

FML 5 ASNMT

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

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

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

```
library(knitr)
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(factoextra)
```

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

Importing dataset

```
cereals_data <- read.csv("/Users/chaithanayayennam/Downloads/Cereals.csv")
cereals <- data.frame(cereals_data[,4:16])
head(cereals_data)
```

```
##           name mfr type calories protein fat sodium fiber carbo
## 1      100%_Bran  N   C       70        4  1   130   10.0   5.0
## 2    100%_Natural_Bran  Q   C      120        3  5    15    2.0   8.0
## 3          All-Bran  K   C       70        4  1   260    9.0   7.0
## 4 All-Bran_with_Extra_Fiber  K   C       50        4  0   140   14.0   8.0
## 5        Almond_Delight  R   C      110        2  2   200    1.0  14.0
## 6  Apple_Cinnamon_Cheerios  G   C      110        2  2   180    1.5  10.5
##  sugars potass vitamins shelf weight cups  rating
## 1      6      280       25     3      1 0.33 68.40297
## 2      8      135        0     3      1 1.00 33.98368
## 3      5      320       25     3      1 0.33 59.42551
## 4      0      330       25     3      1 0.50 93.70491
## 5      8       NA       25     3      1 0.75 34.38484
## 6     10       70       25     1      1 0.75 29.50954
```

Removing missing values

```
cereals <- na.omit(cereals)
```

Performing data normalization and scale the data

```
normalized_cereals <- scale(cereals)
```

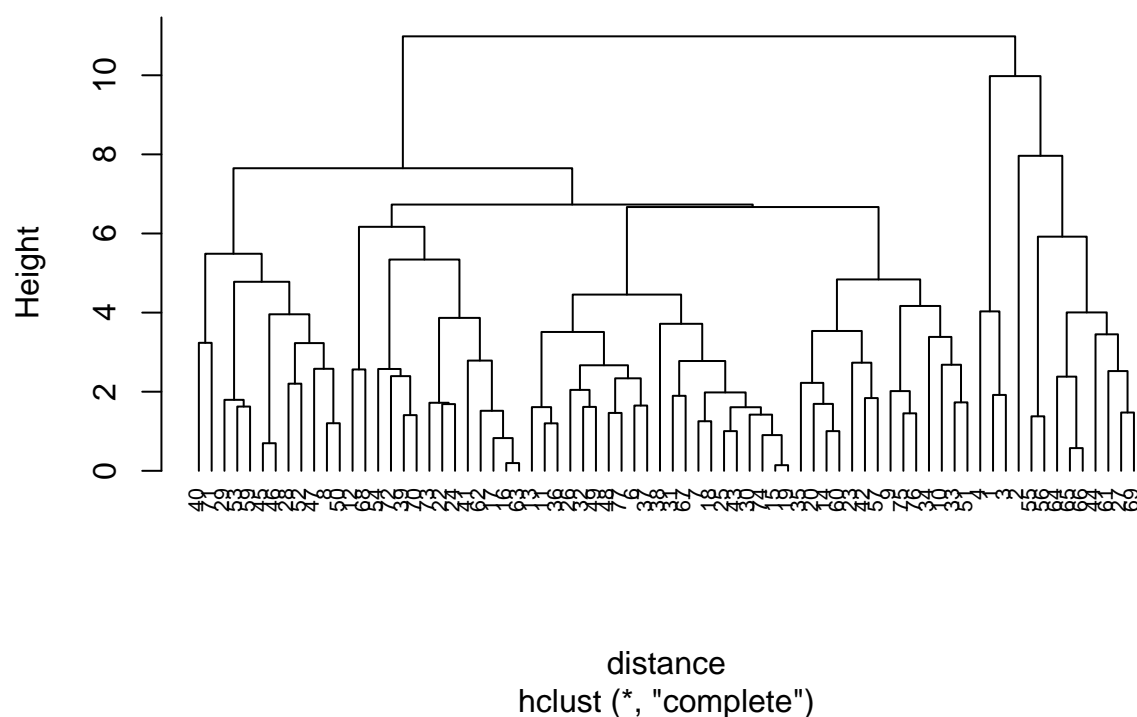
Applying hierarchical clustering to the data using Euclidean distance to the normalized measurements

```
distance <- dist(normalized_cereals, method = "euclidean")
heirarch_cluster <- hclust(distance, method = "complete")
```

Dendrogram plotting

```
plot(heirarch_cluster, cex = 0.7, hang = -1)
```

Cluster Dendrogram

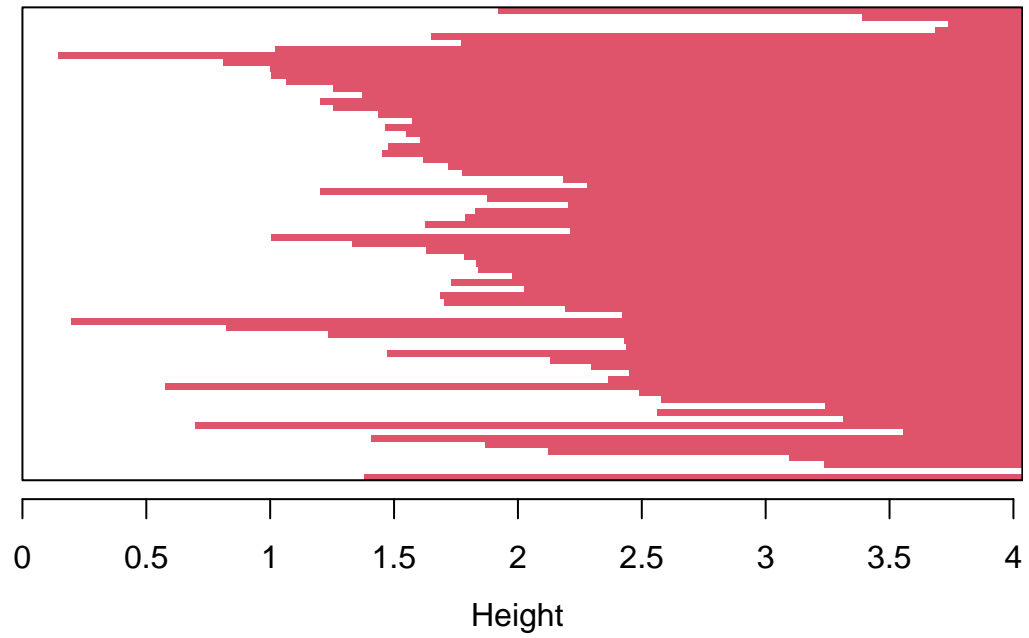


Clustering from single linkage, complete linkage, average linkage, and Ward.

```
heirarch_cluster_single <- agnes(normalized_cereals, method = "single")
heirarch_cluster_complete <- agnes(normalized_cereals, method = "complete")
heirarch_cluster_average <- agnes(normalized_cereals, method = "average")
heirarch_cluster_ward <- agnes(normalized_cereals, method = "ward")

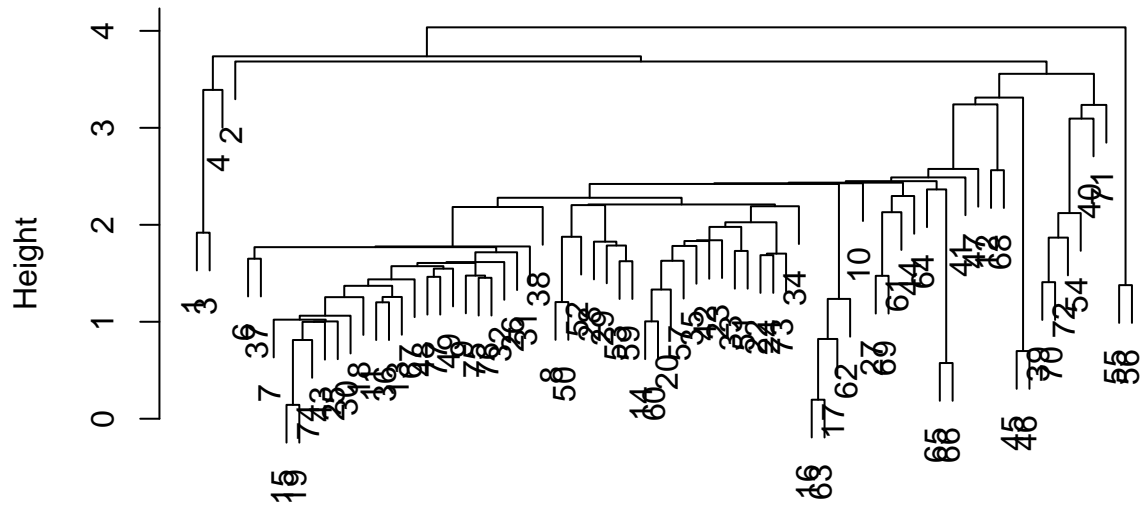
plot(heirarch_cluster_single, main = "Agnes - Single Linkage")
```

Agnes – Single Linkage



Agglomerative Coefficient = 0.61

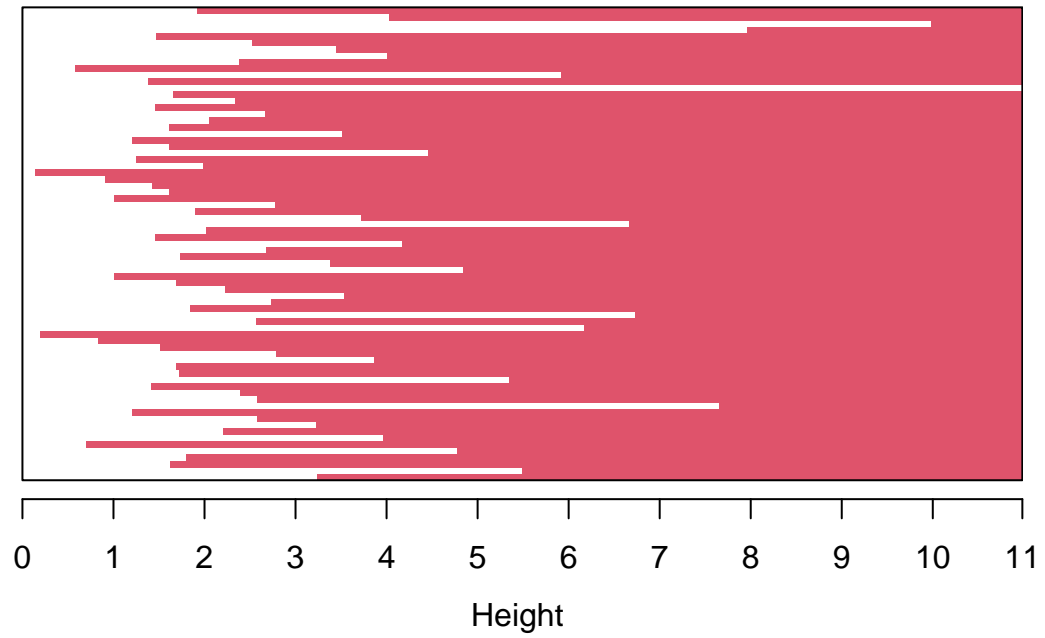
Agnes – Single Linkage



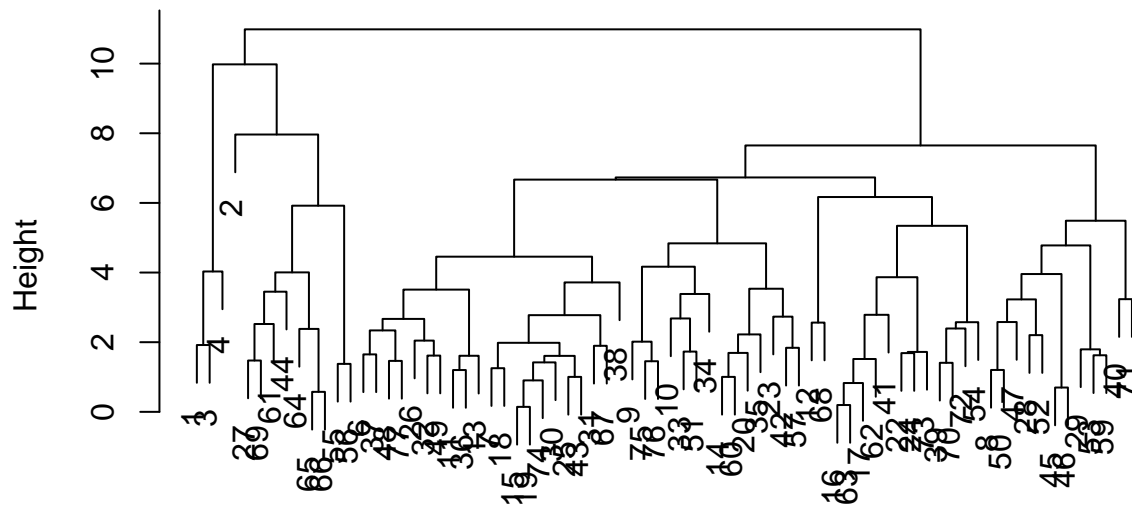
normalized_cereals
Agglomerative Coefficient = 0.61

```
plot(hierarchical_cluster_complete, main = "Agnes - Complete Linkage")
```

Agnes – Complete Linkage



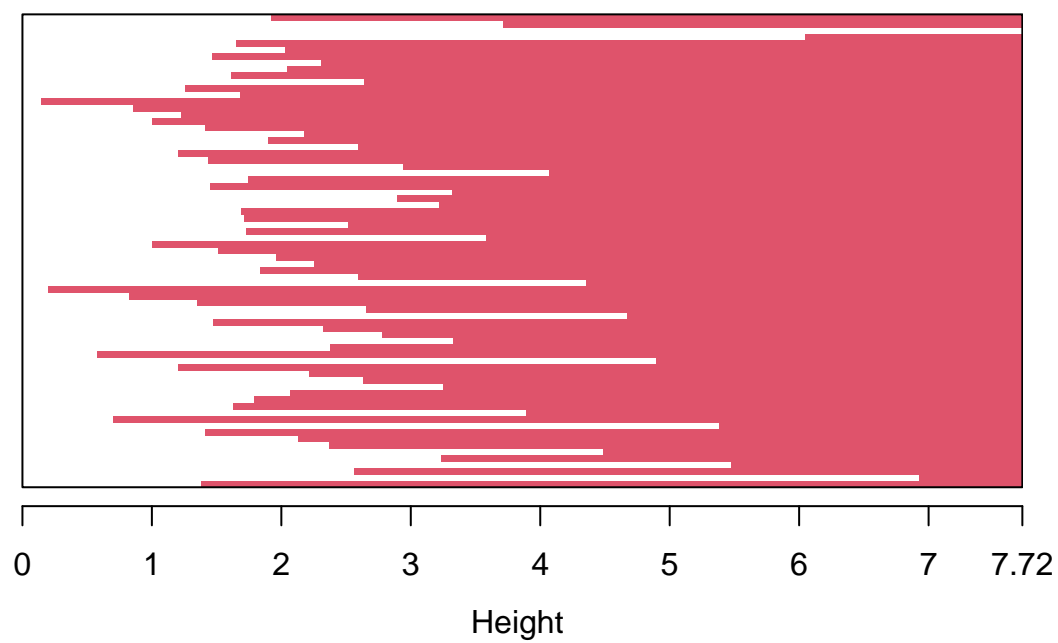
Agnes – Complete Linkage



normalized_cereals
Agglomerative Coefficient = 0.84

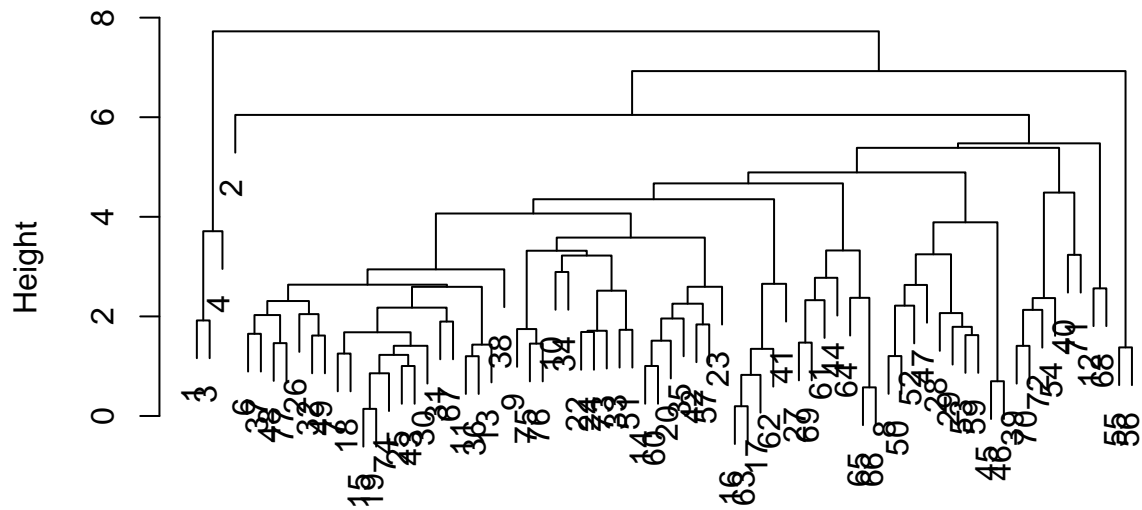
```
plot(heirarch_cluster_average, main = "Agnes - Average Linkage")
```

Agnes – Average Linkage



Agglomerative Coefficient = 0.78

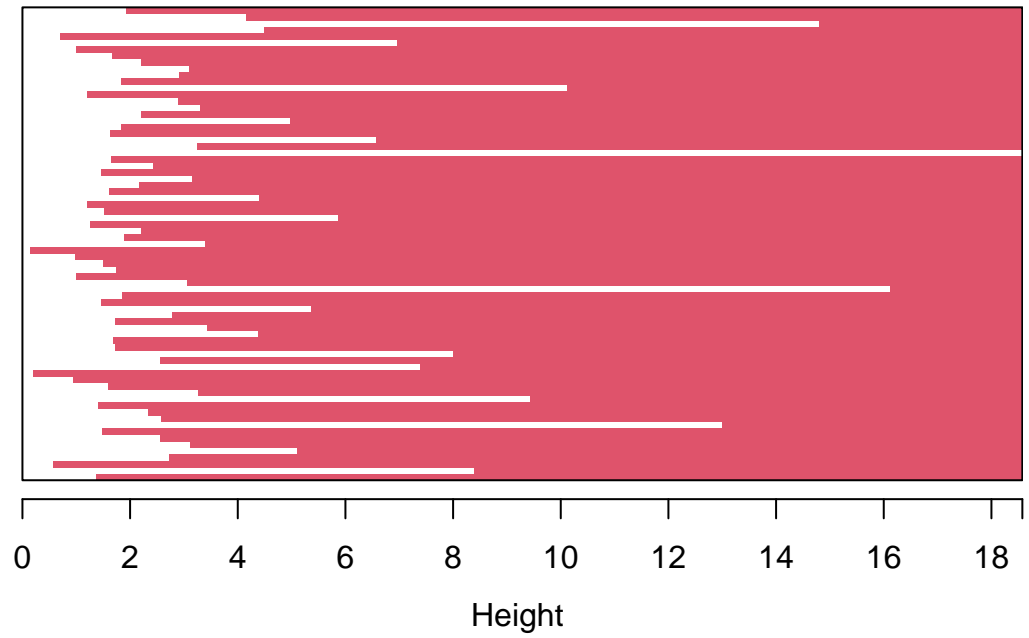
Agnes – Average Linkage



normalized_cereals
Agglomerative Coefficient = 0.78

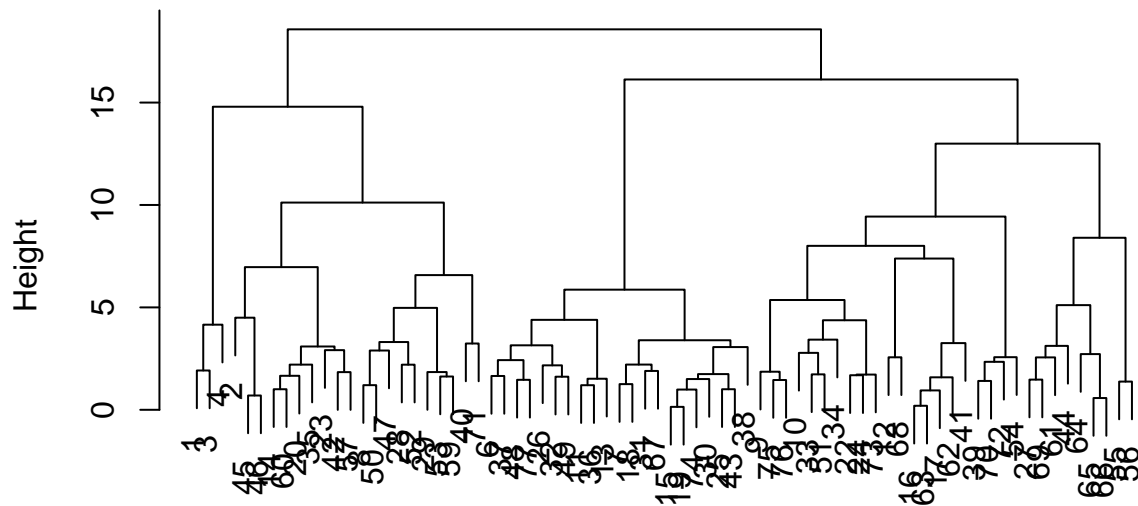
```
plot(heirarch_cluster_ward, main = "Agnes - Ward Linkage")
```

Agnes – Ward Linkage



Agglomerative Coefficient = 0.9

Agnes – Ward Linkage

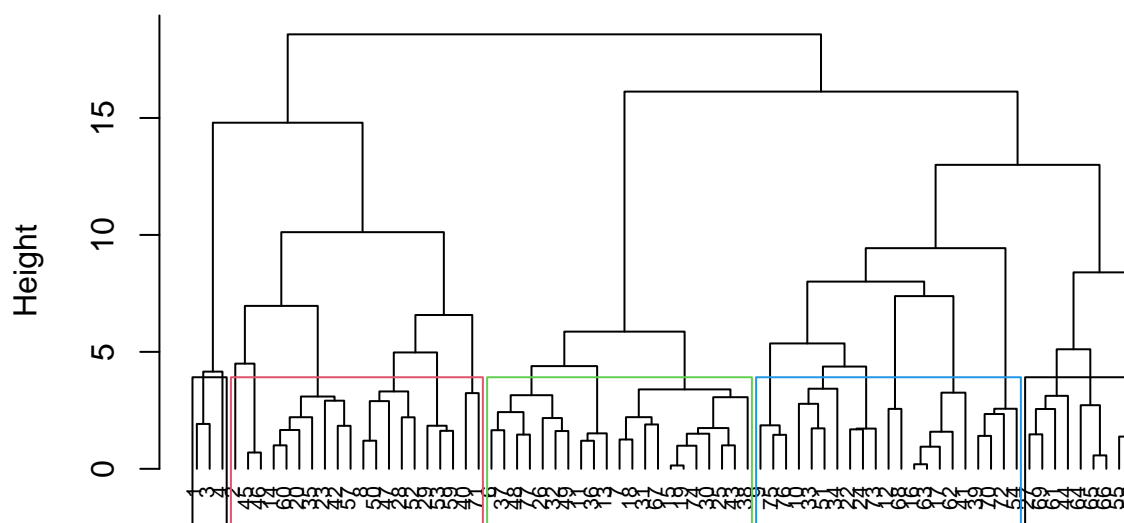


normalized_cereals
Agglomerative Coefficient = 0.9

With the Dendrogram clipped and the agnes plotted using the Ward method, the best result we could get from the output above is 0.9. To obtain $k = 4$, we shall utilize the distance.

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

Dendrogram of agnes using ward



normalized_cereals
agnes (*, "ward")

```
cluster_number_1 <- cutree(heirarch_cluster_ward, k= 5)
dataframe_number_2 <- as.data.frame(cbind(normalized_cereals, cluster_number_1))
```

Having noted the distance, let's select 5 clusters.

Cluster partition

```
set.seed(123)
partition_number_1 <- cereals[1:50,]
partition_number_2 <- cereals[51:74,]
```

Using the cluster centroids from A to assign each record in partition B

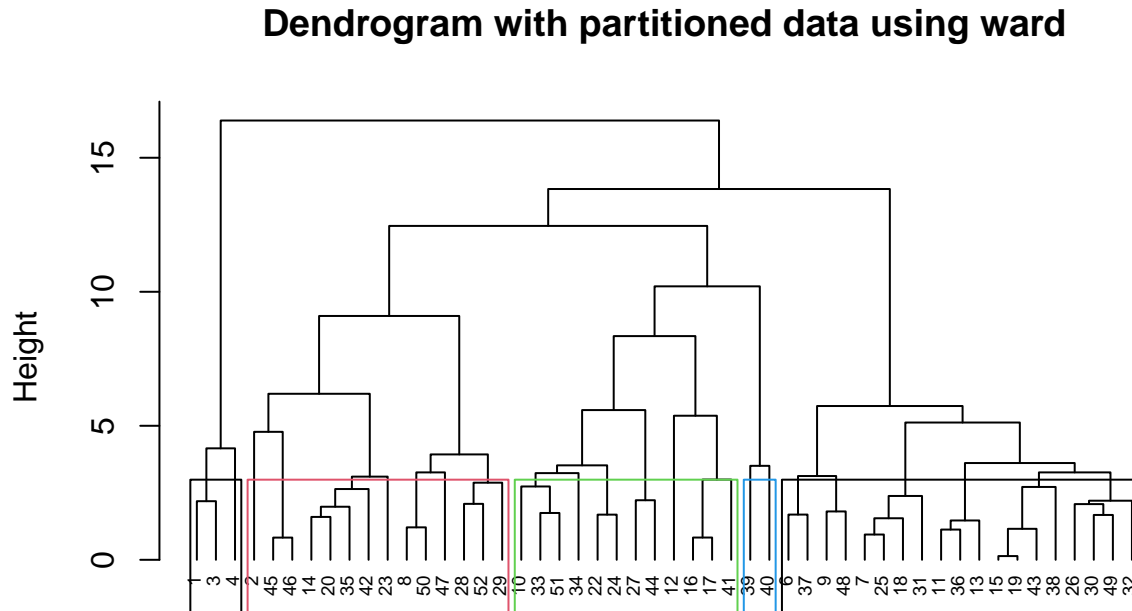
Consider k = 5

```
hc_single <- agnes(scale(partition_number_1), method = "single")
hc_complete <- agnes(scale(partition_number_1), method = "complete")
hc_average <- agnes(scale(partition_number_1), method = "average")
hc_ward <- agnes(scale(partition_number_1), method = "ward")
```

```
cbind(single = hc_single$ac, complete = hc_complete$ac, average = hc_average$ac, ward = hc_ward$ac)
```

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

```
pltree(hc_ward, cex = 0.6, hang = -1, main = "Dendrogram with partitioned data using ward")
rect.hclust(hc_ward, k = 5, border = 1:4)
```



```
scale(partition_number_1)
agnes (*, "ward")
```

```
cut2 <- cutree(hc_ward, k = 5)
```

```
output <- as.data.frame(cbind(partition_number_1, cut2))
output[output$cut2==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 cut2
## 1 0.33 68.40297    1
## 3 0.33 59.42551    1
## 4 0.50 93.70491    1
```

```
centroid_number_1 <- colMeans(output[output$cut2==1,])
output[output$cut2==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 cut2
## 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_number_2 <- colMeans(output[output$cut2==2,])
output[output$cut2==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 cut2
## 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_number_3 <- colMeans(output[output$cut2==3,])
output[output$cut2==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 cut2
## 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_number_4 <- colMeans(output[output$cut2,])
```

```
centroids <- rbind(centroid_number_1, centroid_number_2, centroid_number_3, centroid_number_4)
cut_2 <- as.data.frame(rbind(centroids[, -14], partition_number_2))
```

Calculating the distance

```
distance1 <- get_dist(cut_2)
matrix1 <- as.matrix(distance1)
```

```
dataframe_number_1 <- data.frame(data = seq(1, nrow(partition_number_2),1), clusters = rep(0, nrow(partition_number_2)))
for (i in 1:nrow(partition_number_2))
{dataframe_number_1[i,2] <- which.min(matrix1[i+4, 1+4])}
dataframe_number_1
```

```
##      data clusters
## 1      1         1
## 2      2         1
## 3      3         1
## 4      4         1
## 5      5         1
## 6      6         1
## 7      7         1
## 8      8         1
## 9      9         1
## 10     10        1
## 11     11        1
## 12     12        1
## 13     13        1
## 14     14        1
## 15     15        1
## 16     16        1
## 17     17        1
## 18     18        1
## 19     19        1
## 20     20        1
## 21     21        1
## 22     22        1
## 23     23        1
## 24     24        1
```

```
cbind(dataframe_number_2$cluster_1[51:74], dataframe_number_1$clusters)
```

```
##      [,1]
## [1,]    1
## [2,]    1
## [3,]    1
## [4,]    1
## [5,]    1
## [6,]    1
## [7,]    1
## [8,]    1
## [9,]    1
## [10,]   1
## [11,]   1
## [12,]   1
## [13,]   1
## [14,]   1
```



```
## [15,] 1
## [16,] 1
## [17,] 1
## [18,] 1
## [19,] 1
## [20,] 1
## [21,] 1
## [22,] 1
## [23,] 1
## [24,] 1
```

```
table(dataframe_number_2$cluster_number_1[51:74], dataframe_number_1$clusters)
```

```
##
##      1
##     2 5
##     3 3
##     4 9
##     5 7
```

From the results we can conclude that the model is partially stable

Clustering healthy cereals data

```
cereals_healthy <- cereals_data
new_cereals_healthy <- na.omit(cereals_healthy)
healthy_clust <- cbind(new_cereals_healthy, cluster_number_1)
healthy_clust[healthy_clust$cluster_number_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_number_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_clust[healthy_clust$cluster_number_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						
## 2	2.0 8.0 8 135 0 3	1.00 1.00 33.98368					
## 8	2.0 18.0 8 100 25 3	1.33 0.75 37.03856					
## 14	2.0 13.0 7 105 25 3	1.00 0.50 40.40021					
## 20	4.0 10.0 7 160 25 3	1.00 0.50 40.44877					
## 23	2.0 11.0 10 120 25 3	1.00 0.75 36.17620					
## 28	5.0 12.0 10 200 25 3	1.25 0.67 40.91705					
## 29	5.0 14.0 12 190 25 3	1.33 0.67 41.01549					
## 35	3.0 13.0 4 100 25 3	1.00 0.33 45.81172					
## 40	2.0 20.0 9 95 100 3	1.30 0.75 36.47151					
## 42	2.0 12.0 6 95 25 2	1.00 0.67 45.32807					
## 45	3.0 16.0 11 170 25 3	1.00 1.00 37.13686					
## 46	3.0 16.0 11 170 25 3	1.00 1.00 34.13976					
## 47	3.0 17.0 13 160 25 3	1.50 0.67 30.31335					
## 50	3.0 21.0 7 130 25 3	1.33 0.67 40.69232					
## 52	1.5 13.5 10 120 25 3	1.25 0.50 30.45084					
## 53	6.0 11.0 14 260 25 3	1.33 0.67 37.84059					
## 57	2.0 14.0 6 110 25 3	1.00 0.50 49.51187					
## 59	5.0 14.0 12 240 25 2	1.33 0.75 39.25920					
## 60	2.5 10.5 8 140 25 3	1.00 0.50 39.70340					
## 71	4.0 15.0 14 230 100 3	1.50 1.00 28.59278					
##	cluster_number_1						
## 2	2						
## 8	2						
## 14	2						
## 20	2						
## 23	2						
## 28	2						
## 29	2						
## 35	2						
## 40	2						
## 42	2						
## 45	2						
## 46	2						
## 47	2						
## 50	2						
## 52	2						
## 53	2						
## 57	2						
## 59	2						
## 60	2						
## 71	2						

```
healthy_clust[healthy_clust$cluster_number_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_number_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_clust[healthy_clust$cluster_number_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_number_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	

The elementary public schools would like to choose a set of cereals to include in their daily cafeterias. Every day a different cereal is offered, but all cereals should support a healthy diet. For this goal, you are requested to find a cluster of “healthy cereals.” Should the data be normalized? If not, how should they be used in the cluster analysis?

Given the particular sample of cereals in this case—which may have extreme values like high sugar content and low fiber and iron—it is deemed unacceptable to immediately normalize the cereal nutrition data. Normalization of this kind could be misleading because it obscures the cereals’ actual nutritional worth to children. A better preprocessing strategy would be to compute ratios to a child’s daily recommended levels of calories, fiber, carbs, etc. When analyzing the data, this strategy helps analysts make more educated conclusions regarding the clusters by giving context on the amount of a child’s daily nutritional demands that each cereal meets. In addition, it stops deceptive scaling, making sure that the distance computations aren’t dominated by a few bigger variables.

Analysts can choose “healthy” cereal clusters that best suit a child’s nutritional needs by looking at the average values for each cluster and determining which cereals in a cluster

contribute the most to a student's daily necessary nutrition.

Mean rating

```
mean(healthy_clust[healthy_clust$cluster_number_1==1, "rating"])
```

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

```
mean(healthy_clust[healthy_clust$cluster_number_1==2, "rating"])
```

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

```
mean(healthy_clust[healthy_clust$cluster_number_1==3, "rating"])
```

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

```
mean(healthy_clust[healthy_clust$cluster_number_1==4, "rating"])
```

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

Since cluster 1 has the highest mean ratings (73.84446), we can consider it.