

# Assignment 5

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```
#loading all the required libraries  
library(factoextra)
```

```
## Warning: package 'factoextra' was built under R version 4.1.3
```

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

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

```
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(cluster)  
library(tidyverse)
```

```
## Warning: package 'tidyverse' was built under R version 4.1.3
```

```
## -- Attaching packages ----- tidyverse 1.3.1 --

## v tibble 3.1.6      v dplyr 1.0.8
## v tidyr 1.2.0      v stringr 1.4.0
## v readr 2.1.2      v forcats 0.5.1
## v purrr 0.3.4

## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag() masks stats::lag()
```

```
library(knitr)
```

```
#importing the data
```

```
cereals = read_csv("C:/Users/desineni/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.
```

```
numericaldata = data.frame(cereals[,4:16])
```

```
#omitting all the missing values present in the data
```

```
OmitMissing = na.omit(numericaldata)
```

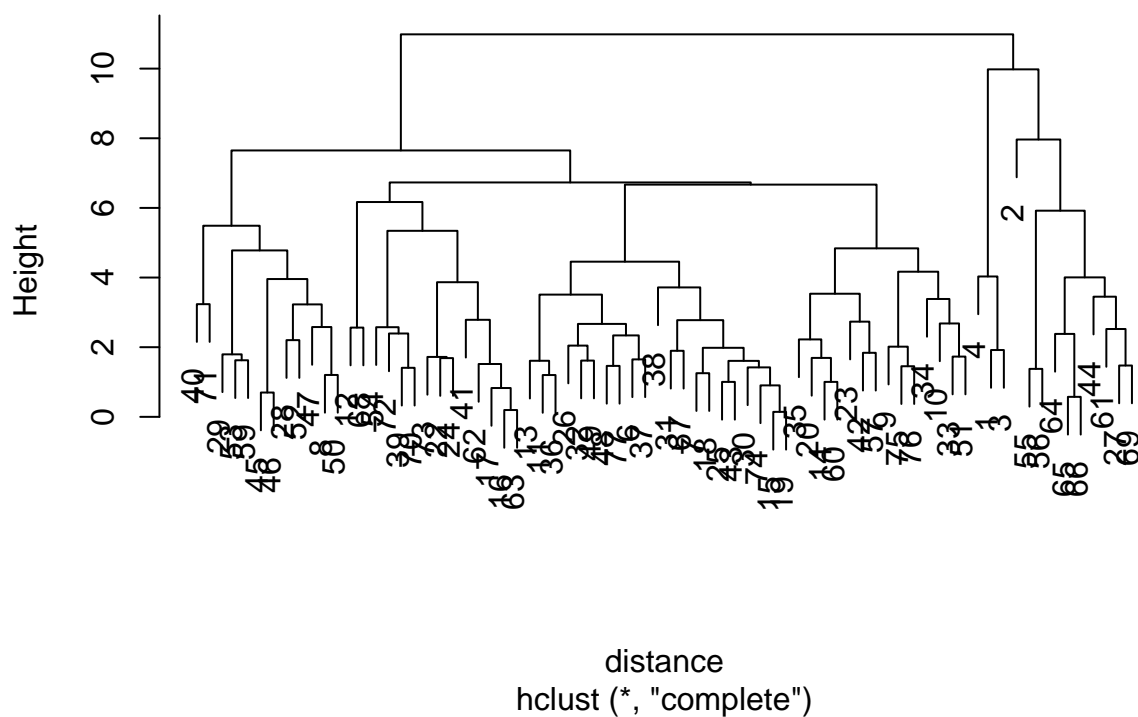
```
#normalizing and scaling the data
```

```
Normalise = scale(OmitMissing)
```

```
#measuring the distance using the euclidian distance and computing the dissimilarity matrix
distance = dist(Normalise, method = "euclidian")
```

```
#performing hierarchial clustering using complete linkage and representing in plot
hierarchial_clustering = hclust(distance, method = "complete")
plot(hierarchial_clustering)
```

## Cluster Dendrogram



*#rounding off the decimals*

```
round(hierarchical_clustering$height, 3)
```

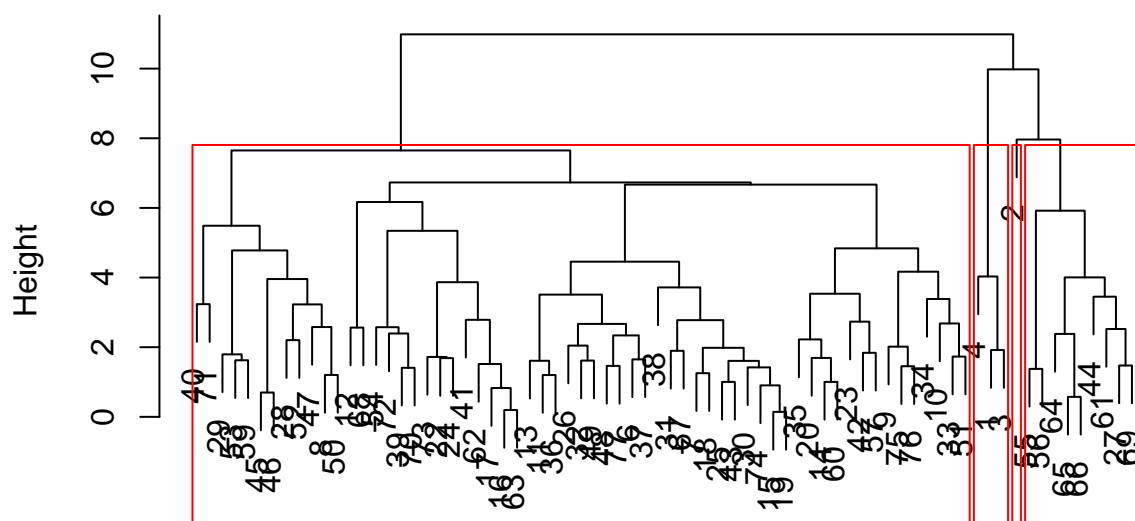
```
## [1] 0.143 0.196 0.575 0.698 0.828 0.904 1.003 1.004 1.201 1.203
## [11] 1.254 1.378 1.408 1.421 1.454 1.463 1.474 1.517 1.608 1.611
## [21] 1.616 1.625 1.650 1.687 1.692 1.720 1.730 1.795 1.839 1.897
## [31] 1.919 1.982 2.015 2.046 2.203 2.224 2.339 2.381 2.394 2.522
## [41] 2.563 2.574 2.579 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 the optimal clusters and highlighting with colours*

```
plot(hierarchical_clustering)
```

```
rect.hclust(hierarchical_clustering, k = 4, border = "red")
```

## Cluster Dendrogram



distance  
hclust (\*, "complete")

*#performing clustering using AGNES*

```
HCsingle = agnes(Normalise, method = "single")
HCcomplete = agnes(Normalise, method = "complete")
HCaverage = agnes(Normalise, method = "average")
HCward = agnes(Normalise, method = "ward")
```

*#comparing the agglomerative cosfficients of single , complete, average, ward*  
print(HCsingle\$ac)

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

```
print(HCcomplete$ac)
```

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

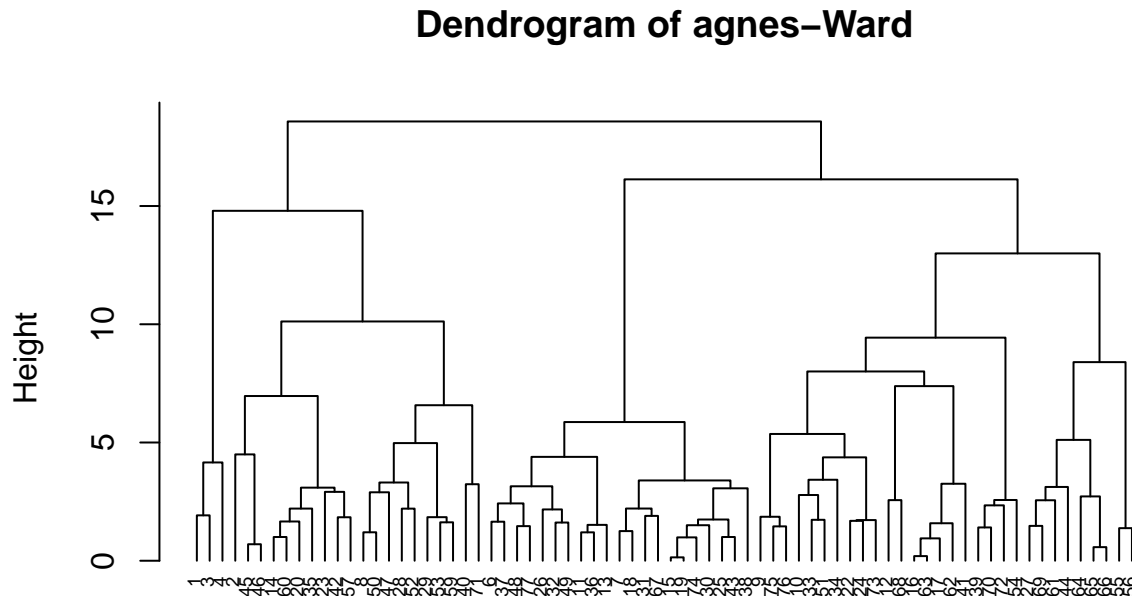
```
print(HCaverage$ac)
```

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

```
print(HCward$ac)
```

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

```
#according to the above values, wards method is the best with the value of 0.904.plotting ward using ag
pltree(HCward, cex = 0.6, hang = -1, main = "Dendrogram of agnes-Ward")
```



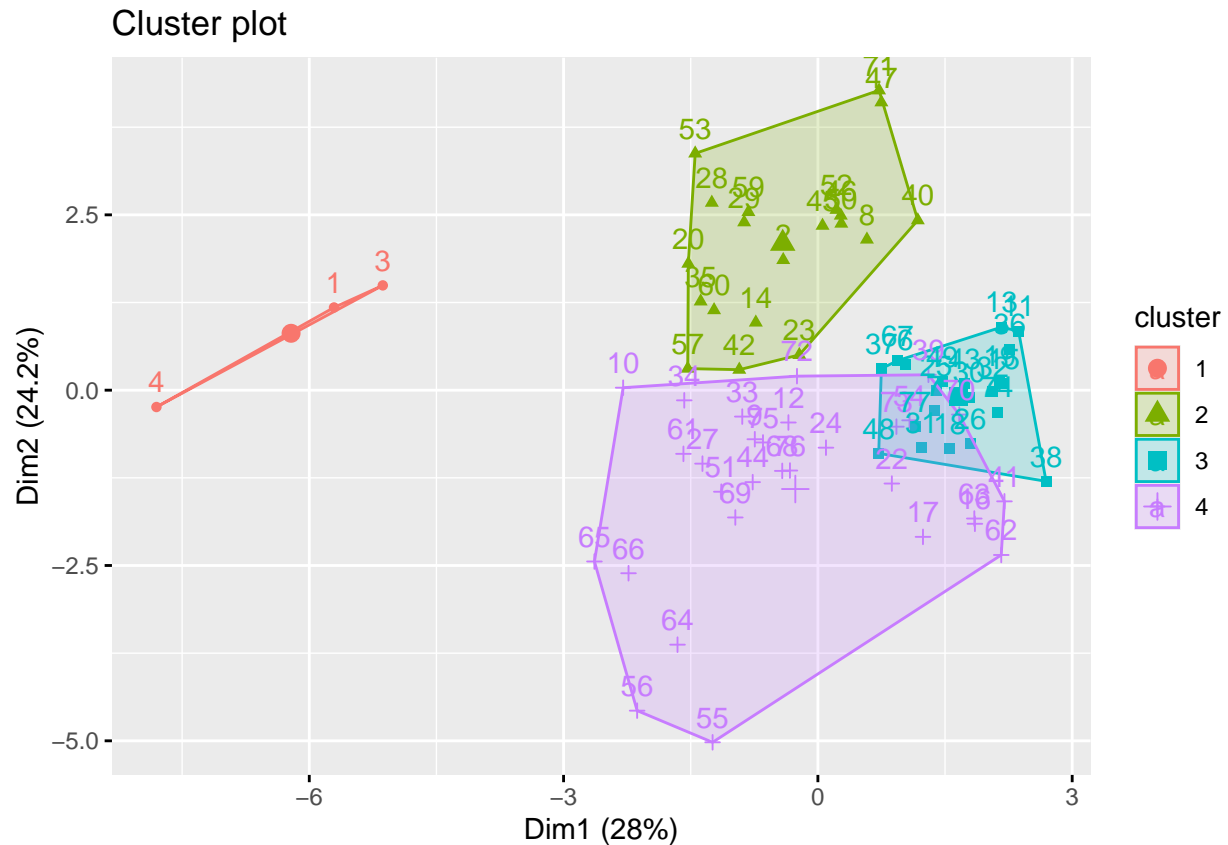
Normalise  
agnes (\*, "ward")

```
#using the ward method for hierarchial clustering
HC1 <- hclust(distance, method = "ward.D2" )
subgrp <- cutree(HC1, k = 4)
table(subgrp)
```

```
## subgrp
##  1  2  3  4
##  3 20 21 30
```

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

```
#visualising the results on scatterplot
fviz_cluster(list(data = Normalise, cluster = subgrp))
```



*#selecting the best breakfast cereal cluster with high protein, fibre and low in sugar and sodium.  
 #choosing the healthy cereal cluster*

```
Newdatacereals = numericaldata
Newdatacereals_omit = na.omit(Newdatacereals)
Clust = cbind(Newdatacereals_omit, subgrp)
Clust[Clust$subgrp==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 subgrp
## 1 0.33 68.40297      1
## 3 0.33 59.42551      1
## 4 0.50 93.70491      1
```

```
Clust[Clust$subgrp==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
## 40	140	3	1	170	2.0	20.0	9	95	100	3	1.30
## 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
## 59	120	3	1	210	5.0	14.0	12	240	25	2	1.33
## 60	100	3	2	140	2.5	10.5	8	140	25	3	1.00
## 71	140	3	1	190	4.0	15.0	14	230	100	3	1.50
##	cups	rating	subgrp								
## 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								
## 40	0.75	36.47151	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								
## 53	0.67	37.84059	2								
## 57	0.50	49.51187	2								
## 59	0.75	39.25920	2								
## 60	0.50	39.70340	2								
## 71	1.00	28.59278	2								

```
Clust[Clust$subgrp==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
## 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
## 67	110	2	1	70	1.0	9.0	15	40	25	2	1
## 74	110	1	1	140	0.0	13.0	12	25	25	2	1
## 77	110	2	1	200	1.0	16.0	8	60	25	1	1
##	cups	rating	subgrp								
## 6	0.75	29.50954	3								
## 7	1.00	33.17409	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								
## 67	0.75	31.23005	3								
## 74	1.00	27.75330	3								
## 77	0.75	36.18756	3								

```
Clust[Clust$subgrp==4,]
```

##	calories	protein	fat	sodium	fiber	carbo	sugars	potass	vitamins	shelf	weight
## 9	90	2	1	200	4	15	6	125	25	1	1.00
## 10	90	3	0	210	5	13	5	190	25	3	1.00
## 12	110	6	2	290	2	17	1	105	25	1	1.00
## 16	110	2	0	280	0	22	3	25	25	1	1.00
## 17	100	2	0	290	1	21	2	35	25	1	1.00
## 22	110	2	0	220	1	21	3	30	25	3	1.00
## 24	100	2	0	190	1	18	5	80	25	3	1.00
## 27	100	3	0	0	3	14	7	100	25	2	1.00
## 33	100	3	1	140	3	15	5	85	25	3	1.00
## 34	110	3	0	170	3	17	3	90	25	3	1.00
## 39	110	2	1	170	1	17	6	60	100	3	1.00
## 41	110	2	1	260	0	21	3	40	25	2	1.00
## 44	100	4	1	0	0	16	3	95	25	2	1.00
## 51	90	3	0	170	3	18	2	90	25	3	1.00
## 54	100	3	0	320	1	20	3	45	100	3	1.00
## 55	50	1	0	0	0	13	0	15	0	3	0.50
## 56	50	2	0	0	1	10	0	50	0	3	0.50
## 61	90	2	0	0	2	15	6	110	25	3	1.00
## 62	110	1	0	240	0	23	2	30	25	1	1.00
## 63	110	2	0	290	0	22	3	35	25	1	1.00
## 64	80	2	0	0	3	16	0	95	0	1	0.83
## 65	90	3	0	0	4	19	0	140	0	1	1.00



```
## 66      90      3  0      0      3  20      0  120      0      1  1.00
## 68     110      6  0    230      1  16      3   55     25      1  1.00
## 69      90      2  0     15      3  15      5   90     25      2  1.00
## 70     110      2  1    200      0  21      3   35    100      3  1.00
## 72     100      3  1    200      3  16      3  110    100      3  1.00
## 73     110      2  1    250      0  21      3   60     25      3  1.00
## 75     100      3  1    230      3  17      3  115     25      1  1.00
## 76     100      3  1    200      3  17      3  110     25      1  1.00
##      cups   rating subgrp
## 9  0.67 49.12025      4
## 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
## 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
## 61 0.50 55.33314      4
## 62 1.13 41.99893      4
## 63 1.00 40.56016      4
## 64 1.00 68.23588      4
## 65 0.67 74.47295      4
## 66 0.67 72.80179      4
## 68 1.00 53.13132      4
## 69 1.00 59.36399      4
## 70 1.00 38.83975      4
## 72 1.00 46.65884      4
## 73 0.75 39.10617      4
## 75 0.67 49.78744      4
## 76 1.00 51.59219      4
```

```
#here we calculate the mean rating in order determine the healthy cluster cereals
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] 51.43111
```

*#From the above results it is clearly evident that mean rating is highest for subgroup 1.  
#so, it is recommended to choose subgrp 1 as the healthy diet cluster.*