**DAY1: EXPERIMENTSo4**

1.The intervals and corresponding frequencies are as follows. age frequency

1-5. 200

5-15 450

15-20 300

20-50 1500

50-80 700

80-110 44

Compute an approximate median value for the data

**INPUT:**

#age, frequency

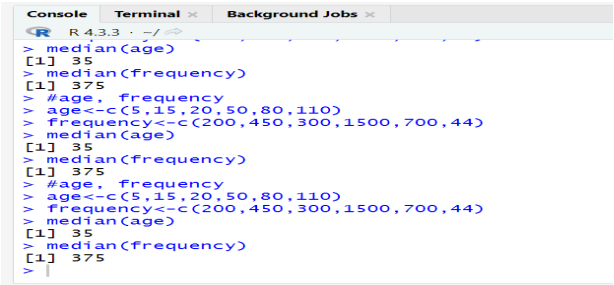
age<-c(5,15,20,50,80,110)

frequency<-c(200,450,300,1500,700,44)

median(age)

median(frequency)

**OUTPUT:**




2.Suppose that the data for analysis includes the attribute age. The age values for the data tuples are (in increasing order) 13, 15, 16, 16, 19, 20, 20, 21, 22, 22, 25, 25, 25, 25, 30, 33, 33, 35, 35, 35, 35, 36, 40, 45, 46, 52, 70.

(a) What is the mean of the data? What is the median?

(b) What is the mode of the data? Comment on the data's modality (i.e., bimodal, trimodal, etc.).

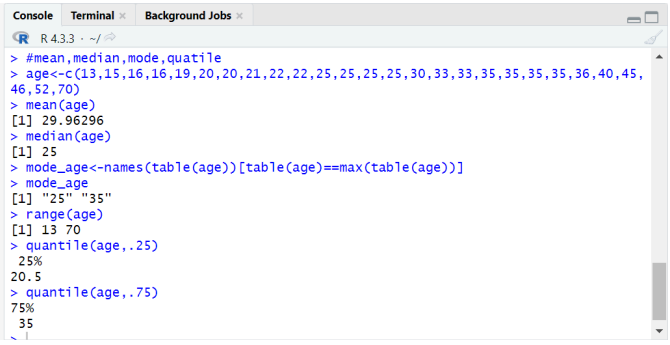
(c) What is the midrange of the data?

(d) Can you find (roughly) the first quartile (Q1) and the third quartile (Q3) of the data?

# Input:

```
#mean,median,mode,quatile

age<-c(13,15,16,16,19,20,20,21,22,22,25,25,25,25,30,33,33,35,35,35,35,36,40,45,46,52,70)

mean(age)

median(age)

mode_age<-names(table(age))[table(age)==max(table(age))]

mode_age

range(age)

quantile(age,.25)

quantile(age,.75)
```

**OUTPUT:**




3.Data Preprocessing :Reduction and Transformation

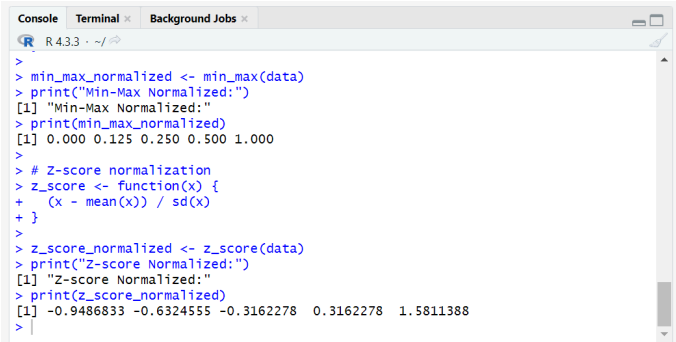
Use the two methods below to normalize the following group of data: 200, 300, 400, 600, 1000 (a) min-max normalization by setting min = 0 and max = 1 (b) z-score normalization

**INPUT:**

```
# Given data
```

```
data <- c(200, 300, 400, 600, 1000)


# Min-Max normalization
min_max <- function(x) {
  (x - min(x)) / (max(x) - min(x))
}
min_max_normalized <- min_max(data)
print("Min-Max Normalized:")
print(min_max_normalized)
# Z-score normalization
z_score <- function(x) {
  (x - mean(x)) / sd(x)
}
z_score_normalized <- z_score(data)
print("Z-score Normalized:")
print(z_score_normalized)
```

**OUTPUT:**




4..Data:11,13,13,15,15,16,19,20,20,20,21,21,22,23,24,30,40,45,45,45,71,

72,73,75  a) Smoothing by bin mean

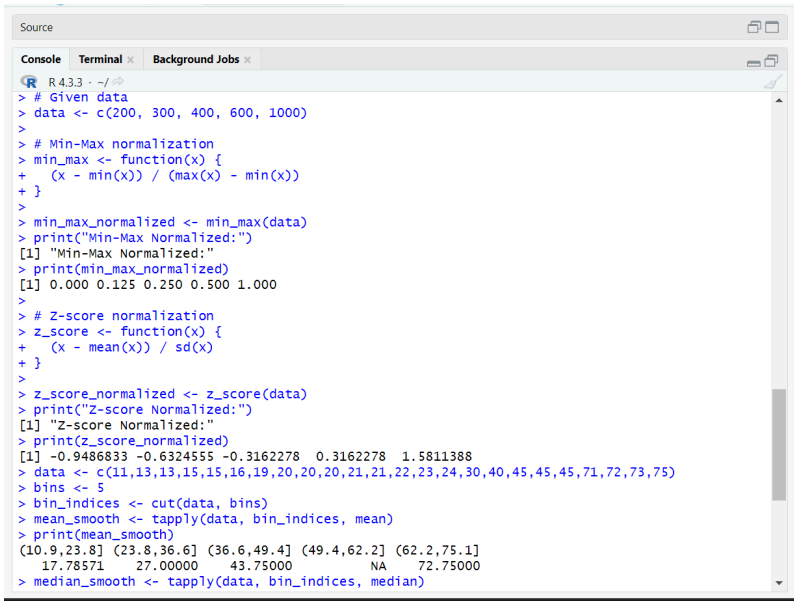
b) Smoothing by bin median

c) Smoothing by bin boundaries

# Input:

```
data <- c(11,13,13,15,15,16,19,20,20,20,21,21,22,23,24,30,40,45,45,45,71,72,73,75)

bins <- 5

bin_indices <- cut(data, bins)

mean_smooth <- tapply(data, bin_indices, mean)

print(mean_smooth)

median_smooth <- tapply(data, bin_indices, median)

median_smooth

min_max_smooth <- tapply(data, bin_indices, function(x) c(min(x), max(x)))

print(min_max_smooth)
```

**OUTPUT:**



```
> median_smooth <- tapply(data, bin_indices, median)
> median_smooth
(10.9,23.8] (23.8,36.6] (36.6,49.4] (49.4,62.2] (62.2,75.1]
       19.5        27.0        45.0          NA        72.5
> min_max_smooth <- tapply(data, bin_indices, function(x) c(min(x), max(x)))
> print(min_max_smooth)
$`(10.9,23.8]`
[1] 11 23

$`(23.8,36.6]`
[1] 24 30

$`(36.6,49.4]`
[1] 40 45

$`(49.4,62.2]`
NULL

$`(62.2,75.1]`
[1] 71 75
```

5.Suppose that a hospital tested the age and body fat data for 18 randomly selected adults with the following results:

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *age* | 23 | 23 | 27 | 27 | 39 | 41 | 47 | 49 | 50 |
| *%fat* | 9.5 | 26.5 | 7.8 | 17.8 | 31.4 | 25.9 | 27.4 | 27.2 | 31.2 |
| *age* | 52 | 54 | 54 | 56 | 57 | 58 | 58 | 60 | 61 |
| *%fat* | 34.6 | 42.5 | 28.8 | 33.4 | 30.2 | 34.1 | 32.9 | 41.2 | 35.7 |

(a) Calculate the mean, median, and standard deviation of age and %fat.

(b) Draw the boxplots for age and %fat.

(c) Draw a scatter plot and a q-q plot based on these two variables.

# Input:

```
age<-c(23,23,27,27,39,41,47,49,50,52,54,54,56,57,58,58,60,61)

fat<-c(9.5,26.5,7.8,17.8,31.4,25.9,27.4,27.2,31.2,34.6,42.5,28.8,33.4,30.2,34.1,32.9,41.2,35.7)

mean(age)

median(age)

sd(age)

mean(fat)

median(fat)

sd(fat)

#boxplot

boxplot(age,fat)
```

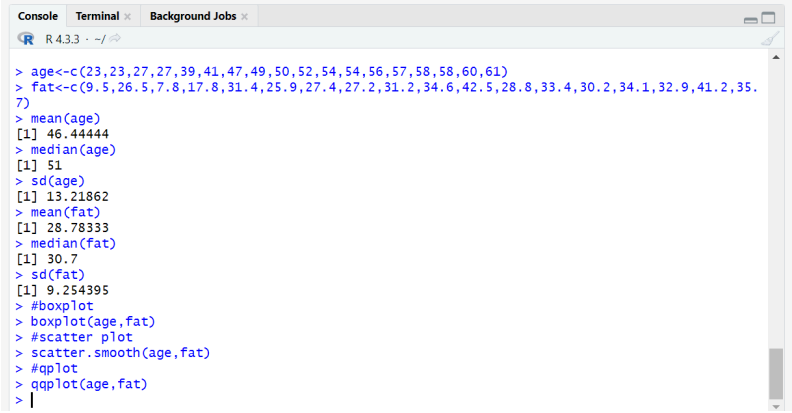
#scatter plot

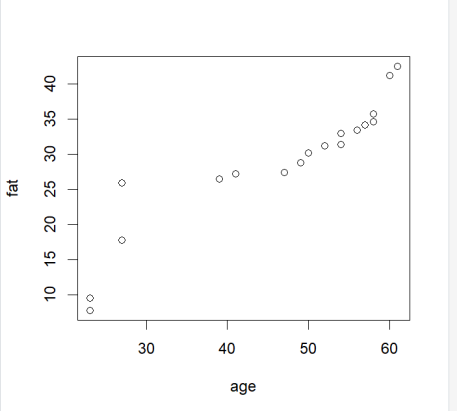
scatter.smooth(age,fat)

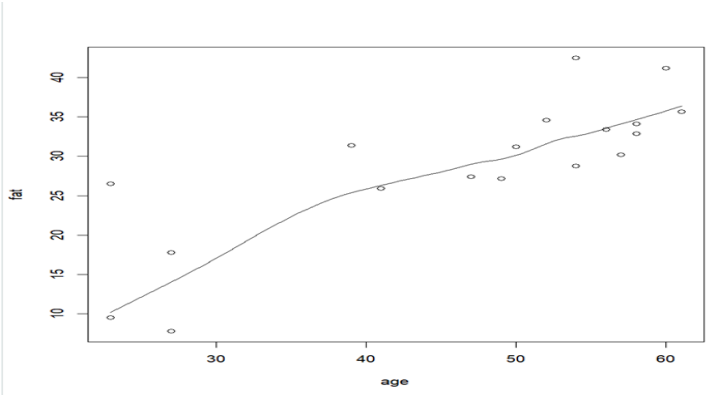
#qplot

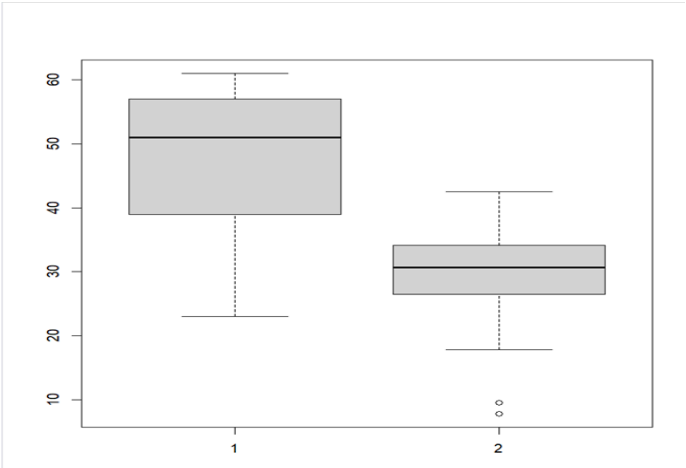
qqplot(age,fat)

**OUTPUT:**



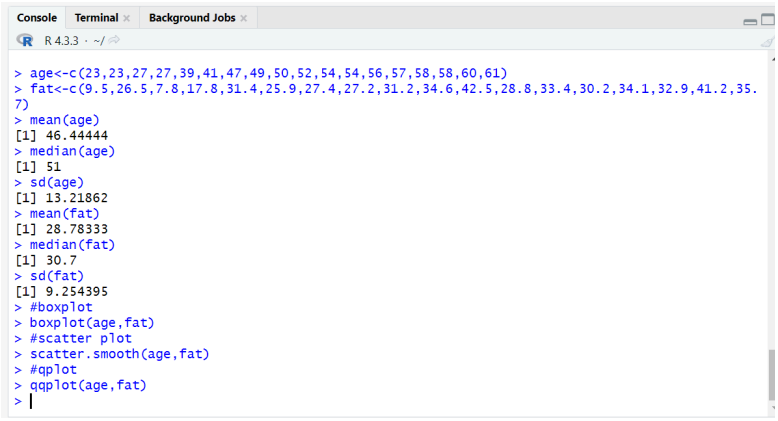
6.Suppose that a hospital tested the age and body fat data for 18 randomly selected adults with the following results:

(i) Use min-max normalization to transform the value 35 for age onto the range [0.0, 1.0].
(ii) Use z-score normalization to transform the value 35 for age, where the standard deviation of age is 12.94 years.
(iii) Use normalization by decimal scaling to transform the value 35 for age. Perform the above functions using R – tool

# Input:

```
v<-c(23,23,27,27,39,41,47,49,50,52,54,54,56,57,58,58,60,61)

min<-0

max<-1

#min_max

min_max=((35-min(v))/(max(v)-min(v)))

print(min_max)

#z-score

m=mean(v)

s<-12.94

z_score=(35-m)/s

print(z_score)

#decimal scaling

m<-35

j=max(m)<1

decimal_scaling=m/10^j

print(decimal_scaling)
```

**OUTPUT:**



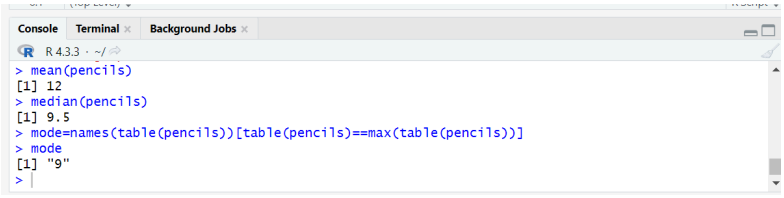

7.The following values are the number of pencils available in the different boxes. Create a vector and find out the mean, median and mode values of set of pencils in the given data.

| Box1 | Box2 | Box3 | Box4 | Box5 | Box6 | Box7 | Box8 | Box9 | Box 10 |
|---|---|---|---|---|---|---|---|---|---|
| 9 | 25 | 23 | 12 | 11 | 6 | 7 | 8 | 9 | 10 |

# Input:

```
pencils<-c(9,25,23,12,11,6,7,8,9,10)

mean(pencils)

median(pencils)

mode=names(table(pencils))[table(pencils)==max(table(pencils))]

Mode
```

**OUTPUT:**




8. the following table would be plotted as (x,y) points, with the first column being the x values as number of mobile phones sold and the second column being the y values as money. To use the scatter plot for how many mobile phones sold.

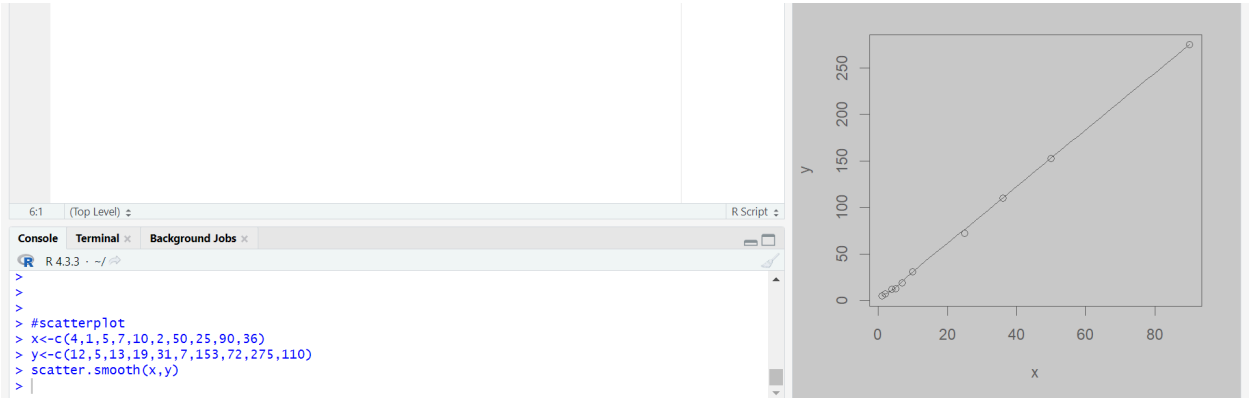
x :4 1 5 7 10 2 50 25 90 36

y :12 5 13 19 31 7 153 72 275 110

**INPUT:**

```
#scatterplot
x<-c(4,1,5,7,10,2,50,25,90,36)
y<-c(12,5,13,19,31,7,153,72,275,110)
scatter.smooth(x,y)
```

**OUTPUT:**




9. Implement of the R script using marks scored by a student in his model exam has been sorted as follows: 55, 60, 71, 63, 55, 65, 50, 55,58,59,61,63,65,67,71,72,75. Partition them into three bins by each of the following methods. Plot the data points using histogram.

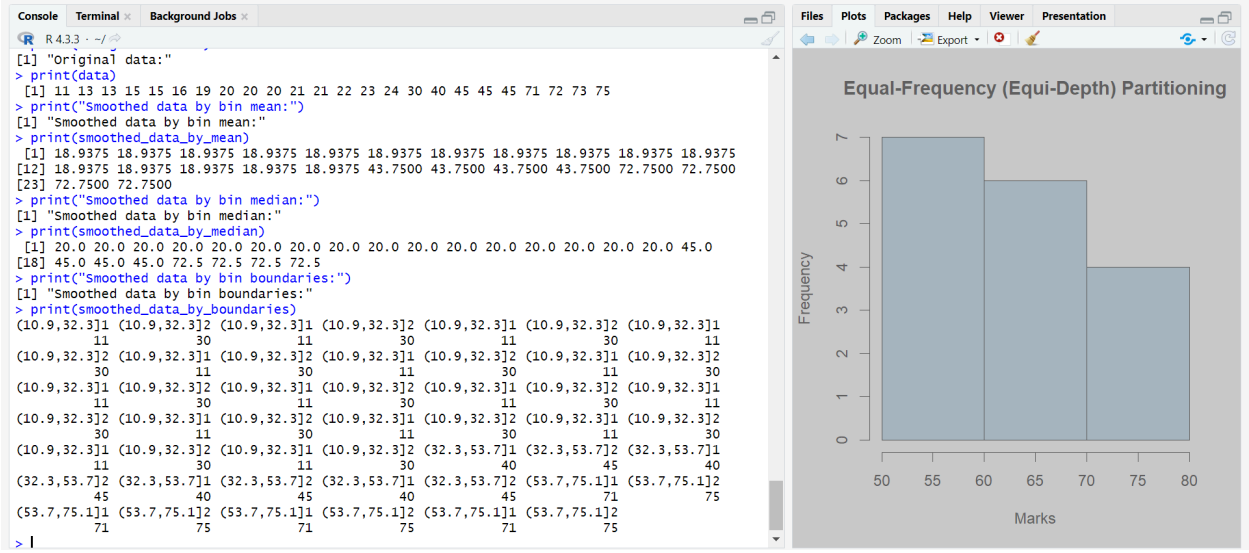
(a) equal-frequency (equi-depth) partitioning (b) equal-width partitioning

## Input:

```
marks <- c(55, 60, 71, 63, 55, 65, 50, 55, 58, 59, 61, 63, 65, 67, 71, 72, 75)

num_bins <- 3

bins_eq_frequency <- cut(marks, breaks = num_bins, labels = FALSE)

hist(marks, breaks = num_bins, col = "lightblue", xlab = "Marks", main =
"Equal-Frequency (Equi-Depth) Partitioning")

marks <- c(55, 60, 71, 63, 55, 65, 50, 55, 58, 59, 61, 63, 65, 67, 71, 72, 75)
```

```
bin_mean <- tapply(data, cut(data, num_bins), mean)

smoothed_data_by_mean <- unname(bin_mean[as.character(cut(data, num_bins))])

bin_median <- tapply(data, cut(data, num_bins), median)

smoothed_data_by_median <- unname(bin_median[as.character(cut(data, num_bins))])

bin_boundaries <- tapply(data, cut(data, num_bins), function(x) c(min(x), max(x)))

smoothed_data_by_boundaries <- unlist(bin_boundaries[as.character(cut(data,
num_bins))])

print("Original data:")

print(data)

print("Smoothed data by bin mean:")

print(smoothed_data_by_mean)

print("Smoothed data by bin median:")

print(smoothed_data_by_median)

print("Smoothed data by bin boundaries:")

print(smoothed_data_by_boundaries)
```

**OUTPUT:**



10. Suppose that the speed car is mentioned in different driving style.

Regular 78.3 81.8 82 74.2 83.4 84.5 82.9 77.5 80.9 70.6 Speed

Calculate the Inter quantile and standard deviation of the given data.

## Input:

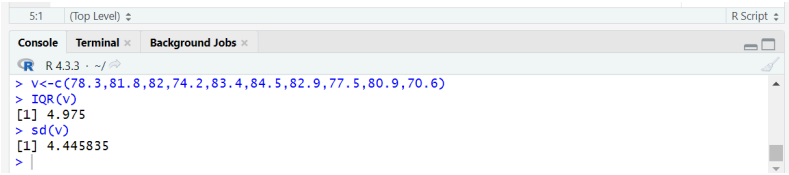
#IQR, SD

v<-c(78.3,81.8,82,74.2,83.4,84.5,82.9,77.5,80.9,70.6)

IQR(v)

sd(v)

**OUTPUT:**




11.Suppose that the data for analysis includes the attribute age. The age values for the data tuples are (in increasing order) 13, 15, 16, 16, 19, 20, 20, 21, 22, 22, 25, 25, 25, 25, 30, 33, 33, 35, 35, 35, 35, 36, 40, 45, 46, 52, 70.

Can you find (roughly) the first quartile (Q1) and the third quartile (Q3) of the data?

## Input:

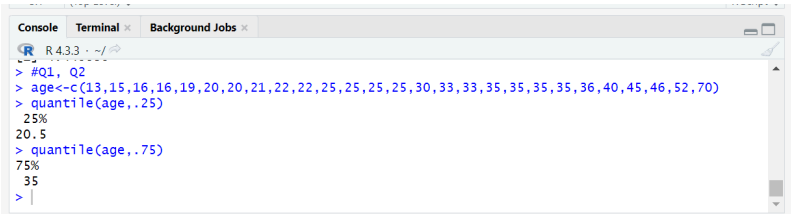
#Q1, Q2

age<-c(13,15,16,16,19,20,20,21,22,22,25,25,25,25,30,33,33,35,35,35,35,36,40,45,46,52,70)

quantile(age,.25)

quantile(age,.75)

**OUTPUT:**




## DAY 2: EXPERIMENTS

1.Covariance and correlation

Children of three ages are asked to indicate their preference for three photographs of adults. Do the data suggest that there is a significant relationship between age and photograph preference? What is wrong with this study?

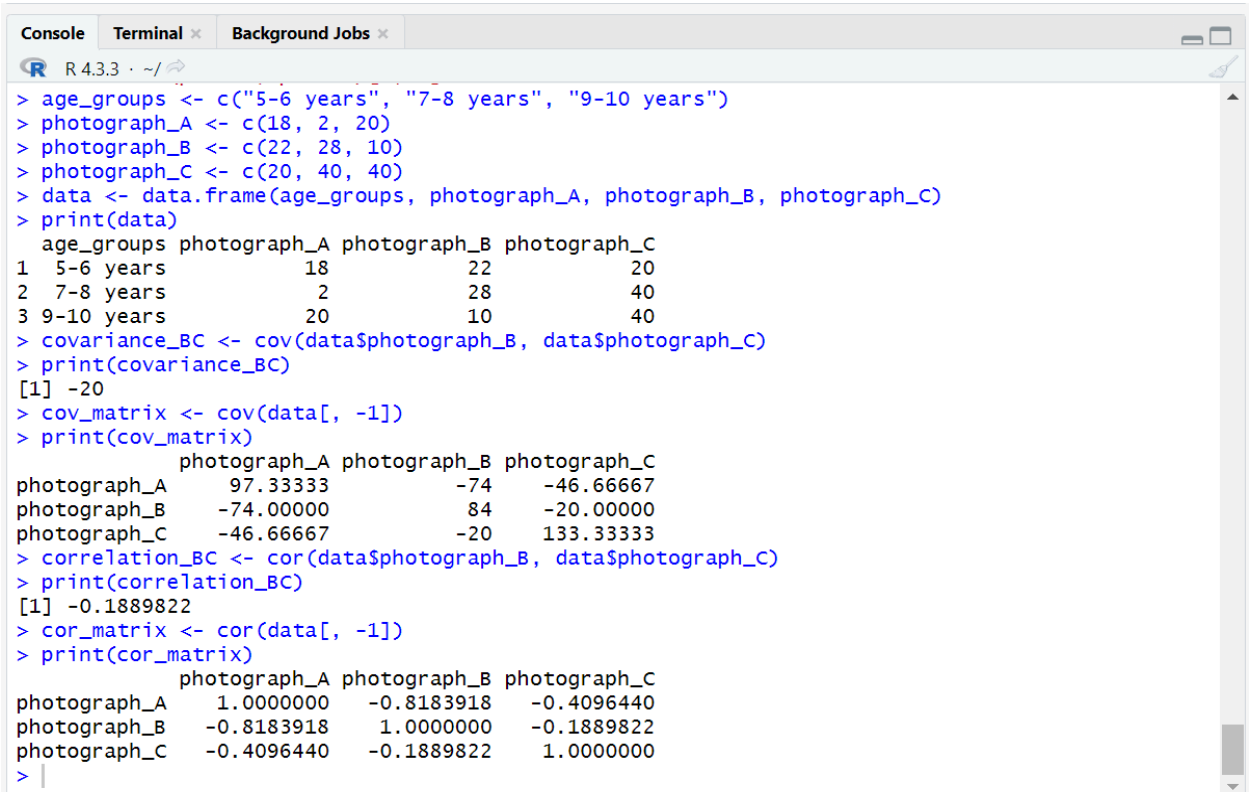
| | **Photograph:** | | |
|---|---|---|---|
| **Age of child** | A | B | C |
| 5-6 years: | 18 | 22 | 20 |
| 7-8 years: | 2 | 28 | 40 |
| 9-10 years: | 20 | 10 | 40 |

1. Use cov() to calculate the sample covariance between B and C.
2. Use another call to cov() to calculate the sample covariance matrix for the preferences.
3. Use cor() to calculate the sample correlation between B and C.
4. Use another call to cor() to calculate the sample correlation matrix for the preferences.

INPUT:

```
age_groups <- c("5-6 years", "7-8 years", "9-10 years")
photograph_A <- c(18, 2, 20)
photograph_B <- c(22, 28, 10)
photograph_C <- c(20, 40, 40)
data <- data.frame(age_groups, photograph_A, photograph_B, photograph_C)
print(data)
covariance_BC <- cov(data$photograph_B, data$photograph_C)
print(covariance_BC)
cov_matrix <- cov(data[, -1])
print(cov_matrix)
correlation_BC <- cor(data$photograph_B, data$photograph_C)
print(correlation_BC)
cor_matrix <- cor(data[, -1])
print(cor_matrix)
```

OUTPUT:




2.Imagine that you have selected data from the All Electronics data warehouse for analysis. The data set will be huge! The following data are a list of All Electronics prices for commonly sold items (rounded to the nearest dollar). The numbers have been

sorted: 1, 1, 5, 5, 5, 5, 5, 8, 8, 10, 10, 10, 10, 12, 14, 14, 14, 15, 15, 15, 15, 15, 15, 18, 18, 18, 18, 18, 8, 8, 10, 10, 10, 10, 12, 14, 14, 14, 15, 15, 15, 15, 15, 15, 18, 18, 18, 18, 18,

| |
|---|
| 18, 18, 18, 20, 20, 20, 20, 20, 20, 20, 21, 21, 21, 21, 25, 25, 25, 25, 25, 28, 28, 30, |
| 30, 30.<br><br>(i) Partition the dataset using an equal-frequency partitioning method with bin equal to 3 (ii) apply data smoothing using bin means and bin boundary.<br>(iii) Plot Histogram for the above frequency division |

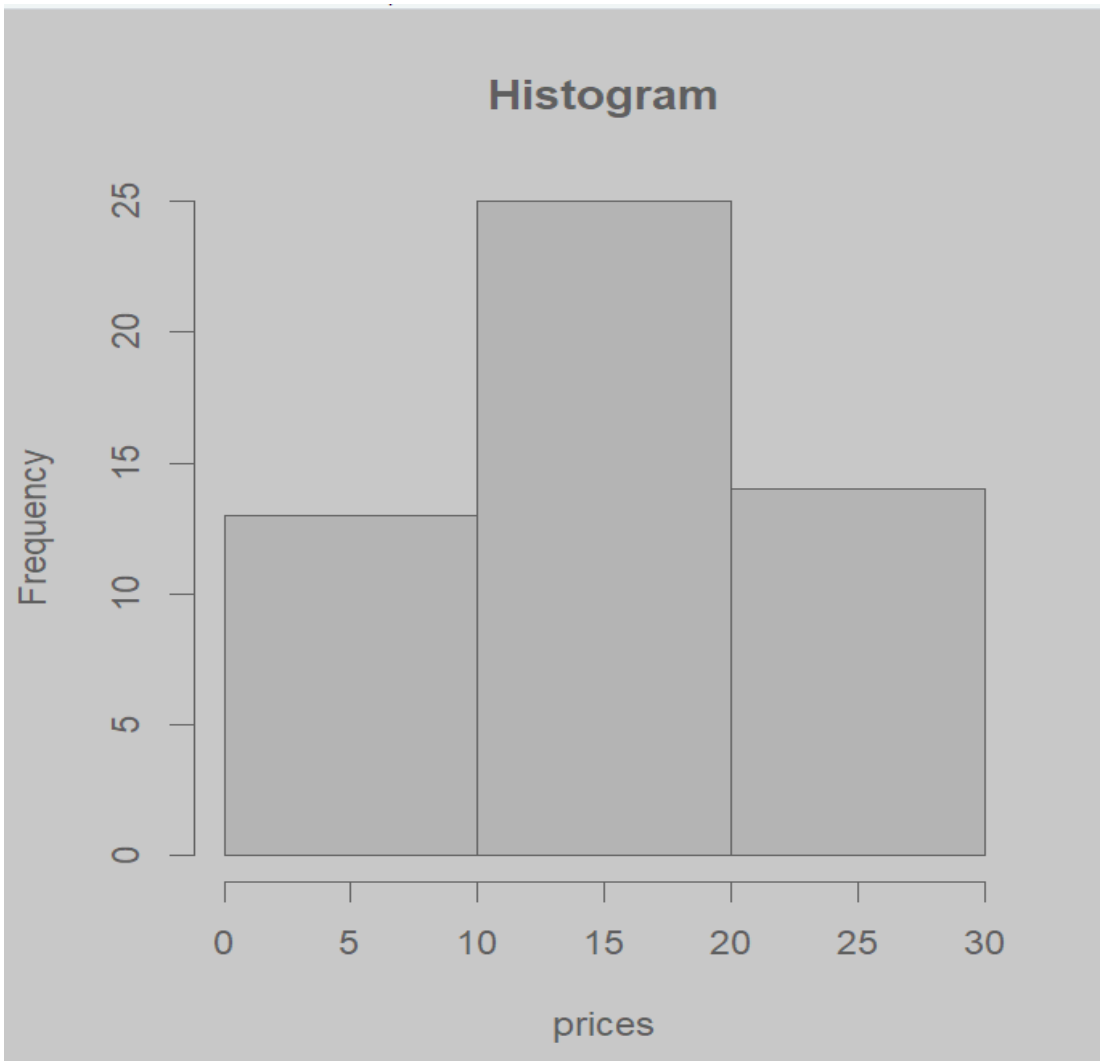
INPUT:

```
# Define the dataset
prices <- c(1, 1, 5, 5, 5, 5, 5, 8, 8, 10, 10, 10, 10, 12, 14, 14, 14, 15, 15, 15, 15, 15, 15, 18, 18, 18, 18, 18, 8, 8, 10, 10, 10, 10, 12, 14, 14, 14, 15, 15, 15, 15, 15, 15, 18, 18, 18, 18, 18, 18, 18, 18, 20, 20, 20, 20, 20, 20, 20, 21, 21, 21, 21, 25, 25, 25, 25, 25, 28, 28, 30, 30, 30)

# (i) Partition the dataset using equal-frequency partitioning with bin equal to 3
partitioned <- cut(prices, breaks = 3, labels = FALSE)

# (ii) Apply data smoothing using bin means
bin_means <- tapply(prices, partitioned, mean)
smoothed_prices <- bin_means[partitioned]

# (iii) Plot Histogram
hist(prices, breaks = 3, main = "Histogram of Prices", xlab = "Price", col = "skyblue", border = "black")
```

Console | Terminal | Background Jobs

R 4.3.3 · ~/

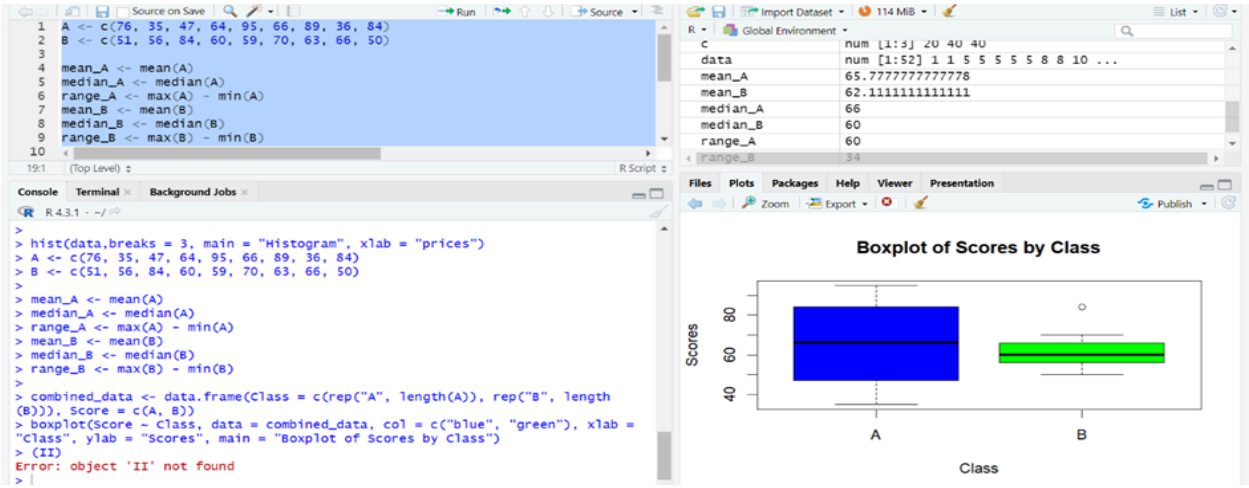
```
> bin<-length(data)/3
> bins<-cut(data, breaks = c(-Inf, quantile(data, probs = seq(0,1, 1/3)),Inf), include.lowest =
TRUE)
> tapply(data,bins,mean)
 [-Inf,1]    (1,15]   (15,20]   (20,30] (30, Inf]
  1.00000  10.71429  18.93333  25.35714        NA
> tapply(data, bins,function(x) c(min(x),max(x)))
$`[-Inf,1]`
[1] 1 1

$`(1,15]`
[1]  5 15

$`(15,20]`
[1] 18 20

$`(20,30]`
[1] 21 30

$`(30, Inf]`
NULL
```



3.Two Maths teachers are comparing how their Year 9 classes performed in the end of year exams. Their results are as follows:
Class A: 76, 35, 47, 64, 95, 66, 89, 36, 8476,35,47,64,95,66,89,36,84

Class B: 51, 56, 84, 60, 59, 70, 63, 66, 5051,56,84,60,59,70,63,66,50

(i) Find which class had scored higher mean, median and range.
(ii) Plot above in boxplot and give the inferences




4.Let us consider one example to make the calculation method clear. Assume that the minimum and maximum values for the feature F are $50,000 and $100,000 correspondingly. It needs to range *F* from 0 to 1. In accordance with min-max normalization, $v$ = $80,

b) Use the two methods below to normalize the following group of data: 200, 300, 400, 600, 1000

(a) min-max normalization by setting min = 0 and max = 1

(b) z-score normalization

INPUT:

data <- c(200, 300, 400, 600, 1000)

min_value <- 50000

max_value <- 100000

v <- 80

min_max_normalized <- (v - min_value) / (max_value - min_value)

min_max_normalized

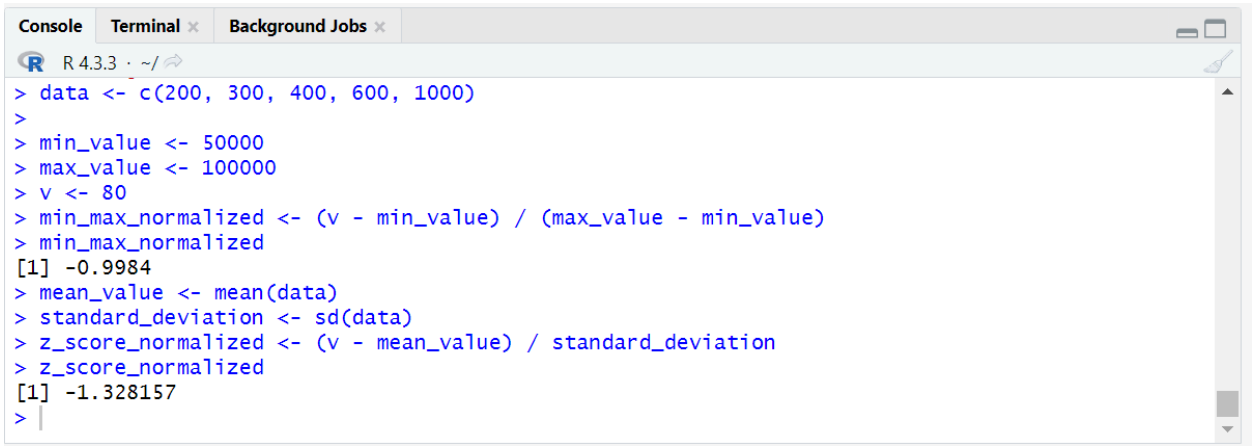
mean_value <- mean(data)

standard_deviation <- sd(data)

z_score_normalized <- (v - mean_value) / standard_deviation

z_score_normalized

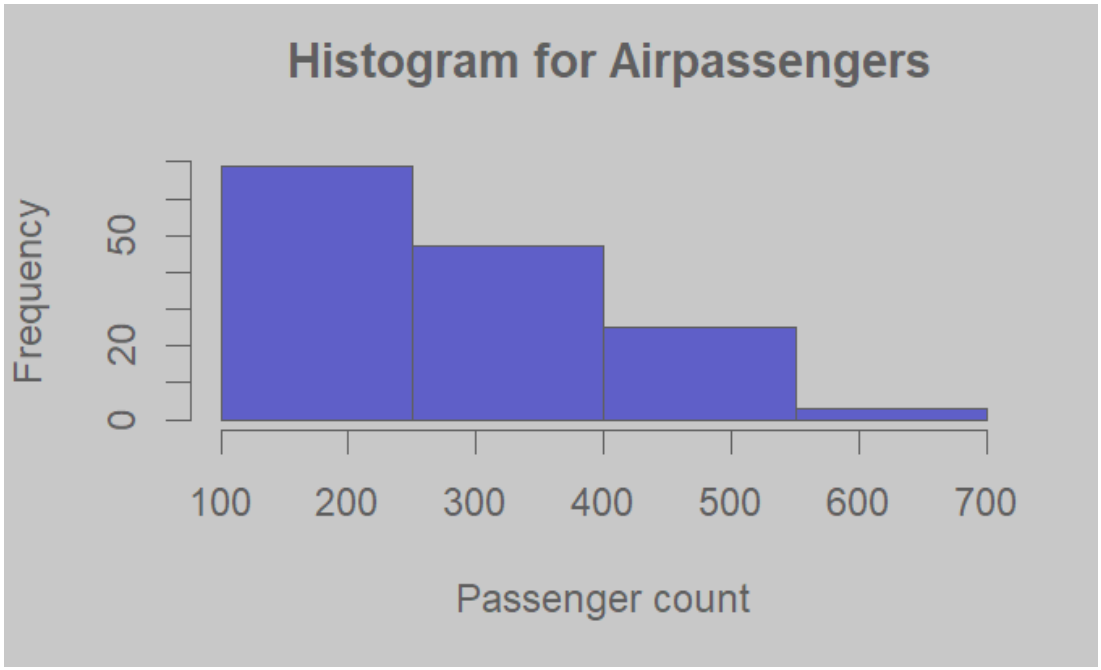
OUTPUT:




5.Make a histogram for the "AirPassengers "dataset, start at 100 on the x-axis, and from values 200 to 700, make the bins 150 wide

INPUT:

```
Console  Terminal  Background Jobs
R 4.3.3 · ~/
> data <- c(200, 300, 400, 600, 1000)
>
> min_value <- 50000
> max_value <- 100000
> v <- 80
> min_max_normalized <- (v - min_value) / (max_value - min_value)
> min_max_normalized
[1] -0.9984
> mean_value <- mean(data)
> standard_deviation <- sd(data)
> z_score_normalized <- (v - mean_value) / standard_deviation
> z_score_normalized
[1] -1.328157
> data("AirPassengers")
> hist(AirPassengers, breaks = seq(100, 700, by = 150), col = "blue", main=" Histogram for Airpa
ssengers", xlab = "Passenger count", ylab = "Frequency")
>
```



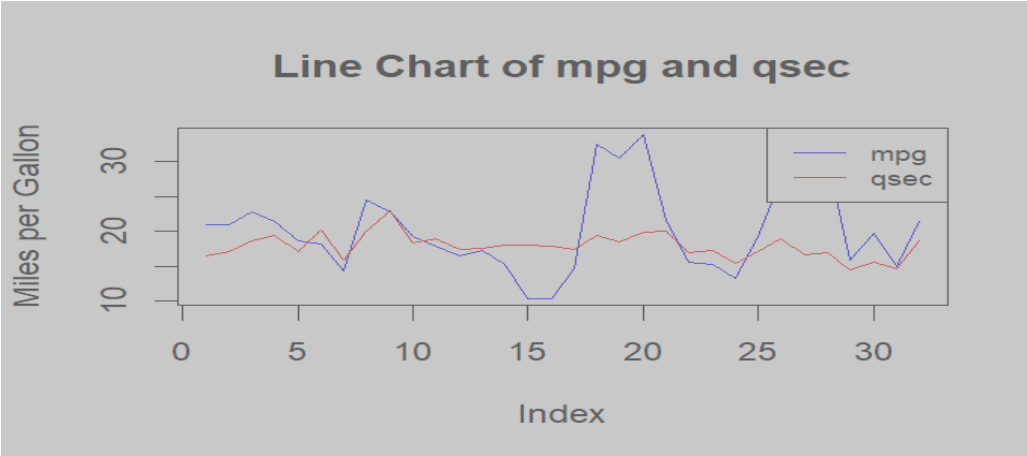

6.Obtain Multiple Lines in Line Chart using a single Plot Function in R.Use attributes“mpg”and“qsec”of the dataset “mtcars”

INPUT:

```
data("mtcars")
plot(mtcars$mpg, type = "l", col = "blue", xlab = "Index", ylab = "Miles per Gallon", main
= "Line Chart of mpg and qsec")
lines(mtcars$qsec, col = "red")
```

legend("topright", legend = c("mpg", "qsec"), col = c("blue", "red"), lty = 1, cex = 0.8)

OUTPUT:




7.Download the Dataset "water" From R dataset Link.Find out whether there is a linear relation between attributes"mortality" and"hardness" by plot function.Fit the Data into the Linear Regression model.Predict the mortality for the hardness=88.

INPUT:

data("iris")

str(iris)

plot(iris$Sepal.Length, iris$Petal.Length, main = "Scatter plot of Sepal.Length vs. Petal.Length",xlab = "Sepal.Length", ylab = "Petal.Length", col = "blue", pch = 16)

model <- lm(Petal.Length ~ Sepal.Length, data = iris)

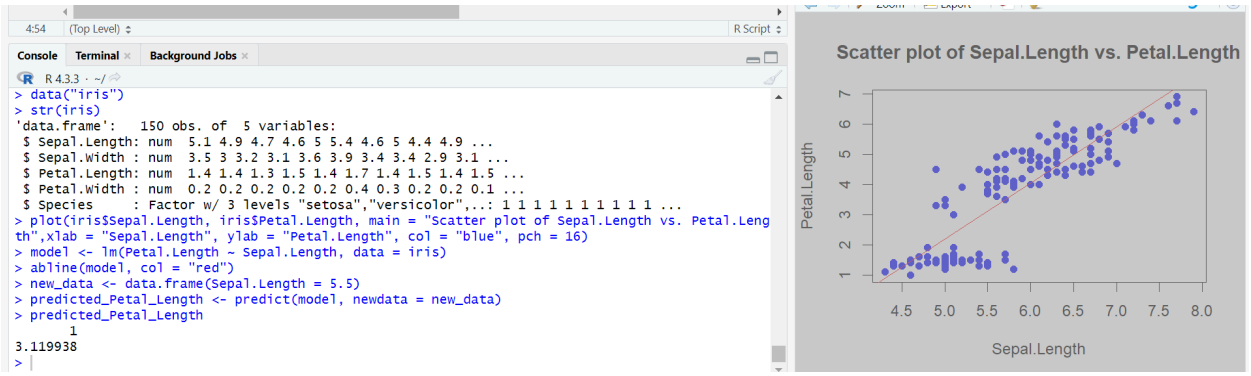
abline(model, col = "red")

new_data <- data.frame(Sepal.Length = 5.5)

predicted_Petal_Length <- predict(model, newdata = new_data)

predicted_Petal_Length

OUTPUT:

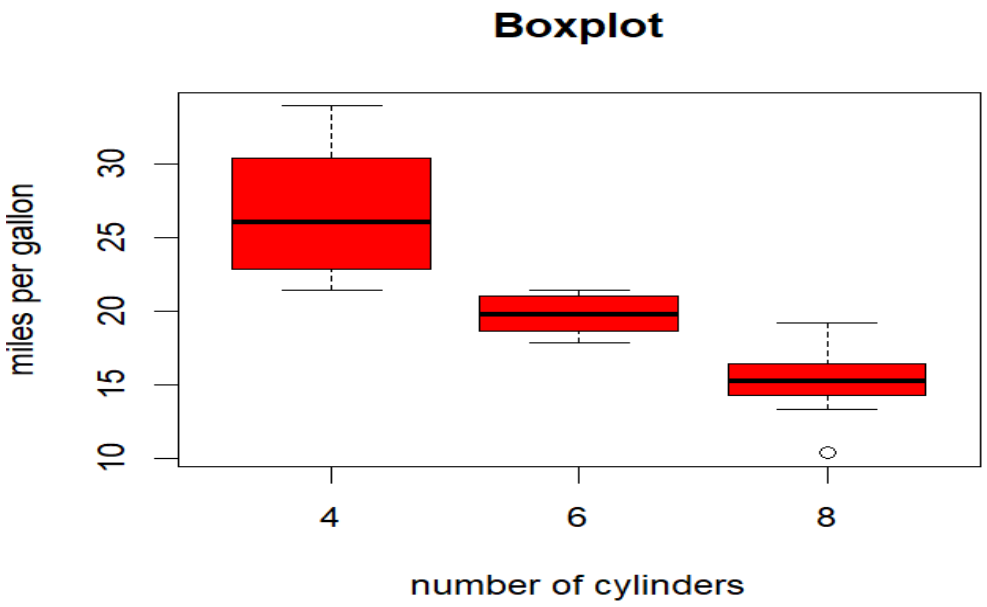



8.Create a Boxplot graph for the relation between "mpg"(miles per galloon) and "cyl"(number of Cylinders) for the dataset "mtcars" available in R Environment.

**INPUT:**

```
data("mtcars")
boxplot(mpg ~ cyl, data = mtcars, main = "Boxplot", xlab = "number of cylinders", ylab = "miles per gallon", col= "red")
```

**OUTPUT:**

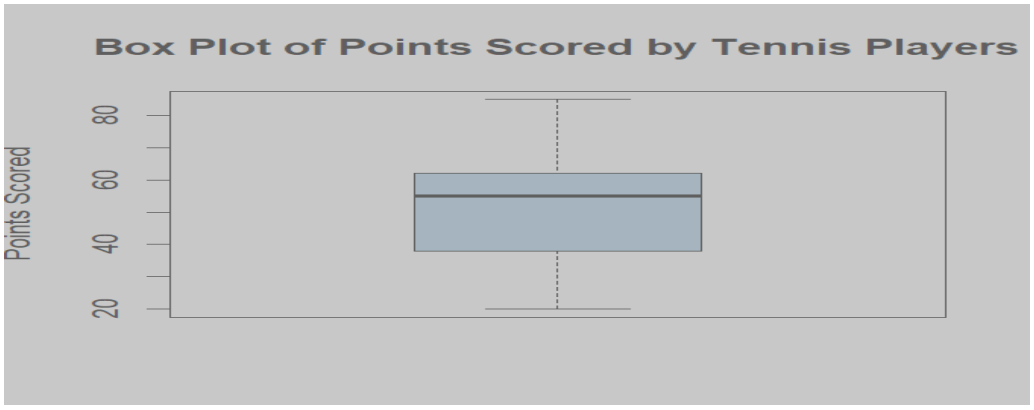


9. Assume the Tennis coach wants to determine if any of his team players are scoring outliers. To visualize the distribution of points scored by his players, then how can he decide to develop the box plot? Give suitable example using Boxplot visualization technique.

INPUT:

```
score <- c(20, 25, 30, 32, 35, 38, 40, 45, 50, 52, 55, 56, 58, 59, 60, 62, 65, 70, 75, 80, 85)

boxplot(score, col = "lightblue", main = "Box Plot of Points Scored by Tennis Players", ylab = "Points Scored")
```

OUTPUT:



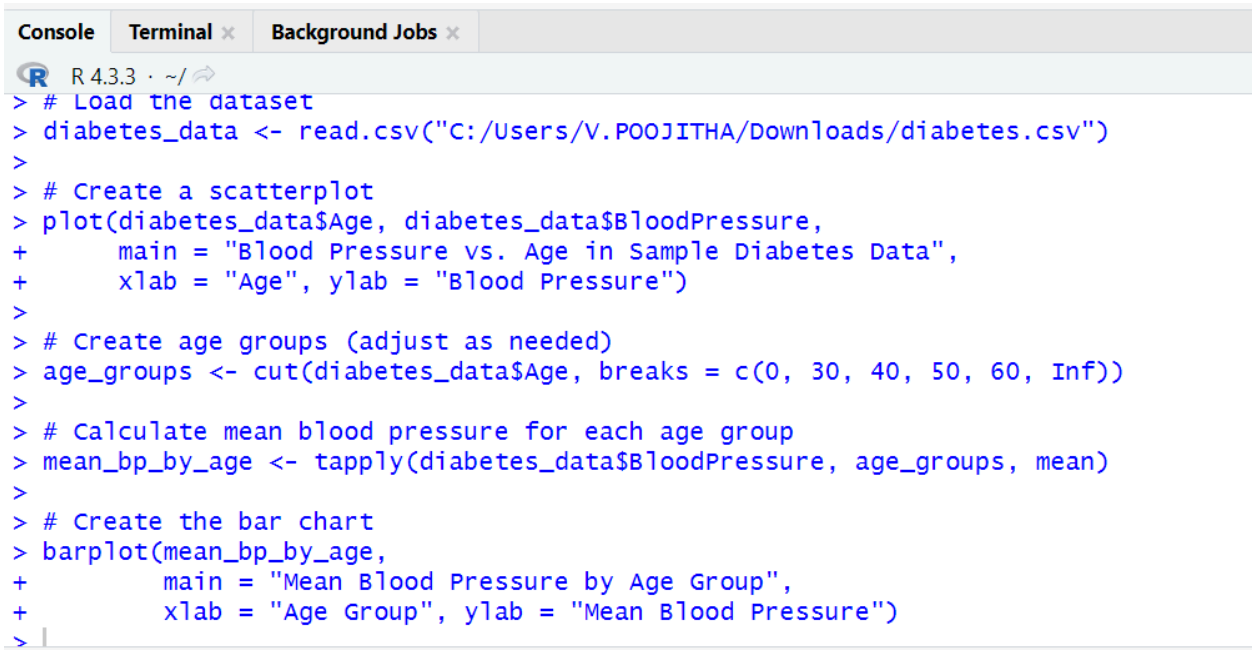

10.Implement using R language in which age group of people are affected by blood pressure based on the diabetes dataset show it using scatter plot and bar chart (that is BloodPressure vs Age using dataset “diabetes.csv”)

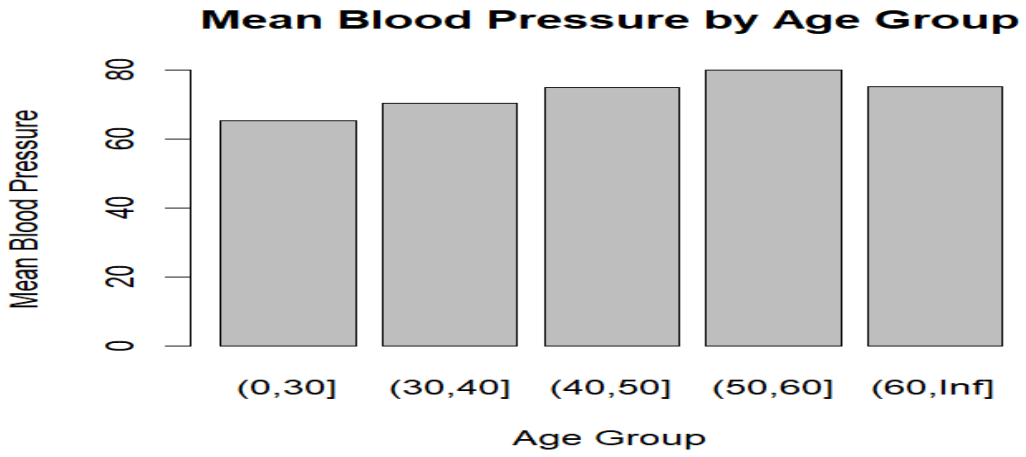
INPUT:

```
# Load the dataset

diabetes_data <- read.csv("C:/Users/V.POOJITHA/Downloads/diabetes.csv")

# Create a scatterplot

plot(diabetes_data$Age, diabetes_data$BloodPressure,

    main = "Blood Pressure vs. Age in Sample Diabetes Data",

    xlab = "Age", ylab = "Blood Pressure")

# Create age groups (adjust as needed)

age_groups <- cut(diabetes_data$Age, breaks = c(0, 30, 40, 50, 60, Inf))
```

```
# Calculate mean blood pressure for each age group

mean_bp_by_age <- tapply(diabetes_data$BloodPressure, age_groups, mean)

# Create the bar chart

barplot(mean_bp_by_age,

    main = "Mean Blood Pressure by Age Group",

    xlab = "Age Group", ylab = "Mean Blood Pressure")
```

OUTPUT:






**DAY 3: EXPERIMENTS**

1.Consider the data set and perform the Apriori Algorithm and FP algorithm support:3 and confidence=50%

| Customer ID | Transaction ID | Items Bought |
|---|---|---|
| 1 | 0001 | $\{a, d, e\}$ |
| 1 | 0024 | $\{a, b, c, e\}$ |
| 2 | 0012 | $\{a, b, d, e\}$ |
| 2 | 0031 | $\{a, c, d, e\}$ |
| 3 | 0015 | $\{b, c, e\}$ |
| 3 | 0022 | $\{b, d, e\}$ |
| 4 | 0029 | $\{c, d\}$ |
| 4 | 0040 | $\{a, b, c\}$ |
| 5 | 0033 | $\{a, d, e\}$ |
| 5 | 0038 | $\{a, b, e\}$ |

Input:

@relation dataset

@attribute a{true,false}

@attribute b{true,false}

@attribute c{true,false}

@attribute d{true,false}

@attribute e{true,false}

@data

true false false true true

true true true false true

true true false true true

true false true true true

false true true false true

false true false true true

false false true true false

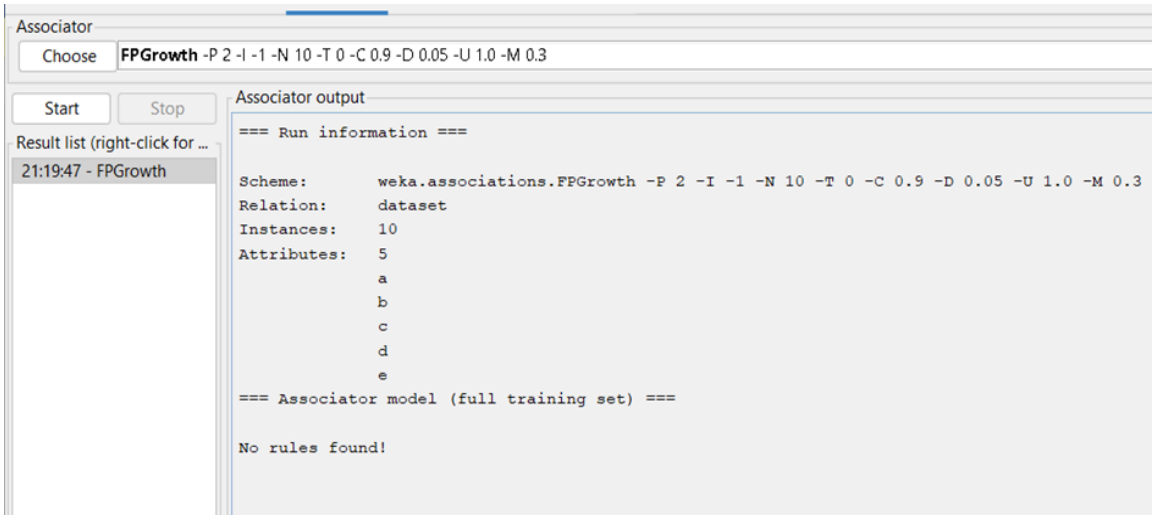
true true true false false

true false false true true

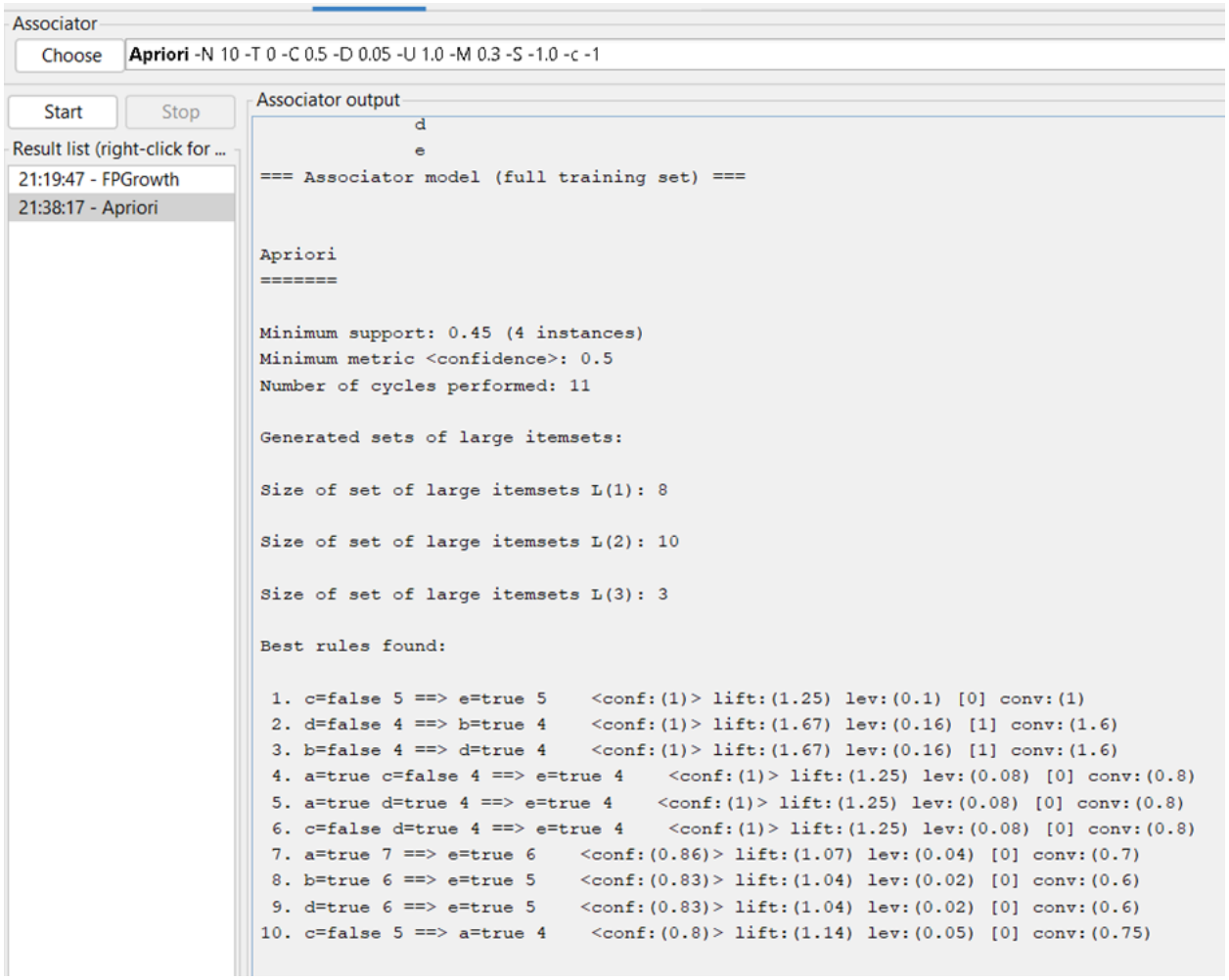
true true false false true

**Output:**

## FP GROWTH:



## APRIORI ALGORITHM:




2.Consider the data set and perform the Apriori Algorithm and FP algorithm support:3 and confidence=50%

Consider the market basket transactions shown in the above table.

(a) What is the maximum number of association rules that can be extracted

from this data (including rules that have zero support)?

(b) What is the maximum size of frequent itemsets that can be extracted

(assuming min sup > 0)?

| Transaction ID | Items Bought |
|---|---|
| 1 | {Milk, Beer, Diapers} |
| 2 | {Bread, Butter, Milk} |
| 3 | {Milk, Diapers, Cookies} |
| 4 | {Bread, Butter, Cookies} |
| 5 | {Beer, Cookies, Diapers} |
| 6 | {Milk, Diapers, Bread, Butter} |
| 7 | {Bread, Butter, Diapers} |
| 8 | {Beer, Diapers} |
| 9 | {Milk, Diapers, Bread, Butter} |
| 10 | {Beer, Cookies} |

INPUT:

@relation items

@attribute milk{t,f}

@attribute beer{t,f}

@attribute diapers{t,f}

@attribute bread{t,f}

@attribute butter{t,f}

@attribute cookies{t,f}

@data

t t t f f f

t f f t t f

t f t f f t

f f f t t t

f t t f f t

t f t t t f

f f t t t f

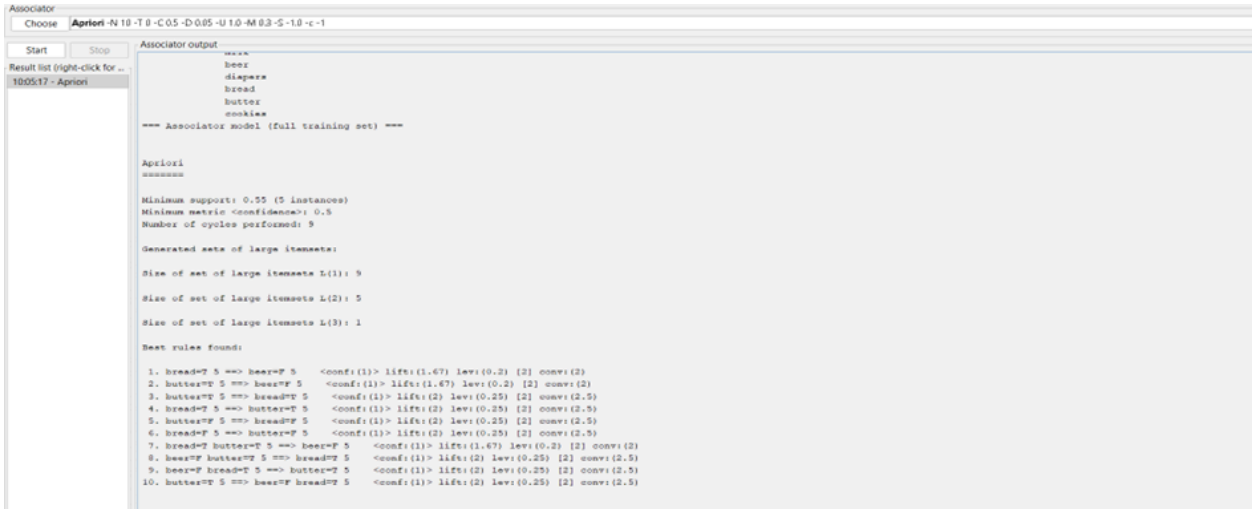
f t t f f f

t f t t t f

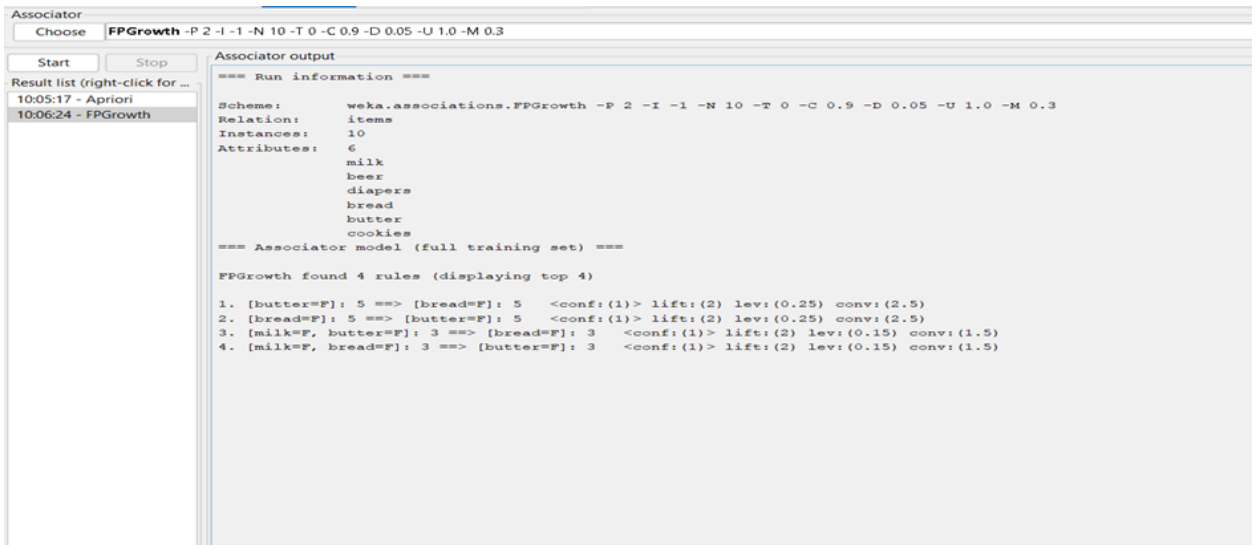
f t f f f t

**Output:**

**APRIORI**




**FP GROWTH**



3.Bayes classification and decision tree (using training and test data)

| RID | age | income | student | credit_rating | Class: buys_computer |
|---|---|---|---|---|---|
| 1 | <=30 | high | no | fair | no |
| 2 | <=30 | high | no | excellent | no |
| 3 | 31 . . . 40 | high | no | fair | yes |
| 4 | >40 | medium | no | fair | yes |
| 5 | >40 | low | yes | fair | yes |
| 6 | >40 | low | yes | excellent | no |
| 7 | 31 . . . 40 | low | yes | excellent | yes |
| 8 | <=30 | medium | no | fair | no |
| 9 | <=30 | low | yes | fair | yes |
| 10 | >40 | medium | yes | fair | yes |
| 11 | <=30 | medium | yes | excellent | yes |
| 12 | 31 . . . 40 | medium | no | excellent | yes |
| 13 | 31 . . . 40 | high | yes | fair | yes |
| 14 | >40 | medium | no | excellent | no |

## Input:

@relation decision_tree

@attribute age{young,middle,old}

@attribute income{low,medium,high}

@attribute student{yes,no}

@attribute Creit_rating{fair,excellent}

@attribute class{yes,no}

@data

young high no fair no

young high no excellent no

middle high no fair yes

old medium no fair yes

old low yes fair yes

old low yes excellent no

middle low yes excellent yes

young medium no fair no

young low yes fair yes

old medium yes fair yes

young medium yes excellent yes

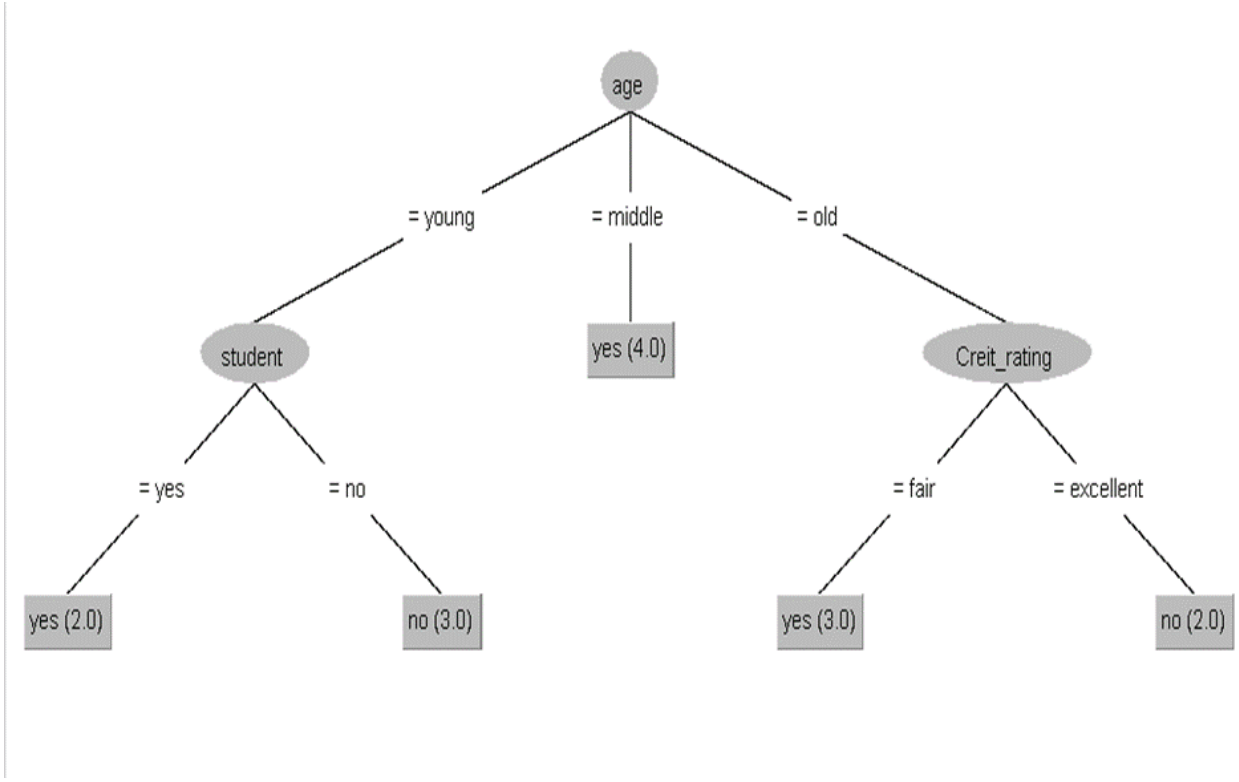
middle medium no excellent yes

middle high yes fair yes

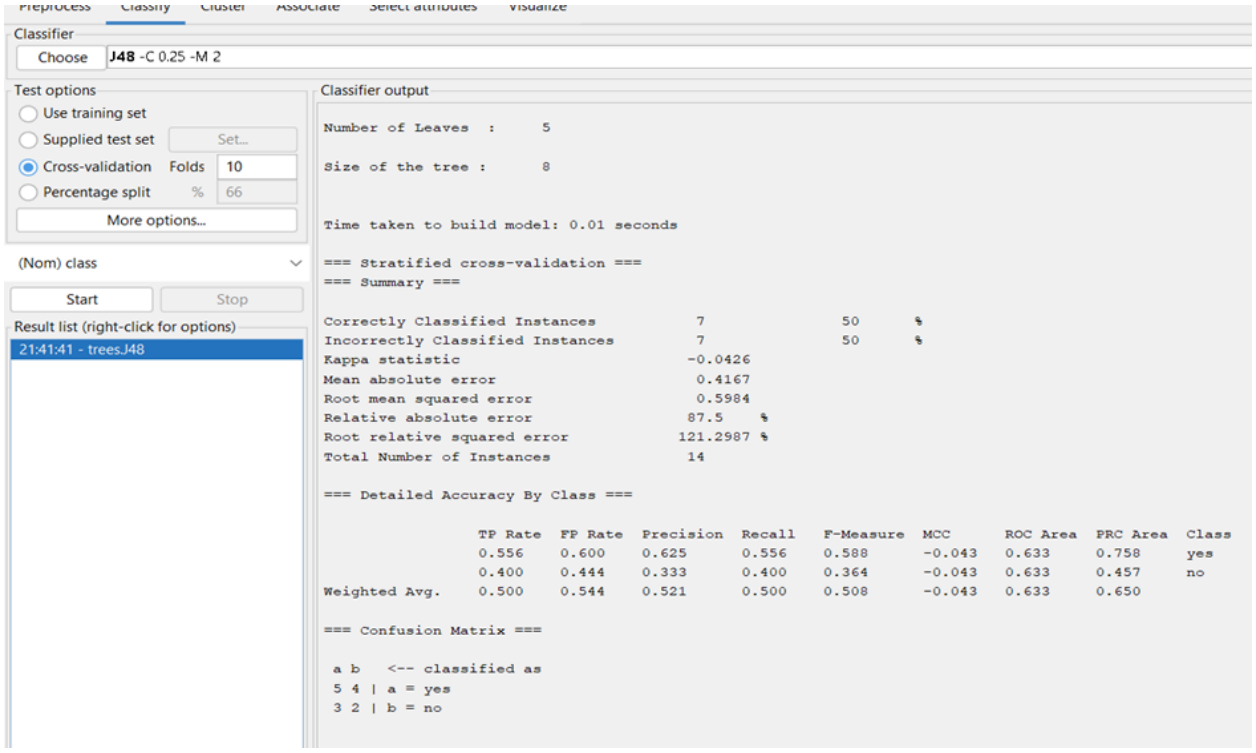
old medium no  excellent no

output:

Tree:


age
= young
= middle
= old
student
yes (4.0)
Creit_rating
= yes
= no
= fair
= excellent
yes (2.0)
no (3.0)
yes (3.0)
no (2.0)

# DECISION


Classifier
Choose
J48 -C 0.25 -M 2
Test options
Use training set
Supplied test set
Set...
Cross-validation
Folds
10
Percentage split
%
66
More options...
(Nom) class
Start
Stop
Result list (right-click for options)
21:41:41 - trees.J48
Classifier output
Number of Leaves : 5
Size of the tree : 8
Time taken to build model: 0.01 seconds
=== Stratified cross-validation ===
=== Summary ===
Correctly Classified Instances 7 50 %
Incorrectly Classified Instances 7 50 %
Kappa statistic -0.0426
Mean absolute error 0.4167
Root mean squared error 0.5984
Relative absolute error 87.5 %
Root relative squared error 121.2987 %
Total Number of Instances 14
=== Detailed Accuracy By Class ===
TP Rate FP Rate Precision Recall F-Measure MCC ROC Area PRC Area Class
0.556 0.600 0.625 0.556 0.588 -0.043 0.633 0.758 yes
0.400 0.444 0.333 0.400 0.364 -0.043 0.633 0.457 no
Weighted Avg. 0.500 0.544 0.521 0.500 0.508 -0.043 0.633 0.650
=== Confusion Matrix ===
a b <-- classified as
5 4 | a = yes
3 2 | b = no

4.Analysis the dataset “diabetes. csv” how the diabetes trend is for different age people, using linear regression and multiple regression.

## Input:

data<-read.csv("C:/Users/Hari Naidu/Desktop/POM/download papers/diabetes.csv")

data

relation<-lm(data$Age~data$Outcome)

relation

relation<-lm(data$Age~data$Outcome+data$BMI)

relation

## output:

```
 [ reached 'max' / getOption("max.print") -- omitted 657 rows ]
> relation<-lm(data$Age~data$Outcome+data$BMI)
> relation

Call:
lm(formula = data$Age ~ data$Outcome + data$BMI)

Coefficients:
 (Intercept)  data$Outcome      data$BMI
    32.84734       6.14177      -0.05469

> relation<-lm(data$Age~data$Outcome)
> relation

Call:
lm(formula = data$Age ~ data$Outcome)

Coefficients:
 (Intercept)  data$Outcome
      31.190         5.877
```

5.Implement using WEKA for the given Suppose a database has five transactions. Let min sup= 50%(2) and min con f = 80%.

| **Transactions** | **Items** |
|---|---|
| T1 | (M, O, N, K, E, Y) |
| T2 | (D, O, N, K, E, Y) |
| T3 | (M, A, K, E) |
| T4 | (M, U, C, K, Y) |
| T5 | (C,O, O, K, I ,E) |

- Find all frequent itemsets using Apriori algorithm

Also draw FP-Growth Tree

INPUT:

@relation items

@attribute M{t,f}

@attribute O{t,f}

@attribute N{t,f}

@attribute K{t,f}

@attribute E{t,f}

@attribute Y{t,f}

@attribute D{t,f}

@attribute A{t,f}

@attribute U{t,f}

@attribute C{t,f}

@attribute I{t,f}

@data

t t t t t t f f f f f

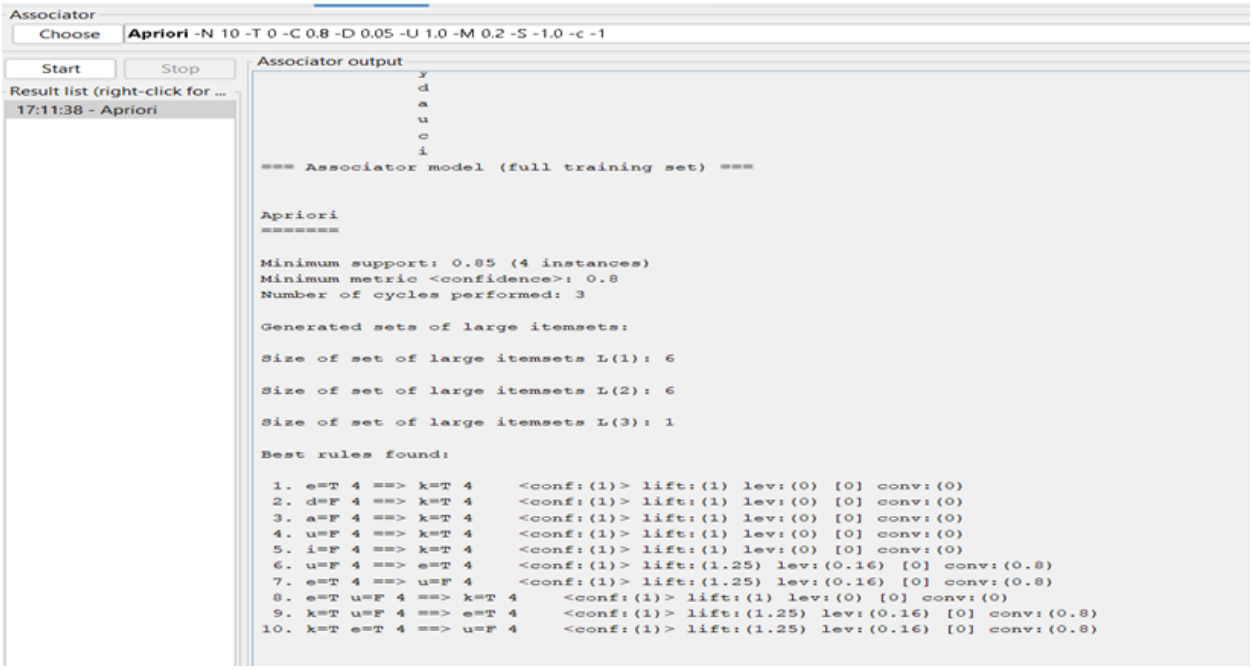
f t t t t t t t f f f

t f f t t f f t f f f

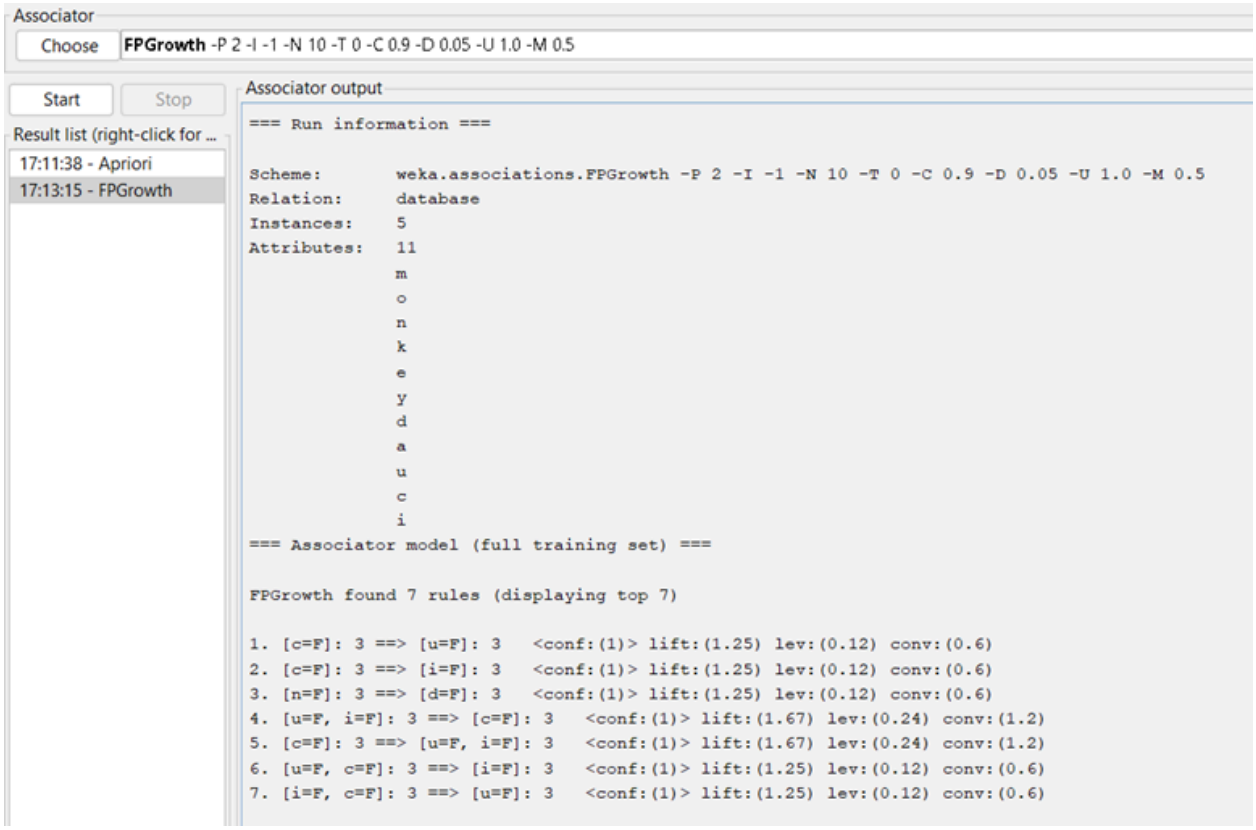
t f f t f t f f t f f

f t f t t f f f f t t

Fp growth algorithm:



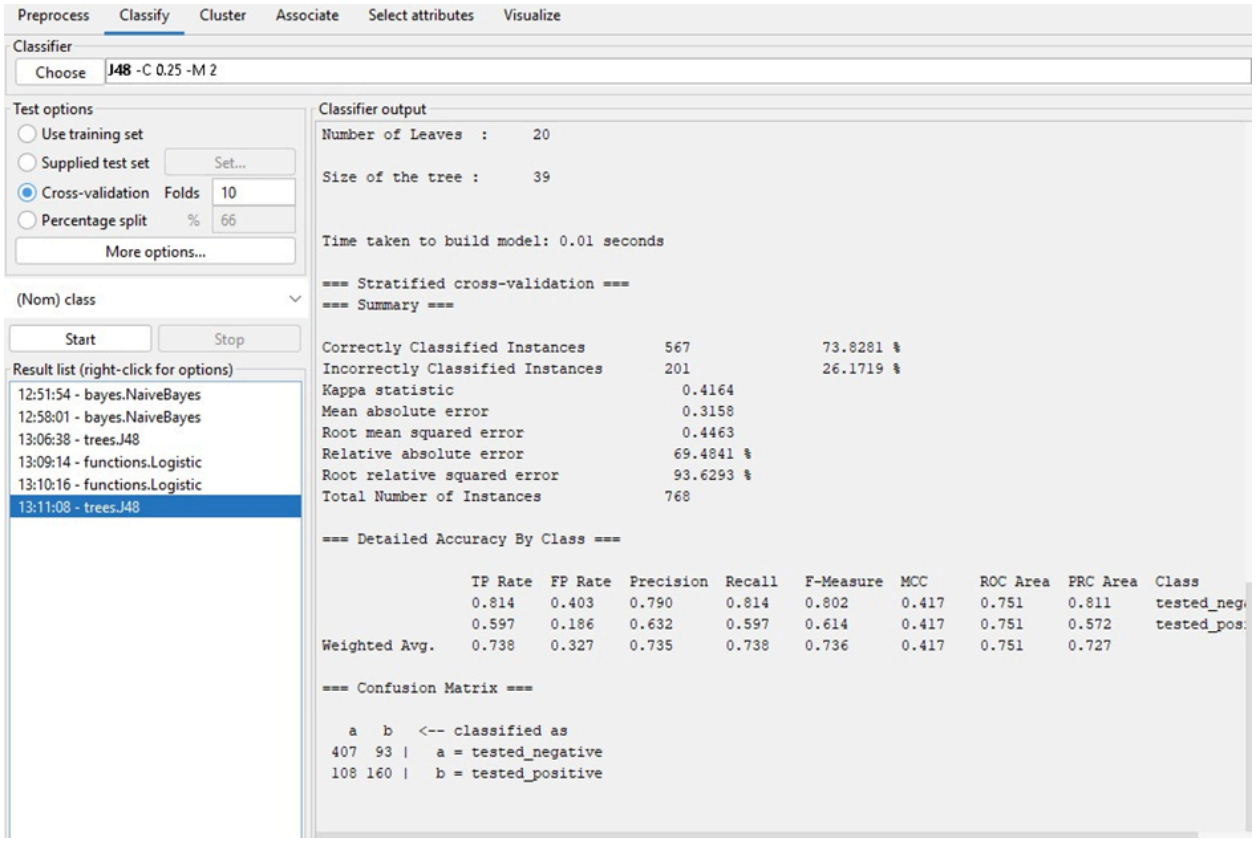

Fp growth algorithm:



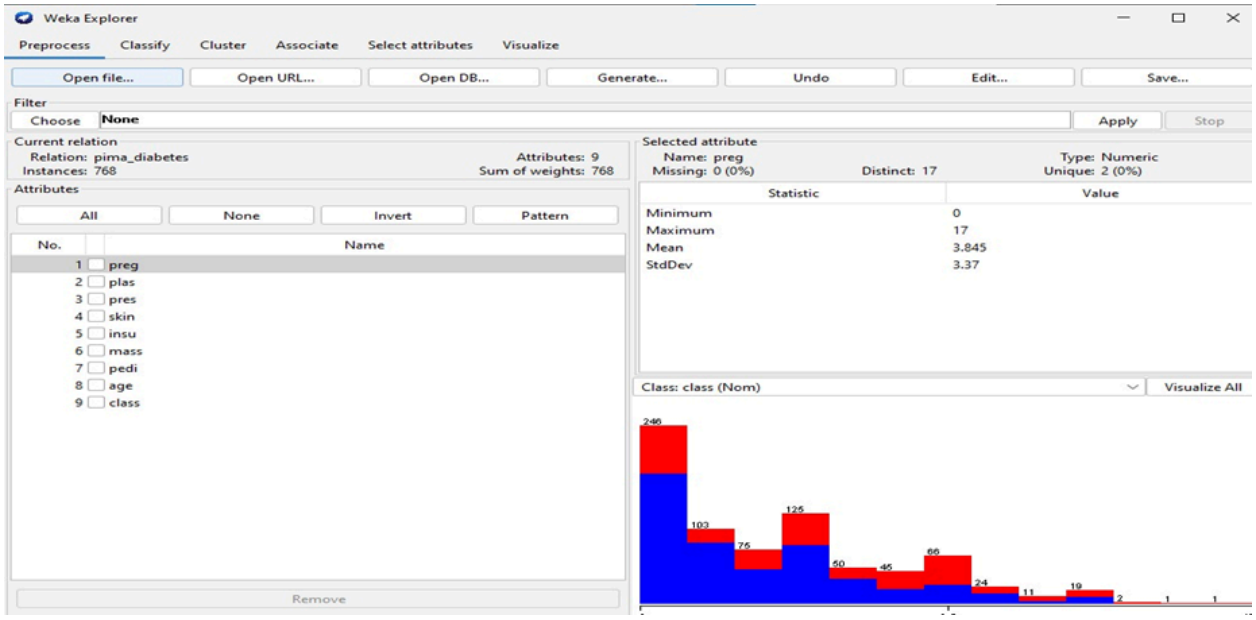

6. Prediction of Categorical Data using Decision Tree Algorithm through WEKA using any datasets. a) Tree b) Preprocess c) Logistic

## Output:

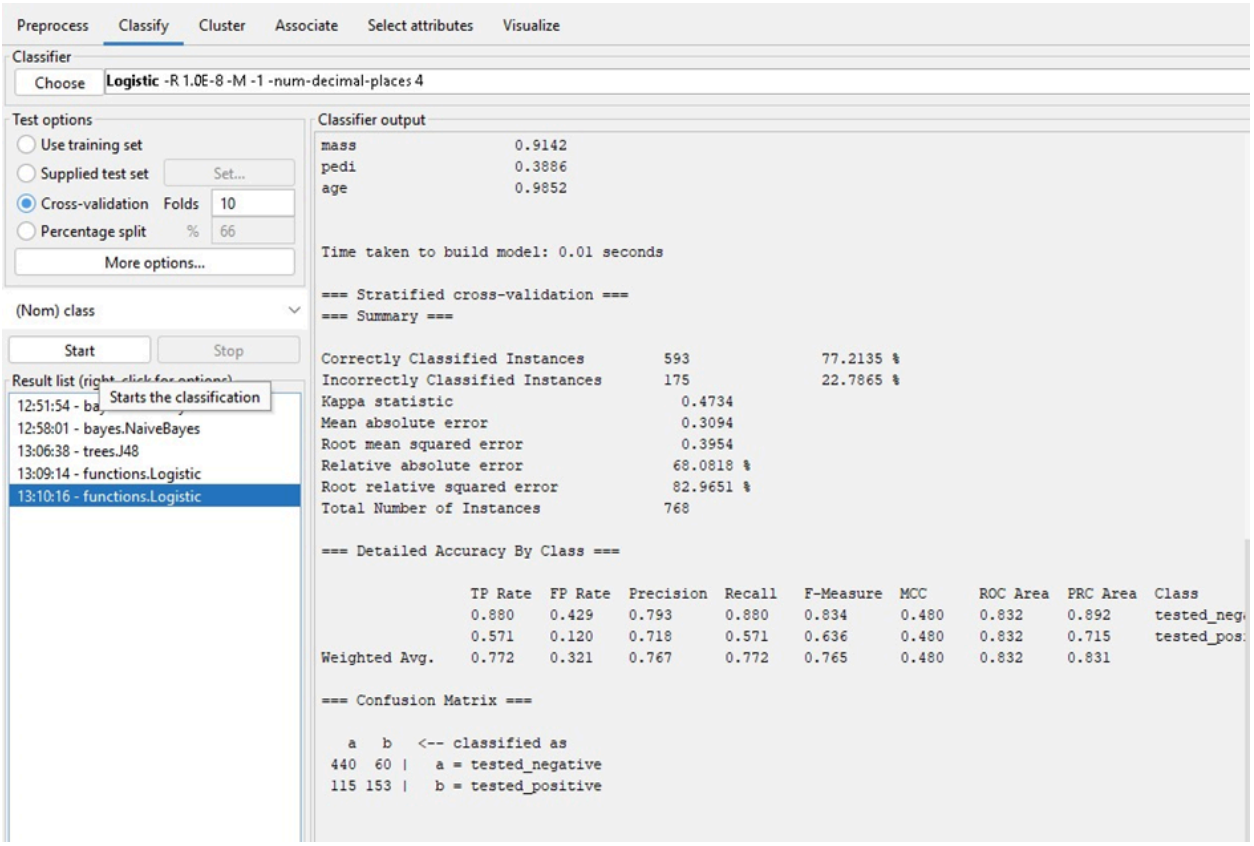
Tree:




Preprocessor:



**logistic:**




7.Create the dataset using ARFF file format:

| Transaction ID | Items |
|---|---|
| T1 | Hot Dogs, Buns, Ketchup |
| T2 | Hot Dogs, Buns |
| T3 | Hot Dogs, Coke, Chips |
| T4 | Chips, Coke |
| T5 | Chips, Ketchup |
| T6 | Hot Dogs, Coke, Chips |

a.Find the **frequent itemsets** and generate **association rules** on this. Assume that minimum support threshold (s = 33.33%) and minimum confident threshold (c = 60%).

b.List the various rule generated by apriori and FP tree algorithm ,mention whether accepted or rejected.

## Input:

@relation hotdogs

@attribute hotdogs{t,f}

@attribute buns{t,f}

@attribute ketchup{t,f}

@attribute coke{t,f}

@attribute chips{t,f}

@data

t t t f f

t t f f f

t f f t t

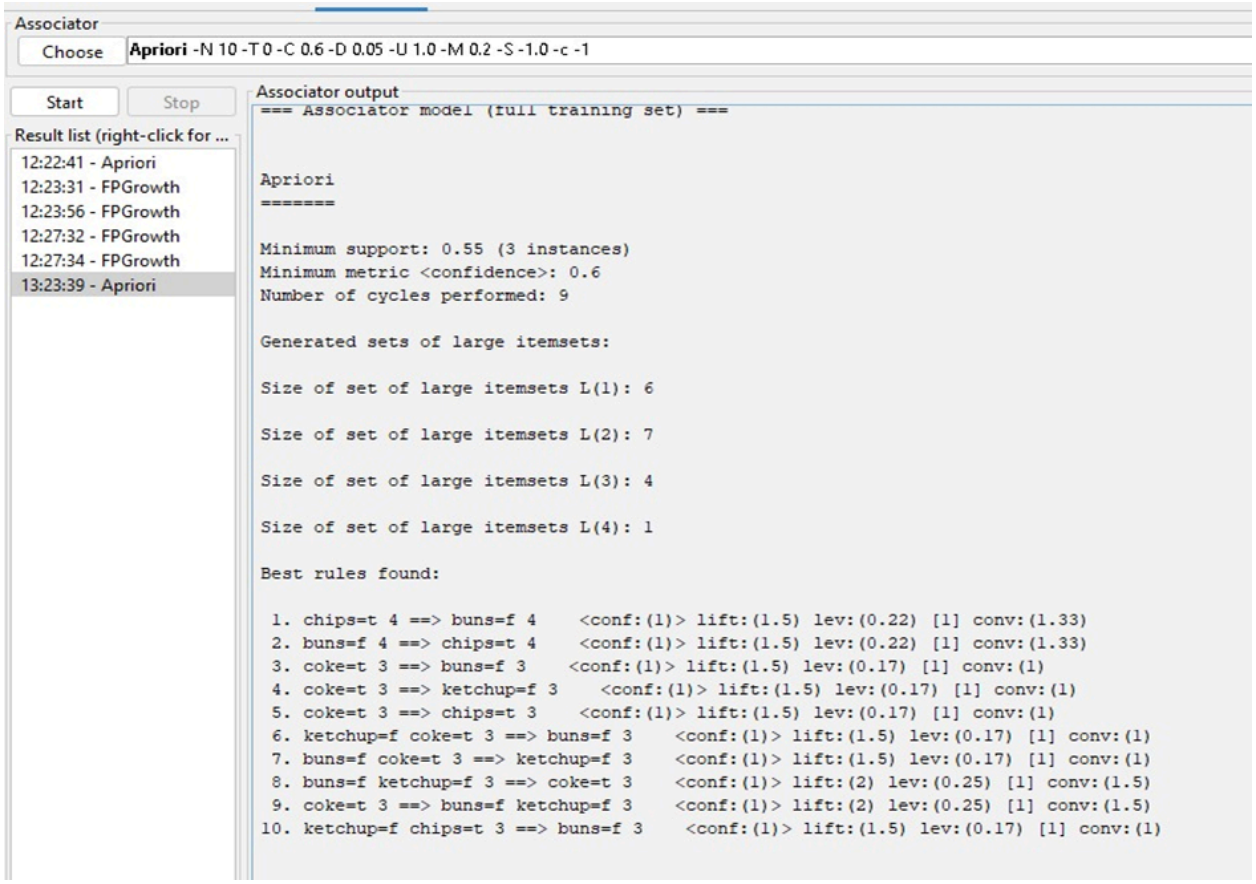
f f f t t

f f t f t

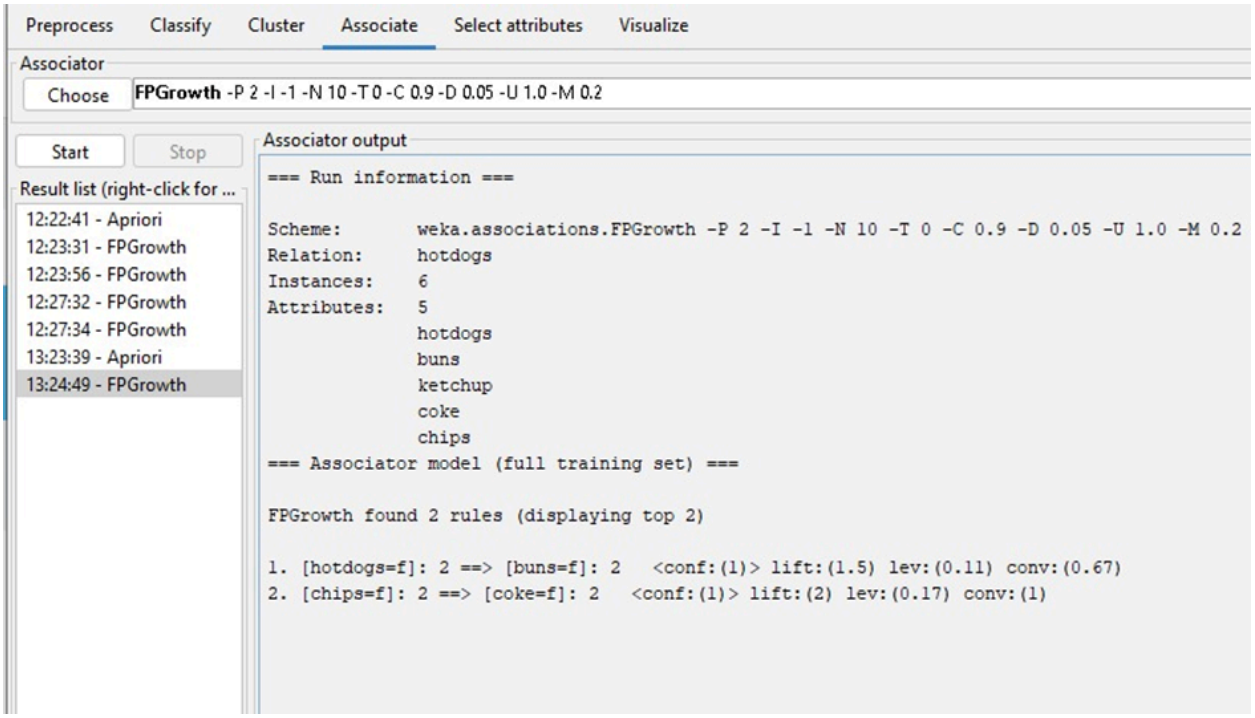
t f f t t

## output:

## apriori algorithm:


Associator
Choose
Apriori -N 10 -T 0 -C 0.6 -D 0.05 -U 1.0 -M 0.2 -S -1.0 -c -1
Start
Stop
Result list (right-click for ...
12:22:41 - Apriori
12:23:31 - FPGrowth
12:23:56 - FPGrowth
12:27:32 - FPGrowth
12:27:34 - FPGrowth
13:23:39 - Apriori
Associator output
=== Associator model (full training set) ===
Apriori
=======
Minimum support: 0.55 (3 instances)
Minimum metric <confidence>: 0.6
Number of cycles performed: 9
Generated sets of large itemsets:
Size of set of large itemsets L(1): 6
Size of set of large itemsets L(2): 7
Size of set of large itemsets L(3): 4
Size of set of large itemsets L(4): 1
Best rules found:
1. chips=t 4 ==> buns=f 4 <conf:(1)> lift:(1.5) lev:(0.22) [1] conv:(1.33)
2. buns=f 4 ==> chips=t 4 <conf:(1)> lift:(1.5) lev:(0.22) [1] conv:(1.33)
3. coke=t 3 ==> buns=f 3 <conf:(1)> lift:(1.5) lev:(0.17) [1] conv:(1)
4. coke=t 3 ==> ketchup=f 3 <conf:(1)> lift:(1.5) lev:(0.17) [1] conv:(1)
5. coke=t 3 ==> chips=t 3 <conf:(1)> lift:(1.5) lev:(0.17) [1] conv:(1)
6. ketchup=f coke=t 3 ==> buns=f 3 <conf:(1)> lift:(1.5) lev:(0.17) [1] conv:(1)
7. buns=f coke=t 3 ==> ketchup=f 3 <conf:(1)> lift:(1.5) lev:(0.17) [1] conv:(1)
8. buns=f ketchup=f 3 ==> coke=t 3 <conf:(1)> lift:(2) lev:(0.25) [1] conv:(1.5)
9. coke=t 3 ==> buns=f ketchup=f 3 <conf:(1)> lift:(2) lev:(0.25) [1] conv:(1.5)
10. ketchup=f chips=t 3 ==> buns=f 3 <conf:(1)> lift:(1.5) lev:(0.17) [1] conv:(1)

Fp growth:




8.Prediction of Categorical Data using Rule base classification and decision tree classification through WEKA using any datasets. Compare the accuracy using two algorithm and plot the graph

**Day 4 experiments:**

1.1.Consider that you are owning a supermarket mall and through membership cards, you have some basic data about your customers like Customer ID, age, gender, annual income and spending score. For the above scenario, the Problem Statement was You want to understand the customers who can easily converge [Target Customers] so that the data can be given to the marketing team and plan the strategy accordingly. For the above scenario prepare a dataset and perform **Clustering Analysis** to segment the customers in the Mall. There are clearly Five segments of Customers based on their Annual Income and Spending Score namely *Usual*

*Customers, Priority Customers, Senior Citizen Target Customers, and Young Target Customers.*Sample data

| | CustomerID | Gender | Age | Annual Income (k$) | Spending Score (1-100) |
|---|---|---|---|---|---|
| 0 | 1 | Male | 19 | 15 | 39 |
| 1 | 2 | Male | 21 | 15 | 81 |
| 2 | 3 | Female | 20 | 16 | 6 |
| 3 | 4 | Female | 23 | 16 | 77 |
| 4 | 5 | Female | 31 | 17 | 40 |

INPUT:

@relation clustering_analysis

@attribute customerid{1,2,3,4,5}

@attribute gender{male,female}

@attribute age{young,middle,old}

@attribute annual_medium{low,half,high}

@attribute spending_score{least,medium,highest}

@data

1 male young low medium

2 male young low highest

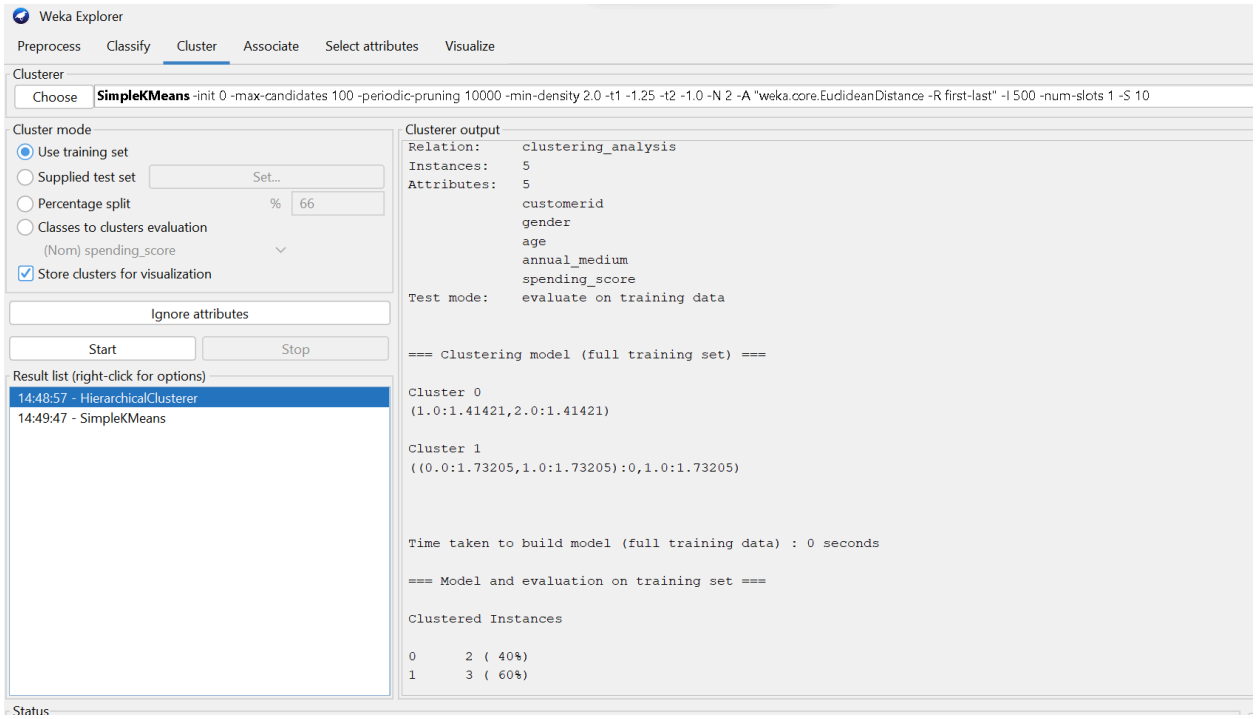
3 female young half least

4 female middle half medium

5 female old high medium

OUTPUT:

## HIERARCHICAL CLUSTERING




## K MEANS CLUSTERING