DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
(ARTIFICIAL INTELLIGENCE & MACHINE LEARNING)

T.E/SEM VI/REV-2019 “C” SCHEME/CSE-(AI&ML)
Academic Year: 2022-23

NAME	**PRATHAMESH CHIKANKAR**
BRANCH	**CSE-(AI&ML)**
ROLL NO.	**AIML11**
SUBJECT	**DATA ANALYTICS AND VISUALIZATION LAB**
COURSE CODE	**CSL601**
PRACTICAL NO.	
DOP	
DOS	

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
(ARTIFICIAL INTELLIGENCE & MACHINE LEARNING)

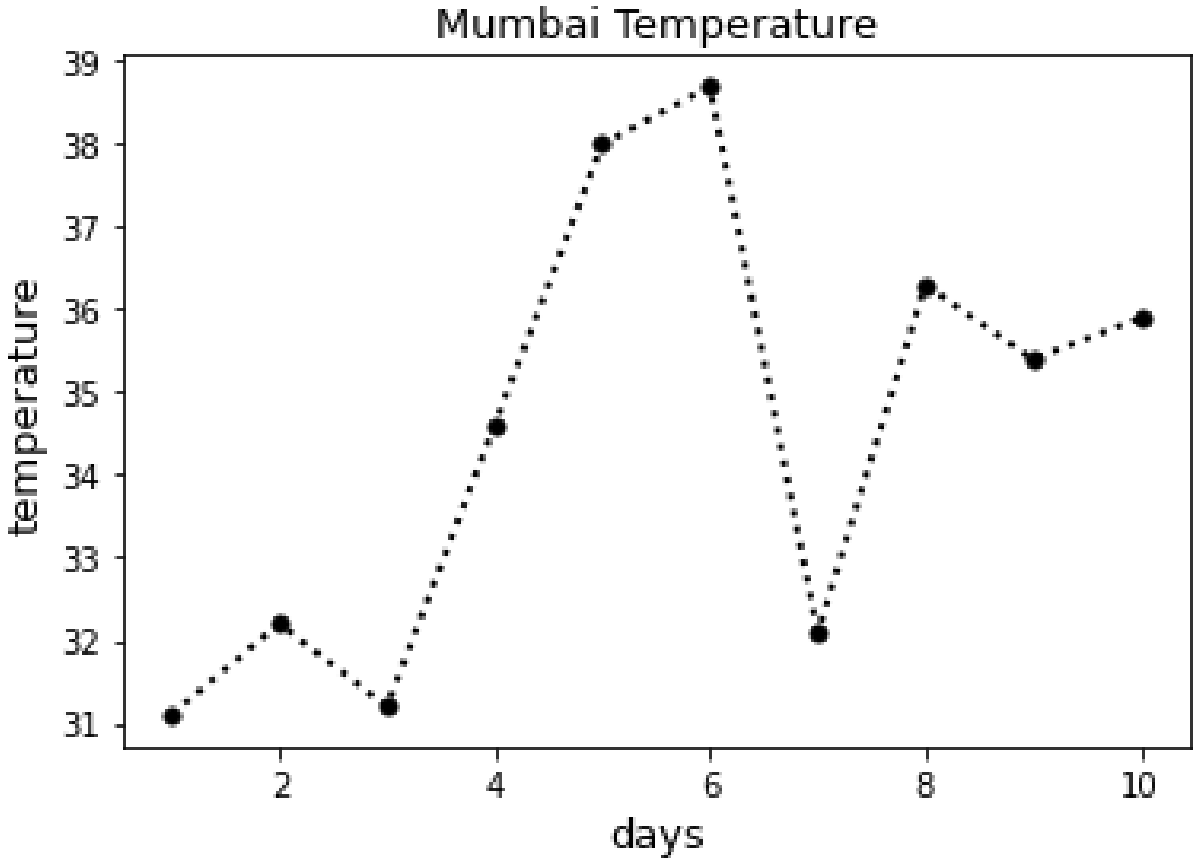
T.E/SEM VI/CBCGS/AIML
Academic Year: 2022-23

NAME	**PRATHAMESH CHIKANKAR**
BRANCH	**CSE-(AI&ML)**
ROLL NO.	**11**
SUBJECT	**DATA ANALYTICS AND VISUALIZATION LAB**
COURSE CODE	**CSL601**
PRACTICAL NO.	**01**
DOP	**16/01/2023**
DOS	

Program(input)/Output :

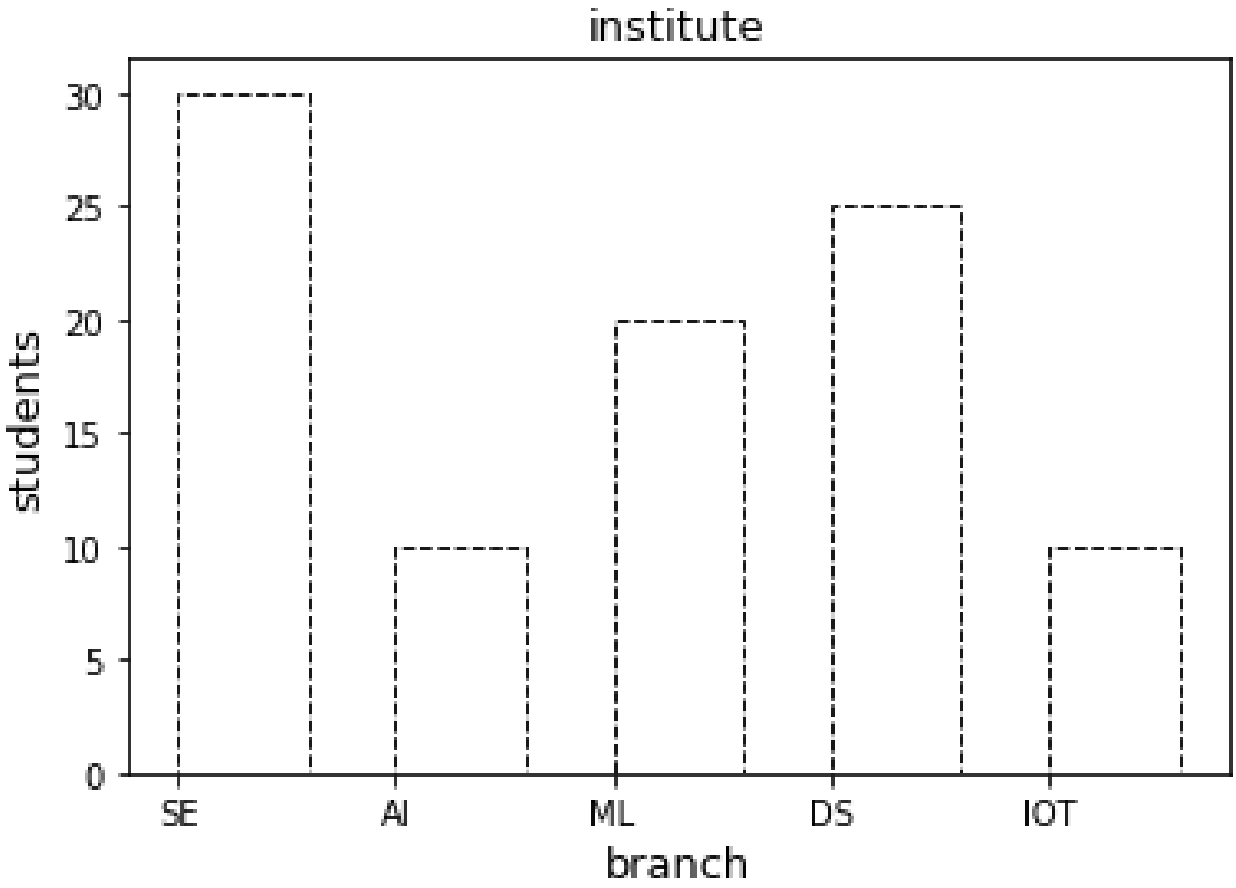
Matplotlib line -

```
import matplotlib.pyplot as plt
days=[1,2,3,4,5,6,7,8,9,10]
temperature=[31.1,32.2,31.2,34.6,38.0,38.7,32.1,36.3,35.4,35.9]
plt.plot(days,temperature,color="k",marker=".",linestyle=":",linewidth=2,markersize=10)
plt.title("Mumbai Temperature")
plt.xlabel("days")
plt.ylabel("temperature")
plt.show()
```



Matplotlib bars -

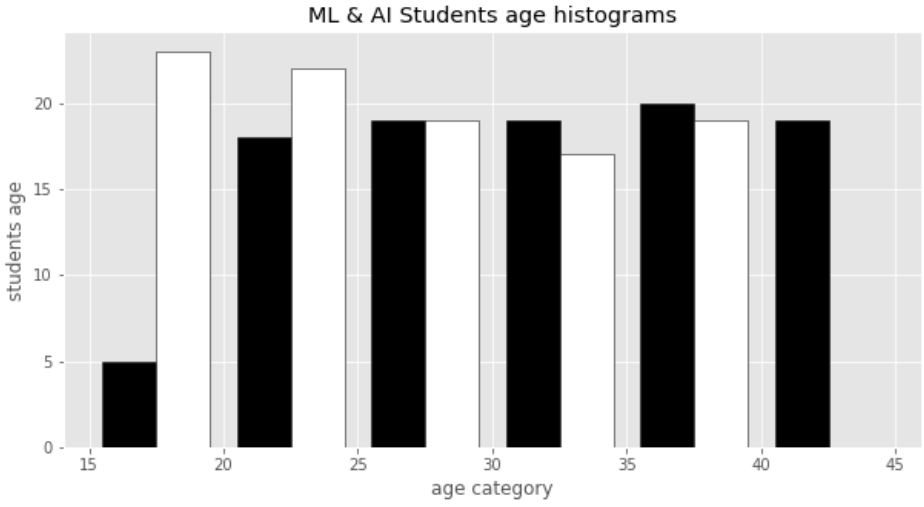
```
import matplotlib.pyplot as plt
import numpy as np
from matplotlib import style
classes=["SE","AI","ML","DS","IOT"]
class_1_students=[30,10,20,25,10]
plt.bar(classes,class_1_students,width=0.6,align="edge",color="w",edgecolor="k",linewi
dth=1,alpha=0.9,linestyle="--",label="Class 1 Students",visible=True)
plt.title("institute",fontsize=13)
plt.xlabel("branch",fontsize=13)
plt.ylabel("students",fontsize=13)
plt.show()
```



Matplotlib histograms -

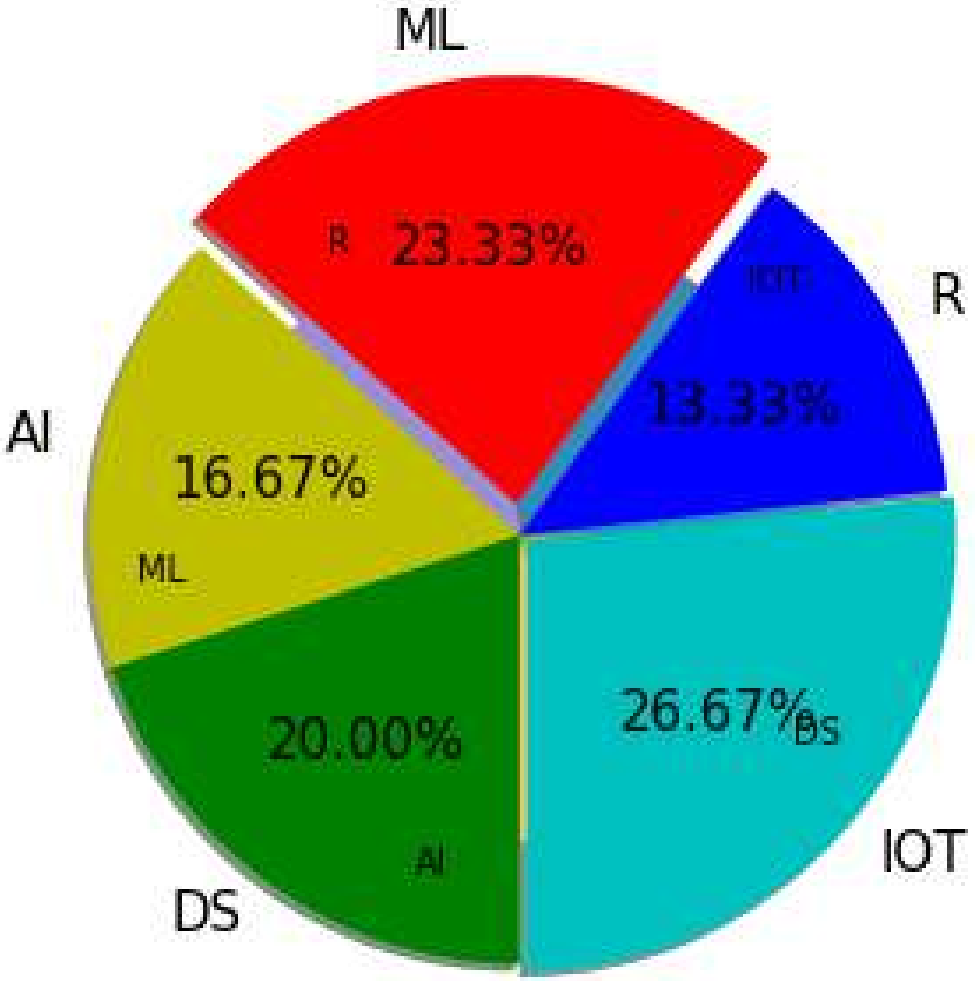
```
import matplotlib.pyplot as plt
import numpy as np
import random
style.use("ggplot")
ml_students_age=np.random.randint(18,45,(100))
ai_students_age=np.random.randint(15,40,(100))
print(ml_students_age)
print(ai_students_age)
bins = [15,20,25,30,35,40,45]
plt.figure(figsize = (10,5))
plt.hist([ml_students_age,ai_students_age],bins,rwidth=0.8,histtype="bar",orientation='v
ertical',color=["k","w"],edgecolor="k",label=["ML Student","AI Student"])
plt.title("ML & AI Students age histograms")
plt.xlabel("age category")
plt.ylabel("students age")
plt.show()
```

```
[31 22 34 22 29 26 40 38 20 41 33 44 32 22 29 29 42 40 20 44 20 28 29 19
 37 37 26 21 31 34 19 35 23 38 20 21 43 31 23 31 25 43 39 19 44 24 33 39
 37 26 44 33 26 26 34 19 36 41 28 30 37 40 19 37 32 23 30 40 21 27 37 37
 29 31 39 35 37 29 44 22 23 32 43 28 41 31 44 40 26 37 33 28 38 31 20 22
 35 40 27 36]
[31 18 39 15 32 23 28 22 37 32 16 35 18 24 15 20 33 36 26 27 31 29 29 32
 20 35 28 39 24 17 26 29 24 38 37 36 24 21 33 34 36 25 25 18 38 17 16 28
 18 20 18 35 26 34 15 24 21 17 36 39 32 27 28 18 33 33 33 25 24 37 27 32
 20 34 23 34 37 37 16 24 16 35 22 17 16 16 26 27 22 16 29 24 24 17 18 32
 24 18 23 39]
```



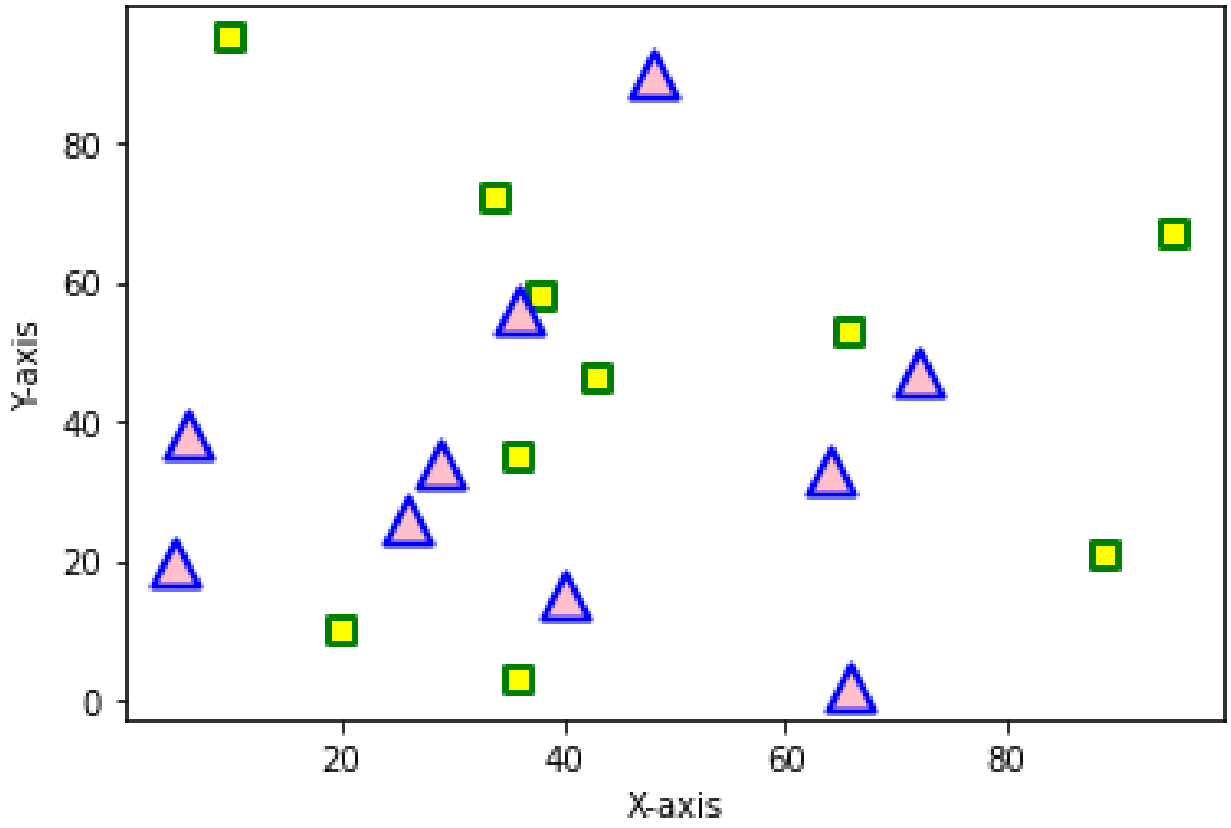
Matplotlib pie-chart -

```
import matplotlib.pyplot as plt
plt.pie([1])
classes = ["IOT",'R','ML', 'AI', 'DS']
class1_students = [40, 20, 35, 25, 30]
plt.pie(class1_students, labels = classes)
explode = [0.03,0,0.1,0,0]
colors = ["c", 'b','r','y','g']
textprops = {"fontsize":15}
plt.pie(class1_students,labels = classes, explode = explode, colors =colors, autopct =
"%0.2f%%", shadow = True, radius = 1.4,startangle = 270,textprops =textprops)
plt.show()
```



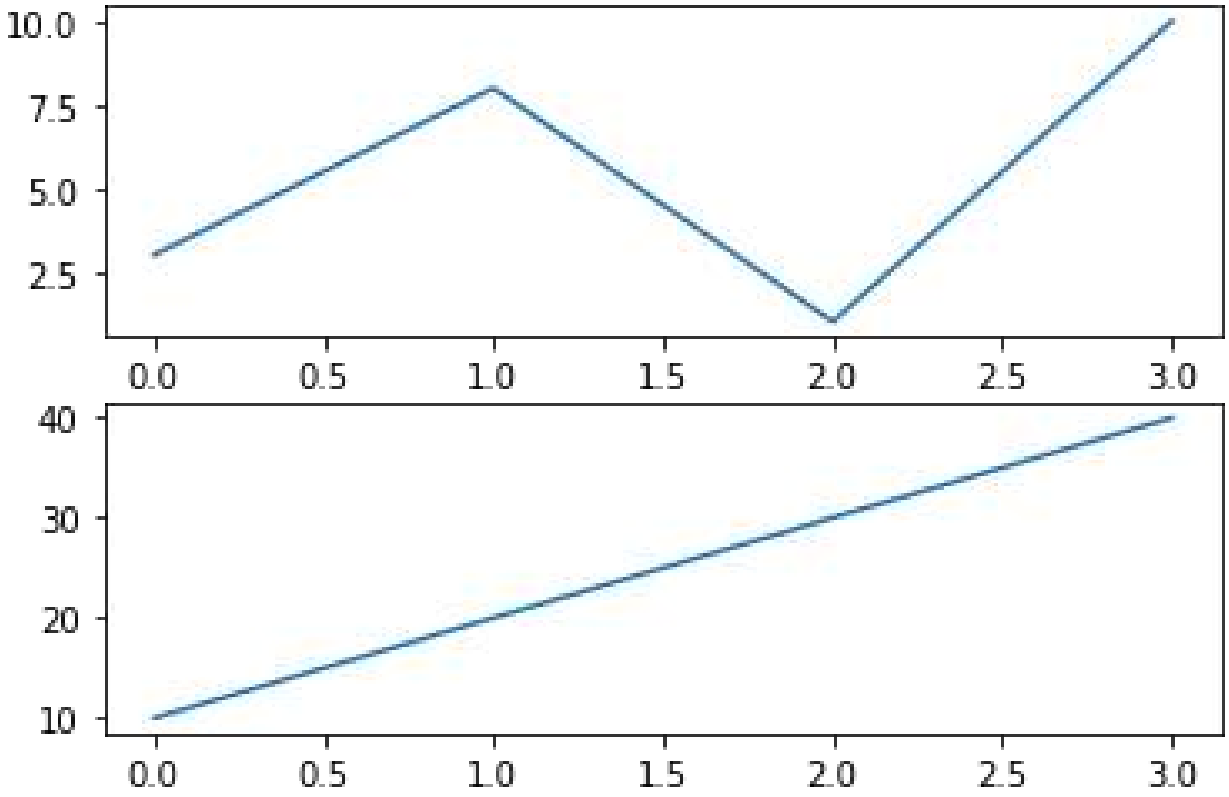
Matplotlib scatter -

```
import matplotlib.pyplot as plt
x1 = [89, 43, 36, 36, 95, 10,66, 34, 38, 20]
y1 = [21, 46, 3, 35, 67, 95,53, 72, 58, 10]
x2 = [26, 29, 48, 64, 6, 5,36, 66, 72, 40]
y2 = [26, 34, 90, 33, 38,20, 56, 2, 47, 15]
plt.scatter(x1, y1, c ="yellow",linewidths = 2,marker ="s",edgecolor ="green",s = 50)
plt.scatter(x2, y2, c ="pink",linewidths = 2,marker ="^",edgecolor ="blue",s = 200)
plt.xlabel("X-axis")
plt.ylabel("Y-axis")
plt.show()
```

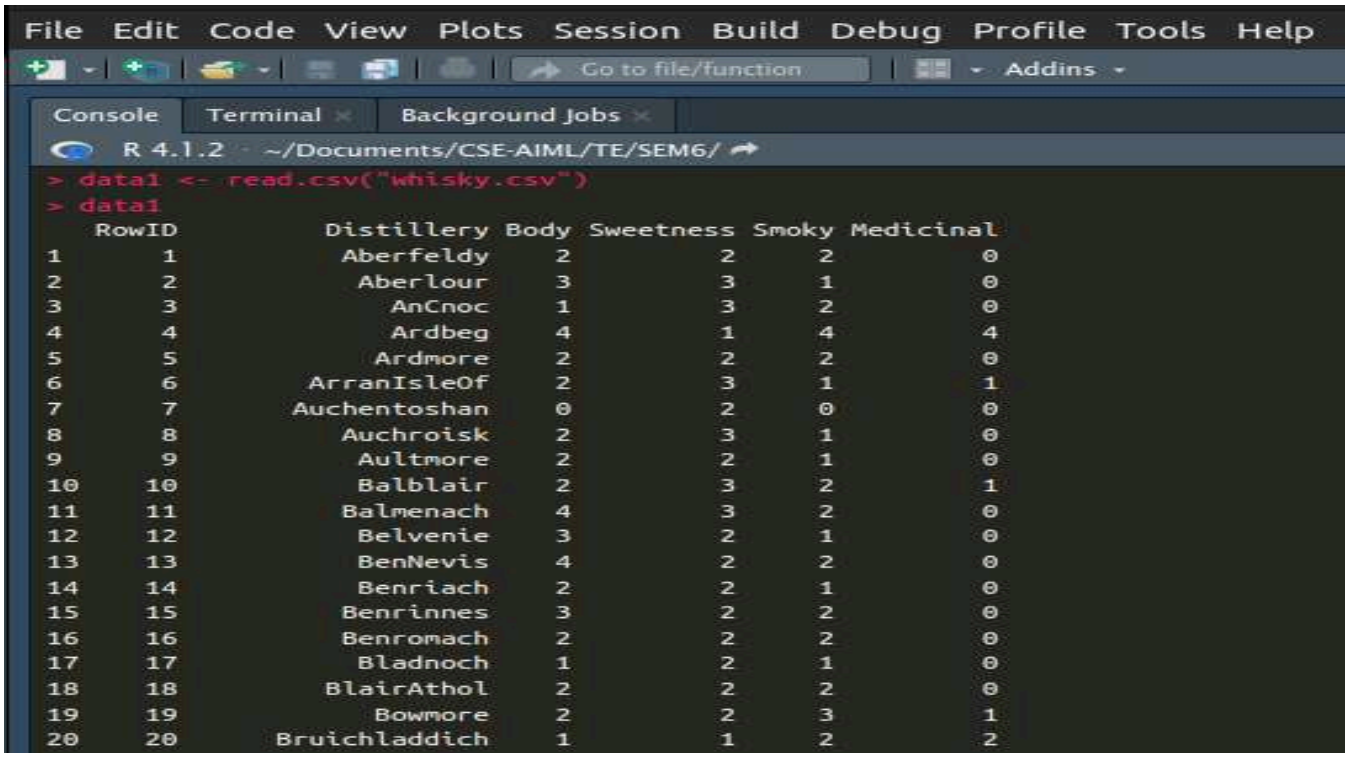


Matplotlib subplot -

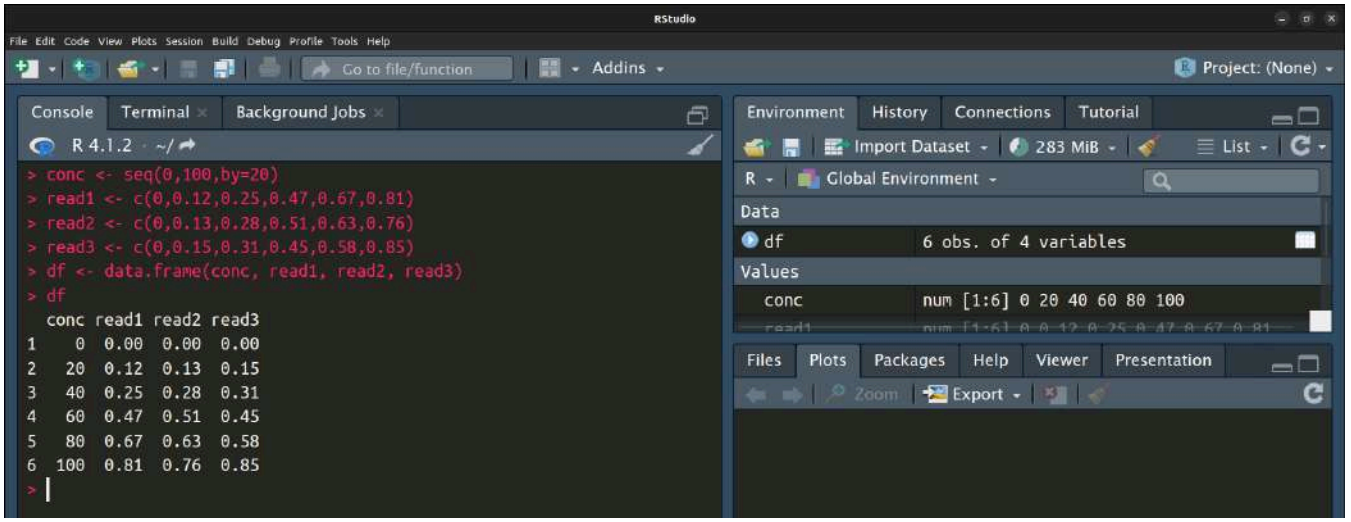
```
import matplotlib.pyplot as plt
import numpy as np
x = np.array([0, 1, 2, 3])
y = np.array([3, 8, 1, 10])
plt.subplot(2, 1, 1)
plt.plot(x,y)
x = np.array([0, 1, 2, 3])
y = np.array([10, 20, 30, 40])
plt.subplot(2, 1, 2)
plt.plot(x,y)
plt.show()
```



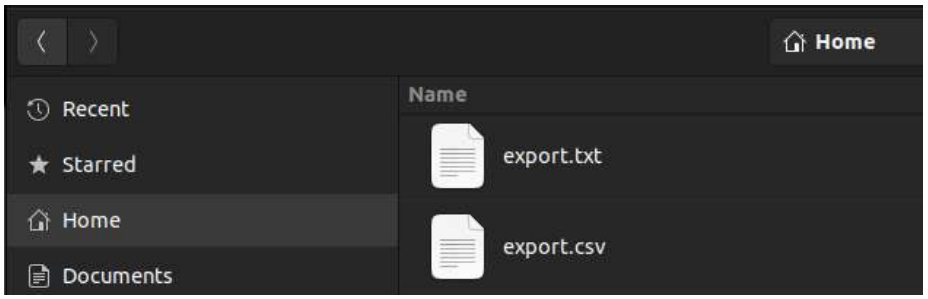
- **Importing dataset in R**



- **Exporting dataset in R**



Output : exported dataset in txt and csv file



- **Quick overview**

-> head(df)
-> tail(df)
-> summary(df)
-> str(df)

```
> head(df)
  RowID  Distillery Body Sweetness Smoky Medicinal Tobacco Honey Spicy Winey Nutty Malty Fruity Floral   Postcode Latitude
1     1   Aberfeldy    2         2     2         0       0     2     1     2     2     2      2      2 \tPH15 2EB   286580
2     2    Aberlour    3         3     1         0       0     4     3     2     2     3      3      2 \tAB38 9PJ   326340
3     3      AnCnoc    1         3     2         0       0     2     0     0     2     2      3      2  \tAB5 5LI   352960
4     4      Ardbeg    4         1     4         4       0     0     2     0     1     2      1      0 \tPA42 7EB   141560
5     5     Ardmore    2         2     2         0       0     1     1     1     2     3      1      1 \tAB54 4NH   355350
6     6 ArranIsleOf    2         3     1         1       0     1     1     1     0     1      1      2   KA27 8HJ   194050
  Longitude
1    749680
2    842570
3    839320
4    646220
5    829140
6    649950
> tail(df)
   RowID   Distillery Body Sweetness Smoky Medicinal Tobacco Honey Spicy Winey Nutty Malty Fruity Floral Postcode Latitude
81    81    Teaninich    2         2     1         0       0     2     0     0     0      2      2 IV17 0XB   265360
82    82    Tobermory    1         1     1         0       0     1     0     0     1      2      2 PA75 6NR   150450
83    83      Tomatin    2         3     2         0       0     2     2     1     1      2      0 IV13 7YT   279120
84    84    Tomintoul    0         3     1         0       0     2     2     1     1      2      1 AB37 9AQ   315100
85    85      Tormore    2         2     1         0       0     1     0     1     2      1      0 PH26 3LR   315180
86    86 Tullibardine    2         3     0         0       1     0     2     1     1      2      2  PH4 1QG   289690
   Longitude
81    869120
82    755070
83    829630
84    825560
85    834960
86    708850
```

```
> summary(df)
     RowID        Distillery             Body        Sweetness         Smoky         Medicinal         Tobacco       
 Min.   : 1.00   Length:86          Min.   :0.00   Min.   :1.000   Min.   :0.000   Min.   :0.0000   Min.   :0.0000  
 1st Qu.:22.25   Class :character   1st Qu.:2.00   1st Qu.:2.000   1st Qu.:1.000   1st Qu.:0.0000   1st Qu.:0.0000  
 Median :43.50   Mode  :character   Median :2.00   Median :2.000   Median :1.000   Median :0.0000   Median :0.0000  
 Mean   :43.50                      Mean   :2.07   Mean   :2.291   Mean   :1.535   Mean   :0.5465   Mean   :0.1163  
 3rd Qu.:64.75                      3rd Qu.:2.00   3rd Qu.:3.000   3rd Qu.:2.000   3rd Qu.:1.0000   3rd Qu.:0.0000  
 Max.   :86.00                      Max.   :4.00   Max.   :4.000   Max.   :4.000   Max.   :4.0000   Max.   :1.0000  
     Honey           Spicy           Winey           Nutty           Malty           Fruity          Floral      
 Min.   :0.000   Min.   :0.000   Min.   :0.0000   Min.   :0.000   Min.   :0.000   Min.   :0.000   Min.   :0.000  
 1st Qu.:1.000   1st Qu.:1.000   1st Qu.:0.0000   1st Qu.:1.000   1st Qu.:1.000   1st Qu.:1.000   1st Qu.:1.000  
 Median :1.000   Median :1.000   Median :1.0000   Median :2.000   Median :2.000   Median :2.000   Median :2.000  
 Mean   :1.244   Mean   :1.384   Mean   :0.9767   Mean   :1.465   Mean   :1.802   Mean   :1.802   Mean   :1.698  
 3rd Qu.:2.000   3rd Qu.:2.000   3rd Qu.:1.0000   3rd Qu.:2.000   3rd Qu.:2.000   3rd Qu.:2.000   3rd Qu.:2.000  
 Max.   :4.000   Max.   :3.000   Max.   :4.0000   Max.   :4.000   Max.   :3.000   Max.   :3.000   Max.   :4.000  
   Postcode            Latitude        Longitude      
 Length:86          Min.   :126680   Min.   : 554260  
 Class :character   1st Qu.:265672   1st Qu.: 755698  
 Mode  :character   Median :319515   Median : 839885  
                    Mean   :287247   Mean   : 802660  
                    3rd Qu.:328630   3rd Qu.: 850770  
                    Max.   :381020   Max.   :1009260  
> str(df)
'data.frame':   86 obs. of  17 variables:
 $ RowID     : int  1 2 3 4 5 6 7 8 9 10 ...
 $ Distillery: chr  "Aberfeldy" "Aberlour" "AnCnoc" "Ardbeg" ...
 $ Body      : int  2 3 1 4 2 2 0 2 2 2 ...
 $ Sweetness : int  2 3 3 1 2 3 2 3 2 3 ...
 $ Smoky     : int  2 1 2 4 2 1 0 1 1 2 ...
 $ Medicinal : int  0 0 0 4 0 1 0 0 0 1 ...
 $ Tobacco   : int  0 0 0 0 0 0 0 0 0 0 ...
 $ Honey     : int  2 4 2 0 1 1 1 2 1 0 ...
 $ Spicy     : int  1 3 0 2 1 1 1 1 0 2 ...
 $ Winey     : int  2 2 0 0 1 1 0 2 0 0 ...
 $ Nutty     : int  2 2 2 1 2 0 2 2 2 2 ...
 $ Malty     : int  2 3 2 2 3 1 2 2 2 1 ...
 $ Fruity    : int  2 3 3 1 1 1 3 2 2 2 ...
 $ Floral    : int  2 2 2 0 1 2 3 1 2 1 ...
 $ Postcode  : chr  "\tPH15 2EB" "\tAB38 9PJ" "\tAB5 5LI" "\tPA42 7EB" ...
 $ Latitude  : int  286580 326340 352960 141560 355350 194050 247670 340754 340754 270820 ...
 $ Longitude : int  749680 842570 839320 646220 829140 649950 672610 848623 848623 885770 ...
```

- **Cleaning dataset**

-> duplicated(df)

-> na.omit(df)

-> is.na(df)

```
> duplicated(df)
  [1] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
 [22] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
 [43] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
 [64] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
 [85] FALSE FALSE
```

```
> na.omit(df)
   RowID        Distillery Body Sweetness Smoky Medicinal Tobacco Honey Spicy Winey Nutty Malty Fruity Floral   Postcode Latitude
1      1         Aberfeldy    2         2     2         0       0     2     1     2     2     2      2      2 \tPH15 2EB   286580
2      2          Aberlour    3         3     1         0       0     4     3     2     2     3      3      2 \tAB38 9PJ   326340
3      3            AnCnoc    1         3     2         0       0     2     0     0     2     2      3      2  \tAB5 5LI   352960
4      4           Ardbeg     4         1     4         4       0     0     2     0     1     2      1      0 \tPA42 7EB   141560
5      5           Ardmore    2         2     2         0       0     1     1     1     2     3      1      1 \tAB54 4NH   355350
6      6       ArranIsleOf    2         3     1         1       0     1     1     1     0     1      1      2   KA27 8HJ   194050
7      7      Auchentoshan    0         2     0         0       0     1     1     0     2     2      3      3    G81 4SJ   247670
8      8         Auchroisk    2         3     1         0       0     2     1     2     2     2      2      1 \tAB55 3XS   340754
9      9          Aultmore    2         2     1         0       0     1     0     0     2     2      2      2 \tAB55 3QY   340754
10    10          Balblair    2         3     2         1       0     0     2     0     2     1      2      1 \tIV19 1LB   270820
11    11         Balmenach    4         3     2         0       0     2     1     3     3     0      1      2 \tPH26 3PF   307750
12    12          Belvenie    3         2     1         0       0     3     2     1     0     2      2      2 \tAB55 4DH   332680
13    13          BenNevis    4         2     2         0       0     2     2     0     2     2      2      2 \tPH33 6TJ   212600
```

```
   Longitude
1     749680
2     842570
3     839320
4     646220
5     829140
6     649950
7     672610
8     848623
9     848623
10    885770
11    827170
12    840840
41    849140
42    841240
43    844930
44    840300
45    838160
46    840840
47    682750
48    666690
49    828780
50    861040
51    883450
52    849170
53    723580
54   1009260
55    863970
56    667040
57    841570
58    645730
 [ reached 'max' / getOption("max.print") -- omitted 28 rows ]
```

```
> is.na(df)
      RowID Distillery  Body Sweetness Smoky Medicinal Tobacco Honey Spicy Winey Nutty Malty Fruity Floral Postcode Latitude
 [1,] FALSE      FALSE FALSE     FALSE FALSE     FALSE   FALSE FALSE FALSE FALSE FALSE FALSE  FALSE  FALSE    FALSE    FALSE
 [2,] FALSE      FALSE FALSE     FALSE FALSE     FALSE   FALSE FALSE FALSE FALSE FALSE FALSE  FALSE  FALSE    FALSE    FALSE
 [3,] FALSE      FALSE FALSE     FALSE FALSE     FALSE   FALSE FALSE FALSE FALSE FALSE FALSE  FALSE  FALSE    FALSE    FALSE
 [4,] FALSE      FALSE FALSE     FALSE FALSE     FALSE   FALSE FALSE FALSE FALSE FALSE FALSE  FALSE  FALSE    FALSE    FALSE
 [5,] FALSE      FALSE FALSE     FALSE FALSE     FALSE   FALSE FALSE FALSE FALSE FALSE FALSE  FALSE  FALSE    FALSE    FALSE
 [6,] FALSE      FALSE FALSE     FALSE FALSE     FALSE   FALSE FALSE FALSE FALSE FALSE FALSE  FALSE  FALSE    FALSE    FALSE
 [7,] FALSE      FALSE FALSE     FALSE FALSE     FALSE   FALSE FALSE FALSE FALSE FALSE FALSE  FALSE  FALSE    FALSE    FALSE
```

- **Exploring pattern**

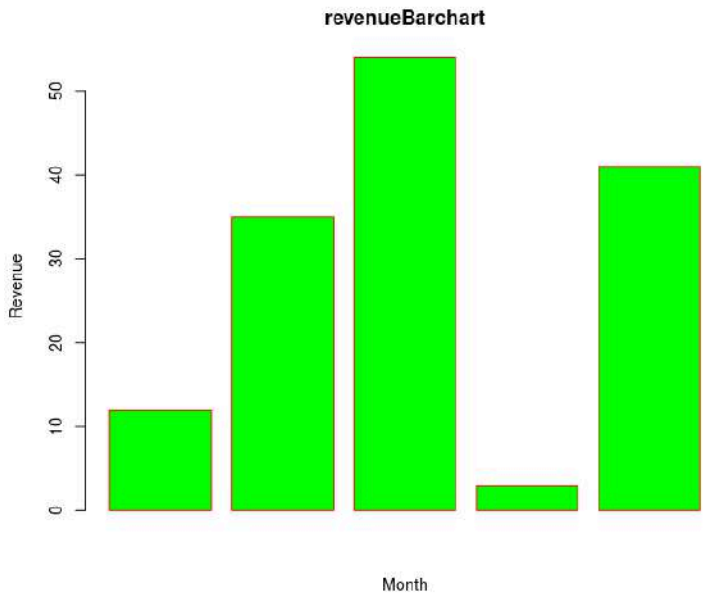
```
> install.packages("ggplot2")
Installing package into '/home/computer/R/x86_64-pc-linux-gnu-library/4.1'
(as 'lib' is unspecified)
also installing the dependencies 'colorspace', 'utf8', 'farver', 'labeling', 'munsell',
le', 'isoband', 'lifecycle', 'rlang', 'scales', 'tibble', 'vctrs', 'withr'
```

```
* DONE (ggplot2)

The downloaded source packages are in
        '/tmp/Rtmpz27f3a/downloaded_packages'
```

```
> library("ggplot2")
> H <- c(12,35,54,3,41)
>
> m <- c("feb","mar","april","may","june")
```

```
> barplot(H,names.arr=m,xlab = "Month",ylab = "Revenue",col = "green",main = "revenueBarchart",border = "red")
Warning messages:
1: In plot.window(xlim, ylim, log = log, ...) :
  "names.arr" is not a graphical parameter
2: In title(main = main, sub = sub, xlab = xlab, ylab = ylab, ...) :
  "names.arr" is not a graphical parameter
3: In axis(if (horiz) 1 else 2, cex.axis = cex.axis, ...) :
  "names.arr" is not a graphical parameter
>
```



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Academic Year: 2022-23

NAME	**PRATHAMESH CHIKANKAR**
BRANCH	**CSE-(AI&ML)**
ROLL NO.	**11**
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COURSE CODE	**CSL601**
PRACTICAL NO.	
DOP	**20/02/2023**
DOS	

Simple linear regression

- **Bitcoin and prediction**

Part 1

Importing important modules and excel-csv dataset file

In [1]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
```

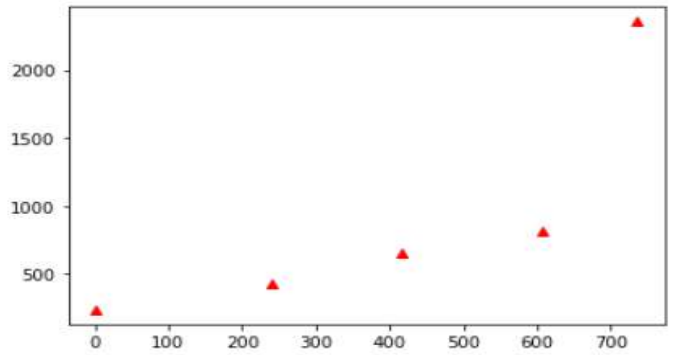
In [2]:
```
df=pd.read_csv('/home/computer/Documents/CSE-AIML/TE/SEM6/AIML11_PRATHAMESH/DAVL/dataset.csv')
df
```

Out[2]:

	Sr. No.	Bitcoin Price	No. Of Days
0	0	234.31	1
1	1	431.76	240
2	2	652.14	417
3	3	817.26	607
4	4	2358.96	736

In [6]:
```
x=df['No. Of Days']
y=df['Bitcoin Price']
plt.scatter(x,y,color='red',marker='^')
```

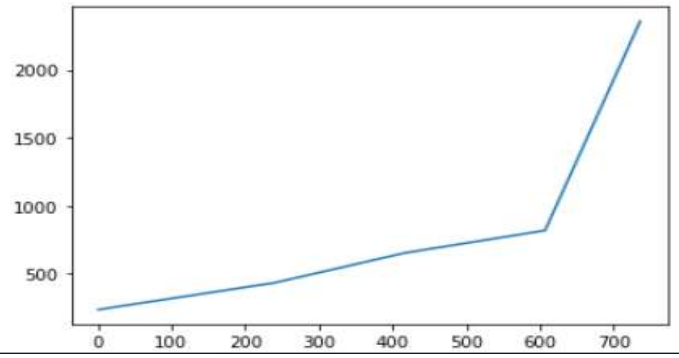
Out[6]:
```
<matplotlib.collections.PathCollection at 0x7f2da1fdce80>
```



In [7]:
```
b,a=np.polyfit(x,y,1)
```

In [8]:
```
plt.plot(x,y)
```

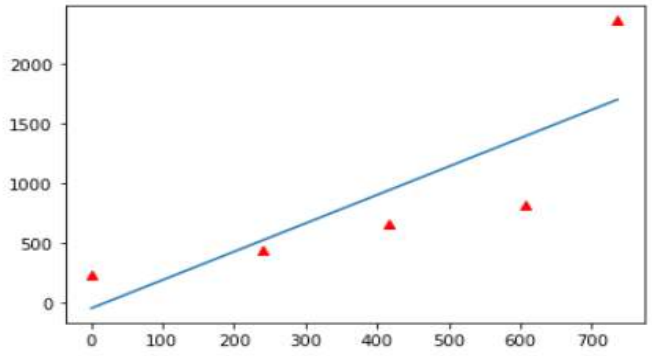
Out[8]:
```
[<matplotlib.lines.Line2D at 0x7f2da1774310>]
```



Part 2

Testing/Predicting the dataset

In [10]:
```
plt.scatter(x,y,color='red',marker='^')
b,a=np.polyfit(x,y,1)
y1=a+b*x
plt.plot(x,y1)
plt.show()
```



In [13]:
```
y1=a+b*800
y1
```

Out[13]: 1848.313563392002

In [14]:
```
y1=a+b*1000
y1
```

Out[14]: 2323.264820716665

In [15]:
```
df=pd.read_csv('/home/computer/Documents/CSE-AIML/TE/SEM6/AIML11_PRATHAMESH/DAVL/dataset1.csv')
df
```

Out[15]:

	Sr. No.	Bitcoin Price	No. Of Days	Days
0	0	234.31	1	800
1	1	431.76	240	900
2	2	652.14	417	1000
3	3	817.26	607	1500
4	4	2358.96	736	2000

In [19]:
```
y1=a+b*df.Days
y1
```

Out[19]:
```
0    1848.313563
1    2085.789192
2    2323.264821
3    3510.642964
4    4698.021107
Name: Days, dtype: float64
```

In [20]:
```
df['price']=y1
df
```

Out[20]:

	Sr. No.	Bitcoin Price	No. Of Days	Days	price
0	0	234.31	1	800	1848.313563
1	1	431.76	240	900	2085.789192
2	2	652.14	417	1000	2323.264821
3	3	817.26	607	1500	3510.642964
4	4	2358.96	736	2000	4698.021107

In [26]:
```
df.to_clipboard('/home/computer/Documents/CSE-AIML/TE/SEM6/AIML11_PRATHAMESH/DAVL/dataset1.csv')
```

```
QXcbClipboard::setMimeData: Cannot set X11 selection owner
```

- **Experience and salary**

Part 1

Importing important modules and excel-csv dataset file

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

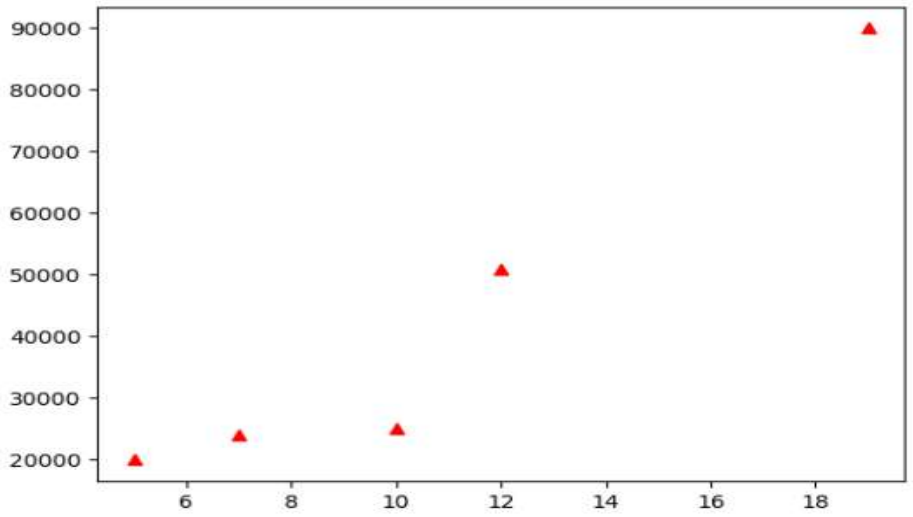
In [2]:
```
df=pd.read_excel('D:/StudyTime/TE/SEM6/DAVL/employee_data.xls.ods')
df
```

Out[2]:

	Sr. No.	Experience	Salary
0	0	5	20000
1	1	7	24000
2	2	10	25000
3	3	12	51000
4	4	19	90000

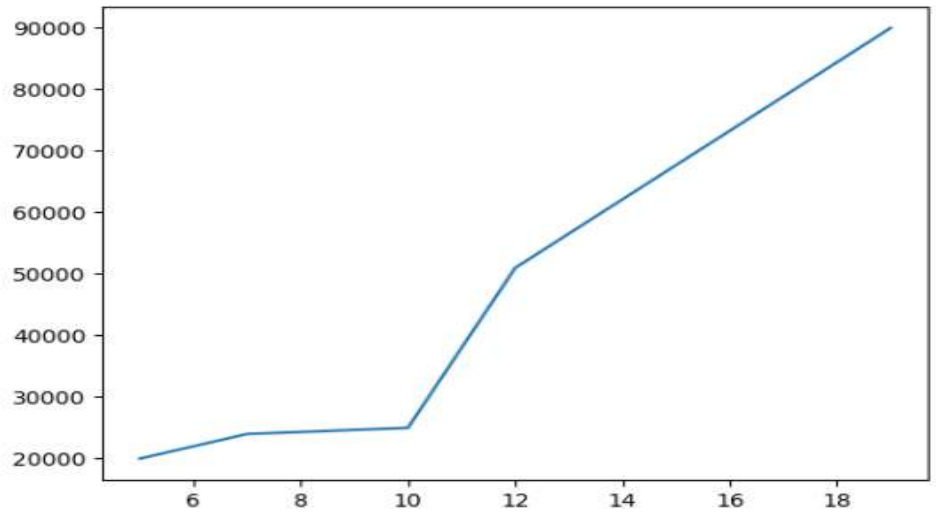
In [3]:
```
x = df['Experience']
y = df['Salary']
plt.scatter(x,y,color='red',marker='^')
```

Out[3]:
```
<matplotlib.collections.PathCollection at 0x16386571a90>
```



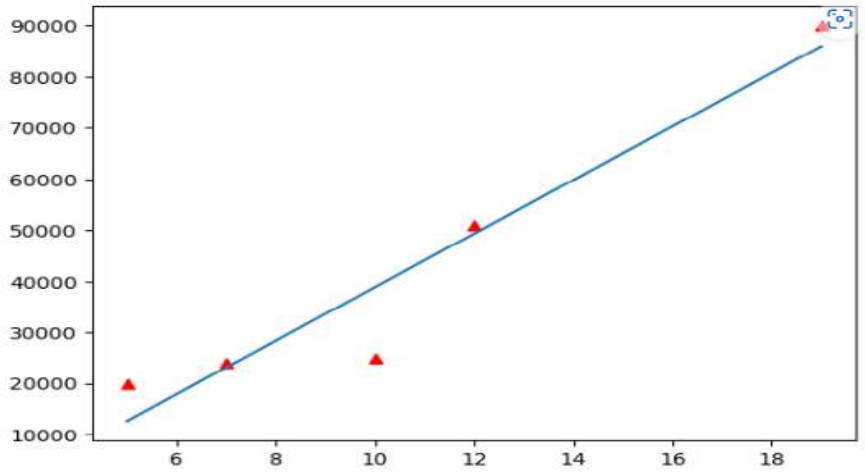
In [5]:
```
b,a=np.polyfit(x,y,1)
plt.plot(x,y)
```

Out[5]:
```
[<matplotlib.lines.Line2D at 0x16386e7d280>]
```



Part 2
Testing/Predicting the dataset

In [6]:
```
plt.scatter(x,y,color='red',marker='^')
b,a=np.polyfit(x,y,1)
y1=a+b*x
plt.plot(x,y1)
plt.show()
```



In [7]:
```
y1=a+b*24
y1
```

Out[7]:
```
112201.36518771334
```

In [9]:
```
df=pd.read_excel('D:/StudyTime/TE/SEM6/DAVL/employee_data1.ods')
df
```

Out[9]:

	Sr. No.	Experience	Salary	Increment
0	0	5	20000	1000
1	1	7	24000	1200
2	2	10	25000	3000
3	3	12	51000	7600
4	4	19	90000	9990

In [10]:
```
y1=a+b*df.Increment
y1
```

Out[10]:
```
0    5.225375e+06
1    6.273157e+06
2    1.570319e+07
3    3.980217e+07
4    5.232316e+07
Name: Increment, dtype: float64
```

In [11]:
```
df['Added']=y1
df
```

Out[11]:

	Sr. No.	Experience	Salary	Increment	Added
0	0	5	20000	1000	5.225375e+06
1	1	7	24000	1200	6.273157e+06
2	2	10	25000	3000	1.570319e+07
3	3	12	51000	7600	3.980217e+07
4	4	19	90000	9990	5.232316e+07

In [16]:
```
df['Bonus']=a+b*df.Increment
df
```

Out[16]:

	Sr. No.	Experience	Salary	Increment	Added	Bonus
0	0	5	20000	1000	5.225375e+06	5.225375e+06
1	1	7	24000	1200	6.273157e+06	6.273157e+06
2	2	10	25000	3000	1.570319e+07	1.570319e+07
3	3	12	51000	7600	3.980217e+07	3.980217e+07
4	4	19	90000	9990	5.232316e+07	5.232316e+07

In [ ]:
```
df.to_clipboard()
```

- **Multiple Linear Regression in Python**

In [2]:
```
import numpy as np

# Creating a two-dimensional array
arr2d = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]])

# Computing the mean of the entire array
mean = np.mean(arr2d)
print("Mean of the entire array:", mean)

# Computing the mean of each column
mean_col = np.mean(arr2d, axis=0)
print("\nMean of each column:")
print(mean_col)

# Computing the standard deviation of each row
std_row = np.std(arr2d, axis=1)
print("\nStandard deviation of each row:")
print(std_row)

# Computing the sum of each row
sum_row = np.sum(arr2d, axis=1)
print("\nSum of each row:")
print(sum_row)

# Computing the maximum value of each column
max_col = np.max(arr2d, axis=0)
print("\nMaximum value of each column:")
print(max_col)
```

```
Mean of the entire array: 5.0

Mean of each column:
[4. 5. 6.]

Standard deviation of each row:
[0.81649658 0.81649658 0.81649658]

Sum of each row:
[ 6 15 24]

Maximum value of each column:
[7 8 9]
```

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COURSE CODE	**CSL601**
PRACTICAL NO.	**04**
DOP	
DOS	

Experiment No. : 04

Aim : Time Series Analysis in Python/R

Theory :

- A time series is a set of observations that are recorded over time, typically at regular intervals. Time series analysis is used to analyze such data to extract useful information and make predictions about future values.
- For example, consider monthly sales data for a company for the past 3 years, where each observation represents the total sales in a particular month. This data can be represented as a time series, where the time variable is the month and the sales variable is the value recorded for that month.
- Using time series analysis, we can extract information about the trend, seasonality, and other patterns in the data. For instance, we can plot the time series to visualize the trend and seasonality, and we can use autocorrelation analysis to identify any correlation between the sales data at different lags.
- Using this information, we can develop a model to forecast future sales. For example, we can use a time series model such as ARIMA (Autoregressive Integrated Moving Average) or exponential smoothing to make predictions about future sales based on past trends and patterns in the data.
- Overall, time series analysis provides a powerful tool for analyzing and forecasting data that is collected over time, and it has applications in various fields such as finance, economics, and engineering.

Implementation :

Write a program to perform Time Series Analysis in Python in :

```
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima_model import ARIMA
data = pd.read_csv("sales_data.csv", parse_dates=["Date"], index_col="Date") # Load the data
# Plot the data
plt.figure(figsize=(10, 4))
plt.plot(data)
plt.title("Sales Data")
plt.xlabel("Date")
plt.ylabel("Sales")
plt.show()
# Check for stationarity using the Augmented Dickey-Fuller Test
result = adfuller(data["Sales"])
print("ADF Statistic:", result[0])
print("p-value:", result[1])
print("Critical Values:")
for key, value in result[4].items():
print(f"\t{key}: {value}")
```

```
# Plot the autocorrelation and partial autocorrelation functions
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(10, 6))
plot_acf(data, ax=ax1, lags=20)
plot_pacf(data, ax=ax2, lags=20)
plt.show()
# Fit an ARIMA model
model = ARIMA(data, order=(1, 0, 0))
results = model.fit()
print(results.summary()) # Print the model summary
# Plot the residuals
plt.figure(figsize=(10, 4))
plt.plot(results.resid)
plt.title("Residuals")
plt.xlabel("Date")
plt.ylabel("Residual")
plt.show()
forecast = results.forecast(steps=3) # Make predictions for the next 3 months
print("Forecasted Sales:", forecast[0])
```

Output -

```
ADF Statistic: -2.5590145552827387
p-value: 0.10236480415917944
Critical Values: 1%: -3.5246240467919034, 5%: -2.902607073170798,10%: -2.5886780263023037
 ARMA Model Results
==============================================================================
Dep. Variable:                  Sales No.   Observations: 100
Model:                     ARMA(1, 0)       Log Likelihood -446.047
Method:                       css-mle       S.D. of innovations 39.365
Date:                Fri, 16 Apr 2023       AIC 898.095
Time:                        15:32:45       BIC 906.743
Sample:                      01-01-2019     HQIC 901.654
                           - 04-10-2021
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         97.1495     50.447      1.924      0.054     -1.696    195.995
ar.L1.Sales    0.3677      0.098      3.751      0.000      0.175      0.560
 Roots
=============================================================================
 Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            2.7185           +0.0000j            2.7185       0.0000
-----------------------------------------------------------------------------
Forecasted Sales: [1117.02566666 1160.17786267 1203.
```

Conclusion : We had successfully studied and understood time series analysis in Python/R

- **Importing dataset**
- **Loading the data**
- **Splitting the data into training and testing sets**
- **Fitting an ARIMA model**
- **Print the model summary**

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.arima_model import ARIMA
df = pd.read_csv('https://raw.githubusercontent.com/liannewriting/YouTube-videos-public
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 393 entries, 0 to 392
Data columns (total 1 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   traffic  393 non-null    int64
dtypes: int64(1)
memory usage: 3.2 KB
```

In [2]:
```
train_data = df[:80]
test_data = df[80:]
```

In [3]:
```
from statsmodels.tsa.arima.model import ARIMA
model = ARIMA(train_data, order=(1, 0, 0))
results = model.fit()
```

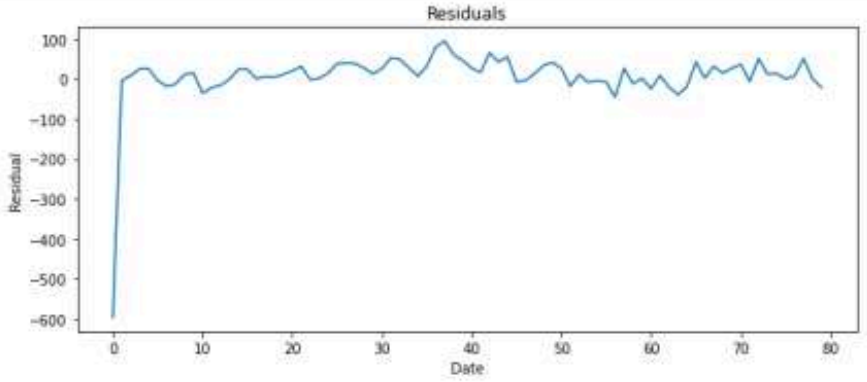
In [4]:
```
print(results.summary())
```

```
                               SARIMAX Results
==============================================================================================
Dep. Variable:                        traffic   No. Observations:                           80
Model:                     ARIMA(1, 0, 0)   Log Likelihood                        -389.610
Date:                    Mon, 17 Apr 2023   AIC                                    785.220
Time:                            14:28:00   BIC                                    792.366
Sample:                                 0   HQIC                                   788.085
                                     - 80
Covariance Type:                      opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const       1528.5952    562.454      2.718      0.007     426.205    2630.985
ar.L1          0.9985      0.010     99.300      0.000       0.979       1.018
sigma2       924.5967    135.454      6.826      0.000     659.112    1190.081
===================================================================================
Ljung-Box (L1) (Q):                  18.54   Jarque-Bera (JB):                 1.37
Prob(Q):                              0.00   Prob(JB):                         0.50
Heteroskedasticity (H):               1.53   Skew:                             0.31
Prob(H) (two-sided):                  0.28   Kurtosis:                         3.15
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

- **Plotting the residuals**
- **Making predictions for the test set**
- **Plotting the actual and predicted values**

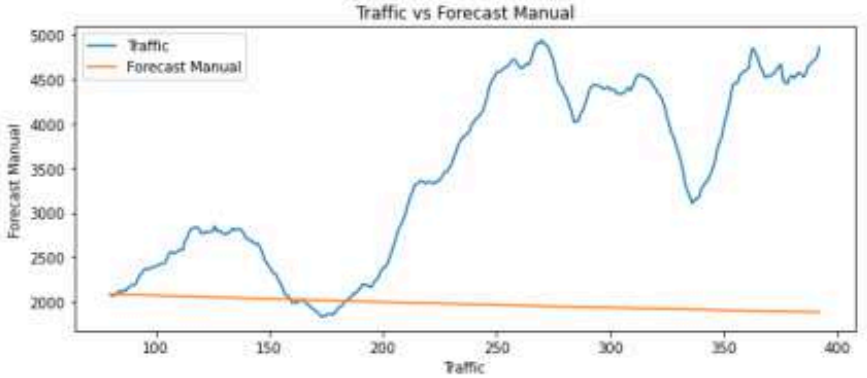
In [5]:
```
plt.figure(figsize=(10, 4))
plt.plot(results.resid)
plt.title("Residuals")
plt.xlabel("Date")
plt.ylabel("Residual")
plt.show()
```



In [6]:
```
predictions = results.forecast(steps=len(test_data))
predictions
```

Out[6]:
```
80     2086.188475
81     2085.378130
82     2084.568962
83     2083.760970
84     2082.954152
          ...
388    1884.865769
389    1884.348004
390    1883.830992
391    1883.314731
392    1882.799220
Name: predicted_mean, Length: 313, dtype: float64
```

In [8]:
```
plt.figure(figsize=(10, 4))
plt.plot(test_data, label="Traffic")
plt.plot(predictions, label="Forecast Manual")
plt.title("Traffic vs Forecast Manual")
plt.xlabel("Traffic")
plt.ylabel("Forecast Manual")
plt.legend()
plt.show()
```



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COURSE CODE	**CSL601**
PRACTICAL NO.	
DOP	**30/01/2023**
DOS	

Program(input)/Output :

data_frame

```
In [1]: import pandas as pd
        wine=pd.read_csv("https://raw.githubusercontent.com/YBI-Foundation/Dataset/main/Wine.csv")
```

```
In [2]: wine
```

Out[2]:

	class_label	class_name	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_phenols	prc
0	1	Barolo	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28	
1	1	Barolo	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	
2	1	Barolo	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	
3	1	Barolo	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	
4	1	Barolo	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	
...	...	...	...	...	...	...	...	...	...	...	
173	3	Barbera	13.71	5.65	2.45	20.5	95	1.68	0.61	0.52	
174	3	Barbera	13.40	3.91	2.48	23.0	102	1.80	0.75	0.43	
175	3	Barbera	13.27	4.28	2.26	20.0	120	1.59	0.69	0.43	
176	3	Barbera	13.17	2.59	2.37	20.0	120	1.65	0.68	0.53	
177	3	Barbera	14.13	4.10	2.74	24.5	96	2.05	0.76	0.56	

178 rows × 15 columns

data_frame.head()

```
In [3]: wine.head()
```

Out[3]:

	class_label	class_name	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_phenols	proar
0	1	Barolo	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28	
1	1	Barolo	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	
2	1	Barolo	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	
3	1	Barolo	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	
4	1	Barolo	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	

data_frame.tail()

```
In [4]: wine.tail()
```

Out[4]:

	class_label	class_name	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_phenols	prc
173	3	Barbera	13.71	5.65	2.45	20.5	95	1.68	0.61	0.52	
174	3	Barbera	13.40	3.91	2.48	23.0	102	1.80	0.75	0.43	
175	3	Barbera	13.27	4.28	2.26	20.0	120	1.59	0.69	0.43	
176	3	Barbera	13.17	2.59	2.37	20.0	120	1.65	0.68	0.53	
177	3	Barbera	14.13	4.10	2.74	24.5	96	2.05	0.76	0.56	

data_frame.info()

```
In [5]: wine.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 178 entries, 0 to 177
Data columns (total 15 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   class_label           178 non-null    int64
 1   class_name            178 non-null    object
 2   alcohol               178 non-null    float64
 3   malic_acid            178 non-null    float64
 4   ash                   178 non-null    float64
 5   alcalinity_of_ash     178 non-null    float64
 6   magnesium             178 non-null    int64
 7   total_phenols         178 non-null    float64
 8   flavanoids            178 non-null    float64
 9   nonflavanoid_phenols  178 non-null    float64
 10  proanthocyanins       178 non-null    float64
 11  color_intensity       178 non-null    float64
 12  hue                   178 non-null    float64
 13  od280                 178 non-null    float64
 14  proline               178 non-null    int64
dtypes: float64(11), int64(3), object(1)
memory usage: 21.0+ KB
```

data_frame.describe()

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

Out[6]:

	class_label	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_phenols	pro
count	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	
mean	1.938202	13.000618	2.336348	2.366517	19.494944	99.741573	2.295112	2.029270	0.361854	
std	0.775035	0.811827	1.117146	0.274344	3.339564	14.282484	0.625851	0.998859	0.124453	
min	1.000000	11.030000	0.740000	1.360000	10.600000	70.000000	0.980000	0.340000	0.130000	
25%	1.000000	12.362500	1.602500	2.210000	17.200000	88.000000	1.742500	1.205000	0.270000	
50%	2.000000	13.050000	1.865000	2.360000	19.500000	98.000000	2.355000	2.135000	0.340000	
75%	3.000000	13.677500	3.082500	2.557500	21.500000	107.000000	2.800000	2.875000	0.437500	
max	3.000000	14.830000	5.800000	3.230000	30.000000	162.000000	3.880000	5.080000	0.660000	

data_frame.columns

```
In [8]: wine.columns
```

```
Out[8]: Index(['class_label', 'class_name', 'alcohol', 'malic_acid', 'ash',
               'alcalinity_of_ash', 'magnesium', 'total_phenols', 'flavanoids',
               'nonflavanoid_phenols', 'proanthocyanins', 'color_intensity', 'hue',
               'od280', 'proline'],
              dtype='object')
```

data_frame.nlargest()

```
In [11]: wine.nlargest(4,'alcohol')
```

Out[11]:

	class_label	class_name	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_phenols	proa
8	1	Barolo	14.83	1.64	2.17	14.0	97	2.8	2.98	0.29	
13	1	Barolo	14.75	1.73	2.39	11.4	91	3.1	3.69	0.43	
6	1	Barolo	14.39	1.87	2.45	14.6	96	2.5	2.52	0.30	
14	1	Barolo	14.38	1.87	2.38	12.0	102	3.3	3.64	0.29	

data_frame.sort values()

```
In [12]: wine.sort values('ash',ascending = False)
```

Out[12]:

	class_label	class_name	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_phenols	prc
121	2	Grignolino	11.56	2.05	3.23	28.5	119	3.18	5.08	0.47	
25	1	Barolo	13.05	2.05	3.22	25.0	124	2.63	2.68	0.47	
112	2	Grignolino	11.76	2.68	2.92	20.0	103	1.75	2.03	0.60	
4	1	Barolo	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	
169	3	Barbera	13.40	4.60	2.86	25.0	112	1.98	0.96	0.27	
...	...	...	...	...	...	...	...	...	...	...	
69	2	Grignolino	12.21	1.19	1.75	16.8	151	1.85	1.28	0.14	
76	2	Grignolino	13.03	0.90	1.71	16.0	86	1.95	2.03	0.24	
66	2	Grignolino	13.11	1.01	1.70	15.0	78	2.98	3.18	0.26	
100	2	Grignolino	12.08	2.08	1.70	17.5	97	2.23	2.17	0.26	
59	2	Grignolino	12.37	0.94	1.36	10.6	88	1.98	0.57	0.28	

178 rows × 15 columns

data_frame.loc[ ]

```
In [13]: wine.loc[100:300,'malic acid']
```

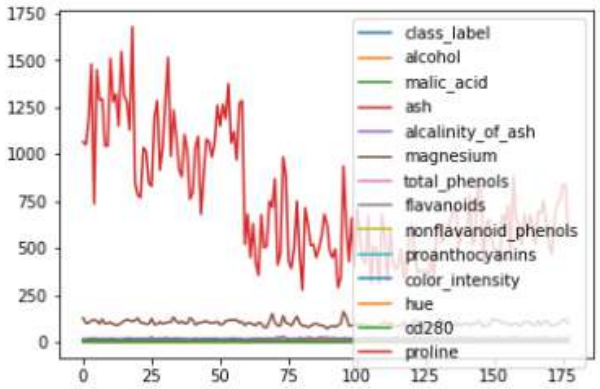
Out[13]:

```
100    2.08
101    1.34
102    2.45
103    1.72
104    1.73
       ...
173    5.65
174    3.91
175    4.28
176    2.59
177    4.10
Name: malic_acid, Length: 78, dtype: float64
```

data_frame.plot()

```
In [15]: wine.plot()
```

```
Out[15]: <AxesSubplot:>
```



data_frame.shape

```
In [18]: wine.shape
```

```
Out[18]: (178, 15)
```

data_frame.corr()

```
In [19]: wine.corr()
```

```
Out[19]:
```

	class_label	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoic
class_label	1.000000	-0.328222	0.437776	-0.049643	0.517859	-0.209179	-0.719163	-0.847498	
alcohol	-0.328222	1.000000	0.094397	0.211545	-0.310235	0.270798	0.289101	0.236815	
malic_acid	0.437776	0.094397	1.000000	0.164045	0.288500	-0.054575	-0.335167	-0.411007	
ash	-0.049643	0.211545	0.164045	1.000000	0.443367	0.286587	0.128980	0.115077	
alcalinity_of_ash	0.517859	-0.310235	0.288500	0.443367	1.000000	-0.083333	-0.321113	-0.351370	
magnesium	-0.209179	0.270798	-0.054575	0.286587	-0.083333	1.000000	0.214401	0.195784	
total_phenols	-0.719163	0.289101	-0.335167	0.128980	-0.321113	0.214401	1.000000	0.864564	
flavanoids	-0.847498	0.236815	-0.411007	0.115077	-0.351370	0.195784	0.864564	1.000000	
nonflavanoid_phenols	0.489109	-0.155929	0.292977	0.186230	0.361922	-0.256294	-0.449935	-0.537900	
proanthocyanins	-0.499130	0.136698	-0.220746	0.009652	-0.197327	0.236441	0.612413	0.652692	
color_intensity	0.265668	0.546364	0.248985	0.258887	0.018732	0.199950	-0.055136	-0.172379	

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
(ARTIFICIAL INTELLIGENCE & MACHINE LEARNING)

T.E/SEM VI/CBCGS/AIML
Academic Year: 2022-23

NAME	**PRATHAMESH CHIKANKAR**
BRANCH	**CSE-(AI&ML)**
ROLL NO.	**11**
SUBJECT	**DATA ANALYTICS AND VISUALIZATION LAB**
COURSE CODE	**CSL601**
PRACTICAL NO.	
DOP	**06/02/2023**
DOS	

HYPOTHESIS TESTING

Program(input)/Output :

- One Sample t test ->

In [2]:

```
ages=[10,20,35,50,28,40,55,18,76,55,30,25,43,18,30,28,
      14,24,16,17,32,35,26,27,65,18,43,23,21,20,19,70]
len(ages)
```

Out[2]:

```
32
```

In [3]:

```
import numpy as np
ages_mean=np.mean(ages)
print(ages_mean)
```

```
32.21875
```

#Let's take sample :

In [22]:

```
sample_size=10
age_sample=np.random.choice(ages,sample_size)
age_sample
```

Out[22]:

```
array([35, 55, 21, 18, 32, 76, 19, 25, 23, 25])
```

In [23]:

```
from scipy.stats import ttest_1samp as ttest_1samp
ttest,p_value=ttest_1samp(age_sample,30)
print(p_value)
```

```
0.6347125419461657
```

In [24]:

```
if p_value < 0.05:
    print("we are rejecting null hypothesis")
else:
    print("we are acceptin null hypothesis")
```

```
we are acceptin null hypothesis
```

#Some more examples :

In [29]:

```
import numpy as np
import pandas as pd
import scipy.stats as stats
import math
np.random.seed(6)
school_ages=stats.poisson.rvs(loc=18,mu=35,size=1500)
classA_ages=stats.poisson.rvs(loc=18,mu=30,size=60)
classA_ages.mean()
```

Out[29]:

```
46.9
```

In [32]:

```
p_value=stats.ttest_1samp(a=classA_ages,popmean=school_ages.mean())
school_ages.mean()
print(p_value)
```

Out[32]:

```
53.303333333333335
```

In [39]:

```
if p_value < 0.05:
    print("we are rejecting null hypothesis")
else:
    print("we are accepting null hypothesis")
```

```
we are accepting null hypothesis
```

- Independent t-test ->

In [40]:

```
np.random.seed(12)
classB_ages=stats.poisson.rvs(loc=18,mu=33,size=60)
classB_ages.mean()
```

Out[40]:

```
50.63333333333333
```

In [58]:

```
_,p_value=stats.ttest_ind(a=classA_ages,b=classB_ages)
if p_value < 0.05:
    print("we are rejecting null hypothesis")
else:
    print("we are accepting null hypothesis")
```

```
we are rejecting null hypothesis
```

- Paired t-test ->

In [45]:

```
weight_1=[25,30,28,35,28,34,26,29,30,26,28,32,31,30,45]
weight_2=weight_1+stats.norm.rvs(scale=5,loc=-1.25,size=15)
print(weight_1)
print(weight_2)
```

```
[25, 30, 28, 35, 28, 34, 26, 29, 30, 26, 28, 32, 31, 30, 45]
[30.57926457 34.91022437 29.00444617 30.54295091 19.86201983 37.578731
74
 18.3299827  21.3771395  36.36420881 32.05941216 26.93827982 29.519014
 26.42851213 30.50667769 41.32984284]
```

In [48]:

```
weight_df=pd.DataFrame({"weight_10":np.array(weight_1),
                        "weight_20":np.array(weight_2),
                        "weight_change":np.array(weight_2)-np.array(weight_1)})
```

In [50]:

```
weight_df,p_value=stats.ttest_rel(a=weight_1,b=weight_2)
print(p_value)
```

```
0.5732936534411279
```

In [51]:

```
if p_value<0.05:
    print("we are rejecting null hypothesis")
else:
    print("we are accepting null hypothesis")
```

```
we are accepting null hypothesis
```

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DOP	**27/02/2023**
DOS	

DATA ANALYTICS LIBRARIES

NUMPY:

NumPy is a very popular python library for large multi-dimensional array and matrix processing, with the help of a large collection of high-level mathematical functions. It is very useful for fundamental scientific computations in Machine Learning. It is particularly useful for linear algebra, Fourier transform, and random number capabilities. High-end libraries like TensorFlow use NumPy internally for manipulation of Tensors.

PROGRAM:

```
# operations
import numpy as np
# Creating two arrays of rank 2
x = np.array([[1, 2], [3, 4]])
y = np.array([[5, 6], [7, 8]])
# Creating two arrays of rank 1
v = np.array([9, 10])
w = np.array([11, 12])
# Inner product of vectors
print(np.dot(v, w), "\n")
# Matrix and Vector product
print(np.dot(x, v), "\n")
# Matrix and matrix product
print(np.dot(x, y))
```

OUTPUT:

In [1]:
```
# Python program using NumPy

import numpy as np

# Creating two arrays of rank 2
x = np.array([[1, 2], [3, 4]])
y = np.array([[5, 6], [7, 8]])

# Creating two arrays of rank 1
v = np.array([9, 10])
w = np.array([11, 12])

# Inner product of vectors
print(np.dot(v, w), "\n")

# Matrix and Vector product
print(np.dot(x, v), "\n")

# Matrix and matrix product
print(np.dot(x, y))
```

```
219

[29 67]

[[19 22]
 [43 50]]
```

SCIPY:

SciPy is a very popular library among Machine Learning enthusiasts as it contains different modules for optimization, linear algebra, integration and statistics. There is a difference between the SciPy library and the SciPy stack. The SciPy is one of the core packages that make up the SciPy stack. SciPy is also very useful for image manipulation.

PROGRAM:

```
from scipy import io
import numpy as np
arr = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9,])
#Export:
io.savemat('arr.mat', {"vec": arr})
#Import:
mydata = io.loadmat('arr.mat')
print(mydata)
```

OUTPUT:

```
from scipy import io
import numpy as np

arr = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9,])

#Export:
io.savemat('arr.mat', {"vec": arr})

#Import:
mydata = io.loadmat('arr.mat')

print(mydata)
```

```
{
  '__header__': b'MATLAB 5.0 MAT-file Platform: nt, Created on: Tue Sep 22 13:12:32 2020',
  '__version__': '1.0',
  '__globals__': [],
  'vec': array([[0, 1, 2, 3, 4, 5, 6, 7, 8, 9]])
}
```

TENSORFLOW:

TensorFlow is a very popular open-source library for high performance numerical computation developed by the Google Brain team in Google. As the name suggests, Tensorflow is a framework that involves defining and running computations involving tensors. It can train and run deep neural networks that can be used to develop several AI applications. TensorFlow is widely used in the field of deep learning research and application.

PROGRAM:

```
<!DOCTYPE html>
<html>
<script src="https://cdn.jsdelivr.net/npm/@tensorflow/tfjs"></script>
<body>
<h1>TensorFlow JavaScript</h1>
<h3>Get the data behind a tensor:</h3>
<div id="demo"></div>
<script>
const myArr = [[1, 2], [3, 4]]; const tensorA = tf.tensor(myArr);
tensorA.data().then(data => display(data));
// Result: 1,2,3,4 function display(data) {
        document.getElementById("demo").innerHTML = data;
}
</script>
</body>
</html>
```

OUTPUT:

```
<!DOCTYPE html>
<html>
<script src="https://cdn.jsdelivr.net/npm/@tensorflow/tfjs"></script>
<body>

<h1>TensorFlow JavaScript</h1>
<h3>Get the data behind a tensor:</h3>

<div id="demo"></div>

<script>
const myArr = [[1, 2], [3, 4]];
const tensorA = tf.tensor(myArr);
tensorA.data().then(data => display(data));

// Result: 1,2,3,4
function display(data) {
  document.getElementById("demo").innerHTML = data;
}
</script>
</body>
</html>
```

TensorFlow JavaScript

Get the data behind a tensor:

1,2,3,4

PANDAS:

Pandas is a popular Python library for data analysis. It is not directly related to Machine Learning. As we know that the dataset must be prepared before training. In this case, Pandas comes handy as it was developed specifically for data extraction and preparation. It provides high-level data structures and a wide variety of tools for data analysis. It provides many inbuilt methods for grouping, combining and filtering data.

PROGRAM:

```
# arranging a given set of data
# into a table
# importing pandas as pd
import pandas as pd
data = {"country": ["Brazil", "Russia", "India", "China", "South Africa"],
        "capital": ["Brasilia", "Moscow", "New Delhi", "Beijing", "Pretoria"],
        "area": [8.516, 17.10, 3.286, 9.597, 1.221],
        "population": [200.4, 143.5, 1252, 1357, 52.98] }
data_table = pd.DataFrame(data)
print(data_table)
```

OUTPUT:

```
In [4]: # Python program using Pandas for
        # arranging a given set of data
        # into a table

        # importing pandas as pd
        import pandas as pd

        data = {"country": ["Brazil", "Russia", "India", "China", "South Africa"],
        ····"capital": ["Brasilia", "Moscow", "New Delhi", "Beijing", "Pretoria"],
        ····"area": [8.516, 17.10, 3.286, 9.597, 1.221],
        ····"population": [200.4, 143.5, 1252, 1357, 52.98] }

        data_table = pd.DataFrame(data)
        print(data_table)
```

```
        country    capital    area  population
0        Brazil   Brasilia   8.516      200.40
1        Russia     Moscow  17.100      143.50
2         India  New Delhi   3.286     1252.00
3         China    Beijing   9.597     1357.00
4  South Africa   Pretoria   1.221       52.98
```

MATPLOTLIB:

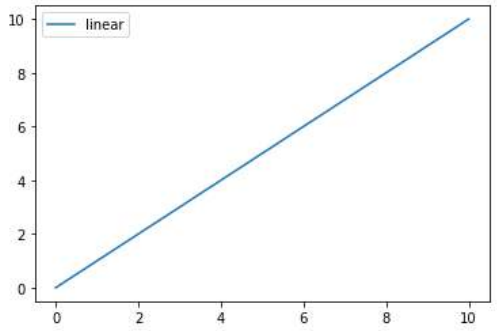
Matplotlib is a very popular Python library for data visualization. Like Pandas, it is not directly related to Machine Learning. It particularly comes in handy when a programmer wants to visualize the patterns in the data. It is a 2D plotting library used for creating 2D graphs and plots. A module named pyplot makes it easy for programmers for plotting as it provides features to control line styles, font properties, formatting axes, etc. It provides various kinds of graphs and plots for data visualization, viz., histogram, error charts, bar charts, etc.

PROGRAM:

```
# for forming a linear plot
import matplotlib.pyplot as plt
import numpy as np
# Prepare the data
x = np.linspace(0, 10, 100)
# Plot the data
plt.plot(x, x, label ='linear')
# Add a legend
plt.legend()
# Show the plot
plt.show()
```

OUTPUT:

In [5]:
```
# Python program using Matplotlib
# for forming a linear plot

import matplotlib.pyplot as plt
import numpy as np

# Prepare the data
x = np.linspace(0, 10, 100)

# Plot the data
plt.plot(x, x, label ='linear')

# Add a legend
plt.legend()

# Show the plot
plt.show()
```



In [ ]:

SCIKIT-LEARN :

Scikit-learn is one of the most popular ML libraries for classical ML algorithms. It is built on top of two basic Python libraries, viz., NumPy and SciPy.

PROGRAM/OUTPUT:

In [11]:
```
# Python script using Scikit-learn
# for Decision Tree Classifier

# Sample Decision Tree Classifier
from sklearn import datasets
from sklearn import metrics
from sklearn.tree import DecisionTreeClassifier

# load the iris datasets
dataset = datasets.load_iris()

# fit a CART model to the data
model = DecisionTreeClassifier()
model.fit(dataset.data, dataset.target)
print(model)

# make predictions
expected = dataset.target
predicted = model.predict(dataset.data)

# summarize the fit of the model
print(metrics.classification_report(expected, predicted))
print(metrics.confusion_matrix(expected, predicted))
```

```
DecisionTreeClassifier()
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        50
           1       1.00      1.00      1.00        50
           2       1.00      1.00      1.00        50

    accuracy                           1.00       150
   macro avg       1.00      1.00      1.00       150
weighted avg       1.00      1.00      1.00       150

[[50  0  0]
 [ 0 50  0]
 [ 0  0 50]]
```

PYTORCH

PyTorch is an open source machine learning library for Python and is completely based on Torch. It is primarily used for applications such as natural language processing.

PROGRAM/OUTPUT:

In [2]:
```
# importing torch
import torch

# creating a tensors
t1=torch.tensor([1, 2, 3, 4])
t2=torch.tensor([[1, 2, 3, 4],
                 [5, 6, 7, 8],
                 [9, 10, 11, 12]])

# printing the tensors:
print("Tensor t1: \n", t1)
print("\nTensor t2: \n", t2)

# rank of tensors
print("\nRank of t1: ", len(t1.shape))
print("Rank of t2: ", len(t2.shape))

# shape of tensors
print("\nRank of t1: ", t1.shape)
print("Rank of t2: ", t2.shape)
```

```
Tensor t1:
 tensor([1, 2, 3, 4])

Tensor t2:
 tensor([[ 1,  2,  3,  4],
         [ 5,  6,  7,  8],
         [ 9, 10, 11, 12]])

Rank of t1:  1
Rank of t2:  2

Rank of t1:  torch.Size([4])
Rank of t2:  torch.Size([3, 4])
```

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
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PRACTICAL NO.	**06**
DOP	
DOS	

Experiment No. : 06

Aim : Implementation of Spam filter/Sentiment analysis in python/R.

Theory :

- **Text analytics** is a branch of natural language processing (NLP) that deals with the automated processing and analysis of large amounts of unstructured text data. Two common applications of text analytics are spam filtering and sentiment analysis.
- **Spam filters** are used to automatically identify and remove unwanted or unsolicited emails, messages or comments. Spam filters typically use machine learning algorithms to learn from a large set of examples and identify patterns that distinguish spam from legitimate messages. They may also use various text processing techniques such as content analysis, text classification, and clustering to identify spam messages.
- **Sentiment analysis**, on the other hand, is the process of automatically detecting the sentiment or emotion expressed in a piece of text, such as a tweet or a review. Sentiment analysis is used to analyze customer feedback, social media posts, and other types of user-generated content to understand the overall sentiment towards a product or service. Sentiment analysis algorithms typically use natural language processing techniques such as part-of-speech tagging, parsing, and machine learning to identify and classify the sentiment expressed in text as positive, negative or neutral.

  Overall, text analytics is a powerful tool for businesses and organizations to gain insights from large volumes of text data, including social media posts, customer reviews, and feedback, and make data driven decisions

Implementation :

Write a program to perform Spam filter/Sentiment analysis in python :

- **Program for Spam filter:**

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
# Load the data
data = pd.read_csv("spam.csv", encoding="latin-1")
# Split the data into training and testing sets
train_data, test_data, train_target, test_target = train_test_split(data["text"], data["class"],
test_size=0.2)
# Vectorize the text data
vectorizer = CountVectorizer()
train_features = vectorizer.fit_transform(train_data)
test_features = vectorizer.transform(test_data)
# Fit a Naive Bayes model
model = MultinomialNB()
model.fit(train_features, train_target)
# Evaluate the model
```

```
accuracy = model.score(test_features, test_target)
print("Accuracy:", accuracy)
# Test the model with new data
new_data = ["Congratulations! You've won a free vacation to Hawaii. Reply now to claim your
prize."]
new_features = vectorizer.transform(new_data)
prediction = model.predict(new_features)
print("Prediction:", prediction[0])
```

Output -

Accuracy: 0.9865470852017937
Prediction: spam

- **Program for Sentiment analysis**

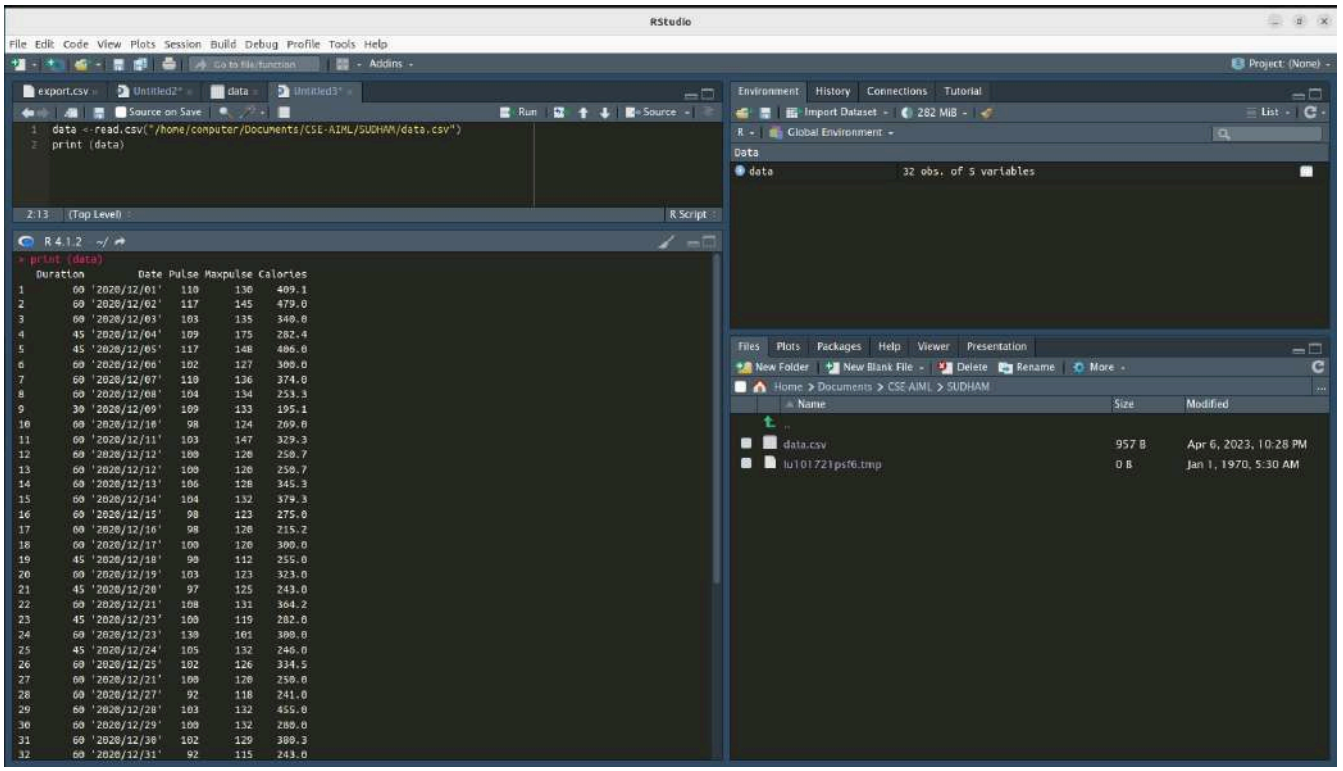
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
# Load the data
data = pd.read_csv("reviews.csv", encoding="latin-1")
# Split the data into training and testing sets
train_data, test_data, train_target, test_target = train_test_split(data["text"],
data["sentiment"], test_size=0.2)
# Vectorize the text data
vectorizer = CountVectorizer()
train_features = vectorizer.fit_transform(train_data)
test_features = vectorizer.transform(test_data)
# Fit a Naive Bayes model
model = MultinomialNB()
model.fit(train_features, train_target)
# Evaluate the model
accuracy = model.score(test_features, test_target)
print("Accuracy:", accuracy)
# Test the model with new data
new_data = ["This movie was great!"]
new_features = vectorizer.transform(new_data)
prediction = model.predict(new_features)
 print("Prediction:", prediction[0])
```

Output :

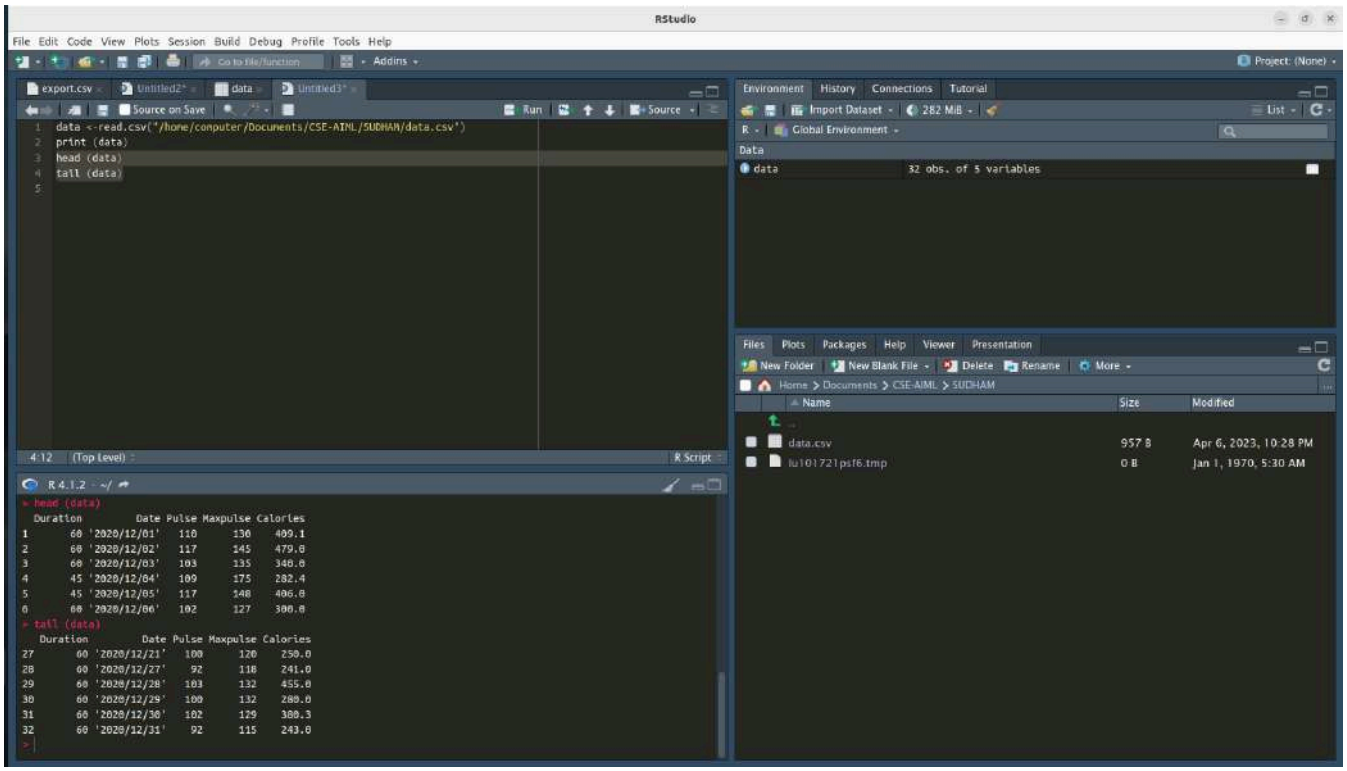
Accuracy: 0.8271
Prediction: positive

Conclusion : We had successfully studied and understood Spam filter/Sentiment analysis in Python/R

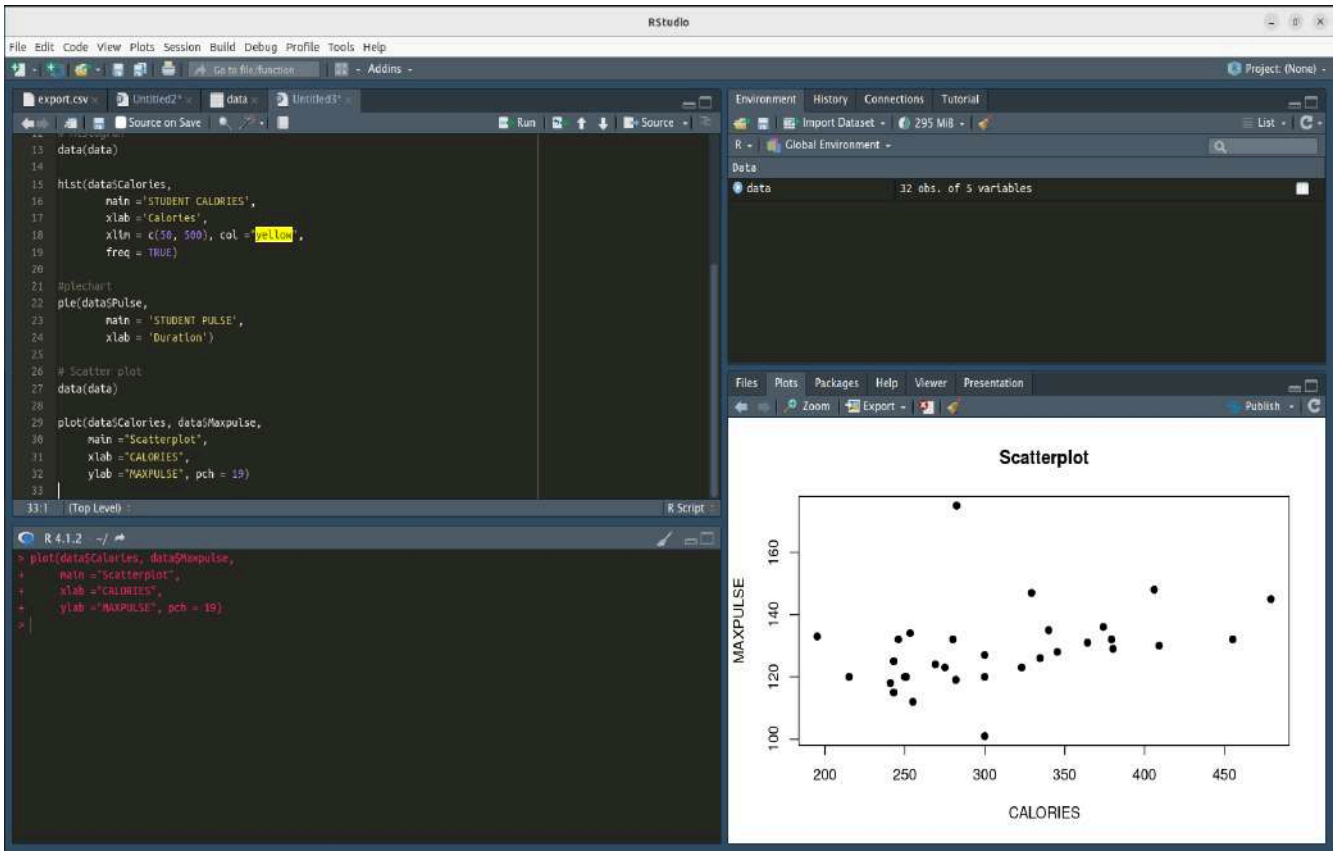
- **Importing dataset**



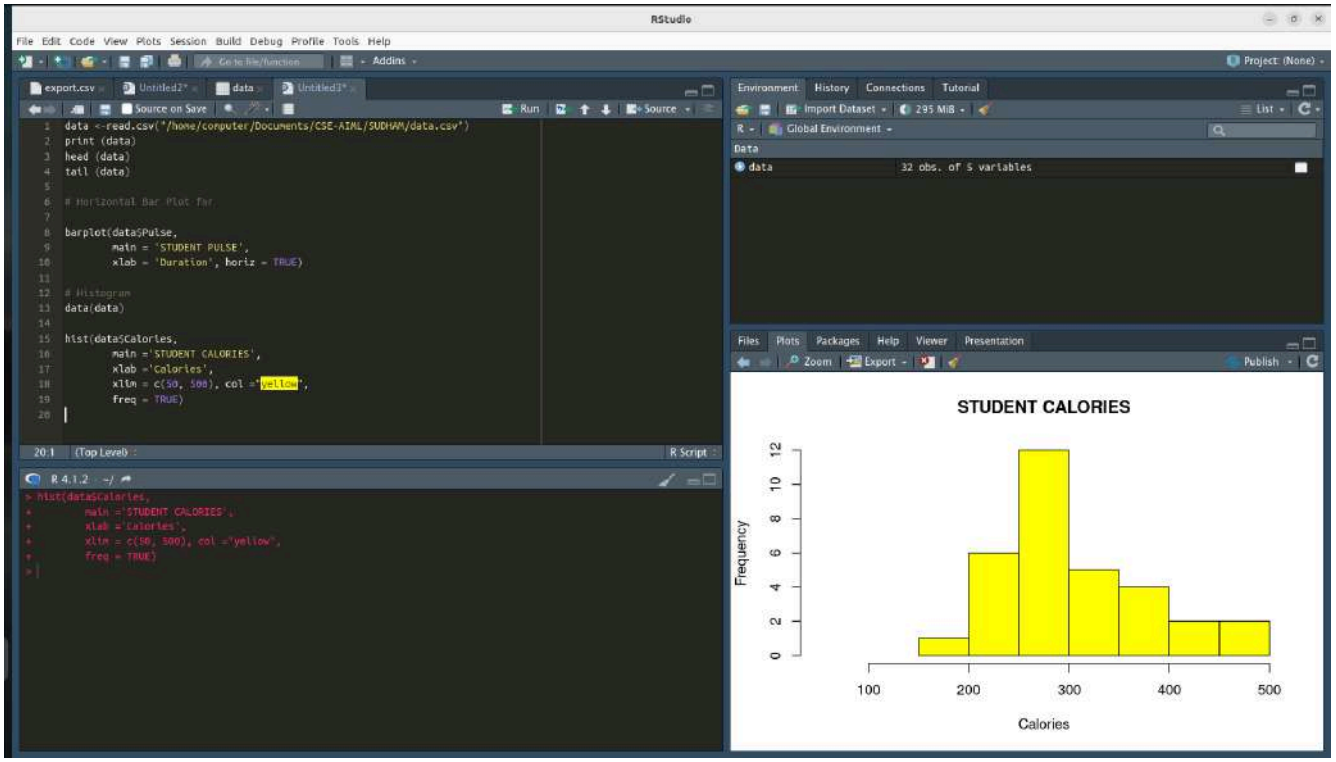
- **Getting quick overview**



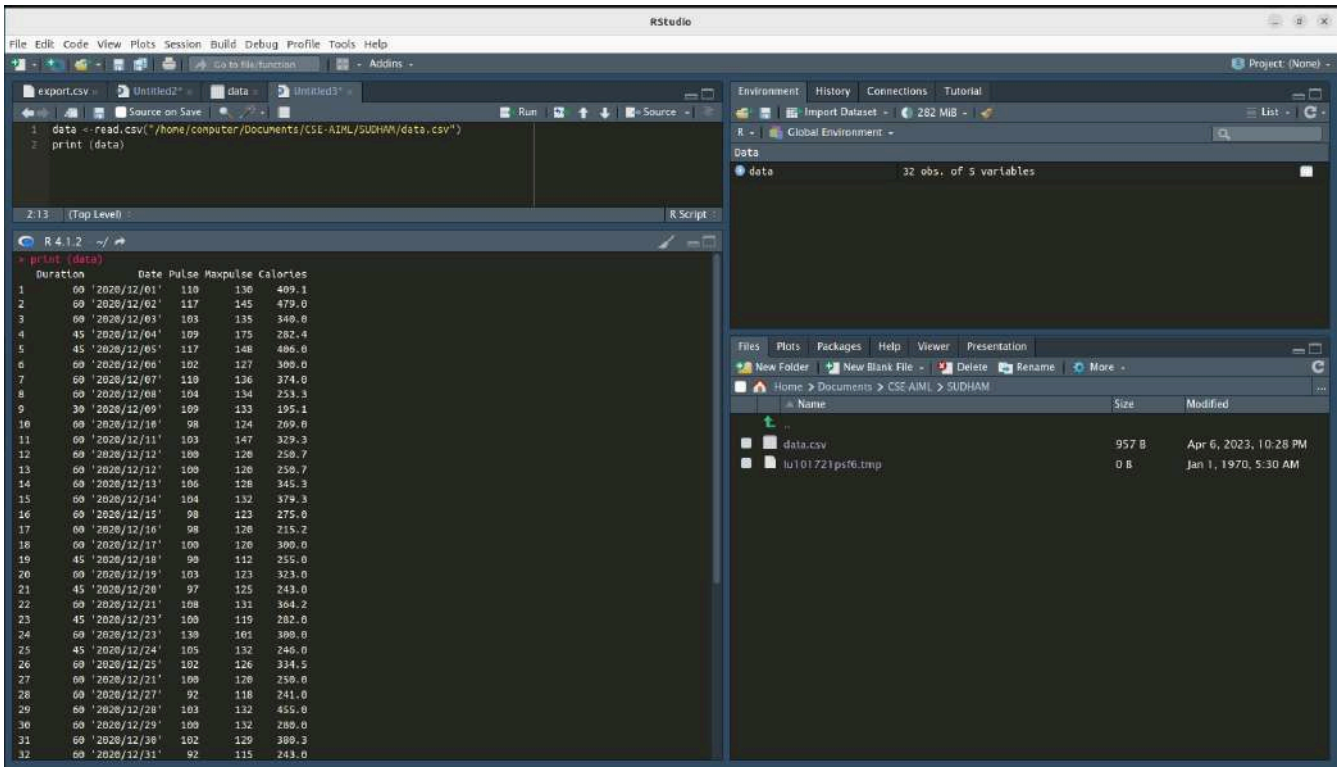
- **Scatter-plot Visualization in R**



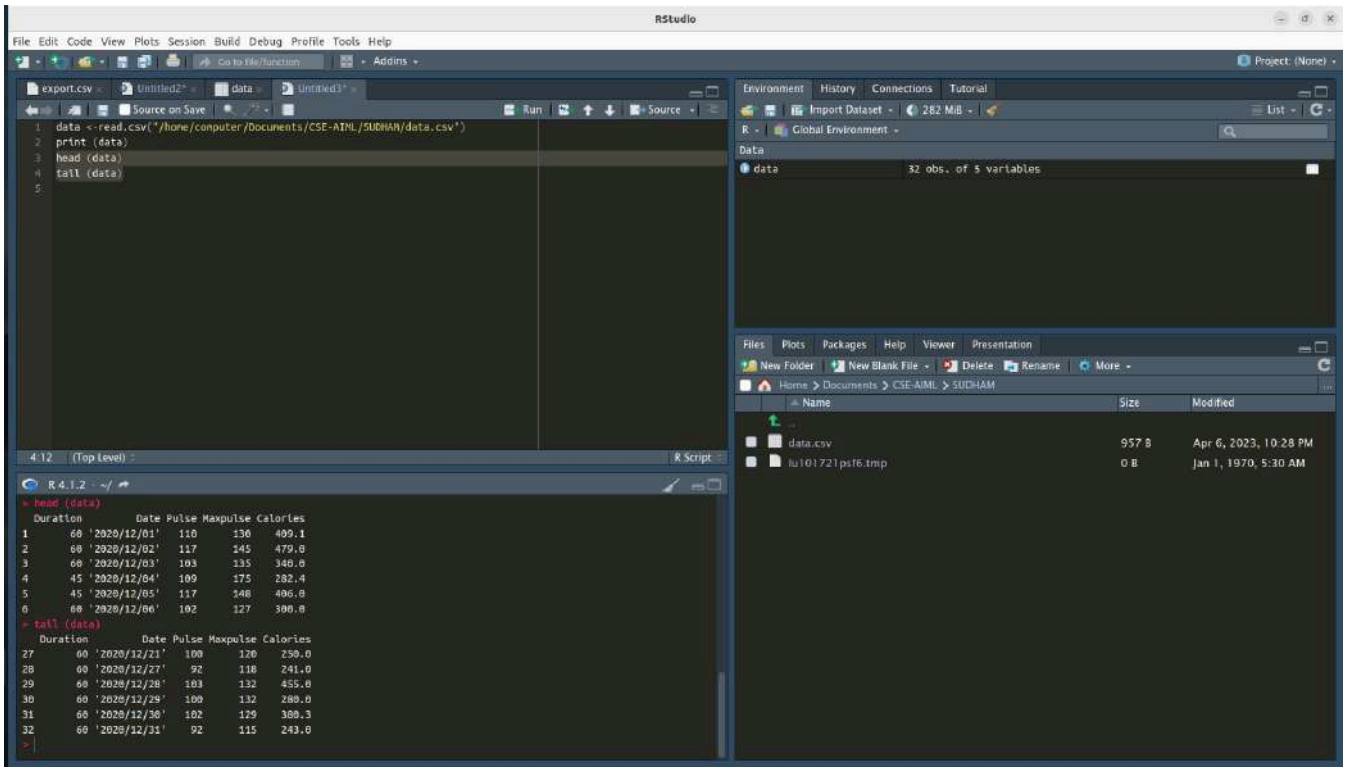
- **Histogram Visualization in R**



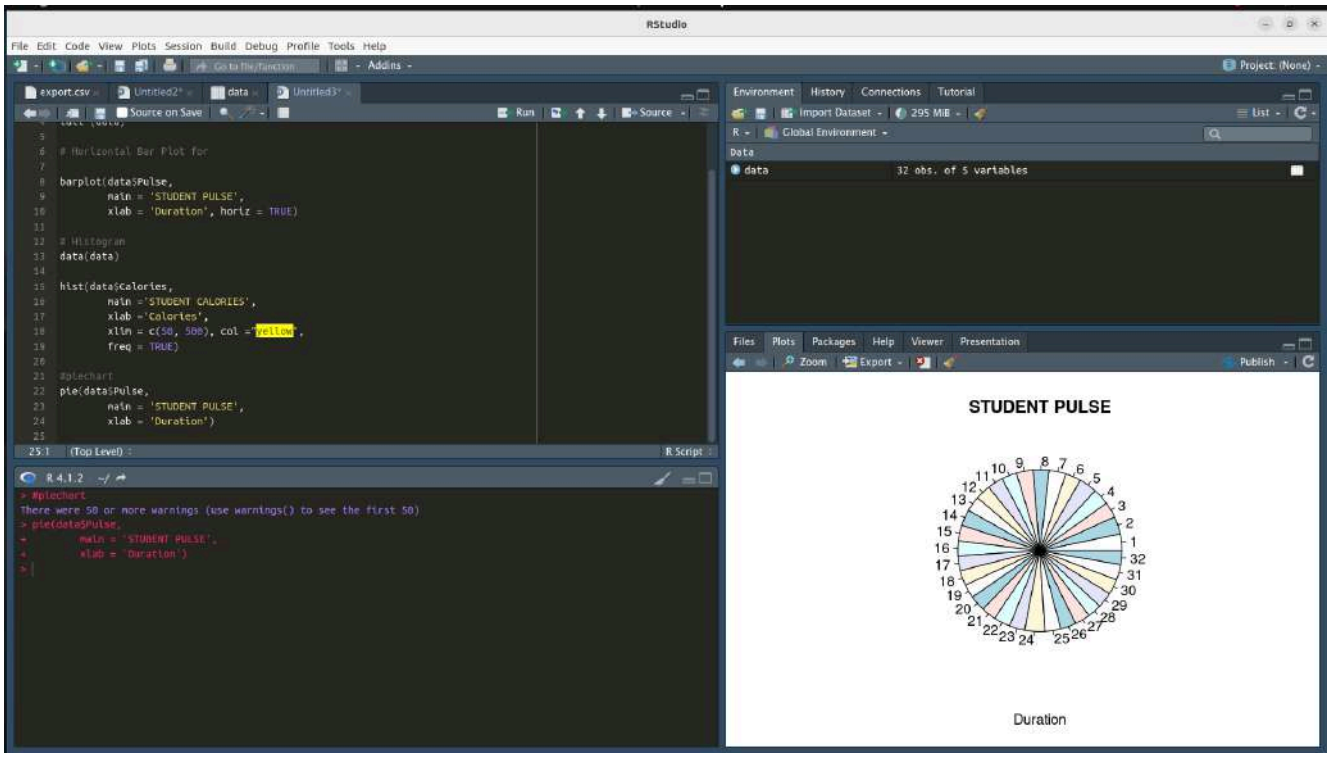
- **Importing dataset**



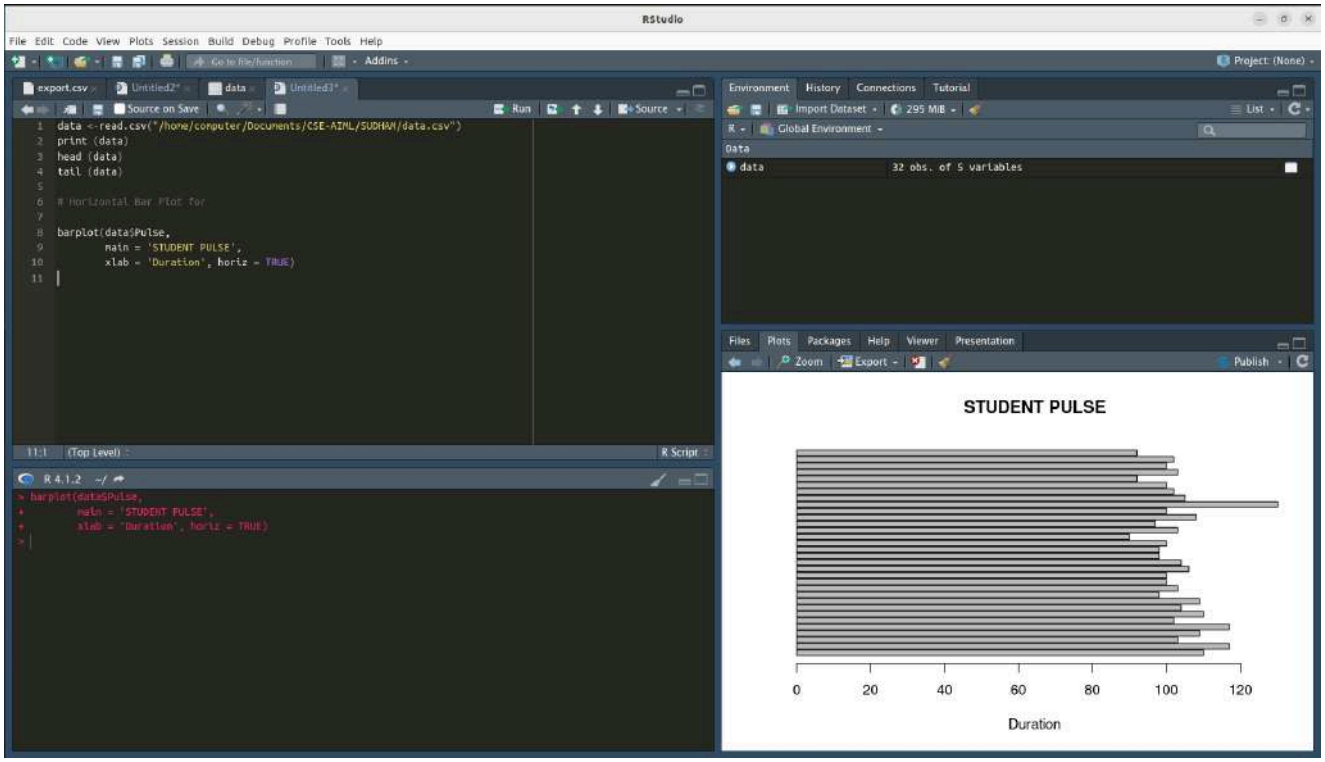
- **Getting quick overview**



- **Pie-Chart Visualization in R**



- **Bar-Chart Visualization in R**



Pandas - Histogram :

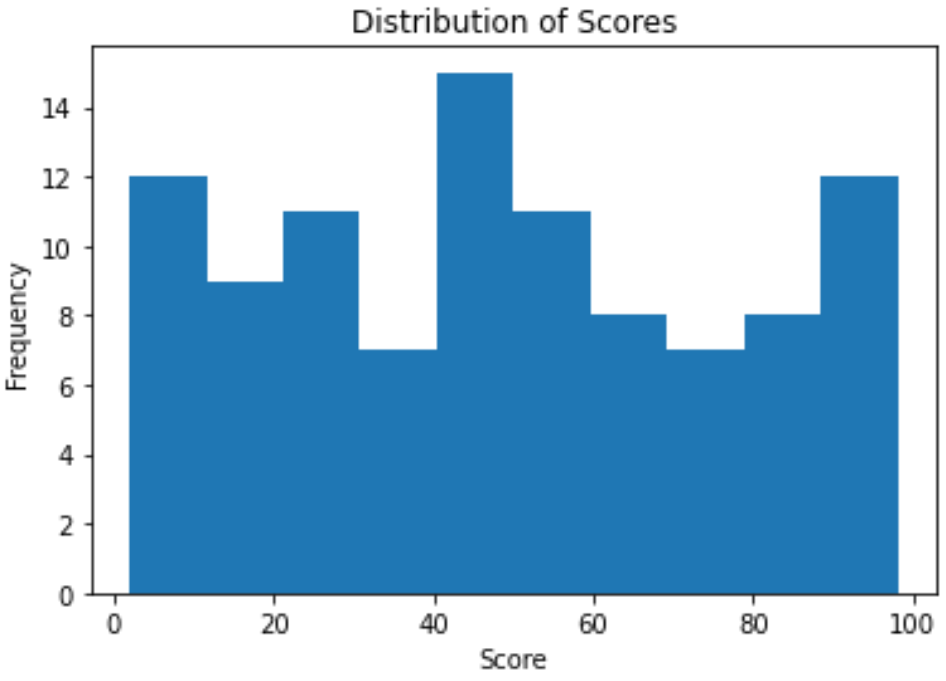
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Generate random data
data = pd.DataFrame({
    'scores': np.random.randint(0, 100, size=100)
})

# Create a histogram of the data
plt.hist(data['scores'], bins=10)

# Set the title and axis labels
plt.title('Distribution of Scores')
plt.xlabel('Score')
plt.ylabel('Frequency')

# Display the plot
plt.show()
```



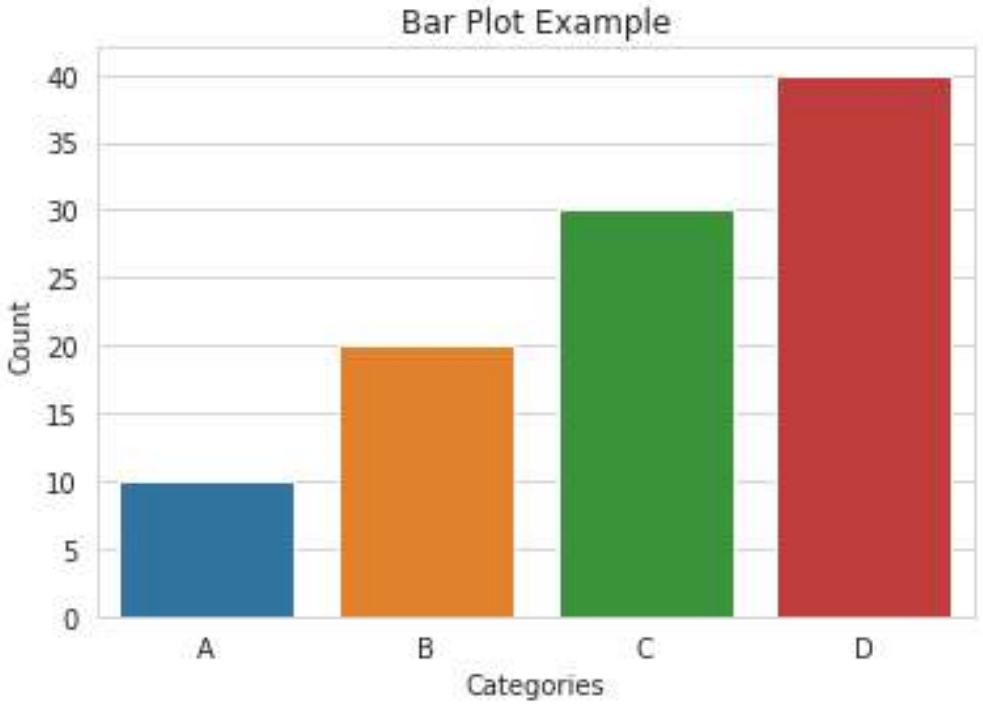
Program :
Seaborn - barplot :

```
import seaborn as sns
import matplotlib.pyplot as plt

# Define your data
x = ["A", "B", "C", "D"]
y = [10, 20, 30, 40]

# Create a Seaborn bar plot
sns.set_style("whitegrid")  # Set the plot style
sns.barplot(x=x, y=y)  # Create the bar plot
plt.xlabel("Categories")  # Set the x-axis label
plt.ylabel("Count")  # Set the y-axis label
plt.title("Bar Plot Example")  # Set the plot title
plt.show()  # Display the plot
```

Output :



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Year :- TE Subject :- Data Analytics and visualizatn (DAV)

Topic :- Assignment No. 01

Sign :- Prathy Date :- February '23

Q.1. What is Data Analytics and life cycle

Data analytics is the process of extracting insights and meaningful information from data using various analytical and statistical techniques. It involves collecting, processing, analyzing and visualizing data to gain insights & make informed decisions. The data analytics life cycle is designed for Big data problems and data science projects. The cycle is iterative to represent real project. It refers various stages involved in data analytics process, from identifying problems to implementing & monitoring the solution.

Explain all phases of Data Analytics and life cycle.

phase 1 : Discovery -

- Data science team learn and investigate the problem
- Develop context and understanding
- data resources needed & available for project will know to get.

phase 2: Data preparation -

- Steps to explore, preprocess and condition data prior to modeling.
- requires presence of an analytic sandbox, team execute, load and transform, to get data in to the sandbox.
- Several tools commonly used : Hadoop, Alpine Miner, Open refine, etc..

phase 3: Model planning -

- Team explores data to learn about relationship blw variables and subsequently, selects key variables & most suitable models.
- Team builds & execute models based on work done in model planning.
- Several tools commonly used for this phase are - Matlab, Statistica.

phase 4 : Model Building -

- Team develops datasets for testing, training & production purposes.
- free or open-source tools - Rand PL/R, Octave, WEKA
- commercial tools - Matlab, STASTICA.

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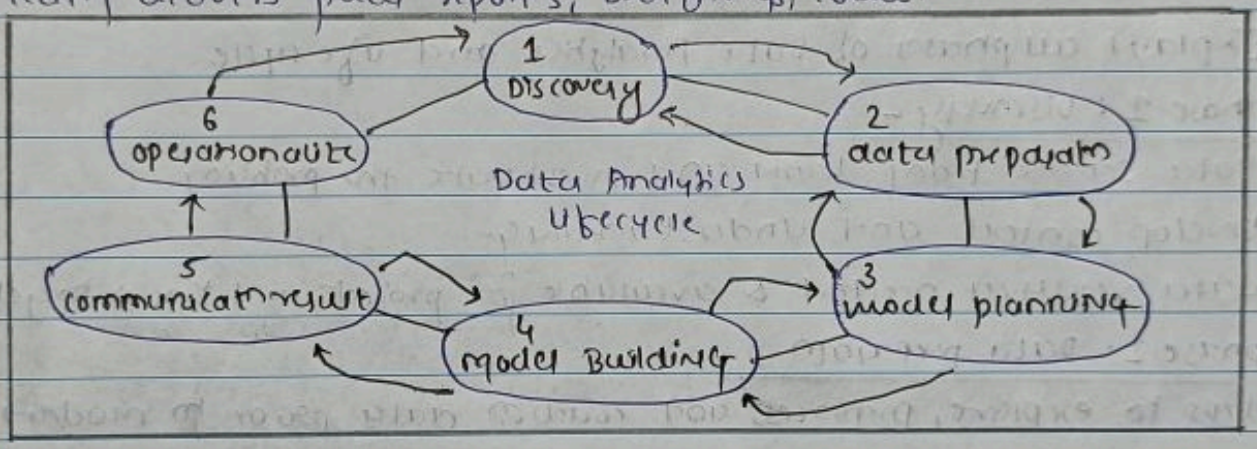
phase 5: communicate Results -

- After executing model team need to compare outcomes of modeling to criteria established for success and failure.
- Team considers how best to articulate findings & outcomes to various team members & stakeholders, taking into account warnings, assumptions.

phase 6: operationalize -

- The team communicate benefits of project more broadly and sets up pilot project to deploy work in controlled way before broadening the work to full enterprise of users.
- Team delivers final reports, briefings, codes.



Q.2. what is sandbox

A sandbox in data Analytics refers to a secure and isolated environment where data scientists and analysts can perform experiments & test new solutions w/o affecting the production environment.

why we use sandbox in Data Analytics?

There are several reasons why sandboxes are used in Data analytics

1] Experimentation: sandboxes provide a safe environment for data scientists and analysts to experiment with new tools and techniques without affecting the production environment.

2] Data protection: Sandboxes ensure that the production data is protected from accidental or unauthorized changes. Analysts can reduce the

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risk of data breaches or unauthorized access.

3) collaboration: sandboxes allow multiple data analysts and scientists to work on the same data set without interfering with each other's work. They can share their findings, workflows, & models with each other.

4) Training: sandboxes provide a safe environment for data analysts and scientists to learn and practise new skills.

Overall, sandboxes are a critical component of data analytics environments. They provide a secure and isolated environment for experimentation, collaboration, training and data protection.

Q.3. What is the difference between ELT and ETL?

Ans:-	ETL	ELT
definition	Data is extracted from a source system, transformed on a secondary processing servers, and loaded into a destination system.	Data is extracted from a source system, loaded into a destination system, & transformed inside the destination system.
Extract	Raw data is extracted using API connectors	Raw data is extracted using API connectors
Transform	Raw data is transformed on a processing server	Raw data is transformed inside the target system.
Load	Transformed data is loaded into a destination system	Raw data is loaded directly into the target system.
privacy	pre-load transformation can eliminate PII (helps for HIPPA)	Direct loading of data requires more privacy safeguards.
Maintenance	Secondary processing server adds to Maintenance burden	With fewer systems, the maintenance burden is reduced.
Costs	Separate servers create cost issues.	Simplified data stack costs less.
Data output	Structured (typically)	Structured, semi-structured and unstructured.

Q.4. Explain the data preparation phase of data analytics life cycle in details.

Ans:- The data preparation phase is a critical part of the data analytics life cycle. In this phase, the data is collected, cleaned, transformed, and prepared for analysis. Steps involved in this are as follow:

1) Data collection: First step is to collect the data from various sources, includes databases, data warehouses, data lakes & external sources such as APIs and social media platforms.

2) Data cleaning: Once the data is collected, it needs to be cleaned to remove any errors, inconsistencies, or duplicates. process involves identifying missing data, invalid values & outliers & correcting or removing them.

3) Data integration: After cleaning the data, the next step is to integrate the data from multiple sources into a single data set. involves identifying common attributes or keys that can be used to join the data sets.

4) Data transformation: The data may need to be transformed to make it suitable for analysis. This involves converting data into common format, aggregating & creating new variables to analysis.

5) Data sampling: Depending on the size of data set, it may be necessary to sample a subset of the data to reduce the processing time and memory requirements.

6) Data Reduction: In some cases, data set may be too large to process or analyze. In such cases, the data can be reduced by aggregating the data at higher level or using techniques further analysis.

7) Data formatting: Finally, the data needs to be formatted for the analysis. This involves converting the data into a format that can be processed by analytical tools and platforms.

Overall, the data preparation phase is critical to success of any data analytics project. The quality and suitability of the data for analysis will determine the accuracy and relevance of the insights which were derived from it.

Q.5. What is regression analysis?

Regression analysis is a statistical method used to analyze the relationship between a dependent variable and one or more independent variables. The goal of regression analysis is to model the relationship b/w the variables and use the model to make predictn or understand the impact of one variable on another.

Explain its types.

1) Simple Linear Regression: This type of regression involves modelling the relationship b/w a dependent variable & a single independent variable

2) Multiple Linear Regression: Multiple linear regression is used when there are multiple independent variables that are hypothesized to have an impact on the dependent variable.

3) Polynomial Regression: Polynomial regression is used when the relationship b/w the dependent & Mdependent variables is not linear.

4) Logistic Regression: Logistic regression is used when the dependent variable is binary. (0 or 1). It models the probability of the dependent variable taking on particular value based on the independent variables.

5) Ridge Regression: Type of regression that is used when there is multicollinearity (high correln) among the independent variables.

6) Lasso Regression: Lasso regression is similar to ridge regression but uses a different penalty term that results in a more sparse model.

In summary, regression analysis is a powerful statistical model used to model the relationship b/w variables and make predictn or understand impact of one variable on another.

Q.6. What is least square method?

The least square method is a mathematical technique used to find the best fit line or curve for a set of data points. It involves finding the line or curve that minimizes the sum of the squared differences

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between the observed data points and the predicted values. Commonly used in regression analysis to estimate coefficients of regression equation.

Formula: for eqn $(y = mx + b)$

$$m = \frac{\Sigma (x_i - x)(y_i - y)}{\Sigma (x_i - x)^2} \qquad b = y - mx$$

where: m is slope ; x mean of independent variable
b is y-intercept ; y mean of dependent variable
x_i is value of independent variable (x) for ith data point
y_i —1— (y) for ith data point

Explain with example.

To illustrate, consider following example,

Suppose we have a dataset that contains no. of hours studied (x) & the corresponding exam score (y) for a group of students. We want to find eqn of line that best fits data & can be used to predict exam score based on the no. of hours studied.

Hours studied (x)	2	3	4	5	6
Exam score (y)	60	70	80	90	100

Soln:- using least square methods, we can find eqn of line that best fits the data by calculating slope and y-intercept.

$x = (2+3+4+5+6)/5 \Rightarrow 4$ & $y = (60+70+80+90+100)/5 \Rightarrow 80$

$\Sigma (x_i - x)(y_i - y) = (2-4)(60-80) + (3-4)(70-80) + (4-4)(80-80) + (5-4)(90-80) + (6-4)(100-80)$

$= 200$ $\Sigma (x_i - x)^2 = (2-4)^2 + (3-4)^2 + (4-4)^2 + (5-4)^2 + (6-4)^2$

$= 10$

$m = \Sigma (x_i - x)(y_i - y) / \Sigma (x_i - x)^2 = 200/10 \Rightarrow 20$

$b = y - mx \Rightarrow 80 - 20(4) \Rightarrow -20$

∴ the eqn of line that best fit data is $y = 20x - 20$, we can use this eqn to predict exam score based on no. of hours studied.

Q.7. What is cross validation?

1) Cross validation is a technique used in machine learning and data analysis to evaluate the performance of model and ensure that it is not overfitting and (or) underfitting the data.
2) It involves dividing the dataset into two or more subsets, where one subset is used to train the model and the remaining subset(s) are used to test the models performance.
3) The most commonly used form of cross-validation is k-fold cross-valdn. where the dataset is divided into k-equal sized subsets or folds.
4) The model is then trained on k-1 folds & tested on remaining fold.
5) This process is repeated k-times, each fold serving as test set once.
6) Cross validation is an important technique in machine learning because it allows us to evaluate the performance of a model on unseen data & estimate how well it will generalize to new data.
7) It also helps to prevent overfitting, where the model performs well on the training data but poorly on a new data.

Q.9. What is the purpose of Matplotlib?

Matplot is a python library that is used for data visualization. It provides a variety of graphs and charts for displaying data in a clear and concise manner. The purpose of matplotlib is to help analysts and data scientists to create visualization that can be effectively communicate insights & trends hidden within the data.
matplot is a python library used for creating static, animated, and interactive visualization in python.

Q.8. How to plot Histogram and Box plot in python using matplotlib?

Here's an example code snippet to plot histogram using matplotlib in python.

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```
import matplotlib.pyplot as plt
import numpy as np
x = np.random.normal(0,1,size=1000)  # Create random dataset
plt.hist(x, bins=30)  # plot histogram
plt.xlabel('values')
plt.ylabel('frequency')
plt.title('Histogram Example')
plt.show()
```

In this example, we generate a random dataset using Numpy's random.normal() function, which generates a set of normally distributed values. We then plot histogram of these values using matplotlib's hist() function, which taken data as first argument & the no. of bins as second argument. We also add labels to the x and y axes, a title to the plot, and display the plot using the show() funcm.

To plot a box plot in python using matplotlib, we can use boxplot() funcm

Here an example code snippet:

```
import matplotlib.pyplot as plt
import numpy as np
x = np.random.normal(0,1,size=1000)  #create random dataset
plt.boxplot(x)  # plot a box plot
plt.xlabel('value')
plt.ylabel('frequency')
plt.title('Box plot')
plt.show()
```

In this example, we generate using Numpy's random.normal() funcm dataset. We then plot box plot of this values using matplotlib's boxplot() funcm. We also add labels to the x and y axes, a title to the plot, and display the plot using show() function.

Q.10. Explain the following libraries of python.

A) pandas :- pandas is a python library used for data manipulation and analysis. It provides data structures for efficiently storing and manipulating labelled data, such as data frames & series. It provides a fast and efficient way to manipulate large & complex datasets, making it a popular tool for data scientists and analysts. panday provides functn for reading and writing data in various file formats, including csv, Excel, and SQL databases. It also provides a wide range of functn for filtering, transforming, and aggregating data. panday is often used in conjunctn with other libraries such as Numpy & matplotlib to perform & data analysis and for visualizatn tasks.

B) Numpy :- Numpy is a python library used for scientific computing and data analytics. It provides a powerful N-dimensional array object that can be used to store and manipulate large datasets efficiently. Numpy provides a wide range of mathematical functn for performing operatn such as linear algebra, fourier transforms, & random number generation. It also provides functn for reading and writing data in various file formats, including csv & binary formats. Numpy is often used in conjuctn with other libraries such as panday & matplotlib to perform data analytics & visualizatn tasks.

C) SeaBorn :- Seaborn is a python library used for data visualizatn. It provides a high-level interface for creating attractive & informative statistical graphics. seaborn provides a wide range of visualizatn functn for displaying relationship blw variables, including scatter plots, line plots, heatmaps, & distribution plots. It also provides functn for visualizing statistical models such as regression and classification models. seaborn is

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often used in conjuction with other libraries such as pandas and matplotlib to perform data analysis and visualization tasks. Seaborn is known for its ability to create visually stunning and informative graphics with minimal code.

Q.11. Write a program to plot pie-chart in python using matplotlib.

```
from matplotlib import pyplot as plt  #import libraries
import numpy as np
cars = ['Duster', 'BMW', 'Mercedes', 'Tesla']  #creating dataset
data = [23, 17, 24, 12]
fig = plt.figure(figsize = (10, 7))  #creating plot
plt.pie(data, labels = cars)  #show plot
plt.show()
```

Q.12. Explain key roles for a successful analytics.

A successful analytics project involves various roles and responsibilities that contribute to its success. Some of keys roles for a successful analytics project are:

1) Business Analyst: A business analyst is responsible for understanding the business objectives, defining requirements and translating them into analytics goals.

2) Data Scientist: A data scientist is responsible for identifying the right data sources, cleaning & preprocessing the data, applying statistical models, & creating predictive models that provide insights into the data.

3) Data Engineer: A data engineer is responsible for building and maintaining the infrastructure that supports the analytics project. They ensure that the data is stored securely, processed efficiently, and made available to data scientists in a timely manner.

4) Visualization Expert: A visualization expert is responsible for creating

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visualization that communicate the insights and findings from the data in a clear and consise manner.

5) Project Manager: A project manager is responsible for managing the analytics project from start to finish. They ensure that the project is delivered on time, within budget, and to satisfaction of stakeholders.

6) Domain Expert: A domain expert is someone who has a deep understanding of the business domain in which the analytics project operates. They provide insights and guidance to the data scientists and business analysts on how to interpret the data & apply it to business problems.

Overall, successful analytics projects require collaboration & communication blw these various roles to ensure that the project meets the business objectives, is technically sound, and provide actionable insights to the available stakeholders.

Q.13 Explain the following terms;

A) Residuals :- Residuals are the differences blw the observed values and the predicted values from a statistical model. In other words, they are the errors of the model. Residuals are used to check the goodness of fit of a model, & they should ideally be randomly distributed around zero with no pattern.

B) fitted value : fitted value, also known as predicted value, is the value predicted by a statistical model for a particular input or observation. It is obtained by applying the model to the input data. The fitted values can be compared to the actual values to evaluate the accuracy of the model.

---

c) overfitting : overfitting is a situation where a statistical model is too complex and captures noise or random fluctuation in the data, instead of

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the underlying pattern or relationship. overfitting occurs when a model is trained too well on the training data, such as result, it peyforms poorly on new, unseen data. Overfitting can be reduced by simplifying the model, using regularization techniques, or using more data for the training.

D) Underfitting: Underfitting is a situation where a statistical model is too simple and does not capture the underlying pattern or relationship in the data. Underfitting occurs when a model is not trained well enough on the training data, and as a result, it performs poorly on both training data and new, unseen data. Underfitting can be reduced by increasing the complexity of the model, adding more features or using more data for training.

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Q.1. What is Text mining?

⇒ Text mining is the process of extracting useful information or knowledge from unstructured text data. Unstructured text refers to any text data that is not organized in a predefined manner, such as emails, social media posts, news articles & customer reviews.

> The goal of text mining is to convert this unstructured data into structured data that can be analyzed and used to make data-driven decisions.

How to extract meaning from unstructured text:

There are several techniques that can be used to extract meaning from unstructured text. These includes;

> ① Text preprocessing: This involves cleaning and preparing the text data for analysis. Involves removing noise and any from the text.

> ② Text classification: Involves categorizing text data into predefined categories based on their content.

> ③ Sentiment analysis: This involves identifying the sentiment expressed in the text, data. Involves techniques like ML algorithms.

> ④ Named Entity Recognition: Involves identifying & categorizing names entities in the text data, such as people, organizations & locations.

> ⑤ Topic modeling: This involves identifying the underlying topics or themes in the text data. Involves techniques like LDA or NMF.

> Overall the goal of text mining is to transform unstructured text data into structured data that can be analyzed to gain insights & make data-driven decisions.

Q2. Explain Term frequency-Inverse Document frequency (TF-IDF) in detail.

⇒ Term frequency-Inverse Document frequency (TF-IDF) is a statistical measure used to evaluate the importance of word in document or a corpus (collection of documents). The method is widely used in information retrieval, text mining and natural language processing to determine the

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relevance of a document to a given query.

TF-IDF is components: term frequency & inverse document frequency.

⇒ ① Term frequency: TF measures how frequently a term appears in a document. It is calculated by counting the number of times a term appears in a document and dividing by the total no. of terms in the document. Formula for calculating TF is as follows:

- TF = $\frac{\text{No. of times the term appeared in a document}}{\text{Total no. of terms in document}}$

> for eg:- suppose we have document containing 100 words, and the word "computer" appears 5 times. Then the term frequency of "computer" in the document would be 0.05.

⇒ ② Inverse-document frequency: IDF measures how rare or common a term is across all document in a corpus. It is calculated by dividing the total no. of documents in the corpus by no. of documents that contain term, & then taking the algorithm logarithm of result. formula is;

- IDF = $\log_e \frac{\text{(total no. of documents in the corpus)}}{\text{No. of documents containing term}}$

> for eg:- suppose we have corpus containing 1000 documents, & the word "computer" appears in 100 documents. Then the inverse document frequency of "computer" in corpus would be $\log_e(1000/100) \Rightarrow 2$.

> Once we have both TF & IDF, we can calculate TF-IDF score, by TF * IDF: **TF-IDF = TF * IDF**.

> for example, for above problem this would be $0.05 * 2 = 0.1$

> The higher the TF-IDF score of a term in a document, the more important the term in the document. This is because the TF-IDF score reflects both frequency of the term in document & rarity of term in corpus.

Q3 what are the applicatn of text mining

- Text mining, also known as text analytics, is a process of extracting valuable information from unstructured or semi-structured text data.
- Here are some common applicatn of text mining:
  - > Analyzing open-ended survey responses.
  - > In review research, it is not unusual to include a variety of open-ended questn related to the topic under analysis.
  - > The idea is to allow respondent to state their views of opinions w/o restricting them to particular dimension or particular response.
  - > Automatic processing of messages, emails, etc.
  - > Analyzing warranty or insurance claims, diagnostic interviews, etc.
  - > In some business domains, the most of the information is gathered in open-ended, textual form.
  - > Investigating competitors by crawling their web sites.
  - > Another type of possibly very helpful applicatn is to automatically process the contents of web pages in a particular domain.

Q4. How can you summarize and analyze data using descriptive statistics in R?

- Descriptive statistics is a branch of statistics that deals with summarizing and analyzing data using quantitative measures such as measures of central tendency, variability and shape.
- R is a popular programming language for statistical analysis, and it provides many built-in functn for computing descriptive statistics.
- Here are some steps for summarizing & analyzing data using the descriptive statistics in R:
  - > (1) Import the data into R: R supports many different data formats, including csv, Excel and SQL database. You can use read.csv() functn.
  - > (2) Calculating measures of central tendency: Measure of central tendency

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such as mean, median and mode, provide information about the typical value of variable. functn - mean(), median(), mode()

> ③ Calculate measure of variability: such as standard deviation, variance and range. functn - sd(), var() and range() to calculate each.

> ④ plot the data: visualization is an important step aspect of data analysis and R provides many functn for creating different types of plot. functn - plot() to create scatterplot(), histogram() or boxplot() & so on..

> ⑤ Identify outliers: outliers are extreme values that lie outside typical range of variable. functn - boxplot() to identify outliers in dataset.

> ⑥ calculate correlation coefficients: measure strength & direction of relationship btw two variables. can use the cor() functn.

> ⑦ conduct hypothesis tests: statistical method for testing whether a hypothesis about population is true. It includes t-test(), chi-square test() and the ANOVA().

> Overall, R provides powerful set of tools for summarizing & analyzing data using descriptive statistics. This helps insight of your data and make informed decisions based on results of your analysis.

---

05 How do you check the attributes & data types of variables in R.

- In R, you can check the attributes & data types of variables using various built-functn. Some commonly used functn are,

> ① str(): Displays the structure of R object, including its type, length. for eg:- to check my_var, type str(my_var) in R console.

> ② class(): returns class of an R object, eg:- class(my_var)

> ③ typeof(): returns type of R object, such as integer, numeric, character or logical. for eg:- typeof(my_var)

> ④ attributes(): returns attributes of an R object, such as names, levels and dimensions. for eg:- attributes(my_var)

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> ⑤ is.na() : returns a logical vector indicating whether each element of an R object is missing or not. for eg:- is.na(my_var) in R console.

> ⑥ summary() : Returns summary of statistical properties of R object, such as maximum(), mean() & quantile() for eg:- summary(my_var)

> By using above function, you can easily check the attributes & data types of variables in R and ensure that they are compatible with operators & function you want to apply to them.

Q6 What is the difference b/w a factor & a character data type in R.

	Factor	character
①	Represents a categorical variable with a limited set of values or categories	Represents a variable with one or more characters or string.
②	Encoded as integers, with each integer representing a specific level or category.	Encoded as a sequence of characters
③	supports ordering of levels or categories	Doesn't support ordering of characters or strings.
④	useful for statistical analysis and modeling	useful for storing textual data or information.
⑤	can be converted to a character data type using as.character()	can be converted to a factor data type using as.factor()
⑥	Example: factor(c("red", "green"))	Example: c("Monu", "Babbu")
⑦	Example levels: "red", "green"	Example characters: "m", "o", "n", "u"

Q7 Write a short notes on the following:

a) Dirty Data:

Dirty data is a term used to describe data that contains errors or inconsistencies that can affect the accuracy and reliability of the

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analysis. Dirty data can arise from various sources such as human error, system errors, data entry errors, or software bugs. It is essential to identify and clean the dirty data before performing any analysis to ensure that the results obtained are accurate & reliable. The process of cleaning the dirty data is known as data cleaning or data cleansing, & it involves detecting & correcting errors in the data.

b) Visualizing single variable:

Visualizing a single variable is the process of creating a graphical representation of a single variable to understand its distribution & characteristics. This type of visualization is useful for exploring the central tendency, spread and shape of the distribution. Common techniques for visualizing a single variable include histograms, boxplots, density plots & bar charts. Histograms are used to represent the frequency distribution of a variable by dividing the data into bins and counting the no. of observations in each bin. Boxplots display the distribution of a variable through five summary statistics: minimum, maximum, median & first / third quartile.

c) Examining multiple variables:

Examining multiple variables involves exploring the relationships & dependencies b/w two or more variables in a dataset. This type of analysis is useful for identifying patterns, trends & correlations b/w the variables. Common techniques for examining multiple variables include scatter plots, correlation matrices, heatmaps, and pair plots.
Scatter plots are used to visualize the relationship b/w two continuous variables, where each point represents an observation in the dataset. correlation matrices show the correlation coefficient b/w all pairs of variables in the dataset. Heatmaps display the correlation matrix as a color-coded matrix, where color intensity indicates strength of correlation.

Q8 What is the difference b/w data exploration & data presentation.

Aspect	Data Exploration	Data presentation
Objective	To understand the data, identify patterns and relationships, and formulate hypotheses	To communicate insight & findings obtained from the data analysis to an audience.
Activities	Cleaning, preprocessing, summarizing and visualizing data.	Selecting appropriate charts, tables & graphs and presenting the insight in a clear manner.
Tools and techniques	Statistical & computational methods such as clustering, regression and hypothesis testing.	Data visualization tools such as charts, graphs and tables.
Audience	Typically the data analyst or the data scientist	The broader audience, which may include decision-makers, stakeholder & non-technical people.
output	Insights, finding & hypothesis about the data	Reports, dashboards, presentation & other visual representation of insight and findings.

Q9 Write program to plot following:

a) histogram:

```
import matplotlib.pyplot as plt
import numpy as np
data = np.random.normal(size=1000)   # Generate random data.
plt.hist(data, bins=300)             # Create the histogram
plt.xlabel('values')                 # add labels
plt.ylabel('frquency')               # add label
plt.title('Histogram')               # add title
plt.show()                           # display the plot
```

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b) Bar chart:

```
import matplotlib.pyplot as plt
values = [23, 45, 56, 12, 67]          #define data
labels = ['A', 'B', 'C', 'D', 'E']
plt.bar(labels, values)                #Create the bar chart
plt.xlabel('categories')               #add labels and title
plt.ylabel('values')
plt.title('Bar chart')
plt.show()                             #display the plot
```

c) Boxplot:

```
import matplotlib.pyplot as plt
import numpy as np
data = np.random.normal(size=1000)     #generate some random data
plt.boxplot(data)                      #Create boxplot
plt.xlabel('values')                   #add labels
#plt.ylabel('Boxplot')
plt.title('Boxplot')                   #add title
plt.show()                             #display the plot
```

d) Line plot:

```
import matplotlib.pyplot as plt
import numpy as np
x=np.linspace(0,10,100)                #Generate some random data
y=np.sin(x)
plt.plot(x,y)                          #Create the line plot.
plt.xlabel('x values')                 #add label
plt.ylabel('y values')
plt.title('line plot')                 #add title
plt.show()                             #display plot
```

in R language :

a) Histogram

```
data ← rnorm(1000)          # generate some random data
hist(data, breaks = 30)     # Create histogram
xlabel ← "values"           # add label
ylabel ← "frequency"
title ← "Histogram"         # add title
title(main = title, xlab = xlabel, ylab = ylabel)
```

b) bar chart

```
values ← c(23, 45, 56, 12, 67)      # define data
labels ← c('A', 'B', 'C', 'D', 'E')
barplot(values, names.arg = labels)  # Create bar chart
xlabel ← "categories"                # add label
ylabel ← "values"
title ← "Bar chart"                  # add title
title(main = title, xlab = xlabel, ylab = ylabel)
```

c) Box plot

```
data ← rnorm(100)           # generate random data
boxplot(data)               # Create box plot
xlabel ← "values"           # add label
#ylabel ← "freq"
title ← "Boxplot"           # add title
title(main = title, xlab = xlabel), # title
```

d) line plot

```
x ← seq(0, 10, length.out = 100)   # Generate random data
y ← sin(x)
```

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```
plot(x, y, type = "l")          # create line plot
xlabel ← "x values"             # add xlabel
ylabel ← "y values"             # add ylabel
title ← "line plot"             # add title
title(main = title, xlab = xlabel, ylab = ylabel)
```

Q10 Explain all steps of text analysis in detail.

- The process of transforming unstructured text in documents into structured data which can be used for analysis, is text analysis.
- The steps involved in analyzing an unstructured text documents are:

> ① Language identification: The first step is to identify language text is written. Language identification is a major and main process for any text analytics function because each language has its own sets of grammar and peculiar syntax. Thus, it is noteworthy.

> ② Tokenization: process of breaking down the sentence into small pieces. Thus Tokens are words, numbers or punctuation in a sentence.

> ③ Sentence Breaking: Small texts like status contain only single sentence many of time. But huge, large document require to separate.

> ④ part of speech tagging: Pos determining the part of speech of every token in document & then tagging it. Indicate noun, adverb, etc..

> ⑤ chunking: refer to range of sentence breaking system that fragment a sentence into its component phrases (verb, noun and so on).

> ⑥ syntax parsing: process determines how sentence is formed. It is very crucial step. Also most computationally-intensive step in text analytics.

> ⑦ sentence chaining: final step for linking individual sentence. It basically tries to make connection.

11 Explain all the components of time series:

Analyst must take complex models.

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- I. Modes of time series also includes:
  ① classificatn: identify and assign categories
  ② Curve-fitting: data is being plotted along curve to study relationship
  ③ Explanative analysis: attempts to understand data and relationship within it.
  ④ Descriptive analysis: identifies patterns in time series data like trends, cycle..
  ⑤ Explorative analysis: Highlights the main characteristics of time series data.
  ⑥ Intervention analysis: Studies how an event can change the data.
  ⑦ segmentatn: splits data into segments to show underlying property.
- II. Data classificatn:
  ① stock time series data: Inputs measuring attributes at certain points.
  ② flow time series data: Measures activities of attributes over certain period.
- III. Data variatn:
  ① functional analysis: pick pattern & relationship to identify notable events.
  ② Trend analysis: Determine consistent movement - i) Deterministic; ii) stochastic...
  ③ Seasonal variatn: describe event that occur at specific & regular intervals.

Q12 How to export and import data in R-language?

> Commonly used methods are:

- Importing data: Easiest way - Simple txt file (for small/medium prob.)
  ① CSV file: To import a CSV file called mydata.csv into R
  code ← mydata ← read.csv("mydata.csv", header = TRUE)
  ② Excel file: mydata ← read_excel("mydata.xlsx", sheet = "sheet1")
  ③ other formats: JSON, XML and SQL DB by using specific packages.
- Exporting Data: less continuous task, but still no. of pitfalls. (Target app)
  ① CSV file: write.csv(mydata, "mydata.csv", row.name = FALSE)
  ② Excel file: Library(xlsx) - to export file called mydata.xlsx.
  write.xlsx(mydata, "mydata.xlsx", sheetName = "sheet 1", row.name = FALSE)
  ③ other formats: JSON, XML & SQL DB by using specific packages.

> Straightforward process that can done using built-in functn or packages.

Q13 How to perform Exploratory Data Analysis in R language?

- First step of data Analysis
- involves exploring dataset in three ways:
  - (1) summarizing a dataset using descriptive statistics.
  - (2) visualizing a dataset using charts.
  - (3) Identifying missing values.
- easiest way to perform → function from the tidyverse package.
- following step-by-step to perform EDA:

> **Step 1: load & view the data:**

first step in EDA is to load the data into R. you can use function like read.csv() or read.table() to load data from file.

> **Step 2: Summarize the data:**

once the data is loaded, it's important to understand or summarize structure of data, including dimension, data types & summary statistics. function like - dim(); str(), head(), summary() to overview of data.

> **Step 3: visualize the Data:**

Important aspect of EDA, which helps to identify patterns & relationship in the data. You can package like ggplot2, plotly & lattice to create wide range visualize, including scatterplot, histograms, timeseries...

> **Step 4: Identify missing values:**

Often our data can have missing value due to variety of reasons. Important that we should analyze our data & get sense of what missing value are so we can decide how we want to handle missing values.

Q12 continued ⇒ Function of importing & exporting

Importing data	Exporting data
(1) CSV file: read.csv() or read.table()	(1) CSV files: write.csv() or write.table()
(2) Excel file: read.xl package (xlsx)	(2) Excel file: xlsx package (.xlsx).