

Assignment_V

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```
library(readr)
cereals <- read_csv("D:/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.
```

```
Data_numerical <- data.frame(cereals[,4:16])
```

Libraries

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

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

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

```
library(dendextend)
```

```
## Warning: package 'dendextend' was built under R version 4.2.2
```

```
##
## -----
## Welcome to dendextend version 1.16.0
## 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(factoextra)
```

```
## Warning: package 'factoextra' was built under R version 4.2.2
```

```
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
```

Remove all cereals with missing values.

Removing missing values in present data.

```
missingvalues_removed <- na.omit(Data_numerical)
```

Data Normalization & Data Scaling:

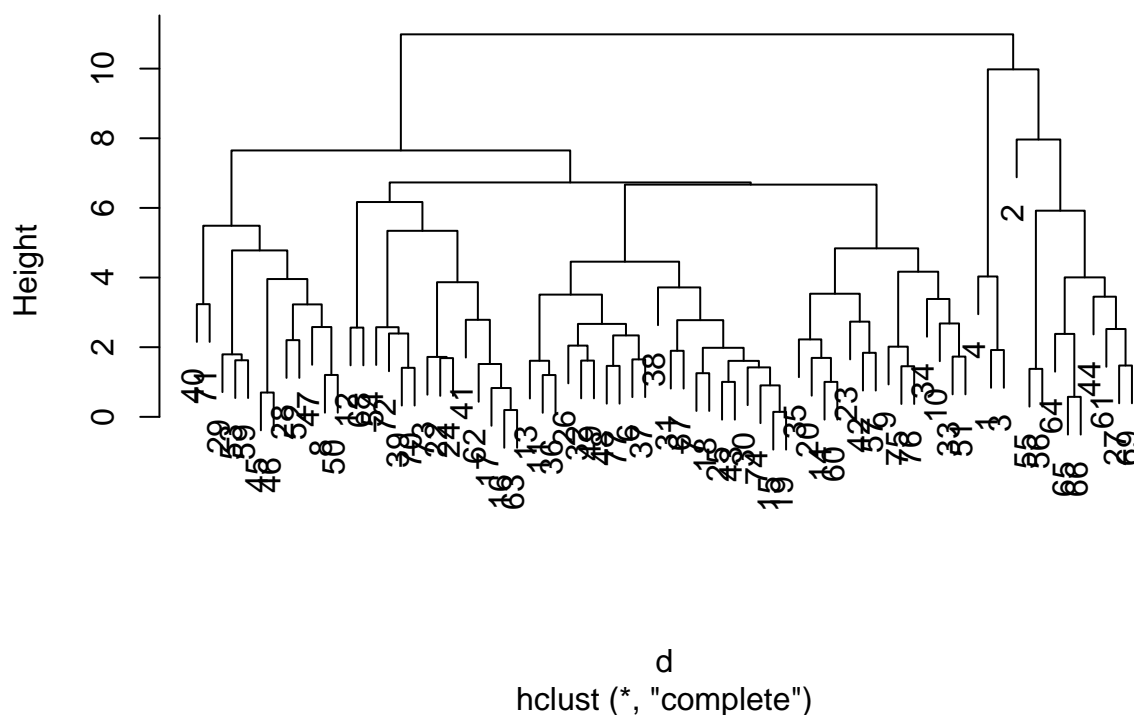
```
Normalise <- scale(missingvalues_removed)
```

euclidean distance to measure the distance:

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

```
##Perform Hierarchical Clustering using complete linkage.  
HC <- hclust(d, method = "complete")  
plot(HC)
```

Cluster 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:

We can also use `agnes()` function to perform clustering. Performing clustering using `agnes()` with single, complete, average and ward.

```
H_C_S <- agnes(Normalise, method = "single")
H_C_C <- agnes(Normalise, method = "complete")
H_C_A <- agnes(Normalise, method = "average")
H_C_W <- agnes(Normalise, method = "ward")
#Comparing the agglomerative coefficients for Single, complete, average and ward.
print(H_C_S$ac)
```

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

```
print(H_C_C$ac)
```

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

```
print(H_C$ac)
```

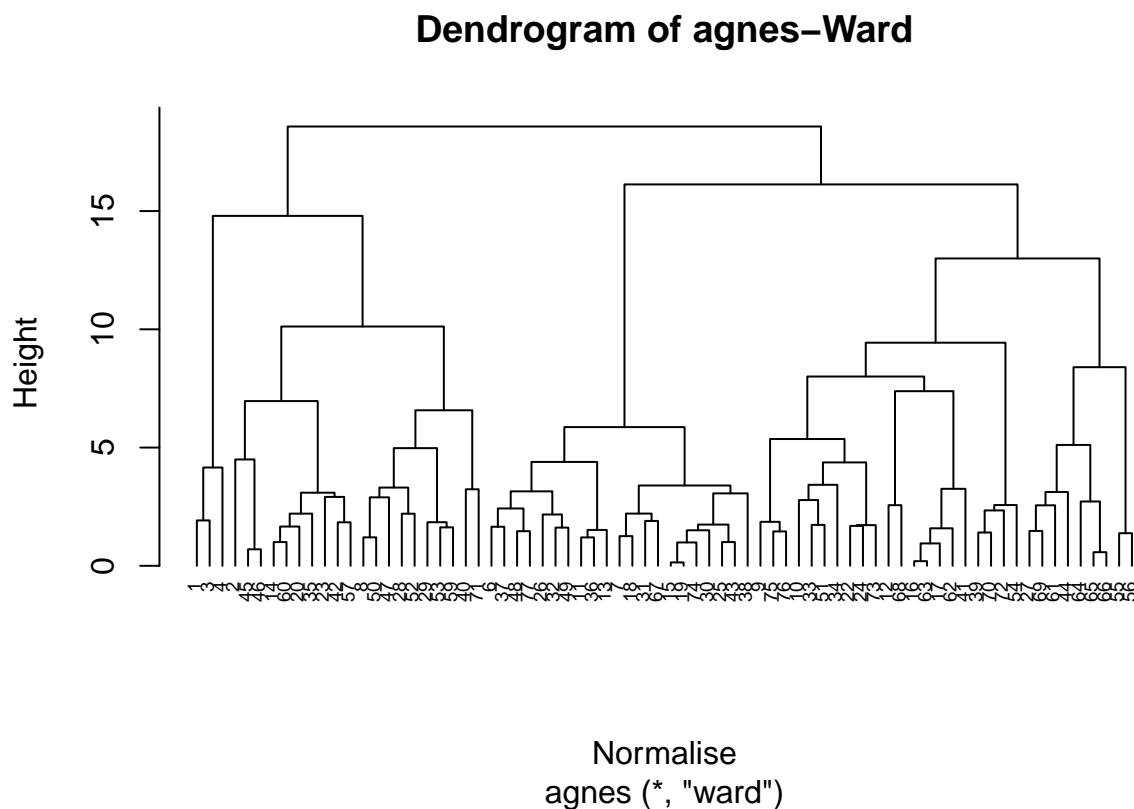
```
## [1] 0.7766075
```

```
print(H_C_W$ac)
```

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

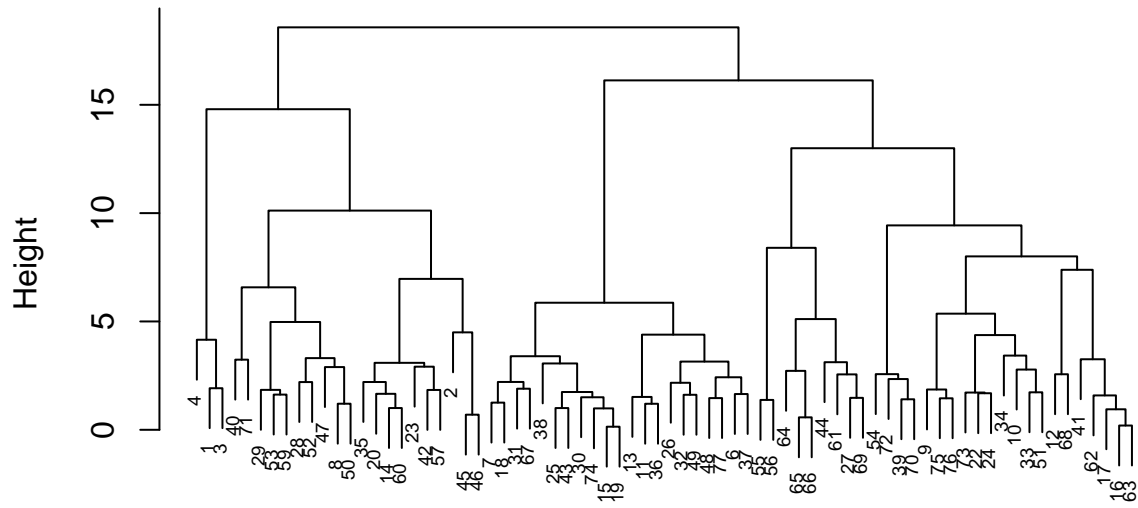
According to the findings, the wards approach is the most effective with a value of 0.904. Using the Ward technique and cutting the dendrogram to plot the agnes. By measuring the distance, we may determine that $k = 5$.

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



```
# Hierarchical clustering using ward method.  
HC1 <- hclust(d, method = "ward.D2" )  
plot(HC1,cex=0.6)
```

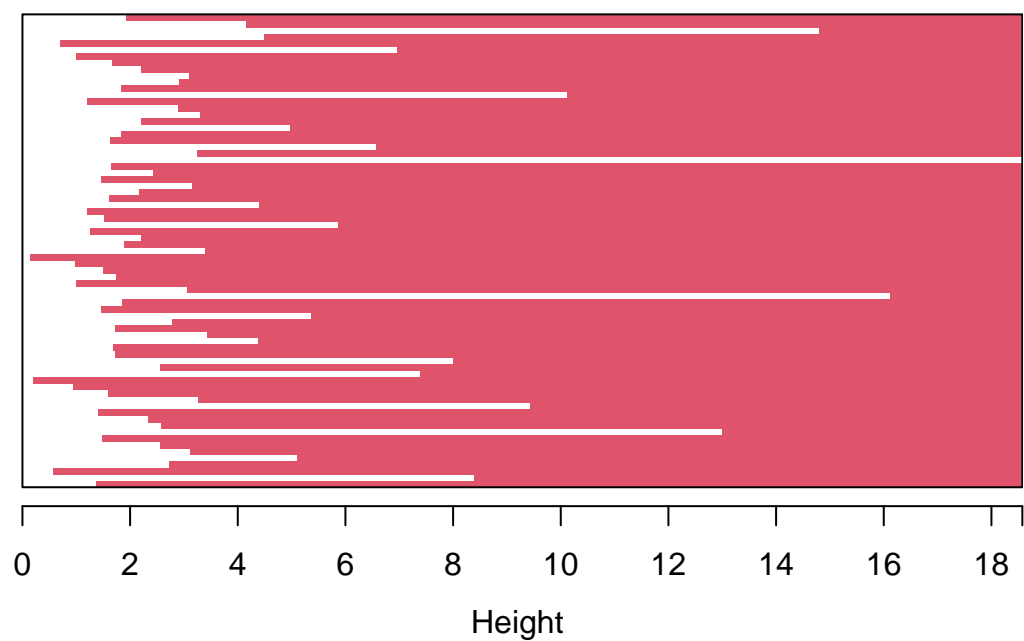
Cluster Dendrogram



d
hclust (*, "ward.D2")

```
plot(H_C_W)
```

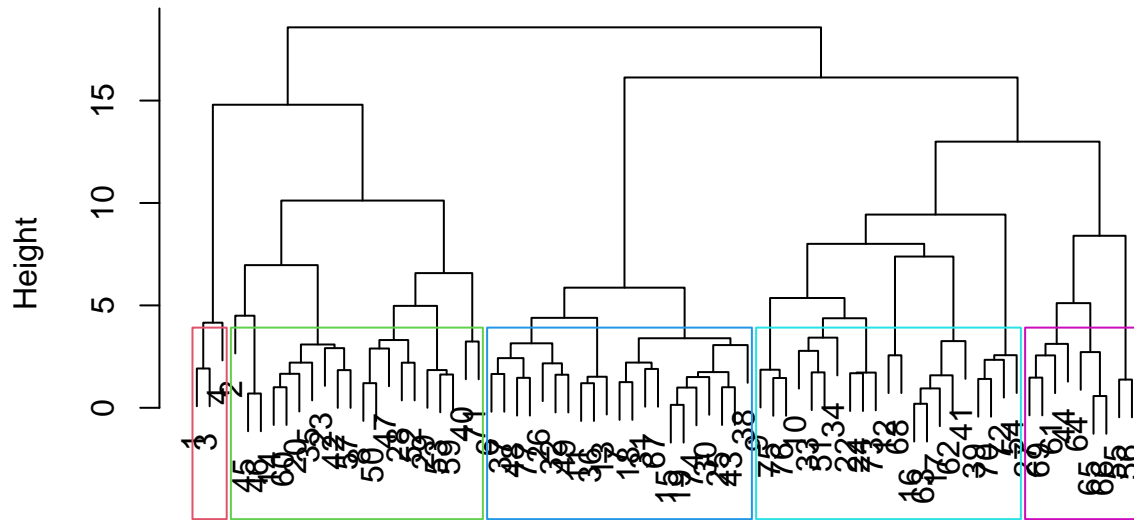
Banner of `agnes(x = Normalise, method = "ward")`



Agglomerative Coefficient = 0.9

```
rect.hclust(H_C_W, k=5, border = 2:10)
```

Dendrogram of `agnes(x = Normalise, method = "ward")`



Normalise
Agglomerative Coefficient = 0.9

```
subgrp <- cutree(HC1, k = 5)
table(subgrp)
```

```
## subgrp
## 1 2 3 4 5
## 3 20 21 21 9
```

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

```
##To visualize the results in scatter plot.
fviz_cluster(list(data = Normalise, cluster = subgrp))
```



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.

```
Newdatacereals <- cereals
Newdatacereals_omission <- na.omit(Newdatacereals)
Clust <- cbind(Newdatacereals_omission, 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
## 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	subgrp
## 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

```
Clust[Clust$subgrp==5,]
```

##		name	mfr	type	calories	protein	fat	sodium	fiber	carbo
## 27		Frosted_Mini-Wheats	K	C	100	3	0	0	3	14
## 44		Maypo	A	H	100	4	1	0	0	16
## 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
## 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
## 69		Strawberry_Fruit_Wheats	N	C	90	2	0	15	3	15

##	sugars	potass	vitamins	shelf	weight	cups	rating	subgrp
## 27	7	100	25	2	1.00	0.80	58.34514	5
## 44	3	95	25	2	1.00	1.00	54.85092	5
## 55	0	15	0	3	0.50	1.00	60.75611	5
## 56	0	50	0	3	0.50	1.00	63.00565	5
## 61	6	110	25	3	1.00	0.50	55.33314	5
## 64	0	95	0	1	0.83	1.00	68.23588	5
## 65	0	140	0	1	1.00	0.67	74.47295	5
## 66	0	120	0	1	1.00	0.67	72.80179	5
## 69	5	90	25	2	1.00	1.00	59.36399	5

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] 46.46513
```

```
mean(Clust[Clust$subgrp==5,"rating"])
```

```
## [1] 63.0184
```

It is advisable to choose cluster 1 and the cereals in cluster 1 for a healthy diet, as we can see that the mean ratings for the subgrp==1 are the highest (73.84).