

Supervised Learning

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Analysis on Ads

Data Understanding

1. Define the question:

I am a data scientist working to create a supervised learning model to identify which individuals are most likely to click on my client's ads on her blog.

2. Metric for success:

- Cleaned data.
- Graphical representation of the relationships in the data as well as the distributions of the different variables in the data.
- Create a model using KNN.
- Sound conclusions and recommendations to the client as per the analysis done.

3. Understanding the context:

A Kenyan entrepreneur has created an online cryptography course and would want to advertise it on her blog.

She currently targets audiences originating from various countries.

In the past, she ran ads to advertise a related course on the same blog and collected data in the process. She would now like to employ my services as a Data Science Consultant to help her identify which individuals are most likely to click on her ads.

4. Experimental design:

Steps to be undertaken during this study include: - Loading the data & needed packages. - Exploring the dataset. - Cleaning the data. - Feature engineering. - Exploratory Data Analysis. - Conclusions. - Recommendations. - Implementing the Solution - Challenging the Solution

5. Data appropriateness:

This will be well checked & described in the data cleaning.

Exploring the data

```
# Loading the libraries
#install.packages("corrplot")
library("corrplot")
```

```
## corplot 0.90 loaded

#install.packages("PerformanceAnalytics")
library("PerformanceAnalytics")

## Loading required package: xts

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##      as.Date, as.Date.numeric

##
## Attaching package: 'PerformanceAnalytics'

## The following object is masked from 'package:graphics':
##
##      legend

#install.packages("ggplot2")
library("ggplot2")
#install.packages("data.table")
library("data.table")

##
## Attaching package: 'data.table'

## The following objects are masked from 'package:xts':
##
##      first, last

#detach("package:dplyr", unload = TRUE)
#install.packages("dplyr", dependencies = TRUE)
library("dplyr")

##
## Attaching package: 'dplyr'

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

## The following objects are masked from 'package:xts':
##
##      first, last

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

```

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

#install.packages("tidyr")
library("tidyr")

# Packages for modelling
#install.packages("rpart",dependencies = TRUE)
library("rpart")
#install.packages("rpart.plot",dependencies=TRUE)
library("rpart.plot")
#install.packages("mlbench",dependencies = TRUE)
library("mlbench")

# Loading the data
data = read.csv('advertising.csv', header = TRUE, sep = ',')

# Previewing the data
head(data)

##   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

# Checking the shape of the data
dim(data)

## [1] 1000   10

```

The dataset has 1000 entries and 10 columns.

```
# Checking column names of our data
colnames(data)
```

```
## [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"
```

Our column titles are as listed above. We shall rename the “Male” column so that it becomes “Gender” then the 0 will represent males, and 0 for females.

```
# Renaming "Male" column
colnames(data)[7] <- "Gender"
```

```
# Checking if column name has changed
colnames(data)
```

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

Data Cleaning

1. Dealing with missing data

```
# Checking for missing values
null_values = is.na(data)
null_values
```

```
##           Daily.Time.Spent.on.Site    Age Area.Income Daily.Internet.Usage
## [1,]                               FALSE FALSE         FALSE              FALSE
## [2,]                               FALSE FALSE         FALSE              FALSE
## [3,]                               FALSE FALSE         FALSE              FALSE
## [4,]                               FALSE FALSE         FALSE              FALSE
## [5,]                               FALSE FALSE         FALSE              FALSE
## [6,]                               FALSE FALSE         FALSE              FALSE
## [7,]                               FALSE FALSE         FALSE              FALSE
## [8,]                               FALSE FALSE         FALSE              FALSE
## [9,]                               FALSE FALSE         FALSE              FALSE
## [10,]                              FALSE FALSE         FALSE              FALSE
## [11,]                              FALSE FALSE         FALSE              FALSE
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##	[973,]	FALSE	FALSE	FALSE	FALSE
##	[974,]	FALSE	FALSE	FALSE	FALSE
##	[975,]	FALSE	FALSE	FALSE	FALSE
##	[976,]	FALSE	FALSE	FALSE	FALSE
##	[977,]	FALSE	FALSE	FALSE	FALSE
##	[978,]	FALSE	FALSE	FALSE	FALSE
##	[979,]	FALSE	FALSE	FALSE	FALSE
##	[980,]	FALSE	FALSE	FALSE	FALSE
##	[981,]	FALSE	FALSE	FALSE	FALSE
##	[982,]	FALSE	FALSE	FALSE	FALSE
##	[983,]	FALSE	FALSE	FALSE	FALSE
##	[984,]	FALSE	FALSE	FALSE	FALSE
##	[985,]	FALSE	FALSE	FALSE	FALSE
##	[986,]	FALSE	FALSE	FALSE	FALSE
##	[987,]	FALSE	FALSE	FALSE	FALSE
##	[988,]	FALSE	FALSE	FALSE	FALSE
##	[989,]	FALSE	FALSE	FALSE	FALSE
##	[990,]	FALSE	FALSE	FALSE	FALSE
##	[991,]	FALSE	FALSE	FALSE	FALSE
##	[992,]	FALSE	FALSE	FALSE	FALSE
##	[993,]	FALSE	FALSE	FALSE	FALSE
##	[994,]	FALSE	FALSE	FALSE	FALSE
##	[995,]	FALSE	FALSE	FALSE	FALSE
##	[996,]	FALSE	FALSE	FALSE	FALSE
##	[997,]	FALSE	FALSE	FALSE	FALSE
##	[998,]	FALSE	FALSE	FALSE	FALSE
##	[999,]	FALSE	FALSE	FALSE	FALSE
##	[1000,]	FALSE	FALSE	FALSE	FALSE

##	Ad.Topic.Line	City	Gender	Country	Timestamp	Clicked.on.Ad
##	[1,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[2,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[3,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[4,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[5,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[6,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[7,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[8,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[9,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[10,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[11,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[12,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[13,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[14,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[15,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[16,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[17,]	FALSE	FALSE	FALSE	FALSE	FALSE
##	[18,]	FALSE	FALSE	FALSE	FALSE	FALSE

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

```
## [969,] FALSE FALSE FALSE FALSE FALSE FALSE
## [970,] FALSE FALSE FALSE FALSE FALSE FALSE
## [971,] FALSE FALSE FALSE FALSE FALSE FALSE
## [972,] FALSE FALSE FALSE FALSE FALSE FALSE
## [973,] FALSE FALSE FALSE FALSE FALSE FALSE
## [974,] FALSE FALSE FALSE FALSE FALSE FALSE
## [975,] FALSE FALSE FALSE FALSE FALSE FALSE
## [976,] FALSE FALSE FALSE FALSE FALSE FALSE
## [977,] FALSE FALSE FALSE FALSE FALSE FALSE
## [978,] FALSE FALSE FALSE FALSE FALSE FALSE
## [979,] FALSE FALSE FALSE FALSE FALSE FALSE
## [980,] FALSE FALSE FALSE FALSE FALSE FALSE
## [981,] FALSE FALSE FALSE FALSE FALSE FALSE
## [982,] FALSE FALSE FALSE FALSE FALSE FALSE
## [983,] FALSE FALSE FALSE FALSE FALSE FALSE
## [984,] FALSE FALSE FALSE FALSE FALSE FALSE
## [985,] FALSE FALSE FALSE FALSE FALSE FALSE
## [986,] FALSE FALSE FALSE FALSE FALSE FALSE
## [987,] FALSE FALSE FALSE FALSE FALSE FALSE
## [988,] FALSE FALSE FALSE FALSE FALSE FALSE
## [989,] FALSE FALSE FALSE FALSE FALSE FALSE
## [990,] FALSE FALSE FALSE FALSE FALSE FALSE
## [991,] FALSE FALSE FALSE FALSE FALSE FALSE
## [992,] FALSE FALSE FALSE FALSE FALSE FALSE
## [993,] FALSE FALSE FALSE FALSE FALSE FALSE
## [994,] FALSE FALSE FALSE FALSE FALSE FALSE
## [995,] FALSE FALSE FALSE FALSE FALSE FALSE
## [996,] FALSE FALSE FALSE FALSE FALSE FALSE
## [997,] FALSE FALSE FALSE FALSE FALSE FALSE
## [998,] FALSE FALSE FALSE FALSE FALSE FALSE
## [999,] FALSE FALSE FALSE FALSE FALSE FALSE
## [1000,] FALSE FALSE FALSE FALSE FALSE FALSE
```

Our data seems to have no nulls since most of the fields are showing “FALSE” for our code. We shall do a coun to check for the total number of null values.

```
length(which(is.na(data)))
```

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

The data has no missing values

2. Checking for duplicates:

```
duplicates = duplicated(data)
duplicates
```

```
## [1] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
## [13] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
## [25] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
```

[illegible]

[illegible]

[illegible]

```

FALSE
## [937] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE
## [949] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE
## [961] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE
## [973] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE
## [985] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE
## [997] FALSE FALSE FALSE FALSE

```

The data seems to have no duplicates. We shall do a count just to make sure.

```

length(which(duplicated(data)))

## [1] 0

```

There are no duplicates in our dataset.

3. Checking column data types

```

# Checking the columns datatypes
str(data)

## 'data.frame': 1000 obs. of 10 variables:
## $ Daily.Time.Spent.on.Site: num 69 80.2 69.5 74.2 68.4 ...
## $ Age : int 35 31 26 29 35 23 33 48 30 20 ...
## $ Area.Income : num 61834 68442 59786 54806 73890 ...
## $ Daily.Internet.Usage : num 256 194 236 246 226 ...
## $ Ad.Topic.Line : chr "Cloned 5thgeneration orchestration"
"Monitored national standardization" "Organic bottom-line service-desk"
"Triple-buffered reciprocal time-frame" ...
## $ City : chr "Wrightburgh" "West Jodi" "Davidton"
"West Terrifurt" ...
## $ Gender : int 0 1 0 1 0 1 0 1 1 1 ...
## $ Country : chr "Tunisia" "Nauru" "San Marino" "Italy"
...
## $ Timestamp : chr "2016-03-27 00:53:11" "2016-04-04
01:39:02" "2016-03-13 20:35:42" "2016-01-10 02:31:19" ...
## $ Clicked.on.Ad : int 0 0 0 0 0 0 0 1 0 0 ...

```

All our columns have the right data type except for the time. We shall convert it to a timestamp for ease of calculation

```

# Converting date from character to a timestamp
data$Timestamp <- as.Date(data$Timestamp)

# Checking data type to confirm change
str(data)

```



```
## 'data.frame': 1000 obs. of 10 variables:
## $ Daily.Time.Spent.on.Site: num 69 80.2 69.5 74.2 68.4 ...
## $ Age : int 35 31 26 29 35 23 33 48 30 20 ...
## $ Area.Income : num 61834 68442 59786 54806 73890 ...
## $ Daily.Internet.Usage : num 256 194 236 246 226 ...
## $ Ad.Topic.Line : chr "Cloned 5thgeneration orchestration"
"Monitored national standardization" "Organic bottom-line service-desk"
"Triple-buffered reciprocal time-frame" ...
## $ City : chr "Wrightburgh" "West Jodi" "Davidton"
"West Terrifurt" ...
## $ Gender : int 0 1 0 1 0 1 0 1 1 1 ...
## $ Country : chr "Tunisia" "Nauru" "San Marino" "Italy"
...
## $ Timestamp : Date, format: "2016-03-27" "2016-04-04" ...
## $ Clicked.on.Ad : int 0 0 0 0 0 0 0 1 0 0 ...
```

The data types are all okay now.

4. Checking for outliers

```
# Checking for outliers in the numerical columns
```

```
Time_spent = data$Daily.Time.Spent.on.Site
```

```
Age = data$Age
```

```
Income = data$Area.Income
```

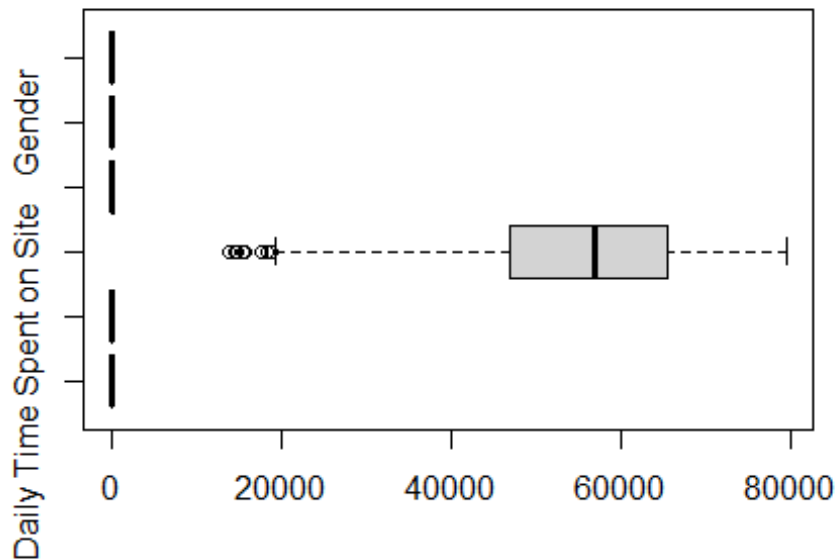
```
Internet = data$Daily.Internet.Usage
```

```
Gender = data$Gender
```

```
Clicked = data$Clicked.on.Ad
```

```
boxplot(Time_spent, Age, Income, Internet, Gender, Clicked, main = "Boxplots
to check for outliers", names = c("Daily Time Spent on Site", "Age",
"Income", "Daily Internet Usage", "Gender", "Clicked on ad"), horizontal =
TRUE)
```

Boxplots to check for outliers



The columns do not have outliers except the income column which has quite a number of outliers, which may be due to the paygaps that exist in the real world. Thus we shall ignore them for this project.

Feature Engineering

We'd like to extract the year, month, & day from the time stamp so we can derive more insights from it.

```
#Separating our Time stamp column into Year, Month and day.
data = separate(data, "Timestamp", c("Year", "Month", "Day"), sep = "-")
```

```
head(data)
```

```
##   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 Gender  Country
Year
## 1   Cloned 5thgeneration orchestration Wrightburgh      0   Tunisia
2016
## 2   Monitored national standardization   West Jodi      1    Nauru
2016
```

```
## 3      Organic bottom-line service-desk      Davidton      0 San Marino
2016
## 4 Triple-buffered reciprocal time-frame West Terrifurt      1      Italy
2016
## 5      Robust logistical utilization      South Manuel      0      Iceland
2016
## 6      Sharable client-driven software      Jamieberg      1      Norway
2016
##      Month Day Clicked.on.Ad
## 1      03  27      0
## 2      04  04      0
## 3      03  13      0
## 4      01  10      0
## 5      06  03      0
## 6      05  19      0
```

Exploratory Data Analysis

1. Univariate Analysis

Measures of Dispersion

a) Mean

```
# Creating a dataframe with only the numeric columns
data_num = data[,c("Daily.Time.Spent.on.Site", "Age",
"Area.Income", "Daily.Internet.Usage", "Gender", "Clicked.on.Ad" )]

# Preview dataset
head(data_num)

##      Daily.Time.Spent.on.Site Age Area.Income Daily.Internet.Usage Gender
## 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

# Calculating the mean

colMeans(data_num)

## Daily.Time.Spent.on.Site      Age      Area.Income
##           65.0002           36.0090           55000.0001
```

##	Daily.Internet.Usage	Gender	Clicked.on.Ad
##	180.0001	0.4810	0.5000

The means for the different columns are as shown in the output above.

b) Mode

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

# Get the mode for different columns
getmode(data$Daily.Time.Spent.on.Site)

## [1] 62.26

getmode(data$Age)

## [1] 31

getmode(data$Area.Income)

## [1] 61833.9

getmode(data$Daily.Internet.Usage)

## [1] 167.22

getmode(data$City)

## [1] "Lisamouth"

getmode(data$Gender)

## [1] 0

getmode(data$Country)

## [1] "Czech Republic"

getmode(data$Clicked.on.Ad)

## [1] 0

getmode(data$Month)

## [1] "02"
```

The most common amount of time spent on the site is 62.26, while the most popular age is 31years. Most of the site visits have an income of 61,833.9. The city with most visitors is Lisamouth while Czech Republic had the most site visitors. I would have expected the city with the most number of visitors to belong to the country with the most visitors, however,

Lisamouth had different countries on the dataset provided. Most of the visitors were female, while most didn't click on the ads. The site had most traffic in February.

c) Median

```
# Calculating median
median(data$Daily.Time.Spent.on.Site)

## [1] 68.215

median(data$Age)

## [1] 35

median(data$Area.Income)

## [1] 57012.3

median(data$Daily.Internet.Usage)

## [1] 183.13

median(data$Gender)

## [1] 0

median(data$Clicked.on.Ad)

## [1] 0.5
```

The medians for each column is as shown above

d) Range

```
# Calculating the ranges
range(data$Daily.Time.Spent.on.Site)

## [1] 32.60 91.43

range(data$Age)

## [1] 19 61

range(data$Area.Income)

## [1] 13996.5 79484.8

range(data$Daily.Internet.Usage)

## [1] 104.78 269.96

range(data$Gender)

## [1] 0 1

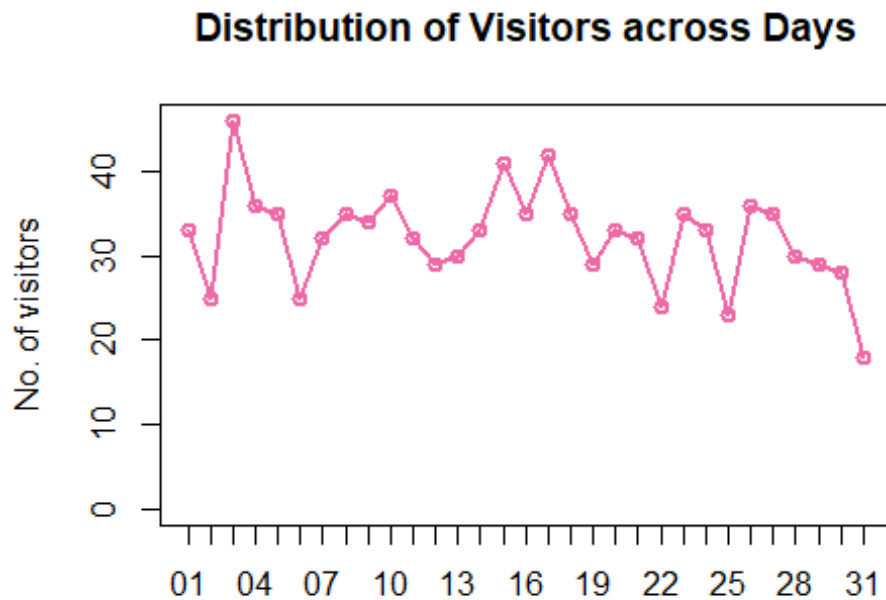
range(data$Clicked.on.Ad)
```

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

The codes above show the ranges for each of the columns in our dataset

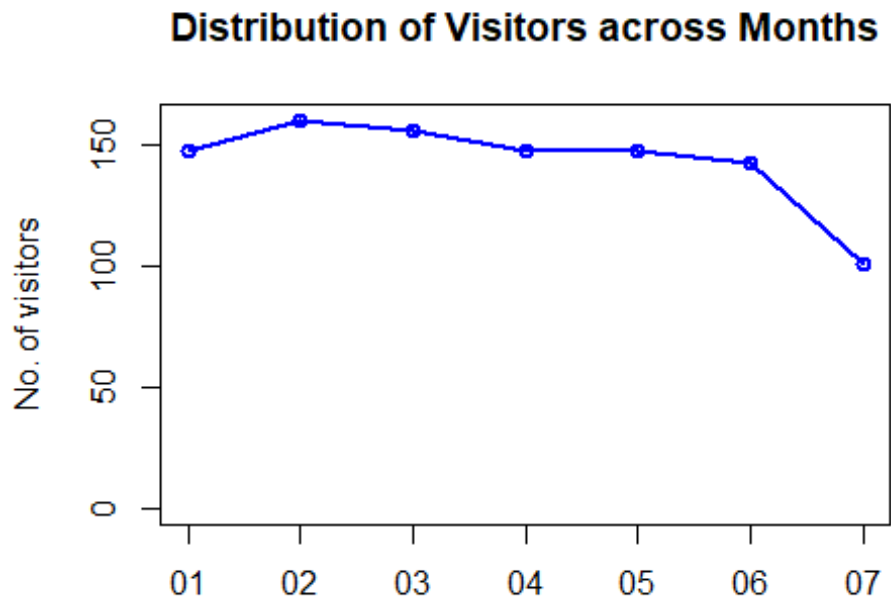
Plots:

```
# A bar plot showing the distribution of visitors accross different days  
plot(table(data$Day), type = "o", main = "Distribution of Visitors across  
Days", ylab = "No. of visitors", col = "hotpink2")
```



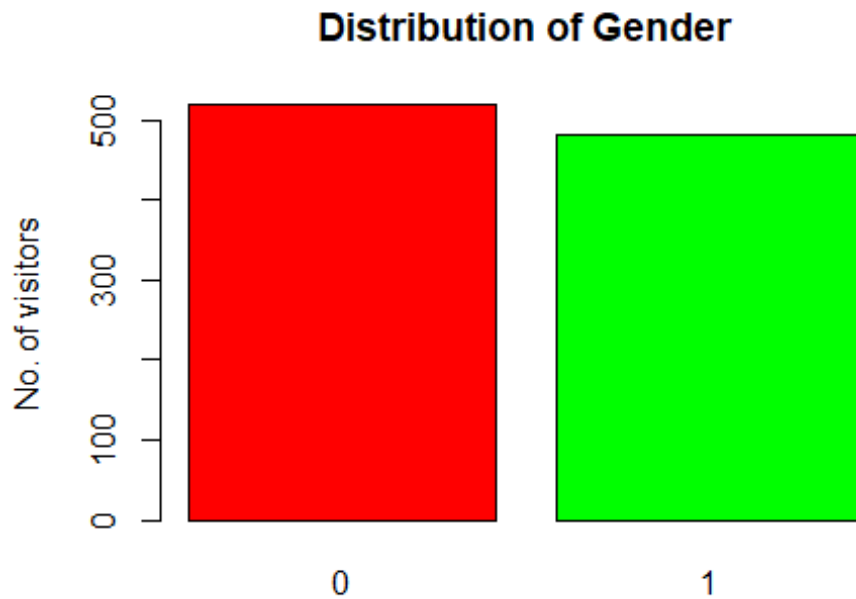
From our plot, we can see that most visitors visited the site on 3rd then 15th. The middle of the month had a high rate of visitors.

```
# A bar plot showing the distribution of visitors accross different months  
plot(table(data$Month), type = "o", main = "Distribution of Visitors across  
Months", ylab = "No. of visitors", col = "blue")
```



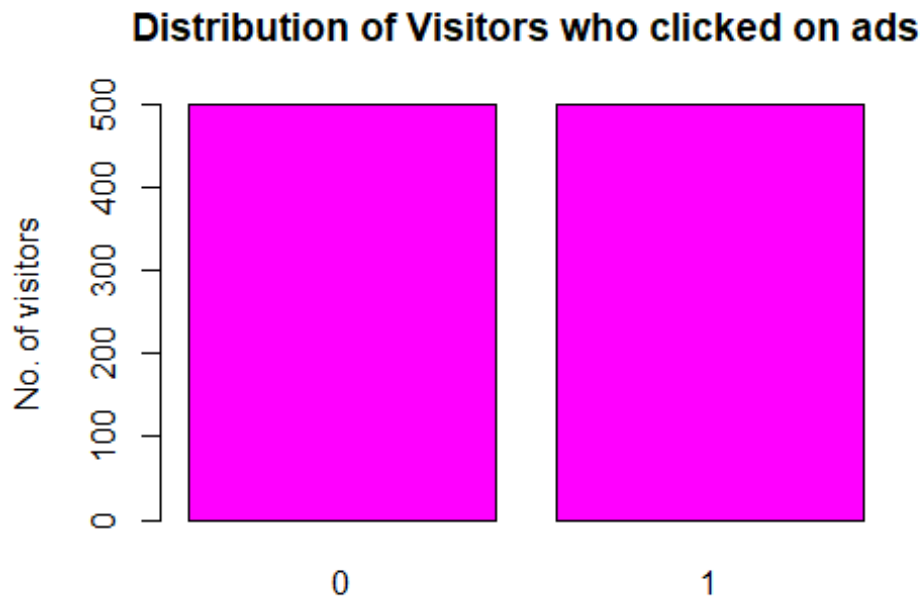
From our plot, we can see that February had the highest site traffic, followed closely by March, then April. July had the least amount of traffic to the site.

```
# A bar plot showing the gender distribution
barplot(table(data$Gender), col = c("red" , "green"), ylab = "No. of
visitors", main = "Distribution of Gender")
```



From the plot, we can see that 0, ie females, caused the highest traffic to the site.

```
# A bar plot showing the distribution of visitors who clicked on the ads  
barplot(table(data$Clicked.on.Ad), main = "Distribution of Visitors who  
clicked on ads", ylab = "No. of visitors", col = "magenta")
```

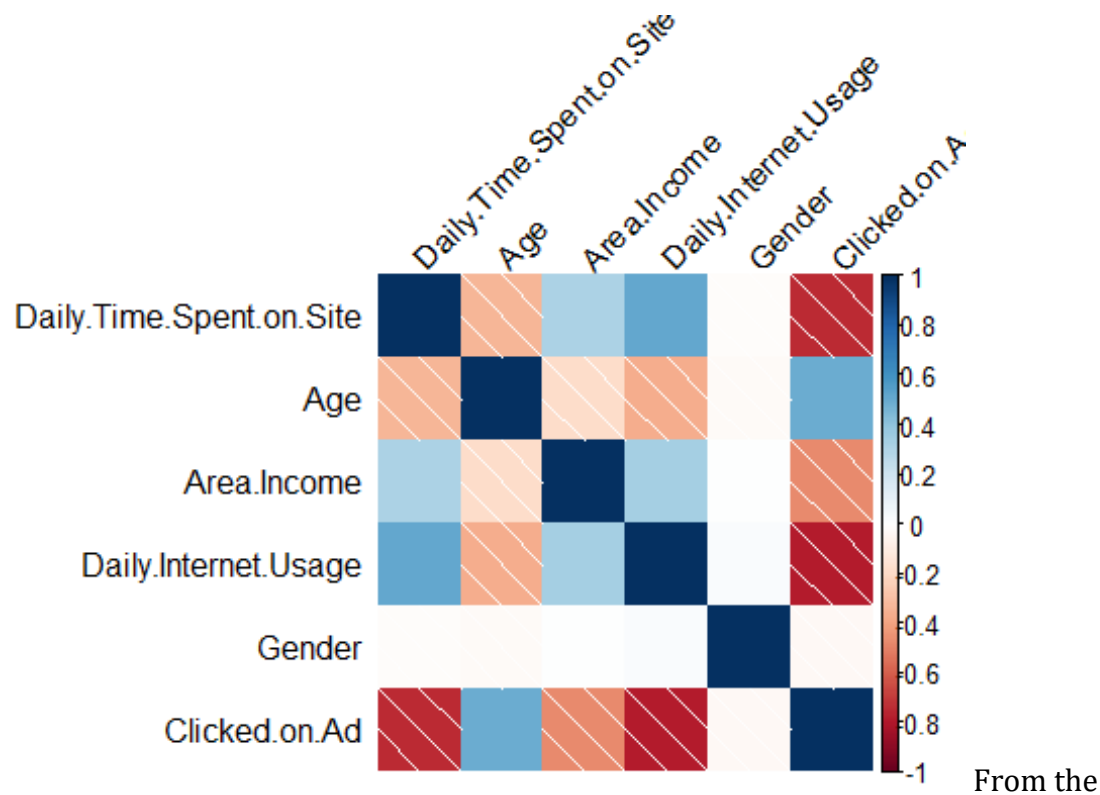
From the plot, it seems like there was an equal amount of visitors who clicked on ads as well as those who didn't.

2. Bivariate Analysis

#Calculating the correlation between columns

```
correlation = cor(data_num)
```

Creating a correlogram to plot our correlation for better presentation
`corrplot(correlation, method="shade", tl.col="black", tl.srt=45)`

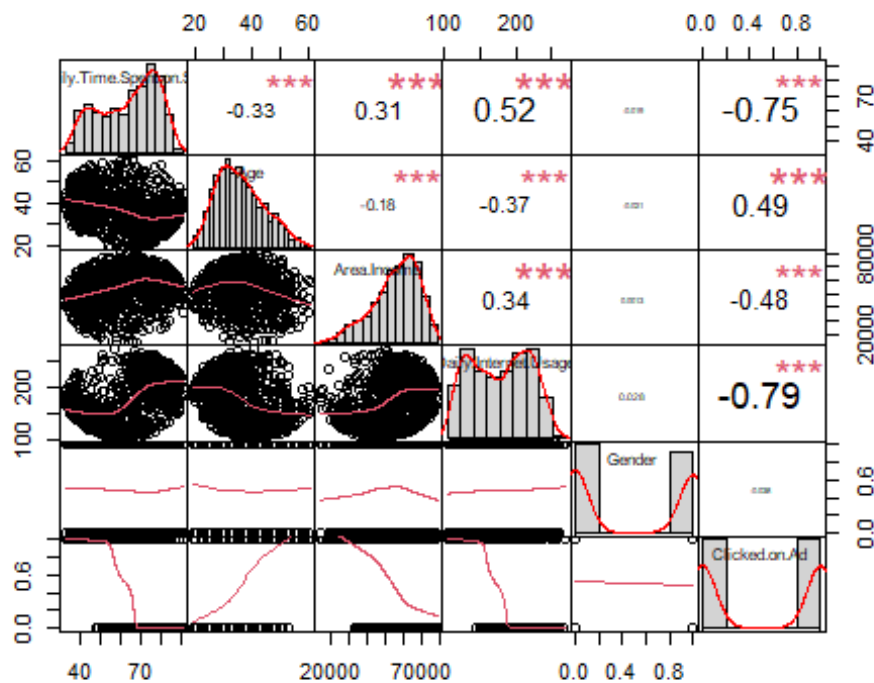


correlogram above & using the legend on the right, we can see that:

- Daily time spent on the site has a high negative relationship with whether one clicked on an ad. Thus if one spends alot of time on the site, there is a high chance of them not clicking on an ad.
- There's a low negative relationship between one's age and the daily time spent on the site as well as their daily internet usage. Thus the higher one's age, the less likely they are to spend more time on the site or to have a high internet usage.
- There is a medium negative relationship between one's income and whether they clicked on an ad. Thus, the higher one's income, the less likely they are to click on ad.
- There's a medium positive relationship between one's daily internet usage and the daily time spent on the site. This shows that there's a medium chance that people with a high internet usage would be those spending a lot of time on the site.
- There is also a medium positive relationship between one's age and whether they clicked on ads. Thus the older one's age, the more like they are to click on an ad, however the reallationship is not too strong.

Plotting scatterplots to get the distributions of the columns as well as the significance value

```
chart.Correlation(data_num, histogram = TRUE,)
```



From the scatterplot above, we can see the significance levels for the different variables, as well as the scatter plots with the fitted lines. We can also see the different distributions for our datasets.

Conclusion

The most common amount of time spent on the site is 62.26, while the most popular age is 31 years. Most of the site visits have an income of 61,833.9. The city with most visitors is Lisamouth while Czech Republic had the most site visitors. Most of the visitors were female, while most didn't click on the ads. The site had most traffic in February. The internet users that are most likely to click on our client's ads are those who spend very little time online. Also the lower ones income is, the higher the chances of them clicking on the ads. The older one is, the more like they are to click on an ad, however the relationship is not too strong.

Recommendations

My recommendation as a data scientist, would be for her to do curate the ads to be mostly on courses that may interest the people most likely to click on the ads as outlined above. She can also include other content so as to pique other users to click more on the ads.

Implementing the Solution using KNN

We will convert our labels on the target variable to be categorical

```
#Converting labels to categorical
data$Clicked.on.Ad <- factor(data$Clicked.on.Ad)
```

We will then check for class imbalance

```
round(prop.table(table(data$Clicked.on.Ad)) * 100, digits = 1)

##
##  0  1
## 50 50
```

There seems to be no data imbalance in our dataset

We will now select the features we shall use for modelling

```
unique(data[c("City")])

##              City
## 1      Wrightburgh
## 2      West Jodi
## 3      Davidton
## 4      West Terrifurt
## 5      South Manuel
## 6      Jamieberg
## 7      Brandonstad
## 8      Port Jefferybury
## 9      West Colin
## 10     Ramirezton
## 11     West Brandonton
## 12     East Theresashire
## 13     West Katiefurt
## 14     North Tara
## 15     West William
## 16     New Travistown
## 17     West Dylanberg
## 18     Pruittmouth
## 19     Jessicastad
## 20     Millertown
## 21     Port Jacqueline
## 22     Lake Nicole
## 23     South John
## 24     Pamelamouth
## 25     Harperborough
## 26     Port Danielleberg
## 27     West Jeremyside
## 28     South Cathyfurt
## 29     Palmerside
## 30     West Guybury
## 31     Phelpschester
## 32     Lake Melindamouth
## 33     North Richardburgh
## 34     Port Cassie
## 35     New Thomas
## 36     Johnstad
```

## 37	West Aprilport
## 38	Kellytown
## 39	Charlesport
## 40	Millerchester
## 41	Mackenziemouth
## 42	Zacharystad
## 43	North Joshua
## 44	Bowenview
## 45	Jamesberg
## 46	Lake Cassandraport
## 47	New Sharon
## 48	Johnport
## 49	Hamiltonfort
## 50	West Christopher
## 51	Hollandberg
## 52	Odomville
## 53	East Samanthashire
## 54	South Lauraton
## 55	Amandahaven
## 56	Thomasview
## 57	Garciaside
## 58	Port Sarahshire
## 59	Port Gregory
## 60	Brendachester
## 61	Lake Amy
## 62	Lake Annashire
## 63	Smithburgh
## 64	North Leonmouth
## 65	Robertfurt
## 66	Jasminefort
## 67	Jensenborough
## 68	Bradleyburgh
## 69	New Sheila
## 70	North Regina
## 71	Davidmouth
## 72	New Michaeltown
## 73	East Tammie
## 74	Wilcoxport
## 75	East Michaelmouth
## 76	East Tiffanyport
## 77	Ramirezhaven
## 78	Cranemouth
## 79	Lake Edward
## 80	Lake Conniefurt
## 81	East Shawncchester
## 82	West Joseph
## 83	Lake Christopherfurt
## 84	East Tylershire
## 85	Sharpberg
## 86	Lake Dustin

## 87	North Kristine
## 88	Grahamberg
## 89	New Tina
## 90	Nelsonfurt
## 91	Christopherport
## 92	Port Sarahhaven
## 93	Bradleyborough
## 94	Whiteport
## 95	New Theresa
## 96	Wongland
## 97	Williammouth
## 98	Williamsborough
## 99	North Michael
## 100	Benjaminchester
## 101	Hernandezville
## 102	Youngburgh
## 103	Wallacechester
## 104	Sanchezmouth
## 105	Bradshawborough
## 106	Amyhaven
## 107	Marcushaven
## 108	Erinton
## 109	Hughesport
## 111	New Lucasburgh
## 112	Michelleside
## 113	Andersonton
## 114	New Rachel
## 115	Port Susan
## 116	West Angelabury
## 117	Port Christopherborough
## 118	Phillipsbury
## 119	Millerside
## 120	Lake Jessica
## 121	Lopezmouth
## 122	Johnsport
## 123	South Ronald
## 124	South Daniel
## 125	Suzannetown
## 126	Lisaberg
## 127	Brianfurt
## 128	Stewartbury
## 130	North Wesleychester
## 131	East Michelleberg
## 132	Port Eric
## 133	Timothyfurt
## 134	Port Jeffrey
## 135	Guzmanland
## 136	East Michele
## 137	East John
## 138	Lesliebury

## 139	Patriciahaven
## 140	Ashleychester
## 141	Lake Josetown
## 142	Debraburgh
## 143	New Debbiestad
## 144	West Shaun
## 145	Kimberlyhaven
## 146	Port Lawrence
## 147	West Ricardo
## 148	Lake Jose
## 149	Heatherberg
## 150	South George
## 151	Tinachester
## 152	Port Jodi
## 153	Jonathantown
## 154	Sylviaview
## 155	East Timothyport
## 156	West Roytown
## 157	Codyburgh
## 158	Port Erikhaven
## 159	Port Chasemouth
## 160	Ramirezside
## 161	East Michaeltown
## 162	West Courtney
## 163	West Michaelhaven
## 164	Walshhaven
## 165	East Rachelview
## 166	Curtisport
## 167	Frankbury
## 168	Timothytown
## 169	Samanthaland
## 170	South Jennifer
## 171	Kyleborough
## 172	North Randy
## 173	South Danielleport
## 174	Dianashire
## 175	East Eric
## 176	Hammondport
## 177	Jacobstad
## 178	Hernandezfort
## 179	Joneston
## 180	New Jeffreychester
## 181	East Stephen
## 182	Turnerchester
## 183	Youngfort
## 184	Ingramberg
## 185	South Denisefort
## 186	Port Melissaberg
## 187	Bernardton
## 188	Port Mathew

## 189	Aliciatown
## 190	Josephstad
## 191	West Ericfurt
## 192	New Brendafurt
## 193	Port Julie
## 194	South Tiffanyton
## 195	North Elizabeth
## 196	Kentmouth
## 197	West Casey
## 198	East Henry
## 199	Hollyfurt
## 200	North Anna
## 201	Port Destiny
## 202	Ianmouth
## 203	North Johntown
## 204	Hannahside
## 205	Wilsonburgh
## 206	North Russellborough
## 207	Murphymouth
## 208	Carterburgh
## 209	Penatown
## 210	Joechester
## 211	East Paul
## 212	Hartmanchester
## 213	Mcdonaldfort
## 214	North Mercedes
## 215	Taylorberg
## 216	Hansenmouth
## 217	Bradyfurt
## 218	West Jessicahaven
## 219	Davilachester
## 220	North Ricardotown
## 221	Melissafurt
## 222	East Brianberg
## 223	Millerbury
## 224	Garciaview
## 225	Townsendfurt
## 226	Williamstad
## 227	West Connor
## 228	West Justin
## 229	Robertbury
## 230	New Tinamouth
## 231	Turnerview
## 232	Reneechester
## 233	West Tinashire
## 234	Jamesfurt
## 235	New Nancy
## 236	Lisamouth
## 237	Harveyport
## 238	Ramosstad

## 239	North Kevinside
## 240	Haleview
## 241	Christinetown
## 242	New Michael
## 243	Jonesland
## 244	North Shannon
## 245	New Sonialand
## 246	Port Jason
## 247	East Barbara
## 248	Port Erinberg
## 249	Petersonfurt
## 250	New Lindaberg
## 251	West Russell
## 252	South Adam
## 253	North Tracyport
## 254	Brownport
## 255	Port Crystal
## 256	Masonhaven
## 257	Derrickhaven
## 258	Olsonstad
## 259	New Brandy
## 260	South Jasminebury
## 261	East Timothy
## 262	Charlotteport
## 263	Lake Beckyburgh
## 264	West Lindseybury
## 265	West Alyssa
## 266	Lake Craigview
## 267	Lake David
## 268	Bruceburgh
## 269	South Lauratown
## 270	Port Robin
## 271	Jacksonburgh
## 272	Erinmouth
## 273	Port Aliciabury
## 274	Port Whitneyhaven
## 275	Jeffreyshire
## 276	Tinaton
## 277	North Loriburgh
## 278	Wendyton
## 279	Lake Jacqueline
## 280	North Christopher
## 281	Alexanderfurt
## 282	West Pamela
## 283	West Amanda
## 284	South Tomside
## 285	Bethburgh
## 286	Jamiefort
## 287	Garciamouth
## 288	West Brenda

## 289	South Kyle
## 290	Combsstad
## 291	Lake Allenville
## 292	Greenechester
## 293	Jordantown
## 294	Gravesport
## 295	South Troy
## 296	Lake Patrick
## 297	Millerland
## 298	Port Jessicamouth
## 299	Paulport
## 300	Clineshire
## 301	Cynthiaside
## 302	Port Juan
## 303	Michellefort
## 304	Port Angelamouth
## 305	Jessicahaven
## 306	North Daniel
## 307	New Juan
## 308	Amyfurt
## 309	Harrishaven
## 310	Roberttown
## 311	Jeremyshire
## 312	Birdshire
## 313	New Amanda
## 314	Curtisview
## 315	Jacksonmouth
## 316	North April
## 317	Hayesmouth
## 318	South Corey
## 319	Juliaport
## 320	Port Paultown
## 321	East Vincentstad
## 322	Kimberlytown
## 323	New Steve
## 324	New Johnberg
## 325	Shawstad
## 326	New Rebecca
## 327	Jeffreyburgh
## 328	Faithview
## 329	Richardsontown
## 330	Port Brookeland
## 331	East Christopherbury
## 332	Port Christinemouth
## 333	South Meghan
## 334	Hessstad
## 335	Rhondaborough
## 336	Lewismouth
## 337	New Paul
## 338	Lake Angela

## 339	East Graceland
## 340	Hartport
## 341	East Yvonnechester
## 342	Burgessside
## 343	Hurleyborough
## 344	Garychester
## 345	East Kevinbury
## 346	Contrerasshire
## 347	Erikville
## 348	Robertsonburgh
## 349	Karenton
## 350	Port Kathleenfort
## 351	Lake Adrian
## 353	Mollyport
## 354	Sandraland
## 355	Charlenetown
## 356	Luischester
## 357	South Johnnymouth
## 358	Hannaport
## 359	East Anthony
## 360	West Daleborough
## 361	Morrismouth
## 362	North Andrewstad
## 364	West Tanya
## 365	Novaktown
## 366	Timothymouth
## 367	Robertmouth
## 368	Stephenborough
## 369	Lake Kurtmouth
## 370	Lauraburgh
## 371	Rogerburch
## 372	Davidside
## 373	West Thomas
## 374	Andersonchester
## 375	North Ronaldshire
## 376	Greghaven
## 377	Jordanmouth
## 378	Meyersstad
## 380	South Robert
## 381	New Tyler
## 382	Jordanshire
## 383	Reyesland
## 384	New Traceystad
## 385	Port Brian
## 386	Lake Courtney
## 387	Samuelborough
## 388	Christinehaven
## 389	Thomasstad
## 390	Kristintown
## 391	New Wanda

## 392	Mariebury
## 393	Christopherville
## 394	New Jasmine
## 395	Lopezberg
## 396	Jenniferstad
## 397	West Eduardotown
## 398	Davisfurt
## 399	Bakerhaven
## 400	Paulshire
## 401	West Jane
## 402	Lake Brian
## 403	Alvaradoport
## 404	Lake Kevin
## 405	Richardsonland
## 406	East Sheriville
## 407	Port Michealburgh
## 408	Monicaview
## 409	Katieport
## 410	East Brittanyville
## 411	West Trivismouth
## 412	Leonchester
## 413	Ramirezland
## 414	Brownton
## 415	New Jessicaport
## 416	New Denisebury
## 417	Keithtown
## 418	Port Melissastad
## 419	Janiceview
## 420	Mataberg
## 421	West Melaniefurt
## 422	Millerfort
## 423	Alexanderview
## 424	South Jade
## 425	Lake Susan
## 426	South Vincentchester
## 427	Williamsmouth
## 428	Taylorport
## 429	Williamsport
## 430	Emilyfurt
## 432	East Deborahhaven
## 433	Port Katelynview
## 434	Paulhaven
## 435	Elizabethmouth
## 436	Lake Jesus
## 437	North Tylerland
## 438	Munozberg
## 439	North Maryland
## 440	West Barbara
## 441	Andrewborough
## 442	New Gabriel

## 443	Port Patrickton
## 444	West Julia
## 445	New Keithburgh
## 446	Richardsland
## 447	North Aaronchester
## 448	Lake Matthewland
## 449	Kevinberg
## 450	Morganfort
## 451	Lovemouth
## 452	Taylorhaven
## 453	Jamesville
## 454	East Toddfort
## 455	East Dana
## 456	West Lucas
## 457	Butlerfort
## 458	Lindaside
## 459	West Chloeborough
## 460	Jayville
## 461	East Lindsey
## 462	Masseyshire
## 463	Sarahnton
## 464	Ryanhaven
## 465	Lake Deborahburgh
## 466	New Williammouth
## 467	Port Blake
## 468	West Richard
## 469	Brandymouth
## 470	Sandraville
## 471	Port Jessica
## 472	Lake Jasonchester
## 473	Pearsonfort
## 474	Sellerstown
## 475	Yuton
## 476	Smithtown
## 477	Joanntown
## 478	South Peter
## 479	Port Mitchell
## 480	Pottermouth
## 481	Lake Jonathanview
## 482	Alanview
## 483	Carterport
## 484	New Daniellefort
## 485	Welchshire
## 486	Russellville
## 487	West Lisa
## 488	Greentown
## 489	Timothyport
## 490	Teresahaven
## 491	Lake Stephenborough
## 492	Silvaton

## 493	West Michaelstad
## 494	Florestown
## 495	New Jay
## 496	North Lisachester
## 497	Port Stacy
## 498	Jensenton
## 499	North Alexandra
## 500	Rivasland
## 501	Helenborough
## 502	Garnerberg
## 503	North Anaport
## 504	Pattymouth
## 505	South Alexisborough
## 506	East Jennifer
## 507	Hallfort
## 508	New Charleschester
## 509	East Breannafurt
## 510	East Susanland
## 511	Estesfurt
## 512	Shirleyfort
## 513	Douglasview
## 514	South Lisa
## 515	Kingshire
## 516	Rebeccamouth
## 517	Brownbury
## 518	South Aaron
## 519	North Andrew
## 520	South Walter
## 521	Catherinefort
## 522	East Donna
## 524	North Kimberly
## 525	South Stephanieport
## 526	North Isabellaville
## 527	North Aaronburgh
## 528	Port James
## 529	Danielview
## 530	Port Stacey
## 531	West Kevinfurt
## 532	Lake Jennifer
## 533	Reyesfurt
## 534	West Carmenfurt
## 535	North Stephanieberg
## 536	East Valerie
## 537	Sherrishire
## 538	Port Daniel
## 539	Brownview
## 540	Greerton
## 541	Hatfieldshire
## 542	Brianabury
## 543	New Maria

## 544	Colebury
## 545	Calebberg
## 546	Lake Ian
## 547	Gomezport
## 548	Shaneland
## 549	East Aaron
## 550	Dustinborough
## 551	East Michaeland
## 552	East Connie
## 553	West Shannon
## 554	North Lauraland
## 555	Port Christopher
## 556	South Patrickfort
## 557	East Georgeside
## 558	Charlesbury
## 560	South Renee
## 561	South Jackieberg
## 562	Loriville
## 563	Amandaland
## 564	West Robertside
## 565	North Sarashire
## 566	Port Maria
## 567	East Jessefort
## 568	Port Anthony
## 569	Edwardmouth
## 570	Dustinchester
## 571	Rochabury
## 573	Austinland
## 574	Lake Gerald
## 575	Wrightview
## 576	Perryburgh
## 577	Tracyhaven
## 578	South Jaimeview
## 579	Sandersland
## 580	South Meredithmouth
## 581	Richardsonshire
## 582	Kimberlymouth
## 583	Meghanchester
## 584	Tammyshire
## 586	Lake Elizabethside
## 587	Villanuevaton
## 588	Greerport
## 589	North Garyhaven
## 590	East Sharon
## 591	Johnstonmouth
## 592	East Heatherside
## 594	Richardsonmouth
## 595	Jenniferhaven
## 596	Boyerberg
## 597	Port Elijah

## 598	Knappburgh
## 599	New Dawnland
## 600	Chapmanmouth
## 601	Robertside
## 602	West Raymondmouth
## 603	Costaburgh
## 604	Kristineberg
## 605	Sandrashire
## 606	Andersonfurt
## 607	Tranland
## 608	Michaeland
## 609	East Rachaelfurt
## 610	Lake Johnbury
## 611	Elizabethstad
## 612	West Brad
## 613	Johnstonshire
## 614	Lake Timothy
## 615	Anthonyfurt
## 616	East Brettton
## 617	New Matthew
## 618	Christopherchester
## 619	Westshire
## 620	Alexisland
## 621	Kevinchester
## 622	New Patriciashire
## 623	Port Brenda
## 624	Port Brianfort
## 625	Portermouth
## 626	Hubbardmouth
## 627	South Brian
## 628	Hendrixmouth
## 629	Julietown
## 630	Lukeport
## 631	New Shane
## 632	Lake Jillville
## 633	Johnsonfort
## 634	Adamsbury
## 635	East Maureen
## 636	North Angelastad
## 637	Amandafort
## 638	Michaelmouth
## 639	Ronaldport
## 640	Port Davidland
## 641	Isaacborough
## 642	Lake Michael
## 643	West Michaelshire
## 644	Port Calvintown
## 645	Parkerhaven
## 646	Markhaven
## 647	Estradashire

## 648	Brianland
## 649	Cassandratown
## 650	West Dannyberg
## 651	East Debraborough
## 652	Frankchester
## 653	Lisafort
## 654	Colemanshire
## 655	Troyville
## 656	Hobbsbury
## 657	Harrisonmouth
## 658	Port Eugeneport
## 659	Karenmouth
## 660	Brendaburgh
## 661	New Christinatown
## 662	Jacksonstad
## 663	South Margaret
## 664	Port Georgebury
## 666	Sanderstown
## 667	Perezland
## 668	Luisfurt
## 669	New Karenberg
## 670	West Leahton
## 671	West Sharon
## 672	Klineside
## 673	Lake Cynthia
## 674	South Cynthiashire
## 675	Lake Jacob
## 676	West Samantha
## 677	Jeremybury
## 678	Blevinstown
## 679	Meyerchester
## 680	Reginamouth
## 681	Donaldshire
## 682	Salazarbury
## 683	Lake Joshuafurt
## 684	Wintersfort
## 685	Jamesmouth
## 686	Laurieside
## 687	Andrewmouth
## 688	West Angela
## 689	East Carlos
## 690	Kennedyfurt
## 691	Blairville
## 692	East Donnatown
## 693	Matthewtown
## 694	Brandonbury
## 695	New Jamestown
## 696	Mosleyburgh
## 697	Leahside
## 698	West Wendyland

## 699	Lawrenceborough
## 700	Kennethview
## 701	West Mariafort
## 702	Port Sherrystad
## 703	West Melissashire
## 705	Lesliefort
## 706	Shawnside
## 707	Josephmouth
## 708	Garciatown
## 709	Chaseshire
## 710	Destinyfurt
## 711	Mezaton
## 712	New Kayla
## 713	Carsonshire
## 714	Jacquelineshire
## 715	South Blakestad
## 716	North Mark
## 717	Kingchester
## 718	Evansfurt
## 719	South Adamhaven
## 720	Brittanyborough
## 721	Barbershire
## 722	East Ericport
## 723	Crawfordfurt
## 724	Turnerville
## 725	Kylieview
## 726	West Zacharyborough
## 727	Watsonfort
## 728	Dayton
## 729	Nicholasport
## 730	Whitneyfort
## 731	Coffeytown
## 732	North Johnside
## 733	Robinsonland
## 735	West Ericaport
## 736	Haleberg
## 737	West Michaelport
## 738	Ericksonmouth
## 739	Yangside
## 740	Estradafurt
## 741	Frankport
## 743	Williamsside
## 744	Johnsonview
## 745	East Heidi
## 746	New Angelview
## 747	Lake Brandonview
## 748	Morganport
## 749	Browntown
## 750	Lake Hailey
## 751	Olsonside

## 752	Coxhaven
## 753	Meaganfort
## 754	North Monicaville
## 755	Mullenside
## 756	Princebury
## 757	Bradleyside
## 758	Elizabethbury
## 759	West Ryan
## 760	New Tammy
## 761	Sanchezland
## 762	Rogerland
## 763	Vanessaview
## 764	Jessicashire
## 765	Melissachester
## 766	Johnsontown
## 767	New Joshuaport
## 768	Hernandezside
## 769	New Williamville
## 770	Gilbertville
## 771	Newmanberg
## 772	West Alice
## 773	Cannonbury
## 774	Shelbyport
## 775	New Henry
## 776	Dustinmouth
## 779	New Hollyberg
## 780	Port Brittanyville
## 781	East Ronald
## 782	South Davidmouth
## 783	Carterton
## 784	Rachelhaven
## 785	New Timothy
## 786	North Jessicaville
## 788	Staceyfort
## 789	South Dianeshire
## 791	Micheletown
## 792	North Brittanyburgh
## 793	Port Jasmine
## 794	New Sabrina
## 795	Lake Charlottestad
## 796	West Rhondamouth
## 797	North Debra
## 798	Villanuevastad
## 799	North Jeremyport
## 801	Lake John
## 802	Courtneyfort
## 803	Tammymouth
## 804	Lake Vanessa
## 805	Lake Amanda
## 806	Mariemouth

## 807	Port Douglasborough
## 808	Port Aprilville
## 810	Lake Faith
## 811	Wendyville
## 812	Angelhaven
## 813	New Sean
## 814	Lake Lisa
## 815	Valerieland
## 816	New Travis
## 817	North Samantha
## 818	Holderville
## 819	Patrickmouth
## 820	Lake Deannaborough
## 821	Jeffreymouth
## 822	Davieshaven
## 823	Lake Jessicaville
## 824	Hernandezchester
## 825	North Kennethside
## 827	Williamport
## 828	Smithside
## 829	Vanessastad
## 831	Lake Rhondaburgh
## 832	Cunninghamhaven
## 833	Robertstown
## 834	South Mark
## 835	New Taylorburgh
## 836	Port Karenfurt
## 837	Carterland
## 838	East Shawn
## 839	West Derekmouth
## 840	Brandiland
## 841	Cervantesshire
## 842	North Debrashire
## 843	Deannaville
## 844	East Christopher
## 845	Rickymouth
## 846	Port Dennis
## 847	Lake Michelle
## 848	East Johnport
## 849	Sabrinaview
## 850	Kristinfurt
## 851	Chapmanland
## 852	North Jonathan
## 853	Port Christina
## 854	Juanport
## 855	East Mike
## 856	North Angelatown
## 857	West Steven
## 858	Riggsstad
## 859	Davidview

## 860	Port Kevinborough
## 861	Lawsonshire
## 862	Wagnerchester
## 863	Daisymouth
## 865	Port Jacquelinestad
## 866	New Teresa
## 867	Henryfort
## 868	Lake Joseph
## 869	Daviesborough
## 870	North Brandon
## 871	Adamside
## 872	Wademouth
## 873	North Raymond
## 874	Randolphport
## 875	East Troyhaven
## 876	Clarkborough
## 877	Josephberg
## 878	Lake Jenniferton
## 880	Ashleymouth
## 881	Henryland
## 882	Lake Danielle
## 883	Joshuaburgh
## 884	South Jeanneport
## 885	New Nathan
## 886	Jonesshire
## 887	Mariahview
## 888	New Julianberg
## 889	Randyshire
## 890	Philipberg
## 891	West Dennis
## 892	Richardshire
## 893	Lake James
## 894	Austinborough
## 895	Alexandrafort
## 896	Melissastad
## 897	Gonzalezburgh
## 898	Port Jennifer
## 899	Chrismouth
## 900	Port Beth
## 901	West David
## 902	Fraziershire
## 904	South Pamela
## 905	North Laurenvew
## 906	Campbellstad
## 907	Port Derekberg
## 908	West Andrew
## 909	West Randy
## 910	South Christopher
## 911	Lake Michellebury
## 912	Zacharyton

## 913	West James
## 914	Millerview
## 915	Hawkinsbury
## 916	Elizabethport
## 918	Wadestad
## 919	Mauriceshire
## 920	West Arielstad
## 921	Adamsstad
## 923	Blairborough
## 924	New Marcusbury
## 925	Evansville
## 926	Huffmanchester
## 927	New Cynthia
## 928	Joshuamouth
## 929	West Benjamin
## 930	Williamsfort
## 931	North Tiffany
## 932	Edwardsport
## 933	Lake Evantown
## 934	South Henry
## 935	Harmonhaven
## 936	West Gregburgh
## 937	Hansenland
## 938	Port Michaelmouth
## 939	Tylerport
## 940	West Lacey
## 941	North Jenniferburgh
## 942	South Davidhaven
## 943	North Charlesbury
## 944	Jonathanland
## 945	North Virginia
## 946	West Tanner
## 947	Jonesmouth
## 949	West Annefort
## 950	East Jason
## 951	North Cassie
## 952	Hintonport
## 953	New James
## 954	North Destiny
## 955	Mclaughlinbury
## 956	West Gabriellamouth
## 957	Alvarezland
## 958	New Julie
## 959	North Frankstad
## 960	Claytonside
## 961	Melanieton
## 962	Lake Michaelport
## 963	East Benjaminville
## 964	Garrettborough
## 965	Port Raymondfort

```
## 966          Waltertown
## 967          Cameronberg
## 968          Kaylashire
## 969          Fosterside
## 970          Davidstad
## 971          Lake Tracy
## 972          Taylormouth
## 973          Dianaville
## 974          Collinsburgh
## 975          Port Rachel
## 976          South Rebecca
## 977          Port Joshuafort
## 978          Robinsontown
## 979          Beckton
## 980          New Frankshire
## 981          North Derekville
## 982          West Sydney
## 983          Lake Matthew
## 984          Lake Zacharyfurt
## 985          Lindsaymouth
## 986          Sarahland
## 988          Michaelshire
## 989          Sarafurt
## 990          South Denise
## 991          North Katie
## 992          Mauricefurt
## 993          New Patrick
## 994          Edwardsmouth
## 995          Nicholasland
## 996          Duffystad
## 997          New Darlene
## 998          South Jessica
## 1000         Ronniemouth
```

```
unique(data[c("Country")])
```

```
##          Country
## 1         Tunisia
## 2          Nauru
## 3       San Marino
## 4          Italy
## 5         Iceland
## 6          Norway
## 7         Myanmar
## 8         Australia
## 9         Grenada
## 10         Ghana
## 11         Qatar
## 12        Burundi
## 13         Egypt
```

## 14	Bosnia and Herzegovina
## 15	Barbados
## 16	Spain
## 17	Palestinian Territory
## 18	Afghanistan
## 19	British Indian Ocean Territory (Chagos Archipelago)
## 20	Russian Federation
## 21	Cameroon
## 24	Korea
## 25	Tokelau
## 26	Monaco
## 27	Tuvalu
## 28	Greece
## 29	British Virgin Islands
## 30	Bouvet Island (Bouvetoya)
## 31	Peru
## 32	Aruba
## 33	Maldives
## 34	Senegal
## 35	Dominica
## 36	Luxembourg
## 37	Montenegro
## 38	Ukraine
## 39	Saint Helena
## 40	Liberia
## 43	Turkmenistan
## 45	Niger
## 48	Sri Lanka
## 49	Trinidad and Tobago
## 52	United Kingdom
## 53	Guinea-Bissau
## 54	Micronesia
## 55	Turkey
## 56	Croatia
## 57	Israel
## 58	Svalbard & Jan Mayen Islands
## 59	Azerbaijan
## 60	Iran
## 62	Saint Vincent and the Grenadines
## 64	Bulgaria
## 65	Christmas Island
## 66	Canada
## 67	Rwanda
## 68	Turks and Caicos Islands
## 70	Norfolk Island
## 73	Cook Islands
## 75	Guatemala
## 76	Cote d'Ivoire
## 77	Faroe Islands
## 79	Ireland

## 81	Moldova
## 82	Nicaragua
## 83	Montserrat
## 84	Timor-Leste
## 86	Puerto Rico
## 87	Central African Republic
## 88	Venezuela
## 90	Wallis and Futuna
## 91	Jersey
## 93	Samoa
## 95	Antarctica (the territory South of 60 deg S)
## 96	Albania
## 97	Hong Kong
## 98	Lithuania
## 100	Bangladesh
## 101	Western Sahara
## 102	Serbia
## 104	Czech Republic
## 105	Guernsey
## 106	Tanzania
## 107	Bhutan
## 109	Guinea
## 111	Madagascar
## 112	Lebanon
## 113	Eritrea
## 114	Guyana
## 117	United Arab Emirates
## 118	Martinique
## 119	Somalia
## 122	Benin
## 123	Papua New Guinea
## 124	Uzbekistan
## 125	South Africa
## 127	Hungary
## 128	Falkland Islands (Malvinas)
## 132	Saint Martin
## 133	Cuba
## 134	United States Minor Outlying Islands
## 135	Belize
## 139	Kuwait
## 140	Thailand
## 141	Gibraltar
## 142	Holy See (Vatican City State)
## 147	Netherlands
## 148	Belarus
## 151	New Zealand
## 152	Togo
## 153	Kenya
## 154	Palau
## 156	Cambodia

## 159	Costa Rica
## 160	Liechtenstein
## 163	Angola
## 165	Equatorial Guinea
## 166	Mongolia
## 169	Brazil
## 170	Chad
## 171	Portugal
## 172	Malawi
## 174	Singapore
## 176	Kazakhstan
## 179	China
## 181	Vietnam
## 184	Mayotte
## 187	Jamaica
## 188	Bahamas
## 190	Algeria
## 191	Fiji
## 193	Argentina
## 195	Philippines
## 197	Suriname
## 199	Guam
## 201	Antigua and Barbuda
## 203	Georgia
## 204	Jordan
## 205	Saudi Arabia
## 210	Sao Tome and Principe
## 212	Cyprus
## 213	Kyrgyz Republic
## 214	Pakistan
## 215	Seychelles
## 218	Mauritania
## 220	Chile
## 221	Poland
## 222	Estonia
## 224	Latvia
## 228	Bahrain
## 229	Colombia
## 230	Brunei Darussalam
## 231	Taiwan
## 233	Saint Pierre and Miquelon
## 238	Finland
## 243	French Southern Territories
## 248	Sierra Leone
## 249	Tajikistan
## 251	Ecuador
## 252	Switzerland
## 255	France
## 265	Malaysia
## 266	Mauritius

## 269	Japan
## 270	Greenland
## 273	Guadeloupe
## 274	Belgium
## 276	Honduras
## 278	Paraguay
## 281	French Guiana
## 282	Northern Mariana Islands
## 285	American Samoa
## 286	Austria
## 287	Tonga
## 291	New Caledonia
## 293	United States of America
## 294	Morocco
## 296	Macedonia
## 299	Gabon
## 304	Uganda
## 314	Saint Lucia
## 315	Niue
## 321	Zambia
## 322	Congo
## 324	Pitcairn Islands
## 326	Anguilla
## 332	Sweden
## 339	Indonesia
## 342	Mexico
## 344	Haiti
## 348	Gambia
## 352	El Salvador
## 353	Libyan Arab Jamahiriya
## 355	Saint Barthelemy
## 356	Reunion
## 370	Panama
## 384	Dominican Republic
## 385	Zimbabwe
## 394	Swaziland
## 398	Saint Kitts and Nevis
## 399	Burkina Faso
## 411	Heard Island and McDonald Islands
## 413	Bolivia
## 417	Netherlands Antilles
## 428	French Polynesia
## 455	Germany
## 461	Malta
## 463	Sudan
## 464	Lao People's Democratic Republic
## 495	Isle of Man
## 500	Macao
## 502	United States Virgin Islands
## 504	Djibouti

```
## 506 Mali
## 508 Romania
## 509 Cayman Islands
## 521 Ethiopia
## 535 Uruguay
## 558 Comoros
## 562 Vanuatu
## 566 Nepal
## 571 Yemen
## 572 India
## 621 Cape Verde
## 635 Slovenia
## 643 Denmark
## 651 Syrian Arab Republic
## 662 Andorra
## 710 Namibia
## 718 Slovakia (Slovak Republic)
## 729 Armenia
## 755 South Georgia and the South Sandwich Islands
## 786 Kiribati
## 809 Marshall Islands
## 931 Bermuda
## 935 Mozambique
## 946 Lesotho
```

#Feature selection

```
data_f <- data[c('Daily.Time.Spent.on.Site', 'Age', 'Area.Income',
'Daily.Internet.Usage', 'Gender', 'Clicked.on.Ad')]
```

#Previewing dataset

```
head(data_f)
```

```
##   Daily.Time.Spent.on.Site Age Area.Income Daily.Internet.Usage Gender
## 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
```

#Displaying the structure of our dataframe

```
str(data)
```

```
## 'data.frame':   1000 obs. of  12 variables:
## $ Daily.Time.Spent.on.Site: num  69 80.2 69.5 74.2 68.4 ...
```

```
## $ Age : int 35 31 26 29 35 23 33 48 30 20 ...
## $ Area.Income : num 61834 68442 59786 54806 73890 ...
## $ Daily.Internet.Usage : num 256 194 236 246 226 ...
## $ Ad.Topic.Line : chr "Cloned 5thgeneration orchestration"
"Monitored national standardization" "Organic bottom-line service-desk"
"Triple-buffered reciprocal time-frame" ...
## $ City : chr "Wrightburgh" "West Jodi" "Davidton"
"West Terrifurt" ...
## $ Gender : int 0 1 0 1 0 1 0 1 1 1 ...
## $ Country : chr "Tunisia" "Nauru" "San Marino" "Italy"
...
## $ Year : chr "2016" "2016" "2016" "2016" ...
## $ Month : chr "03" "04" "03" "01" ...
## $ Day : chr "27" "04" "13" "10" ...
## $ Clicked.on.Ad : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 2 1
1 ...
```

Normalizing our data

```
#Normalization function
normalize <- function(x) {
  return ((x - min(x)) / (max(x) - min(x))) }

#Normalizing the data
data_norm <- as.data.frame(lapply(data_f[,1:5], normalize))
#Previewing the dataset
head(data_norm)

##   Daily.Time.Spent.on.Site   Age Area.Income Daily.Internet.Usage
Gender
## 1          0.6178820 0.3809524    0.7304725          0.9160310
0
## 2          0.8096209 0.2857143    0.8313752          0.5387456
1
## 3          0.6267211 0.1666667    0.6992003          0.7974331
0
## 4          0.7062723 0.2380952    0.6231599          0.8542802
1
## 5          0.6080231 0.3809524    0.9145678          0.7313234
0
## 6          0.4655788 0.0952381    0.6988280          0.7383460
1
```

Splitting our dataset

```
set.seed(1234)
#random selection of 70% data.
ad_data <- sample(1:nrow(data_norm),size=nrow(data_norm)*0.7,replace = FALSE)

train <- data_f[ad_data,]
test <- data_f[-ad_data,]
```

```
train_label <- data_f[ad_data,6]
test_label <-data_f[-ad_data,6]
```

Building the model

```
#Installing class packages required
#install.packages("class", dependencies = TRUE)

#Loading the libraries required
library("class")
library("caret")

## Loading required package: lattice

library("kernlab")

##
## Attaching package: 'kernlab'

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

library("e1071")

##
## Attaching package: 'e1071'

## The following objects are masked from 'package:PerformanceAnalytics':
##
##      kurtosis, skewness

#Checking the number of observations
NROW(train_label)

## [1] 700

# Instantiating the KNN function
knn <- knn(train=train, test=test, cl=train_label, k=26)

confusionMatrix(table(knn,test_label))

## Confusion Matrix and Statistics
##
##      test_label
## knn    0    1
##    0 110   53
##    1  42   95
##
##
##              Accuracy : 0.6833
##              95% CI : (0.6274, 0.7356)
##    No Information Rate : 0.5067
```

```
##      P-Value [Acc > NIR] : 4.241e-10
##
##      Kappa : 0.3659
##
##      McNemar's Test P-Value : 0.3049
##
##      Sensitivity : 0.7237
##      Specificity : 0.6419
##      Pos Pred Value : 0.6748
##      Neg Pred Value : 0.6934
##      Prevalence : 0.5067
##      Detection Rate : 0.3667
##      Detection Prevalence : 0.5433
##      Balanced Accuracy : 0.6828
##
##      'Positive' Class : 0
##
```

Challenging the solution using SVM

```
intrain <- createDataPartition(y = data_f$Clicked.on.Ad, p= 0.7, list =
FALSE)
train <- data_f[intrain,]
test <- data_f[-intrain,]

#Ensuring the variabke to be predicted is categorical
train[["Clicked.on.Ad"]] = factor(train[["Clicked.on.Ad"]])

#Train control to train data on different algorithm
tr_ctl <- trainControl(method = "repeatedcv", number = 10, repeats = 5)

svm_linear <- train(Clicked.on.Ad ~., data = train, method = "svmLinear",
trControl=tr_ctl, preProcess = c("center", "scale"), tuneLength = 10)

test_pred <- predict(svm_linear, newdata = test)
confusionMatrix(table(test_pred, test$Clicked.on.Ad))

## Confusion Matrix and Statistics
##
##
## test_pred    0    1
##      0 146    7
##      1   4 143
##
##      Accuracy : 0.9633
##      95% CI : (0.9353, 0.9816)
##      No Information Rate : 0.5
##      P-Value [Acc > NIR] : <2e-16
##
##      Kappa : 0.9267
##
```

```
## McNemar's Test P-Value : 0.5465
##
##          Sensitivity : 0.9733
##          Specificity : 0.9533
##          Pos Pred Value : 0.9542
##          Neg Pred Value : 0.9728
##          Prevalence : 0.5000
##          Detection Rate : 0.4867
##          Detection Prevalence : 0.5100
##          Balanced Accuracy : 0.9633
##
##          'Positive' Class : 0
##
```

SVM has a much higher accuracy at 96% as compared to KNN at 68%, thus it is a better model