Feature Selection

2022-04-01

```r
# Load Libraries
library(tidyverse)
```

```
## Warning: package 'tidyverse' was built under R version 4.1.3

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

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.6     v dplyr   1.0.8
## v tidyr   1.2.0     v stringr 1.4.0
## v readr   2.1.2     v forcats 0.5.1

## Warning: package 'ggplot2' was built under R version 4.1.3

## Warning: package 'dplyr' was built under R version 4.1.3

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

```r
library(moments)
library(heatmaply)
```

```
## Warning: package 'heatmaply' was built under R version 4.1.3

## Loading required package: plotly

##
## Attaching package: 'plotly'

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

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

## The following object is masked from 'package:graphics':
##
##     layout
```

```
## Loading required package: viridis

## Warning: package 'viridis' was built under R version 4.1.3

## Loading required package: viridisLite

##
## ======================
## Welcome to heatmaply version 1.3.0
##
## Type citation('heatmaply') for how to cite the package.
## Type ?heatmaply for the main documentation.
##
## The github page is: https://github.com/talgalili/heatmaply/
## Please submit your suggestions and bug-reports at: https://github.com/talgalili/heatmaply/issues
## You may ask questions at stackoverflow, use the r and heatmaply tags:
##   https://stackoverflow.com/questions/tagged/heatmaply
## ======================
```

```
library(dummies)
```

```
## dummies-1.5.6 provided by Decision Patterns
```

```
# Import the dataset
smarket <- read.csv("http://bit.ly/CarreFourDataset")
```

```
# Preview the first few rows
head(smarket)
```

```
##    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
```

```r
# Preview the last few rows
tail(smarket)
```

```
##       Invoice.ID Branch Customer.type Gender           Product.line Unit.price
## 995  652-49-6720      C        Member Female Electronic accessories      60.95
## 996  233-67-5758      C        Normal   Male      Health and beauty      40.35
## 997  303-96-2227      B        Normal Female     Home and lifestyle      97.38
## 998  727-02-1313      A        Member   Male     Food and beverages      31.84
## 999  347-56-2442      A        Normal   Male     Home and lifestyle      65.82
## 1000 849-09-3807      A        Member Female    Fashion accessories      88.34
##      Quantity     Tax      Date  Time Payment   cogs gross.margin.percentage
## 995         1  3.0475 2/18/2019 11:40 Ewallet  60.95                4.761905
## 996         1  2.0175 1/29/2019 13:46 Ewallet  40.35                4.761905
## 997        10 48.6900  3/2/2019 17:16 Ewallet 973.80                4.761905
## 998         1  1.5920  2/9/2019 13:22    Cash  31.84                4.761905
## 999         1  3.2910 2/22/2019 15:33    Cash  65.82                4.761905
## 1000        7 30.9190 2/18/2019 13:28    Cash 618.38                4.761905
##      gross.income Rating     Total
## 995        3.0475    5.9   63.9975
## 996        2.0175    6.2   42.3675
## 997       48.6900    4.4 1022.4900
## 998        1.5920    7.7   33.4320
## 999        3.2910    4.1   69.1110
## 1000      30.9190    6.6  649.2990
```

```r
# Check number of records and variables
dim(smarket)
```

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

We have 1,000 records and 16 variables

```r
# Check the datatypes of our dataset
glimpse(smarket)
```

```
## Rows: 1,000
## Columns: 16
## $ Invoice.ID              <chr> "750-67-8428", "226-31-3081", "631-41-3108", "~
## $ Branch                  <chr> "A", "C", "A", "A", "A", "C", "A", "C", "A", "~
## $ Customer.type           <chr> "Member", "Normal", "Normal", "Member", "Norma~
## $ Gender                  <chr> "Female", "Female", "Male", "Male", "Male", "M~
## $ Product.line            <chr> "Health and beauty", "Electronic accessories",~
## $ Unit.price              <dbl> 74.69, 15.28, 46.33, 58.22, 86.31, 85.39, 68.8~
## $ Quantity                <int> 7, 5, 7, 8, 7, 7, 6, 10, 2, 3, 4, 4, 5, 10, 10~
## $ Tax                     <dbl> 26.1415, 3.8200, 16.2155, 23.2880, 30.2085, 29~
## $ Date                    <chr> "1/5/2019", "3/8/2019", "3/3/2019", "1/27/2019~
## $ Time                    <chr> "13:08", "10:29", "13:23", "20:33", "10:37", "~
## $ Payment                 <chr> "Ewallet", "Cash", "Credit card", "Ewallet", "~
## $ cogs                    <dbl> 522.83, 76.40, 324.31, 465.76, 604.17, 597.73,~
## $ gross.margin.percentage <dbl> 4.761905, 4.761905, 4.761905, 4.761905, 4.7619~
## $ gross.income            <dbl> 26.1415, 3.8200, 16.2155, 23.2880, 30.2085, 29~
## $ Rating                  <dbl> 9.1, 9.6, 7.4, 8.4, 5.3, 4.1, 5.8, 8.0, 7.2, 5~
## $ Total                   <dbl> 548.9715, 80.2200, 340.5255, 489.0480, 634.378~
```

```r
# Check the summary of our dataset
summary(smarket)
```

```
##   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
```

```r
# Check the column names
names(smarket)
```

```
##  [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"
```

Data Cleaning

```r
# Let's check for missing values
colSums(is.na(smarket))
```

```
##              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
```

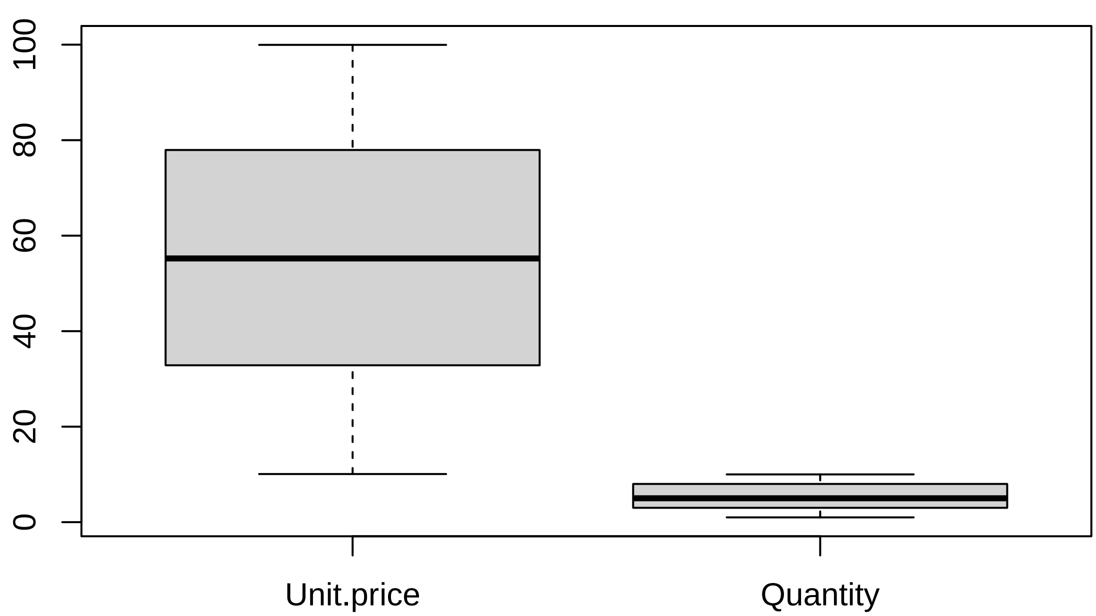
We have no missing values.

```r
# Check for duplicate values
sum(duplicated(smarket))
```

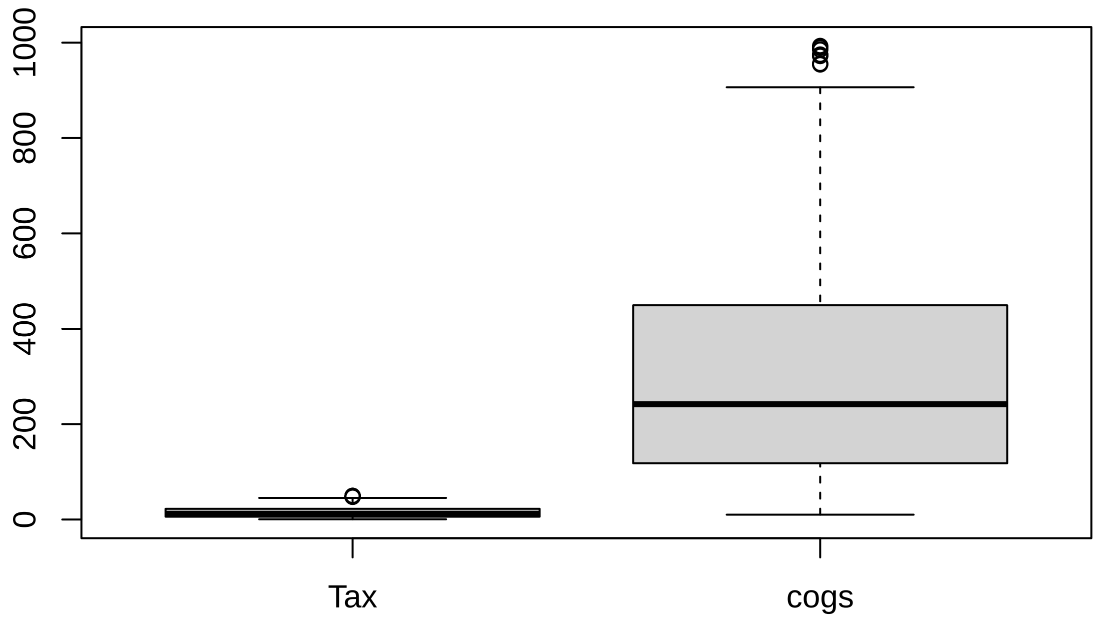
```
## [1] 0
```

We have no duplicate values

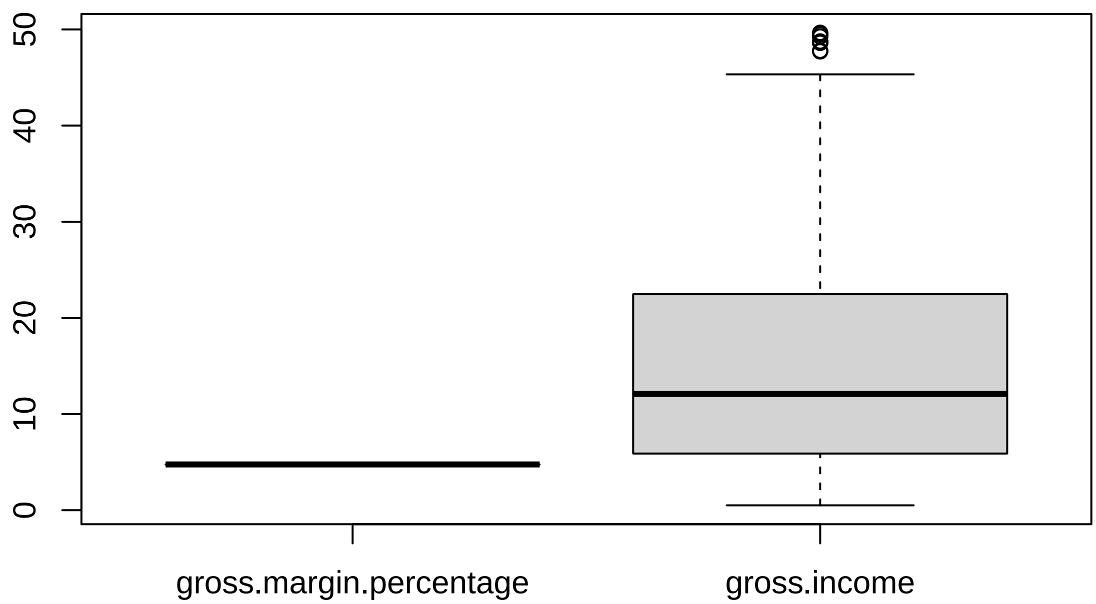
```r
# Checking for outliers in our numerical variables
boxplot(smarket[, c(6,7)])
```



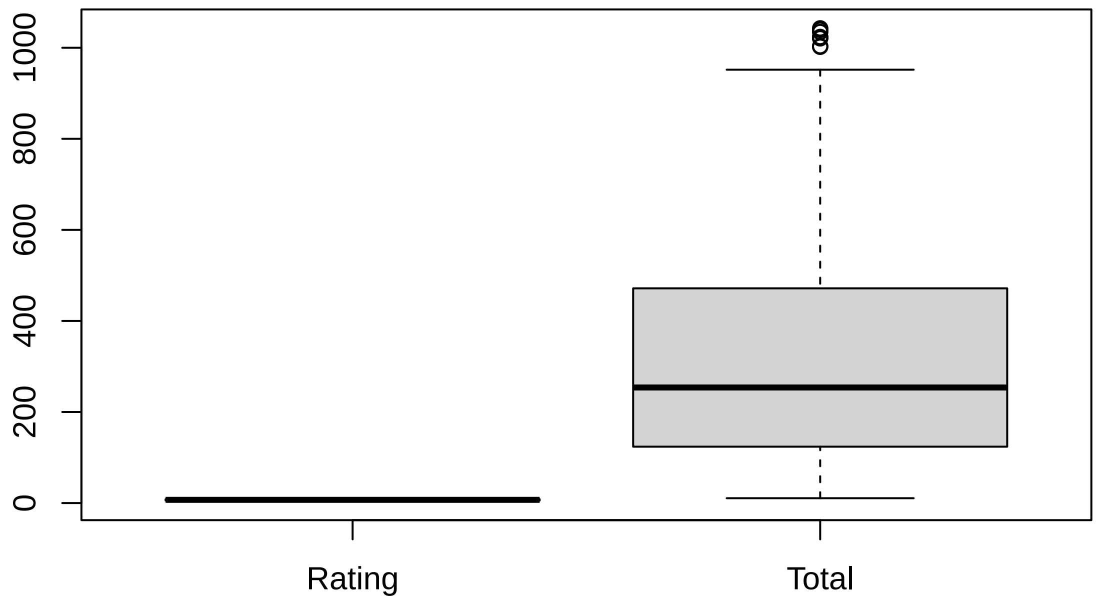
```r
# Checking for outliers in our numerical variables
boxplot(smarket[, c(8,12)])
```




```r
# Checking for outliers in our numerical variables
boxplot(smarket[, c(13,14)])
```




```r
# Checking for outliers in our numerical variables
boxplot(smarket[, c(15,16)])
```



There is presence of outliers in Tax, Cogs, Gross income and Total Variables

```r
# Convert the date column from character datatype to date datatype
smarket$Date <- as.Date(smarket$Date, "%m/%d/%Y")
# Confirm changes made
glimpse(smarket)
```

```
## Rows: 1,000
## Columns: 16
## $ Invoice.ID              <chr> "750-67-8428", "226-31-3081", "631-41-3108", "~
## $ Branch                  <chr> "A", "C", "A", "A", "A", "C", "A", "C", "A", "~
## $ Customer.type           <chr> "Member", "Normal", "Normal", "Member", "Norma~
## $ Gender                  <chr> "Female", "Female", "Male", "Male", "Male", "M~
## $ Product.line            <chr> "Health and beauty", "Electronic accessories",~
## $ Unit.price              <dbl> 74.69, 15.28, 46.33, 58.22, 86.31, 85.39, 68.8~
## $ Quantity                <int> 7, 5, 7, 8, 7, 7, 6, 10, 2, 3, 4, 4, 5, 10, 10~
## $ Tax                     <dbl> 26.1415, 3.8200, 16.2155, 23.2880, 30.2085, 29~
## $ Date                    <date> 2019-01-05, 2019-03-08, 2019-03-03, 2019-01-2~
## $ Time                    <chr> "13:08", "10:29", "13:23", "20:33", "10:37", "~
## $ Payment                 <chr> "Ewallet", "Cash", "Credit card", "Ewallet", "~
## $ cogs                    <dbl> 522.83, 76.40, 324.31, 465.76, 604.17, 597.73,~
## $ gross.margin.percentage <dbl> 4.761905, 4.761905, 4.761905, 4.761905, 4.7619~
## $ gross.income            <dbl> 26.1415, 3.8200, 16.2155, 23.2880, 30.2085, 29~
## $ Rating                  <dbl> 9.1, 9.6, 7.4, 8.4, 5.3, 4.1, 5.8, 8.0, 7.2, 5~
## $ Total                   <dbl> 548.9715, 80.2200, 340.5255, 489.0480, 634.378~
```

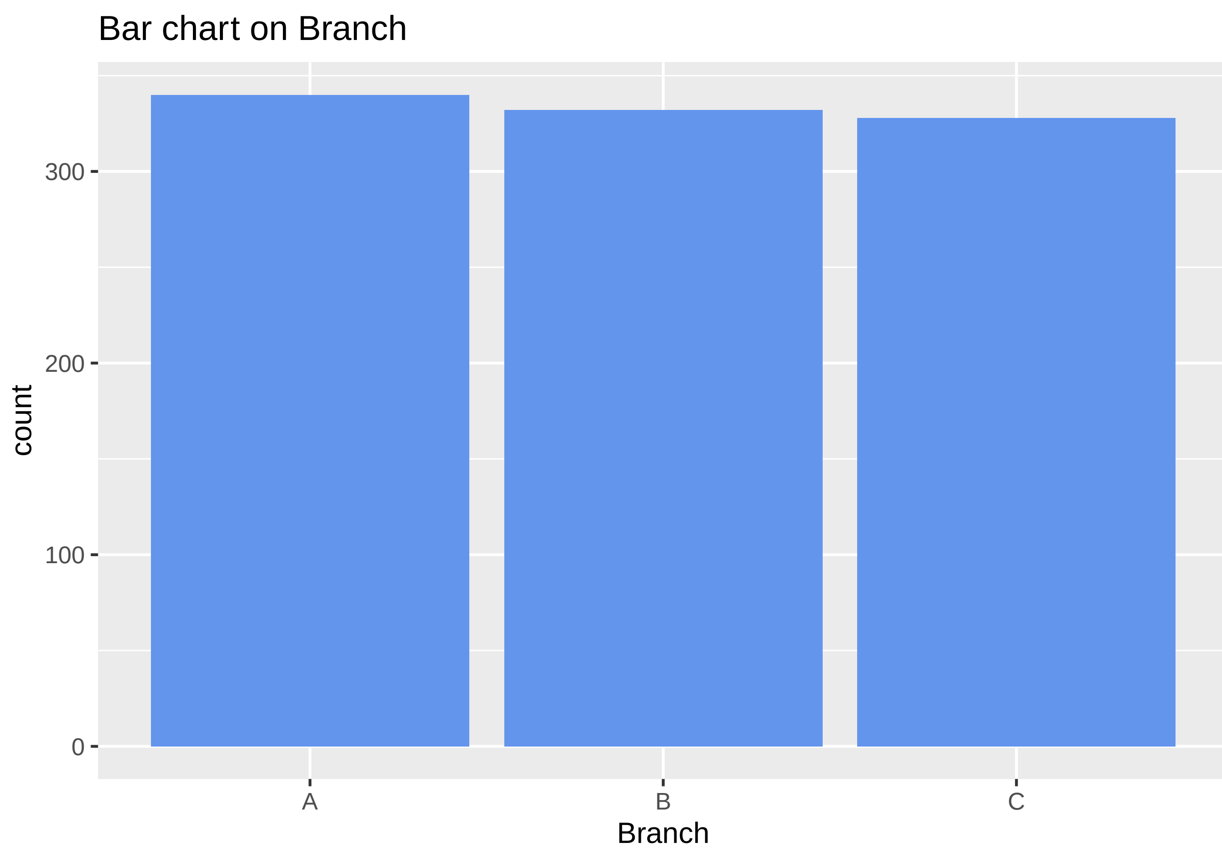
```
# We will extract month from the date column
smarket$Month<- format(smarket$Date, "%m")
head(smarket)
```

```
##    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 2019-01-05 13:08     Ewallet 522.83                4.761905
## 2        5  3.8200 2019-03-08 10:29        Cash  76.40                4.761905
## 3        7 16.2155 2019-03-03 13:23 Credit card 324.31                4.761905
## 4        8 23.2880 2019-01-27 20:33     Ewallet 465.76                4.761905
## 5        7 30.2085 2019-02-08 10:37     Ewallet 604.17                4.761905
## 6        7 29.8865 2019-03-25 18:30     Ewallet 597.73                4.761905
##   gross.income Rating    Total Month
## 1      26.1415    9.1 548.9715    01
## 2       3.8200    9.6  80.2200    03
## 3      16.2155    7.4 340.5255    03
## 4      23.2880    8.4 489.0480    01
## 5      30.2085    5.3 634.3785    02
## 6      29.8865    4.1 627.6165    03
```

```
# Replace the numbers in months with the name of the month
smarket$Month[smarket$Month == "01"] <- "January"
smarket$Month[smarket$Month == "02"] <- "February"
smarket$Month[smarket$Month == "03"] <- "March"
```

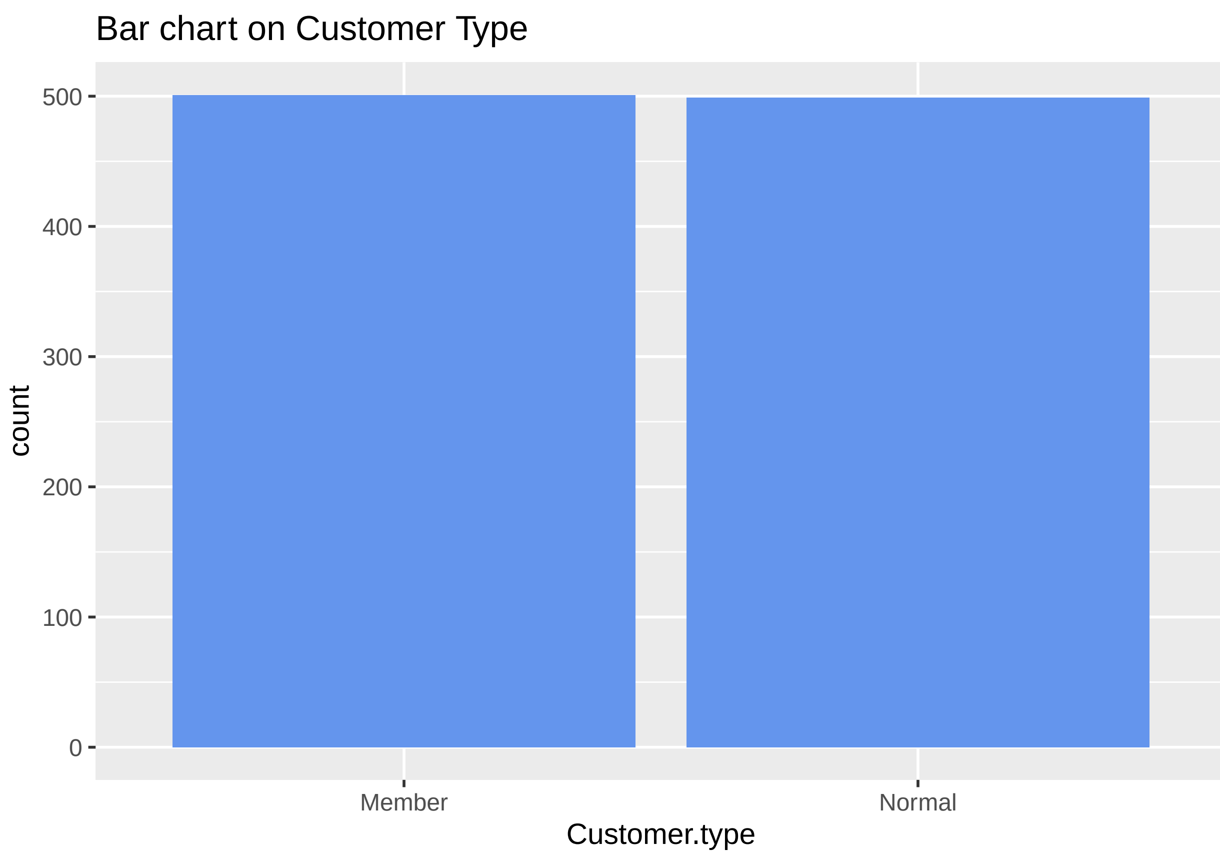
Univariate Analysis

```
# Bar chart on revenue
gg.1 <- ggplot (data = smarket, aes(x= Branch)) +
  geom_bar(fill = "cornflowerblue")
gg.1 + ggtitle("Bar chart on Branch")
```



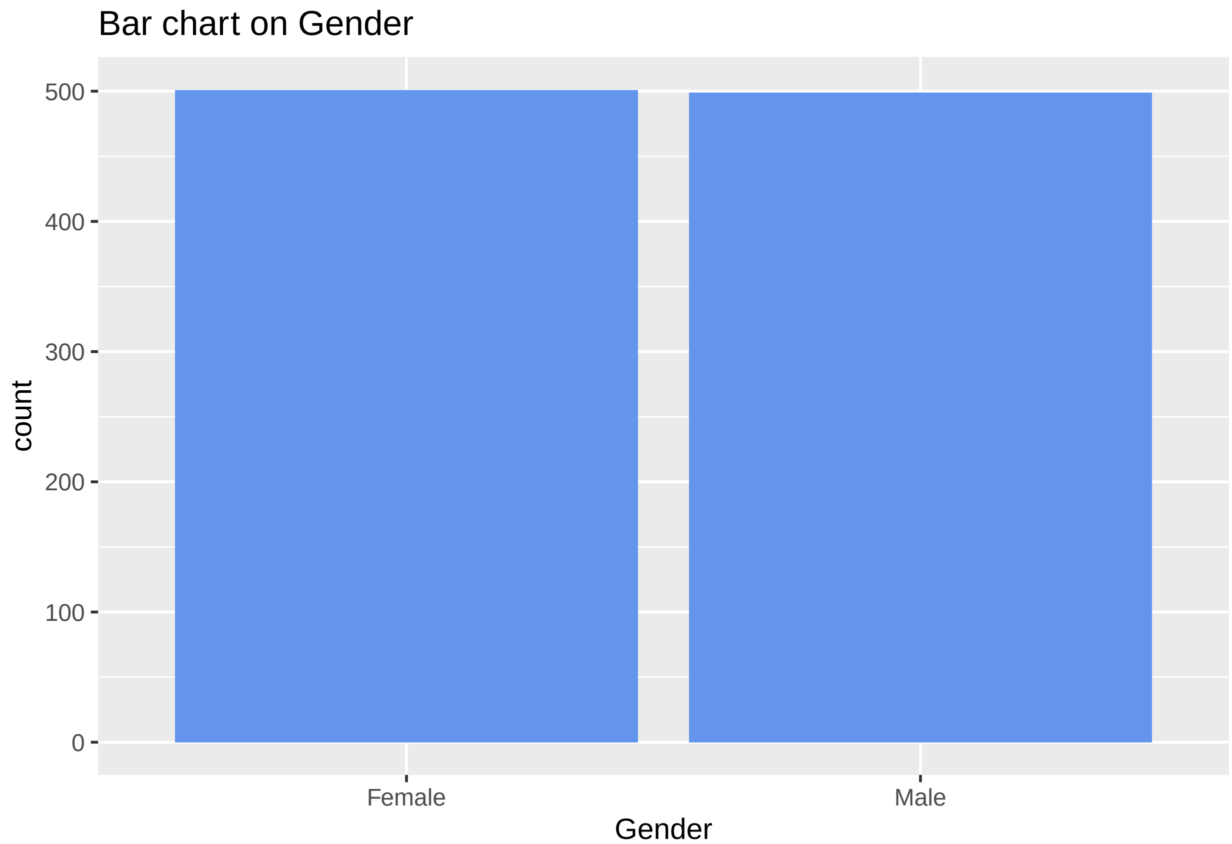
The number of branches in our data are not too different from each other

```
# Bar Chart on Customer Type
gg.2 <- ggplot (data = smarket, aes(x= Customer.type)) +
  geom_bar(fill = "cornflowerblue")
gg.2 + ggtitle("Bar chart on Customer Type")
```



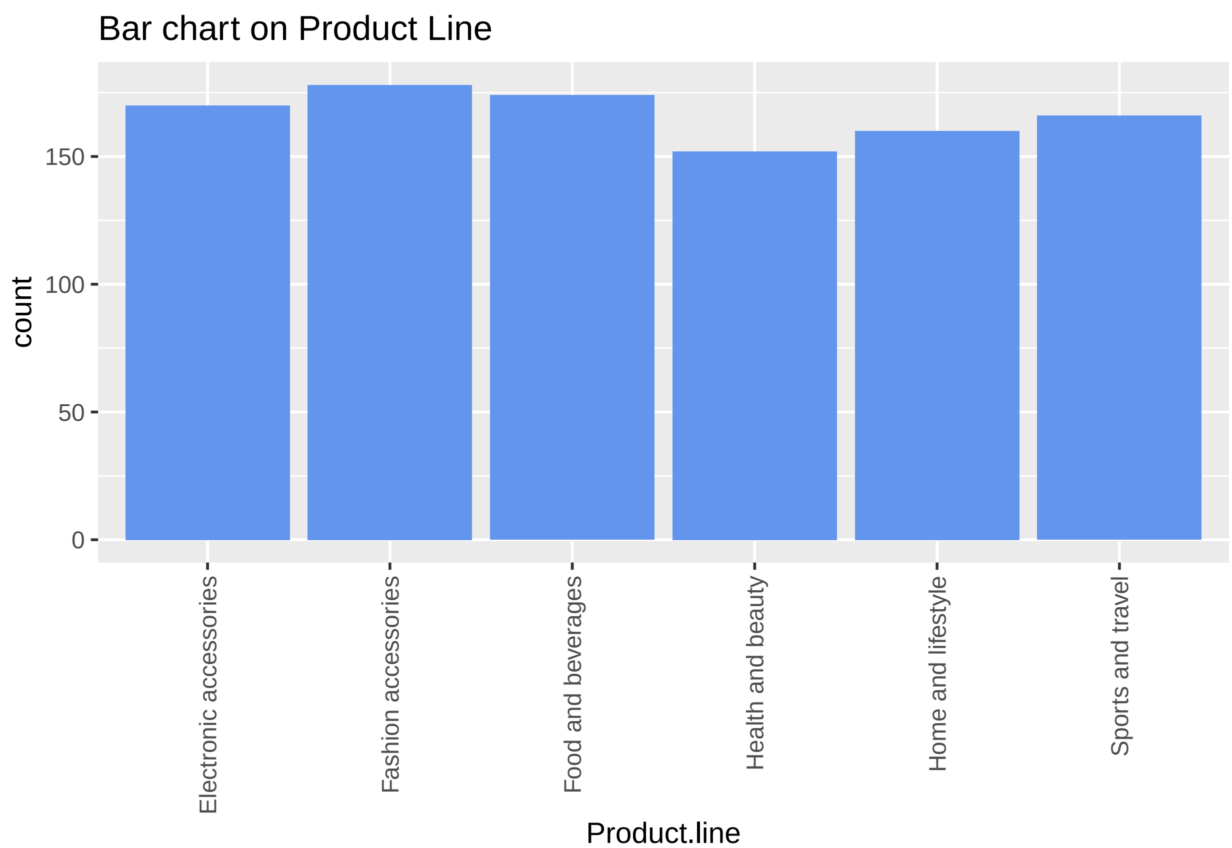
There isn't a big difference in the number of member and normal customers

```
# Bar Chart on Gender
gg.3 <- ggplot (data = smarket, aes(x= Gender)) +
  geom_bar(fill = "cornflowerblue")
gg.3 + ggtitle("Bar chart on Gender")
```



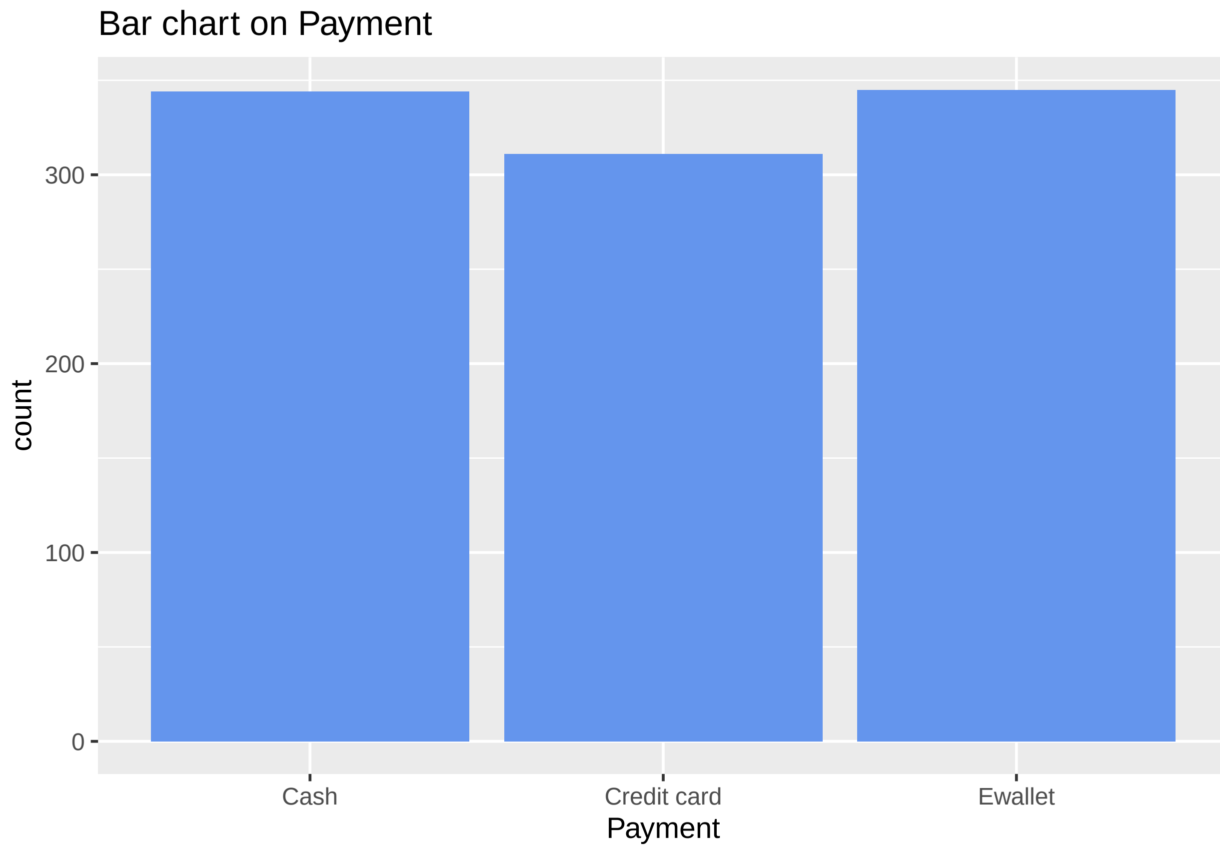
There isn't a big difference in the number of male and female customers

```
# Bar Chart on Product Line
gg.4 <- ggplot (data = smarket, aes(x= Product.line)) +
  geom_bar(fill = "cornflowerblue") + theme(axis.text.x = element_text(
    angle = 90, vjust =.5, hjust = 1
  ))
gg.4 + ggtitle("Bar chart on Product Line")
```



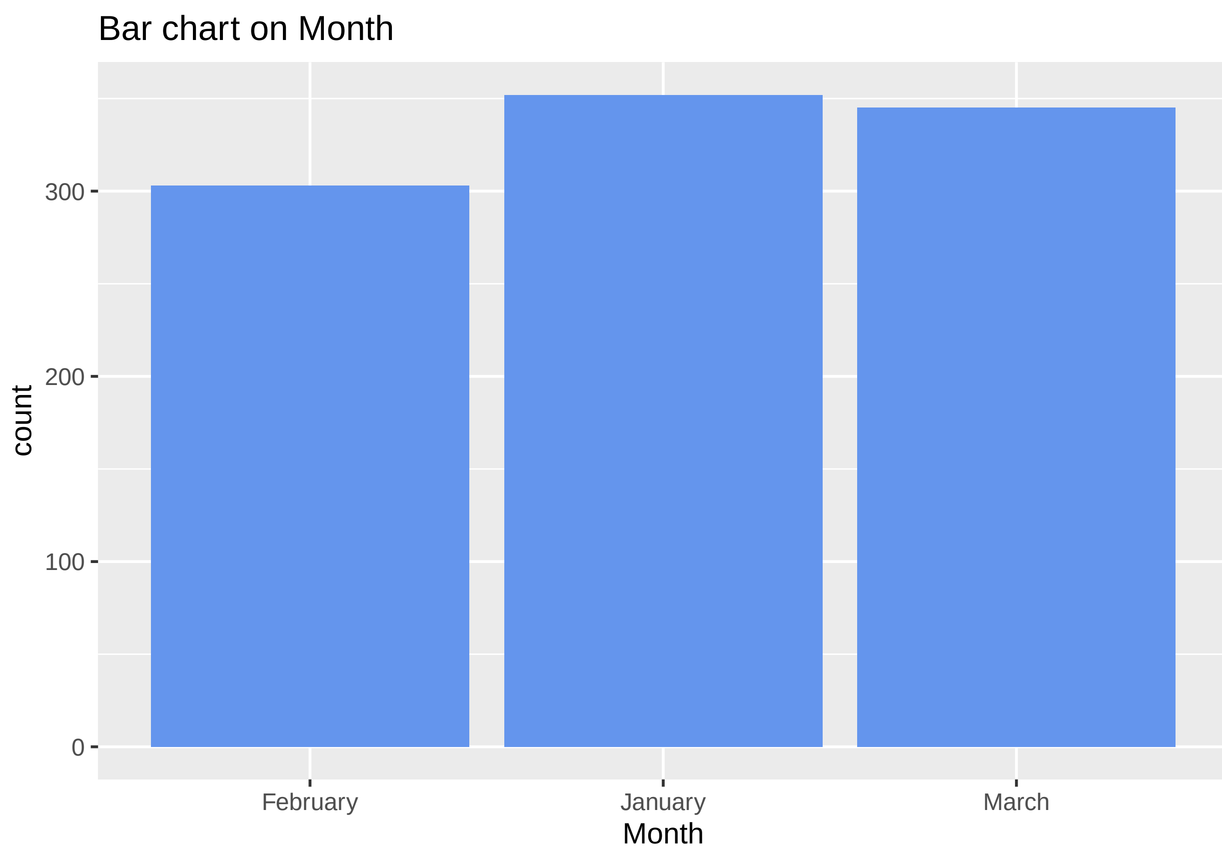
Fashion accessories is the most popular product followed closely by food and beverages

```
# Bar Chart on Payment
gg.5 <- ggplot (data = smarket, aes(x= Payment)) +
  geom_bar(fill = "cornflowerblue")
gg.5 + ggtitle("Bar chart on Payment")
```



There is no big difference in the number of customers who paid via Ewallet and cash

```
# Bar Chart on Month
gg.6<- ggplot (data = smarket, aes(x= Month)) +
  geom_bar(fill = "cornflowerblue")
gg.6 + ggtitle("Bar chart on Month")
```



January had the most transactions followed closely by March

```
# Frequency chart on Unit price
freq.1 <- table(smarket$Unit.price)
head(sort(freq.1, decreasing = T))
```

```
##
## 83.77  15.5  15.8 18.08 19.15 20.01
##     3     2     2     2     2     2
```

```
# Frequency chart on Quantity
freq.2 <- table(smarket$Quantity)
head(sort(freq.2, decreasing = T))
```

```
##
##  10   1   4   5   7   6
## 119 112 109 102 102  98
```

```
# Frequency chart on Tax
freq.3 <- table(smarket$Tax)
head(sort(freq.3, decreasing = T),n=15)
```

```
##
##   4.154    4.464    8.377  9.0045   10.326 10.3635    12.57  13.188  22.428    39.48
##       2        2        2       2        2       2        2       2       2        2
```

```
##  0.5085  0.6045   0.627   0.639   0.699
##       1       1       1       1       1
```

```r
# Frequency chart on cogs
freq.4 <- table(smarket$cogs)
head(sort(freq.4, decreasing = T), n=15)
```

```
##
##  83.08  89.28 167.54 180.09 206.52 207.27  251.4 263.76 448.56  789.6  10.17
##      2      2      2      2      2      2      2      2      2      2      1
##  12.09  12.54  12.78  13.98
##      1      1      1      1
```

```r
# Frequency chart on gross margin percentage
freq.5 <- table(smarket$gross.margin.percentage)
head(sort(freq.5, decreasing = T))
```

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

```r
# Frequency chart on Rating
freq.5 <- table(smarket$Rating)
head(sort(freq.5, decreasing = T))
```

```
##
##   6 6.6 4.2 9.5   5 5.1
##  26  24  22  22  21  21
```

```r
# Frequency chart on Gross Income
freq.5 <- table(smarket$gross.income)
head(sort(freq.5, decreasing = T), n=10)
```

```
##
##   4.154   4.464   8.377  9.0045  10.326 10.3635   12.57  13.188  22.428   39.48
##       2       2       2       2       2       2       2       2       2       2
```

```r
# Frequency chart on Total
freq.5 <- table(smarket$Total)
head(sort(freq.5, decreasing = T), n=15)
```

```
##
##   87.234    93.744  175.917 189.0945  216.846 217.6335   263.97  276.948
##        2         2        2        2        2        2        2        2
##  470.988    829.08  10.6785  12.6945   13.167   13.419   14.679
##        2         2        1        1        1        1        1
```

```r
# Identify the mean, median, min, max and quantile of our numerical variables
summary(smarket[,c(6:8,12:16)])
```

```
##    Unit.price       Quantity          Tax                cogs
##  Min.   :10.08   Min.   : 1.00   Min.   : 0.5085   Min.   : 10.17
##  1st Qu.:32.88   1st Qu.: 3.00   1st Qu.: 5.9249   1st Qu.:118.50
##  Median :55.23   Median : 5.00   Median :12.0880   Median :241.76
##  Mean   :55.67   Mean   : 5.51   Mean   :15.3794   Mean   :307.59
##  3rd Qu.:77.94   3rd Qu.: 8.00   3rd Qu.:22.4453   3rd Qu.:448.90
##  Max.   :99.96   Max.   :10.00   Max.   :49.6500   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
```

```
# We'll also check the mode of our numerical variables
mode <- function(x) {
  u <- unique(x)
  tab <- tabulate(match(x, u))
  u[tab == max(tab)]
}

print("Mode of unit price is:")
```

```
## [1] "Mode of unit price is:"
```

```
mode(smarket$Unit.price)
```

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

```
print("Mode of tax is:")
```

```
## [1] "Mode of tax is:"
```

```
mode(smarket$Tax)
```

```
##  [1] 39.4800  9.0045 10.3260 12.5700 10.3635 13.1880  4.1540  8.3770 22.4280
## [10]  4.4640
```

```
print("Mode of COGS is:")
```

```
## [1] "Mode of COGS is:"
```

```
mode(smarket$cogs)
```

```
##  [1] 789.60 180.09 206.52 251.40 207.27 263.76  83.08 167.54 448.56  89.28
```

```r
print("Mode of gross margin percentage is:")
```

```
## [1] "Mode of gross margin percentage is:"
```

```r
mode(smarket$gross.margin.percentage)
```

```
## [1] 4.761905
```

```r
print("Mode of Gross income:")
```

```
## [1] "Mode of Gross income:"
```

```r
mode(smarket$gross.income)
```

```
##  [1] 39.4800  9.0045 10.3260 12.5700 10.3635 13.1880  4.1540  8.3770 22.4280
## [10]  4.4640
```

```r
print("Mode of Rating is:")
```

```
## [1] "Mode of Rating is:"
```

```r
mode(smarket$Rating)
```

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

```r
print("Mode of Total is:")
```

```
## [1] "Mode of Total is:"
```

```r
mode(smarket$Total)
```

```
##  [1] 829.0800 189.0945 216.8460 263.9700 217.6335 276.9480  87.2340 175.9170
##  [9] 470.9880  93.7440
```

```r
# Check the variance of our numerical variables
print("Variance of unit price is:")
```

```
## [1] "Variance of unit price is:"
```

```r
var(smarket$Unit.price)
```

```
## [1] 701.9653
```

```r
print("Variance of tax is:")
```

```
## [1] "Variance of tax is:"
```

```r
var(smarket$Tax)
```

```
## [1] 137.0966
```

```r
print("Variance of COGS is:")
```

```
## [1] "Variance of COGS is:"
```

```r
var(smarket$cogs)
```

```
## [1] 54838.64
```

```r
print("Variance of gross margin percentage is:")
```

```
## [1] "Variance of gross margin percentage is:"
```

```r
var(smarket$gross.margin.percentage)
```

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

```r
print("Variance of Gross income:")
```

```
## [1] "Variance of Gross income:"
```

```r
var(smarket$gross.income)
```

```
## [1] 137.0966
```

```r
print("Variance of Rating is:")
```

```
## [1] "Variance of Rating is:"
```

```r
var(smarket$Rating)
```

```
## [1] 2.953518
```

```r
print("Variance of Total is:")
```

```
## [1] "Variance of Total is:"
```

```r
var(smarket$Total)
```

```
## [1] 60459.6
```

```r
# Check the skewness of our variables
print("The skewness of our variables:")
```

```
## [1] "The skewness of our variables:"
```

```r
sapply(smarket[,c(6:8,12:16)],skewness)
```

```
##              Unit.price                Quantity                     Tax
##             0.007066827             0.012921628             0.891230392
##                    cogs gross.margin.percentage            gross.income
##             0.891230392                     NaN             0.891230392
##                  Rating                   Total
##             0.008996129             0.891230392
```

```r
# Check the kurtosis of our variables
print("The kurtosis of our variables:")
```

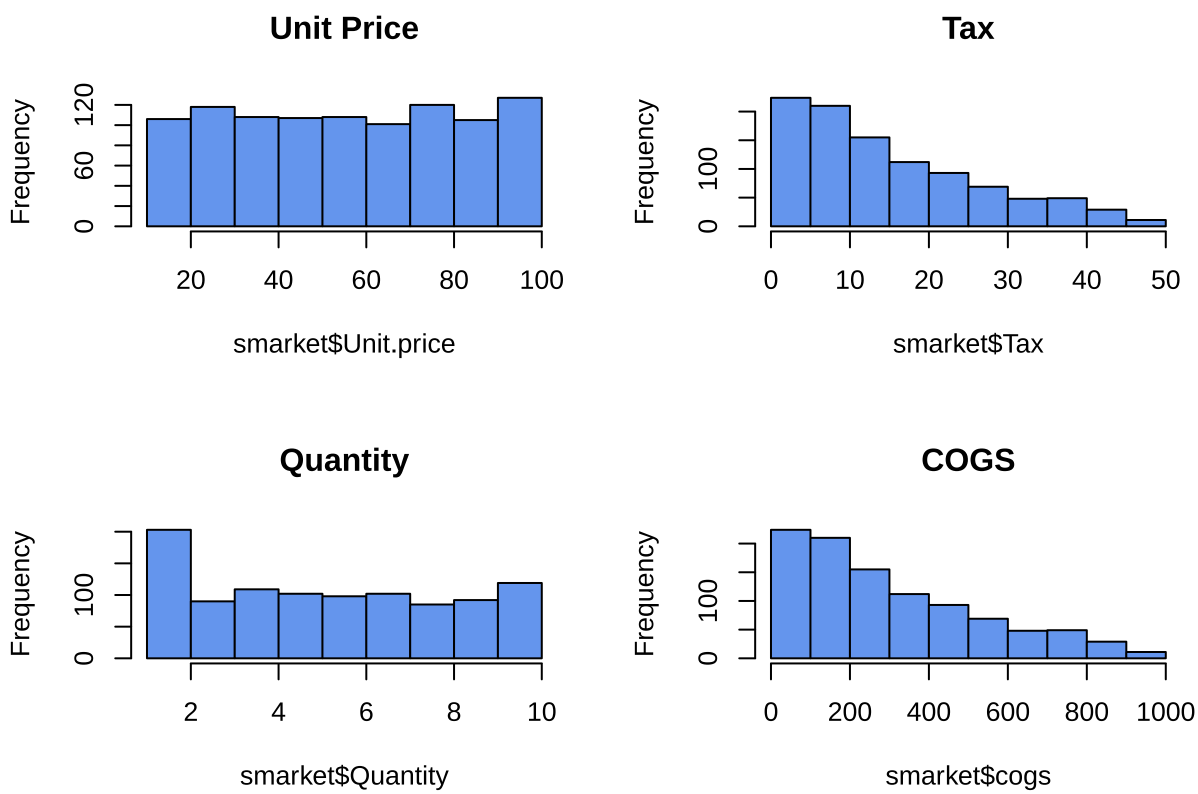
```
## [1] "The kurtosis of our variables:"
```

```r
sapply(smarket[,c(6:8,12:16)],kurtosis)
```

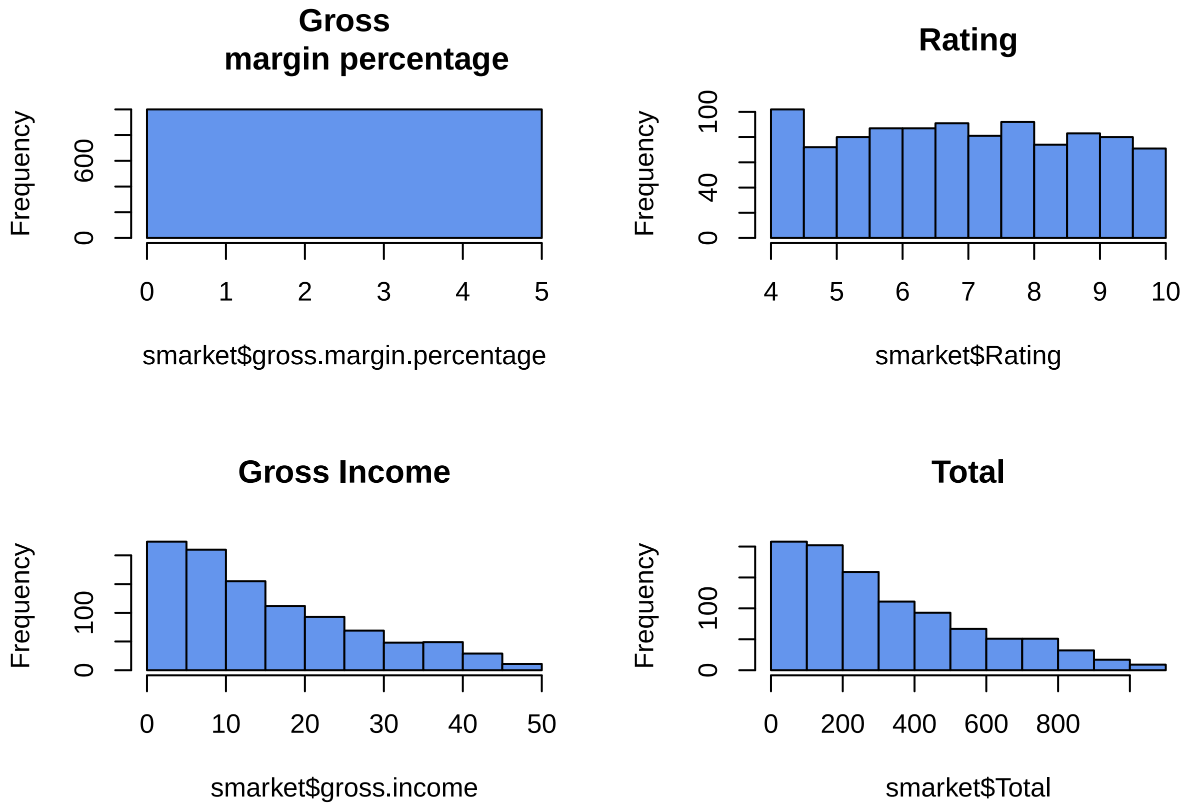
```
##              Unit.price                Quantity                     Tax
##                1.781499                1.784528                2.912530
##                    cogs gross.margin.percentage            gross.income
##                2.912530                     NaN                2.912530
##                  Rating                   Total
##                1.848169                2.912530
```

Our numerical variables do not have heavy tails

```r
# Plot histograms of our numeric variables
par(mfcol=c(2,2))
hist(smarket$Unit.price, col = "cornflowerblue", main = "Unit Price")
hist(smarket$Quantity, col = "cornflowerblue",
     main = "Quantity")
hist(smarket$Tax, col = "cornflowerblue", main="Tax")
hist(smarket$cogs, col = "cornflowerblue",
     main ="COGS")
```




```r
# Plot histograms of our numeric variables
par(mfcol=c(2,2))
hist(smarket$gross.margin.percentage, col = "cornflowerblue", main = "Gross
     margin percentage")
hist(smarket$gross.income, col = "cornflowerblue",
     main = "Gross Income")
hist(smarket$Rating, col = "cornflowerblue", main="Rating")
hist(smarket$Total, col = "cornflowerblue",
     main ="Total")
```



Unit price quantity and Rating are symmetrical and the rest are moderately skewed.

Bivariate Analysis

```
# Assess the correlation of our numerical variables
cor(smarket[,c(6:8,12:16)])
```

```
## Warning in cor(smarket[, c(6:8, 12:16)]): the standard deviation is zero
```

```
##                          Unit.price    Quantity        Tax       cogs
## Unit.price              1.000000000  0.01077756  0.6339621  0.6339621
## Quantity                0.010777564  1.00000000  0.7055102  0.7055102
## Tax                     0.633962089  0.70551019  1.0000000  1.0000000
## cogs                    0.633962089  0.70551019  1.0000000  1.0000000
## gross.margin.percentage          NA          NA         NA         NA
## gross.income            0.633962089  0.70551019  1.0000000  1.0000000
## Rating                 -0.008777507 -0.01581490 -0.0364417 -0.0364417
## Total                   0.633962089  0.70551019  1.0000000  1.0000000
##                        gross.margin.percentage gross.income       Rating
## Unit.price                                  NA    0.6339621 -0.008777507
## Quantity                                    NA    0.7055102 -0.015814905
## Tax                                         NA    1.0000000 -0.036441705
## cogs                                        NA    1.0000000 -0.036441705
## gross.margin.percentage                      1           NA           NA
```

```
## gross.income                                NA    1.0000000 -0.036441705
## Rating                                      NA   -0.0364417  1.000000000
## Total                                       NA    1.0000000 -0.036441705
##                              Total
## Unit.price               0.6339621
## Quantity                 0.7055102
## Tax                      1.0000000
## cogs                     1.0000000
## gross.margin.percentage         NA
## gross.income             1.0000000
## Rating                  -0.0364417
## Total                    1.0000000
```

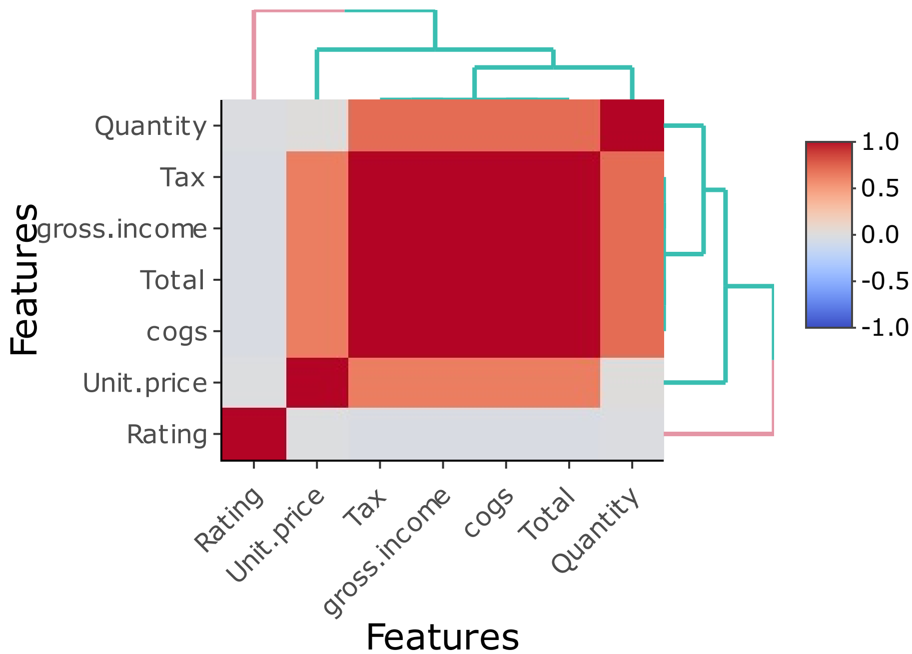
```
# Check for correlation without the gross.margin.percentage
cor(smarket[,c(6:8,12,14,15,16)])
```

```
##                 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
```

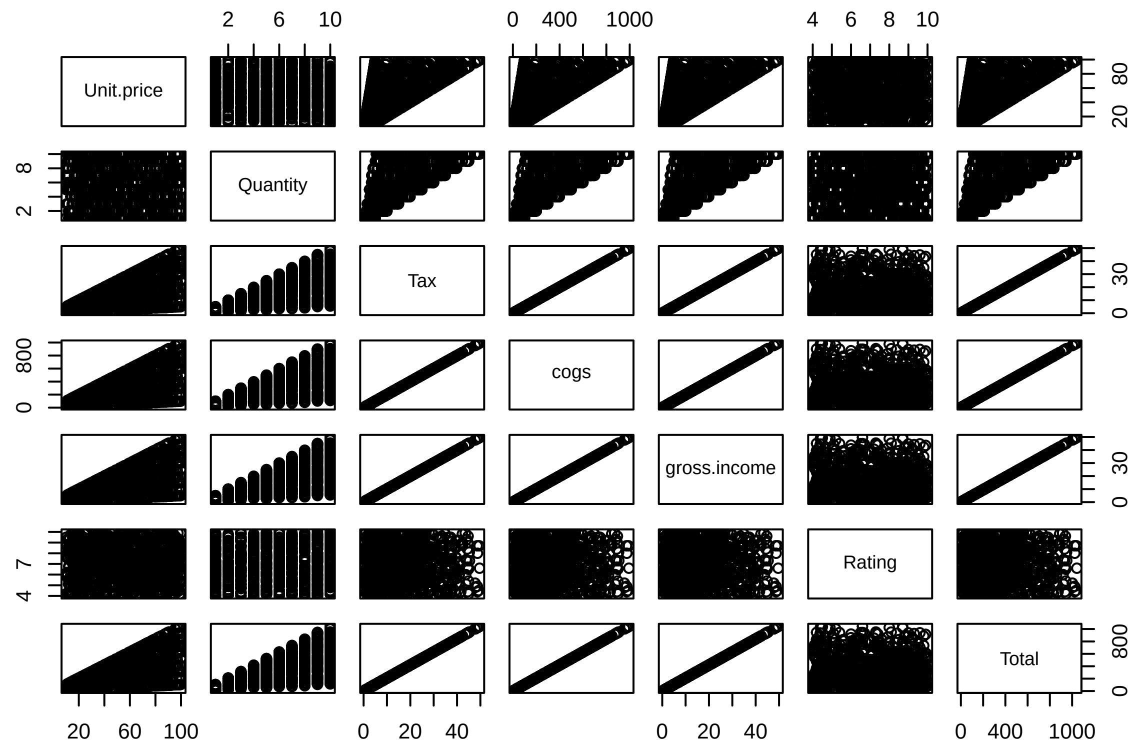
There is a strong positive correlation between quantity and Tax ,cog, Gross income and total Which makes sense because Quantity is used in the calculation of these variables

There's a weak negative correlation between Rating and Tax ,cog, Gross income and total

```
# Plotting corr heatmap
heatmaply_cor(x = cor(smarket[,c(6:8,12,14:16)]), xlab = "Features",
              ylab = "Features", k_col = 2, k_row = 2)
```



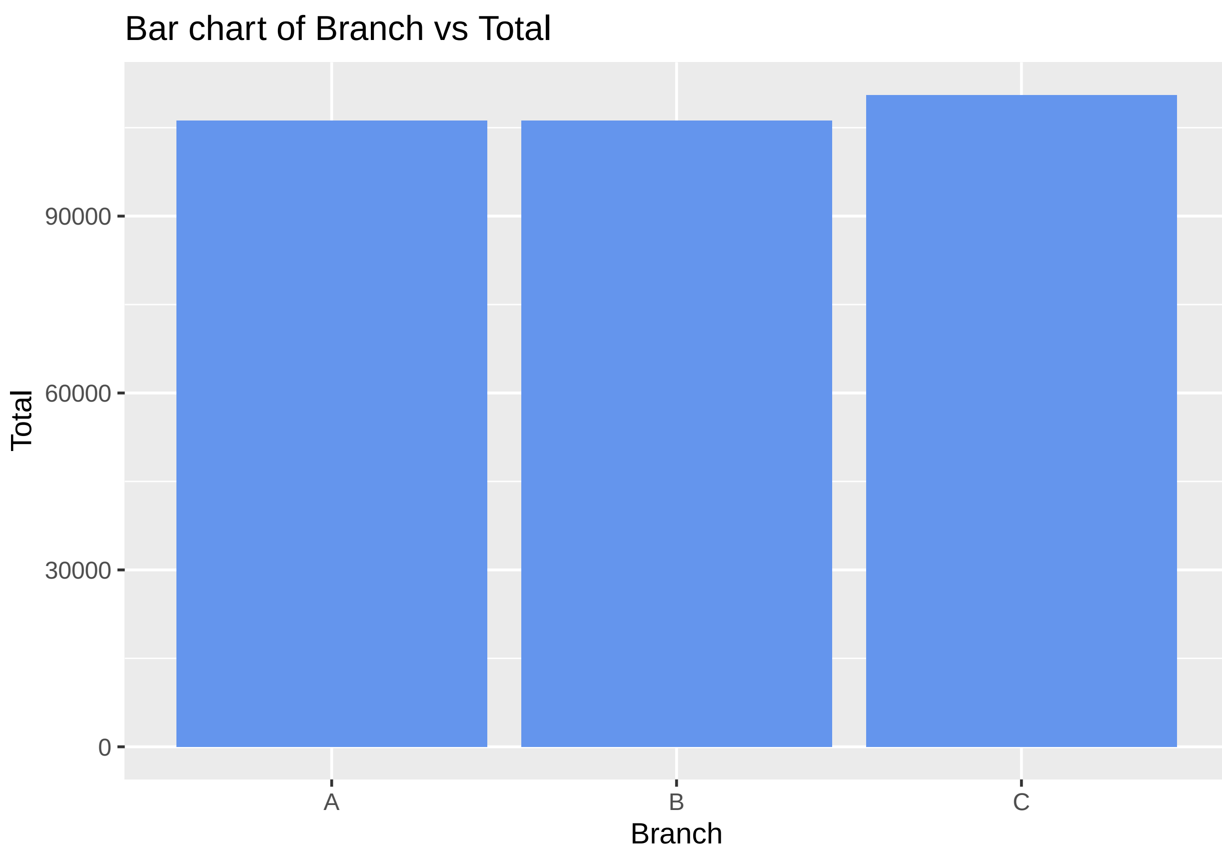

```r
# Plot a pairplot
pairs(smarket[,c(6:8,12,14:16)])
```




```
# Bar Chart of Branch vs Total
agg_1 <- aggregate(smarket$Total,list(smarket$Branch),sum)
agg_1
```

```
##   Group.1        x
## 1       A 106200.4
## 2       B 106197.7
## 3       C 110568.7
```

```
ggplot(data = agg_1 , aes(x= Group.1, y =x)) + geom_col(fill ="cornflowerblue") +
  labs(y="Total", x="Branch")+ggtitle("Bar chart of Branch vs Total")
```

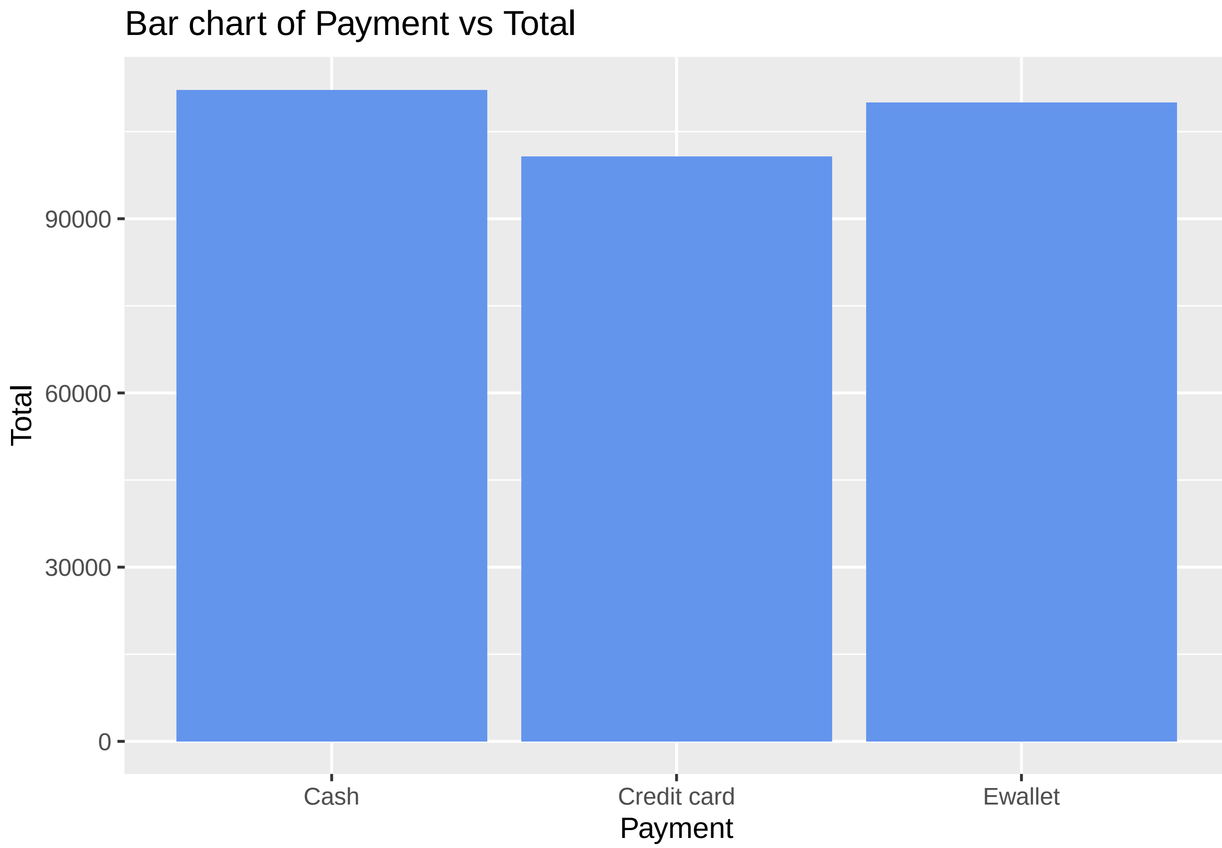


The branch with the highest number of sales is c

```r
# Bar chart of Payment vs Total
agg_2 <- aggregate(smarket$Total,list(smarket$Payment),sum)
agg_2
```

```
##      Group.1        x
## 1       Cash 112206.6
## 2 Credit card 100767.1
## 3    Ewallet 109993.1
```

```r
ggplot(data = agg_2 , aes(x= Group.1, y =x)) + geom_col(fill ="cornflowerblue") +
  labs(y="Total", x="Payment")+ggtitle("Bar chart of Payment vs Total")
```

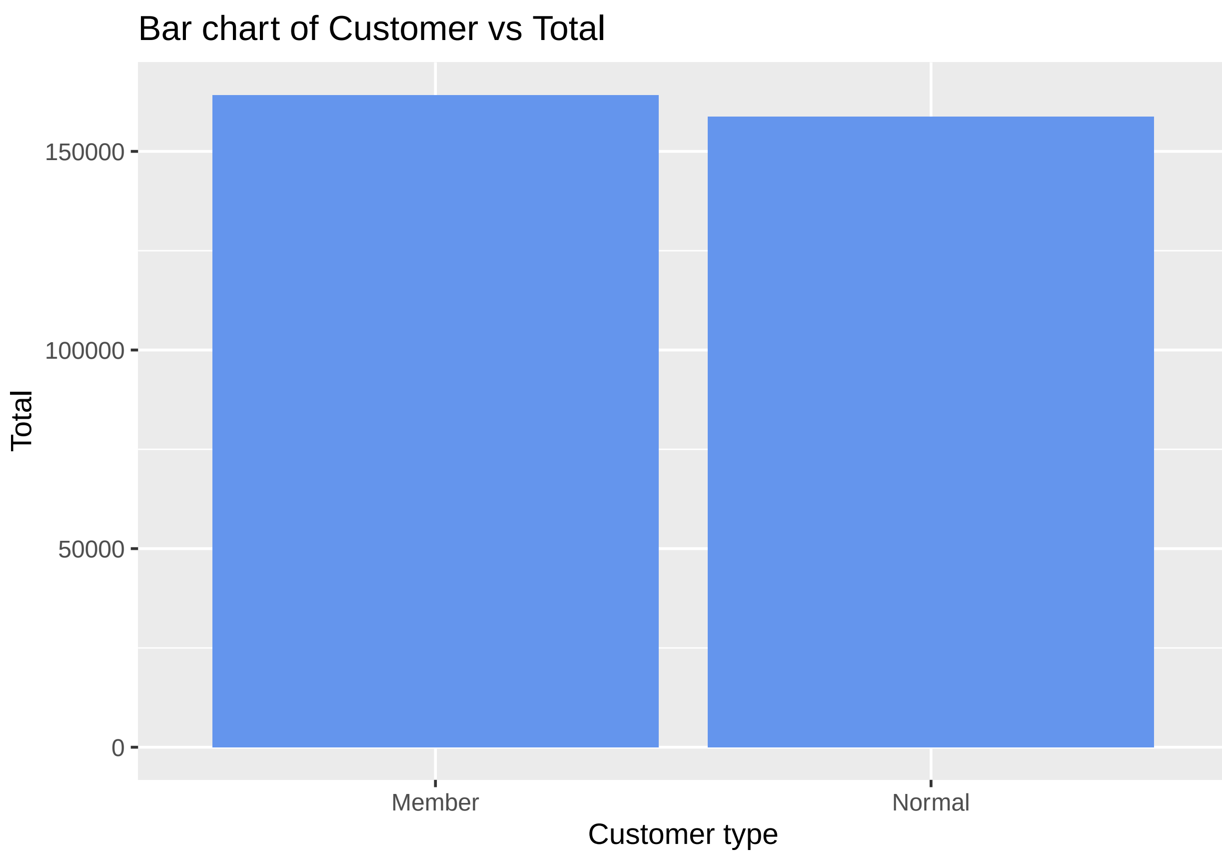


The Payment method with the highest number of sales is cash

```
# Bar chart of Customer type vs Total
agg_3 <- aggregate(smarket$Total,list(smarket$Customer.type),sum)
agg_3
```

```
##   Group.1        x
## 1  Member 164223.4
## 2  Normal 158743.3
```

```
ggplot(data = agg_3 , aes(x= Group.1, y =x)) + geom_col(fill ="cornflowerblue") +
  labs(y="Total", x="Customer type")+ggtitle("Bar chart of Customer vs Total")
```

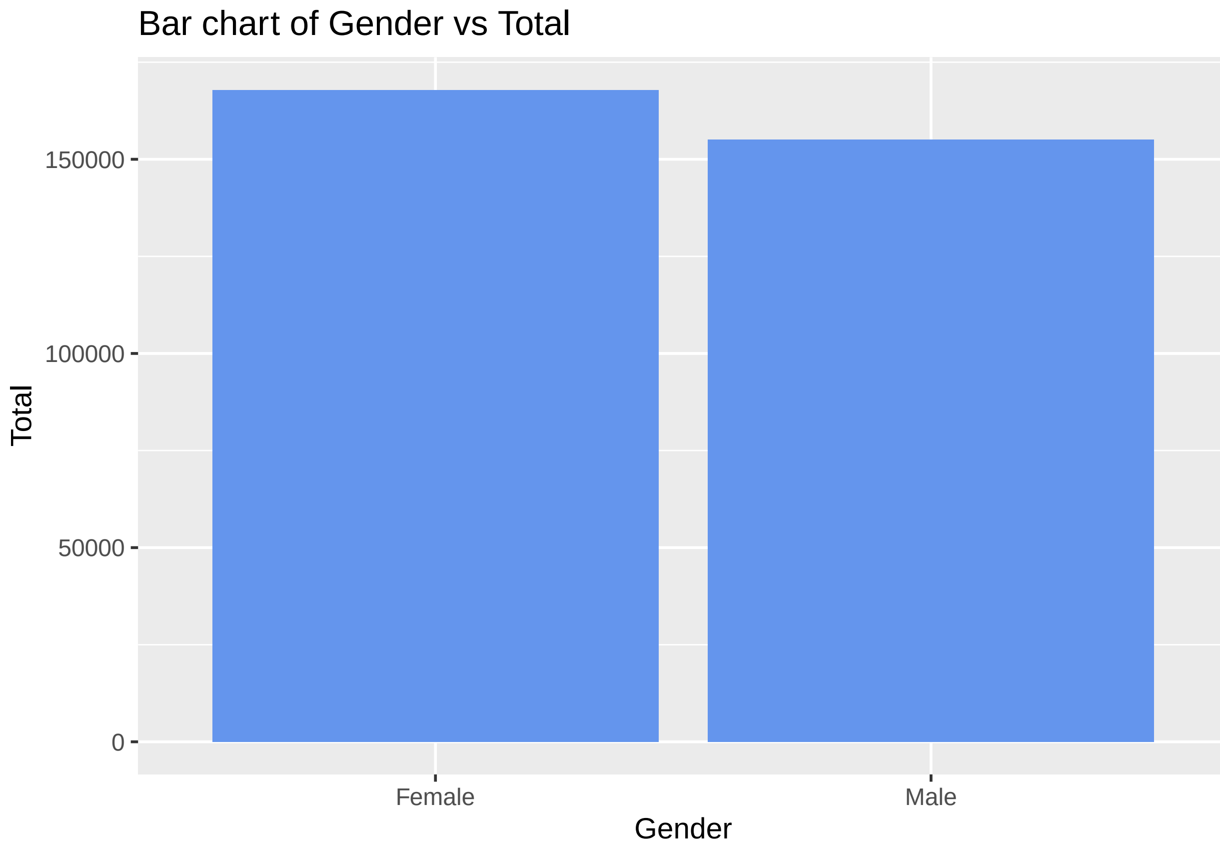


Member customer type have the highest number of sales

```
# Bar chart of Gender vs Total
agg_4 <- aggregate(smarket$Total,list(smarket$Gender),sum)
agg_4
```

```
##   Group.1        x
## 1  Female 167882.9
## 2    Male 155083.8
```

```
ggplot(data = agg_4 , aes(x= Group.1, y =x)) + geom_col(fill ="cornflowerblue") +
  labs(y="Total", x="Gender")+ggtitle("Bar chart of Gender vs Total")
```

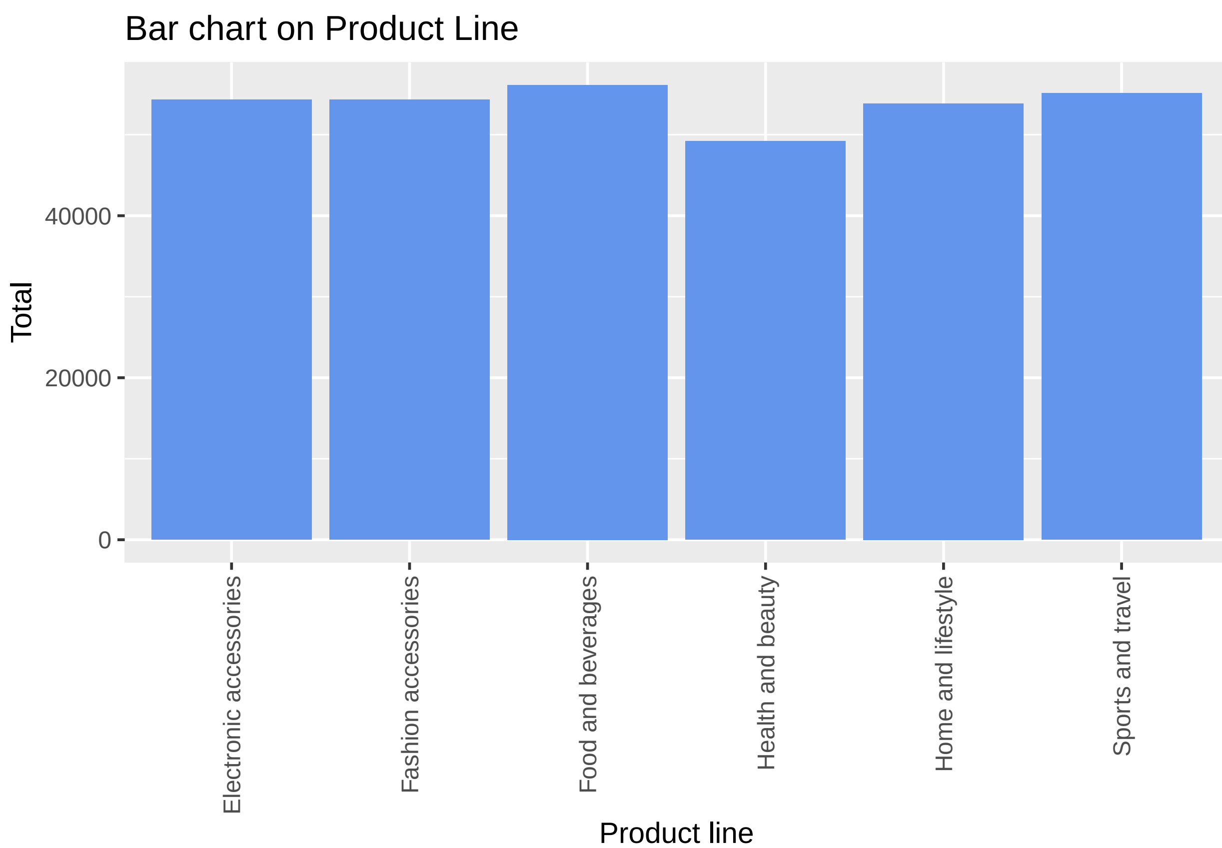


Female customers have highest number of sales

```
# Bar chart of Product line vs Total
agg_5 <- aggregate(smarket$Total,list(smarket$Product.line),sum)
agg_5
```

```
##                 Group.1        x
## 1 Electronic accessories 54337.53
## 2    Fashion accessories 54305.89
## 3     Food and beverages 56144.84
## 4      Health and beauty 49193.74
## 5     Home and lifestyle 53861.91
## 6      Sports and travel 55122.83
```

```
gg.agg <- ggplot (data = agg_5, aes(x= Group.1, y =x)) +
  geom_col(fill = "cornflowerblue") + theme(axis.text.x = element_text(
    angle = 90, vjust =.5, hjust = 1
  )) + labs(y="Total", x="Product line")+ggtitle("Bar chart of Product line vs Total")
gg.agg + ggtitle("Bar chart on Product Line")
```

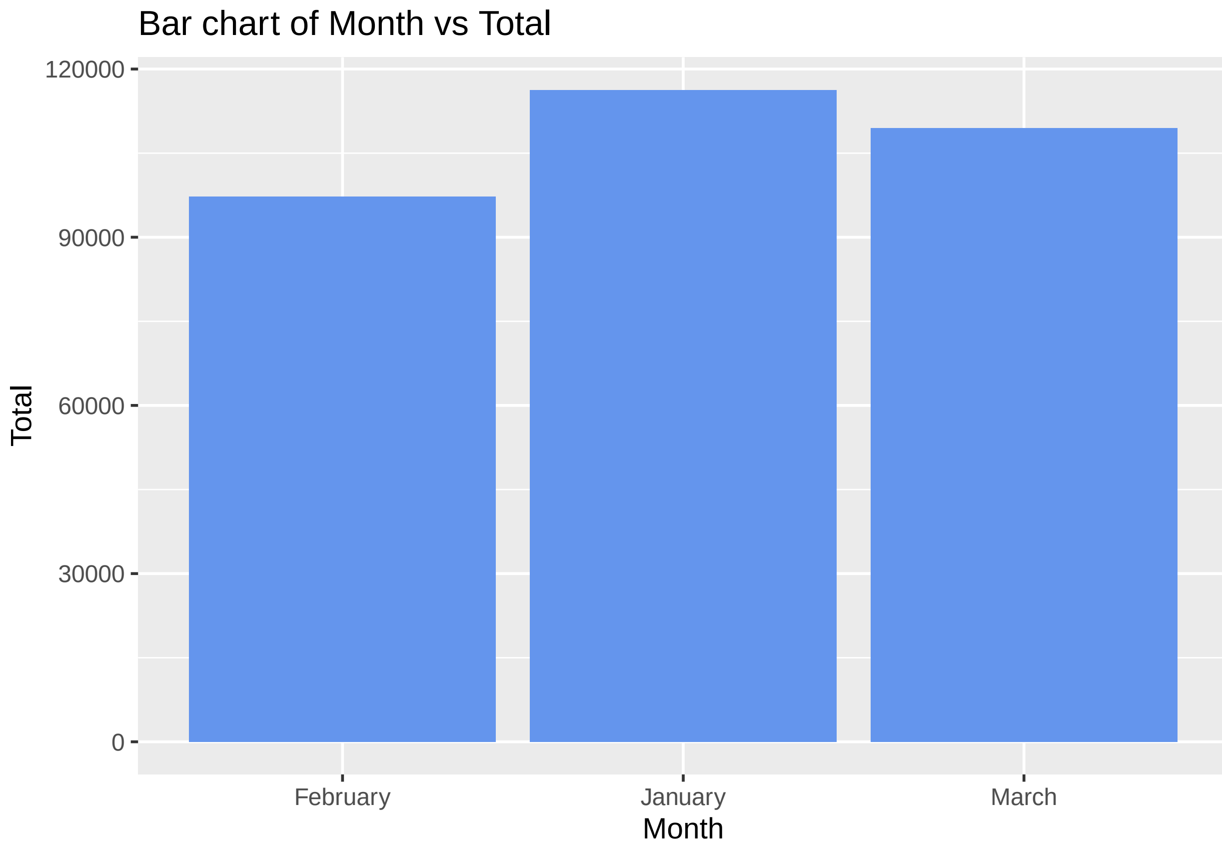


Food and beverages have the highest number of sales

```
# Bar chart of Month vs Total
agg_6 <- aggregate(smarket$Total,list(smarket$Month),sum)
agg_6
```

```
##    Group.1         x
## 1 February  97219.37
## 2  January 116291.87
## 3    March 109455.51
```

```
ggplot(data = agg_6 , aes(x= Group.1, y =x)) + geom_col(fill ="cornflowerblue") +
  labs(y="Total", x="Month")+ggtitle("Bar chart of Month vs Total")
```



January is the month with the highest number of sales

Data Preprocessing

```
# We will start with converting our categorical data to numerical data type
# Convert our variables to factor datatype
final.market <- smarket
final.market$Branch<- as.factor(final.market$Branch)
final.market$Product.line <- as.factor(final.market$Product.line)
final.market$Month <- as.factor(final.market$Month)
final.market$Customer.type <- as.factor(final.market$Customer.type)
final.market$Gender <- as.factor(final.market$Gender)
final.market$Payment<- as.factor(final.market$Payment)
```

```
# Convert our variables from factor to numeric datatype
final.market$Branch<- as.numeric(final.market$Branch)
final.market$Product.line <- as.numeric(final.market$Product.line)
final.market$Month <- as.numeric(final.market$Month)
final.market$Customer.type <- as.numeric(final.market$Customer.type)
final.market$Gender <- as.numeric(final.market$Gender)
final.market$Payment<- as.numeric(final.market$Payment)
```

```r
# Confirm changes made
head(final.market)
```

```
##    Invoice.ID Branch Customer.type Gender Product.line Unit.price Quantity
## 1 750-67-8428      1             1      1            4      74.69        7
## 2 226-31-3081      3             2      1            1      15.28        5
## 3 631-41-3108      1             2      2            5      46.33        7
## 4 123-19-1176      1             1      2            4      58.22        8
## 5 373-73-7910      1             2      2            6      86.31        7
## 6 699-14-3026      3             2      2            1      85.39        7
##       Tax       Date  Time Payment   cogs gross.margin.percentage gross.income
## 1 26.1415 2019-01-05 13:08       3 522.83                4.761905      26.1415
## 2  3.8200 2019-03-08 10:29       1  76.40                4.761905       3.8200
## 3 16.2155 2019-03-03 13:23       2 324.31                4.761905      16.2155
## 4 23.2880 2019-01-27 20:33       3 465.76                4.761905      23.2880
## 5 30.2085 2019-02-08 10:37       3 604.17                4.761905      30.2085
## 6 29.8865 2019-03-25 18:30       3 597.73                4.761905      29.8865
##   Rating    Total Month
## 1    9.1 548.9715     2
## 2    9.6  80.2200     3
## 3    7.4 340.5255     3
## 4    8.4 489.0480     2
## 5    5.3 634.3785     1
## 6    4.1 627.6165     3
```

```r
# We will carry out our analysis without invoice variable because it's a
# unique variables, gross.margin.percentage variable only has one value hence
# 0 variance, instead of using the date and time variable we will use month
final <- final.market[,c(-1,-9,-10,-13)]
# View the new dataset
head(final)
```

```
##   Branch Customer.type Gender Product.line Unit.price Quantity     Tax Payment
## 1      1             1      1            4      74.69        7 26.1415       3
## 2      3             2      1            1      15.28        5  3.8200       1
## 3      1             2      2            5      46.33        7 16.2155       2
## 4      1             1      2            4      58.22        8 23.2880       3
## 5      1             2      2            6      86.31        7 30.2085       3
## 6      3             2      2            1      85.39        7 29.8865       3
##     cogs gross.income Rating    Total Month
## 1 522.83      26.1415    9.1 548.9715     2
## 2  76.40       3.8200    9.6  80.2200     3
## 3 324.31      16.2155    7.4 340.5255     3
## 4 465.76      23.2880    8.4 489.0480     2
## 5 604.17      30.2085    5.3 634.3785     1
## 6 597.73      29.8865    4.1 627.6165     3
```

Feature Selection

```r
# Loading the relevant packages
library(caret)
```

```
## Warning: package 'caret' was built under R version 4.1.3

## Loading required package: lattice

##
## Attaching package: 'caret'

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

```r
library(corrplot)
```

```
## Warning: package 'corrplot' was built under R version 4.1.3

## corrplot 0.92 loaded
```

Filter Method

```r
# Calculating the correlation matrix
corr_final <- cor(final[,-12])
corr_final
```

```
##                    Branch Customer.type       Gender Product.line   Unit.price
## Branch         1.00000000   -0.01960787 -0.056317558 -0.053937557  0.028202440
## Customer.type -0.01960787    1.00000000  0.039996160 -0.036800311 -0.020237875
## Gender        -0.05631756    0.03999616  1.000000000  0.005193197  0.015444630
## Product.line  -0.05393756   -0.03680031  0.005193197  1.000000000  0.019321028
## Unit.price     0.02820244   -0.02023787  0.015444630  0.019321028  1.000000000
## Quantity       0.01596379   -0.01676271 -0.074258307  0.020256001  0.010777564
## Tax            0.04104666   -0.01967028 -0.049450989  0.031620725  0.633962089
## Payment       -0.05010429    0.01807344  0.044577609  0.029896383 -0.015941048
## cogs           0.04104666   -0.01967028 -0.049450989  0.031620725  0.633962089
## gross.income   0.04104666   -0.01967028 -0.049450989  0.031620725  0.633962089
## Rating         0.01023848    0.01888867  0.004800208 -0.020528973 -0.008777507
## Month         -0.04033140    0.04488694  0.059814418  0.044994245 -0.034715674
##                   Quantity          Tax      Payment         cogs gross.income
## Branch         0.015963788  0.041046665 -0.050104288  0.041046665  0.041046665
## Customer.type -0.016762706 -0.019670283  0.018073436 -0.019670283 -0.019670283
## Gender        -0.074258307 -0.049450989  0.044577609 -0.049450989 -0.049450989
## Product.line   0.020256001  0.031620725  0.029896383  0.031620725  0.031620725
## Unit.price     0.010777564  0.633962089 -0.015941048  0.633962089  0.633962089
## Quantity       1.000000000  0.705510186 -0.003920990  0.705510186  0.705510186
## Tax            0.705510186  1.000000000 -0.012433637  1.000000000  1.000000000
## Payment       -0.003920990 -0.012433637  1.000000000 -0.012433637 -0.012433637
```

```
## cogs           0.705510186  1.000000000 -0.012433637  1.000000000  1.000000000
## gross.income   0.705510186  1.000000000 -0.012433637  1.000000000  1.000000000
## Rating        -0.015814905 -0.036441705 -0.005381289 -0.036441705 -0.036441705
## Month          0.002375544 -0.006724205  0.041898766 -0.006724205 -0.006724205
##                     Rating        Month
## Branch         0.010238476 -0.040331403
## Customer.type  0.018888672  0.044886937
## Gender         0.004800208  0.059814418
## Product.line  -0.020528973  0.044994245
## Unit.price    -0.008777507 -0.034715674
## Quantity      -0.015814905  0.002375544
## Tax           -0.036441705 -0.006724205
## Payment       -0.005381289  0.041898766
## cogs          -0.036441705 -0.006724205
## gross.income  -0.036441705 -0.006724205
## Rating         1.000000000 -0.054714932
## Month         -0.054714932  1.000000000
```

```
# Find attributes that are highly correlated
# Cut off value of 0.70
high.corr <- findCorrelation(corr_final, cutoff=0.70)
high.corr
```

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

```
# Highly correlated attributes
names(final[,high.corr])
```

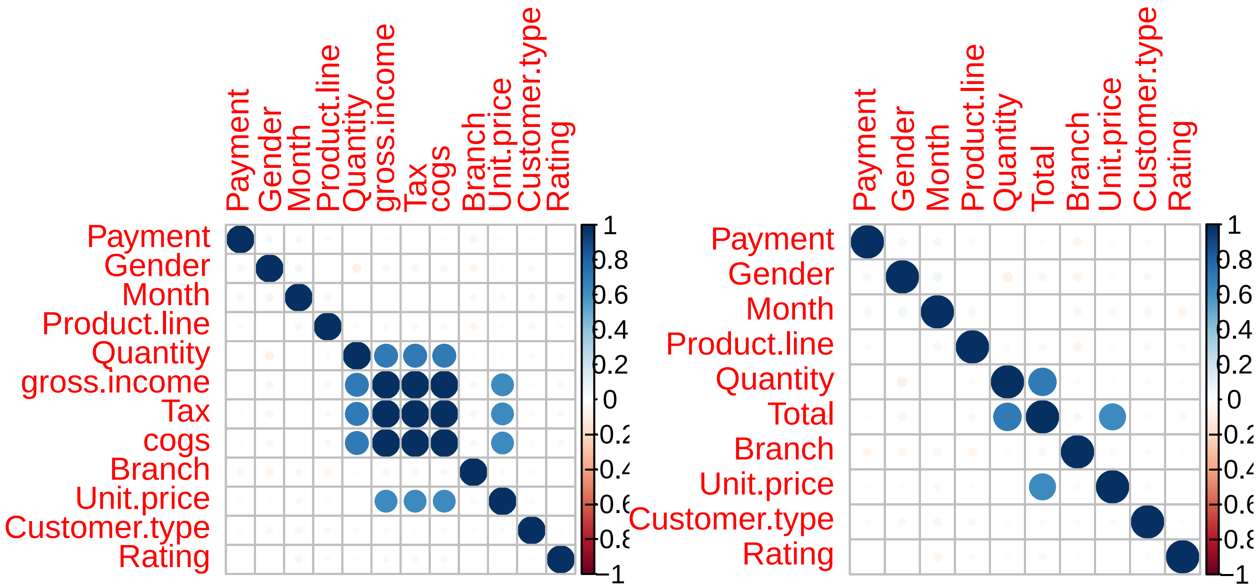
```
## [1] "Tax"          "cogs"         "gross.income"
```

Variables with higher correlation are Tax , Cogs and gross income

```
# We will remove the variables with a higher correlation
# and compare the results graphically

# Removing Highly correlated attributes Features
final_1 <- final[-high.corr]

# Performing our graphical comparison
par(mfrow = c(1, 2))
corrplot(corr_final, order = "hclust")
corrplot(cor(final_1), order = "hclust")
```



Wrapper Method

```
# Loading packages
library(clustvarsel)
```

```
## Warning: package 'clustvarsel' was built under R version 4.1.3

## Loading required package: mclust

## Warning: package 'mclust' was built under R version 4.1.3

## Package 'mclust' version 5.4.9
## Type 'citation("mclust")' for citing this R package in publications.

##
## Attaching package: 'mclust'

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

## Package 'clustvarsel' version 2.3.4
```

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

```
library(mclust)
# Sequential forward greedy search (default)
frwrd = clustvarsel(final[,-12], G = 1:5)
frwrd
```

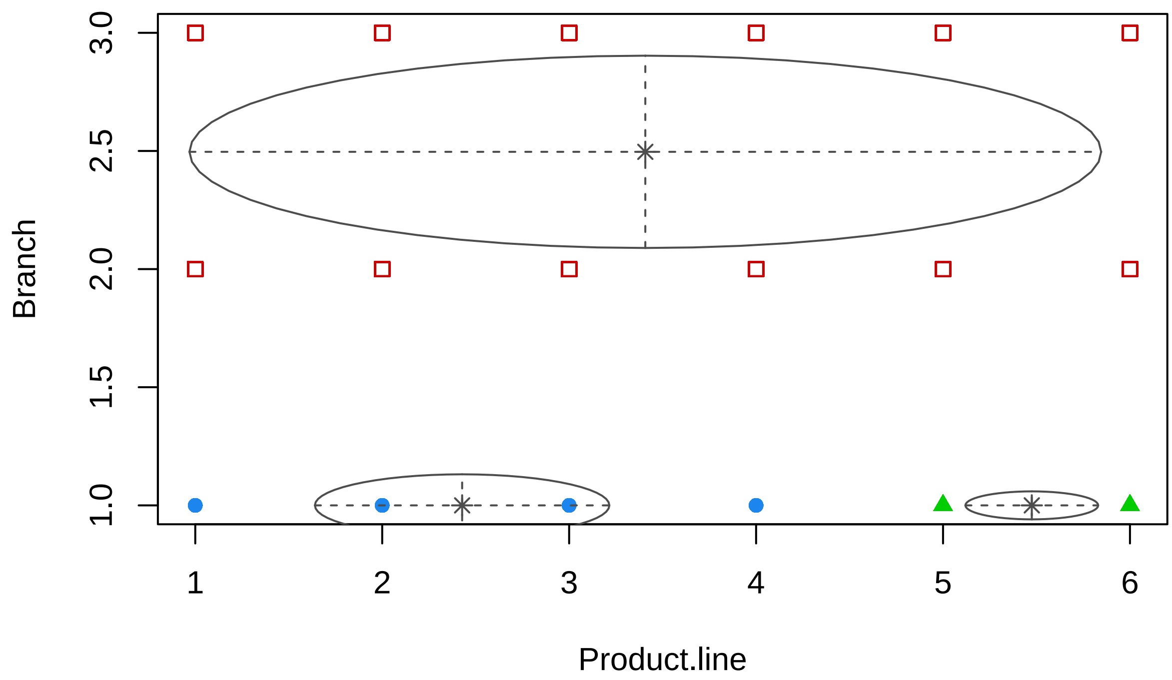
```
## ------------------------------------------------------
## Variable selection for Gaussian model-based clustering
## Stepwise (forward/backward) greedy search
## ------------------------------------------------------
##
##  Variable proposed Type of step  BICclust Model G   BICdiff Decision
##       Product.line          Add -3521.631     E 5 408.36743 Accepted
##             Branch          Add -5233.923   VEV 5 735.71798 Accepted
##      Customer.type          Add -6722.774   VEV 4 -23.45627 Rejected
##             Branch       Remove -3498.098     E 5 712.18492 Rejected
##
## Selected subset: Product.line, Branch
```

The selection algorithm indicates that the subset we use for the clustering model is composed of variables product line and Branch

```
# Let's build clustering model:
Subset = final[,-12][,frwrd$subset]
mod = Mclust(Subset, G = 1:5)
summary(mod)
```

```
## ----------------------------------------------------
## Gaussian finite mixture model fitted by EM algorithm
## ----------------------------------------------------
##
## Mclust VEI (diagonal, equal shape) model with 3 components:
##
##  log-likelihood    n df       BIC       ICL
##       -2723.585 1000 12 -5530.063 -5531.496
##
## Clustering table:
##   1   2   3
## 216 660 124
```

```
# Plot the clustering model
plot(mod,c("classification"))
```



Feature Ranking

```
# Import the library
library(FSelector)
```

```
## Warning: package 'FSelector' was built under R version 4.1.3
```

```
# We'll use the correlation coefficient as a unit of valuation.
fr <- linear.correlation(Total~., final)
fr
```

```
##                attr_importance
## Branch             0.041046665
## Customer.type      0.019670283
## Gender             0.049450989
## Product.line       0.031620725
## Unit.price         0.633962089
## Quantity           0.705510186
## Tax                1.000000000
## Payment            0.012433637
## cogs               1.000000000
## gross.income       1.000000000
```

```
## Rating            0.036441705
## Month             0.006724205
```

```
# Top five representative variables
var <- cutoff.k(fr, 5)
as.data.frame(var)
```

```
##              var
## 1            Tax
## 2           cogs
## 3 gross.income
## 4       Quantity
## 5     Unit.price
```

```
# Instead of using the scores for the correlation coefficient,
# we can use information gain
fr.1 <- information.gain(Total~., final)

# Top five representative variables
var.1 <- cutoff.k(fr.1, 5)
as.data.frame(var.1)
```

```
##            var.1
## 1            Tax
## 2           cogs
## 3 gross.income
## 4       Quantity
## 5     Unit.price
```

The top 5 representative variables are the same for both correlation coefficient and information gain scores. They are Tax,cogs,gross.income,quantity and unit.price.

Embedded Methods

```
# load the wskm package
library(wskm)
```

```
## Warning: package 'wskm' was built under R version 4.1.3

## Loading required package: latticeExtra

## Warning: package 'latticeExtra' was built under R version 4.1.3

##
## Attaching package: 'latticeExtra'

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

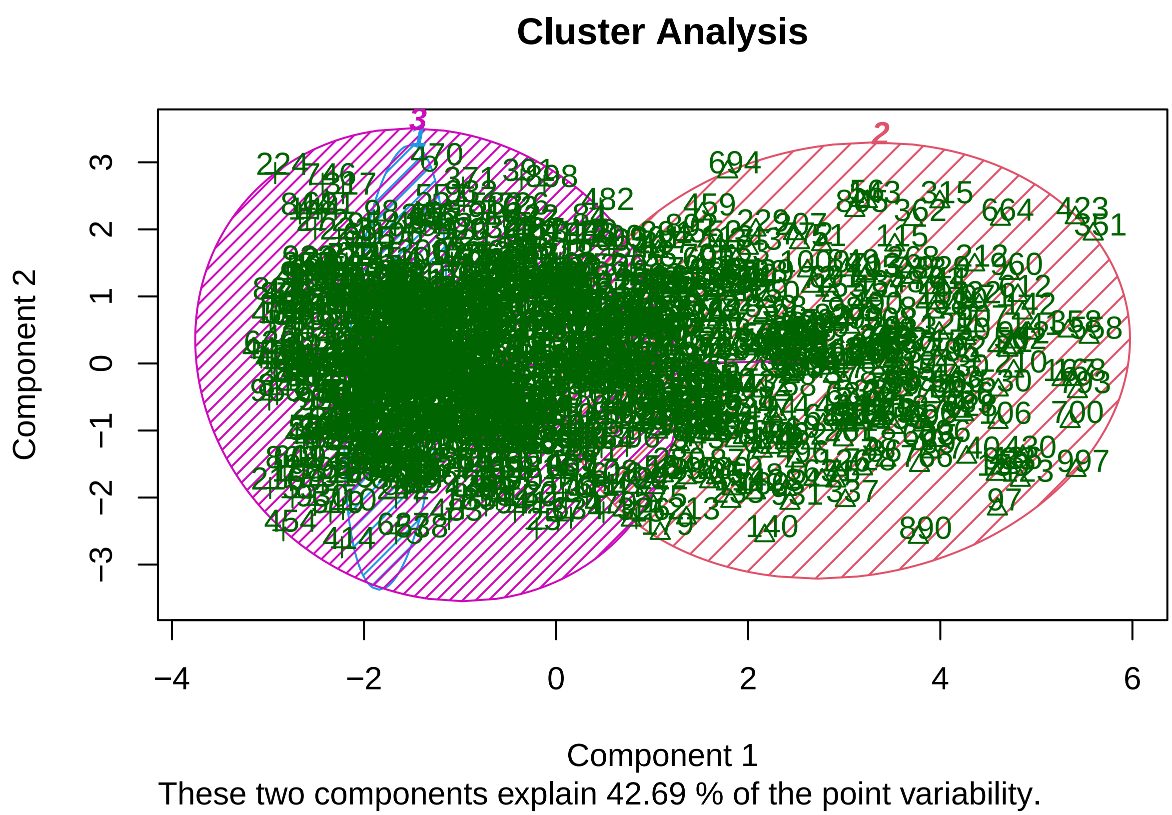
```
## Loading required package: fpc

## Warning: package 'fpc' was built under R version 4.1.3
```

```
# Set up the model
set.seed(2)
model <- ewkm(final[,-12], 3, lambda=2, maxiter=1000)
```

```
# Loading and installing our cluster package
library("cluster")

# Cluster Plot against 1st 2 principal components
clusplot(final[,-12], model$cluster, color=TRUE, shade=TRUE,
         labels=2, lines=1,main='Cluster Analysis')
```




```
# 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    Tax Payment
```

```
## 1      0          0.13   0.14            0           0         0 49.86        0
## 2      0         48.12  51.87            0           0         0  0.00        0
## 3      0         50.00  50.00            0           0         0  0.00        0
##   cogs gross.income Rating Month
## 1    0        49.86      0     0
## 2    0         0.00      0     0
## 3    0         0.00      0     0
```

Customer type and gender hold weight across the 3 clusters.