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

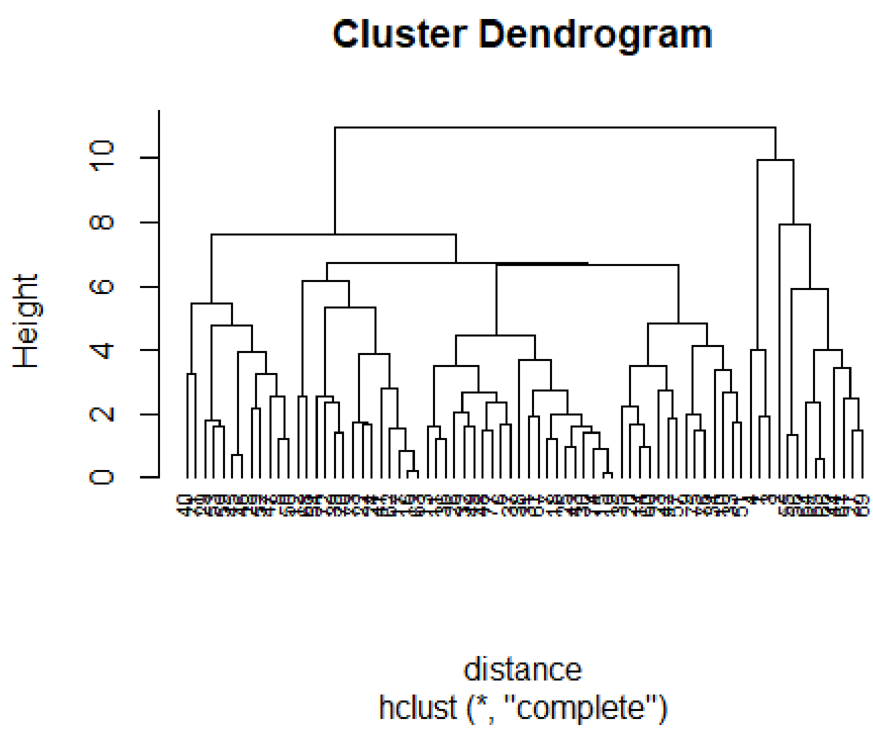
```
data_cereals_scaled <- scale(data_cereals)
```

#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

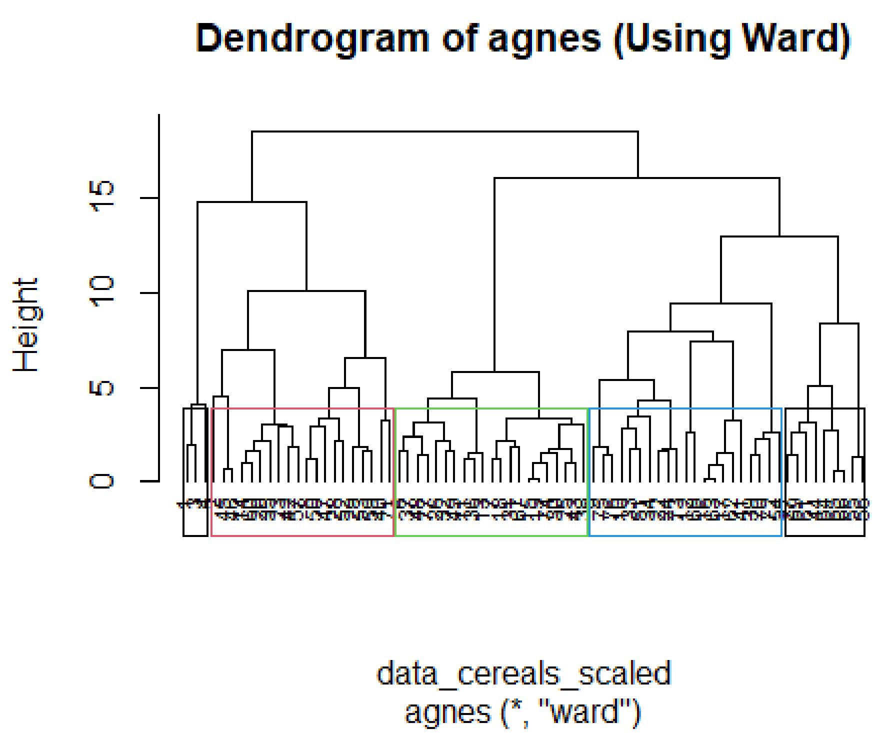
```
print(hier.clust_single$ac)

## [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.

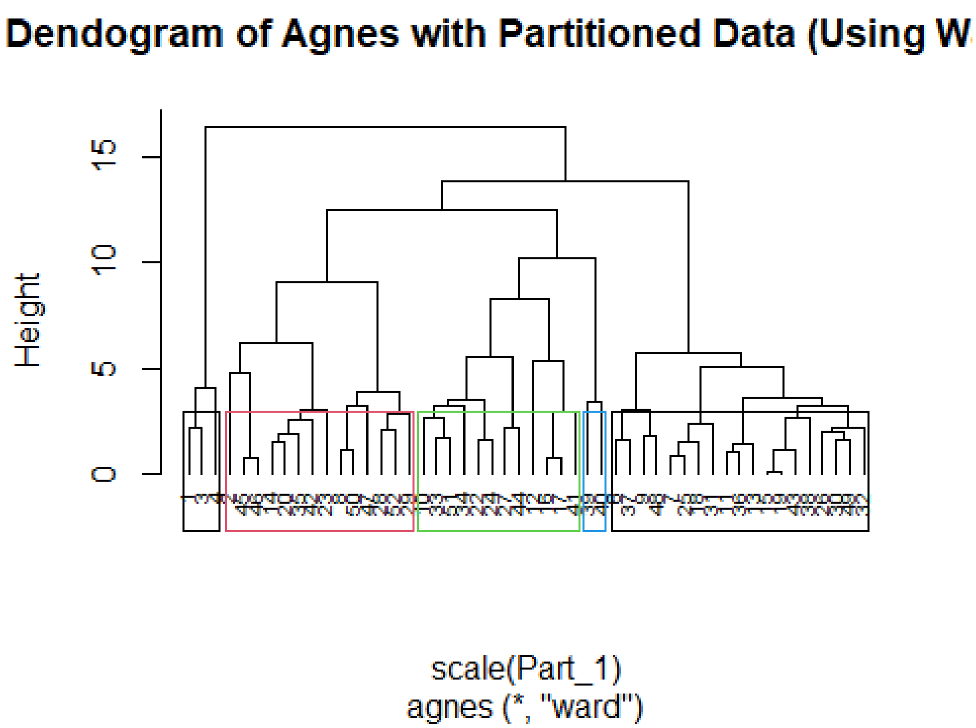
#Commenting on the structure of the clusters and on their stability

#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.