accuracy_score(y_test, y_pred)))
```

Output:

```
Model accuracy score with linear kernel and C=1000.0 : 0.5333
```

 # instantiate classifier with polynomial kernel and C=1.0

```
poly_svc=SVC(kernel='poly', C=1.0)

poly_svc.fit(X_train,y_train)

y_pred_test=poly_svc.predict(X_test)

print('Model accuracy score with polynomial kernel and C=1.0 : {0:0.4f}'.
format(accuracy_score(y_test, y_pred_test)))
```

Output:

```
Model accuracy score with polynomial kernel and C=1.0 : 0.5200
```

 # instantiate classifier with polynomial kernel and C=100.0

```
poly_svc=SVC(kernel='poly', C=100.0)

poly_svc.fit(X_train,y_train)

y_pred_test=poly_svc.predict(X_test)

print('Model accuracy score with polynomial kernel and C=100.0 : {0:0.4f}'.
format(accuracy_score(y_test, y_pred_test)))
```

Output:

```
Model accuracy score with polynomial kernel and C=100.0 : 0.5333
```

 # instantiate classifier with sigmoid kernel and C=1.0

```
sig_svc=SVC(kernel='sigmoid', C=1.0)

sig_svc.fit(X_train,y_train)

y_pred_test=sig_svc.predict(X_test)

print('Model accuracy score with sigmoid kernel and C=1.0 : {0:0.4f}'.
format(accuracy_score(y_test, y_pred_test)))
```

Output:

```
Model accuracy score with sigmoid kernel and C=1.0 : 0.4600
```

 # instantiate classifier with sigmoid kernel and C=100.0

```
sig_svc=SVC(kernel='sigmoid', C=100.0)

sig_svc.fit(X_train,y_train)

y_pred_test=sig_svc.predict(X_test)

print('Model accuracy score with sigmoid kernel and C=100.0 : {0:0.4f}'.
format(accuracy_score(y_test, y_pred_test)))
```

Output:

```
Model accuracy score with sigmoid kernel and C=100.0 : 0.4733
```

y_pred_train = linear_svc.predict(X_train)

print('Training-set accuracy score: {0:0.4f}'. format(accuracy_score(y_train, y_pred_train)))

Output:

```
Training-set accuracy score: 0.5283
```

 # print the scores on training and test set

print('Training set score: {:.4f}'.format(linear_svc.score(X_train, y_train)))

print('Test set score: {:.4f}'.format(linear_svc.score(X_test, y_test)))

Output:

```
Training set score: 0.5283
Test set score: 0.5200
```

 # check class distribution in test set

y_test.value_counts()

Output:

```
2    80
1    70
Name: quarter, dtype: int64
```

check null accuracy score

null_accuracy = (80/(80+70))

print('Null accuracy score: {0:0.4f}'. format(null_accuracy))

Output:

```
Null accuracy score: 0.5333
```

from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, y_pred_test)

print('Confusion matrix\n\n', cm)

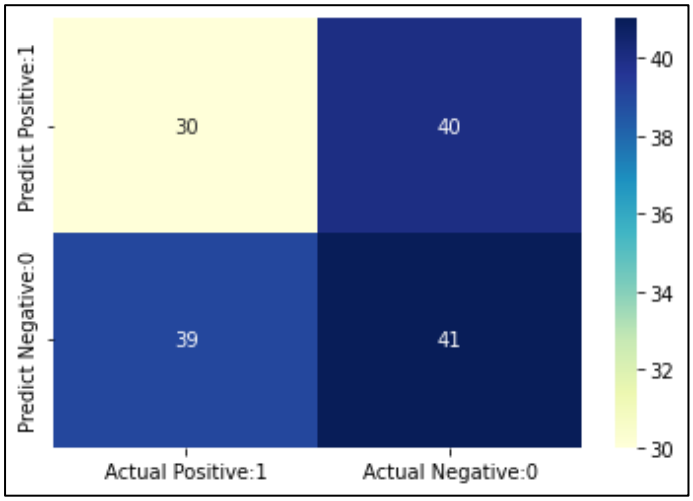
```
print('\nTrue Positives(TP) = ', cm[0,0])

print('\nTrue Negatives(TN) = ', cm[1,1])

print('\nFalse Positives(FP) = ', cm[0,1])

print('\nFalse Negatives(FN) = ', cm[1,0])
```

Output:

```
Confusion matrix

 [[30 40]
 [39 41]]

True Positives(TP) =  30

True Negatives(TN) =  41

False Positives(FP) =  40

False Negatives(FN) =  39
```

```
cm_matrix = pd.DataFrame(data=cm, columns=['Actual Positive:1', 'Actual Negative:0'],
                         index=['Predict Positive:1', 'Predict Negative:0'])
sns.heatmap(cm_matrix, annot=True, fmt='d', cmap='YlGnBu')
```

Output:




```
from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred_test))
```

Output:

	precision	recall	f1-score	support
1	0.43	0.43	0.43	70
2	0.51	0.51	0.51	80
accuracy			0.47	150
macro avg	0.47	0.47	0.47	150
weighted avg	0.47	0.47	0.47	150

TP = cm[0,0]

TN = cm[1,1]

FP = cm[0,1]

FN = cm[1,0]

classification_accuracy = (TP + TN) / float(TP + TN + FP + FN)

print('Classification accuracy : {0:0.4f}'.format(classification_accuracy))

Output:

```
Classification accuracy : 0.4733
```

classification_error = (FP + FN) / float(TP + TN + FP + FN)

print('Classification error : {0:0.4f}'.format(classification_error))

Output:

```
Classification error : 0.5267
```

precision = TP / float(TP + FP)

print('Precision : {0:0.4f}'.format(precision))

Output:

```
Precision : 0.4286
```

recall = TP / float(TP + FN)

print('Recall or Sensitivity : {0:0.4f}'.format(recall))

Output:

```
Recall or Sensitivity : 0.4348
```

```
true_positive_rate = TP / float(TP + FN)

print('True Positive Rate : {0:0.4f}'.format(true_positive_rate))
```

Output:

```
True Positive Rate : 0.4348
```

```
false_positive_rate = FP / float(FP + TN)

print('False Positive Rate : {0:0.4f}'.format(false_positive_rate))
```

Output:

```
False Positive Rate : 0.4938
```

```
specificity = TN / (TN + FP)

print('Specificity : {0:0.4f}'.format(specificity))
```

Output:

```
Specificity : 0.5062
```

```
# calculate cross-validated ROC AUC

from sklearn.model_selection import cross_val_score

Cross_validated_ROC_AUC = cross_val_score(linear_svc, X_train, y_train, cv=10,
scoring='roc_auc').mean()

print('Cross validated ROC AUC : {:.4f}'.format(Cross_validated_ROC_AUC))
```

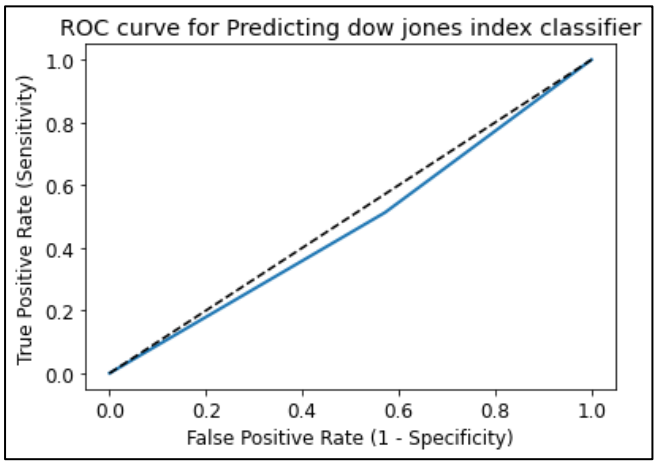
Output:

```
Cross validated ROC AUC : 0.5186
```

```
import numpy as np

arr = np.array(y_test)

indices_one = arr == 1

indices_zero = arr == 2

arr[indices_one] = 0 # replacing 1s with 0s

arr[indices_zero] = 1 # replacing 2s with 1s

arr1=arr
```

```
import numpy as np
arr = np.array(y_pred_test)
indices_one = arr == 1
indices_zero = arr == 2
arr[indices_one] = 0 # replacing 1s with 0s
arr[indices_zero] = 1 # replacing 2s with 1s
arr2=arr

from sklearn.metrics import roc_curve
fpr, tpr, thresholds = roc_curve(arr1, arr2)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, linewidth=2)
plt.plot([0,1], [0,1], 'k--' )
plt.rcParams['font.size'] = 12
plt.title('ROC curve for Predicting dow jones index classifier')
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.show()
```

Output:



Result:

SVM model has been successfully completed and the results are verified.

Exp.No : 15 **Date:**07/06/22

Hive – Installation

1)**Aim:**

A study on Hive architecture and its working

Hive:

Hive is a Hadoop data warehouse infrastructure solution that allows you to process structured data. It sits atop Hadoop to summarise Big Data and facilitate searching and analysis.Hive is a declarative SQL-based programming language that is mostly used for data analysis and report generation. Hive is a server-side cluster management system.

Hive makes schema flexibility and evolution, as well as data summarization, data querying, and analysis, more easier.We may create two sorts of tables in Hive: partitioned and bucketed, which allow us to process data stored in HDFS while also improving performance.

HIVE Architecture:

METASTORE – It is used to store metadata of tables schema, time of creation, location, etc. It also provides metadata partition to help the driver to keep the track of the progress of various datasets distributed over the cluster.

DRIVER – It acts as a controller. The driver starts the execution of the statement by creating sessions and monitors the life cycle and progress of execution.

COMPILER – It is used to compile a Hive query, which converts the query to an execution plan.

OPTIMIZER – It optimizes and performs transformations on an execution plan to get an optimized Directed Acyclic Graph abbreviated as DAG.

EXECUTOR – It executes tasks after compilation and optimization have been done. It interacts with the job tracker of Hadoop to schedule tasks to be run.

Result:

Study on HIVE has been successfully executed and the results are verified.

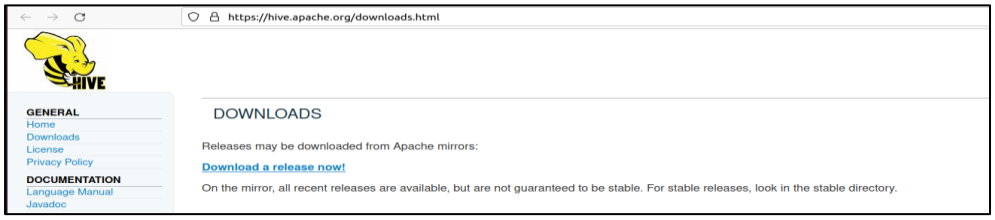
2)Aim:

To install HIVE above Hadoop in the system

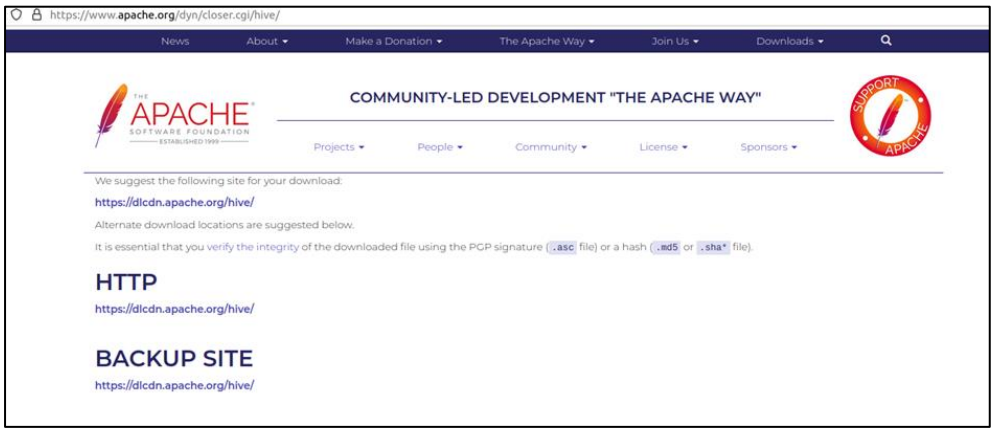
Steps to installation:

Step-1 Download Apache HIVE

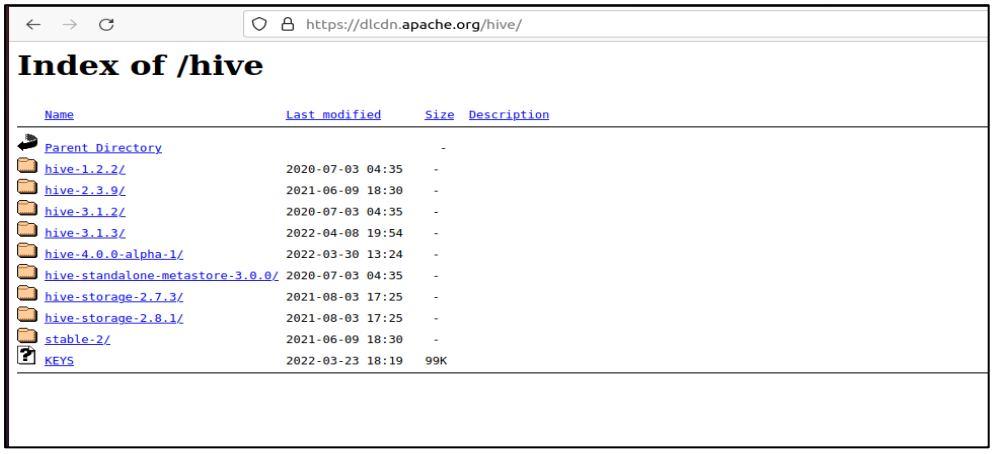
Visit https://hive.apache.org/downloads.html



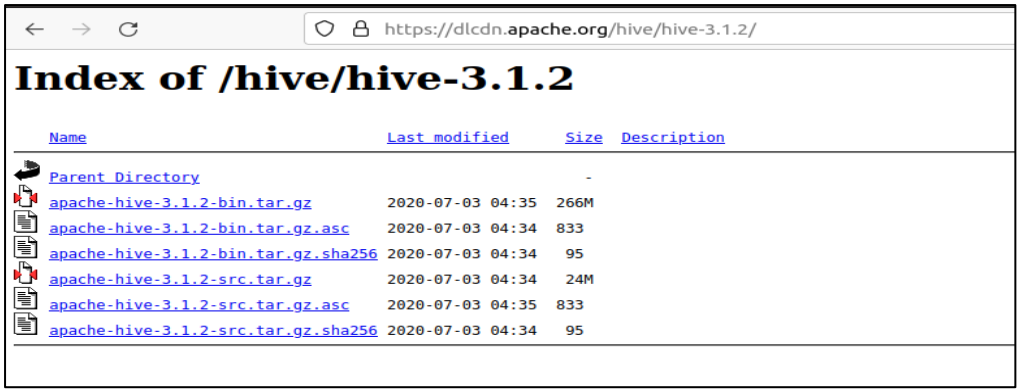
Click on download a release now! Link



Click on https://dlcdn.apache.org/hive/



Select the apache-hive-3.1.2-bin.tar.gz file to begin the download process.



Step-2 su - hdoop

wget https://dlcdn.apache.org/hive/hive-3.1.2/apache-hive-3.1.2-bin.tar.gz

Step 3 tar xvzf apache-hive-3.1.2-bin.tar.gz

```
hdoop@PRLAB-22:~$ tar xvzf apache-hive-3.1.2-bin.tar.gz
apache-hive-3.1.2-bin/LICENSE
apache-hive-3.1.2-bin/NOTICE
apache-hive-3.1.2-bin/RELEASE_NOTES.txt
apache-hive-3.1.2-bin/binary-package-licenses/asm-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/com.google.protobuf-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/com.ibm.icu.icu4j-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/com.sun.jersey-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/com.thoughtworks.paranamer-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/javax.transaction.transaction-api-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/javolution-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/jline-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/NOTICE
apache-hive-3.1.2-bin/binary-package-licenses/org.abego.treelayout.core-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/org.antlr-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/org.antlr.antlr4-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/org.antlr.stringtemplate-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/org.codehaus.janino-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/org.jamon.jamon-runtime-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/org.jruby-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/org.mozilla.rhino-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/org.slf4j-LICENSE
apache-hive-3.1.2-bin/binary-package-licenses/sqlline-LICENSE
apache-hive-3.1.2-bin/examples/files/2000_cols_data.csv
apache-hive-3.1.2-bin/examples/files/3col_data.txt
apache-hive-3.1.2-bin/examples/files/4col_data.txt
```

Step 4 vi .bashrc

```
hdoop@PRLAB-22:~$ vi .bashrc
hdoop@PRLAB-22:~$
```

Append the following Hive environment variables to the .bashrc file:

export HIVE_HOME= "/home/hdoop/apache-hive-3.1.2-bin"

export PATH=$PATH:$ HIVE_HOME/bin

```
hdoop@PRLAB-22: ~
# this, if it's already enabled in /etc/bash.bashrc and /etc/profile
# sources /etc/bash.bashrc).
if ! shopt -oq posix; then
  if [ -f /usr/share/bash-completion/bash_completion ]; then
    . /usr/share/bash-completion/bash_completion
  elif [ -f /etc/bash_completion ]; then
    . /etc/bash_completion
  fi
fi
#Hadoop Related Options
export JAVA_HOME=/usr/lib/jvm/java-8-openjdk-amd64
export HADOOP_HOME=/home/hdoop/hadoop
export HADOOP_INSTALL=$HADOOP_HOME
export HADOOP_MAPRED_HOME=$HADOOP_HOME
export HADOOP_COMMON_HOME=$HADOOP_HOME
export HADOOP_HDFS_HOME=$HADOOP_HOME
export YARN_HOME=$HADOOP_HOME
export HADOOP_COMMON_LIB_NATIVE_DIR=$HADOOP_HOME/lib/native
export PATH=$PATH:$HADOOP_HOME/sbin:$HADOOP_HOME/bin
export HADOOP_OPTS="-Djava.library.path=$HADOOP_HOME/lib/native"
#Hive Related Options
export HIVE_HOME="/home/hdoop/apache-hive-3.1.2-bin"
export PATH=$PATH:$HIVE_HOME/bin
```

Step 5 source ~/.bashrc

```
hdoop@PRLAB-22:~$ source ~/.bashrc
```

Step 6 vi $HIVE_HOME/bin/hive-config.sh

```
hdoop@PRLAB-22: ~/apache-hive-3.1.2-bin/bin
        HIVE_CONF_DIR=$confdir
        ;;
    --auxpath)
        shift
        HIVE_AUX_JARS_PATH=$1
        shift
        ;;
    *)
        break;
        ;;
  esac
done


# Allow alternate conf dir location.
HIVE_CONF_DIR="${HIVE_CONF_DIR:-$HIVE_HOME/conf}"

export HIVE_CONF_DIR=$HIVE_CONF_DIR
export HADOOP_HOME=/home/hdoop/hadoop
export HIVE_AUX_JARS_PATH=$HIVE_AUX_JARS_PATH
```

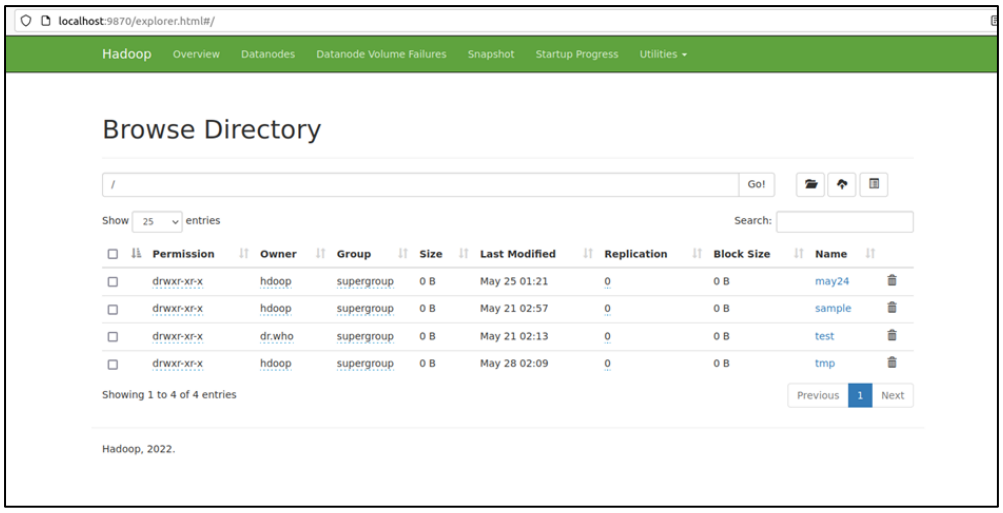
Start hadoop file system and yarn

```
itadmin@PRLAB-22:~$ su - hdoop
Password:
hdoop@PRLAB-22:~$ cd hadoop
hdoop@PRLAB-22:~/hadoop$ cd sbin
hdoop@PRLAB-22:~/hadoop/sbin$ ./start-dfs.sh
Starting namenodes on [localhost]
Starting datanodes
Starting secondary namenodes [PRLAB-22]
hdoop@PRLAB-22:~/hadoop/sbin$ ./start-yarn.sh
Starting resourcemanager
Starting nodemanagers
hdoop@PRLAB-22:~/hadoop/sbin$ jps
37620 NodeManager
38374 Jps
36616 DataNode
36856 SecondaryNameNode
37467 ResourceManager
36060 NameNode
```

Step-7 Create two separate directories to store data in the HDFS layer:

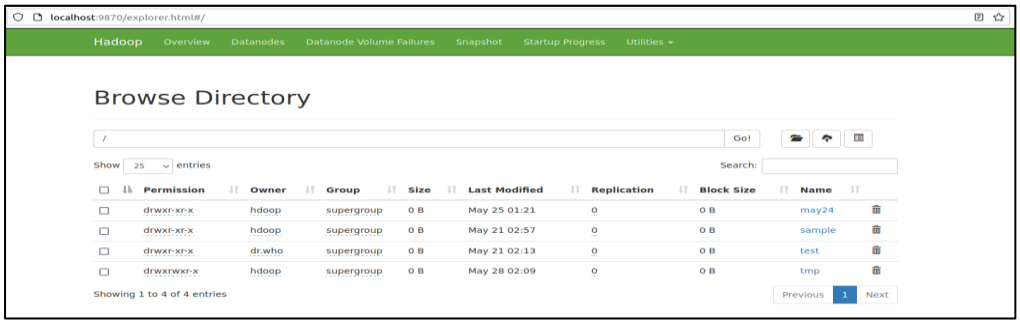
Step 7.1 hadoop fs -mkdir /tmp

```
hdoop@PRLAB-22:~$ hadoop fs -mkdir /tmp
hdoop@PRLAB-22:~$
```



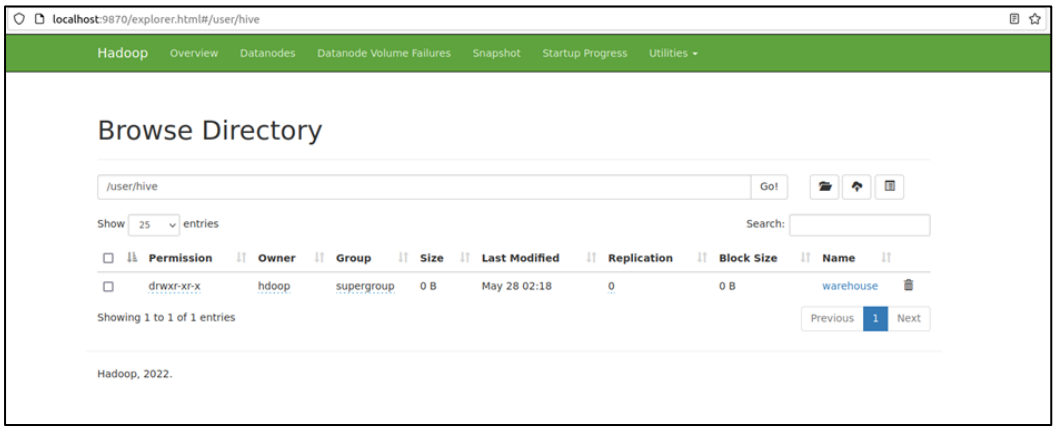
Step 7.2 hadoop fs -chmod g+w /tmp

Step 7.3 hadoop fs -ls /



```
hdoop@PRLAB-22:~$ hadoop fs -ls /
Found 4 items
drwxr-xr-x   - hdoop  supergroup          0 2022-05-25 01:21 /may24
drwxr-xr-x   - hdoop  supergroup          0 2022-05-21 02:57 /sample
drwxr-xr-x   - dr.who supergroup          0 2022-05-21 02:13 /test
drwxrwxr-x   - hdoop  supergroup          0 2022-05-28 02:09 /tmp
hdoop@PRLAB-22:~$
```

Step 7.4 hadoop fs -mkdir -p /user/hive/warehouse



Step 7.5 hadoop fs -chmod g+w /user/hive/warehouse

```
hdoop@PRLAB-22:~$ hadoop fs -chmod g+w /user/hive/warehouse
hdoop@PRLAB-22:~$
```

```
hdoop@PRLAB-22:~$ hadoop fs -ls /user/hive
Found 1 items
drwxrwxr-x   - hdoop supergroup          0 2022-05-28 02:18 /user/hive/warehouse
hdoop@PRLAB-22:~$
```

Step 8 cd $HIVE_HOME/conf

```
hdoop@PRLAB-22: ~/apache-hive-3.1.2-bin/conf
ser/hive/warehouse
hdoop@PRLAB-22:~$ cd $HIVE_HOME/conf
hdoop@PRLAB-22:~/apache-hive-3.1.2-bin/conf$ ls
beeline-log4j2.properties.template
hive-default.xml.template
hive-env.sh.template
hive-exec-log4j2.properties.template
hive-log4j2.properties.template
ivysettings.xml
llap-cli-log4j2.properties.template
llap-daemon-log4j2.properties.template
parquet-logging.properties
hdoop@PRLAB-22:~/apache-hive-3.1.2-bin/conf$
```

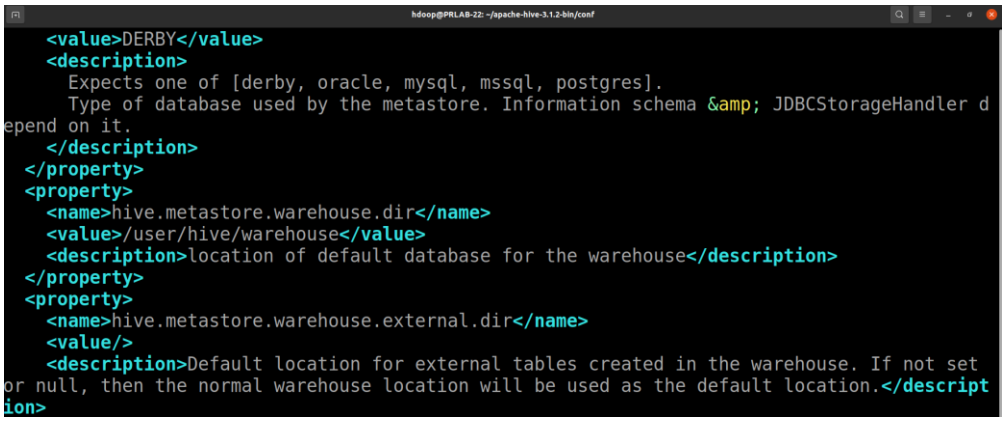
Use the hive-default.xml.template to create the hive-site.xml file:

```
hdoop@PRLAB-22:~/apache-hive-3.1.2-bin/conf$ cp hive-default.xml.template hive-site.xml
hdoop@PRLAB-22:~/apache-hive-3.1.2-bin/conf$
```

Access the hive-site.xml file using the text editor of your choice

```
hdoop@PRLAB-22:~/apache-hive-3.1.2-bin/conf$ vi hive-site.xml
hdoop@PRLAB-22:~/apache-hive-3.1.2-bin/conf$
```

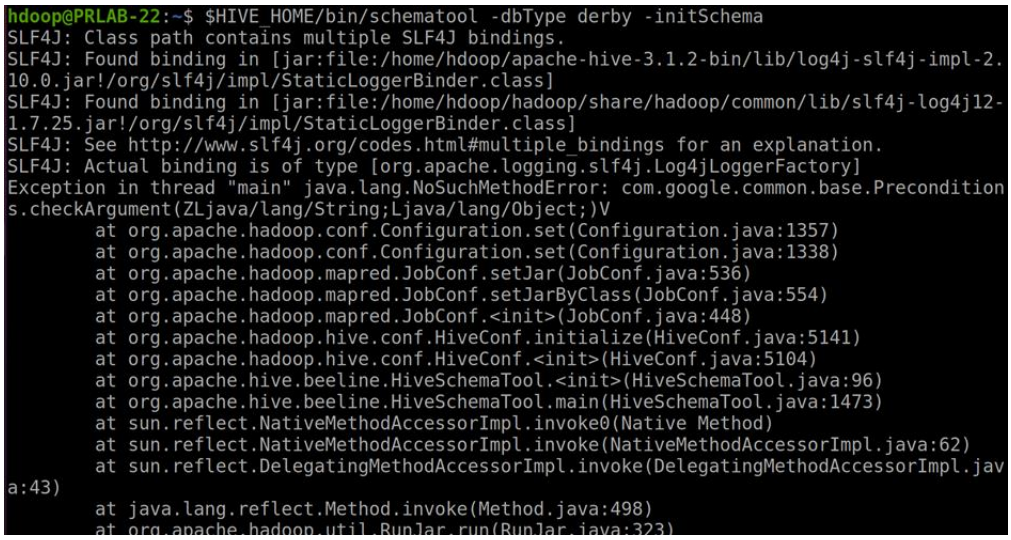
Configure the system to use your local storage rather than the HDFS layer by setting the hive.metastore.warehouse.dir parameter value to the location of your Hive warehouse directory.



```
    <value>DERBY</value>
    <description>
      Expects one of [derby, oracle, mysql, mssql, postgres].
      Type of database used by the metastore. Information schema &amp;amp; JDBCStorageHandler d
epend on it.
    </description>
  </property>
  <property>
    <name>hive.metastore.warehouse.dir</name>
    <value>/user/hive/warehouse</value>
    <description>location of default database for the warehouse</description>
  </property>
  <property>
    <name>hive.metastore.warehouse.external.dir</name>
    <value/>
    <description>Default location for external tables created in the warehouse. If not set
or null, then the normal warehouse location will be used as the default location.</descript
ion>
```

Step 9: Initiate Database

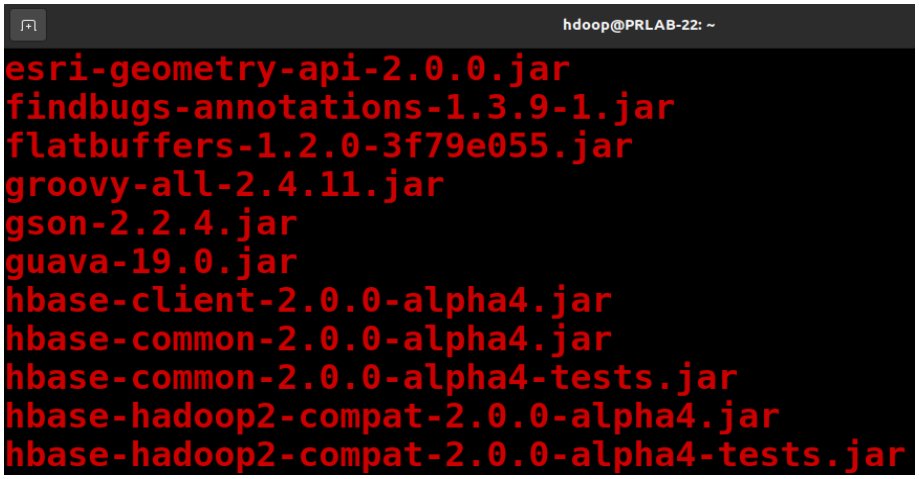
$HIVE_HOME/bin/schematool -dbType derby -initSchema



```
hdoop@PRLAB-22:~$ $HIVE_HOME/bin/schematool -dbType derby -initSchema
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/home/hdoop/apache-hive-3.1.2-bin/lib/log4j-slf4j-impl-2.
10.0.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/home/hdoop/hadoop/share/hadoop/common/lib/slf4j-log4j12-
1.7.25.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.apache.logging.slf4j.Log4jLoggerFactory]
Exception in thread "main" java.lang.NoSuchMethodError: com.google.common.base.Precondition
s.checkArgument(ZLjava/lang/String;Ljava/lang/Object;)V
        at org.apache.hadoop.conf.Configuration.set(Configuration.java:1357)
        at org.apache.hadoop.conf.Configuration.set(Configuration.java:1338)
        at org.apache.hadoop.mapred.JobConf.setJar(JobConf.java:536)
        at org.apache.hadoop.mapred.JobConf.setJarByClass(JobConf.java:554)
        at org.apache.hadoop.mapred.JobConf.<init>(JobConf.java:448)
        at org.apache.hadoop.hive.conf.HiveConf.initialize(HiveConf.java:5141)
        at org.apache.hadoop.hive.conf.HiveConf.<init>(HiveConf.java:5104)
        at org.apache.hive.beeline.HiveSchemaTool.<init>(HiveSchemaTool.java:96)
        at org.apache.hive.beeline.HiveSchemaTool.main(HiveSchemaTool.java:1473)
        at sun.reflect.NativeMethodAccessorImpl.invoke0(Native Method)
        at sun.reflect.NativeMethodAccessorImpl.invoke(NativeMethodAccessorImpl.java:62)
        at sun.reflect.DelegatingMethodAccessorImpl.invoke(DelegatingMethodAccessorImpl.jav
a:43)
        at java.lang.reflect.Method.invoke(Method.java:498)
        at org.apache.hadoop.util.RunJar.run(RunJar.java:323)
```

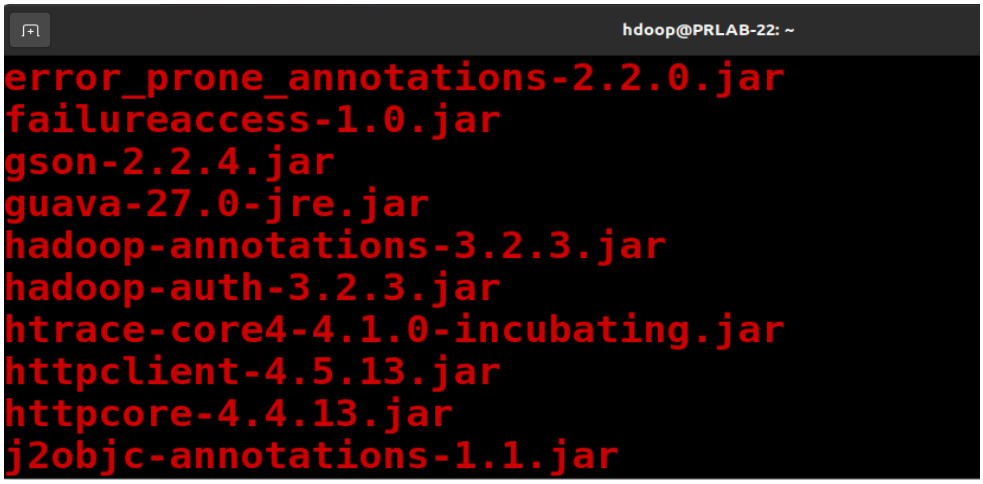
Step 10.1 Locate the guava jar file in the Hive lib directory:

ls $HIVE_HOME/lib



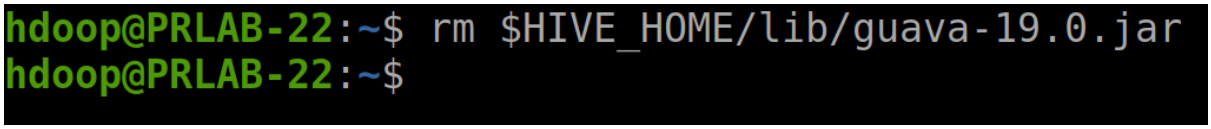
Step 10.2 Locate the guava jar file in the Hadoop lib directory as well:

ls $HADOOP_HOME/share/hadoop/hdfs/lib



Step 10.3 The two listed versions are not compatible and are causing the error. Remove the existing guava file from the Hive lib directory:

rm $HIVE_HOME/lib/guava-19.0.jar



Step 10.4 Copy the guava file from the Hadoop lib directory to the Hive lib directory:

cp $HADOOP_HOME/share/hadoop/hdfs/lib/guava-27.0-jre.jar $HIVE_HOME/lib/

Step 11-Use the schematool command once again to initiate the Derby database:

$HIVE_HOME/bin/schematool -dbType derby -initSchema

```
hdoop@PRLAB-22:~$ $HIVE_HOME/bin/schematool -dbType derby -initSchema
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/home/hdoop/apache-hive-3.1.2-bin/lib/log4j-slf4j-impl-2.
10.0.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/home/hdoop/hadoop/share/hadoop/common/lib/slf4j-log4j12-
1.7.25.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.apache.logging.slf4j.Log4jLoggerFactory]
Metastore connection URL:        jdbc:derby:;databaseName=metastore_db;create=true
Metastore Connection Driver :    org.apache.derby.jdbc.EmbeddedDriver
Metastore connection User:       APP
Starting metastore schema initialization to 3.1.0
Initialization script hive-schema-3.1.0.derby.sql
```

```
Initialization script completed
schemaTool completed
hdoop@PRLAB-22:~$
hdoop@PRLAB-22:~$
hdoop@PRLAB-22:~$
hdoop@PRLAB-22:~$
```

Step-12 Launch Hive Client Shell on Ubuntu

cd $HIVE_HOME/bin

hive

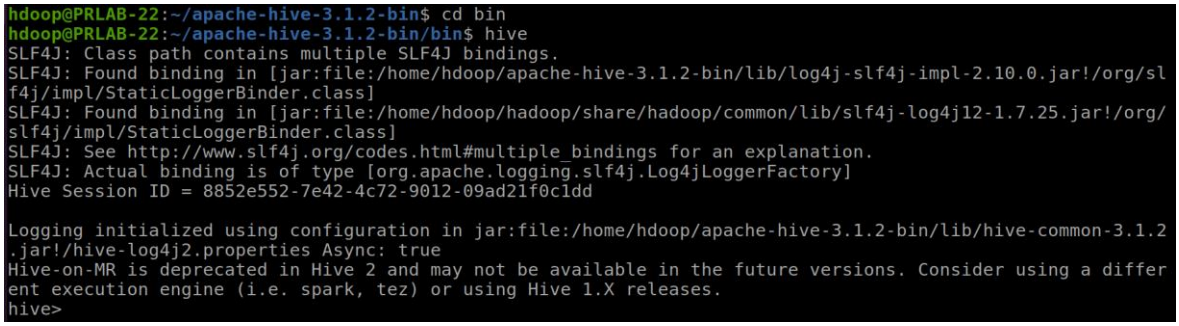
Step 12.1 While starting hive if these types or errors occur

```
hdoop@PRLAB-22:~/apache-hive-3.1.2-bin/bin$ hive
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/home/hdoop/apache-hive-3.1.2-bin/lib/log4j-slf4j-impl-2.10.0.jar!/org/sl
f4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/home/hdoop/hadoop/share/hadoop/common/lib/slf4j-log4j12-1.7.25.jar!/org/
slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.apache.logging.slf4j.Log4jLoggerFactory]
Hive Session ID = 981ad83d-79b6-4856-89f7-9a1c51cef3f2

Logging initialized using configuration in jar:file:/home/hdoop/apache-hive-3.1.2-bin/lib/hive-common-3.1.2
.jar!/hive-log4j2.properties Async: true
Exception in thread "main" java.lang.IllegalArgumentException: java.net.URISyntaxException: Relative path i
n absolute URI: ${system:java.io.tmpdir%7D/$%7Bsystem:user.name%7D
        at org.apache.hadoop.fs.Path.initialize(Path.java:263)
        at org.apache.hadoop.fs.Path.<init>(Path.java:221)
        at org.apache.hadoop.hive.ql.session.SessionState.createSessionDirs(SessionState.java:710)
        at org.apache.hadoop.hive.ql.session.SessionState.start(SessionState.java:627)
        at org.apache.hadoop.hive.ql.session.SessionState.beginStart(SessionState.java:591)
        at org.apache.hadoop.hive.cli.CliDriver.run(CliDriver.java:747)
        at org.apache.hadoop.hive.cli.CliDriver.main(CliDriver.java:683)
        at sun.reflect.NativeMethodAccessorImpl.invoke0(Native Method)
        at sun.reflect.NativeMethodAccessorImpl.invoke(NativeMethodAccessorImpl.java:62)
        at sun.reflect.DelegatingMethodAccessorImpl.invoke(DelegatingMethodAccessorImpl.java:43)
        at java.lang.reflect.Method.invoke(Method.java:498)
        at org.apache.hadoop.util.RunJar.run(RunJar.java:323)
        at org.apache.hadoop.util.RunJar.main(RunJar.java:236)
```

Step 12.2 If you are receiving the below exception then open the hive-site.xml file using nano editor and press CTRL+W and search for “system:java.io.tmpdir” and replace it with /tmp/mydir.

```
hdoop@PRLAB-22:~/apache-hive-3.1.2-bin$ cd conf
hdoop@PRLAB-22:~/apache-hive-3.1.2-bin/conf$ ls
beeline-log4j2.properties.template    hive-site.xml
hive-default.xml.template             ivysettings.xml
hive-env.sh.template                  llap-cli-log4j2.properties.template
hive-exec-log4j2.properties.template  llap-daemon-log4j2.properties.template
hive-log4j2.properties.template       parquet-logging.properties
hdoop@PRLAB-22:~/apache-hive-3.1.2-bin/conf$ vi hive-site.xml
hdoop@PRLAB-22:~/apache-hive-3.1.2-bin/conf$ nano hive-site.xml
```

Step 12.3 Now after that again Launch Hive Client Shell on Ubuntu



Step 13- error may occur when hive-shell started before metastore_db service. To avoid this just delete or move your metastore_db and try the below command.

$ mv metastore_db metastore_db.tmp

Step-14 : once again to initiate the Derby database

$ schematool -dbType derby -initSchema

Result:

HIVE has been successfully installed above Hadoop in the system

Exp.No : 16 **Date:**07/06/22

Hive – CRUD Operations

1)**Aim:**

To implement any schema definition in HIVE and perform CRUD operations.

Code:

Table Creation:

create table studentnew (id int, name string, location string) clustered by (location) into 3 buckets row format delimited fields terminated by ',' lines terminated by '\n' stored as orc TBLPROPERTIES ('transactional'='true');

While table creation you might face some errors so do use these commands in terminal for as temporary solution

Set hive.support.concurrency = true;

Set hive.enforce.bucketing = true;

set hive.exec.dynamic.partition.mode = nonstrict;

set hive.txn.manager = org.apache.hadoop.hive.ql.lockmgr.DbTxnManager;

set hive.compactor.initiator.on = true;

set hive.compactor.worker.threads =1;

Output:

```
hive> Set hive.support.concurrency = true;
hive> Set hive.enforce.bucketing = true;
hive> set hive.exec.dynamic.partition.mode = nonstrict;
hive> set hive.txn.manager = org.apache.hadoop.hive.ql.lockmgr.DbTxnManager;
hive> set hive.compactor.initiator.on = true;
hive> set hive.compactor.worker.threads =1;
hive> create table studentnew  (id int, name string, location string) clustered by (location) into 3 bucket
s row format delimited fields terminated by ',' lines terminated by '\n' stored as orc TBLPROPERTIES ('tran
sactional'='true');
OK
Time taken: 0.807 seconds
```

Insertion of records:

INSERT INTO TABLE studentnew VALUES (101,'abc','GST Road'),

(102,'A','Guindy'),

(103,'PRABU','henry road'),

(104,'KUMAR','gandhi road');

Output:

```
hive> insert into table studentnew values(101,'abc','GST Road');
Query ID = hdoop_20220531030502_54f3eff2-c5fa-452d-85e0-c728e6b2a704
Total jobs = 2
Launching Job 1 out of 2
Number of reduce tasks determined at compile time: 3
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
Starting Job = job_1653941890266_0001, Tracking URL = http://PRLAB-22:8088/proxy/application_1653941890266_
0001/
Kill Command = /home/hdoop/hadoop/bin/mapred job  -kill job_1653941890266_0001
Hadoop job information for Stage-1: number of mappers: 1; number of reducers: 3
2022-05-31 03:05:13,825 Stage-1 map = 0%,  reduce = 0%
2022-05-31 03:05:16,916 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 1.7 sec
2022-05-31 03:05:22,021 Stage-1 map = 100%,  reduce = 67%, Cumulative CPU 4.5 sec
2022-05-31 03:05:24,050 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 6.36 sec
MapReduce Total cumulative CPU time: 6 seconds 360 msec
Ended Job = job_1653941890266_0001
Loading data to table default.studentnew
Launching Job 2 out of 2
Number of reduce tasks determined at compile time: 1
```

```
hive> insert into table studentnew values(102,'prabhu','guindy');
Query ID = hdoop_20220531030612_c8da22c1-8645-4bf3-a5aa-a4fd8b25f306
Total jobs = 2
Launching Job 1 out of 2
Number of reduce tasks determined at compile time: 3
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
Starting Job = job_1653941890266_0003, Tracking URL = http://PRLAB-22:8088/proxy/application_1653941890266_0003/
Kill Command = /home/hdoop/hadoop/bin/mapred job  -kill job_1653941890266_0003
Hadoop job information for Stage-1: number of mappers: 1; number of reducers: 3
2022-05-31 03:06:17,426 Stage-1 map = 0%,  reduce = 0%
2022-05-31 03:06:20,519 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 1.72 sec
2022-05-31 03:06:24,612 Stage-1 map = 100%,  reduce = 33%, Cumulative CPU 3.08 sec
2022-05-31 03:06:26,677 Stage-1 map = 100%,  reduce = 67%, Cumulative CPU 5.09 sec
2022-05-31 03:06:27,691 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 6.44 sec
MapReduce Total cumulative CPU time: 6 seconds 440 msec
Ended Job = job_1653941890266_0003
Loading data to table default.studentnew
Launching Job 2 out of 2
Number of reduce tasks determined at compile time: 1
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
Starting Job = job_1653941890266_0004, Tracking URL = http://PRLAB-22:8088/proxy/application_1653941890266_0004/
Kill Command = /home/hdoop/hadoop/bin/mapred job  -kill job_1653941890266_0004
Hadoop job information for Stage-3: number of mappers: 1; number of reducers: 1
2022-05-31 03:06:37,734 Stage-3 map = 0%,  reduce = 0%
2022-05-31 03:06:41,839 Stage-3 map = 100%,  reduce = 0%, Cumulative CPU 0.98 sec
2022-05-31 03:06:45,934 Stage-3 map = 100%,  reduce = 100%, Cumulative CPU 2.37 sec
MapReduce Total cumulative CPU time: 2 seconds 370 msec
Ended Job = job_1653941890266_0004
MapReduce Jobs Launched:
Stage-Stage-1: Map: 1  Reduce: 3   Cumulative CPU: 6.44 sec   HDFS Read: 25696 HDFS Write: 1503 SUCCESS
Stage-Stage-3: Map: 1  Reduce: 1   Cumulative CPU: 2.37 sec   HDFS Read: 12604 HDFS Write: 201 SUCCESS
Total MapReduce CPU Time Spent: 8 seconds 810 msec
OK
Time taken: 34.986 seconds
```

```
hive> insert into table studentnew values(103,'gandhi','radha nagar chrompet');
Query ID = hdoop_20220531030844_f8903933-7850-4c09-a4c3-2bae37a525d9
Total jobs = 2
Launching Job 1 out of 2
Number of reduce tasks determined at compile time: 3
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
Starting Job = job_1653941890266_0005, Tracking URL = http://PRLAB-22:8088/proxy/application_1653941890266_0005/
Kill Command = /home/hdoop/hadoop/bin/mapred job  -kill job_1653941890266_0005
Hadoop job information for Stage-1: number of mappers: 1; number of reducers: 3
2022-05-31 03:08:49,897 Stage-1 map = 0%,  reduce = 0%
2022-05-31 03:08:52,959 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 1.99 sec
2022-05-31 03:08:57,012 Stage-1 map = 100%,  reduce = 33%, Cumulative CPU 3.33 sec
2022-05-31 03:08:59,079 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 6.42 sec
MapReduce Total cumulative CPU time: 6 seconds 420 msec
Ended Job = job_1653941890266_0005
Loading data to table default.studentnew
Launching Job 2 out of 2
Number of reduce tasks determined at compile time: 1
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
Starting Job = job_1653941890266_0006, Tracking URL = http://PRLAB-22:8088/proxy/application_1653941890266_0006/
Kill Command = /home/hdoop/hadoop/bin/mapred job  -kill job_1653941890266_0006
Hadoop job information for Stage-3: number of mappers: 1; number of reducers: 1
2022-05-31 03:09:09,700 Stage-3 map = 0%,  reduce = 0%
2022-05-31 03:09:13,772 Stage-3 map = 100%,  reduce = 0%, Cumulative CPU 0.89 sec
2022-05-31 03:09:17,832 Stage-3 map = 100%,  reduce = 100%, Cumulative CPU 2.08 sec
MapReduce Total cumulative CPU time: 2 seconds 80 msec
Ended Job = job_1653941890266_0006
MapReduce Jobs Launched:
Stage-Stage-1: Map: 1  Reduce: 3   Cumulative CPU: 6.42 sec   HDFS Read: 25813 HDFS Write: 1574 SUCCESS
Stage-Stage-3: Map: 1  Reduce: 1   Cumulative CPU: 2.08 sec   HDFS Read: 12604 HDFS Write: 203 SUCCESS
Total MapReduce CPU Time Spent: 8 seconds 500 msec
OK
Time taken: 34.621 seconds
```

```
hive> select * from studentnew;
OK
101     abc     GST Road
102     prabhu  guindy
103     gandhi  radha nagar chrompet
Time taken: 0.333 seconds, Fetched: 3 row(s)
```

Updation of records:

Update studentnew SET id = 113 WHERE id = 103;

Output:

```
hive> Update studentnew SET id = 113 WHERE id = 103;
Query ID = hdoop_20220531031127_9ec9ac2d-39f9-4bd5-b809-5c4ea6ceb5d2
Total jobs = 1
Launching Job 1 out of 1
Number of reduce tasks determined at compile time: 3
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
Starting Job = job_1653941890266_0007, Tracking URL = http://PRLAB-22:8088/proxy/application_1653941890266_0007/
Kill Command = /home/hdoop/hadoop/bin/mapred job  -kill job_1653941890266_0007
Hadoop job information for Stage-1: number of mappers: 3; number of reducers: 3
2022-05-31 03:11:33,595 Stage-1 map = 0%,  reduce = 0%
2022-05-31 03:11:38,685 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 8.12 sec
2022-05-31 03:11:42,751 Stage-1 map = 100%,  reduce = 33%, Cumulative CPU 9.56 sec
2022-05-31 03:11:43,770 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 12.97 sec
MapReduce Total cumulative CPU time: 12 seconds 970 msec
Ended Job = job_1653941890266_0007
Loading data to table default.studentnew
MapReduce Jobs Launched:
Stage-Stage-1: Map: 3  Reduce: 3   Cumulative CPU: 12.97 sec   HDFS Read: 43124 HDFS Write: 1801 SUCCESS
Total MapReduce CPU Time Spent: 12 seconds 970 msec
OK
Time taken: 18.984 seconds
```

```
hive> select * from studentnew;
OK
101     abc     GST Road
102     prabhu  guindy
113     gandhi  radha nagar chrompet
Time taken: 0.16 seconds, Fetched: 3 row(s)
```

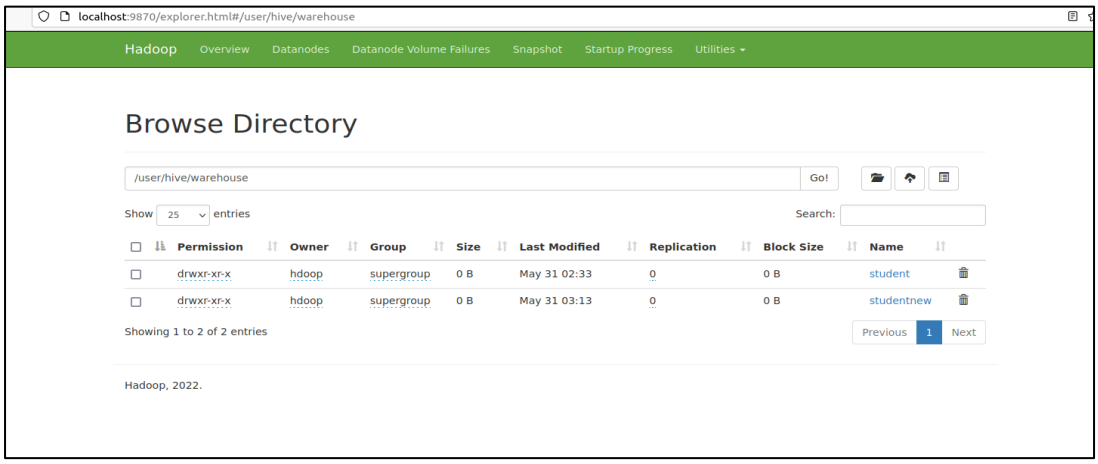
Deletion of records:

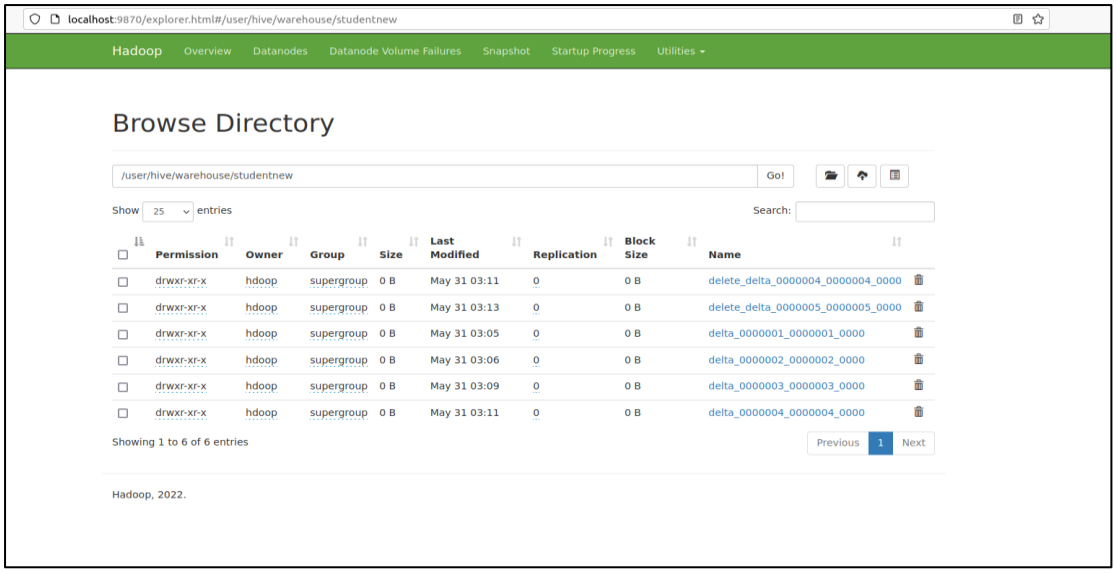
delete from studentnew where id=102;

Output:

```
hive> delete from studentnew where id=102;
Query ID = hdoop_20220531031339_a531bcab-2da2-4826-81af-a8d4f44dc0f4
Total jobs = 1
Launching Job 1 out of 1
Number of reduce tasks determined at compile time: 3
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
Starting Job = job_1653941890266_0008, Tracking URL = http://PRLAB-22:8088/proxy/application_1653941890266_0008/
Kill Command = /home/hdoop/hadoop/bin/mapred job  -kill job_1653941890266_0008
Hadoop job information for Stage-1: number of mappers: 4; number of reducers: 3
2022-05-31 03:13:45,465 Stage-1 map = 0%,  reduce = 0%
2022-05-31 03:13:51,592 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 11.5 sec
2022-05-31 03:13:55,652 Stage-1 map = 100%,  reduce = 33%, Cumulative CPU 13.28 sec
2022-05-31 03:13:57,690 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 16.71 sec
MapReduce Total cumulative CPU time: 16 seconds 710 msec
Ended Job = job_1653941890266_0008
Loading data to table default.studentnew
MapReduce Jobs Launched:
Stage-Stage-1: Map: 4  Reduce: 3   Cumulative CPU: 16.71 sec   HDFS Read: 51452 HDFS Write: 896 SUCCESS
Total MapReduce CPU Time Spent: 16 seconds 710 msec
OK
Time taken: 19.13 seconds
hive> select * from studentnew;
OK
101     abc     GST Road
113     gandhi  radha nagar chrompet
Time taken: 0.168 seconds, Fetched: 2 row(s)
```

View the table created in Browser-UI





Result:

CRUD operations have been successfully executed in HIVE and the results are verified.