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Exercises

¬ **Plot histogram of hp**

¬ **Plot density of wt**

¬ **Plot gear using barplot**

¬ **Find the covariance of all the variables**

¬ **Obtain the correlation of all the variables**

¬ **Plot boxplot chart mpg to gear**

¬ **Find the relationship between mpg and wt**

¬ **Apply kmeans clustering and plot the data points**

o 2 clusters

o 3 clusters

o 4 clusters

o 5 clusters

¬ **Apply hierarchical clustering and plot the data datapoint**

PROGRAM:

```
df=read.csv('C:\\Users\\aryam\\Desktop\\Fall Sem 2021\\Data Visualization Lab\\LAB 7 21-9-21/cars.csv')

library(factoextra)

print(df)

df=na.omit(df)

df=scale(df)

png(file="KMeansExample.png")



#saving the file

dev.off()
```

```
hist(df$hp)
plot(density(df$wt))
pie(table(df$gear))
barplot(table(df$gear))
cov(df[,2:11])
cor(mtcars[,1:11])
boxplot(mpg~gear,data=df)
#Hierarichal Clustering
d=dist(df)
h=hclust(d)
h
plot(h)
rect.hclust(h,k=3)
rect.hclust(h,k=4,border='blue')
library(cluster)
#normalization
cov(mtcars[,1:11])
cor(df$mpg, df$wt, method ="pearson")
cor(df$mpg, df$wt, method ="kendall")
cor(df$mpg, df$wt, method ="spearman")

km=kmeans(df[,2],center=2,nstart=25)
km$cluster
#visualize the clusters
fviz_cluster(km,data=df[,5:6]) #PCA Principle Component Analysis
km=kmeans(df[,2],center=3,nstart=25)
km$cluster
#visualize the clusters
fviz_cluster(km,data=df[,5:6]) #PCA Principle Component Analysis
```

km=kmeans(df[,2],center=4,nstart=25)

km$cluster

#visualize the clusters

fviz_cluster(km,data=df[,5:6]) #PCA Principle Component Analysis

km=kmeans(df[,2],center=5,nstart=25)

km$cluster

#visualize the clusters

fviz_cluster(km,data=df[,5:6]) #PCA Principle Component Analysis

CONSOLE:

> df=read.csv('C:\\Users\\aryam\\Desktop\\Fall Sem 2021\\Data Visualization Lab\\LAB 7 21-9-21/cars.csv')

> library(factoextra)

> print(df)

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

```
15  Cadillac Fleetwood 10.4   8 472.0 205 2.93 5.250 17.98  0  0    3    4
16 Lincoln Continental 10.4   8 460.0 215 3.00 5.424 17.82  0  0    3    4
17   Chrysler Imperial 14.7   8 440.0 230 3.23 5.345 17.42  0  0    3    4
18            Fiat 128 32.4   4  78.7  66 4.08 2.200 19.47  1  1    4    1
19         Honda Civic 30.4   4  75.7  52 4.93 1.615 18.52  1  1    4    2
20      Toyota Corolla 33.9   4  71.1  65 4.22 1.835 19.90  1  1    4    1
21       Toyota Corona 21.5   4 120.1  97 3.70 2.465 20.01  1  0    3    1
22    Dodge Challenger 15.5   8 318.0 150 2.76 3.520 16.87  0  0    3    2
23         AMC Javelin 15.2   8 304.0 150 3.15 3.435 17.30  0  0    3    2
24          Camaro Z28 13.3   8 350.0 245 3.73 3.840 15.41  0  0    3    4
25    Pontiac Firebird 19.2   8 400.0 175 3.08 3.845 17.05  0  0    3    2
26           Fiat X1-9 27.3   4  79.0  66 4.08 1.935 18.90  1  1    4    1
27       Porsche 914-2 26.0   4 120.3  91 4.43 2.140 16.70  0  1    5    2
28        Lotus Europa 30.4   4  95.1 113 3.77 1.513 16.90  1  1    5    2
29      Ford Pantera L 15.8   8 351.0 264 4.22 3.170 14.50  0  1    5    4
30        Ferrari Dino 19.7   6 145.0 175 3.62 2.770 15.50  0  1    5    6
31       Maserati Bora 15.0   8 301.0 335 3.54 3.570 14.60  0  1    5    8
32          Volvo 142E 21.4   4 121.0 109 4.11 2.780 18.60  1  1    4    2
> df=na.omit(df)
> df=scale(df)
Error in colMeans(x, na.rm = TRUE) : 'x' must be numeric
> png(file="KMeansExample.png")
>
>
> #saving the file
> dev.off()
null device
          1
> hist(df$hp)
```

```
> plot(density(df$wt))

> pie(table(df$gear))

> barplot(table(df$gear))

> cov(df[,2:11])

        mpg       cyl      disp       hp       drat       wt       qsec        vs        am      gear

mpg   36.324103  -9.1723790  -633.09721 -320.732056   2.19506351  -5.1166847
4.50914919   2.01713710   1.80393145   2.1356855

cyl   -9.172379   3.1895161   199.66028  101.931452  -0.66836694   1.3673710  -1.88685484
-0.72983871  -0.46572581  -0.6491935

disp -633.097208 199.6602823 15360.79983 6721.158669 -47.06401915 107.6842040 -
96.05168145 -44.37762097 -36.56401210 -50.8026210

hp   -320.732056 101.9314516  6721.15867 4700.866935 -16.45110887  44.1926613 -
86.77008065 -24.98790323  -8.32056452  -6.3588710

drat   2.195064  -0.6683669   -47.06402  -16.451109   0.28588135  -0.3727207   0.08714073
0.11864919   0.19015121   0.2759879

wt    -5.116685   1.3673710   107.68420   44.192661  -0.37272073   0.9573790  -0.30548161
-0.27366129  -0.33810484  -0.4210806

qsec   4.509149  -1.8868548   -96.05168  -86.770081   0.08714073  -0.3054816   3.19316613
0.67056452  -0.20495968  -0.2804032

vs     2.017137  -0.7298387   -44.37762  -24.987903   0.11864919  -0.2736613   0.67056452
0.25403226   0.04233871   0.0766129

am     1.803931  -0.4657258   -36.56401   -8.320565   0.19015121  -0.3381048  -0.20495968
0.04233871   0.24899194   0.2923387

gear   2.135685  -0.6491935   -50.80262   -6.358871   0.27598790  -0.4210806  -0.28040323
0.07661290   0.29233871   0.5443548

> cor(mtcars[,1:11])

        mpg       cyl      disp       hp       drat       wt       qsec       vs        am      gear      carb

mpg   1.0000000 -0.8521620 -0.8475514 -0.7761684  0.68117191 -0.8676594  0.41868403
0.6640389  0.59983243  0.4802848 -0.55092507

cyl  -0.8521620  1.0000000  0.9020329  0.8324475 -0.69993811  0.7824958 -0.59124207 -
0.8108118 -0.52260705 -0.4926866  0.52698829

disp -0.8475514  0.9020329  1.0000000  0.7909486 -0.71021393  0.8879799 -0.43369788 -
0.7104159 -0.59122704 -0.5555692  0.39497686
```

hp   -0.7761684 0.8324475 0.7909486 1.0000000 -0.44875912 0.6587479 -0.70822339 -0.7230967 -0.24320426 -0.1257043 0.74981247

drat 0.6811719 -0.6999381 -0.7102139 -0.4487591 1.00000000 -0.7124406 0.09120476 0.4402785 0.71271113 0.6996101 -0.09078980

wt   -0.8676594 0.7824958 0.8879799 0.6587479 -0.71244065 1.0000000 -0.17471588 -0.5549157 -0.69249526 -0.5832870 0.42760594

qsec 0.4186840 -0.5912421 -0.4336979 -0.7082234 0.09120476 -0.1747159 1.00000000 0.7445354 -0.22986086 -0.2126822 -0.65624923

vs   0.6640389 -0.8108118 -0.7104159 -0.7230967 0.44027846 -0.5549157 0.74453544 1.0000000 0.16834512 0.2060233 -0.56960714

am   0.5998324 -0.5226070 -0.5912270 -0.2432043 0.71271113 -0.6924953 -0.22986086 0.1683451 1.00000000 0.7940588 0.05753435

gear 0.4802848 -0.4926866 -0.5555692 -0.1257043 0.69961013 -0.5832870 -0.21268223 0.2060233 0.79405876 1.0000000 0.27407284

carb -0.5509251 0.5269883 0.3949769 0.7498125 -0.09078980 0.4276059 -0.65624923 -0.5696071 0.05753435 0.2740728 1.00000000

> boxplot(mpg~gear,data=df)

> #Hierarichal Clustering

> d=dist(df)

Warning message:

In dist(df) : NAs introduced by coercion

> h=hclust(d)

> h

Call:

hclust(d = d)

Cluster method   : complete

Distance   : euclidean

Number of objects: 32

> plot(h)

```
> rect.hclust(h,k=3)

> rect.hclust(h,k=4,border='blue')

> library(cluster)

> #normalization

> cov(mtcars[,1:11])

          mpg        cyl       disp        hp        drat        wt       qsec        vs         am       gear

mpg    36.324103  -9.1723790  -633.09721 -320.732056   2.19506351  -5.1166847
4.50914919   2.01713710   1.80393145   2.1356855

cyl   -9.172379   3.1895161   199.66028  101.931452  -0.66836694   1.3673710  -1.88685484
-0.72983871  -0.46572581  -0.6491935

disp -633.097208 199.6602823 15360.79983 6721.158669 -47.06401915 107.6842040 -
96.05168145 -44.37762097 -36.56401210 -50.8026210

hp   -320.732056 101.9314516  6721.15867 4700.866935 -16.45110887  44.1926613 -
86.77008065 -24.98790323  -8.32056452  -6.3588710

drat    2.195064  -0.6683669   -47.06402  -16.451109   0.28588135  -0.3727207   0.08714073
0.11864919   0.19015121   0.2759879

wt    -5.116685   1.3673710   107.68420   44.192661  -0.37272073   0.9573790  -0.30548161
-0.27366129  -0.33810484  -0.4210806

qsec    4.509149  -1.8868548   -96.05168  -86.770081   0.08714073  -0.3054816   3.19316613
0.67056452  -0.20495968  -0.2804032

vs     2.017137  -0.7298387   -44.37762  -24.987903   0.11864919  -0.2736613   0.67056452
0.25403226   0.04233871   0.0766129

am     1.803931  -0.4657258   -36.56401   -8.320565   0.19015121  -0.3381048  -0.20495968
0.04233871   0.24899194   0.2923387

gear    2.135685  -0.6491935   -50.80262   -6.358871   0.27598790  -0.4210806  -0.28040323
0.07661290   0.29233871   0.5443548

carb   -5.363105   1.5201613    79.06875   83.036290  -0.07840726   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
> cor(df$mpg, df$wt, method ="pearson")
[1] -0.8676594
> cor(df$mpg, df$wt, method ="kendall")
[1] -0.7278321
> cor(df$mpg, df$wt, method ="spearman")
[1] -0.886422
>
> km=kmeans(df[,2],center=2,nstart=25)
> km$cluster
 [1] 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 1 1 1 2 2 2 2
> #visualize the clusters
> fviz_cluster(km,data=df[,5:6]) #PCA Principle Component Analysis
> km=kmeans(df[,2],center=3,nstart=25)
> km$cluster
 [1] 1 1 1 1 1 1 3 1 1 1 1 3 3 3 3 3 3 2 2 2 1 3 3 3 1 2 2 2 3 1 3 1
> #visualize the clusters
> fviz_cluster(km,data=df[,5:6]) #PCA Principle Component Analysis
> km=kmeans(df[,2],center=4,nstart=25)
> km$cluster
 [1] 3 3 2 3 3 3 4 2 2 3 3 4 3 4 4 4 4 1 1 1 3 4 4 4 3 2 2 1 4 3 4 3
> #visualize the clusters
> fviz_cluster(km,data=df[,5:6]) #PCA Principle Component Analysis
```

>

> km=kmeans(df[,2],center=5,nstart=25)

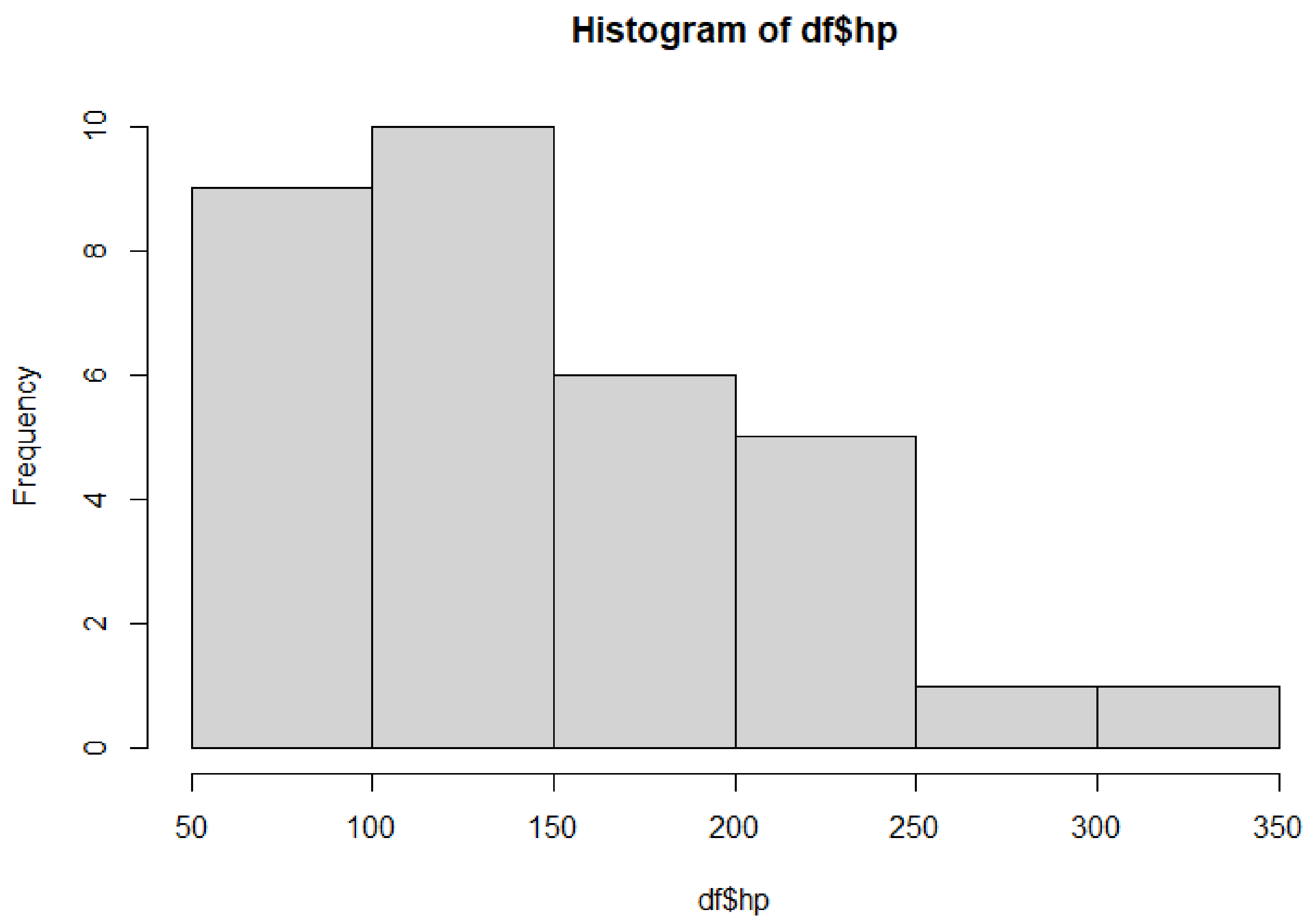
> km$cluster

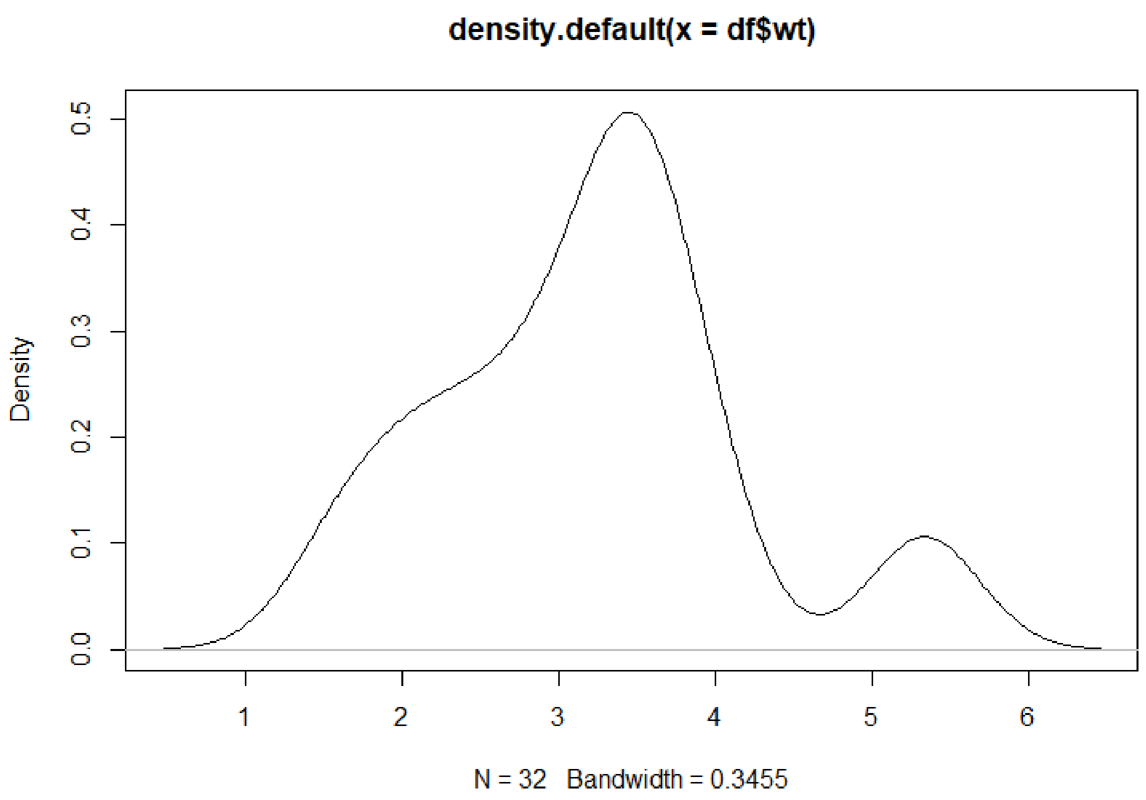
[1] 5 5 3 5 5 5 4 3 3 5 5 4 4 4 2 2 4 1 1 1 5 4 4 4 5 3 3 1 4 5 4 5

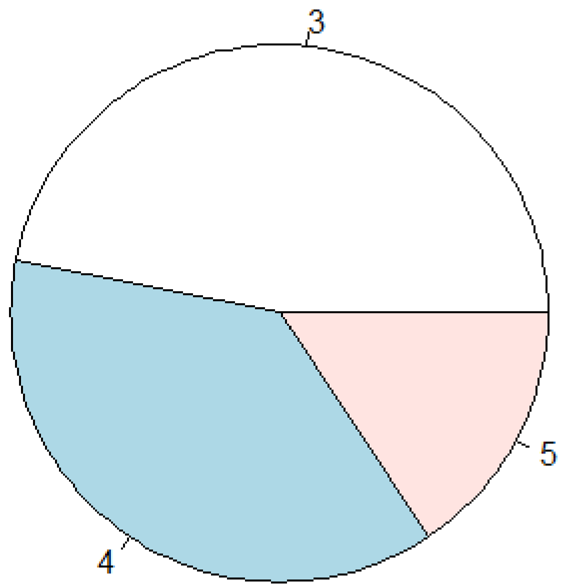
> #visualize the clusters

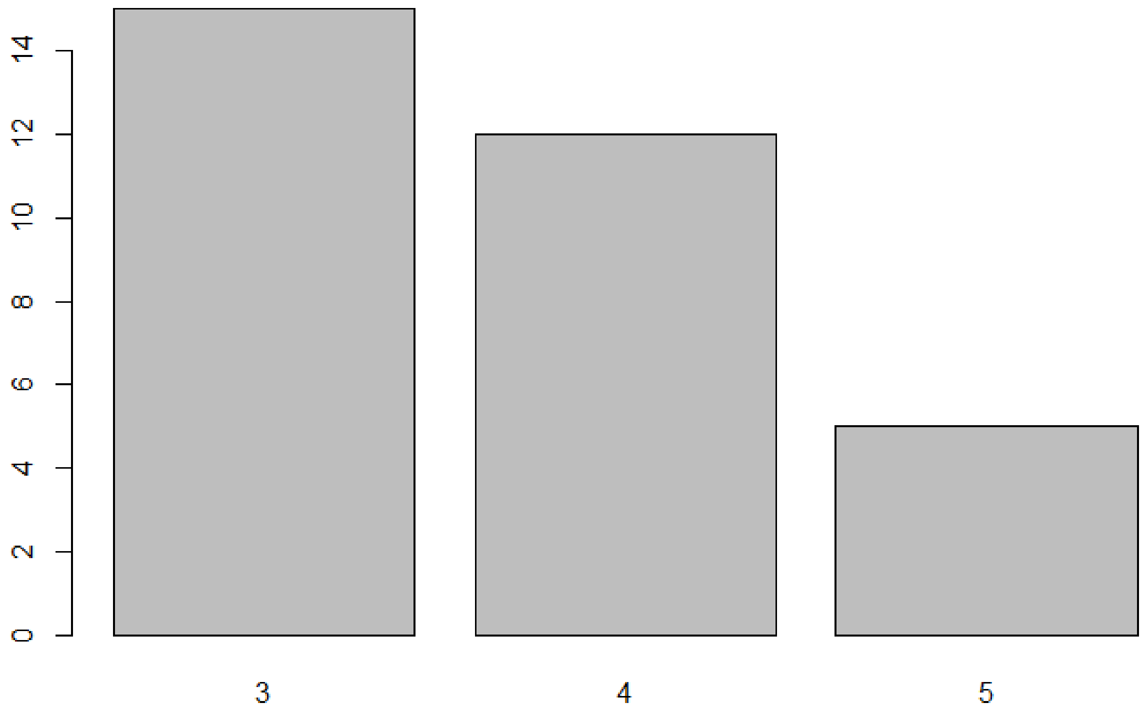
> fviz_cluster(km,data=df[,5:6]) #PCA Principle Component Analysis

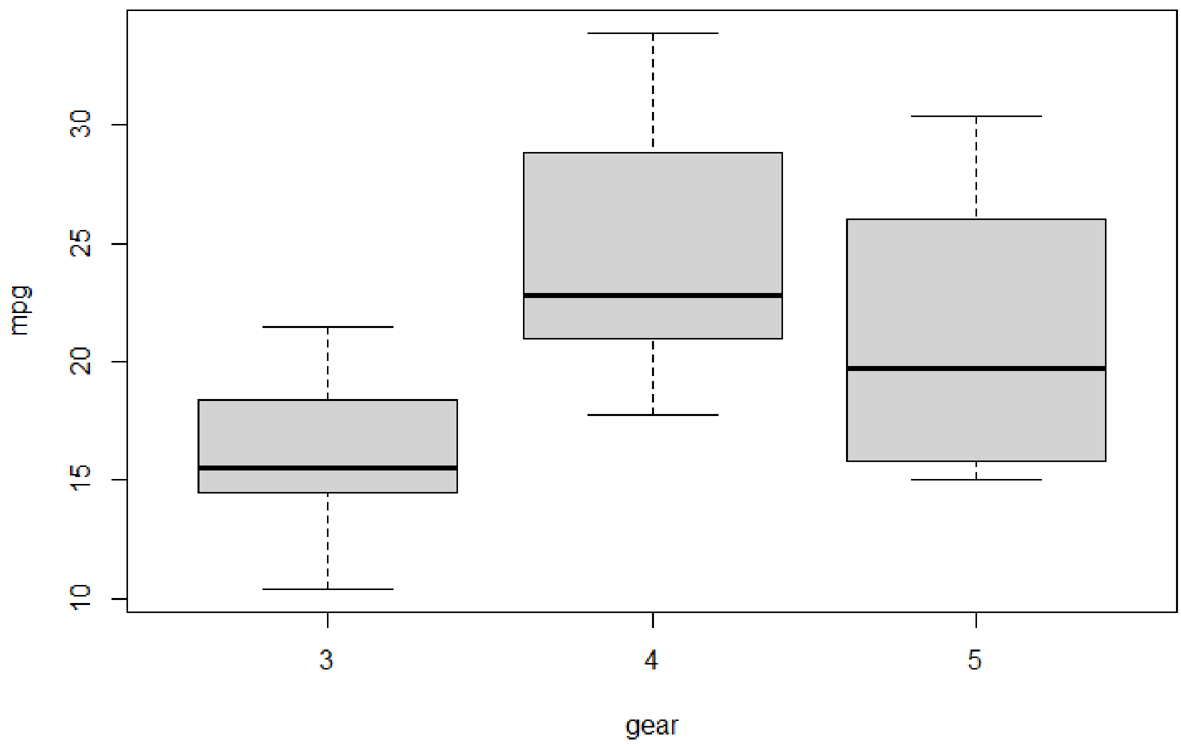
Plots:

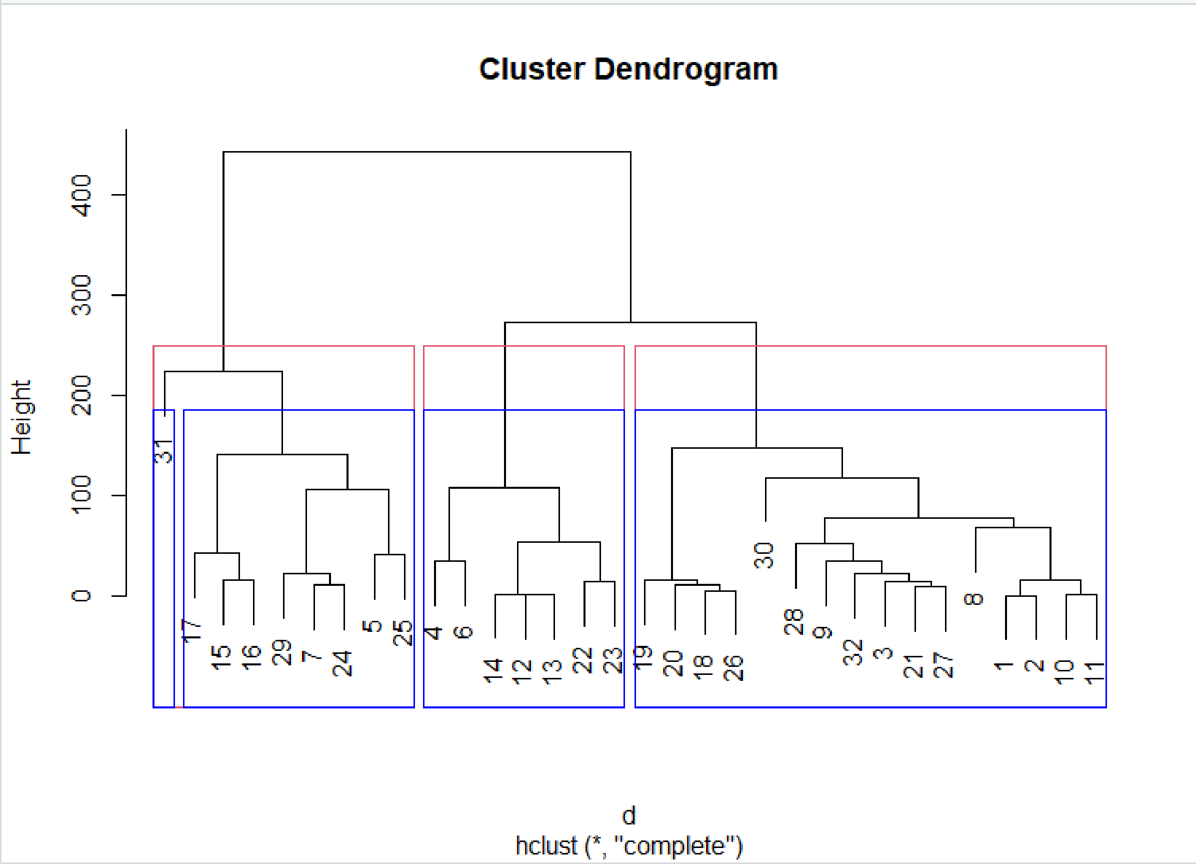


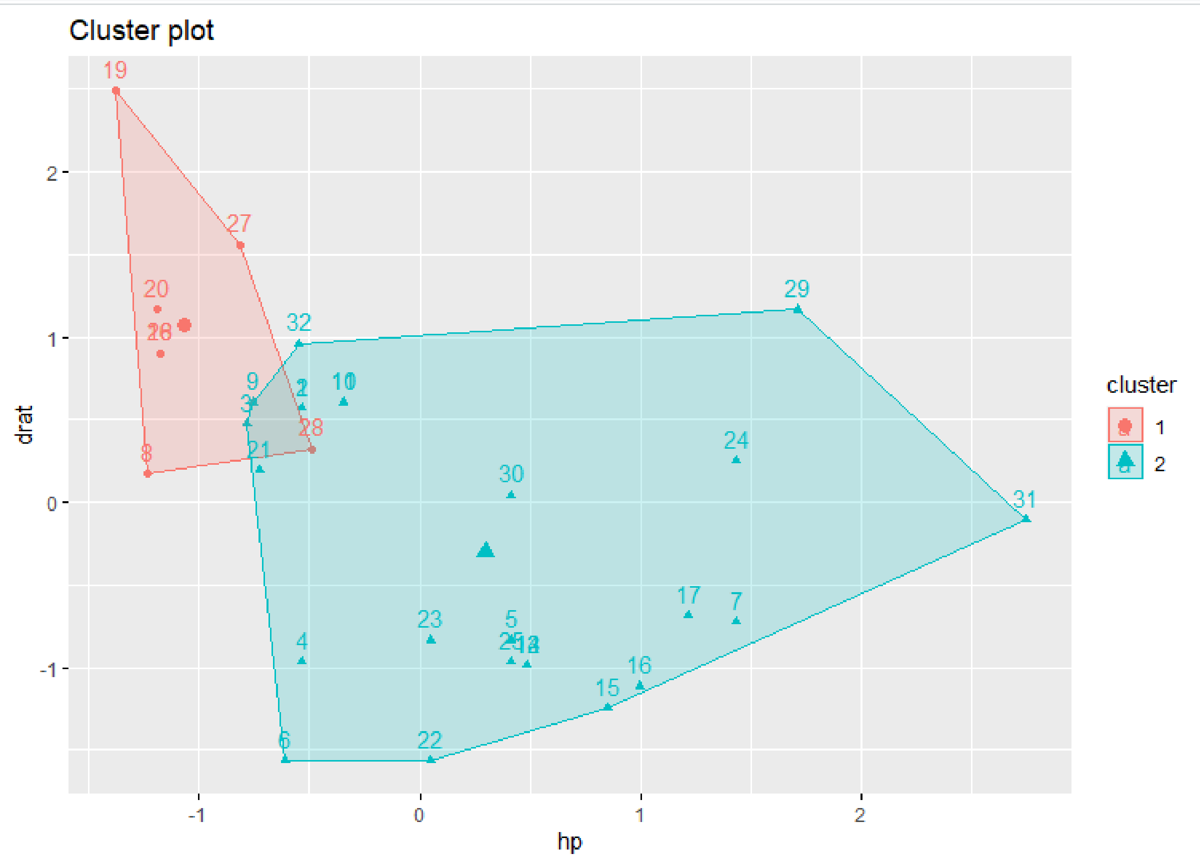

density.default(x = df$wt)
Density
0.0
0.1
0.2
0.3
0.4
0.5
1
2
3
4
5
6
N = 32 Bandwidth = 0.3455

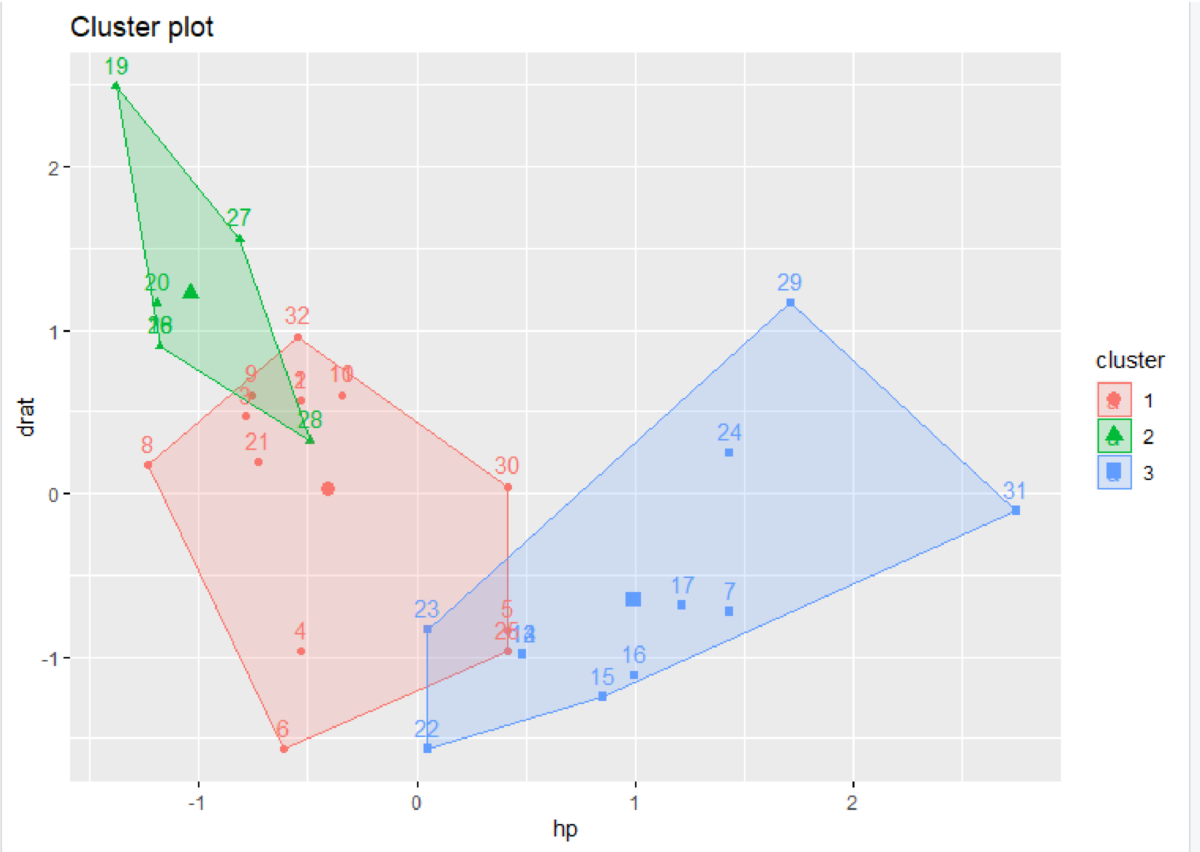

3
4
5

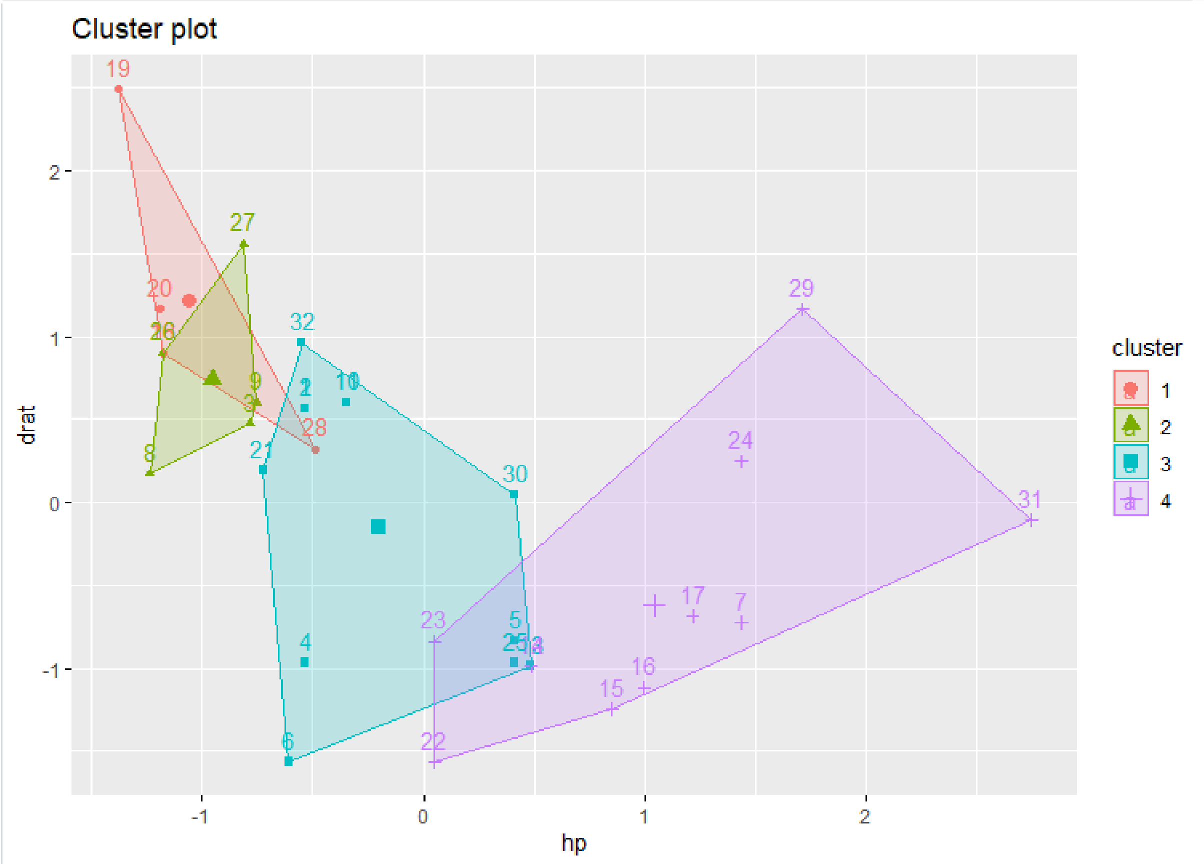

0
2
4
6
8
10
12
14
3
4
5

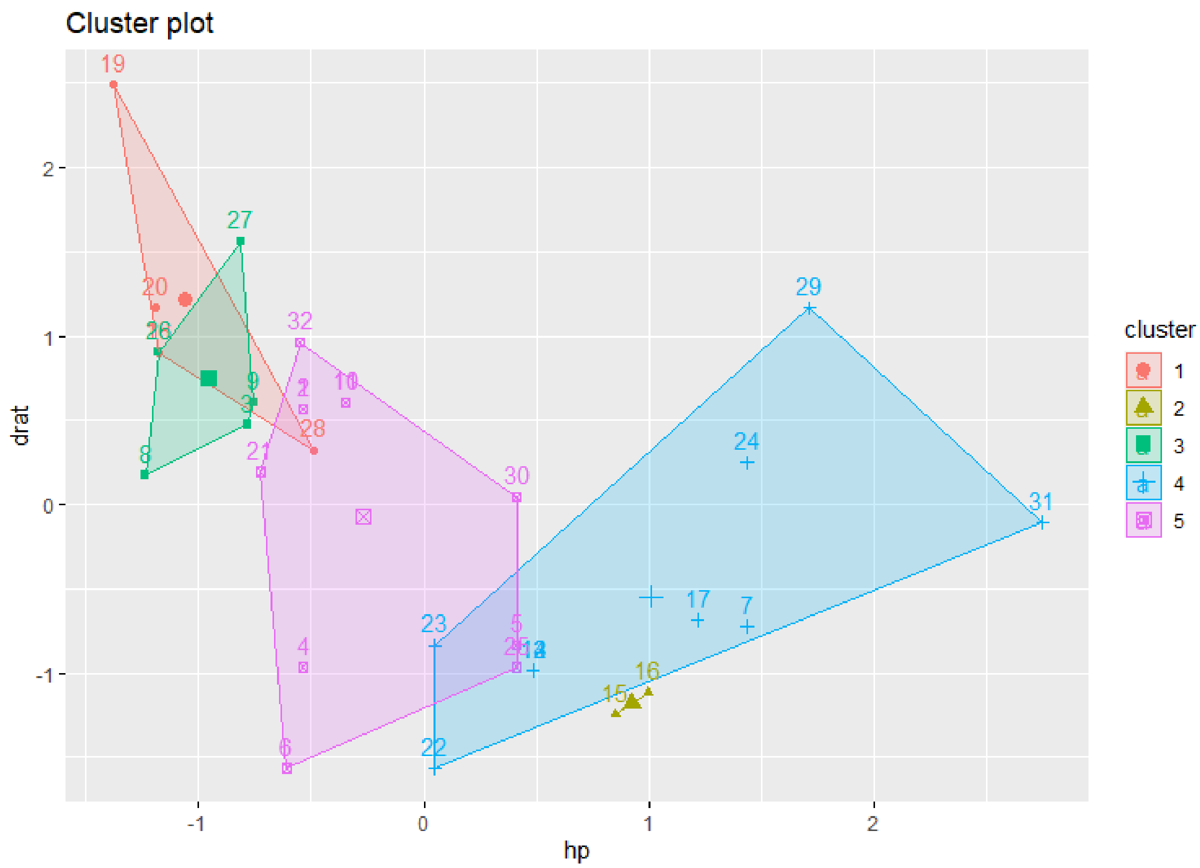

mpg
10
15
20
25
30
3
4
5
gear


Cluster Dendrogram
Height
0
100
200
300
400
31 17 15 16 29 7 24 5 25 4 6 14 12 13 22 23 19 20 18 26 30 28 9 32 3 21 27 8 1 2 10 11
d
hclust (*, "complete")


Cluster plot
drat
hp
cluster
1
2


Cluster plot
drat
hp
cluster
1
2
3


Cluster plot
drat
hp
cluster
1
2
3
4



HIERARICHAL CLUSTERING AND K-MEANS ON ANY OTHER DATASET:

df=read.csv('C:\\Users\\aryam\\Desktop\\Fall Sem 2021\\Data Visualization Lab\\LAB 7 21-9-21/Mall_Customers.csv')

#Hierarichal Clustering

d=dist(df)

h=hclust(d)

h

plot(h)

rect.hclust(h,k=4,border='blue')

rect.hclust(h,k=3,border='red')

rect.hclust(h,k=2,border='yellow')

km=kmeans(df[,3],center=2,nstart=25)

km$cluster

#visualize the clusters

fviz_cluster(km,data=df[,4:5]) #PCA Principle Component Analysis

km=kmeans(df[,3],center=3,nstart=25)

km$cluster

#visualize the clusters

fviz_cluster(km,data=df[,4:5]) #PCA Principle Component Analysis

km=kmeans(df[,3],center=4,nstart=25)

km$cluster

#visualize the clusters

fviz_cluster(km,data=df[,4:5]) #PCA Principle Component Analysis

km=kmeans(df[,3],center=5,nstart=25)

km$cluster

#visualize the clusters

fviz_cluster(km,data=df[,4:5]) #PCA Principle Component Analysis

Console:

df=read.csv('C:\\Users\\aryam\\Desktop\\Fall Sem 2021\\Data Visualization Lab\\LAB 7 21-9-21/Mall_Customers.csv')

> #Hierarichal Clustering

> d=dist(df)

Warning message:

In dist(df) : NAs introduced by coercion

> h=hclust(d)

> h

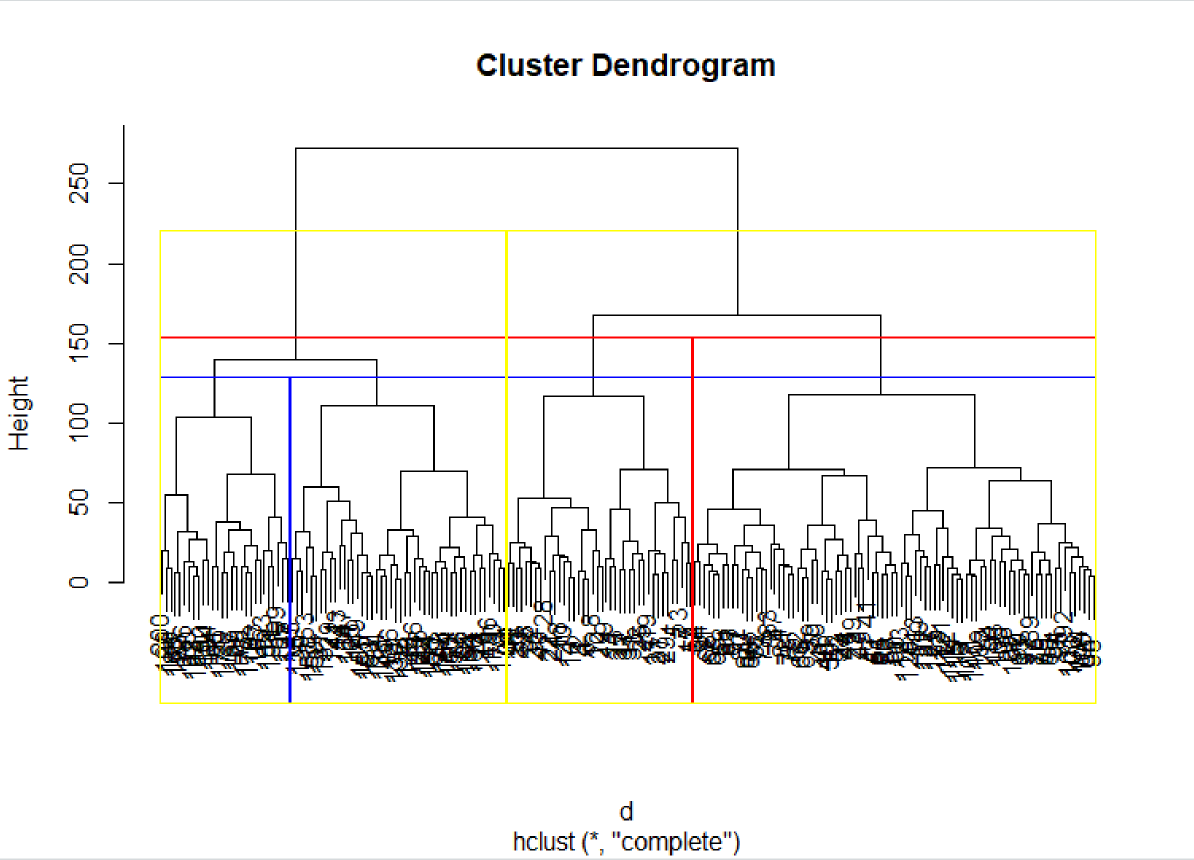
Call:

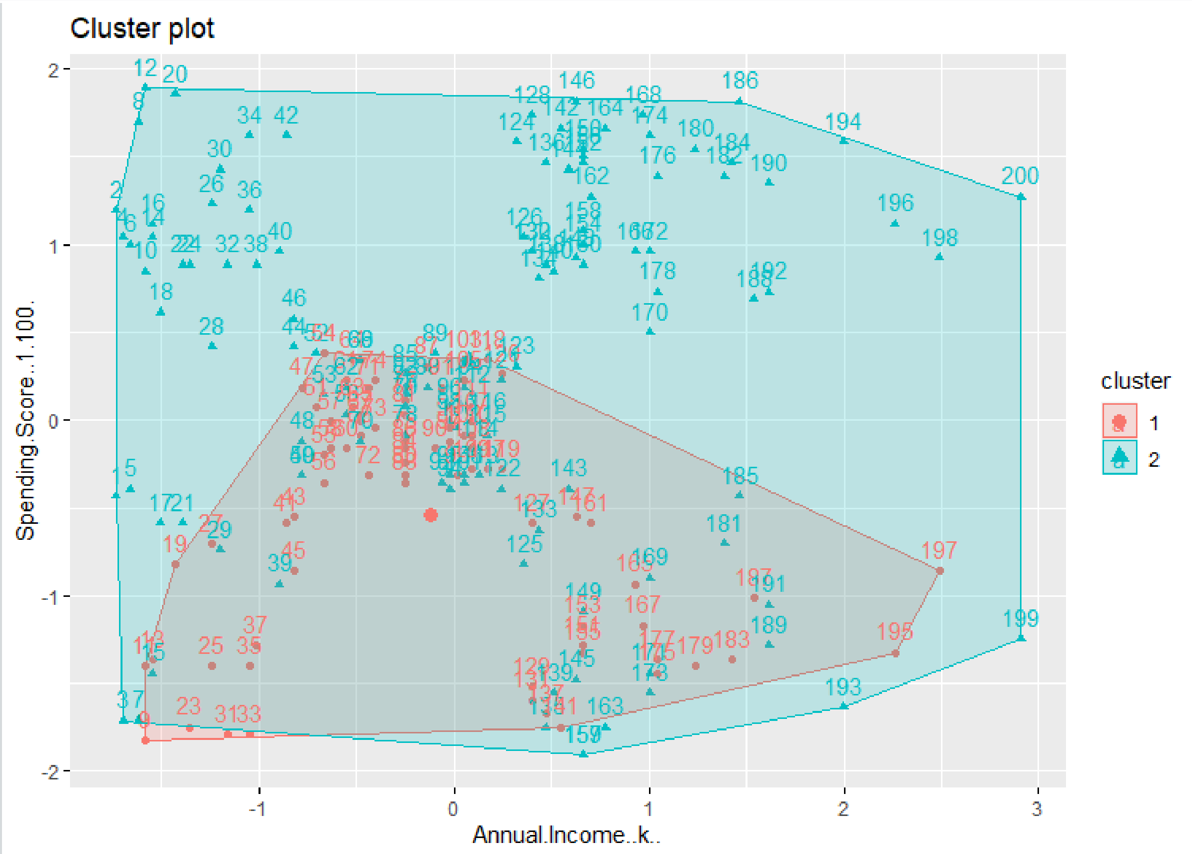
hclust(d = d)

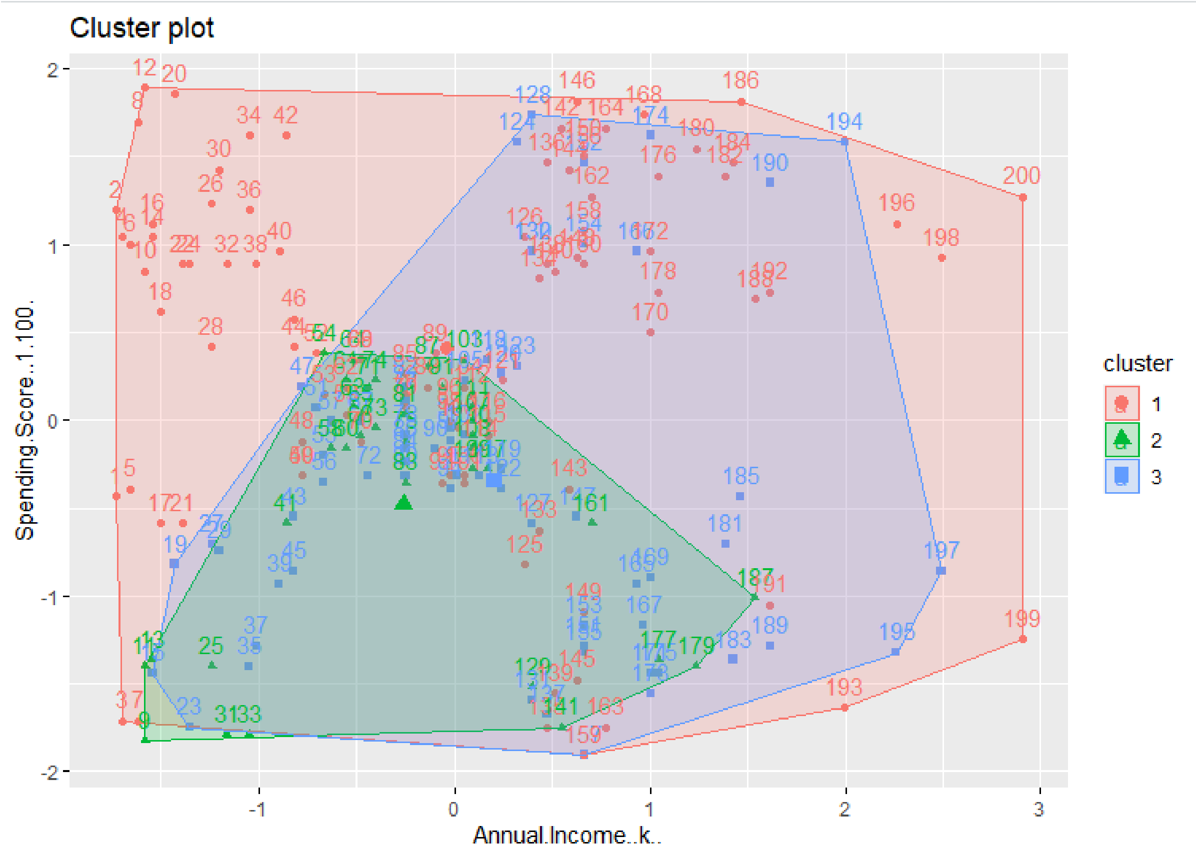
```
Cluster method   : complete
Distance         : euclidean
Number of objects: 200

> plot(h)
> rect.hclust(h,k=4,border='blue')
> rect.hclust(h,k=3,border='red')
> rect.hclust(h,k=2,border='yellow')
> km=kmeans(df[,3],center=2,nstart=25)
> km$cluster
  [1] 2 2 2 2 2 2 2 2 1 2 1 2 1 2 2 2 2 2 1 2 2 2 1 2 1 2 1 2 2 2 1 2 1 2 1 2 1 2 2 2 1 2 1 2 1 2 1 2 2 2 1 2 2 1 1 1 1 1 2 1 1 2 1 1 1
 [66] 2 1 1 2 2 1 1 1 1 1 2 1 2 2 1 1 2 1 1 2 1 1 2 2 1 1 2 1 2 2 2 1 2 1 2 2 1 1 2 1 2 1 1 1 1 1 2 2 2 2 2 1 1 1 1 2 2 2 2 2 2 2 1 2 1 2
[131] 1 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 1 2 2 2 1 2 1 2 1 2 2 2 2 2 1 2 2 2 1 2 1 2 2 2 2 2 2 2 1 2 1 2 1 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 1
[196] 2 1 2 2 2
> #visualize the clusters
> fviz_cluster(km,data=df[,4:5]) #PCA Principle Component Analysis
>
> km=kmeans(df[,3],center=3,nstart=25)
> km$cluster
  [1] 1 1 1 1 1 1 1 1 2 1 2 1 2 1 3 1 1 1 3 1 1 1 3 1 2 1 3 1 3 1 2 1 2 1 3 1 3 1 3 1 2 1 3 1 3 1 3 1 1 1 3 1 1 2 3 3 3 2 1 2 2 1 2 2 2
 [66] 1 3 2 1 1 2 3 2 2 2 1 3 3 1 3 2 3 2 3 1 3 2 1 1 3 2 1 3 3 1 1 3 1 3 1 1 3 2 1 3 1 2 2 2 2 2 1 3 1 1 1 2 3 3 3 1 3 3 3 1 1 3 3 2 3
[131] 3 3 1 1 1 1 3 1 1 1 2 1 1 1 1 1 3 1 1 1 3 3 3 3 3 1 3 1 1 1 2 1 1 1 3 3 3 1 3 1 3 1 3 3 3 1 2 1 2 1 3 1 3 1 3 1 2 1 3 3 1 1 1 3 3
[196] 1 3 1 1 1
> #visualize the clusters
> fviz_cluster(km,data=df[,4:5]) #PCA Principle Component Analysis
```

```
>

> km=kmeans(df[,3],center=4,nstart=25)

> km$cluster

  [1] 1 1 1 1 3 1 3 1 2 3 2 3 2 1 3 1 3 1 4 3 3 1 4 3 4 3 4 3 3 1 2 1 4 1 4 1 4 3 3 1 2 1 4 3 4 1 4 1 3
3 4 3 3 2 4 4 4 2 1 4 2 1 2 4 2

 [66] 1 4 2 1 3 2 4 2 2 2 1 4 3 1 4 2 3 2 4 1 4 4 1 3 4 2 1 4 3 3 1 4 1 4 1 1 4 2 1 4 1 2 4 2 2 2 1 3
1 1 1 2 4 4 4 1 3 3 3 1 3 4 3 2 3

[131] 4 3 1 3 1 3 4 3 1 3 2 3 1 3 1 1 4 3 3 3 4 3 4 3 4 1 3 3 3 3 2 3 1 3 4 3 4 3 3 3 3 1 3 3 4 3 2 1
2 3 3 3 4 3 3 3 4 1 3 3 3 3 3 3 4

[196] 3 4 3 3 3

> #visualize the clusters

> fviz_cluster(km,data=df[,4:5]) #PCA Principle Component Analysis

>

> km=kmeans(df[,3],center=5,nstart=25)

> km$cluster

  [1] 3 3 3 3 2 3 4 3 1 2 1 4 1 3 4 3 4 3 5 4 4 3 5 2 5 2 5 4 4 3 1 3 5 3 5 3 4 2 4 3 1 3 5 2 5 3 5 2 2
2 5 2 2 1 5 5 5 1 2 5 1 3 1 5 1

 [66] 3 4 1 3 2 1 5 1 1 1 2 5 4 3 5 1 4 1 5 3 5 5 3 2 5 1 3 5 4 2 3 5 2 5 3 3 5 1 2 5 3 1 5 1 1 1 3 4
3 3 3 1 5 5 5 2 4 4 4 3 2 4 4 1 4

[131] 5 4 3 2 3 2 5 2 3 4 1 2 2 2 3 2 5 2 2 2 4 4 5 4 5 2 4 2 2 2 5 2 3 2 5 4 4 2 4 2 4 2 4 4 5 2 1 2
1 4 4 2 5 2 4 2 5 2 4 4 2 2 2 4 5

[196] 4 5 2 2 2

> #visualize the clusters

> fviz_cluster(km,data=df[,4:5]) #PCA Principle Component Analysis
```

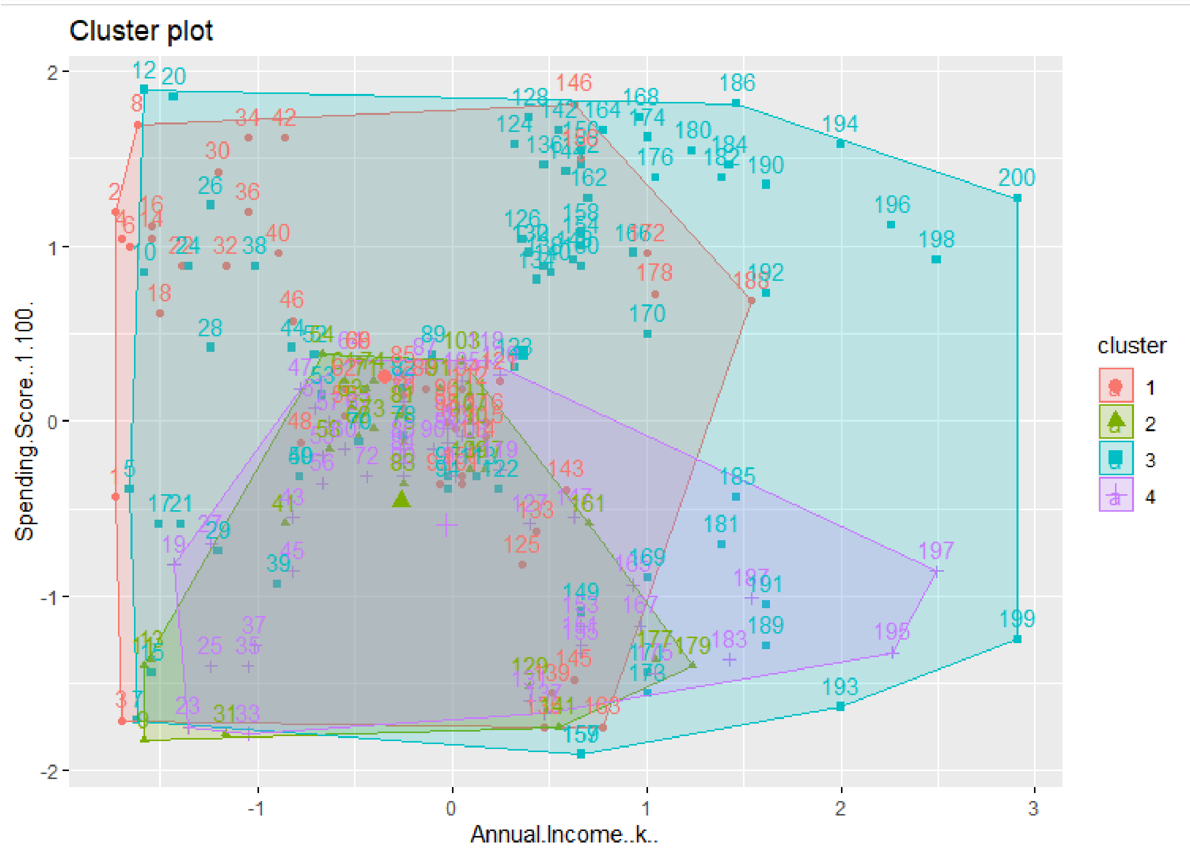
PLOTS:


Cluster Dendrogram
Height
250
200
150
100
50
0
d
hclust (*, "complete")

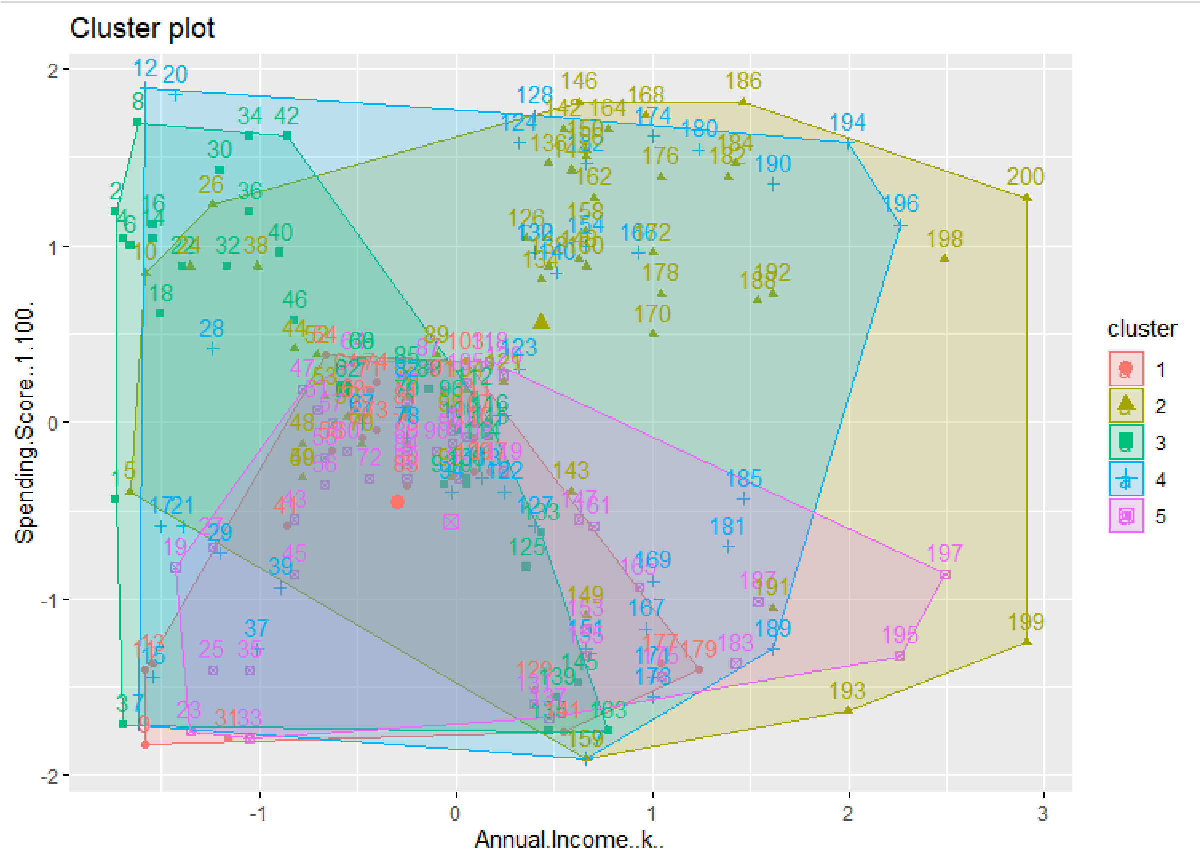

Cluster plot
Spending.Score..1.100.
Annual.Income..k..
cluster
1
2



Cluster plot
Spending.Score..1.100.
Annual.Income..k..
cluster
1
2
3



Cluster plot
Spending.Score..1.100.
Annual.Income..k..
cluster
1
2
3
4



CONCLUSION:

PROGRAMS HAVE BEEN EXECUTED AND PLOTS HAVE BEEN SUCCESFULLY RECORDED AND FILED.