

Assignment5_Hierarchical Clustering

Ram

11/29/2021

Setting up working directory

```
setwd("C:/Users/ramne/Desktop/ML Assignment/Hierarchical Clustering")
set.seed(123)
```

Loading required libraries.

```
library(cluster)
library(caret)

## Loading required package: ggplot2
## Loading required package: lattice
library(dendextend)

##
## -----
## Welcome to dendextend version 1.15.2
## 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
```

Data Importing cereals dataset

```
library(readr)  
cereals<-read.csv("Cereals.csv")  
DataFrame <- data.frame(cereals[,4:16])
```

Data Pre-Processing

To remove any missing value that might be present in the data.

```
OmitMissing <- na.omit(DataFrame)
```

Data Normalization & Data Scaling:

Normalizing the Data using Scale function.

```
Normalise <- scale(OmitMissing)
```

Using the euclidean distance to measure the distance:

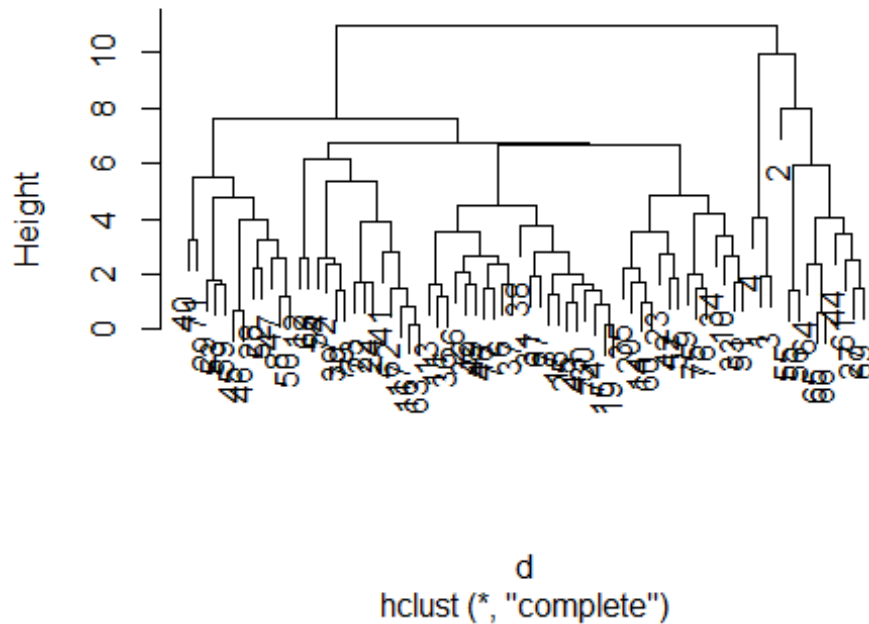
Computing the dissimilarity matrix values by using Dist and the method is Euclidean.

```
d <- dist(Normalise, method = "euclidean")
```

Perform Hierarchical Clustering using complete linkage.

```
HC <- hclust(d, method = "complete")  
plot(HC)
```

Cluster Dendrogram



Plotting the

dendrogram.

```
round(HC$height, 3)
```

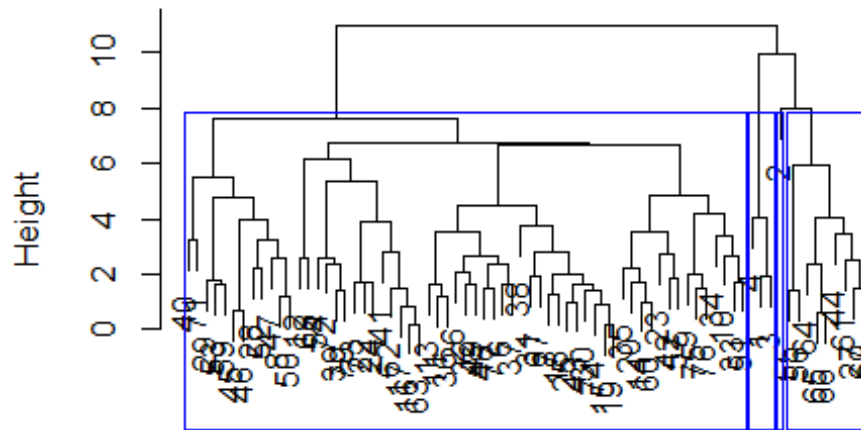
## [1]	0.143	0.196	0.575	0.698	0.828	0.904	1.003	1.004	1.201	1.203
## [11]	1.254	1.378	1.408	1.421	1.454	1.463	1.474	1.517	1.608	1.611
## [21]	1.616	1.625	1.650	1.687	1.692	1.720	1.730	1.795	1.839	1.897
## [31]	1.919	1.982	2.015	2.046	2.203	2.224	2.339	2.381	2.394	2.522
## [41]	2.563	2.574	2.579	2.668	2.682	2.734	2.776	2.787	3.229	3.236
## [51]	3.385	3.451	3.510	3.535	3.717	3.866	3.957	4.005	4.031	4.168
## [61]	4.456	4.779	4.839	5.342	5.488	5.920	6.169	6.669	6.731	7.650
## [71]	7.964	9.979	10.984							

Determining Optimal Clusters:

Highlighting the clusters directly in dendrogram

```
plot(HC)
rect.hclust(HC,
  k = 4, # k is used to specify the number of clusters
  border = "Blue"
)
```

Cluster Dendrogram



d
hclust (*, "complete")

We can also use `agnes()` function to perform clustering.

Performing clustering using `agnes()` with single, complete, average and ward.

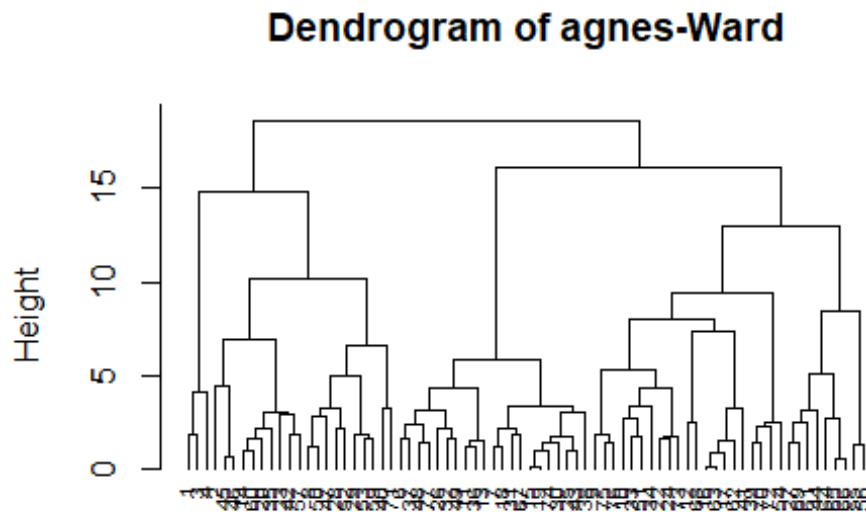
```
HCsingle <- agnes(Normalise, method = "single")
HCcomplete <- agnes(Normalise, method = "complete")
HCaverage <- agnes(Normalise, method = "average")
HCward <- agnes(Normalise, method = "ward")
```

Now we will compare the agglomerative coefficients for Single, complete, average and ward.

```
print(HCsingle$ac)
## [1] 0.6067859
print(HCcomplete$ac)
## [1] 0.8353712
print(HCaverage$ac)
## [1] 0.7766075
print(HCward$ac)
## [1] 0.9046042
```

The results say that the wards method is the best with the value of 0.904. Plotting the agnes using ward method and Cutting the Dendrogram. We will take $k = 4$ by observing the distance.

```
pltree(HCward, cex = 0.6, hang = -1, main = "Dendrogram of agnes-Ward")
```



Normalise
agnes (*, "ward")

Hierarchical clustering using ward method.

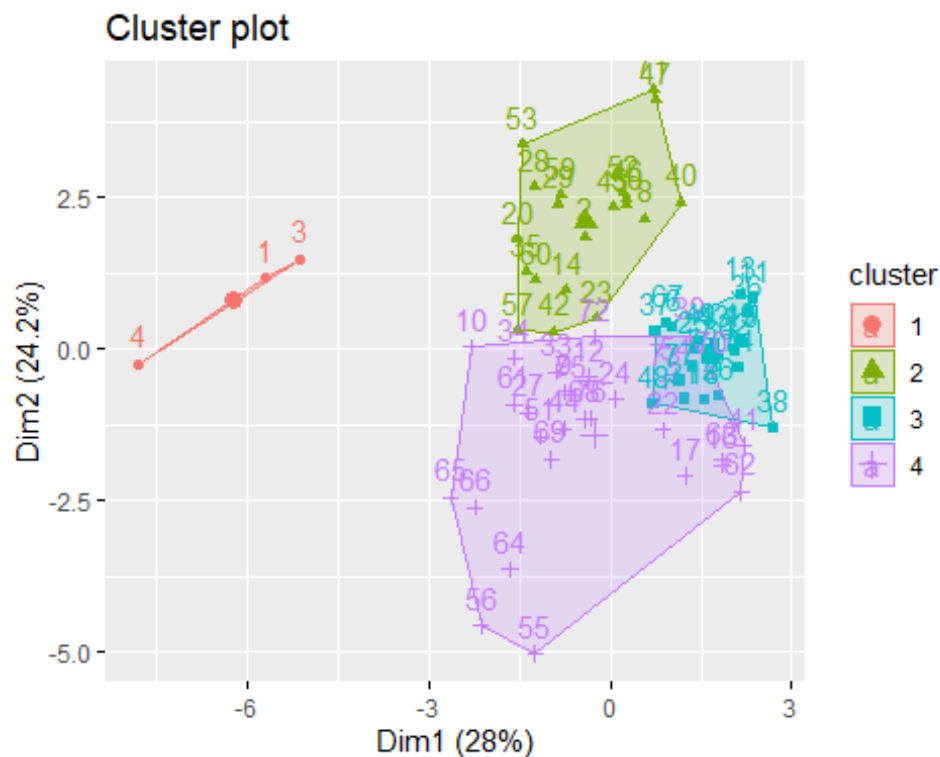
```
HC1 <- hclust(d, method = "ward.D2" )
subgrp <- cutree(HC1, k = 4)
table(subgrp)

## subgrp
##  1  2  3  4
##  3 20 21 30

dataframe <- as.data.frame(cbind(Normalise, subgrp))
```

To visualize the results in scatter plot.

```
fviz_cluster(list(data = Normalise, cluster = subgrp))
```



To check the structure of the clusters and on their stability.

We will partition the data and apply one part to the other part

```
Datapart1 <- OmitMissing[1:50,]
Datapart2 <- OmitMissing[51:74,]
```

Performing Hierarchical Clustering using `agnes()` with single, complete, average and ward with partitioned data, plotting dendrogram and then cutting the dendrogram by taking $k = 4$.

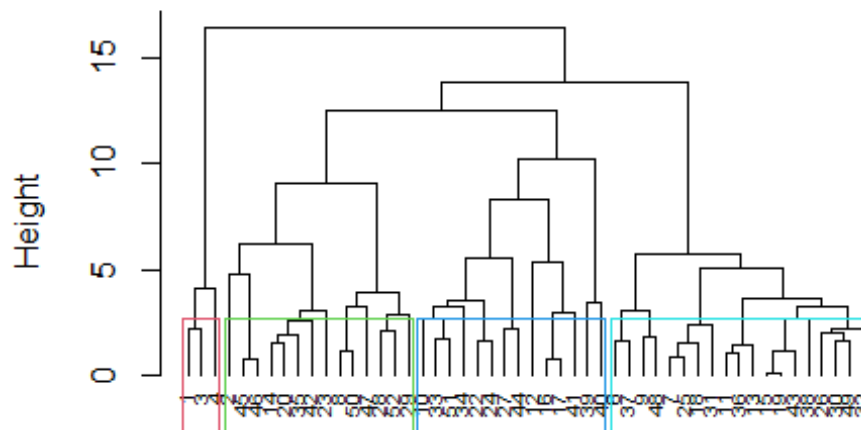
```
Award <- agnes(scale(Datapart1), method = "ward")
Aaverage <- agnes(scale(Datapart1), method = "average")
Acomplete <- agnes(scale(Datapart1), method = "complete")
Asingle <- agnes(scale(Datapart1), method = "single")
cbind(ward=Aaward$ac, average=Aaverage$ac, complete=Acomplete$ac,
      single=Asingle$ac)
```

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

Plot dendrogram for the partitioned data.

```
pltree(Aaward, cex = 0.6, hang = -1, main = "Dendrogram of Agnes-Ward")
rect.hclust(Aaward, k = 4, border = 2:5)
```

Dendrogram of Agnes-Ward



```
scale(Datapart1)
agnes (*, "ward")
```

Using Cutree to divide into groups cluster = 4.

```
c <- cutree(Award, k = 4)
print(c)

## 1  2  3  4  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 22 23 24 25 26 27
28
## 1  2  1  1  3  3  2  3  4  3  4  3  2  3  4  4  3  3  2  4  2  4  3  3  4
2
## 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52
## 2  3  3  3  4  4  2  3  3  3  4  4  4  2  3  4  2  2  2  3  3  2  4  2
```

Calculating centers to assess the consistency of data.

```
Assess <- as.data.frame(cbind(Datapart1,c))
Assess[Assess$c==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 c
## 1 0.33 68.40297 1
```

```
## 3 0.33 59.42551 1
## 4 0.50 93.70491 1

c1 <- colMeans(Assess[Assess$c==1,])
Assess[Assess$c==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 c
## 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

c2 <- colMeans(Assess[Assess$c==2,])
Assess[Assess$c==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 c
## 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
```

```
c3 <- colMeans(Assess[Assess$c==3,])
Assess[Assess$c==4,]
```

```
##      calories protein fat sodium fiber carbo sugars potass vitamins shelf
weight
## 10         90        3  0    210     5   13        5    190        25     3
1.0
## 12        110        6  2    290     2   17        1    105        25     1
1.0
## 16        110        2  0    280     0   22        3     25        25     1
1.0
## 17        100        2  0    290     1   21        2     35        25     1
1.0
## 22        110        2  0    220     1   21        3     30        25     3
1.0
## 24        100        2  0    190     1   18        5     80        25     3
1.0
## 27        100        3  0      0     3   14        7    100        25     2
1.0
## 33        100        3  1    140     3   15        5     85        25     3
1.0
## 34        110        3  0    170     3   17        3     90        25     3
1.0
## 39        110        2  1    170     1   17        6     60       100     3
1.0
## 40        140        3  1    170     2   20        9     95       100     3
1.3
## 41        110        2  1    260     0   21        3     40        25     2
1.0
## 44        100        4  1      0     0   16        3     95        25     2
1.0
## 51         90        3  0    170     3   18        2     90        25     3
1.0
```

```
## cups rating c
## 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
## 39 1.00 36.52368 4
## 40 0.75 36.47151 4
## 41 1.50 39.24111 4
## 44 1.00 54.85092 4
## 51 1.00 59.64284 4

c4 <- colMeans(Assess[Assess$c==4,])
```

Binding the 4 centers.

```
centers <- rbind(c1,c2,c3,c4)
centers

## calories protein fat sodium fiber carbo sugars
## c1 63.33333 4.000000 0.6666667 176.6667 11.0000000 6.666667 3.666667
## c2 125.71429 3.142857 2.2857143 146.7857 2.8928571 13.892857 8.857143
## c3 110.00000 1.526316 1.0000000 179.4737 0.7368421 12.736842 10.947368
## c4 105.71429 2.857143 0.5000000 182.8571 1.7857143 17.857143 4.071429
## potass vitamins shelf weight cups rating c
## c1 310.00000 25.00000 3.000000 1.000000 0.3866667 73.84446 1
## c2 139.64286 23.21429 2.928571 1.142143 0.6914286 38.13235 2
## c3 50.78947 25.00000 1.631579 1.000000 0.8842105 29.46119 3
## c4 80.00000 35.71429 2.357143 1.021429 0.9178571 48.08120 4
```

Calculating Distance and comparing the record in B with the closest centroid in A

```
d1 <- as.data.frame(rbind(centers[, -14], Datapart2))
d2 <- get_dist(d1)
matrix <- as.matrix(d2)
df1 <-
data.frame(data=seq(1,nrow(Datapart2),1),clusters=rep(0,nrow(Datapart2)))
for(i in 1:nrow(Datapart2)) {

  df1[i,2] <- which.min(matrix[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(dataframe$subgrp[51:74], df1$clusters)
```

```
##      [,1] [,2]
## [1,]    2    1
## [2,]    4    4
## [3,]    4    3
## [4,]    4    2
## [5,]    2    2
## [6,]    2    1
## [7,]    2    2
## [8,]    4    2
## [9,]    4    3
## [10,]   4    3
## [11,]   4    2
## [12,]   4    2
## [13,]   4    2
## [14,]   3    3
## [15,]   4    4
## [16,]   4    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(dataframe$subgrp[51:74] == df1$clusters)
```

```
##
## FALSE  TRUE
##    12    12
```

From above Results , 12 are True and 12 are False, so we can say the model may be stable.

Selecting the cluster that is best cereal for breakfast, which will have high protein, fiber and low in sugar, sodium.

Choosing the Cluster of Healthy Cereals.

```
newdata <- cereals
newdata_omit <- na.omit(newdata)
Clust <- cbind(newdata_omit, subgrp)
Clust[Clust$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
```

```
Clust[Clust$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

```

```

Clust[Clust$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
```

```
Clust[Clust$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
## 27             Frosted_Mini-Wheats  K  C     100      3  0      0      3
14
## 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
## 44             Maypo       A  H     100      4  1      0      0
16
## 51             Nutri-grain_Wheat  K  C      90      3  0    170      3
18
## 54             Product_19    K  C     100      3  0    320      1
20
## 55             Puffed_Rice    Q  C      50      1  0      0      0
```


13									
## 56		Puffed_Wheat	Q	C	50	2	0	0	1
10									
## 61		Raisin_Squares	K	C	90	2	0	0	2
15									
## 62		Rice_Chex	R	C	110	1	0	240	0
23									
## 63		Rice_Krispies	K	C	110	2	0	290	0
22									
## 64		Shredded_Wheat	N	C	80	2	0	0	3
16									
## 65		Shredded_Wheat_'n'Bran	N	C	90	3	0	0	4
19									
## 66		Shredded_Wheat_spoon_size	N	C	90	3	0	0	3
20									
## 68		Special_K	K	C	110	6	0	230	1
16									
## 69		Strawberry_Fruit_Wheats	N	C	90	2	0	15	3
15									
## 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	1.00	0.67	49.12025	4	
## 10	5	190	25	3	1.00	0.67	53.31381	4	
## 12	1	105	25	1	1.00	1.25	50.76500	4	
## 16	3	25	25	1	1.00	1.00	41.44502	4	
## 17	2	35	25	1	1.00	1.00	45.86332	4	
## 22	3	30	25	3	1.00	1.00	46.89564	4	
## 24	5	80	25	3	1.00	0.75	44.33086	4	
## 27	7	100	25	2	1.00	0.80	58.34514	4	
## 33	5	85	25	3	1.00	0.88	52.07690	4	
## 34	3	90	25	3	1.00	0.25	53.37101	4	
## 39	6	60	100	3	1.00	1.00	36.52368	4	
## 41	3	40	25	2	1.00	1.50	39.24111	4	
## 44	3	95	25	2	1.00	1.00	54.85092	4	
## 51	2	90	25	3	1.00	1.00	59.64284	4	
## 54	3	45	100	3	1.00	1.00	41.50354	4	
## 55	0	15	0	3	0.50	1.00	60.75611	4	
## 56	0	50	0	3	0.50	1.00	63.00565	4	
## 61	6	110	25	3	1.00	0.50	55.33314	4	
## 62	2	30	25	1	1.00	1.13	41.99893	4	
## 63	3	35	25	1	1.00	1.00	40.56016	4	

## 64	0	95	0	1	0.83	1.00	68.23588	4
## 65	0	140	0	1	1.00	0.67	74.47295	4
## 66	0	120	0	1	1.00	0.67	72.80179	4
## 68	3	55	25	1	1.00	1.00	53.13132	4
## 69	5	90	25	2	1.00	1.00	59.36399	4
## 70	3	35	100	3	1.00	1.00	38.83975	4
## 72	3	110	100	3	1.00	1.00	46.65884	4
## 73	3	60	25	3	1.00	0.75	39.10617	4
## 75	3	115	25	1	1.00	0.67	49.78744	4
## 76	3	110	25	1	1.00	1.00	51.59219	4

Calculating mean ratings to determine the best cluster.

```
mean(Clust[Clust$subgrp==1,"rating"])
## [1] 73.84446
mean(Clust[Clust$subgrp==2,"rating"])
## [1] 38.26161
mean(Clust[Clust$subgrp==3,"rating"])
## [1] 28.84825
mean(Clust[Clust$subgrp==4,"rating"])
## [1] 51.43111
```

As we can see that the mean ratings for the subgrp==1 is the highest(73.84), it's the best option to choose cluster 1 and the cereals in the cluster 1 for healthy diet.