

# Customers behaviour analysis

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## CUSTOMER BEHAVIOUR ANALYSIS

### 1. Problem Definition

#### 1.1 Specifying the Question

what is the characteristics of the customer groups.

#### 1.2 Metric for success

Come up with an analysis that will make our client identify the behaviour and characteristics of it's customers.

#### 1.3 Understanding the Context

Consumer/customer behaviour is the study of how individual customers, groups or organizations select, buy, use, and dispose ideas, goods, and services to satisfy their needs and wants. It refers to the actions of the consumers in the marketplace and the underlying motives for those actions. Marketers need to understand the buying behaviour of consumers for their products to do well. It is really important for marketers to understand what prompts a consumer to purchase a particular product and what stops him from buying, Thus the need to do customer behaviour analysis.

#### 1.4 Experimental Design taken

1. Problem Definition
2. Data Sourcing
3. Check the Data
4. Perform Data Cleaning
5. Perform Exploratory Data Analysis (Univariate, Bivariate & Multivariate)
6. Implement the Solution(Clustering)
7. Challenge the Solution
8. Follow up Questions

#### 1.5 Data relevance

The data collected is relevant as it is sourced from Ecommerce customer

<http://bit.ly/EcommerceCustomersDataset>

## 2. Data Sourcing

### Loading the data

### Loading the necessary packages

```
library("data.table")
customer <- read.csv("online_shoppers_intention.csv")
```

```
#loading libraries
#library(ggplot2) # Data visualization
```

```
#install.packages("plotly")
library(plotly) # Interactive data visualizations
```

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

```
##
```

```
## 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
```

```
library(dplyr) # Data manipulation
```

```
##
```

```
## 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
```

```
library(psych) # Will be used for correlation visualization
```

```
##  
## Attaching package: 'psych'  
  
## The following objects are masked from 'package:ggplot2':  
##  
## %+%, alpha
```

### 3. checking the data

```
##Previewing the first 6 rows of dataset
```

```
head(customer)
```

```
##      Administrative Administrative_Duration Informational Informational_Duration  
## 1                0                      0                0                      0  
## 2                0                      0                0                      0  
## 3                0                     -1                0                     -1  
## 4                0                      0                0                      0  
## 5                0                      0                0                      0  
## 6                0                      0                0                      0  
##      ProductRelated ProductRelated_Duration BounceRates ExitRates PageValues  
## 1                1          0.000000  0.20000000 0.2000000          0  
## 2                2          64.000000  0.00000000 0.1000000          0  
## 3                1          -1.000000  0.20000000 0.2000000          0  
## 4                2           2.666667  0.05000000 0.1400000          0  
## 5               10          627.500000  0.02000000 0.0500000          0  
## 6               19          154.216667  0.01578947 0.0245614          0  
##      SpecialDay Month OperatingSystems Browser Region TrafficType  
## 1                0   Feb                1      1      1          1  
## 2                0   Feb                2      2      1          2  
## 3                0   Feb                4      1      9          3  
## 4                0   Feb                3      2      2          4  
## 5                0   Feb                3      3      1          4  
## 6                0   Feb                2      2      1          3  
##      VisitorType Weekend Revenue  
## 1 Returning_Visitor  FALSE  FALSE  
## 2 Returning_Visitor  FALSE  FALSE  
## 3 Returning_Visitor  FALSE  FALSE  
## 4 Returning_Visitor  FALSE  FALSE  
## 5 Returning_Visitor   TRUE  FALSE  
## 6 Returning_Visitor  FALSE  FALSE
```

```
##Previewing the last 6 rows of dataset
```

```
tail(customer)
```

```
##      Administrative Administrative_Duration Informational
```

```

## 12325      0      0      1
## 12326      3     145      0
## 12327      0      0      0
## 12328      0      0      0
## 12329      4      75      0
## 12330      0      0      0
##      Informational_Duration ProductRelated ProductRelated_Duration BounceRates
## 12325      0      16      503.000 0.000000000
## 12326      0      53     1783.792 0.007142857
## 12327      0      5      465.750 0.000000000
## 12328      0      6      184.250 0.083333333
## 12329      0      15      346.000 0.000000000
## 12330      0      3      21.250 0.000000000
##      ExitRates PageValues SpecialDay Month OperatingSystems Browser Region
## 12325 0.03764706 0.00000      0 Nov      2      2      1
## 12326 0.02903061 12.24172      0 Dec      4      6      1
## 12327 0.02133333 0.00000      0 Nov      3      2      1
## 12328 0.08666667 0.00000      0 Nov      3      2      1
## 12329 0.02105263 0.00000      0 Nov      2      2      3
## 12330 0.06666667 0.00000      0 Nov      3      2      1
##      TrafficType      VisitorType Weekend Revenue
## 12325      1 Returning_Visitor  FALSE  FALSE
## 12326      1 Returning_Visitor  TRUE   FALSE
## 12327      8 Returning_Visitor  TRUE   FALSE
## 12328     13 Returning_Visitor  TRUE   FALSE
## 12329     11 Returning_Visitor  FALSE  FALSE
## 12330      2      New_Visitor   TRUE   FALSE

```

```

##Basic structure of the data
str(customer)

```

```

## 'data.frame': 12330 obs. of 18 variables:
## $ Administrative : int 0 0 0 0 0 0 0 1 0 0 ...
## $ Administrative_Duration: num 0 0 -1 0 0 0 -1 -1 0 0 ...
## $ Informational : int 0 0 0 0 0 0 0 0 0 0 ...
## $ Informational_Duration : num 0 0 -1 0 0 0 -1 -1 0 0 ...
## $ ProductRelated : int 1 2 1 2 10 19 1 1 2 3 ...
## $ ProductRelated_Duration: num 0 64 -1 2.67 627.5 ...
## $ BounceRates : num 0.2 0 0.2 0.05 0.02 ...
## $ ExitRates : num 0.2 0.1 0.2 0.14 0.05 ...
## $ PageValues : num 0 0 0 0 0 0 0 0 0 0 ...
## $ SpecialDay : num 0 0 0 0 0 0 0.4 0 0.8 0.4 ...
## $ Month : chr "Feb" "Feb" "Feb" "Feb" ...
## $ OperatingSystems : int 1 2 4 3 3 2 2 1 2 2 ...
## $ Browser : int 1 2 1 2 3 2 4 2 2 4 ...
## $ Region : int 1 1 9 2 1 1 3 1 2 1 ...
## $ TrafficType : int 1 2 3 4 4 3 3 5 3 2 ...
## $ VisitorType : chr "Returning_Visitor" "Returning_Visitor" "Returning_Visitor" "Return
## $ Weekend : logi FALSE FALSE FALSE FALSE TRUE FALSE ...
## $ Revenue : logi FALSE FALSE FALSE FALSE FALSE FALSE ...

```

```

# previewing the column names
colnames(customer)

```

```
## [1] "Administrative"      "Administrative_Duration"
## [3] "Informational"        "Informational_Duration"
## [5] "ProductRelated"      "ProductRelated_Duration"
## [7] "BounceRates"         "ExitRates"
## [9] "PageValues"          "SpecialDay"
## [11] "Month"               "OperatingSystems"
## [13] "Browser"             "Region"
## [15] "TrafficType"         "VisitorType"
## [17] "Weekend"             "Revenue"
```

```
# previewing the dataset
class(customer)
```

```
## [1] "data.frame"
```

```
# previewing the datatypes of the dataset
sapply(customer, class)
```

```
##      Administrative Administrative_Duration      Informational
##      "integer"          "numeric"          "integer"
## Informational_Duration      ProductRelated ProductRelated_Duration
##      "numeric"          "integer"          "numeric"
##      BounceRates          ExitRates          PageValues
##      "numeric"          "numeric"          "numeric"
##      SpecialDay          Month      OperatingSystems
##      "numeric"          "character"      "integer"
##      Browser          Region      TrafficType
##      "integer"          "integer"      "integer"
##      VisitorType      Weekend      Revenue
##      "character"      "logical"      "logical"
```

```
# checking the shape of the data
dim(customer)
```

```
## [1] 12330    18
```

There are 12330 records of data and 18 columns.

## 4. Perform Data Cleaning

### missing values

```
# checking for missing values
sum(is.na(customer))
```

```
## [1] 112
```

There are 112 missing values

```
# displaying all rows from the dataset that don't contain any missing values
customer1 <- na.omit(customer)
head(customer1)
```

```
##      Administrative Administrative_Duration Informational Informational_Duration
## 1              0              0              0              0
## 2              0              0              0              0
## 3              0             -1              0             -1
## 4              0              0              0              0
## 5              0              0              0              0
## 6              0              0              0              0
##      ProductRelated ProductRelated_Duration BounceRates ExitRates PageValues
## 1              1          0.000000 0.20000000 0.2000000      0
## 2              2          64.000000 0.00000000 0.1000000      0
## 3              1          -1.000000 0.20000000 0.2000000      0
## 4              2           2.666667 0.05000000 0.1400000      0
## 5             10          627.500000 0.02000000 0.0500000      0
## 6             19          154.216667 0.01578947 0.0245614      0
##      SpecialDay Month OperatingSystems Browser Region TrafficType
## 1              0   Feb              1      1      1          1
## 2              0   Feb              2      2      1          2
## 3              0   Feb              4      1      9          3
## 4              0   Feb              3      2      2          4
## 5              0   Feb              3      3      1          4
## 6              0   Feb              2      2      1          3
##      VisitorType Weekend Revenue
## 1 Returning_Visitor  FALSE  FALSE
## 2 Returning_Visitor  FALSE  FALSE
## 3 Returning_Visitor  FALSE  FALSE
## 4 Returning_Visitor  FALSE  FALSE
## 5 Returning_Visitor   TRUE  FALSE
## 6 Returning_Visitor  FALSE  FALSE
```

## Duplicates

```
# Identifying duplicates
duplicates <- customer1[duplicated(customer1), ]
head(duplicates)
```

```
##      Administrative Administrative_Duration Informational Informational_Duration
## 159              0              0              0              0
## 179              0              0              0              0
## 419              0              0              0              0
## 457              0              0              0              0
## 484              0              0              0              0
## 513              0              0              0              0
##      ProductRelated ProductRelated_Duration BounceRates ExitRates PageValues
## 159              1              0          0.2          0.2      0
## 179              1              0          0.2          0.2      0
## 419              1              0          0.2          0.2      0
## 457              1              0          0.2          0.2      0
```

```
## 484          1          0          0.2          0.2          0
## 513          1          0          0.2          0.2          0
##      SpecialDay Month OperatingSystems Browser Region TrafficType
## 159          0   Feb          1          1          1          3
## 179          0   Feb          3          2          3          3
## 419          0   Mar          1          1          1          1
## 457          0   Mar          2          2          4          1
## 484          0   Mar          3          2          3          1
## 513          0   Mar          2          2          1          1
##      VisitorType Weekend Revenue
## 159 Returning_Visitor FALSE FALSE
## 179 Returning_Visitor FALSE FALSE
## 419 Returning_Visitor TRUE  FALSE
## 457 Returning_Visitor FALSE FALSE
## 484 Returning_Visitor FALSE FALSE
## 513 Returning_Visitor FALSE FALSE
```

There are 119 duplicated rows

```
#dealing with duplicates
# showing unique items from the dataset and assigning to a variable unique_items below

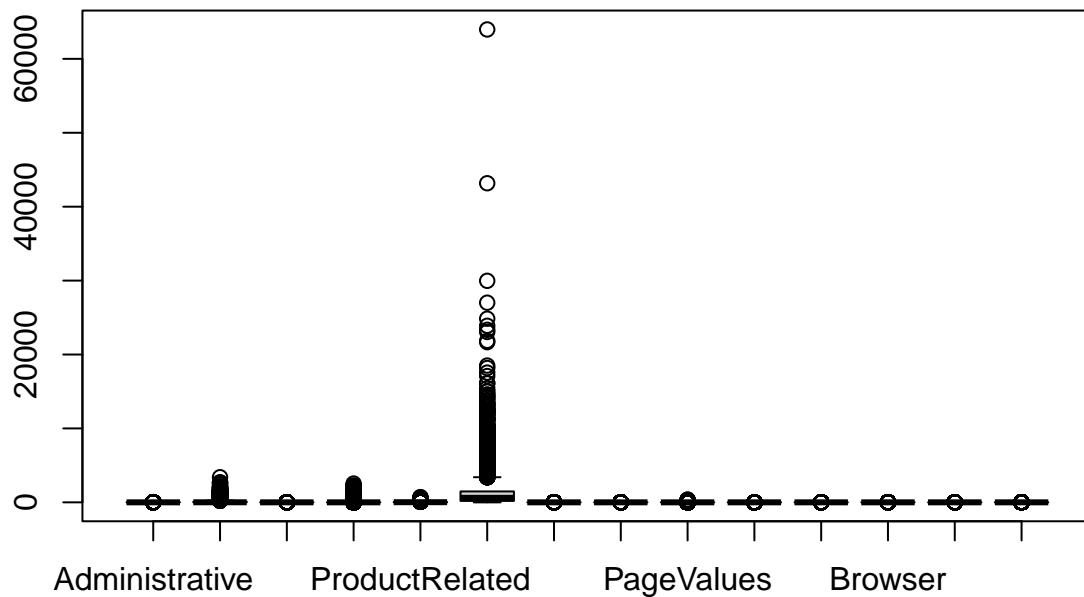
customer_unique <- unique(customer1)
head(customer_unique)
```

```
##      Administrative Administrative_Duration Informational Informational_Duration
## 1          0          0          0          0
## 2          0          0          0          0
## 3          0         -1          0         -1
## 4          0          0          0          0
## 5          0          0          0          0
## 6          0          0          0          0
##      ProductRelated ProductRelated_Duration BounceRates ExitRates PageValues
## 1          1          0.000000 0.20000000 0.2000000 0
## 2          2          64.000000 0.00000000 0.1000000 0
## 3          1          -1.000000 0.20000000 0.2000000 0
## 4          2          2.666667 0.05000000 0.1400000 0
## 5         10          627.500000 0.02000000 0.0500000 0
## 6         19          154.216667 0.01578947 0.0245614 0
##      SpecialDay Month OperatingSystems Browser Region TrafficType
## 1          0   Feb          1          1          1          1
## 2          0   Feb          2          2          1          2
## 3          0   Feb          4          1          9          3
## 4          0   Feb          3          2          2          4
## 5          0   Feb          3          3          1          4
## 6          0   Feb          2          2          1          3
##      VisitorType Weekend Revenue
## 1 Returning_Visitor FALSE FALSE
## 2 Returning_Visitor FALSE FALSE
## 3 Returning_Visitor FALSE FALSE
## 4 Returning_Visitor FALSE FALSE
## 5 Returning_Visitor TRUE  FALSE
## 6 Returning_Visitor FALSE FALSE
```

There are 12,199 unique rows in our dataset “customer\_unique”.

## Outliers

```
numeric_df <- customer_unique %>% select_if(is.numeric)
boxplot(numeric_df)
```



Most of the column outliers and i will choose to work with them since they might be a true representaion of the data.

## checking for anomalies

Anomalies are inconsistencies in the data

```
###Checking the number of unique values in each column
lengths(lapply(customer1, unique))
```

```
##      Administrative Administrative_Duration      Informational
##              27              3336              17
## Informational_Duration      ProductRelated ProductRelated_Duration
##              1259              311              9552
##      BounceRates      ExitRates      PageValues
##              1872              4777              2704
```



```
##           SpecialDay           Month           OperatingSystems
##           6           10           8
##           Browser           Region           TrafficType
##           13           9           20
##           VisitorType           Weekend           Revenue
##           3           2           2
```

```
str(customer1)
```

```
## 'data.frame': 12316 obs. of 18 variables:
## $ Administrative : int 0 0 0 0 0 0 0 1 0 0 ...
## $ Administrative_Duration: num 0 0 -1 0 0 0 -1 -1 0 0 ...
## $ Informational : int 0 0 0 0 0 0 0 0 0 0 ...
## $ Informational_Duration : num 0 0 -1 0 0 0 -1 -1 0 0 ...
## $ ProductRelated : int 1 2 1 2 10 19 1 1 2 3 ...
## $ ProductRelated_Duration: num 0 64 -1 2.67 627.5 ...
## $ BounceRates : num 0.2 0 0.2 0.05 0.02 ...
## $ ExitRates : num 0.2 0.1 0.2 0.14 0.05 ...
## $ PageValues : num 0 0 0 0 0 0 0 0 0 0 ...
## $ SpecialDay : num 0 0 0 0 0 0 0.4 0 0.8 0.4 ...
## $ Month : chr "Feb" "Feb" "Feb" "Feb" ...
## $ OperatingSystems : int 1 2 4 3 3 2 2 1 2 2 ...
## $ Browser : int 1 2 1 2 3 2 4 2 2 4 ...
## $ Region : int 1 1 9 2 1 1 3 1 2 1 ...
## $ TrafficType : int 1 2 3 4 4 3 3 5 3 2 ...
## $ VisitorType : chr "Returning_Visitor" "Returning_Visitor" "Returning_Visitor" "Return
## $ Weekend : logi FALSE FALSE FALSE FALSE TRUE FALSE ...
## $ Revenue : logi FALSE FALSE FALSE FALSE FALSE FALSE ...
## - attr(*, "na.action")= 'omit' Named int [1:14] 1066 1133 1134 1135 1136 1137 1474 1475 1476 1477 .
## ..- attr(*, "names")= chr [1:14] "1066" "1133" "1134" "1135" ...
```

From the results of the anomalies, we can see that there are no anomalies detected, so I will retain the outliers since they might be as a result of the nature of the dataset.

## 5. Exploratory Data Analysis (Univariate, Bivariate & Multivariate)

### 5.1 Univariate analysis

```
#descriptive statistics
summary(customer_unique)
```

```
## Administrative Administrative_Duration Informational
## Min. : 0.00 Min. : -1.00 Min. : 0.0000
## 1st Qu.: 0.00 1st Qu.: 0.00 1st Qu.: 0.0000
## Median : 1.00 Median : 9.00 Median : 0.0000
## Mean : 2.34 Mean : 81.68 Mean : 0.5088
## 3rd Qu.: 4.00 3rd Qu.: 94.75 3rd Qu.: 0.0000
## Max. : 27.00 Max. : 3398.75 Max. : 24.0000
```

```
## Informational_Duration ProductRelated ProductRelated_Duration
## Min. : -1.00 Min. : 0.00 Min. : -1.0
## 1st Qu.: 0.00 1st Qu.: 8.00 1st Qu.: 193.6
## Median : 0.00 Median : 18.00 Median : 609.5
## Mean : 34.84 Mean : 32.06 Mean : 1207.5
## 3rd Qu.: 0.00 3rd Qu.: 38.00 3rd Qu.: 1477.6
## Max. :2549.38 Max. :705.00 Max. :63973.5
## BounceRates ExitRates PageValues SpecialDay
## Min. :0.00000 Min. :0.00000 Min. : 0.000 Min. :0.00000
## 1st Qu.:0.00000 1st Qu.:0.01422 1st Qu.: 0.000 1st Qu.:0.00000
## Median :0.00293 Median :0.02500 Median : 0.000 Median :0.00000
## Mean :0.02045 Mean :0.04150 Mean : 5.952 Mean :0.06197
## 3rd Qu.:0.01667 3rd Qu.:0.04848 3rd Qu.: 0.000 3rd Qu.:0.00000
## Max. :0.20000 Max. :0.20000 Max. :361.764 Max. :1.00000
## Month OperatingSystems Browser Region
## Length:12199 Min. :1.000 Min. : 1.000 Min. :1.000
## Class :character 1st Qu.:2.000 1st Qu.: 2.000 1st Qu.:1.000
## Mode :character Median :2.000 Median : 2.000 Median :3.000
## Mean :2.124 Mean : 2.358 Mean :3.153
## 3rd Qu.:3.000 3rd Qu.: 2.000 3rd Qu.:4.000
## Max. :8.000 Max. :13.000 Max. :9.000
## TrafficType VisitorType Weekend Revenue
## Min. : 1.000 Length:12199 Mode :logical Mode :logical
## 1st Qu.: 2.000 Class :character FALSE:9343 FALSE:10291
## Median : 2.000 Mode :character TRUE :2856 TRUE :1908
## Mean : 4.075
## 3rd Qu.: 4.000
## Max. :20.000
```

From the above summeries, 1. more people visited the online site less during the weekedn as compared to weekdays. 2. Revenue collected was very little like about 20% of what was expected.

```
#this will show the measures of central tendancies and dispersion of the numerical column
describe(customer_unique)
```

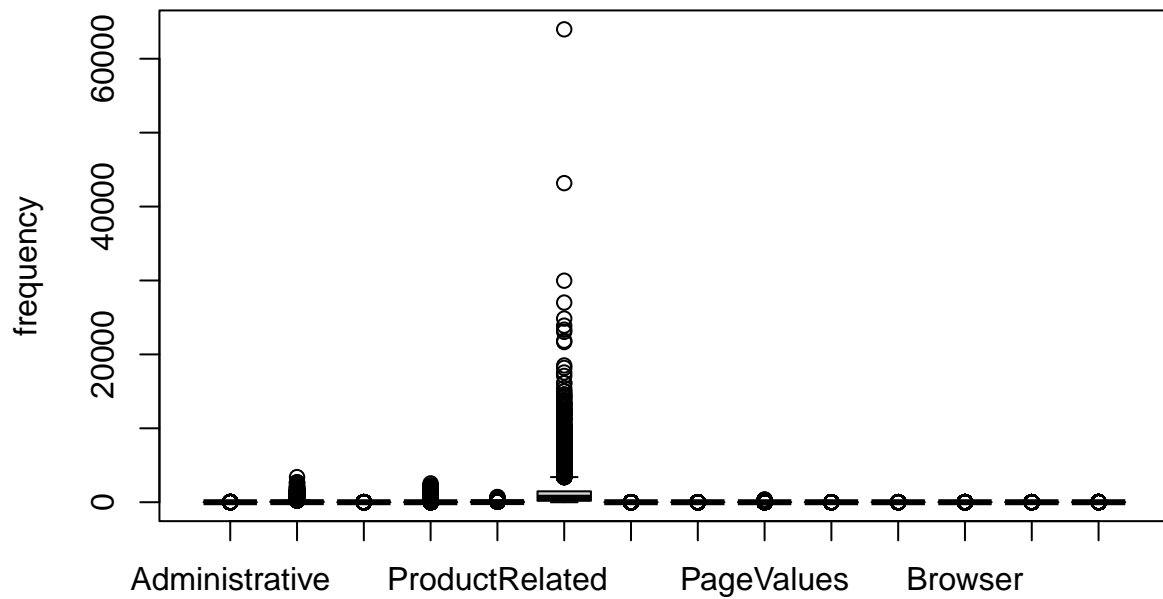
```
## Warning in FUN(newX[, i], ...): no non-missing arguments to min; returning Inf
## Warning in FUN(newX[, i], ...): no non-missing arguments to min; returning Inf
## Warning in FUN(newX[, i], ...): no non-missing arguments to max; returning -Inf
## Warning in FUN(newX[, i], ...): no non-missing arguments to max; returning -Inf

##          vars      n    mean      sd median trimmed   mad min
## Administrative      1 12199    2.34    3.33    1.00    1.66    1.48    0
## Administrative_Duration  2 12199   81.68  177.53    9.00   42.87   13.34   -1
## Informational          3 12199    0.51    1.28    0.00    0.18    0.00    0
## Informational_Duration  4 12199   34.84  141.46    0.00    3.73    0.00   -1
## ProductRelated         5 12199   32.06   44.60   18.00   23.06   19.27    0
## ProductRelated_Duration  6 12199 1207.51 1919.93  609.54  832.36  745.12   -1
## BounceRates            7 12199    0.02    0.05    0.00    0.01    0.00    0
## ExitRates              8 12199    0.04    0.05    0.03    0.03    0.02    0
## PageValues             9 12199    5.95   18.66    0.00    1.33    0.00    0
```

## SpecialDay	10	12199	0.06	0.20	0.00	0.00	0.00	0
## Month*	11	12199	6.17	2.37	7.00	6.36	1.48	1
## OperatingSystems	12	12199	2.12	0.91	2.00	2.06	0.00	1
## Browser	13	12199	2.36	1.71	2.00	2.00	0.00	1
## Region	14	12199	3.15	2.40	3.00	2.79	2.97	1
## TrafficType	15	12199	4.07	4.02	2.00	3.22	1.48	1
## VisitorType*	16	12199	2.72	0.69	3.00	2.89	0.00	1
## Weekend	17	12199	NaN	NA	NA	NaN	NA	Inf
## Revenue	18	12199	NaN	NA	NA	NaN	NA	Inf
##		max	range	skew	kurtosis	se		
## Administrative		27.00	27.00	1.95	4.63	0.03		
## Administrative_Duration		3398.75	3399.75	5.59	50.09	1.61		
## Informational		24.00	24.00	4.01	26.64	0.01		
## Informational_Duration		2549.38	2550.38	7.54	75.45	1.28		
## ProductRelated		705.00	705.00	4.33	31.04	0.40		
## ProductRelated_Duration		63973.52	63974.52	7.25	136.57	17.38		
## BounceRates		0.20	0.20	3.15	9.25	0.00		
## ExitRates		0.20	0.20	2.23	4.62	0.00		
## PageValues		361.76	361.76	6.35	64.93	0.17		
## SpecialDay		1.00	1.00	3.28	9.78	0.00		
## Month*		10.00	9.00	-0.83	-0.37	0.02		
## OperatingSystems		8.00	7.00	2.03	10.27	0.01		
## Browser		13.00	12.00	3.22	12.53	0.02		
## Region		9.00	8.00	0.98	-0.16	0.02		
## TrafficType		20.00	19.00	1.96	3.47	0.04		
## VisitorType*		3.00	2.00	-2.05	2.23	0.01		
## Weekend		-Inf	-Inf	NA	NA	NA		
## Revenue		-Inf	-Inf	NA	NA	NA		

```
# creating a boxplot graph for all numerical variables
boxplot(numeric_df, ylab = 'frequency', main = 'boxplot for numerical variables')
```

## boxplot for numerical variables

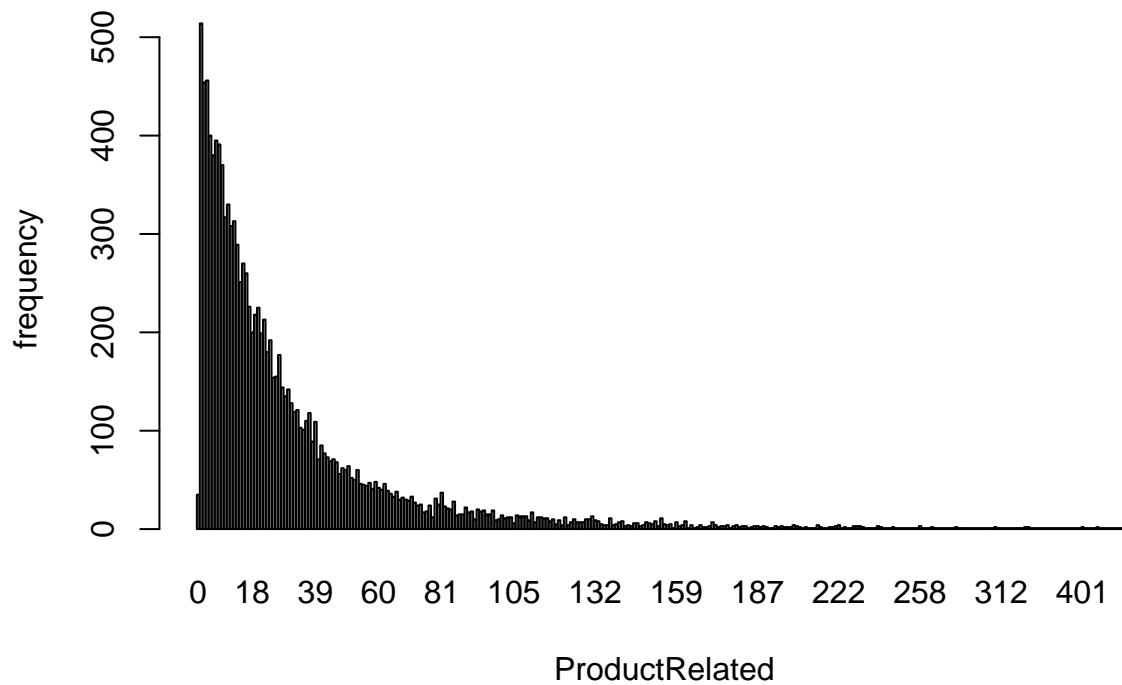


```
# fetching the columns
ProductRelated <- numeric_df$ProductRelated

# fetching the frequency distribution
ProductRelated_frequency <- table(ProductRelated)

# plotting the bargraph
barplot(ProductRelated_frequency, xlab = 'ProductRelated', ylab = 'frequency', main = 'barplot on cus
```

## barplot on customer visits to the ProductRelated pages



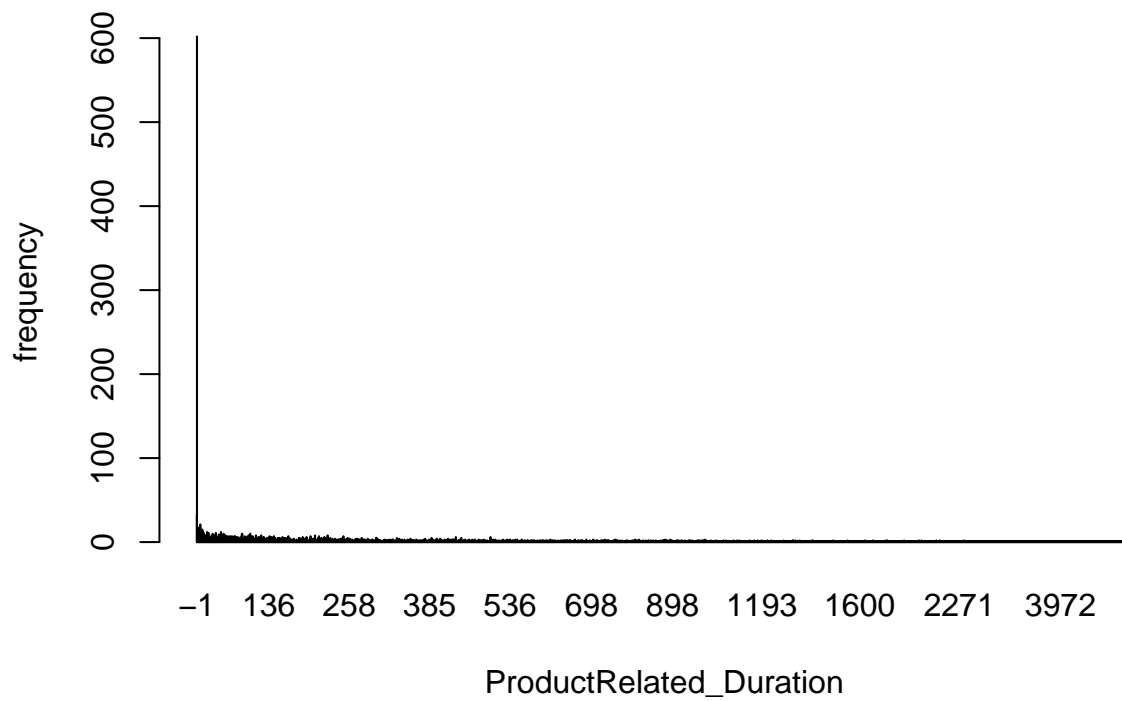
There are high frequency on few numbers of visited sites, the higher the number the lower the frequency.

```
# fetching the columns
ProductRelated_Duration <- numeric_df$ProductRelated_Duration

# fetching the frequency distribution
ProductRelated_Duration_frequency <- table(ProductRelated_Duration)

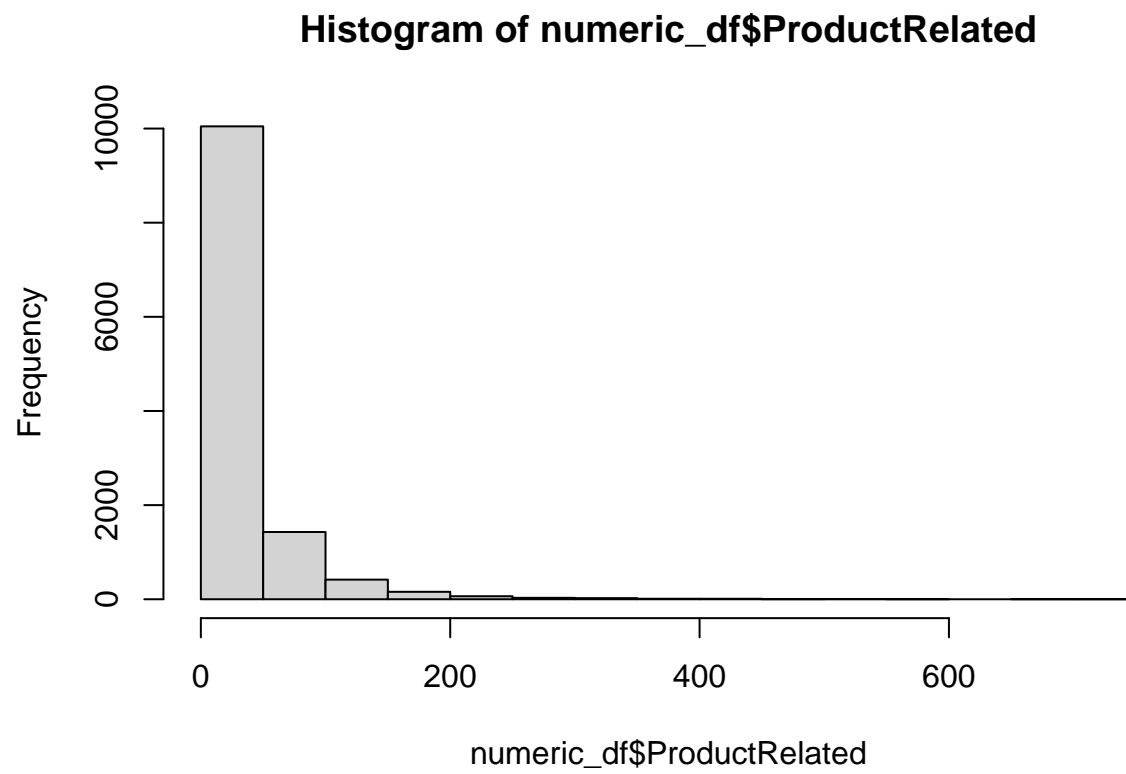
# plotting the bargraph
barplot(ProductRelated_Duration_frequency, xlab = 'ProductRelated_Duration', ylab = 'frequency', main = 'ProductRelated_Duration_frequency')
```

## barplot on duration of customer visits to the ProductRelated pages



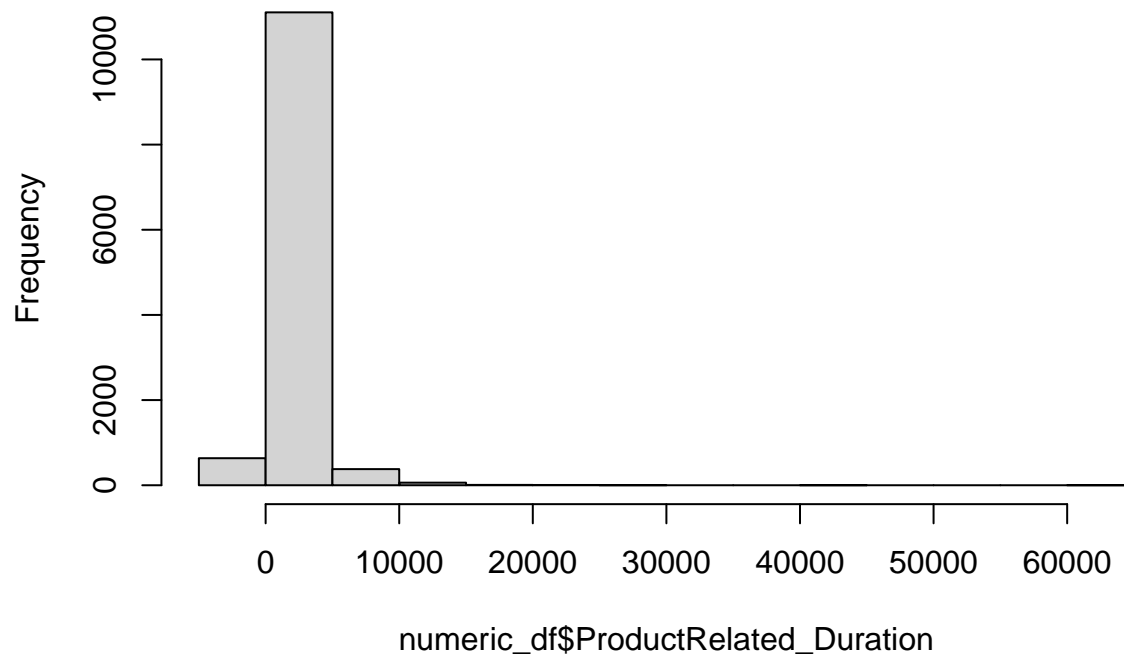
Most individuals spend less time on product related sites.

```
# histogram of product related variable  
hist(numeric_df$ProductRelated)
```



```
hist(numeric_df$ProductRelated_Duration)
```

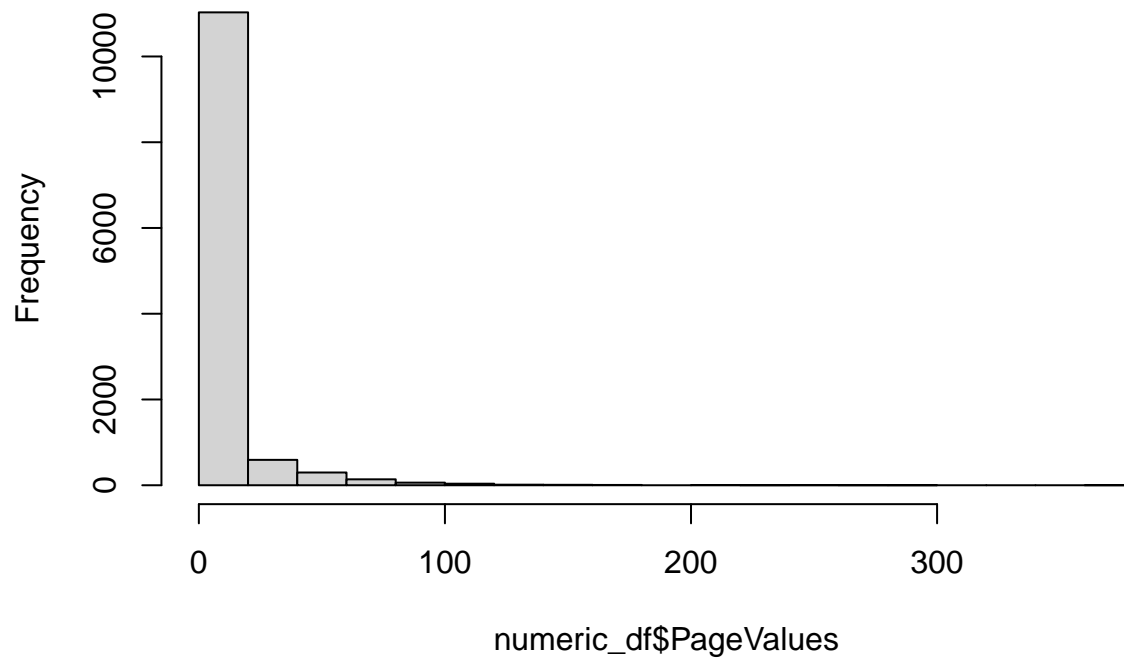
**Histogram of numeric\_df\$ProductRelated\_Duration**



```
# fetching the columns  
hist(numeric_df$PageValues)
```



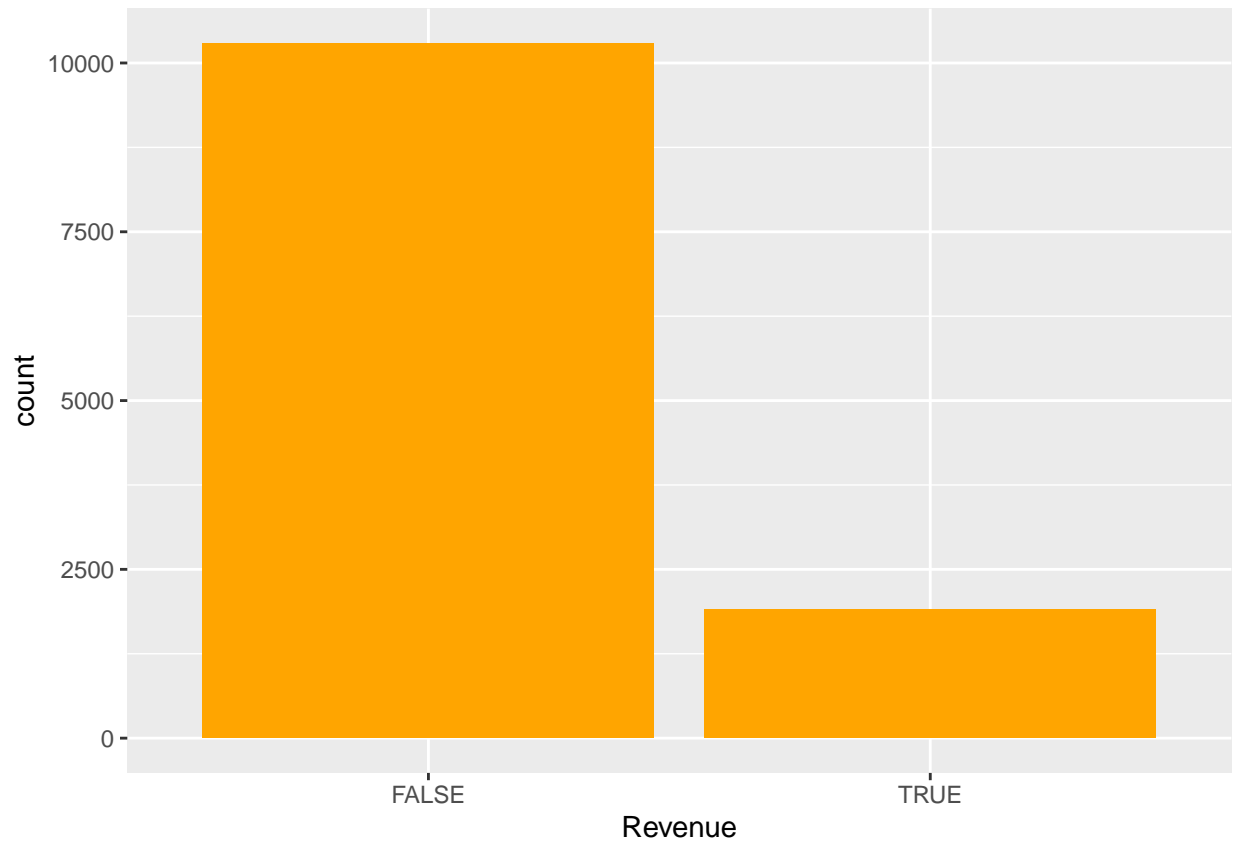
## Histogram of numeric\_df\$PageValues



The lowest page value like value of 20 has very high frequency compared to higher page values.

## 5.2 Bivariate analysis

```
#Plotting the number of customers who brought in revenues.  
ggplot(customer_unique, aes(Revenue)) +  
  geom_bar(fill = "orange")
```



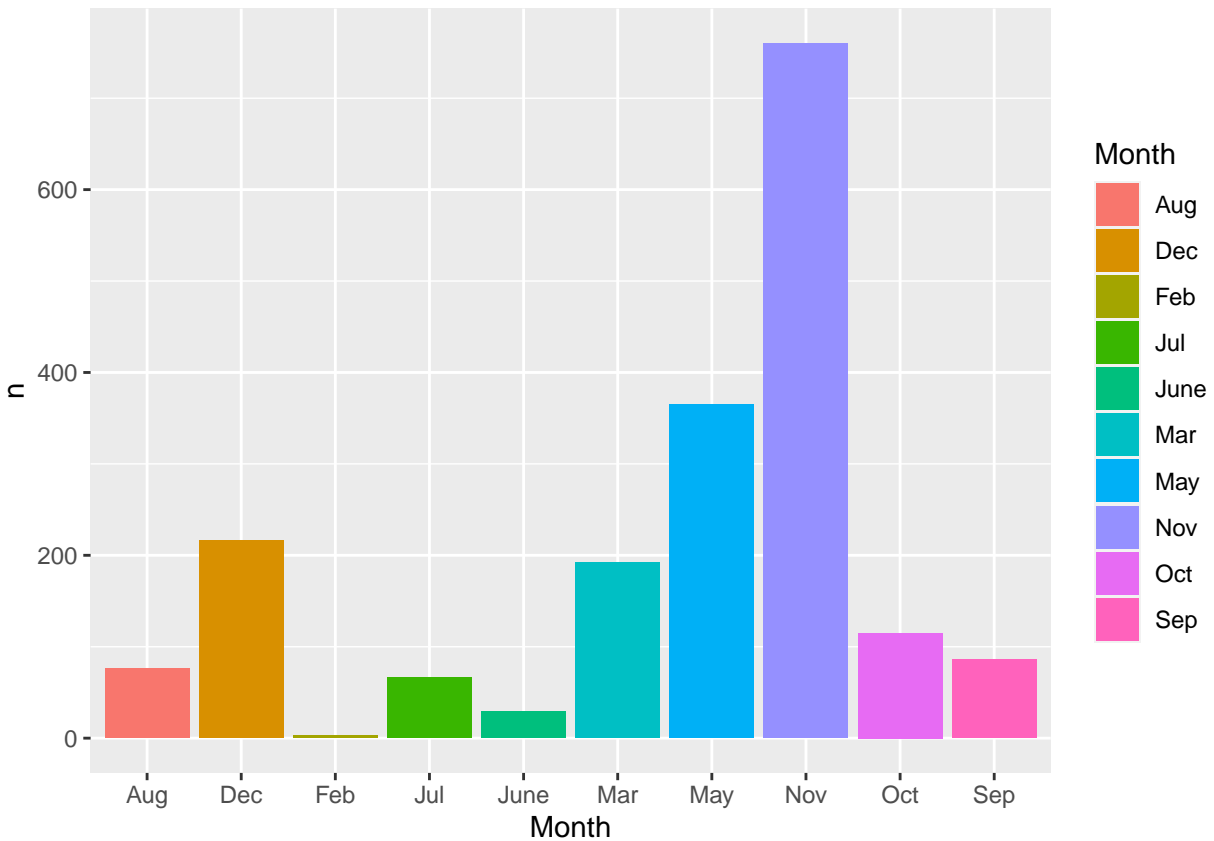
Very few customers brought in revenue

```
#changing the datatype of revenue to numeric
customer_unique$Revenue = as.character(customer_unique$Revenue)
customer_unique$Revenue <- recode(customer_unique$Revenue , 'TRUE' = 1, 'FALSE' = 0 )
```

```
#Grouping the month with the total number of persons who had revenue
month <- customer_unique %>%
  group_by(Month) %>%
  summarise(n=sum(Revenue, na.rm=TRUE)) %>%
  arrange(desc(n))%>%
  head(10)
```

```
#now plotting the months
m <- ggplot(month, aes(x = `Month`, y = n))

m + geom_col(aes(fill = `Month`))
```



The following months had the most revenues:

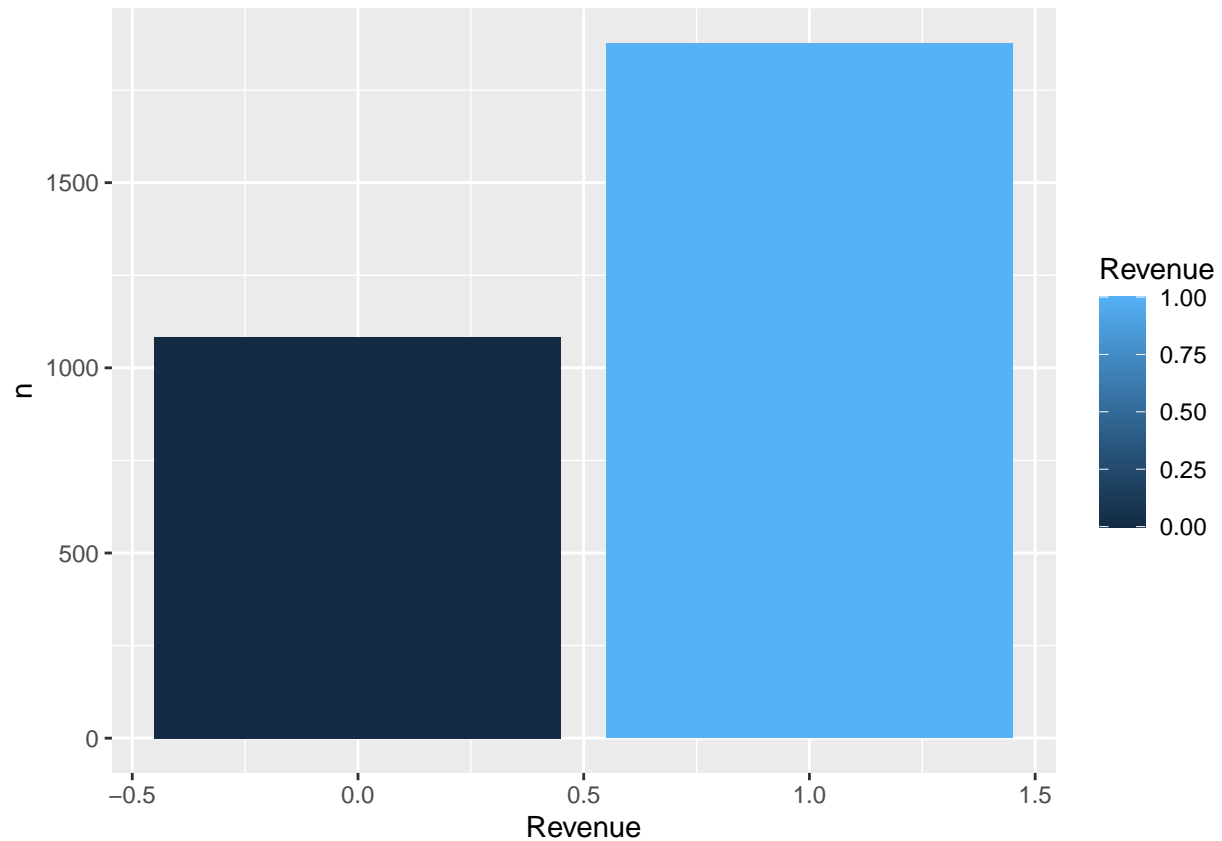
1.November 2.December 3.May 4.March

The month of november has the most revenue collected, it might be there are alot of offers during that month.

```
#Grouping the mean number of product related duration by whether one brought in revenue or not.
product_related <- customer_unique %>%
  group_by(Revenue) %>%
  summarise(n=mean(ProductRelated_Duration, na.rm=TRUE)) %>%
  arrange(desc(n))%>%
  head(10)
```

```
#Viewing the results.
p <- ggplot(product_related, aes(x = `Revenue`, y = n))

p + geom_col(aes(fill = `Revenue`))
```



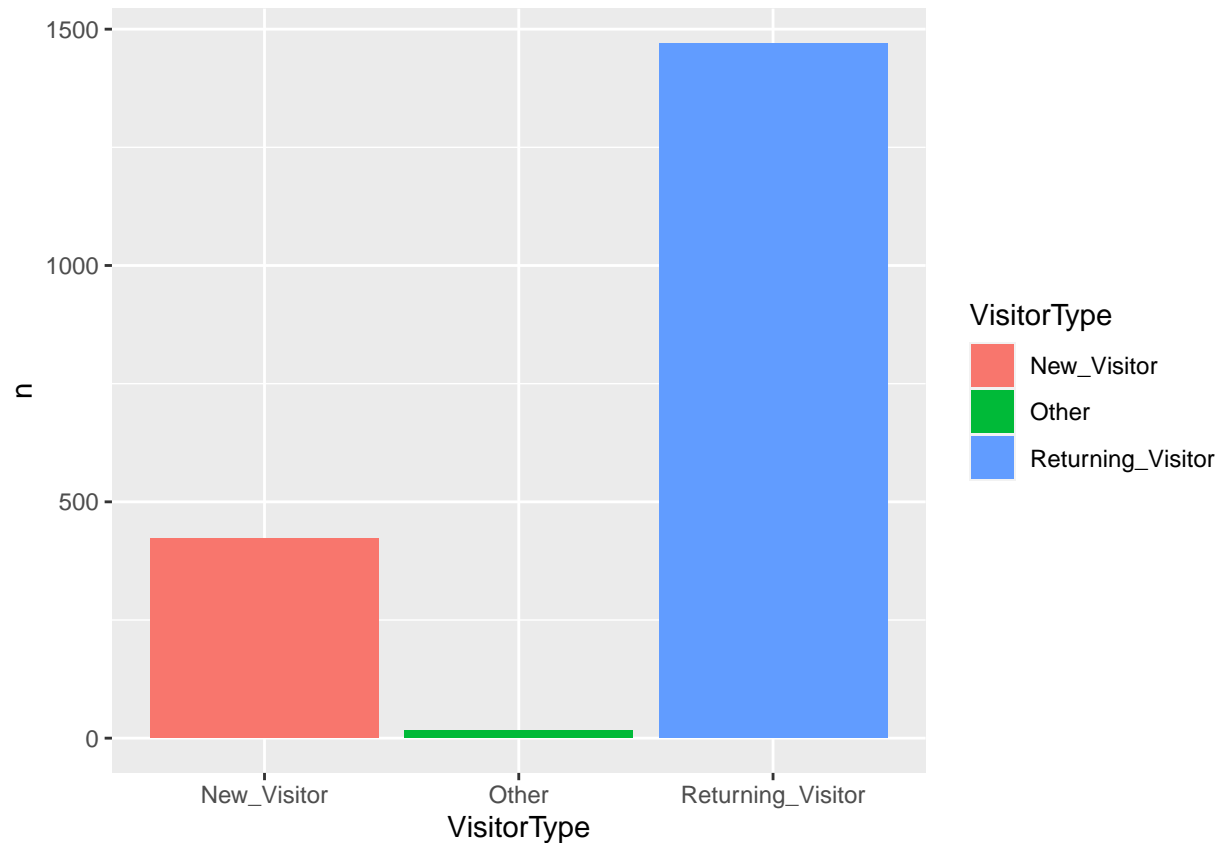
```
# scale_fill_manual(values = c('yellow', 'Red'))
```

The more time spent on the product related pages the more likely that they will bring revenue.

```
#Grouping the visitor type by the revenues
visitor <- customer_unique %>%
  group_by(VisitorType) %>%
  summarise(n=sum(Revenue, na.rm=TRUE)) %>%
  arrange(desc(n))%>%
  head(10)
```

```
#Viewing the results of the visitor type
V <- ggplot(visitor, aes(x = `VisitorType`, y = n))

V + geom_col(aes(fill = `VisitorType`))
```

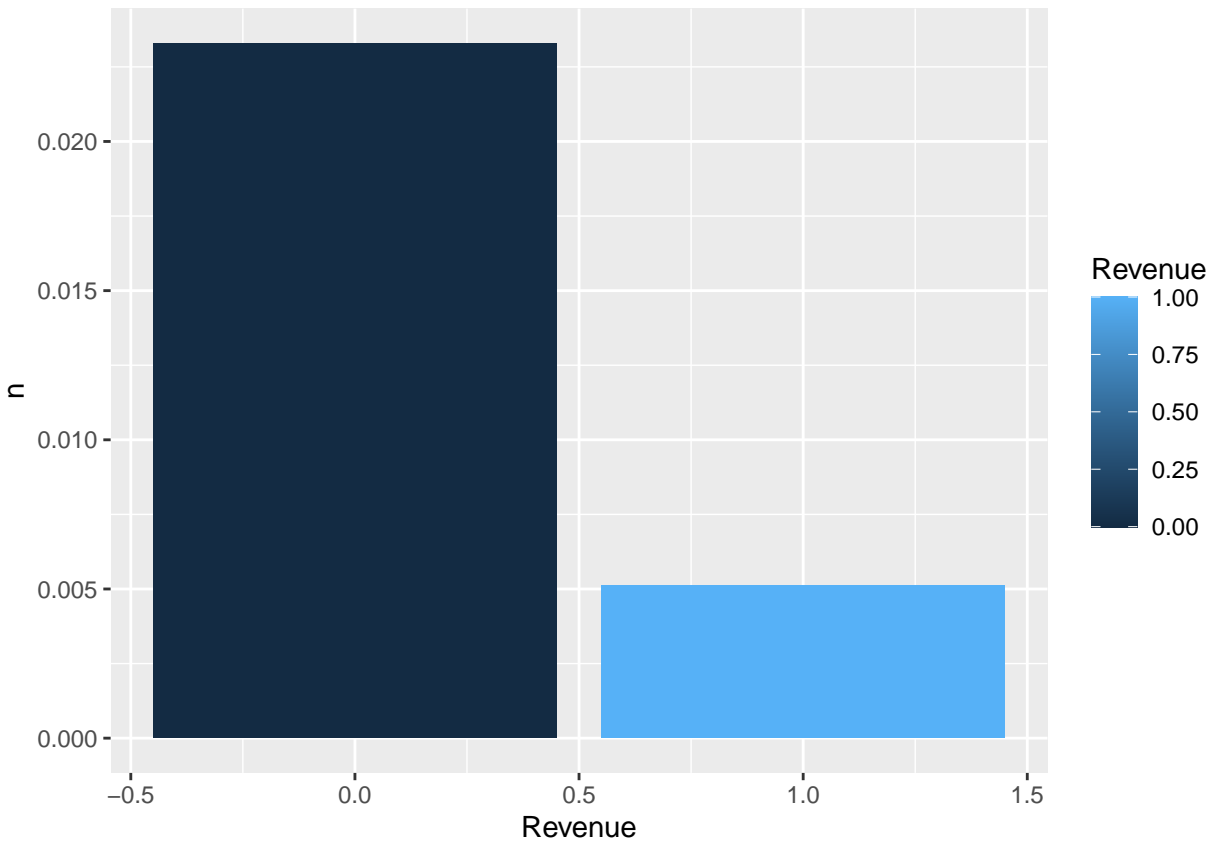


A returning visitor is more likely to purchase the product

```
#Grouping the mean bounce rate by the earning of revenue
bounce_rate <- customer_unique %>%
  group_by(Revenue) %>%
  summarise(n=mean(BounceRates, na.rm=TRUE)) %>%
  arrange(desc(n))%>%
  head(10)
```

```
#Viewing the results.
c <- ggplot(bounce_rate, aes(x = `Revenue`, y = n))

c + geom_col(aes(fill = `Revenue`))
```

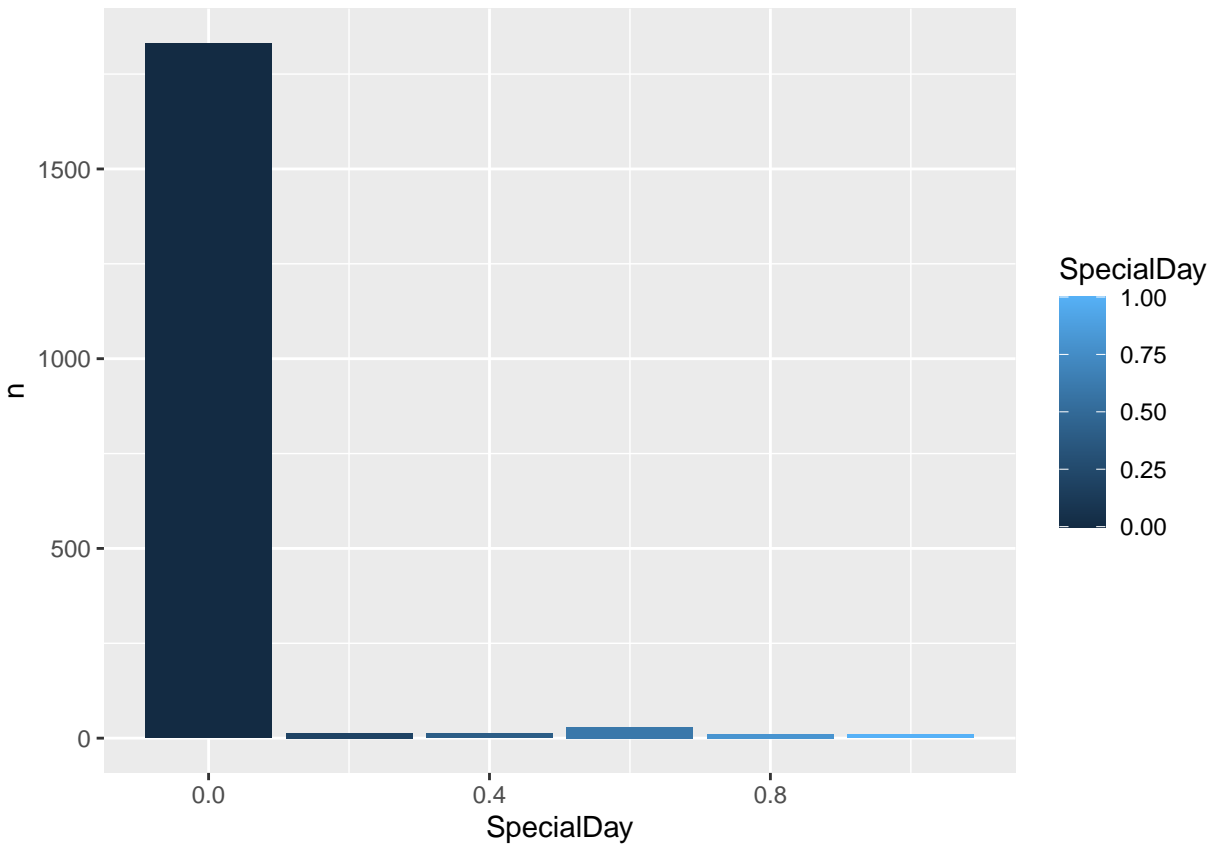


The mean bouncing rate for an individual who does not bring in revenue is higher compared to the one who brings in revenue.

```
#Grouping the special days by the number of generated revenues
special_day <- customer_unique %>%
  group_by(SpecialDay) %>%
  summarise(n=sum(Revenue, na.rm=TRUE)) %>%
  arrange(desc(n))%>%
  head(6)
```

```
#Viewing the results.
c <- ggplot(special_day, aes(x = `SpecialDay`, y = n))

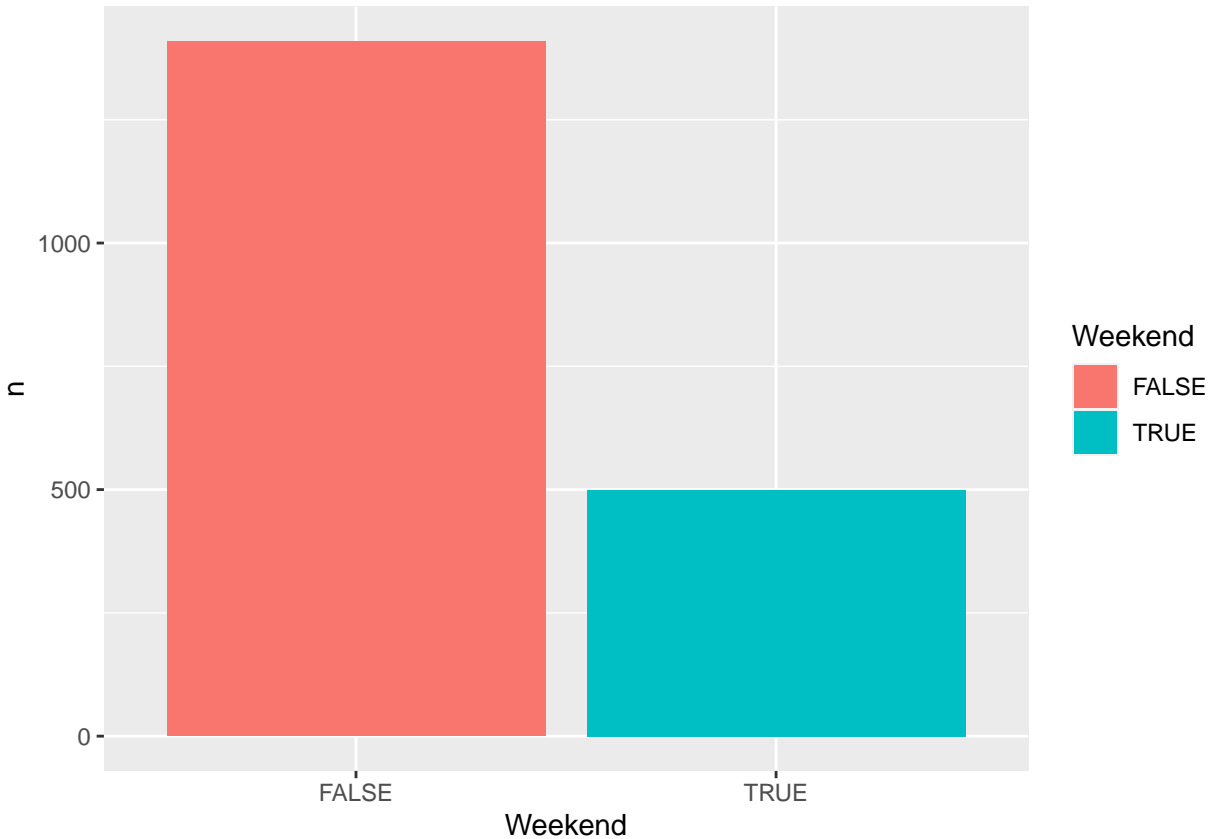
c + geom_col(aes(fill = `SpecialDay`))
```



There is no relationship between the special days and the amount of revenue generated.

```
#Grouping the weekends by the number of Revenues generated  
weekend <- customer_unique %>%  
  group_by(Weekend) %>%  
  summarise(n=sum(Revenue, na.rm=TRUE))
```

```
#Viewing the results.  
w <- ggplot(weekend, aes(x = `Weekend`, y = n))  
  
w + geom_col(aes(fill = `Weekend`))
```



The most number of revenues was generated during weekdays.

```
#Printing out correlations in our dataset
cols <-cor(numeric_df)
cols
```

```
##
## Administrative Administrative_Duration Informational
## Administrative 1.000000000 0.600409653 0.37528761
## Administrative_Duration 0.600409653 1.000000000 0.30143630
## Informational 0.375287611 0.301436296 1.000000000
## Informational_Duration 0.254786021 0.237189860 0.61867795
## ProductRelated 0.428191515 0.286783914 0.37260472
## ProductRelated_Duration 0.371027224 0.353513793 0.38608372
## BounceRates -0.213666635 -0.137333397 -0.10950530
## ExitRates -0.311274132 -0.202024452 -0.15956681
## PageValues 0.096920968 0.066168365 0.04739015
## SpecialDay -0.097072098 -0.074736885 -0.04937677
## OperatingSystems -0.006697922 -0.007610715 -0.00962587
## Browser -0.025763658 -0.015833675 -0.03876681
## Region -0.007262053 -0.006723711 -0.03047732
## TrafficType -0.034784126 -0.015075015 -0.03518669
##
## Informational_Duration ProductRelated
## Administrative 0.254786021 0.428191515
## Administrative_Duration 0.237189860 0.286783914
## Informational 0.618677947 0.372604721
## Informational_Duration 1.000000000 0.279061948
## ProductRelated 0.279061948 1.000000000
```



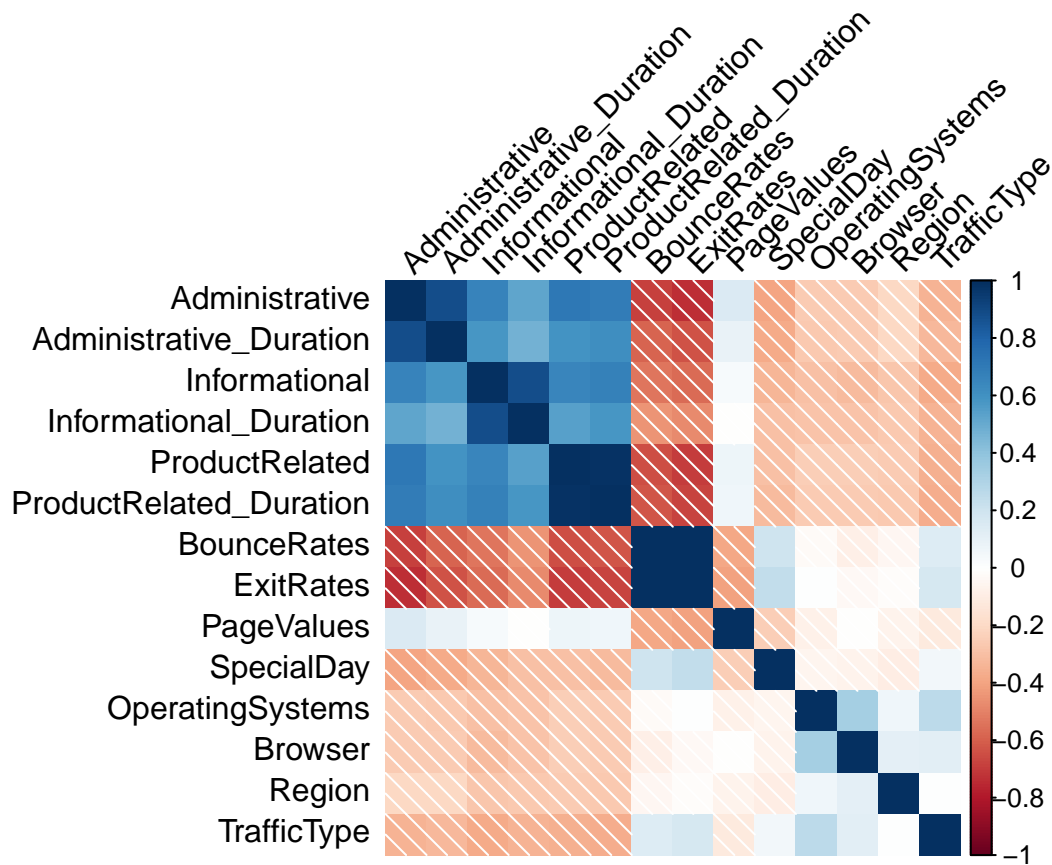
## ProductRelated_Duration	0.346580691	0.860308186		
## BounceRates	-0.070159472	-0.193515772		
## ExitRates	-0.102932678	-0.286163211		
## PageValues	0.030064160	0.054115494		
## SpecialDay	-0.031293040	-0.025930622		
## OperatingSystems	-0.009749983	0.004090351		
## Browser	-0.019609349	-0.013706213		
## Region	-0.027920098	-0.040106501		
## TrafficType	-0.025163571	-0.044344333		
##	ProductRelated_Duration	BounceRates	ExitRates	
## Administrative	0.371027224	-0.213666635	-0.311274132	
## Administrative_Duration	0.353513793	-0.137333397	-0.202024452	
## Informational	0.386083717	-0.109505298	-0.159566815	
## Informational_Duration	0.346580691	-0.070159472	-0.102932678	
## ProductRelated	0.860308186	-0.193515772	-0.286163211	
## ProductRelated_Duration	1.000000000	-0.174375499	-0.245334012	
## BounceRates	-0.174375499	1.000000000	0.903358192	
## ExitRates	-0.245334012	0.903358192	1.000000000	
## PageValues	0.050840624	-0.115991977	-0.173571542	
## SpecialDay	-0.038210652	0.087839995	0.116783762	
## OperatingSystems	0.002775788	0.026839839	0.016482012	
## Browser	-0.007838332	-0.016018380	-0.003565541	
## Region	-0.034862498	0.001432015	-0.001837556	
## TrafficType	-0.037506944	0.089199039	0.087386232	
##	PageValues	SpecialDay	OperatingSystems	Browser
## Administrative	0.09692097	-0.097072098	-0.006697922	-0.025763658
## Administrative_Duration	0.06616837	-0.074736885	-0.007610715	-0.015833675
## Informational	0.04739015	-0.049376774	-0.009625870	-0.038766808
## Informational_Duration	0.03006416	-0.031293040	-0.009749983	-0.019609349
## ProductRelated	0.05411549	-0.025930622	0.004090351	-0.013706213
## ProductRelated_Duration	0.05084062	-0.038210652	0.002775788	-0.007838332
## BounceRates	-0.11599198	0.087839995	0.026839839	-0.016018380
## ExitRates	-0.17357154	0.116783762	0.016482012	-0.003565541
## PageValues	1.00000000	-0.064532709	0.018583782	0.045845065
## SpecialDay	-0.06453271	1.000000000	0.012757766	0.003465984
## OperatingSystems	0.01858378	0.012757766	1.000000000	0.212244823
## Browser	0.04584506	0.003465984	0.212244823	1.000000000
## Region	0.01059087	-0.016452464	0.071953240	0.091889464
## TrafficType	0.01223694	0.052827944	0.182874100	0.102886237
##	Region	TrafficType		
## Administrative	-0.007262053	-0.03478413		
## Administrative_Duration	-0.006723711	-0.01507502		
## Informational	-0.030477323	-0.03518669		
## Informational_Duration	-0.027920098	-0.02516357		
## ProductRelated	-0.040106501	-0.04434433		
## ProductRelated_Duration	-0.034862498	-0.03750694		
## BounceRates	0.001432015	0.08919904		
## ExitRates	-0.001837556	0.08738623		
## PageValues	0.010590868	0.01223694		
## SpecialDay	-0.016452464	0.05282794		
## OperatingSystems	0.071953240	0.18287410		
## Browser	0.091889464	0.10288624		
## Region	1.000000000	0.04252523		
## TrafficType	0.042525234	1.00000000		

```
#Importing the library to do the correlation plot
#install.packages("corrplot",dependencies=TRUE)
```

```
#Loading the corrplot in our google colab
library("corrplot")
```

```
## corrplot 0.90 loaded
```

```
#Printing out the correlation plot
corrplot(cor(cols), method="shade", tl.col="black", tl.srt=45)
```



There is an evident of positive correlation between the following columns:

Administrative Administrative Duration Informational Informational Duration ProductRelated ProductRelated\_Duration

The following columns are negatively linear:

BounceRates ExitRates.

### 5.3 Multivariate analysis

```
#Factorizing categorical variables in our dataset.
customer_unique$VisitorType <- as.integer(as.factor(customer_unique$VisitorType))
customer_unique$Month <- as.integer(as.factor(customer_unique$Month))
customer_unique$Weekend <- as.integer(as.factor(customer_unique$Weekend))
```

```
# previewing the datatypes of the dataset and check if the data types have changed.
sapply(customer_unique, class)
```

```
##      Administrative Administrative_Duration      Informational
##      "integer"          "numeric"          "integer"
## Informational_Duration      ProductRelated ProductRelated_Duration
##      "numeric"          "integer"          "numeric"
##      BounceRates          ExitRates          PageValues
##      "numeric"          "numeric"          "numeric"
##      SpecialDay          Month      OperatingSystems
##      "numeric"          "integer"          "integer"
##      Browser          Region      TrafficType
##      "integer"          "integer"          "integer"
##      VisitorType      Weekend      Revenue
##      "integer"          "integer"          "numeric"
```

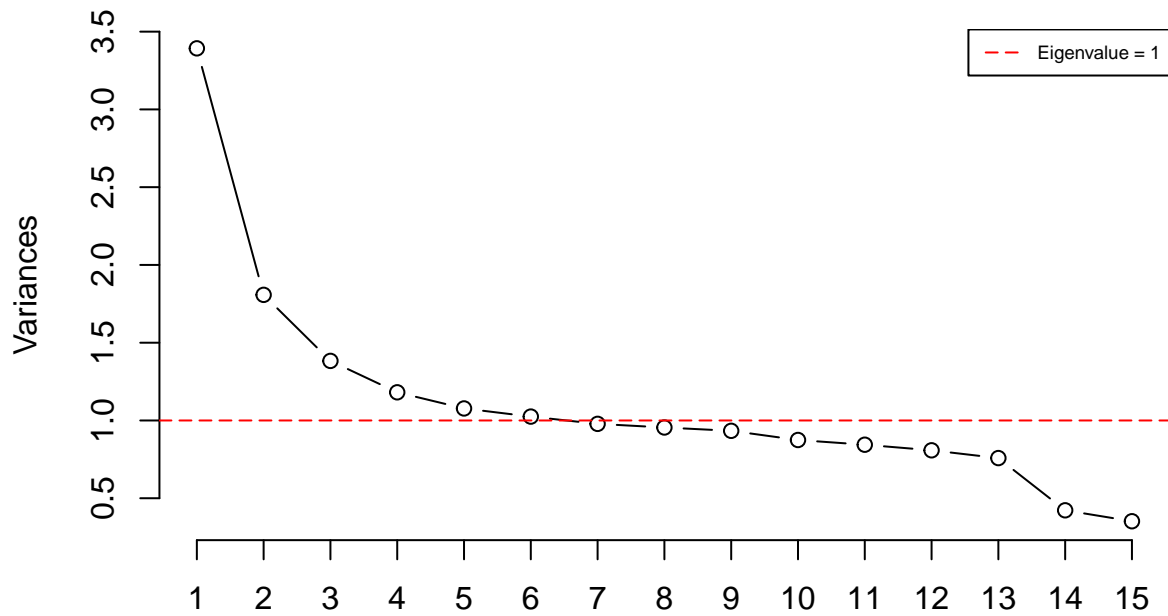
```
#Using the principal component analysis to check for component variance.
customer.pca <- prcomp(customer_unique[,c(1:17)], center = TRUE, scale. = TRUE)
summary(customer.pca)
```

```
## Importance of components:
##      PC1      PC2      PC3      PC4      PC5      PC6      PC7
## Standard deviation  1.8419 1.3445 1.17602 1.08676 1.03789 1.01238 0.98900
## Proportion of Variance 0.1996 0.1063 0.08135 0.06947 0.06337 0.06029 0.05754
## Cumulative Proportion 0.1996 0.3059 0.38725 0.45672 0.52009 0.58038 0.63791
##      PC8      PC9      PC10      PC11      PC12      PC13      PC14
## Standard deviation  0.97717 0.96615 0.93509 0.91878 0.89899 0.8707 0.64989
## Proportion of Variance 0.05617 0.05491 0.05143 0.04966 0.04754 0.0446 0.02484
## Cumulative Proportion 0.69408 0.74899 0.80042 0.85008 0.89762 0.9422 0.96706
##      PC15      PC16      PC17
## Standard deviation  0.59337 0.35182 0.28991
## Proportion of Variance 0.02071 0.00728 0.00494
## Cumulative Proportion 0.98778 0.99506 1.00000
```

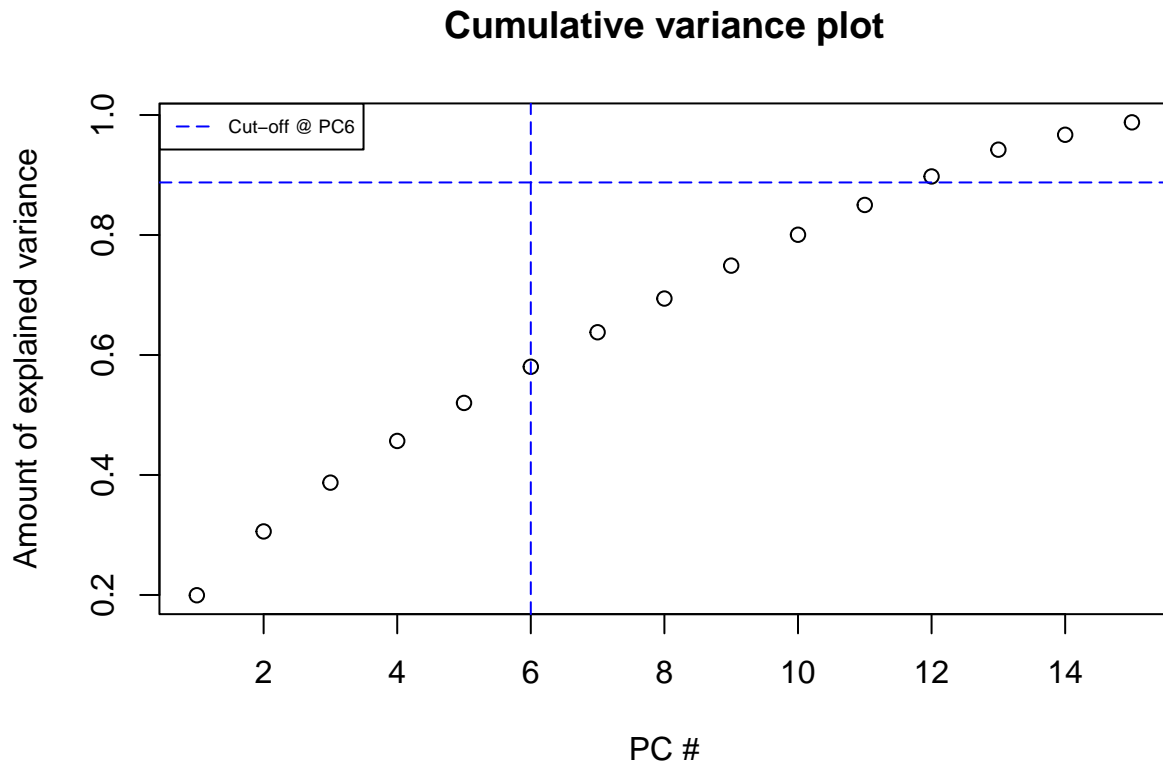
Proportion of Variance: This is the amount of variance the component accounts for in the data, ie PC1 accounts for 19% of total variance in the data alone! Cumulative Proportion: This is simply the accumulated amount of explained variance, ie. if we used the first 10 components we would be able to account for 80% of total variance in the data.

```
screeplot(customer.pca, type = "l", npcs = 15, main = "Screeplot of the first 10 PCs")
abline(h = 1, col="red", lty=5)
legend("topright", legend=c("Eigenvalue = 1"),
      col=c("red"), lty=5, cex=0.6)
```

## Screeplot of the first 10 PCs



```
cumpro <- cumsum(customer.pca$sdev^2 / sum(customer.pca$sdev^2))
plot(cumpro[0:15], xlab = "PC #", ylab = "Amount of explained variance", main = "Cumulative variance plot")
abline(v = 6, col="blue", lty=5)
abline(h = 0.88759, col="blue", lty=5)
legend("topleft", legend=c("Cut-off @ PC6"),
      col=c("blue"), lty=5, cex=0.6)
```



We notice that the first 6 components has an Eigenvalue  $>1$  and explains almost 60% of variance. so we will use the first 6 variables in our analysis.

## 6. Implement the Solution

### 6.1 K-means Clustering

```
#Separating the response variables and the class variable.
customer.new<- customer_unique[, c(1:6)]
customer.class<- customer_unique[, "Revenue"]
head(customer.new)
```

```
##      Administrative Administrative_Duration Informational Informational_Duration
## 1              0              0              0              0
## 2              0              0              0              0
## 3              0             -1              0             -1
## 4              0              0              0              0
## 5              0              0              0              0
## 6              0              0              0              0
##      ProductRelated ProductRelated_Duration
## 1              1          0.000000
## 2              2          64.000000
## 3              1          -1.000000
```

```
## 4          2          2.666667
## 5         10         627.500000
## 6         19         154.216667
```

```
head(customer.class)
```

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

```
#Normalizing our continuous variables.
normalize <- function(x){
  return ((x-min(x)) / (max(x)-min(x)))
}
customer.new$Administrative<- normalize(customer.new$Administrative)
customer.new$Administrative_Duration<- normalize(customer.new$Administrative_Duration)
customer.new$ProductRelated<- normalize(customer.new$ProductRelated)
customer.new$ProductRelated_Duration<- normalize(customer.new$ProductRelated_Duration)
customer.new$Informational<- normalize(customer.new$Informational)
customer.new$Informational_Duration<- normalize(customer.new$Informational_Duration)
head(customer.new)
```

```
##      Administrative Administrative_Duration Informational Informational_Duration
## 1              0          0.0002941393              0          0.0003920992
## 2              0          0.0002941393              0          0.0003920992
## 3              0          0.0000000000              0          0.0000000000
## 4              0          0.0002941393              0          0.0003920992
## 5              0          0.0002941393              0          0.0003920992
## 6              0          0.0002941393              0          0.0003920992
##      ProductRelated ProductRelated_Duration
## 1      0.001418440          1.563122e-05
## 2      0.002836879          1.016029e-03
## 3      0.001418440          0.000000e+00
## 4      0.002836879          5.731448e-05
## 5      0.014184397          9.824223e-03
## 6      0.026950355          2.426226e-03
```

```
# Applying the K-means clustering algorithm with no. of centroids(k)=3
# ---
#
result<- kmeans(customer.new,3)

# Previewing the no. of records in each cluster
#
result$size
```

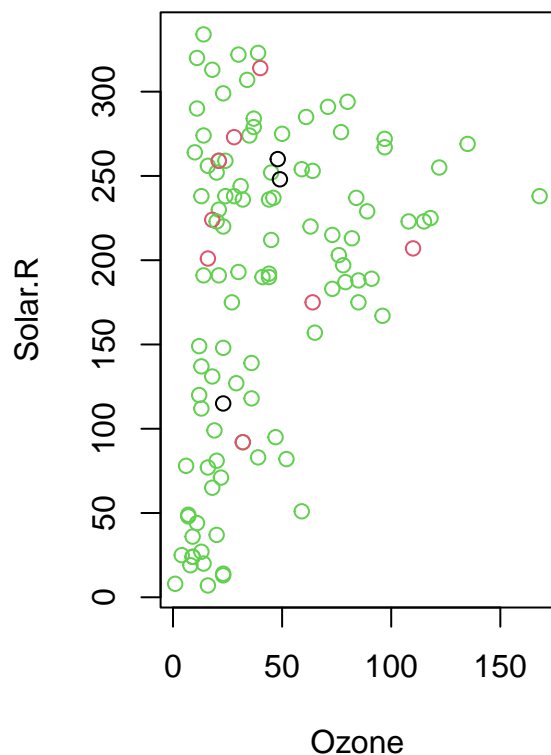
```
## [1] 1001 3258 7940
```

```
# Getting the value of cluster center datapoint value(3 centers for k=3)
# ---
#
result$centers
```

```
##      Administrative Administrative_Duration Informational Informational_Duration
## 1      0.38805639          0.108557639      0.09565435      0.077862078
## 2      0.16803083          0.046259705      0.02889042      0.016117333
## 3      0.01528594          0.004697754      0.00865869      0.005159646
##      ProductRelated ProductRelated_Duration
## 1      0.13769635          0.05828508
## 2      0.05635316          0.02301451
## 3      0.02938189          0.01223175
```

```
# Visualizing the clustering results
# ---
#
par(mfrow = c(1,2), mar = c(5,4,2,2))

# Plotting to see how Ozone and Solar.R data points have been distributed in clusters
# ---
#
plot(airquality[,1:2], col = result$cluster)
```

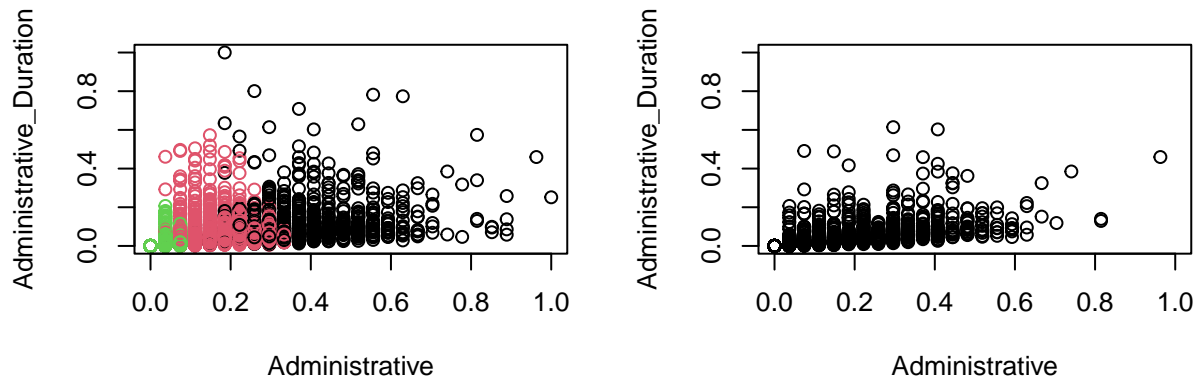


```
# Verifying the results of clustering
# ---
#
par(mfrow = c(2,2), mar = c(5,4,2,2))

# Plotting to see how administrative and administrative_duration data points have been distributed in c
```

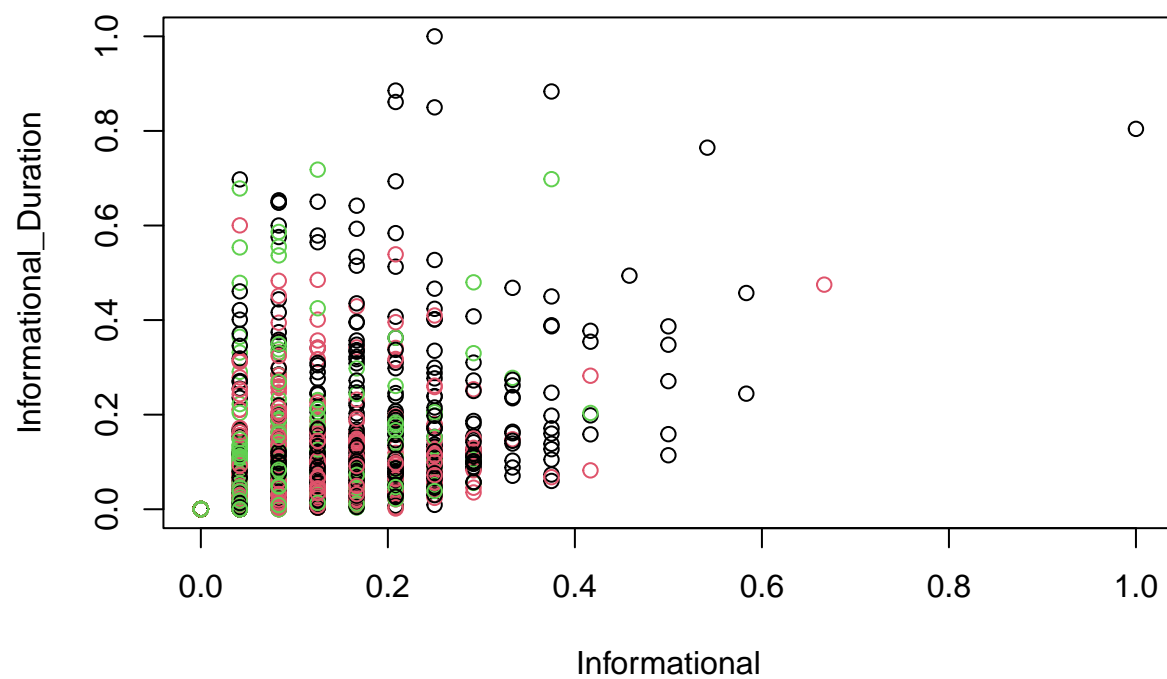
```
plot(customer.new[c(1,2)], col = result$cluster)

# Plotting to see how administrative and administrative_duration data points have been distributed
# originally as per "class" attribute in dataset
# ---
#
plot(customer.new[c(1,2)], col = customer.class)
```

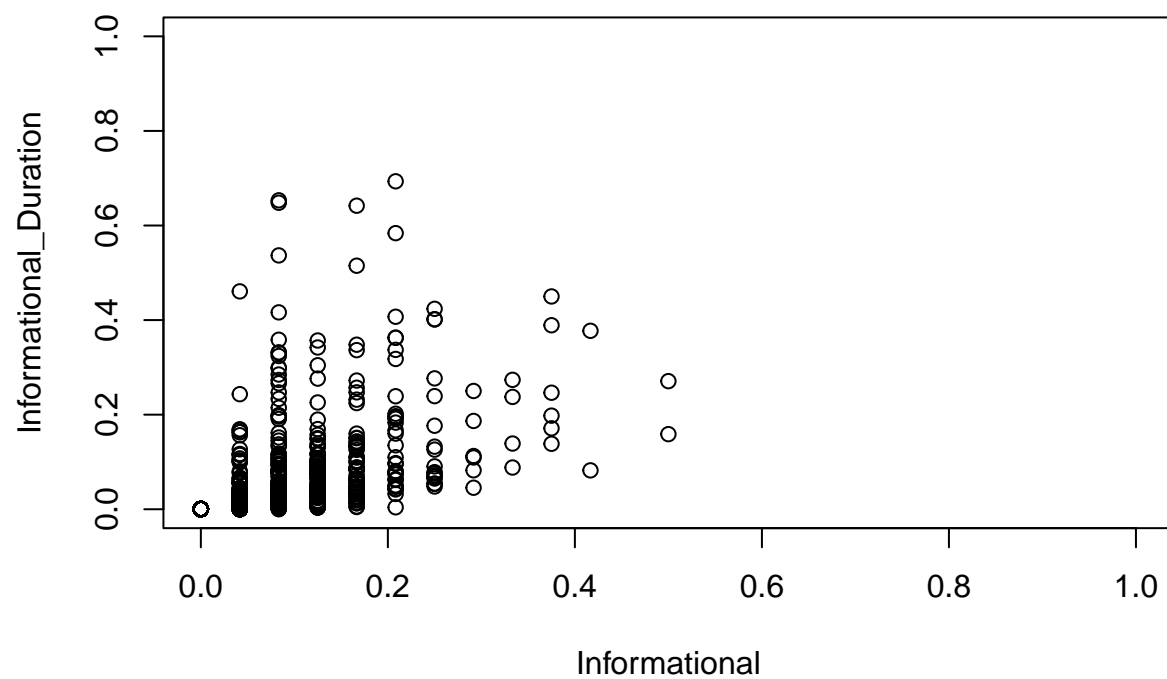


```
# Plotting to see how informational and informational_duration data points have been distributed in clu
# ---
#
plot(customer.new[c(3,4)], col = result$cluster)
```

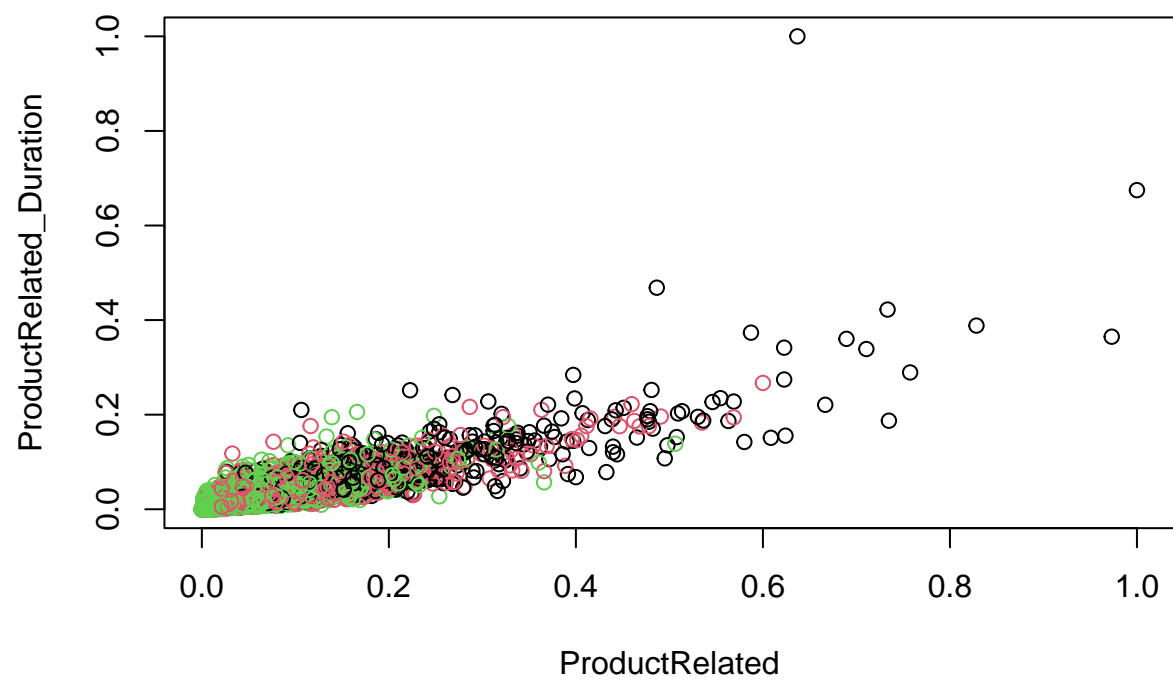




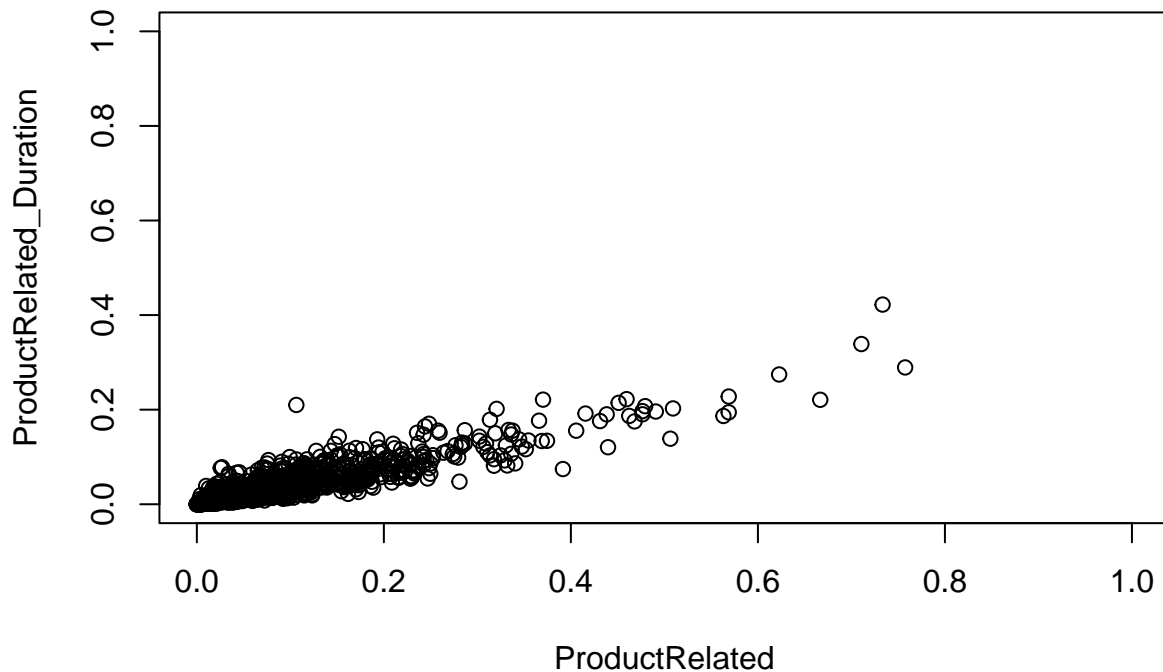
```
plot(customer.new[c(3,4)], col = customer.class)
```



```
# Plotting to see how product reated and product related duration data points have been distributed in
# ---
#
plot(customer.new[c(5,6)], col = result$cluster)
```



```
plot(customer.new[c(5,6)], col = customer.class)
```



```
table(result$cluster, customer.class)
```

```
##      customer.class
##      0      1
## 1  727  274
## 2 2590  668
## 3 6974  966
```

The first cluster correctly classified 6974 values correctly and 966 incorrectly. The second cluster correctly classified 727 values correctly and 274 values incorrectly. The third cluster correctly classified 2590 values correctly and 668 values incorrectly.

## 6.2 Hierarchical Clustering

*# we start by scaling the data using the R function scale() as follows*

```
customer_h <- scale(customer_unique[, c(1:6)])
head(customer_h)
```

```
##      Administrative Administrative_Duration Informational Informational_Duration
## 1      -0.7025315          -0.4601081      -0.3988128          -0.2462725
## 2      -0.7025315          -0.4601081      -0.3988128          -0.2462725
## 3      -0.7025315          -0.4657410      -0.3988128          -0.2533417
```

```
## 4      -0.7025315      -0.4601081      -0.3988128      -0.2462725
## 5      -0.7025315      -0.4601081      -0.3988128      -0.2462725
## 6      -0.7025315      -0.4601081      -0.3988128      -0.2462725
##      ProductRelated ProductRelated_Duration
## 1      -0.6963635      -0.6289343
## 2      -0.6739424      -0.5955997
## 3      -0.6963635      -0.6294551
## 4      -0.6739424      -0.6275453
## 5      -0.4945739      -0.3020990
## 6      -0.2927843      -0.5486101
```

```
# We now use the R function hclust() for hierarchical clustering
```

```
d <- dist(customer_h, method = "euclidean")
```

```
# We then hierarchical clustering using the Ward's method
```

```
res.hc <- hclust(d, method = "ward.D2" )
```

```
# Lastly, we plot the obtained dendrogram
```

```
# ---
```

```
#
```

```
plot(res.hc, cex = 0.6, hang = -1)
```

## Cluster Dendrogram



```
d
hclust (*, "ward.D2")
```

We were not really able to draw insights from the dendrogram above.

## 7. Challenging the Solution

Our Hierarchical Clustering Method did not perform as well even after performing feature reduction using PCA. This might have been caused by the high number of records that was in our dataset.