

assignment 5

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

## Loading required package: ggplot2
## Loading required package: lattice
library(dendextend)

##
## -----
## 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(factoextra)

## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
Cereals <- read_csv("~/Downloads/assignment_5/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 importing cereals dataset

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

data processing. removing the missing values that might present in the data

```
removed_missingvalue <- na.omit(data.frame)
```

```
#Data normalization and data scaling
```

```
Normalize <- scale(removed_missingvalue)
```

using the euclidean distance to measure the distance

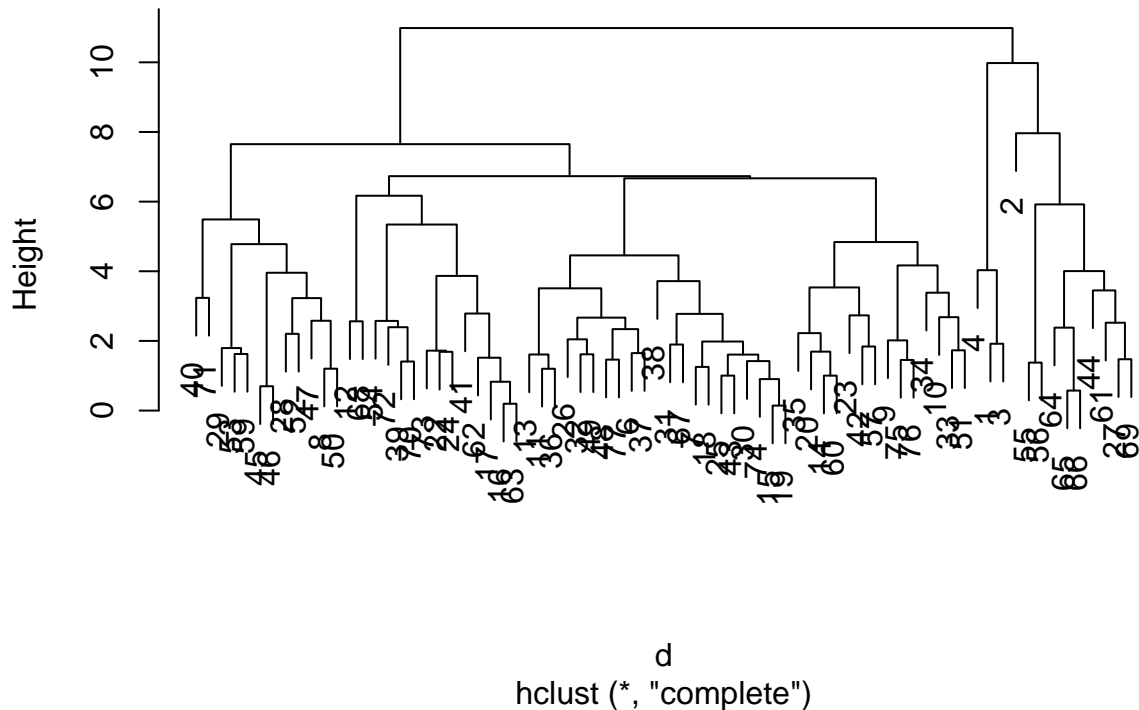
```
d <- dist(Normalize, method = "euclidean")
```

```
#perform hierarchical clustering using complete linkage.
```

```
Hc <- hclust(d, method = "complete")
```

```
plot(Hc)
```

Cluster Dendrogram



```
#dendrogram
```

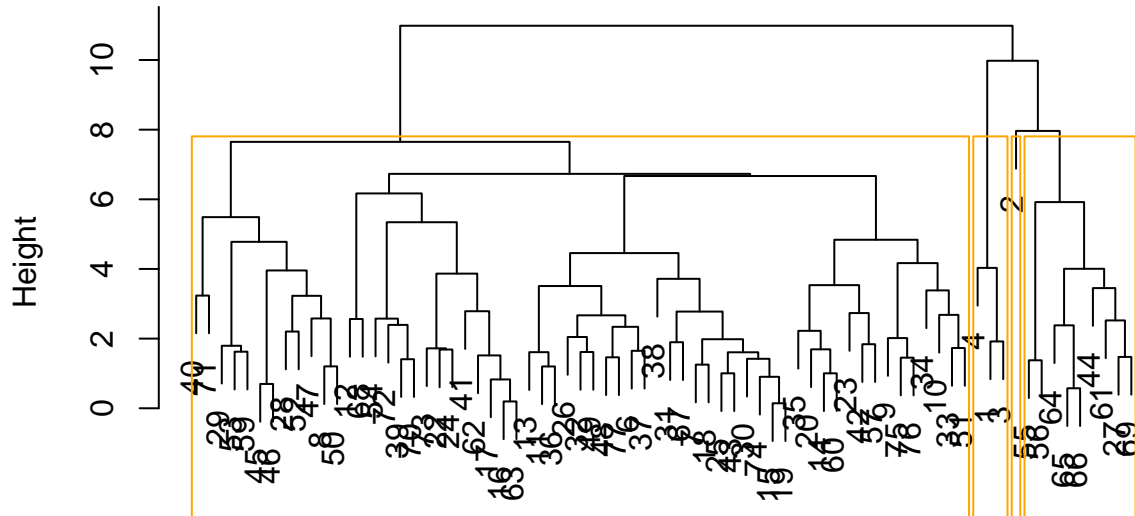
```
round(Hc$height, 3)
```

```
## [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: highlighting the clusters in dendrogram directly.

```
plot(Hc)
rect.hclust(Hc,k = 4, border = "orange")
```

Cluster Dendrogram



d
hclust (*, "complete")

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

```
Hcsingle <- agnes(Normalize, method = "single")
Hccomplete <- agnes(Normalize, method = "complete")
Hcaverage <- agnes(Normalize, method = "average")
Hcward <- agnes(Normalize, method = "ward")
```

Compare the agglomerative coefficients for single,complete,average and ward.

```
print(Hcsingle$ac)
```

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

```
print(Hccomplete$ac)
```

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

```
print(Hcaverage$ac)
```

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

```
print(Hcward$ac)
```

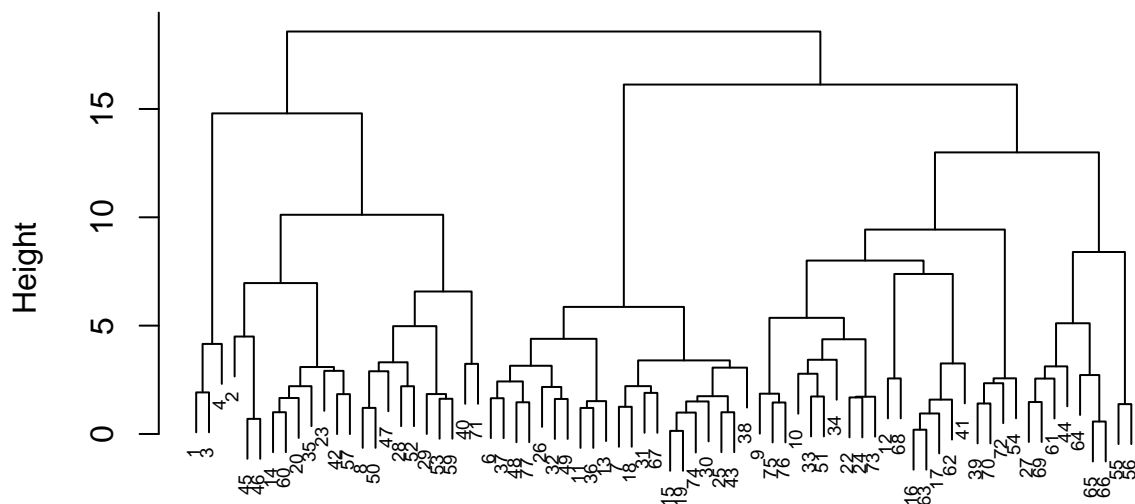
```
## [1] 0.9046042
```

From the above results the best value we got is 0.904. Plotting the agnes using ward method and cutting the Dendrogram. we will take k =4 by observing the distance

```
pltree(Hcward, cex = 0.6, hand = -1, main = "Dendrogram of agnes ward")
```

```
## Warning in graphics::plotHclust(n1, merge, height, order(x$order), hang, :  
## "hand" is not a graphical parameter  
  
## Warning in graphics::plotHclust(n1, merge, height, order(x$order), hang, :  
## "hand" is not a graphical parameter  
  
## Warning in axis(2, at = pretty(range(height)), ...): "hand" is not a graphical  
## parameter  
  
## Warning in title(main = main, sub = sub, xlab = xlab, ylab = ylab, ...): "hand"  
## is not a graphical parameter
```

Dendrogram of agnes ward



Normalize
agnes (*, "ward")

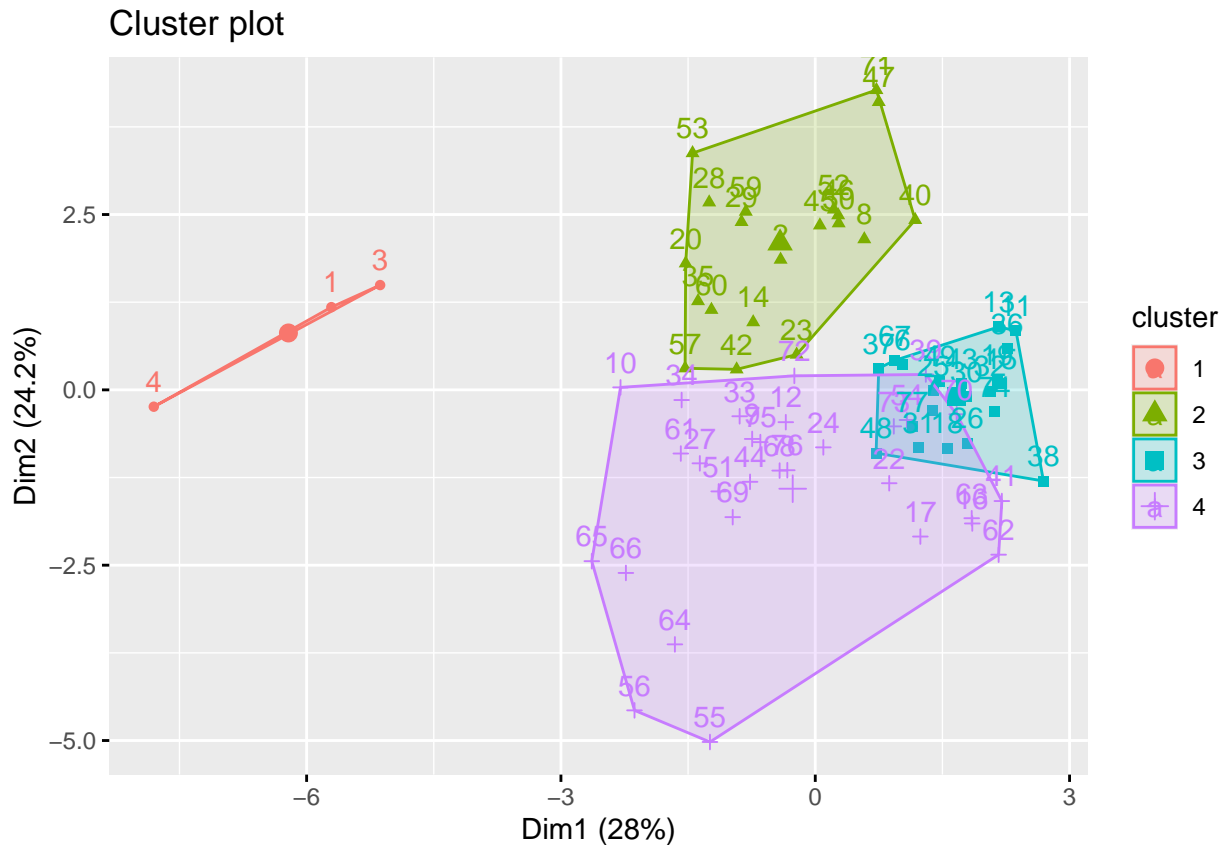
Hierarchi-

cal clustering using ward method.

```
hc1 <- hclust(d, method = "ward.D2")  
subgroup <- cutree(hc1, k =4)  
table(subgroup)
```

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

```
datafram <- as.data.frame(cbind(Normalize,subgroup))  
#the results in scatter plot.  
fviz_cluster(list(data = Normalize,cluster=subgroup))
```



```
datacereals <- Cereals
datacereals.omi <- na.omit(datacereals)
clust <- cbind(datacereals.omi, subgroup)
clust[clust$subgroup==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	subgroup	
## 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$subgroup==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 subgroup						
## 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$subgroup==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	subgroup
## 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$subgroup==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
## 27		Frosted_Mini-Wheats	K	C	100		3	0	0	3	14
## 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
## 44		Maypo	A	H	100		4	1	0	0	16
## 51		Nutri-grain_Wheat	K	C	90		3	0	170	3	18
## 54		Product_19	K	C	100		3	0	320	1	20
## 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
## 62		Rice_Chex	R	C	110		1	0	240	0	23
## 63		Rice_Krispies	K	C	110		2	0	290	0	22
## 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
## 68		Special_K	K	C	110		6	0	230	1	16
## 69		Strawberry_Fruit_Wheats	N	C	90		2	0	15	3	15
## 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	subgroup			
## 9	6	125	25	1	1.00	0.67	49.12025		4			
## 10	5	190	25	3	1.00	0.67	53.31381		4			
## 12	1	105	25	1	1.00	1.25	50.76500		4			
## 16	3	25	25	1	1.00	1.00	41.44502		4			
## 17	2	35	25	1	1.00	1.00	45.86332		4			
## 22	3	30	25	3	1.00	1.00	46.89564		4			
## 24	5	80	25	3	1.00	0.75	44.33086		4			
## 27	7	100	25	2	1.00	0.80	58.34514		4			
## 33	5	85	25	3	1.00	0.88	52.07690		4			
## 34	3	90	25	3	1.00	0.25	53.37101		4			
## 39	6	60	100	3	1.00	1.00	36.52368		4			
## 41	3	40	25	2	1.00	1.50	39.24111		4			
## 44	3	95	25	2	1.00	1.00	54.85092		4			
## 51	2	90	25	3	1.00	1.00	59.64284		4			
## 54	3	45	100	3	1.00	1.00	41.50354		4			
## 55	0	15	0	3	0.50	1.00	60.75611		4			
## 56	0	50	0	3	0.50	1.00	63.00565		4			
## 61	6	110	25	3	1.00	0.50	55.33314		4			
## 62	2	30	25	1	1.00	1.13	41.99893		4			
## 63	3	35	25	1	1.00	1.00	40.56016		4			
## 64	0	95	0	1	0.83	1.00	68.23588		4			
## 65	0	140	0	1	1.00	0.67	74.47295		4			
## 66	0	120	0	1	1.00	0.67	72.80179		4			
## 68	3	55	25	1	1.00	1.00	53.13132		4			
## 69	5	90	25	2	1.00	1.00	59.36399		4			
## 70	3	35	100	3	1.00	1.00	38.83975		4			
## 72	3	110	100	3	1.00	1.00	46.65884		4			
## 73	3	60	25	3	1.00	0.75	39.10617		4			
## 75	3	115	25	1	1.00	0.67	49.78744		4			
## 76	3	110	25	1	1.00	1.00	51.59219		4			

calculating the mean ratings to determine the cluster cereals

```
mean(clust[clust$subgroup==1,"rating"])
```

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

```
mean(clust[clust$subgroup==2,"rating"])
```

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

```
mean(clust[clust$subgroup==3,"rating"])
```

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

```
mean(clust[clust$subgroup==4,"rating"])
```

```
## [1] 51.43111
```

from the above results we can clearly that the mean rating is high for subgroup 1.