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**DEPARTMENT OF COMPUTER APPLICATIONS**  
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**CLASS & SEM: II MCA/ III SEM**

**MC4311- MACHINE LEARNING LABORATORY MANUAL  
(R-2021 -2 YEARS)**

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## **Download, Install And Explore The Features Of R For Data Analytics.**

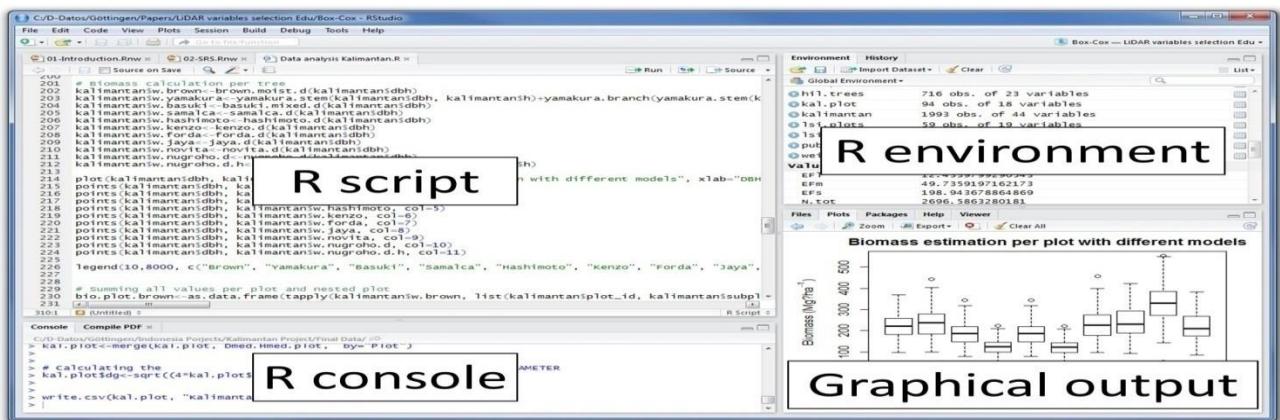
**AIM:-To Download, install and explore the features of R for data analytics.**

**PROCEDURE:-**

### **1. Download R in Windows :**

Follow the steps below for installing R Studio:

1. Go to <https://www.rstudio.com/products/rstudio/download/>
2. In ‘Installers for Supported Platforms’ section, choose and click the R Studio installer based on your operating system. The download should begin as soon as you click.
3. Click Next..Next..Finish.
4. Download Complete.
5. To Start R Studio, click on its desktop icon or use ‘search windows’ to access the program. It looks like this:



### **2. Installation of R Packages**

In R, most data handling tasks can be performed in 2 ways: Using R packages and R base functions. To install a package, simply type:

```
install.packages("package name")
```

As a first time user, a pop might appear to select your CRAN mirror (country server), choose accordingly and press OK.

**Note:** You can type this either in console directly and press ‘Enter’ or in R script and click ‘Run’.

### **3. (i). R AS Calculator Application**

#### **a.Using without R objects on console**

```
> 2587+2149  
[1] 4736  
> 287954-135479  
[1] 152475  
> 257*52  
[1] 13364  
> 257/21  
[1] 12.2381
```

#### **Using with R objects on console:**

```
> A=1000  
> B=2000  
> C=A+B  
> C  
[1] 3000  
> D=A - B  
> D  
[1] -1000  
> E=A * B  
> E  
[1] 2e+06  
> F=A/B  
> F  
[1] 0.5
```

#### **b. Using mathematical functions on console**

```
> a=100  
> a=100  
> class(a)  
[1] "numeric"  
> b=500  
> c=a-b  
> class(b)  
[1] "numeric"  
> sum<-a-b  
> [1] FALSE  
> sum  
[1] -400
```

**c. Write an R script, to create R objects for calculator application and save in a specified location in disk.**

```
> getwd()  
[1] "E:/JOSI SMIT21/DS LAB 21/DS RPrgr"  
> write.csv(a,'diabetes.csv')  
> write.csv(a,'file:///E:/JOSI SMIT21/DS LAB 21/DS RPrgr/diabetes.csv')
```

## **(ii). Descriptive Statistics In R**

**a. Write an R script to find basic descriptive statistics using summary, str, quartile function on mtcars& cars datasets.**

```
> mtcars
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am
Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1
Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1
Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1
Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0
Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0
Valiant	18.1	6	225.0	105	2.76	3.460	20.22	1	0
Duster 360	14.3	8	360.0	245	3.21	3.570	15.84	0	0
Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0
Merc 230	22.8	4	140.8	95	3.92	3.150	22.90	1	0
Merc 280	19.2	6	167.6	123	3.92	3.440	18.30	1	0
Merc 280C	17.8	6	167.6	123	3.92	3.440	18.90	1	0
Merc 450SE	16.4	8	275.8	180	3.07	4.070	17.40	0	0
Merc 450SL	17.3	8	275.8	180	3.07	3.730	17.60	0	0
Merc 450SLC	15.2	8	275.8	180	3.07	3.780	18.00	0	0
Cadillac Fleetwood 10.4	8	472.0	205	2.93	5.250	17.98	0	0	
Lincoln Continental10.4	8	460.0	215	3.00	5.424	17.82	0	0	
Chrysler Imperial	14.7	8	440.0	230	3.23	5.345	17.42	0	0
Fiat 128	32.4	4	78.7	66	4.08	2.200	19.47	1	1
Honda Civic	30.4	4	75.7	52	4.93	1.615	18.52	1	1
Toyota Corolla	33.9	4	71.1	65	4.22	1.835	19.90	1	1
Toyota Corona	21.5	4	120.1	97	3.70	2.465	20.01	1	0
Dodge Challenger	15.5	8	318.0	150	2.76	3.520	16.87	0	0
AMC Javelin	15.2	8	304.0	150	3.15	3.435	17.30	0	0
Camaro Z28	13.3	8	350.0	245	3.73	3.840	15.41	0	0
Pontiac Firebird	19.2	8	400.0	175	3.08	3.845	17.05	0	0
Fiat X1-9	27.3	4	79.0	66	4.08	1.935	18.90	1	1

Porsche 914-2	26.0	4	120.3	91	4.43	2.140	16.70	0	1
Lotus Europa	30.4	4	95.1	113	3.77	1.513	16.90	1	1
Ford Pantera L	15.8	8	351.0	264	4.22	3.170	14.50	0	1
Ferrari Dino	19.7	6	145.0	175	3.62	2.770	15.50	0	1
Maserati Bora	15.0	8	301.0	335	3.54	3.570	14.60	0	1
Volvo 142E	21.4	4	121.0	109	4.11	2.780	18.60	1	1
			gear	carb					
Mazda RX4		4	4						
Mazda RX4 Wag		4	4						
Datsun 710		4	1						
Hornet 4 Drive		3	1						
Hornet Sportabout		3	2						
Valiant		3	1						
Duster 360		3	4						
Merc 240D		4	2						
Merc 230		4	2						
Merc 280		4	4						
Merc 280C		4	4						
Merc 450SE		3	3						
Merc 450SL		3	3						
Merc 450SLC		3	3						
Cadillac Fleetwood		3	4						
Lincoln Continental		3	4						
Chrysler Imperial		3	4						
Fiat 128		4	1						
Honda Civic		4	2						
Toyota Corolla		4	1						
Toyota Corona		3	1						
Dodge Challenger		3	2						
AMC Javelin		3	2						
Camaro Z28		3	4						
Pontiac Firebird		3	2						
Fiat X1-9		4	1						
Porsche 914-2		5	2						
Lotus Europa		5	2						
Ford Pantera L		5	4						
Ferrari Dino		5	6						
Maserati Bora		5	8						
Volvo 142E		4	2						

```

> str(mtcars)
'data.frame':   32 obs. of  11 variables:
 $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
 $ cyl : num  6 6 4 6 8 6 8 4 4 6 ...
 $ disp: num  160 160 108 258 360 ...
 $ hp  : num  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  : num  0 0 1 1 0 1 0 1 1 1 ...
 $ am  : num  1 1 1 0 0 0 0 0 0 0 ...
 $ gear: num  4 4 4 3 3 3 3 4 4 4 ...
 $ carb: num  4 4 1 1 2 1 4 2 2 4 ...

```

```

>quantile(mtcars$mpg)
 0%  25%  50%  75% 100%
10.400 15.425 19.200 22.800 33.900

```

```

> summary(cars)
      speed      dist
Min. : 4.0  Min. : 2.00
1st Qu.:12.0  1st Qu.: 26.00
Median :15.0  Median : 36.00
Mean  :15.4  Mean  :42.98
3rd Qu.:19.0  3rd Qu.: 56.00
Max. :25.0  Max. :120.00

```

```

> class(cars)
[1] "data.frame"

```

**b. Write an R script to find subset of dataset by using subset (), aggregate () functions on iris dataset.**

```

>aggregate(. ~ Species, data = iris, mean)
  Species Sepal.Length Sepal.Width Petal.Length
1  setosa     5.006    3.428     1.462
2 versicolor   5.936    2.770     4.260
3 virginica    6.588    2.974     5.552
  Petal.Width
1     0.246
2     1.326
3     2.026

```

```
> subset(iris,iris$Sepal.Length==5.0)
   Sepal.Length Sepal.Width Petal.Length Petal.Width
5            5       3.6        1.4       0.2
8            5       3.4        1.5       0.2
26           5       3.0        1.6       0.2
27           5       3.4        1.6       0.4
36           5       3.2        1.2       0.2
41           5       3.5        1.3       0.3
44           5       3.5        1.6       0.6
50           5       3.3        1.4       0.2
61           5       2.0        3.5       1.0
94           5       2.3        3.3       1.0

Species
5  setosa
8  setosa
26 setosa
27 setosa
36 setosa
41 setosa
44 setosa
50 setosa
61 versicolor
94 versicolor
```

**Result:** Thus RStudio & R is downloaded, installed and explore the features of R for calculator applications and descriptive statistics for data analytics.

<b>EX.NO.1(ii)</b>	<b>Reading And Writing Different Types Of Datasets Using R</b>
<b>DATE:04.09.23</b>	

**Aim:- To read and write different types of Dataset using R**

**a. Reading different types of data sets (.txt, .csv) from web and disk and writing in file in specific disk location.**

**Source Code:-**

```
#Create the following Student DataSet using Microsoft Excel and save it as .c  
sv file
```

```
student.csv
```

RegNo	Name	Class	MARKS
2126162001	Priya	IIMCA	70
2126162002	Kala	IIMCA	78
2126162003	Lotus	IIMCA	90
2126162004	Jasmine	IIMCA	65
2126162005	Fathima	IIMCA	73

```
# a. Read data from Student.csv
```

```
>library(utils)  
> data<- read.csv("Student.csv")  
> data
```

**Output:-**

	RegNo	Name	Class	MARKS
1	2126162001	Priya	II MCA	70
2	2126162002	Kala	II MCA	78
3	2126162003	Lotus	II MCA	90
4	2126162004	Jasmine	II MCA	65
5	2126162005	Fathima	II MCA	73

```
> library(readr)  
> data<- read.csv("Student.csv")  
> print(is.data.frame(data))  
[1] TRUE  
> print(ncol(data))  
[1] 4  
> print(nrow(data))  
[1] 5  
# Create Employee DataSet
```

### Employee.csv

<b>Id</b>	<b>name</b>	<b>salary</b>	<b>start_date</b>	<b>dept</b>
<b>10001</b>	<b>Mark</b>	<b>30000</b>	<b>12/10/2021</b>	<b>IT</b>
<b>10002</b>	<b>RICK</b>	<b>20000</b>	<b>12/10/2021</b>	<b>HR</b>
<b>10003</b>	<b>Michael</b>	<b>60000</b>	<b>20/11/2021</b>	<b>FINANCE</b>
<b>10004</b>	<b>Gary</b>	<b>70000</b>	<b>20/11/2021</b>	<b>OPERATION</b>
<b>10005</b>	<b>Jasmine</b>	<b>50000</b>	<b>21/12/2021</b>	<b>IT</b>

```
> # Create a data frame.  
> library(readr)  
> data<- read_csv("Employee.csv")  
Rows: 5 Columns: 5  
-- Column specification -----  
Delimiter: ","  
chr (3): name, start_date, dept  
dbl (2): Id, salary
```

- i Use `spec()` to retrieve the full column specification for this data.
- i Specify the column types or set `show\_col\_types = FALSE` to quiet this message

```
.  
> # Get the max salary from data frame.  
> sal<- max(data$salary)  
> # Get the person detail having max salary.  
> retval<- subset(data, salary == max(salary))  
> retval  
# A tibble: 1 x 5  
  Id name salary start_date dept  
  <dbl> <chr> <dbl> <chr>   <chr>  
1 10004 Gary  70000 20/11/2021 OPERATION
```

```
> #Get all the people working in IT department  
> # Create a data frame.  
> library(readr)  
> data<- read_csv("Employee.csv")  
Rows: 5 Columns: 5  
-- Column specification -----  
Delimiter: ","  
chr (3): name, start_date, dept
```

dbl (2): Id, salary

- i Use `spec()` to retrieve the full column specification for this data.
- i Specify the column types or set `show\_col\_types = FALSE` to quiet this message

```

> retval<- subset( data, dept == "IT")
> retval
# A tibble: 2 x 5
  Id name   salary start_date dept
  <dbl> <chr>   <dbl> <chr>    <chr>
1 10001 Mark    30000 12/10/2021 IT
2 10005 Jasmine 50000 21/12/2021 IT

```

### b. Reading Excel data sheet in R.

#Create Emp.xlsx file using Microsoft Excel

Id	name	salary	start_date	dept
10001	Mark	30000	21/12/2021	IT
10002	RICK	20000	21/12/2021	HR
10003	Michael	60000	20/11/2021	FINANCE
10004	Gary	70000	20/11/2021	OPERATION
10005	Jasmine	50000	21/12/2021	IT

**Source:-**

```

install.packages("xlsx")
# Loading
library("readxl")
# xlsx files
my_data <- read_excel("Emp.xlsx")
my_data

```

### OUTPUT:-

# A tibble: 5 x 5

	Id	name	salary	start_date	dept
1	10001	Mark	30000	44540	IT
2	10002	RICK	20000	44540	HR
3	10003	Michael	60000	20/11/2021	FINANCE
4	10004	Gary	70000	20/11/2021	OPERATION
5	10005	Jasmine	50000	21/12/2021	IT

### **c. Reading XML dataset in R.**

#### **Create Input.xml file using notepad**

```
<?xml version="1.0"?>
<Address>
  <No> 1</No>
  <Name> Rick </Name>
  <DNO>458</DNO>
  <Street>SMIT STREET</Street>
  <City> Chennai </City>
  <State>Tamil Nadu</State>
  <Pincode> 600001</Pincode>
</Address>
```

#### **Source code:-**

```
install.packages("XML")
> library("XML")
> library("methods")
> result<- xmlParse(file = "input.xml")
> result
```

#### **Output:-**

```
<?xml version="1.0"?>
<Address>
  <No> 1</No>
  <Name> Rick </Name>
  <DNO>458</DNO>
  <Street>SMIT STREET</Street>
  <City> Chennai </City>
  <State>Tamil Nadu</State>
  <Pincode> 600001</Pincode>
</Address>
```

**Result:-** Thus read and write different types of Dataset using R is executed successfully.

<b>EX.NO.1 (iii)</b>	<b>Structure Data In Machine Learning Using R</b>
<b>DATE:04.09.23</b>	

**Aim:** To demonstrate how do you structure data in Machine Learning

The most essential data structures used in R include:

**1.Vectors:-** A vector is an ordered collection of basic data types of a given length. The only key thing here is all the elements of a vector must be of the identical data type e.g homogeneous data structures. Vectors are one-dimensional data structures.

**Program Code:-**

```
# R program to illustrate Vector  
# Vectors(ordered collection of same data type)
```

```
X = c(1, 3, 5, 7, 8)
```

```
# Printing those elements in console
```

```
print(X)
```

**Output:-**

```
[1] 1 3 5 7 8
```

**2.Lists:-** A list is a generic object consisting of an ordered collection of objects. Lists are heterogeneous data structures. These are also one-dimensional data structures. A list can be a list of vectors, list of matrices, a list of characters and a list of functions and so on.

**Program Code:-**

```
# R program to illustrate a List  
# The first attributes is a numeric vector  
# containing the employee IDs which is  
# created using the 'c' command here  
empId = c(1, 2, 3, 4)
```

```
# The second attribute is the employee name  
# which is created using this line of code here  
# which is the character vector  
empName = c("Debi", "Sandeep", "Subham", "Shiba")
```

```
# The third attribute is the number of employees  
# which is a single numeric variable.  
numberOfEmp = 4  
# We can combine all these three different  
# data types into a list  
# containing the details of employees  
# which can be done using a list command  
empList = list(empId, empName, numberOfEmp)  
print(empList)
```

### **Output:**

```
[[1]]  
[1] 1 2 3 4  
  
[[2]]  
[1] "Debi"  "Sandeep" "Subham" "Shiba"  
  
[[3]]  
[1] 4
```

**3.Dataframes:-** Dataframes are generic data objects of R which are used to store the tabular data. Dataframes are the foremost popular data objects in R programming because we are comfortable in seeing the data within the tabular form. They are two-dimensional, heterogeneous data structures. These are lists of vectors of equal lengths.

Data frames have the following constraints placed upon them:

- A data-frame must have column names and every row should have a unique name.
- Each column must have the identical number of items.
- Each item in a single column must be of the same data type.
- Different columns may have different data types.

To create a data frame we use the `data.frame()` function.

### **Program Code:-**

```
# R program - dataframe  
# A vector which is a character vector  
Name = c("Amiya", "Raj", "Asish")  
# A vector which is a character vector  
Language = c("R", "Python", "Java")  
# A vector which is a numeric vector  
Age = c(22, 25, 45)  
  
# To create dataframe use data.frame command  
# and then pass each of the vectors  
# we have created as arguments  
# to the function data.frame()  
df = data.frame(Name, Language, Age)  
print(df)
```

### **Output:**

	Name	Language	Age
1	Amiya	R	22
2	Raj	Python	25
3	Asish	Java	45

**4. Matrices:-**A matrix is a rectangular arrangement of numbers in rows and columns. In a matrix, as we know rows are the ones that run horizontally and columns are the ones that run vertically. Matrices are two-dimensional, homogeneous data structures.

### **Program Code:-**

```
# R program -matrix  
A = matrix(c(1, 2, 3, 4, 5, 6, 7, 8, 9), nrow = 3, ncol = 3, byrow = TRUE )  
print(A)
```

### **OUTPUT:**

```
[,1] [,2] [,3]  
[1,] 1 2 3  
[2,] 4 5 6  
[3,] 7 8 9
```

**5. Arrays:-** Arrays are the R data objects which store the data in more than two dimensions. Arrays are n-dimensional data structures. For example, if we create an array of dimensions (2, 3, 3) then it creates 3 rectangular matrices each with 2 rows and 3 columns. They are homogeneous data structures.

**Program Code:-**

```
# R program to illustrate an array  
A = array(c(1, 2, 3, 4, 5, 6, 7, 8), dim = c(2, 2, 2))  
print(A)
```

**Output:**

```
, , 1 [1] [,2]  
[1,] 1 3  
[2,] 2 4  
, , 2 [1] [,2]  
[1,] 5 7  
[2,] 6 8
```

**Result:-** Thus Structure data in Machine Learning using R is executed successfully

<b>EX.NO.1(iv)</b>	<b>PERFORM UNIVARIATE ANALYSIS FOR PIMA INDIANS DIABETES DATA SET USING R</b>
<b>DATE:11.09.23</b>	

**Aim:** To Use the Diabetes data set from UCI and Pima Indians Diabetes data set for performing Univariate Analysis such as Frequency, Mean, Median, Mode, Variance, Standard Deviation using R and also compare the results of the above analysis for the two data sets.

### **SOURCE Code:-Univar2A.R**

```
diabetSet=scan()
```

```
1: 6 148 72 35 0 33.6 50 1 1 85 66 29 0 26.6 31 0 8 183 64 0 0 23.3 32 1
```

```
25:
```

```
Read 24 items
```

#### **# Mean of DiabetSet**

```
> mean(diabetSet)
```

```
[1] 37.3125
```

#### **# Median of DiabetSet**

```
> median(diabetSet)
```

```
[1] 27.8
```

#### **#Mode of DiabetSet**

```
> mode(diabetSet)
```

```
[1] "numeric"
```

#### **#Variance of DiabetSet**

```
var(diabetSet)
```

```
[1] 2255.394
```

#### **#Standard Deviation of DiabetSet**

```
> sd(diabetSet)
```

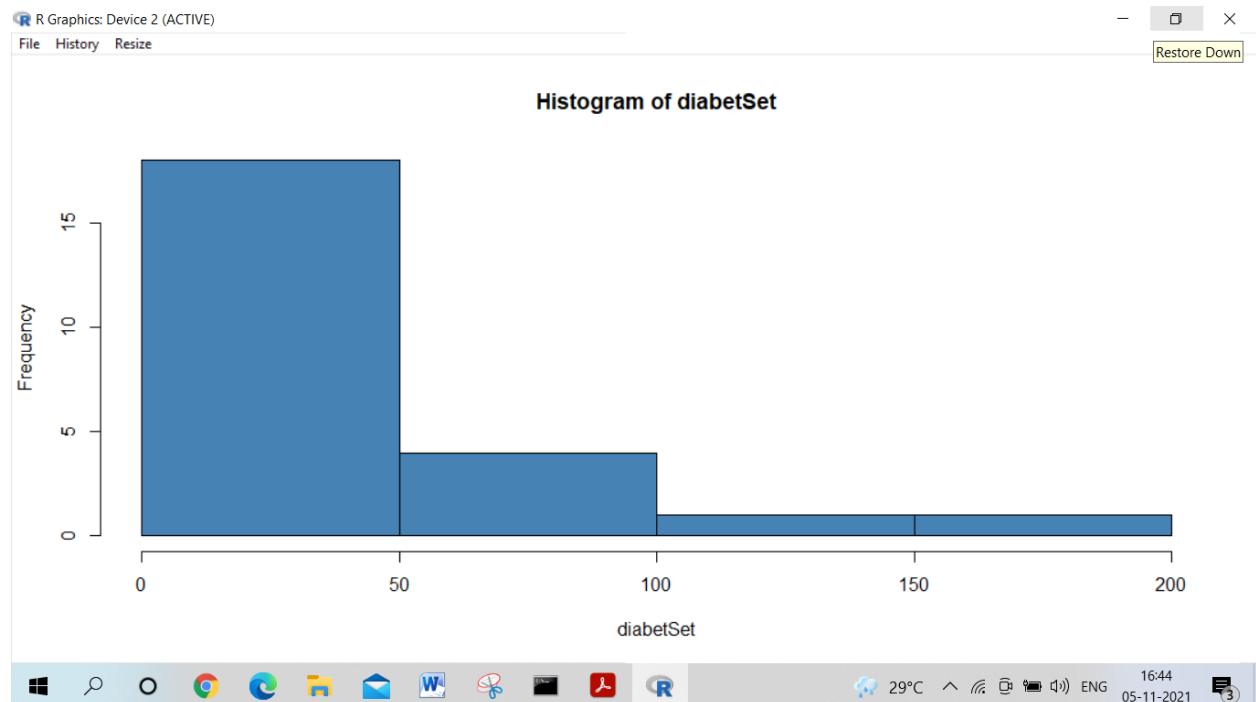
```
[1] 47.49099
```

```

diabetSet<-read.table("D:\Josi(2017-20)\JOSI
Science Lab\diabets.csv",header=TRUE,sep=",")
diabetScore<-diabetSet$BMI
hist(diabetScore,col='steelblue')

```

**MCALAb-2017-21\Data**



### **diabetSet.csv**

6	148	72	35	0	33.6	50	1
1	85	66	29	0	26.6	31	0
8	183	64	0	0	23.3	32	1

**Result:-**Thus the Univariate Analysis for PIMA diabetes dataset using R is implemented and executed successfully.

<b>EX.NO.1(v)</b>	<b>Perform Bivariate Analysis For Pima Indians Diabetes Data Set Using R</b>
<b>DATE:11.09.23</b>	

**Aim:** To Use the Diabetes data set from UCI and Pima Indians Diabetes data set for performing Bivariate Analysis such as Linear and logistic regression modeling using R and also compare the results of the above analysis for the two data sets.

**Program:-**

**EXI-2BBIVARDIA.R**

```
library(tidyverse)
library(ggplot2)
library(readr)
library(scales)
library(dplyr)
library(reshape2)
library(readxl)
library(corrplot)
# loading data (.csv)

data <- read_csv(/diabetes.csv")
diabetes<- as_tibble(data)
diabetes #display data as tibble
```

**output:-**

```
Rows: 3 Columns: 8
-- Column specification -----
Delimiter: ","
dbl (8): Pregnancies, Glucose, BloodPressure, SkinThickness...
```

- i Use `spec()` to retrieve the full column specification for this data.
  - i Specify the column types or set `show\_col\_types = FALSE` to quiet this message .
- ```
tibble [3 x 8] (S3: tbl_df/tbl/data.frame)
```

```
$ Pregnancies : num [1:3] 6 1 8  
$ Glucose     : num [1:3] 148 85 183  
$ BloodPressure: num [1:3] 72 66 64  
$ SkinThickness: num [1:3] 35 29 0  
$ Insulin      : num [1:3] 0 0 0  
$ BMI         : num [1:3] 33.6 26.6 23.3  
$ Age          : num [1:3] 50 31 32  
$ Outcome      : num [1:3] 1 0 1
```

> summary(diabetes)

**Output:-**

| Pregnancies | Glucose       | BloodPressure |
|-------------|---------------|---------------|
| Min. :1.0   | Min. :85.0    | Min. :64.00   |
| 1st Qu.:3.5 | 1st Qu.:116.5 | 1st Qu.:65.00 |
| Median :6.0 | Median :148.0 | Median :66.00 |
| Mean :5.0   | Mean :138.7   | Mean :67.33   |
| 3rd Qu.:7.0 | 3rd Qu.:165.5 | 3rd Qu.:69.00 |
| Max. :8.0   | Max. :183.0   | Max. :72.00   |

| SkinThickness | Insulin   | BMI           | Age           |
|---------------|-----------|---------------|---------------|
| Min. :0.00    | Min. :0   | Min. :23.30   | Min. :31.00   |
| 1st Qu.:14.50 | 1st Qu.:0 | 1st Qu.:24.95 | 1st Qu.:31.50 |
| Median :29.00 | Median :0 | Median :26.60 | Median :32.00 |
| Mean :21.33   | Mean :0   | Mean :27.83   | Mean :37.67   |
| 3rd Qu.:32.00 | 3rd Qu.:0 | 3rd Qu.:30.10 | 3rd Qu.:41.00 |
| Max. :35.00   | Max. :0   | Max. :33.60   | Max. :50.00   |

**Outcome**

|                |
|----------------|
| Min. :0.0000   |
| 1st Qu.:0.5000 |
| Median :1.0000 |
| Mean :0.6667   |
| 3rd Qu.:1.0000 |
| Max. :1.0000   |

>head(diabetes)

**Output:-**

```
# A tibble: 3 x 8
```

|   | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin |       |       |
|---|-------------|---------|---------------|---------------|---------|-------|-------|
|   | <dbl>       | <dbl>   | <dbl>         | <dbl>         | <dbl>   | <dbl> | <dbl> |
| 1 | 6           | 148     | 72            | 35            | 0       |       |       |
| 2 | 1           | 85      | 66            | 29            | 0       |       |       |
| 3 | 8           | 183     | 64            | 0             | 0       |       |       |

|   |   |     |    |    |   |  |  |
|---|---|-----|----|----|---|--|--|
| 1 | 6 | 148 | 72 | 35 | 0 |  |  |
| 2 | 1 | 85  | 66 | 29 | 0 |  |  |
| 3 | 8 | 183 | 64 | 0  | 0 |  |  |

```
# ... with 3 more variables: BMI <dbl>, Age <dbl>,
```

```
>dim(diabetes) # to find the dimensions of the dataset(Diabetes)
```

```
>names(diabetes) # Name of each variable in the dataset
```

```
[1] "Pregnancies"    "Glucose"        "BloodPressure"  
[4] "SkinThickness"  "Insulin"        "BMI"  
[7] "Age"           "Outcome"
```

```
>str(diabetes)
```

**output:-**

```
tibble [3 x 8] (S3: tbl_df/tbl/data.frame)  
$ Pregnancies : num [1:3] 6 1 8  
$ Glucose     : num [1:3] 148 85 183  
$ BloodPressure: num [1:3] 72 66 64  
$ SkinThickness: num [1:3] 35 29 0  
$ Insulin      : num [1:3] 0 0 0  
$ BMI         : num [1:3] 33.6 26.6 23.3  
$ Age          : num [1:3] 50 31 32  
$ Outcome      : num [1:3] 1 0 1
```

```
>sapply(diabetes, typeof) # individual feature's datatype in the dataset
```

**output:-**

| Pregnancies | Glucose  | BloodPressure | SkinThickness |
|-------------|----------|---------------|---------------|
| "double"    | "double" | "double"      | "double"      |
| Insulin     | BMI      | Age           | Outcome       |
| "double"    | "double" | "double"      | "double"      |

```
>table(diabetes$Outcome)
```

**output:-**

```
0 1
```

```
1 2
```

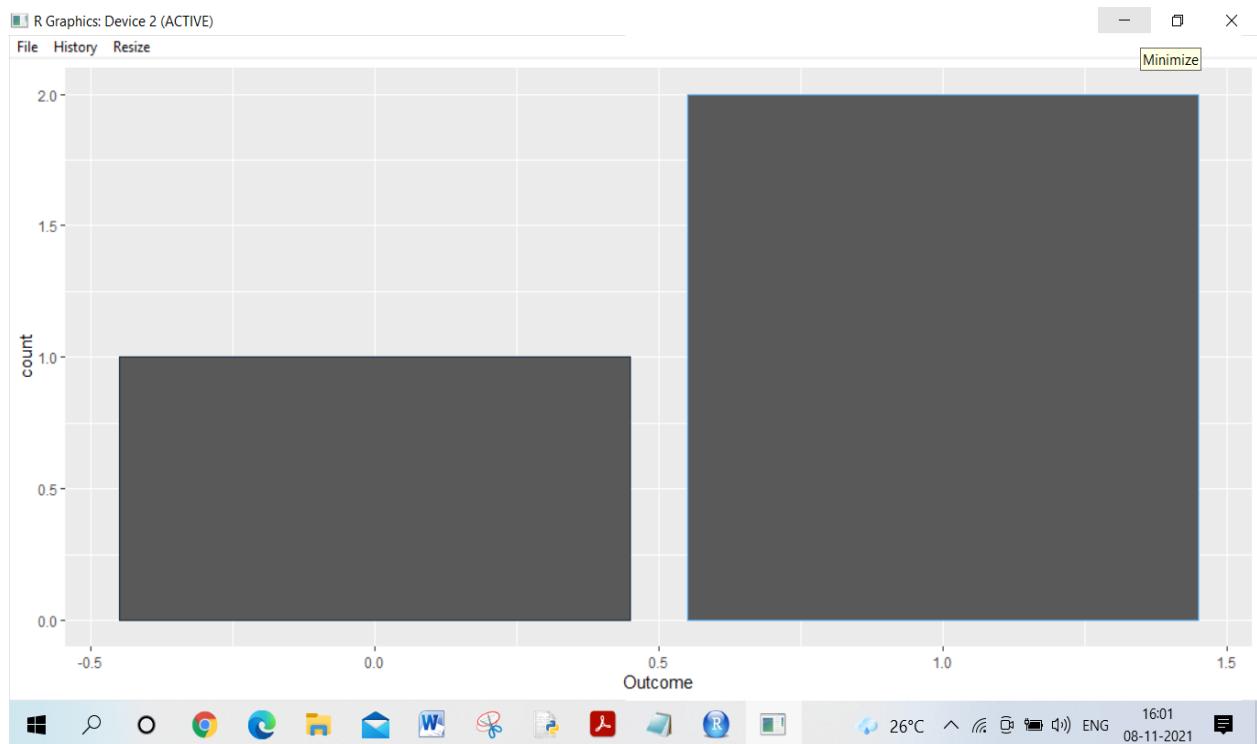
```
># bar chart displaying target variable "Outcome"
```

```
># variable, 268 of 768 people have diabetes and 500 are normal
```

```
>g <- ggplot(diabetes, aes(Outcome))
```

```
>g + geom_bar(aes(group=Outcome, color=Outcome)) +
```

```
theme(legend.position = "none")
```



```
>#Bivariate test
```

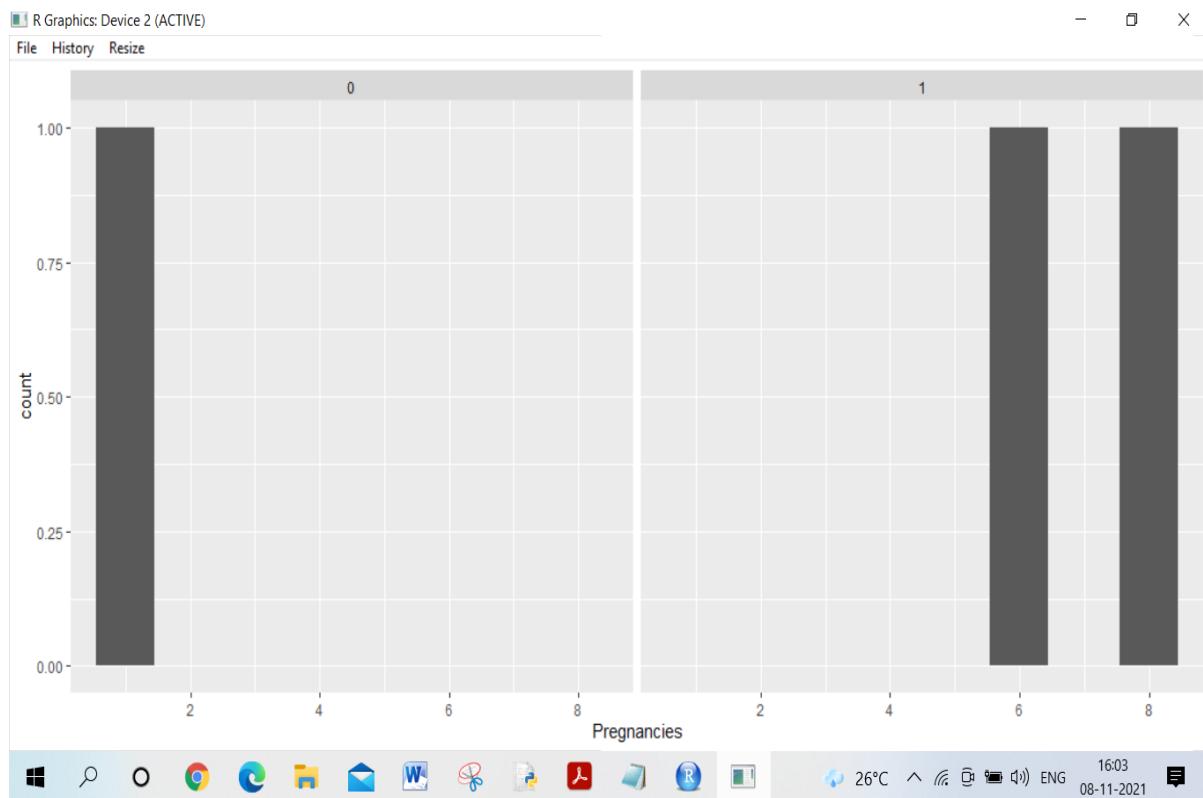
```
># # ggplot (Pregnancies Outcome)
```

```
>g <- ggplot(diabetes, aes(Pregnancies))
```

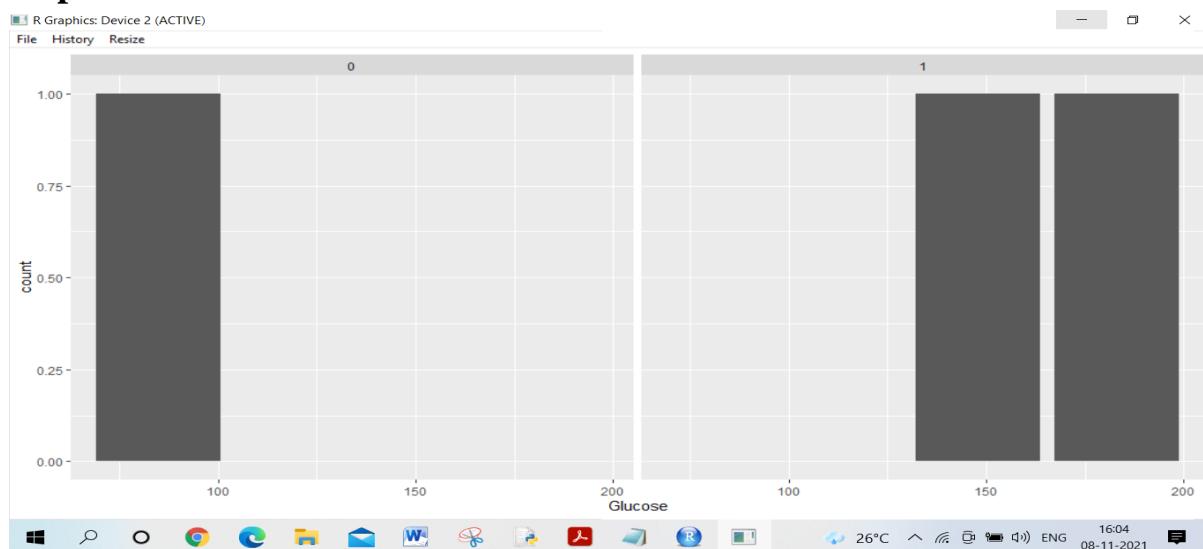
```
>g + geom_bar(aes(group=Outcome)) + facet_wrap(~Outcome) +
```

```
theme(legend.position = "none")
```

## Output:-



```
># # ggplot (Glucose and Outcome)
>g <- ggplot(diabetes, aes(Glucose))
>g + geom_bar(aes(group=Outcome)) + facet_wrap(~Outcome) +
  theme(legend.position = "none")
output:-
```

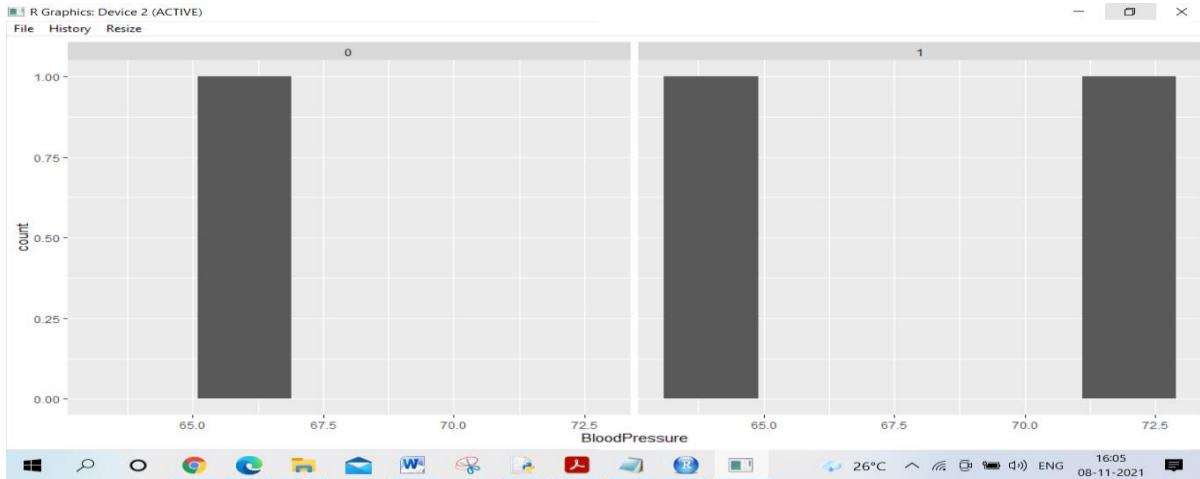


```

># ggplot (BloodPressure and Outcome)
>g <- ggplot(diabetes, aes(BloodPressure))
>g + geom_bar(aes(group=Outcome)) + facet_wrap(~Outcome) +
theme(legend.position = "none")

```

**output:-**



```

># ggplot (SkinThickness and Outcome)
>g <- ggplot(diabetes, aes(SkinThickness))
>g + geom_bar(aes(group=Outcome)) + facet_wrap(~Outcome) +
theme(legend.position = "none")

```

**Output:-**



**Result:-** Thus the Bivariate Analysis such as Linear and logistic regression modeling using R is implemented and executed successfully.

|                      |                                                                                                                     |
|----------------------|---------------------------------------------------------------------------------------------------------------------|
| <b>EX.NO.1(vi)</b>   | <b>Perform Multiple Regression Analysis Compare The Results Of The Above Analysis For The Two Data Sets Using R</b> |
| <b>DATE:11.09.23</b> |                                                                                                                     |

**Aim:** To use the Diabetes data set from UCI and Pima Indians Diabetes data set for performing Multiple Regression Analysis using R and also compare the results of the above analysis for the two data sets.

**PROBLEM DEFINATION:**

**REGRESSION MODEL:**

Import a data from web storage. Name the dataset and now do Logistic Regression to find out relation between variables that are affecting the admission of a student in a institute based on his or her GRE score, GPA obtained and rank of the student. Also check the model is fit or not. require (foreign), require(MASS)

**SOURCE CODE:**

```
>input <- mtcars[,c("mpg","disp","hp","wt")]
```

```
> print(head(input))
```

|                   | mpg  | disp | hp  | wt    |
|-------------------|------|------|-----|-------|
| Mazda RX4         | 21.0 | 160  | 110 | 2.620 |
| Mazda RX4 Wag     | 21.0 | 160  | 110 | 2.875 |
| Datsun 710        | 22.8 | 108  | 93  | 2.320 |
| Hornet 4 Drive    | 21.4 | 258  | 110 | 3.215 |
| Hornet Sportabout | 18.7 | 360  | 175 | 3.440 |
| Valiant           | 18.1 | 225  | 105 | 3.460 |

```
>> # Create the relationship model.
```

```
> model <- lm(mpg~disp+hp+wt, data = input)
```

```
>> # Show the model.
```

```
> print(model)
```

**Output:-**

**Call:**

```
lm(formula = mpg ~ disp + hp + wt, data = input)
```

**Coefficients:**

| (Intercept) | disp      | hp        | wt        |
|-------------|-----------|-----------|-----------|
| 37.105505   | -0.000937 | -0.031157 | -3.800891 |

```
> # Get the Intercept and coefficients as vector elements.
```

```
>cat('### The Coefficient Values ### "\n")
```

```
> a <- coef(model)[1]
```

```
> print(a)
```

**Output:-**

```
(Intercept)
```

```
37.10551
```

```
>Xdisp<- coef(model)[2]
```

```
>Xhp<- coef(model)[3]
```

```
>Xwt<- coef(model)[4]
```

```
>x1 = 221
```

```
>x2 = 102
```

```
>x3 = 2.91
```

```
>print(Xdisp)
```

```
disp
```

```
-0.0009370091
```

```
>print(Xhp)
```

**Output:-**

**hp**

**-0.03115655**

**>print(Xwt)**

**Output:-**

**wt**

**-3.800891**

**>#Create Equation for Regression Model**

**> Y = a+Xdisp \* x1+Xhp \* x2+Xwt \* x3**

**> print(Y)**

**Output:-**

**(Intercept)**

**22.65987**

**Result:-** Thus the Multiple Regression Analysis using R is implemented and executed successfully.

|                      |                                                                                                                          |
|----------------------|--------------------------------------------------------------------------------------------------------------------------|
| <b>EX.NO.1(vii)</b>  | <b>Perform Multiple Regression Analysis Compare The Results Of The Above Analysis For The Two Data Sets Using Python</b> |
| <b>DATE:18.09.23</b> |                                                                                                                          |

**Aim:** To perform multiple linear regression for a fictitious economy, where the index\_price is the dependent variable, and the 2 independent/input variables are:

- interest\_rate
- unemployment\_rate

### SOURCE CODE

```
import pandas as pd
import matplotlib.pyplot as plt
data = {'year':
[2017,2017,2017,2017,2017,2017,2017,2017,2017,2017,2017,2017,2016,2016,201
6,2016,2016,2016,2016,2016,2016,2016],
'month': [12,11,10,9,8,7,6,5,4,3,2,1,12,11,10,9,8,7,6,5,4,3,2,1],
'interest_rate':
[2.75,2.5,2.5,2.5,2.5,2.5,2.25,2.25,2.25,2,2,2,1.75,1.75,1.75,1.75,1.75,1.75
,1.75,1.75,1.75,1.75],
'unemployment_rate':
[5.3,5.3,5.3,5.3,5.4,5.6,5.5,5.5,5.5,5.6,5.7,5.9,6,5.9,5.8,6.1,6.2,6.1,6.1,6.1,5.9,6.2,6.
2,6.1],
'index_price':
[1464,1394,1357,1293,1256,1254,1234,1195,1159,1167,1130,1075,1047,965,943,
958,971,949,884,866,876,822,704,719]
}
df = pd.DataFrame(data)
print(df)
print("Index Price vs Interest rate:\n")
plt.scatter(df['interest_rate'], df['index_price'], color='red')
plt.title('Index Price Vs Interest Rate', fontsize=14)
plt.xlabel('Interest Rate', fontsize=14)
plt.ylabel('Index Price', fontsize=14)
plt.grid(True)
plt.show()
```

```

print("Unemployment Rate and index Price:\n")
plt.scatter(df['unemployment_rate'], df['index_price'], color='green')
plt.title('Index Price Vs Unemployment Rate', fontsize=14)
plt.xlabel('Unemployment Rate', fontsize=14)
plt.ylabel('Index Price', fontsize=14)
plt.grid(True)
plt.show()

```

### **Output:-**

Python 3.11.1 (tags/v3.11.1:a7a450f, Dec 6 2022, 19:58:39) [MSC v.1934 64 bit (AMD64)] on win32

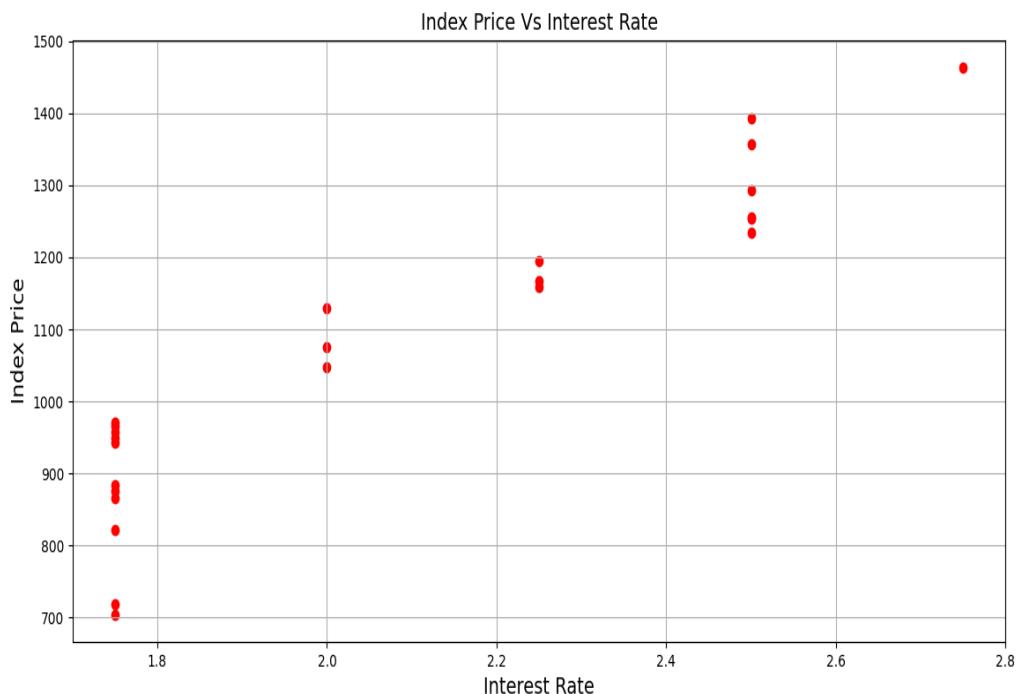
Type "help", "copyright", "credits" or "license()" for more information.

===== RESTART: E:/JosiSMit 2023/MLLAB 23/MultiRegr.py ==

|    | year | month | interest_rate | unemployment_rate | index_price |
|----|------|-------|---------------|-------------------|-------------|
| 0  | 2017 | 12    | 2.75          | 5.3               | 1464        |
| 1  | 2017 | 11    | 2.50          | 5.3               | 1394        |
| 2  | 2017 | 10    | 2.50          | 5.3               | 1357        |
| 3  | 2017 | 9     | 2.50          | 5.3               | 1293        |
| 4  | 2017 | 8     | 2.50          | 5.4               | 1256        |
| 5  | 2017 | 7     | 2.50          | 5.6               | 1254        |
| 6  | 2017 | 6     | 2.50          | 5.5               | 1234        |
| 7  | 2017 | 5     | 2.25          | 5.5               | 1195        |
| 8  | 2017 | 4     | 2.25          | 5.5               | 1159        |
| 9  | 2017 | 3     | 2.25          | 5.6               | 1167        |
| 10 | 2017 | 2     | 2.00          | 5.7               | 1130        |
| 11 | 2017 | 1     | 2.00          | 5.9               | 1075        |
| 12 | 2016 | 12    | 2.00          | 6.0               | 1047        |
| 13 | 2016 | 11    | 1.75          | 5.9               | 965         |
| 14 | 2016 | 10    | 1.75          | 5.8               | 943         |
| 15 | 2016 | 9     | 1.75          | 6.1               | 958         |
| 16 | 2016 | 8     | 1.75          | 6.2               | 971         |
| 17 | 2016 | 7     | 1.75          | 6.1               | 949         |
| 18 | 2016 | 6     | 1.75          | 6.1               | 884         |
| 19 | 2016 | 5     | 1.75          | 6.1               | 866         |

|    |      |   |      |     |     |
|----|------|---|------|-----|-----|
| 20 | 2016 | 4 | 1.75 | 5.9 | 876 |
| 21 | 2016 | 3 | 1.75 | 6.2 | 822 |
| 22 | 2016 | 2 | 1.75 | 6.2 | 704 |
| 23 | 2016 | 1 | 1.75 | 6.1 | 719 |

Index Price vs Interest rate:



index Price and Unemployment Rate :



**Result:-**Thus the Multiple Regression Analysis using Python is implemented and executed successfully.

|                      |                                                             |
|----------------------|-------------------------------------------------------------|
| <b>EX.NO. 2</b>      | <b>Implement Data Preprocessing Techniques On Real Time</b> |
| <b>DATE:18.09.23</b> | <b>Dataset</b>                                              |

**Aim:-**To implement data preprocessing techniques on real time dataset

**First create dataset data.csv using Microsoft Excel**  
**data.csv**

| Country | Age | Salary | Purchased |
|---------|-----|--------|-----------|
| France  | 44  | 72000  | No        |
| Spain   | 27  | 48000  | Yes       |
| Germany | 30  | 54000  | No        |
| Spain   | 38  | 61000  | No        |
| Germany | 40  | NA     | Yes       |
| France  | 35  | 58000  | Yes       |
| Spain   | NA  | 52000  | No        |
| France  | 48  | 79000  | Yes       |
| Germany | 50  | 83000  | No        |
| France  | 37  | 67000  | Yes       |

### **Procedure & Coding :-**

Data preprocessing is the initial phase of Machine Learning where data is prepared for machine learning models.

#### **Step 1: Importing the dataset**

```
Dataset = read_csv('data.csv')
```

```
view(Dataset)
```

**Output:-**

|    | Country | Age | Salary | Purchased |
|----|---------|-----|--------|-----------|
| 1  | France  | 44  | 72000  | No        |
| 2  | Spain   | 27  | 48000  | Yes       |
| 3  | Germany | 30  | 54000  | No        |
| 4  | Spain   | 38  | 61000  | No        |
| 5  | Germany | 40  | NA     | Yes       |
| 6  | France  | 35  | 58000  | Yes       |
| 7  | Spain   | NA  | 52000  | No        |
| 8  | France  | 48  | 79000  | Yes       |
| 9  | Germany | 50  | 83000  | No        |
| 10 | France  | 37  | 67000  | Yes       |

#Handling the missing data

**Step 2:- Replace the missing Age data with the average of the feature in which the data is missing:**

```
Dataset$Age = ifelse(is.na(Dataset$Age),  
                     ave(Dataset$Age, FUN = function (x)mean(x, na.rm = TRUE)),  
                     Dataset$Age)
```

**Output:-**

|    | Country | Age      | Salary | Purchased |
|----|---------|----------|--------|-----------|
| 1  | France  | 44.00000 | 72000  | No        |
| 2  | Spain   | 27.00000 | 48000  | Yes       |
| 3  | Germany | 30.00000 | 54000  | No        |
| 4  | Spain   | 38.00000 | 61000  | No        |
| 5  | Germany | 40.00000 | NA     | Yes       |
| 6  | France  | 35.00000 | 58000  | Yes       |
| 7  | Spain   | 38.77778 | 52000  | No        |
| 8  | France  | 48.00000 | 79000  | Yes       |
| 9  | Germany | 50.00000 | 83000  | No        |
| 10 | France  | 37.00000 | 67000  | Yes       |

```
Dataset$Salary = ifelse(is.na(Dataset$Salary),  
                       ave(Dataset$Salary, FUN = function (x)mean(x, na.rm =  
                           TRUE)), Dataset$Salary)
```

**Output:-**

|    | Country | Age      | Salary   | Purchased |
|----|---------|----------|----------|-----------|
| 1  | France  | 44.00000 | 72000.00 | No        |
| 2  | Spain   | 27.00000 | 48000.00 | Yes       |
| 3  | Germany | 30.00000 | 54000.00 | No        |
| 4  | Spain   | 38.00000 | 61000.00 | No        |
| 5  | Germany | 40.00000 | 63777.78 | Yes       |
| 6  | France  | 35.00000 | 58000.00 | Yes       |
| 7  | Spain   | 38.77778 | 52000.00 | No        |
| 8  | France  | 48.00000 | 79000.00 | Yes       |
| 9  | Germany | 50.00000 | 83000.00 | No        |
| 10 | France  | 37.00000 | 67000.00 | Yes       |

**Step 3: Encoding categorical data**

```
Dataset$Country = factor(Dataset$Country,  
                         levels = c('France','Spain','Germany'),  
                         labels = c(1.0, 2.0 , 3.0 ))
```

## Output:-

|    | Country | Age      | Salary   | Purchased |
|----|---------|----------|----------|-----------|
| 1  | 1       | 44.00000 | 72000.00 | No        |
| 2  | 2       | 27.00000 | 48000.00 | Yes       |
| 3  | 3       | 30.00000 | 54000.00 | No        |
| 4  | 2       | 38.00000 | 61000.00 | No        |
| 5  | 3       | 40.00000 | 63777.78 | Yes       |
| 6  | 1       | 35.00000 | 58000.00 | Yes       |
| 7  | 2       | 38.77778 | 52000.00 | No        |
| 8  | 1       | 48.00000 | 79000.00 | Yes       |
| 9  | 3       | 50.00000 | 83000.00 | No        |
| 10 | 1       | 37.00000 | 67000.00 | Yes       |

#the purchased column.

```
Dataset$Purchased = factor(Dataset$Purchased,  
                           levels = c('No', 'Yes'),  
                           labels = c(0, 1))  
  
Dataset$Purchased[is.na(Dataset$Purchased)] <- 0  
as.factor(Dataset$Purchased)
```

## Output:-

|    | Country | Age      | Salary   | Purchased |
|----|---------|----------|----------|-----------|
| 1  | 1       | 44.00000 | 72000.00 | 0         |
| 2  | 2       | 27.00000 | 48000.00 | 1         |
| 3  | 3       | 30.00000 | 54000.00 | 0         |
| 4  | 2       | 38.00000 | 61000.00 | 0         |
| 5  | 3       | 40.00000 | 63777.78 | 1         |
| 6  | 1       | 35.00000 | 58000.00 | 1         |
| 7  | 2       | 38.77778 | 52000.00 | 0         |
| 8  | 1       | 48.00000 | 79000.00 | 1         |
| 9  | 3       | 50.00000 | 83000.00 | 0         |
| 10 | 1       | 37.00000 | 67000.00 | 1         |

## Step 4: Splitting the dataset into the training and test set

#Using our dataset, let's split it into the training and test sets.

#To begin with, we first load the required library.

```
library(caTools)# required library for data splition
```

```
set.seed(123)
```

```
split = sample.split(Dataset$Purchased, SplitRatio = 0.8)
```

```
# returns true if observation goes to the Training set and false if observation  
goes to the test set.
```

```
#Creating the training set and test set separately
```

```
training_set = subset(Dataset, split == TRUE)
```

```
test_set = subset(Dataset, split == FALSE)
```

```
training_set
```

```
test_set
```

**Output:**

**Training Set**

```
> training_set  
   Country     Age   Salary Purchased  
1      1 44.00000 72000.00      0  
2      2 27.00000 48000.00      1  
3      3 30.00000 54000.00      0  
4      2 38.00000 61000.00      0  
5      3 40.00000 63777.78      1  
7      2 38.77778 52000.00      0  
8      1 48.00000 79000.00      1  
10     1 37.00000 67000.00      1
```

**Test Set:-**

```
> test_set  
   Country Age Salary Purchased  
6      1    35  58000      1  
9      3    50  83000      0  
> |
```

```
# returns true if observation goes to the Training set and false if observation  
goes to the test set.
```

**Step 5:- Feature scale**

```
training_set[, 2:3] = scale(training_set[, 2:3])
```

```
test_set[, 2:3] = scale(test_set[, 2:3])
```

```
training_set
```

```
test_set
```

**Output:-**

**Training Set:-**

```
> training_set
  Country      Age     Salary Purchased
1       1  0.90101716  0.9392746      0
2       2 -1.58847494 -1.3371160      1
3       3 -1.14915281 -0.7680183      0
4       2  0.02237289 -0.1040711      0
5       3  0.31525431  0.1594000      1
7       2  0.13627122 -0.9577176      0
8       1  1.48678000  1.6032218      1
10      1 -0.12406783  0.4650265      1
```

Test Set:-

```
> test_set
  Country      Age     Salary Purchased
6       1 -0.7071068 -0.7071068      1
9       3  0.7071068  0.7071068      0
> |
```

**Result:-** Thus the program is implemented for data preprocessing techniques on real time dataset is executed successfully.

|                      |                                                                     |
|----------------------|---------------------------------------------------------------------|
| <b>EX.NO.3.</b>      | <b>Implement Boruta Feature Subset Selection Techniques Using R</b> |
| <b>DATE:25.09.23</b> |                                                                     |

**AIM:-** to implement Boruta Feature subset selection techniques using R

**Program:-**

```
# Load Packages and prepare dataset
library(TH.data)
library(caret)
data("GlaucomaM", package = "TH.data")
trainData <- GlaucomaM
```

**head(trainData)**

**Output:-**

Glaucoma Dataset

|    | ag    | at    | as    | an    | ai    | eag   | eat   | eas   | ean   | eai   | ... | tmt    | tms    | tmn    | tmi    | mr    | rnf   | mdic  | emd   | mv    | Class  |
|----|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-----|--------|--------|--------|--------|-------|-------|-------|-------|-------|--------|
| 2  | 2.220 | 0.354 | 0.580 | 0.686 | 0.601 | 1.267 | 0.336 | 0.346 | 0.255 | 0.331 | ... | -0.018 | -0.230 | -0.510 | -0.158 | 0.841 | 0.410 | 0.137 | 0.239 | 0.035 | normal |
| 43 | 2.681 | 0.475 | 0.672 | 0.868 | 0.667 | 2.053 | 0.440 | 0.520 | 0.639 | 0.454 | ... | -0.014 | -0.165 | -0.317 | -0.192 | 0.924 | 0.256 | 0.252 | 0.329 | 0.022 | normal |
| 25 | 1.979 | 0.343 | 0.508 | 0.624 | 0.504 | 1.200 | 0.299 | 0.396 | 0.259 | 0.246 | ... | -0.097 | -0.235 | -0.337 | -0.020 | 0.795 | 0.378 | 0.152 | 0.250 | 0.029 | normal |
| 65 | 1.747 | 0.269 | 0.476 | 0.525 | 0.476 | 0.612 | 0.147 | 0.017 | 0.044 | 0.405 | ... | -0.035 | -0.449 | -0.217 | -0.091 | 0.746 | 0.200 | 0.027 | 0.078 | 0.023 | normal |
| 70 | 2.990 | 0.599 | 0.686 | 1.039 | 0.667 | 2.513 | 0.543 | 0.607 | 0.871 | 0.492 | ... | -0.105 | 0.084  | -0.012 | -0.054 | 0.977 | 0.193 | 0.297 | 0.354 | 0.034 | normal |
| 16 | 2.917 | 0.483 | 0.763 | 0.901 | 0.770 | 2.200 | 0.462 | 0.637 | 0.504 | 0.597 | ... | 0.087  | 0.018  | -0.094 | -0.051 | 0.965 | 0.339 | 0.333 | 0.442 | 0.028 | normal |

```
# install.packages('Boruta')
```

**library(Boruta)**

# Perform Boruta search

```
boruta_output <- Boruta(Class ~ ., data=na.omit(trainData), doTrace=0)
names(boruta_output)
```

**OUTPUT:-**

1. ‘finalDecision’
2. ‘ImpHistory’
3. ‘pValue’
4. ‘maxRuns’
5. ‘light’
6. ‘mcAdj’
7. ‘timeTaken’
8. ‘roughfixed’
9. ‘call’
10. ‘impSource’

```
# Get significant variables including tentatives
boruta_signif <- getSelectedAttributes(boruta_output, withTentative =
TRUE)
print(boruta_signif)
```

**Output:-**

```
[1] "as"  "ean" "abrg" "abrs" "abrn" "abri" "hic"  "mhcg" "mhcn" "mhci"
[11] "phcg" "phcn" "phci" "hvc"  "vbss" "vbsn" "vbsi" "vasg" "vass" "vasi"
[21] "vbrg" "vbrs" "vbrn" "vbri" "varg" "vart" "vars" "varn" "vari" "mdn"
[31] "tmg"  "tmt" "tms"  "tmn" "tmi"  "rnf"  "mdic" "emd"
```

```
# Do a tentative rough fix
roughFixMod <- TentativeRoughFix(boruta_output)
boruta_signif <- getSelectedAttributes(roughFixMod)
print(boruta_signif)
```

**Output:-**

```
[1] "abrg" "abrs" "abrn" "abri" "hic"  "mhcg" "mhcn" "mhci" "phcg" "phcn"
[11] "phci" "hvc"  "vbss" "vbsn" "vbsi" "vasg" "vbrg" "vbrs" "vbrn" "vbri" "varg"
[21] "vart" "vars" "varn" "vari" "tmg"  "tms"  "tmn" "tmi"  "rnf"  "mdic" "emd"
```

**# Variable Importance Scores**

```
imps <- attStats(roughFixMod)
imps2 = imps[imps$decision != 'Rejected', c('meanImp', 'decision')]
head(imps2[order(-imps2$meanImp), ]) # descending sort
```

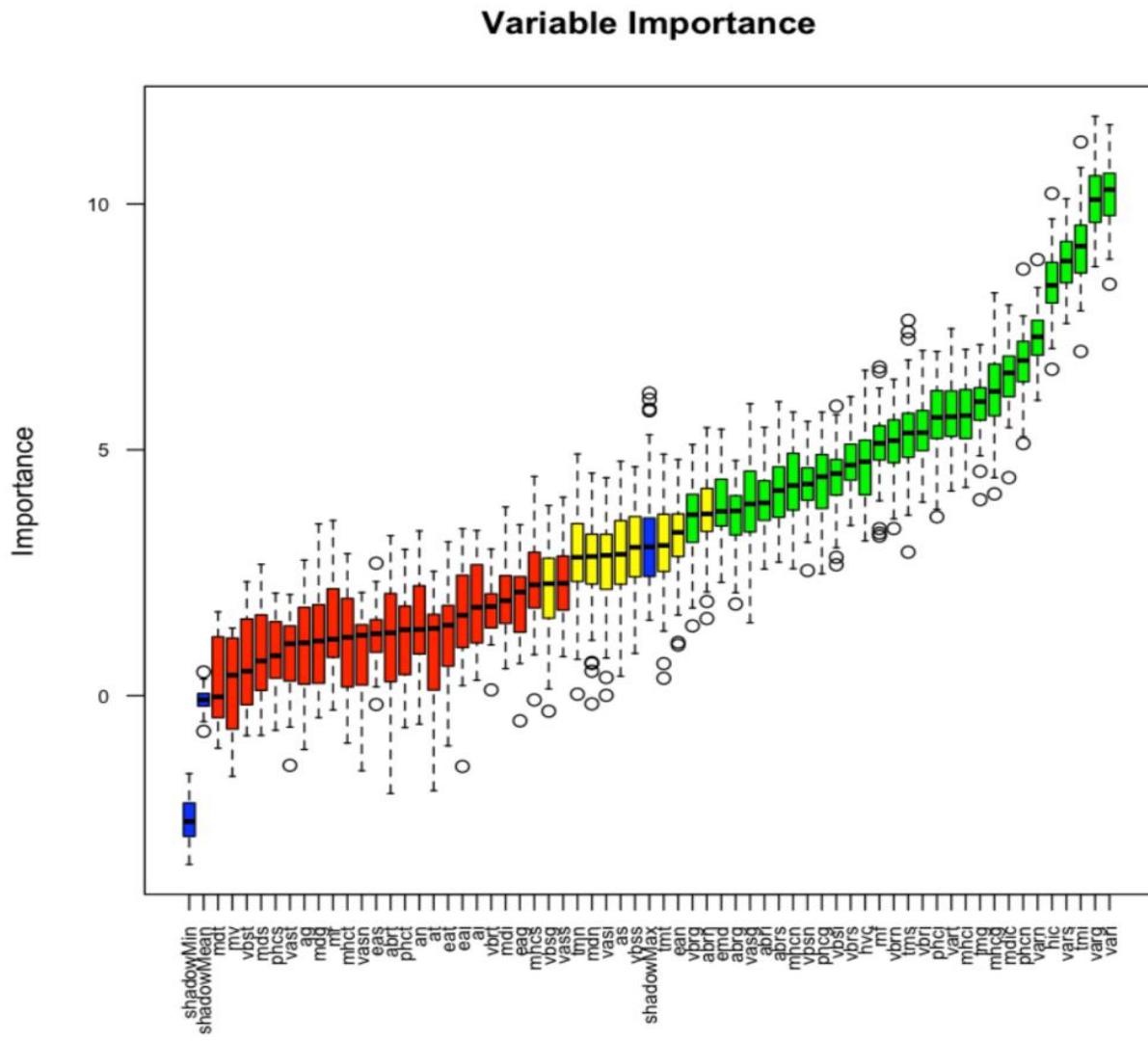
**Output:-**

|      | Mean      | Imp | decision  |
|------|-----------|-----|-----------|
| varg | 10.279747 |     | Confirmed |
| vari | 10.245936 |     | Confirmed |
| tmi  | 9.067300  |     | Confirmed |
| vars | 8.690654  |     | Confirmed |
| hic  | 8.324252  |     | Confirmed |
| varn | 7.327045  |     | Confirmed |

**# Plot variable importance**

```
plot(boruta_output, cex.axis=.7, las=2, xlab="", main="Variable
Importance")
```

## **Output:-**



**Result:** Thus the feature subset selection techniques in R is implemented successfully.

|                      |                                                            |
|----------------------|------------------------------------------------------------|
| <b>EX.NO.4.</b>      | <b>MEASURE THE PERFORMANCE OF A MACHINE LEARNING MODEL</b> |
| <b>DATE:25.09.23</b> |                                                            |

**Aim:- To demonstrate how will you measure the performance of a machine learning model**

**Program:- Modelperf.py**

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score
from sklearn.metrics import log_loss
X_actual = [1, 1, 0, 1, 0, 0, 1, 0, 0, 0]
Y_predic = [1, 0, 1, 1, 1, 0, 1, 1, 0, 0]
results = confusion_matrix(X_actual, Y_predic)
print ('Confusion Matrix :')
print(results)
print ('Accuracy Score is',accuracy_score(X_actual, Y_predic))
print ('Classification Report :')
print (classification_report(X_actual, Y_predic))
print('AUC-ROC:',roc_auc_score(X_actual, Y_predic))
print('LOGLOSS Value is',log_loss(X_actual, Y_predic))
```

**Output:-**

Confusion Matrix :

```
[[3 3]
 [1 3]]
```

Accuracy Score is 0.6

Classification Report :

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.75      | 0.50   | 0.60     | 6       |
| 1            | 0.50      | 0.75   | 0.60     | 4       |
| accuracy     |           |        | 0.60     | 10      |
| macro avg    | 0.62      | 0.62   | 0.60     | 10      |
| weighted avg | 0.65      | 0.60   | 0.60     | 10      |

AUC-ROC: 0.625

LOGLOSS Value is 13.815750437193334

**Result:-** Thus measure the performance of a machine learning model is executed successfully.

**EX.NO. 5.****DATE:09.10.23****Implement The Naïve Bayesian Classifier For Sample Training Data Set Stored As A tennisdata.csv File.****Aim:**

To implement the naïve Bayesian classifier for a sample training data set stored as a naivedata.CSV file. Compute the accuracy of the classifier, considering few test data sets.

**tennisdata.csv**

| Outlook  | Temperature | Humidity | Windy | PlayTennis |
|----------|-------------|----------|-------|------------|
| Sunny    | Hot         | High     | FALSE | No         |
| Sunny    | Hot         | High     | TRUE  | No         |
| Overcast | Hot         | High     | FALSE | Yes        |
| Rainy    | Mild        | High     | FALSE | Yes        |
| Rainy    | Cool        | Normal   | FALSE | Yes        |
| Rainy    | Cool        | Normal   | TRUE  | No         |
| Overcast | Cool        | Normal   | TRUE  | Yes        |
| Sunny    | Mild        | High     | FALSE | No         |
| Sunny    | Cool        | Normal   | FALSE | Yes        |
| Rainy    | Mild        | Normal   | FALSE | Yes        |
| Sunny    | Mild        | Normal   | TRUE  | Yes        |
| Overcast | Mild        | High     | TRUE  | Yes        |
| Overcast | Hot         | Normal   | FALSE | Yes        |
| Rainy    | Mild        | High     | TRUE  | No         |

**PROGRAM :-NaiveBay.py**

```
# import necessary libarities
import pandas as pd
from sklearn import tree
from sklearn.preprocessing import LabelEncoder
from sklearn.naive_bayes import GaussianNB

# load data from CSV
data = pd.read_csv('tennisdata.csv')
print("THe first 5 values of data is :\n",data.head())
# obtain Train data and Train output
```

```

X = data.iloc[:, :-1]
print("\nThe First 5 values of train data is\n", X.head())
y = data.iloc[:, -1]
print("\nThe first 5 values of Train output is\n", y.head())
# Convert then in numbers
le_outlook = LabelEncoder()
X.Outlook = le_outlook.fit_transform(X.Outlook)

le_Temperature = LabelEncoder()
X.Temperature = le_Temperature.fit_transform(X.Temperature)

le_Humidity = LabelEncoder()
X.Humidity = le_Humidity.fit_transform(X.Humidity)

le_Windy = LabelEncoder()
X.Windy = le_Windy.fit_transform(X.Windy)

print("\nNow the Train data is :\n", X.head())
le_PlayTennis = LabelEncoder()
y = le_PlayTennis.fit_transform(y)
print("\nNow the Train output is\n", y)
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20)

classifier = GaussianNB()
classifier.fit(X_train, y_train)

from sklearn.metrics import accuracy_score
print("Accuracy is:", accuracy_score(classifier.predict(X_test), y_test))

```

## **Output:-**

THe first 5 values of data is :

|   | Outlook | Temperature | Humidity | Windy | PlayTennis |
|---|---------|-------------|----------|-------|------------|
| 0 | Sunny   | Hot         | High     | False | No         |
| 1 | Sunny   | Hot         | High     | True  | No         |

|   |          |      |        |       |     |
|---|----------|------|--------|-------|-----|
| 2 | Overcast | Hot  | High   | False | Yes |
| 3 | Rainy    | Mild | High   | False | Yes |
| 4 | Rainy    | Cool | Normal | False | Yes |

The First 5 values of train data is

|   | Outlook  | Temperature | Humidity | Windy |
|---|----------|-------------|----------|-------|
| 0 | Sunny    | Hot         | High     | False |
| 1 | Sunny    | Hot         | High     | True  |
| 2 | Overcast | Hot         | High     | False |
| 3 | Rainy    | Mild        | High     | False |
| 4 | Rainy    | Cool        | Normal   | False |

The first 5 values of Train output is

- 0 No
- 1 No
- 2 Yes
- 3 Yes
- 4 Yes

Name: PlayTennis, dtype: object

Now the Train data is :

|   | Outlook | Temperature | Humidity | Windy |
|---|---------|-------------|----------|-------|
| 0 | 2       | 1           | 0        | 0     |
| 1 | 2       | 1           | 0        | 1     |
| 2 | 0       | 1           | 0        | 0     |
| 3 | 1       | 2           | 0        | 0     |
| 4 | 1       | 0           | 1        | 0     |

Now the Train output is

[0 0 1 1 1 0 1 0 1 1 1 1 1 0]

Accuracy is: 0.3333333333333333

**Result:-** Thus the naïve Bayesian classifier for a sample training data set stored as tennisdata.csv file is implemented and executed successfully.

|                      |                                                      |
|----------------------|------------------------------------------------------|
| <b>EX.NO.6</b>       | <b>Construct A Bayesian Network For Medical Data</b> |
| <b>DATE:16.10.23</b> |                                                      |

**AIM:-** To construct a Bayesian network considering medical data. Use this model to demonstrate the diagnosis of heart patients using standard Heart Disease Data Set using Python.

**#create the dataset such as data7\_names.csv and data7\_heart.csv using Microsoft excel.**

**data7\_names.csv**

|     |      |              |          |      |    |         |         |       |
|-----|------|--------------|----------|------|----|---------|---------|-------|
| age | sex  | cp           | trestbps | chol | fb | restecg | thalach | exang |
|     |      | oldpeak      | slope    |      |    |         |         |       |
| ca  | thal | heartdisease |          |      |    |         |         |       |

**data7\_heart.csv**

|    |   |   |     |     |   |   |     |   |     |   |   |   |   |
|----|---|---|-----|-----|---|---|-----|---|-----|---|---|---|---|
| 63 | 1 | 3 | 145 | 233 | 1 | 0 | 150 | 0 | 2.3 | 0 | 0 | 1 | 1 |
| 37 | 1 | 2 | 130 | 250 | 0 | 1 | 187 | 0 | 3.5 | 0 | 0 | 2 | 1 |
| 41 | 0 | 1 | 130 | 204 | 0 | 0 | 172 | 0 | 1.4 | 2 | 0 | 2 | 1 |

**PROGRAM:-BayesMed.py**

```
import numpy as np
import pandas as pd
import csv
from pgmpy.estimators import MaximumLikelihoodEstimator
from pgmpy.models import BayesianModel
from pgmpy.inference import VariableElimination
#Read the attributes
lines=list(csv.reader(open('data7_names.csv','r')))
attributes=lines[0]
#Read Cleveland Heart disease data
heartDisease = pd.read_csv('data7_heart.csv')
heartDisease = heartDisease.replace('?',np.nan)
#Display data
print('Few examples from the dataset are given below')
print(heartDisease.head())
print ('\nAttributes and datatypes')
print(heartDisease.dtypes)
```

```

#Model Bayesian Network model
BayesianModel([('age','trestbps'),('age','fbs'),('sex','trestbps'),('exang','trestbps'),('trestbps','heartdisease'),('fbs','heartdisease'),('heartdisease','restecg'),('heartdisease','thalach'),('heartdisease','chol')])
print(model)
print("\nLearning CPD using Maximum likelihood estimators")
model.fit(heartDisease,estimator=MaximumLikelihoodEstimator)
print("\n Inferencing with Bayesian Network:")
HeartDisease_infer = VariableElimination(model)
print("\n 1. Probability of HeartDisease given Age=28")
q=HeartDisease_infer.query(variables=['heartdisease'],evidence={'age':28})
print(q['heartdisease'])
print("\n 2. Probability of HeartDisease given cholesterol=100")
q=HeartDisease_infer.query(variables=['heartdisease'],evidence={'chol':100})
print(q['heartdisease'])

```

## OUTPUT:-

```

IDLE Shell 3.9.6
File Edit Shell Debug Options Window Help
Python 3.9.6 (tags/v3.9.6:db3ff76, Jun 28 2021, 15:26:21) [MSC v.1929 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>>
= RESTART: D:\Josi(2017-20)\MCALAB-2017-21\AI&ML LAB 21\AI&ML PGM\BayesianNetEx7.py
Few examples from the dataset are given below
   63  1  3  145  233  1.1  0  150  0.1  2.3  0.2  0.3  1.2  1.3
0  37  1  2  130  250  0  1  187  0  3.5  0  0  2  1
1  41  0  1  130  204  0  0  172  0  1.4  2  0  2  1

Attributes and datatypes
63      int64
1      int64
3      int64
145     int64
233     int64
1.1     int64
0      int64
150     int64
0.1     int64
2.3     float64
0.2     int64
0.3     int64
1.2     int64
1.3     int64
dtype: object
BayesianModel with 9 nodes and 9 edges

Learning CPD using Maximum likelihood estimators
>>> |

```

The screenshot shows the Python IDLE shell interface. The code above is run, and the output displays the dataset, attribute types, and the creation of a BayesianModel. The final message indicates that CPDs are being learned using Maximum Likelihood Estimation.

**RESULT:**Thus a Bayesian Network considering medical data is constructed and executed successfully.

|                      |                                                                                       |
|----------------------|---------------------------------------------------------------------------------------|
| <b>EX.NO.7</b>       | <b>Apply EM Algorithm To Cluster A Set Of Data Stored In A .csv File Using Python</b> |
| <b>DATE:23.10.23</b> |                                                                                       |

**AIM:-** To Apply EM algorithm to cluster a set of data stored in a .CSV file. Use the same data set for clustering using k-Means algorithm. Compare the results of these two algorithms and comment on the quality of clustering using Python.

### **PROGRAM:- EMEx7.py**

```
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.cluster import KMeans
import sklearn.metrics as sm
import pandas as pd
import numpy as np
#import matplotlib inline
iris = datasets.load_iris()
X = pd.DataFrame(iris.data)
X.columns = ['Sepal_Length','Sepal_Width','Petal_Length','Petal_Width']
y = pd.DataFrame(iris.target)
y.columns = ['Targets']
#colormap = np.array(['red', 'lime', 'black'])
# K Means Cluster
model = KMeans(n_clusters=3)
model.fit(X)
# This is what KMeans thought
model.labels_
# View the results
# Set the size of the plot
plt.figure(figsize=(14,7))
# Create a colormap
colormap = np.array(['red', 'lime', 'black'])
# Plot the Original Classifications
plt.subplot(1, 2, 1)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y.Targets], s=40)
plt.title('Real Classification')
```

```

# Plot the Models Classifications
plt.subplot(1, 2, 2)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[model.labels_], s=40)
plt.title('K Mean Classification')
# View the results
# Set the size of the plot
plt.figure(figsize=(14,7))
# Create a colormap
#print('The accuracy score : ',sm.accuracy_score(y, model.labels_))
#sm.confusion_matrix(y, model.labels_)
predY = np.choose(model.labels_, [0, 1, 2]).astype(np.int64)
print (predY)
#colormap = np.array(['red', 'lime', 'black'])
# Plot Orginal
plt.subplot(1, 2, 1)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y.Targets], s=40)
plt.title('Real Classification')

# Plot Predicted with corrected values
plt.subplot(1, 2, 2)
plt.scatter(X.Petal_Length,X.Petal_Width, c=colormap[predY], s=40)
plt.title('K Mean Classification')
print('The accuracy score of K-Mean: ',sm.accuracy_score(y, model.labels_))
print('The Confusion matrixof K-Mean: ',sm.confusion_matrix(y, model.labels_))
from sklearn import preprocessing
scaler = preprocessing.StandardScaler()
scaler.fit(X)
xsa = scaler.transform(X)
xs = pd.DataFrame(xsa, columns = X.columns)
#xs.sample(5)
from sklearn.mixture import GaussianMixture
gmm = GaussianMixture(n_components=3)
gmm.fit(xs)
y_cluster_gmm = gmm.predict(xs)

```

```
#y_cluster_gmm  
plt.subplot(2, 2, 3)  
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y_cluster_gmm], s=40)  
plt.title('GMM Classification')  
print('The accuracy score of EM: ',sm.accuracy_score(y, y_cluster_gmm))  
print('The Confusion matrix of EM: ',sm.confusion_matrix(y, y_cluster_gmm))
```

## **OUTPUT:-**

**Result:-** Thus Apply EM algorithm using k-Means algorithm is implemented and executed successfully.

**EX.NO.8.(i)**

**DATE:30.10.23**

## **Implement K-Nearest Neighbour Algorithm using Python**

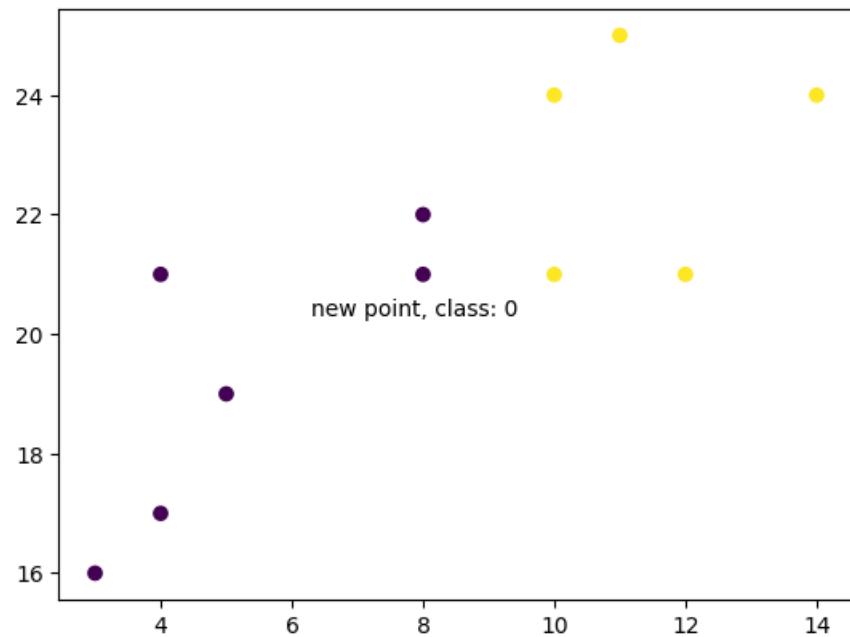
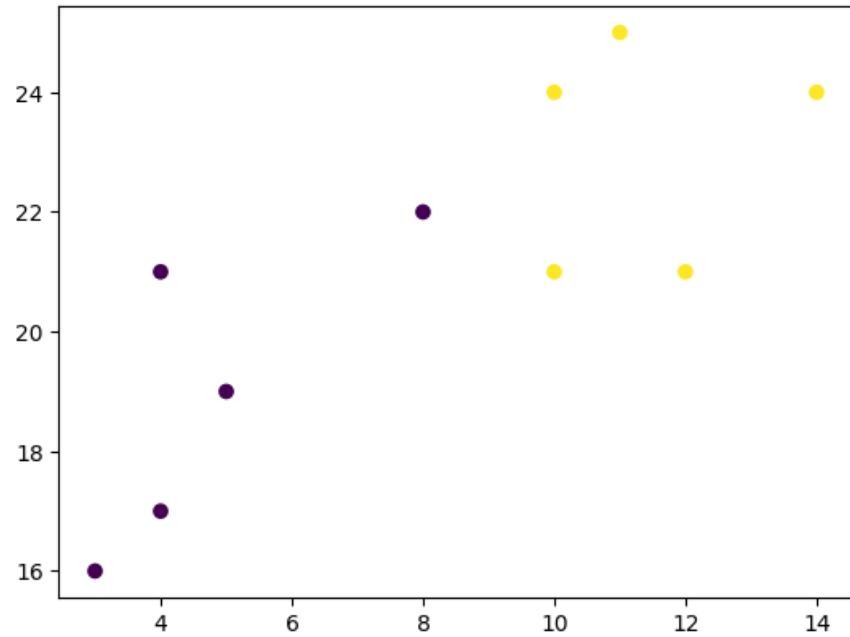
### **Aim:**

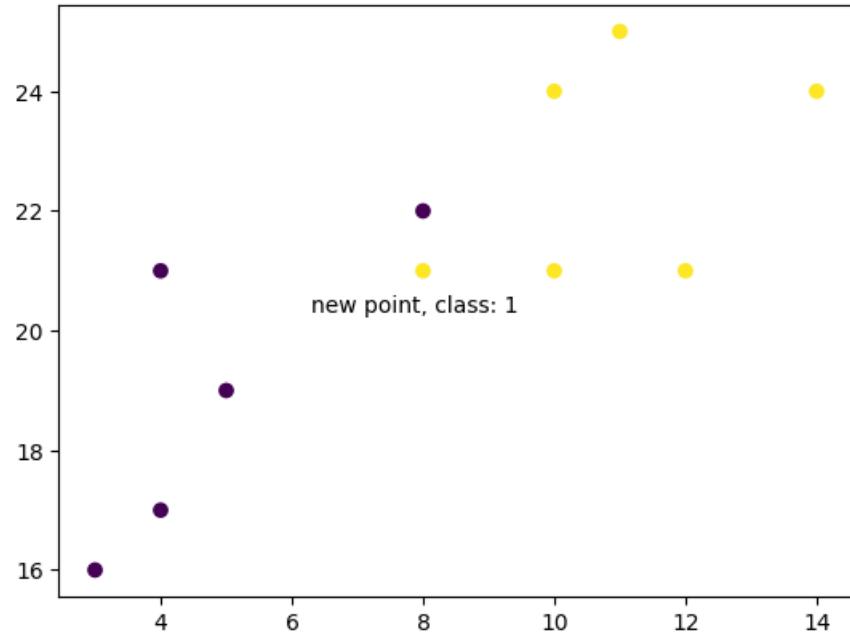
To write a program to implement k-Nearest Neighbour algorithm for predictions using Python

### **PROGRAM :-KNearNei.py**

```
import matplotlib.pyplot as plt
x = [4, 5, 10, 4, 3, 11, 14 , 8, 10, 12]
y = [21, 19, 24, 17, 16, 25, 24, 22, 21, 21]
classes = [0, 0, 1, 0, 0, 1, 1, 0, 1, 1]
plt.scatter(x, y, c=classes)
plt.show()
from sklearn.neighbors import KNeighborsClassifier
data = list(zip(x, y))
knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(data, classes)
new_x = 8
new_y = 21
new_point = [(new_x, new_y)]
prediction = knn.predict(new_point)
plt.scatter(x + [new_x], y + [new_y], c=classes + [prediction[0]])
plt.text(x=new_x-1.7, y=new_y-0.7, s=f"new point, class: {prediction[0]}")
plt.show()
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(data, classes)
prediction = knn.predict(new_point)
plt.scatter(x + [new_x], y + [new_y], c=classes + [prediction[0]])
plt.text(x=new_x-1.7, y=new_y-0.7, s=f"new point, class: {prediction[0]}")
plt.show()
```

## Output:-





**Result:-** Thus k-Nearest Neighbour algorithm to classify the iris data set is implemented and executed successfully.

**EX.NO.8.(ii)****DATE:30.10.23****Implement K-Nearest Neighbour Algorithm To Classify  
The iris Data Set using Python**

**Aim:-**To write a program to implement k-Nearest Neighbour algorithm to classify the iris data set. Print both correct and wrong predictions using Python

**#create iris.csv using Microsoft excel**

**iris.csv**

| sepal_length | sepal_width | petal_length | petal_width | Variety     |
|--------------|-------------|--------------|-------------|-------------|
| 5.1          | 3.5         | 1.4          | 0.2         | Iris-setosa |
| 4.9          | 3           | 1.4          | 0.2         | Iris-setosa |
| 4.7          | 3.2         | 1.3          | 0.2         | Iris-setosa |
| 4.6          | 3.1         | 1.5          | 0.2         | Iris-setosa |
| 5            | 3.6         | 1.4          | 0.2         | Iris-setosa |
| 5.4          | 3.9         | 1.7          | 0.4         | Iris-setosa |
| 4.6          | 3.4         | 1.4          | 0.3         | Iris-setosa |
| 5            | 3.4         | 1.5          | 0.2         | Iris-setosa |
| 4.4          | 2.9         | 1.4          | 0.2         | Iris-setosa |
| 4.9          | 3.1         | 1.5          | 0.1         | Iris-setosa |
| 5.4          | 3.7         | 1.5          | 0.2         | Iris-setosa |
| 4.8          | 3.4         | 1.6          | 0.2         | Iris-setosa |
| 4.8          | 3           | 1.4          | 0.1         | Iris-setosa |
| 4.3          | 3           | 1.1          | 0.1         | Iris-setosa |
| 5.8          | 4           | 1.2          | 0.2         | Iris-setosa |
| 5.7          | 4.4         | 1.5          | 0.4         | Iris-setosa |
| 5.4          | 3.9         | 1.3          | 0.4         | Iris-setosa |
| 5.1          | 3.5         | 1.4          | 0.3         | Iris-setosa |
| 5.7          | 3.8         | 1.7          | 0.3         | Iris-setosa |
| 5.1          | 3.8         | 1.5          | 0.3         | Iris-setosa |
| 5.4          | 3.4         | 1.7          | 0.2         | Iris-setosa |
| 5.1          | 3.7         | 1.5          | 0.4         | Iris-setosa |
| 4.6          | 3.6         | 1            | 0.2         | Iris-setosa |
| 5.1          | 3.3         | 1.7          | 0.5         | Iris-setosa |
| 4.8          | 3.4         | 1.9          | 0.2         | Iris-setosa |
| 5            | 3           | 1.6          | 0.2         | Iris-setosa |
| 5            | 3.4         | 1.6          | 0.4         | Iris-setosa |
| 5.2          | 3.5         | 1.5          | 0.2         | Iris-setosa |
| 5.2          | 3.4         | 1.4          | 0.2         | Iris-setosa |
| 4.7          | 3.2         | 1.6          | 0.2         | Iris-setosa |

|     |     |     |     |                 |
|-----|-----|-----|-----|-----------------|
| 4.8 | 3.1 | 1.6 | 0.2 | Iris-setosa     |
| 5.4 | 3.4 | 1.5 | 0.4 | Iris-setosa     |
| 5.2 | 4.1 | 1.5 | 0.1 | Iris-setosa     |
| 5.5 | 4.2 | 1.4 | 0.2 | Iris-setosa     |
| 4.9 | 3.1 | 1.5 | 0.1 | Iris-setosa     |
| 5   | 3.2 | 1.2 | 0.2 | Iris-setosa     |
| 5.5 | 3.5 | 1.3 | 0.2 | Iris-setosa     |
| 4.9 | 3.1 | 1.5 | 0.1 | Iris-setosa     |
| 4.4 | 3   | 1.3 | 0.2 | Iris-setosa     |
| 5.1 | 3.4 | 1.5 | 0.2 | Iris-setosa     |
| 5   | 3.5 | 1.3 | 0.3 | Iris-setosa     |
| 4.5 | 2.3 | 1.3 | 0.3 | Iris-setosa     |
| 4.4 | 3.2 | 1.3 | 0.2 | Iris-setosa     |
| 5   | 3.5 | 1.6 | 0.6 | Iris-setosa     |
| 5.1 | 3.8 | 1.9 | 0.4 | Iris-setosa     |
| 4.8 | 3   | 1.4 | 0.3 | Iris-setosa     |
| 5.1 | 3.8 | 1.6 | 0.2 | Iris-setosa     |
| 4.6 | 3.2 | 1.4 | 0.2 | Iris-setosa     |
| 5.3 | 3.7 | 1.5 | 0.2 | Iris-setosa     |
| 5   | 3.3 | 1.4 | 0.2 | Iris-setosa     |
| 7   | 3.2 | 4.7 | 1.4 | Iris-versicolor |
| 6.4 | 3.2 | 4.5 | 1.5 | Iris-versicolor |
| 6.9 | 3.1 | 4.9 | 1.5 | Iris-versicolor |
| 5.5 | 2.3 | 4   | 1.3 | Iris-versicolor |
| 6.5 | 2.8 | 4.6 | 1.5 | Iris-versicolor |
| 5.7 | 2.8 | 4.5 | 1.3 | Iris-versicolor |
| 6.3 | 3.3 | 4.7 | 1.6 | Iris-versicolor |
| 4.9 | 2.4 | 3.3 | 1   | Iris-versicolor |
| 6.6 | 2.9 | 4.6 | 1.3 | Iris-versicolor |
| 5.2 | 2.7 | 3.9 | 1.4 | Iris-versicolor |
| 5   | 2   | 3.5 | 1   | Iris-versicolor |
| 5.9 | 3   | 4.2 | 1.5 | Iris-versicolor |
| 6   | 2.2 | 4   | 1   | Iris-versicolor |
| 6.1 | 2.9 | 4.7 | 1.4 | Iris-versicolor |
| 5.6 | 2.9 | 3.6 | 1.3 | Iris-versicolor |
| 6.7 | 3.1 | 4.4 | 1.4 | Iris-versicolor |
| 5.6 | 3   | 4.5 | 1.5 | Iris-versicolor |
| 5.8 | 2.7 | 4.1 | 1   | Iris-versicolor |
| 6.2 | 2.2 | 4.5 | 1.5 | Iris-versicolor |
| 5.6 | 2.5 | 3.9 | 1.1 | Iris-versicolor |

|     |     |     |     |                 |
|-----|-----|-----|-----|-----------------|
| 5.9 | 3.2 | 4.8 | 1.8 | Iris-versicolor |
| 6.1 | 2.8 | 4   | 1.3 | Iris-versicolor |
| 6.3 | 2.5 | 4.9 | 1.5 | Iris-versicolor |
| 6.1 | 2.8 | 4.7 | 1.2 | Iris-versicolor |
| 6.4 | 2.9 | 4.3 | 1.3 | Iris-versicolor |
| 6.6 | 3   | 4.4 | 1.4 | Iris-versicolor |
| 6.8 | 2.8 | 4.8 | 1.4 | Iris-versicolor |
| 6.7 | 3   | 5   | 1.7 | Iris-versicolor |
| 6   | 2.9 | 4.5 | 1.5 | Iris-versicolor |
| 5.7 | 2.6 | 3.5 | 1   | Iris-versicolor |
| 5.5 | 2.4 | 3.8 | 1.1 | Iris-versicolor |
| 5.5 | 2.4 | 3.7 | 1   | Iris-versicolor |
| 5.8 | 2.7 | 3.9 | 1.2 | Iris-versicolor |
| 6   | 2.7 | 5.1 | 1.6 | Iris-versicolor |
| 5.4 | 3   | 4.5 | 1.5 | Iris-versicolor |
| 6   | 3.4 | 4.5 | 1.6 | Iris-versicolor |
| 6.7 | 3.1 | 4.7 | 1.5 | Iris-versicolor |
| 6.3 | 2.3 | 4.4 | 1.3 | Iris-versicolor |
| 5.6 | 3   | 4.1 | 1.3 | Iris-versicolor |
| 5.5 | 2.5 | 4   | 1.3 | Iris-versicolor |
| 5.5 | 2.6 | 4.4 | 1.2 | Iris-versicolor |
| 6.1 | 3   | 4.6 | 1.4 | Iris-versicolor |
| 5.8 | 2.6 | 4   | 1.2 | Iris-versicolor |
| 5   | 2.3 | 3.3 | 1   | Iris-versicolor |
| 5.6 | 2.7 | 4.2 | 1.3 | Iris-versicolor |
| 5.7 | 3   | 4.2 | 1.2 | Iris-versicolor |
| 5.7 | 2.9 | 4.2 | 1.3 | Iris-versicolor |
| 6.2 | 2.9 | 4.3 | 1.3 | Iris-versicolor |
| 5.1 | 2.5 | 3   | 1.1 | Iris-versicolor |
| 5.7 | 2.8 | 4.1 | 1.3 | Iris-versicolor |
| 6.3 | 3.3 | 6   | 2.5 | Iris-virginica  |
| 5.8 | 2.7 | 5.1 | 1.9 | Iris-virginica  |
| 7.1 | 3   | 5.9 | 2.1 | Iris-virginica  |
| 6.3 | 2.9 | 5.6 | 1.8 | Iris-virginica  |
| 6.5 | 3   | 5.8 | 2.2 | Iris-virginica  |
| 7.6 | 3   | 6.6 | 2.1 | Iris-virginica  |
| 4.9 | 2.5 | 4.5 | 1.7 | Iris-virginica  |
| 7.3 | 2.9 | 6.3 | 1.8 | Iris-virginica  |
| 6.7 | 2.5 | 5.8 | 1.8 | Iris-virginica  |
| 7.2 | 3.6 | 6.1 | 2.5 | Iris-virginica  |

|     |     |     |     |                |
|-----|-----|-----|-----|----------------|
| 6.5 | 3.2 | 5.1 | 2   | Iris-virginica |
| 6.4 | 2.7 | 5.3 | 1.9 | Iris-virginica |
| 6.8 | 3   | 5.5 | 2.1 | Iris-virginica |
| 5.7 | 2.5 | 5   | 2   | Iris-virginica |
| 5.8 | 2.8 | 5.1 | 2.4 | Iris-virginica |
| 6.4 | 3.2 | 5.3 | 2.3 | Iris-virginica |
| 6.5 | 3   | 5.5 | 1.8 | Iris-virginica |
| 7.7 | 3.8 | 6.7 | 2.2 | Iris-virginica |
| 7.7 | 2.6 | 6.9 | 2.3 | Iris-virginica |
| 6   | 2.2 | 5   | 1.5 | Iris-virginica |
| 6.9 | 3.2 | 5.7 | 2.3 | Iris-virginica |
| 5.6 | 2.8 | 4.9 | 2   | Iris-virginica |
| 7.7 | 2.8 | 6.7 | 2   | Iris-virginica |
| 6.3 | 2.7 | 4.9 | 1.8 | Iris-virginica |
| 6.7 | 3.3 | 5.7 | 2.1 | Iris-virginica |
| 7.2 | 3.2 | 6   | 1.8 | Iris-virginica |
| 6.2 | 2.8 | 4.8 | 1.8 | Iris-virginica |
| 6.1 | 3   | 4.9 | 1.8 | Iris-virginica |
| 6.4 | 2.8 | 5.6 | 2.1 | Iris-virginica |
| 7.2 | 3   | 5.8 | 1.6 | Iris-virginica |
| 7.4 | 2.8 | 6.1 | 1.9 | Iris-virginica |
| 7.9 | 3.8 | 6.4 | 2   | Iris-virginica |
| 6.4 | 2.8 | 5.6 | 2.2 | Iris-virginica |
| 6.3 | 2.8 | 5.1 | 1.5 | Iris-virginica |
| 6.1 | 2.6 | 5.6 | 1.4 | Iris-virginica |
| 7.7 | 3   | 6.1 | 2.3 | Iris-virginica |
| 6.3 | 3.4 | 5.6 | 2.4 | Iris-virginica |
| 6.4 | 3.1 | 5.5 | 1.8 | Iris-virginica |
| 6   | 3   | 4.8 | 1.8 | Iris-virginica |
| 6.9 | 3.1 | 5.4 | 2.1 | Iris-virginica |
| 6.7 | 3.1 | 5.6 | 2.4 | Iris-virginica |
| 6.9 | 3.1 | 5.1 | 2.3 | Iris-virginica |
| 5.8 | 2.7 | 5.1 | 1.9 | Iris-virginica |
| 6.8 | 3.2 | 5.9 | 2.3 | Iris-virginica |
| 6.7 | 3.3 | 5.7 | 2.5 | Iris-virginica |
| 6.7 | 3   | 5.2 | 2.3 | Iris-virginica |
| 6.3 | 2.5 | 5   | 1.9 | Iris-virginica |
| 6.5 | 3   | 5.2 | 2   | Iris-virginica |
| 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| 5.9 | 3   | 5.1 | 1.8 | Iris-virginica |

**Program:-**

```
import numpy as np
import pandas as pd
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn import metrics
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'Class']
# Read dataset to pandas dataframe
dataset = pd.read_csv("iris.csv", names=names)
X = dataset.iloc[:, :-1]
y = dataset.iloc[:, -1]
print(X.head())
Xtrain, Xtest, ytrain, ytest = train_test_split(X, y, test_size=0.10)
classifier = KNeighborsClassifier(n_neighbors=5).fit(Xtrain, ytrain)
ypred = classifier.predict(Xtest)
i = 0
print ("\n-----")
print ('%-25s %-25s %-25s' % ('Original Label', 'Predicted Label',
'Correct/Wrong'))
print ("-----")
for label in ytest:
    print ('%-25s %-25s' % (label, ypred[i]), end="")
    if (label == ypred[i]):
        print (' %-25s' % ('Correct'))
    else:
        print (' %-25s' % ('Wrong'))
    i = i + 1
print ("-----")
print("\nConfusion Matrix:\n",metrics.confusion_matrix(ytest, ypred))
print ("-----")
print("\nClassification Report:\n",metrics.classification_report(ytest, ypred))
print ("-----")
print('Accuracy of the classifier is %0.2f % metrics.accuracy_score(ytest,ypred)')
print ("-----")
```

**Output:-**

|   | sepal-length | sepal-width | petal-length | petal-width |
|---|--------------|-------------|--------------|-------------|
| 0 | 5.1          | 3.5         | 1.4          | 0.2         |
| 1 | 4.9          | 3.0         | 1.4          | 0.2         |
| 2 | 4.7          | 3.2         | 1.3          | 0.2         |
| 3 | 4.6          | 3.1         | 1.5          | 0.2         |
| 4 | 5.0          | 3.6         | 1.4          | 0.2         |

| Original Label  | Predicted Label | Correct/Wrong |
|-----------------|-----------------|---------------|
| Iris-virginica  | Iris-virginica  | Correct       |
| Iris-setosa     | Iris-setosa     | Correct       |
| Iris-versicolor | Iris-versicolor | Correct       |
| Iris-virginica  | Iris-virginica  | Correct       |
| Iris-setosa     | Iris-setosa     | Correct       |
| Iris-setosa     | Iris-setosa     | Correct       |
| Iris-versicolor | Iris-versicolor | Correct       |
| Iris-versicolor | Iris-versicolor | Correct       |
| Iris-versicolor | Iris-versicolor | Correct       |
| Iris-setosa     | Iris-setosa     | Correct       |
| Iris-versicolor | Iris-versicolor | Correct       |
| Iris-versicolor | Iris-versicolor | Correct       |
| Iris-virginica  | Iris-virginica  | Correct       |
| Iris-virginica  | Iris-virginica  | Correct       |
| Iris-virginica  | Iris-virginica  | Correct       |

## Confusion Matrix:

```
[[4 0 0]
 [0 6 0]
 [0 0 5]]
```

## Classification Report:

|                 | precision | recall | f1-score | support |
|-----------------|-----------|--------|----------|---------|
| Iris-setosa     | 1.00      | 1.00   | 1.00     | 4       |
| Iris-versicolor | 1.00      | 1.00   | 1.00     | 6       |
| Iris-virginica  | 1.00      | 1.00   | 1.00     | 5       |
| accuracy        |           |        | 1.00     | 15      |

|              |      |      |      |    |
|--------------|------|------|------|----|
| macro avg    | 1.00 | 1.00 | 1.00 | 15 |
| weighted avg | 1.00 | 1.00 | 1.00 | 15 |

---

Accuracy of the classifier is 1.00

---

**Result:-** Thus k-Nearest Neighbour algorithm to classify the iris data set is implemented and executed successfully.

**EX.NO.9.(i)****Apply The Technique Of Pruning For A Noisy Data Monk2 Data, And Derive The Decision Tree From This Data Using Python.**

**Aim** :- To apply the technique of pruning for a noisy data monk2 data, and derive the decision tree from this data. Analyze the results by comparing the structure of pruned and unpruned tree

**Program:DeciTee1.py**

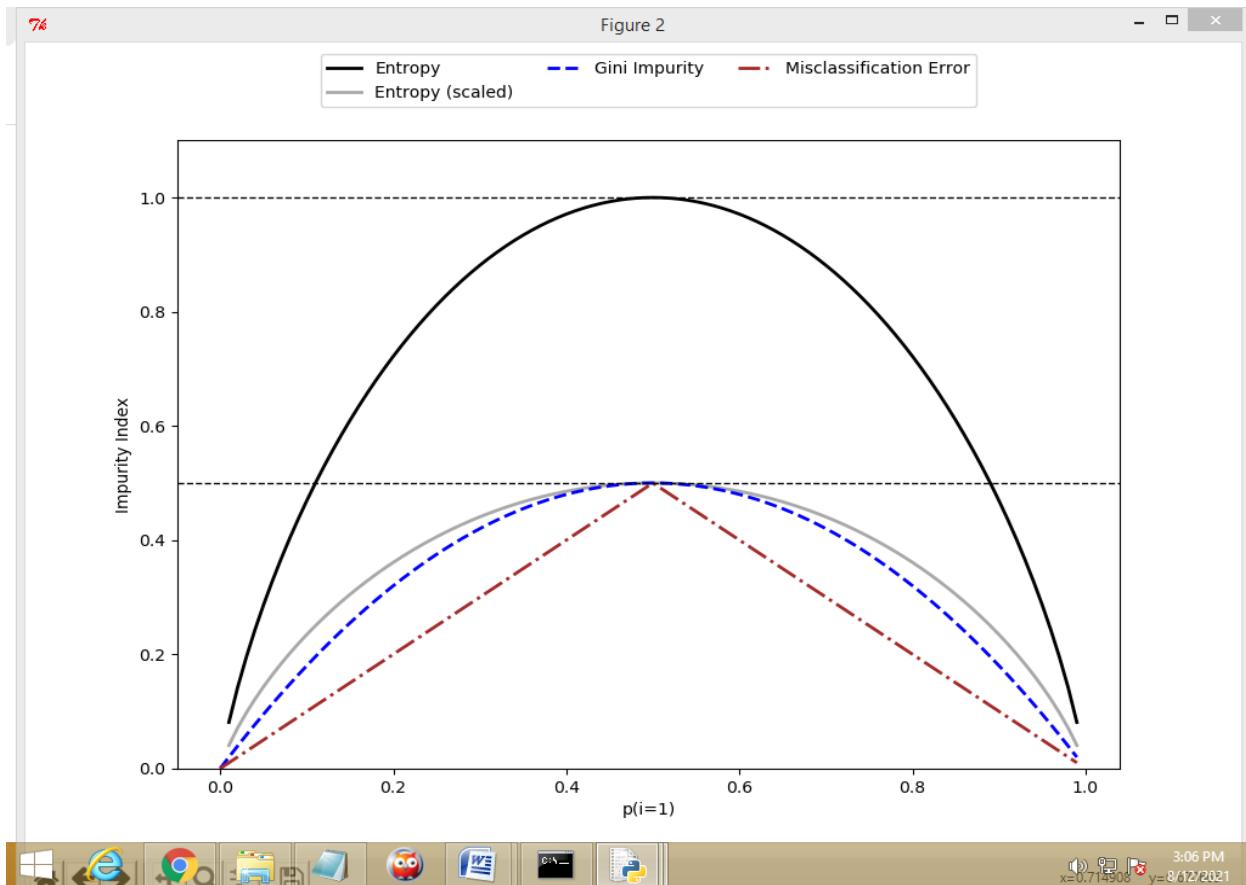
```
import matplotlib.pyplot as plt
import numpy as np
#----Calculating Gini Index
def gini(p):
    return (p)*(1 - (p)) + (1 - p)*(1 - (1-p))
#----Calculating Entropy
def entropy(p):
    return - p*np.log2(p) - (1 - p)*np.log2((1 - p))
#----Calculating Classification Error
def classification_error(p):
    return 1 - np.max([p, 1 - p])
#----Creating a Numpy Array of probability values from 0 to 1, with an #increment of 0.01
x = np.arange(0.0, 1.0, 0.01)
#---Obtaining Entropy for different values of p
ent = [entropy(p) if p != 0 else None for p in x]
#---Obtaining scaled entropy
sc_ent = [e*0.5 if e else None for e in ent]
#--Classification Error
err = [classification_error(i) for i in x]
#--Plotting
fig = plt.figure();
plt.figure(figsize=(10,8));
ax = plt.subplot(111);
for i, lab, ls, c, in zip([ent, sc_ent, gini(x), err], ['Entropy', 'Entropy (scaled)', 'Gini Impurity', 'Misclassification Error'], ['-', '--', '-.', '-.'], ['black', 'darkgray', 'blue', 'brown', 'cyan']):
```

```

line = ax.plot(x, i, label=lab,
    linestyle=ls, lw=2, color=c)
ax.legend(loc='upper center', bbox_to_anchor=(0.5, 1.15), ncol=3, fancybox=True,
shadow=False)
ax.axhline(y=0.5, linewidth=1, color='k', linestyle='--')
ax.axhline(y=1.0, linewidth=1, color='k', linestyle='--')
plt.ylim([0, 1.1])
plt.xlabel('p(i=1)')
plt.ylabel('Impurity Index')
plt.show()

```

## OUTPUT:



**RESULT:** Thus the technique of pruning for a noisy data monk2 data, and derive the decision tree from this data is implemented and executed successfully.

**EX.NO.9.(ii)**

**Demonstrate The Working Of The Decision Tree Based ID3 Algorithm. Use An Appropriate Data Set For Building The Decision Tree And Apply This Knowledge To Classify A New Sample.**

**Date:06.11.23**

**Aim:-** To write a program to demonstrate the working of the decision tree based ID3 algorithm. Use an appropriate data set for building the decision tree and apply this knowledge to classify a new sample.

**3dataset.csv**

| outlook  | temperature | humidity | wind   | Answer |
|----------|-------------|----------|--------|--------|
| sunny    | hot         | high     | weak   | No     |
| sunny    | hot         | high     | strong | No     |
| overcast | hot         | high     | weak   | Yes    |
| rain     | mild        | high     | weak   | Yes    |
| rain     | cool        | normal   | weak   | Yes    |
| rain     | cool        | normal   | strong | No     |
| overcast | cool        | normal   | strong | Yes    |
| sunny    | mild        | high     | weak   | No     |
| sunny    | cool        | normal   | weak   | Yes    |
| rain     | mild        | normal   | weak   | Yes    |
| sunny    | mild        | normal   | strong | Yes    |
| overcast | mild        | high     | strong | Yes    |
| overcast | hot         | normal   | weak   | Yes    |
| rain     | mild        | high     | strong | No     |

**Program:DeciTree2.py**

```
import pandas as pd
import math
import numpy as np
data = pd.read_csv('/content/drive/My Drive//3-dataset.csv')
features = [feat for feat in data]
features.remove("answer")
```

**#Create a class named Node with four members children, value, isLeaf and #pred.**

```
class Node:
    def __init__(self):
```

```
self.children = []
self.value = ""
self.isLeaf = False
self.pred = ""
```

**#Define a function called entropy to find the entropy oof the dataset.**

```
def entropy(examples):
    pos = 0.0
    neg = 0.0
    for _, row in examples.iterrows():
        if row["answer"] == "yes":
            pos += 1
        else:
            neg += 1
    if pos == 0.0 or neg == 0.0:
        return 0.0
    else:
        p = pos / (pos + neg)
        n = neg / (pos + neg)
        return -(p * math.log(p, 2) + n * math.log(n, 2))
```

**#Define a function named info\_gain to find the gain of the attribute**

```
def info_gain(examples, attr):
    uniq = np.unique(examples[attr])
    #print ("\n",uniq)
    gain = entropy(examples)
    #print ("\n",gain)
    for u in uniq:
        subdata = examples[examples[attr] == u]
        #print ("\n",subdata)
        sub_e = entropy(subdata)
        gain -= (float(len(subdata)) / float(len(examples))) * sub_e
        #print ("\n",gain)
    return gain

def ID3(examples, attrs):
```

```

root = Node()
max_gain = 0
max_feat = ""
for feature in attrs:
    #print ("\n",examples)
    gain = info_gain(examples, feature)
    if gain > max_gain:
        max_gain = gain
        max_feat = feature
root.value = max_feat
#print ("\nMax feature attr",max_feat)
uniq = np.unique(examples[max_feat])
#print ("\n",uniq)
for u in uniq:
    #print ("\n",u)
    subdata = examples[examples[max_feat] == u]
    #print ("\n",subdata)
    if entropy(subdata) == 0.0:
        newNode = Node()
        newNode.isLeaf = True
        newNode.value = u
        newNode.pred = np.unique(subdata["answer"])
        root.children.append(newNode)
    else:
        dummyNode = Node()
        dummyNode.value = u
        newAttrs = attrs.copy()
        newAttrs.remove(max_feat)
        child = ID3(subdata, newAttrs)
        dummyNode.children.append(child)
        root.children.append(dummyNode)
return root

#Define a function named printTree to draw the decision tree
def printTree(root: Node, depth=0):
    for i in range(depth):

```

```
    print("\t", end="")
print(root.value, end="")
if root.isLeaf:
    print(" -> ", root.pred)
print()
for child in root.children:
    printTree(child, depth + 1)
```

### #Define a function named classify to classify the new example

```
def classify(root: Node, new):
    for child in root.children:
        if child.value == new[root.value]:
            if child.isLeaf:
                print ("Predicted Label for new example", new, " is:", child.pred)
                exit
            else:
                classify (child.children[0], new)
```

### #Finally, call the ID3, printTree and classify functions

```
root = ID3(data, features)
print("Decision Tree is:")
printTree(root)
print ("-----")
new = { "outlook":"sunny", "temperature":"hot", "humidity":"normal",
"wind":"strong" }
classify (root, new)
```

**Output:-**

Decision Tree is:

outlook

    overcast -> ['yes']

    rain

        wind

            strong -> ['no']

            weak -> ['yes']

        sunny

            humidity

                high -> ['no']

                normal -> ['yes']

---

Predicted Label for new example {'outlook': 'sunny', 'temperature': 'hot', 'humidity': 'normal', 'wind': 'strong'} is: ['yes']

**Result:-**

Thus the program of the decision tree based ID3 algorithm is used an appropriate data set for building the decision tree and apply this knowledge to classify a new sample is executed successfully.

|                      |                                                                                                                                        |
|----------------------|----------------------------------------------------------------------------------------------------------------------------------------|
| <b>EX.NO.10.</b>     | <b>Build An Artificial Neural Network By Implementing The Backpropagation Algorithm And Test The Same Using Appropriate Data Sets.</b> |
| <b>DATE:13.11.23</b> |                                                                                                                                        |

**Aim:**

To build an Artificial Neural Network by implementing the Backpropagation algorithm and test the same using appropriate data sets.

**PROGRAM :-Backprop.py**

```
import numpy as np
```

```
X = np.array(([2, 9], [1, 5], [3, 6]), dtype=float)
```

```
y = np.array(([92], [86], [89]), dtype=float)
```

```
X = X/np.amax(X, axis=0) # maximum of X array longitudinally
```

```
y = y/100
```

```
#Sigmoid Function
```

```
def sigmoid (x):
```

```
    return 1/(1 + np.exp(-x))
```

```
#Derivative of Sigmoid Function
```

```
def derivatives_sigmoid(x):
```

```
    return x * (1 - x)
```

```
#Variable initialization
```

```
epoch=7000 #Setting training iterations
```

```
lr=0.1 #Setting learning rate
```

```
inputlayer_neurons = 2 #number of features in data set
```

```
hiddenlayer_neurons = 3 #number of hidden layers neurons
```

```
output_neurons = 1 #number of neurons at output layer
```

```
#weight and bias initialization
```

```

wh=np.random.uniform(size=(inputlayer_neurons,hiddenlayer_neurons))

bh=np.random.uniform(size=(1,hiddenlayer_neurons))

wout=np.random.uniform(size=(hiddenlayer_neurons,output_neurons))

bout=np.random.uniform(size=(1,output_neurons))

#draws a random range of numbers uniformly of dim x*y

for i in range(epoch):

    #Forward Propogation

    hinp1=np.dot(X,wh)

    hinp=hinp1 + bh

    hlayer_act = sigmoid(hinp)

    outinp1=np.dot(hlayer_act,wout)

    outinp= outinp1+ bout

    output = sigmoid(outinp)

    #Backpropagation

    EO = y-output

    outgrad = derivatives_sigmoid(output)

    d_output = EO* outgrad

    EH = d_output.dot(wout.T)

    hiddengrad = derivatives_sigmoid(hlayer_act)#how much hidden layer wts
    contributed to error

    d_hiddenlayer = EH * hiddengrad

    wout += hlayer_act.T.dot(d_output) *lr# dotproduct of nextlayererror and
    currentlayerop

```

```
# bout += np.sum(d_output, axis=0,keepdims=True) *lr  
wh += X.T.dot(d_hiddenlayer) *lr  
#bh += np.sum(d_hiddenlayer, axis=0,keepdims=True) *lr  
print("Input: \n" + str(X))  
print("Actual Output: \n" + str(y))  
print("Predicted Output: \n" ,output)
```

## OUTPUT

### Input:

```
[[ 0.66666667 1. ]  
[ 0.33333333 0.55555556]  
[ 1. 0.66666667]]
```

Actual Output:

```
[[ 0.92]  
[ 0.86]  
[ 0.89]]
```

Predicted Output:

```
[[ 0.89559591]  
[ 0.88142069]  
[ 0.8928407 ]]
```

**Result:-** Thus to build an Artificial Neural Network by implementing the Backpropagation algorithm and test the same using appropriate data sets.

**EX.NO.11**  
**DATE:20.11.23**

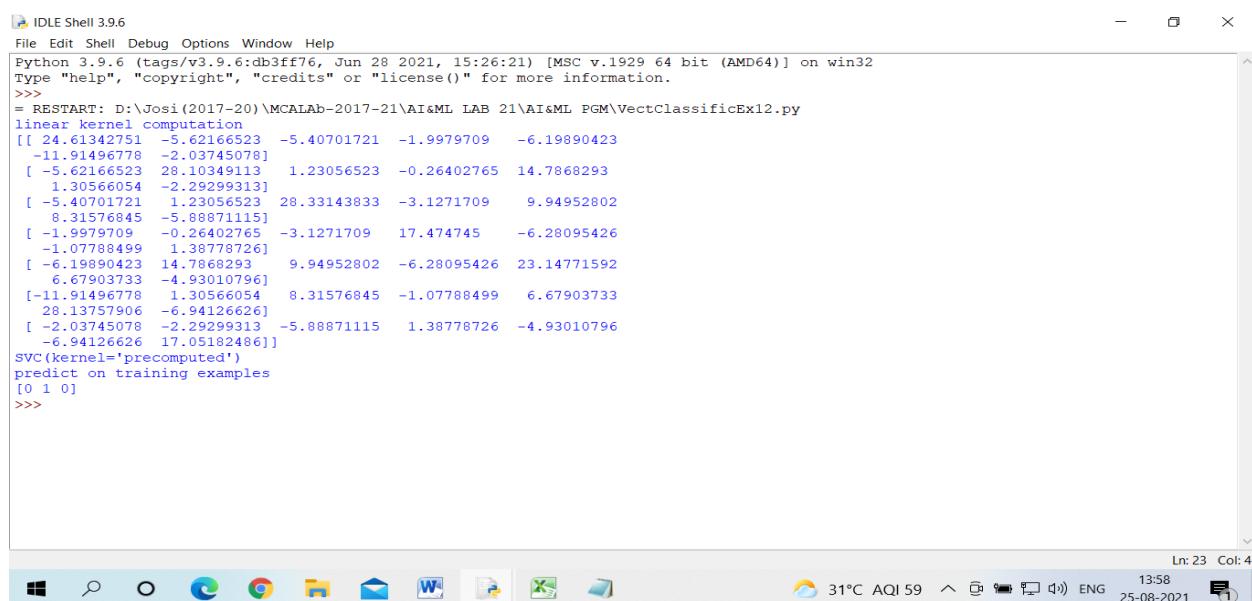
## Implement Support Vector Classification For Linear Kernel.

**AIM:** To implement Support Vector Classification for linear kernel.

### PROGRAM:- SVCLK.py

```
import numpy as np
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn import svm
X, y = make_classification(n_samples=10, random_state=0)
X_train ,X_test , y_train, y_test = train_test_split(X, y, random_state=0)
clf = svm.SVC(kernel='precomputed')
# linear kernel computation
gram_train = np.dot(X_train, X_train.T)
print("Linear kernel computation")
print(gram_train)
print(clf.fit(gram_train, y_train))
# predict on training examples
gram_test = np.dot(X_test, X_train.T)
print("Predict on Training examples")
print(clf.predict(gram_test))
```

### OUTPUT:



```
IDLE Shell 3.9.6
File Edit Shell Debug Options Window Help
Python 3.9.6 (tags/v3.9.6:db3ff76, Jun 28 2021, 15:26:21) [MSC v.1929 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>>
= RESTART: D:\Josi(2017-20)\MCALAB-2017-21\AI&ML LAB 21\AI&ML PGM\VectClassificEx12.py
linear kernel computation
[[ 24.61342751 -5.62166523 -5.40701721 -1.9979709 -6.19890423
[-11.91496778 -2.03745078]
[-5.62166523 28.10349113 1.23056523 -0.26402765 14.7868293
1.30566054 -2.29299313]
[-5.40701721 1.23056523 28.33143833 -3.1271709 9.94952802
8.31576845 -5.88871115]
[-1.9979709 -0.26402765 -3.1271709 17.474745 -6.28095426
-1.07788499 1.38778726]
[-6.19890423 14.7868293 9.94952802 -6.28095426 23.14771592
6.67903733 -4.93010796]
[-11.91496778 1.30566054 8.31576845 -1.07788499 6.67903733
28.13757906 -6.94126626]
[-2.03745078 -2.29299313 -5.88871115 1.38778726 -4.93010796
-6.94126626 17.05182486]]
svc(kernel='precomputed')
predict on training examples
[0 1 0]
>>>
```

**RESULT:** Thus the Support Vector Classification for linear kernel has been executed successfully.

**EX.NO.12****Implement Logistic Regression To Classify The Problems****DATE:27.11.23****Such As Spam Detection**

**AIM:-**To implement Logistic Regression to classify the problems such as spam detection.

**PROGRAM: LogiReg.py**

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
import csv
data = ['This is the first document.',
        'This document is the second document.',
        'And this is the third one.',
        'Is this the first document?']
#pre-processing on message text, like removing-
# punctuation and stop words.
def text_preprocess(text):
    text = text.translate(str.maketrans(", ", string.punctuation))
    text = [word for word in text.split() if word.lower() not in
            stopwords.words('english')]
    return " ".join(text)
#vectorize the data
vectorizer = TfidfVectorizer()
message_mat = vectorizer.fit_transform(data)
print(message_mat)
print(vectorizer.get_feature_names())
['and', 'document', 'first', 'is', 'one', 'second', 'the', 'third', 'this']
print(message_mat.shape)
#vector matrix can be used create train/test split.
message_train, message_test, spam_nospam_train,spam_nospam_test =
train_test_split(message_mat, data,test_size=0.3, random_state=20)
# Choose logistic regression model
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
Spam_model = LogisticRegression(solver='liblinear', penalty='l1')
print("Logistic Regression:")
```

```
print(Spam_model.fit(message_train, spam_nospam_train))
print("Prediction:")
pred = Spam_model.predict(message_test)
print(pred)
print('Accuracy Score')
print(accuracy_score(spam_nospam_test,pred))
```

## OUTPUT:

The screenshot shows a Windows desktop environment with a Python 3.8.6 Shell window open. The shell displays the execution of a Python script named LogicRegSpamEx13.py. The output shows the creation of a LogisticRegression model with specific parameters, followed by a prediction for two test messages ('And this is the third one.'), and finally an accuracy score of 0.0.

```
Python 3.8.6 Shell
File Edit Shell Debug Options Window Help
Python 3.8.6 (tags/v3.8.6:db45529, Sep 23 2020, 15:52:53) [MSC v.1927 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>>
= RESTART: A:\Josi(2017-20)\MCALab-2017-21\AI&ML LAB 21\AI&ML PGM\LogicRegSpamEx13.py
['and', 'detection', 'document', 'first', 'is', 'not', 'one', 'or', 'second', 'spam', 'the', 'third', 'this']
(5, 13)
Logistic Regression:
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                     intercept_scaling=1, l1_ratio=None, max_iter=100,
                     multi_class='auto', n_jobs=None, penalty='l1',
                     random_state=None, solver='liblinear', tol=0.0001, verbose=0,
                     warm_start=False)
Prediction:
['And this is the third one.' 'And this is the third one.']
Accuracy Score
0.0
>>> |
```

**RESULT:** Thus the Logistic Regression to classify the problems such as spam detection is implemented and executed successfully.