1. R AS CALCULATOR APPLICATION
(i) Without using R objects on console

> 25+32

Output:
[1] 57

> 36-15

Output:
[1] 21

> 145*8
[1] 1160

> 365/7
Output:
[1] 52.14

(ii) Using R objects on console:
>A=45
>B=2
>c=A+B
>c

Output:
[1]47

>A=5
>B=2
>c=A-B
>c

Output:
[1]3
>A=10
>B=2
>c=A*B
>c

Output:
[1]20

```
>A=4
>B=2
>c=A/B
>c
```

Output:
[1]2

(c) Program make a simple calculator that can add, subtract, multiply and divide using functions

```
add <- function(x, y) {
 return(x + y)
 }
subtract <- function(x, y) {
 return(x - y)
 }
multiply <- function(x, y) {
 return(x * y)
 }
divide <- function(x, y) {
 return(x / y)
 }

# take input from the user
print("Select operation.")
print("1.Add")
print("2.Subtract")
print("3.Multiply")
print("4.Divide")
choice = as.integer(readline(prompt="Enter choice[1/2/3/4]: "))
num1 = as.integer(readline(prompt="Enter first number: "))
num2 = as.integer(readline(prompt="Enter second number: "))
operator <- switch(choice,"+","-","*","/")
result <- switch(choice, add(num1, num2), subtract(num1, num2), multiply(num1, num2), divide(num1,
num2))
print(paste(num1, operator, num2, "=", result))
```

OUTPUT

```
> source("~/Documents/305.R")
 [1] "Select operation."
 [1] "1.Add"
 [1] "2.Subtract"
 [1] "3.Multiply"
 [1] "4.Divide"
Enter choice[1/2/3/4]: 3
Enter first number: 3
Enter second number: 4
 [1] "3 * 4 = 12"
```

2.DESCRIPTIVE STATISTICS IN R

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

load data mtcars:

```
data(mtcars)
```

structure of mtcars:

```
str(mtcars)
```

Output:

```
## '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 ...
```

str( ) → This function compactly displays the internal structure of an R object, a diagnostic function and an alternative to summary. Ideally, only one line for each 'basic' structure is displayed. It is especially well suited to compactly display the (abbreviated) contents of (possibly nested) lists.

dimension of dataset:

```
dim(mtcars)
```

Output:

```
[1] 32 11
```

get names of each variables or columns:

```
names(mtcars)
```

Output:

```
[1] "mpg" "cyl" "disp" "hp" "drat" "wt" "qsec" "vs" "am" "gear" "carb"
```

Summaries of the datasets:

summary( )→ is a generic function used to produce summaries of the results of various model fitting functions. The function invokes particular methods which depend on the class of the first argument.

Usage: >

```
summary(mtcars)
```

Output:

mpg cyl disp hp drat

Min. :10.40 Min. :4.000 Min. : 71.1 Min. : 52.0 Min. :2.760

1st Qu.:15.43 1st Qu.:4.000 1st Qu.:120.8 1st Qu.: 96.5 1st Qu.:3.080

Median :19.20 Median :6.000 Median :196.3 Median :123.0 Median :3.695

Mean :20.09 Mean :6.188 Mean :230.7 Mean :146.7 Mean :3.597

3rd Qu.:22.80 3rd Qu.:8.000 3rd Qu.:326.0 3rd Qu.:180.0 3rd Qu.:3.920

Max. :33.90 Max. :8.000 Max. :472.0 Max. :335.0 Max. :4.930

wt qsec vs am gear

Min. :1.513 Min. :14.50 Min. :0.0000 Min. :0.0000 Min. :3.000

1st Qu.:2.581 1st Qu.:16.89 1st Qu.:0.0000 1st Qu.:0.0000 1st Qu.:3.000

Median :3.325 Median :17.71 Median :0.0000 Median :0.0000 Median :4.000

Mean :3.217 Mean :17.85 Mean :0.4375 Mean :0.4062 Mean :3.688

3rd Qu.:3.610 3rd Qu.:18.90 3rd Qu.:1.0000 3rd Qu.:1.0000 3rd Qu.:4.000

Max. :5.424 Max. :22.90 Max. :1.0000 Max. :1.0000 Max. :5.000

carb

Min. :1.000

1st Qu.:2.000

Median :2.000

Mean :2.812

3rd Qu.:4.000

Max. :8.000

quantiles of dataset:

quantile()

The generic function quantile produces sample quantiles corresponding to the given probabilities. The smallest observation corresponds to a probability of 0 and the largest to a probability of 1.

Common quantiles have special names, such as quartiles (four groups), deciles (ten groups), and percentiles (100 groups). The groups created are termed halves, thirds, quarters, etc., though sometimes the terms for the quantile are used for the groups created, rather than for the cut points.

Ex:

x=1:10

> x

Output:

[1] 1 2 3 4 5 6 7 8 9 10

> quantile(x)

Output:

0% 25% 50% 75% 100% 1.00

3.25 5.50 7.75 10.00

> quantile(mtcars$mpg)

Output:

0% 25% 50% 75% 100% 10.400

15.425 19.200 22.800 33.900

select quantiles by percent

quantile(mtcars$wt, c(.2, .4, .8))

Output:

20% 40% 80%

2.349 3.158 3.770

variance

variance of weight:

var(mtcars$wt)

Output:

[1] 0.957379

Covariance

get covariance between mpg and gear: cov(mtcars$mpg, mtcars$gear)

Output:

[1] 2.135685

get covariance all variables:

cov(mtcars[,1:11])

Output:

```
mpg        cyl        disp          hp        drat

## mpg    36.324103  -9.1723790  -633.09721 -320.732056   2.19506351
## cyl    -9.172379   3.1895161   199.66028  101.931452  -0.66836694
## disp -633.097208 199.6602823 15360.79983 6721.158669 -47.06401915
## hp   -320.732056 101.9314516  6721.15867 4700.866935 -16.45110887
## drat    2.195064  -0.6683669   -47.06402  -16.451109   0.28588135
## wt     -5.116685   1.3673710   107.68420   44.192661  -0.37272073
## qsec    4.509149  -1.8868548   -96.05168  -86.770081   0.08714073
## vs      2.017137  -0.7298387   -44.37762  -24.987903   0.11864919
## am      1.803931  -0.4657258   -36.56401   -8.320565   0.19015121
## gear    2.135685  -0.6491935   -50.80262   -6.358871   0.27598790
## carb   -5.363105   1.5201613    79.06875   83.036290  -0.07840726
##               wt        qsec          vs          am        gear
## mpg   -5.1166847   4.50914919   2.01713710   1.80393145   2.1356855
## cyl    1.3673710  -1.88685484  -0.72983871  -0.46572581  -0.6491935
## disp 107.6842040 -96.05168145 -44.37762097 -36.56401210 -50.8026210
## hp    44.1926613 -86.77008065 -24.98790323  -8.32056452  -6.3588710
## drat  -0.3727207   0.08714073   0.11864919   0.19015121   0.2759879
## wt     0.9573790  -0.30548161  -0.27366129  -0.33810484  -0.4210806
## qsec  -0.3054816   3.19316613   0.67056452  -0.20495968  -0.2804032
## vs    -0.2736613   0.67056452   0.25403226   0.04233871   0.0766129
## am    -0.3381048  -0.20495968   0.04233871   0.24899194   0.2923387
## gear  -0.4210806  -0.28040323   0.07661290   0.29233871   0.5443548
## carb   0.6757903  -1.89411290  -0.46370968   0.04637097   0.3266129
##              carb
## mpg  -5.36310484
## cyl   1.52016129
## disp 79.06875000
## hp   83.03629032
## drat -0.07840726
## wt    0.67579032
## qsec -1.89411290
## vs   -0.46370968
## am    0.04637097
## gear  0.32661290
## carb  2.60887097
```

Correlation

get correlation between mpg and gear:

```
cor(mtcars$mpg, mtcars$gear)
```

Output:

```
[1] 0.4802848
```

get correlation all variables:

```
cor(mtcars[,1:11])
```

Output:

```
                mpg        cyl       disp         hp       drat         wt
## mpg   1.0000000 -0.8521620 -0.8475514 -0.7761684  0.68117191 -0.8676594
## cyl  -0.8521620  1.0000000  0.9020329  0.8324475 -0.69993811  0.7824958
## disp -0.8475514  0.9020329  1.0000000  0.7909486 -0.71021393  0.8879799
## hp   -0.7761684  0.8324475  0.7909486  1.0000000 -0.44875912  0.6587479
## drat  0.6811719 -0.6999381 -0.7102139 -0.4487591  1.00000000 -0.7124406
## wt   -0.8676594  0.7824958  0.8879799  0.6587479 -0.71244065  1.0000000
## qsec  0.4186840 -0.5912421 -0.4336979 -0.7082234  0.09120476 -0.1747159
## vs    0.6640389 -0.8108118 -0.7104159 -0.7230967  0.44027846 -0.5549157
## am    0.5998324 -0.5226070 -0.5912270 -0.2432043  0.71271113 -0.6924953
## gear  0.4802848 -0.4926866 -0.5555692 -0.1257043  0.69961013 -0.5832870
## carb -0.5509251  0.5269883  0.3949769  0.7498125 -0.09078980  0.4276059
##             qsec         vs         am       gear        carb
## mpg   0.41868403  0.6640389  0.59983243  0.4802848 -0.55092507
## cyl  -0.59124207 -0.8108118 -0.52260705 -0.4926866  0.52698829
## disp -0.43369788 -0.7104159 -0.59122704 -0.5555692  0.39497686
## hp   -0.70822339 -0.7230967 -0.24320426 -0.1257043  0.74981247
## drat  0.09120476  0.4402785  0.71271113  0.6996101 -0.09078980
## wt   -0.17471588 -0.5549157 -0.69249526 -0.5832870  0.42760594
## qsec  1.00000000  0.7445354 -0.22986086 -0.2126822 -0.65624923
## vs    0.74453544  1.0000000  0.16834512  0.2060233 -0.56960714
## am   -0.22986086  0.1683451  1.00000000  0.7940588  0.05753435
## gear -0.21268223  0.2060233  0.79405876  1.0000000  0.27407284
## carb -0.65624923 -0.5696071  0.05753435  0.2740728  1.00000000
```

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

Subset

It returns subsets of vectors, matrices or data frames meeting given conditions.

```
>subset(iris,iris$Sepal.Length>7)
```

Output:

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
103	7.1	3.0	5.9	2.1	virginica
106	7.6	3.0	6.6	2.1	virginica
108	7.3	2.9	6.3	1.8	virginica
110	7.2	3.6	6.1	2.5	virginica
118	7.7	3.8	6.7	2.2	virginica
119	7.7	2.6	6.9	2.3	virginica
123	7.7	2.8	6.7	2.0	virginica
126	7.2	3.2	6.0	1.8	virginica
130	7.2	3.0	5.8	1.6	virginica
131	7.4	2.8	6.1	1.9	virginica
132	7.9	3.8	6.4	2.0	virginica
136	7.7	3.0	6.1	2.3	virginica

aggregate ()

aggregate() Function in R Splits the data into subsets, computes summary statistics for each subsets and returns the result in a group by form. Aggregate function in R is similar to group by in SQL. Aggregate() function is useful in performing all the aggregate operations like sum,count,mean, minimum and Maximum. It splits the data into subsets, computes summary statistics for each, and returns the result in a convenient form.

The most basic uses of aggregate involve base functions such as mean and sd. It is indeed one of the most common uses of aggregate to compare the mean or other properties of sample groups.

Aggregate() function in R applied on iris dataset:

Step1:

Load the dataset

```
data(iris)
```

Step 2:

Apply aggregate() to calculate mean, sum

```
agg_mean = aggregate(iris[,1:4], by=list(iris$Species),FUN=mean)
```

Step 3:

Display the result

```
agg_mean
```

Similarly use aggregate() function to calculate:

- Sum:

```
agg_sum = aggregate(iris[,1:4], by=list(iris$Species),FUN=sum)
```

- standard deviation:

```
agg_sd = aggregate(iris[,1:4], by=list(iris$Species),FUN=sd)
```

- Min value

```
agg_min = aggregate(iris[,1:4], by=list(iris$Species),FUN=min)
```

- Max value

```
agg_max = aggregate(iris[,1:4], by=list(iris$Species),FUN=max)
```

3. READING AND WRITING DIFFERENT TYPES OF DATASETS

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

```
# Set current working directory.
setwd("/DH/rprog”)
#Read the file
data <- read.csv("input.csv")
print(data)
```

b. Reading Excel data sheet in R.

```
#Install xlsx Package
install.packages("xlsx")

# Read the file input.xlsx.
data <- read.xlsx("input.xlsx")
print(data)
```

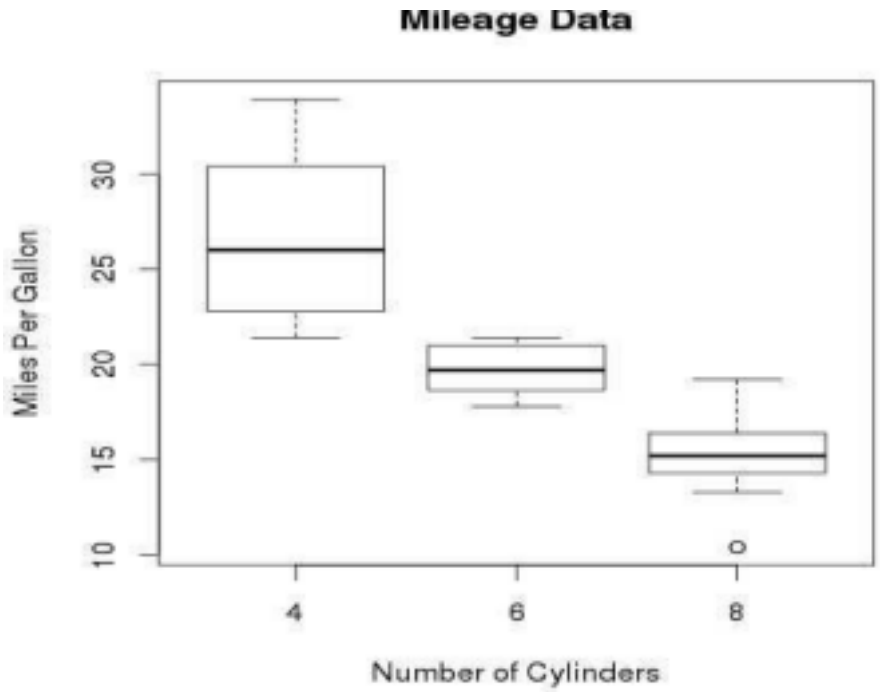
4.VISUALIZATIONS

Find the data distributions using box and scatter plot.

```
Install.packages(“ggplot2”)
Library(ggplot2)
Input <- mtcars[,c('mpg','cyl')]input

Boxplot(mpg ~ cyl, data = mtcars, xlab = "number of cylinders",ylab =
"miles per gallon", main = "mileage data")
Dev.off()
```

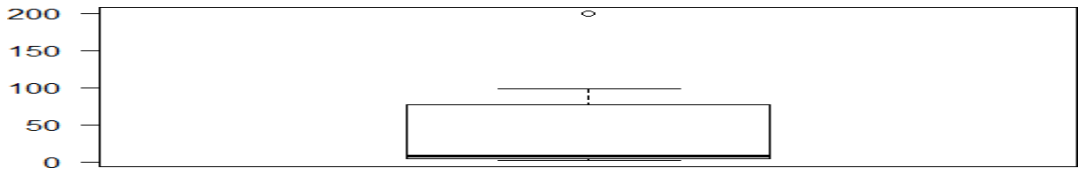
Output :-

```
mpg cyl
Mazda rx4 21.0 6
Mazda rx4 wag 21.0 6
Datsun 710 22.8 4
Hornet 4 drive 21.4 6
Hornet sportabout 18.7 8
Valiant 18.1 6
```



a. Find the outliers using plot.

```
v=c(50,75,100,125,150,175,200)
boxplot(v)
```

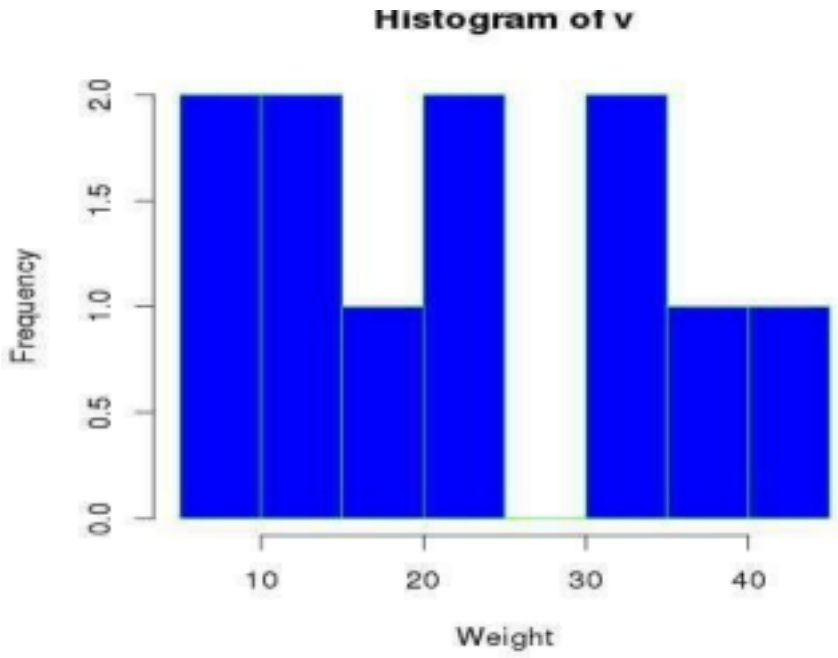


b. Plot the histogram, bar chart and pie chart on sample data.

Histogram

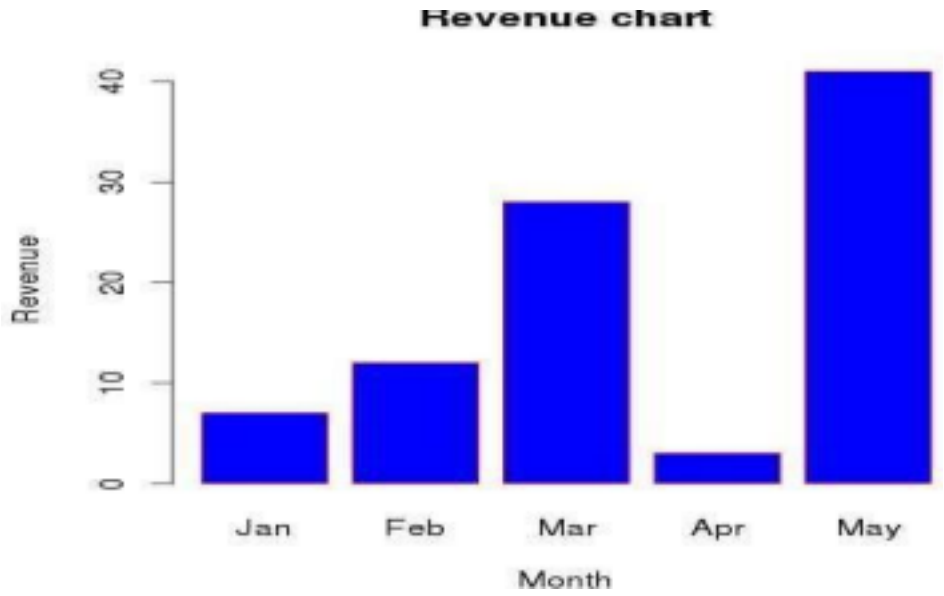
```
library(graphics)
v <- c(9,13,21,8,36,22,12,41,31,33,19)

# Create the histogram.
hist(v,xlab = "Weight",col = "blue",border = "green")
dev.off()
```

Output:-



Bar chart

```
library(graphics)
H <- c(7,12,28,3,41)
M <- c("Jan","Feb","Mar","Apr","May")
# Plot the bar chart.
barplot(H, names. arg = M, xlab = "Month", ylab = "Revenue", col = "blue", main = "Revenue chart")
dev.off()
```



Pie Chart

```
library(graphics)
x <- c(21, 62, 10, 53)
labels<- c("London", "NewYork", "Singapore", "Mumbai")
# Plot the Pie chart.
pie(x,labels)
dev.off()
```

5.CORRELATION AND COVARIANCE

a) Find the corelation matrix

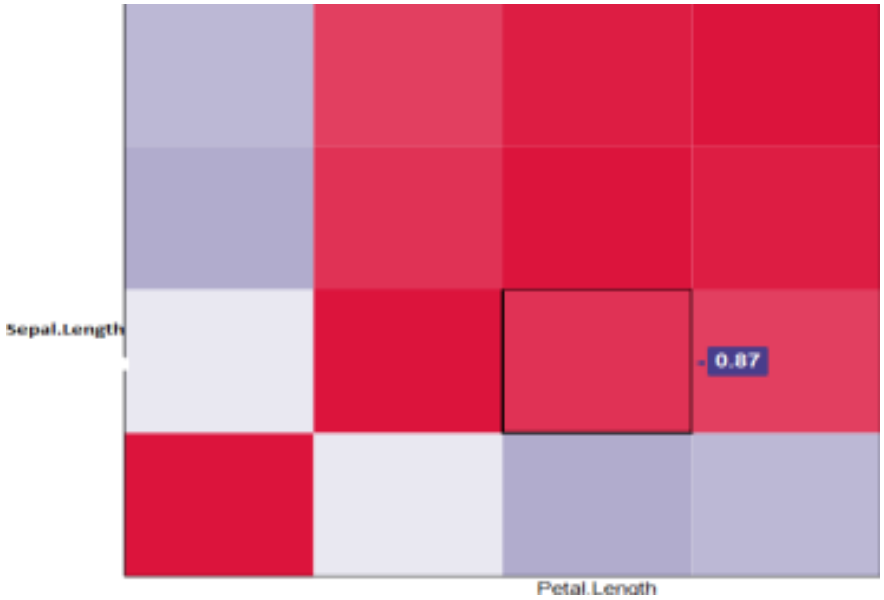
```
d<-data.frame(x1=rnorm(!0),x2=rnorm(10),x3=rnorm(10))
cor(d)
m<-cor(d) #get correlations
library(„corrplot“)
corrplot(m,method=”square”)
x<-matrix(rnorm(2),,nrow=5,ncol=4)
y<-matrix(rnorm(15),nrow=5,ncol=3)
COR<-cor(x,y)
COR
```

b) Plot the correlation plot on dataset and visualize giving an overview of relationships amongdata on iris data.

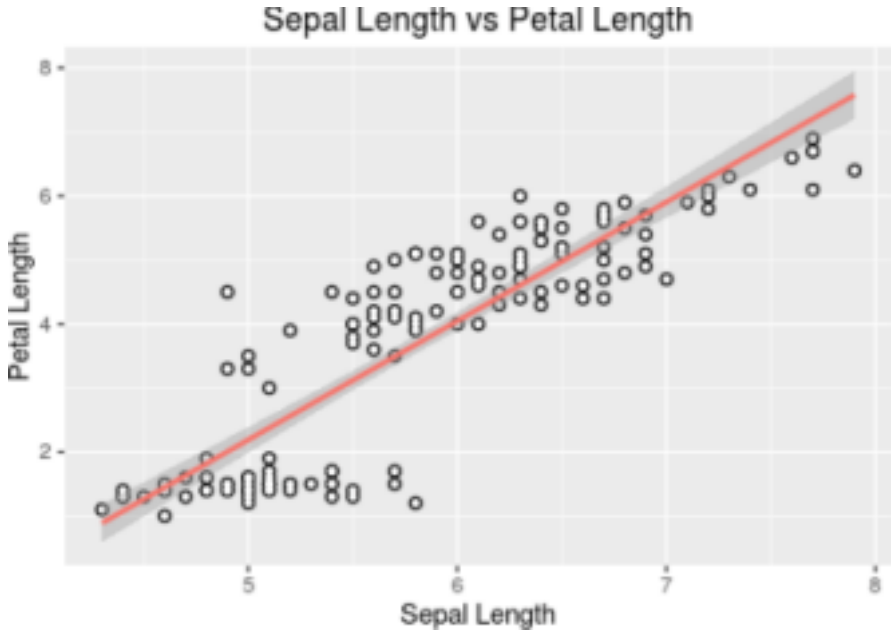
```
Image(x=seq(dim(x)[2])
Y<-seq(dim(y)[2])
Z=COR,xlab=”xcolumn”,ylab=”y
column”)Library(gtlcharts)
Data(iris) Iris$species<-NULL
Iplotcorr(iris,reoder=TRUE)
```

c) Analysis of covariance: variance (ANOVA), if data have categorical variables on iris data.

```
library(ggplot2)data(iris) str(iris)
ggplot(data=iris,aes(x=sepal.length,y=petal.length))+geom_point(size=2,colour=”black”)+ge
om_
point(size=1,colour=”white”)+geom_smooth(aes(colour=”black”),method=”lm“)+ggtitle(“se
pal.l
engthvspetal.length”)+xlab(“sepal.length”)+ylab(“petal.length”)+these(legend.position=”none”)
```



OUTPUT:



6. REGRESSION MODEL

Import a data from web storage. Name the dataset and perform Logistic Regression to find out relation between variables the model. Also check the model is fit or not [require (foreign), require(MASS)]

>mydata$rank<-factor(mydata$rank)
>mylogit<-glm(admit~gre+gpa+rank,data=mydata,family="binomial")
>summary(mylogit)

OUTPUT:

```
> mydata$rank <- factor(mydata$rank)
> mylogit <- glm(admit ~ gre + gpa + rank, data = mydata, family = "binomial")
> summary(mylogit)

Call:
glm(formula = admit ~ gre + gpa + rank, family = "binomial",
    data = mydata)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6268  -0.8662  -0.6388   1.1490   2.0790

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -3.989979   1.139951  -3.500 0.000465 ***
gre          0.002264   0.001094   2.070 0.038465 *
gpa          0.804038   0.331819   2.423 0.015388 *
rank2       -0.675443   0.316490  -2.134 0.032829 *
rank3       -1.340204   0.345306  -3.881 0.000104 ***
rank4       -1.551464   0.417832  -3.713 0.000205 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 499.98  on 399  degrees of freedom
Residual deviance: 458.52  on 394  degrees of freedom
AIC: 470.52

Number of Fisher Scoring iterations: 4
```

7.CLASSIFICATION MODEL

b. Choose classifier for classification problem.

Classifier used: Decision Tree.

The R package "party" is used to create decision trees.

Use the below command in R console to install the package. You also have to install the dependent packages if any.

install. packages("party")

The package "party" has the function ctree() which is used to create and analyze decison tree.

Syntax

The basic syntax for creating a decision tree in R is –

ctree(formula, data)

Here,

formula is a formula describing the predictor and response variables.

data is the name of the data set used.

Input Data

We will use the R in-built data set named readingSkills to create a decision tree. It describes the score of someone's readingSkills if we know the variables "age", "shoesize", "score" and whether the person is a native speaker or not.

Sample data from dataset readingSkills

Sno	nativeSpeaker	age	shoeSize	score
1	yes	5	24.83189	32.29385
2	yes	6	25.95238	36.63105
3	no	11	30.42170	49.60593
4	yes	7	28.66450	40.28456
5	yes	11	31.88207	55.46085
6	yes	10	30.07843	52.83124

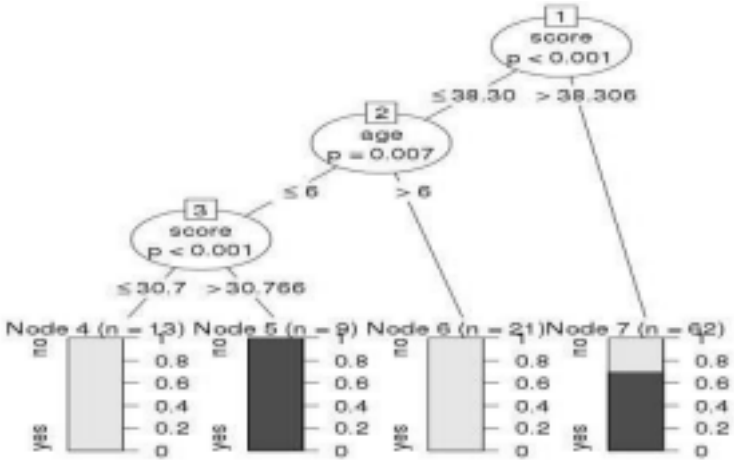
Program:

```
# Load the party package. It will automatically load other dependent packages. library(party)
# Create the input data frame.
input.dat <- readingSkills[c(1:105),]
# Give the chart file a name.
png(file = "decision_tree.png")
```

```
# Create the tree.
 output.tree <- ctree( nativeSpeaker ~ age + shoeSize + score, data = input.dat) # Plot the tree.
plot(output.tree)
# Save the file.
dev.off()
```

Output:

```
null device
 1
Loading required package: methods
Loading required package: grid
Loading required package: mvtnorm
Loading required package: modeltools
Loading required package: stats4
Loading required package: strucchange
Loading required package: zoo

Attaching package: ‘zoo’

The following objects are masked from ‘package:base’:

 as.Date, as.Date.numeric

Loading required package: sandwich
```



8.CLUSTERING MODEL

a. Clustering algorithms for unsupervised classification.

Using iris dataset and K-means Clustering algorithm

```
library(cluster)
> set.seed(20)
> irisCluster <- kmeans(iris[, 3:4], 3, nstart = 20)
# nstart = 20. This means that R will try 20 different random starting assignments and then  select
```

the onewith the lowest within cluster variation.
> irisCluster

Output:

Petal.Length Petal.Width
1 1.462000 0.246000
2 4.269231 1.342308
3 5.595833 2.037500

Clustering vector:

[1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 [42] 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 [83] 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 3 3 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3 3 2 3 3 3 [124] 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3

Within cluster sum of squares by cluster:

[1] 2.02200 13.05769 16.29167
(between_SS / total_SS = 94.3 %)

Available components:

[1] "cluster" "centers" "totss" "withinss" "tot.withinss"
[6] "betweenss" "size" "iter" "ifault"

b. Plot the cluster data using R visualizations

> irisCluster$cluster <- as.factor(irisCluster$cluster)
> ggplot(iris, aes(Petal.Length, Petal.Width, color = irisCluster$cluster)) + geom_point()

Output: