Feature Selection

2022-04-03

Research Question

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

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.

Defining the question

i)Specifying the Data Analytic Question

Perform feature selection through the use of the unsupervised learning methods.

ii)Defining the Metric for Success

Being able to Perform feature selection

iii) Understanding the Context

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.

Dataset link http://bit.ly/CarreFourDataset

```r
#necessary libraries
library(caret)
```

```
## Loading required package: ggplot2
```

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

```r
library(caretEnsemble)
```

```
##
## Attaching package: 'caretEnsemble'

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

```r
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```r
library(wskm)
```

```
## Loading required package: latticeExtra

##
## Attaching package: 'latticeExtra'

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

## Loading required package: fpc
```

```r
library(tidyr)
library(cluster)
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
```

```r
#First we load the dataset into our environment.
df<-read.csv('http://bit.ly/CarreFourDataset')
#Lets preview the head
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
```

```
#Lets preview the head
head(df)
```

```
##    Invoice.ID Branch Customer.type Gender           Product.line Unit.price
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## 5      30.2085    5.3 634.3785
## 6      29.8865    4.1 627.6165
```

```
#previewing the last 6 observations
tail(df)
```

```
##       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
```

```
#Check the dimensions
dim(df)
```

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

1000 observations of 16 variables

```
#checking null values in our dataset
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 null values on our dataset

```
#Check for duplicate values.
duplicated_rows <- df[duplicated(df),]
duplicated_rows
```

```
##  [1] Invoice.ID              Branch                  Customer.type
##  [4] Gender                  Product.line            Unit.price
##  [7] Quantity                Tax                     Date
## [10] Time                    Payment                 cogs
## [13] gross.margin.percentage gross.income            Rating
## [16] Total
## <0 rows> (or 0-length row.names)
```

there are no duplicated values in our dataset.

```
#Check the Summary of the dataframe
summary(df)
```

```
##   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
```

EXPLORATORY DATA ANALYSIS

Univariate Data Analysis

```
# Mean
df %>% summarise_if(is.numeric, mean)
```

```
##   Unit.price Quantity      Tax     cogs gross.margin.percentage gross.income
## 1   55.67213     5.51 15.37937 307.5874                4.761905     15.37937
##   Rating    Total
## 1 6.9727 322.9667
```

```
# Median
df %>% summarise_if(is.numeric, median)
```

```
##   Unit.price Quantity    Tax   cogs gross.margin.percentage gross.income Rating
## 1      55.23        5 12.088 241.76                4.761905       12.088      7
##     Total
## 1 253.848
```

```
# Mode
getmode <- function(v) {
  uniqv <- unique(v)
  uniqv[which.max(tabulate(match(v, uniqv)))]
}
df %>% summarise_if(is.numeric, getmode)
```

```
##   Unit.price Quantity   Tax  cogs gross.margin.percentage gross.income Rating
## 1      83.77       10 39.48 789.6                4.761905        39.48      6
##    Total
## 1 829.08
```

```
# Range
df %>% summarise_if(is.numeric, range)
```

```
##   Unit.price Quantity     Tax   cogs gross.margin.percentage gross.income
## 1      10.08        1  0.5085  10.17                4.761905       0.5085
## 2      99.96       10 49.6500 993.00                4.761905      49.6500
##   Rating     Total
## 1      4   10.6785
## 2     10 1042.6500
```

```
# Quantiles
df %>% summarise_if(is.numeric, quantile)
```

```
##   Unit.price Quantity       Tax     cogs gross.margin.percentage gross.income
## 1     10.080        1  0.508500  10.1700                4.761905     0.508500
## 2     32.875        3  5.924875 118.4975                4.761905     5.924875
## 3     55.230        5 12.088000 241.7600                4.761905    12.088000
## 4     77.935        8 22.445250 448.9050                4.761905    22.445250
## 5     99.960       10 49.650000 993.0000                4.761905    49.650000
##   Rating     Total
## 1    4.0   10.6785
## 2    5.5  124.4224
## 3    7.0  253.8480
## 4    8.5  471.3502
## 5   10.0 1042.6500
```

```
# Standard Deviation
df %>% summarise_if(is.numeric, sd)
```

```
##   Unit.price Quantity      Tax     cogs gross.margin.percentage gross.income
## 1   26.49463 2.923431 11.70883 234.1765                       0     11.70883
##    Rating    Total
## 1 1.71858 245.8853
```

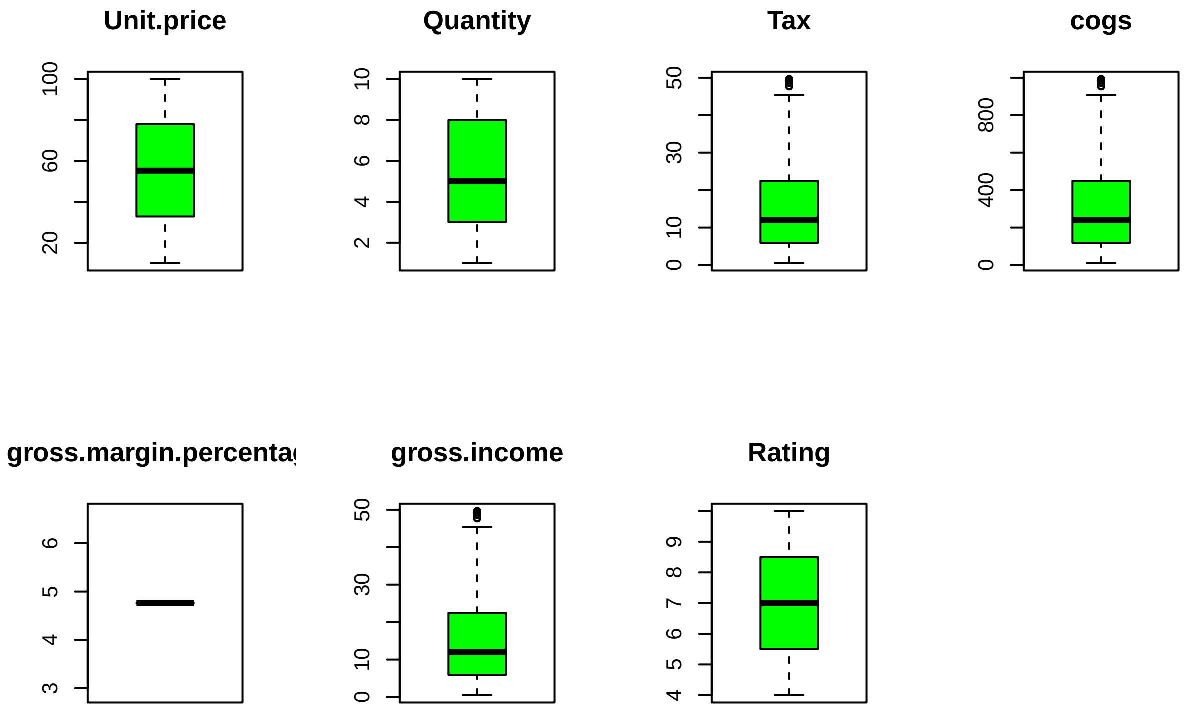
```
# Variance
df %>% summarise_if(is.numeric, var)
```

```
##   Unit.price Quantity      Tax     cogs gross.margin.percentage gross.income
## 1   701.9653 8.546446 137.0966 54838.64                       0     137.0966
##     Rating   Total
## 1 2.953518 60459.6
```

```
#selecting the numerical variables
numeric <- df %>% select_if(is.numeric)
head(numeric)
```

```
##   Unit.price Quantity     Tax   cogs gross.margin.percentage gross.income
## 1      74.69        7 26.1415 522.83                4.761905      26.1415
## 2      15.28        5  3.8200  76.40                4.761905       3.8200
## 3      46.33        7 16.2155 324.31                4.761905      16.2155
## 4      58.22        8 23.2880 465.76                4.761905      23.2880
## 5      86.31        7 30.2085 604.17                4.761905      30.2085
## 6      85.39        7 29.8865 597.73                4.761905      29.8865
##   Rating    Total
## 1    9.1 548.9715
## 2    9.6  80.2200
## 3    7.4 340.5255
## 4    8.4 489.0480
## 5    5.3 634.3785
## 6    4.1 627.6165
```

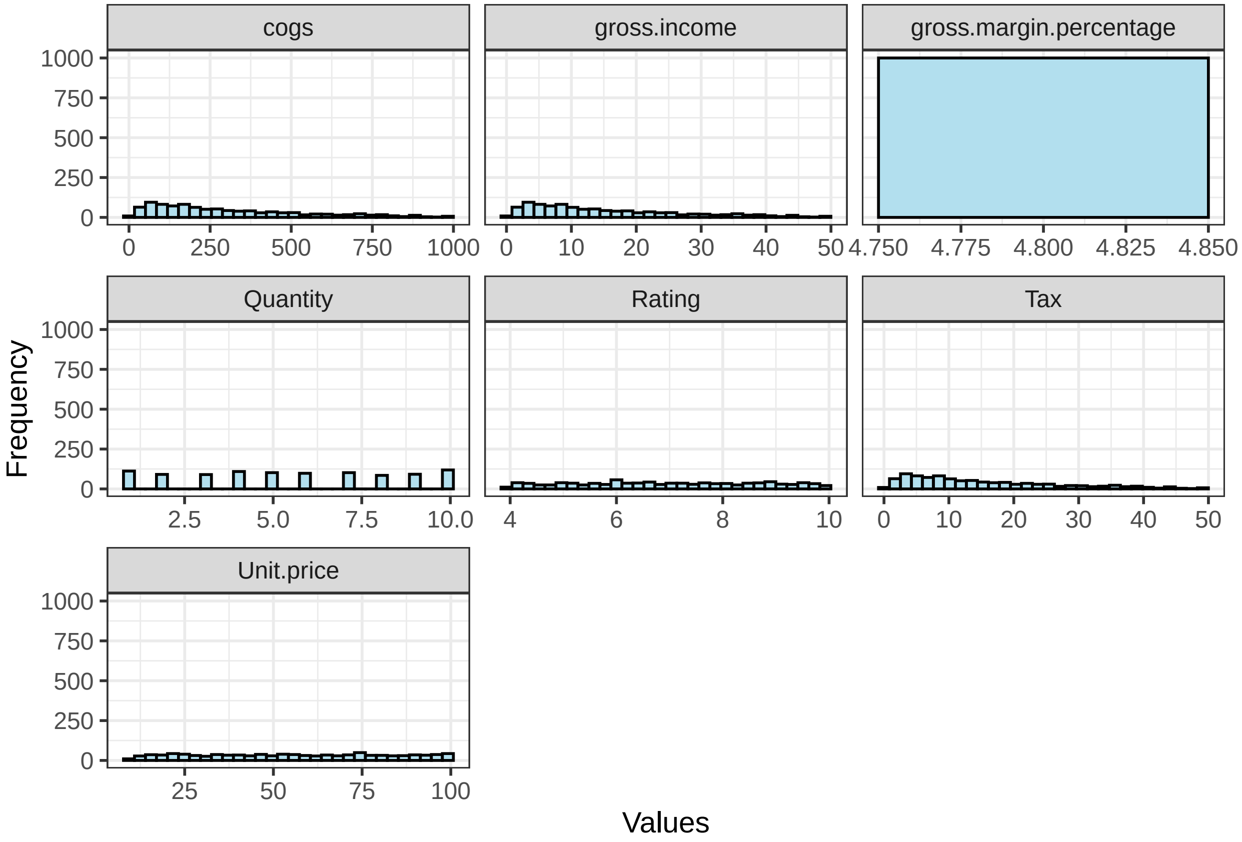
```
# Creating separate boxplots for each attribute
par(mfrow=c(2,4))
for(i in 1:7) {
    boxplot(numeric[,i], main=names(numeric)[i], col = "green")}
```



We have outliers but we won't drop the outliers as they represent real data

```
#histogram representation of the numerical variables
numeric %>%
  gather(attributes, value, 1:7) %>%
  ggplot(aes(x = value)) +
  geom_histogram(fill = 'lightblue2', color = 'black') +
  facet_wrap(~attributes, scales = 'free_x') +
  labs(x="Values", y="Frequency") +
  theme_bw()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Most of the data is skewed

IMPLEMENTING THE SOLUTION

i) Filter Method

```
#If there are integers, then you'll get variances of 0, causing the scaling to fail.
numeric$Quantity <- as.numeric(numeric$Quantity)
```

```
# If the standard deviation is zero, you can remove the variable

df1 <- numeric %>% select(-gross.margin.percentage)
```

```
correlationMatrix <- cor(df1)
```

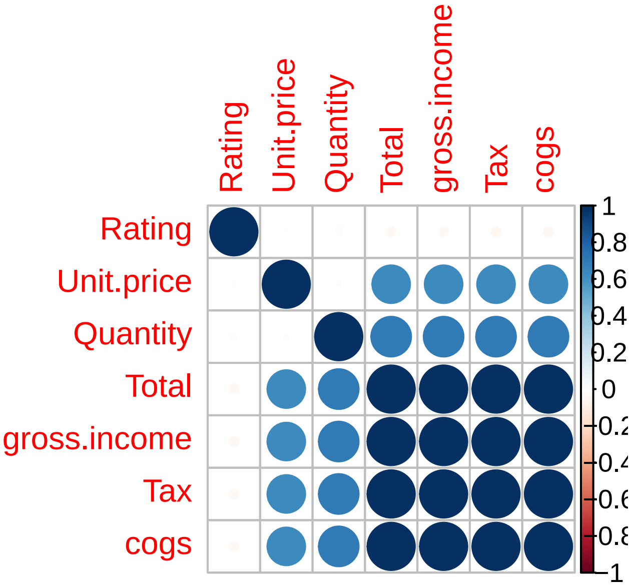
```
highlyCorrelated <- findCorrelation(correlationMatrix, cutoff=0.75)
names(df1[,highlyCorrelated])
```

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

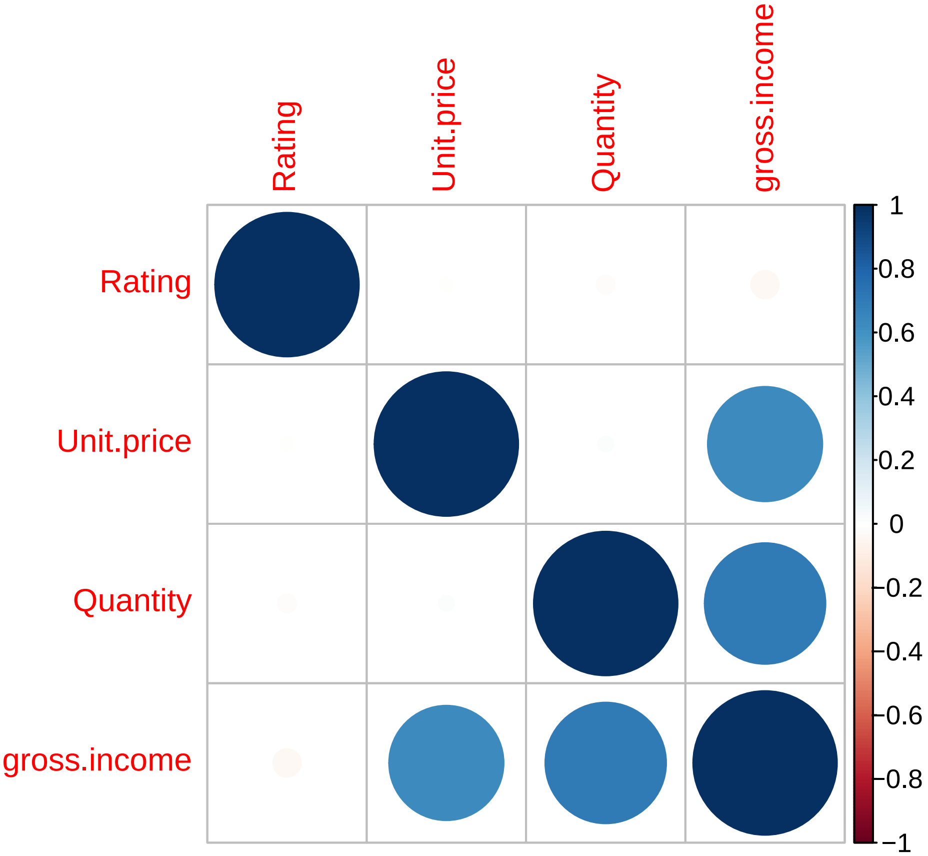
Using the filter method for feature selection, we can conclude that the attributes “Total” ‘cogs’ and ‘tax’ are highly correlated/redundant and thus should be removed from the subset of features in our dataset.

```r
## Removing Redundant Features
df2 <- df1[-highlyCorrelated]
```

```r
## Performing our graphical comparison
#with highly correlated variables
par(mfrow = c(1, 2))
corrplot(correlationMatrix, order = "hclust")
```



```r
# Without redundant features
corrplot(cor(df2), order = "hclust")
```



From the above we can see that there are no highly correlated variables.

Using the filter method, we can establish that the important features are :

1. Unit Price of the items
2. Quantity of items purchased
3. Gross Income
4. Rating of items

CONCLUSION

The important features in our dataset that will bring the highest number of sales are ;

1. Unit Price of the items in the supermarkets.
2. Gross Income
3. Quantity of items purchased
4. Rating of the items in the supermarkets.