

Assignment_5

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importing libraries

```
library(cluster)
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)
```

```
## 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)
```

importing the data set

```
Cereals <- read_csv("C:/Users/kramr/Downloads/Cereals.csv", col_types = cols(calories = col_number(), p
data_df <- data.frame(Cereals[,4:16])
```

processing the given data set and removing all the cereals with missing values. normalizing of the data is also done.

```
data_df <- na.omit(data_df)
data_df_scaled <- scale(data_df)
summary(data_df_scaled)
```

```
##      calories      protein      fat      sodium
##  Min.   :-2.8738  Min.   :-1.40687  Min.   :-0.9932  Min.   :-1.9616
##  1st Qu.: -0.3541  1st Qu.: -0.47733  1st Qu.: -0.9932  1st Qu.: -0.3306
##  Median :  0.1498  Median : -0.01256  Median :  0.0000  Median :  0.2131
##  Mean   :  0.0000  Mean   :  0.00000  Mean   :  0.0000  Mean   :  0.0000
##  3rd Qu.:  0.1498  3rd Qu.:  0.45221  3rd Qu.:  0.0000  3rd Qu.:  0.6661
##  Max.    :  2.6695  Max.    :  3.24083  Max.    :  3.9729  Max.    :  1.9045
##      fiber      carbo      sugars      potass
##  Min.   :-0.89778  Min.   :-2.50014  Min.   :-1.6306  Min.   :-1.1783
##  1st Qu.: -0.79462  1st Qu.: -0.70143  1st Qu.: -0.9424  1st Qu.: -0.8079
##  Median : -0.07249  Median : -0.05903  Median : -0.0248  Median : -0.1201
##  Mean   :  0.00000  Mean   :  0.00000  Mean   :  0.0000  Mean   :  0.0000
##  3rd Qu.:  0.34015  3rd Qu.:  0.58337  3rd Qu.:  0.8928  3rd Qu.:  0.3031
##  Max.    :  4.87925  Max.    :  2.12512  Max.    :  1.8104  Max.    :  3.2660
##      vitamins      shelf      weight      cups
##  Min.   :-1.3032  Min.   :-1.4617  Min.   :-3.4600  Min.   :-2.4251
##  1st Qu.: -0.1818  1st Qu.: -1.1612  1st Qu.: -0.2008  1st Qu.: -0.6432
##  Median : -0.1818  Median : -0.2599  Median : -0.2008  Median : -0.3038
##  Mean   :  0.0000  Mean   :  0.0000  Mean   :  0.0000  Mean   :  0.0000
##  3rd Qu.: -0.1818  3rd Qu.:  0.9420  3rd Qu.: -0.2008  3rd Qu.:  0.7568
##  Max.    :  3.1822  Max.    :  0.9420  Max.    :  3.0583  Max.    :  2.8780
##      rating
##  Min.   :-1.7336
##  1st Qu.: -0.7071
##  Median : -0.1510
##  Mean   :  0.0000
##  3rd Qu.:  0.5807
##  Max.    :  3.6578
```

now we are going to calculate the dissimilarity matrix and after that we are going to perform Hierarchical Clustering using hclust().

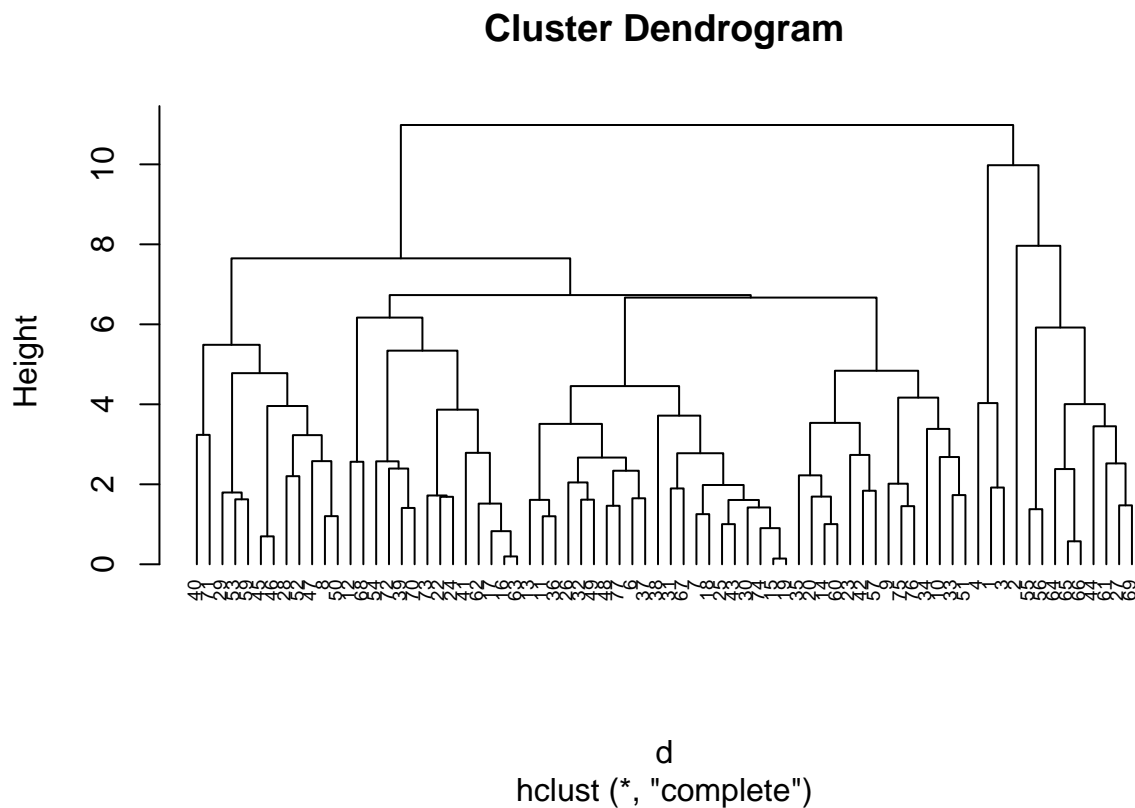
```
d <- dist(data_df_scaled, method = "euclidean")
```

Perform Hierarchical Clustering using complete linkage

```
hc1_complete <- hclust(d, method = "complete")
```

plotting dendrogram

```
plot(hc1_complete, cex = 0.6, hang = -1)
```



Clustering can also be done with the `agnes()` method. The sole contrast between `agnes()` and `hclust()` is that `agnes` includes an agglomerative coefficient. This coefficient shows if the clustering structure is robust or weak.

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

```
hc_single <- agnes(data_df_scaled, method = "single")
hc_complete <- agnes(data_df_scaled, method = "complete")
hc_average <- agnes(data_df_scaled, method = "average")
hc_ward <- agnes(data_df_scaled, method = "ward")
```

In Hierarchical clustering we have ward.D and ward.D2. The only difference between ward.D & ward.D2 is the input parameter. The Ward2 criterion values are “on a scale of distances” whereas the Ward1 criterion values are “on a scale of distances squared. Now we will compare the agglomerative coefficients

For Single

```
print(hc_single$ac)
```

```
## [1] 0.6067859
```

For complete

```
print(hc_complete$ac)
```

```
## [1] 0.8353712
```

For average

```
print(hc_average$ac)
```

```
## [1] 0.7766075
```

For Ward

```
print(hc_ward$ac)
```

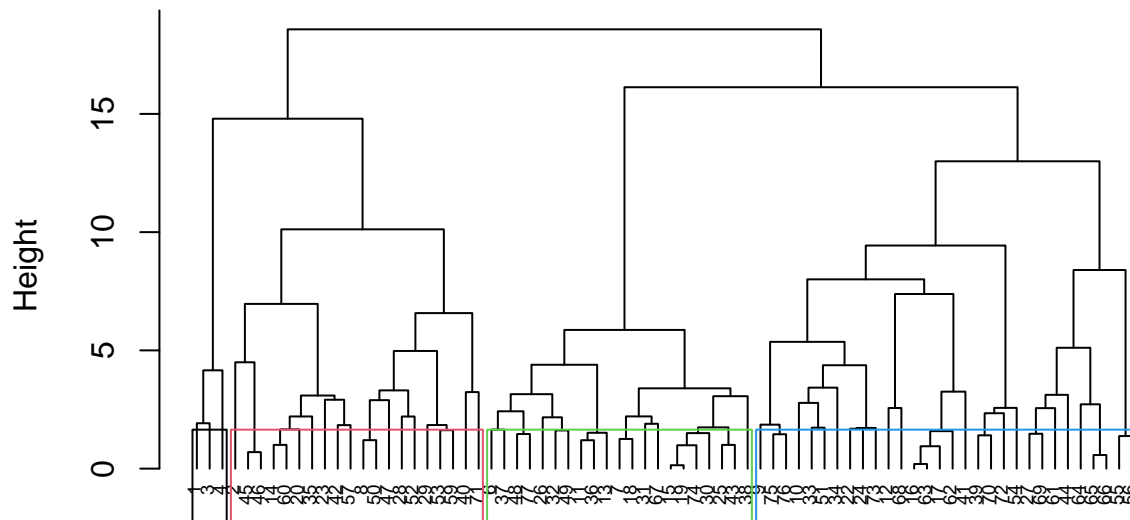
```
## [1] 0.9046042
```

results indicate that wards is the best method with 0.904

now we are going to plot agnes with wards method and cut the dendrogram. we are going to take k=4, keeping distance in mind.

```
pltree(hc_ward, cex = 0.6, hang = -1, main = "Dendrogram of agnes (Using Ward)")  
rect.hclust(hc_ward, k = 4, border = 1:4)
```

Dendrogram of agnes (Using Ward)



data_df_scaled
agnes (*, "ward")

```
cluster1 <- cutree(hc_ward, k=4)
df2 <- as.data.frame(cbind(data_df_scaled, cluster1))
```

creating partition

```
part_1 <- data_df[1:55,]
part_2 <- data_df[56:74,]
```

now we are going to Performing Hierarchical Clustering, plotting dendrogram and then cutting the dendrogram by taking $k = 4$.

```
agnes_ward <- agnes(scale(part_1), method = "ward")
agnes_average <- agnes(scale(part_1), method = "average")
agnes_complete <- agnes(scale(part_1), method = "complete")
agnes_single <- agnes(scale(part_1), method = "single")

cbind(ward=agnes_ward$ac, average=agnes_average$ac, complete=agnes_complete$ac,
      single=agnes_single$ac)
```

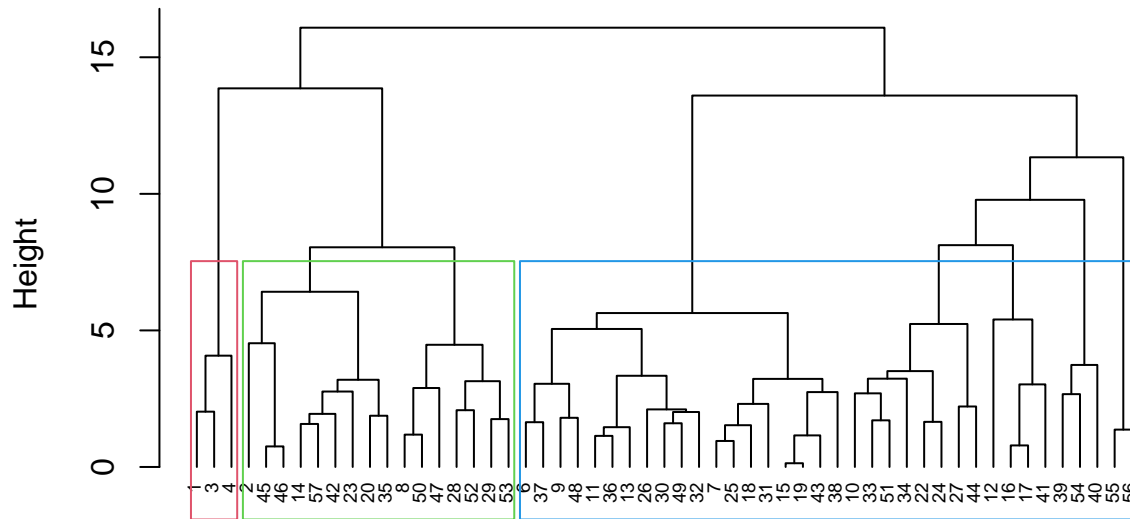
```
##           ward  average complete  single
## [1,] 0.8808195 0.7449303 0.8120228 0.6564842
```

```

pltree(agnes_ward, cex = 0.6, hang = -1, main = "Dendrogram of Agnes with Partitioned Data (Using Ward)".
rect.hclust(agnes_ward, k = 3, border = 2:5)

```

Dendrogram of Agnes with Partitioned Data (Using Ward)



```

scale(part_1)
agnes (*, "ward")

```

```

cut_2 <- cutree(agnes_ward, k = 4)

```

in the following step we are going to calculate centers.

```

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

```

```

center1 <- 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
## 53	120	3	1	200	6.0	11.0	14	260	25	3	1.33
## 57	100	4	1	135	2.0	14.0	6	110	25	3	1.00
##	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	34.13977	2								
## 47	0.67	30.31335	2								
## 50	0.67	40.69232	2								
## 52	0.50	30.45084	2								
## 53	0.67	37.84059	2								
## 57	0.50	49.51187	2								

```
center2 <- 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 26.73452      3
## 48 1.00 40.10597      3
## 49 0.67 29.92429      3
```

```
center3 <- 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     1.0
## 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
## 54     100      3  0    320     1    20      3     45     100     3     1.0
## 55      50      1  0      0     0    13      0     15       0     3     0.5
## 56      50      2  0      0     1    10      0     50       0     3     0.5
##      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
## 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
## 54 1.00 41.50354      4
## 55 1.00 60.75611      4
## 56 1.00 63.00565      4
```

```
center4 <- colMeans(result[result$cut_2==4,])

centers <- rbind(center1, center2, center3, center4)

x2 <- as.data.frame(rbind(centers[, -14], part_2))
```

in the following step we are going to calculate distance.

```
d1 <- get_dist(x2)

mat1 <- as.matrix(d1)

df1 <- data.frame(data=seq(1,nrow(part_2),1), clusters = rep(0,nrow(part_2)))

for(i in 1:nrow(part_2)) {
  df1[i,2] <- which.min(mat1[i+4, 1:4])
}
df1
```

```
##      data clusters
## 1      1         1
## 2      2         2
## 3      3         2
## 4      4         3
## 5      5         3
## 6      6         2
## 7      7         2
## 8      8         2
## 9      9         4
## 10     10        3
## 11     11        2
## 12     12        3
## 13     13        2
## 14     14        4
## 15     15        3
## 16     16        3
## 17     17        4
## 18     18        4
## 19     19        3
```

```
cbind(df2$cluster1[56:74], df1$clusters)
```

```
##      [,1] [,2]
## [1,]    2    1
## [2,]    2    2
## [3,]    4    2
## [4,]    4    3
## [5,]    4    3
## [6,]    4    2
## [7,]    4    2
## [8,]    4    2
## [9,]    3    4
## [10,]   4    3
## [11,]   4    2
## [12,]   4    3
## [13,]    2    2
## [14,]   4    4
## [15,]   4    3
## [16,]    3    3
## [17,]   4    4
## [18,]   4    4
## [19,]    3    3
```

```
table(df2$cluster1[56:74] == df1$clusters)
```

```
##
## FALSE  TRUE
##     12     7
```

now we can conclude that this model is not stable as 12 out of 19 are false.

now we are going to cluster of healthy cereals.

```
new_data <- Cereals
new_data_na <- na.omit(new_data)

Clust <- cbind(new_data_na, cluster1)

Clust[Clust$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
```

```
Clust[Clust$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	34.13977	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$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	26.73452	3	
## 48	6	90	25	1	1	1.00	40.10597	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$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
## 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	cluster1	
## 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	

now we are going to calculate mean rating so that we can find out the best cereal.

```
mean(Clust[Clust$cluster1==1,"rating"])
```

```
## [1] 73.84446
```

```
mean(Clust[Clust$cluster1==2,"rating"])
```

```
## [1] 38.26161
```

```
mean(Clust[Clust$cluster1==3,"rating"])
```

```
## [1] 28.84825
```

```
mean(Clust[Clust$cluster1==4,"rating"])
```

```
## [1] 51.43111
```

from the above readings we can conclude that cluster 1 is the best cereal as it has highest rating.