

# HC on Cereals\_\_Data

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## Data Pre-processing

Find the number of missing values and either remove or omit them

```
cereals_data <- read.csv("Cereals.csv")
cereals<-read.csv("cereals.csv")
str(cereals_data)
```

```
## 'data.frame': 77 obs. of 16 variables:
## $ name : Factor w/ 77 levels "100%_Bran","100%_Natural_Bran",...: 1 2 3 4 5 6 7 8 9 10 ...
## $ mfr : Factor w/ 7 levels "A","G","K","N",...: 4 6 3 3 7 2 3 2 7 5 ...
## $ type : Factor w/ 2 levels "C","H": 1 1 1 1 1 1 1 1 1 1 ...
## $ calories: int 70 120 70 50 110 110 110 130 90 90 ...
## $ protein : int 4 3 4 4 2 2 2 3 2 3 ...
## $ fat : int 1 5 1 0 2 2 0 2 1 0 ...
## $ sodium : int 130 15 260 140 200 180 125 210 200 210 ...
## $ fiber : num 10 2 9 14 1 1.5 1 2 4 5 ...
## $ carbo : num 5 8 7 8 14 10.5 11 18 15 13 ...
## $ sugars : int 6 8 5 0 8 10 14 8 6 5 ...
## $ potass : int 280 135 320 330 NA 70 30 100 125 190 ...
## $ vitamins: int 25 0 25 25 25 25 25 25 25 25 ...
## $ shelf : int 3 3 3 3 3 1 2 3 1 3 ...
## $ weight : num 1 1 1 1 1 1 1 1.33 1 1 ...
## $ cups : num 0.33 1 0.33 0.5 0.75 0.75 1 0.75 0.67 0.67 ...
## $ rating : num 68.4 34 59.4 93.7 34.4 ...
```

```
sum(is.na(cereals_data))
```

```
## [1] 4
```

To remove any missing value that might be present in the data, type this:

```
cereals_data <- na.omit(cereals_data)
cereals<-na.omit(cereals)
sum(is.na(cereals_data))
```

```
## [1] 0
```

Convert the names of the breakfast cereals to the row names, as this will later help us in visualising the clusters

```
rownames(cereals_data) <- cereals_data$name
rownames(cereals) <- cereals$name
```

Drop the name column as it is now just redundant information

```
cereals_data$name = NULL
cereals$name = NULL
```

The data must be scaled, before measuring any type of distance metric as the variables with higher ranges will significantly influence the distance

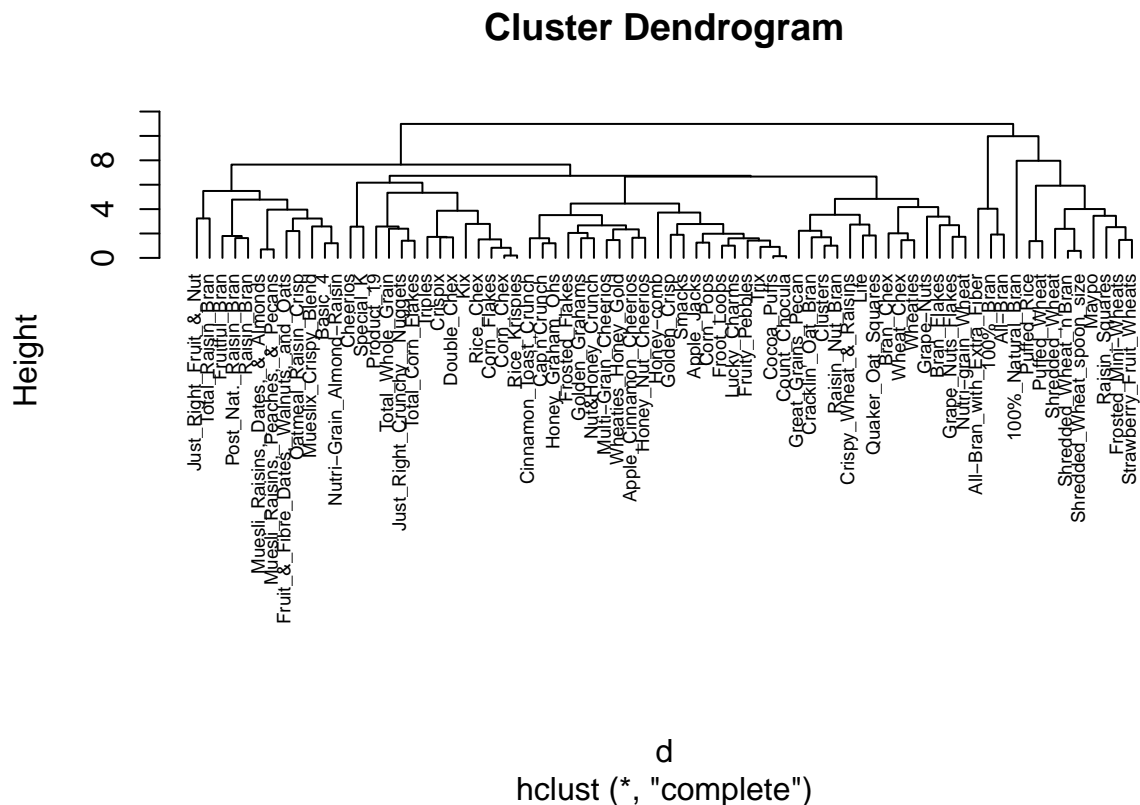
```
cereals_data <- scale(cereals_data[,3:15])
```

we will apply hierarchical clustering to the data using Euclidean distance

```
# Dissimilarity matrix
d <- dist(cereals_data, method = "euclidean")

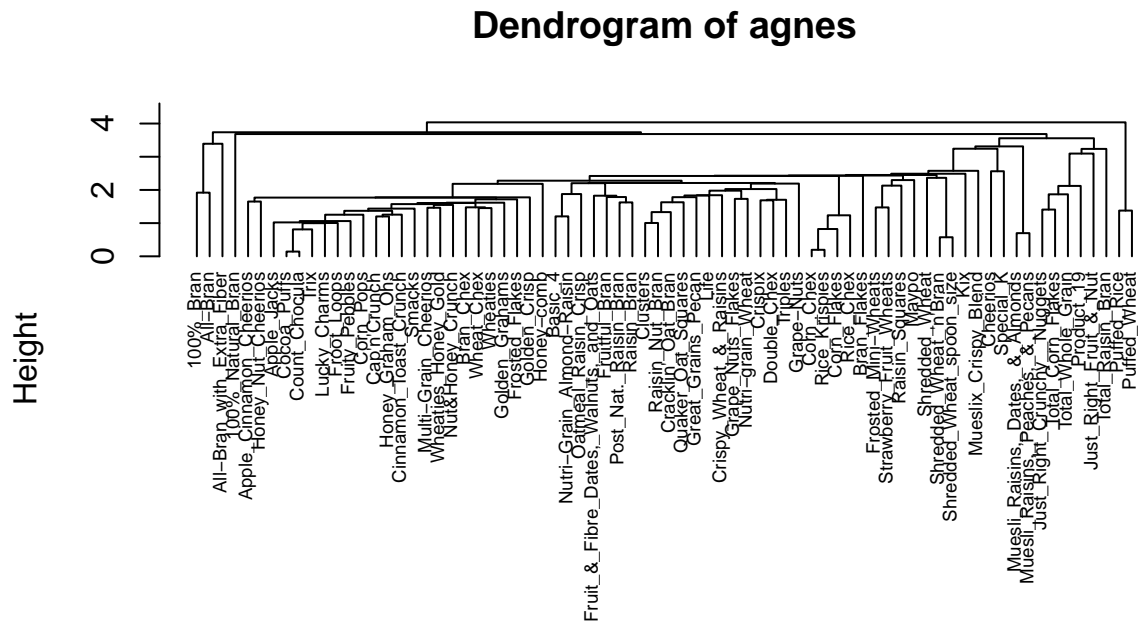
# Hierarchical clustering using Complete Linkage
hc_complete <- hclust(d, method = "complete")

# Plot the obtained dendrogram
plot(hc_complete, cex = 0.6, hang = -1)
```



Using Agnes to compare the clustering from single linkage, complete linkage, average linkage, and Ward and comparing agglomerative coefficients of each method.

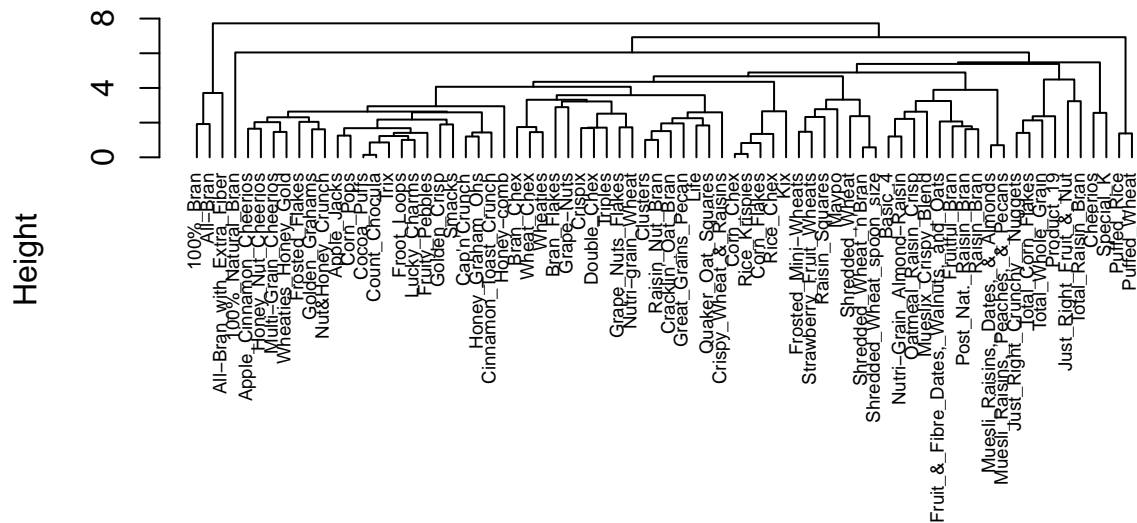
```
library(cluster)
hc_single <- agnes(cereals_data, method = "single")
pltree(hc_single, cex = 0.6, hang = -1, main = "Dendrogram of agnes")
```



cereals\_data  
agnes (\*, "single")

```
hc_average <- agnes(cereals_data, method = "average")
pltree(hc_average, cex = 0.6, hang = -1, main = "Dendrogram of agnes")
```

## Dendrogram of agnes



```
cereals_data
agnes (*, "average")
```

We will find the agnes coefficient of all the methods.

```
# methods to assess
m <- c( "average", "single", "complete", "ward")
names(m) <- c( "average", "single", "complete", "ward")

# function to compute coefficient
ac <- function(x) {
  agnes(cereals_data, method = x)$ac
}

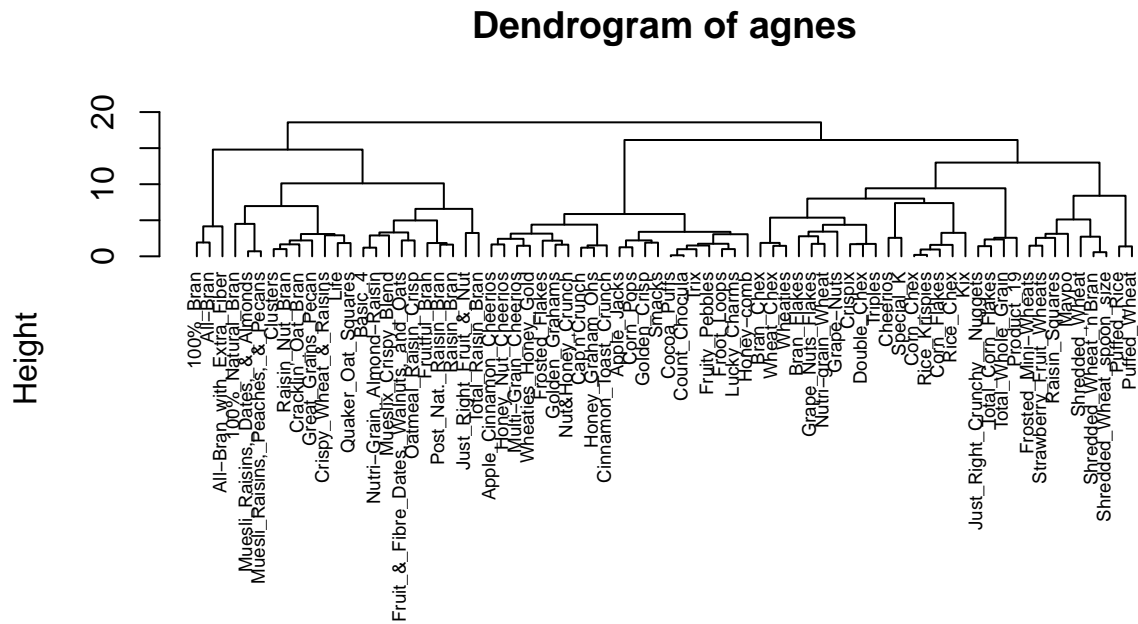
map_dbl(m, ac)
```

```
##      average      single  complete      ward
## 0.7766075 0.6067859 0.8353712 0.9046042
```

The best linkage method is ward with agglomerative coefficient of 0.9046042.

visualizing the dendrogram using wards method:

```
hc_ward <- agnes(cereals_data, method = "ward")
pltree(hc_ward, cex = 0.6, hang = -1, main = "Dendrogram of agnes")
```



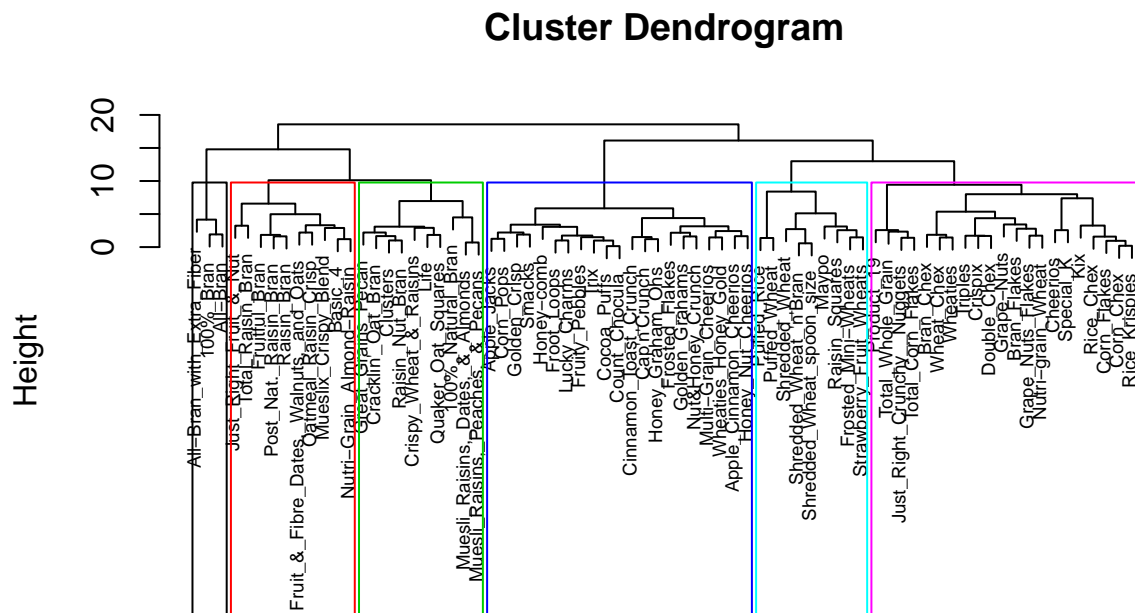
cereals\_data  
agnes (\*, "ward")

In order to identify sub-groups (i.e. clusters), we can cut the dendrogram with `cutree()`:

```
#Create the distance matrix
d <- dist(cereals_data, method = "euclidean")

# Ward's method for Hierarchical clustering
hc_ward_cut <- hclust(d, method = "ward.D2" )

plot(hc_ward_cut, cex=0.6 )
rect.hclust(hc_ward_cut,k=6,border = 1:6)
```



d  
hclust (\*, "ward.D2")

Lets see how many number of records of the data grouped and assigned to clusters:

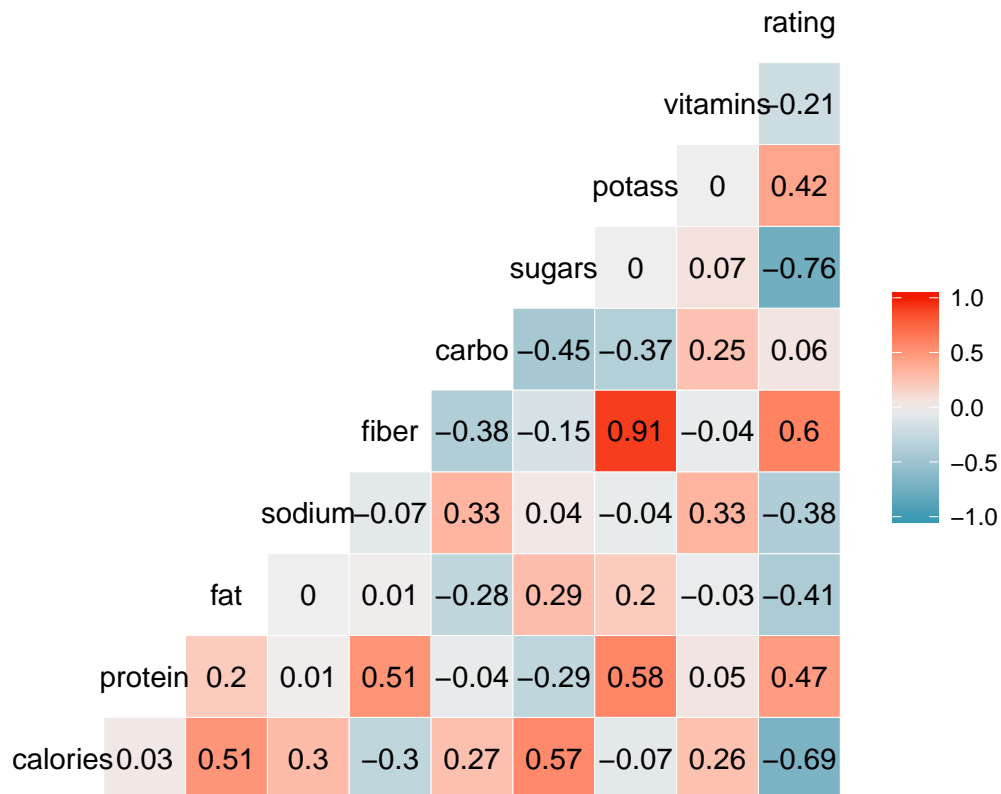
```
# Cut tree into 6 groups
sub_grp <- cutree(hc_ward_cut, k = 6)

# Number of members in each cluster
table(sub_grp)
```

```
## sub_grp
##  1  2  3  4  5  6
##  3 10 21 10 21  9
```

Correlation matrix:

```
#install.packages("GGally")
cereals %>%
  select(calories, protein, fat, sodium, fiber, carbo, sugars, potass, vitamins, rating) %>%
  ggcorr(palette = "RdBu", label = TRUE, label_round = 2)
```



The correlation matrix helps us in gauging whether strong or weak relation existing between the variables. This will give us a better perspective in deriving descriptive statistics between the variables.

The `pvcust()` function in the `pvcust` package provides p-values for hierarchical clustering based on multiscale bootstrap resampling. Clusters that are highly supported by the data will have large p values. Interpretation details are provided Suzuki. Be aware that `pvcust` clusters columns, not rows. Transpose your data before using.

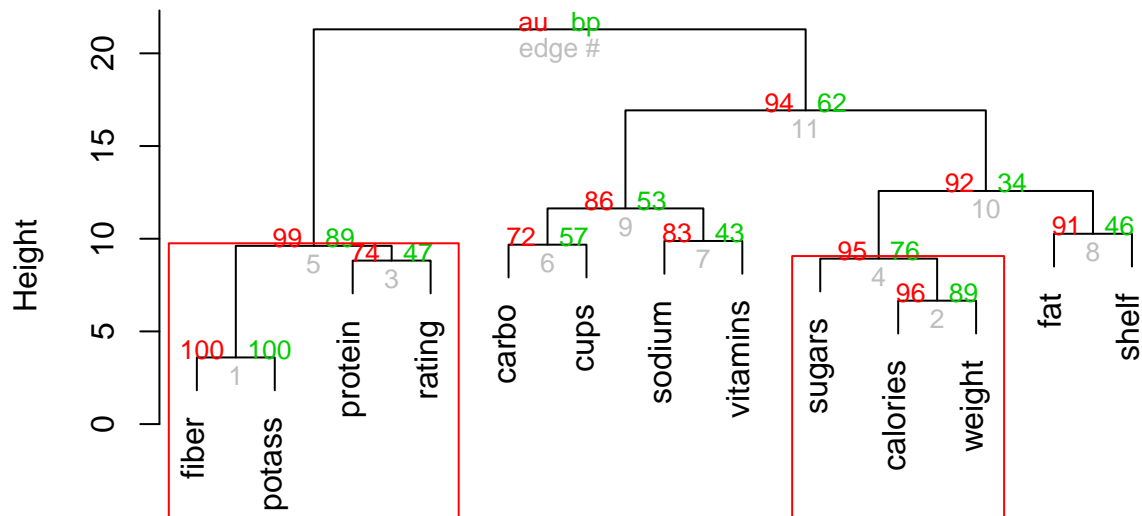
```
# Ward Hierarchical Clustering with Bootstrapped p values
#install.packages("pvcust")
library(pvcust)
```

```
## Registered S3 method overwritten by 'pvcust':
##   method      from
##   text.pvcust dendextend
```

```
fit.pv <- pvcust(cereals_data, method.hclust="ward.D2",
                 method.dist="euclidean")
```

```
plot(fit.pv) # dendrogram with p values
# add rectangles around groups highly supported by the data
pvrect(fit.pv, alpha=.95)
```

## Cluster dendrogram with AU/BP values (%)



Distance: euclidean  
Cluster method: ward.D2

The cluster stability of each cluster in the original clustering is the mean value of its Jaccard coefficient over all the bootstrap iterations. As a rule of thumb, clusters with a stability value less than 0.6 should be considered unstable. Values between 0.6 and 0.75 indicate that the cluster is measuring a pattern in the data, but there isn't high certainty about which points should be clustered together. Clusters with stability values above about 0.85 can be considered highly stable

1. Clusterwise Jaccard bootstrap mean should be maximised
2. number of dissolved clusters should be minimised and
3. number of recovered clusters should be maximised and as close to the number of pre-defined bootstraps as possible

#Running clusterboot()

```
library(fpc)
library(cluster)
kbest.p<-6
cboot.hclust <- clusterboot(cereals_data,clustermethod=hclustCBI,method="ward.D2", k=kbest.p)
```

```
summary(cboot.hclust$result)
```

```
##          Length Class  Mode
## result          7    hclust list
## noise           1   -none- logical
## nc              1   -none- numeric
## clusterlist     6   -none- list
```



```
## partition      74      -none- numeric
## clustermethod  1      -none- character
## nccl           1      -none- numeric
```

```
groups<-cboot.hclust$result$partition
head(data.frame(groups))
```

```
##                groups
## 100%_Bran          1
## 100%_Natural_Bran  2
## All-Bran           1
## All-Bran_with_Extra_Fiber  1
## Apple_Cinnamon_Cheerios  3
## Apple_Jacks        3
```

```
#The vector of cluster stabilities
cboot.hclust$bootmean
```

```
## [1] 0.8712583 0.5168806 0.8914939 0.6191970 0.5964205 0.6728449
```

```
#The count of how many times each cluste was dissolved. By default clusterboot() runs 100 bootstrap iterations
cboot.hclust$bootbrd
```

```
## [1] 14 56  0 42 33 37
```

By looking the output, we can say cluster 1 and cluster 3 are Highly stable. Cluster 4, 5 are measuring a pattern and there isn't high certainty about which points should be clustered together. cluster 2 and 5 are unstable.

Extracting the clusters found by hclust()

```
groups <- cutree(hc_ward_cut, k = 6)
print_clusters <- function(labels, k) {
  for(i in 1:k) {
    print(paste("cluster", i))
    print(cereals[labels==i,c("mfr","calories","protein","fat","sodium","fiber","carbo","sugars","potass","")])
  }
}
print_clusters(groups, 6)
```

```
## [1] "cluster 1"
##                mfr calories protein fat sodium fiber carbo sugars
## 100%_Bran       N      70        4   1   130    10     5     6
## All-Bran        K      70        4   1   260     9     7     5
## All-Bran_with_Extra_Fiber K      50        4   0   140    14     8     0
##                potass vitamins   rating
## 100%_Bran       280        25 68.40297
## All-Bran        320        25 59.42551
## All-Bran_with_Extra_Fiber 330        25 93.70491
## [1] "cluster 2"
##                mfr calories protein fat sodium fiber carbo
## 100%_Natural_Bran Q      120        3   5    15    2.0    8.0
```

```

## Clusters G 110 3 2 140 2.0 13.0
## Cracklin'_Oat_Bran K 110 3 3 140 4.0 10.0
## Crispy_Wheat_&_Raisins G 100 2 1 140 2.0 11.0
## Great_Grains_Pecan P 120 3 3 75 3.0 13.0
## Life Q 100 4 2 150 2.0 12.0
## Muesli_Raisins,_Dates,_&_Almonds R 150 4 3 95 3.0 16.0
## Muesli_Raisins,_Peaches,_&_Pecans R 150 4 3 150 3.0 16.0
## Quaker_Oat_Squares Q 100 4 1 135 2.0 14.0
## Raisin_Nut_Bran G 100 3 2 140 2.5 10.5
## sugars potass vitamins rating
## 100%_Natural_Bran 8 135 0 33.98368
## Clusters 7 105 25 40.40021
## Cracklin'_Oat_Bran 7 160 25 40.44877
## Crispy_Wheat_&_Raisins 10 120 25 36.17620
## Great_Grains_Pecan 4 100 25 45.81172
## Life 6 95 25 45.32807
## Muesli_Raisins,_Dates,_&_Almonds 11 170 25 37.13686
## Muesli_Raisins,_Peaches,_&_Pecans 11 170 25 34.13976
## Quaker_Oat_Squares 6 110 25 49.51187
## Raisin_Nut_Bran 8 140 25 39.70340
## [1] "cluster 3"
## mfr calories protein fat sodium fiber carbo sugars
## Apple_Cinnamon_Cheerios G 110 2 2 180 1.5 10.5 10
## Apple_Jacks K 110 2 0 125 1.0 11.0 14
## Cap'n'_Crunch Q 120 1 2 220 0.0 12.0 12
## Cinnamon_Toast_Crunch G 120 1 3 210 0.0 13.0 9
## Cocoa_Puffs G 110 1 1 180 0.0 12.0 13
## Corn_Pops K 110 1 0 90 1.0 13.0 12
## Count_Chocula G 110 1 1 180 0.0 12.0 13
## Froot_Loops K 110 2 1 125 1.0 11.0 13
## Frosted_Flakes K 110 1 0 200 1.0 14.0 11
## Fruity_Pebbles P 110 1 1 135 0.0 13.0 12
## Golden_Crisp P 100 2 0 45 0.0 11.0 15
## Golden_Grahams G 110 1 1 280 0.0 15.0 9
## Honey_Graham_Ohs Q 120 1 2 220 1.0 12.0 11
## Honey_Nut_Cheerios G 110 3 1 250 1.5 11.5 10
## Honey-comb P 110 1 0 180 0.0 14.0 11
## Lucky_Charms G 110 2 1 180 0.0 12.0 12
## Multi-Grain_Cheerios G 100 2 1 220 2.0 15.0 6
## Nut&Honey_Crunch K 120 2 1 190 0.0 15.0 9
## Smacks K 110 2 1 70 1.0 9.0 15
## Trix G 110 1 1 140 0.0 13.0 12
## Wheaties_Honey_Gold G 110 2 1 200 1.0 16.0 8
## potass vitamins rating
## Apple_Cinnamon_Cheerios 70 25 29.50954
## Apple_Jacks 30 25 33.17409
## Cap'n'_Crunch 35 25 18.04285
## Cinnamon_Toast_Crunch 45 25 19.82357
## Cocoa_Puffs 55 25 22.73645
## Corn_Pops 20 25 35.78279
## Count_Chocula 65 25 22.39651
## Froot_Loops 30 25 32.20758
## Frosted_Flakes 25 25 31.43597
## Fruity_Pebbles 25 25 28.02576

```

```

## Golden_Crisp          40      25 35.25244
## Golden_Grahams        45      25 23.80404
## Honey_Graham_Ohs      45      25 21.87129
## Honey_Nut_Cheerios    90      25 31.07222
## Honey-comb            35      25 28.74241
## Lucky_Charms          55      25 26.73451
## Multi-Grain_Cheerios  90      25 40.10596
## Nut&Honey_Crunch      40      25 29.92429
## Smacks                 40      25 31.23005
## Trix                   25      25 27.75330
## Wheaties_Honey_Gold   60      25 36.18756
## [1] "cluster 4"
##
##               mfr calories protein fat sodium fiber
## Basic_4        G      130         3  2    210    2.0
## Fruit_&Fibre_Dates,_Walnuts,_and_Oats P      120         3  2    160    5.0
## Fruitful_Bran   K      120         3  0    240    5.0
## Just_Right_Fruit_&Nut K      140         3  1    170    2.0
## Mueslix_Crispy_Blend K      160         3  2    150    3.0
## Nutri-Grain_Almond-Raisin K      140         3  2    220    3.0
## Oatmeal_Raisin_Crisp G      130         3  2    170    1.5
## Post_Nat._Raisin_Bran P      120         3  1    200    6.0
## Raisin_Bran     K      120         3  1    210    5.0
## Total_Raisin_Bran G      140         3  1    190    4.0
##
##               carbo sugars potass vitamins rating
## Basic_4        18.0      8    100         25 37.03856
## Fruit_&Fibre_Dates,_Walnuts,_and_Oats 12.0     10    200         25 40.91705
## Fruitful_Bran   14.0     12    190         25 41.01549
## Just_Right_Fruit_&Nut 20.0      9     95        100 36.47151
## Mueslix_Crispy_Blend 17.0     13    160         25 30.31335
## Nutri-Grain_Almond-Raisin 21.0      7    130         25 40.69232
## Oatmeal_Raisin_Crisp 13.5     10    120         25 30.45084
## Post_Nat._Raisin_Bran 11.0     14    260         25 37.84059
## Raisin_Bran     14.0     12    240         25 39.25920
## Total_Raisin_Bran 15.0     14    230        100 28.59278
## [1] "cluster 5"
##
##               mfr calories protein fat sodium fiber carbo sugars
## Bran_Chex      R      90         2  1    200      4    15      6
## Bran_Flakes     P      90         3  0    210      5    13      5
## Cheerios        G     110         6  2    290      2    17      1
## Corn_Chex       R     110         2  0    280      0    22      3
## Corn_Flakes     K     100         2  0    290      1    21      2
## Crispix         K     110         2  0    220      1    21      3
## Double_Chex     R     100         2  0    190      1    18      5
## Grape_Nuts_Flakes P     100         3  1    140      3    15      5
## Grape-Nuts      P     110         3  0    170      3    17      3
## Just_Right_Crunchy__Nuggets K     110         2  1    170      1    17      6
## Kix             G     110         2  1    260      0    21      3
## Nutri-grain_Wheat K      90         3  0    170      3    18      2
## Product_19      K     100         3  0    320      1    20      3
## Rice_Chex       R     110         1  0    240      0    23      2
## Rice_Krispies   K     110         2  0    290      0    22      3
## Special_K       K     110         6  0    230      1    16      3
## Total_Corn_Flakes G     110         2  1    200      0    21      3
## Total_Whole_Grain G     100         3  1    200      3    16      3

```

```

## Triples          G      110      2  1    250      0    21      3
## Wheat_Chex       R      100      3  1    230      3    17      3
## Wheaties         G      100      3  1    200      3    17      3
##                  potass vitamins  rating
## Bran_Chex        125      25 49.12025
## Bran_Flakes       190      25 53.31381
## Cheerios          105      25 50.76500
## Corn_Chex         25      25 41.44502
## Corn_Flakes       35      25 45.86332
## Crispix           30      25 46.89564
## Double_Chex       80      25 44.33086
## Grape_Nuts_Flakes 85      25 52.07690
## Grape-Nuts        90      25 53.37101
## Just_Right_Crunchy__Nuggets 60    100 36.52368
## Kix               40      25 39.24111
## Nutri-grain_Wheat 90      25 59.64284
## Product_19        45    100 41.50354
## Rice_Chex         30      25 41.99893
## Rice_Krispies     35      25 40.56016
## Special_K         55      25 53.13132
## Total_Corn_Flakes 35      100 38.83975
## Total_Whole_Grain 110     100 46.65884
## Triples           60      25 39.10617
## Wheat_Chex        115     25 49.78744
## Wheaties          110     25 51.59219
## [1] "cluster 6"
##                  mfr calories protein fat sodium fiber carbo sugars
## Frosted_Mini-Wheats K      100      3  0      0      3    14      7
## Maypo              A      100      4  1      0      0    16      3
## Puffed_Rice         Q       50      1  0      0      0    13      0
## Puffed_Wheat        Q       50      2  0      0      1    10      0
## Raisin_Squares      K       90      2  0      0      2    15      6
## Shredded_Wheat      N       80      2  0      0      3    16      0
## Shredded_Wheat_'n'Bran N       90      3  0      0      4    19      0
## Shredded_Wheat_spoon_size N       90      3  0      0      3    20      0
## Strawberry_Fruit_Wheats N       90      2  0     15      3    15      5
##                  potass vitamins  rating
## Frosted_Mini-Wheats 100      25 58.34514
## Maypo               95      25 54.85092
## Puffed_Rice         15       0 60.75611
## Puffed_Wheat        50       0 63.00565
## Raisin_Squares     110      25 55.33314
## Shredded_Wheat      95       0 68.23588
## Shredded_Wheat_'n'Bran 140      0 74.47295
## Shredded_Wheat_spoon_size 120      0 72.80179
## Strawberry_Fruit_Wheats 90      25 59.36399

```

Note\*\*\*

Since there is no proper mention of measure/scale to become a healthy diet, I decided to choose clusters based on statistical values and rich in nutritional values to form a healthy diet and this is purely subjective.

To answer whether needed to be normalized or not? I would say no. When we normalize the data, the magnitude of the data would be lost and it will become very difficult for us to read and decide.

The clusters contain nutritionally rich, adequate and poor levels of the cereal diet. We grouped all the records in to 6 clusters, we will evaluate these clusters considering all the variables/factors.

even though Cluster 1 has nutritionally stable values to form a healthy diet, the options are very limited. Cluster 2 and cluster 3 have poor ratings and have high Fat and sugars which are not good for a healthy meal. Cluster 4 and 5 have balanced nutritional values with good average customer ratings. Hence Cluster 4 and 5 should be a good option for elementary public schools to include this in their cafeterias.