#### **CAT 3 PROJECT:**

#### ANALYSIS OF PERSONALITY AND SOCIAL BEHAVIOUR

#### **Problem statement:**

To classify general public of different age groups based on the analysis of 'Personality and Social Behaviour'.

#### **Methods:**

- 1. Elbow method of clustering.
- 2. Kmeans clustering.
- 3. Hierarchial clustering
- 4. PCA

#### **Tools and libraries:**

- 1. R studio.
- 2. library(dplyr)
- 3. library(factoextra)
- 4. library(ggplot2)
- 5. library(ggpubr)
- 6. library(cluster)

#### Code:

```
library(dplyr)
library(factoextra)
library(ggplot2)
library(ggpubr)
library(cluster)
dataset1=read.csv("C:\\Users\\Navika M S\\OneDrive\\Documents\\Semester 4\\PA
lab\\Revision material\\Personality and Social Behavior Dataset For Analysis.csv")
print(dataset1)
summary(dataset1)
datasetm=read.csv("C:\\Users\\Navika M S\\OneDrive\\Documents\\Semester 4\\PA
lab\\male.csv")
print(datasetm)
summary(datasetm)
datasetf=read.csv("C:\\Users\\Navika M S\\OneDrive\\Documents\\Semester 4\\PA
lab\\female.csv")
print(datasetf)
summary(datasetf)
```

```
fviz_nbclust(dataset, kmeans, method="wss")
labs(subtitle="Elbow Method")
results11<-kmeans(dataset1,5)
results11
results11$size
results11$cluster
dataset1[,1:7] < -scale(dataset1[,1:7])
plot(dataset1[c("AGE","MIND")],col=results11$cluster)
points(results11$centers,pch=2,col="red")
plot(dataset1[c("AGE","ENERGY")],col=results11$cluster)
points(results11$centers,pch=2,col="red")
plot(dataset1[c("AGE","NATURE")],col=results11$cluster)
points(results11$centers,pch=2,col="red")
plot(dataset1[c("AGE","TACTICS")],col=results11$cluster)
points(results11$centers,pch=2,col="red")
plot(dataset1[c("AGE","IDENTITY")],col=results11$cluster)
points(results11$centers,pch=2,col="red")
clusplot(dataset1,results11$cluster)
sil <- silhouette(results11$cluster, dist(dataset1))</pre>
fviz_silhouette(sil)
#EUCLIDEAN
data.exc1<-dist(dataset1,method="euclidean")
round(as.matrix(data.exc1)[1:7,1:7],1)
# Use hcut() which compute hclust and cut the tree
hc.cut <- hcut(dataset1, k = 5, hc method = "complete")
# Visualize dendrogram
fviz_dend(hc.cut, show_labels = TRUE, rect = TRUE)
res.pca <- prcomp(dataset1, scale = TRUE)
fviz_eig(res.pca)
```

```
fviz_pca_ind(res.pca,
        col.ind = "cos2", # Color by the quality of representation
        gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
        repel = TRUE # Avoid text overlapping
)
# Dimension reduction using PCA
res.pca <- prcomp(dataset1, scale = TRUE)
res.pca
# Coordinates of individuals
ind.coord <- as.data.frame(get_pca_ind(res.pca)$coord)</pre>
# Add clusters obtained using the K-means algorithm
ind.coord$cluster <- factor(results11$cluster)</pre>
# Add Species groups from the original data sett
ind.coord$Species <- df$Species
# Data inspection
head(ind.coord)
# Percentage of variance explained by dimensions
eigenvalue <- round(get_eigenvalue(res.pca), 1)</pre>
variance.percent <- eigenvalue$variance.percent
head(eigenvalue)
ggscatter(
 ind.coord, x = "Dim.1", y = "Dim.2",
 color = "cluster", palette = "npg", ellipse = TRUE, ellipse.type = "convex",
 shape = "circle", size = 1.5, legend = "right", ggtheme = theme_bw(),
 xlab = paste0("Dim 1 (", variance.percent[1], "% )" ),
 ylab = paste0("Dim 2 (", variance.percent[2], "% )" )
) +
 stat_mean(aes(color = cluster), size = 4)
```

## **Output:**

	GENDER		MIND	<b>ENERGY</b>		TACTICS	IDENTITY	
1	1 2	2	3 3	3 3	2	3	2	
2	2	1	3	3	2	3	3	
3	2	2	2	1	1	2	3	
4	2	2	3	3	3	3	3	
5	2	2	3	2	3	3	2	
,	1		2	2	2	2	2	
6		5	2	3	2	3	3	
7	1	3	2	3	2	3	3	
8	1	2	3	3	2 2 2 2 2	3	2	
9	1	2	3	3	2	3	3	
10	2	2	2	2	2	2	2	
11	1	2	2	2	1	3	2	
12	1	2	4	2	3		3	
13	1	2	2	3	3 2	2	3	
14	2	4	2	2 3 3	2	3 2 2	3	
15	2	7	2			2	1	
16	1	2	2	2 3 2	1 2 3	2 2 2	1 2	
			3 2	3	2	2	2	
17	2	1	2	2	3	2	1	
18	1	2	3	3 3 2	2	2	3 2 2	
19	1	2	3	3	2	3	2	
20	2	1	3		2	2	2	
21	1	2	2	3 3 3	2 2 2 3 2 2 2 2 2 2 2 2 2	3	3	
22	1	1	2	3	3	3	3	
23	2	2	2	3	2	3	3	
24	1	2	2	3	2	3		
25	1	4	2	3	2	3	3	
26	2	1	3	3	2	2	3	
27	2	2	3	3 3 3	2	2 2 2	3	
		2	3	2	2	2	3	
28	1		3	2	2	2	3	
29	2	1	3	3	2 2 2	3	3	
30	2	1	3	2	2	2	2	
31	1	2	3	2	2	2	2	
32	1	2	1	1	1	1	2	
33	1	2	1	1	1	1	2	
34	2	1	2	2	3	2	3	
35	1	1	2	2	2	3	2	
36	2	2	3	3	2	3	2	
37	1	4	3	3	2	3	3	
38	1	4	2	1	1	2	3	
			2	, T	3	3	3	
39	1	4	3	3	3	3	3	
40	1	2	3	2	3	3	2	
41	1	4	2	3	3 2 2	3	3	
42	1	4	2	3		3	3	
4.7	٦.				٦.		٦.	

# > summary(dataset1)

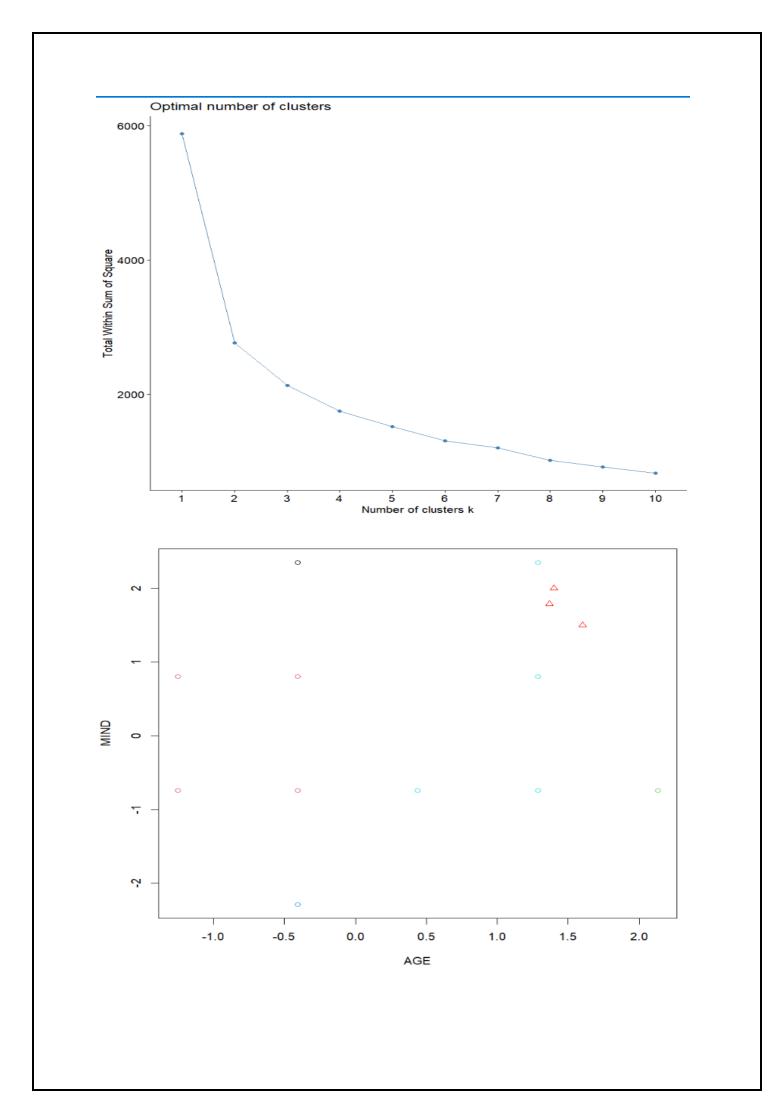
GENDER	AGE	MIND	ENERGY	NATURE	TACTICS	IDENTITY
Min. :1.00						
1st Qu.:1.00	1st Qu.:2.00					
Median :1.00	Median :2.00	Median :2.00	Median :3.00	Median :2.00	Median :3.00	Median :3.00
Mean :1.38	Mean :2.48	Mean :2.48	Mean :2.52	Mean :2.02	Mean :2.52	Mean :2.52
3rd Qu.:2.00	3rd Qu.:4.00	3rd Qu.:3.00	3rd Qu.:3.00	3rd Qu.:2.00	3rd Qu.:3.00	3rd Qu.:3.00
Max. :2.00	Max. :5.00	Max. :4.00	Max. :3.00	Max. :3.00	Max. :3.00	Max. :3.00

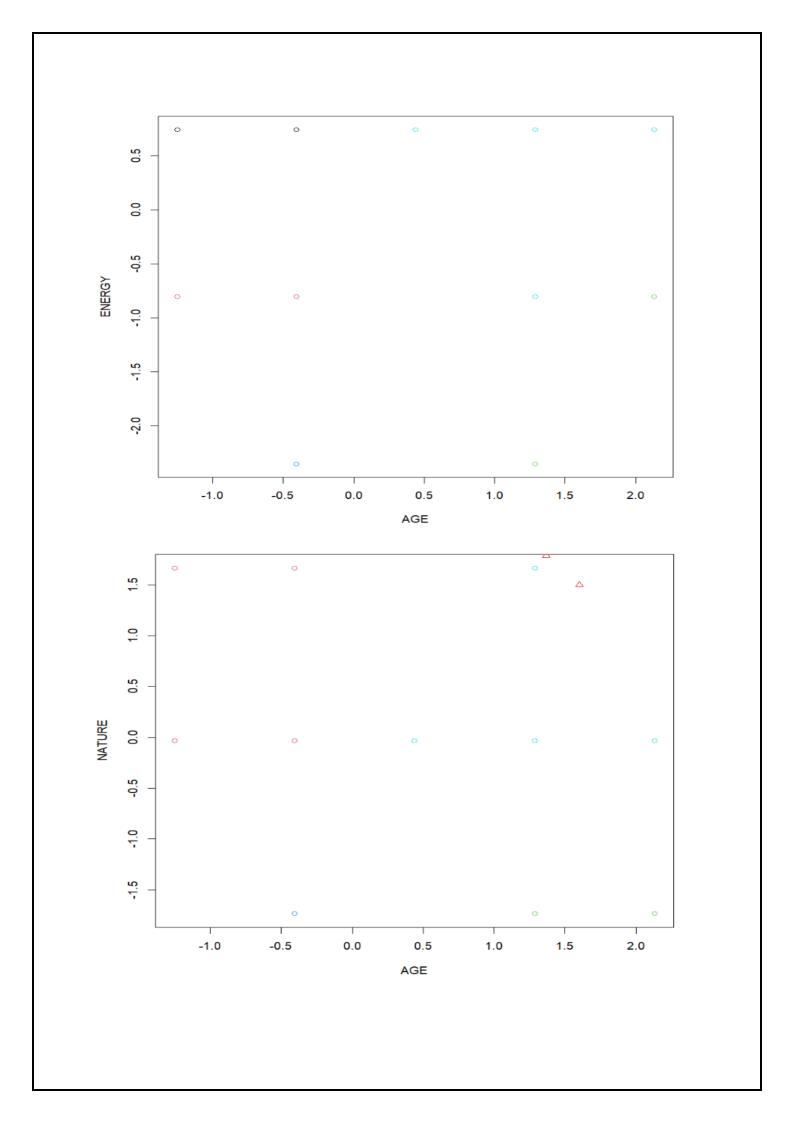
```
> fviz_nbclust(dataset, kmeans, method="wss")
> labs(subtitle="Elbow Method")
 $subtitle
[1] "Elbow Method"
attr(,"class")
[1] "labels"
> results11<-kmeans(dataset1,5)
K-means clustering with 5 clusters of sizes 19, 10, 3, 5, 13
GENDER AGE MIND ENERGY NATURE TACTICS IDENTITY
1 1.368421 1.789474 2.789474 2.947368 2.157895 2.684211 2.736842
2 1.600000 1.500000 2.500000 2.000000 2.400000 2.300000 2.000000
3 1.333333 4.333333 2.000000 1.666667 1.000000 2.333333 2.000000
4 1.400000 2.000000 1.600000 1.400000 1.000000 1.800000 2.0000000
5 1.230769 4.000000 2.461538 2.923077 2.153846 2.769231 2.923077
Clustering vector:
[1] 1 1 4 1 2 5 5 1 1 2 4 1 1 5 4 1 2 1 1 2 1 1 1 1 5 1 1 1 1 2 2 4 4 2 2 1 5 3 5 2 5 5 5 5 2 3 5 5 5 3
Within cluster sum of squares by cluster:

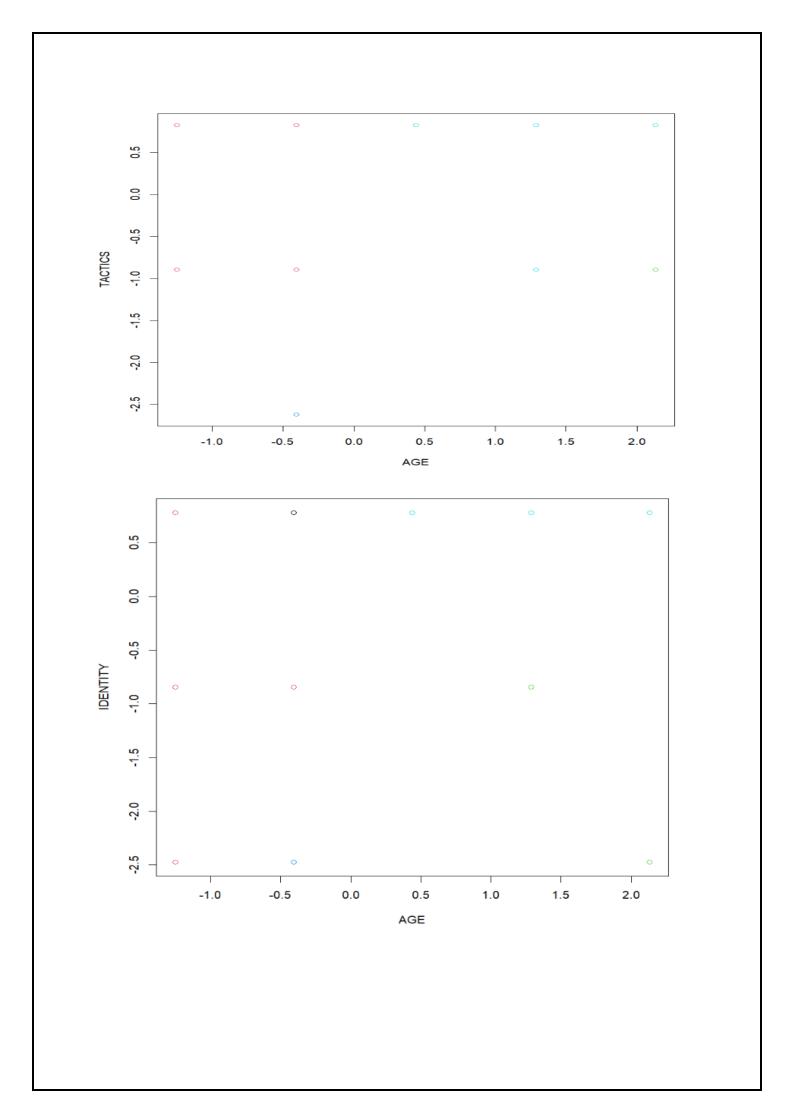
[1] 24.000000 13.900000 4.666667 8.400000 15.384615

(between_SS / total_SS = 61.7 %)
Available components:
[1] "cluster"
[9] "ifault"
                "centers"
                            "totss"
                                         "withinss"
                                                      "tot.withinss" "betweenss"
                                                                              "size"
                                                                                             "iter"
  results11$size
[1] 19 10 3
 > dataset1[,1:7] <-scale(dataset1[,1:7])</pre>
 > plot(dataset1[c("AGE","MIND")],col=results11$cluster)
   points(results11$centers,pch=2,col="red")
 > plot(dataset1[c("AGE","ENERGY")],col=results11$cluster)
   points(results11$centers,pch=2,col="red")
 > plot(dataset1[c("AGE","NATURE")],col=results11$cluster)
   points(results11$centers,pch=2,col="red")
 > plot(dataset1[c("AGE","TACTICS")],col=results11$cluster)
   points(results11$centers,pch=2,col="red")
 > plot(dataset1[c("AGE","IDENTITY")],col=results11$cluster)
> points(results11$centers,pch=2,col="red")
 > clusplot(dataset1, results11$cluster)
 > sil <- silhouette(results11$cluster, dist(dataset1))</pre>
 > fviz_silhouette(sil)
    cluster size ave.sil.width
 1
             1
                   19
                                      0.16
 2
             2
                   10
                                      0.17
 3
                                      0.05
             3
                     3
 4
             4
                     5
                                      0.09
 5
                   13
                                      0.25
    #EUCLIDEAN
   data.exc1<-dist(dataset1,method="euclidean")</pre>
    round(as.matrix(data.exc1)[1:7,1:7],1)
                   3
                          4
                                5
                                     6
   0.\overline{0} 2.7 5.0 3.1 3.1 3.4 2.4
 1
    2.7 0.0 4.3 1.9 2.9 4.2 3.1
 2
 3
    5.0 4.3 0.0 5.1 4.7
                                   5.1 4.5
    3.1 1.9 5.1 0.0 2.2 4.0 3.2
 4
 5
    3.1 2.9 4.7 2.2 0.0 4.6 3.9
   3.4 4.2 5.1 4.0 4.6 0.0 1.7 2.4 3.1 4.5 3.2 3.9 1.7 0.0
 6
```

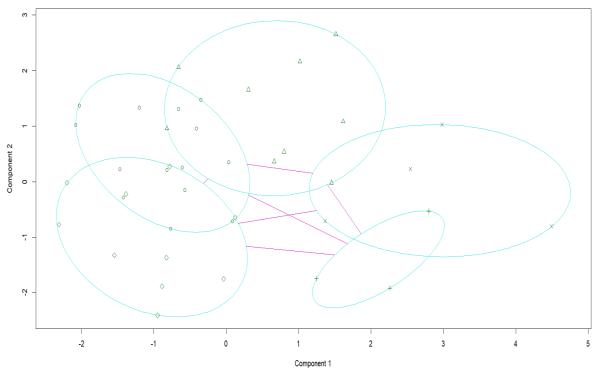
```
> # Use hcut() which compute hclust and cut the tree
> hc.cut <- hcut(dataset1, k = 5, hc_method = "complete")</pre>
> # Visualize dendrogram
> fviz_dend(hc.cut, show_labels = TRUE, rect = TRUE)
> res.pca <- prcomp(dataset1, scale = TRUE)</pre>
> fviz_eig(res.pca)
> fviz_pca_ind(res.pca,
                   col.ind = "cos2", # Color by the quality of representation
                   gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
                                        # Avoid text overlapping
                   repel = TRUE
+ )
> # Dimension reduction using PCA
> res.pca <- prcomp(dataset1, scale = TRUE)
> res.pca
Standard deviations (1,
                          ., p=7):
[1] 1.5682067 1.2390121 0.8990680 0.8837855 0.7506537 0.6708209 0.6345826
Rotation (n x k) = (7 \times 7):
                              PC2
                 PC1
                                         PC3
                                                     PC4
                                                                 PC5
                                                                             PC6
                                                                      0.1463238 -0.17604903
          0.07723116 -0.53503227
                                   0.6798017 -0.4357959
                                                          0.05765008
         -0.07109846 0.60733950 0.5411088 0.1614479
                                                          0.48867591 0.2138506 0.15060994
AGE
         -0.42026964 \ -0.35851515 \ \ 0.0765270 \ \ 0.3055440 \ \ 0.44899894 \ -0.6234309
MTND
                                                                                  0.07321646
         -0.49033796 0.12342216
ENERGY
                                  0.2164341 -0.2543599 -0.50662508 -0.1330876
                                                                                  0.59867498
         -0.44553406 \ -0.32181719 \ -0.2968844 \ \ 0.0360027 \ \ 0.28128147 \ \ 0.6946220 \ \ 0.21651221
TACTICS -0.48913138 0.07826014 0.2038592 0.3845004 -0.39088833 0.1431537 -0.62605118 IDENTITY -0.36629546 0.30236089 -0.2503436 -0.6905242 0.26017368 -0.1532518 -0.37912186
> # Coordinates of individuals
> ind.coord <- as.data.frame(get_pca_ind(res.pca)$coord)</pre>
> # Add clusters obtained using the K-means algorithm
> ind.coord$cluster <- factor(results11$cluster)</p>
> # Add Species groups from the original data sett
> ind.coord$Species <- df$Species</pre>
> # Data inspection
> head(ind.coord)
       Dim.1
                  Dim.2
                              Dim.3
                                          Dim.4
                                                      Dim.5
                                                                 Dim.6
                                                                              Dim.7 cluster
3 2.5156771 -0.2233651 0.2101749 -1.19229918 0.7987185 -0.5777534 -1.85581985
4 -2.0084231 -1.3545243
                         0.3409609 \ -0.72124750 \ \ 0.2075711 \ \ 0.6530279 \ -0.23442940
                                                                                           1
5 -0.6535140 -2.0377818  0.4138279  0.79660870  0.5675637
                                                             1.1084344 -0.54311543
6 -0.9394401 2.3791499 0.7136231 0.04349154 0.1577616 0.6816165 0.02577351
> # Percentage of variance explained by dimensions
> eigenvalue <- round(get_eigenvalue(res.pca), 1)</pre>
> variance.percent <- eigenvalue$variance.percent
> head(eigenvalue)
       eigenvalue variance.percent cumulative.variance.percent
Dim.1
              2.5
                                 35.1
                                                                  35.1
Dim.2
              1.5
                                 21.9
                                                                  57.1
                                                                 68.6
Dim. 3
              0.8
                                 11.5
Dim.4
               0.8
                                 11.2
                                                                  79.8
Dim.5
               0.6
                                  8.0
                                                                  87.8
               0.5
                                                                 94.2
Dim. 6
                                  6.4
> ggscatter(
    ind.coord, x = "Dim.1", y = "Dim.2",
color = "cluster", palette = "npg", ellipse = TRUE, ellipse.type = "convex",
shape = "circle", size = 1.5, legend = "right", ggtheme = theme_bw(),
xlab = paste0("Dim 1 (", variance.percent[1], "%)"),
ylab = paste0("Dim 2 (", variance.percent[2], "%)")
+ ) +
    stat_mean(aes(color = cluster), size = 4)
```





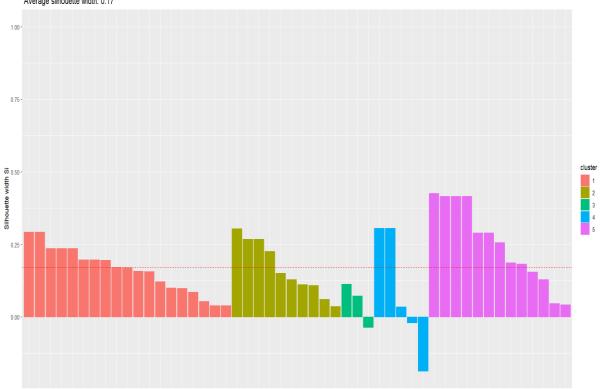


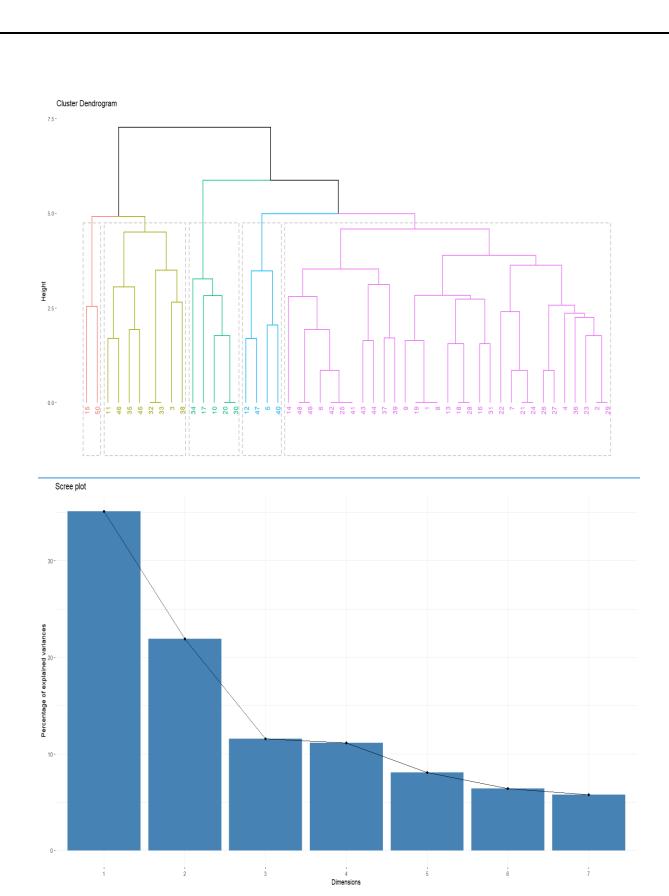
### CLUSPLOT( dataset1 )

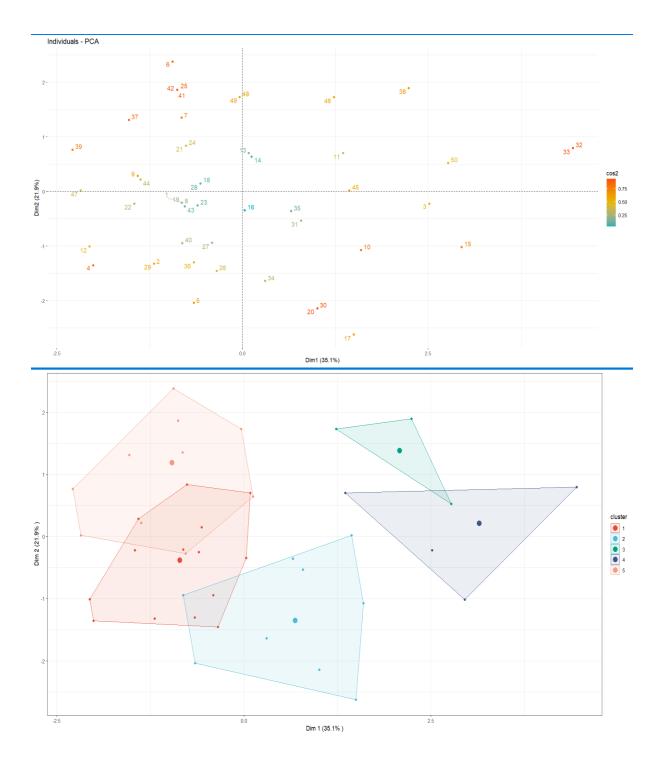


These two components explain 57.06 % of the point variability.

Clusters silhouette plot Average silhouette width: 0.17







## **Interpretation:**

- From the plot of the elbow method, we could observe that the line is bent at the range 5 making it the optimal number of clusters for the dataset.
- By using k means clustering the clusters have been formed.
- By using PCA we found that the variables whose value is greater than 0.5 has a great influence on once personality and social behaviour.
- The within-cluster sum of squares is a measure of the variability of the observations within each cluster. In general, a cluster that has a small sum of squares is more

compact than a cluster that has a large sum of squares. Clusters that have higher values exhibit greater variability of the observations within the cluster

- In Silhouhette method
  - o Observations with a large silhouhette Si (almost 1) are very well clustered.
  - o A small Si (around 0) means that the observation lies between two clusters.
  - o Observations with a negative Si are probably placed in the wrong cluster
- For the age category 13-18 it observed that people under this category are **extroverts and intuitive**. They can cope with emotions and are well planned. They are assertive.
- The people under age category 19-24 have similar personality and behavioural pattern of people below 19.
- People of age between 25-30 are **extroverts and strongly intuitive** people. Their capacity to cope with emotions are high. They are very well planned and assertive people.
- 31-59 highly **extroverted and highly intuitive**, can easily manage their emotions and are planned.
- Within sum of squares less, the cluster is more compact.
- Within sum of squares of MIND is the greatest, hence making it the most dissimilar cluster.