Carrefour Kenya Data Analysis

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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 three parts where you'll explore a recent marketing dataset by performing various unsupervised learning techniques and later providing recommendations based on your insights.

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.

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.

Part 3: Association Rules

This section will require that you create association rules that will allow you to identify relationships between variables in the dataset. You are provided with a separate dataset that comprises groups of items that will be associated with others. Just like in the other sections, you will also be required to provide insights for your analysis.

Part 4: Anomaly Detection

You have also been requested to check whether there are any anomalies in the given sales dataset. The objective of this task being fraud detection.

Defining the question

Based on project data provided,inform the marketing department on the most relevant marketing strategies that will result in the highest no. of sales (total price including tax)

Experimental design

Business understanding Data understanding Analysis Conclusion Recommendation

Loading the libraries required for analysis

```
#install.packages("Rtsne")
#library(Rtsne)
library(lattice)
#install.packages("dplyr")
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
#install.packages("tidyverse")
library(tidyverse)
```

```
## -- Attaching packages ---------------------------------------------------------------------------

## v ggplot2 3.1.1     v readr   1.3.1
## v tibble  2.1.1     v purrr   0.3.3
## v tidyr   0.8.3     v stringr 1.4.0
## v ggplot2 3.1.1     v forcats 0.4.0

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

```
#install.packages("ggplot2")
library(ggplot2)
#install.packages("devtools",dependencies=TRUE)
library(devtools) #Load devtools before running ggbiplot otherwise will encounter install_github error
#install_github("vqv/ggbiplot", force = TRUE) #For plotting PCA
library(ggbiplot)
```

```
## Loading required package: plyr

## ------------------------------------------------------------------------------

## You have loaded plyr after dplyr - this is likely to cause problems.
## If you need functions from both plyr and dplyr, please load plyr first, then dplyr:
## library(plyr); library(dplyr)

## ------------------------------------------------------------------------------

##
## Attaching package: 'plyr'

## The following object is masked from 'package:purrr':
##
##     compact
```

```
## The following objects are masked from 'package:dplyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize

## Loading required package: scales

##
## Attaching package: 'scales'

## The following object is masked from 'package:purrr':
##
##     discard

## The following object is masked from 'package:readr':
##
##     col_factor

## Loading required package: grid
```

```r
# Create a working directory
path <- "C:/Users/comp5/Downloads/R_Program"
data <- file.path(path, "Supermarket_Dataset_1 - Sales Data.csv")

# Reading the dataset
Data1 <- read.csv(data)
head(Data1)
```

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

Exploring the dataset

Number of rows and Columns

```r
dim(Data1)
```

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

We have 1000 entries and 16 columns

Get the datatypes

```r
sapply(Data1, class)
```

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

Check for null values

```r
sum(is.na(Data1))
```

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

There no null values in the dataset

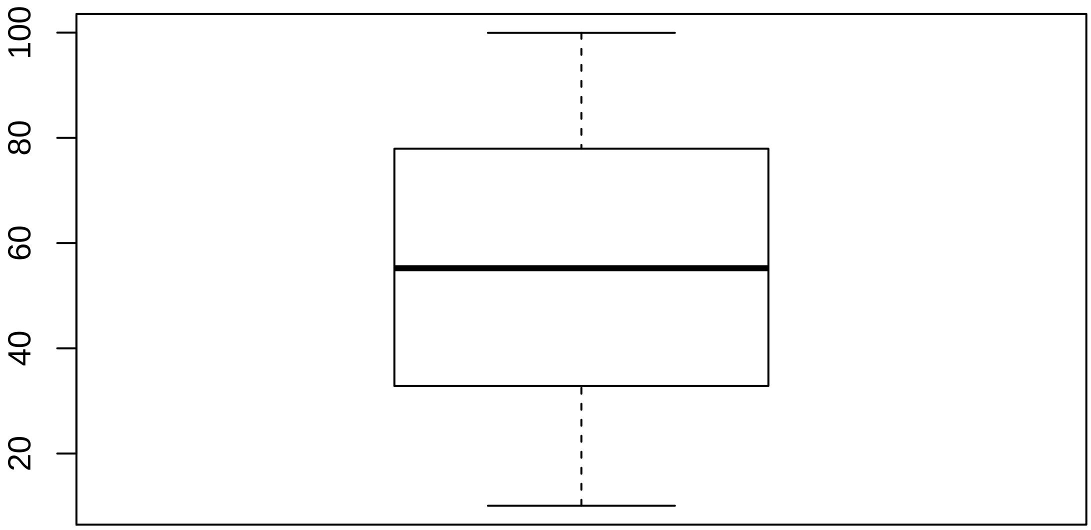
Check for duplicates

```r
anyDuplicated(Data1)
```

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

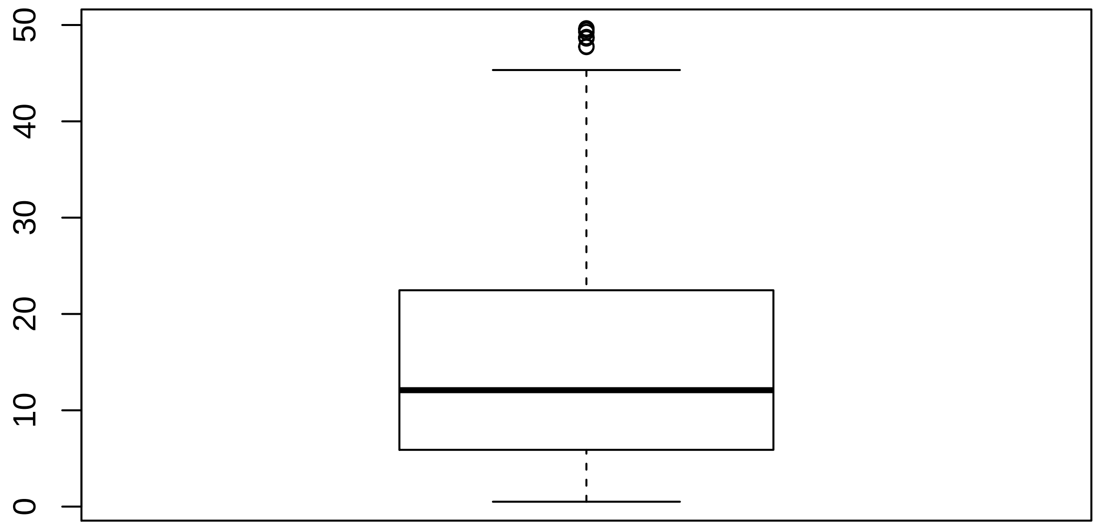
Check for outliers This is done on the numeric variables in the provided dataset.

```r
#Unit Price
boxplot(Data1$Unit.price)
```



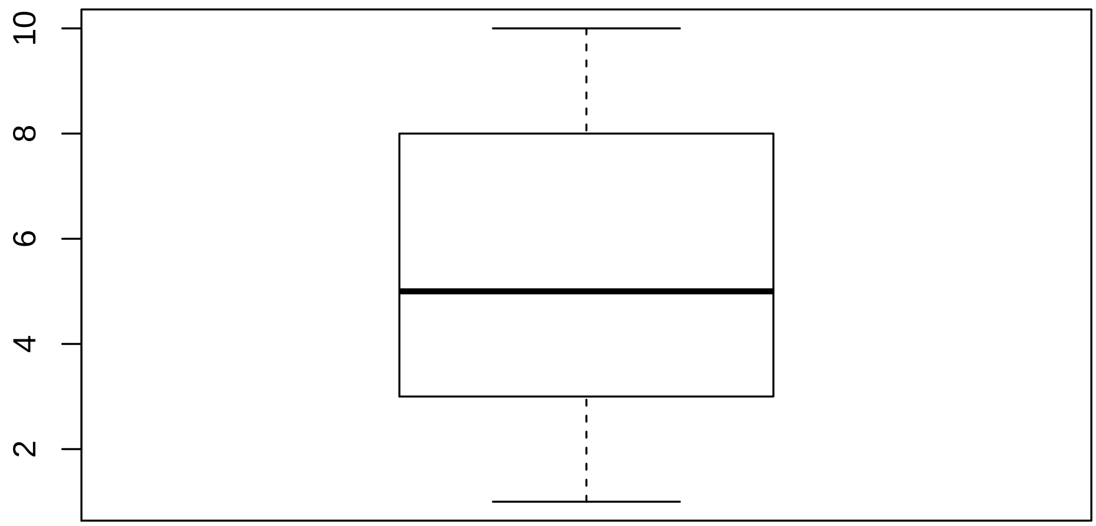
There are no outliers in the unit price dataset.

```r
#Tax Column
boxplot(Data1$Tax)
```



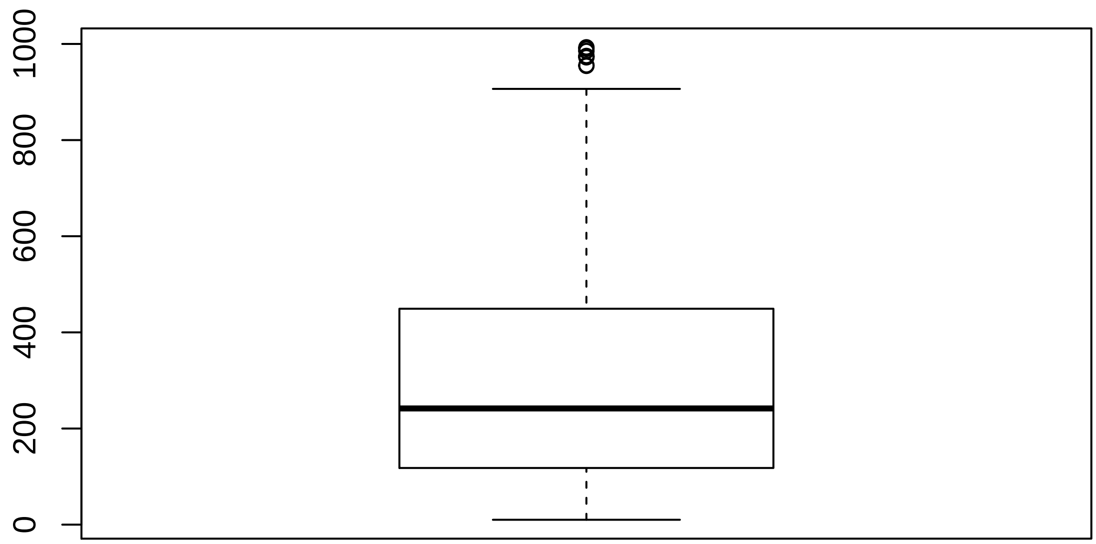
There are some outliers in the tax column which is allowed because different products have different tax rates based on the price of the product

```r
#Quantity Column
boxplot(Data1$Quantity)
```



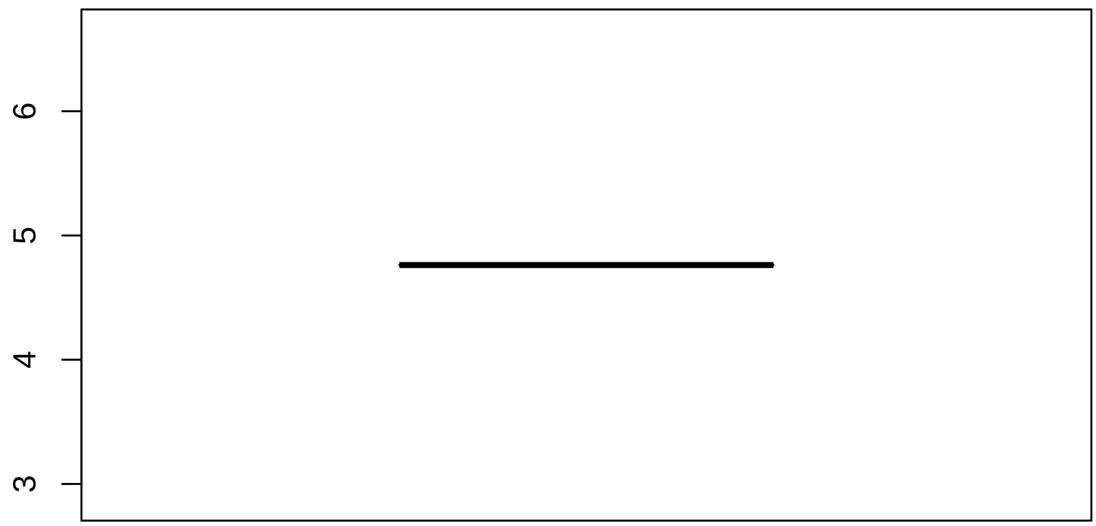
No outliers in the quantity column

```
#Cogs Column
boxplot(Data1$cogs)
```



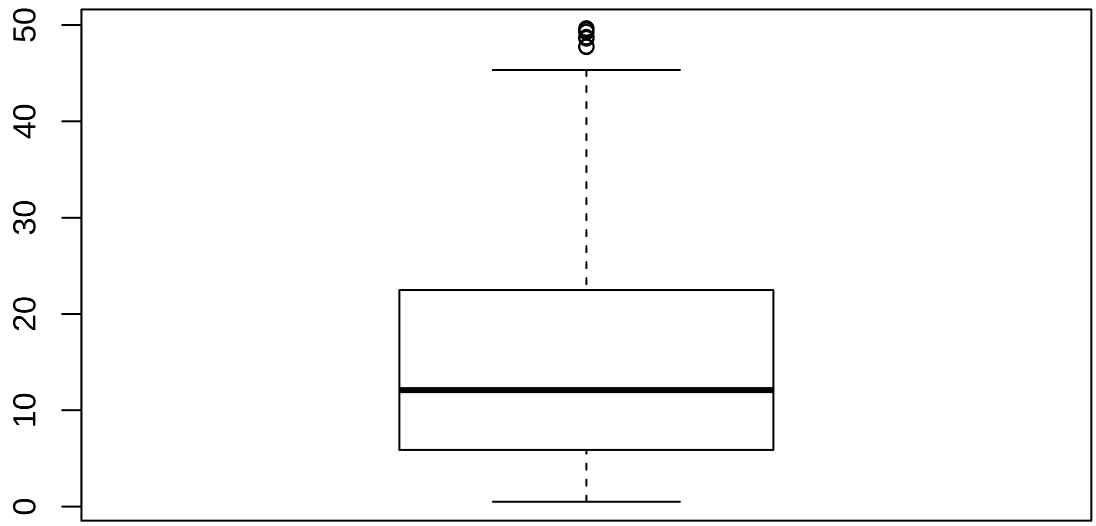
Cogs refers to the price of the item bought (Unit Price * Quantity) There are some outliers in the specified column which comes in due to the different price rates of the different items sold.

```
# gross.margin.percentage Column
boxplot(Data1$gross.margin.percentage)
```



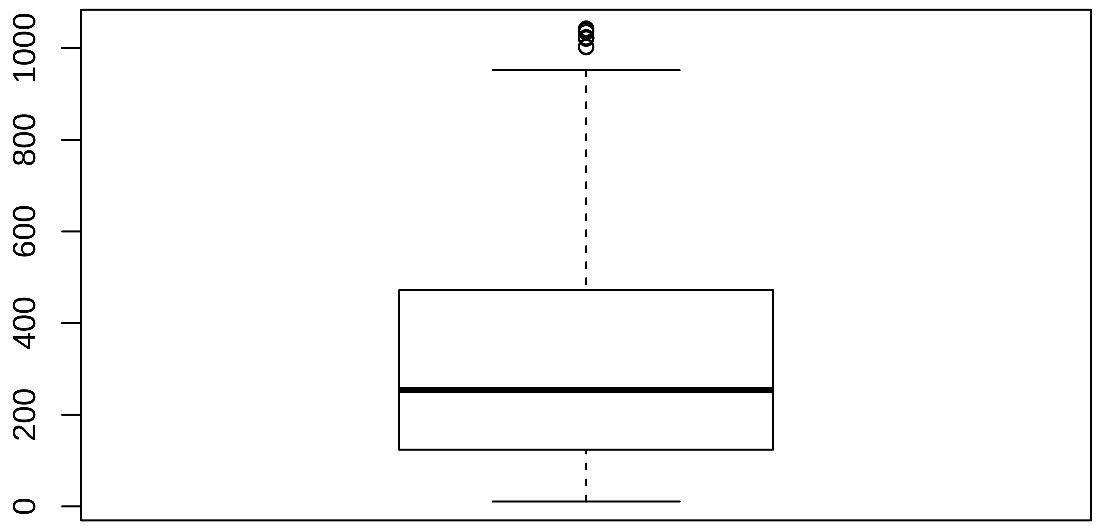
The above visulaization appeared like that due to the fact that the value provided was same all through the rest entries

```r
#Gross income Column
boxplot(Data1$gross.income)
```



We observe some outliers in the gross income column which is explained by the different unit prices for the various products

```
#Total Column
boxplot(Data1$Total)
```

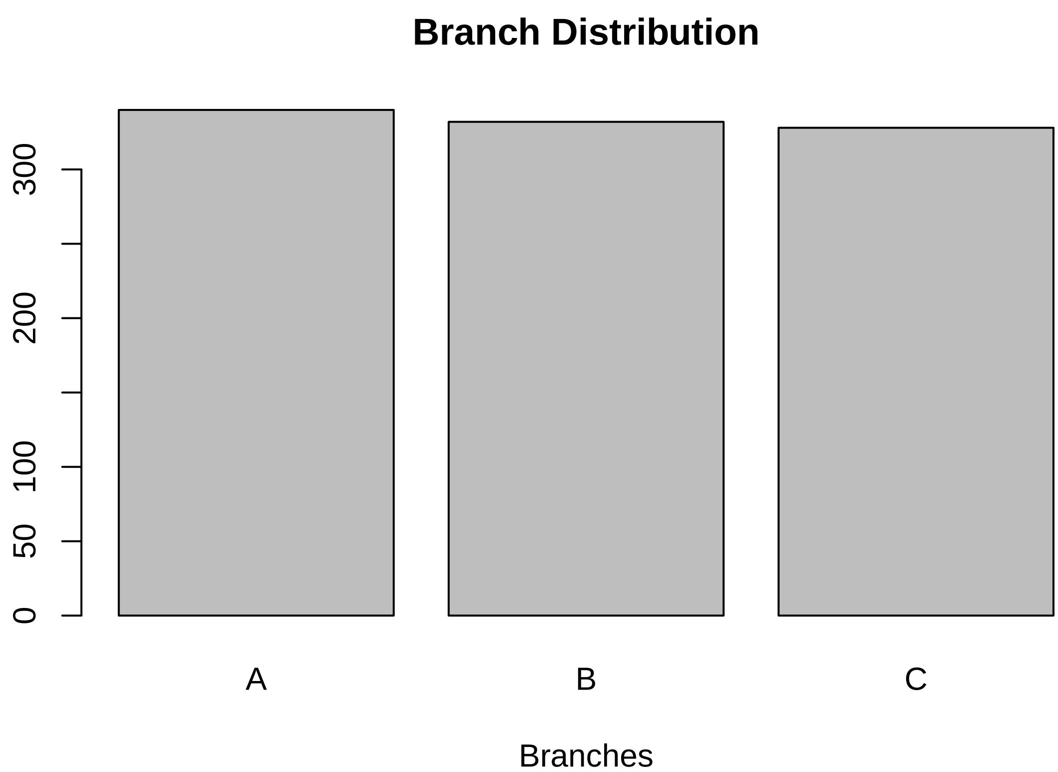


Get unique entries in the non-numeric columns

```r
# Branch column
unique(Data1$Branch)
```

```
## [1] A C B
## Levels: A B C
```

```r
Branch <- Data1$Branch
Branch_freq <- table(Branch)
barplot(Branch_freq, main = "Branch Distribution", xlab = "Branches")
```

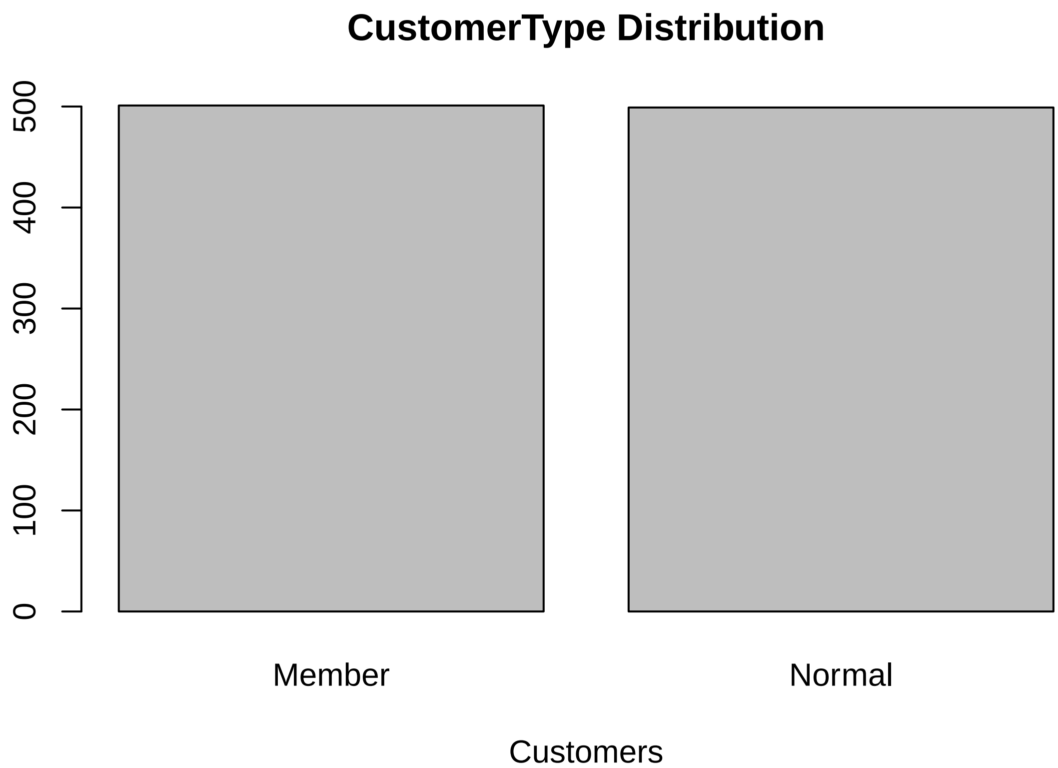


Branch B and C have almost the same count with a slight difference in branch A

```
# CustomerType column
unique(Data1$Customer.type)
```

```
## [1] Member Normal
## Levels: Member Normal
```

```
customer <- Data1$Customer.type
customer_freq <- table(customer)
barplot(customer_freq, main = "CustomerType Distribution", xlab = "Customers")
```

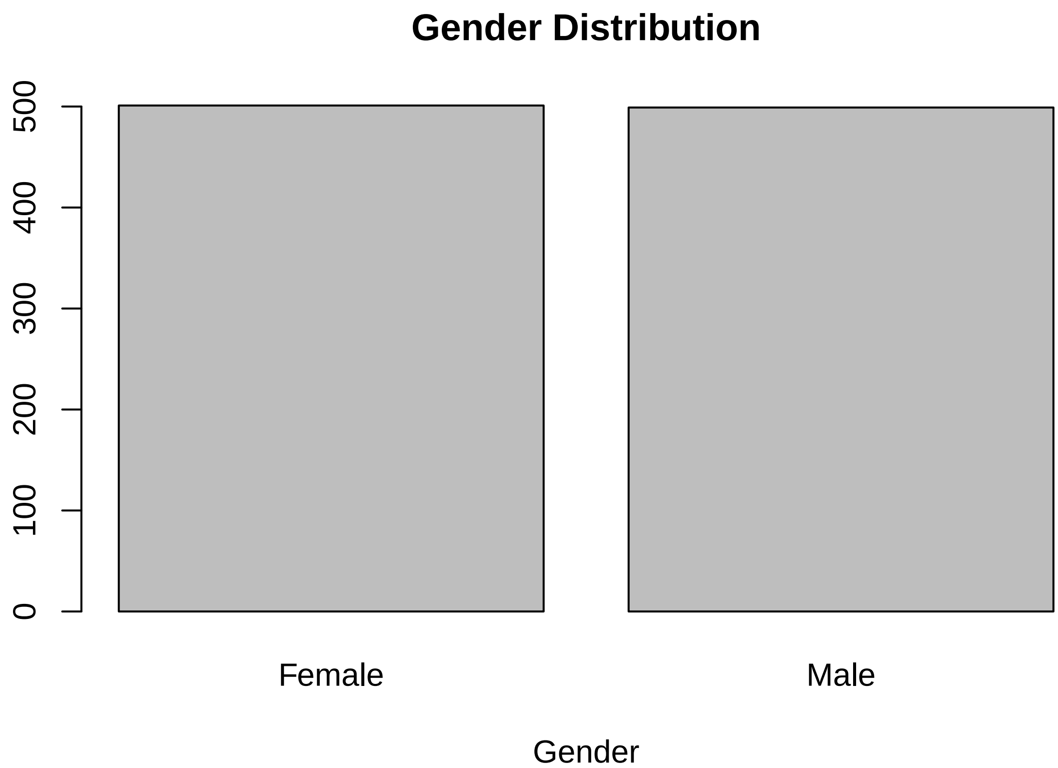


Walk-ins of both Member and Normal customers was same.

```
# Gender column
unique(Data1$Gender)
```

```
## [1] Female Male
## Levels: Female Male
```

```
Gender <- Data1$Gender
Gender_freq <- table(Gender)
barplot(Gender_freq, main = "Gender Distribution", xlab = "Gender")
```




```
# Branch column
unique(Data1$Product.line)
```

```
## [1] Health and beauty      Electronic accessories Home and lifestyle
## [4] Sports and travel      Food and beverages     Fashion accessories
## 6 Levels: Electronic accessories ... Sports and travel
```

```
product <- Data1$Product.line
product_freq <- table(product)
product_freq
```

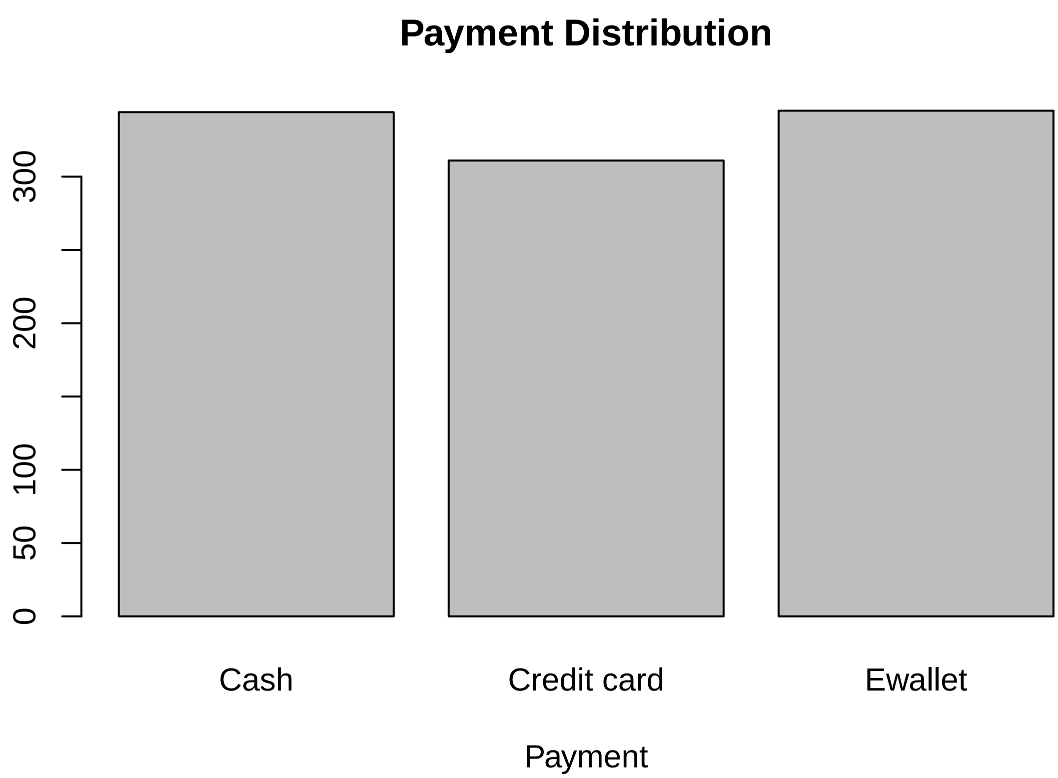
```
## product
## Electronic accessories    Fashion accessories     Food and beverages
##                    170                    178                    174
##      Health and beauty     Home and lifestyle      Sports and travel
##                    152                    160                    166
```

Most customers where more on Fashion accessories followed by Food and beverages, Electronics, Sports and travel, Home and lifestyle , and Health and beauty respectively.

```
# Branch column
unique(Data1$Payment)
```

```
## [1] Ewallet     Cash        Credit card
## Levels: Cash Credit card Ewallet
```

```r
payment <- Data1$Payment
payment_freq <- table(payment)
barplot(payment_freq, main = "Payment Distribution", xlab = "Payment")
```



Cash and Ewallet hold the same count of about 350 with credit card having a count of 300

#Encode the categorical columns to integers We prefer interger over numeric because interger can't take decimals which is what we need for the specific columns.

```r
# Branch column
Data1$Branch<-as.integer(Data1$Branch)
# Customer Type column
Data1$Customer.type<-as.integer(Data1$Customer.type)
# Gender column
Data1$Gender<-as.integer(Data1$Gender)
# Product.line column
Data1$Product.line<-as.integer(Data1$Product.line)
#Payment column
Data1$Payment<-as.integer(Data1$Payment)
```

```r
#install.packages("lubridate") #Date split package
library(lubridate)
```

```
##
## Attaching package: 'lubridate'
```

```
## The following object is masked from 'package:plyr':
##
##     here

## The following object is masked from 'package:base':
##
##     date
```

```
# Convert to date datatype first then split thereafter
Data1$Date <- as.Date(Data1$Date, "%m/%d/%Y")
Data1$year <- year(ymd(Data1$Date))
Data1$month <- month(ymd(Data1$Date))
Data1$day <- day(ymd(Data1$Date))
```

Dimensionality reduction

Apply PCA Algorithm

Principal component analysis (PCA) is a technique used to emphasize variation and bring out strong patterns in a dataset. It's often used to make data easy to explore and visualize.

```
#Extract numerical and integer columns only
Data1_df <- select_if(Data1,is.numeric)
str(Data1_df)
```

```
## 'data.frame':    1000 obs. of  16 variables:
##  $ Branch                 : int  1 3 1 1 1 3 1 3 1 2 ...
##  $ Customer.type          : int  1 2 2 1 2 2 1 2 1 1 ...
##  $ Gender                 : int  1 1 2 2 2 2 1 1 1 1 ...
##  $ Product.line           : int  4 1 5 4 6 1 1 5 4 3 ...
##  $ 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 ...
##  $ Payment                : int  3 1 2 3 3 3 3 3 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 ...
##  $ year                   : num  2019 2019 2019 2019 2019 ...
##  $ month                  : num  1 3 3 1 2 3 2 2 1 2 ...
##  $ day                    : int  5 8 3 27 8 25 25 24 10 20 ...
```

```
# Remove the constant/zero column to avaoid an error which comes about by including them
names(Data1_df[, sapply(Data1_df, function(v) var(v, na.rm=TRUE)==0)])
```

```
## [1] "gross.margin.percentage" "year"
```

```
# Drop the columns as they result to error "stop("cannot rescale a constant/zero column to unit varianc
Data1_df <- subset(Data1_df, select = -c(gross.margin.percentage, year))
```

```r
#The prcomp() function also provides the facility to compute standard deviation of each principal compo
# We then pass df to the prcomp(). We also set two arguments, center and scale,
# to be TRUE then preview our object with summary
# ---
#
Data1_pca <- prcomp(Data1_df, center = TRUE, scale. = TRUE)
summary(Data1_pca)
```

```
## Importance of components:
##                           PC1     PC2     PC3     PC4     PC5     PC6
## Standard deviation     2.2203 1.08227 1.06969 1.02580 1.00895 0.99359
## Proportion of Variance 0.3521 0.08367 0.08173 0.07516 0.07271 0.07052
## Cumulative Proportion  0.3521 0.43578 0.51751 0.59267 0.66538 0.73590
##                            PC7     PC8     PC9   PC10    PC11      PC12
## Standard deviation     0.97647 0.96596 0.94903 0.9057 0.29961 1.824e-16
## Proportion of Variance 0.06811 0.06665 0.06433 0.0586 0.00641 0.000e+00
## Cumulative Proportion  0.80401 0.87066 0.93499 0.9936 1.00000 1.000e+00
##                             PC13      PC14
## Standard deviation     1.518e-16 4.039e-18
## Proportion of Variance 0.000e+00 0.000e+00
## Cumulative Proportion  1.000e+00 1.000e+00
```

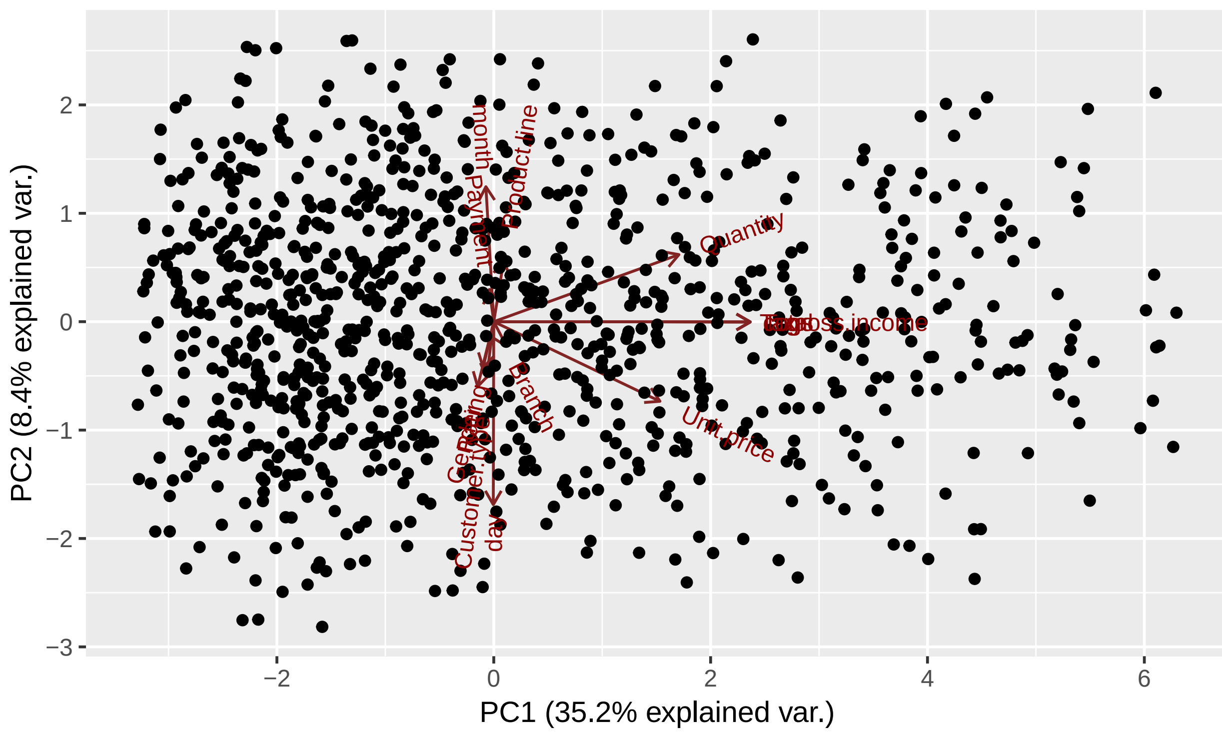
A principal component is a normalized linear combination of the original predictors in a data set. We have a total of 14 components since we removed 2 columns from the dataset PC1 captures the maximum variance in the data set which we observe in the dataset(35%) As we move across the PCA results above, the variability decreases as you move to the last component.

```r
# Calling str() to have a look at your PCA object
#
str(Data1_pca)
```

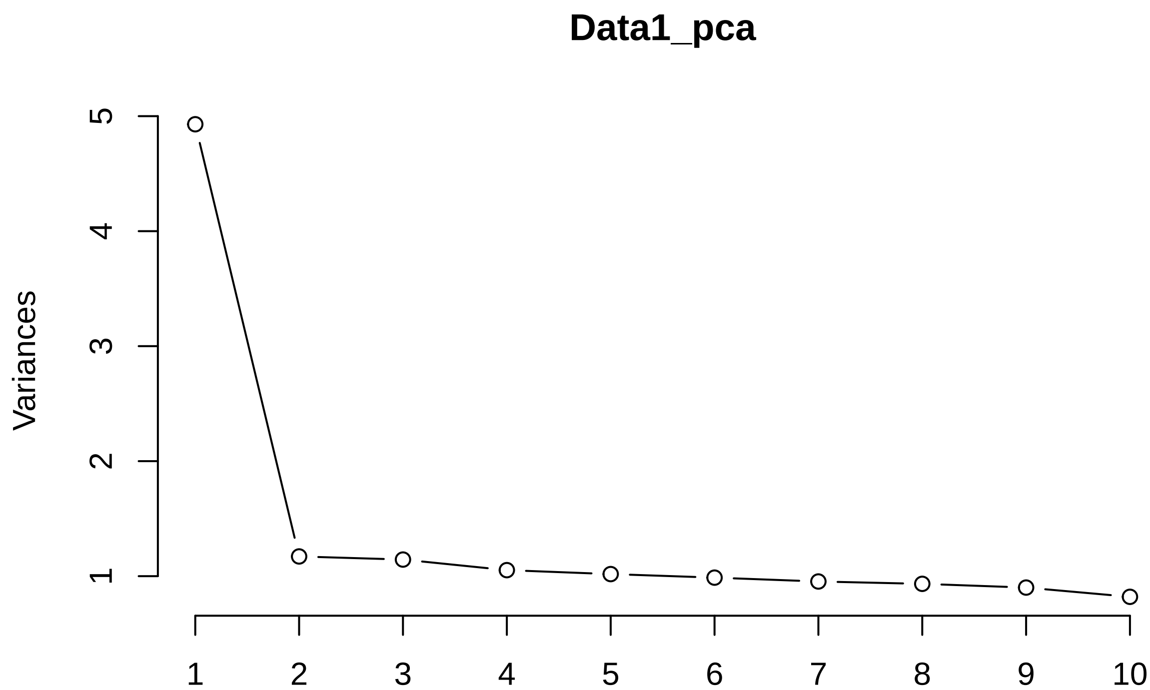
```
## List of 5
##  $ sdev    : num [1:14] 2.22 1.08 1.07 1.03 1.01 ...
##  $ rotation: num [1:14, 1:14] 0.0226 -0.0126 -0.0283 0.0175 0.2912 ...
##   ..- attr(*, "dimnames")=List of 2
##   .. ..$ : chr [1:14] "Branch" "Customer.type" "Gender" "Product.line" ...
##   .. ..$ : chr [1:14] "PC1" "PC2" "PC3" "PC4" ...
##  $ center  : Named num [1:14] 1.99 1.5 1.5 3.45 55.67 ...
##   ..- attr(*, "names")= chr [1:14] "Branch" "Customer.type" "Gender" "Product.line" ...
##  $ scale   : Named num [1:14] 0.818 0.5 0.5 1.715 26.495 ...
##   ..- attr(*, "names")= chr [1:14] "Branch" "Customer.type" "Gender" "Product.line" ...
##  $ x       : num [1:1000, 1:14] 2.03 -2.291 0.118 1.471 2.745 ...
##   ..- attr(*, "dimnames")=List of 2
##   .. ..$ : chr [1:1000] "1" "2" "3" "4" ...
##   .. ..$ : chr [1:14] "PC1" "PC2" "PC3" "PC4" ...
##  - attr(*, "class")= chr "prcomp"
```

From the analysis above we see the center point ($center$), $scaling$(scale), standard deviation(sdev) of each principal component. We also see the relationship (correlation or anticorrelation, etc) between the initial variables and the principal components ($rotation).

```r
ggbiplot(Data1_pca, labels=rownames(Data1_pca),ellipse = TRUE,obs.scale=1,var.scale=1)
```




```r
plot(Data1_pca, type="l")
```



The plot above shows that 10 components contribute most in the variance observed in the dataset provided with PC1 contributing the most.

Feature Selection

Feature selection is the process of selecting a subset of relevant features (variables, predictors) for use in model construction. This becomes even more important when the number of features are very large. We can use the findCorrelation function included in the caret package to create a subset of variabes. This function would allows us to remove redundancy by correlation using the given dataset. It would search through a correlation matrix and return a vector of integers corresponding to the columns, to remove or reduce pair-wise correlations

```
suppressWarnings(
        suppressMessages(if
                         (!require(caret, quietly=TRUE))
                install.packages("caret")))
library(caret)

suppressWarnings(
        suppressMessages(if
                         (!require(corrplot, quietly=TRUE))
                install.packages("corrplot")))
library(corrplot)

# Calculating the correlation matrix
```

```r
#
correlationMatrix <- cor(Data1_df)
#
# Find attributes that are highly correlated
#
highlyCorrelated <- findCorrelation(correlationMatrix, cutoff=0.75)
#
# Highly correlated attributes
#
highlyCorrelated
```

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

```r
names(Data1_df[,highlyCorrelated])
```

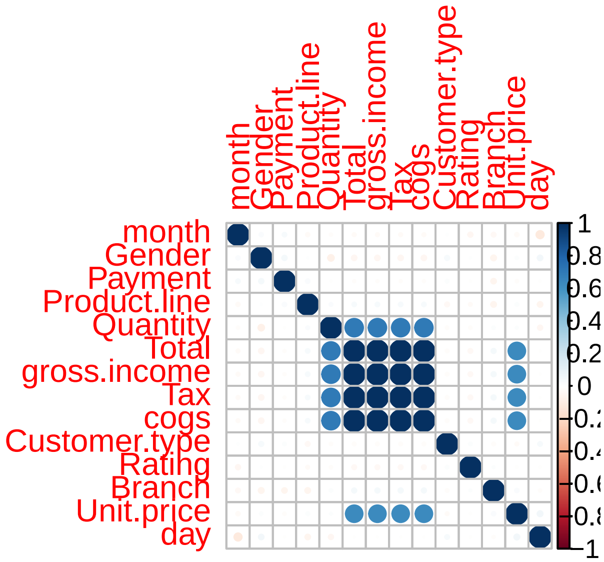
```
## [1] "Tax"          "cogs"         "gross.income"
```

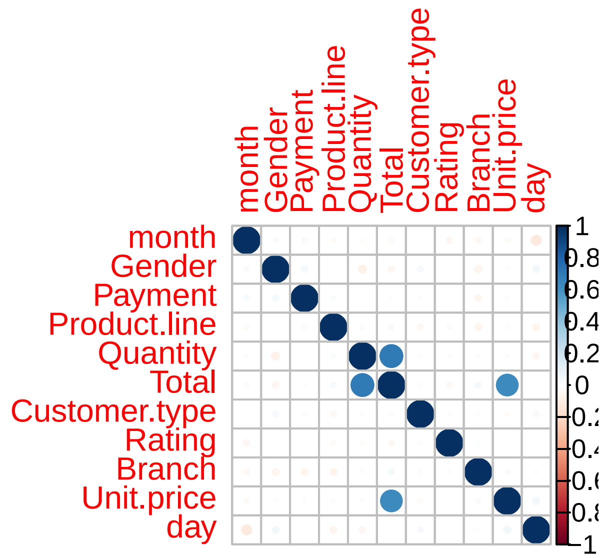
These are the highly correlated features in the dataset

```r
# We can remove the variables with a higher correlation to remove redudancy.
Data2_df <- Data1_df[-highlyCorrelated]
colnames(Data2_df)
```

```
##  [1] "Branch"        "Customer.type" "Gender"        "Product.line"
##  [5] "Unit.price"    "Quantity"      "Payment"       "Rating"
##  [9] "Total"         "month"         "day"
```

```r
# Performing our graphical comparison
#
par(mfrow = c(1, 2))
corrplot(correlationMatrix, order = "hclust")
corrplot(cor(Data2_df), order = "hclust")
```





Association rules

Association rules are algorithms used to find relationships between items using point-of-sale systems. These rules are used to predict the likelihood of different products being purchased together.

```
suppressWarnings(
        suppressMessages(if
                         (!require(arules, quietly=TRUE))
                install.packages("arules")))
library(arules)

library(arulesViz)
```

```
# Loading the dataset
#
# We will use read.transactions fuction which will load data from comma-separated files and convert the

Rules_df <- read.transactions("Supermarket_Sales_Dataset II.csv",sep=",")
Rules_df
```

```
path <- "C:/Users/comp5/Downloads/R_Program"
data <- file.path(path, "Supermarket_Sales_Dataset II.csv")
Rules_df <- read.csv(data)
head(Rules_df )
```

```
##              shrimp      almonds    avocado   vegetables.mix green.grapes
## 1           burgers    meatballls       eggs
## 2           chutney
## 3            turkey      avocado
## 4     mineral water         milk energy bar whole wheat rice    green tea
## 5    low fat yogurt
## 6 whole wheat pasta french fries
##   whole.weat.flour yams cottage.cheese energy.drink tomato.juice
## 1
## 2
## 3
## 4
## 5
## 6
##   low.fat.yogurt green.tea honey salad mineral.water salmon
## 1
## 2
## 3
## 4
## 5
## 6
##   antioxydant.juice frozen.smoothie spinach olive.oil
## 1                                                  NA
## 2                                                  NA
## 3                                                  NA
## 4                                                  NA
## 5                                                  NA
## 6                                                  NA
```

```r
#Check for number of rows and columns
dim(Rules_df)
```

```
## [1] 7500   20
```

The data has 7500 entries and 20 columns

```r
# Look at the data structure of the dataset
str(Rules_df)
```

```
## 'data.frame':    7500 obs. of  20 variables:
##  $ shrimp          : Factor w/ 115 levels "almonds","antioxydant juice",..: 15 27 108 72 65 112 98 4
##  $ almonds         : Factor w/ 118 levels "","almonds","antioxydant juice",..: 69 1 5 71 1 43 63 99
##  $ avocado         : Factor w/ 116 levels "","almonds","antioxydant juice",..: 36 1 1 37 1 1 93 53 1
##  $ vegetables.mix  : Factor w/ 115 levels "","almonds","antioxydant juice",..: 1 1 1 112 1 1 1 1 1 1
##  $ green.grapes    : Factor w/ 111 levels "","almonds","antioxydant juice",..: 1 1 1 51 1 1 1 1 1 1
##  $ whole.weat.flour : Factor w/ 107 levels "","almonds","antioxydant juice",..: 1 1 1 1 1 1 1 1 1 1
##  $ yams            : Factor w/ 103 levels "","almonds","antioxydant juice",..: 1 1 1 1 1 1 1 1 1 1
##  $ cottage.cheese   : Factor w/ 99 levels ""," asparagus",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ energy.drink     : Factor w/ 89 levels "","almonds","antioxydant juice",..: 1 1 1 1 1 1 1 1 1 1 .
##  $ tomato.juice     : Factor w/ 81 levels "","asparagus",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ low.fat.yogurt   : Factor w/ 67 levels "","asparagus",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ green.tea        : Factor w/ 51 levels "","blueberries",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ honey            : Factor w/ 43 levels "","asparagus",..: 1 1 1 1 1 1 1 1 1 1 ...
```

```
##  $ salad            : Factor w/ 29 levels "","babies food",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ mineral.water    : Factor w/ 19 levels "","candy bars",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ salmon           : Factor w/ 8 levels "","antioxydant juice",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ antioxydant.juice: Factor w/ 3 levels "","french fries",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ frozen.smoothie  : Factor w/ 3 levels "","protein bar",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ spinach          : Factor w/ 3 levels "","cereals","mayonnaise": 1 1 1 1 1 1 1 1 1 1 ...
##  $ olive.oil        : logi  NA NA NA NA NA NA ...
```

All of the 19 items are in factor datatype with Olive.oil appearing in logic form

```
# Check for null values per column in the dataset
colSums(is.na(Rules_df))
```

```
##            shrimp           almonds           avocado     vegetables.mix
##                 0                 0                 0                  0
##      green.grapes  whole.weat.flour              yams     cottage.cheese
##                 0                 0                 0                  0
##      energy.drink      tomato.juice     low.fat.yogurt          green.tea
##                 0                 0                 0                  0
##             honey             salad     mineral.water             salmon
##                 0                 0                 0                  0
## antioxydant.juice   frozen.smoothie           spinach          olive.oil
##                 0                 0                 0               7500
```

Olive.oil is the only item with no entries whic means that the item was not purchased. Since all the data for the specific column is missing, we delete it.

```
# Drop olive oil column from the dataframe
#
Rules_df$olive.oil <- NULL
colnames(Rules_df)
```

```
##  [1] "shrimp"            "almonds"           "avocado"
##  [4] "vegetables.mix"    "green.grapes"      "whole.weat.flour"
##  [7] "yams"              "cottage.cheese"    "energy.drink"
## [10] "tomato.juice"      "low.fat.yogurt"    "green.tea"
## [13] "honey"             "salad"             "mineral.water"
## [16] "salmon"            "antioxydant.juice" "frozen.smoothie"
## [19] "spinach"
```

We have a total of 19 column to work with.

```
# Do a summary to see how different items were purchased
summary(Rules_df)
```

```
##                  shrimp                almonds                avocado
##   mineral water    : 577                   :1754                  :3112
##   burgers          : 576   mineral water: 484   mineral water: 375
##   turkey           : 458   spaghetti    : 411   spaghetti    : 279
##   chocolate        : 391   eggs         : 302   eggs         : 225
##   frozen vegetables: 373   ground beef  : 291   milk         : 213
##   spaghetti        : 354   french fries : 243   french fries : 180
```

```
##  (Other)          :4771   (Other)      :4015   (Other)      :3116
##        vegetables.mix       green.grapes      whole.weat.flour
##              :4156               :4972               :5637
##  mineral water: 201   green tea   : 153   french fries: 107
##  eggs         : 181   eggs        : 134   eggs        : 102
##  french fries : 174   french fries: 130   green tea   : 100
##  spaghetti    : 167   chocolate   : 115   chocolate   :  71
##  milk         : 149   milk        : 114   pancakes    :  69
##  (Other)      :2472   (Other)     :1882   (Other)     :1414
##              yams            cottage.cheese          energy.drink
##               :6132                 :6520                 :6847
##  green tea     :  96   green tea     :  67   green tea     :  57
##  french fries  :  81   pancakes      :  44   low fat yogurt :  38
##  pancakes      :  69   low fat yogurt:  43   frozen smoothie:  35
##  eggs          :  59   french fries  :  40   french fries  :  34
##  low fat yogurt:  55   chocolate     :  38   fresh bread   :  28
##  (Other)       :1008   (Other)       : 748   (Other)       : 461
##          tomato.juice         low.fat.yogurt           green.tea
##               :7106                 :7245                 :7347
##  green tea     :  31   low fat yogurt:  21   green tea     :  14
##  french fries  :  19   green tea     :  20   french fries  :  10
##  low fat yogurt:  17   fresh bread   :  14   frozen smoothie:  10
##  tomato juice  :  16   french fries  :  12   low fat yogurt :   9
##  pancakes      :  14   light mayo    :   9   fresh bread   :   7
##  (Other)       : 297   (Other)       : 179   (Other)       : 103
##             honey                 salad            mineral.water
##               :7414                  :7454                :7476
##  green tea     :   8   green tea      :   4   magazines     :   3
##  fresh bread   :   6   french fries   :   3   fresh bread   :   2
##  low fat yogurt:   6   frozen smoothie:   3   green tea     :   2
##  escalope      :   4   cottage cheese :   2   low fat yogurt:   2
##  french fries  :   4   eggplant       :   2   pancakes      :   2
##  (Other)       :  58   (Other)        :  32   (Other)       :  13
##                salmon           antioxydant.juice    frozen.smoothie
##                  :7493                  :7497                 :7497
##  antioxydant juice:   1   french fries    :   1    protein bar:   2
##  cake             :   1   frozen smoothie:   2    spinach    :   1
##  chocolate        :   1
##  frozen smoothie  :   1
##  magazines        :   1
##  (Other)          :   2
##        spinach
##            :7498
##  cereals   :   1
##  mayonnaise:   1
##
##
##
##
```

```r
# Plot a frequency plot to see what items topped the list with more purchases
Plot_data <- as(Rules_df, "transactions")
# plot item frequency
itemFrequencyPlot(Plot_data,topN=20,type="absolute", col="darkgreen")
```

We observe sales of over 7000 for a couple of items such as Spinach,antioxydant juice, frozen smoothie, salmon, mineral water, salad,honey and green tea respectively. Shrimp mineral water and shrimp burgers were at the bottom of the list regarding the sales.

```r
# Build a model based on association rules using the apriori function
# We use Min Support as 0.001 and confidence as 0.8
#
rules <- apriori(Rules_df, parameter = list(supp = 0.5, conf = 0.8, target = "rules",minlen=2))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.8    0.1    1 none FALSE            TRUE       5     0.5      2
##  maxlen target   ext
##      10  rules FALSE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 3750
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[1280 item(s), 7500 transaction(s)] done [0.04s].
## sorting and recoding items ... [16 item(s)] done [0.00s].
## creating transaction tree ... done [0.02s].
## checking subsets of size 1 2 3 4 5 6 7 8 9 10
```

```
## Warning in apriori(Rules_df, parameter = list(supp = 0.5, conf = 0.8,
## target = "rules", : Mining stopped (maxlen reached). Only patterns up to a
## length of 10 returned!
```

```
##  done [0.04s].
## writing ... [425218 rule(s)] done [0.14s].
## creating S4 object  ... done [0.30s].
```

```r
# Get a summary of the rules
summary(rules)
```

```
## set of 425218 rules
##
## rule length distribution (lhs + rhs):sizes
##     2     3     4     5     6     7     8     9    10
##   204  1478  6576 20134 45002 75943 98616 99417 77848
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   2.000   7.000   8.000   7.986   9.000  10.000
##
## summary of quality measures:
##     support          confidence          lift           count
##  Min.   :0.5541   Min.   :0.8108   Min.   :1.000   Min.   :4156
```

```
##  1st Qu.:0.5541   1st Qu.:1.0000   1st Qu.:1.001   1st Qu.:4156
##  Median :0.6629   Median :1.0000   Median :1.021   Median :4972
##  Mean   :0.6455   Mean   :0.9882   Mean   :1.095   Mean   :4841
##  3rd Qu.:0.7516   3rd Qu.:1.0000   3rd Qu.:1.150   3rd Qu.:5637
##  Max.   :0.9996   Max.   :1.0000   Max.   :1.508   Max.   :7497
##
## mining info:
##      data ntransactions support confidence
##  Rules_df          7500     0.5        0.8
```

```
# Observing rules built in our model i.e. first 10 model rules
#
inspect(rules[1:10])
```

```
##      lhs                     rhs                  support   confidence
## [1]  {vegetables.mix=} => {green.grapes=}     0.5541333 1.0000000
## [2]  {green.grapes=}   => {vegetables.mix=}   0.5541333 0.8358809
## [3]  {vegetables.mix=} => {whole.weat.flour=} 0.5541333 1.0000000
## [4]  {vegetables.mix=} => {yams=}             0.5541333 1.0000000
## [5]  {vegetables.mix=} => {cottage.cheese=}   0.5541333 1.0000000
## [6]  {vegetables.mix=} => {energy.drink=}     0.5541333 1.0000000
## [7]  {vegetables.mix=} => {tomato.juice=}     0.5541333 1.0000000
## [8]  {vegetables.mix=} => {low.fat.yogurt=}   0.5541333 1.0000000
## [9]  {vegetables.mix=} => {green.tea=}        0.5541333 1.0000000
## [10] {vegetables.mix=} => {honey=}            0.5541333 1.0000000
##      lift     count
## [1]  1.508447 4156
## [2]  1.508447 4156
## [3]  1.330495 4156
## [4]  1.223092 4156
## [5]  1.150307 4156
## [6]  1.095370 4156
## [7]  1.055446 4156
## [8]  1.035197 4156
## [9]  1.020825 4156
## [10] 1.011600 4156
```

Interpretation of the above results

If a customer gets green.grapes, the possibility of picking vegetable mix is 84% A customer who picks green.grapes, energy drink is 83% more likely to pick vegetable mix

```
# We can order the rules by either confidence or support then view top 10 rules again
rules<-sort(rules, by="confidence", decreasing=TRUE)
inspect(rules[1:10])
```

```
##      lhs                     rhs                  support   confidence
## [1]  {vegetables.mix=} => {green.grapes=}     0.5541333 1
## [2]  {vegetables.mix=} => {whole.weat.flour=} 0.5541333 1
## [3]  {vegetables.mix=} => {yams=}             0.5541333 1
## [4]  {vegetables.mix=} => {cottage.cheese=}   0.5541333 1
## [5]  {vegetables.mix=} => {energy.drink=}     0.5541333 1
## [6]  {vegetables.mix=} => {tomato.juice=}     0.5541333 1
```

```
## [7]  {vegetables.mix=} => {low.fat.yogurt=}   0.5541333 1
## [8]  {vegetables.mix=} => {green.tea=}        0.5541333 1
## [9]  {vegetables.mix=} => {honey=}            0.5541333 1
## [10] {vegetables.mix=} => {salad=}            0.5541333 1
##      lift     count
## [1]  1.508447 4156
## [2]  1.330495 4156
## [3]  1.223092 4156
## [4]  1.150307 4156
## [5]  1.095370 4156
## [6]  1.055446 4156
## [7]  1.035197 4156
## [8]  1.020825 4156
## [9]  1.011600 4156
## [10] 1.006171 4156
```

There's is 100% confidence that if a customer get vegetable.mix, he is likely to get green.grapes

Anomaly Detection

An anomaly is a deviation from the norm, strange condition, situation or quality, an incongruity or inconsistency

```
#Loading packages
#
install.packages("anomalize")
```

```
## Installing package into 'C:/Users/comp5/Documents/R/win-library/3.5'
## (as 'lib' is unspecified)
```

```
## package 'anomalize' successfully unpacked and MD5 sums checked
##
## The downloaded binary packages are in
##  C:\Users\comp5\AppData\Local\Temp\Rtmpwr5LyZ\downloaded_packages
```

```
library(anomalize)

library(factoextra)
```

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

```
suppressWarnings(
        suppressMessages(if
                        (!require(tibble, quietly=TRUE))
                install.packages("tibble")))
library(tibble)


suppressWarnings(
        suppressMessages(if
                        (!require(dplyr, quietly=TRUE))
```

```r
                install.packages("dplyr")))
library(dplyr)

suppressWarnings(
        suppressMessages(if
                         (!require(tibbletime, quietly=TRUE))
                install.packages("tibbletime")))

library(tibbletime)

suppressWarnings(
        suppressMessages(if
                         (!require(tidyverse, quietly=TRUE))
                install.packages("tidyverse")))
library(tidyverse)
```

```r
#loading the dataset
path <- "C:/Users/comp5/Downloads/R_Program"
data <- file.path(path, "Supermarket_Sales_Forecasting - Sales.csv")
Anoma_df <- read.csv(data)
head(Anoma_df)
```

```
##        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
```

```r
# Check the data types of the 2 columns
sapply(Anoma_df, class)
```

```
##      Date     Sales
##  "factor" "numeric"
```

```r
# convert Date datatype from factor to Date
#
Anoma_df$Date <- as.Date(Anoma_df$Date )
sapply(Anoma_df, class)
```

```
##      Date     Sales
##    "Date" "numeric"
```

```r
#Convert the data frame to tibble
#
Anoma_tb <- as_tibble(Anoma_df)
head(Anoma_tb)
```

```
## # A tibble: 6 x 2
##   Date       Sales
```

```
##   <date>     <dbl>
## 1 0001-05-20 549.
## 2 0003-08-20  80.2
## 3 0003-03-20 341.
## 4 NA         489.
## 5 0002-08-20 634.
## 6 NA         628.
```

```
Anoma_tb <- Anoma_tb %>%
                    tibbletime::as_tbl_time(index = Date)
```

```
Anoma_tb %>%
    time_decompose(Date) %>%
    anomalize(remainder) %>%
    time_recompose() %>%
    plot_anomalies(time_recomposed = TRUE, ncol = 3, alpha_dots = 0.5)
```