Week14-Part 1&2

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```
#import and read dataset
ds1<- read.csv("http://bit.ly/CarreFourDataset")
head(ds1)
```

```
##    Invoice.ID Branch Customer.type Gender           Product.line Unit.price
## 1 750-67-8428      A        Member Female      Health and beauty      74.69
## 2 226-31-3081      C        Normal Female Electronic accessories      15.28
## 3 631-41-3108      A        Normal   Male     Home and lifestyle      46.33
## 4 123-19-1176      A        Member   Male      Health and beauty      58.22
## 5 373-73-7910      A        Normal   Male      Sports and travel      86.31
## 6 699-14-3026      C        Normal   Male Electronic accessories      85.39
##   Quantity     Tax      Date  Time     Payment   cogs gross.margin.percentage
## 1        7 26.1415  1/5/2019 13:08     Ewallet 522.83                4.761905
## 2        5  3.8200  3/8/2019 10:29        Cash  76.40                4.761905
## 3        7 16.2155  3/3/2019 13:23 Credit card 324.31                4.761905
## 4        8 23.2880 1/27/2019 20:33     Ewallet 465.76                4.761905
## 5        7 30.2085  2/8/2019 10:37     Ewallet 604.17                4.761905
## 6        7 29.8865 3/25/2019 18:30     Ewallet 597.73                4.761905
##   gross.income Rating    Total
## 1      26.1415    9.1 548.9715
## 2       3.8200    9.6  80.2200
## 3      16.2155    7.4 340.5255
## 4      23.2880    8.4 489.0480
## 5      30.2085    5.3 634.3785
## 6      29.8865    4.1 627.6165
```

```
# getting the shape of our dataset
dim(ds1)
```

```
## [1] 1000   16
```

There are 1000 records and 16 variables

```
# getting basic information about our dataset
str(ds1)
```

```
## 'data.frame':    1000 obs. of  16 variables:
##  $ Invoice.ID            : chr  "750-67-8428" "226-31-3081" "631-41-3108" "123-19-1176" ...
##  $ Branch                : chr  "A" "C" "A" "A" ...
##  $ Customer.type         : chr  "Member" "Normal" "Normal" "Member" ...
```

```
##  $ Gender                 : chr  "Female" "Female" "Male" "Male" ...
##  $ Product.line           : chr  "Health and beauty" "Electronic accessories" "Home and lifestyle" "
##  $ Unit.price             : num  74.7 15.3 46.3 58.2 86.3 ...
##  $ Quantity               : int  7 5 7 8 7 7 6 10 2 3 ...
##  $ Tax                    : num  26.14 3.82 16.22 23.29 30.21 ...
##  $ Date                   : chr  "1/5/2019" "3/8/2019" "3/3/2019" "1/27/2019" ...
##  $ Time                   : chr  "13:08" "10:29" "13:23" "20:33" ...
##  $ Payment                : chr  "Ewallet" "Cash" "Credit card" "Ewallet" ...
##  $ cogs                   : num  522.8 76.4 324.3 465.8 604.2 ...
##  $ gross.margin.percentage: num  4.76 4.76 4.76 4.76 4.76 ...
##  $ gross.income           : num  26.14 3.82 16.22 23.29 30.21 ...
##  $ Rating                 : num  9.1 9.6 7.4 8.4 5.3 4.1 5.8 8 7.2 5.9 ...
##  $ Total                  : num  549 80.2 340.5 489 634.4 ...
```

```
#for ease in analysis,we convert the data into a tibble
df_sales<-as_tibble(ds1)
df_sales
```

```
## # A tibble: 1,000 x 16
##    Invoice.ID Branch Customer.type Gender Product.line Unit.price Quantity   Tax
##    <chr>      <chr>  <chr>         <chr>  <chr>             <dbl>    <int> <dbl>
##  1 750-67-84~ A      Member        Female Health and ~       74.7        7 26.1
##  2 226-31-30~ C      Normal        Female Electronic ~       15.3        5  3.82
##  3 631-41-31~ A      Normal        Male   Home and li~       46.3        7 16.2
##  4 123-19-11~ A      Member        Male   Health and ~       58.2        8 23.3
##  5 373-73-79~ A      Normal        Male   Sports and ~       86.3        7 30.2
##  6 699-14-30~ C      Normal        Male   Electronic ~       85.4        7 29.9
##  7 355-53-59~ A      Member        Female Electronic ~       68.8        6 20.7
##  8 315-22-56~ C      Normal        Female Home and li~       73.6       10 36.8
##  9 665-32-91~ A      Member        Female Health and ~       36.3        2  3.63
## 10 692-92-55~ B      Member        Female Food and be~       54.8        3  8.23
## # ... with 990 more rows, and 8 more variables: Date <chr>, Time <chr>,
## #   Payment <chr>, cogs <dbl>, gross.margin.percentage <dbl>,
## #   gross.income <dbl>, Rating <dbl>, Total <dbl>
```

```
### dataset summary
summary(df_sales)
```

```
##   Invoice.ID           Branch           Customer.type        Gender
##  Length:1000        Length:1000        Length:1000        Length:1000
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##  Product.line         Unit.price       Quantity          Tax
##  Length:1000        Min.   :10.08   Min.   : 1.00   Min.   : 0.5085
##  Class :character   1st Qu.:32.88   1st Qu.: 3.00   1st Qu.: 5.9249
##  Mode  :character   Median :55.23   Median : 5.00   Median :12.0880
##                     Mean   :55.67   Mean   : 5.51   Mean   :15.3794
##                     3rd Qu.:77.94   3rd Qu.: 8.00   3rd Qu.:22.4453
##                     Max.   :99.96   Max.   :10.00   Max.   :49.6500
##      Date               Time             Payment               cogs
```

```
##  Length:1000        Length:1000        Length:1000        Min.   : 10.17
##  Class :character   Class :character   Class :character   1st Qu.:118.50
##  Mode  :character   Mode  :character   Mode  :character   Median :241.76
##                                                           Mean   :307.59
##                                                           3rd Qu.:448.90
##                                                           Max.   :993.00
##  gross.margin.percentage  gross.income         Rating           Total
##  Min.   :4.762           Min.   : 0.5085   Min.   : 4.000   Min.   :  10.68
##  1st Qu.:4.762           1st Qu.: 5.9249   1st Qu.: 5.500   1st Qu.: 124.42
##  Median :4.762           Median :12.0880   Median : 7.000   Median : 253.85
##  Mean   :4.762           Mean   :15.3794   Mean   : 6.973   Mean   : 322.97
##  3rd Qu.:4.762           3rd Qu.:22.4453   3rd Qu.: 8.500   3rd Qu.: 471.35
##  Max.   :4.762           Max.   :49.6500   Max.   :10.000   Max.   :1042.65
```

```
# Identify missing data in our entire dataset using is.na() function
#
colSums(is.na(df_sales))
```

```
##              Invoice.ID                  Branch           Customer.type
##                       0                       0                       0
##                  Gender            Product.line              Unit.price
##                       0                       0                       0
##                Quantity                     Tax                    Date
##                       0                       0                       0
##                    Time                 Payment                    cogs
##                       0                       0                       0
## gross.margin.percentage            gross.income                  Rating
##                       0                       0                       0
##                   Total
##                       0
```

```
# using complete function
df_sales[!complete.cases(df_sales),]
```

```
## # A tibble: 0 x 16
## # ... with 16 variables: Invoice.ID <chr>, Branch <chr>, Customer.type <chr>,
## #   Gender <chr>, Product.line <chr>, Unit.price <dbl>, Quantity <int>,
## #   Tax <dbl>, Date <chr>, Time <chr>, Payment <chr>, cogs <dbl>,
## #   gross.margin.percentage <dbl>, gross.income <dbl>, Rating <dbl>,
## #   Total <dbl>
```

There are no missing values

```
#Identifying Duplicated Data
#
anyDuplicated(df_sales)
```

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

There are no duplicated values

```
#Checking the numeric data types of the columns
#
Numeric<- df_sales %>% select_if(is.numeric)
Numeric
```

```
## # A tibble: 1,000 x 8
##    Unit.price Quantity   Tax  cogs gross.margin.perce~ gross.income Rating Total
##         <dbl>    <int> <dbl> <dbl>               <dbl>        <dbl>  <dbl> <dbl>
##  1       74.7        7 26.1  523.                4.76        26.1     9.1 549.
##  2       15.3        5  3.82  76.4               4.76         3.82    9.6  80.2
##  3       46.3        7 16.2  324.                4.76        16.2     7.4 341.
##  4       58.2        8 23.3  466.                4.76        23.3     8.4 489.
##  5       86.3        7 30.2  604.                4.76        30.2     5.3 634.
##  6       85.4        7 29.9  598.                4.76        29.9     4.1 628.
##  7       68.8        6 20.7  413.                4.76        20.7     5.8 434.
##  8       73.6       10 36.8  736.                4.76        36.8     8   772.
##  9       36.3        2  3.63  72.5               4.76         3.63    7.2  76.1
## 10       54.8        3  8.23 165.                4.76         8.23    5.9 173.
## # ... with 990 more rows
```

Part 1: Dimensionality Reduction

This section of the project entails reducing your dataset to a low dimensional dataset using the t-SNE algorithm or PCA. You will be required to perform your analysis and provide insights gained from your analysis.

1.1 Principal Component Analysis (PCA)

```
# Selecting the numerical data (excluding the categorical variables)
# ---
#
numeric <- df_sales[,c(6:8,12:16)]
head(numeric)
```

```
## # A tibble: 6 x 8
##   Unit.price Quantity   Tax  cogs gross.margin.percen~ gross.income Rating Total
##        <dbl>    <int> <dbl> <dbl>               <dbl>        <dbl>  <dbl> <dbl>
## 1       74.7        7 26.1  523.                4.76        26.1     9.1 549.
## 2       15.3        5  3.82  76.4               4.76         3.82    9.6  80.2
## 3       46.3        7 16.2  324.                4.76        16.2     7.4 341.
## 4       58.2        8 23.3  466.                4.76        23.3     8.4 489.
## 5       86.3        7 30.2  604.                4.76        30.2     5.3 634.
## 6       85.4        7 29.9  598.                4.76        29.9     4.1 628.
```

PCA only works with numerical values, thus the selection of numerical variables from the dataset.

```
# Ensuring our variances is not 0, this replaces center argument.
#
non_zero_var <- numeric[ , which(apply(numeric, 2, var) != 0)]
head(non_zero_var)
```

```
## # A tibble: 6 x 7
##   Unit.price Quantity   Tax  cogs gross.income Rating Total
##        <dbl>    <int> <dbl> <dbl>        <dbl>  <dbl> <dbl>
## 1       74.7        7 26.1  523.         26.1     9.1 549.
## 2       15.3        5  3.82  76.4         3.82    9.6  80.2
## 3       46.3        7 16.2  324.         16.2     7.4 341.
## 4       58.2        8 23.3  466.         23.3     8.4 489.
## 5       86.3        7 30.2  604.         30.2     5.3 634.
## 6       85.4        7 29.9  598.         29.9     4.1 628.
```

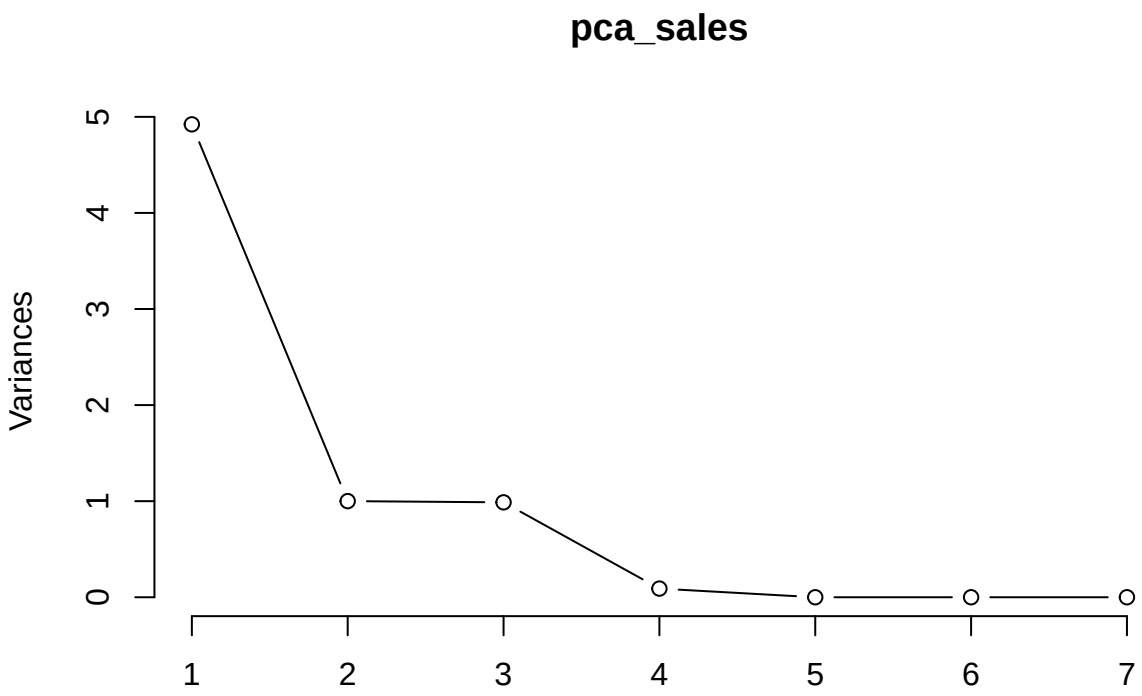
apply function is used instead of center to ensure there is no zero variance and also helps in ensuring no column has zero mean. As seen,the gross.margin.percentage column was removed.

```
# now carrying out PCA with scale set to true
pca_sales <- prcomp(non_zero_var,scale=TRUE)
# previewing our PCA summary
summary(pca_sales)
```

```
## Importance of components:
##                           PC1    PC2    PC3     PC4       PC5       PC6
## Standard deviation     2.2185 1.0002 0.9939 0.30001 2.981e-16 1.493e-16
## Proportion of Variance 0.7031 0.1429 0.1411 0.01286 0.000e+00 0.000e+00
## Cumulative Proportion  0.7031 0.8460 0.9871 1.00000 1.000e+00 1.000e+00
##                            PC7
## Standard deviation     9.831e-17
## Proportion of Variance 0.000e+00
## Cumulative Proportion  1.000e+00
```

PC1 describes 70.31% of the total variation of the dataset, PC2 describes 14.29%, and so on. PC1 has 2.22 of standard deviation, PC2 has 1.0 of standard deviation and so on

```
#plotting of pca
plot(pca_sales,type = 'l')
```



Most of the variability in our data are in the first and second component of our PCa. Variance explained keeps on reducing as PC increases.

Part 2: Feature Selection

This section requires you to perform feature selection through the use of the unsupervised learning methods learned earlier this week. You will be required to perform your analysis and provide insights on the features that contribute the most information to the dataset.

2.1 Filter Method

```
#dataset to be used for feature selection
#
feature<- df_sales
head(feature)
```

```
## # A tibble: 6 x 16
##   Invoice.ID  Branch Customer.type Gender Product.line Unit.price Quantity   Tax
##   <chr>       <chr>  <chr>         <chr>  <chr>             <dbl>    <int> <dbl>
## 1 750-67-8428 A      Member        Female Health and ~       74.7        7 26.1
## 2 226-31-3081 C      Normal        Female Electronic ~       15.3        5  3.82
## 3 631-41-3108 A      Normal        Male   Home and li~       46.3        7 16.2
## 4 123-19-1176 A      Member        Male   Health and ~       58.2        8 23.3
```

```
## 5 373-73-7910 A      Normal        Male   Sports and ~       86.3        7 30.2
## 6 699-14-3026 C      Normal        Male   Electronic ~       85.4        7 29.9
## # ... with 8 more variables: Date <chr>, Time <chr>, Payment <chr>, cogs <dbl>,
## #   gross.margin.percentage <dbl>, gross.income <dbl>, Rating <dbl>,
## #   Total <dbl>
```

```
#
#Checking the columns with numeric datatypes
#
feature_num<- feature %>% select_if(is.numeric)
feature_num
```

```
## # A tibble: 1,000 x 8
##    Unit.price Quantity   Tax  cogs gross.margin.perce~ gross.income Rating Total
##         <dbl>    <int> <dbl> <dbl>               <dbl>        <dbl>  <dbl> <dbl>
##  1       74.7        7 26.1  523.                4.76        26.1     9.1 549.
##  2       15.3        5  3.82  76.4               4.76         3.82    9.6  80.2
##  3       46.3        7 16.2  324.                4.76        16.2     7.4 341.
##  4       58.2        8 23.3  466.                4.76        23.3     8.4 489.
##  5       86.3        7 30.2  604.                4.76        30.2     5.3 634.
##  6       85.4        7 29.9  598.                4.76        29.9     4.1 628.
##  7       68.8        6 20.7  413.                4.76        20.7     5.8 434.
##  8       73.6       10 36.8  736.                4.76        36.8     8   772.
##  9       36.3        2  3.63  72.5               4.76         3.63    7.2  76.1
## 10       54.8        3  8.23 165.                4.76         8.23    5.9 173.
## # ... with 990 more rows
```

```
# just like in pca, gross.margin.percentage column is dropped because it has a constant value (has zero
to_drop <- c("gross.margin.percentage")
```

```
#dropping the highly correlated columms
#
feature_num <- feature_num[, !names(feature_num) %in% to_drop]
head(feature_num)
```

```
## # A tibble: 6 x 7
##   Unit.price Quantity   Tax  cogs gross.income Rating Total
##        <dbl>    <int> <dbl> <dbl>        <dbl>  <dbl> <dbl>
## 1       74.7        7 26.1  523.         26.1     9.1 549.
## 2       15.3        5  3.82  76.4         3.82    9.6  80.2
## 3       46.3        7 16.2  324.         16.2     7.4 341.
## 4       58.2        8 23.3  466.         23.3     8.4 489.
## 5       86.3        7 30.2  604.         30.2     5.3 634.
## 6       85.4        7 29.9  598.         29.9     4.1 628.
```

```
# Calculating the correlation matrix
# ---
#
cor_Matrix <- cor(feature_num)
cor_Matrix
```

```
##                Unit.price    Quantity        Tax       cogs gross.income
```

```
## Unit.price    1.000000000  0.01077756  0.6339621  0.6339621    0.6339621
## Quantity      0.010777564  1.00000000  0.7055102  0.7055102    0.7055102
## Tax           0.633962089  0.70551019  1.0000000  1.0000000    1.0000000
## cogs          0.633962089  0.70551019  1.0000000  1.0000000    1.0000000
## gross.income  0.633962089  0.70551019  1.0000000  1.0000000    1.0000000
## Rating       -0.008777507 -0.01581490 -0.0364417 -0.0364417   -0.0364417
## Total         0.633962089  0.70551019  1.0000000  1.0000000    1.0000000
##                    Rating      Total
## Unit.price   -0.008777507  0.6339621
## Quantity     -0.015814905  0.7055102
## Tax          -0.036441705  1.0000000
## cogs         -0.036441705  1.0000000
## gross.income -0.036441705  1.0000000
## Rating        1.000000000 -0.0364417
## Total        -0.036441705  1.0000000
```

```
# Find attributes that are highly correlated
high_cor <- findCorrelation(cor_Matrix, cutoff=0.75)
high_cor
```

```
## [1] 4 7 3
```

```
#
names(feature_num[,high_cor])
```

```
## [1] "cogs"  "Total" "Tax"
```

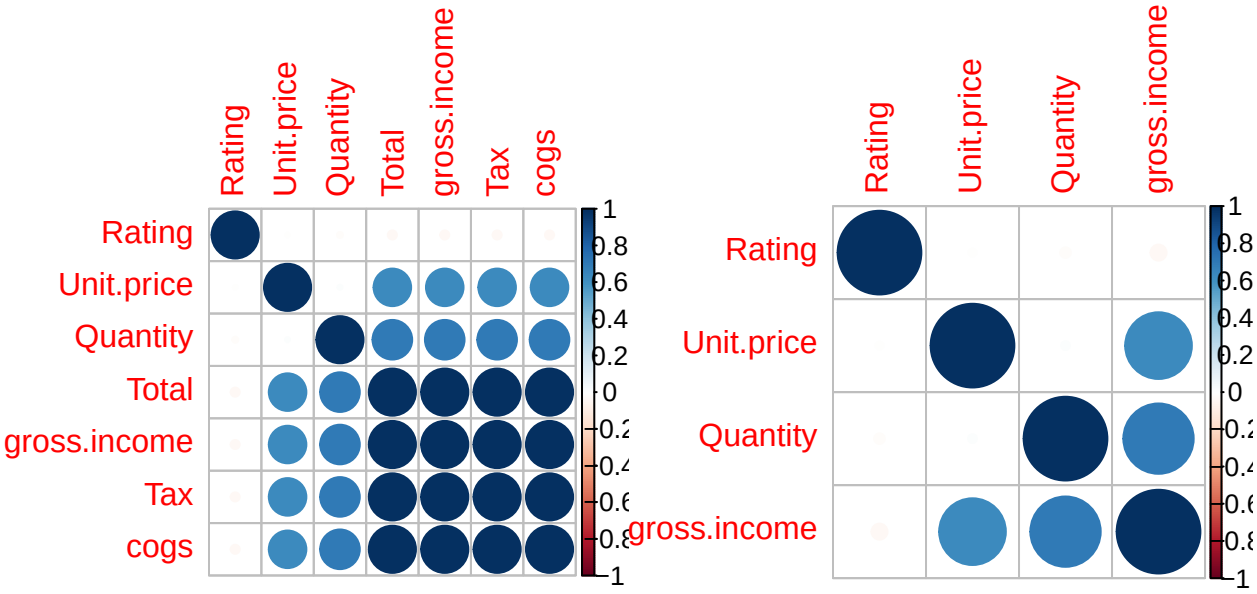
Columns cogs, total and tax are highly correlated

```
# We can remove the variables with a higher correlation
# ---
#
high_cor2<-feature_num[-high_cor]
high_cor2
```

```
## # A tibble: 1,000 x 4
##    Unit.price Quantity gross.income Rating
##         <dbl>    <int>        <dbl>  <dbl>
##  1       74.7        7        26.1     9.1
##  2       15.3        5         3.82    9.6
##  3       46.3        7        16.2     7.4
##  4       58.2        8        23.3     8.4
##  5       86.3        7        30.2     5.3
##  6       85.4        7        29.9     4.1
##  7       68.8        6        20.7     5.8
##  8       73.6       10        36.8     8
##  9       36.3        2         3.63    7.2
## 10       54.8        3         8.23    5.9
## # ... with 990 more rows
```

We remain with 4 columns after removing the highly correlated ones

```
# Performing our graphical comparison
# ---
#
par(mfrow = c(1, 2))
corrplot(cor_Matrix, order = "hclust")
corrplot(cor(high_cor2), order = "hclust")
```



The final features that contribute the most information to the dataset are Unit.price, Quantity, and gross.income

2.2 Wrapper Method

```
#getting the dataset
wrapper <- df_sales
#
#checking the dateset
#
head(wrapper)
```

```
## # A tibble: 6 x 16
##   Invoice.ID  Branch Customer.type Gender Product.line Unit.price Quantity   Tax
##   <chr>       <chr>  <chr>         <chr>  <chr>             <dbl>    <int> <dbl>
## 1 750-67-8428 A      Member        Female Health and ~       74.7        7 26.1
## 2 226-31-3081 C      Normal        Female Electronic ~       15.3        5  3.82
```

```
## 3 631-41-3108 A      Normal        Male   Home and li~       46.3        7 16.2
## 4 123-19-1176 A      Member        Male   Health and ~       58.2        8 23.3
## 5 373-73-7910 A      Normal        Male   Sports and ~       86.3        7 30.2
## 6 699-14-3026 C      Normal        Male   Electronic ~       85.4        7 29.9
## # ... with 8 more variables: Date <chr>, Time <chr>, Payment <chr>, cogs <dbl>,
## #   gross.margin.percentage <dbl>, gross.income <dbl>, Rating <dbl>,
## #   Total <dbl>
```

```
# Selecting the numerical data (excluding the categorical variables)
# ---
#
wrapper_num <- wrapper[,c(6:8,12:16)]
head(wrapper_num)
```

```
## # A tibble: 6 x 8
##   Unit.price Quantity   Tax  cogs gross.margin.percen~ gross.income Rating Total
##        <dbl>    <int> <dbl> <dbl>                <dbl>        <dbl>  <dbl> <dbl>
## 1       74.7        7 26.1  523.                 4.76        26.1     9.1 549.
## 2       15.3        5  3.82  76.4                4.76         3.82    9.6  80.2
## 3       46.3        7 16.2  324.                 4.76        16.2     7.4 341.
## 4       58.2        8 23.3  466.                 4.76        23.3     8.4 489.
## 5       86.3        7 30.2  604.                 4.76        30.2     5.3 634.
## 6       85.4        7 29.9  598.                 4.76        29.9     4.1 628.
```

```
## dropping "gross.margin.percentage" columns since it leads to zero variance.
# selecting highly correlated columns to be dropped
to_drop <- c("gross.margin.percentage")
#
#dropping the columm
#
wrapper_num <- wrapper_num[, !names(wrapper_num) %in% to_drop]
head(wrapper_num)
```

```
## # A tibble: 6 x 7
##   Unit.price Quantity   Tax  cogs gross.income Rating Total
##        <dbl>    <int> <dbl> <dbl>        <dbl>  <dbl> <dbl>
## 1       74.7        7 26.1  523.         26.1     9.1 549.
## 2       15.3        5  3.82  76.4         3.82    9.6  80.2
## 3       46.3        7 16.2  324.         16.2     7.4 341.
## 4       58.2        8 23.3  466.         23.3     8.4 489.
## 5       86.3        7 30.2  604.         30.2     5.3 634.
## 6       85.4        7 29.9  598.         29.9     4.1 628.
```

```
# normalizing our dataset by use of scale function.
#
library(dplyr)
wrapper_norm <- as.data.frame(scale(wrapper_num))
#
#previewing the scaled dataset.
head(wrapper_norm)
```

```
##    Unit.price   Quantity         Tax        cogs gross.income     Rating
```

```
## 1  0.71780097  0.5096752  0.91914693  0.91914693   0.91914693  1.2378240
## 2 -1.52454035 -0.1744526 -0.98723557 -0.98723557  -0.98723557  1.5287619
## 3 -0.35260468  0.5096752  0.07141032  0.07141032   0.07141032  0.2486355
## 4  0.09616553  0.8517391  0.67544187  0.67544187   0.67544187  0.8305111
## 5  1.15638044  0.5096752  1.26649176  1.26649176   1.26649176 -0.9733034
## 6  1.12165642  0.5096752  1.23899114  1.23899114   1.23899114 -1.6715541
##         Total
## 1  0.91914693
## 2 -0.98723557
## 3  0.07141032
## 4  0.67544187
## 5  1.26649176
## 6  1.23899114
```

```
#Selecting the best features
# Sequential forward greedy search (default)
# ---
#
out = clustvarsel(wrapper_norm, G = 1:7)
out
```

```
## ----------------------------------------------------
## Variable selection for Gaussian model-based clustering
## Stepwise (forward/backward) greedy search
## ----------------------------------------------------
##
##  Variable proposed Type of step  BICclust Model G   BICdiff Decision
##                Tax          Add -2460.877     V 4  389.8147 Accepted
##           Quantity          Add -3640.069   VEV 7  989.7613 Accepted
##         Unit.price          Add -1510.703   EVV 7 3474.0832 Accepted
##         Unit.price       Remove -3640.069   VEV 7 3474.0832 Rejected
##             Rating          Add -4599.859   EVV 7 -238.4641 Rejected
##         Unit.price       Remove -3640.069   VEV 7 3474.0832 Rejected
##
## Selected subset: Tax, Quantity, Unit.price
```

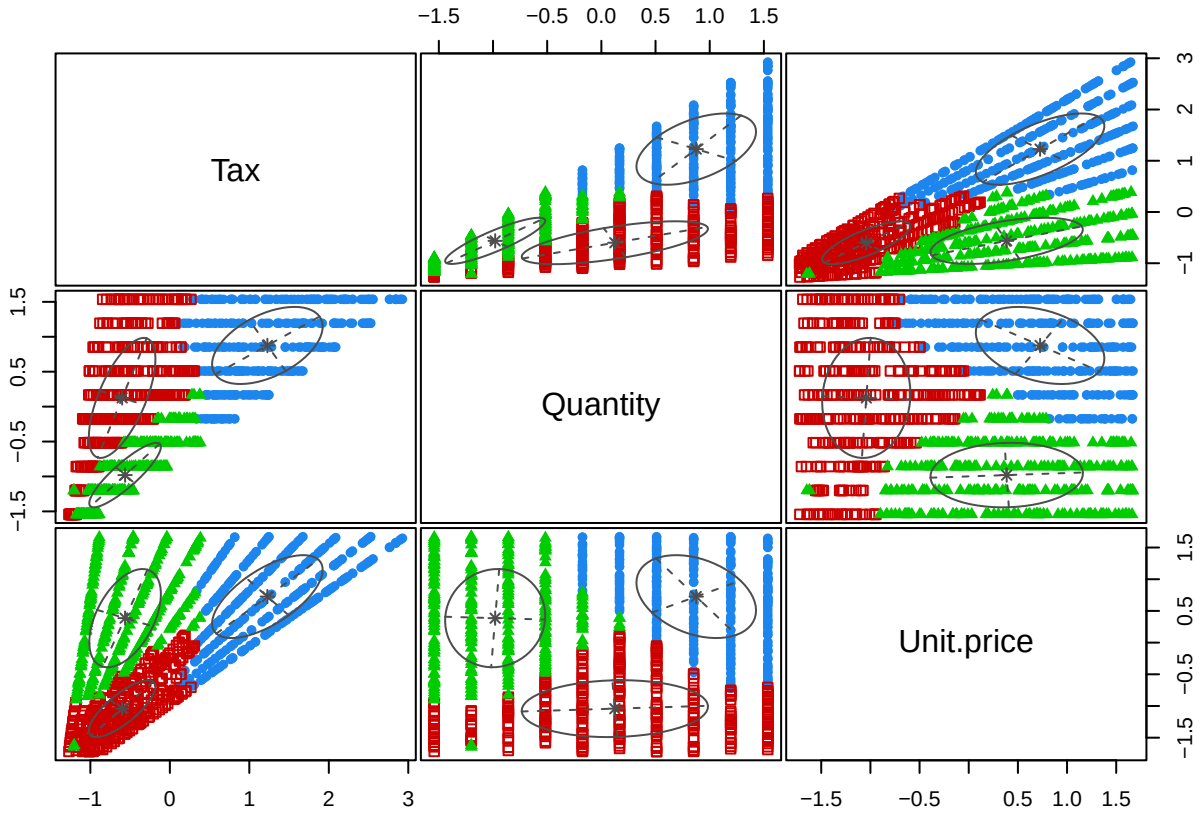
3 variables were accepted, they include Tax, Quantity, and unit price.

```
# Having identified the variables that we use, we proceed to build the clustering model:
# ---
#
Subset1 = wrapper_norm[out$subset]
mod = Mclust(Subset1, G = 1:3)
summary(mod)
```

```
## ----------------------------------------------------
## Gaussian finite mixture model fitted by EM algorithm
## ----------------------------------------------------
##
## Mclust EVV (ellipsoidal, equal volume) model with 3 components:
##
##  log-likelihood    n df       BIC      ICL
##       -1846.246 1000 27 -3879.002 -3986.31
```

```
##
## Clustering table:
##   1   2   3
## 319 357 324
```

```
plot(mod,c("classification"))
```



Above is a distribution of 3 clusters

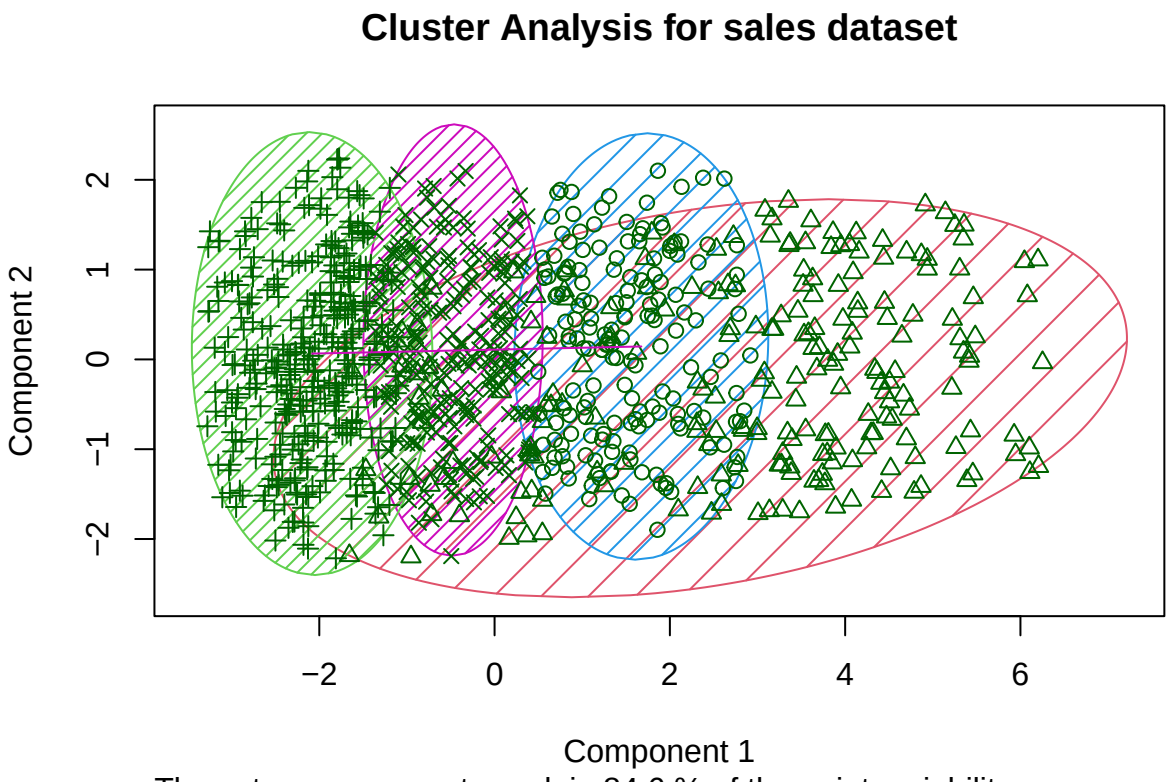
2.3 Embedded Methods

```
set.seed(6)
model <- ewkm(wrapper_norm[1:7], 4, lambda=2, maxiter=1000)
model
```

```
## K-means clustering with 4 clusters of sizes 175, 214, 360, 251
##
## Cluster means:
##     Unit.price   Quantity        Tax       cogs gross.income       Rating
## 1  0.655541452  0.3845775  0.6592411  0.6592411    0.6592411  0.009567698
## 2  0.483694270  1.2049919  1.3087741  1.3087741    1.3087741 -0.120882760
## 3 -0.612643766 -0.8243739 -0.9228006 -0.9228006   -0.9228006  0.010389713
## 4  0.009248717 -0.1131264 -0.2519389 -0.2519389   -0.2519389  0.081491103
##        Total
```

```
## 1  0.6592411
## 2  1.3087741
## 3 -0.9228006
## 4 -0.2519389
##
## Clustering vector:
##    [1] 1 3 4 1 1 1 1 2 3 3 3 3 4 1 2 1 1 1 3 3 1 4 3 4 4 1 3 4 1 2 1 2 2 4 1 3 4
##   [38] 2 1 4 3 3 1 2 3 1 2 2 3 2 2 4 3 3 3 2 3 2 2 4 3 4 2 3 4 3 3 1 2 3 2 2 3 1
##   [75] 2 1 2 2 2 3 1 4 3 4 4 1 1 4 3 1 4 1 3 2 3 3 2 3 3 1 3 2 2 4 4 2 3 1 2 2 3
##  [112] 4 1 2 2 3 3 3 3 3 2 1 2 1 1 2 3 2 2 2 4 1 3 1 1 4 3 4 1 2 2 2 2 3 1 4 4 4
##  [149] 2 4 1 4 2 3 2 1 3 4 2 1 2 3 4 3 1 2 2 2 4 1 4 1 3 4 3 2 4 3 1 4 1 4 3 4 3
##  [186] 3 2 4 3 4 4 3 2 3 3 3 3 3 3 1 3 4 1 4 3 2 2 4 3 2 2 2 1 3 4 3 3 4 2 4 4 1
##  [223] 3 3 3 4 2 3 1 1 3 3 2 4 1 4 3 4 3 3 2 3 4 4 2 1 4 3 4 1 2 2 3 3 1 3 3 3 3
##  [260] 4 2 3 3 4 3 2 3 2 4 2 4 3 2 3 1 4 4 1 2 1 2 3 3 1 4 4 3 2 4 2 1 4 3 3 4 4
##  [297] 3 1 4 3 4 3 3 4 3 1 4 2 3 3 1 3 3 2 2 4 3 1 4 4 2 3 3 4 3 1 1 1 4 3 2 3 1
##  [334] 3 3 3 2 4 3 2 3 1 1 1 3 2 3 2 4 3 2 1 1 2 3 1 2 2 3 3 2 2 4 1 3 4 1 4 3 2
##  [371] 4 3 1 4 4 1 2 2 1 3 4 3 1 4 4 3 4 4 2 3 4 2 3 1 3 1 4 2 4 2 4 4 3 4 2 4 3
##  [408] 4 4 3 2 3 3 3 1 3 4 3 3 4 3 4 2 4 3 2 1 3 4 2 3 3 3 2 3 2 4 4 3 4 3 2 2 3
##  [445] 3 3 4 3 3 3 1 3 4 3 3 3 2 2 1 3 4 2 4 3 4 2 4 4 3 3 1 3 1 2 4 4 3 4 2 3 1
##  [482] 2 4 2 2 4 1 3 3 2 3 4 4 3 4 2 3 1 3 1 3 3 3 4 3 4 3 1 4 3 2 4 1 2 1 3 4 4
##  [519] 3 1 3 1 4 3 1 1 3 3 2 2 3 2 4 2 3 3 3 3 4 1 3 3 3 3 3 3 4 2 4 1 4 2 2 3 3
##  [556] 3 3 2 4 4 2 2 2 1 4 2 1 2 1 1 1 4 3 3 1 1 4 3 4 3 3 4 4 3 4 4 3 4 2 3 4 3
##  [593] 3 4 4 3 3 2 4 3 3 3 2 4 1 3 1 4 3 3 3 2 4 3 2 2 1 1 1 4 4 3 2 2 3 3 3 2 3
##  [630] 3 2 4 3 4 4 2 4 3 3 3 4 2 3 2 3 2 1 3 3 4 1 4 2 2 4 3 3 4 3 3 3 3 4 2 4 4
##  [667] 4 3 4 3 2 4 4 4 1 3 1 4 2 4 3 3 4 3 3 3 3 2 3 4 2 1 1 1 2 1 3 4 2 2 1 3 4
##  [704] 2 2 1 4 3 3 3 1 4 2 2 2 4 1 3 3 3 4 2 3 4 3 4 3 2 1 1 3 3 3 1 3 2 1 2 2 2
##  [741] 1 3 3 3 4 3 2 3 2 1 3 3 4 1 4 2 4 1 4 4 2 2 1 3 4 2 4 3 1 3 1 1 1 3 3 3 1
##  [778] 3 3 2 4 1 3 2 3 1 2 3 4 1 3 4 2 2 3 3 3 4 3 1 3 4 1 2 2 4 4 4 3 2 3 1 4 3
##  [815] 1 1 4 4 1 4 4 3 3 4 1 3 2 3 2 2 3 4 3 3 4 3 4 4 2 4 3 3 3 3 3 4 3 3 2 1 3
##  [852] 4 1 1 1 2 3 3 4 2 3 3 2 1 4 3 2 3 3 4 4 3 4 1 3 1 3 3 2 3 2 3 4 4 3 4 3 2
##  [889] 3 2 1 1 1 3 4 2 1 4 1 2 2 4 3 3 3 4 2 1 3 1 3 4 2 1 4 4 3 1 4 3 2 3 3 1 4
##  [926] 3 3 2 2 3 1 3 2 1 1 4 1 1 4 4 4 2 1 4 3 2 3 3 4 4 3 3 4 3 1 4 2 4 3 2 3 3
##  [963] 3 4 3 3 2 4 3 4 2 4 1 4 4 3 4 3 3 3 4 4 2 2 2 4 3 1 2 2 4 2 3 4 3 3 2 3 3
## [1000] 1
##
## Within cluster sum of squares by cluster:
## [1]  370.8787 1209.3451  902.6170  599.9935
##  (between_SS / total_SS =  55.9 %)
##
## Available components:
##
##  [1] "cluster"          "centers"          "totss"            "withinss"
##  [5] "tot.withinss"     "betweenss"        "size"             "iterations"
##  [9] "total.iterations" "restarts"         "weights"
```

```
# Cluster Plot against 1st 2 principal components
# ---
#
clusplot(wrapper_norm[1:7], model$cluster, color=TRUE, shade=TRUE,
         labels=6, lines=1,main='Cluster Analysis for sales dataset')
```



With 4 clusters, the two components explains 84.6% of the point variability.

```
# checking the Weights of each cluster
#
round(model$weights*100,3)
```

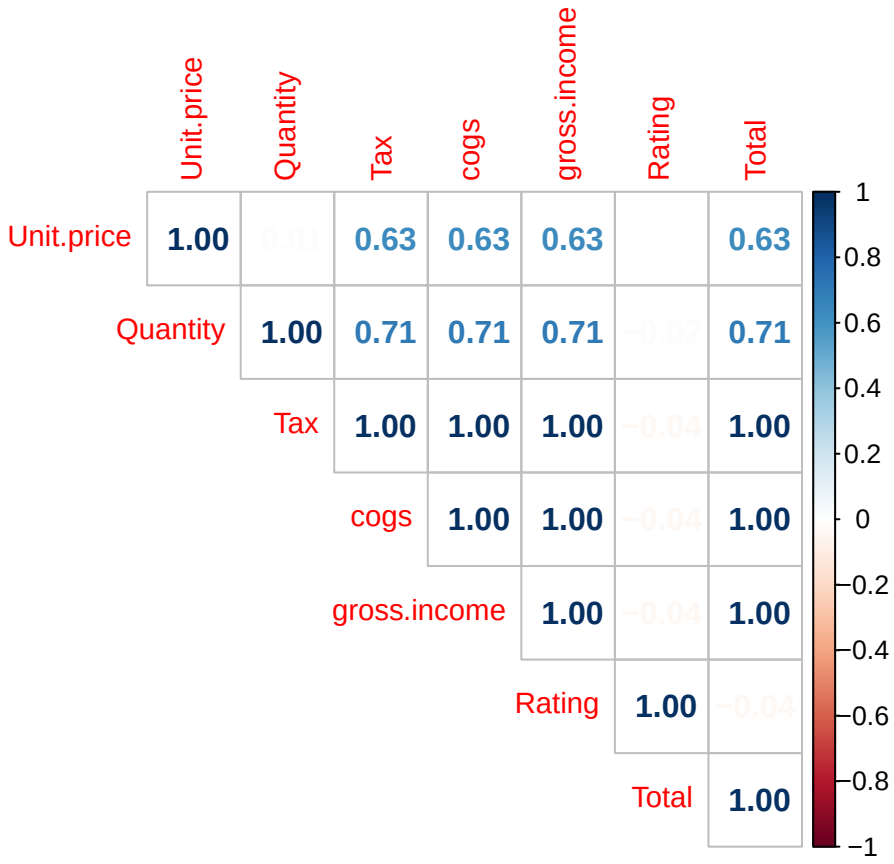
```
##   Unit.price Quantity    Tax   cogs gross.income Rating  Total
## 1      0.001    0.001 24.999 24.999       24.999  0.001 24.999
## 2      0.001   99.991  0.001  0.001        0.001  0.001  0.001
## 3      0.001    0.001 24.999 24.999       24.999  0.001 24.999
## 4      0.001    0.001 24.999 24.999       24.999  0.001 24.999
```

In cluster 1, 3 and 4 , Tax, Cogs, gross.income, and Total variables have high weight of 25

In cluster 2, Quantity has a high weigh of 100

2.4. Feature ranking

```
corrplot(cor(wrapper_norm), type = 'upper', method = 'number', tl.cex = 0.9)
```




```
#rank the variables.
# ---
#
Scores <- linear.correlation(wrapper_norm)
Scores
```

```
##              attr_importance
## Quantity         0.010777564
## Tax              0.633962089
## cogs             0.633962089
## gross.income     0.633962089
## Rating           0.008777507
## Total            0.633962089
```

```
# In order to make a decision on the above list, we define a cutoff by using the top 5 variables.

# cutoff.k: The algorithms selects a subset from a ranked attributes.
Subset <- cutoff.k(Scores, 4)
as.data.frame(Subset)
```

```
##         Subset
## 1          Tax
## 2         cogs
## 3 gross.income
## 4        Total
```

The top 4 features are Tax,Cogs, gross income and Total.

```
#cutoff as a percentage

Subset2 <-cutoff.k.percent(Scores, 0.5)
Subset2
```

```
## [1] "Tax"          "cogs"         "gross.income"
```

At 50% cutoff, we get 3 variables best fit to work with . Namely; Tax, cogs and gross.income