Business Understanding

My-Duka is an online shop that recently launched their services. As a new company, they would like to use effective and strategic marketing techniques to reach their clientelle.

Specifying the analytic Question

My-duka would like to understand which customers are highly likely to click on an add ontheir site and vice-versa.

Define the Metric for Success

Thorough Data Cleaning Perform Univariate analysis Perform Bivariate Analysis

Experimental design

Data Understanding Univariate Analysis Bivariate Analysis Plotting the summaries Conclusion

```
output:
  pdf_document: default
---

title: "Data Cleaning with R"
author: "Vivian Njau"
date: "2/26/2020"
output: pdf_document
```

R Markdown

Data Cleaning

```
#specify the path where the file is located
library("data.table")
```

obtaining the path to the working directrory

```
getwd()

## [1] "C:/Users/hp/Documents"
```

Loading the datasets

```
library("readr")
df <- read.csv("advertising.csv")
head(df)
```

```
##   Daily.Time.Spent.on.Site Age Area.Income Daily.Internet.Usage
## 1                    68.95  35    61833.90               256.09
## 2                    80.23  31    68441.85               193.77
## 3                    69.47  26    59785.94               236.50
## 4                    74.15  29    54806.18               245.89
## 5                    68.37  35    73889.99               225.58
## 6                    59.99  23    59761.56               226.74
##                           Ad.Topic.Line           City Male    Country
## 1    Cloned 5thgeneration orchestration    Wrightburgh    0    Tunisia
## 2    Monitored national standardization      West Jodi    1      Nauru
## 3      Organic bottom-line service-desk       Davidton    0 San Marino
## 4 Triple-buffered reciprocal time-frame West Terrifurt    1      Italy
## 5         Robust logistical utilization   South Manuel    0    Iceland
## 6       Sharable client-driven software      Jamieberg    1     Norway
##             Timestamp Clicked.on.Ad
## 1 2016-03-27 00:53:11             0
## 2 2016-04-04 01:39:02             0
## 3 2016-03-13 20:35:42             0
## 4 2016-01-10 02:31:19             0
## 5 2016-06-03 03:36:18             0
## 6 2016-05-19 14:30:17             0
```

Previewing the top of the dataset

```r
advert_df <- data.frame(df)
head(advert_df)
```


```
##   Daily.Time.Spent.on.Site Age Area.Income Daily.Internet.Usage
## 1                    68.95  35    61833.90               256.09
## 2                    80.23  31    68441.85               193.77
## 3                    69.47  26    59785.94               236.50
## 4                    74.15  29    54806.18               245.89
## 5                    68.37  35    73889.99               225.58
## 6                    59.99  23    59761.56               226.74
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## 4 Triple-buffered reciprocal time-frame West Terrifurt    1      Italy
## 5         Robust logistical utilization   South Manuel    0    Iceland
## 6       Sharable client-driven software      Jamieberg    1     Norway
##             Timestamp Clicked.on.Ad
## 1 2016-03-27 00:53:11             0
## 2 2016-04-04 01:39:02             0
## 3 2016-03-13 20:35:42             0
## 4 2016-01-10 02:31:19             0
## 5 2016-06-03 03:36:18             0
## 6 2016-05-19 14:30:17             0
```


Previewing the summary of the dataset

```r
summary(advert_df)
```

```
##  Daily.Time.Spent.on.Site      Age          Area.Income    
Daily.Internet.Usage
##  Min.   :32.60             Min.   :19.00   Min.   :13996   Min.   :104.8  
##  1st Qu.:51.36             1st Qu.:29.00   1st Qu.:47032   1st Qu.:138.8  
##  Median :68.22             Median :35.00   Median :57012   Median :183.1  
##  Mean   :65.00             Mean   :36.01   Mean   :55000   Mean   :180.0  
##  3rd Qu.:78.55             3rd Qu.:42.00   3rd Qu.:65471   3rd Qu.:218.8  
##  Max.   :91.43             Max.   :61.00   Max.   :79485   Max.   :270.0  
##                                                                           
##                                  Ad.Topic.Line              City    
##  Adaptive 24hour Graphic Interface      :  1   Lisamouth      :  3  
##  Adaptive asynchronous attitude         :  1   Williamsport   :  3  
##  Adaptive context-sensitive application :  1   Benjaminchester:  2  
##  Adaptive contextually-based methodology:  1   East John      :  2  
##  Adaptive demand-driven knowledgebase   :  1   East Timothy   :  2  
##  Adaptive uniform capability            :  1   Johnstad       :  2  
##  (Other)                                :994   (Other)        :986  
##       Male                   Country                   Timestamp    
Clicked.on.Ad
##  Min.   :0.000   Czech Republic:  9   2016-01-01 02:52:10:  1   Min.   
:0.0  
##  1st Qu.:0.000   France        :  9   2016-01-01 03:35:35:  1   1st 
Qu.:0.0  
##  Median :0.000   Afghanistan   :  8   2016-01-01 05:31:22:  1   Median 
:0.5  
##  Mean   :0.481   Australia     :  8   2016-01-01 08:27:06:  1   Mean   
:0.5  
##  3rd Qu.:1.000   Cyprus        :  8   2016-01-01 15:14:24:  1   3rd 
Qu.:1.0  
##  Max.   :1.000   Greece        :  8   2016-01-01 20:17:49:  1   Max.   
:1.0  
##                  (Other)       :950   (Other)            :994
```

Properties of the dataset

Length

```r
length(advert_df)

## [1] 10

#The dataframe has 1000 entries
```

Dimensions

```r
dim(advert_df)

## [1] 1000   10

#The dataframe has 1000 row entries and 10 columns
```

Column Names

```
colnames(advert_df)
```

```
##  [1] "Daily.Time.Spent.on.Site" "Age"
##  [3] "Area.Income"              "Daily.Internet.Usage"
##  [5] "Ad.Topic.Line"            "City"
##  [7] "Male"                     "Country"
##  [9] "Timestamp"                "Clicked.on.Ad"
```

```
#The ten column names are:
```

Column data types

```
sapply(advert_df, class)
```

```
## Daily.Time.Spent.on.Site                      Age              Area.Income
##                "numeric"                "integer"                "numeric"
##     Daily.Internet.Usage            Ad.Topic.Line                     City
##                "numeric"                 "factor"                 "factor"
##                     Male                  Country                Timestamp
##                "integer"                 "factor"                 "factor"
##            Clicked.on.Ad
##                "integer"
```

Data Cleaning

Missing values

```
#Checking the sum of missing values per column
colSums(is.na(advert_df))
```

```
## Daily.Time.Spent.on.Site                      Age              Area.Income
##                        0                        0                        0
##     Daily.Internet.Usage            Ad.Topic.Line                     City
##                        0                        0                        0
##                     Male                  Country                Timestamp
##                        0                        0                        0
##            Clicked.on.Ad
##                        0
```

```
#there are no misssing values in the data
```

Duplicates

```
duplicated_rows <- advert_df[duplicated(advert_df),]
duplicated_rows
```

```
##  [1] Daily.Time.Spent.on.Site Age                      Area.Income
##  [4] Daily.Internet.Usage     Ad.Topic.Line            City
##  [7] Male                     Country                  Timestamp
## [10] Clicked.on.Ad
## <0 rows> (or 0-length row.names)
```

```
#there are no duplicate entries in the data
```

Assigning the appropriate datatypes for each column

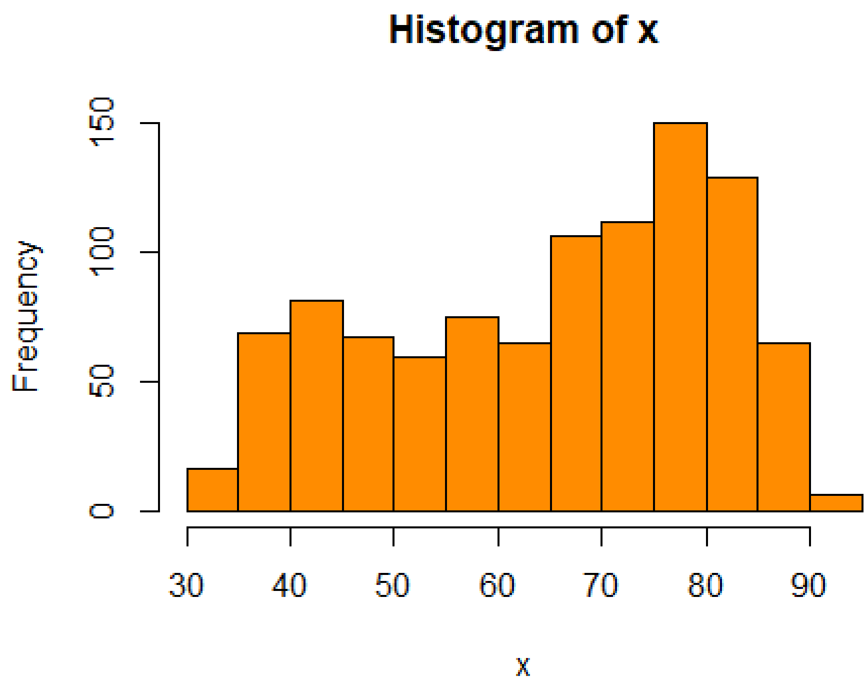
Changing the timestamp datatype from factor to date_time

```
#changing the timestamp datatype from factor to date_time
advert_df$Timestamp <- as.Date(advert_df$Timestamp, format = "%Y-%m-%s-%h-%m-
%s")

#checking the new datatype for the Timestamp column
sapply(advert_df, class)

## Daily.Time.Spent.on.Site                      Age              Area.Income
##                "numeric"                "integer"                "numeric"
##     Daily.Internet.Usage            Ad.Topic.Line                     City
##                "numeric"                 "factor"                 "factor"
##                     Male                  Country                Timestamp
##                "integer"                 "factor"                   "Date"
##             Clicked.on.Ad
##                "integer"
```

Univarite analysis

Daily.Time.Spent.on.Site

```
#This column represents the amount of time that a user spends on the website
# measures of central tendency

# mean
mean(advert_df$Daily.Time.Spent.on.Site)

## [1] 65.0002

# median
median(advert_df$Daily.Time.Spent.on.Site)

## [1] 68.215

# mode
x <- advert_df$Daily.Time.Spent.on.Site
#sort(x)
names(table(x))[table(x)==max(table(x))]

## [1] "62.26" "75.55" "77.05" "78.76" "84.53"

#each of the values printed below appear thrice in the dataset

#distribution
hist(x, col=c("darkorange"))
```



The users spend an average 65.002 minutes on the website.

The modal time is “62.26” “75.55” “77.05” “78.76” “84.53”

The median time is 68.215.

The distribution above is left-skewed.

The highest frequency is 80 units of time(minutes).

Age

```
# Age of the user
#This column represents the Age of the user
# measures of central tendency

# mean
mean(advert_df$Age)

## [1] 36.009

# median
median(advert_df$Age)

## [1] 35

# mode
Age_x <- advert_df$Age
```

```r
#sort(Age_x)
names(table(Age_x))[table(Age_x)==max(table(Age_x))]

## [1] "31"

#each of the values printed below appear thrice in the dataset

#distribution
hist(Age_x, col = c("pink"))
```

The age distribution is right skewed

The respondents on the website are mostly 25-40 years old.

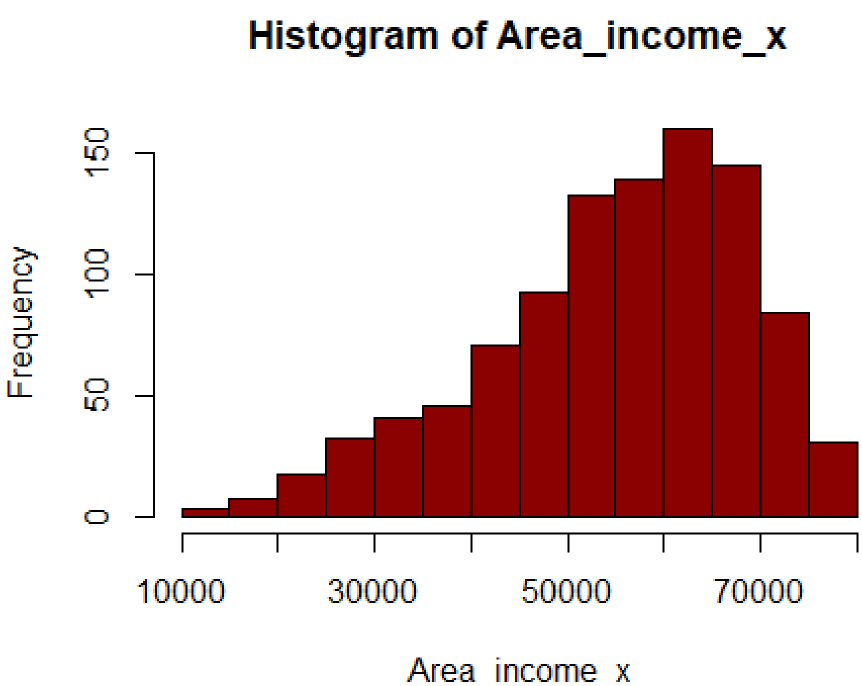
The mean age is 36.

The median age is 35

Area.Income

```r
#income

# mean
mean(advert_df$Area.Income)

## [1] 55000

# median
median(advert_df$Area.Income)
```

```
## [1] 57012.3

# mode
Area_income_x <- advert_df$Area.Income
#sort(Daily.Internet.Usage_x)
#names(table(Area_income_x))[table(Area_income_x)==max(table(Area_income_x))]
#each of the values printed below appear thrice in the dataset

#distribution
hist(Area_income_x, col = c('darkred'))
```



The income distribution is left skewed

The respondents on the website mostly earn between 55,000 to 70,000.

The mean income is 55,000.

The median income is 57,012.

Daily.Internet.Usage

```
#This column represents the amount of data that the user consumers in a day
# measures of central tendency

# mean
mean(advert_df$Daily.Internet.Usage)

## [1] 180.0001
```

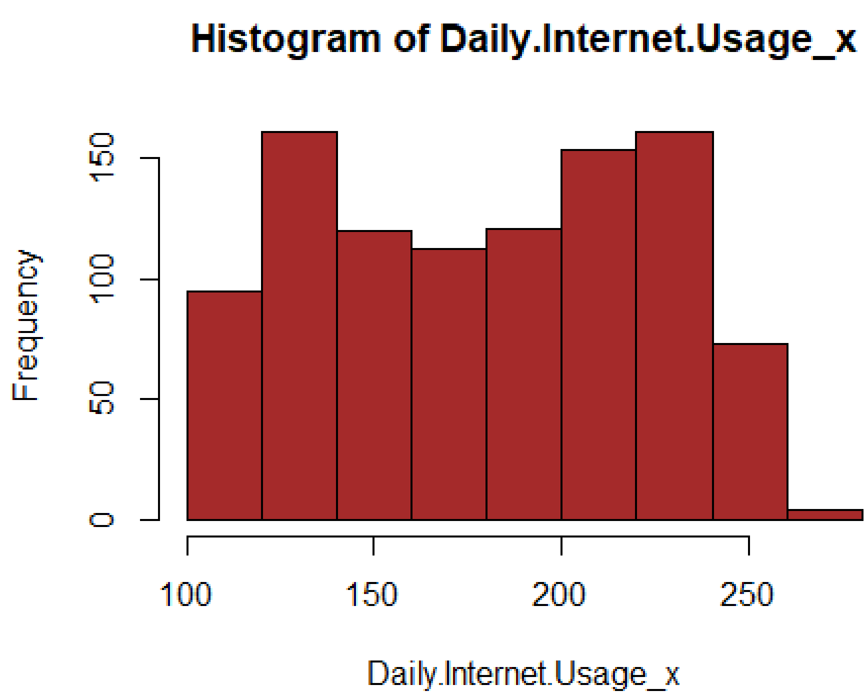
```r
# median
median(advert_df$Daily.Internet.Usage)
```

```
## [1] 183.13
```

```r
# mode
Daily.Internet.Usage_x <- advert_df$Daily.Internet.Usage
#sort(Daily.Internet.Usage_x)
names(table(Daily.Internet.Usage_x))[table(Daily.Internet.Usage_x)==max(table
(Daily.Internet.Usage_x))]
```

```
##  [1] "113.53" "115.91" "117.3"  "119.3"  "120.06" "125.45" "132.38"
"135.24"
##  [9] "136.18" "138.35" "158.22" "161.16" "162.44" "164.25" "167.22"
"169.4"
## [17] "178.75" "182.65" "190.95" "194.23" "201.15" "211.87" "214.42"
"215.18"
## [25] "219.72" "222.11" "223.16" "228.81" "230.36" "234.75" "235.28"
"236.96"
## [33] "247.05" "256.4"
```

```r
#each of the values printed below appear thrice in the dataset

#distribution
hist(Daily.Internet.Usage_x, col = c('brown'))
```



The mean data usage is 180 units.

The median data usage is 183.13 units .

Ad.Topic.Line

```
Ad_topic_line <- advert_df$Ad.Topic.Line
#all the values are unique in this column thus we would drop it when
modelling since it
#does not provide any additional meaningful information

#levels(unique(Ad_topic_line))

#factor(unique(Ad_topic_line))
```

City

City where the user is located

```
#city where the user is located
# measures of central tendency

length(levels(advert_df$City))

## [1] 969

#there are 969 unique cities in the dataset

# mode
City_x <- advert_df$City

#sort(City_x) #this code gives an ordered list of all the elements in the
cities column

#The modal cities in the dataset
names(table(City_x))[table(City_x)==max(table(City_x))]

## [1] "Lisamouth"    "Williamsport"

#the most popular cities in the dataset are: Lisamouth and williamsport
```

Male

```
#gender of the user
#1 indicates that the user is male while indicates that they are female
# measures of central tendency

#levels(advert_df$Male) #this code does not work
#obtaining the unique levels in the gender(Male column)

unique(factor(advert_df$Male))

## [1] 0 1
## Levels: 0 1
```

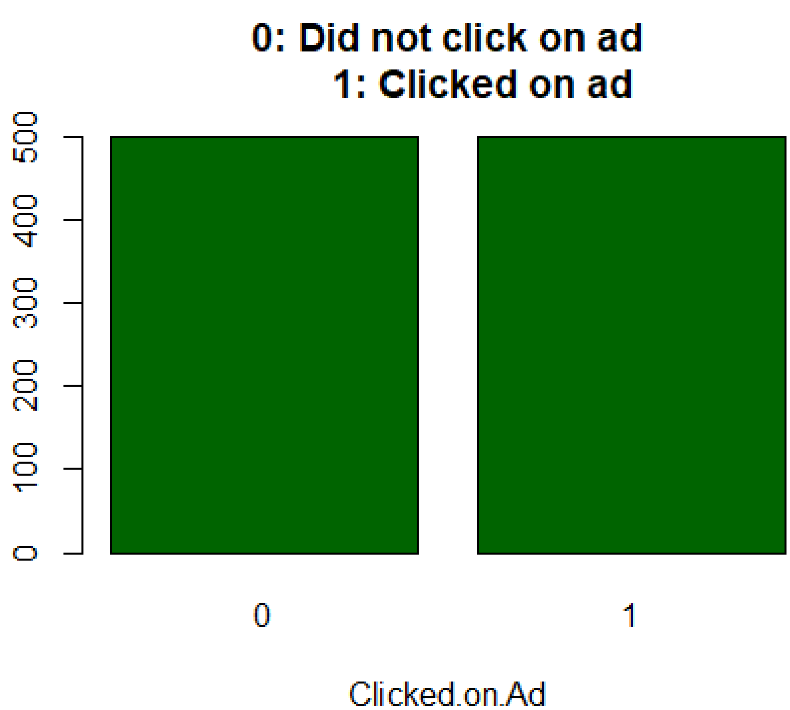
```r
Male_x <- table(advert_df$Male)
#distribution
barplot(Male_x, main="Gender Distribution",col=c("darkgreen"),xlab="Gender")
```

Country

```r
#country where the user belongs
# measures of central tendency

# mode
Country_x <- advert_df$Country

#levels(Country_x) #this code gives the names of the countries

#There are 237 unique countries represented in the dataset
length(levels(Country_x))

## [1] 237

#the modal countries in the dataset
names(table(Country_x))[table(Country_x)==max(table(Country_x))]

## [1] "Czech Republic" "France"

#the most popular countries are:Czech Republic and France
```

Clicked.on.Ad

```r
#zero indicates that a user did not click on an add while 1 indicates that a
user clicked on an add
# measures of central tendency

#levels(advert_df$Clicked.on.Ad) #this code does not work

unique(factor(advert_df$Clicked.on.Ad))

## [1] 0 1
## Levels: 0 1

#there are two unique factors in the clicked on ad column
# mode
Clicked.on.Ad_x <- table(advert_df$Clicked.on.Ad)
#sort(Daily.Internet.Usage_x)
names(table(Clicked.on.Ad_x))[table(Clicked.on.Ad_x)==max(table(Clicked.on.Ad
_x))]

## [1] "500"

#

#distribution
barplot(Clicked.on.Ad_x, main="0: Did not click on ad
        1: Clicked on ad " , col=c("darkgreen"),xlab="Clicked.on.Ad")
```



```
#the distribution is equal. 500 0's and 500 1's
```

Bivariate Analysis and Multivariate Graphical Data Analysis

```
advert_df2 <- subset(advert_df, select = c(Daily.Time.Spent.on.Site,
Age,Area.Income,Daily.Internet.Usage,Male,Clicked.on.Ad ))

head(advert_df2)

##   Daily.Time.Spent.on.Site Age Area.Income Daily.Internet.Usage Male
## 1                    68.95  35    61833.90               256.09    0
## 2                    80.23  31    68441.85               193.77    1
## 3                    69.47  26    59785.94               236.50    0
## 4                    74.15  29    54806.18               245.89    1
## 5                    68.37  35    73889.99               225.58    0
## 6                    59.99  23    59761.56               226.74    1
##   Clicked.on.Ad
## 1             0
## 2             0
## 3             0
## 4             0
## 5             0
## 6             0
```

Correlation

```
#The default method is Pearson, but we can also compute Spearman or Kendall
coefficients.
mydata = cor(advert_df2, method = c("spearman"))
mydata1= cor(advert_df2, method = c("kendall"))
mydata2= cor(advert_df2, method = c("pearson"))

mydata #spearman

##                          Daily.Time.Spent.on.Site         Age Area.Income
## Daily.Time.Spent.on.Site               1.00000000 -0.31686155  0.28313439
## Age                                   -0.31686155  1.00000000 -0.13595396
## Area.Income                            0.28313439 -0.13595396  1.00000000
## Daily.Internet.Usage                   0.51410805 -0.37086395  0.33916021
## Male                                  -0.01592213 -0.02315468 -0.01436909
## Clicked.on.Ad                         -0.74487253  0.48633733 -0.46722440
##                          Daily.Internet.Usage        Male Clicked.on.Ad
## Daily.Time.Spent.on.Site           0.51410805 -0.01592213   -0.74487253
## Age                               -0.37086395 -0.02315468    0.48633733
## Area.Income                        0.33916021 -0.01436909   -0.46722440
## Daily.Internet.Usage               1.00000000  0.02820432   -0.77660702
## Male                               0.02820432  1.00000000   -0.03802747
## Clicked.on.Ad                     -0.77660702 -0.03802747    1.00000000

mydata1 #kendall
```

```
##                         Daily.Time.Spent.on.Site         Age Area.Income
## Daily.Time.Spent.on.Site               1.00000000 -0.19668659  0.16578119
## Age                                   -0.19668659  1.00000000 -0.08005810
## Area.Income                            0.16578119 -0.08005810  1.00000000
## Daily.Internet.Usage                   0.29323600 -0.23244607  0.20837546
## Male                                  -0.01300823 -0.01921715 -0.01173817
## Clicked.on.Ad                         -0.60855366  0.40363397 -0.38167782
##                         Daily.Internet.Usage        Male Clicked.on.Ad
## Daily.Time.Spent.on.Site           0.29323600 -0.01300823   -0.60855366
## Age                               -0.23244607 -0.01921715    0.40363397
## Area.Income                        0.20837546 -0.01173817   -0.38167782
## Daily.Internet.Usage               1.00000000  0.02304102   -0.63443547
## Male                               0.02304102  1.00000000   -0.03802747
## Clicked.on.Ad                     -0.63443547 -0.03802747    1.00000000
```

```r
mydata2 #pearson
```

```
##                         Daily.Time.Spent.on.Site         Age  Area.Income
## Daily.Time.Spent.on.Site               1.00000000 -0.33151334  0.310954413
## Age                                   -0.33151334  1.00000000 -0.182604955
## Area.Income                            0.31095441 -0.18260496  1.000000000
## Daily.Internet.Usage                   0.51865848 -0.36720856  0.337495533
## Male                                  -0.01895085 -0.02104406  0.001322359
## Clicked.on.Ad                         -0.74811656  0.49253127 -0.476254628
##                         Daily.Internet.Usage         Male Clicked.on.Ad
## Daily.Time.Spent.on.Site           0.51865848 -0.018950855   -0.74811656
## Age                               -0.36720856 -0.021044064    0.49253127
## Area.Income                        0.33749553  0.001322359   -0.47625463
## Daily.Internet.Usage               1.00000000  0.028012326   -0.78653918
## Male                               0.02801233  1.000000000   -0.03802747
## Clicked.on.Ad                     -0.78653918 -0.038027466    1.00000000
```

Using the 3 correlation coefficients to get the correlation between the features, we can see that the correlation is very low and negative in most cases.

This means that most of the variables are NOT dependent of each other

Significance levels (p-values) can also be generated using the rcorr function which is

found in the Hmisc package.

First install the required package and load the library.

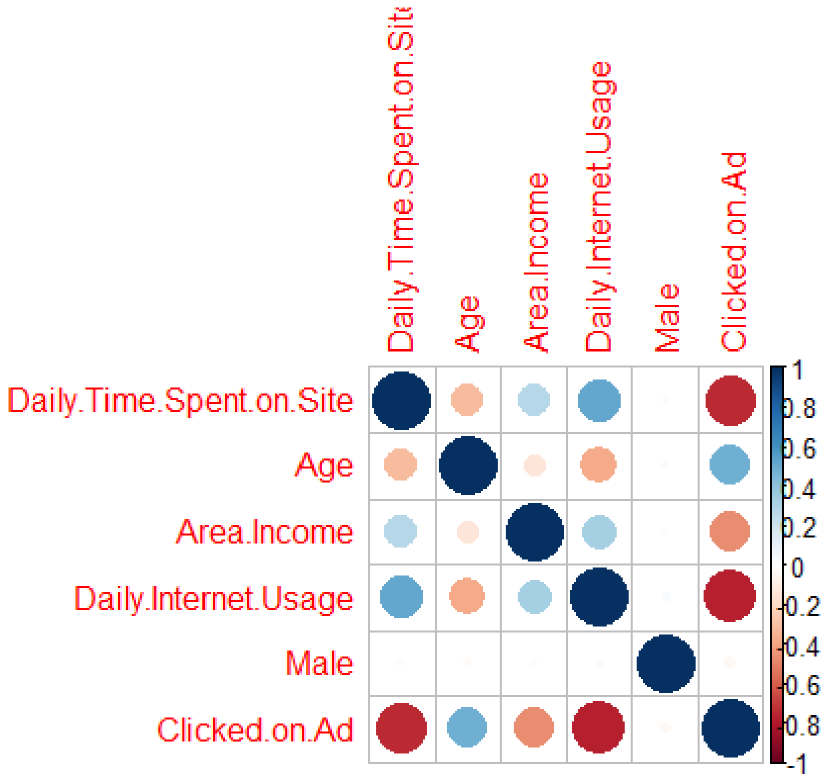
```r
#install_version("latticeExtra")
#install.packages("Hmisc", dependencies = T)
library("Hmisc")
```

```
## Loading required package: lattice

## Loading required package: survival

## Loading required package: Formula
```

```
## Loading required package: ggplot2

##
## Attaching package: 'Hmisc'

## The following objects are masked from 'package:base':
##
##     format.pval, units

mydata.rcorr = rcorr(as.matrix(mydata)) #feed the data as a matrix
mydata.rcorr

##                          Daily.Time.Spent.on.Site   Age Area.Income
## Daily.Time.Spent.on.Site                     1.00 -0.79        0.65
## Age                                         -0.79  1.00       -0.61
## Area.Income                                  0.65 -0.61        1.00
## Daily.Internet.Usage                         0.88 -0.83        0.70
## Male                                        -0.08 -0.15       -0.15
## Clicked.on.Ad                               -0.95  0.85       -0.77
##                          Daily.Internet.Usage  Male Clicked.on.Ad
## Daily.Time.Spent.on.Site                 0.88 -0.08         -0.95
## Age                                     -0.83 -0.15          0.85
## Area.Income                              0.70 -0.15         -0.77
## Daily.Internet.Usage                     1.00 -0.03         -0.97
## Male                                    -0.03  1.00          0.00
## Clicked.on.Ad                           -0.97  0.00          1.00
##
## n= 6
##
##
## P
##                          Daily.Time.Spent.on.Site Age    Area.Income
## Daily.Time.Spent.on.Site                          0.0626 0.1620
## Age                      0.0626                          0.1966
## Area.Income              0.1620                   0.1966
## Daily.Internet.Usage     0.0213                   0.0422 0.1252
## Male                     0.8853                   0.7736 0.7717
## Clicked.on.Ad            0.0034                   0.0335 0.0742
##                          Daily.Internet.Usage Male   Clicked.on.Ad
## Daily.Time.Spent.on.Site 0.0213               0.8853 0.0034
## Age                      0.0422               0.7736 0.0335
## Area.Income              0.1252               0.7717 0.0742
## Daily.Internet.Usage                          0.9623 0.0015
## Male                     0.9623                      0.9936
## Clicked.on.Ad            0.0015               0.9936
```

This generates one table of correlation coefficients (the correlation matrix) and another table of the p-values. By default, the correlations and p-values are stored in an object of class type rcorr.

```
#mydata.coeff = mydata.rcorr$r
#mydata.p = mydata.rcorr$P
library(corrplot)

## corrplot 0.84 loaded

corrplot(mydata)
```



A default correlation matrix plot (called a Correlogram) is generated. Positive correlations are displayed in a blue scale while negative correlations are displayed in a red scale

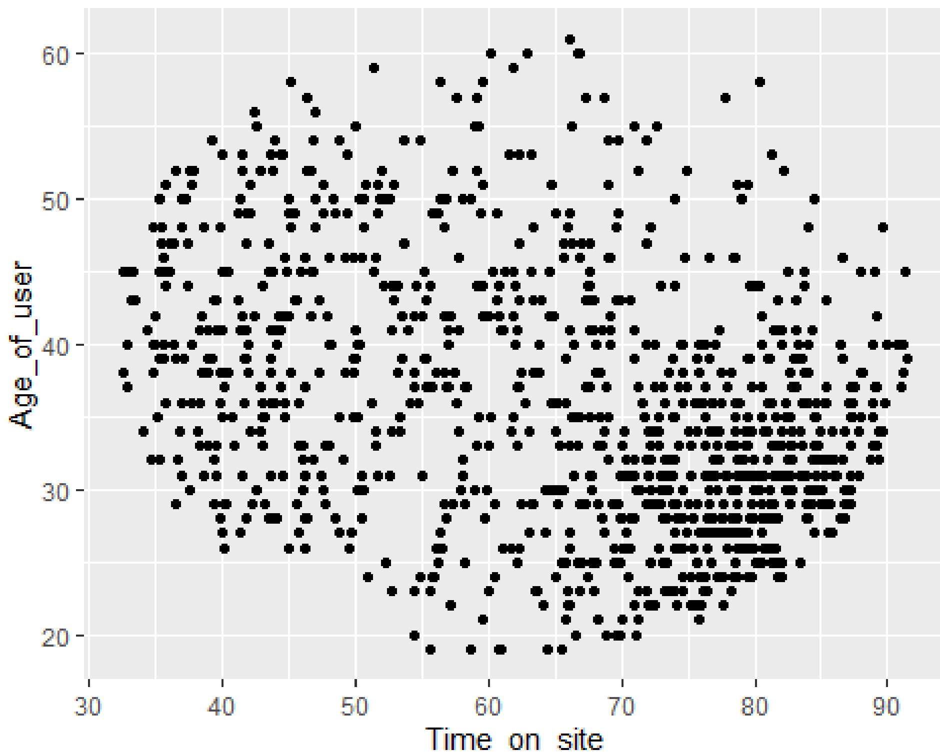
There is very minimal positive correlation between the variables in the data

The Plots below are scatterplots of a few pairs of variables

Time spent on the site vs age of the user

```
#Time spent on the site vs age of the user
# Libraries
library(ggplot2)

# create data
Time_on_site <- advert_df$Daily.Time.Spent.on.Site
Age_of_user <- advert_df$Age
data <- data.frame(Time_on_site,Age_of_user)
```

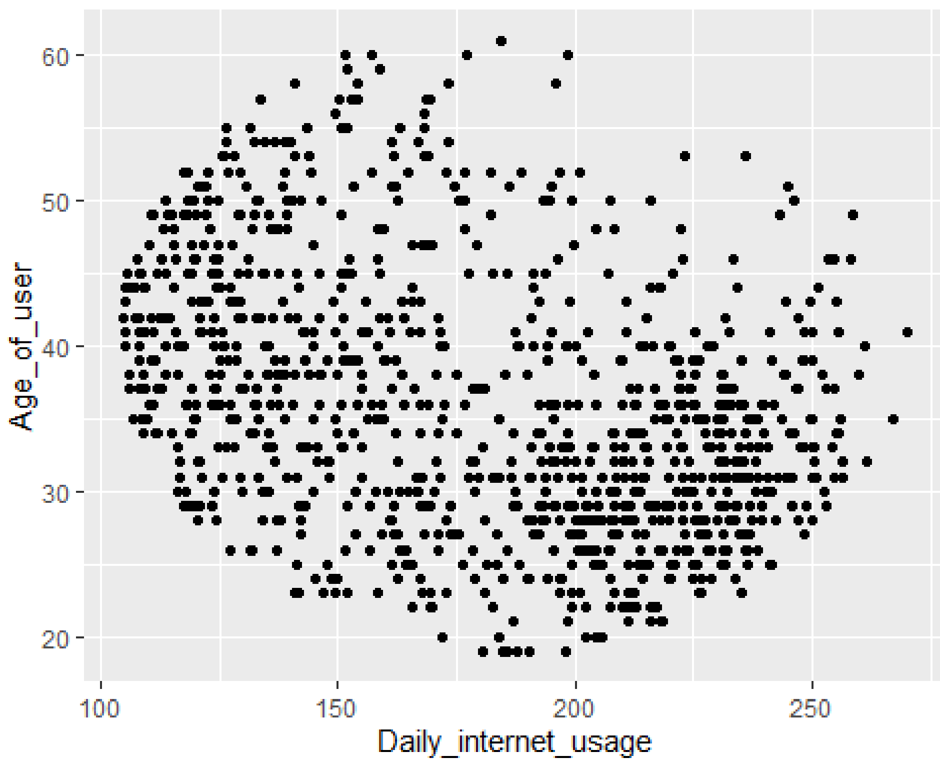
```
# Plot
ggplot(data, aes(x=Time_on_site, y=Age_of_user)) + geom_point()
```




```
#positive non-linear correlation
```

#Age of the user vs daily internet usage

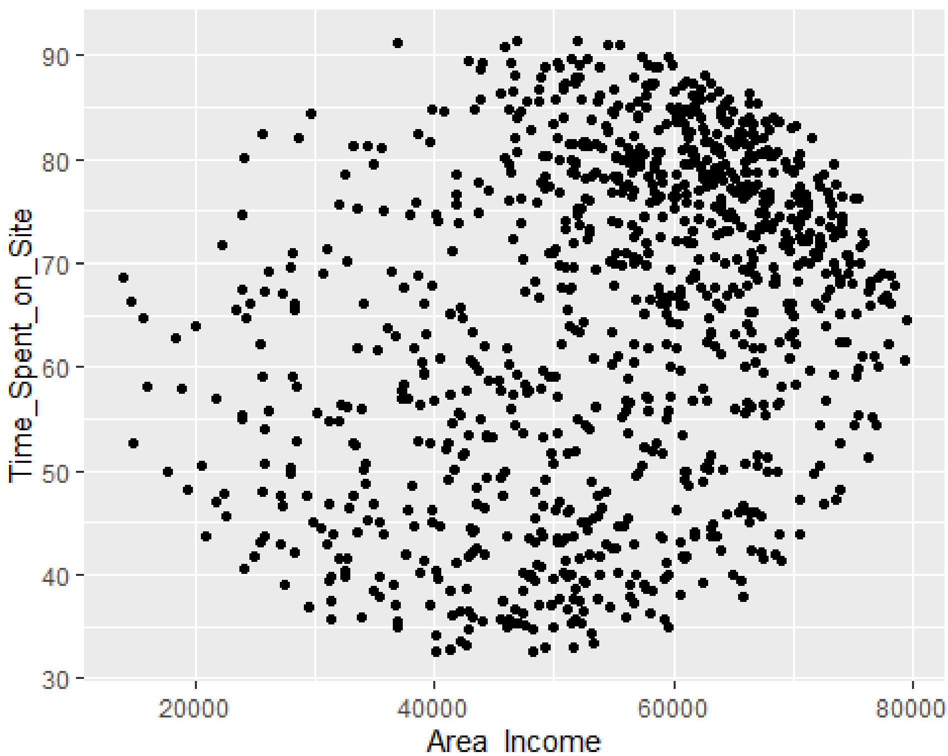
```
Daily_internet_usage <- advert_df$Daily.Internet.Usage
Age_of_user <- advert_df$Age
data1 <- data.frame(Daily_internet_usage,Age_of_user)

# Plot
ggplot(data1, aes(x=Daily_internet_usage, y=Age_of_user)) + geom_point()
```




```
#the plot shows that there is positive non-linear correlation
```

#time spent on the site vs area.income

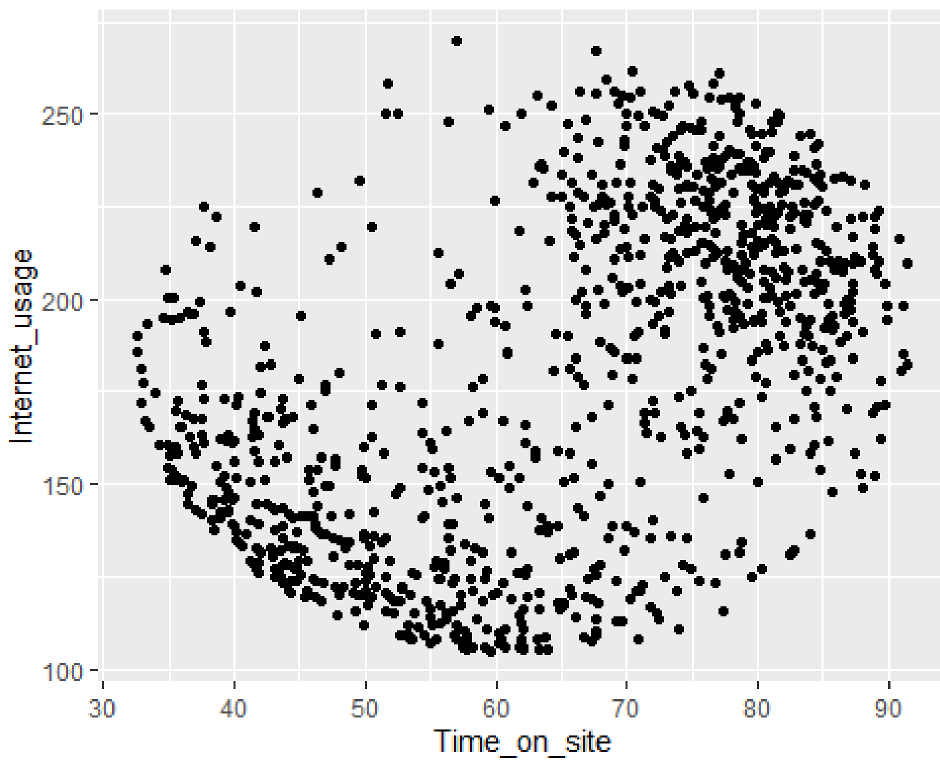
```
Area_Income <- advert_df$Area.Income
Time_Spent_on_Site <- advert_df$Daily.Time.Spent.on.Site
data2 <- data.frame(Area_Income,Time_Spent_on_Site)

# Plot
ggplot(data2, aes(x=Area_Income, y=Time_Spent_on_Site)) + geom_point()
```




```r
#positive non-linear correlation
```

#time spent on the site vs daily iternet usage

```r
Time_on_site <- advert_df$Daily.Time.Spent.on.Site
Internet_usage <- advert_df$Daily.Internet.Usage
data3 <- data.frame(Time_on_site,Internet_usage)

# Plot
ggplot(data3, aes(x=Time_on_site, y=Internet_usage)) + geom_point()
```



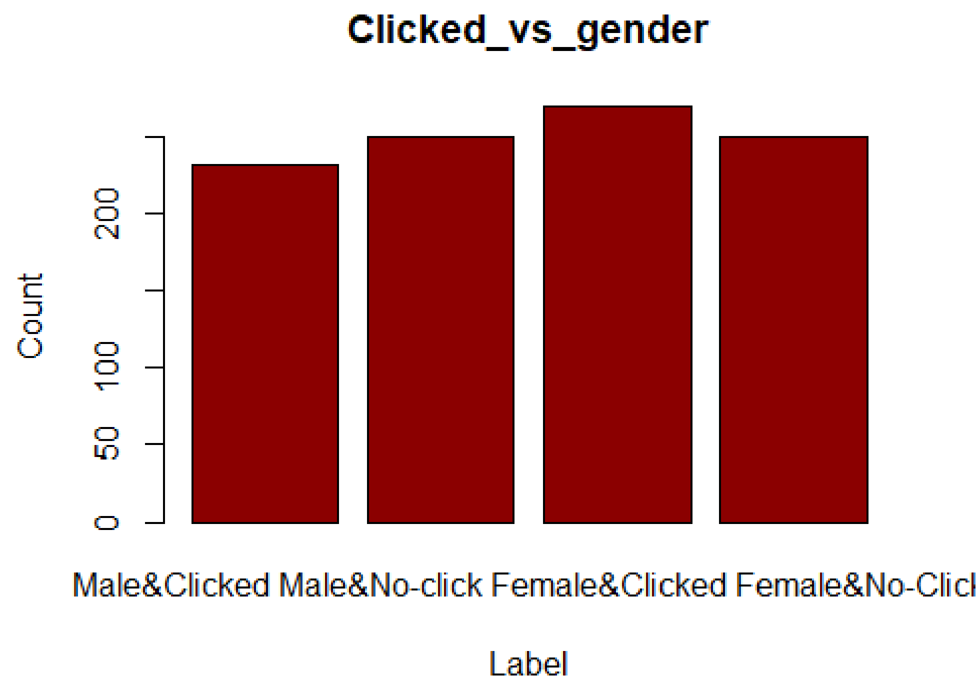
Seperating the data Clicked and Gender columns

```
#creating a new column with null values
advert_df2["Female"] <- NA
dim(advert_df2)

## [1] 1000    7

#populating the column with false values from the male column
advert_df2$Female <- advert_df2$Male == 0
dim(advert_df2)

## [1] 1000    7

#converting the column to nu,eric
dim(advert_df2 <- apply(advert_df2, 2, as.numeric))

## [1] 1000    7
```

Gender VS Clicked on Add

```
library(tidyverse)

## -- Attaching packages ---------------------------------------------------
------- tidyverse 1.3.0 --

## v tibble  2.1.3     v dplyr   0.8.4
## v tidyr   1.0.2     v stringr 1.4.0
## v purrr   0.3.3     v forcats 0.5.0
```

```
## -- Conflicts ---------------------------------------------------------------
- tidyverse_conflicts() --
## x dplyr::between()   masks data.table::between()
## x dplyr::filter()    masks stats::filter()
## x dplyr::first()     masks data.table::first()
## x dplyr::lag()       masks stats::lag()
## x dplyr::last()      masks data.table::last()
## x dplyr::src()       masks Hmisc::src()
## x dplyr::summarize() masks Hmisc::summarize()
## x purrr::transpose() masks data.table::transpose()

#Male respondents who clicked on an add
dim(advert_df%>% filter(Male == 1 , Clicked.on.Ad == 1))

## [1] 231  10

#231

#Male respondents did not click on an add
dim(advert_df%>% filter(Male == 1, Clicked.on.Ad == 0))

## [1] 250  10

#250

#Female respondents who clicked on an add
dim(advert_df%>% filter(Male == 0 , Clicked.on.Ad == 1))

## [1] 269  10

# 269

#Female respondents who clicked did not on an add
dim(advert_df%>% filter(Male == 0, Clicked.on.Ad == 0))

## [1] 250  10

# 250

Clicked_vs_gender <- c( 231 , 250 , 269 , 250 )

# barchart with added parameters
barplot(Clicked_vs_gender, main = " Clicked_vs_gender " , xlab = " Label ",
ylab = " Count ",
names.arg = c("Male&Clicked Male&No-click Female&Clicked Female&No-Click"),
col = "darkred",
horiz = FALSE)
```



Multivariate Analysis

```
# A glimpse of the data
library(dplyr)
glimpse(advert_df2)

##  num [1:1000, 1:7] 69 80.2 69.5 74.2 68.4 ...
##  - attr(*, "dimnames")=List of 2
##   ..$ : NULL
##   ..$ : chr [1:7] "Daily.Time.Spent.on.Site" "Age" "Area.Income"
"Daily.Internet.Usage" ...

# One hot encoding of the factor variables.

# dummify the data
library(caret)

##
## Attaching package: 'caret'

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

## The following object is masked from 'package:survival':
##
##     cluster
```

```
dmy <- dummyVars(" ~ .", data = advert_df2)
dummy_df <- data.frame(predict(dmy, newdata = advert_df2))
#print(dummy_df)
glimpse(dummy_df)

## Observations: 1,000
## Variables: 7
## $ Daily.Time.Spent.on.Site <dbl> 68.95, 80.23, 69.47, 74.15, 68.37, 59.99,
...
## $ Age                      <dbl> 35, 31, 26, 29, 35, 23, 33, 48, 30, 20,
49...
## $ Area.Income              <dbl> 61833.90, 68441.85, 59785.94, 54806.18,
73...
## $ Daily.Internet.Usage     <dbl> 256.09, 193.77, 236.50, 245.89, 225.58,
22...
## $ Male                     <dbl> 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0,
...
## $ Clicked.on.Ad            <dbl> 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0,
...
## $ Female                   <dbl> 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1,
...

sapply(dummy_df, class)

## Daily.Time.Spent.on.Site                      Age              Area.Income
##                "numeric"                "numeric"                "numeric"
##     Daily.Internet.Usage                     Male            Clicked.on.Ad
##                "numeric"                "numeric"                "numeric"
##                   Female
##                "numeric"

#removing the revenue column from the data
#we select all the column indexes before 30

dummy_df2 <-
dummy_df[c("Daily.Time.Spent.on.Site","Age","Area.Income","Daily.Internet.Usa
ge","Male","Female")]
dim(dummy_df2)

## [1] 1000    6

#6 columns in dummy_df2

dummy_df.class<- advert_df2[, "Clicked.on.Ad"]
```

SCALING VS NORMALIZATION

Scaling

In this step the data is transformed to fit within the range between 0 and 1

```r
dummy_df2_scaled <- scale(dummy_df2)
summary(dummy_df2_scaled)
```

```
##  Daily.Time.Spent.on.Site      Age              Area.Income
##  Min.   :-2.0437          Min.   :-1.9360   Min.   :-3.0566
##  1st Qu.:-0.8604          1st Qu.:-0.7978   1st Qu.:-0.5940
##  Median : 0.2028          Median :-0.1148   Median : 0.1500
##  Mean   : 0.0000          Mean   : 0.0000   Mean   : 0.0000
##  3rd Qu.: 0.8545          3rd Qu.: 0.6819   3rd Qu.: 0.7805
##  Max.   : 1.6671          Max.   : 2.8446   Max.   : 1.8252
##  Daily.Internet.Usage      Male              Female
##  Min.   :-1.71335     Min.   :-0.9622   Min.   :-1.0382
##  1st Qu.:-0.93777     1st Qu.:-0.9622   1st Qu.:-1.0382
##  Median : 0.07129     Median :-0.9622   Median : 0.9622
##  Mean   : 0.00000     Mean   : 0.0000   Mean   : 0.0000
##  3rd Qu.: 0.88361     3rd Qu.: 1.0382   3rd Qu.: 0.9622
##  Max.   : 2.04909     Max.   : 1.0382   Max.   : 0.9622
```

Normalizing

Normalization is a technique often applied to change the values of numeric columns in the dataset to a common scale, without distorting differences in the ranges of values.

```r
dummy_df2_norm <- as.data.frame(apply(dummy_df2, 2, function(x) (x -
min(x))/(max(x)-min(x))))
summary(dummy_df2_norm)
```

```
##  Daily.Time.Spent.on.Site      Age             Area.Income
##  Min.   :0.0000           Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.3189           1st Qu.:0.2381   1st Qu.:0.5044
##  Median :0.6054           Median :0.3810   Median :0.6568
##  Mean   :0.5507           Mean   :0.4050   Mean   :0.6261
##  3rd Qu.:0.7810           3rd Qu.:0.5476   3rd Qu.:0.7860
##  Max.   :1.0000           Max.   :1.0000   Max.   :1.0000
##  Daily.Internet.Usage      Male            Female
##  Min.   :0.0000       Min.   :0.000   Min.   :0.000
##  1st Qu.:0.2061       1st Qu.:0.000   1st Qu.:0.000
##  Median :0.4743       Median :0.000   Median :1.000
##  Mean   :0.4554       Mean   :0.481   Mean   :0.519
##  3rd Qu.:0.6902       3rd Qu.:1.000   3rd Qu.:1.000
##  Max.   :1.0000       Max.   :1.000   Max.   :1.000
```

The distance Matrix

How the elements are represented in the Euclidean space

There are 4 distinct quarters which means that four of the elements in the data explian a great

percentage of the variance.

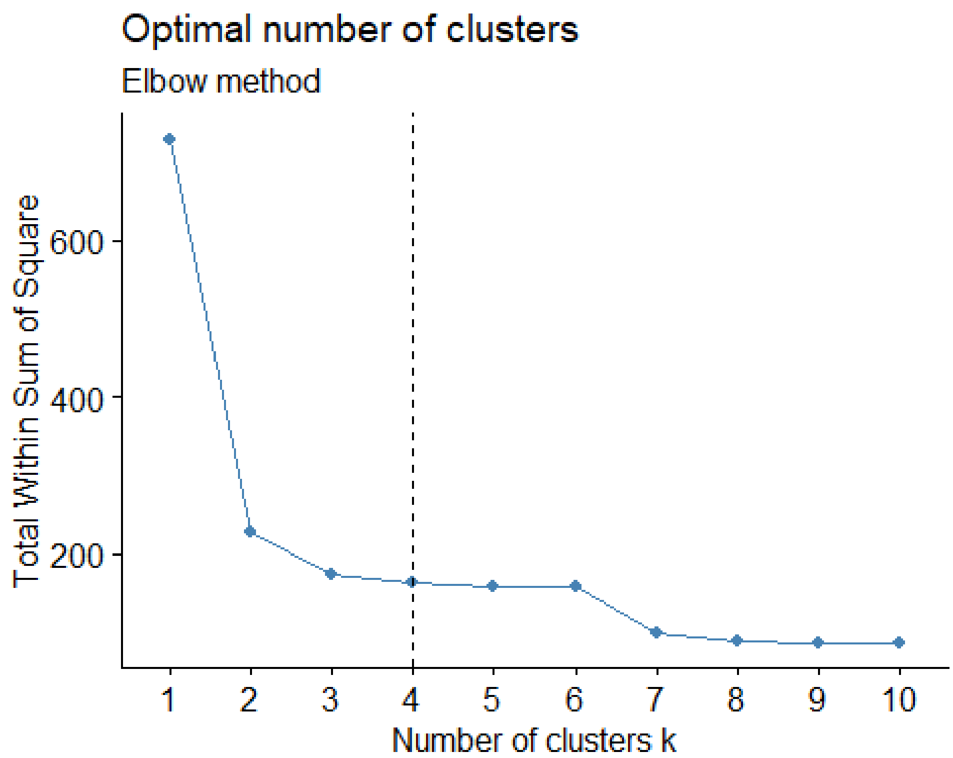
```r
library(factoextra)

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

distance <- get_dist(dummy_df2_norm)
fviz_dist(distance, gradient = list(low = "#00AFBB", mid = "white", high =
"#FC4E07"))
```

The normalized dataset has a smaller range for the values which are between 0 and 1 unlike the standardized dataset which has values ranging from -2 to 2.9

Finding the Optimal number of clusters

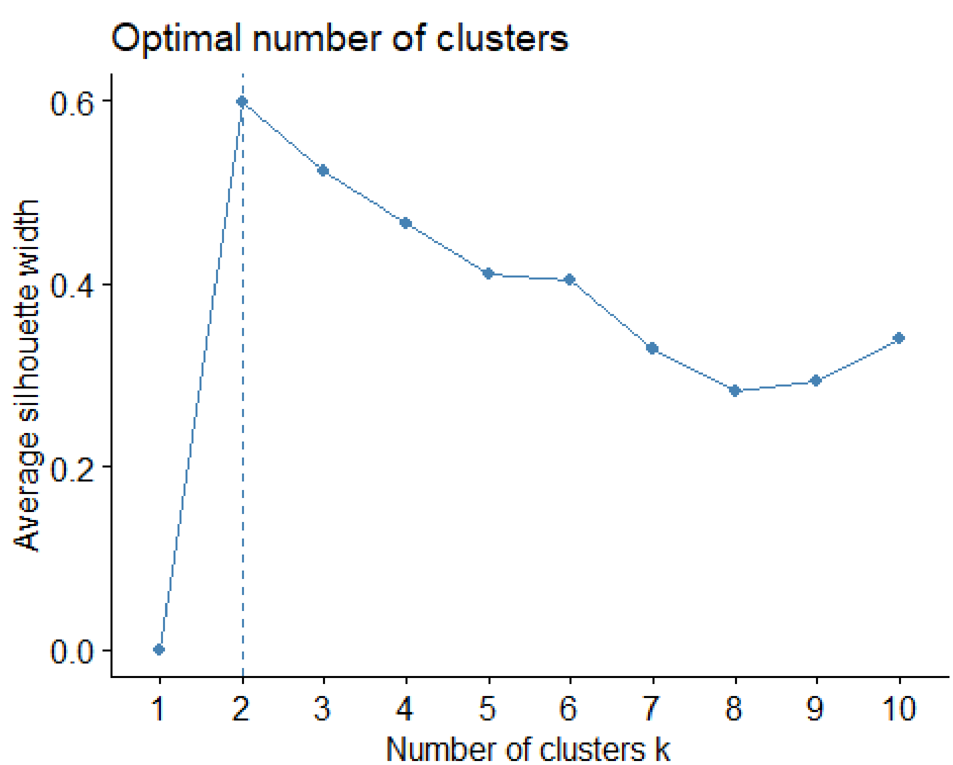
Method 1: Elbow method

```r
# Searching for the optimal number of clusters
# # Elbow method

# Searching for the optimal number of clusters
# # Elbow method
library(factoextra)
fviz_nbclust(dummy_df2_norm, kmeans, method = "wss") +
    geom_vline(xintercept = 4, linetype = 2)+
  labs(subtitle = "Elbow method")
```



Method 2: Silhouette

```r
library(cluster)
fviz_nbclust(dummy_df2_norm, kmeans, method = "silhouette")
```



Implement the Solution

K-MEANS CLUSTERING

Using 4 clusters [Elbow Method]

```
outputk <- kmeans(dummy_df2_norm, 4)
```

Results

```
# Previewing the number of records in each cluster

outputk$size

## [1] 210 273 271 246
```

The cluster center datapoints Per attribute

```
outputk$centers

##   Daily.Time.Spent.on.Site       Age Area.Income Daily.Internet.Usage Male
## 1                0.2932032 0.5329932   0.5288059            0.2175739    1
## 2                0.7438650 0.3108320   0.7245788            0.6545227    0
## 3                0.7409015 0.2976630   0.7020277            0.6533823    1
## 4                0.3467916 0.5183895   0.5163038            0.2192715    0
##   Female
## 1      0
## 2      1
## 3      0
## 4      1
```

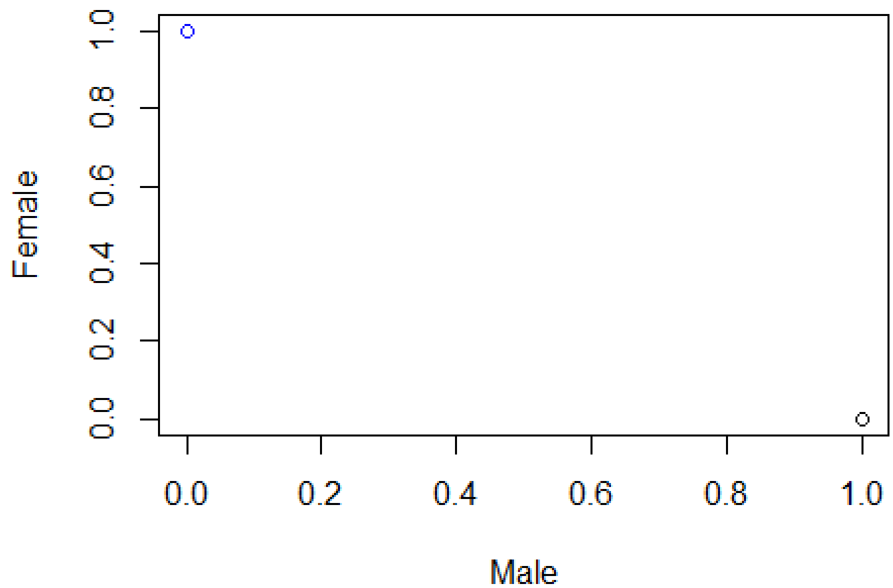
Visualising the clusters of the whole dataset

```
options(repr.plot.width = 11, repr.plot.height = 6)
fviz_cluster(outputk, dummy_df2_norm)
```

while using four points, we can see that the data is divided into two distinct clusters first then two more clusters from the two.

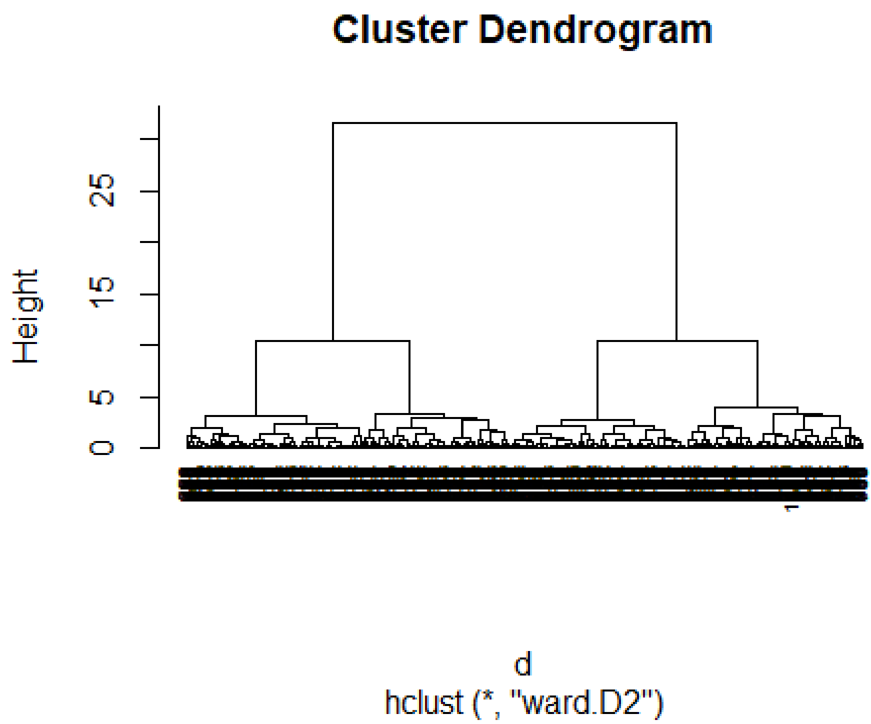
Visualizing variable datatypes on a scatter plot

```
# Plotting two variables to see how their data points
# have been distributed in the cluster
# Product Related, vs Product Related Duration

plot(dummy_df2_norm[, 5:6], col = outputk$cluster)
```



HIERACHICAL CLUSTERING

```
d <- dist(dummy_df2_norm, method = "euclidean")

# We then apply 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)
```

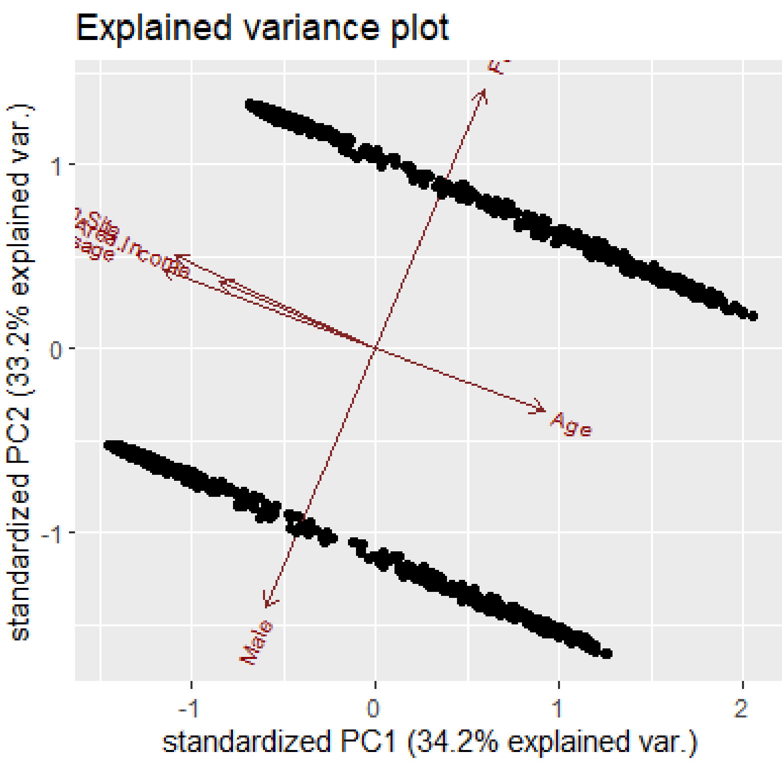


Challenge the Solution

1. PCA

```
# Reducing the dimensionality of the dataset
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
```

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

## The following objects are masked from 'package:Hmisc':
##
##     is.discrete, summarize

## Loading required package: scales

##
## Attaching package: 'scales'

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

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

## Loading required package: grid

pca_residual = prcomp(dummy_df2_norm, scale = T, center = T)

# Visualising the pca results
options(repr.plot.width = 6, repr.plot.height = 6)
ggbiplot(pca_residual) +
  labs(title = 'Explained variance plot')
```

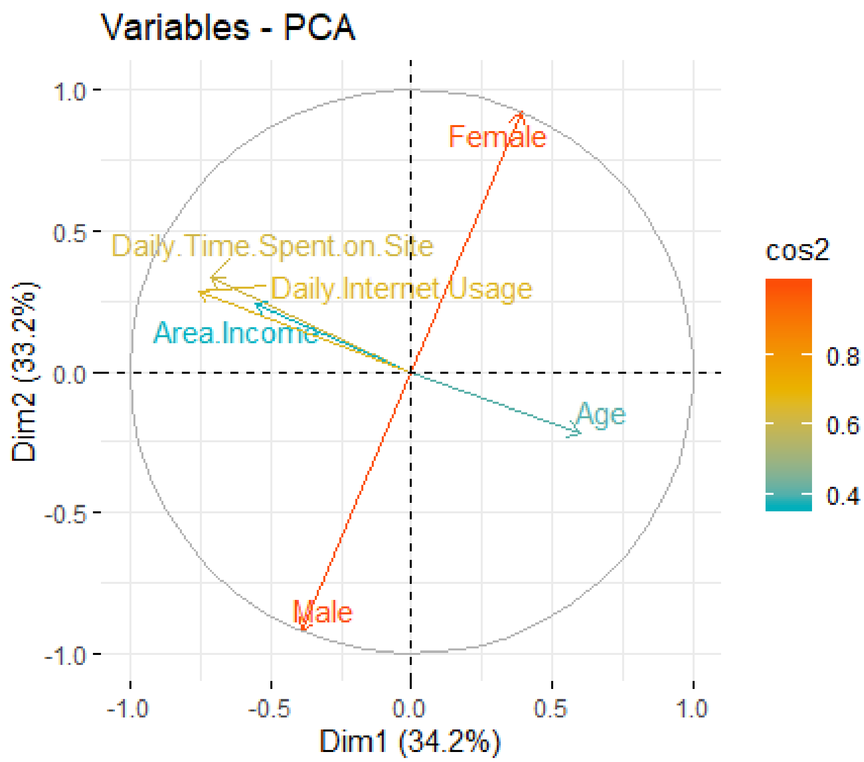



```
# Applying PCA
# We pass df_norm to the prcomp().
# We also set two arguments, center and scale,
# to be TRUE then preview our object with summary
dummy_PCA <- prcomp(dummy_df2_norm,
              center = TRUE,
              scale = FALSE)
summary(dummy_PCA)

## Importance of components:
##                           PC1    PC2     PC3     PC4     PC5       PC6
## Standard deviation     0.7070 0.3565 0.18840 0.18680 0.17726 6.742e-17
## Proportion of Variance 0.6859 0.1744 0.04871 0.04788 0.04311 0.000e+00
## Cumulative Proportion  0.6859 0.8603 0.90900 0.95689 1.00000 1.000e+00
```

The first two pricipal components explain about 85% of the variance in the data.

The first four pricipal components explain about 94% of the variance in the data.

```
fviz_pca_var(pca_residual, col.var = "cos2",
             gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
             repel = TRUE # Avoid text overlapping
             )
```



Variables that are closed to the center of the plot are less important for the first components.

The most important pair is the Gender MALE VS FEMALE

The Second most important pair is the Daily time spent on the site AND Daily Internet Usage

Lastly, the third most important pair is the Age And Income

The Principal Components and how well they explain the variance

```
var <- get_pca_var(pca_residual)
head(var$contrib, 4)

##                             Dim.1    Dim.2       Dim.3    Dim.4      Dim.5
## Daily.Time.Spent.on.Site 24.69277 5.492810  0.09228036 27.71248 42.0096538
## Age                      17.52931 2.424065 41.39842659 37.80309  0.8451116
## Area.Income              15.13875 2.836987 58.36061211 23.20349  0.4601642
## Daily.Internet.Usage     27.99866 4.017474  0.12468752 11.25869 56.6004915
##                                 Dim.6
## Daily.Time.Spent.on.Site 0.000000e+00
## Age                      3.037003e-27
## Area.Income              2.959446e-27
## Daily.Internet.Usage     6.950296e-30
```

For the First principal component, the Daily internet usage and amount spent ont the site explain more that 50% of the variance.

In the second principal component, the Daily internet usage and amount spent ont the site explain more that 9% of the variance

In the Third Principal component, Age and income explain almost 100% of the valriance

From this therefore, We can order the components based on how well they explain the variance as:

a) Daily Internet Usage

b) Daily time spent on the site

c) Income

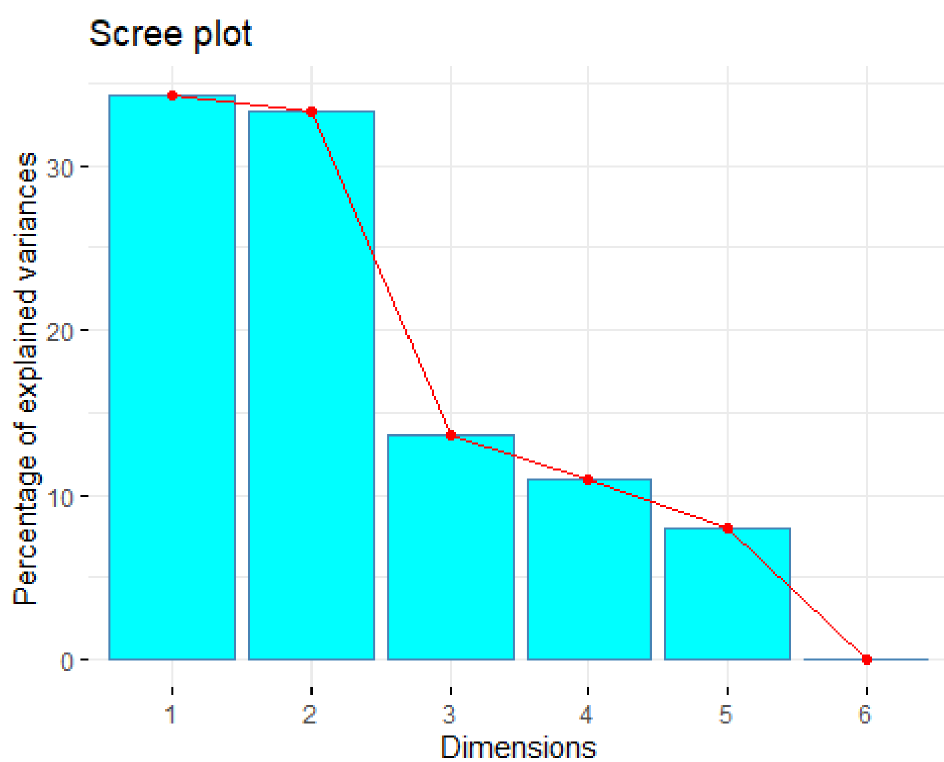
d) Age

SCREE PLOT

A scree plot shows the eigenvalues on the y-axis and the number of factors on the x-axis. It always displays a downward curve.

The point where the slope of the curve is clearly leveling off (the “elbow) indicates the number of factors that should be generated by the analysis.

```
fviz_eig(pca_residual, barfill = 'cyan',linecolor = 'red' )
```



From the plot above, the elbow forms after the 2nd and 4th dimensions. This indicates that the analysis should yield 2 or 4 major factors.

The PCA explains the following properties about the data

```
var <- get_pca_var(pca_residual)
var

## Principal Component Analysis Results for variables
##  ===================================================
##   Name       Description
## 1 "$coord"   "Coordinates for the variables"
## 2 "$cor"     "Correlations between variables and dimensions"
## 3 "$cos2"    "Cos2 for the variables"
## 4 "$contrib" "contributions of the variables"
```

2. K-MEANS CLUSTERING

Using a different number of clusters 2 clusters using the silhouette method

Using 2 clusters [Silhouette Method]

```
outputs <- kmeans(dummy_df2_norm, 2)
```

Results

```
# Previewing the number of records in each cluster

outputs$size

## [1] 481 519
```

Visualising the clusters of the whole dataset

```
options(repr.plot.width = 11, repr.plot.height = 6)
fviz_cluster(outputs, dummy_df2_norm)
```

Summary

Compasiron Between K-MEANS and HIERACHICAL clustering From the Analysis, we can identify that:

1. K-means Cluster Analysis performs much better in identyfing patterns as compared to Hierrachical clustering.
2. Since the dataset is large, visualizing hierrachical clusters is abit cumbersome as compared to K-means clustering.
3. K-means clustering yields better reults using the optimal number of clusters which can be determined by Elbow and Silhouette Methods
4. Clicking on an add is dependent on the gender of the respondent
5. We can conclude that,The order of the factors that affect if a respondent clicks on an ad is:
    a) Gender
    b) Daily Internet Usage
    c) Daily time spent on the site
    d) Income

e) Age