session22_assignment_modified.R

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2. Perform the below given activities:
a. apply K-means clustering to identify similar recipies
b. apply K-means clustering to identify similar attributes
c. how many unique recipies that people order often

d. what are their typical profiles

Discussion:-

Based on the assumption that o and 1 are indication of people order recipes, we have modified the data base , based on higher no of 1 and sorted then named it as epir_1 and the cluster analysis is performed.

Based on the analysis the aggregate group and cluster are given below.

```
head(df_train)
```

```
##      rating calories protein fat sodium cl
## 175   3.125      259       3  22    164  3
## 868   3.750      619       3   9    255  3
## 850   5.000      587       7  26    172  3
## 1369  3.750      203       6  11   1040  3
## 1185  4.375      408       9  20    461  3
## 889   4.375      188       2   1     10  3
```

```
# profiles of clusters
aggregate(df_train[,1:5],list(df_train[,6]),mean)
```

```
##   Group.1    rating  calories   protein       fat    sodium
## 1       1 0.8088235  214.7353  3.647059   8.50000  205.0588
## 2       2 3.4134615 1891.3462 81.346154 108.53846 2303.0769
## 3       3 4.1368626  315.8584  9.114731  16.76204  280.6119
```

```r
setwd("C:/Users/Seshan/Desktop/sv R related/acadgild/assignments/session 22/epicurious")
library(readr)
epi_r1 <- read.csv("epi_r1.csv")
View(epi_r1)
df<-epi_r1
df[df==""] <- NA
df1<-na.exclude(df)
View(df1)


str(df1)
```

```
## 'data.frame':    15864 obs. of  681 variables:
##  $ title                   : Factor w/ 17736 levels "'Wichcraft's Roasted
Turkey, Avocado, Bacon, Onion Relish, & AÃ¯oli on Ciabatta ",..: 2728 12026 7
098 12233 4953 16811 5964 5951 4907 13864 ...
##  $ rating                  : num  4.38 4.38 4.38 5 4.38 ...
##  $ calories                : int  148 274 466 150 208 512 438 338 215 247
...
##  $ protein                 : int  2 10 48 0 5 14 12 2 6 6 ...
##  $ fat                     : int  10 0 28 0 17 47 40 1 20 15 ...
##  $ sodium                  : int  57 28 998 1 347 562 868 33 250 418 ...
##  $ X.cakeweek              : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ X.wasteless             : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ X22.minute.meals        : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ X3.ingredient.recipes   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ X30.days.of.groceries   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ advance.prep.required   : int  0 1 0 0 0 0 1 0 1 0 ...
##  $ alabama                 : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ alaska                  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ alcoholic               : int  0 1 0 1 0 0 0 0 0 0 ...
##  $ almond                  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ amaretto                : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ anchovy                 : int  0 0 0 0 0 1 0 0 0 0 ...
##  $ anise                   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ anniversary             : int  0 1 0 0 0 0 0 0 0 0 ...
##  $ anthony.bourdain        : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ aperitif                : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ appetizer               : int  0 0 0 0 1 0 1 0 0 0 ...
##  $ apple                   : int  1 0 0 0 0 0 0 0 0 0 ...
##  $ apple.juice             : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ apricot                 : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ arizona                 : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ artichoke               : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ arugula                 : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ asian.pear              : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ asparagus               : int  0 0 0 0 0 0 0 0 0 0 ...
```

```
##  $ aspen                  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ atlanta                : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ australia              : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ avocado                : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ back.to.school         : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ backyard.bbq           : int  1 0 1 0 1 1 0 1 0 0 ...
##  $ bacon                  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ bake                   : int  0 0 0 0 0 0 0 0 0 1 ...
##  $ banana                 : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ barley                 : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ basil                  : int  0 0 0 0 0 0 1 0 1 0 ...
##  $ bass                   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ bastille.day           : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ bean                   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ beef                   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ beef.rib               : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ beef.shank             : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ beef.tenderloin        : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ beer                   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ beet                   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ bell.pepper            : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ berry                  : int  0 1 0 0 0 0 0 0 0 0 ...
##  $ beverly.hills          : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ birthday               : int  0 1 0 0 0 0 0 1 0 0 ...
##  $ biscuit                : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ bitters                : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ blackberry             : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ blender                : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ blue.cheese            : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ blueberry              : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ boil                   : int  0 1 0 0 0 0 0 0 1 0 ...
##  $ bok.choy               : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ bon.appÃ.tit           : int  1 1 1 0 1 1 0 0 0 1 ...
##  $ bon.appï..ï..tit       : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ boston                 : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ bourbon                : int  0 0 0 1 0 0 0 0 0 0 ...
##  $ braise                 : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ bran                   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ brandy                 : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ bread                  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ breadcrumbs            : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ breakfast              : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ brie                   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ brine                  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ brisket                : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ broccoli               : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ broccoli.rabe          : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ broil                  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ brooklyn               : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ brown.rice             : int  0 0 0 0 0 0 0 0 0 0 ...
```

```
##  $ brownie                 : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ brunch                  : int  0 0 0 1 0 0 0 0 0 0 ...
##  $ brussel.sprout          : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ buffalo                 : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ buffet                  : int  1 0 0 0 1 1 0 0 0 0 ...
##  $ bulgaria                : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ bulgur                  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ burrito                 : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ butter                  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ buttermilk              : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ butternut.squash        : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ butterscotch.caramel    : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ cabbage                 : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ cake                    : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ california              : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ calvados                : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ cambridge               : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ campari                 : int  0 0 0 0 0 0 0 0 0 0 ...
##   [list output truncated]
##  - attr(*, "na.action")= 'exclude' Named int  1 3 11 14 19 21 25 26 31 35
...
##   ..- attr(*, "names")= chr  "1" "3" "11" "14" ...
```

```
library(factoextra)
```

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

```
## Welcome! Related Books: `Practical Guide To Cluster Analysis in R` at http
s://goo.gl/13EFCZ
```

```
library("factoextra")
```

```
df <- df1[1:1000, 1:6]
na.exclude(df)
```

```
##
title
## 2                                                                  Celery, App
le, and Fennel Slaw
## 4                                                                       Prosec
co-Raspberry GelÃ©e
## 5                                                  Grilled Lemon-Oregano
Chicken Drumsticks
## 6
Rabbit Punch
## 7                                                               Cucumber, To
mato and Feta Salad
## 8                                                                     Tusc
an Kale Caesar Slaw
## 9                                                             Fresh Herb Plat
```

```
ter (Sabzi Khordan)
## 10                                          Fresh Fruit Ice Trio: Lime, Wat
ermelon & Pineapple
## 12                                                                   Radic
chio with Garlic
## 1363                              FrisÃ©e and Celery Salad with Toasted F
ennel-Seed Dressing
## 1364                                                                 B
ourbon Creamed Corn
## 1365                                                          Romaine wit
h Parmesan Dressing
## 1367
Plum Applesauce
## 1368                                                 Gratin Dauphinoise (
Scalloped Potatoes)
## 1369                                                       Quinoa and Bul
gur Salad with Feta
## 1370                                          Crab and Cucumber Pastries
with Mustard Sauce
##      rating calories protein fat sodium
## 2     4.375      148       2  10     57
## 4     4.375      274      10   0     28
## 5     4.375      466      48  28    998
## 6     5.000      150       0   0      1
## 7     4.375      208       5  17    347
## 8     4.375      512      14  47    562
## 9     0.000      438      12  40    868
## 10    4.375      338       2   1     33
## 12    3.750      215       6  20    250
## 13    4.375      247       6  15    418
## 15    3.750      295       5  16    480
## 16    3.750      324      11  19    618
## 17    3.125       83       1   7     11
## 18    4.375      196       5  10    400
## 20    3.125       83       1   7     11
## 22    3.125      627       1  61     81
## 23    4.375      142       2   1     14
## 24    5.000      503       6  23    430
## 27    4.375      375      18  26    578
## 28    4.375      391       6  21     19
## 29    4.375      431      33  17    135
## 30    4.375      138       0   0      5
## 32    4.375      221       6  17     52
## 33    2.500      179       1   0     32
## 1344  3.750      186       2  10    118
## 1345  3.750      248       0  27    321
## 1347  0.000      419      19  15    328
## 1349  4.375      738      42  43    209
## 1350  4.375     1051      13  72    518
## 1351  3.125      176      11  14     35
```

```
## 1352  2.500      188       1   0      4
## 1353  0.000      222       2   1      3
## 1354  3.750      414       6  30     29
## 1355  4.375      859       8  50    486
## 1356  4.375       84       1   8     40
## 1357  4.375     2330      31  94    992
## 1358  3.125      102       4   4     48
## 1359  3.750      412       7  26    901
## 1360  4.375      123       4   9    404
## 1362  3.125       67       3   3     12
## 1363  5.000       81       1   7    329
## 1364  3.750      414       6  30     29
## 1365  3.750      249      11  21    399
## 1367  5.000       94       1   0      1
## 1368  3.750      228       6   8     42
## 1369  3.750      203       6  11   1040
## 1370  4.375      453      13  35    621
```

```
View(df)
head(df[, 1:6])
```

```
##                                       title rating calories protein fat
## 2           Celery, Apple, and Fennel Slaw   4.375      148       2  10
## 4                Prosecco-Raspberry GelÃ©e   4.375      274      10   0
## 5 Grilled Lemon-Oregano Chicken Drumsticks   4.375      466      48  28
## 6                                Rabbit Punch   5.000      150       0   0
## 7          Cucumber, Tomato and Feta Salad   4.375      208       5  17
## 8                  Tuscan Kale Caesar Slaw   4.375      512      14  47
##   sodium
## 2     57
## 4     28
## 5    998
## 6      1
## 7    347
## 8    562
```

```
# Prepare Data
df <- na.omit(df) # listwise deletion of missing
#df <- scale(df) # standardize variables
View(df)
set.seed(1234)
ind = sample(1:nrow(df),0.8*nrow(df),replace = F)
df_train =df[ind,-1]
df_test = df[-ind,-1]
```

```
summary(df)
```

```
##                                       title         rating
##  Classic Red Rice                        :  3   Min.   :0.000
##  Amaretto Olive Oil Cake                 :  2   1st Qu.:3.750
##  Apple and Celery Salad                  :  2   Median :4.375
```

```
##  Arugula Salad with Lemon-Pepper Dressing :  2   Mean   :3.834
##  Asian Cabbage Salad                      :  2   3rd Qu.:4.375
##  Avocado Salsa                            :  2   Max.   :5.000
##  (Other)                                  :987
##     calories         protein            fat             sodium
##  Min.   :   3.0   Min.   :  0.00   Min.   :  0.00   Min.   :    1.0
##  1st Qu.: 146.8   1st Qu.:  2.00   1st Qu.:  5.00   1st Qu.:   32.0
##  Median : 247.0   Median :  5.00   Median : 12.00   Median :  152.0
##  Mean   : 352.9   Mean   : 10.96   Mean   : 18.79   Mean   :  359.6
##  3rd Qu.: 426.0   3rd Qu.: 11.00   3rd Qu.: 23.25   3rd Qu.:  405.0
##  Max.   :4562.0   Max.   :348.00   Max.   :460.00   Max.   :15061.0
##
```

```
dim(df)
```

```
## [1] 1000    6
```

```
# outlier definition
# x > Q3+1.5*IQR - positive side outlier
# x < Q1-1.5*IQR - negative or lower side outlier
par(mfrow=c(2,3))
(boxplot(df1$rating)$out);(boxplot(df1$calories)$out);(boxplot(df1$protein)$o
ut);(boxplot(df1$fat)$out);(boxplot(df1$sodium)$out)
```

```
##    [1] 0.000 2.500 2.500 0.000 1.250 2.500 0.000 1.875 0.000 2.500 0.000
##   [12] 0.000 1.250 0.000 0.000 0.000 0.000 1.250 2.500 0.000 2.500 0.000
##   [23] 0.000 0.000 1.250 0.000 2.500 0.000 0.000 0.000 0.000 2.500 2.500
##   [34] 1.875 0.000 0.000 0.000 0.000 0.000 2.500 2.500 0.000 0.000 0.000
##   [45] 0.000 0.000 0.000 0.000 0.000 0.000 2.500 0.000 0.000 2.500 2.500
##   [56] 1.875 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 2.500 1.250
##   [67] 0.000 0.000 2.500 2.500 0.000 1.875 2.500 0.000 0.000 1.875 2.500
##   [78] 2.500 2.500 2.500 0.000 2.500 0.000 1.250 1.250 0.000 0.000 1.250
##   [89] 0.000 1.250 0.000 1.875 2.500 2.500 2.500 1.875 0.000 2.500 0.000
##  [100] 1.250 0.000 0.000 0.000 2.500 0.000 0.000 0.000 1.250 0.000 2.500
##  [111] 0.000 2.500 1.250 0.000 0.000 0.000 0.000 2.500 2.500 0.000 0.000
##  [122] 0.000 2.500 2.500 1.250 0.000 1.250 1.250 0.000 2.500 1.875 0.000
##  [133] 1.250 2.500 0.000 0.000 2.500 2.500 0.000 2.500 0.000 0.000 2.500
##  [144] 0.000 0.000 0.000 0.000 1.250 0.000 2.500 0.000 0.000 1.250 0.000
##  [155] 1.875 2.500 0.000 0.000 2.500 1.875 1.875 2.500 2.500 0.000 2.500
##  [166] 0.000 1.250 0.000 1.250 2.500 1.875 2.500 0.000 2.500 0.000 0.000
##  [177] 2.500 1.250 0.000 2.500 0.000 2.500 2.500 2.500 0.000 2.500 2.500
##  [188] 0.000 0.000 0.000 0.000 1.875 0.000 0.000 2.500 2.500 0.000 2.500
##  [199] 1.875 0.000 1.875 0.000 0.000 1.250 2.500 0.000 0.000 0.000 2.500
##  [210] 0.000 0.000 0.000 0.000 2.500 1.250 2.500 0.000 2.500 0.000 2.500
```

```
## [1079]     1731     2178     2244     1792     1918     2155     1914
## [1086]     2715    11462     1914     1945     1844     1745     1731
## [1093]     2320     3525    22859     3196     3525     1792     2475
## [1100]     2102     2492     1867     1663     2492     3604     2310
```

```
## [1107]     1729     2509     2434     1814     2320     1844     2934
## [1114]     2861     2725     2773     5757     2391     1786     3196
## [1121]     2419     3526     1786     2866     4092     4646     2312
## [1128]     2724     2505     2079     2505     3340     1809     2938
## [1135]     3715     2866     1706     1706     1865     2032     2295
## [1142]     1701     4595     2293     2883     2032     1738     2509
## [1149]     2875     6502     2377     2420     2377     1780     2420
```

```
apply(df,2,range)
```

```
##      title                                  rating  calories protein fat
## [1,] "\"Cannoli\" Ice Cream Sandwiches " "0.000" "   3"    "  0"    "  0"
## [2,] "Zucchini, Tomato, and Corn Salad " "5.000" "4562"   "348"   "460"
##      sodium
## [1,] "    1"
## [2,] "15061"
```

```
apply(df,2,summary)
```

```
##        title       rating      calories    protein     fat
## Length "1000"      "1000"      "1000"      "1000"      "1000"
## Class  "character" "character" "character" "character" "character"
## Mode   "character" "character" "character" "character" "character"
##        sodium
## Length "1000"
## Class  "character"
## Mode   "character"
```

```
# KMeans - comes from Rcmdr library
# Kmeans- from amap library
# kmeans- from stats library

# steps in k-means clustering
#1- preprocessing the data (impute missing values, remove outliers, feature t
rasnformation)
#2- scaling or standardization of data set
#3- decide the number of clusters (value of K)
#4- iterate over the samples to create clusters
#5- decide the distance measure
#6- calculate the group accuracy

# scaling of data
df_train1 <- scale(df_train)

head(df_train1)
```

```
##           rating   calories     protein         fat     sodium
## 175  -0.61680701 -0.2289947 -0.38653872  0.10460888 -0.3003865
## 868  -0.07035562  0.5998100 -0.38653872 -0.35521036 -0.1450024
## 850   1.02254716  0.5261385 -0.19320894  0.24609172 -0.2867264
## 1369 -0.07035562 -0.3579199 -0.24154139 -0.28446894  1.1953990
```

```
## 1185  0.47609577  0.1140383 -0.09654406  0.03386746  0.2067463
## 889   0.47609577 -0.3924534 -0.43487116 -0.63817604 -0.5633443

class(df_train1)

## [1] "matrix"

# screeplot approach to decide the number of clusters
km = kmeans(df_train1,1)
km$withinss

## [1] 3995

km$tot.withinss

## [1] 3995

km = kmeans(df_train1,2)
km$withinss

## [1] 1782.1249  992.6804

km$tot.withinss

## [1] 2774.805

km = kmeans(df_train1,3)
km$withinss

## [1]   72.89837 1166.04827  992.68042

km$tot.withinss

## [1] 2231.627

km = kmeans(df_train1,4)
km$withinss

## [1] 451.6621 837.1245 148.6584 486.3105

km$tot.withinss

## [1] 1923.755

km = kmeans(df_train1,5)
km$withinss

## [1]  58.43936 178.41998 206.90469 743.44042 352.97788

km$tot.withinss

## [1] 1540.182

km = kmeans(df_train1,6)
km$withinss
```

```
## [1] 148.65838 122.95590 451.66212 383.87247 121.73544  69.63142
```

```
km$tot.withinss
```

```
## [1] 1298.516
```

```
km = kmeans(df_train1,7)
km$withinss
```

```
## [1]  62.80186 174.34790 384.84071 223.46541  26.14207 214.57696 148.65838
```

```
km$tot.withinss
```

```
## [1] 1234.833
```

```
km = kmeans(df_train1,8)
km$withinss
```

```
## [1]  41.97872 183.68202 180.83736  88.90418 185.51602 159.69707 148.65838
## [8]  89.09993
```

```
km$tot.withinss
```

```
## [1] 1078.374
```

```
km = kmeans(df_train1,9)
km$withinss
```

```
## [1]  27.30353  47.43438  85.55081 142.64389 145.19211 246.45766 148.65838
## [8] 176.23962  41.44880
```

```
km$tot.withinss
```

```
## [1] 1060.929
```

```
km = kmeans(df_train1,10)
km$withinss
```

```
##  [1]  73.22619  68.49062 124.91473 114.14763   0.00000 110.33940 148.65838
##  [8]  81.46543 106.42891  27.30353
```

```
km$tot.withinss
```

```
## [1] 854.9748
```

```
dev.off()
```

```
## null device
##           1
```

```
sumsq=NULL
for (i in 1:25)
  sumsq[i] = sum(kmeans(df_train,centers=i,
                        iter.max = 1000,
                        nstart=i,
```

```
                        algorithm='Forgy')$withinss)
plot(1:25,sumsq,type='b', main='Screeplot showing within group sum of squares
')

km = kmeans(df_train1,3)
km$withinss

## [1]  115.3271  992.6804 1127.6139

km$tot.withinss

## [1] 2235.621

class(km$cluster)

## [1] "integer"

summary(km)

##              Length Class  Mode
## cluster      800    -none- numeric
## centers       15    -none- numeric
## totss          1    -none- numeric
## withinss       3    -none- numeric
## tot.withinss   1    -none- numeric
## betweenss      1    -none- numeric
## size           3    -none- numeric
## iter           1    -none- numeric
## ifault         1    -none- numeric

km$centers

##       rating    calories     protein        fat     sodium
## 1 -2.6418916 -0.33090248 -0.35526478 -0.3728957 -0.2302779
## 2 -0.3645987  3.52905020  3.40012235  3.1655357  3.3521253
## 3  0.2678870 -0.09809339 -0.09099883 -0.0806615 -0.1012696

as.numeric(km$cluster)

##   [1] 3 3 3 3 3 3 3 3 3 3 3 3 3 2 1 3 3 3 1 3 3 3 3 3 3 3 3 3 3 3 3 3 3
3
##  [36] 3 3 3 3 3 3 1 3 3 3 3 3 3 3 3 1 3 3 2 3 3 3 2 3 3 3 1 1 3 3 3 3 3 3
3
##  [71] 1 3 3 3 3 3 3 3 1 3 3 3 3 3 3 3 3 3 1 3 3 3 3 3 1 3 3 3 3 3 3 3 3 3
3
## [106] 3 3 3 3 3 1 3 3 3 3 3 3 3 3 3 3 3 3 3 1 3 3 3 3 3 3 3 3 3 3 3 3 3
3
## [141] 3 3 2 3 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
3
## [176] 3 3 3 3 3 3 3 3 3 1 3 3 2 3 3 3 3 3 3 3 3 3 2 3 3 3 3 3 3 3 3 3 3 1 3
3
## [211] 3 3 3 3 3 3 2 3 3 3 1 1 3 3 3 3 2 1 3 1 3 3 3 3 3 3 3 3 3 3 3 3 3
```

```
3
## [246] 3 3 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
2
## [281] 3 1 3 3 3 1 1 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 1 3 3 3
3
## [316] 3 2 3 3 3 3 3 1 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 1 3 3 3
3
## [351] 3 3 3 3 3 3 3 3 3 3 3 1 3 3 3 3 3 3 3 1 3 3 3 3 3 3 1 3 3 3 1 3 3
3
## [386] 1 3 3 3 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
3
## [421] 3 3 3 3 3 3 3 1 3 1 3 3 3 3 3 3 3 3 3 3 2 3 3 3 3 3 3 3 1 3 1 3 3 2
3
## [456] 3 2 3 3 3 3 1 3 3 3 3 3 3 1 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 1 3 3 3
3
## [491] 1 3 3 3 3 3 3 3 3 3 3 3 3 3 3 1 3 3 3 3 3 3 3 2 2 3 1 3 3 1 3 3 3 3
3
## [526] 3 3 3 2 3 3 1 3 3 3 3 3 3 1 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
3
## [561] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 1 3 3 3 3 1 3 3 3 3 1 3 3 3
3
## [596] 3 3 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 1 3 3 3 3 3 1 3 3 3 3 3 1 3 3
3
## [631] 3 1 3 3 3 3 3 3 3 3 3 3 3 3 3 1 3 3 3 3 3 3 3 3 3 3 3 3 3 2 3 3 3 3 3
1
## [666] 3 1 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3 1 3 3 3 1 3 3 3 3 3 3 3 3 3 3 3 3
3
## [701] 3 1 3 1 3 3 3 3 2 3 3 3 3 3 1 3 3 3 3 1 3 3 1 3 1 1 3 3 3 3 2 3 3 3
3
## [736] 3 3 3 3 3 3 3 3 1 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 1 3 3 3 3 3 3 3 3
3
## [771] 3 3 3 3 3 2 3 3 3 1 3 3 1 3 3 3 3 1 3 1 3 3 3 3 3 1 3 3 3 3
```

```
length(km$cluster)
```

```
## [1] 800
```

```
dim(df_train)
```

```
## [1] 800   5
```

```
class(df_train)
```

```
## [1] "data.frame"
```

```
df_train$cl <- km$cluster
```

```
head(df_train)
```

```
##      rating calories protein fat sodium cl
## 175   3.125      259       3  22    164  3
## 868   3.750      619       3   9    255  3
```

```
## 850   5.000      587       7  26    172  3
## 1369  3.750      203       6  11   1040  3
## 1185  4.375      408       9  20    461  3
## 889   4.375      188       2   1     10  3
```

```
# profiles of clusters
aggregate(df_train[,1:5],list(df_train[,6]),mean)
```

```
##   Group.1    rating  calories   protein       fat    sodium
## 1       1 0.8088235  214.7353  3.647059   8.50000  205.0588
## 2       2 3.4134615 1891.3462 81.346154 108.53846 2303.0769
## 3       3 4.1368626  315.8584  9.114731  16.76204  280.6119
```

```
table(df1$rating)
```

```
##
##     0  1.25 1.875   2.5 3.125  3.75 4.375     5
##  1296   123    81   405  1165  4136  6552  2106
```

```
table(df1$calories)
```

```
##
##        0        1        2        3        4        5        6        7
##        8        4       11        7        7        1        9        5
##        8        9       10       11       12       13       14       15
##        5        6        8        9        9       12       10       12
##       16       17       18       19       20       21       22       23
##       13        9       13       21       18       18       15       19
##       24       25       26       27       28       29       30       31
##     6370     6694     6836     6841     6857     6912     6927     6929
##        1        1        1        1        1        1        1        1
##     6996     7141     7202     7469     7576     8179     8275     8406
##        1        1        1        1        1        1        1        1
##     8414     8603     8624     8844     8858     9101     9799     9811
##        1        1        1        1        1        1        1        1
##     9831    11453    12010    12213    12824    16050    16761    19576
##        1        1        1        1        1        1        1        1
##    22312    24117    54512  3358029  3358273  4157357  4518216 13062948
##        3        2        1        1        1        2        1        1
## 29997918 30111218
##        1        1
```

```
table(df1$X22.minute.meals)
```

```
##
##     0     1
## 15849    15
```

```
table(df1$sodium)
```

```
##
##        0        1        2        3        4        5        6        7
```

```
##       52      141      172      160      152      116      108      114
##        8        9       10       11       12       13       14       15
##       91       83       93       76       79       78       74       61
##       16       17       18       19       20       21       22       23
##       36       71       58       50       43       42       50       61
##       24       25       26       27       28       29       30       31
##       37       33       62       36       31       34       43       44
##       32       33       34       35       36       37       38       39
##       42       34       55       45       39       36       28       20
##       40       41       42       43       44       45       46       47
##       42       34       40       34       37       30       35       38
##       48       49       50       51       52       53       54       55
##       29       38       35       28       34       20       34       26
##       56       57       58       59       60       61       62       63

##     8644     8748     8945     9040     9286     9465     9478     9573
##        1        1        2        1        1        1        1        1
##     9792    10042    10231    10543    10635    10672    11150    11298
##        2        1        1        1        1        1        2        1
##    11306    11349    11416    11428    11451    11462    11628    11670
##        1        1        1        1        1        1        1        1
##    11779    11846    11919    12450    12845    12862    13006    13430
##        1        1        1        2        1        1        1        1
##    13447    13767    13805    13806    13820    13869    13875    13999
##        1        1        1        1        3        1        1        1
##    14276    15061    15065    15300    15350    15416    15804    16056
##        1        1        1        1        1        1        1        1
##    16104    16443    16813    16984    16988    17544    18212    18898
##        1        1        1        2        1        1        1        1
##    19149    19986    20492    22579    22583    22593    22859    22932
##        1        1        2        1        1        1        1        1
##    23061    23273    23361    24382    30466    34351    37191    45166
##        1        1        1        1        1        1        2        1
##    45240    45351    45407    45573    55097    55369    62059    62368
##        1        1        1        1        1        1        1        1
##    66833    67253    67615    67884    67909    90572    97225   116178
##        1        1        1        1        1        1        1        1
##   132025   132220  3134853  3449373  3449512  7540990 12005810 27570999
##        1        1        2        1        1        1        1        1
## 27675110
##        1
```

```
library(cluster)

clusplot(df_train,df_train$cl,cex=0.9,color=T,shade=T, labels=4,lines=0)

#HC clustering or Hierarchical Clustering
# distance (euclidean, manhattan, cosine distance)

# Divisive method (top down)
```

```r
# Agglomorative method (bottom up)

df_train = df_train[,-5]
head(df_train)
```

```
##      rating calories protein fat cl
## 175   3.125      259       3  22  3
## 868   3.750      619       3   9  3
## 850   5.000      587       7  26  3
## 1369  3.750      203       6  11  3
## 1185  4.375      408       9  20  3
## 889   4.375      188       2   1  3
```

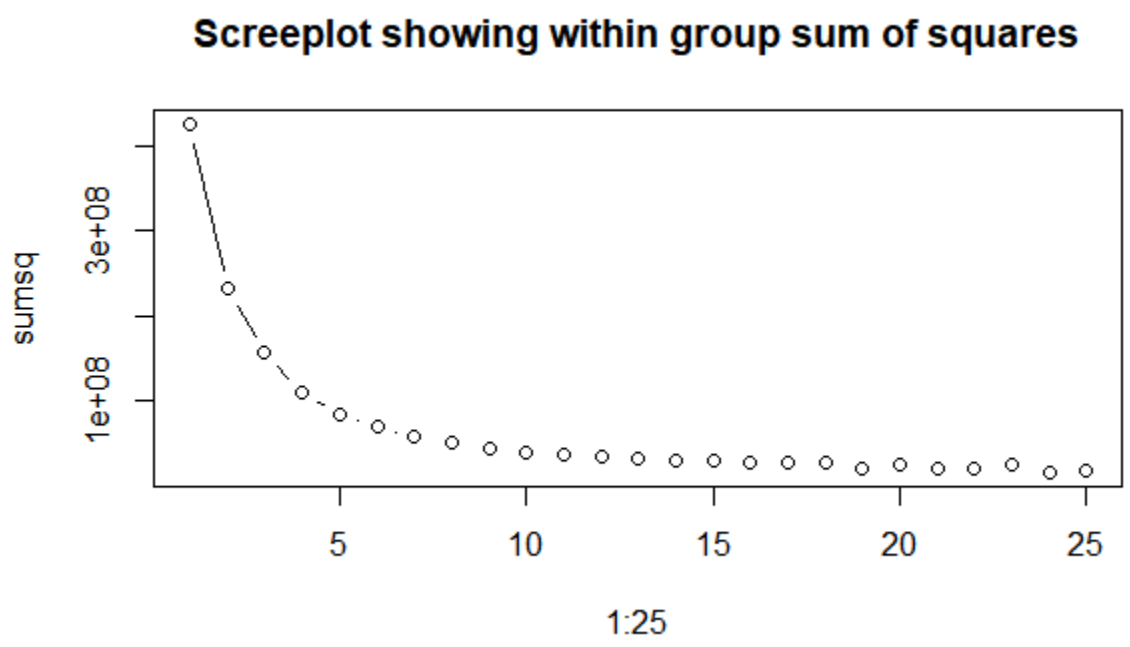
```r
str(df_train)
```

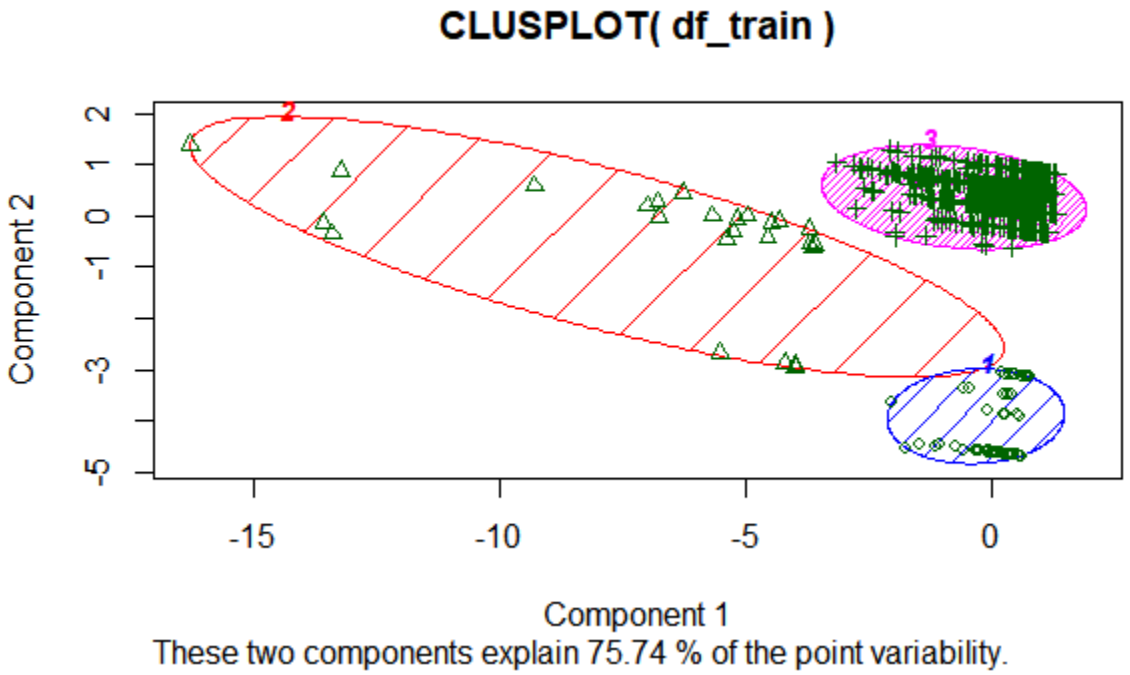
```
## 'data.frame':    800 obs. of  5 variables:
##  $ rating  : num  3.12 3.75 5 3.75 4.38 ...
##  $ calories: int  259 619 587 203 408 188 247 35 57 101 ...
##  $ protein : int  3 3 7 6 9 2 6 1 1 1 ...
##  $ fat     : int  22 9 26 11 20 1 15 1 0 7 ...
##  $ cl      : int  3 3 3 3 3 3 3 3 3 3 ...
```

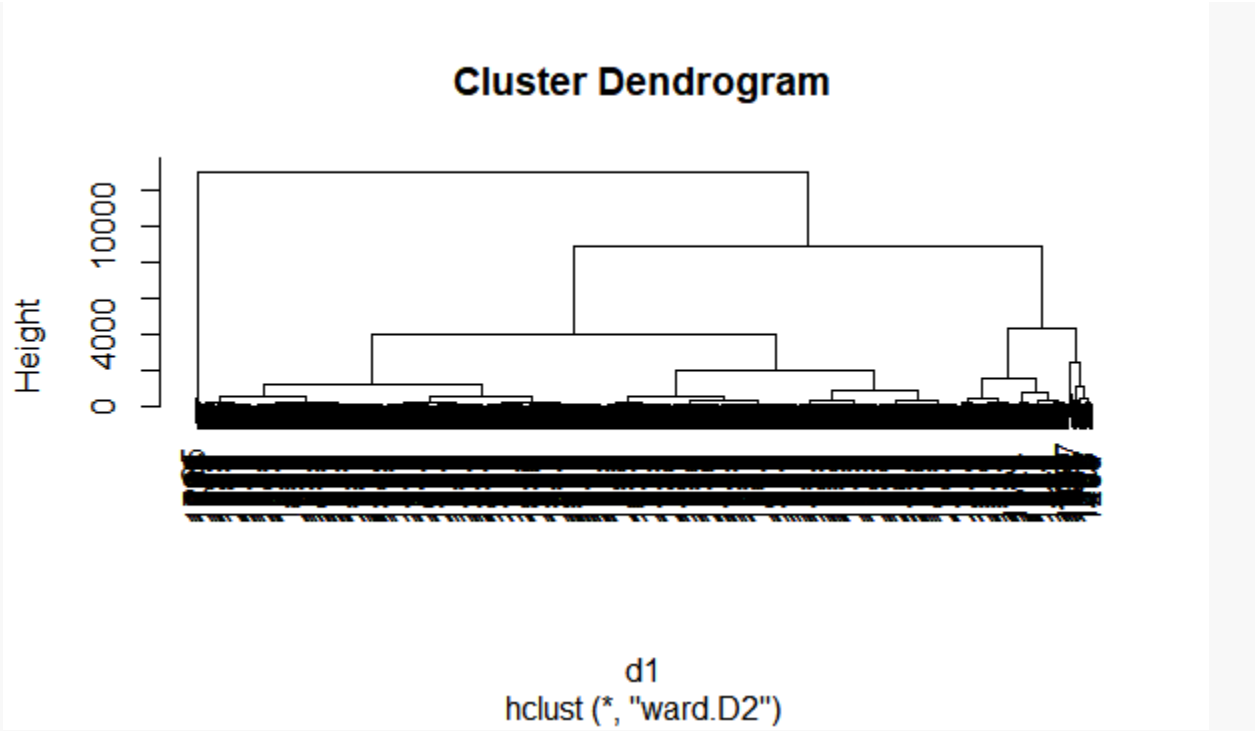
```r
# compute the distance metrix
d1 <- dist(df_train,method='euclidean')
summary(d1)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00   81.81  185.29  324.25  373.77 4560.68
```

```r
# HC
fit <- hclust(d1,method = 'ward.D2')
plot(fit)
```


Screeplot showing within group sum of squares
sumsq
1e+08
3e+08
5
10
15
20
25
1:25


CLUSPLOT(df_train)
Component 2
-5
-3
-1
0
1
2
-15
-10
-5
0
Component 1
These two components explain 75.74 % of the point variability.


Cluster Dendrogram
Height
0
4000
10000
d1
hclust (*, "ward.D2")