1. Define the Question

(a) Specify the Question

You are a Data analyst at Carrefour Kenya and are currently undertaking a project that will inform the marketing department on the most relevant marketing strategies that will result in the highest no. of sales (total price including tax).

(b) Metric for success

The project will be considered successful when we are able to draw meaningful insights that would be benefit to the marketing department

(c) Understanding the context

You are a Data analyst at Carrefour Kenya and are currently undertaking a project that will inform the marketing department on the most relevant marketing strategies that will result in the highest no. of sales (total price including tax). Your project has been divided into four parts where you'll explore a recent marketing dataset by performing various unsupervised learning techniques and later providing recommendations based on your insights.

(d) Experimental design

1. Import the data to R
2. Perform data exploration
3. Define metrics for success
4. Perform Univariate and Bivariate data Analysis
5. Build an associative model
6. Provide conclusion

```
# Importing the relevant libraries
library(superml)
```

```
## Loading required package: R6
```

```
library(naniar)
library(ggplot2)
library(Rtsne)
library(data.table)
library(ggbiplot)
```

```
## Loading required package: plyr
```

```
## Loading required package: scales
```

```
## Loading required package: grid
```

```r
library(tibbletime)
```

```
##
## Attaching package: 'tibbletime'

## The following object is masked from 'package:stats':
##
##     filter
```

1.Reading of the Dataset

```r
# Lets read the data
carrefour <- fread("http://bit.ly/CarreFourDataset")
head(carrefour)
```

```
##     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
```

2.Previewing the Dataset

```r
# Lets check the shape of the dataset

dim(carrefour)
```

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

3.Data Cleaning

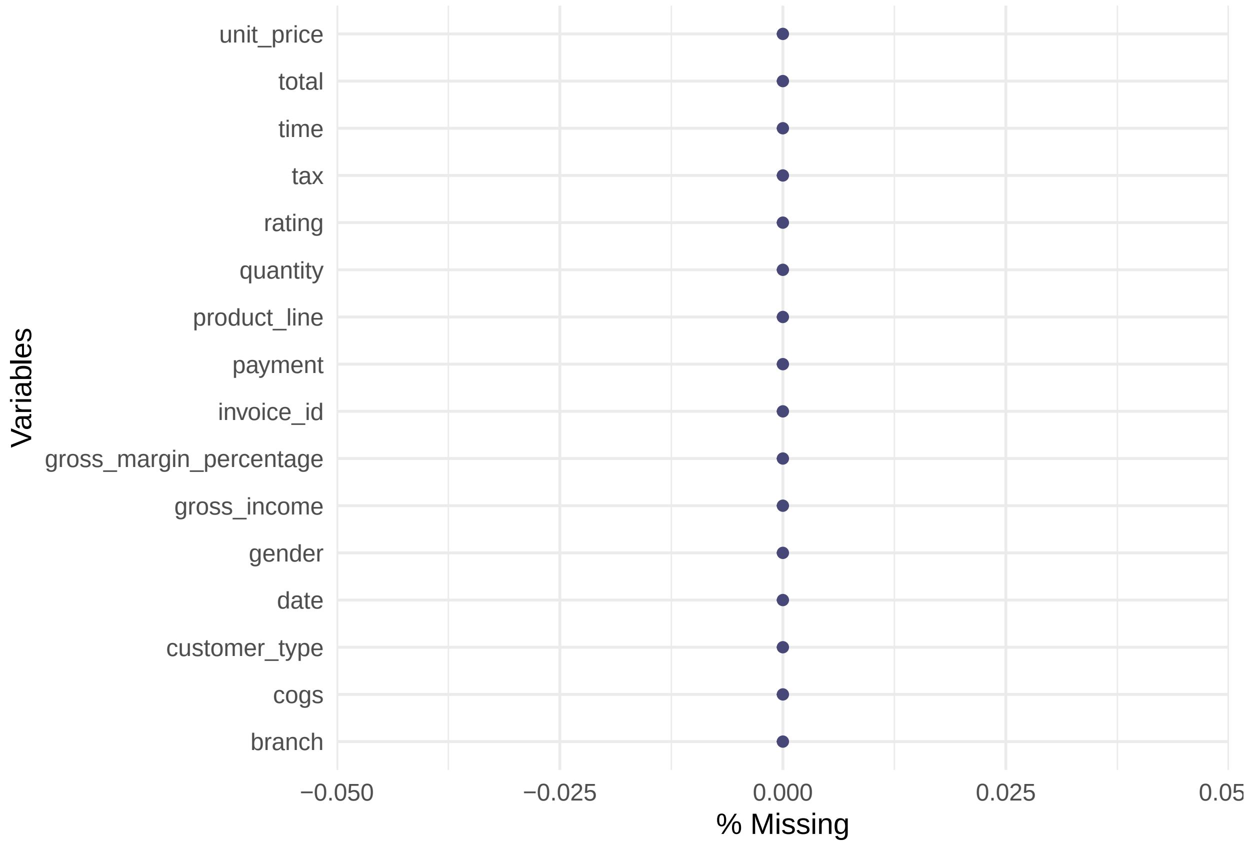
```
# clean the data by changing the names of columns.
# First we need to change the column names to lowercase and remove and replace spaces with an underscor
# replace the spaces with underscores using gsub() function
names(carrefour) <- gsub(" ","_", names(carrefour))
# lowercase
names(carrefour) <- tolower(names(carrefour))
# display the column names to confirm the changes
colnames(carrefour)
```

```
##  [1] "invoice_id"              "branch"
##  [3] "customer_type"           "gender"
##  [5] "product_line"            "unit_price"
##  [7] "quantity"                "tax"
##  [9] "date"                    "time"
## [11] "payment"                 "cogs"
## [13] "gross_margin_percentage" "gross_income"
## [15] "rating"                  "total"
```

Checking for missing values

```
# Lets check for missing values
gg_miss_var(carrefour, show_pct = TRUE)
```

```
## Warning: It is deprecated to specify `guide = FALSE` to remove a guide. Please
## use `guide = "none"` instead.
```




```r
colSums(is.na(carrefour))
```

```
##              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
```

From the dataset there is no row with missing data.

Duplicates

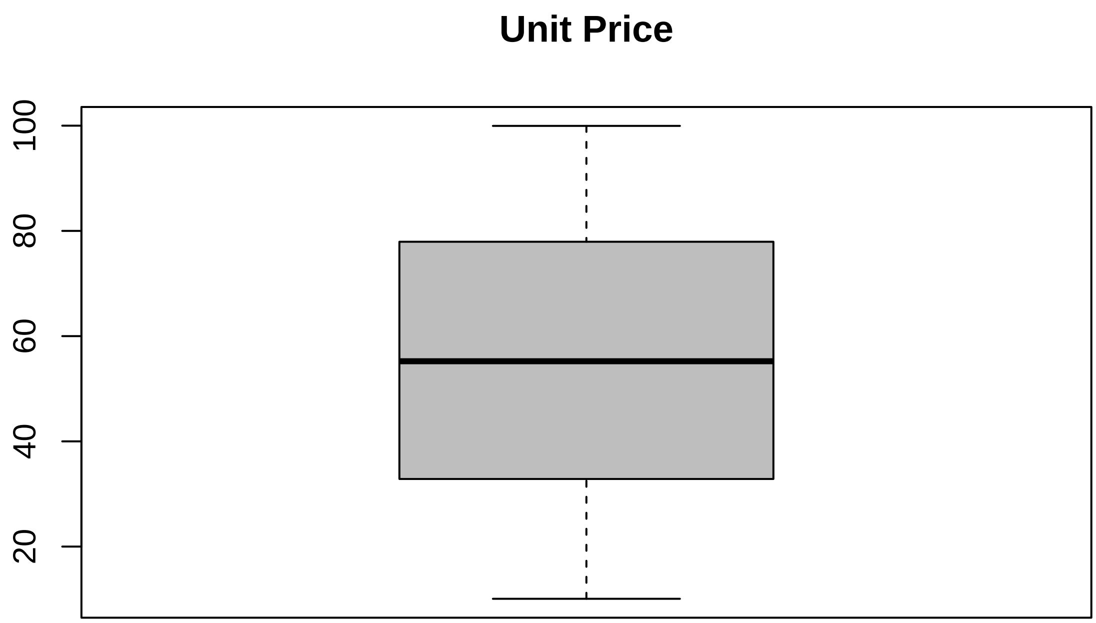
```r
# Lets check for duplicated values
duplicates <- carrefour[duplicated(carrefour),]
duplicates
```

```
## Empty data.table (0 rows and 16 cols): invoice_id,branch,customer_type,gender,product_line,unit_pric
```

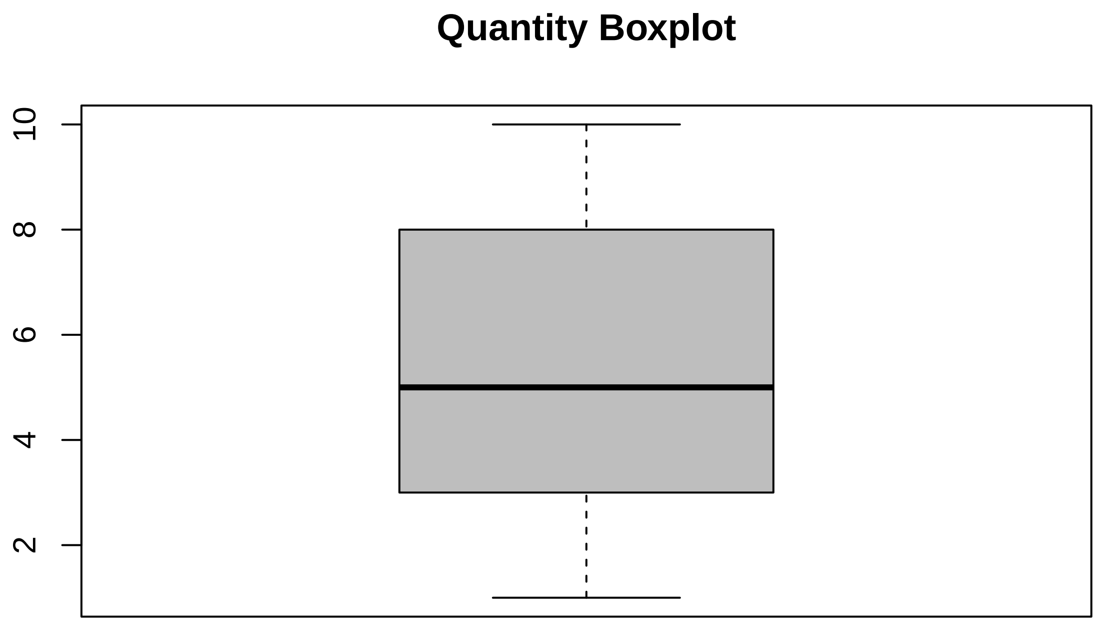
There is also no duplicates in the data.

Outliers

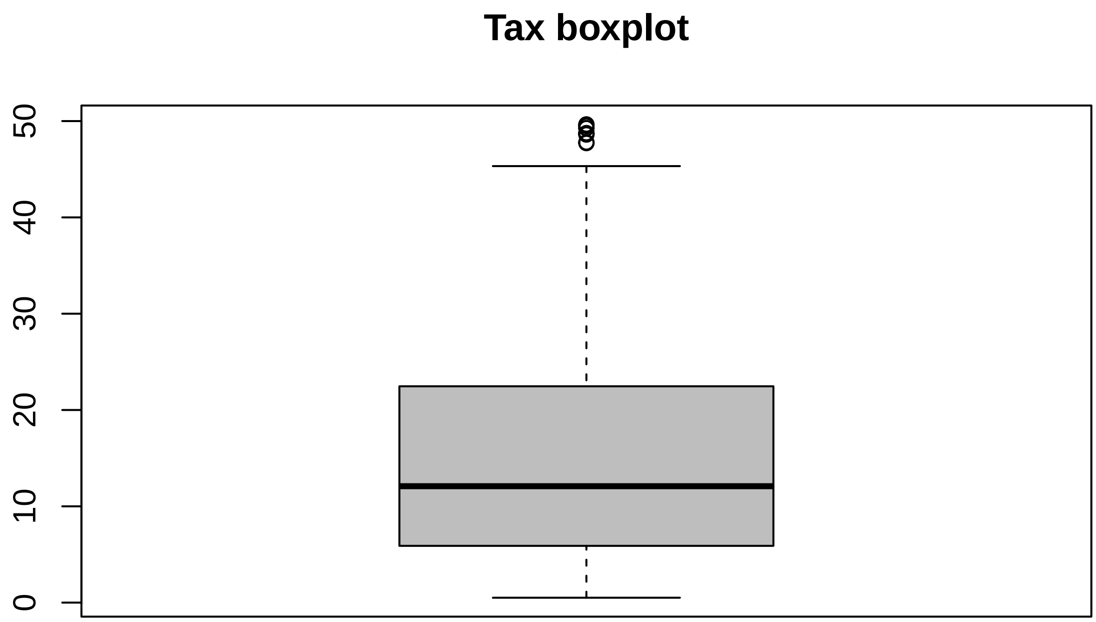
```r
# Lets check for outliers using boxplots
boxplot(carrefour$unit_price,col='grey', main = 'Unit Price')
```



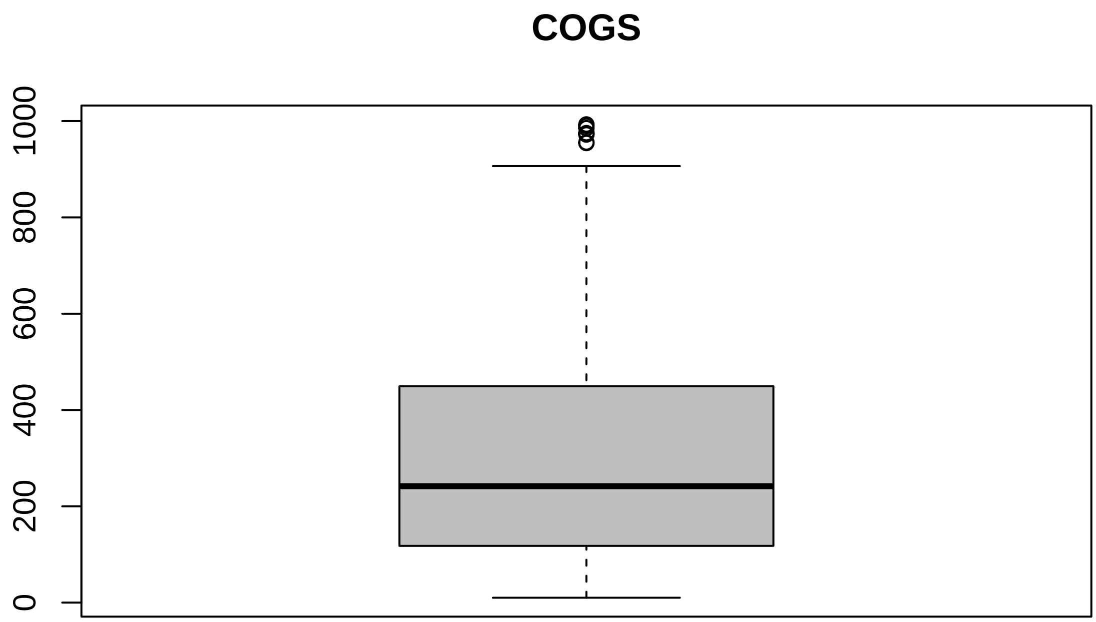

```r
boxplot(carrefour$quantity,col='grey', main = 'Quantity Boxplot')
```



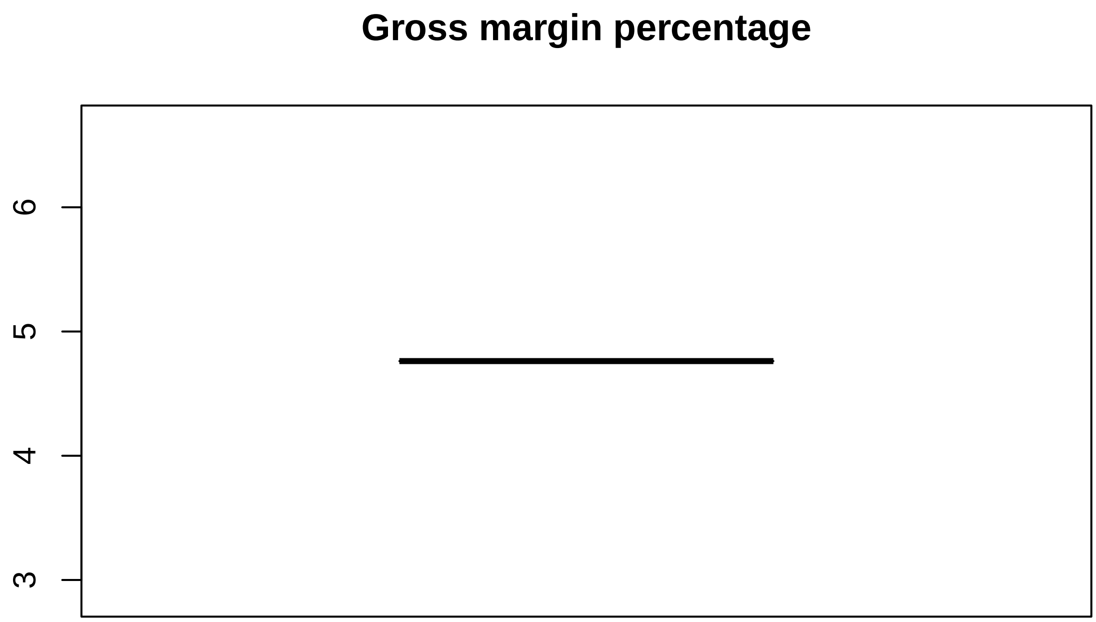

```
boxplot(carrefour$tax,col='grey', main = 'Tax boxplot')
```



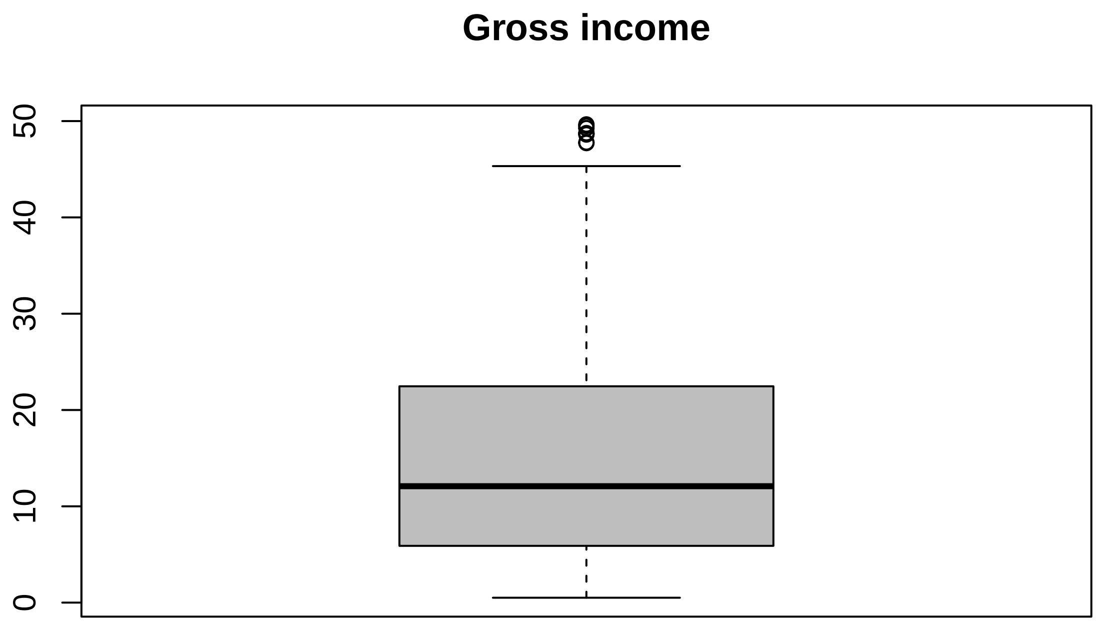

```
boxplot(carrefour$cogs,col='grey', main = 'COGS')
```



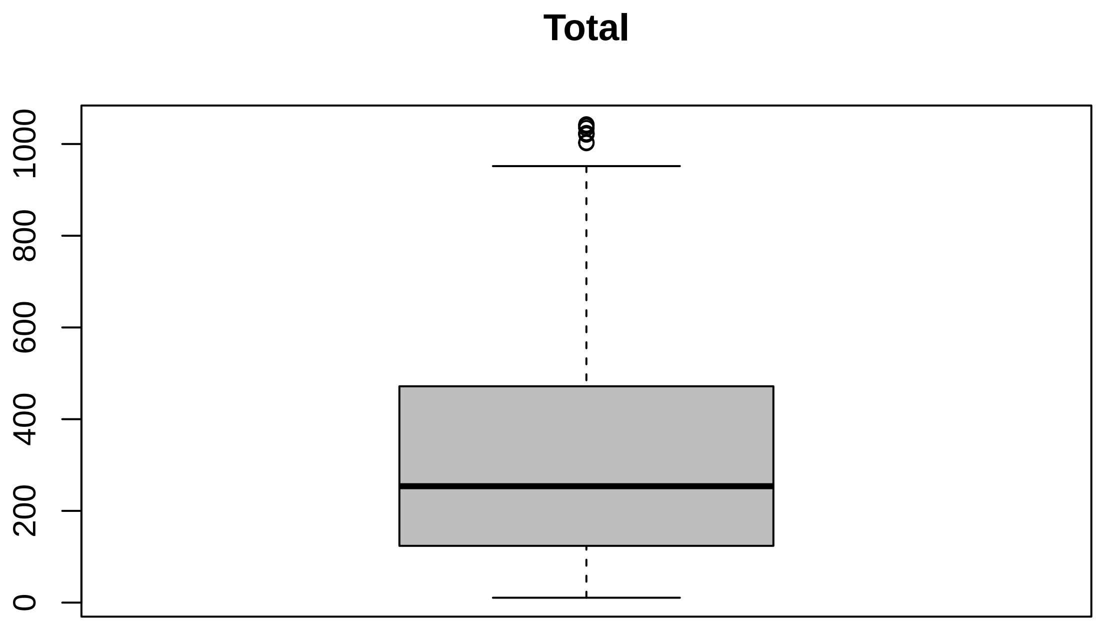

```
boxplot(carrefour$gross_margin_percentage,col='grey', main = 'Gross margin percentage')
```




```
boxplot(carrefour$gross_income,col='grey', main = 'Gross income')
```




```
boxplot(carrefour$total,col='grey', main = 'Total')
```

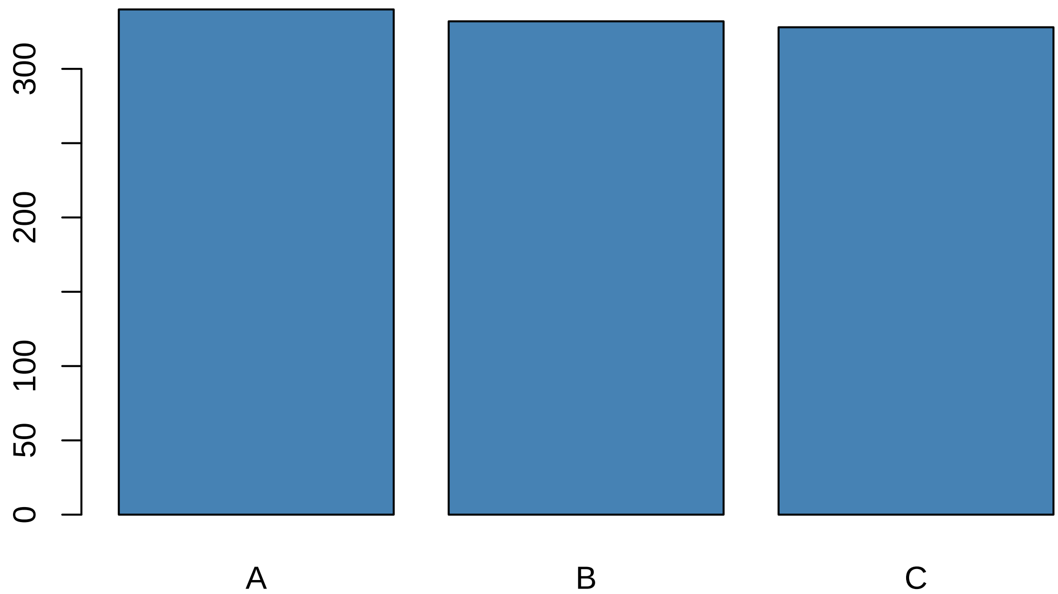


On the numerical columns, there are a few outliers. We will not drop these outliers since they maybe a representation of true values of goods with high taxes.

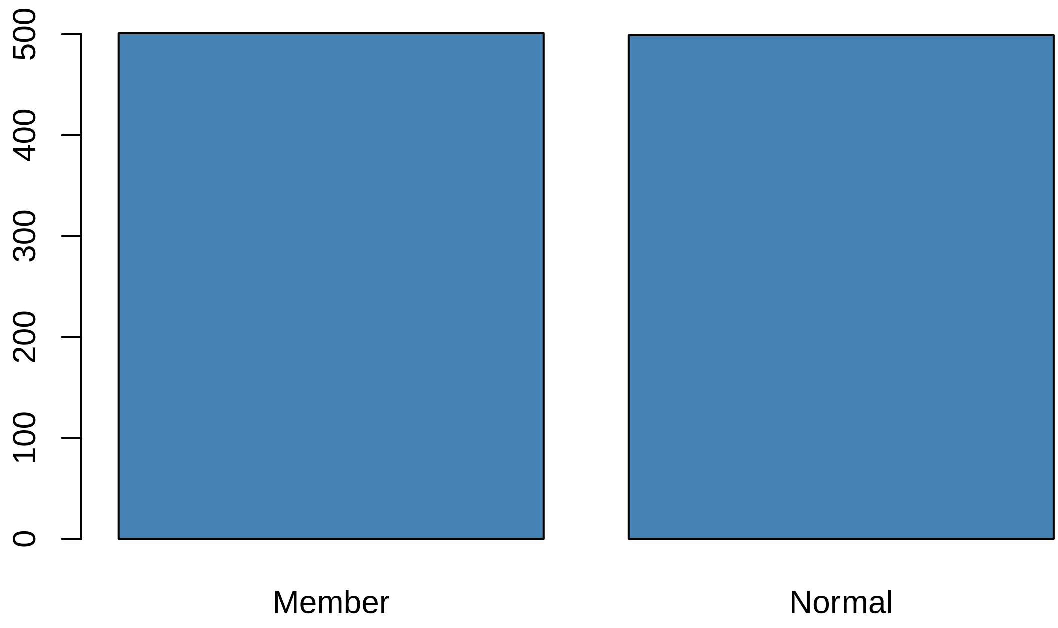
4. Exploratory Data Analysis

Univariate & Bivariate Analysis

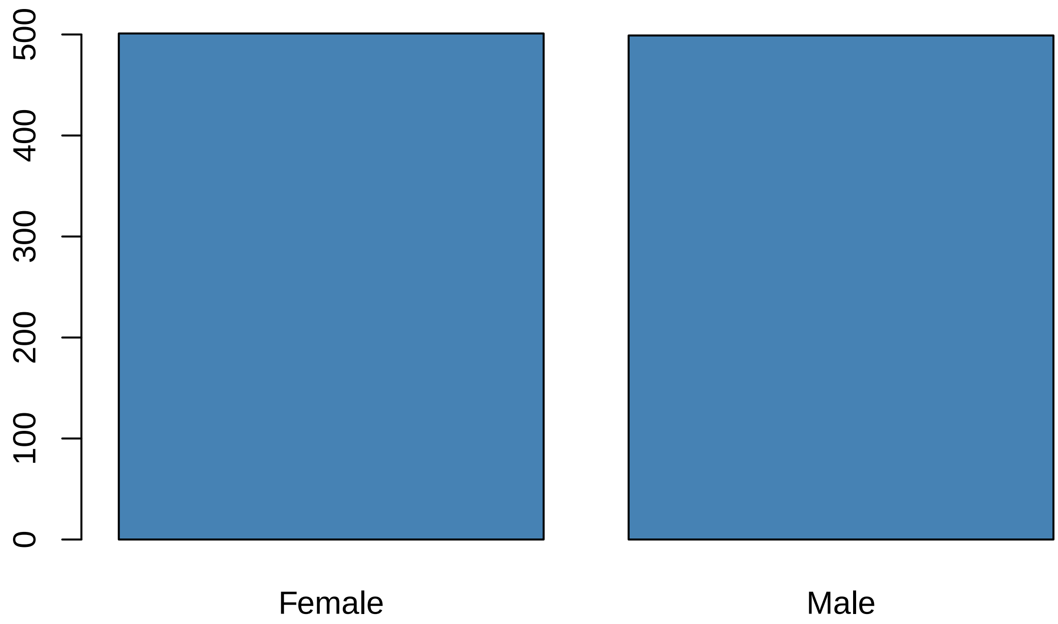
```
# Frequency of categorical columns

#Branch,customer_type, Gender, product-line , payment
branch <- table(carrefour$branch)
barplot(branch, col = "steelblue")
```



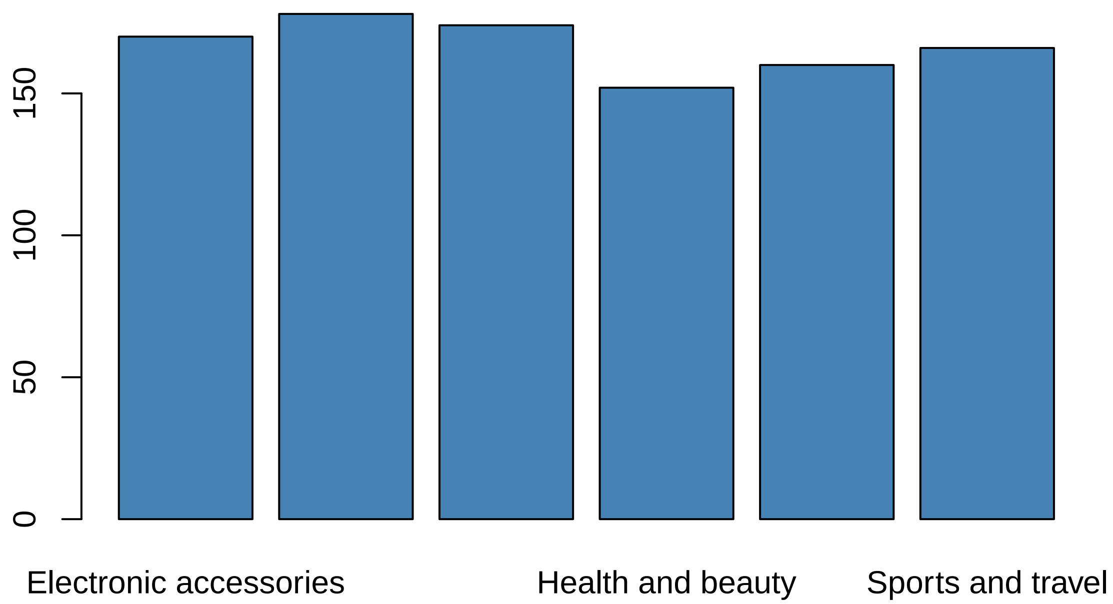

```r
customer_type_freq <- table (carrefour$customer_type)
barplot(customer_type_freq, col = "steelblue")
```



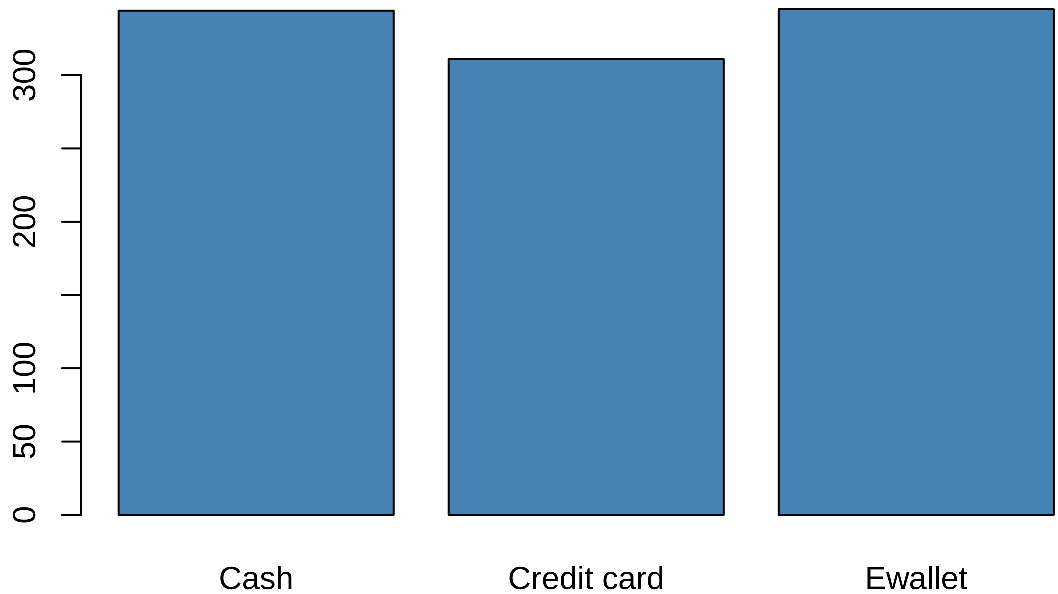

```
gender <- table(carrefour$gender)
barplot(gender, col = "steelblue")
```




```
product_line <- table(carrefour$product_line)
barplot(product_line, col = "steelblue")
```

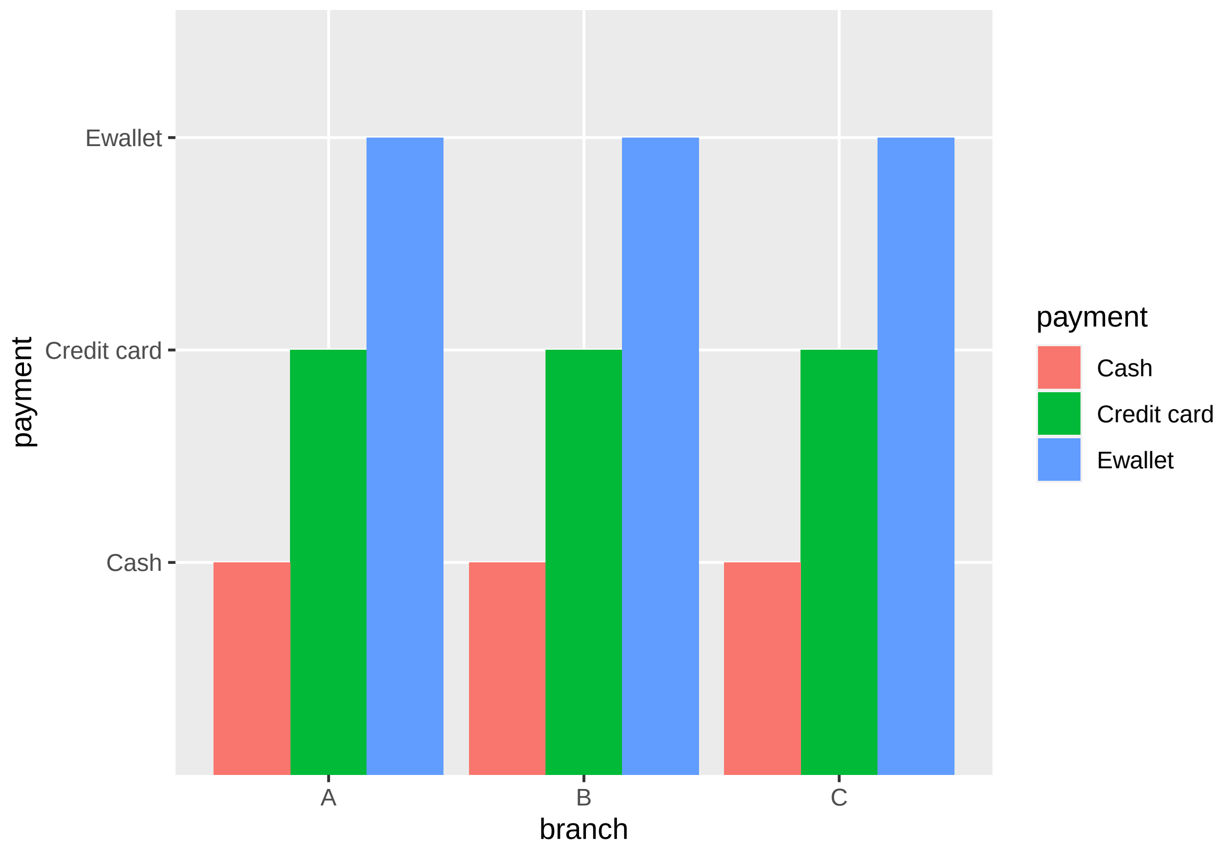



```
payment <- table(carrefour$payment)
barplot(payment, col = "steelblue")
```



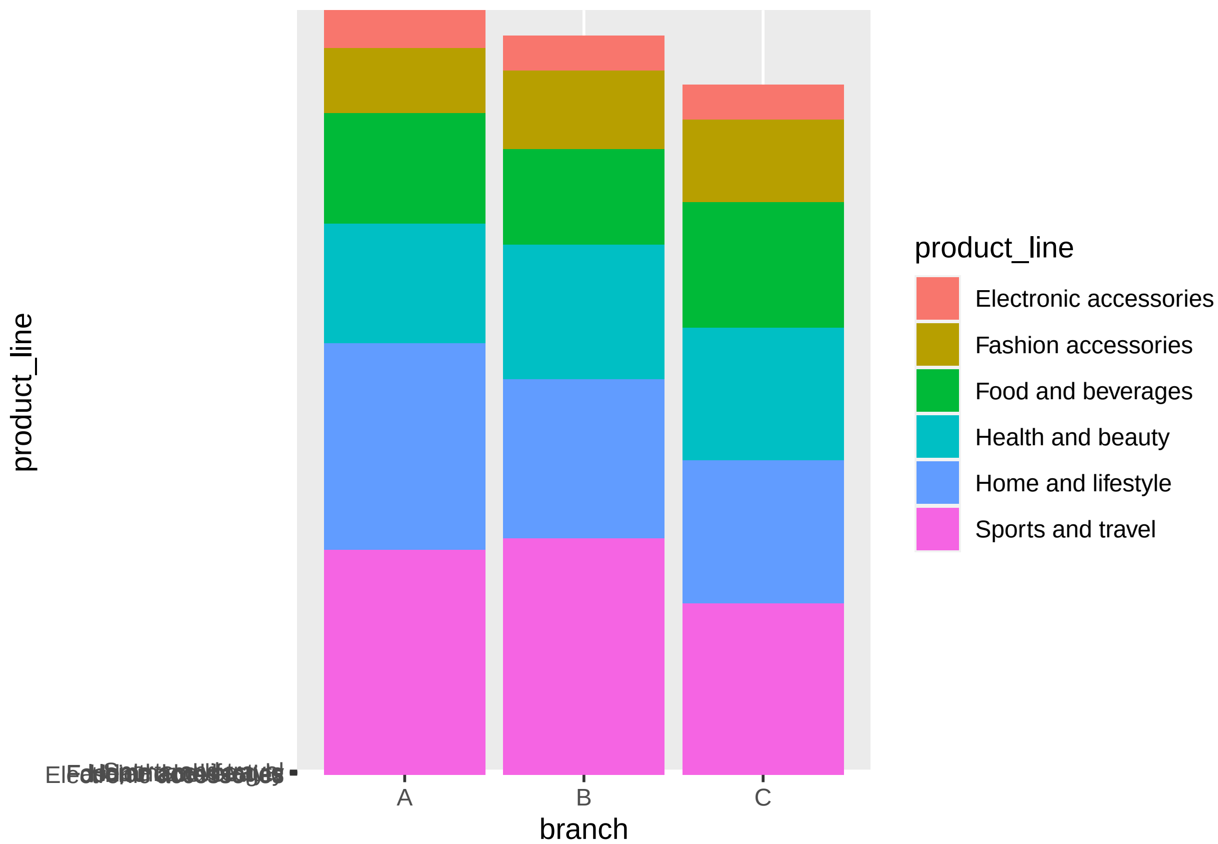
From the bar plots above we can deduce that: (i) Sales are equally distributed in collected on the Branches A, B and C. (ii) The information collected was half from the carrefour members and half from the normal customers. (iii) The gender was equally balanced in the data. (iv)Most people paid their bills with E wallet and cash rather than Credit card

```
# Lets plot using a ggplot

ggplot(carrefour, aes(fill=payment, y= payment, x=branch)) +
    geom_bar(position="dodge", stat="identity")
```



From the plot, Ewallet payments are the most popular in all the three branches.

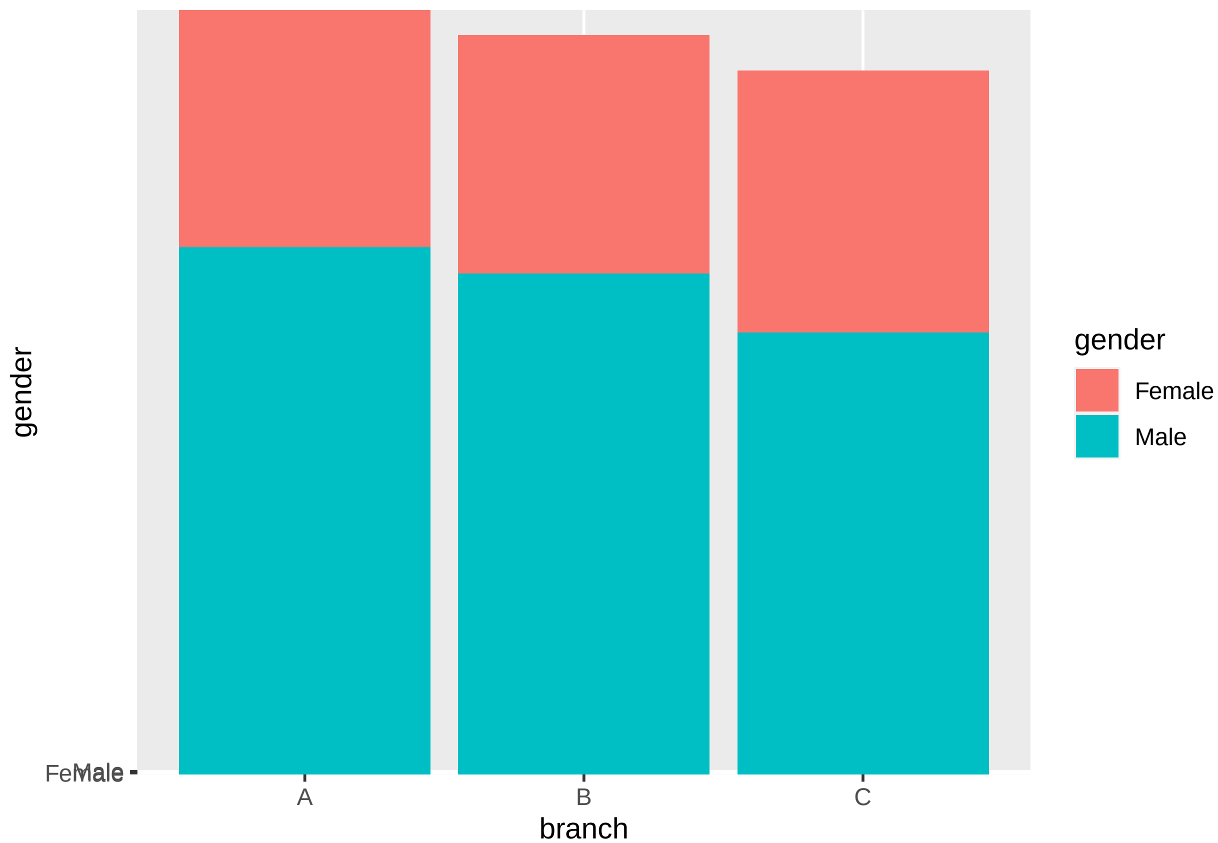
```
# Lets plot a stacked graph

ggplot(carrefour, aes(fill=product_line, y= product_line, x=branch)) +
    geom_bar(position="stack", stat="identity")
```



From the stacked graph, Branch B sells more sports and travel goods than the other branches. Branch A sells more home and lifestyle goods than the other branches.

We can conclude that the marketing team should stack these branches with the product with which they sell more.

```
# Lets plot a stacked graph for
ggplot(carrefour, aes(fill=gender, y= gender, x=branch)) +
    geom_bar(position="stack", stat="identity")
```



There are more males in the Carrefour branches than the females.

This is not what many people assume as many people erroneously think that there are usually more females doing shopping.

Measures of central tendency for the numerical columns

```
# numerical columns.
num_col <- unlist(lapply(carrefour, is.numeric))
carrefour_num <- subset(carrefour, select = num_col)
head (carrefour_num)
```

```
##    unit_price quantity     tax   cogs gross_margin_percentage gross_income
## 1:      74.69        7 26.1415 522.83                4.761905      26.1415
## 2:      15.28        5  3.8200  76.40                4.761905       3.8200
## 3:      46.33        7 16.2155 324.31                4.761905      16.2155
## 4:      58.22        8 23.2880 465.76                4.761905      23.2880
## 5:      86.31        7 30.2085 604.17                4.761905      30.2085
## 6:      85.39        7 29.8865 597.73                4.761905      29.8865
##    rating    total
## 1:    9.1 548.9715
## 2:    9.6  80.2200
## 3:    7.4 340.5255
## 4:    8.4 489.0480
## 5:    5.3 634.3785
## 6:    4.1 627.6165
```

Measures of dispersion

```r
# Lets get the measures of dispersion in the numerical columns.
summary_stats <- data.frame(
  Mean = apply(carrefour_num, 2, mean),
  Median = apply(carrefour_num, 2, median),
  Min = apply(carrefour_num, 2, min),
  Max = apply(carrefour_num, 2, max))
summary_stats
```

```
##                               Mean     Median       Min         Max
## unit_price               55.672130  55.230000 10.080000   99.960000
## quantity                  5.510000   5.000000  1.000000   10.000000
## tax                      15.379369  12.088000  0.508500   49.650000
## cogs                    307.587380 241.760000 10.170000  993.000000
## gross_margin_percentage   4.761905   4.761905  4.761905    4.761905
## gross_income             15.379369  12.088000  0.508500   49.650000
## rating                    6.972700   7.000000  4.000000   10.000000
## total                   322.966749 253.848000 10.678500 1042.650000
```

```r
# Define the function
getmode <- function(v) {
  uniqv <- unique(v)
  uniqv[which.max(tabulate(match(v, uniqv)))]
}
```

```r
# Mode
mode.unit_price <- getmode(carrefour$unit_price)
mode.unit_price
```

```
## [1] 83.77
```

```r
mode.quantity <- getmode(carrefour$quantity)
mode.quantity
```

```
## [1] 10
```

```r
mode.tax <- getmode(carrefour$tax)
mode.tax
```

```
## [1] 39.48
```

```r
mode.cogs <- getmode(carrefour$cogs)
mode.cogs
```

```
## [1] 789.6
```

```
mode.gross_income <- getmode(carrefour$gross_income)
mode.gross_income
```

```
## [1] 39.48
```

```
mode.rating <- getmode(carrefour$rating)
mode.rating
```

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

```
mode.total  <- getmode(carrefour$total)
mode.total
```

```
## [1] 829.08
```

Part One (Dimensionality Reduction)

```
# Label Encoder
#Branch , customer_type, Gender, productline , payment
lbl <- LabelEncoder$new()
lbl$fit(carrefour$branch)
carrefour$branch <- lbl$fit_transform(carrefour$branch)
lbl$fit(carrefour$customer_type)
carrefour$customer_type <- lbl$fit_transform(carrefour$customer_type)
lbl$fit(carrefour$gender)
carrefour$gender <- lbl$fit_transform(carrefour$gender)
lbl$fit(carrefour$product_line)
carrefour$product_line <- lbl$fit_transform(carrefour$product_line)
lbl$fit(carrefour$payment)
carrefour$payment <- lbl$fit_transform(carrefour$payment)
```

```
str(carrefour)
```

```
## Classes 'data.table' and 'data.frame':   1000 obs. of  16 variables:
##  $ invoice_id             : chr  "750-67-8428" "226-31-3081" "631-41-3108" "123-19-1176" ...
##  $ branch                 : num  0 1 0 0 0 1 0 1 0 2 ...
##  $ customer_type          : num  0 1 1 0 1 1 0 1 0 0 ...
##  $ gender                 : num  0 0 1 1 1 1 0 0 0 0 ...
##  $ product_line           : num  0 1 2 0 3 1 1 2 0 4 ...
##  $ 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                : num  0 1 2 0 0 0 0 0 2 2 ...
##  $ 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 ...
##  - attr(*, ".internal.selfref")=<externalptr>
```

```r
# Since the gross margin percentage has only one value we can drop the column.
table(carrefour$gross_margin_percentage)
```

```
##
## 4.761904762
##        1000
```

```r
carrefour$gross_margin_percentage <- NULL
```

```r
# Lets drop the categorical columns

carrefour$invoice_id <- NULL
carrefour$date <- NULL
carrefour$time <- NULL
```

```r
# Separate the data

carrefour.x <-  carrefour[ , 1:11]
carrefour.y <-  carrefour[, 12]
```

```r
head(carrefour.x)
```

```
##    branch customer_type gender product_line unit_price quantity     tax payment
## 1:      0             0      0            0      74.69        7 26.1415       0
## 2:      1             1      0            1      15.28        5  3.8200       1
## 3:      0             1      1            2      46.33        7 16.2155       2
## 4:      0             0      1            0      58.22        8 23.2880       0
## 5:      0             1      1            3      86.31        7 30.2085       0
## 6:      1             1      1            1      85.39        7 29.8865       0
##      cogs gross_income rating
## 1: 522.83      26.1415    9.1
## 2:  76.40       3.8200    9.6
## 3: 324.31      16.2155    7.4
## 4: 465.76      23.2880    8.4
## 5: 604.17      30.2085    5.3
## 6: 597.73      29.8865    4.1
```

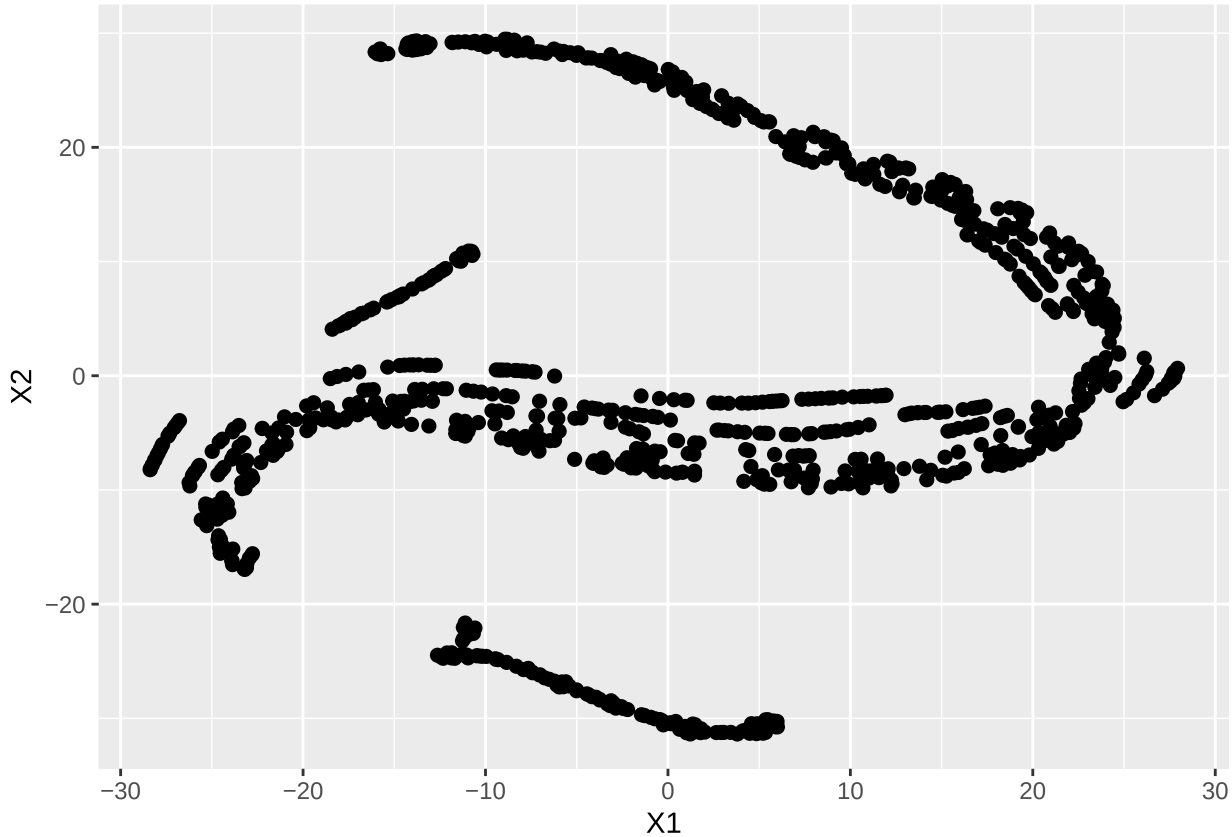
```r
head(carrefour.y)
```

```
##       total
## 1: 548.9715
## 2:  80.2200
## 3: 340.5255
## 4: 489.0480
## 5: 634.3785
## 6: 627.6165
```

t- SNE

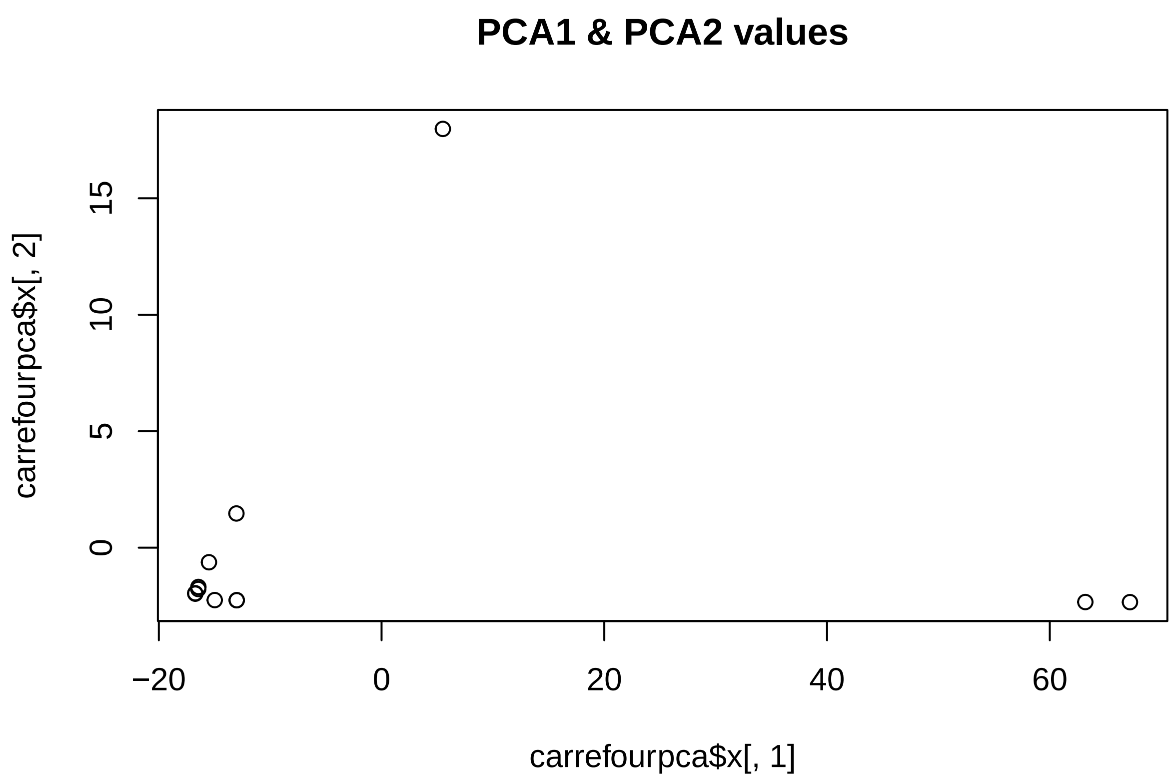
```
# Lets perform tsne

tsne = Rtsne(carrefour.x, dims = 2,  perplexity = 30)
```

```
# Lets visualize the t-SNE
carrefour.tsne = data.frame(tsne$Y)
ggplot(carrefour.tsne, aes(x=X1, y=X2)) + geom_point(size=2)
```



Performing the PCA

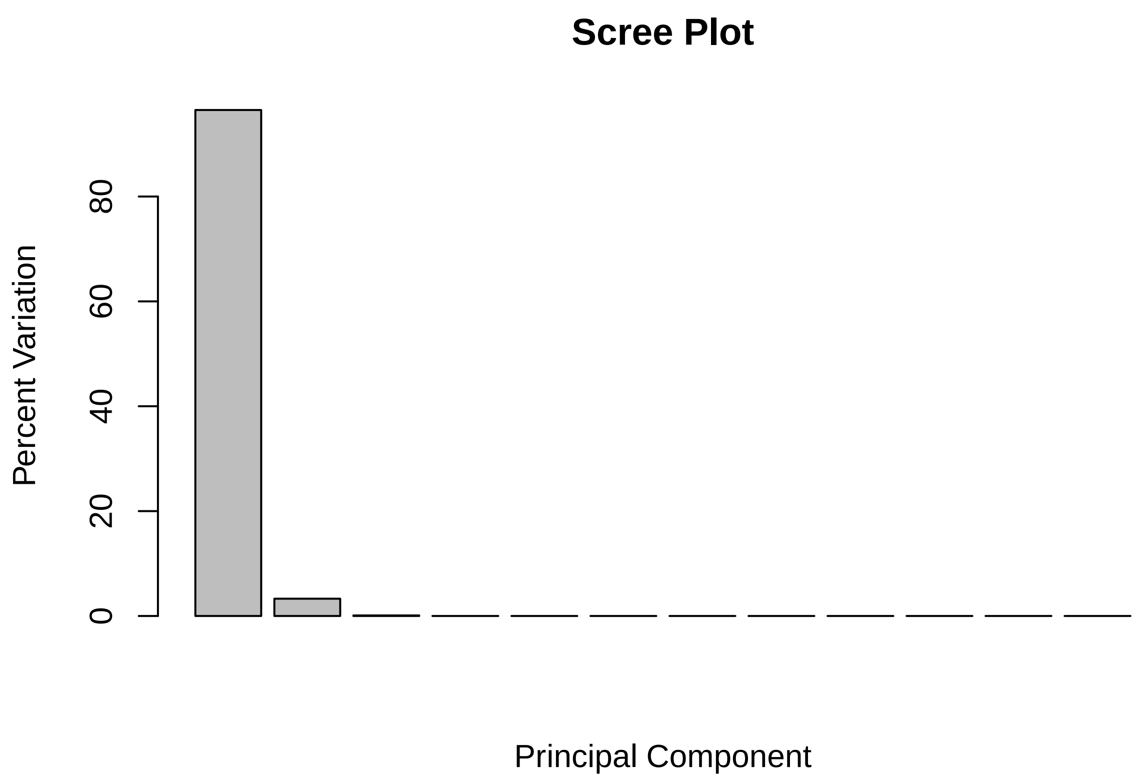
```
# Run the PCA on the dataframe

carrefourpca <- prcomp(t(carrefour),center = TRUE, scale=TRUE)
## plot pc1 and pc2

plot(carrefourpca$x[,1], carrefourpca$x[,2], main = "PCA1 & PCA2 values")
```




```r
# Lets get a summary of the PCA

summary (carrefourpca)
```

```
## Importance of components:
##                            PC1     PC2     PC3     PC4     PC5     PC6     PC7
## Standard deviation     31.0616 5.76498 1.21319 0.50237 0.29831 0.23451 0.20497
## Proportion of Variance  0.9648 0.03323 0.00147 0.00025 0.00009 0.00005 0.00004
## Cumulative Proportion   0.9648 0.99806 0.99953 0.99978 0.99987 0.99993 0.99997
##                            PC8     PC9      PC10      PC11      PC12
## Standard deviation     0.14119 0.09579 2.638e-14 1.965e-15 6.211e-17
## Proportion of Variance 0.00002 0.00001 0.000e+00 0.000e+00 0.000e+00
## Cumulative Proportion  0.99999 1.00000 1.000e+00 1.000e+00 1.000e+00
```

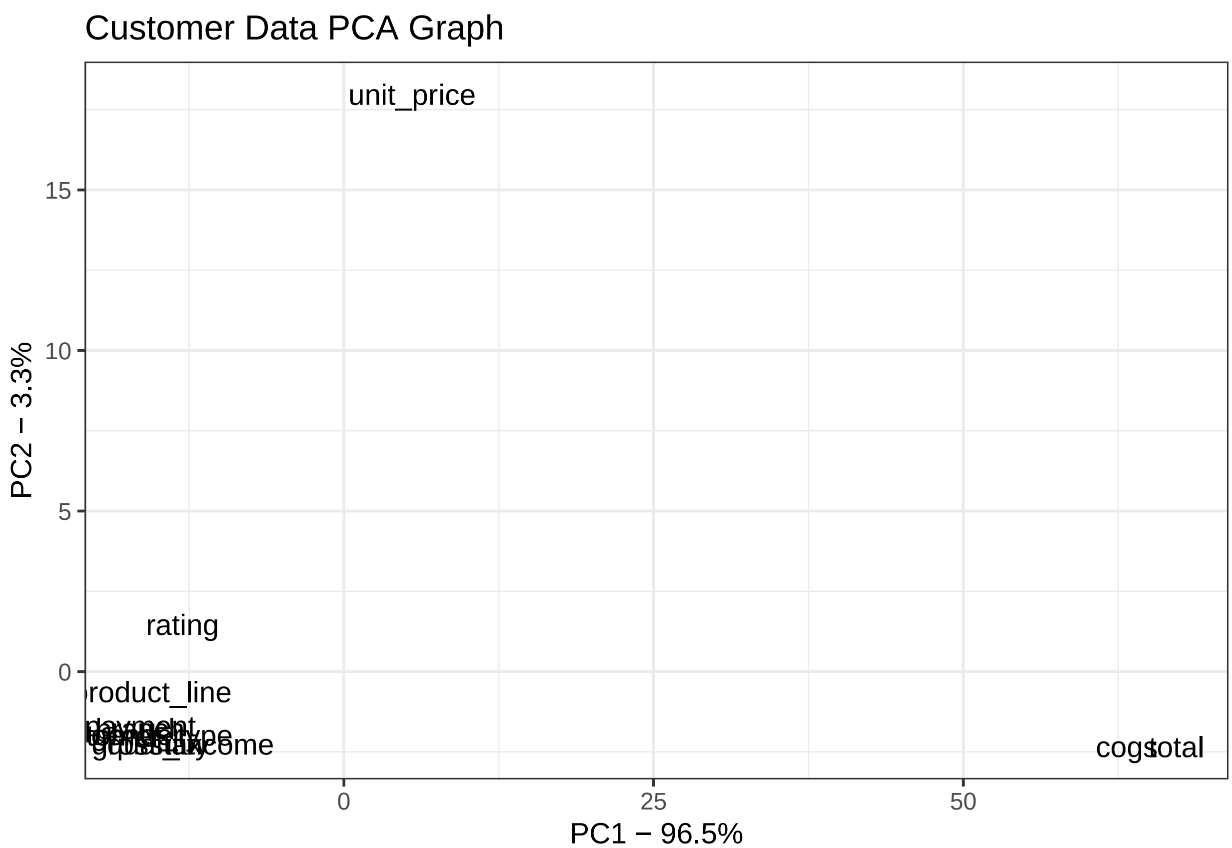
```r
## make a scree plot

pca.var <- carrefourpca$sdev^2
pca.var.per <- round(pca.var/sum(pca.var)*100, 1)
barplot(pca.var.per, main="Scree Plot", xlab="Principal Component", ylab="Percent Variation")
```




```
# Create a plot that shows the PCs and the variation:
pca.data <- data.frame(Sample=rownames(carrefourpca$x),
                       X=carrefourpca$x[,1],
                       Y=carrefourpca$x[,2])
pca.data
```

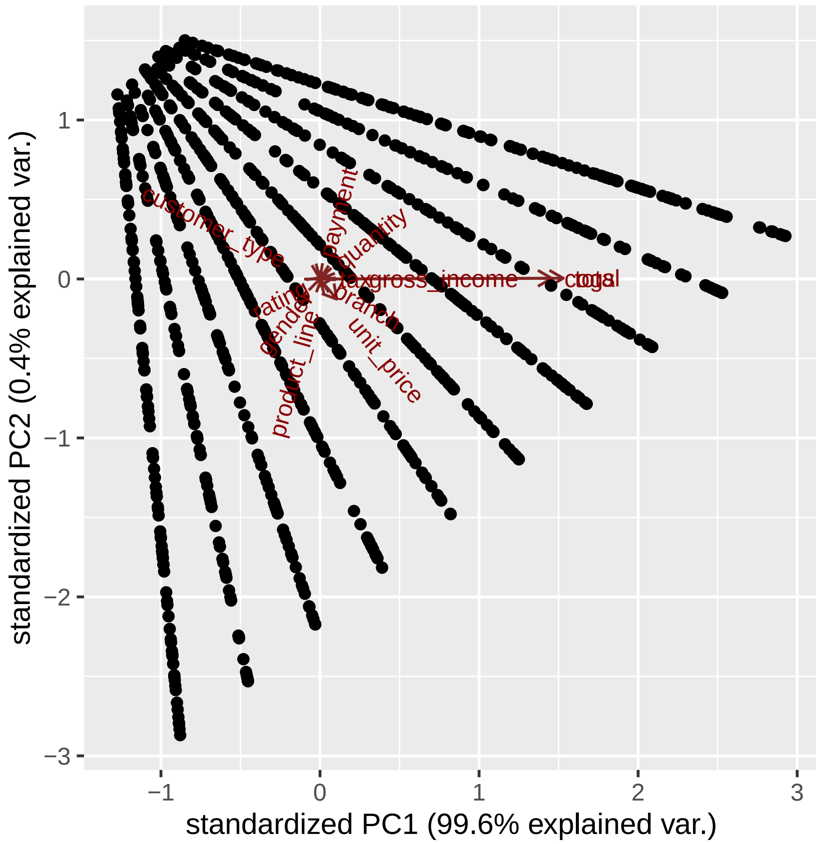
```
##                      Sample          X         Y
## branch               branch -16.460925 -1.774218
## customer_type customer_type -16.728657 -1.974943
## gender               gender -16.727800 -1.955175
## product_line   product_line -15.501089 -0.625429
## unit_price       unit_price   5.501295 17.977265
## quantity           quantity -14.979897 -2.249242
## tax                     tax -13.006234 -2.255524
## payment             payment -16.446861 -1.686001
## cogs                   cogs  63.189817 -2.333115
## gross_income   gross_income -13.006234 -2.255524
## rating               rating -13.033551  1.469104
## total                 total  67.200135 -2.337199
```

```
ggplot(data=pca.data, aes(x=X, y=Y, label=Sample)) +
  geom_text() +
  xlab(paste("PC1 - ", pca.var.per[1], "%", sep="")) +
  ylab(paste("PC2 - ", pca.var.per[2], "%", sep="")) +
  theme_bw() +
  ggtitle("Customer Data PCA Graph")
```



PC1 explains 96.5% of the total variance, which means that nearly 96% of the information in the dataset (11 variables) can be encapsulated by just that one Principal Component. PC2 explains 3.3% of the variance. etc

```
library(ggbiplot)
ggbiplot (prcomp(carrefour))
```



Part 2: Feature Selection

Using the Filter method.

```
# Loading a library
library(caret)
```

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

```
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```
# Calculating the correlation matrix
correlationMatrix <- cor(carrefour)
# Find attributes that are highly correlated
# ---
highlyCorrelated <- findCorrelation(correlationMatrix, cutoff=0.75)
highlyCorrelated
```

```
## [1]  7  9 10
```

```r
correlationMatrix
```

```
##                    branch customer_type       gender product_line   unit_price
## branch         1.000000000  -0.004899261 -0.012218875   0.01257525  0.013763477
## customer_type -0.004899261   1.000000000  0.039996160  -0.02510945 -0.020237875
## gender        -0.012218875   0.039996160  1.000000000  -0.06612647  0.015444630
## product_line   0.012575246  -0.025109450 -0.066126475   1.00000000  0.038427649
## unit_price     0.013763477  -0.020237875  0.015444630   0.03842765  1.000000000
## quantity       0.002120920  -0.016762706 -0.074258307  -0.06251471  0.010777564
## tax            0.012811933  -0.019670283 -0.049450989  -0.01854396  0.633962089
## payment        0.026725563  -0.069286242 -0.049514182   0.01051098 -0.019637884
## cogs           0.012811933  -0.019670283 -0.049450989  -0.01854396  0.633962089
## gross_income   0.012811933  -0.019670283 -0.049450989  -0.01854396  0.633962089
## rating        -0.049585348   0.018888672  0.004800208   0.02339096 -0.008777507
## total          0.012811933  -0.019670283 -0.049450989  -0.01854396  0.633962089
##                   quantity          tax      payment         cogs gross_income
## branch         0.002120920  0.012811933  0.026725563  0.012811933  0.012811933
## customer_type -0.016762706 -0.019670283 -0.069286242 -0.019670283 -0.019670283
## gender        -0.074258307 -0.049450989 -0.049514182 -0.049450989 -0.049450989
## product_line  -0.062514713 -0.018543956  0.010510982 -0.018543956 -0.018543956
## unit_price     0.010777564  0.633962089 -0.019637884  0.633962089  0.633962089
## quantity       1.000000000  0.705510186  0.007333388  0.705510186  0.705510186
## tax            0.705510186  1.000000000  0.008823723  1.000000000  1.000000000
## payment        0.007333388  0.008823723  1.000000000  0.008823723  0.008823723
## cogs           0.705510186  1.000000000  0.008823723  1.000000000  1.000000000
## gross_income   0.705510186  1.000000000  0.008823723  1.000000000  1.000000000
## rating        -0.015814905 -0.036441705  0.013001094 -0.036441705 -0.036441705
## total          0.705510186  1.000000000  0.008823723  1.000000000  1.000000000
##                     rating        total
## branch        -0.049585348  0.012811933
## customer_type  0.018888672 -0.019670283
## gender         0.004800208 -0.049450989
## product_line   0.023390962 -0.018543956
## unit_price    -0.008777507  0.633962089
## quantity      -0.015814905  0.705510186
## tax           -0.036441705  1.000000000
## payment        0.013001094  0.008823723
## cogs          -0.036441705  1.000000000
## gross_income  -0.036441705  1.000000000
## rating         1.000000000 -0.036441705
## total         -0.036441705  1.000000000
```

```r
# Names of highly correlations
names (carrefour[, 7])
```

```
## [1] "tax"
```

```r
names (carrefour[, 9])
```

```
## [1] "cogs"
```

```r
names (carrefour[, 11])
```

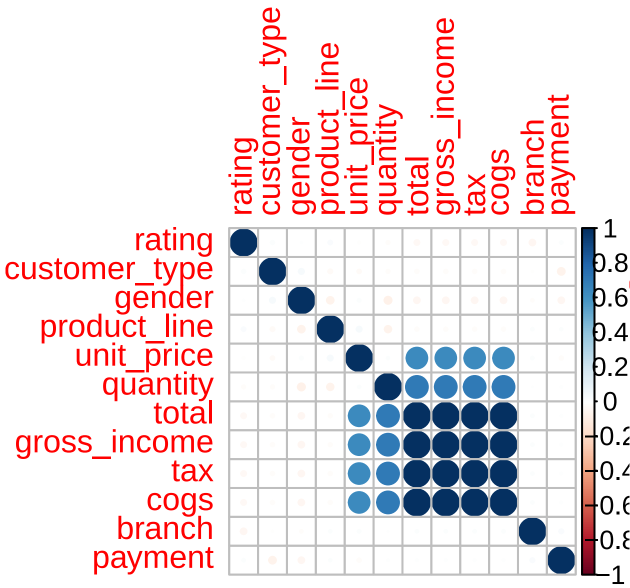
```
## [1] "rating"
```

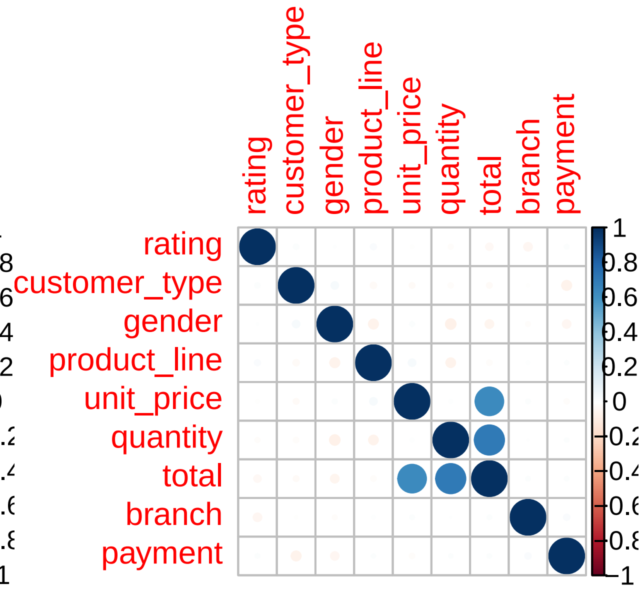
```r
# Next step is removing the variables with high correlation
carrefour_low <- carrefour[-highlyCorrelated]
carrefour_low$tax <- NULL
carrefour_low$cogs <- NULL
carrefour_low$gross_income <- NULL
```

```r
cor2 <- cor(carrefour_low)
cor2
```

```
##                   branch customer_type       gender product_line   unit_price
## branch         1.000000000  -0.006113857 -0.013460802  0.008640181  0.013551891
## customer_type -0.006113857   1.000000000  0.037110365 -0.026797451 -0.020544234
## gender        -0.013460802   0.037110365  1.000000000 -0.067954892  0.015205909
## product_line   0.008640181  -0.026797451 -0.067954892  1.000000000  0.037893893
## unit_price     0.013551891  -0.020544234  0.015205909  0.037893893  1.000000000
## quantity       0.001930628  -0.018705894 -0.076351656 -0.063649293  0.009800802
## payment        0.025373513  -0.068185247 -0.048336870  0.010315646 -0.018116773
## rating        -0.049616876   0.017746989  0.003631188  0.023536164 -0.008367916
## total          0.012931022  -0.020884334 -0.050733456 -0.019186236  0.633734080
##                   quantity     payment       rating       total
## branch         0.001930628  0.02537351 -0.049616876  0.01293102
## customer_type -0.018705894 -0.06818525  0.017746989 -0.02088433
## gender        -0.076351656 -0.04833687  0.003631188 -0.05073346
## product_line  -0.063649293  0.01031565  0.023536164 -0.01918624
## unit_price     0.009800802 -0.01811677 -0.008367916  0.63373408
## quantity       1.000000000  0.01020392 -0.016105001  0.70504027
## payment        0.010203918  1.00000000  0.012852398  0.01146344
## rating        -0.016105001  0.01285240  1.000000000 -0.03642915
## total          0.705040267  0.01146344 -0.036429151  1.00000000
```

```r
# Lets perform our graphical comparison
# ---
#
library(stats)
par(mfrow = c(1, 2))
corrplot(correlationMatrix, order = "hclust")
corrplot(cor(carrefour_low), order = "hclust")
```





From the filter method, There are a few columns that have been eliminated because of high such a high correlation: - Tax - Cogs __ Gross Income

We should try another method and see what other features we will remain with

Wrapper method

```
# Library
library(clustvarsel)
```

```
## Loading required package: mclust

## Package 'mclust' version 5.4.10
## Type 'citation("mclust")' for citing this R package in publications.

## Package 'clustvarsel' version 2.3.4

## Type 'citation("clustvarsel")' for citing this R package in publications.
```

```
library(mclust)
```

```
# Sequential forward greedy search (default)
#
out = clustvarsel(carrefour_low, G = 1:5)
out
```

```
## ------------------------------------------------------
## Variable selection for Gaussian model-based clustering
## Stepwise (forward/backward) greedy search
## ------------------------------------------------------
##
##  Variable proposed Type of step  BICclust Model G    BICdiff Decision
##              total          Add -13434.37     V 4   385.9196 Accepted
##         unit_price          Add -21507.86   VEV 5   800.0361 Accepted
##           quantity          Add -22352.30   VVV 5  2462.4005 Accepted
##           quantity       Remove -21507.86   VEV 5  2462.4005 Rejected
##             rating          Add -24954.28   VEV 5  1322.0645 Accepted
##             rating       Remove -22352.30   VVV 5  1322.0645 Rejected
##       product_line          Add -30232.02   EVV 5 -1369.5858 Rejected
##             rating       Remove -22352.30   VVV 5  1322.0645 Rejected
##
## Selected subset: total, unit_price, quantity, rating
```

For the wrapper method only a few columns have been selected for modelling. these are: - Total - Quantity - Unit Price

Embended methods

```
library(wskm)
```

```
## Loading required package: latticeExtra

##
## Attaching package: 'latticeExtra'

## The following object is masked from 'package:ggplot2':
##
##     layer

## Loading required package: fpc
```

```
set.seed(2)
model <- ewkm(carrefour_low, 3, lambda=2, maxiter=1000)
```

```
library("cluster")
clusplot(carrefour_low, model$cluster, color=TRUE, cor = TRUE, shade=TRUE,
         labels=2, lines=1,main='Cluster Analysis for dataframe')
```

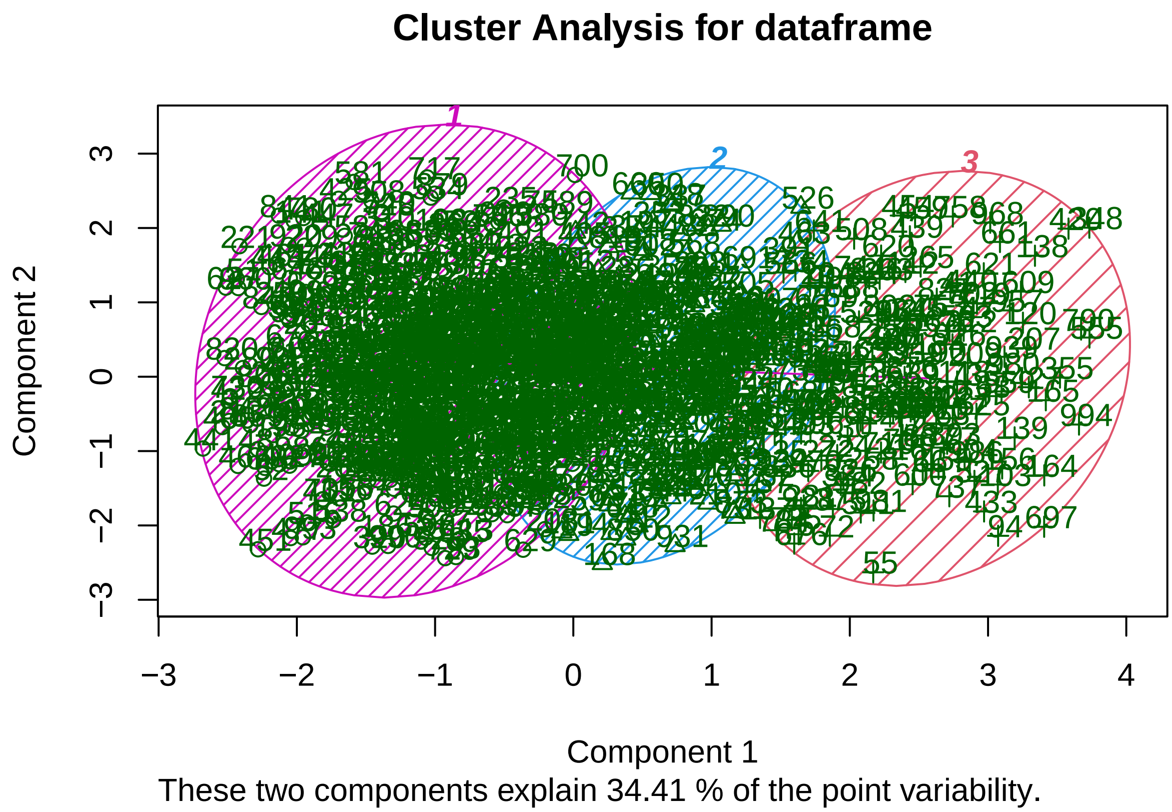
```
## Warning in plot.window(...): "cor" is not a graphical parameter

## Warning in plot.xy(xy, type, ...): "cor" is not a graphical parameter

## Warning in axis(side = side, at = at, labels = labels, ...): "cor" is not a
## graphical parameter

## Warning in axis(side = side, at = at, labels = labels, ...): "cor" is not a
## graphical parameter
```

```
## Warning in box(...): "cor" is not a graphical parameter

## Warning in title(...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in polygon(z[[k]], density = if (shade) density[k] else 0, col =
## col.clus[jInd[i]], : "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
```

```
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in polygon(z[[k]], density = if (shade) density[k] else 0, col =
## col.clus[jInd[i]], : "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
```

```
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter
```

```
## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in segments(lx1, ly1, lx2, ly2, ...): "cor" is not a graphical parameter

## Warning in polygon(z[[k]], density = if (shade) density[k] else 0, col =
## col.clus[jInd[i]], : "cor" is not a graphical parameter

## Warning in plot.xy(xy.coords(x, y), type = type, ...): "cor" is not a graphical
## parameter

## Warning in plot.xy(xy.coords(x, y), type = type, ...): "cor" is not a graphical
## parameter

## Warning in plot.xy(xy.coords(x, y), type = type, ...): "cor" is not a graphical
## parameter

## Warning in segments(loc[i, 1], loc[i, 2], loc[j, 1], loc[j, 2], col = 6, : "cor"
## is not a graphical parameter

## Warning in text.default(xy, labels = labs, ...): "cor" is not a graphical
## parameter

## Warning in text.default(xy, labels = labs, ...): "cor" is not a graphical
## parameter
```




```
# Weights are calculated for each variable and cluster.
# They are a measure of the relative importance of each variable
# with regards to the membership of the observations to that cluster.
# The weights are incorporated into the distance function,
# typically reducing the distance for more important variables.
# Weights remain stored in the model and we can check them as follows:
#
round(model$weights*100,2)
```

```
##   branch customer_type gender product_line unit_price quantity payment rating
## 1      0         45.15  54.84            0          0        0       0      0
## 2      0         43.39  56.60            0          0        0       0      0
## 3      0         50.00  50.00            0          0        0       0      0
##   total
## 1     0
## 2     0
## 3     0
```

Part 3(Association Rule)

```
library(arules)
```

```
## Loading required package: Matrix
```

```
##
## Attaching package: 'arules'

## The following objects are masked from 'package:base':
##
##     abbreviate, write
```

```r
# Loading
path <- "http://bit.ly/SupermarketDatasetII"
Transactions<-read.transactions(path, sep = ",")
```

```
## Warning in asMethod(object): removing duplicated items in transactions
```

```r
Transactions
```

```
## transactions in sparse format with
##  7501 transactions (rows) and
##  119 items (columns)
```

```r
# verifying the object class
class(Transactions)
```

```
## [1] "transactions"
## attr(,"package")
## [1] "arules"
```

```r
# Previewing our first 5 transactions
inspect(Transactions[1:5])
```

```
##     items
## [1] {almonds,
##      antioxydant juice,
##      avocado,
##      cottage cheese,
##      energy drink,
##      frozen smoothie,
##      green grapes,
##      green tea,
##      honey,
##      low fat yogurt,
##      mineral water,
##      olive oil,
##      salad,
##      salmon,
##      shrimp,
##      spinach,
##      tomato juice,
##      vegetables mix,
##      whole weat flour,
##      yams}
## [2] {burgers,
```

```
##      eggs,
##      meatballs}
## [3] {chutney}
## [4] {avocado,
##      turkey}
## [5] {energy bar,
##      green tea,
##      milk,
##      mineral water,
##      whole wheat rice}
```

```
# preview the items that make up our dataset,
# alternatively we can do the following
# ---
#
items<-as.data.frame(itemLabels(Transactions))
colnames(items) <- "Item"
head(items, 10)
```

```
##                 Item
## 1            almonds
## 2  antioxydant juice
## 3          asparagus
## 4            avocado
## 5        babies food
## 6              bacon
## 7     barbecue sauce
## 8          black tea
## 9        blueberries
## 10        body spray
```

```
# Generating a summary of the transaction dataset
# ---
# This would give us some information such as the most purchased items,
# distribution of the item sets (no. of items purchased in each transaction), etc.
summary(Transactions)
```

```
## transactions as itemMatrix in sparse format with
##  7501 rows (elements/itemsets/transactions) and
##  119 columns (items) and a density of 0.03288973
##
## most frequent items:
## mineral water          eggs     spaghetti  french fries     chocolate
##          1788          1348          1306          1282          1229
##       (Other)
##         22405
##
## element (itemset/transaction) length distribution:
## sizes
##    1    2    3    4    5    6    7    8    9   10   11   12   13   14   15   16
## 1754 1358 1044  816  667  493  391  324  259  139  102   67   40   22   17    4
##   18   19   20
##    1    2    1
```

```
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   2.000   3.000   3.914   5.000  20.000
##
## includes extended item information - examples:
##              labels
## 1           almonds
## 2 antioxydant juice
## 3         asparagus
```

In the dataset, the most frequently bought item is Mineral water followed by eggs.

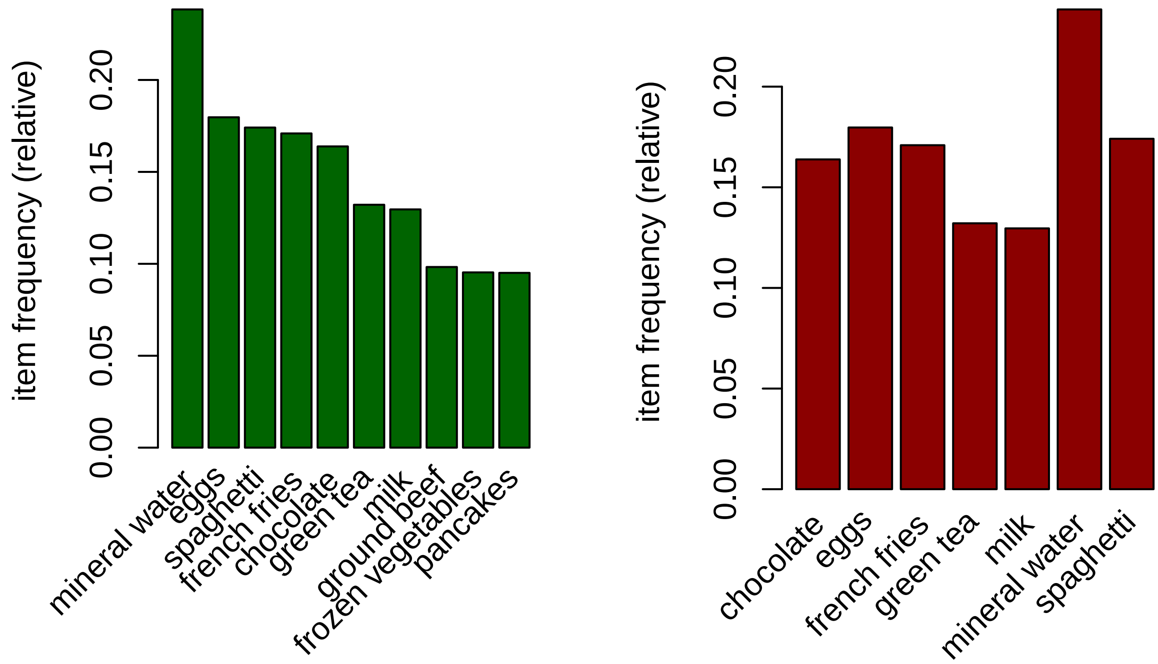
```r
# Exploring the frequency of some articles

itemFrequency(Transactions[, 8:10],type = "absolute")
```

```
##   black tea blueberries  body spray
##         107          69          86
```

```r
round(itemFrequency(Transactions[, 8:10],type = "relative")*100,2)
```

```
##   black tea blueberries  body spray
##        1.43        0.92        1.15
```

```r
# Producing a chart of frequencies and filtering
# to consider only items with a minimum percentage
# of support/ considering a top x of items
# ---
# Displaying top 10 most common items in the transactions dataset
# and the items whose relative importance is at least 10%
#
par(mfrow = c(1, 2))
# plot the frequency of items
itemFrequencyPlot(Transactions, topN = 10,col="darkgreen")
itemFrequencyPlot(Transactions, support = 0.1,col="darkred")
```




```r
# Building a model based on association rules
# We use Min Support as 0.001 and confidence as 0.8
rules <- apriori (Transactions, parameter = list(supp = 0.001, conf = 0.8))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.8    0.1    1 none FALSE            TRUE       5   0.001      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 7
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[119 item(s), 7501 transaction(s)] done [0.00s].
## sorting and recoding items ... [116 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 6 done [0.01s].
## writing ... [74 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```r
rules
```

```
## set of 74 rules
```

Using a confidence level of 0.80 and support of 0.001 we have a model with 74 rules. An increase in minimum support will result in a decrease in the number of rules by the model. However, a slight decrease in the confidence level will result in a huge increase in the rules created by the models.

```r
# Lets get more information on the rules formed
# More statistical information such as support, lift and confidence is also provided.
# ---
#
summary(rules)
```

```
## set of 74 rules
##
## rule length distribution (lhs + rhs):sizes
##  3  4  5  6
## 15 42 16  1
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   3.000   4.000   4.000   4.041   4.000   6.000
##
## summary of quality measures:
##     support           confidence        coverage             lift
##  Min.   :0.001067   Min.   :0.8000   Min.   :0.001067   Min.   : 3.356
##  1st Qu.:0.001067   1st Qu.:0.8000   1st Qu.:0.001333   1st Qu.: 3.432
##  Median :0.001133   Median :0.8333   Median :0.001333   Median : 3.795
##  Mean   :0.001256   Mean   :0.8504   Mean   :0.001479   Mean   : 4.823
##  3rd Qu.:0.001333   3rd Qu.:0.8889   3rd Qu.:0.001600   3rd Qu.: 4.877
##  Max.   :0.002533   Max.   :1.0000   Max.   :0.002666   Max.   :12.722
##      count
##  Min.   : 8.000
##  1st Qu.: 8.000
##  Median : 8.500
##  Mean   : 9.419
##  3rd Qu.:10.000
##  Max.   :19.000
##
## mining info:
##          data ntransactions support confidence
##  Transactions          7501   0.001        0.8
##                                                                    call
##  apriori(data = Transactions, parameter = list(supp = 0.001, conf = 0.8))
```

The set of 74 rules has a maximum rule length of 6 and a minimum of 3.

```r
# lets take a peek at the first 5 rules of the associative model formed.
inspect(rules[1:5])
```

```
##     lhs                              rhs             support     confidence
## [1] {frozen smoothie, spinach}    => {mineral water} 0.001066524 0.8888889
```

```
## [2] {bacon, pancakes}             => {spaghetti}     0.001733102 0.8125000
## [3] {nonfat milk, turkey}         => {mineral water} 0.001199840 0.8181818
## [4] {ground beef, nonfat milk}    => {mineral water} 0.001599787 0.8571429
## [5] {mushroom cream sauce, pasta} => {escalope}      0.002532996 0.9500000
##     coverage    lift      count
## [1] 0.001199840  3.729058  8
## [2] 0.002133049  4.666587 13
## [3] 0.001466471  3.432428  9
## [4] 0.001866418  3.595877 12
## [5] 0.002666311 11.976387 19
```

The interpretation of this will require the understanding of several words. - Support -> How popular an itemset is, as measured by the proportion of transactions in which an itemset appears. - Confidence -> How often one item A appears whenever another item B appears in a transaction. This is usually a conditional probability. - Lift -> A rule with a lift of > 1 it would imply that those two occurrences are dependent on one another and useful for predicting.

Thus in the 5th rule with a confidence level ~ 0.95 means that it is very likely that these three items are bought together by every customer.

```
# So lets sort the rules by the conficence levels to see the items are mostly bought together
rules<-sort(rules, by="confidence", decreasing=TRUE)
inspect(rules[1:5])
```

```
##     lhs                           rhs                 support confidence    coverage      lift count
## [1] {french fries,
##      mushroom cream sauce,
##      pasta}                    => {escalope}      0.001066524       1.00 0.001066524 12.606723     8
## [2] {ground beef,
##      light cream,
##      olive oil}                => {mineral water} 0.001199840       1.00 0.001199840  4.195190     9
## [3] {cake,
##      meatballs,
##      mineral water}            => {milk}          0.001066524       1.00 0.001066524  7.717078     8
## [4] {cake,
##      olive oil,
##      shrimp}                   => {mineral water} 0.001199840       1.00 0.001199840  4.195190     9
## [5] {mushroom cream sauce,
##      pasta}                    => {escalope}      0.002532996       0.95 0.002666311 11.976387    19
```

The following rules with a confidence level of 1 means that the items are almost always bought in that combination. Therefore, the marketing division would have to find a way to create promotions on these items. For instance, a promotion campaign would be like buy french fries and get 50 percent off on Mushroom cream sauce.

Part 4: Anomaly Detection

```
# Load tidyverse and anomalize
# ---
#
library(tidyverse)
```

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

## v tibble  3.1.7     v dplyr   1.0.9
## 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::arrange()      masks plyr::arrange()
## x dplyr::between()      masks data.table::between()
## x readr::col_factor()   masks scales::col_factor()
## x purrr::compact()      masks plyr::compact()
## x dplyr::count()        masks plyr::count()
## x purrr::discard()      masks scales::discard()
## x tidyr::expand()       masks Matrix::expand()
## x dplyr::failwith()     masks plyr::failwith()
## x dplyr::filter()       masks tibbletime::filter(), stats::filter()
## x dplyr::first()        masks data.table::first()
## x dplyr::id()           masks plyr::id()
## x dplyr::lag()          masks stats::lag()
## x dplyr::last()         masks data.table::last()
## x latticeExtra::layer() masks ggplot2::layer()
## x purrr::lift()         masks caret::lift()
## x purrr::map()          masks mclust::map()
## x dplyr::mutate()       masks plyr::mutate()
## x tidyr::pack()         masks Matrix::pack()
## x dplyr::recode()       masks arules::recode()
## x dplyr::rename()       masks plyr::rename()
## x dplyr::summarise()    masks plyr::summarise()
## x dplyr::summarize()    masks plyr::summarize()
## x purrr::transpose()    masks data.table::transpose()
## x tidyr::unpack()       masks Matrix::unpack()
```

```
library(anomalize)
```

```
## == Use anomalize to improve your Forecasts by 50%! ============================
## Business Science offers a 1-hour course - Lab #18: Time Series Anomaly Detection!
## </> Learn more at: https://university.business-science.io/p/learning-labs-pro </>
```

```
# load data and convert it to as_tbl_time
anom <- read.csv('http://bit.ly/CarreFourSalesDataset')
head(anom)
```

```
##        Date    Sales
## 1  1/5/2019 548.9715
## 2  3/8/2019  80.2200
## 3  3/3/2019 340.5255
## 4 1/27/2019 489.0480
## 5  2/8/2019 634.3785
## 6 3/25/2019 627.6165
```

First we have to format the Date column as date attribute.

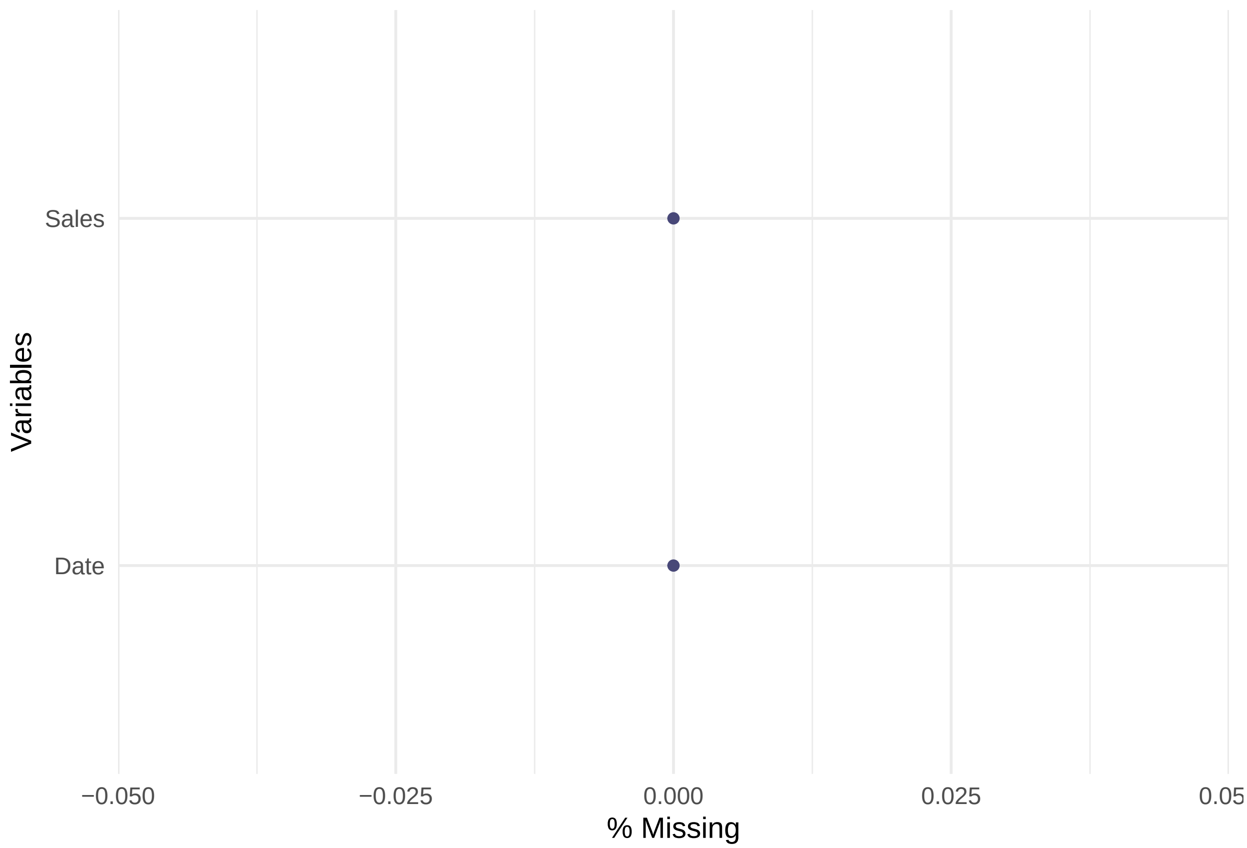
```r
# conversion to date
anom$Date <- as.Date(anom$Date , format = "%m/%d/%y")
dim(anom)
```

```
## [1] 1000    2
```

For the Carrefour sales data, there are 1000 rows and 2 columns

```r
library(naniar)
gg_miss_var(anom, show_pct = TRUE)
```

```
## Warning: It is deprecated to specify ‘guide = FALSE‘ to remove a guide. Please
## use ‘guide = "none"‘ instead.
```




```r
colSums(is.na(anom))
```

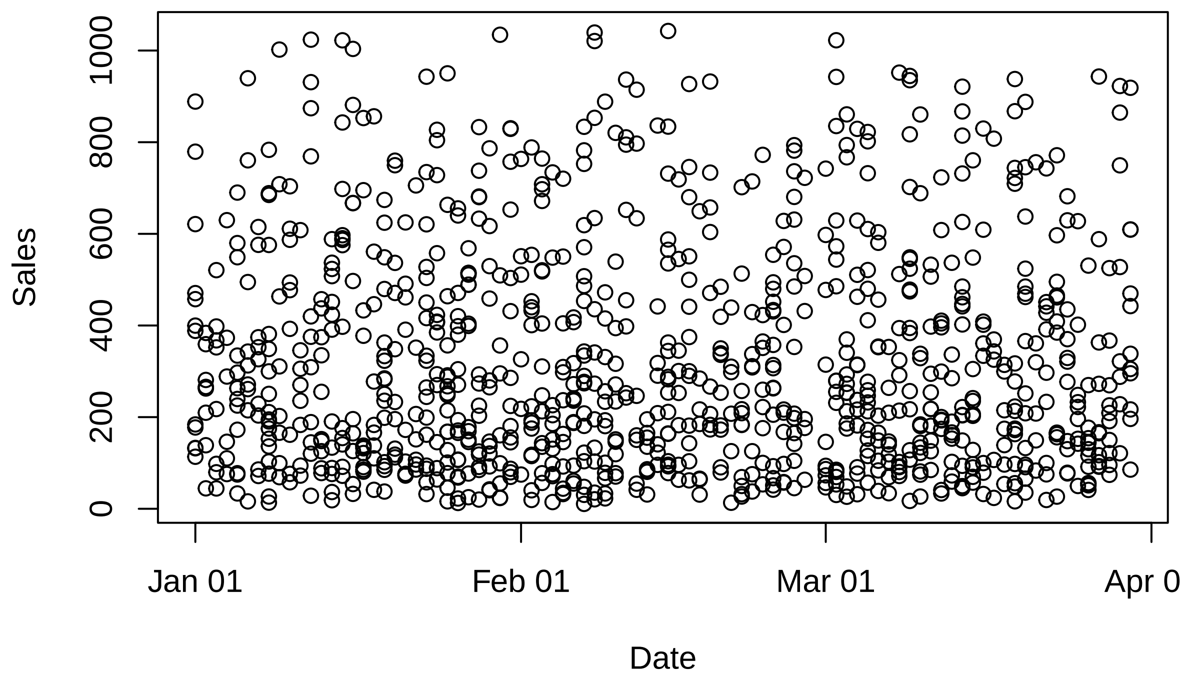
```
##  Date Sales
##     0     0
```

There are no missing values in the sales Data First lets convert the df to a different format.

```
anomX <- as_tbl_time(anom, Date)
class(anomX)
```

```
## [1] "tbl_time"   "tbl_df"     "tbl"        "data.frame"
```

```
plot (anomX)
```




```
#install.packages("devtools")
#devtools::install_github("twitter/AnomalyDetection")
library(AnomalyDetection)
```

```
sales_an <- AnomalyDetectionVec (x = anomX$Sales,period = 3 , direction= "both", plot = TRUE)
```

```
# Anomalize
#anomX %>%
#    time_decompose(dates) %>%
#    anomalize(remainder) %>%
#    time_recompose() %>%
#    plot_anomalies(time_recomposed = TRUE, ncol = 3, alpha_dots = 0.5)
```

Conclusions

The data provided was accurate and more than sufficient to perform all the analysis that was initially intended for the project. The marketing team will find insight and leads on various topics such as: - product distribution. - marketing strategies