

FML Assignment 5

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Loading relevant libraries

```
library(cluster)
library(caret)
```

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

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

```
library(dendextend)
```

```
##
## -----
## Welcome to dendextend version 1.17.1
## 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)
```

Creating a dataset that includes numbers and omitting all the NA values in the dataset. This is stored in `cereals.df`. The function `scale()` is used to normalize the data. Euclidean distance is used to apply hierarchical clustering and is stored in `distance_eu`. Plotting the dendrogram using the `plot()` function.

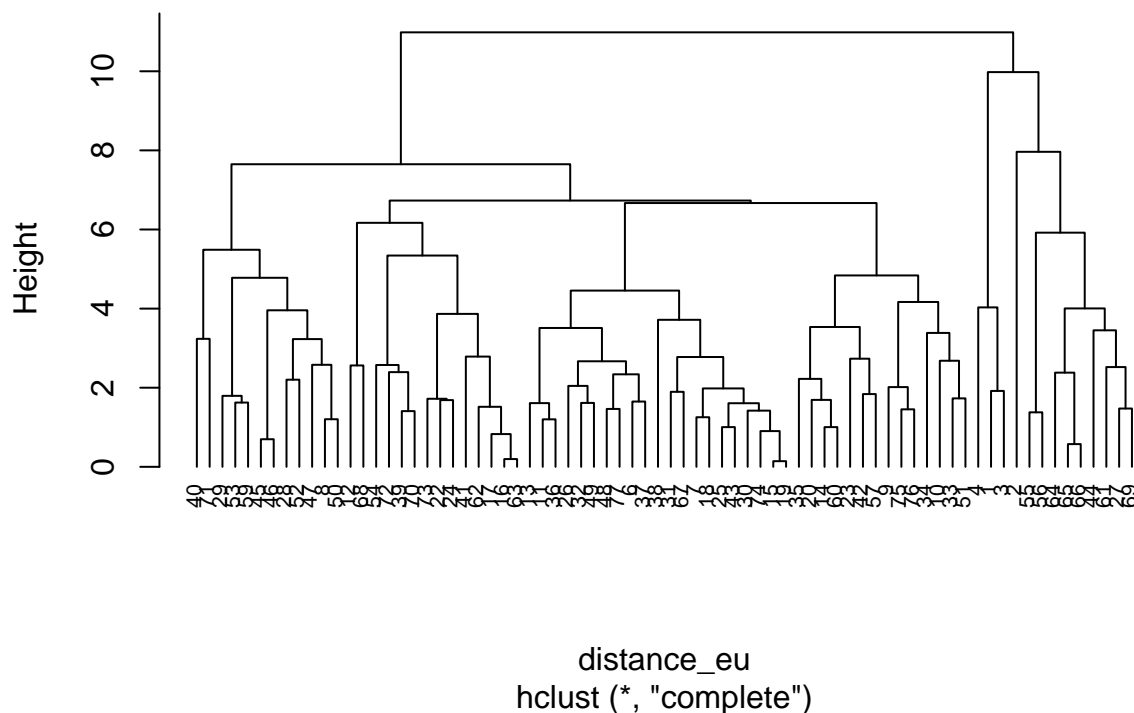
```
library(readr)
```

```
Cereals <- read_csv("~/Downloads/Cereals.csv")
```

```
## Rows: 77 Columns: 16
## -- Column specification -----
## Delimiter: ","
## chr (3): name, mfr, type
## dbl (13): calories, protein, fat, sodium, fiber, carbo, sugars, potass, vita...
##
## i Use 'spec()' to retrieve the full column specification for this data.
## i Specify the column types or set 'show_col_types = FALSE' to quiet this message.
```

```
cereals.df <- data.frame(Cereals[,4:16])
cereals.df <- na.omit(cereals.df)
cereals.df_scaled <- scale(cereals.df)
distance_eu <- dist(cereals.df_scaled, method = "euclidean")
hierarchical_complete <- hclust(distance_eu, method = "complete")
plot(hierarchical_complete, cex = 0.7, hang = -1)
```

Cluster Dendrogram



`agnes()` function is used to implement clustering with single, complete, average and ward linkage. The single linkage is printed using the `print()` function.

```
hierarchial_single <- agnes(cereals.df_scaled, method = "single")
hierarchial_complete <- agnes(cereals.df_scaled, method = "complete")
hierarchial_avg <- agnes(cereals.df_scaled, method = "average")
hierarchial_ward <- agnes(cereals.df_scaled, method = "ward")
print(hierarchial_single$ac)
```

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

Complete linkage is printed below.

```
print(hierarchial_complete$ac)
```

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

Average linkage is printed below.

```
print(hierarchial_avg$ac)
```

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

Ward hierarchial linkage is printed below. The ward method is chosen given the fact that it has the highest value of 0.9046042 in comparison to other linkages.

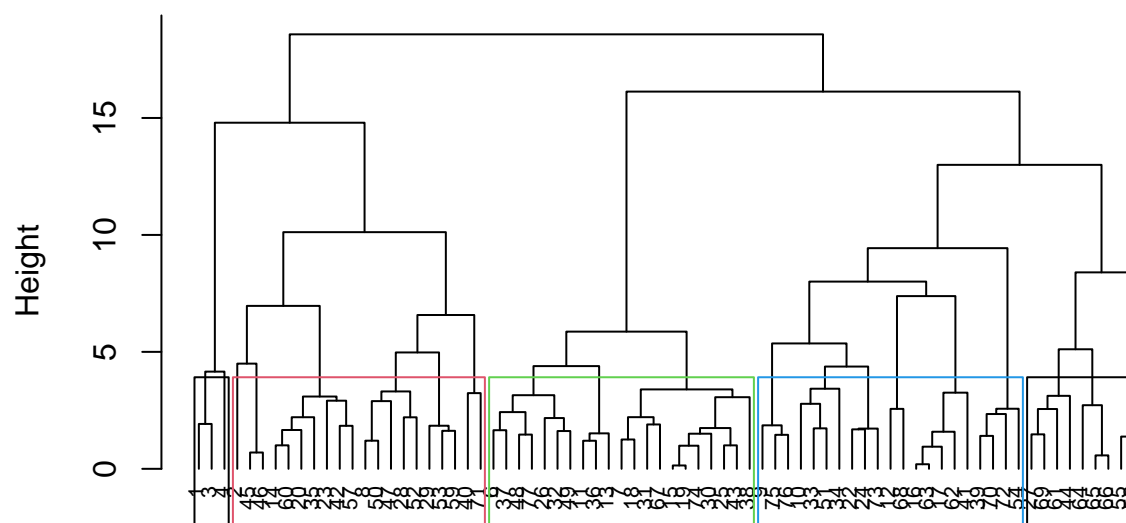
```
print(hierarchial_ward$ac)
```

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

The `pltree()` and the `rect.hclust()` function is used to represent the dendrogram of agnes using the ward linkage.

```
pltree(hierarchial_ward, cex = 0.7, hang = -1, main = "Dendrogram of agnes Using Ward")
rect.hclust(hierarchial_ward, k = 5, border = 1:4)
```

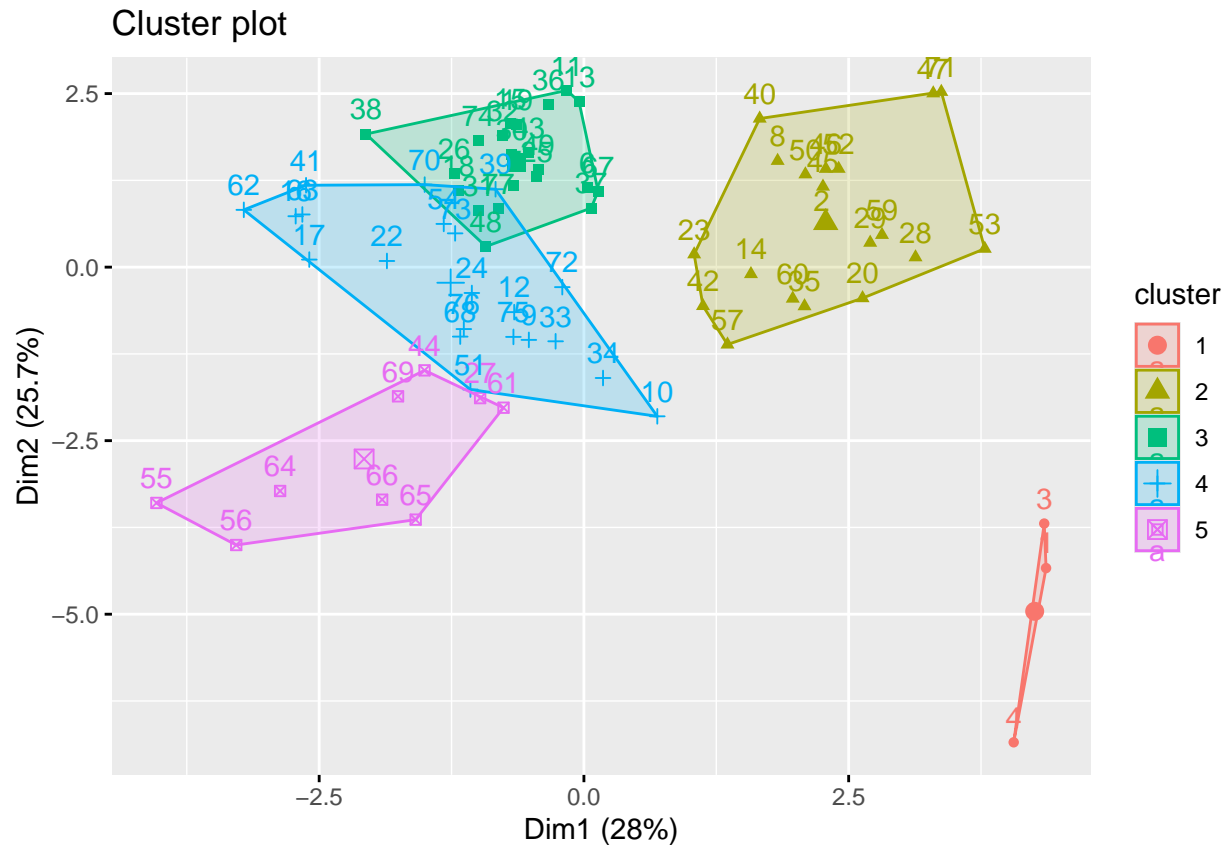
Dendrogram of agnes Using Ward



cereals.df_scaled
agnes (*, "ward")

The `fviz_cluster()` function is used to form clusters as represented below.

```
Cluster_1 <- cutree(hierarchial_ward, k=5)
df_2 <- as.data.frame(cbind(cereals.df_scaled,Cluster_1))
fviz_cluster(list(data = df_2 , cluster = Cluster_1))
```



Five clusters are chosen after observing the distance. Creating partitions and determining the stability and structure of the clusters. By considering $k=5$, hierarchical clustering is performed.

```
set.seed(123)
Partition_1 <- cereals.df[1:50,]
Partition_2 <- cereals.df[51:74,]
single_agnes <- agnes(scale(Partition_1), method = "single")
single_agnes
```

```
## Call:      agnes(x = scale(Partition_1), method = "single")
## Agglomerative coefficient:  0.6393338
## Order of objects:
## [1] 1  3  4  6  37 7  25 15 19 43 18 30 11 36 13 49 32 26 31 9  48 38 14 20 35
## [26] 42 23 22 24 33 51 10 16 17 34 41 8  50 52 28 29 27 44 47 45 46 2  12 39 40
## Height (summary):
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.1395  1.5998   1.9818   2.1040  2.5164   5.0678
##
## Available components:
## [1] "order"      "height"     "ac"         "merge"      "diss"       "call"
## [7] "method"     "order.lab"  "data"
```

```
Complete_agnes <- agnes(scale(Partition_1), method = "complete")
Complete_agnes
```

```
## Call:      agnes(x = scale(Partition_1), method = "complete")
```

```
## Agglomerative coefficient: 0.8138238
## Order of objects:
## [1] 1 3 4 2 14 20 35 42 45 46 6 37 26 32 49 11 36 13 7 25 18 15 19 43 30
## [26] 23 9 48 31 38 8 50 47 28 52 29 10 33 51 34 27 44 12 16 17 41 22 24 39 40
## Height (summary):
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 0.1395 1.6874 2.7335 3.2009 4.1021 10.8673
##
## Available components:
## [1] "order" "height" "ac" "merge" "diss" "call"
## [7] "method" "order.lab" "data"
```

```
Avg_agnes <- agnes(scale(Partition_1), method = "average")
Avg_agnes
```

```
## Call: agnes(x = scale(Partition_1), method = "average")
## Agglomerative coefficient: 0.7408904
## Order of objects:
## [1] 1 3 4 2 6 37 9 48 7 25 18 15 19 43 30 26 11 36 13 32 49 38 31 10 34
## [26] 22 24 33 51 14 20 35 42 23 27 44 8 50 28 52 29 47 45 46 12 16 17 41 39 40
## Height (summary):
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 0.1395 1.6874 2.3623 2.6778 3.2878 7.7084
##
## Available components:
## [1] "order" "height" "ac" "merge" "diss" "call"
## [7] "method" "order.lab" "data"
```

```
Ward_agnes <- agnes(scale(Partition_1), method = "ward")
Ward_agnes
```

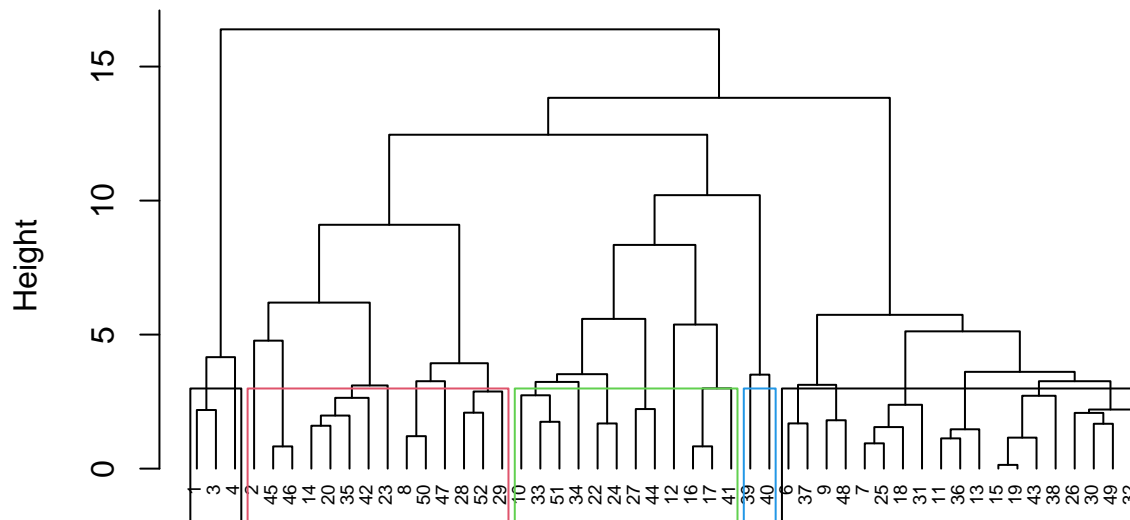
```
## Call: agnes(x = scale(Partition_1), method = "ward")
## Agglomerative coefficient: 0.8764323
## Order of objects:
## [1] 1 3 4 2 45 46 14 20 35 42 23 8 50 47 28 52 29 10 33 51 34 22 24 27 44
## [26] 12 16 17 41 39 40 6 37 9 48 7 25 18 31 11 36 13 15 19 43 38 26 30 49 32
## Height (summary):
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 0.1395 1.6874 2.7356 3.8040 4.1584 16.3888
##
## Available components:
## [1] "order" "height" "ac" "merge" "diss" "call"
## [7] "method" "order.lab" "data"
```

```
cbind(single=single_agnes$ac , complete=Complete_agnes$ac , average= Avg_agnes$ac , ward= Ward_agnes$ac)
```

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

```
pltree(Ward_agnes, cex = 0.6, hang = -1, main = "Dendrogram of Agnes with Partitioned Data (Using Ward)"
rect.hclust(Ward_agnes, k = 5, border = 1:4)
```

Dendrogram of Agnes with Partitioned Data (Using Ward)



```
scale(Partition_1)
agnes (*, "ward")
```

The centroids are calculated as seen below.

```
cutree_2 <- cutree(Ward_agnes, k = 5)
result <- as.data.frame(cbind(Partition_1, cutree_2))
result[result$cutree_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 cutree_2
## 1 0.33 68.40297         1
## 3 0.33 59.42551         1
## 4 0.50 93.70491         1
```

centroid.1 stores the centroid 1.

```
centroid.1 <- colMeans(result[result$cutree_2==1,])
result[result$cutree_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 cutree_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.2stores the centroid 2.

```
centroid.2 <- colMeans(result[result$cutree_2==2,])
result[result$cutree_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 cutree_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 stores the centroid 3.

```
centroid.3 <- colMeans(result[result$cutree_2==3,])
result[result$cutree_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 cutree_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 stores the centroid 4.

```
centroid.4 <- colMeans(result[result$cutree_2==4,])
all_centroids <- rbind(centroid.1, centroid.2, centroid.3, centroid.4)
all_centroids
```

```
##           calories protein      fat  sodium      fiber      carbo      sugars
## centroid.1  63.33333 4.000000 0.6666667 176.6667 11.0000000  6.666667  3.666667
## centroid.2 125.71429 3.142857 2.2857143 146.7857  2.8928571 13.892857  8.857143
## centroid.3 110.00000 1.526316 1.0000000 179.4737  0.7368421 12.736842 10.947368
## centroid.4 102.50000 2.916667 0.4166667 185.0000  1.8333333 17.750000  3.500000
##           potass vitamins  shelf  weight      cups  rating cutree_2
## centroid.1 310.00000 25.00000 3.000000 1.000000 0.3866667 73.84446      1
## centroid.2 139.64286 23.21429 2.928571 1.142143 0.6914286 38.13235      2
## centroid.3  50.78947 25.00000 1.631579 1.000000 0.8842105 29.46119      3
## centroid.4  80.41667 25.00000 2.250000 1.000000 0.9250000 50.01180      4
```

The distance is calculated and stored in Distance_1.

```
z <- as.data.frame(rbind(all_centroids[, -14], Partition_2))
Distance_1 <- get_dist(z)
Matrix.1 <- as.matrix(Distance_1)
dataf_1 <- data.frame(data=seq(1,nrow(Partition_2),1), Clusters = rep(0,nrow(Partition_2)))
for(i in 1:nrow(Partition_2))
{dataf_1[i,2] <- which.min(Matrix.1[i+4, 1:4])}
dataf_1
```

```
##    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_2$Cluster_1[51:74], dataf_1$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_2$Cluster_1[51:74] == dataf_1$Clusters)
```

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

The data is partially stable as there are 12 TRUE and FALSE in count respectively.

#Since we are getting 12 FALSE and 12 TRUE, we can conclude that the model is partially stable by looking at the counts.

```
Health.Cereals <- Cereals
Health.Cereals_na <- na.omit(Health.Cereals)
Healthy.Cluster <- cbind(Health.Cereals_na, Cluster_1)
Healthy.Cluster[Healthy.Cluster$Cluster_1==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 Cluster_1
## 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
```

```
Healthy.Cluster[Healthy.Cluster$Cluster_1==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	Cluster_1
## 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

```
Healthy.Cluster[Healthy.Cluster$Cluster_1==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	Cluster_1	
## 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	

```
Healthy.Cluster[Healthy.Cluster$Cluster_1==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 Cluster_1
## 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(Healthy.Cluster[Healthy.Cluster$Cluster_1==1,"rating"])
```

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

```
mean(Healthy.Cluster[Healthy.Cluster$Cluster_1==2,"rating"])
```

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

```
mean(Healthy.Cluster[Healthy.Cluster$Cluster_1==3,"rating"])
```

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

The mean of `Cluster_1` is 73.84446 which is the highest. Hence `Cluster_1` is chosen for a healthier cereal to the menu. With respect to this dataset, normalization of numerical measurements is performed using the `scale()` function. This is due to the fact that Euclidean distance is used and this parameter calculates the distance. This is highly scale dependent, sensitive to outliers and change in units of one variable have high influence on the results.

```
mean(Healthy.Cluster[Healthy.Cluster$Cluster_1==4,"rating"])
```

```
## [1] 46.46513
```