

# ML\_Assignment\_5

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2022-04-18

```
#installing needed libraries
```

```
library(cluster)
```

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

```
library(caret)
```

```
## Loading required package: ggplot2
```

```
## Warning: package 'ggplot2' was built under R version 4.1.3
```

```
## Loading required package: lattice
```

```
library(dendextend)
```

```
## Warning: package 'dendextend' was built under R version 4.1.3
```

```
##
```

```
## -----
```

```
## 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)
```

```
## 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)
```

```
## Warning: package 'readr' was built under R version 4.1.3
```

```
#Importing dataset
```

```
Cereals<- read.csv("C:/Users/ravin/Downloads/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)
```

```
#normalize data
```

```
cereals_normalized <- scale(data_cereals)
```

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

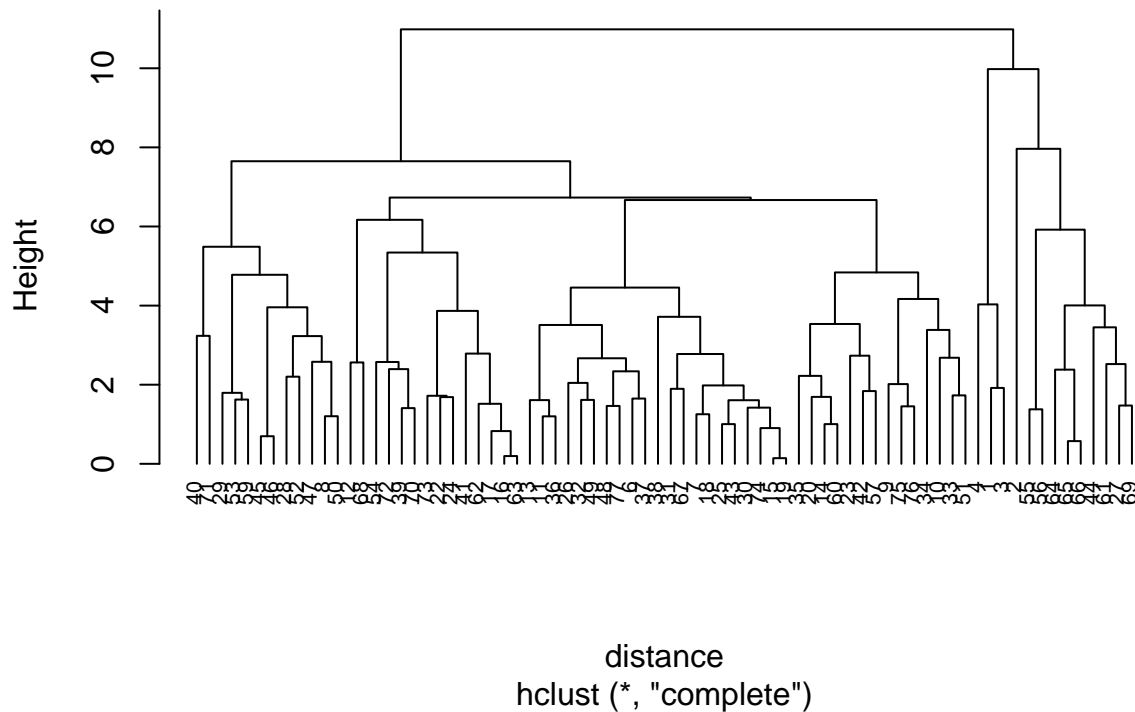
```
distance <- dist(data_cereals_scaled, method = "euclidean")
```

```
hier.clust_complete <- hclust(distance, method = "complete")
```

```
#Plotting the dendrogram
```

```
plot(hier.clust_complete, cex = 0.7, hang = -1)
```

## Cluster Dendrogram



*#Using agnes function to perform clustering with single linkage, complete linkage, average linkage and*

```
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
```

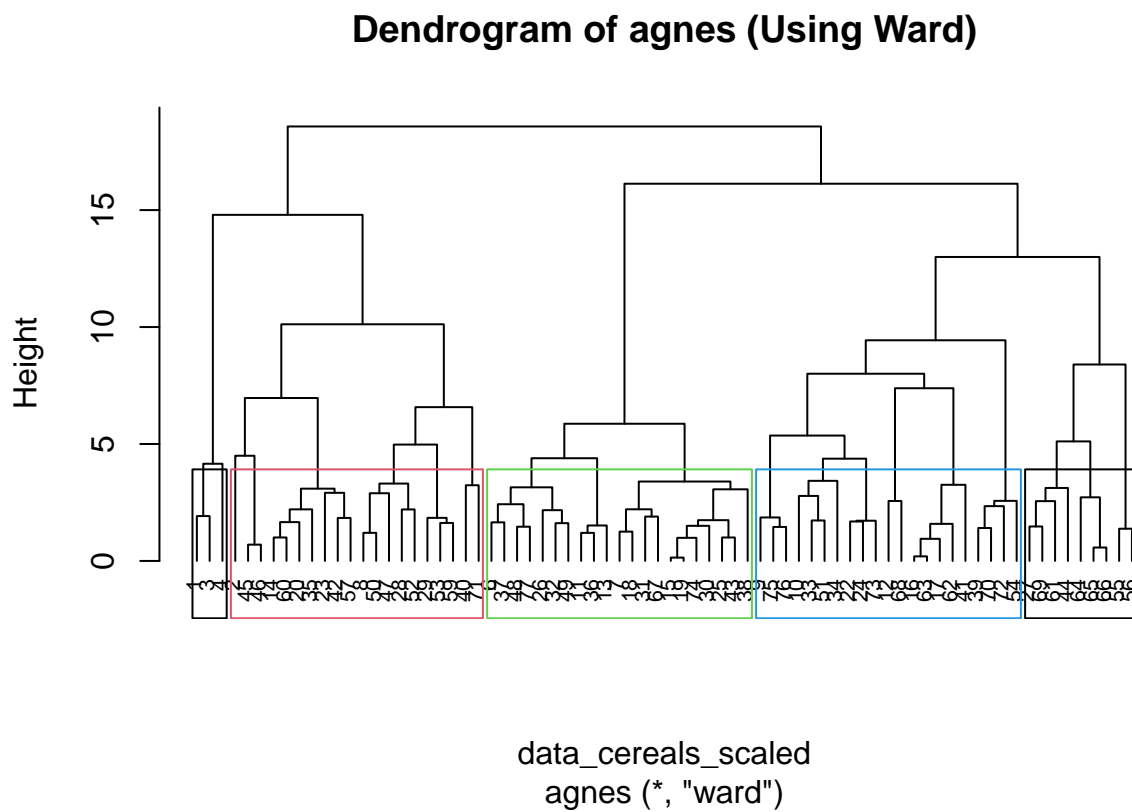
```
print(hier.clust_ward$ac)
```

```
## [1] 0.9046042
```

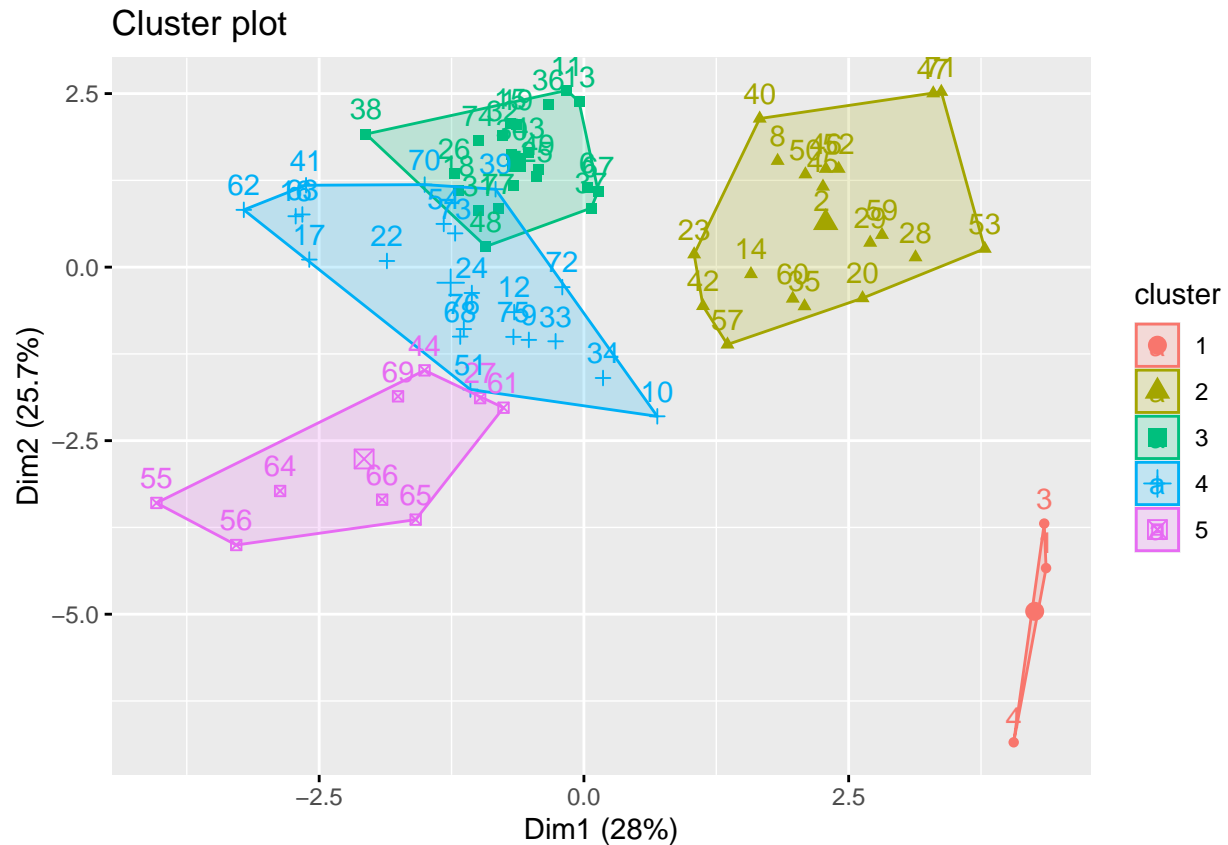
*#We will choose the WARD method because it has the highest value of 0.9046042.*

*#(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))  
  
fviz_cluster(list(data = dataframe2, cluster = 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,]

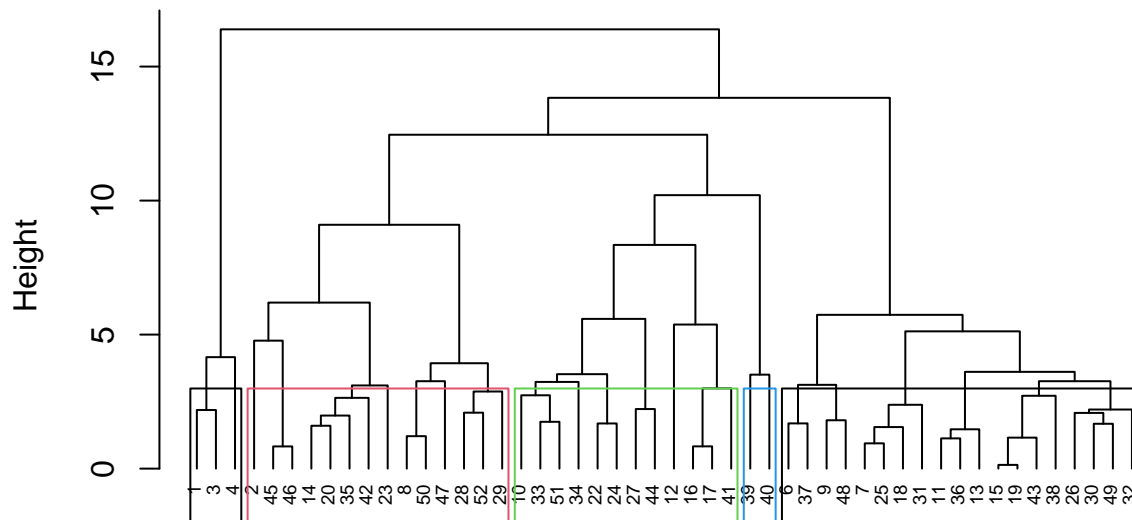
#Performing Hierarchical Clustering, considering k = 5.

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 = "Dendrogram of Agnes with Partitioned Data (Using Ward)")
rect.hclust(ag_ward, k = 5, border = 1:4)
```

## Dendrogram of Agnes with Partitioned Data (Using Ward)



scale(Part\_1)  
agnes (\*, "ward")

```
cut_2 <- cutree(ag_ward, k = 5)
```

*#Calculating the centroids.*

```
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 cafet*

*#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.*