Practical 1

Aim: Write a python program to plot word cloud for a wikipedia page of any topic.

Code:

```
from wordcloud import WordCloud,
STOPWORDS
import matplotlib.pyplot as plt
import wikipedia as wp

result = wp.page('Computer Science')
final_result = result.content  print(final_result)

def plot_wordcloud(wc):
plt.axis("off")
plt.figure(figsize=(10,10))
    plt.imshow(wc)
    plt.show()

wc=WordCloud(width=500, height=500, background_color="blue",
random_state=10,stopwords=STOPWORDS).generate(final_result)
wc.to_file("cs.png")
plot_wordcloud(wc)
```

Output:

```
Computer science is the study of computation, information, and automation. Computer science spans theoretical disciplines (su
ch as algorithms, theory of computation, and information theory) to applied disciplines (including the design and implementat
ion of hardware and software). Though more often considered an academic discipline, computer science is closely related to co
mputer programming.Algorithms and data structures are central to computer science.
The theory of computation concerns abstract models of computation and general classes of problems that can be solved using th
em. The fields of cryptography and computer security involve studying the means for secure communication and for preventing s
ecurity vulnerabilities. Computer graphics and computational geometry address the generation of images. Programming language
 theory considers different ways to describe computational processes, and database theory concerns the management of repositor
ies of data. Human-computer interaction investigates the interfaces through which humans and computers interact, and software
engineering focuses on the design and principles behind developing software. Areas such as operating systems, networks and em
bedded systems investigate the principles and design behind complex systems. Computer architecture describes the construction
of computer components and computer-operated equipment. Artificial intelligence and machine learning aim to synthesize goal-o
rientated processes such as problem-solving, decision-making, environmental adaptation, planning and learning found in humans
and animals. Within artificial intelligence, computer vision aims to understand and process image and video data, while natur
al language processing aims to understand and process textual and linguistic data.
The fundamental concern of computer science is determining what can and cannot be automated. The Turing Award is generally re
cognized as the highest distinction in computer science.
```

Name of Instructor: Maya Nair

Practical 2:

Web scraping : Web scraping is the process of collecting and parsing raw data from the Web.

Aim: Write a python program to perform Web Scrapping

01.Html scrapping- use Beautiful Soup

Code:

```
import pandas as pd  from bs4
import BeautifulSoup  from
urllib.request import urlopen
url = "https://en.wikipedia.org/wiki/List_of_Asian_countries_by_area"
page = urlopen(url)  html_page = page.read().decode("utf-8")

soup=BeautifulSoup(html_page,"html.parser")
table=soup.find("table")
print(table)

SrNo=[]
Country=[]  Area=[]
rows=table.find("tbody").find_all("tr")
for row in rows:      cells =
row.find_all("td")      if(cells):
      SrNo.append(cells[0].get_text().strip("\n"))
      Country.append(cells[1].get_text().strip("\xa0").strip("\n").strip("\[2]*"))
      Area.append(cells[3].get_text().strip("\n").replace(",",""))
countries_df=pd.DataFrame()
countries_df["ID"]=SrNo  countries_df["Country
Name"]=Country
countries_df["Area"] = Area  print(countries_df.head(10))
```

Output:

```
<table class="sortable wikitable sticky-header col2left" style="text-align: center">
<tbody><tr>
<th></th>
<th>Country / dependency</th>
<th>%<br/>total</th>
<th>Asia area<br/>in km<sup>2</sup> (mi<sup>2</sup>)</th>
<th class="unsortable">
</th></tr>
<tr>
<td>1</td>
<td><span class="flagicon"><span class="mw-image-border" typeof="mw:File"><span><img alt="" class="mw-file-element" data-file
-height="600" data-file-width="900" decoding="async" height="15" src="//upload.wikimedia.org/wikipedia/en/thumb/f/f3/Flag_of_
Russia.svg/23px-Flag_of_Russia.svg.png" srcset="//upload.wikimedia.org/wikipedia/en/thumb/f/f3/Flag_of_Russia.svg/35px-Flag_o
f_Russia.svg.png 1.5x, //upload.wikimedia.org/wikipedia/en/thumb/f/f3/Flag_of_Russia.svg/45px-Flag_of_Russia.svg.png 2x" widt
h="23"/></span></span> </span><a href="/wiki/Russia" title="Russia">Russia</a></td>
<td>29.3%</td>
<td><span data-sort-value="7013130831000000000♠"></span>13,083,100 (5,051,400)</td>
<td><sup class="reference" id="cite_ref-3"><a href="#cite_note-3">[a]</a></sup>
</td></tr>
```

```
   ID  Country Name                 Area
0   1        Russia  13083100 (5051400)
1   2         China   9596961 (3705407)
2   3         India   3287263 (1269219)
3   4    Kazakhstan   2600000 (1000000)
4   5  Saudi Arabia    2149690 (830000)
5   6          Iran    1648195 (636372)
6   7      Mongolia    1564110 (603910)
7   8     Indonesia    1488509 (574717)
8   9      Pakistan     881913 (340509)
9  10        Turkey     759805 (293362)
```

02.json scrapping

Code:

import pandas as pd
import urllib.request import
json

url = "https://jsonplaceholder.typicode.com/users" response
= urllib.request.urlopen(url)
data = json.loads(response.read())

id=[] username=[]
email=[]

for item in data: if "id"
in item.keys():
id.append(item["id"])
else:
        id.append("NA")   if
"username" in item.keys():

```
username.append(item["userna
me"])      else:
       username.append("NA")
if "email" in item.keys():
       email.append(item["email"])
else:
       email.append("NA")

user_df = pd.DataFrame()
user_df["User ID"]=id  user_df["User
Name"]=username  user_df["Email
Address"] = email
print(user_df.head(10))
```

Output:

```
   User ID         User Name               Email Address
0        1              Bret           Sincere@april.biz
1        2         Antonette           Shanna@melissa.tv
2        3          Samantha          Nathan@yesenia.net
3        4          Karianne   Julianne.OConner@kory.org
4        5            Kamren    Lucio_Hettinger@annie.ca
5        6  Leopoldo_Corkery     Karley_Dach@jasper.info
6        7      Elwyn.Skiles       Telly.Hoeger@billy.biz
7        8     Maxime_Nienow        Sherwood@rosamond.me
8        9          Delphine      Chaim_McDermott@dana.io
9       10    Moriah.Stanton      Rey.Padberg@karina.biz
```

Practical 3:

Aim: Exploratory Data Analysis of mtcars.csv Dataset in R (Use functions of dplyr like select, filter, mutate , rename, arrange, group by, summarize and data visualizations) mtcars.csv:

Motor Trend Car Road Tests-The data was extracted from the 1974 Motor Trend US magazine, and comprises fuel consumption and 10 aspects of automobile design and performance for 32 automobiles (1973--74 models).

Format

A data frame with 32 observations on 12 (numeric) variables.

[, 1] mpg Miles/(US) gallon

[, 2] cyl Number of cylinders

[, 3] disp Displacement (cu.in.)

[, 4] hp Gross horsepower

[, 5] drat Rear axle ratio

[, 6] wt Weight (1000 lbs)

[, 7] qsec 1/4 mile time

[, 8] vs Engine (0 = V-shaped, 1 = straight)

[, 9] am Transmission (0 = automatic, 1 = manual)
[,10] gear Number of forward gears

[,11] Carb Number of carburetors

Motor Trend is a magazine about the automobile industry. Looking at a data set of a collection of cars, they are interested in exploring the relationship between a set of variables and miles per gallon (MPG) (outcome).

Code: #Do In

Rstudio

cars_df=read.csv("mtcars.csv")#read

View(cars_df) str(cars_df)

dim(cars_df) names(cars_df)

row.names(cars_df)

row.names(cars_df)=cars_df$model

cars_df=cars_df[,-1] View(cars_df)

library(dplyr)

#Select fuction - for extracting specific columns

#df1=select(cars_df,mpg:hp)

df1=cars_df %>% select(mpg:hp) #pipe of dplyr it will take out content of one column to the output of other column View(df1)

df1 = cars_df %>% select(c(mpg,disp,wt,gear))

View(df1)

#Filter function - for extracting specific rows or observation

#extract record where gears=4 and columns to be displayed are mpg, disp, wt and gears. df1 = cars_df %>% filter(gear==4) %>%
select(c(mpg,disp,wt,gear))

View(df1)

# extract record where cyl=4 or mpg>20 and columns are required are mpg,cl
df1 = cars_df %>% filter(cyl==4 | mpg > 20) %>% select(c(mpg,cyl))

View(df1)

#extract records where mpg<20 and carb = 3 and coumns needed are mpg and carb df1 = cars_df %>% filter(mpg < 20 & carb == 3) %>% select(c(mpg,carb))

view(df1)

Arrange function -Sort as per specific columns df1

=cars_df %>% arrange(cyl,desc(mpg))

View(df1)

#Rename function - change names of one or more column df1

= cars_df %>%

rename(MilesPerGallon=mpg,Cylinders=cyl,Displacement=disp)

View(df1)

#Mutate function - creating new columns on the basis of existing column df1

= cars_df %>% mutate(Power=hp*wt)

View(df1)

#Group_by and summaries - segregating data as per categorical variable and summarizing

df1$gear = as.factor(df1$gear) str(df1)

summary_df = df1%>% group_by(df1$gear) %>% summarise(no=n(), mean_mpg=mean(mpg), mean_wt=mean(wt)) summary_df

summary_df = df1%>% group_by(df1$Cylinders) %>% summarise(no=n(), mean_mpg=mean(mpg), mean_wt=mean(wt)) summary_df

#Data Visualization

#histogram - for single column frequency hist(df1$mpg,

main="Histogeam of

MilePergallon(mtcars)",col="lightgreen",xlab="Miles Per Gallon")

#box plot - diagrammatic representation of summary

summary(df1$mpg) boxplot(df1$mpg)

#bar plot - categorical variable representation'

table(df1$gear) barplot(table(df1$gear))

#scatter plot - plot() - plots relationship between two variable

plot(df1$mpg~df1$disp) plot(df1$mpg~df1$cyl)

plot(df1$mpg~df1$wt)

Output:

	model	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
1	Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
2	Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
3	Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
4	Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
5	Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2
6	Valiant	18.1	6	225.0	105	2.76	3.460	20.22	1	0	3	1
7	Duster 360	14.3	8	360.0	245	3.21	3.570	15.84	0	0	3	4
8	Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4	2
9	Merc 230	22.8	4	140.8	95	3.92	3.150	22.90	1	0	4	2
10	Merc 280	19.2	6	167.6	123	3.92	3.440	18.30	1	0	4	4
11	Merc 280C	17.8	6	167.6	123	3.92	3.440	18.90	1	0	4	4
12	Merc 450SE	16.4	8	275.8	180	3.07	4.070	17.40	0	0	3	3
13	Merc 450SL	17.3	8	275.8	180	3.07	3.730	17.60	0	0	3	3
14	Merc 450SLC	15.2	8	275.8	180	3.07	3.780	18.00	0	0	3	3

```
'data.frame':	32 obs. of  12 variables:
 $ model: chr  "Mazda RX4" "Mazda RX4 Wag" "Datsun 710" "Hornet 4 Drive" ...
 $ mpg  : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
 $ cyl  : int  6 6 4 6 8 6 8 4 4 6 ...
 $ disp : num  160 160 108 258 360 ...
 $ hp   : int  110 110 93 110 175 105 245 62 95 123 ...
 $ drat : num  3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
 $ wt   : num  2.62 2.88 2.32 3.21 3.44 ...
 $ qsec : num  16.5 17 18.6 19.4 17 ...
 $ vs   : int  0 0 1 1 0 1 0 1 1 1 ...
 $ am   : int  1 1 1 0 0 0 0 0 0 0 ...
 $ gear : int  4 4 4 3 3 3 3 4 4 4 ...
 $ carb : int  4 4 1 1 2 1 4 2 2 4 ...
[1] 32 12
 [1] "model" "mpg"   "cyl"   "disp"  "hp"    "drat"  "wt"    "qsec"  "vs"    "am"    "gear"
[12] "carb"
 [1] "1"  "2"  "3"  "4"  "5"  "6"  "7"  "8"  "9"  "10" "11" "12" "13" "14" "15" "16" "17" "18"
[19] "19" "20" "21" "22" "23" "24" "25" "26" "27" "28" "29" "30" "31" "32"
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2
Valiant	18.1	6	225.0	105	2.76	3.460	20.22	1	0	3	1
Duster 360	14.3	8	360.0	245	3.21	3.570	15.84	0	0	3	4
Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4	2
Merc 230	22.8	4	140.8	95	3.92	3.150	22.90	1	0	4	2
Merc 280	19.2	6	167.6	123	3.92	3.440	18.30	1	0	4	4
Merc 280C	17.8	6	167.6	123	3.92	3.440	18.90	1	0	4	4
Merc 450SE	16.4	8	275.8	180	3.07	4.070	17.40	0	0	3	3
Merc 450SL	17.3	8	275.8	180	3.07	3.730	17.60	0	0	3	3
Merc 450SLC	15.2	8	275.8	180	3.07	3.780	18.00	0	0	3	3

	mpg	cyl	disp	hp
Mazda RX4	21.0	6	160.0	110
Mazda RX4 Wag	21.0	6	160.0	110
Datsun 710	22.8	4	108.0	93
Hornet 4 Drive	21.4	6	258.0	110
Hornet Sportabout	18.7	8	360.0	175
Valiant	18.1	6	225.0	105
Duster 360	14.3	8	360.0	245
Merc 240D	24.4	4	146.7	62
Merc 230	22.8	4	140.8	95
Merc 280	19.2	6	167.6	123
Merc 280C	17.8	6	167.6	123
Merc 450SE	16.4	8	275.8	180
Merc 450SL	17.3	8	275.8	180
Merc 450SLC	15.2	8	275.8	180

	mpg	disp	wt	gear
Mazda RX4	21.0	160.0	2.620	4
Mazda RX4 Wag	21.0	160.0	2.875	4
Datsun 710	22.8	108.0	2.320	4
Hornet 4 Drive	21.4	258.0	3.215	3
Hornet Sportabout	18.7	360.0	3.440	3
Valiant	18.1	225.0	3.460	3
Duster 360	14.3	360.0	3.570	3
Merc 240D	24.4	146.7	3.190	4
Merc 230	22.8	140.8	3.150	4
Merc 280	19.2	167.6	3.440	4
Merc 280C	17.8	167.6	3.440	4
Merc 450SE	16.4	275.8	4.070	3
Merc 450SL	17.3	275.8	3.730	3
Merc 450SLC	15.2	275.8	3.780	3

	mpg	disp	wt	gear
Mazda RX4	21.0	160.0	2.620	4
Mazda RX4 Wag	21.0	160.0	2.875	4
Datsun 710	22.8	108.0	2.320	4
Merc 240D	24.4	146.7	3.190	4
Merc 230	22.8	140.8	3.150	4
Merc 280	19.2	167.6	3.440	4
Merc 280C	17.8	167.6	3.440	4
Fiat 128	32.4	78.7	2.200	4
Honda Civic	30.4	75.7	1.615	4
Toyota Corolla	33.9	71.1	1.835	4
Fiat X1-9	27.3	79.0	1.935	4
Volvo 142E	21.4	121.0	2.780	4

	mpg	cyl
Mazda RX4	21.0	6
Mazda RX4 Wag	21.0	6
Datsun 710	22.8	4
Hornet 4 Drive	21.4	6
Merc 240D	24.4	4
Merc 230	22.8	4
Fiat 128	32.4	4
Honda Civic	30.4	4
Toyota Corolla	33.9	4
Toyota Corona	21.5	4
Fiat X1-9	27.3	4
Porsche 914-2	26.0	4
Lotus Europa	30.4	4
Volvo 142E	21.4	4

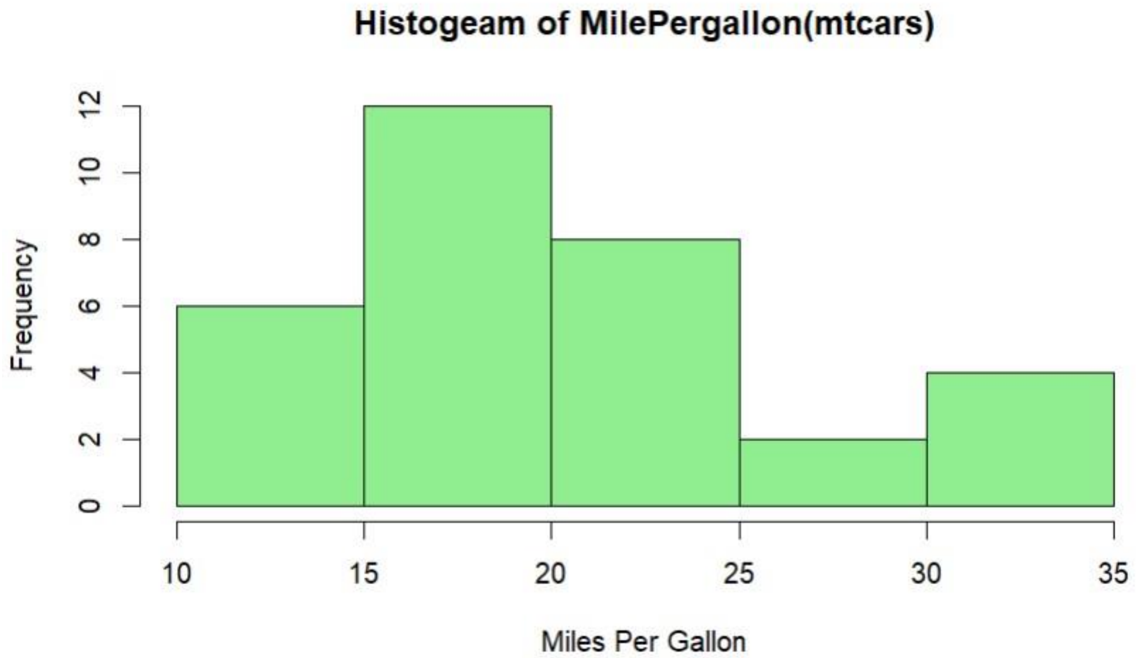
	mpg	carb
Merc 450SE	16.4	3
Merc 450SL	17.3	3
Merc 450SLC	15.2	3

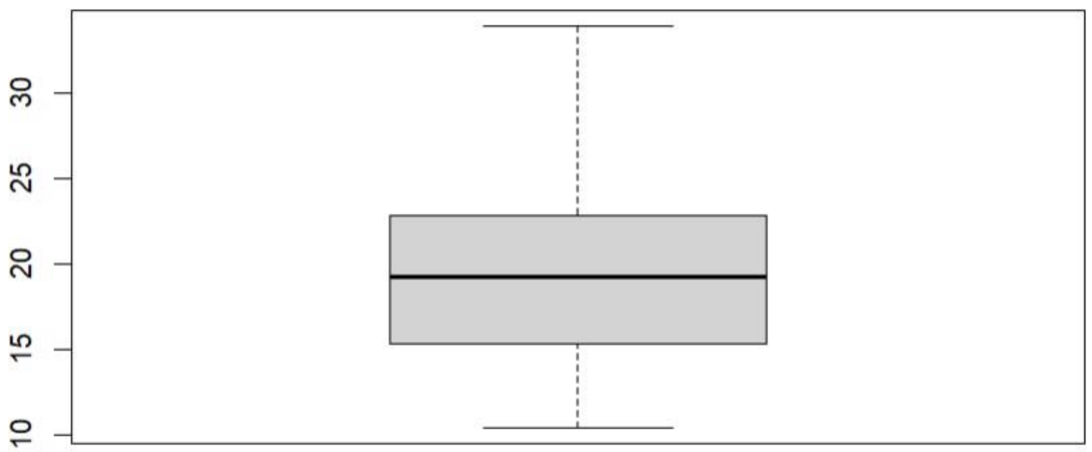
	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Toyota Corolla	33.9	4	71.1	65	4.22	1.835	19.90	1	1	4	1
Fiat 128	32.4	4	78.7	66	4.08	2.200	19.47	1	1	4	1
Honda Civic	30.4	4	75.7	52	4.93	1.615	18.52	1	1	4	2
Lotus Europa	30.4	4	95.1	113	3.77	1.513	16.90	1	1	5	2
Fiat X1-9	27.3	4	79.0	66	4.08	1.935	18.90	1	1	4	1
Porsche 914-2	26.0	4	120.3	91	4.43	2.140	16.70	0	1	5	2
Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4	2
Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
Merc 230	22.8	4	140.8	95	3.92	3.150	22.90	1	0	4	2
Toyota Corona	21.5	4	120.1	97	3.70	2.465	20.01	1	0	3	1
Volvo 142E	21.4	4	121.0	109	4.11	2.780	18.60	1	1	4	2
Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4

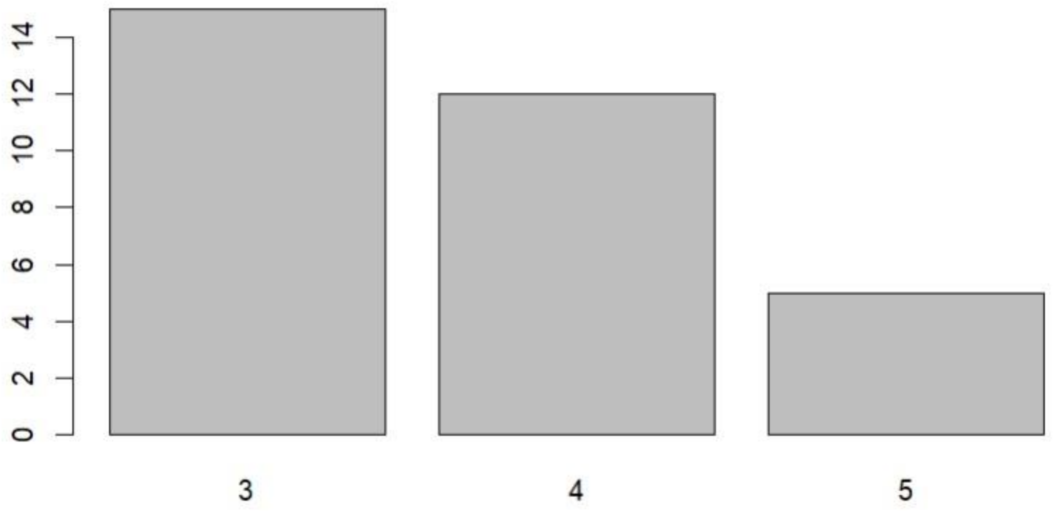
	MilesPerGallon	Cylinders	Displacement	hp	drat	wt	qsec	vs	am	gear	ca
Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	
Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	
Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	
Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	
Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	
Valiant	18.1	6	225.0	105	2.76	3.460	20.22	1	0	3	
Duster 360	14.3	8	360.0	245	3.21	3.570	15.84	0	0	3	
Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4	
Merc 230	22.8	4	140.8	95	3.92	3.150	22.90	1	0	4	
Merc 280	19.2	6	167.6	123	3.92	3.440	18.30	1	0	4	
Merc 280C	17.8	6	167.6	123	3.92	3.440	18.90	1	0	4	
Merc 450SE	16.4	8	275.8	180	3.07	4.070	17.40	0	0	3	
Merc 450SL	17.3	8	275.8	180	3.07	3.730	17.60	0	0	3	
Merc 450SLC	15.2	8	275.8	180	3.07	3.780	18.00	0	0	3	

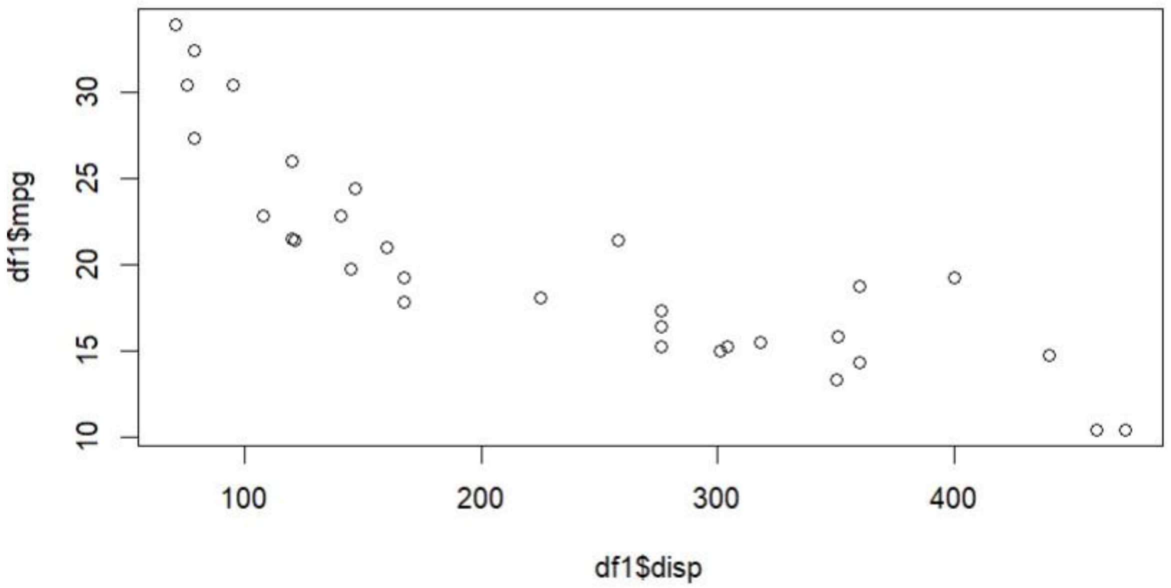
	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb	Power
Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4	288.200
Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4	316.250
Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1	215.760
Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1	353.650
Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2	602.000
Valiant	18.1	6	225.0	105	2.76	3.460	20.22	1	0	3	1	363.300
Duster 360	14.3	8	360.0	245	3.21	3.570	15.84	0	0	3	4	874.650
Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4	2	197.780
Merc 230	22.8	4	140.8	95	3.92	3.150	22.90	1	0	4	2	299.250
Merc 280	19.2	6	167.6	123	3.92	3.440	18.30	1	0	4	4	423.120
Merc 280C	17.8	6	167.6	123	3.92	3.440	18.90	1	0	4	4	423.120
Merc 450SE	16.4	8	275.8	180	3.07	4.070	17.40	0	0	3	3	732.600
Merc 450SL	17.3	8	275.8	180	3.07	3.730	17.60	0	0	3	3	671.400
Merc 450SLC	15.2	8	275.8	180	3.07	3.780	18.00	0	0	3	3	680.400

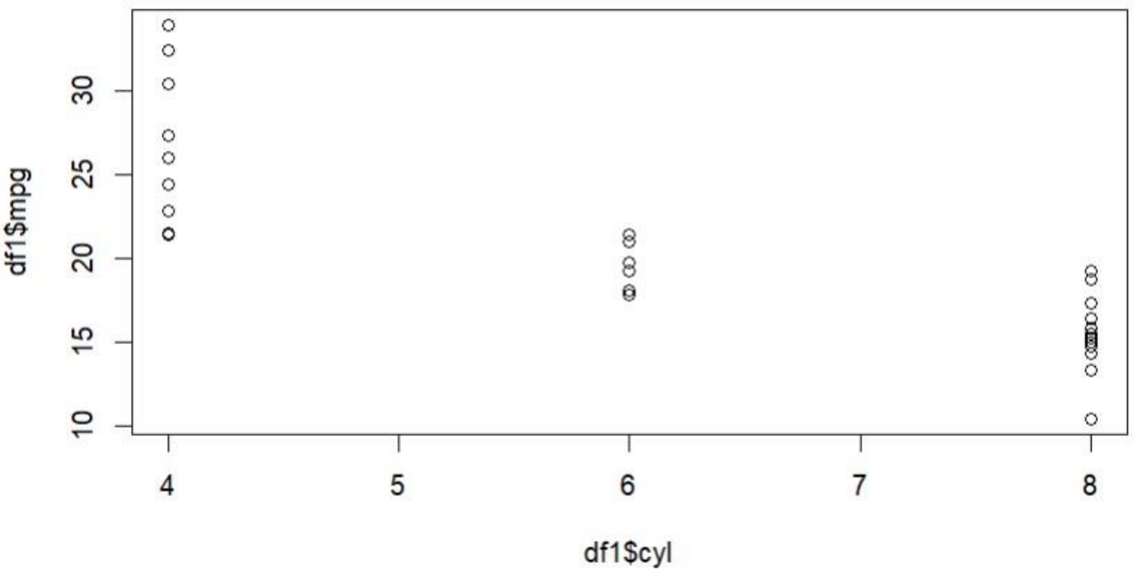
```
'data.frame':   32 obs. of  12 variables:
 $ mpg  : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
 $ cyl  : int  6 6 4 6 8 6 8 4 4 6 ...
 $ disp : num  160 160 108 258 360 ...
 $ hp   : int  110 110 93 110 175 105 245 62 95 123 ...
 $ drat : num  3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
 $ wt   : num  2.62 2.88 2.32 3.21 3.44 ...
 $ qsec : num  16.5 17 18.6 19.4 17 ...
 $ vs   : int  0 0 1 1 0 1 0 1 1 1 ...
 $ am   : int  1 1 1 0 0 0 0 0 0 0 ...
 $ gear : Factor w/ 3 levels "3","4","5": 2 2 2 1 1 1 1 2 2 2 ...
 $ carb : int  4 4 1 1 2 1 4 2 2 4 ...
 $ Power: num  288 316 216 354 602 ...
> summary_df
# A tibble: 3 x 4
  `df1$gear`     no mean_mpg mean_wt
  <fct>       <int>    <dbl>   <dbl>
1 3              15     16.1    3.89
2 4              12     24.5    2.62
3 5               5     21.4    2.63
```

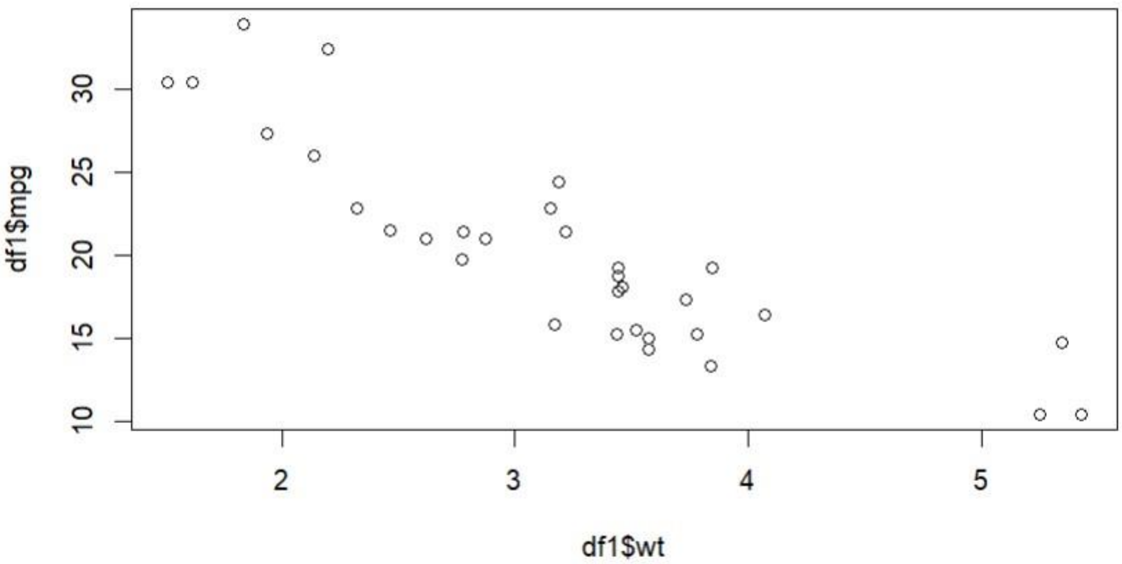

Histogeam of MilePergallon(mtcars)
Frequency
0
2
4
6
8
10
12
10
15
20
25
30
35
Miles Per Gallon


10
15
20
25
30


0
2
4
6
8
10
12
14
3
4
5


df1$mpg
10
15
20
25
30
100
200
300
400
df1$disp


df1$mpg
df1$cyl
10
15
20
25
30
4
5
6
7
8


df1$mpg
df1$wt
10
15
20
25
30
2
3
4
5

Practical No:4

Aim: Exploratory data analysis in Python using Titanic Dataset **It is one of the most popular datasets used for understanding machine learning basics. It contains information of all the passengers aboard the RMS Titanic, which unfortunately was shipwrecked. This dataset can be used to predict whether a given passenger survived or not.**

Data Dictionary

Variable	**Definition**	**Key**
Survival	Survival	0 = No, 1 = Yes
Pclass	Ticket class	1 = 1st, 2 = 2nd, 3 = 3rd
Sex	Sex	
Age	Age in years	
Sibsp	# of siblings / spouses aboard the Titanic	
Parch	# of parents / children aboard the Titanic	
Ticket	Ticket number	
Fare	Passenger fare	
Cabin	Cabin number	
Embarked	Port of Embarkation	C = Cherbourg, Q = Queenstown, S = Southampton

Seaborn:

It is a python library used to statistically visualize data. Seaborn, built over Matplotlib, provides a better interface and ease of usage. It can be installed using the following command,

pip3 install seaborn

Features: The titanic dataset has roughly the following types of features:

- **Categorical/Nominal**: Variables that can be divided into multiple categories but having no order or priority.
  Eg. Embarked (C = Cherbourg; Q = Queenstown; S = Southampton)
- **Binary**: A subtype of categorical features, where the variable has only two categories. Eg: Sex (Male/Female)
- **Ordinal**: They are similar to categorical features but they have an order(i.e can be sorted).
  Eg. Pclass (1, 2, 3)

- **Continuous**: They can take up any value between the minimum and maximum values in a column.
Eg. Age, Fare
- **Count**: They represent the count of a variable. Eg. SibSp, Parch
Useless: They don't contribute to the final outcome of an ML model. Here, *PassengerId, Name, Cabin* and *Ticket* might fall into this category.

Code:

```
import pandas as pd titanic =
pd.read_csv("train.csv")
titanic.head() titanic.info()
titanic.describe()
titanic.isnull().sum()
titanic_cleaned =
titanic.drop(['PassengerId','Name','Ticket','Fare','Cabin'],axis=1)
titanic_cleaned.info() import seaborn as sns import
matplotlib.pyplot as plt
%matplotlib inline
sns.catplot(x="Sex",hue="Survived",kind="count",data=titanic_cleaned)
titanic_cleaned.groupby(['Sex','Survived'])['Survived'].count()) group1
= titanic_cleaned.groupby(['Sex','Survived'])
sns.heatmap(gender_survived,annot=True,fmt="d")
sns.heatmap(gender_survived,annot=True,fmt="d")
sns.violinplot(x="Sex",y="Age",hue="Survived",data=titanic_cleaned,split=Tru
e)
print("Oldest Person on Board:",titanic_cleaned['Age'].max()) print("Youngest
Person on Board:",titanic_cleaned['Age'].min()) print("Average age of Person
on Board:",titanic_cleaned['Age'].mean()) titanic_cleaned.isnull().sum() def
impute(cols):    Age = cols[0]    Pclass = cols[1]    if pd.isnull(Age):       if
Pclass==1:          return 38        elif Pclass==2:
         return 29
else:
         return 24
else:
       return Age
titanic_cleaned['Age']=titanic_cleaned[['Age','Pclass']].apply(impute,axis=1)
titanic_cleaned.isnull().sum() titanic_cleaned.corr(method='pearson')
sns.heatmap(titanic_cleaned.corr(method="pearson"),annot=True,vmax=1)
import numpy as np  from sklearn import datasets
x,y,coef=datasets.make_regression(n_samples=100, n_features=1,
n_informative=1, noise=10,coef=True, random_state = 0)
```

```
x=np.interp(x,(x.min(),x.max()),(0,20))
print(len(x))  print(x)
y=np.interp(y,(y.min(),y.max()),(20000,150000))  print(len(y))
print(y)
```

Output:

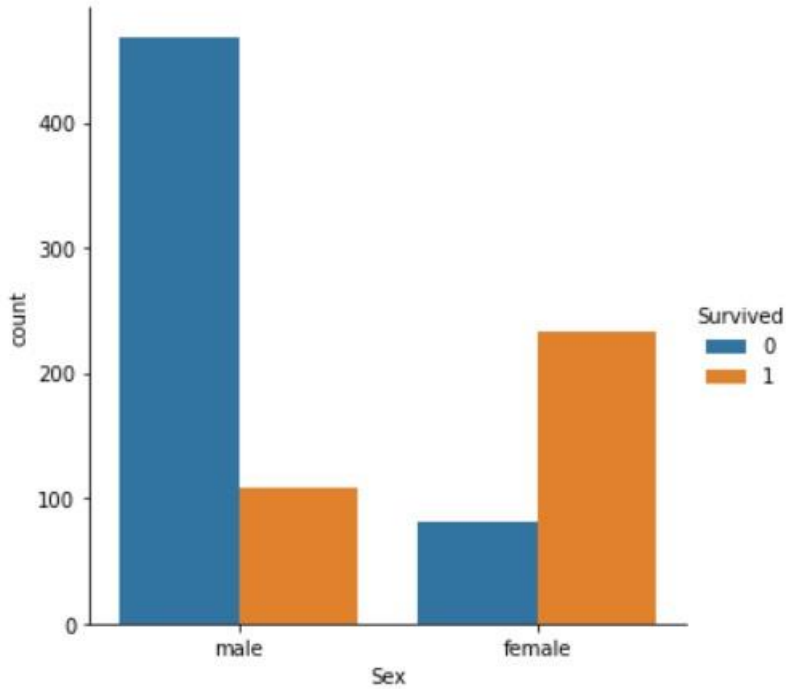
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

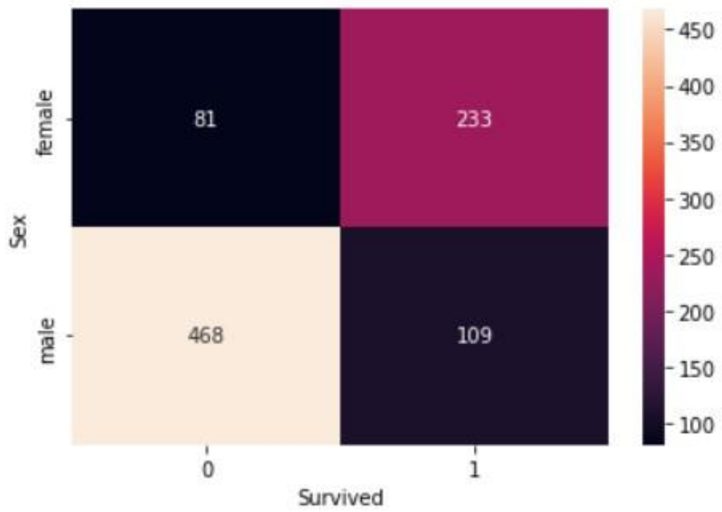
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Survived  891 non-null    int64  
 1   Pclass    891 non-null    int64  
 2   Sex       891 non-null    object 
 3   Age       714 non-null    float64
 4   SibSp     891 non-null    int64  
 5   Parch     891 non-null    int64  
 6   Embarked  889 non-null    object 
dtypes: float64(1), int64(4), object(2)
memory usage: 48.9+ KB
```



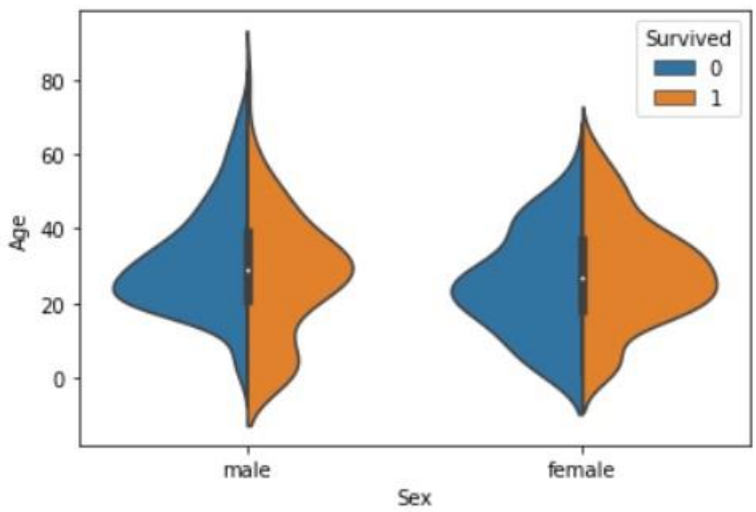

```
Sex     Survived
female  0            81
        1           233
male    0           468
        1           109
Name: Survived, dtype: int64
```

Survived	0	1
Sex		
female	81	233
male	468	109

<AxesSubplot:xlabel='Survived', ylabel='Sex'>



<AxesSubplot:xlabel='Sex', ylabel='Age'>




```
Oldest Person on Board: 80.0

Youngest Person on Board: 0.42
```

```
Average age of Person on Board: 29.69911764705882

Survived      0
Pclass        0
Sex           0
Age         177
SibSp         0
Parch         0
Embarked      2
dtype: int64
```

```
Survived     0
Pclass       0
Sex          0
Age          0
SibSp        0
Parch        0
Embarked     2
dtype: int64
```

	Survived	Pclass	Age	SibSp	Parch
Survived	1.000000	-0.338481	-0.046746	-0.035322	0.081629
Pclass	-0.338481	1.000000	-0.411805	0.083081	0.018443
Age	-0.046746	-0.411805	1.000000	-0.243877	-0.171917
SibSp	-0.035322	0.083081	-0.243877	1.000000	0.414838
Parch	0.081629	0.018443	-0.171917	0.414838	1.000000

```
&lt;AxesSubplot:&gt;
```

```
100
[[ 9.09621765]
 [14.63742853]
 [12.25580785]
 [ 7.21515957]
 [ 6.90562848]
 [12.42799856]
 [ 6.53450315]
 [12.36358975]
 [11.45101022]
 [ 9.29527704]
 [ 8.46897323]
 [11.11359701]
 [ 4.21646281]
 [ 8.92109838]
 [13.29785748]
 [15.47570863]
 [ 9.84113925]
 [17.99332461]
 [16.61818648]
 [ 7.74737185]
```

```
100
[ 78311.16075377 103897.6645258   97836.26101499  80550.25638039
  68555.820963   108021.44227128  55778.0199934  101586.97979347
 103966.61856971  76826.00913959  73657.03907056  96439.33831133
  43282.85644907  73119.73495559 109692.0380975  128125.74670244
  87499.26503386 136438.82955292 140414.06203468  75920.22641562
 122765.94046351 138676.79599883  90840.21480164  99453.36502726
 118663.17132396 125247.52951645 144470.99004202  98454.6493064
  92321.3919241  133162.35931048  61723.07434352  77095.35501897
  59042.68149761 109559.00643186  77206.62874325 109743.44545302
 103902.53136675  82585.66146856  81088.97054957  62200.35300958
 111971.74647069 101515.0451792   47090.60230288 141613.36480828
  99370.060872    72953.14343772 131312.34257614  68957.25418311
 135509.14233685  90658.86260334  75147.59074288  46071.12989863
```

Practical 5

Aim: Exploratory data analysis in Python using Titanic Dataset The following figure illustrates simple linear regression:

The package **scikit-learn** is a widely used Python library for machine learning, built on top of NumPy and some other packages, It provides the means for preprocessing data, reducing dimensionality, implementing regression, classification, clustering, and more. Like NumPy, scikit-learn is also open source.

It is used as sklearn in python

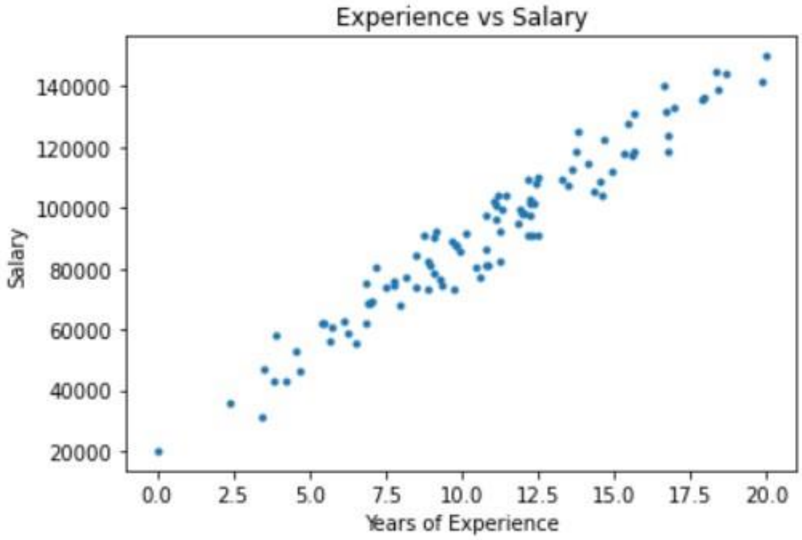
1)**Write a python program to build a regression model that could predict the salary of an employee from the given experience and visualize univariate linear regression on it.**

Code:

```
import numpy as np  from sklearn import datasets
x,y,coef=datasets.make_regression(n_samples=100, n_features=1,
n_informative=1, noise=10,coef=True, random_state = 0)
x=np.interp(x,(x.min(),x.max()),(0,20))
print(len(x))  print(x)
y=np.interp(y,(y.min(),y.max()),(20000,150000))
print(len(y))  print(y)  import matplotlib.pyplot as
plt  plt.plot(x,t,'.',label="training data")
plt.xlabel("Years of Experience")
plt.ylabel("Salary")  plt.title("Experience vs
Salary")  from sklearn.linear_model import
LinearRegression  reg_model = LinearRegression()
reg_model.fit(x,y)  y_pred=reg_model.predict(x)
plt.plot(x,y_pred,color="black")
plt.plot(x,y,'.',label="training data")
plt.xlabel("Years of Experience")
plt.ylabel("Salary")  plt.title("Experience vs
Salary")
import pandas as pd
data = {'Experience':np.round(x.flatten()),'Salary':np.round(y)}
df=pd.DataFrame(data)
df.head(10)
```

Output:

```
Text(0.5, 1.0, 'Experience vs Salary')
```




```
Text(0.5, 1.0, 'Experience vs Salary')
```

	Experience	Salary
0	9.0	78311.0
1	15.0	103898.0
2	12.0	97836.0
3	7.0	80550.0
4	7.0	68556.0
5	12.0	108021.0
6	7.0	55778.0
7	12.0	101587.0
8	11.0	103967.0
9	9.0	76826.0

2) **Write a python program to simulate linear model Y=10+7*x+e for random 100 samples and visualize univariate linear regression on it.**

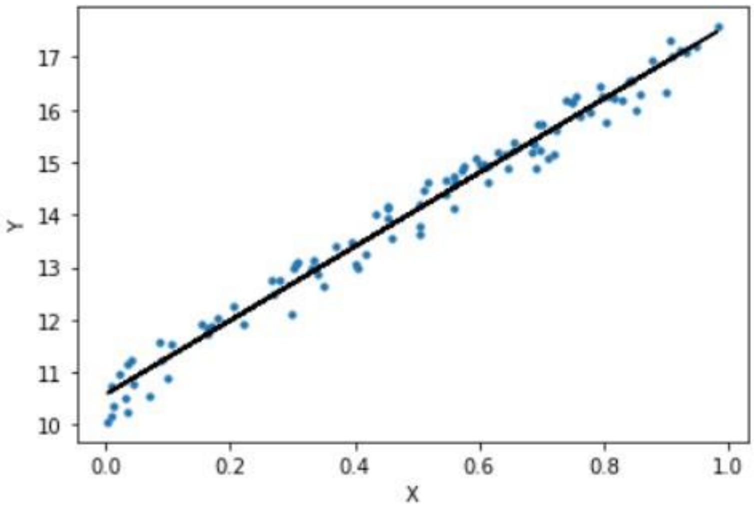
Code:

```
x1=[[13.0]]  y1=reg_model.predict(x1)
print(np.round(y1))
reg_model1=LinearRegression()
x=np.random.rand(100,1)
yintercept=10  slope=7
error=np.random.rand(100,1)
y=yintercept+slope*x+error
reg_model1.fit(x,y)
y_pred=reg_model1.predict(x)
plt.scatter(x,y,s=10)
plt.xlabel("X")  plt.ylabel("Y")
plt.plot(x,y_pred,color="black")
```

Output:

```
[105534.]
```

```
[<matplotlib.lines.Line2D at 0x26fbd74c8b0>]
```



Practical 6
Aim: Write a python program to implement multiple linear regression on the Dataset Boston.csv
The dataset provides Housing Values in Suburbs of Boston The medv(Price) variable is the target /dependent variable.
Data description
The Boston data frame has 506 rows and 14 columns.
This data frame contains the following columns:
crim per capita crime rate by town.
zn proportion of residential land zoned for lots over 25,000 sq.ft. indus proportion of non-retail business acres per town.
chas
Charles River dummy variable (= 1 if tract bounds river; 0 otherwise).
nox nitrogen oxides concentration (parts per 10 million). rm average number of rooms per dwelling. age proportion of owner-occupied units built prior to 1940.
dis weighted mean of distances to five Boston employment centres. rad index of accessibility to radial highways.
tax full-value property-tax rate per \$10,000.
ptratio pupil-teacher ratio by town.
black
1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town.
lstat lower status of the population (percent).
Medv(Price) median value of owner-occupied homes in \$1000s.

Code:
```
import pandas as pd  import
matplotlib.pyplot as plt
import sklearn
boston = pd.read_csv("Boston.csv")  boston.head()
boston.info()
boston = boston.drop(columns="Unnamed: 0")
boston.info()  boston_x =
pd.DataFrame(boston.iloc[:,:13])  boston_y =
pd.DataFrame(boston.iloc[:,-1])
boston_x.head()  boston_y.head()
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, Y_train, Y_test = train_test_split(boston_x, boston_y,
test_size=0.3)  print("xtrain shape", X_train.shape)  print("ytrain shape",
Y_train.shape)  print("xtest shape", X_test.shape)  print("ytest shape",
Y_test.shape)
from sklearn.linear_model import LinearRegression
regression=LinearRegression()  regression.fit(X_train,Y_train)
Y_pred_linear = regression.predict(X_test)
Y_pred_df = pd.DataFrame(Y_pred_linear,columns=["Predicted"])
Y_pred_df.head()
plt.scatter(Y_test, Y_pred_linear, c="green")
plt.xlabel("Actual Price(medv)")
plt.ylabel("Predicted Pric(medv)")
plt.title("Actual vs Prediction")  plt.show()
```

Output:

	Unnamed: 0	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	black	lstat	medv
0	1	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98	24.0
1	2	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14	21.6
2	3	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03	34.7
3	4	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	33.4
4	5	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.33	36.2

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 15 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  506 non-null    int64
 1   crim        506 non-null    float64
 2   zn          506 non-null    float64
 3   indus       506 non-null    float64
 4   chas        506 non-null    int64
 5   nox         506 non-null    float64
 6   rm          506 non-null    float64
 7   age         506 non-null    float64
 8   dis         506 non-null    float64
 9   rad         506 non-null    int64
 10  tax         506 non-null    int64
 11  ptratio     506 non-null    float64
 12  black       506 non-null    float64
 13  lstat       506 non-null    float64
 14  medv        506 non-null    float64
dtypes: float64(11), int64(4)
memory usage: 59.4 KB
```

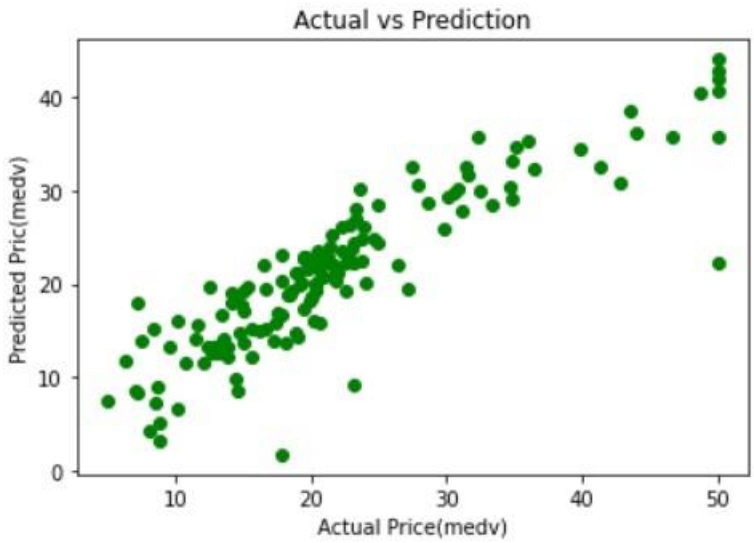
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   crim     506 non-null    float64
 1   zn       506 non-null    float64
 2   indus    506 non-null    float64
 3   chas     506 non-null    int64
 4   nox      506 non-null    float64
 5   rm       506 non-null    float64
 6   age      506 non-null    float64
 7   dis      506 non-null    float64
 8   rad      506 non-null    int64
 9   tax      506 non-null    int64
 10  ptratio  506 non-null    float64
 11  black    506 non-null    float64
 12  lstat    506 non-null    float64
 13  medv     506 non-null    float64
dtypes: float64(11), int64(3)
memory usage: 55.5 KB
```

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	black	lstat
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.33

	medv
0	24.0
1	21.6
2	34.7
3	33.4
4	36.2

```
xtrain shape (354, 13)
ytrain shape (354, 1)
xtest shape (152, 13)
ytest shape (152, 1)
```

	Predicted
0	22.984672
1	23.549732
2	19.280036
3	25.237437
4	36.235906



Practical 7:
K Nearest Neighbor classification Algorithm
Aim: Write a python program to implement KNN algorithm to predict breast cancer using breast cancer wisconsin dataset .

Data Set Information:
Features are computed from a digitized image of a fine needle aspirate (FNA) of a breast mass. They describe characteristics of the cell nuclei present in the image.

Attribute Information:
1) ID number
2) Diagnosis (M = malignant, B = benign)
(3-32)

Ten real-valued features are computed for each cell nucleus:

a) radius (mean of distances from center to points on the perimeter)
b) texture (standard deviation of gray-scale values)
c) perimeter
d) area
e) smoothness (local variation in radius lengths)
f) compactness (perimeter^2 / area - 1.0)
g) concavity (severity of concave portions of the contour)

h) concave points (number of concave contour) portions of the i) symmetry

j) fractal dimension ("coastline approximation" - 1)

Code:

```
import numpy as np  import pandas as pd  import
matplotlib.pyplot as plt  from sklearn.datasets
import load_breast_cancer  from sklearn.metrics
import confusion_matrix  from sklearn.neighbors
import KNeighborsClassifier  from
sklearn.model_selection import train_test_split
import seaborn as sns
breast_cancer_df = load_breast_cancer()
x=pd.DataFrame(breast_cancer_df.data,columns=breast_cancer_df.feature_nam
es)
x.head()
columns_to_select = ["mean area", "mean compactness"]
x=x[columns_to_select] x.head()
y=pd.Categorical.from_codes(breast_cancer_df.target,breast_cancer_df.target_n
ames)
print(y)
y=pd.get_dummies(y,drop_first=True)  print(y)
X_train, X_test, Y_train, Y_test = train_test_split(x, y, random_state=1)
knn=KNeighborsClassifier(n_neighbors=5,metric="euclidewan")
knn.fit(X_train,Y_train)  sns.set()
sns.scatterplot(x="mean area",y="mean
compactness",hue="benign",data=X_text.join(Y_test,how="outer"))
y_pred=knn.predict(X_test)
plt.scatter(X_test["mean area"],X_test["mean
compactness"],c=y_pred,cmap="coolwarm",alpha=0.7)
cf=confusion_matrix(Y_test,y_pred)  print(cf)
labels=["True Negative","False Positive","False Negative","True Positive"]
labels=np.asarray(labels).reshape(2,2)  categories=["Zero","One"]
ax=plt.subplot()  sns.heatmap(cf,annot=True,ax=ax)
ax.set_xlabel("Predicted Values")
ax.set_ylabel("Actual Values")
ax.set_title("Confusion Matrix")
ax.xaxis.set_ticklabels(["Malignant","Benign"])
ax.yaxis.set_ticklabels(["Malignant","Benign"])
```

Output:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst radius	worst texture	worst perimeter	worst area	worst smoothness
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	0.07871	...	25.38	17.33	184.60	2019.0	0.1622
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667	...	24.99	23.41	158.80	1956.0	0.1238
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	0.05999	...	23.57	25.53	152.50	1709.0	0.1444
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	0.09744	...	14.91	26.50	98.87	567.7	0.2098
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	0.05883	...	22.54	16.67	152.20	1575.0	0.1374

5 rows × 30 columns

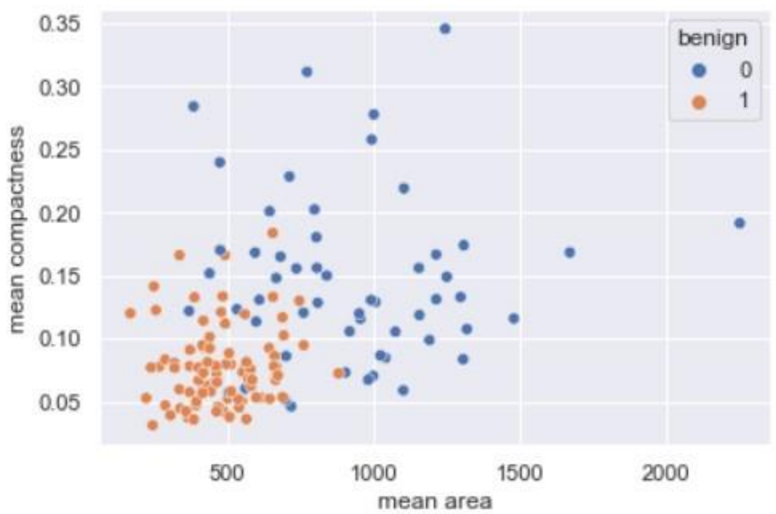
	mean area	mean compactness
0	1001.0	0.27760
1	1326.0	0.07864
2	1203.0	0.15990
3	386.1	0.28390
4	1297.0	0.13280

```
['malignant', 'malignant', 'malignant', 'malignant', 'malignant', ..., 'malignant', 'malignant', 'malignant', 'malignant', 'ben
ign']
Length: 569
Categories (2, object): ['malignant', 'benign']
```

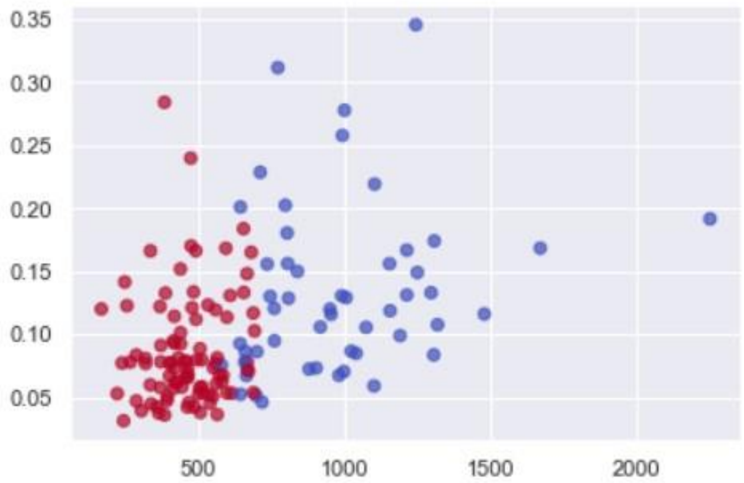
```
     benign
0         0
1         0
2         0
3         0
4         0
..      ...
564       0
565       0
566       0
567       0
568       1

[569 rows x 1 columns]
```

```
<AxesSubplot:xlabel='mean area', ylabel='mean compactness'>
```

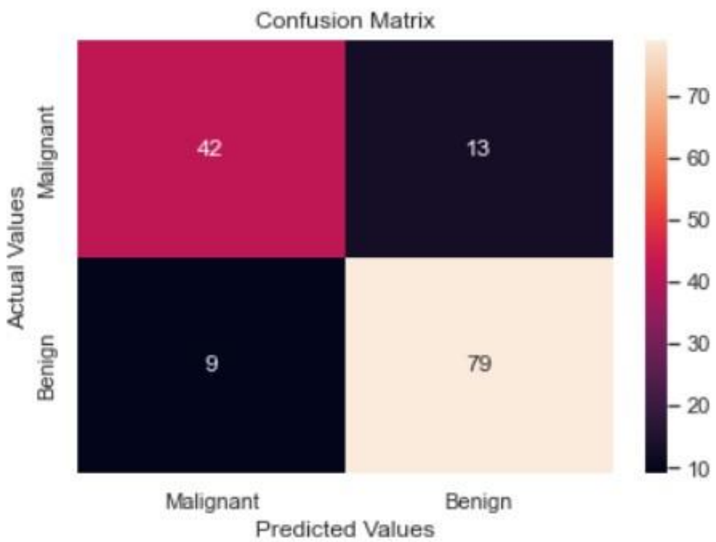


```
<matplotlib.collections.PathCollection at 0x260054d1fa0>
```




```
[[42 13]
 [ 9 79]]
```

```
[Text(0, 0.5, 'Malignant'), Text(0, 1.5, 'Benign')]
```



Practical 8:
Aim: Introduction to NOSQL using MongoDB

Perform the following:

1.Create a database Company ,Create a Collection Staff and Insert ten documents in it with fields: empid,empname,salary and designation.

- Display all documents in Staff and display only empid and designation.db
- Sort the documents in descending order of Salary
- Display employee with designation with “Manager” or salary greater than Rs. 50,000/-.
- Update the salary of all employees with designation as
“Accountant” to Rs.45000.
- Remove the documents of employees whose salary is greater than Rs100000.

2. Create a database Institution .Create a Collection Student and Insert ten documents in it with fields: RollNo,Name,Class and TotalMarks(out of 500).

- Display all documents in Student.
- Sort the documents in descending order of TotalMarks.
- Display students of class “MSc” or marks greater than 400.
- Remove all the documents with TotalMarks<200

Code and Output:

1.Create a database Institution ,Create a Collection Staff and Insert ten

documents in it with fields: empid,empname,salary and designation.

use Institution db.createCollection(“Staff”)

```
> use Institution
switched to db Institution
> db.createCollection("Staff")
```

db

db.Staff.insertMany([{ "empid": 1, "empname": "John Doe", "salary": 60000, "designation": "Manager" }, { "empid": 2, "empname": "Jane Smith", "salary": 55000, "designation": "Accountant" }, { "empid": 3, "empname": "Michael Johnson", "salary": 70000, "designation": "Manager" }, { "empid": 4, "empname": "Emily Brown", "salary": 45000, "designation": "Accountant" }, { "empid": 5, "empname": "David Wilson", "salary": 80000, "designation": "Developer" }, { "empid": 6, "empname": "Sarah Lee", "salary": 95000, "designation": "Manager" }, { "empid": 7, "empname": "Christopher Martinez", "salary": 50000, "designation": "Accountant" }, { "empid": 8, "empname": "Amanda Davis", "salary": 120000, "designation": "Manager" }, { "empid": 9, "empname": "Jason Rodriguez", "salary": 40000, "designation": "Intern" }, { "empid": 10, "empname": "Jessica Taylor", "salary": 110000, "designation": "Manager" }])

```
> db
Institution
> db.Staff.insertMany([
...     { "empid": 1, "empname": "John Doe", "salary": 60000, "designation": "Manager" },
...     { "empid": 2, "empname": "Jane Smith", "salary": 55000, "designation": "Accountant" },
...     { "empid": 3, "empname": "Michael Johnson", "salary": 70000, "designation": "Manager" },
...     { "empid": 4, "empname": "Emily Brown", "salary": 45000, "designation": "Accountant" },
...     { "empid": 5, "empname": "David Wilson", "salary": 80000, "designation": "Developer" },
...     { "empid": 6, "empname": "Sarah Lee", "salary": 95000, "designation": "Manager" },
...     { "empid": 7, "empname": "Christopher Martinez", "salary": 50000, "designation": "Accountant" },
...     { "empid": 8, "empname": "Amanda Davis", "salary": 120000, "designation": "Manager" },
...     { "empid": 9, "empname": "Jason Rodriguez", "salary": 40000, "designation": "Intern" },
...     { "empid": 10, "empname": "Jessica Taylor", "salary": 110000, "designation": "Manager" }
... ])
{
        "acknowledged" : true,
        "insertedIds" : [
                ObjectId("65deecde8cbdbaebf7136c4f"),
                ObjectId("65deecde8cbdbaebf7136c50"),
                ObjectId("65deecde8cbdbaebf7136c51"),
                ObjectId("65deecde8cbdbaebf7136c52"),
                ObjectId("65deecde8cbdbaebf7136c53"),
                ObjectId("65deecde8cbdbaebf7136c54"),
                ObjectId("65deecde8cbdbaebf7136c55"),
                ObjectId("65deecde8cbdbaebf7136c56"),
                ObjectId("65deecde8cbdbaebf7136c57"),
                ObjectId("65deecde8cbdbaebf7136c58")
        ]
}
```

Db.Staff.find().pretty()

```
> db.Staff.find().pretty()
{
        "_id" : ObjectId("65deecde8cbdbaebf7136c4f"),
        "empid" : 1,
        "empname" : "John Doe",
        "salary" : 60000,
        "designation" : "Manager"
}
{
        "_id" : ObjectId("65deecde8cbdbaebf7136c50"),
        "empid" : 2,
        "empname" : "Jane Smith",
        "salary" : 55000,
        "designation" : "Accountant"
}
{
        "_id" : ObjectId("65deecde8cbdbaebf7136c51"),
        "empid" : 3,
        "empname" : "Michael Johnson",
        "salary" : 70000,
        "designation" : "Manager"
}
{
        "_id" : ObjectId("65deecde8cbdbaebf7136c52"),
        "empid" : 4,
        "empname" : "Emily Brown",
        "salary" : 45000,
        "designation" : "Accountant"
}
```

- Display all documents in Staff and display only empid and designation. db.Staff.find().pretty()

```
> db.Staff.find().pretty()
{
        "_id" : ObjectId("65deecde8cbdbaebf7136c4f"),
        "empid" : 1,
        "empname" : "John Doe",
        "salary" : 60000,
        "designation" : "Manager"
}
{
        "_id" : ObjectId("65deecde8cbdbaebf7136c50"),
        "empid" : 2,
        "empname" : "Jane Smith",
        "salary" : 55000,
        "designation" : "Accountant"
}
{
        "_id" : ObjectId("65deecde8cbdbaebf7136c51"),
        "empid" : 3,
        "empname" : "Michael Johnson",
        "salary" : 70000,
        "designation" : "Manager"
}
{
        "_id" : ObjectId("65deecde8cbdbaebf7136c52"),
        "empid" : 4,
        "empname" : "Emily Brown",
        "salary" : 45000,
        "designation" : "Accountant"
}
```

```
{
        "_id" : ObjectId("65deecde8cbdbaebf7136c54"),
        "empid" : 6,
        "empname" : "Sarah Lee",
        "salary" : 95000,
        "designation" : "Manager"
}
{
        "_id" : ObjectId("65deecde8cbdbaebf7136c55"),
        "empid" : 7,
        "empname" : "Christopher Martinez",
        "salary" : 50000,
        "designation" : "Accountant"
}
{
        "_id" : ObjectId("65deecde8cbdbaebf7136c56"),
        "empid" : 8,
        "empname" : "Amanda Davis",
        "salary" : 120000,
        "designation" : "Manager"
}
{
        "_id" : ObjectId("65deecde8cbdbaebf7136c57"),
        "empid" : 9,
        "empname" : "Jason Rodriguez",
        "salary" : 40000,
        "designation" : "Intern"
}
```

Db.staff.find({], {"_id":0, "empid":1, "designation":1}).pretty()

```
> db.Staff.find({}, { "_id": 0, "empid": 1, "designation": 1 }).pretty()
{ "empid" : 1, "designation" : "Manager" }
{ "empid" : 2, "designation" : "Accountant" }
{ "empid" : 3, "designation" : "Manager" }
{ "empid" : 4, "designation" : "Accountant" }
{ "empid" : 5, "designation" : "Developer" }
{ "empid" : 6, "designation" : "Manager" }
{ "empid" : 7, "designation" : "Accountant" }
{ "empid" : 8, "designation" : "Manager" }
{ "empid" : 9, "designation" : "Intern" }
{ "empid" : 10, "designation" : "Manager" }
```

- Sort the documents in descending order of Salary

  db.Staff.find().sort({ "salary": -1 })

```
> db.Staff.find().sort({ "salary": -1 })
{ "_id" : ObjectId("65deecde8cbdbaebf7136c56"), "empid" : 8, "empname" : "Amanda Davis", "salary" : 120000, "designation
" : "Manager" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c58"), "empid" : 10, "empname" : "Jessica Taylor", "salary" : 110000, "designat
ion" : "Manager" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c54"), "empid" : 6, "empname" : "Sarah Lee", "salary" : 95000, "designation" :
"Manager" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c53"), "empid" : 5, "empname" : "David Wilson", "salary" : 80000, "designation"
 : "Developer" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c51"), "empid" : 3, "empname" : "Michael Johnson", "salary" : 70000, "designati
on" : "Manager" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c4f"), "empid" : 1, "empname" : "John Doe", "salary" : 60000, "designation" : "
Manager" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c50"), "empid" : 2, "empname" : "Jane Smith", "salary" : 55000, "designation" :
 "Accountant" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c55"), "empid" : 7, "empname" : "Christopher Martinez", "salary" : 50000, "desi
gnation" : "Accountant" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c52"), "empid" : 4, "empname" : "Emily Brown", "salary" : 45000, "designation"
: "Accountant" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c57"), "empid" : 9, "empname" : "Jason Rodriguez", "salary" : 40000, "designati
on" : "Intern" }
```

- Display employee with designation with “Manager” or salary greater than Rs. 50,000/-.

db.Staff.find({ $or: [{ "designation": "Manager" }, { "salary": { $gt: 50000 } }] })

```
> db.Staff.find({ $or: [{ "designation": "Manager" }, { "salary": { $gt: 50000 } }] })
{ "_id" : ObjectId("65deecde8cbdbaebf7136c4f"), "empid" : 1, "empname" : "John Doe", "salary" : 60000, "designation" : "
Manager" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c51"), "empid" : 3, "empname" : "Michael Johnson", "salary" : 70000, "designati
on" : "Manager" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c53"), "empid" : 5, "empname" : "David Wilson", "salary" : 80000, "designation"
 : "Developer" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c54"), "empid" : 6, "empname" : "Sarah Lee", "salary" : 95000, "designation" :
"Manager" }
```

- Update the salary of all employees with designation as “Accountant” to Rs.45000.

db.Staff.updateMany({ "designation": "Accountant" }, { $set: { "salary": 45000 } })

```
> db.Staff.updateMany({ "designation": "Accountant" }, { $set: { "salary": 45000 } })
{ "acknowledged" : true, "matchedCount" : 3, "modifiedCount" : 2 }
```

db.Staff.din({“designation”: “Accountant”})

```
> db.Staff.find({"designation": "Accountant"})
{ "_id" : ObjectId("65deecde8cbdbaebf7136c50"), "empid" : 2, "empname" : "Jane Smith", "salary" : 45000, "designation" :
 "Accountant" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c52"), "empid" : 4, "empname" : "Emily Brown", "salary" : 45000, "designation"
: "Accountant" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c55"), "empid" : 7, "empname" : "Christopher Martinez", "salary" : 45000, "desi
gnation" : "Accountant" }
```

- Remove the documents of employees whose salary is greater than Rs100000.

db.Staff.deleteMany({ "salary": { $gt: 100000 } }) db.Staff.find()

```
> db.Staff.deleteMany({ "salary": { $gt: 100000 } })
{ "acknowledged" : true, "deletedCount" : 2 }
> db.Staff.find()
{ "_id" : ObjectId("65deecde8cbdbaebf7136c4f"), "empid" : 1, "empname" : "John Doe", "salary" : 60000, "designation" : "
Manager" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c50"), "empid" : 2, "empname" : "Jane Smith", "salary" : 45000, "designation" :
 "Accountant" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c51"), "empid" : 3, "empname" : "Michael Johnson", "salary" : 70000, "designati
on" : "Manager" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c52"), "empid" : 4, "empname" : "Emily Brown", "salary" : 45000, "designation"
: "Accountant" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c53"), "empid" : 5, "empname" : "David Wilson", "salary" : 80000, "designation"
 : "Developer" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c54"), "empid" : 6, "empname" : "Sarah Lee", "salary" : 95000, "designation" :
"Manager" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c55"), "empid" : 7, "empname" : "Christopher Martinez", "salary" : 45000, "desi
gnation" : "Accountant" }
{ "_id" : ObjectId("65deecde8cbdbaebf7136c57"), "empid" : 9, "empname" : "Jason Rodriguez", "salary" : 40000, "designati
on" : "Intern" }
>
```

2. Create a database Institution .Create a Collection Student and Insert ten documents in it with fields: RollNo,Name,Class and TotalMarks(out of 500). db.createCollection(“Student”) db

```
> db.createCollection("Student")
{ "ok" : 1 }
> db
Institution
```

db.Student.insertMany([{ "RollNo": 101, "Name": "Alice Johnson", "Class": "BSc", "TotalMarks": 480 }, { "RollNo": 102, "Name": "Bob Smith", "Class": "MSc", "TotalMarks": 450 }, { "RollNo": 103, "Name": "Charlie Brown", "Class": "MSc", "TotalMarks": 420 }, { "RollNo": 104, "Name": "David Davis", "Class": "BSc", "TotalMarks": 400 }, { "RollNo": 105, "Name": "Eva Wilson", "Class": "MSc", "TotalMarks": 490 }, { "RollNo": 106, "Name": "Frank Martinez", "Class": "BSc", "TotalMarks": 360 }, { "RollNo": 107, "Name": "Grace Lee", "Class": "MSc", "TotalMarks": 510 }, { "RollNo": 108, "Name": "Henry Taylor", "Class": "BSc", "TotalMarks": 320 }, { "RollNo": 109, "Name": "Isabel Rodriguez", "Class": "MSc", "TotalMarks": 380 }, { "RollNo": 110, "Name": "Jack Harris", "Class": "BSc", "TotalMarks": 250 }])

```
> db.Student.insertMany([
...     { "RollNo": 101, "Name": "Alice Johnson", "Class": "BSc", "TotalMarks": 480 },
...     { "RollNo": 102, "Name": "Bob Smith", "Class": "MSc", "TotalMarks": 450 },
...     { "RollNo": 103, "Name": "Charlie Brown", "Class": "MSc", "TotalMarks": 420 },
...     { "RollNo": 104, "Name": "David Davis", "Class": "BSc", "TotalMarks": 400 },
...     { "RollNo": 105, "Name": "Eva Wilson", "Class": "MSc", "TotalMarks": 490 },
...     { "RollNo": 106, "Name": "Frank Martinez", "Class": "BSc", "TotalMarks": 360 },
...     { "RollNo": 107, "Name": "Grace Lee", "Class": "MSc", "TotalMarks": 510 },
...     { "RollNo": 108, "Name": "Henry Taylor", "Class": "BSc", "TotalMarks": 320 },
...     { "RollNo": 109, "Name": "Isabel Rodriguez", "Class": "MSc", "TotalMarks": 380 },
...     { "RollNo": 110, "Name": "Jack Harris", "Class": "BSc", "TotalMarks": 250 }
... ])
{
        "acknowledged" : true,
        "insertedIds" : [
                ObjectId("65def1918cbdbaebf7136c59"),
                ObjectId("65def1918cbdbaebf7136c5a"),
                ObjectId("65def1918cbdbaebf7136c5b"),
                ObjectId("65def1918cbdbaebf7136c5c"),
                ObjectId("65def1918cbdbaebf7136c5d"),
                ObjectId("65def1918cbdbaebf7136c5e"),
                ObjectId("65def1918cbdbaebf7136c5f"),
                ObjectId("65def1918cbdbaebf7136c60"),
                ObjectId("65def1918cbdbaebf7136c61"),
                ObjectId("65def1918cbdbaebf7136c62")
        ]
}
```

db.Student.find({})

```
> db.Student.find({})
{ "_id" : ObjectId("65def1918cbdbaebf7136c59"), "RollNo" : 101, "Name" : "Alice Johnson", "Class" : "BSc", "TotalMarks"
: 480 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5a"), "RollNo" : 102, "Name" : "Bob Smith", "Class" : "MSc", "TotalMarks" : 45
0 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5b"), "RollNo" : 103, "Name" : "Charlie Brown", "Class" : "MSc", "TotalMarks"
: 420 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5c"), "RollNo" : 104, "Name" : "David Davis", "Class" : "BSc", "TotalMarks" :
400 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5d"), "RollNo" : 105, "Name" : "Eva Wilson", "Class" : "MSc", "TotalMarks" : 4
90 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5e"), "RollNo" : 106, "Name" : "Frank Martinez", "Class" : "BSc", "TotalMarks"
 : 360 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5f"), "RollNo" : 107, "Name" : "Grace Lee", "Class" : "MSc", "TotalMarks" : 51
0 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c60"), "RollNo" : 108, "Name" : "Henry Taylor", "Class" : "BSc", "TotalMarks" :
 320 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c61"), "RollNo" : 109, "Name" : "Isabel Rodriguez", "Class" : "MSc", "TotalMark
s" : 380 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c62"), "RollNo" : 110, "Name" : "Jack Harris", "Class" : "BSc", "TotalMarks" :
250 }
>
```

- Display all documents in Student.

db.Student.find({})

- Sort the documents in descending order of TotalMarks.

  db.Student.find().sort({ "TotalMarks": -1 })

```
> db.Student.find({})
{ "_id" : ObjectId("65def1918cbdbaebf7136c59"), "RollNo" : 101, "Name" : "Alice Johnson", "Class" : "BSc", "TotalMarks"
: 480 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5a"), "RollNo" : 102, "Name" : "Bob Smith", "Class" : "MSc", "TotalMarks" : 45
0 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5b"), "RollNo" : 103, "Name" : "Charlie Brown", "Class" : "MSc", "TotalMarks"
: 420 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5c"), "RollNo" : 104, "Name" : "David Davis", "Class" : "BSc", "TotalMarks" :
400 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5d"), "RollNo" : 105, "Name" : "Eva Wilson", "Class" : "MSc", "TotalMarks" : 4
90 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5e"), "RollNo" : 106, "Name" : "Frank Martinez", "Class" : "BSc", "TotalMarks"
 : 360 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5f"), "RollNo" : 107, "Name" : "Grace Lee", "Class" : "MSc", "TotalMarks" : 51
0 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c60"), "RollNo" : 108, "Name" : "Henry Taylor", "Class" : "BSc", "TotalMarks" :
 320 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c61"), "RollNo" : 109, "Name" : "Isabel Rodriguez", "Class" : "MSc", "TotalMark
s" : 380 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c62"), "RollNo" : 110, "Name" : "Jack Harris", "Class" : "BSc", "TotalMarks" :
250 }
>
```

```
> db.Student.find().sort({ "TotalMarks": -1 })
{ "_id" : ObjectId("65def1918cbdbaebf7136c5f"), "RollNo" : 107, "Name" : "Grace Lee", "Class" : "MSc", "TotalMarks" : 51
0 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5d"), "RollNo" : 105, "Name" : "Eva Wilson", "Class" : "MSc", "TotalMarks" : 4
90 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c59"), "RollNo" : 101, "Name" : "Alice Johnson", "Class" : "BSc", "TotalMarks"
: 480 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5a"), "RollNo" : 102, "Name" : "Bob Smith", "Class" : "MSc", "TotalMarks" : 45
0 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5b"), "RollNo" : 103, "Name" : "Charlie Brown", "Class" : "MSc", "TotalMarks"
: 420 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5c"), "RollNo" : 104, "Name" : "David Davis", "Class" : "BSc", "TotalMarks" :
400 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c61"), "RollNo" : 109, "Name" : "Isabel Rodriguez", "Class" : "MSc", "TotalMark
s" : 380 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5e"), "RollNo" : 106, "Name" : "Frank Martinez", "Class" : "BSc", "TotalMarks"
 : 360 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c60"), "RollNo" : 108, "Name" : "Henry Taylor", "Class" : "BSc", "TotalMarks" :
 320 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c62"), "RollNo" : 110, "Name" : "Jack Harris", "Class" : "BSc", "TotalMarks" :
250 }
```

- Display students of class "MSc" or marks greater than 400.
  db.Student.find({ $or: [{ "Class": "MSc" }, { "TotalMarks": { $gt:
  400 } }] })

```
> db.Student.find({ $or: [{ "Class": "MSc" }, { "TotalMarks": { $gt: 400 } }] })
{ "_id" : ObjectId("65def1918cbdbaebf7136c59"), "RollNo" : 101, "Name" : "Alice Johnson", "Class" : "BSc", "TotalMarks"
: 480 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5a"), "RollNo" : 102, "Name" : "Bob Smith", "Class" : "MSc", "TotalMarks" : 45
0 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5b"), "RollNo" : 103, "Name" : "Charlie Brown", "Class" : "MSc", "TotalMarks"
: 420 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5d"), "RollNo" : 105, "Name" : "Eva Wilson", "Class" : "MSc", "TotalMarks" : 4
90 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5f"), "RollNo" : 107, "Name" : "Grace Lee", "Class" : "MSc", "TotalMarks" : 51
0 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c61"), "RollNo" : 109, "Name" : "Isabel Rodriguez", "Class" : "MSc", "TotalMark
s" : 380 }
```

- Remove all the documents with TotalMarks<200

  db.Student.deleteMany({ "TotalMarks": { $lt: 200 } })

  db.Student.find({})

```
> db.Student.deleteMany({ "TotalMarks": { $lt: 200 } })
{ "acknowledged" : true, "deletedCount" : 0 }
> db.Student.find({})
{ "_id" : ObjectId("65def1918cbdbaebf7136c59"), "RollNo" : 101, "Name" : "Alice Johnson", "Class" : "BSc", "TotalMarks"
: 480 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5a"), "RollNo" : 102, "Name" : "Bob Smith", "Class" : "MSc", "TotalMarks" : 45
0 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5b"), "RollNo" : 103, "Name" : "Charlie Brown", "Class" : "MSc", "TotalMarks"
: 420 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5c"), "RollNo" : 104, "Name" : "David Davis", "Class" : "BSc", "TotalMarks" :
400 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5d"), "RollNo" : 105, "Name" : "Eva Wilson", "Class" : "MSc", "TotalMarks" : 4
90 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5e"), "RollNo" : 106, "Name" : "Frank Martinez", "Class" : "BSc", "TotalMarks"
 : 360 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c5f"), "RollNo" : 107, "Name" : "Grace Lee", "Class" : "MSc", "TotalMarks" : 51
0 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c60"), "RollNo" : 108, "Name" : "Henry Taylor", "Class" : "BSc", "TotalMarks" :
 320 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c61"), "RollNo" : 109, "Name" : "Isabel Rodriguez", "Class" : "MSc", "TotalMark
s" : 380 }
{ "_id" : ObjectId("65def1918cbdbaebf7136c62"), "RollNo" : 110, "Name" : "Jack Harris", "Class" : "BSc", "TotalMarks" :
250 }
```