Assignment 5

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2022-12-01

#Importing required libraries and packages  
library(cluster)  
library(caret)

## Loading required package: ggplot2

## Loading required package: lattice

library(dendextend)

##   
## ---------------------  
## Welcome to dendextend version 1.16.0  
## Type citation('dendextend') for how to cite the package.  
##   
## Type browseVignettes(package = 'dendextend') for the package vignette.  
## The github page is: https://github.com/talgalili/dendextend/  
##   
## Suggestions and bug-reports can be submitted at: https://github.com/talgalili/dendextend/issues  
## You may ask questions at stackoverflow, use the r and dendextend tags:   
## https://stackoverflow.com/questions/tagged/dendextend  
##   
## To suppress this message use: suppressPackageStartupMessages(library(dendextend))  
## ---------------------

##   
## Attaching package: 'dendextend'

## The following object is masked from 'package:stats':  
##   
## cutree

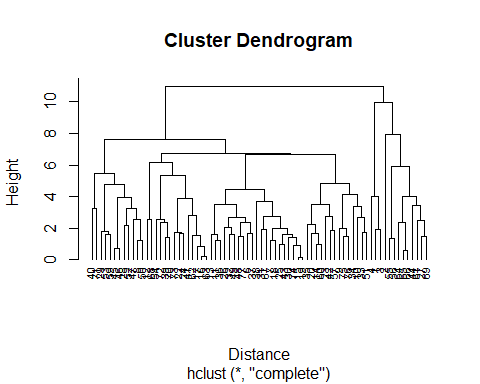
library(knitr)  
library(factoextra)

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

library(readr)

#Importing dataset and creating data set with only numeric data  
Cereals <- read.csv("C:/Users/RAJEEV VARMA/Downloads/Cereals.csv")  
Num\_data <- data.frame(Cereals[,4:16])  
  
#Omitting missing values from the data  
Num\_data <- na.omit(Num\_data)  
  
#Normalizing the data  
Cereals\_norm <- scale(Num\_data)

#Applying hierarchical clustering using Euclidean distance method.  
Distance <- dist(Cereals\_norm, method = "euclidean")  
Hier\_Clustering <- hclust(Distance, method = "complete")  
  
#Plotting of the dendogram.  
plot(Hier\_Clustering, cex = 0.7, hang = -1)



#Using Agnes function to perform clustering with single, complete, average and ward linkages  
  
Hier\_Clust\_single <- agnes(Cereals\_norm, method = "single")  
Hier\_Clust\_complete <- agnes(Cereals\_norm, method = "complete")  
Hier\_Clust\_average <- agnes(Cereals\_norm, method = "average")  
Hier\_Clust\_ward <- agnes(Cereals\_norm, method = "ward")  
  
print(Hier\_Clust\_single$ac)

## [1] 0.6067859

print(Hier\_Clust\_complete$ac)

## [1] 0.8353712

print(Hier\_Clust\_average$ac)

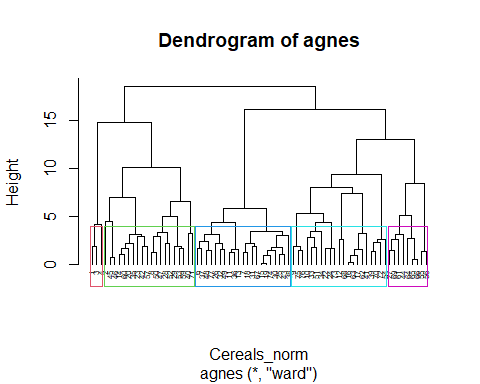
## [1] 0.7766075

print(Hier\_Clust\_ward$ac)

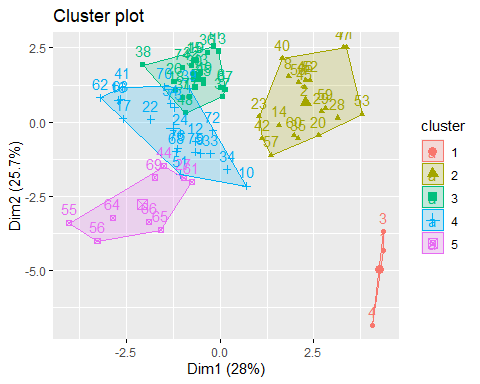
## [1] 0.9046042

#From the data it is shown that the ward method is best as it has the value of 0.9046042.

pltree(Hier\_Clust\_ward, cex = 0.5, hang = -1, main = "Dendrogram of agnes")  
rect.hclust(Hier\_Clust\_ward, k = 5, border = 2:7)



SubGrp <- cutree(Hier\_Clust\_ward, k=5)  
df <- as.data.frame(cbind(Cereals\_norm,SubGrp))  
fviz\_cluster(list(data = df, cluster = SubGrp))



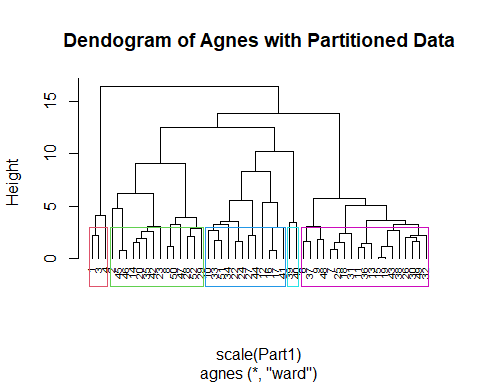
#From the above results, 5 clusters can be selected.

#Creating Partitions  
set.seed(123)  
Part1 <- Num\_data[1:50,]  
Part2 <- Num\_data[51:74,]

#Performing Hierarchial Clustering,consedering k = 5.  
AG\_single <- agnes(scale(Part1), method = "single")  
AG\_complete <- agnes(scale(Part1), method = "complete")  
AG\_average <- agnes(scale(Part1), method = "average")  
AG\_ward <- agnes(scale(Part1), 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")  
  
rect.hclust(AG\_ward, k = 5, border = 2:7)



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

#Calculating the centroids.  
Res <- as.data.frame(cbind(Part1, cut))  
Res[Res$cut==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  
## 1 0.33 68.40297 1  
## 3 0.33 59.42551 1  
## 4 0.50 93.70491 1

cent\_1 <- colMeans(Res[Res$cut==1,])  
Res[Res$cut==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 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

cent\_2 <- colMeans(Res[Res$cut==2,])  
Res[Res$cut==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  
## 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

cent\_3 <- colMeans(Res[Res$cut==3,])  
Res[Res$cut==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  
## 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

cent\_4 <- colMeans(Res[Res$cut==4,])  
centroids <- rbind(cent\_1, cent\_2, cent\_3, cent\_4)  
x2 <- as.data.frame(rbind(centroids[,-14], Part2))

#Calculating the Distance.  
  
Dist1 <- get\_dist(x2)  
Matrix1 <- as.matrix(Dist1)  
df1 <- data.frame(data=seq(1,nrow(Part2),1), Clusters = rep(0,nrow(Part2)))  
  
for(i in 1:nrow(Part2))   
 {df1[i,2] <- which.min(Matrix1[i+4, 1:4])}  
df1

## 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(df$SubGrp[51:74], df1$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(df$SubGrp[51:74] == df1$Clusters)

##   
## FALSE TRUE   
## 12 12

#From the above results, we are getting 12 False and 12 True. So, we can tell that the model is partially stable.

#Clustering Healthy Cereals.  
Healthy.Cereals <- Cereals  
Healthy.Cereals\_na <- na.omit(Healthy.Cereals)  
Clusthealthy <- cbind(Healthy.Cereals\_na, SubGrp)  
Clusthealthy[Clusthealthy$SubGrp==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 SubGrp  
## 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$SubGrp==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 SubGrp  
## 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$SubGrp==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 SubGrp  
## 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$SubGrp==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 SubGrp  
## 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$SubGrp==1,"rating"])

## [1] 73.84446

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

## [1] 38.26161

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

## [1] 28.84825

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

## [1] 46.46513

#From the above results, the cluster 1 can choose as it is the highest.  
#So, Cluster 1 can be considered as healthy cluster.