title: “Internet Marketing Analysis” author: “Maureen Gatu” date: “27/08/2021”

Overview

Targeted advertising is a form of advertising, including online advertising, that is directed towards an audience with certain traits, based on the product or person the advertiser is promoting. These traits can either be demographic with a focus on race, economic status, sex, age, generation, level of education, income level, and employment, or there can be a psychographic focus which is based on the consumer values, personality, attitude, opinion, lifestyle and interest. This focus can also entail behavioral variables, such as browser history, purchase history, and other recent online activities. Targeted advertising is focused on certain traits and consumers who are likely to have a strong preference. These individuals will receive messages instead of those who have no interest and whose preferences do not match a particular product’s attributes. This eliminates waste.

Defining the Question

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 your services as a Data Science Consultant to help her identify which individuals are most likely to click on her ads.

Metric of Success

Successfuly identify the characteristics of individuals most likely to click on the ads.

Research Design

1. Defing the question
2. Loading and previewing the data
3. Data Cleaning
4. Data Analysis
5. Modeling
6. Recomendations
7. Conclusion

The Data

Loading the Data

```
#setting up the enviroment
getwd()
```

```
## [1] "A:/PROGRAMMING WITH R/Projects/Advertising Project"
```

```
#locating the dataset A:\PROGRAMMING WITH R\Projects\Advertising Project
setwd("A:\\PROGRAMMING WITH R\\Projects\\Advertising Project")

#Loading the dataset
advt <- read.csv("advertising.csv",TRUE,",")
```

Previewing the Data

```
#Preview the top of the dataset
head(advt)
```

```
##   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
```

```
#Preview thr bottom of the dataset
tail(advt)
```

```
##      Daily.Time.Spent.on.Site Age Area.Income Daily.Internet.Usage
## 995                     43.70  28    63126.96               173.01
## 996                     72.97  30    71384.57               208.58
## 997                     51.30  45    67782.17               134.42
## 998                     51.63  51    42415.72               120.37
## 999                     55.55  19    41920.79               187.95
## 1000                    45.01  26    29875.80               178.35
##                            Ad.Topic.Line          City Male
```

```
## 995         Front-line bifurcated ability  Nicholasland    0
## 996         Fundamental modular algorithm     Duffystad    1
## 997       Grass-roots cohesive monitoring   New Darlene    1
## 998          Expanded intangible solution South Jessica    1
## 999  Proactive bandwidth-monitored policy   West Steven    0
## 1000      Virtual 5thgeneration emulation   Ronniemouth    0
##                     Country           Timestamp Clicked.on.Ad
## 995                 Mayotte 2016-04-04 03:57:48             1
## 996                 Lebanon 2016-02-11 21:49:00             1
## 997  Bosnia and Herzegovina 2016-04-22 02:07:01             1
## 998                Mongolia 2016-02-01 17:24:57             1
## 999               Guatemala 2016-03-24 02:35:54             0
## 1000                 Brazil 2016-06-03 21:43:21             1
```

Getting information about the dataset

Size of the dataset

```
#Size  of the dataset
dim(advt)

## [1] 1000   10
```

The dataset has 1000 rows and 10 columns

Viewing the column names

```
names(advt)

##  [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"
```

Checking the variables data types

```
sapply(advt, class)

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

Checking the number of unique entries in each variable

```
print(advt %>% summarise_all(n_distinct))

##   Daily.Time.Spent.on.Site Age Area.Income Daily.Internet.Usage
Ad.Topic.Line
## 1                      900  43        1000                  966
```

```
1000
##   City Male Country Timestamp Clicked.on.Ad
## 1  969    2     237      1000             2
```

Data Cleaning

Checking for duplicates

```
#Checking the duplicates using duplicated.data.frame() function
dim(advt)

## [1] 1000   10

table(duplicated.data.frame(advt))

##
## FALSE
##  1000
```

The dataset has no duplicated records

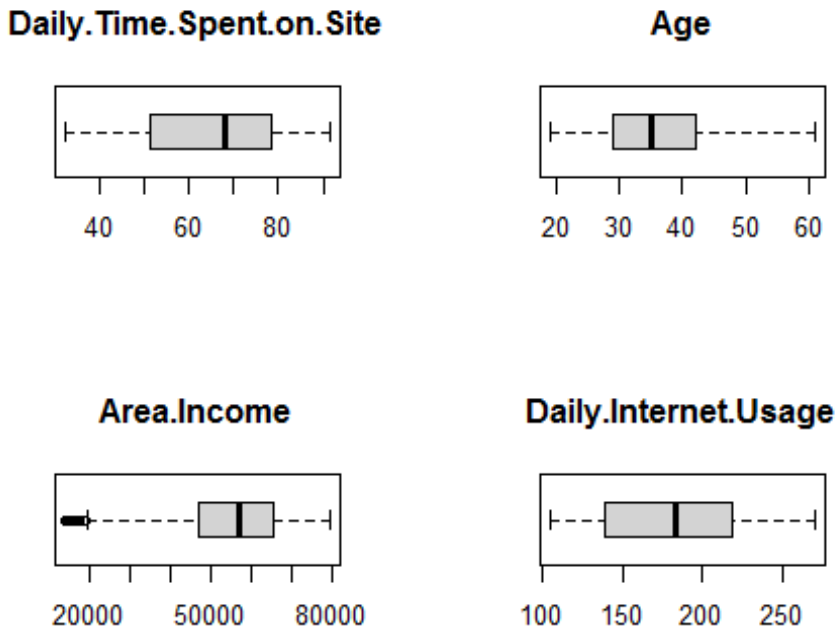
Check for misisng values

```
null <- advt[!complete.cases(advt),]          #Give total number of rows with
missing values
dim(null)

## [1]  0 10
```

The data has no incomplete rows i.e there are no missing values in the dataset. #### Outliers using the boxplot

```
par(mfrow = c(2,2))
for (i in 1:4){
 boxplot(advt[,i], main = names(advt)[i], horizontal = TRUE)
}
```



There are a few outliers in the Area.income variable. We preview these outliers using the quantile method

```
lower_bound <- quantile(advt$Area.Income, 0.025)

# get the data index
lower_ind <- which(advt$Area.Income < lower_bound)

#Preview these data
lower <- advt[lower_ind, ]
lower                          #Since the outlier is in regards to income, we
choose to retain it.

##     Daily.Time.Spent.on.Site Age Area.Income Daily.Internet.Usage
## 17                     55.39  37    23936.86               129.41
## 20                     74.58  40    23821.72               135.51
## 97                     45.72  36    22473.08               154.02
## 131                    46.98  50    21644.91               175.37
## 136                    49.89  39    17709.98               160.03
## 220                    43.60  38    20856.54               170.49
## 241                    80.03  44    24030.06               150.84
## 310                    54.92  54    23975.35               161.16
## 390                    63.88  38    19991.72               136.85
## 411                    48.09  33    19345.36               180.42
## 511                    57.86  30    18819.34               166.86
## 603                    71.83  40    22205.74               135.48
## 606                    64.67  51    24316.61               138.35
```

```
## 641                    64.63  45    15598.29              158.80
## 666                    58.05  32    15879.10              195.54
## 680                    65.57  46    23410.75              130.86
## 693                    66.26  47    14548.06              179.04
## 769                    68.58  41    13996.50              171.54
## 779                    52.67  44    14775.50              191.26
## 810                    67.51  43    23942.61              127.20
## 881                    47.74  33    22456.04              154.93
## 902                    40.47  38    24078.93              203.90
## 909                    56.91  50    21773.22              146.44
## 953                    62.79  36    18368.57              231.87
## 973                    50.48  50    20592.99              162.43
##                                   Ad.Topic.Line              City Male
## 17           Customizable multi-tasking website    West Dylanberg    0
## 20                   Advanced 24/7 productivity        Millertown    1
## 97               Versatile homogeneous capacity      Williammouth    1
## 131           Down-sized well-modulated archive East Michelleberg    0
## 136          Enhanced system-worthy application      East Michele    1
## 220      Virtual bandwidth-monitored initiative North Ricardotown    0
## 241                    Automated static concept     Christinetown    0
## 310                  Extended interactive model        Roberttown    0
## 390              Upgradable even-keeled hardware       Kristintown    0
## 411                Balanced motivating help-desk  West Travismouth    0
## 511                   Horizontal modular success         Estesfurt    0
## 603                   Diverse background ability        Costaburgh    1
## 606                Horizontal incremental website      Andersonfurt    1
## 641 Triple-buffered high-level Internet solution      Isaacborough    1
## 666               Total asynchronous architecture       Sanderstown    1
## 680         Implemented asynchronous application       Reginamouth    0
## 693               Optional full-range projection       Matthewtown    1
## 769                  Exclusive discrete firmware  New Williamville    1
## 779     Persevering 5thgeneration knowledge user     New Hollyberg    0
## 810                    Digitized homogeneous core        Lake Faith    0
## 881           Open-source 5thgeneration leverage         Henryland    1
## 902                Sharable 5thgeneration access      Fraziershire    0
## 909                 Team-oriented executive core        West Randy    0
## 953                       Total coherent archive         New James    1
## 973                Switchable real-time product        Dianaville    0
##                            Country           Timestamp Clicked.on.Ad
## 17               Palestinian Territory 2016-01-30 19:20:41             1
## 20                  Russian Federation 2016-02-27 04:43:07             1
## 97                          Hong Kong 2016-04-19 15:14:58             1
## 131                         Lithuania 2016-05-04 09:00:24             1
## 136                            Belize 2016-04-16 12:09:25             1
## 220                             Chile 2016-01-11 07:36:22             1
## 241                       Afghanistan 2016-07-23 14:47:23             1
## 310         Saint Pierre and Miquelon 2016-06-13 13:59:51             1
## 390                        Madagascar 2016-02-29 23:56:06             1
## 411 Heard Island and McDonald Islands 2016-05-28 12:38:37             1
## 511                           Algeria 2016-07-08 17:14:01             1
```

```
## 603                            Rwanda 2016-02-18 22:42:33             1
## 606                              Togo 2016-02-14 16:33:29             1
## 641                        Azerbaijan 2016-06-12 03:11:04             1
## 666                        Tajikistan 2016-02-12 10:39:10             1
## 680                           Belgium 2016-04-15 15:07:17             1
## 693                           Lebanon 2016-04-25 19:31:39             1
## 769                       El Salvador 2016-07-06 12:04:29             1
## 779                            Jersey 2016-05-19 06:37:38             1
## 810                    Western Sahara 2016-04-29 14:10:00             1
## 881                       Saint Lucia 2016-05-14 14:49:05             1
## 902                           Burundi 2016-07-22 07:44:43             1
## 909                    Norfolk Island 2016-04-01 05:17:28             1
## 953                        Luxembourg 2016-05-30 20:08:51             1
## 973                            Malawi 2016-05-16 18:51:59             1
```

Range of the outlier income

```
range(lower$Area.Income)

## [1] 13996.50 24316.61
```

The outliers in the dataset are in the Area.Income varaible which includes income between 13,996.50 upto 24,316.61. Since a person's income does affect their actions when interacting with website, the outliers are kept in orders to well see the influence of person's income on whether they clicked on an ad or not.

Exploratory Data Analysis

Univariate Analysis

Descriptive stattistics of the dataset

```
summary(advt[c(1:10)])

##  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                Male         Country
##  Length:1000        Length:1000        Min.   :0.000   Length:1000
##  Class :character   Class :character   1st Qu.:0.000   Class :character
##  Mode  :character   Mode  :character   Median :0.000   Mode  :character
##                                        Mean   :0.481
##                                        3rd Qu.:1.000
##                                        Max.   :1.000
##   Timestamp         Clicked.on.Ad
```

```
##  Length:1000        Min.   :0.0
##  Class :character   1st Qu.:0.0
##  Mode  :character   Median :0.5
##                     Mean   :0.5
##                     3rd Qu.:1.0
##                     Max.   :1.0

describe(advt)

## advt
##
##  10  Variables      1000  Observations
## ---------------------------------------------------------------------------
------
## Daily.Time.Spent.on.Site
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     1000        0      900        1       65    18.11    37.58    41.34
##      .25      .50      .75      .90      .95
##    51.36    68.22    78.55    83.89    86.20
##
## lowest : 32.60 32.84 32.91 32.99 33.21, highest: 90.97 91.10 91.15 91.37
91.43
## ---------------------------------------------------------------------------
------
## Age
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     1000        0       43    0.999    36.01    9.943    23.95    26.00
##      .25      .50      .75      .90      .95
##    29.00    35.00    42.00    49.00    52.00
##
## lowest : 19 20 21 22 23, highest: 57 58 59 60 61
## ---------------------------------------------------------------------------
------
## Area.Income
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     1000        0     1000        1    55000    15037    28275    35223
##      .25      .50      .75      .90      .95
##    47032    57012    65471    70506    73601
##
## lowest : 13996.50 14548.06 14775.50 15598.29 15879.10
## highest: 78092.95 78119.50 78520.99 79332.33 79484.80
## ---------------------------------------------------------------------------
------
## Daily.Internet.Usage
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     1000        0      966        1      180    50.63    113.5    120.5
##      .25      .50      .75      .90      .95
##    138.8    183.1    218.8    236.2    246.7
##
## lowest : 104.78 105.00 105.04 105.15 105.22, highest: 259.76 261.02 261.52
```

```
267.01 269.96
## ---------------------------------------------------------------------------
------
## Ad.Topic.Line
##        n  missing distinct
##     1000        0     1000
##
## lowest : Adaptive 24hour Graphic Interface       Adaptive asynchronous
attitude          Adaptive context-sensitive application  Adaptive
contextually-based methodology Adaptive demand-driven knowledgebase
## highest: Visionary client-driven installation    Visionary maximized
process improvement Visionary mission-critical application  Visionary multi-
tasking alliance        Visionary reciprocal circuit
## ---------------------------------------------------------------------------
------
## City
##        n  missing distinct
##     1000        0      969
##
## lowest : Adamsbury     Adamside      Adamsstad     Alanview
Alexanderfurt
## highest: Youngburgh    Youngfort     Yuton         Zacharystad
Zacharyton
## ---------------------------------------------------------------------------
------
## Male
##        n  missing distinct     Info      Sum     Mean      Gmd
##     1000        0        2    0.749      481    0.481   0.4998
##
## ---------------------------------------------------------------------------
------
## Country
##        n  missing distinct
##     1000        0      237
##
## lowest : Afghanistan       Albania           Algeria           American
Samoa    Andorra
## highest: Wallis and Futuna Western Sahara    Yemen             Zambia
Zimbabwe
## ---------------------------------------------------------------------------
------
## Timestamp
##        n  missing distinct
##     1000        0     1000
##
## lowest : 2016-01-01 02:52:10 2016-01-01 03:35:35 2016-01-01 05:31:22 2016-
01-01 08:27:06 2016-01-01 15:14:24
## highest: 2016-07-23 05:21:39 2016-07-23 06:18:51 2016-07-23 11:46:28 2016-
07-23 14:47:23 2016-07-24 00:22:16
## ---------------------------------------------------------------------------
```

```
------
## Clicked.on.Ad
##        n  missing distinct     Info      Sum     Mean      Gmd
##     1000        0        2     0.75      500      0.5   0.5005
##
## ------------------------------------------------------------------------
------

#Change the data type of the categorical variables to factor for analysis
names <- c(5:10)
advt[,names] <- lapply(advt[,5:10], factor)
glimpse(advt)

## Rows: 1,000
## Columns: 10
## $ Daily.Time.Spent.on.Site <dbl> 68.95, 80.23, 69.47, 74.15, 68.37, 59.99,
88.~
## $ Age                      <int> 35, 31, 26, 29, 35, 23, 33, 48, 30, 20,
49, 3~
## $ Area.Income              <dbl> 61833.90, 68441.85, 59785.94, 54806.18,
73889~
## $ Daily.Internet.Usage     <dbl> 256.09, 193.77, 236.50, 245.89, 225.58,
226.7~
## $ Ad.Topic.Line            <fct> Cloned 5thgeneration orchestration,
Monitored~
## $ City                     <fct> Wrightburgh, West Jodi, Davidton, West
Terrif~
## $ Male                     <fct> 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0,
0, ~
## $ Country                  <fct> Tunisia, Nauru, San Marino, Italy,
Iceland, N~
## $ Timestamp                <fct> 2016-03-27 00:53:11, 2016-04-04 01:39:02,
201~
## $ Clicked.on.Ad            <fct> 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0,
1, ~

summary(advt[,c(5:10)])

##                                  Ad.Topic.Line              City     Male
##  Adaptive 24hour Graphic Interface      :  1   Lisamouth      :  3   0:519
##  Adaptive asynchronous attitude         :  1   Williamsport   :  3   1:481
##  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
##            Country                   Timestamp   Clicked.on.Ad
##  Czech Republic:  9   2016-01-01 02:52:10:  1   0:500
##  France        :  9   2016-01-01 03:35:35:  1   1:500
##  Afghanistan   :  8   2016-01-01 05:31:22:  1
##  Australia     :  8   2016-01-01 08:27:06:  1
```

```
##  Cyprus         :  8   2016-01-01 15:14:24:  1
##  Greece         :  8   2016-01-01 20:17:49:  1
##  (Other)        :950   (Other)            :994
```

City: Lisamuth and Williamsport were the top 2 cities in the data set with both appearing 3 times in the data frame.

Country: Czech Republic and France were the two most popular countries with both appearing 9 times in the data.

Gender: 481 were male and 519 we female.

Clicked.on.Ad: half of the add titles were clicked on.

Mean

```
sapply(advt[,c(1:4)], mean)
```

```
## Daily.Time.Spent.on.Site                      Age             Area.Income
##                  65.0002                  36.0090              55000.0001
##     Daily.Internet.Usage
##                 180.0001
```

Standard deviation

```
sapply(advt[,c(1:4)], sd)
```

```
## Daily.Time.Spent.on.Site                      Age             Area.Income
##                15.853615                 8.785562            13414.634022
##     Daily.Internet.Usage
##                43.902339
```

Variance

```
sapply(advt[,c(1:4)], var)
```

```
## Daily.Time.Spent.on.Site                      Age             Area.Income
##             2.513371e+02             7.718611e+01            1.799524e+08
##     Daily.Internet.Usage
##             1.927415e+03
```

Daily.Time.Spent.on.Site: The mean amount of time spent on the site was 65.002 with a standard deviation of 15.8536 and a variance of 2.513371e+02.

Age: The mean age of person was 36years with a standard deviation of 8 years and a variance of 7.718611e+01.

Area.Income:The mean Area.Income was 55,000 with a standard deviation of 13414.634 and a variance of 1.799524e+08.

Daily.Internet.Usage: The mean internet usage was 180 with a standard deviation of 43.90 and a variance of 1.927415e+03.

Range

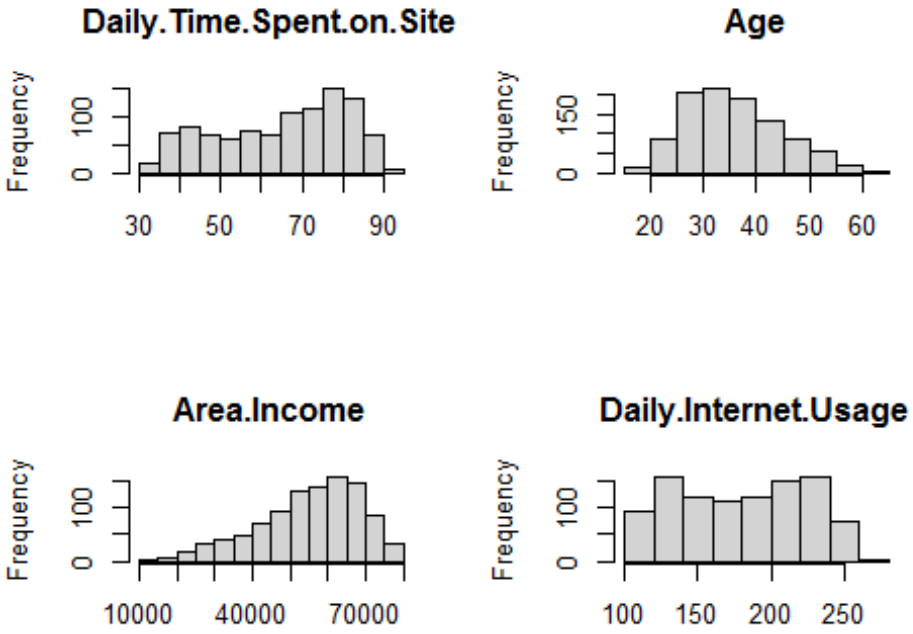
```
sapply(advt[,c(1:4)], IQR)
```

```
## Daily.Time.Spent.on.Site                    Age                Area.Income
##                  27.1875                13.0000                 18438.8325
##     Daily.Internet.Usage
##                  79.9625
```

Data distribution(Histogram)

```
par(mfrow = c(2,2))
for (i in 1:4){
  hist(advt[,i],main = names(advt)[i], xlab = NULL)

}
```



Skewness

```
skew <- apply(advt[,c(1:4)],2, skewness)
skew
```

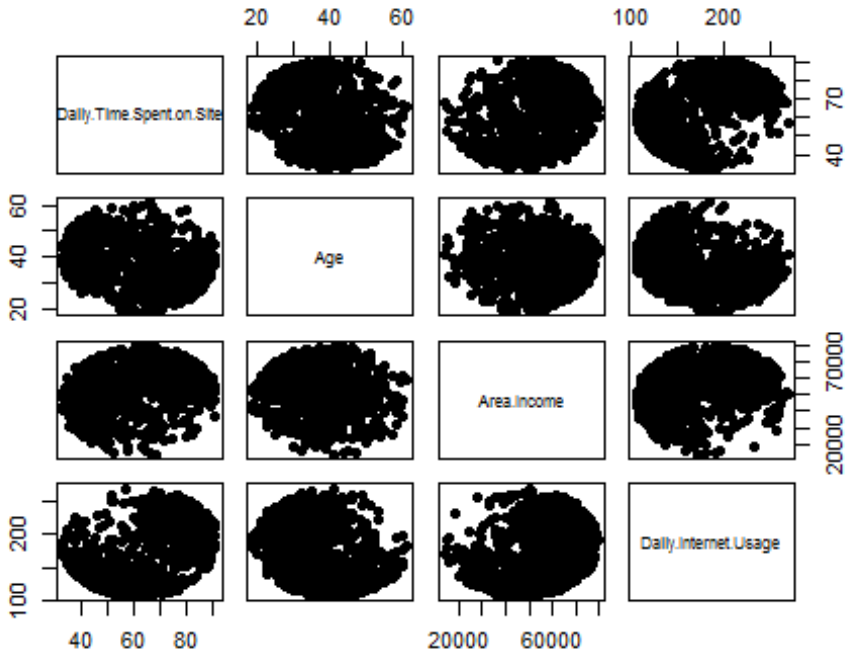
```
## Daily.Time.Spent.on.Site                    Age                Area.Income
##              -0.37064595             0.47770522                -0.64842285
##     Daily.Internet.Usage
##              -0.03343681
```

Daily.Time.Spent.on.Site, Age, Daily.Internet.Usage all have an approximately symetrical distribution. Area.Income distribution is moderately skewed to the right.

Correlation

Scatter plots

```
num <- advt[,1:4]
pairs(num, pch = 19)
```



Correlation coefficients

```
num <- advt[,1:4]
cor(num)
```

```
##                           Daily.Time.Spent.on.Site        Age Area.Income
## Daily.Time.Spent.on.Site                 1.0000000 -0.3315133   0.3109544
## Age                                     -0.3315133  1.0000000  -0.1826050
## Area.Income                              0.3109544 -0.1826050   1.0000000
## Daily.Internet.Usage                     0.5186585 -0.3672086   0.3374955
##                           Daily.Internet.Usage
## Daily.Time.Spent.on.Site            0.5186585
## Age                                -0.3672086
## Area.Income                         0.3374955
## Daily.Internet.Usage                1.0000000
```

Daily time spent on site, area.income and daily internet usage are all positively correlated to each other.

Age has a negative correlation to each of these three variable.

The correlation between all variables is weak with the highest correlation being between time spent on site and daily internet usage, with a correlation on 0.519.

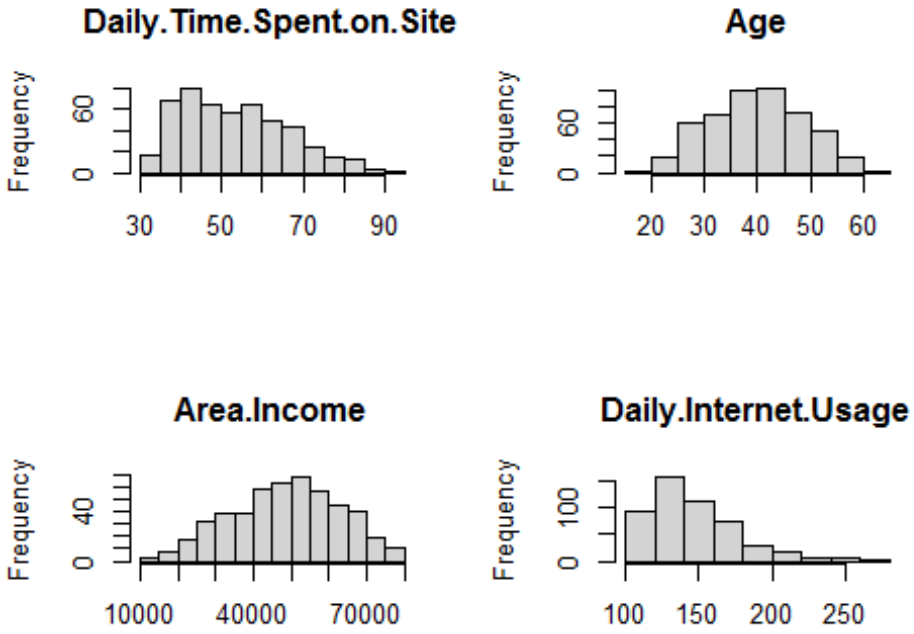
Clicked on ads

Separate between ads that were clicked on(1) and those that were not.

created a subset data of only ads that were clicked on to anlyze the target customers that click on the ads.

```
clicked <- advt[advt$Clicked.on.Ad == 1,]
par(mfrow = c(2,2))
for (i in 1:4){
  hist(clicked[,i],main = names(clicked)[i], xlab = NULL)

}
```



There is a difference in the histograms. Looking at the clicked on ads, the age peaked between ages 35 to 45 unlike in the general population that peaked only between ages 30 to 35.

In the daily internet usage, we see that most of the ads clicked were by people who spent less on internet with the data now clearly skewed to the left.

Looking at the time spent on the site. We can see a difference in the frequencies where in the general population the amount of time spent on site peaked between 75 and 80 but looking at those that clicked on the ad, the time peaked at 40 to 45.

```
summary(clicked[,c(5:10)])
```

```
##                                 Ad.Topic.Line           City     Male
##  Adaptive asynchronous attitude         :  1   Lake David  :  2   0:269
##  Adaptive context-sensitive application :  1   Lake James  :  2   1:231
##  Adaptive contextually-based methodology:  1   Lisamouth   :  2
##  Adaptive demand-driven knowledgebase   :  1   Michelleside:  2
##  Adaptive uniform capability            :  1   Millerbury  :  2
##  Advanced 24/7 productivity             :  1   Robertfurt  :  2
##  (Other)                                :494   (Other)     :488
##          Country                   Timestamp   Clicked.on.Ad
##  Australia    :  7   2016-01-01 15:14:24:  1   0:  0
##  Ethiopia     :  7   2016-01-01 20:17:49:  1   1:500
##  Turkey       :  7   2016-01-02 12:25:36:  1
##  Liberia      :  6   2016-01-03 03:22:15:  1
##  Liechtenstein:  6   2016-01-03 04:39:47:  1
##  South Africa :  6   2016-01-03 05:34:33:  1
##  (Other)      :461   (Other)            :494
```

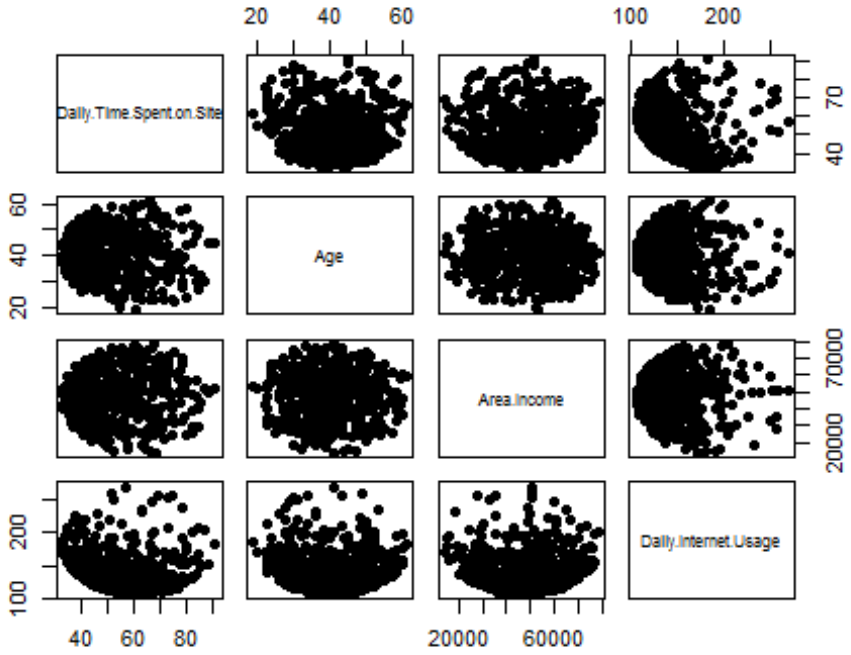
The above summary shows that the top cities that clicked on the ad were Lake David and Lake James and the top countries are Australia Ethiopia and Turkey.(None of these locations were among the top locations in the general population analysis.)

231 of the people that clicked on the ads were male and 269 were female.

Correlation

Scatter plots

```
num_c <- clicked[,1:4]
pairs(num_c, pch = 19)
```




```
#Correlationcoefficients
cor(num_c)

##                          Daily.Time.Spent.on.Site         Age  Area.Income
## Daily.Time.Spent.on.Site              1.000000000 -0.01280025  0.007982346
## Age                                  -0.012800250  1.00000000 -0.023701770
## Area.Income                           0.007982346 -0.02370177  1.000000000
## Daily.Internet.Usage                 -0.170916216 -0.05693449 -0.010679858
##                          Daily.Internet.Usage
## Daily.Time.Spent.on.Site          -0.17091622
## Age                               -0.05693449
## Area.Income                       -0.01067986
## Daily.Internet.Usage               1.00000000
```

Among the ads clicked, all the above variables had a weak negative correlation to each other except for Area.Income and Daily.Time.Spent.on.Site which maintained a weak positive correlation.

Gender analysis on the ads clicked on

Males who clicked on the add

```
Male <- clicked[clicked$Male == 1,]
par(mfrow = c(2,2))
for (i in 1:4){
  hist(Male[,i],main = names(Male)[i], xlab = NULL)

}
```

Females that clicked on the ad

```
Female <- clicked[clicked$Male == 0,]
par(mfrow = c(2,2))
for (i in 1:4){
  hist(Female[,i],main = names(Female)[i], xlab = NULL)

}
```

There is a lot more variance in female Area.Income than for male, the peak for Male salaries was between 50,000 to 55,000 while for female it was between 45,00 to 50,000.

On average Male who clicked on the ad spent less time on the site than female.

Time Spent on Site

```
#Sort dataframe based on time spent on site variable
time_spent <- clicked[order(-clicked$Daily.Time.Spent.on.Site),]
head(time_spent$Ad.Topic.Line)

## [1] Re-engineered composite moratorium
## [2] Advanced web-enabled standardization
## [3] Fully-configurable 5thgeneration circuit
## [4] Stand-alone radical throughput
## [5] Synchronized leadingedge help-desk
## [6] Stand-alone tangible moderator
## 1000 Levels: Adaptive 24hour Graphic Interface ... Visionary reciprocal
circuit
```

These are the ad topic line clicked among the people that spent the most amount of time on the site

```
tail(time_spent$Ad.Topic.Line)

## [1] Polarized clear-thinking budgetary management
## [2] Phased full-range hardware
## [3] Future-proofed fresh-thinking conglomeration
```

```
## [4] Triple-buffered 3rdgeneration migration
## [5] Multi-tiered interactive neural-net
## [6] Customizable homogeneous contingency
## 1000 Levels: Adaptive 24hour Graphic Interface ... Visionary reciprocal
circuit
```

These are the ad topics clicked by persons that spent the least time on the site.

** Modeling **

Naive Bayes

```
#dependent variable to check for class imbalance
kable(table(advt$Clicked.on.Ad),
      col.names = c("Clicked.on.add", "Frequency"), align = 'l')
```

Clicked.on.add	Frequency
0	500
1	500

```
head(advt)
```

```
##   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
```

Label Encoding

```
#Ad.Topic.Line
lab_top = LabelEncoder.fit(advt[,'Ad.Topic.Line'])
advt$Ad.Topic.Line = transform(lab_top, advt[,'Ad.Topic.Line'])

#City
```

```
lab_city = LabelEncoder.fit(advt[,'City'])
advt$City = transform(lab_city, advt[,'City'])

#Country
lab_cntry = LabelEncoder.fit(advt[,'Country'])
advt$Country = transform(lab_cntry, advt[,'Country'])

#Preview the dataset
head(advt)
```

```
##   Daily.Time.Spent.on.Site Age Area.Income Daily.Internet.Usage
Ad.Topic.Line
## 1                    68.95  35    61833.90               256.09
92
## 2                    80.23  31    68441.85               193.77
465
## 3                    69.47  26    59785.94               236.50
567
## 4                    74.15  29    54806.18               245.89
904
## 5                    68.37  35    73889.99               225.58
767
## 6                    59.99  23    59761.56               226.74
806
##   City Male Country           Timestamp Clicked.on.Ad
## 1  962    0     216 2016-03-27 00:53:11             0
## 2  904    1     148 2016-04-04 01:39:02             0
## 3  112    0     185 2016-03-13 20:35:42             0
## 4  940    1     104 2016-01-10 02:31:19             0
## 5  806    0      97 2016-06-03 03:36:18             0
## 6  283    1     159 2016-05-19 14:30:17             0
```

###Split the train and test data

```
# drop timestamp
advt[,c('Timestamp')] <- list(NULL)
#- split data in training and test set.
library(caTools)
sample <- sample.split(advt$Clicked.on.Ad, SplitRatio = 0.7)
train <- subset(advt, sample == TRUE)
test <- subset(advt, sample == FALSE)

#Dimention of the train and test data
dim(train)
```

```
## [1] 700   9
```

```
dim(test)
```

```
## [1] 300   9
```

Model Training and Prediction

```
#Training the model
NBClassifier = naiveBayes(Clicked.on.Ad ~., data = train)
NBClassifier
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##   0   1
## 0.5 0.5
##
## Conditional probabilities:
##    Daily.Time.Spent.on.Site
## Y       [,1]      [,2]
##   0 76.66477  7.636579
##   1 53.48497 12.858939
##
##    Age
## Y       [,1]     [,2]
##   0 32.02857 6.156906
##   1 40.39429 8.784525
##
##    Area.Income
## Y       [,1]      [,2]
##   0 61722.21  8966.762
##   1 48962.81 14070.159
##
##    Daily.Internet.Usage
## Y       [,1]     [,2]
##   0 215.5311 23.92741
##   1 145.0671 30.37232
##
##    Ad.Topic.Line
## Y       [,1]     [,2]
##   0 496.0571 281.0002
##   1 504.4600 291.5649
##
##    City
## Y       [,1]     [,2]
##   0 493.0657 274.7824
##   1 482.4629 281.1992
##
##    Male
## Y          0         1
##   0 0.5171429 0.4828571
```

```
##   1 0.5514286 0.4485714
##
##    Country
## Y       [,1]     [,2]
##   0 115.8143 70.00755
##   1 117.8429 70.01556
```

Predicting the test

```
# Predict using Naive Bayes
test$predicted = predict(NBClassifier,test)
test$actual = test$Clicked.on.Ad
```

Model Evaulation

```
confusionMatrix(factor(test$predicted),
                factor(test$actual))

## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 146   5
##          1   4 145
##
##                Accuracy : 0.97
##                  95% CI : (0.9438, 0.9862)
##     No Information Rate : 0.5
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.94
##
##  Mcnemar's Test P-Value : 1
##
##             Sensitivity : 0.9733
##             Specificity : 0.9667
##          Pos Pred Value : 0.9669
##          Neg Pred Value : 0.9732
##              Prevalence : 0.5000
##          Detection Rate : 0.4867
##    Detection Prevalence : 0.5033
##       Balanced Accuracy : 0.9700
##
##        'Positive' Class : 0
##
```

The model performed very well with an accuracy of 96.33%. Only 11 records were wrongly classified.

** K-Nearest Neighbors Classification **

```
#split the x and y in the train and test data
```

```
#Independent variables
advt_tr_feat <- train[,1:8]
advt_va_feat <- test[,1:8]
#Dependent variable
trLabels <- train$Clicked.on.Ad
tsLabels <- test$Clicked.on.Ad

#Training the model
tsPred <- knn(advt_tr_feat, advt_va_feat, trLabels, k=4)

#CrossTable(tsLabels, tsPred)
table(tsLabels,tsPred)
```

```
##         tsPred
## tsLabels   0   1
##        0 100  50
##        1  48 102
```

Model evaluation

```
accu0 <- length(which(tsLabels==tsPred)==TRUE)/length(tsLabels)
sens0 <- length(which((tsLabels==tsPred) & (tsLabels==0))) /
length(which(tsLabels==0))
spec0 <- length(which((tsLabels==tsPred) & (tsLabels==1))) /
length(which(tsLabels==1))
cat("Accuracy=",round(accu0,2),'\n',"Sensitivity=",round(sens0,2),'\n',"Speci
ficity=",round(spec0,2))
```

```
## Accuracy= 0.67
##  Sensitivity= 0.67
##  Specificity= 0.68
```

The model has an accuracy of 63% 111 mis-classifications. We try and improve model performance by find the best value for k

Choosing the best value of k Function to generate Training & Test Error rates for various k

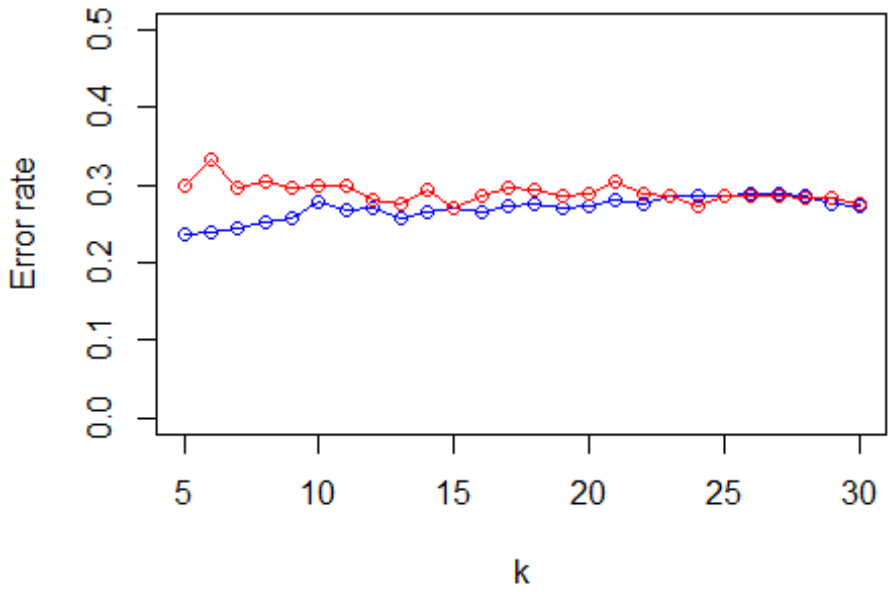
```
trData <- advt_tr_feat
tsData <- advt_va_feat

#Assess models between k values of 5 to 30
bestK <- function(trData, trLabels, tsData, tsLabels) {
  ctr <- c(); cts <- c()
  for (k in 5:30) {
    knnTr <- knn(trData, trData, trLabels, k)
    knnTs <- knn(trData, tsData, trLabels, k)
    trTable <- prop.table(table(knnTr, trLabels))
    tsTable <- prop.table(table(knnTs, tsLabels))
    erTr <- trTable[1,2] + trTable[2,1]
    erTs <- tsTable[1,2] + tsTable[2,1]
    ctr <- c(ctr,erTr)
    cts <- c(cts,erTs)
```

```
  }
  #acc <- data.frame(k=1/c(1:100), trER=ctr, tsER=cts)
  err <- data.frame(k=5:30, trER=ctr, tsER=cts)
  return(err)
}
```

Invoke the function bestK to create dataset and Plot Training and Test Error rates for various values of k

```
err <- bestK(trData, trLabels, tsData, tsLabels)
plot(err$k,err$trER,type='o',ylim=c(0,.5),xlab="k",ylab="Error
rate",col="blue")
lines(err$k,err$tsER,type='o',col="red")
```



The test error rate begins to stablelize at k≈23.

```
#Build a model with k = 23
tsPred2 <- knn(trData, tsData, trLabels, k=23)
table(tsLabels,tsPred2)

##         tsPred2
## tsLabels   0   1
##        0 113  37
##        1  49 101
```

evaluating

```
#paste("The accuracy of prediction is",
length(which(tsLabels==tsPred)==TRUE)/length(tsLabels))
accu1 <- length(which(tsLabels==tsPred2)==TRUE)/length(tsLabels)
sens1 <- length(which((tsLabels==tsPred2) & (tsLabels==0))) /
length(which(tsLabels==0))
spec1 <- length(which((tsLabels==tsPred2) & (tsLabels==1))) /
length(which(tsLabels==1))
cat("Accuracy=",round(accu1,2),'\n',"Sensitivity=",round(sens1,2),'\n',"Speci
ficity=",round(spec1,2))
```

```
## Accuracy= 0.71
##  Sensitivity= 0.75
##  Specificity= 0.67
```

The model improved by 8% in accuracy and the wrong classification reducing to 86. Sensitivity and Specificity also improved in this model.

** Support Vector Machine **

```
#Independent variables
advt_tr_feat <- train[,1:8]
advt_va_feat <- test[,1:8]
#Dependent variable
trLabels <- train$Clicked.on.Ad
tsLabels <- test$Clicked.on.Ad


#Building the model
svm.fit <- svm(trLabels ~., advt_tr_feat, kernel='radial', gamma=1, cost=1)

#plot(svm.fit, advt_tr_feat)
summary(svm.fit)
```

```
##
## Call:
## svm(formula = trLabels ~ ., data = advt_tr_feat, kernel = "radial",
##     gamma = 1, cost = 1)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  radial
##        cost:  1
##
## Number of Support Vectors:  636
##
##  ( 293 343 )
##
##
## Number of Classes:  2
##
```

```
## Levels:
##  0 1
```

Predict and evaluate

```
#Predicting the test data
ypred_svm <- predict(svm.fit,advt_va_feat )

#Evaluating the model performance
confusionMatrix(ypred_svm, tsLabels)

## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 142   7
##          1   8 143
##
##                Accuracy : 0.95
##                  95% CI : (0.9189, 0.9717)
##     No Information Rate : 0.5
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.9
##
##  Mcnemar's Test P-Value : 1
##
##             Sensitivity : 0.9467
##             Specificity : 0.9533
##          Pos Pred Value : 0.9530
##          Neg Pred Value : 0.9470
##              Prevalence : 0.5000
##          Detection Rate : 0.4733
##    Detection Prevalence : 0.4967
##       Balanced Accuracy : 0.9500
##
##        'Positive' Class : 0
##
```

The model performed very well with an accuracy of 94%. Only 18 records were wrongly classified.

Model summary

Of the 3 models used inn this analysis Naive bayes was the best model with an accuracy of 96.33% followed by the support vector which had 94% accuracy.

Recommendations

- Target the ads to persons between the ages of 35 years to 45 years.

- Ads should be tailored towards both male and female equally.
- Target persons earn an income between 45,000 to 55,000.
- The top countries to target are Australia, Ethiopia, Turkey, Liberia and Liechtenstein.
- The top cities to target are Lake David lake James, Lisamouth, Michelleside, Millerbury and Robertfurt.
- Men take 35 to 45 minutes before clicking on an ad while women spend 40 to 60 minutes on the site before clicking on an add.

Conclusion

The data provided did have the necessary information needed to analyze the site visitors. However there were 1000 unique ad topics for the 1000 records provided. Providing more data per topic would have been useful in determing the kinds of topic that were more popular thn others.