ML\_Assignment5

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#Importing required libraries

library(cluster)

## Warning: package 'cluster' was built under R version 4.1.3

library(caret)

## Loading required package: ggplot2

## Warning in register(): Can't find generic `scale\_type` in package ggplot2 to  
## register S3 method.

## Loading required package: lattice

#library(dendextend)  
library(knitr)  
library(factoextra)

## Warning: package 'factoextra' was built under R version 4.1.3

## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa

library(readr)

**#Importing dataset**

setwd("C:/Users/shari/OneDrive/Desktop/Business Analytics/Sem 1/Machine Learning/ML\_Assignment5")  
  
Cereals<- read.csv("C:/Users/shari/OneDrive/Desktop/Business Analytics/Sem 1/Machine Learning/ML\_Assignment5/Cereals.csv")  
  
data\_cereals <- data.frame(Cereals[,4:16])

**#Preprocessing the data**

data\_cereals <- na.omit(data\_cereals)

**#Data Normalization**

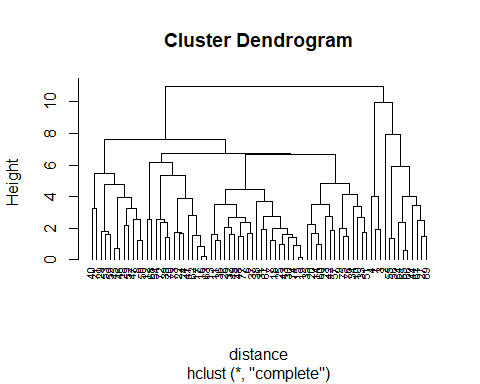
data\_cereals\_scaled <- scale(data\_cereals)

**#Applying hierarchical clustering to the data using Euclidean distance to the normalize measurements.**

distance <- dist(data\_cereals\_scaled, method = "euclidean")  
hier.clust\_complete <- hclust(distance, method = "complete")

**#Plotting the dendogram**

plot(hier.clust\_complete, cex = 0.7, hang = -1)



**#Using agnes function to perfrom clustering with single linkage, complete linkage, average linkage and Ward.**

hier.clust\_single <- agnes(data\_cereals\_scaled, method = "single")  
hier.clust\_complete <- agnes(data\_cereals\_scaled, method = "complete")  
hier.clust\_average <- agnes(data\_cereals\_scaled, method = "average")  
hier.clust\_ward <- agnes(data\_cereals\_scaled, method = "ward")

**#Single Linkage vs Complete Linkage vs Average Linkage vs Ward**

print(hier.clust\_single$ac)

## [1] 0.6067859

print(hier.clust\_complete$ac)

## [1] 0.8353712

print(hier.clust\_average$ac)

## [1] 0.7766075

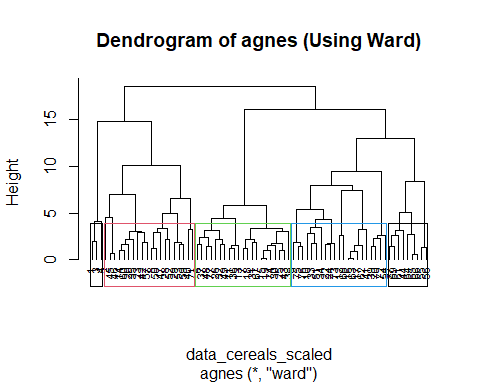
print(hier.clust\_ward$ac)

## [1] 0.9046042

**#We will choose the WARD method because it has the highest value of 0.9046042.**

**#(2) Choosing the clusters:**

pltree(hier.clust\_ward, cex = 0.7, hang = -1, main = "Dendrogram of agnes (Using Ward)")  
rect.hclust(hier.clust\_ward, k = 5, border = 1:4)



Cluster1 <- cutree(hier.clust\_ward, k=5)  
dataframe2 <- as.data.frame(cbind(data\_cereals\_scaled,Cluster1))

**#We will choose 5 clusters after observing the distance.**

**#Commenting on the structure of the clusters and on their stability**

**#Creating Partitions**

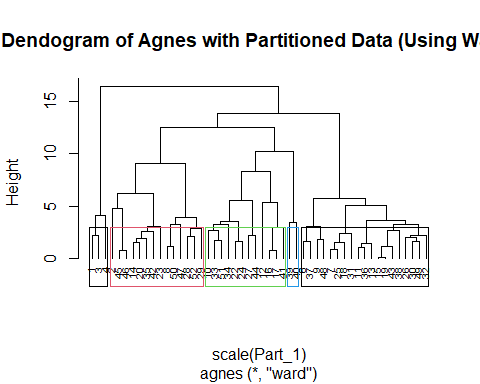
set.seed(123)  
Part\_1 <- data\_cereals[1:50,]  
Part\_2 <- data\_cereals[51:74,]

**#Performing Hierarchial Clustering,consedering k = 5.**

ag\_single <- agnes(scale(Part\_1), method = "single")  
ag\_complete <- agnes(scale(Part\_1), method = "complete")  
ag\_average <- agnes(scale(Part\_1), method = "average")  
ag\_ward <- agnes(scale(Part\_1), method = "ward")  
cbind(single=ag\_single$ac , complete=ag\_complete$ac , average= ag\_average$ac , ward= ag\_ward$ac)

## single complete average ward  
## [1,] 0.6393338 0.8138238 0.7408904 0.8764323

pltree(ag\_ward, cex = 0.6, hang = -1, main = "Dendogram of Agnes with Partitioned Data (Using Ward)")  
rect.hclust(ag\_ward, k = 5, border = 1:4)



cut\_2 <- cutree(ag\_ward, k = 5)

**#Calculating the centeroids.**

result <- as.data.frame(cbind(Part\_1, cut\_2))  
result[result$cut\_2==1,]

## calories protein fat sodium fiber carbo sugars potass vitamins shelf weight  
## 1 70 4 1 130 10 5 6 280 25 3 1  
## 3 70 4 1 260 9 7 5 320 25 3 1  
## 4 50 4 0 140 14 8 0 330 25 3 1  
## cups rating cut\_2  
## 1 0.33 68.40297 1  
## 3 0.33 59.42551 1  
## 4 0.50 93.70491 1

centroid\_1 <- colMeans(result[result$cut\_2==1,])  
result[result$cut\_2==2,]

## calories protein fat sodium fiber carbo sugars potass vitamins shelf weight  
## 2 120 3 5 15 2.0 8.0 8 135 0 3 1.00  
## 8 130 3 2 210 2.0 18.0 8 100 25 3 1.33  
## 14 110 3 2 140 2.0 13.0 7 105 25 3 1.00  
## 20 110 3 3 140 4.0 10.0 7 160 25 3 1.00  
## 23 100 2 1 140 2.0 11.0 10 120 25 3 1.00  
## 28 120 3 2 160 5.0 12.0 10 200 25 3 1.25  
## 29 120 3 0 240 5.0 14.0 12 190 25 3 1.33  
## 35 120 3 3 75 3.0 13.0 4 100 25 3 1.00  
## 42 100 4 2 150 2.0 12.0 6 95 25 2 1.00  
## 45 150 4 3 95 3.0 16.0 11 170 25 3 1.00  
## 46 150 4 3 150 3.0 16.0 11 170 25 3 1.00  
## 47 160 3 2 150 3.0 17.0 13 160 25 3 1.50  
## 50 140 3 2 220 3.0 21.0 7 130 25 3 1.33  
## 52 130 3 2 170 1.5 13.5 10 120 25 3 1.25  
## cups rating cut\_2  
## 2 1.00 33.98368 2  
## 8 0.75 37.03856 2  
## 14 0.50 40.40021 2  
## 20 0.50 40.44877 2  
## 23 0.75 36.17620 2  
## 28 0.67 40.91705 2  
## 29 0.67 41.01549 2  
## 35 0.33 45.81172 2  
## 42 0.67 45.32807 2  
## 45 1.00 37.13686 2  
## 46 1.00 34.13976 2  
## 47 0.67 30.31335 2  
## 50 0.67 40.69232 2  
## 52 0.50 30.45084 2

centroid\_2 <- colMeans(result[result$cut\_2==2,])  
result[result$cut\_2==3,]

## calories protein fat sodium fiber carbo sugars potass vitamins shelf weight  
## 6 110 2 2 180 1.5 10.5 10 70 25 1 1  
## 7 110 2 0 125 1.0 11.0 14 30 25 2 1  
## 9 90 2 1 200 4.0 15.0 6 125 25 1 1  
## 11 120 1 2 220 0.0 12.0 12 35 25 2 1  
## 13 120 1 3 210 0.0 13.0 9 45 25 2 1  
## 15 110 1 1 180 0.0 12.0 13 55 25 2 1  
## 18 110 1 0 90 1.0 13.0 12 20 25 2 1  
## 19 110 1 1 180 0.0 12.0 13 65 25 2 1  
## 25 110 2 1 125 1.0 11.0 13 30 25 2 1  
## 26 110 1 0 200 1.0 14.0 11 25 25 1 1  
## 30 110 1 1 135 0.0 13.0 12 25 25 2 1  
## 31 100 2 0 45 0.0 11.0 15 40 25 1 1  
## 32 110 1 1 280 0.0 15.0 9 45 25 2 1  
## 36 120 1 2 220 1.0 12.0 11 45 25 2 1  
## 37 110 3 1 250 1.5 11.5 10 90 25 1 1  
## 38 110 1 0 180 0.0 14.0 11 35 25 1 1  
## 43 110 2 1 180 0.0 12.0 12 55 25 2 1  
## 48 100 2 1 220 2.0 15.0 6 90 25 1 1  
## 49 120 2 1 190 0.0 15.0 9 40 25 2 1  
## cups rating cut\_2  
## 6 0.75 29.50954 3  
## 7 1.00 33.17409 3  
## 9 0.67 49.12025 3  
## 11 0.75 18.04285 3  
## 13 0.75 19.82357 3  
## 15 1.00 22.73645 3  
## 18 1.00 35.78279 3  
## 19 1.00 22.39651 3  
## 25 1.00 32.20758 3  
## 26 0.75 31.43597 3  
## 30 0.75 28.02576 3  
## 31 0.88 35.25244 3  
## 32 0.75 23.80404 3  
## 36 1.00 21.87129 3  
## 37 0.75 31.07222 3  
## 38 1.33 28.74241 3  
## 43 1.00 26.73451 3  
## 48 1.00 40.10596 3  
## 49 0.67 29.92429 3

centroid\_3 <- colMeans(result[result$cut\_2==3,])  
result[result$cut\_2==4,]

## calories protein fat sodium fiber carbo sugars potass vitamins shelf weight  
## 10 90 3 0 210 5 13 5 190 25 3 1  
## 12 110 6 2 290 2 17 1 105 25 1 1  
## 16 110 2 0 280 0 22 3 25 25 1 1  
## 17 100 2 0 290 1 21 2 35 25 1 1  
## 22 110 2 0 220 1 21 3 30 25 3 1  
## 24 100 2 0 190 1 18 5 80 25 3 1  
## 27 100 3 0 0 3 14 7 100 25 2 1  
## 33 100 3 1 140 3 15 5 85 25 3 1  
## 34 110 3 0 170 3 17 3 90 25 3 1  
## 41 110 2 1 260 0 21 3 40 25 2 1  
## 44 100 4 1 0 0 16 3 95 25 2 1  
## 51 90 3 0 170 3 18 2 90 25 3 1  
## cups rating cut\_2  
## 10 0.67 53.31381 4  
## 12 1.25 50.76500 4  
## 16 1.00 41.44502 4  
## 17 1.00 45.86332 4  
## 22 1.00 46.89564 4  
## 24 0.75 44.33086 4  
## 27 0.80 58.34514 4  
## 33 0.88 52.07690 4  
## 34 0.25 53.37101 4  
## 41 1.50 39.24111 4  
## 44 1.00 54.85092 4  
## 51 1.00 59.64284 4

centroid\_4 <- colMeans(result[result$cut\_2==4,])  
centroids <- rbind(centroid\_1, centroid\_2, centroid\_3, centroid\_4)  
x2 <- as.data.frame(rbind(centroids[,-14], Part\_2))

**#Calculating the Distance**

Distance\_1 <- get\_dist(x2)  
Matrix\_1 <- as.matrix(Distance\_1)  
dataframe1 <- data.frame(data=seq(1,nrow(Part\_2),1), Clusters = rep(0,nrow(Part\_2)))  
for(i in 1:nrow(Part\_2))   
 {dataframe1[i,2] <- which.min(Matrix\_1[i+4, 1:4])}  
dataframe1

## data Clusters  
## 1 1 1  
## 2 2 4  
## 3 3 3  
## 4 4 2  
## 5 5 2  
## 6 6 1  
## 7 7 2  
## 8 8 2  
## 9 9 3  
## 10 10 3  
## 11 11 2  
## 12 12 2  
## 13 13 2  
## 14 14 3  
## 15 15 4  
## 16 16 2  
## 17 17 3  
## 18 18 2  
## 19 19 4  
## 20 20 4  
## 21 21 3  
## 22 22 4  
## 23 23 4  
## 24 24 3

cbind(dataframe2$Cluster1[51:74], dataframe1$Clusters)

## [,1] [,2]  
## [1,] 2 1  
## [2,] 4 4  
## [3,] 5 3  
## [4,] 5 2  
## [5,] 2 2  
## [6,] 2 1  
## [7,] 2 2  
## [8,] 5 2  
## [9,] 4 3  
## [10,] 4 3  
## [11,] 5 2  
## [12,] 5 2  
## [13,] 5 2  
## [14,] 3 3  
## [15,] 4 4  
## [16,] 5 2  
## [17,] 4 3  
## [18,] 2 2  
## [19,] 4 4  
## [20,] 4 4  
## [21,] 3 3  
## [22,] 4 4  
## [23,] 4 4  
## [24,] 3 3

table(dataframe2$Cluster1[51:74] == dataframe1$Clusters)

##   
## FALSE TRUE   
## 12 12

**#Since we are getting 12 FALSE and 12 TRUE, we can conclude that the model is partially stable.**

**#3) The elementary public schools would like to choose a set of cereals to include in their daily cafeterias. Every day a different cereal is offered, but all cereals should support a healthy diet. For this goal, you are requested to find a cluster of “healthy cereals.” Should the data be normalized? If not, how should they be used in the cluster analysis?**

**#Clustering Healthy Cereals.**

Healthy\_Cereals <- Cereals  
Healthy\_Cereals\_na <- na.omit(Healthy\_Cereals)  
Clusthealthy <- cbind(Healthy\_Cereals\_na, Cluster1)  
Clusthealthy[Clusthealthy$Cluster1==1,]

## name mfr type calories protein fat sodium fiber carbo  
## 1 100%\_Bran N C 70 4 1 130 10 5  
## 3 All-Bran K C 70 4 1 260 9 7  
## 4 All-Bran\_with\_Extra\_Fiber K C 50 4 0 140 14 8  
## sugars potass vitamins shelf weight cups rating Cluster1  
## 1 6 280 25 3 1 0.33 68.40297 1  
## 3 5 320 25 3 1 0.33 59.42551 1  
## 4 0 330 25 3 1 0.50 93.70491 1

Clusthealthy[Clusthealthy$Cluster1==2,]

## name mfr type calories protein fat sodium  
## 2 100%\_Natural\_Bran Q C 120 3 5 15  
## 8 Basic\_4 G C 130 3 2 210  
## 14 Clusters G C 110 3 2 140  
## 20 Cracklin'\_Oat\_Bran K C 110 3 3 140  
## 23 Crispy\_Wheat\_&\_Raisins G C 100 2 1 140  
## 28 Fruit\_&\_Fibre\_Dates,\_Walnuts,\_and\_Oats P C 120 3 2 160  
## 29 Fruitful\_Bran K C 120 3 0 240  
## 35 Great\_Grains\_Pecan P C 120 3 3 75  
## 40 Just\_Right\_Fruit\_&\_Nut K C 140 3 1 170  
## 42 Life Q C 100 4 2 150  
## 45 Muesli\_Raisins,\_Dates,\_&\_Almonds R C 150 4 3 95  
## 46 Muesli\_Raisins,\_Peaches,\_&\_Pecans R C 150 4 3 150  
## 47 Mueslix\_Crispy\_Blend K C 160 3 2 150  
## 50 Nutri-Grain\_Almond-Raisin K C 140 3 2 220  
## 52 Oatmeal\_Raisin\_Crisp G C 130 3 2 170  
## 53 Post\_Nat.\_Raisin\_Bran P C 120 3 1 200  
## 57 Quaker\_Oat\_Squares Q C 100 4 1 135  
## 59 Raisin\_Bran K C 120 3 1 210  
## 60 Raisin\_Nut\_Bran G C 100 3 2 140  
## 71 Total\_Raisin\_Bran G C 140 3 1 190  
## fiber carbo sugars potass vitamins shelf weight cups rating Cluster1  
## 2 2.0 8.0 8 135 0 3 1.00 1.00 33.98368 2  
## 8 2.0 18.0 8 100 25 3 1.33 0.75 37.03856 2  
## 14 2.0 13.0 7 105 25 3 1.00 0.50 40.40021 2  
## 20 4.0 10.0 7 160 25 3 1.00 0.50 40.44877 2  
## 23 2.0 11.0 10 120 25 3 1.00 0.75 36.17620 2  
## 28 5.0 12.0 10 200 25 3 1.25 0.67 40.91705 2  
## 29 5.0 14.0 12 190 25 3 1.33 0.67 41.01549 2  
## 35 3.0 13.0 4 100 25 3 1.00 0.33 45.81172 2  
## 40 2.0 20.0 9 95 100 3 1.30 0.75 36.47151 2  
## 42 2.0 12.0 6 95 25 2 1.00 0.67 45.32807 2  
## 45 3.0 16.0 11 170 25 3 1.00 1.00 37.13686 2  
## 46 3.0 16.0 11 170 25 3 1.00 1.00 34.13976 2  
## 47 3.0 17.0 13 160 25 3 1.50 0.67 30.31335 2  
## 50 3.0 21.0 7 130 25 3 1.33 0.67 40.69232 2  
## 52 1.5 13.5 10 120 25 3 1.25 0.50 30.45084 2  
## 53 6.0 11.0 14 260 25 3 1.33 0.67 37.84059 2  
## 57 2.0 14.0 6 110 25 3 1.00 0.50 49.51187 2  
## 59 5.0 14.0 12 240 25 2 1.33 0.75 39.25920 2  
## 60 2.5 10.5 8 140 25 3 1.00 0.50 39.70340 2  
## 71 4.0 15.0 14 230 100 3 1.50 1.00 28.59278 2

Clusthealthy[Clusthealthy$Cluster1==3,]

## name mfr type calories protein fat sodium fiber carbo  
## 6 Apple\_Cinnamon\_Cheerios G C 110 2 2 180 1.5 10.5  
## 7 Apple\_Jacks K C 110 2 0 125 1.0 11.0  
## 11 Cap'n'Crunch Q C 120 1 2 220 0.0 12.0  
## 13 Cinnamon\_Toast\_Crunch G C 120 1 3 210 0.0 13.0  
## 15 Cocoa\_Puffs G C 110 1 1 180 0.0 12.0  
## 18 Corn\_Pops K C 110 1 0 90 1.0 13.0  
## 19 Count\_Chocula G C 110 1 1 180 0.0 12.0  
## 25 Froot\_Loops K C 110 2 1 125 1.0 11.0  
## 26 Frosted\_Flakes K C 110 1 0 200 1.0 14.0  
## 30 Fruity\_Pebbles P C 110 1 1 135 0.0 13.0  
## 31 Golden\_Crisp P C 100 2 0 45 0.0 11.0  
## 32 Golden\_Grahams G C 110 1 1 280 0.0 15.0  
## 36 Honey\_Graham\_Ohs Q C 120 1 2 220 1.0 12.0  
## 37 Honey\_Nut\_Cheerios G C 110 3 1 250 1.5 11.5  
## 38 Honey-comb P C 110 1 0 180 0.0 14.0  
## 43 Lucky\_Charms G C 110 2 1 180 0.0 12.0  
## 48 Multi-Grain\_Cheerios G C 100 2 1 220 2.0 15.0  
## 49 Nut&Honey\_Crunch K C 120 2 1 190 0.0 15.0  
## 67 Smacks K C 110 2 1 70 1.0 9.0  
## 74 Trix G C 110 1 1 140 0.0 13.0  
## 77 Wheaties\_Honey\_Gold G C 110 2 1 200 1.0 16.0  
## sugars potass vitamins shelf weight cups rating Cluster1  
## 6 10 70 25 1 1 0.75 29.50954 3  
## 7 14 30 25 2 1 1.00 33.17409 3  
## 11 12 35 25 2 1 0.75 18.04285 3  
## 13 9 45 25 2 1 0.75 19.82357 3  
## 15 13 55 25 2 1 1.00 22.73645 3  
## 18 12 20 25 2 1 1.00 35.78279 3  
## 19 13 65 25 2 1 1.00 22.39651 3  
## 25 13 30 25 2 1 1.00 32.20758 3  
## 26 11 25 25 1 1 0.75 31.43597 3  
## 30 12 25 25 2 1 0.75 28.02576 3  
## 31 15 40 25 1 1 0.88 35.25244 3  
## 32 9 45 25 2 1 0.75 23.80404 3  
## 36 11 45 25 2 1 1.00 21.87129 3  
## 37 10 90 25 1 1 0.75 31.07222 3  
## 38 11 35 25 1 1 1.33 28.74241 3  
## 43 12 55 25 2 1 1.00 26.73451 3  
## 48 6 90 25 1 1 1.00 40.10596 3  
## 49 9 40 25 2 1 0.67 29.92429 3  
## 67 15 40 25 2 1 0.75 31.23005 3  
## 74 12 25 25 2 1 1.00 27.75330 3  
## 77 8 60 25 1 1 0.75 36.18756 3

Clusthealthy[Clusthealthy$Cluster1==4,]

## name mfr type calories protein fat sodium fiber carbo  
## 9 Bran\_Chex R C 90 2 1 200 4 15  
## 10 Bran\_Flakes P C 90 3 0 210 5 13  
## 12 Cheerios G C 110 6 2 290 2 17  
## 16 Corn\_Chex R C 110 2 0 280 0 22  
## 17 Corn\_Flakes K C 100 2 0 290 1 21  
## 22 Crispix K C 110 2 0 220 1 21  
## 24 Double\_Chex R C 100 2 0 190 1 18  
## 33 Grape\_Nuts\_Flakes P C 100 3 1 140 3 15  
## 34 Grape-Nuts P C 110 3 0 170 3 17  
## 39 Just\_Right\_Crunchy\_\_Nuggets K C 110 2 1 170 1 17  
## 41 Kix G C 110 2 1 260 0 21  
## 51 Nutri-grain\_Wheat K C 90 3 0 170 3 18  
## 54 Product\_19 K C 100 3 0 320 1 20  
## 62 Rice\_Chex R C 110 1 0 240 0 23  
## 63 Rice\_Krispies K C 110 2 0 290 0 22  
## 68 Special\_K K C 110 6 0 230 1 16  
## 70 Total\_Corn\_Flakes G C 110 2 1 200 0 21  
## 72 Total\_Whole\_Grain G C 100 3 1 200 3 16  
## 73 Triples G C 110 2 1 250 0 21  
## 75 Wheat\_Chex R C 100 3 1 230 3 17  
## 76 Wheaties G C 100 3 1 200 3 17  
## sugars potass vitamins shelf weight cups rating Cluster1  
## 9 6 125 25 1 1 0.67 49.12025 4  
## 10 5 190 25 3 1 0.67 53.31381 4  
## 12 1 105 25 1 1 1.25 50.76500 4  
## 16 3 25 25 1 1 1.00 41.44502 4  
## 17 2 35 25 1 1 1.00 45.86332 4  
## 22 3 30 25 3 1 1.00 46.89564 4  
## 24 5 80 25 3 1 0.75 44.33086 4  
## 33 5 85 25 3 1 0.88 52.07690 4  
## 34 3 90 25 3 1 0.25 53.37101 4  
## 39 6 60 100 3 1 1.00 36.52368 4  
## 41 3 40 25 2 1 1.50 39.24111 4  
## 51 2 90 25 3 1 1.00 59.64284 4  
## 54 3 45 100 3 1 1.00 41.50354 4  
## 62 2 30 25 1 1 1.13 41.99893 4  
## 63 3 35 25 1 1 1.00 40.56016 4  
## 68 3 55 25 1 1 1.00 53.13132 4  
## 70 3 35 100 3 1 1.00 38.83975 4  
## 72 3 110 100 3 1 1.00 46.65884 4  
## 73 3 60 25 3 1 0.75 39.10617 4  
## 75 3 115 25 1 1 0.67 49.78744 4  
## 76 3 110 25 1 1 1.00 51.59219 4

**#Mean ratings to determine the best cluster.**

mean(Clusthealthy[Clusthealthy$Cluster1==1,"rating"])

## [1] 73.84446

mean(Clusthealthy[Clusthealthy$Cluster1==2,"rating"])

## [1] 38.26161

mean(Clusthealthy[Clusthealthy$Cluster1==3,"rating"])

## [1] 28.84825

mean(Clusthealthy[Clusthealthy$Cluster1==4,"rating"])

## [1] 46.46513

**#Mean ratings of the cluster1 is the highest(i.e. 73.84446), Hence we can choose cluster 1.**