

# Week 14 - Dimensionality Reduction

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## CarreFour Marketing - Dimensionality Reduction

### Defining The Question

#### Specifying the Question

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

#### Metric of success

- Importing the data
- Cleaning the data
- performing a thorough EDA
- Performing Dimensionality Reduction

#### Data relevance

The data has been provided by the supermarket itself

#### 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.

#### Experimental design

The experimental design will involve the following steps:

- Dealing with missing values.
- Dropping variables of low variance.
- Use of decision trees to tackle missing values, outliers and identifying significant variables.
- Use of random forest to select a smaller subset of input features.
- Using the Pearson correlation matrix to identify and later drop variables with high correlation.
- Performing backward feature elimination.
- Performing factor analysis to group high correlated variables.
- Using Principal Component Analysis (PCA).

## Reading The Data

```
# Importing Libraries
```

```
library (tidyr)
library(naniar)
library (ggplot2)
library (e1071)
library (corrplot)
```

```
## corrplot 0.92 loaded
```

```
library(factoextra)
```

```
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
```

```
library(NbClust)
library(superml)
```

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

```
#installing packages
```

```
library(data.table)
```

```
#
```

```
#Loading the dataset
```

```
df <- fread("http://bit.ly/CarreFourDataset")
```

## Checking The Data

```
# Preview the data
```

```
head(df)
```

```
##      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
```

```
# Preview the data
tail(df)
```

```
##      Invoice ID Branch Customer type Gender      Product line Unit price
## 1: 652-49-6720      C      Member Female Electronic accessories      60.95
## 2: 233-67-5758      C      Normal  Male   Health and beauty      40.35
## 3: 303-96-2227      B      Normal Female Home and lifestyle      97.38
## 4: 727-02-1313      A      Member  Male   Food and beverages      31.84
## 5: 347-56-2442      A      Normal  Male   Home and lifestyle      65.82
## 6: 849-09-3807      A      Member Female Fashion accessories      88.34
##      Quantity      Tax      Date Time Payment      cogs gross margin percentage
## 1:          1  3.0475 2/18/2019 11:40 Ewallet  60.95              4.761905
## 2:          1  2.0175 1/29/2019 13:46 Ewallet  40.35              4.761905
## 3:         10 48.6900 3/2/2019 17:16 Ewallet 973.80              4.761905
## 4:          1  1.5920 2/9/2019 13:22   Cash  31.84              4.761905
## 5:          1  3.2910 2/22/2019 15:33   Cash  65.82              4.761905
## 6:          7 30.9190 2/18/2019 13:28   Cash 618.38              4.761905
##      gross income Rating      Total
## 1:          3.0475      5.9    63.9975
## 2:          2.0175      6.2    42.3675
## 3:         48.6900      4.4 1022.4900
## 4:          1.5920      7.7    33.4320
## 5:          3.2910      4.1    69.1110
## 6:         30.9190      6.6   649.2990
```

```
# Dimensionality of the data
dim(df)
```

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

The dataframe has 1000 rows and 16 columns

## Tidying The Dataset

```
# check the column names
colnames(df)
```

```
## [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"
```

```

# standardize column names with standard naming convention ie lowercase and replace spaces with '_'
# replace the spaces with underscores using gsub() function
names(df) <- gsub(" ", "_", names(df))

# The column names have a mixture of uppercase and lowercase characters we should correct that and
# make all the characters lowercase.
names(df) <- tolower(names(df))
# Confirmation
colnames(df)

```

```

## [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"

```

```

# Let us find the datatypes of the data
str(df)

```

```

## 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          : chr  "A" "C" "A" "A" ...
## $ customer_type    : chr  "Member" "Normal" "Normal" "Member" ...
## $ gender           : chr  "Female" "Female" "Male" "Male" ...
## $ product_line     : chr  "Health and beauty" "Electronic accessories" "Home and lifestyle" ...
## $ unit_price       : num  74.7 15.3 46.3 58.2 86.3 ...
## $ quantity         : int   7 5 7 8 7 7 6 10 2 3 ...
## $ tax              : num  26.14 3.82 16.22 23.29 30.21 ...
## $ date             : chr  "1/5/2019" "3/8/2019" "3/3/2019" "1/27/2019" ...
## $ time             : chr  "13:08" "10:29" "13:23" "20:33" ...
## $ payment          : chr  "Ewallet" "Cash" "Credit card" "Ewallet" ...
## $ cogs             : num  522.8 76.4 324.3 465.8 604.2 ...
## $ gross_margin_percentage: num  4.76 4.76 4.76 4.76 4.76 ...
## $ gross_income     : num  26.14 3.82 16.22 23.29 30.21 ...
## $ rating           : num  9.1 9.6 7.4 8.4 5.3 4.1 5.8 8 7.2 5.9 ...
## $ total            : num  549 80.2 340.5 489 634.4 ...
## - attr(*, ".internal.selfref")=<externalptr>

```

The dataset has character, integer and numerical datatypes Time and date are in the incorrect format

```

# Change date to date format
df$date <- as.Date(df$date, "%m/%d/%Y")

# Change time to time format
df$time <- as.ITime(df$time)

head(df)

```

```
##      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
## 1:          7 26.1415 2019-01-05 13:08:00      Ewallet 522.83
## 2:          5  3.8200 2019-03-08 10:29:00      Cash  76.40
## 3:          7 16.2155 2019-03-03 13:23:00 Credit card 324.31
## 4:          8 23.2880 2019-01-27 20:33:00      Ewallet 465.76
## 5:          7 30.2085 2019-02-08 10:37:00      Ewallet 604.17
## 6:          7 29.8865 2019-03-25 18:30:00      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
```

```
#Finding the total number of missing values in each column
colSums(is.na(df))
```

```
##      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
```

There are no missing values in the dataset

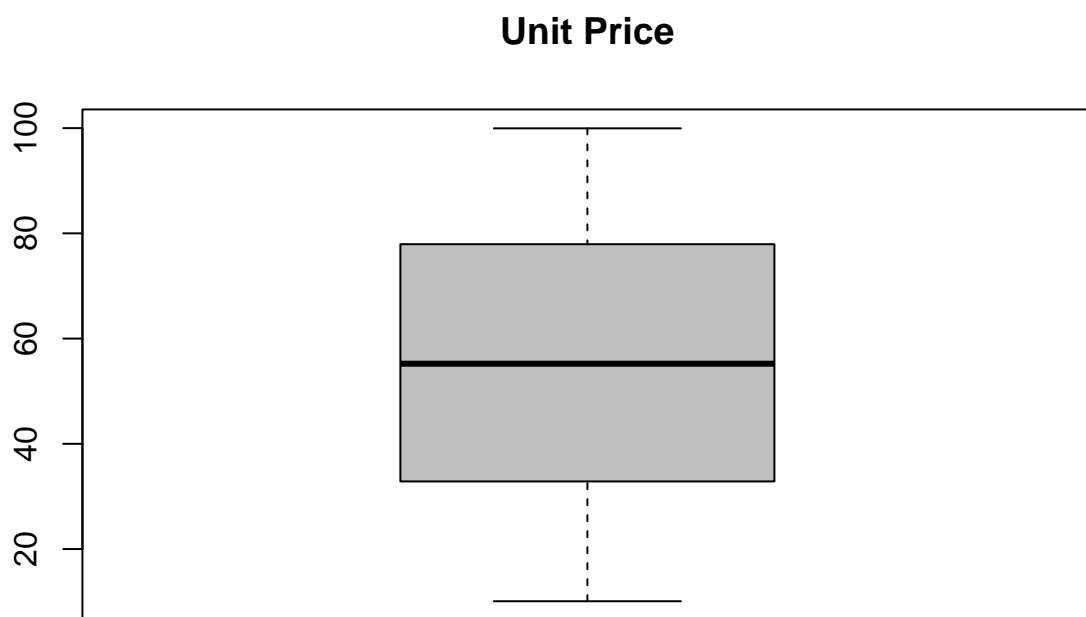
```
# Cheking for duplicates
df_dup <- df[duplicated(df),]
df_dup
```

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

There is no duplicate data in this dataset

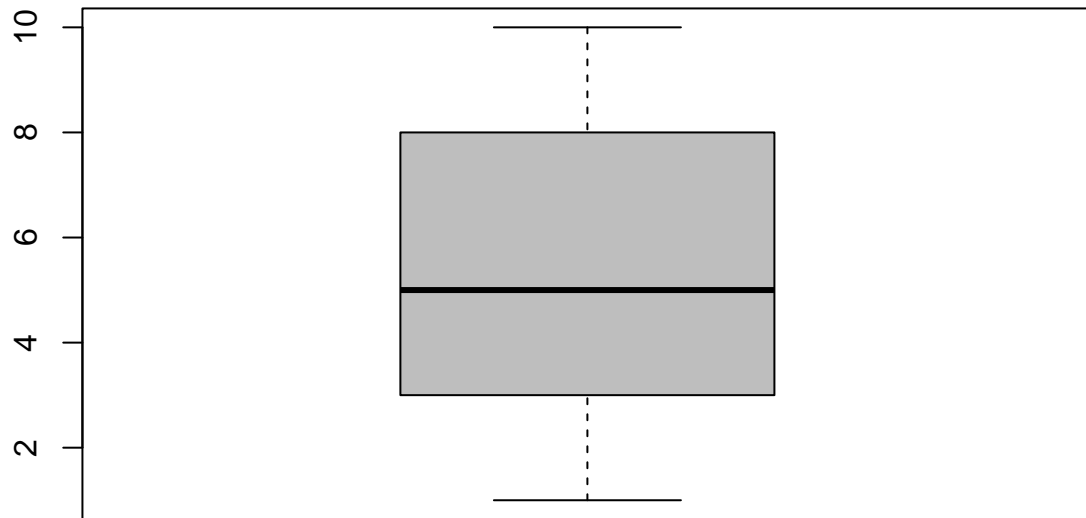
### Checking for outliers

```
# Plotting boxplots to check for outliers
boxplot(df$unit_price,col='grey', main = 'Unit Price')
```

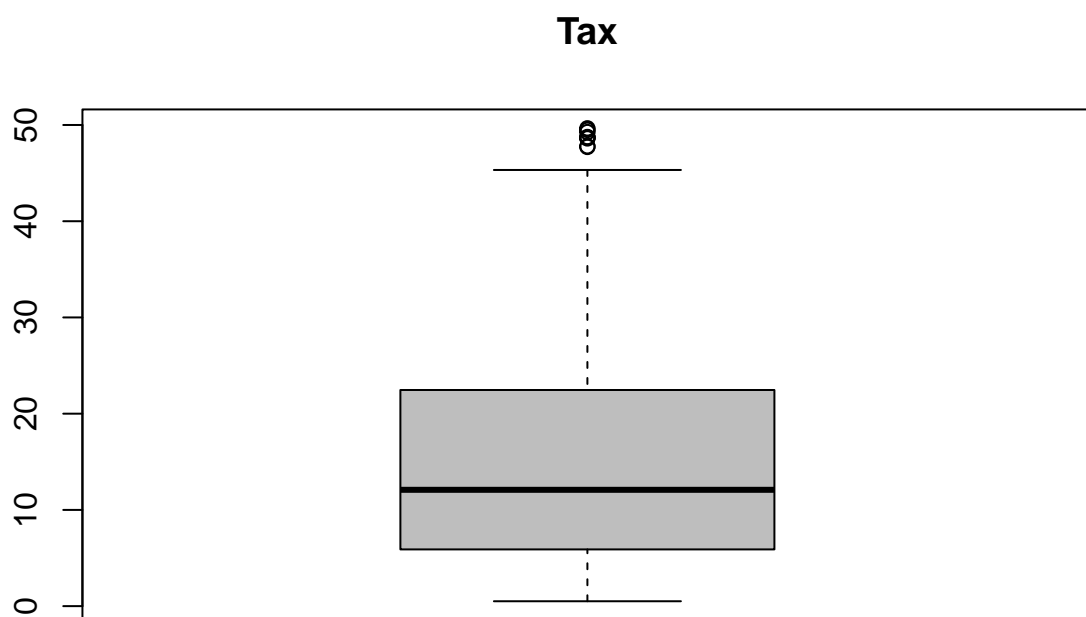


```
boxplot(df$quantity,col='grey', main = 'Quantity Boxplot')
```

**Quantity Boxplot**

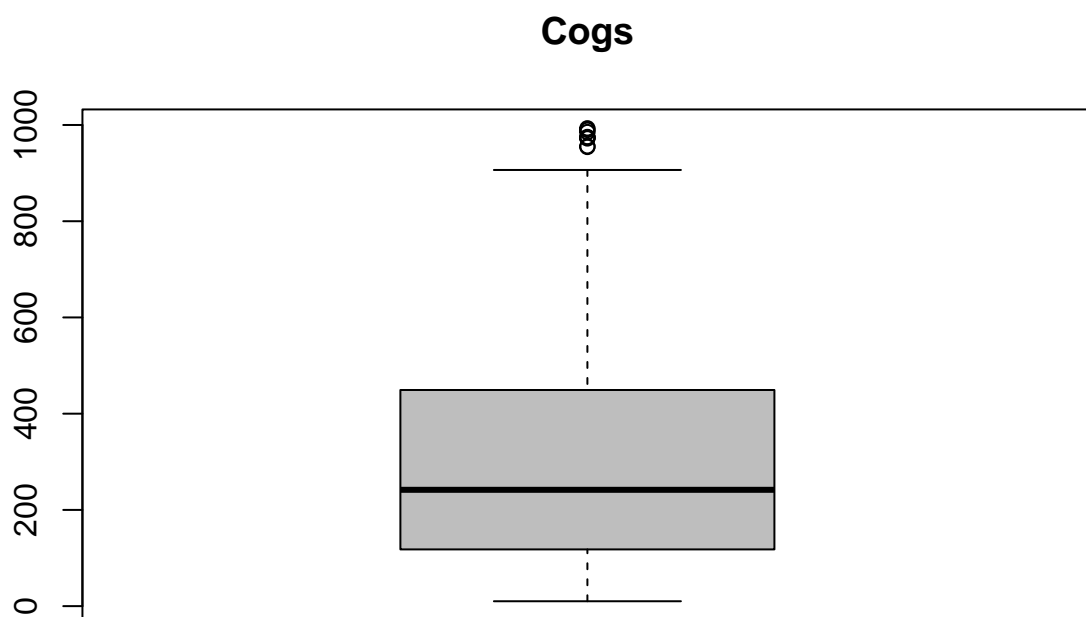


```
boxplot(df$tax,col='grey', main = 'Tax')
```



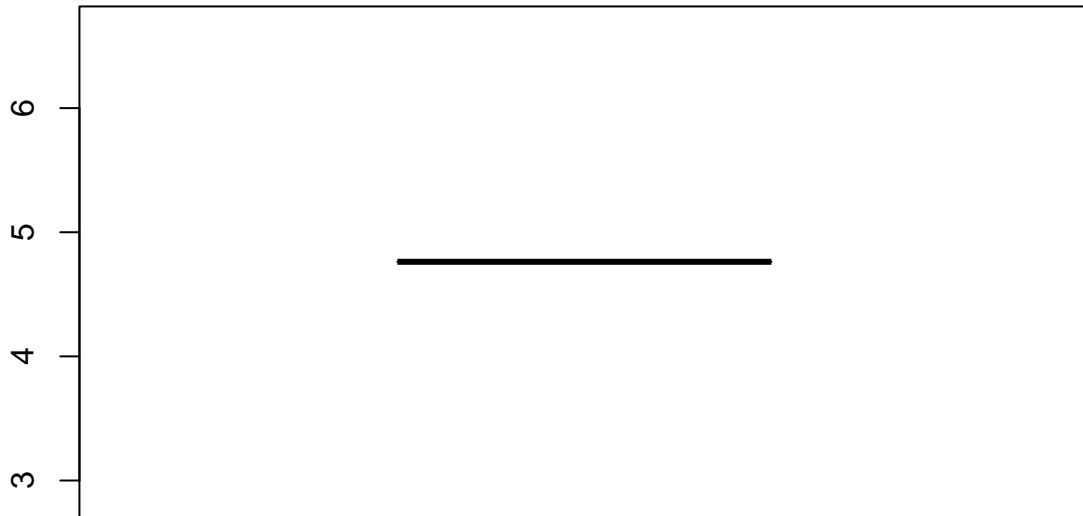
```
boxplot(df$cogs,col='grey', main = 'Cogs')
```





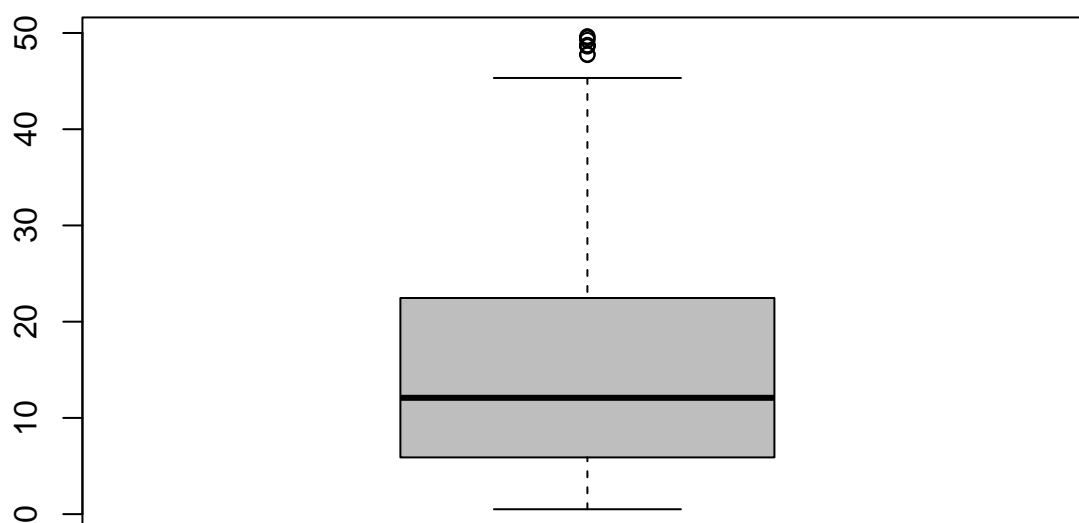
```
boxplot(df$gross_margin_percentage,col='grey', main = 'Gross Margin Percentage')
```

## Gross Margin Percentage

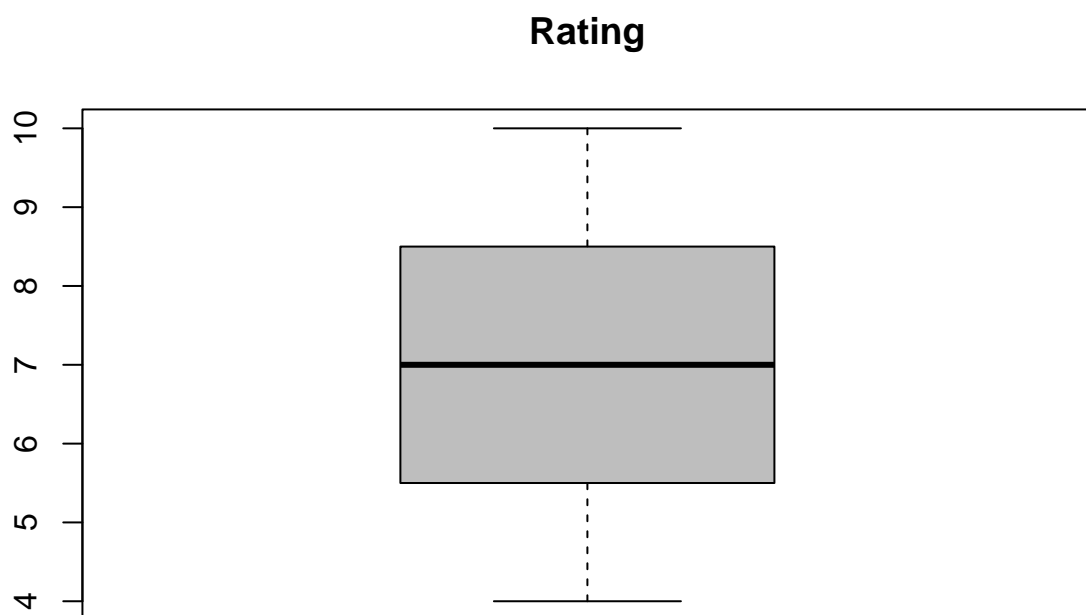


```
boxplot(df$gross_income,col='grey', main = 'Gross Income')
```

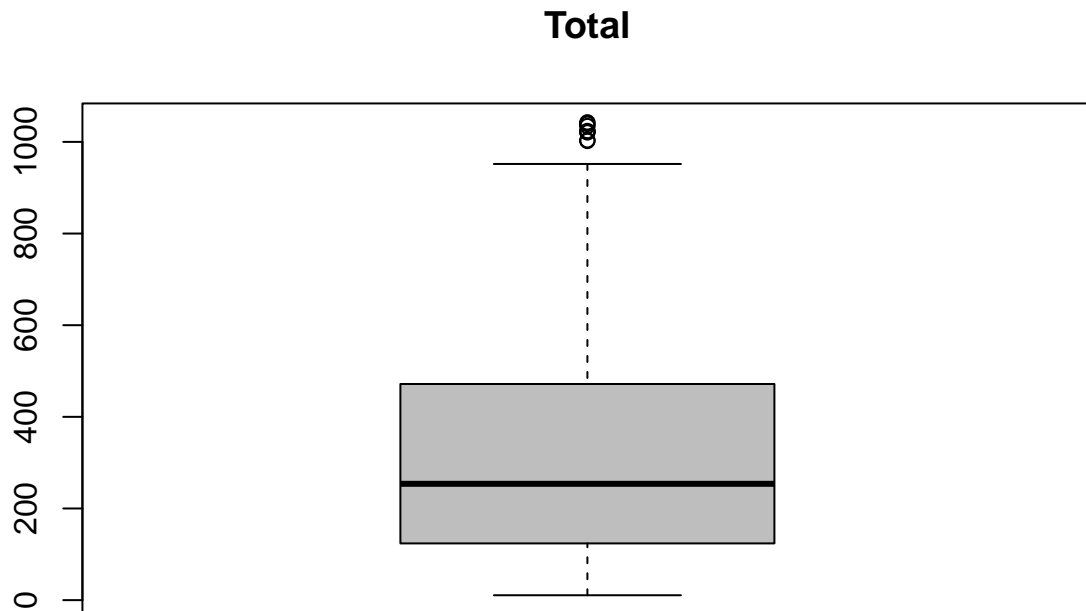
## Gross Income



```
boxplot(df$rating,col='grey', main = 'Rating')
```



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



Tax, Cogs, Gross Income, Total has some outliers but we will leave them because they are actual representation of the data

```
# removing irrelevant column - gross_margin_percentage it has the same amount through out
setDT(df)[, c( 'gross_margin_percentage') := NULL]
# check the dimensions of the dataframe after cleaning
dim(df)
```

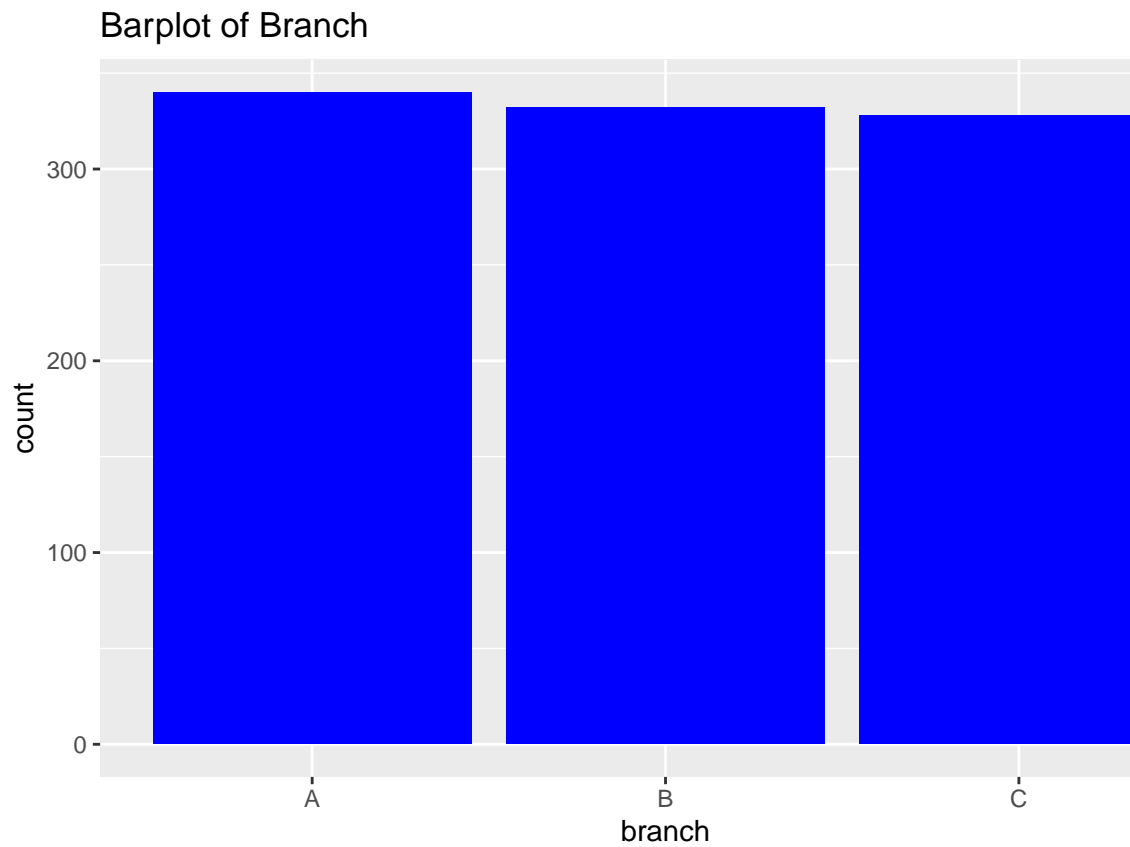
```
## [1] 1000  15
```

## Exploratory Data Analysis

### Univariate Analysis

```
# Frequency of Branch column

ggplot(df, aes(x = branch)) +
  geom_bar(fill="blue") + ggtitle('Barplot of Branch')
```

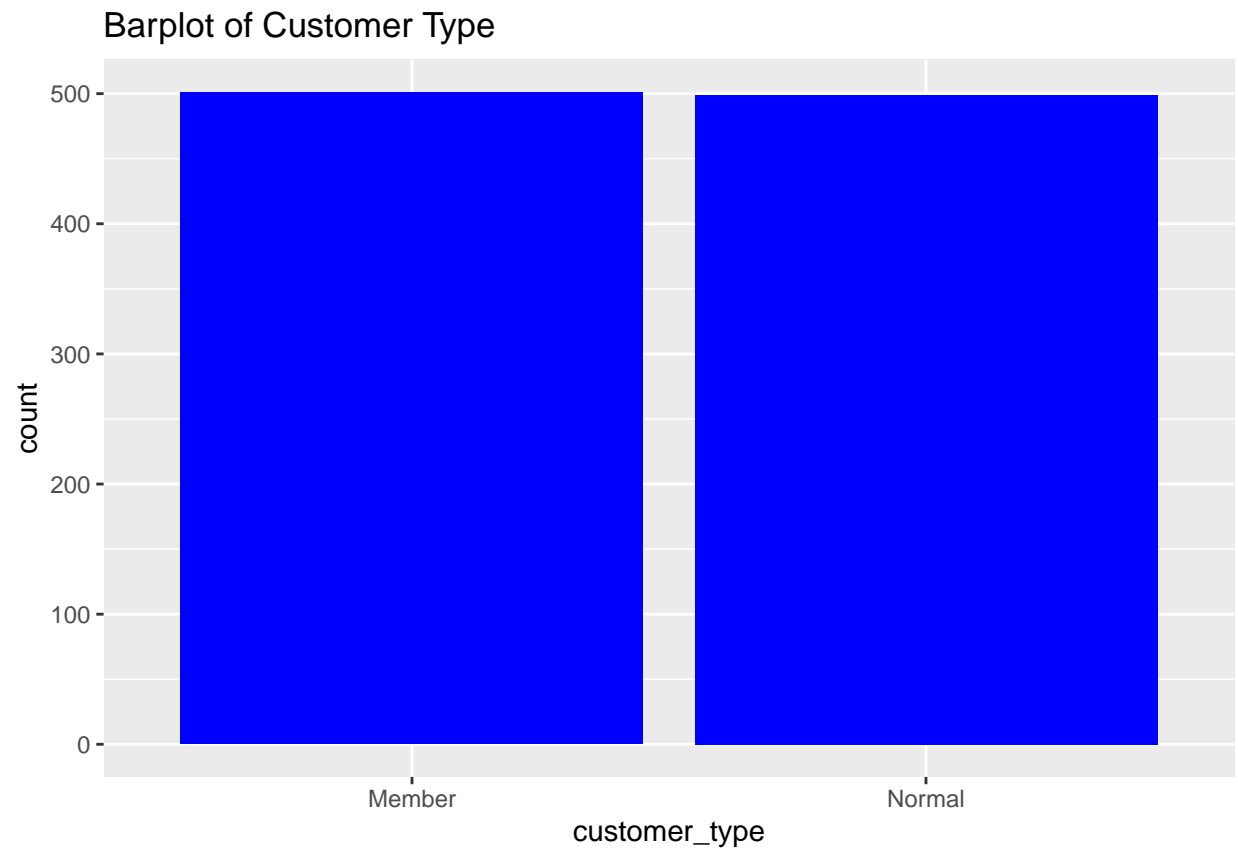


#### Categorical Variables

The data collected on Branches A is slightly more than branch B and C .

*# Frequency of Customer Type column*

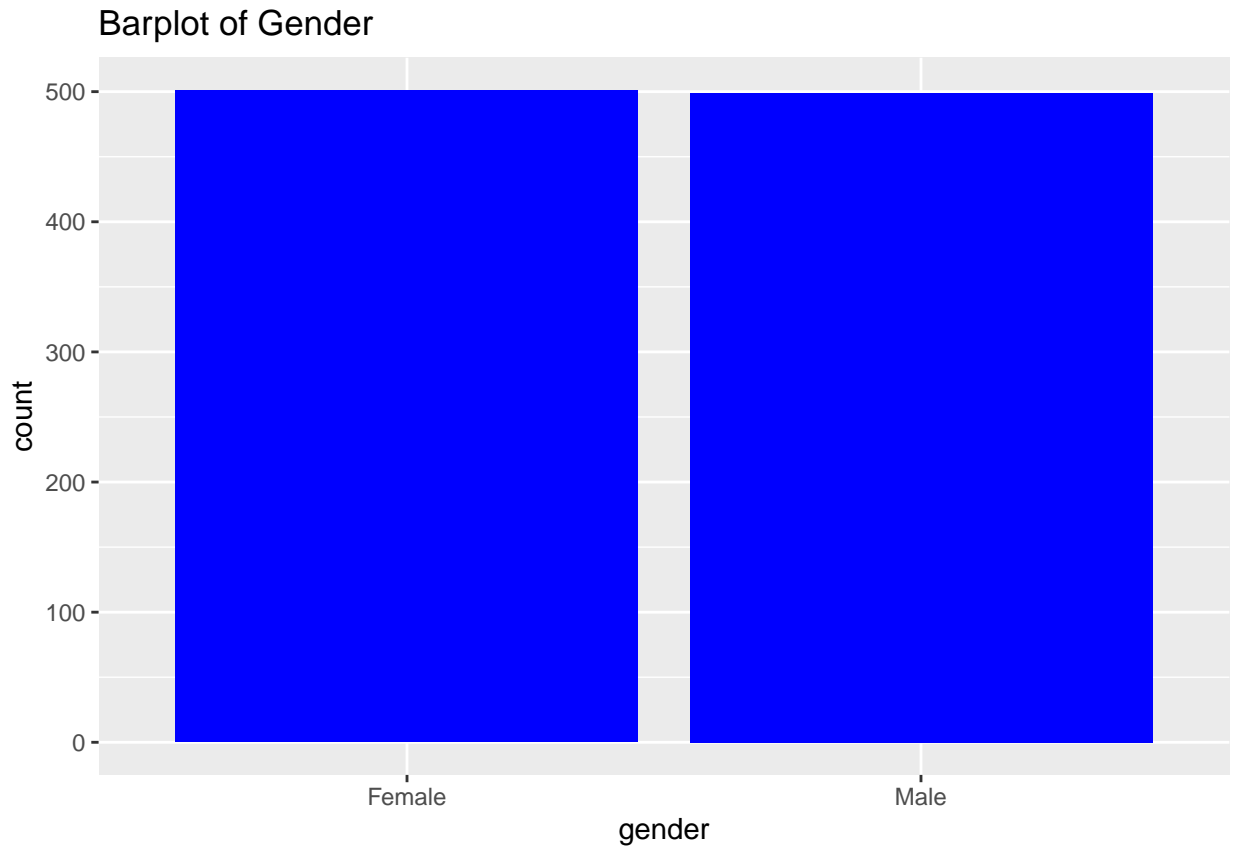
```
ggplot(df, aes(x = customer_type)) +  
  geom_bar(fill="blue") + ggtitle('Barplot of Customer Type')
```



The information collected was half from the members and half from the normal customers.

*# Frequency of Gender column*

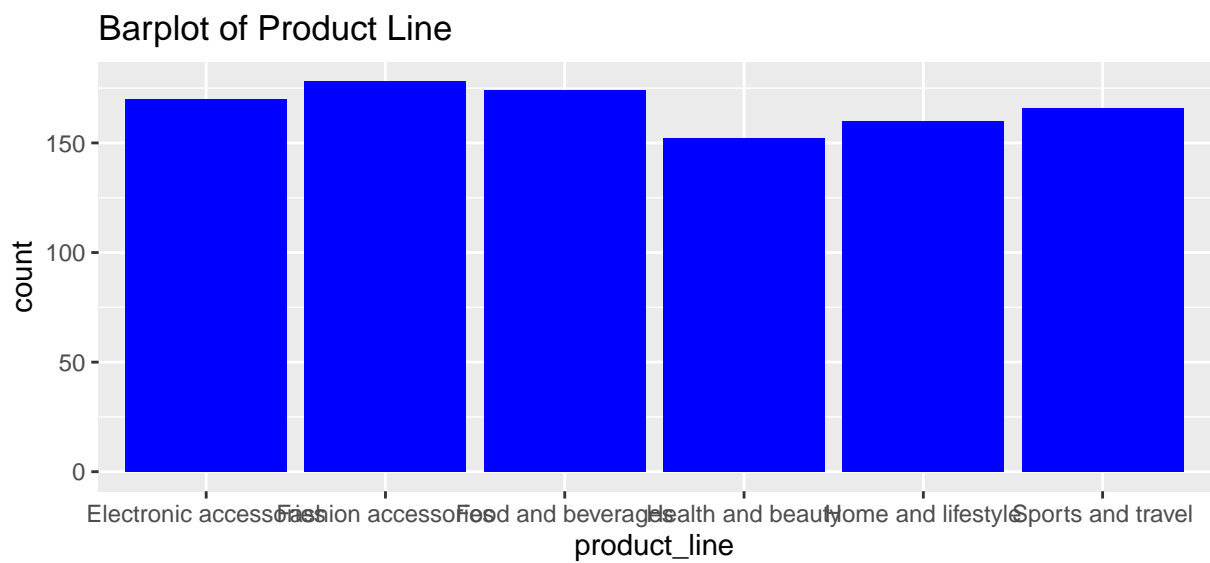
```
ggplot(df, aes(x = gender)) +  
  geom_bar(fill="blue") + ggtitle('Barplot of Gender')
```



The data from male and female persons is equal

*# Frequency of Product Line column*

```
ggplot(df, aes(x = product_line)) +  
  geom_bar(fill="blue") + ggtitle('Barplot of Product Line')
```

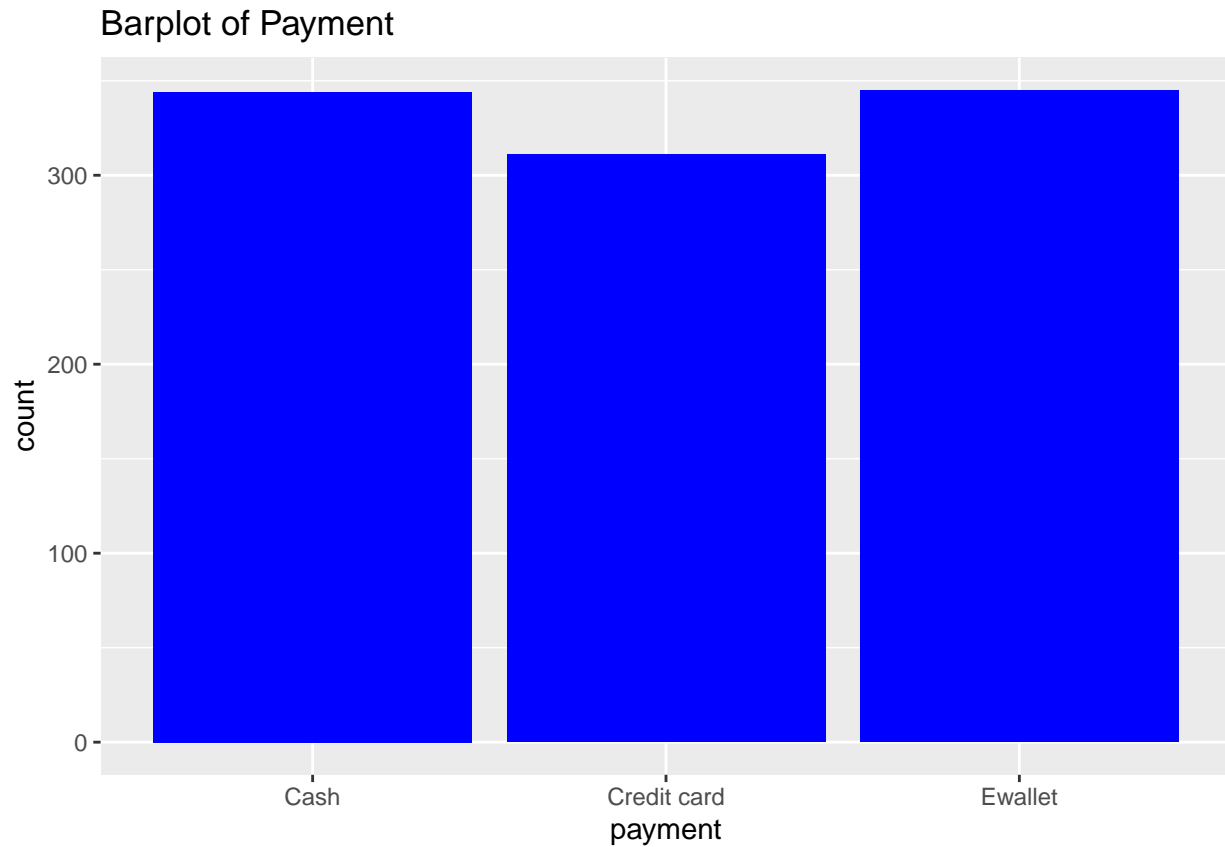


The most popular product line is Fashion accessories followed by food and beverages



```
# Frequency of Payment column
```

```
ggplot(df, aes(x = payment)) +  
  geom_bar(fill="blue") + ggtitle('Barplot of Payment')
```



Slightly More people paid their bills with E wallet and cash rather than Credit card

```
# numerical columns.
```

```
num_col <- unlist(lapply(df, is.numeric))  
df_num <- subset(df, select = num_col)  
head (df_num)
```

Numerical Variables

	unit_price	quantity	tax	time	cogs	gross_income	rating	total
## 1:	74.69	7	26.1415	13:08:00	522.83	26.1415	9.1	548.9715
## 2:	15.28	5	3.8200	10:29:00	76.40	3.8200	9.6	80.2200
## 3:	46.33	7	16.2155	13:23:00	324.31	16.2155	7.4	340.5255
## 4:	58.22	8	23.2880	20:33:00	465.76	23.2880	8.4	489.0480
## 5:	86.31	7	30.2085	10:37:00	604.17	30.2085	5.3	634.3785
## 6:	85.39	7	29.8865	18:30:00	597.73	29.8865	4.1	627.6165

```
#Getting the measures of dispersion in the numerical columns.
```

```
summary_stats <- data.frame(
  Mean = apply(df_num, 2, mean),
  Median = apply(df_num, 2, median),
  Min = apply(df_num, 2, min),
  Max = apply(df_num, 2, max))
summary_stats
```

	Mean	Median	Min	Max
unit_price	55.67213	55.230	10.0800	99.96
quantity	5.51000	5.000	1.0000	10.00
tax	15.37937	12.088	0.5085	49.65
time	55481.88000	55140.000	36000.0000	75540.00
cogs	307.58738	241.760	10.1700	993.00
gross_income	15.37937	12.088	0.5085	49.65
rating	6.97270	7.000	4.0000	10.00
total	322.96675	253.848	10.6785	1042.65

```
# compute the measures of cenral tendancy and the measures of dispersion of the numerical variables and
library(moments)
```

```
##
## Attaching package: 'moments'

## The following objects are masked from 'package:e1071':
##
## kurtosis, moment, skewness
```

```
statistics <- data.frame(
  Variance= apply(df_num, 2, var),
  Std = apply(df_num, 2, sd),
  Skewness = apply(df_num, 2, skewness),
  Kurtosis = apply(df_num, 2, kurtosis))
# round off the values to 2 decimal places and display the dataframe
statistics <- round(statistics, 2)
statistics
```

	Variance	Std	Skewness	Kurtosis
unit_price	701.97	26.49	0.01	1.78
quantity	8.55	2.92	0.01	1.78
tax	137.10	11.71	0.89	2.91
time	132058417.28	11491.67	0.02	1.77
cogs	54838.64	234.18	0.89	2.91
gross_income	137.10	11.71	0.89	2.91
rating	2.95	1.72	0.01	1.85
total	60459.60	245.89	0.89	2.91

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

```
}  
  
# Mode  
mode.unit_price <- getmode(df$unit_price)  
mode.unit_price
```

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

```
mode.quantity <- getmode(df$quantity)  
mode.quantity
```

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

```
mode.tax <- getmode(df$tax)  
mode.tax
```

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

```
mode.cogs <- getmode(df$cogs)  
mode.cogs
```

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

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

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

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

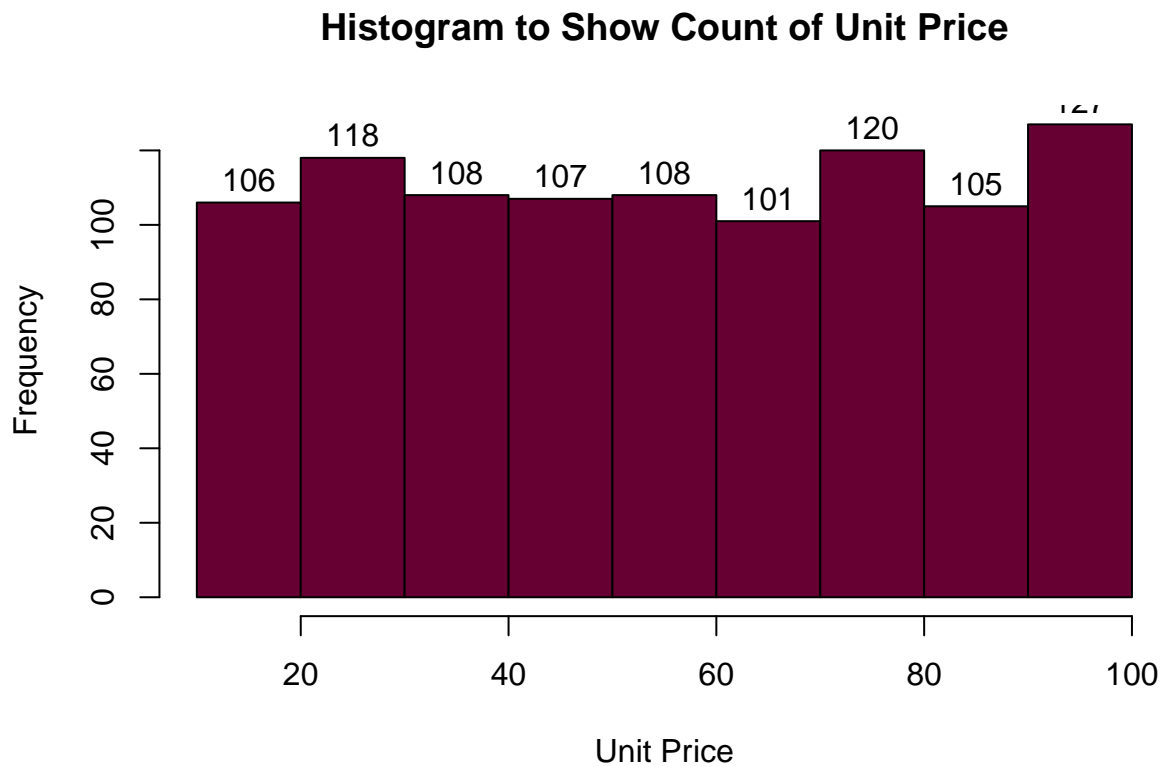
```
## [1] 6
```

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

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

## Histograms for Numerical Variables

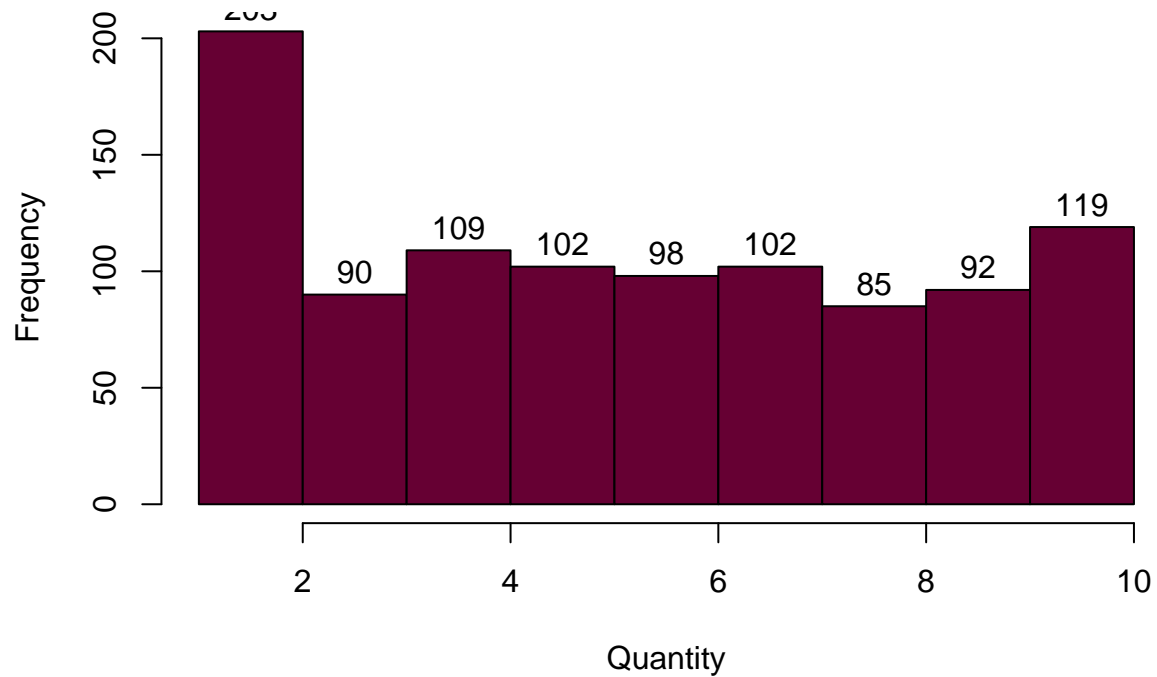
```
# plot a histogram to visualize the distribution of values in 'Unit Price' column  
hist(df$unit_price,  
      col="#660033",  
      main="Histogram to Show Count of Unit Price",  
      xlab="Unit Price",  
      ylab="Frequency",  
      labels=TRUE)
```



More items have a unit price of 90 - 100

```
# plot a histogram to visualize the distribution of values in 'Quantity' column
hist(df$quantity,
     col="#660033",
     main="Histogram to Show Count of Quantity",
     xlab="Quantity",
     ylab="Frequency",
     labels=TRUE)
```

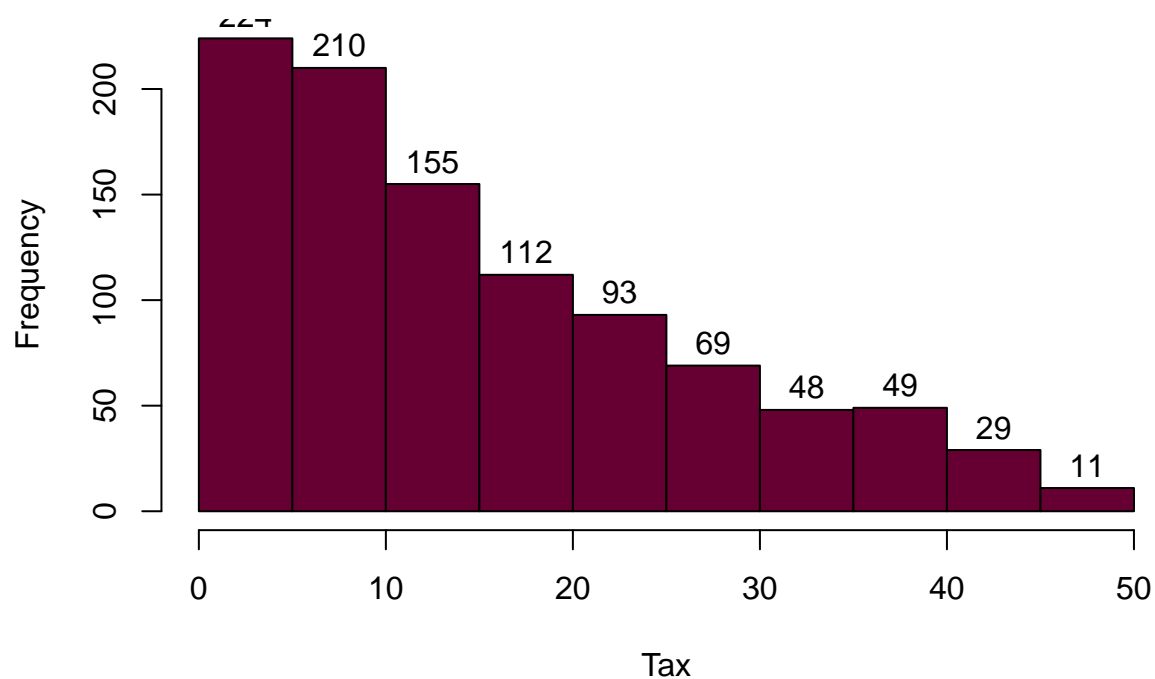
## Histogram to Show Count of Quantity



Most customers bought 1 item at a time

```
# plot a histogram to visualize the distribution of values in 'Tax' column
hist(df$tax,
      col="#660033",
      main="Histogram to Show Count of Tax",
      xlab="Tax",
      ylab="Frequency",
      labels=TRUE)
```

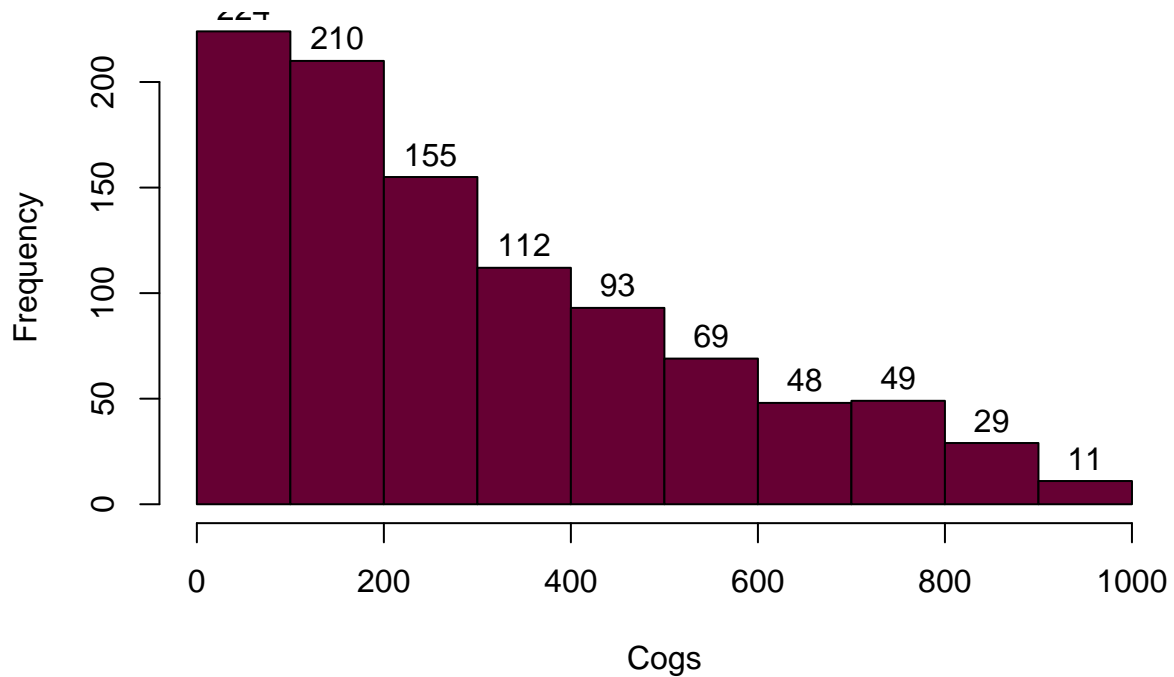
## Histogram to Show Count of Tax



The tax bracket 0 - 5 had a higher number of items

```
# plot a histogram to visualize the distribution of values in 'Cogs' column
hist(df$cogs,
      col="#660033",
      main="Histogram to Show Count of Cogs",
      xlab="Cogs",
      ylab="Frequency",
      labels=TRUE)
```

## Histogram to Show Count of Cogs



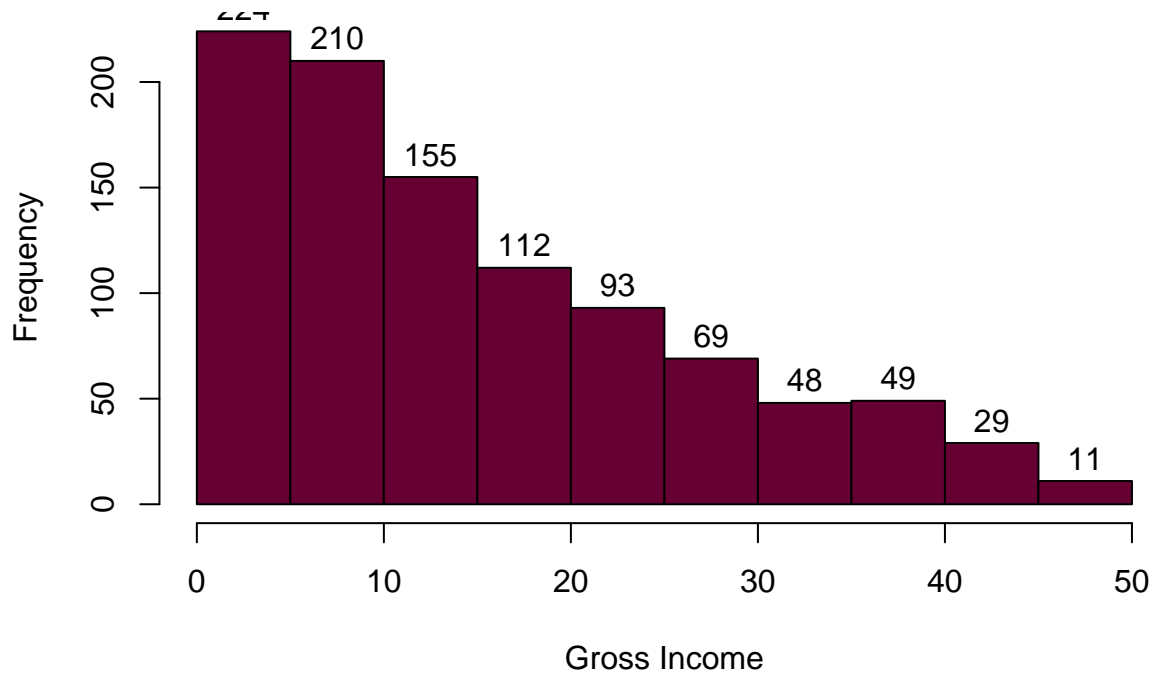
Cogs (Cost of goods sold) The items cost bracket of 0 - 100 has the higher amount of items

Tax and Cogs have a similar histogram

*# plot a histogram to visualize the distribution of values in 'Gross Income' column*

```
hist(df$gross_income,  
     col="#660033",  
     main="Histogram to Show Count of Gross Income",  
     xlab="Gross Income",  
     ylab="Frequency",  
     labels=TRUE)
```

## Histogram to Show Count of Gross Income



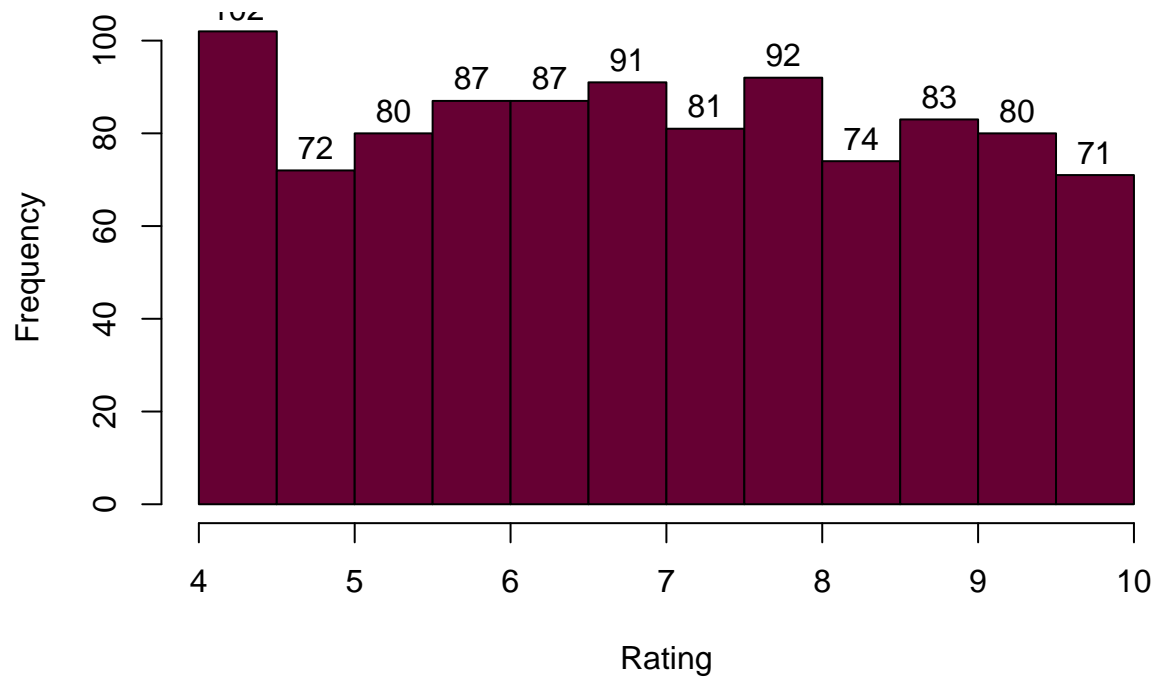
Gross Income, Tax and Cogs have a similar histogram

```
# plot a histogram to visualize the distribution of values in 'Rating' column
```

```
hist(df$rating,  
     col="#660033",  
     main="Histogram to Show Count of Rating",  
     xlab="Rating",  
     ylab="Frequency",  
     labels=TRUE)
```



## Histogram to Show Count of Rating

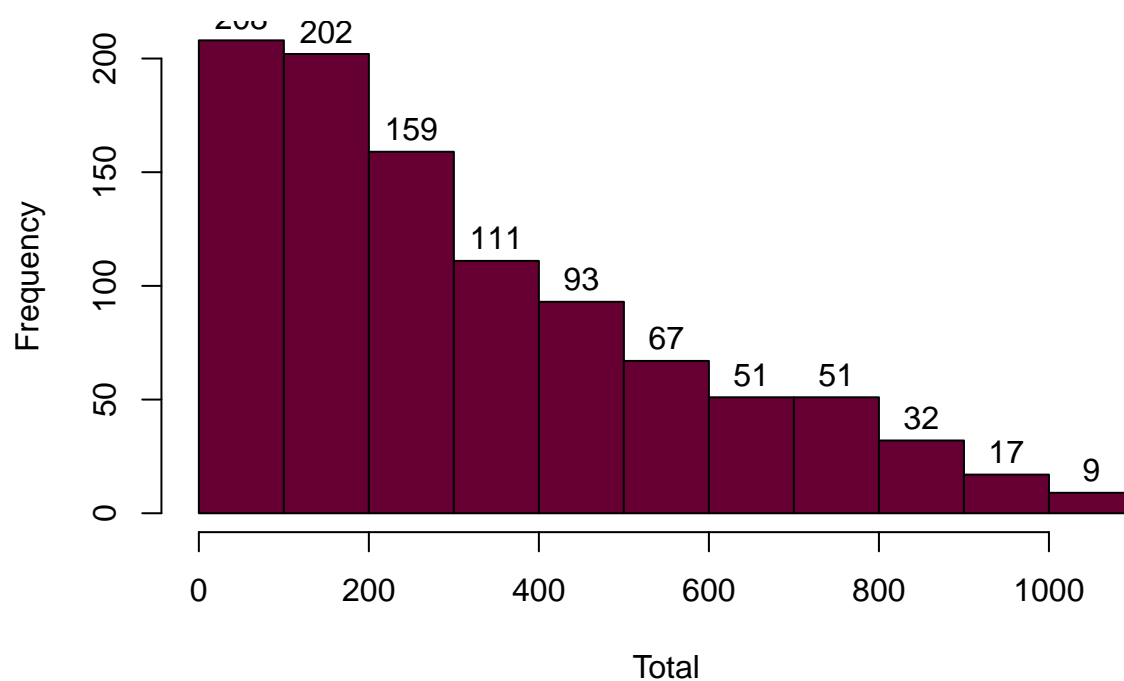


The rating 4 - 4.5 had higher amount of items than other rating brackets

```
# plot a histogram to visualize the distribution of values in 'total' column
```

```
hist(df$total,  
     col="#660033",  
     main="Histogram to Show Count of Total",  
     xlab="Total",  
     ylab="Frequency",  
     labels=TRUE)
```

## Histogram to Show Count of Total



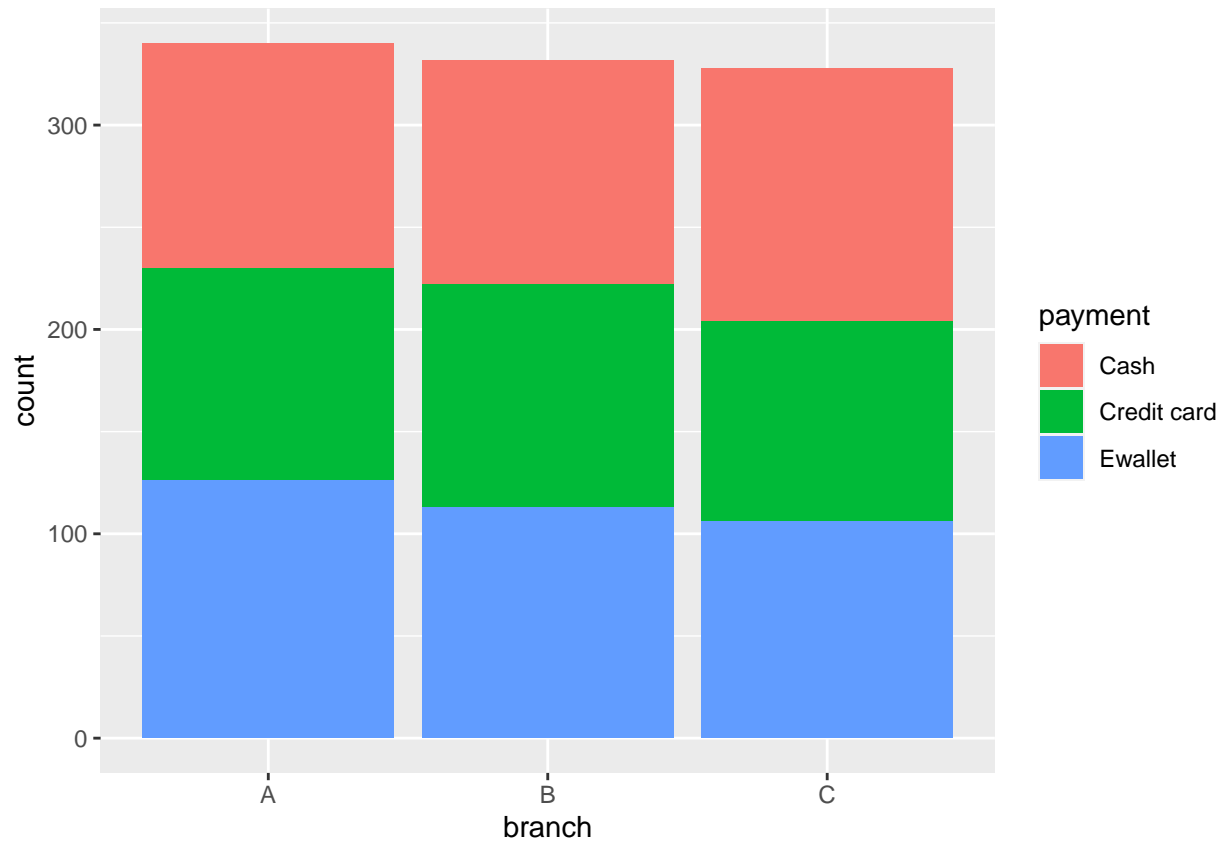
A higher number of items fell into the total price bracket 0 - 100

## Bivariate Analysis

Payment method frequency in every branch

*# Create barplot*

```
ggplot(df, aes(fill=payment, x=branch)) +  
  geom_bar(position="stack")
```



Most popular method of payment in Branch A is E-wallet

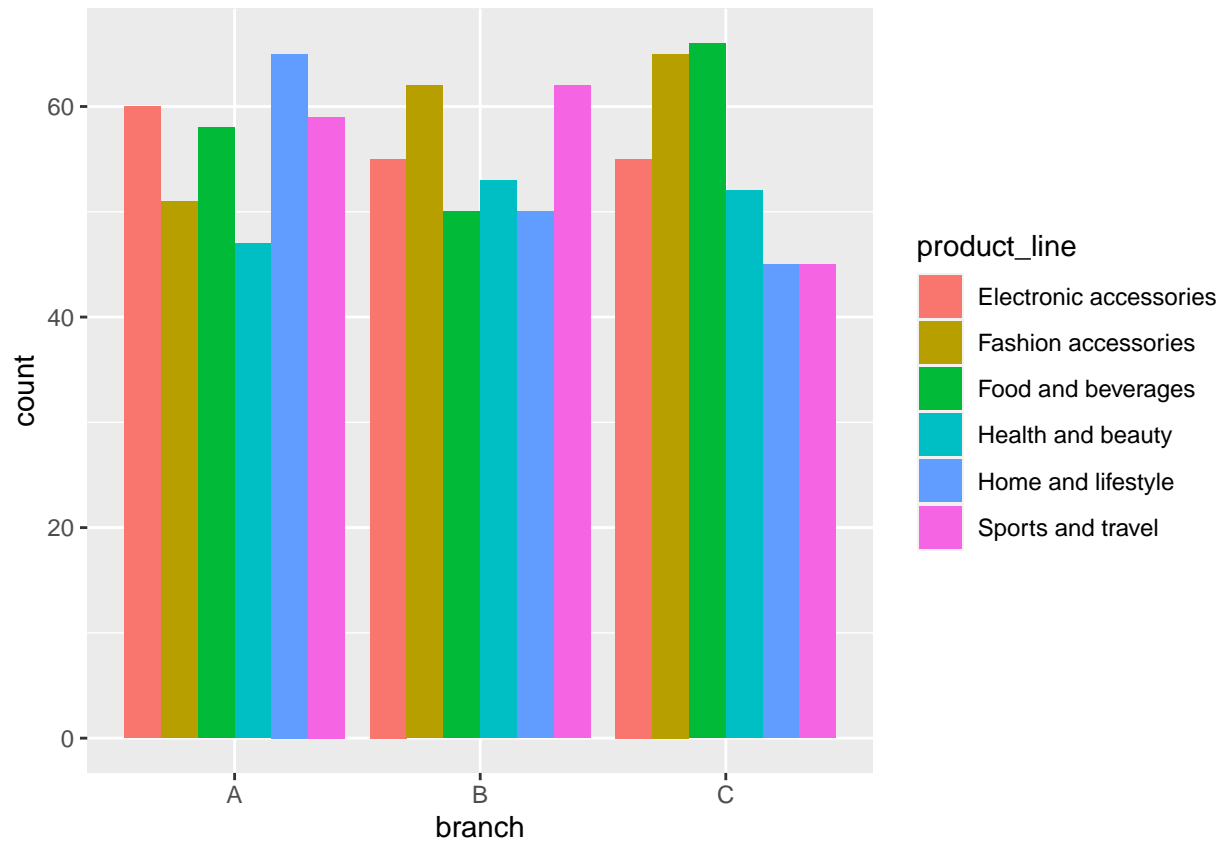
Most popular method of payment in Branch B is E-wallet but the other 2 modes of payment are also popular

Most popular method of payment in Branch B is Cash

### Product line Frequency in every branch

*# Create Barplot*

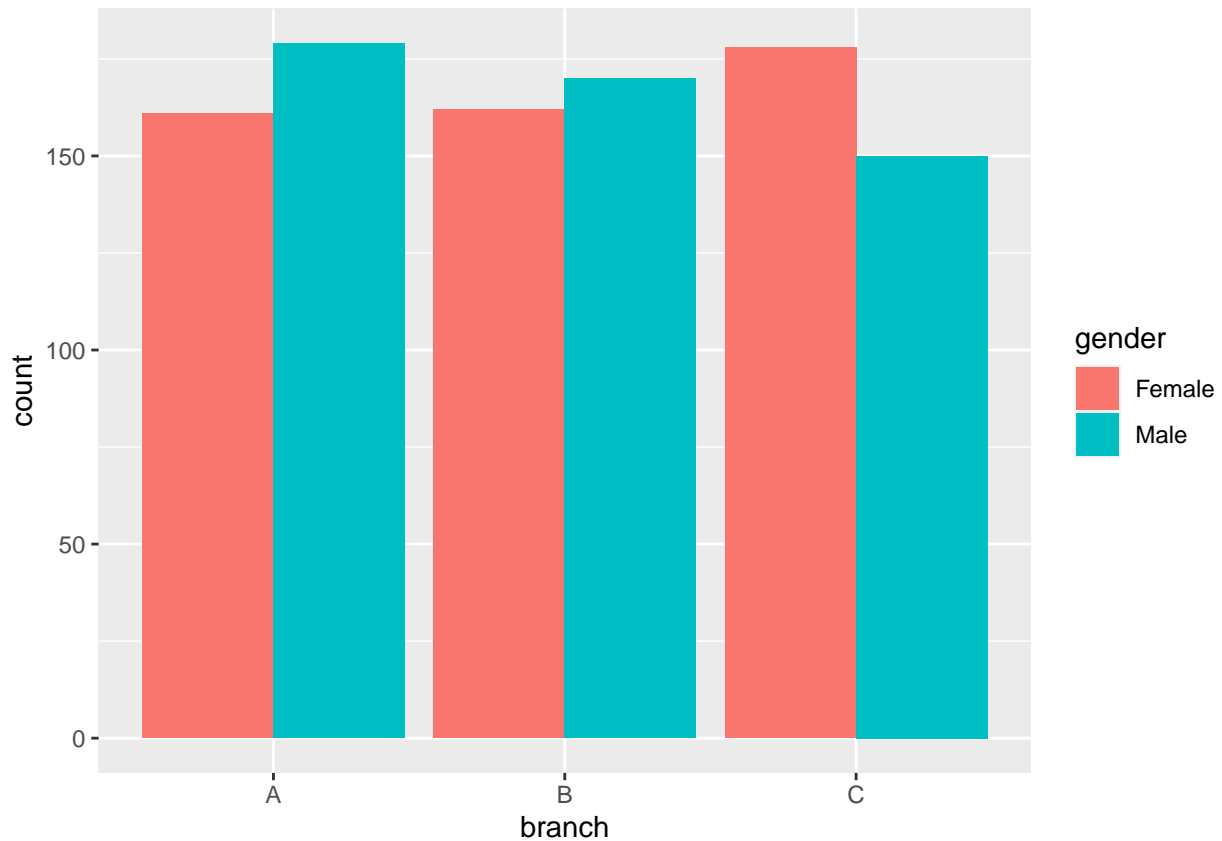
```
ggplot(df, aes(fill=product_line, x=branch)) +  
  geom_bar(position="dodge")
```



From the plot, Branch B sells more sports & travel and Health & Beauty goods than the other branches. Branch A sells more home and lifestyle goods than the other branches. Branch c sells more Food & Beverages, Fashion Accessories and Electronic accessories than the other branches Therefore, the marketing team should stack these branches with the product with which they sell more.

#### Gender Frequency in every branch

```
ggplot(df, aes(fill=gender, x=branch)) +  
  geom_bar(position="dodge")
```



There are more males in the Carrefour branches A and B than the females. This is not what many people assume as many people erroneously think that there are usually more females doing shopping. In branch C, there are more females shopping than males

```
head(df)
```

```
##      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_income rating
## 1:          7 26.1415 2019-01-05 13:08:00      Ewallet 522.83      26.1415      9.1
## 2:          5  3.8200 2019-03-08 10:29:00      Cash 76.40      3.8200      9.6
## 3:          7 16.2155 2019-03-03 13:23:00 Credit card 324.31      16.2155      7.4
## 4:          8 23.2880 2019-01-27 20:33:00      Ewallet 465.76      23.2880      8.4
## 5:          7 30.2085 2019-02-08 10:37:00      Ewallet 604.17      30.2085      5.3
## 6:          7 29.8865 2019-03-25 18:30:00      Ewallet 597.73      29.8865      4.1
##      total
## 1: 548.9715
## 2: 80.2200
## 3: 340.5255
## 4: 489.0480
## 5: 634.3785
## 6: 627.6165
```

## Mean Rating for items every branch

```
# calculate mean rating for each branch
library(dplyr)

##
## Attaching package: 'dplyr'

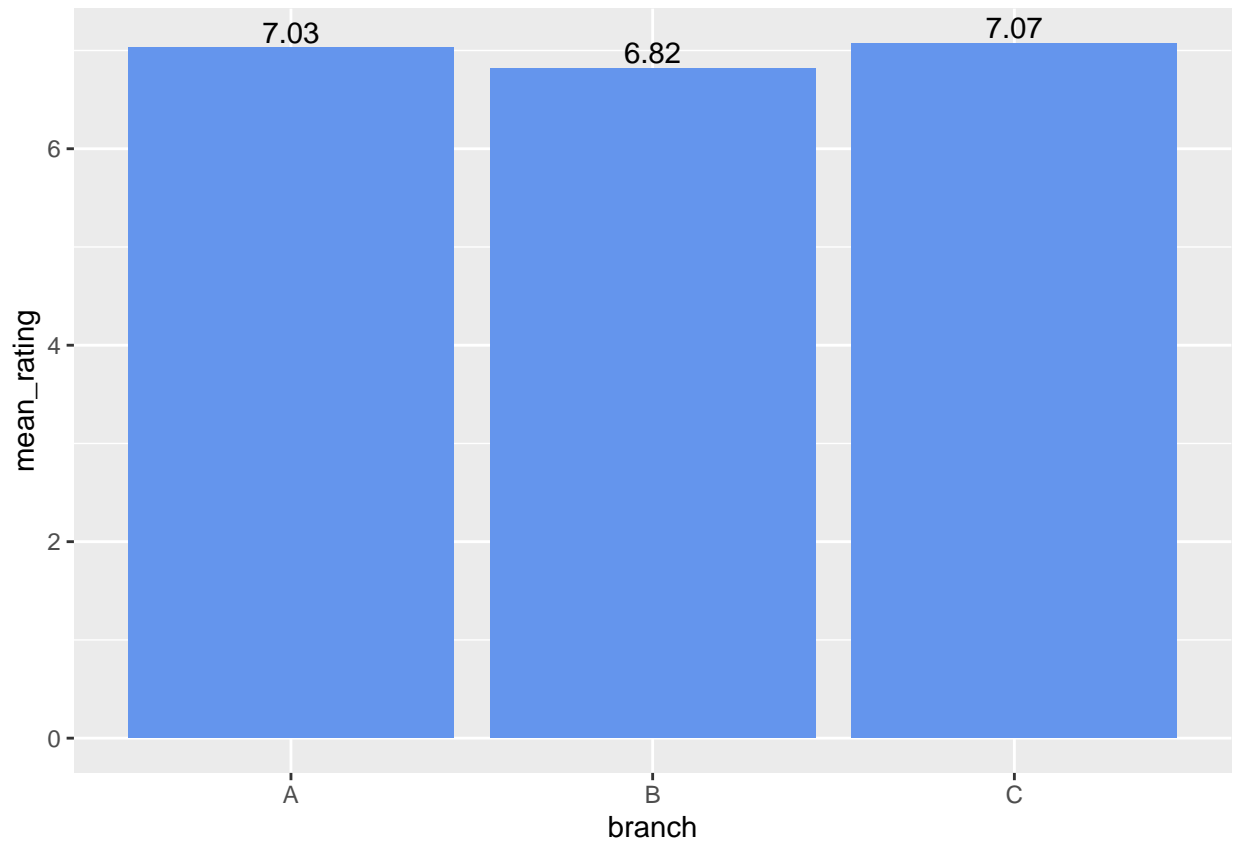
## The following objects are masked from 'package:data.table':
##
##   between, first, last

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

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

plotdata <- df %>%
  group_by(branch) %>%
  summarize(mean_rating = mean(rating))

# plot mean salaries
ggplot(plotdata, aes(x = branch, y = mean_rating)) +
  geom_bar(stat = "identity", fill = "cornflowerblue") +
  geom_text(aes(label = round(mean_rating, 2)),
            vjust = -0.25)
```

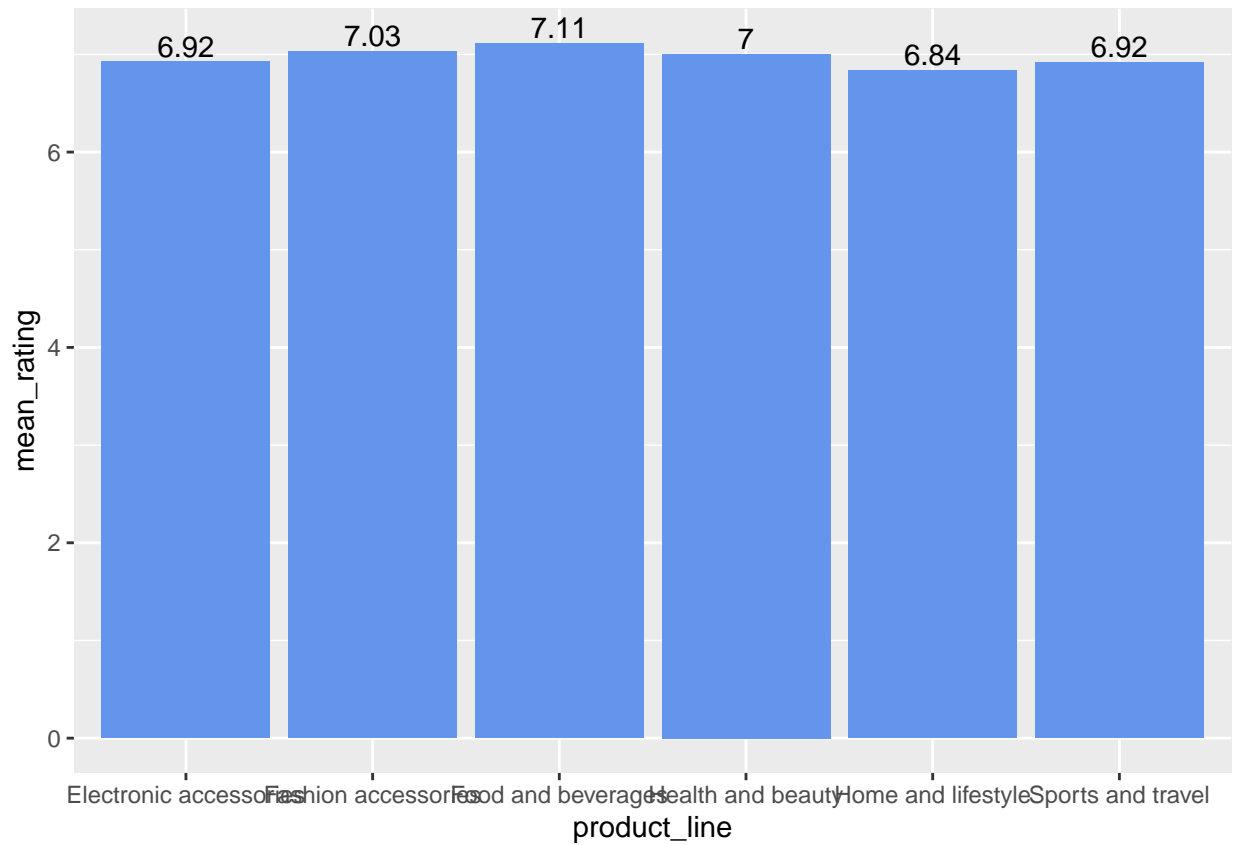


Branch C has a higher mean rating of the product line items than the other branches

#### Mean Rating for items in every product line

```
# calculate mean rating for each product line
library(dplyr)
plotdata1 <- df %>%
  group_by(product_line) %>%
  summarize(mean_rating = mean(rating))

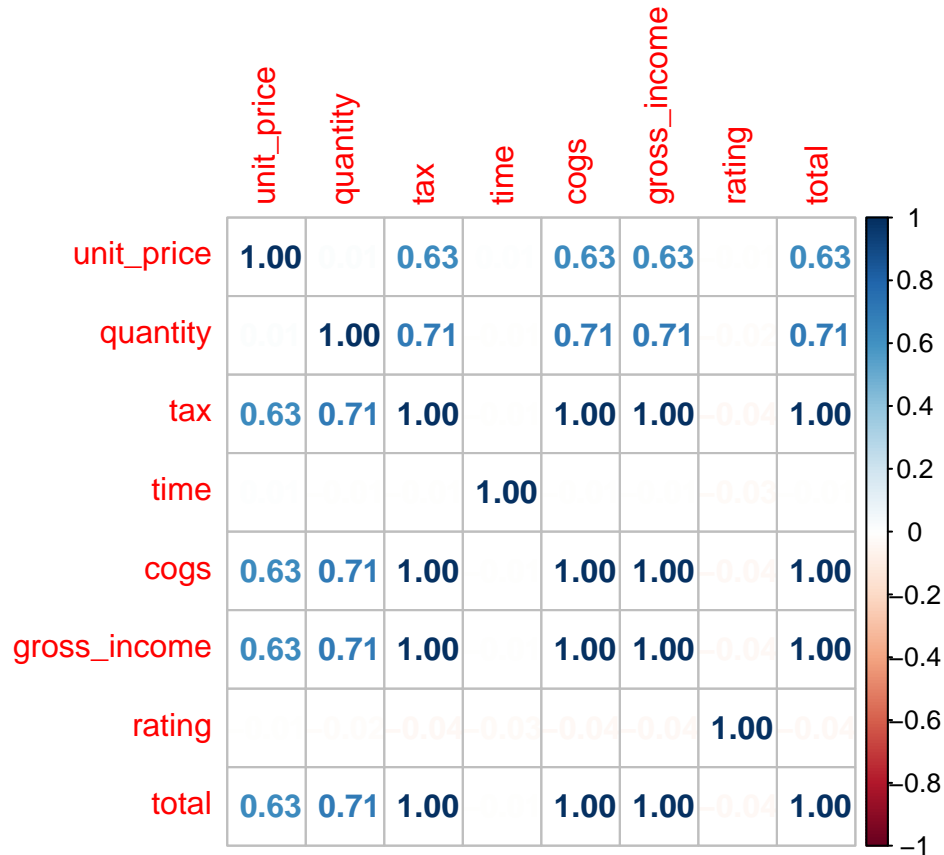
# plot mean salaries
ggplot(plotdata1, aes(x = product_line, y = mean_rating)) +
  geom_bar(stat = "identity", fill = "cornflowerblue") +
  geom_text(aes(label = round(mean_rating, 2)),
            vjust = -0.25)
```



Food and Beverages has the highest rating and Home & Lifestyle has the least rating

```
# calculate correlations  
correlations <- cor(df_num)  
# create correlation plot  
corrplot(correlations, method="number")
```





Gross income, tax, cogs and total have a correlation of 1 because they are calculated from the same starting point (Cogs) and with the same fractions for tax, gross income and total.

```
# Make a copy of the df
df_copy <- df

# Label Encoder
#Branch , customer_type, Gender, productline , payment
lbl <- LabelEncoder$new()

lbl$fit(df$branch)
df$branch <- lbl$fit_transform(df$branch)
lbl$fit(df$customer_type)
df$customer_type <- lbl$fit_transform(df$customer_type)
lbl$fit(df$gender)
df$gender <- lbl$fit_transform(df$gender)
lbl$fit(df$product_line)
df$product_line <- lbl$fit_transform(df$product_line)
lbl$fit(df$payment)
df$payment <- lbl$fit_transform(df$payment)

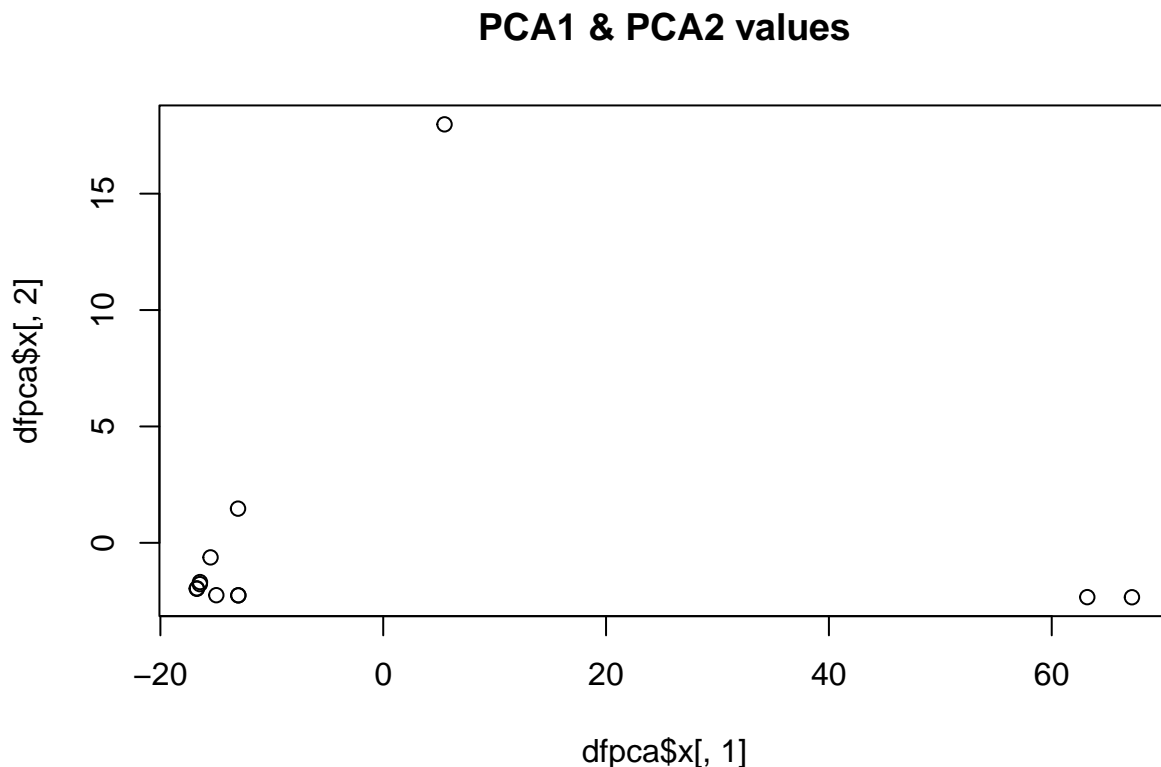
# Drop the categorical columns
df$invoice_id <- NULL
df$date <- NULL
df$time <- NULL
```

```
str(df)
```

```
## Classes 'data.table' and 'data.frame':  1000 obs. of  12 variables:
## $ 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 ...
## $ 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_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>
```

## Performing the PCA

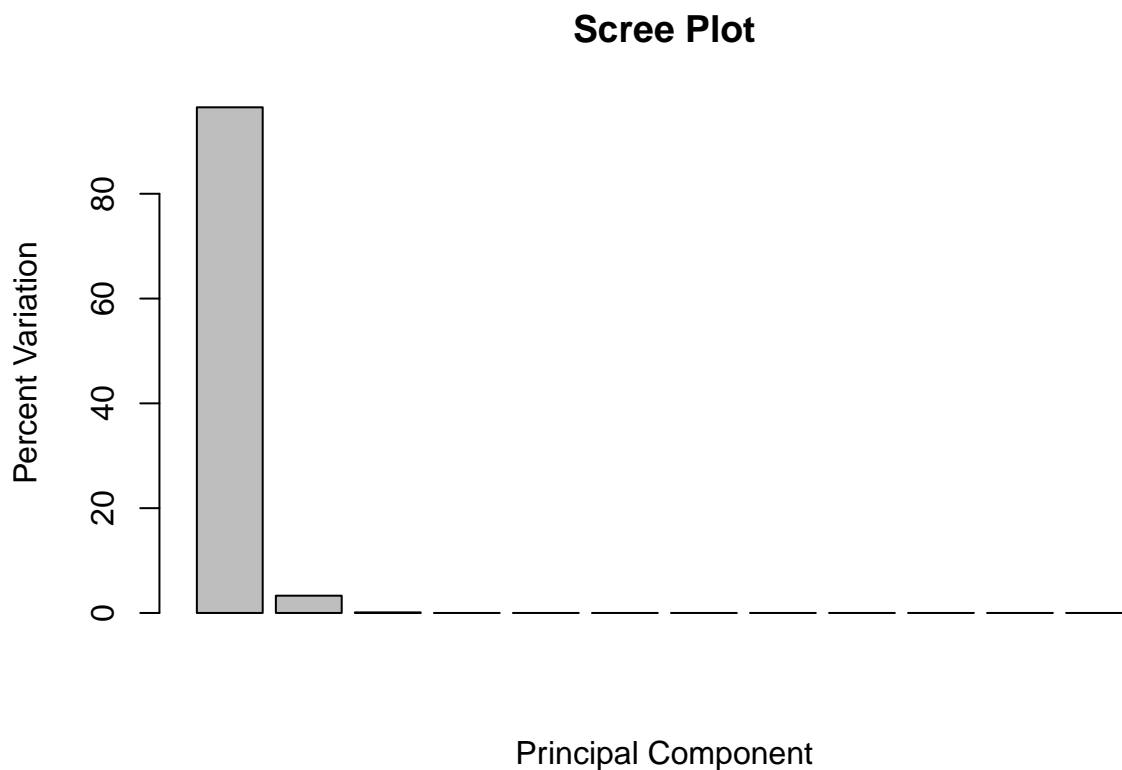
```
## Run the PCA on the df
dfpca <- prcomp(t(df), center = TRUE, scale=TRUE)
## plot pc1 and pc2
plot(dfpca$x[,1], dfpca$x[,2], main = "PCA1 & PCA2 values")
```



```
# Lets get a summary of the pca
summary (dfpca)
```

```
## 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
```

```
## make a scree plot
pca.var <- dfpca$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")
```



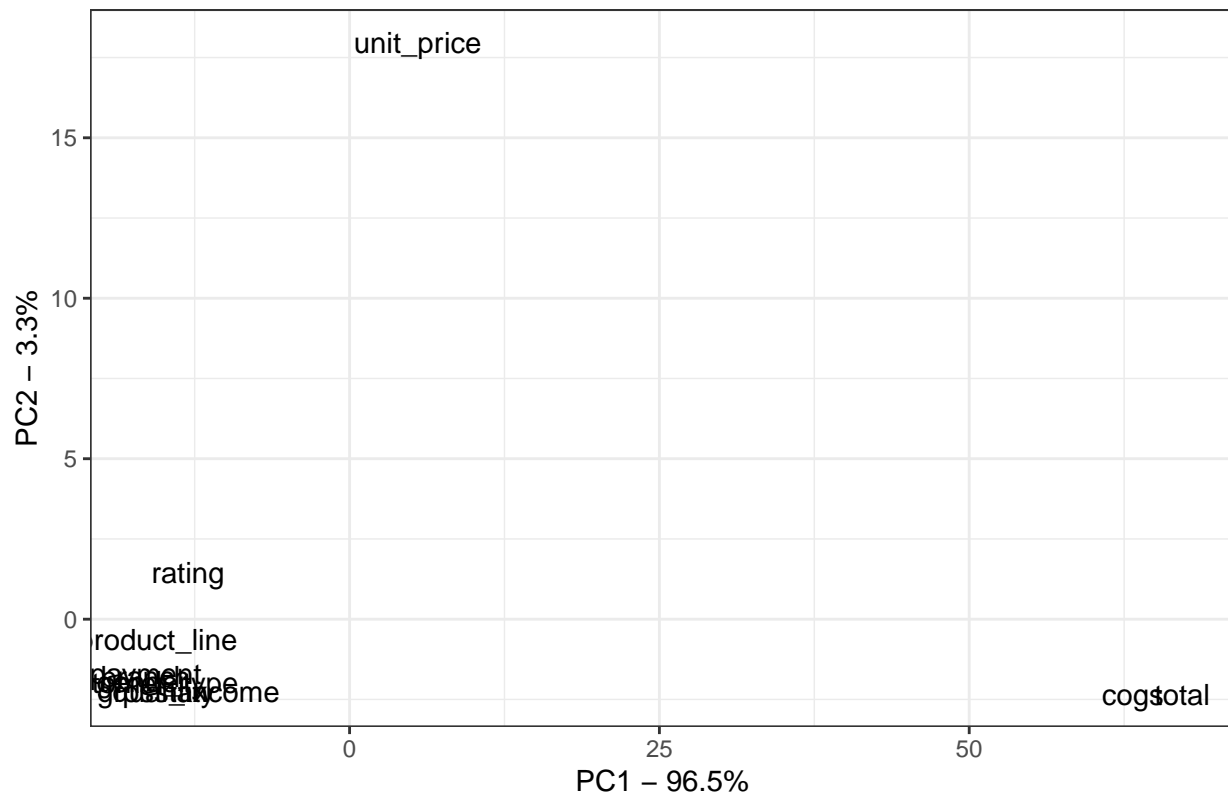
```
## plot that shows the PCs and the variation:
pca.data <- data.frame(Sample=rownames(dfpca$x),
                      X=dfpca$x[,1],
                      Y=dfpca$x[,2])
pca.data
```

```
##          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")
```

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)
```

```
## 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)

## -----

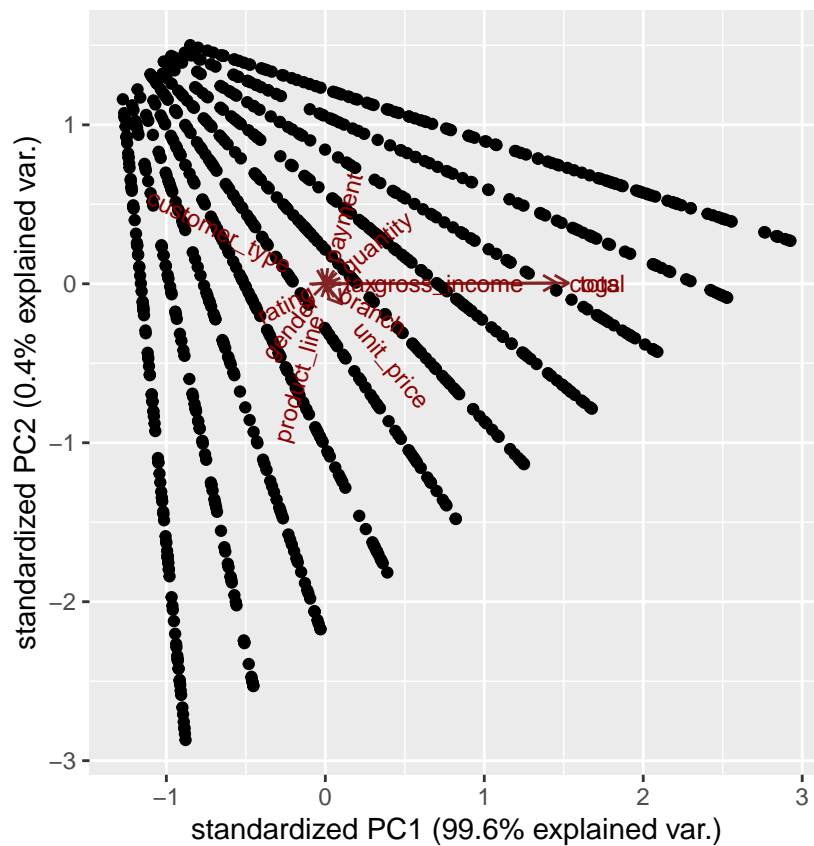
##
## Attaching package: 'plyr'

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

## Loading required package: scales

## Loading required package: grid

ggbiplot (prcomp(df))
```



## Part 2: Feature Selection

using the filter method.

```
# Installing and loading our caret package
suppressWarnings(
  suppressMessages(if
    (!require(caret, quietly=TRUE))
      install.packages("caret")))
library(caret)

# Installing and loading the corrplot package for plotting
# ---
#
suppressWarnings(
  suppressMessages(if
    (!require(corrplot, quietly=TRUE))
      install.packages("corrplot")))
library(corrplot)

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

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

```
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  1.000000000  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
```

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

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

```
names (df[, 9])
```

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

```
names (df[, 11])
```

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

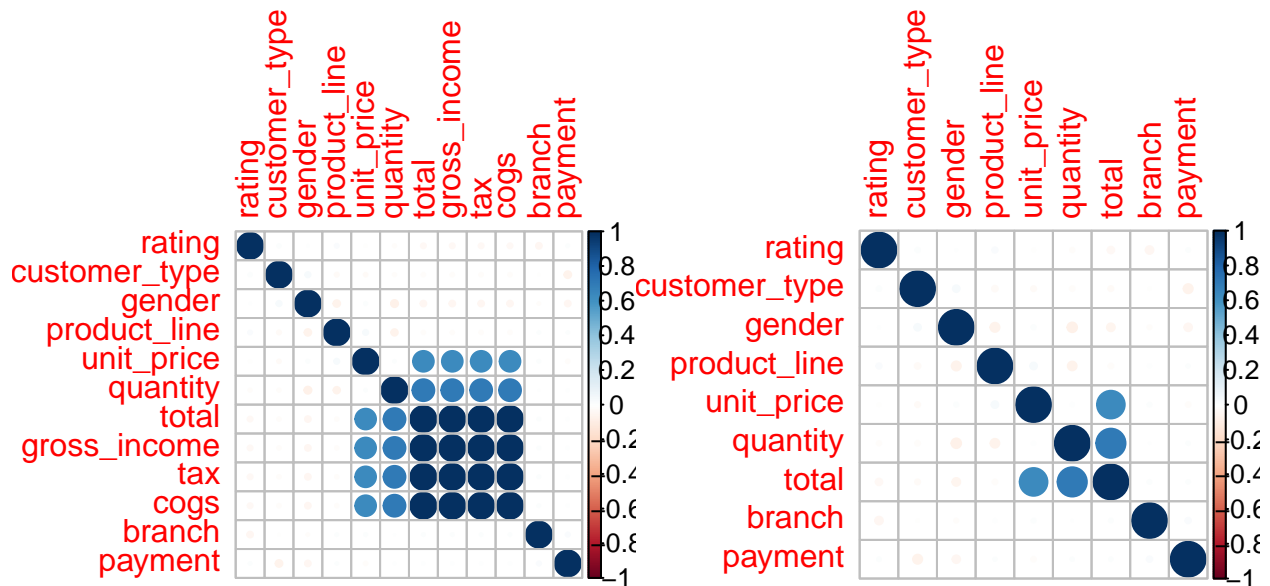
```
# Next step is removing the variables with high correlation
df_low <- df[!highlyCorrelated]
df_low$tax <- NULL
df_low$cogs <- NULL
df_low$gross_income <- NULL
```

```
cor2 <- cor(df_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  1.000000000  0.012852398  0.01146344
## rating      -0.016105001  0.01285240  1.000000000 -0.03642915
## total      0.705040267  0.01146344 -0.036429151  1.000000000
```

```
# Performing our graphical comparison
# ---
#
library(stats)
par(mfrow = c(1, 2))
corrplot(correlationMatrix, order = "hclust")
corrplot(cor(df_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

```
# Installing and loading our clustvarsel package
suppressWarnings(
  suppressMessages(if
    (!require(clustvarsel, quietly=TRUE))
      install.packages("clustvarsel")))

library(clustvarsel)
# Installing and loading our mclust package
suppressWarnings(
  suppressMessages(if
    (!require(mclust, quietly=TRUE))
      install.packages("mclust")))
library(mclust)
```

```
# Sequential forward greedy search (default)
#
out = clustvarsel(df_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

```
suppressWarnings(
  suppressMessages(if
    (!require(wskm, quietly=TRUE))
      install.packages("wskm")))
library(wskm)
set.seed(2)
model <- ewkm(df_low, 3, lambda=2, maxiter=1000)
```

```

suppressWarnings(
  suppressMessages(if
    (!require(cluster, quietly=TRUE))
      install.packages("cluster")))
library("cluster")
clusplot(df_low, model$cluster, color=TRUE, cor = TRUE, shade=TRUE,
  labels=2, lines=1,main='Cluster Analysis for df')

## 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

```

[illegible]







##	total
## 1	0
## 2	0
## 3	0