LEAD CASE STUDY

step1: Importing and Merging Data

In [1]:

```
# Suppressing Warnings
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
# Importing Pandas and NumPy
import pandas as pd, numpy as np
```

In [3]:

```
# Importing all datasets
leads = pd.read_csv("C:/Users/Hari/Desktop/place/logistics asignment/Leads.csv")
leads.head()
```

Out[3]:

	Prospect ID	Lead Number	Lead Origin	Lead Source	Do Not Email	Do Not Call	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	...	Get updates on DM Content	Lead Profile	City	As A
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	660737	API	Olark Chat	No	No	0	0.0	0	0.0	...	No	Select	Select	
1	2a272436-5132-4136-86fa-dcc88c88f482	660728	API	Organic Search	No	No	0	5.0	674	2.5	...	No	Select	Select	
2	8cc8c611-a219-4f35-ad23-fdfd2656bd8a	660727	Landing Page Submission	Direct Traffic	No	No	1	2.0	1532	2.0	...	No	Potential Lead	Mumbai	
3	0cc2df48-7cf4-4e39-9de9-19797f9b38cc	660719	Landing Page Submission	Direct Traffic	No	No	0	1.0	305	1.0	...	No	Select	Mumbai	
4	3256f628-e534-4826-9d63-4a8b88782852	660681	Landing Page Submission	Google	No	No	1	2.0	1428	1.0	...	No	Select	Mumbai	

5 rows × 37 columns

Step 2: Inspecting the Dataframe

In [4]:

```
leads.dtypes
```

Out[4]:

```
Prospect ID                                       object
Lead Number                                        int64
Lead Origin                                       object
Lead Source                                       object
Do Not Email                                      object
Do Not Call                                       object
```

```
Converted                                        int64
TotalVisits                                    float64
Total Time Spent on Website                      int64
Page Views Per Visit                           float64
Last Activity                                   object
Country                                         object
Specialization                                  object
How did you hear about X Education              object
What is your current occupation                 object
What matters most to you in choosing a course   object
Search                                          object
Magazine                                        object
Newspaper Article                               object
X Education Forums                              object
Newspaper                                       object
Digital Advertisement                           object
Through Recommendations                         object
Receive More Updates About Our Courses          object
Tags                                            object
Lead Quality                                    object
Update me on Supply Chain Content               object
Get updates on DM Content                       object
Lead Profile                                    object
City                                            object
Asymmetrique Activity Index                     object
Asymmetrique Profile Index                      object
Asymmetrique Activity Score                    float64
Asymmetrique Profile Score                     float64
I agree to pay the amount through cheque        object
A free copy of Mastering The Interview          object
Last Notable Activity                           object
dtype: object
```

In [5]:

```
leads.shape
```

Out[5]:

```
(9240, 37)
```

In [6]:

```
leads.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9240 entries, 0 to 9239
Data columns (total 37 columns):
 #   Column                                         Non-Null Count  Dtype  
---  ------                                         --------------  -----  
 0   Prospect ID                                    9240 non-null   object 
 1   Lead Number                                    9240 non-null   int64  
 2   Lead Origin                                    9240 non-null   object 
 3   Lead Source                                    9204 non-null   object 
 4   Do Not Email                                   9240 non-null   object 
 5   Do Not Call                                    9240 non-null   object 
 6   Converted                                      9240 non-null   int64  
 7   TotalVisits                                    9103 non-null   float64
 8   Total Time Spent on Website                    9240 non-null   int64  
 9   Page Views Per Visit                           9103 non-null   float64
 10  Last Activity                                  9137 non-null   object 
 11  Country                                        6779 non-null   object 
 12  Specialization                                 7802 non-null   object 
 13  How did you hear about X Education             7033 non-null   object 
 14  What is your current occupation                6550 non-null   object 
 15  What matters most to you in choosing a course  6531 non-null   object 
 16  Search                                         9240 non-null   object 
 17  Magazine                                       9240 non-null   object 
 18  Newspaper Article                              9240 non-null   object 
 19  X Education Forums                             9240 non-null   object 
 20  Newspaper                                      9240 non-null   object 
 21  Digital Advertisement                          9240 non-null   object 
 22  Through Recommendations                        9240 non-null   object 
 23  Receive More Updates About Our Courses         9240 non-null   object 
```

```
 24  Tags                                           5887 non-null   object
 25  Lead Quality                                   4473 non-null   object
 26  Update me on Supply Chain Content              9240 non-null   object
 27  Get updates on DM Content                      9240 non-null   object
 28  Lead Profile                                   6531 non-null   object
 29  City                                           7820 non-null   object
 30  Asymmetrique Activity Index                    5022 non-null   object
 31  Asymmetrique Profile Index                     5022 non-null   object
 32  Asymmetrique Activity Score                    5022 non-null   float64
 33  Asymmetrique Profile Score                     5022 non-null   float64
 34  I agree to pay the amount through cheque       9240 non-null   object
 35  A free copy of Mastering The Interview         9240 non-null   object
 36  Last Notable Activity                          9240 non-null   object
dtypes: float64(4), int64(3), object(30)
memory usage: 2.6+ MB
```

In [7]:

```
leads.describe()
```

Out[7]:

	Lead Number	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Asymmetrique Activity Score	Asymmetrique Profile Score
count	9240.000000	9240.000000	9103.000000	9240.000000	9103.000000	5022.000000	5022.000000
mean	617188.435606	0.385390	3.445238	487.698268	2.362820	14.306252	16.344883
std	23405.995698	0.486714	4.854853	548.021466	2.161418	1.386694	1.811395
min	579533.000000	0.000000	0.000000	0.000000	0.000000	7.000000	11.000000
25%	596484.500000	0.000000	1.000000	12.000000	1.000000	14.000000	15.000000
50%	615479.000000	0.000000	3.000000	248.000000	2.000000	14.000000	16.000000
75%	637387.250000	1.000000	5.000000	936.000000	3.000000	15.000000	18.000000
max	660737.000000	1.000000	251.000000	2272.000000	55.000000	18.000000	20.000000

Step 3: Data Preparation

In [8]:

```
# removing duplicate rows
leads.drop_duplicates(subset='Lead Number')
leads.shape
```

Out[8]:

```
(9240, 37)
```

In [9]:

```
# Checking for total count and percentage of null values in all columns of the dataframe.

total = pd.DataFrame(leads.isnull().sum().sort_values(ascending=False), columns=['Total'])
percentage = pd.DataFrame(round(100*(leads.isnull().sum()/leads.shape[0]),2).sort_values(ascending=
False)\
                          ,columns=['Percentage'])
pd.concat([total, percentage], axis = 1)
```

Out[9]:

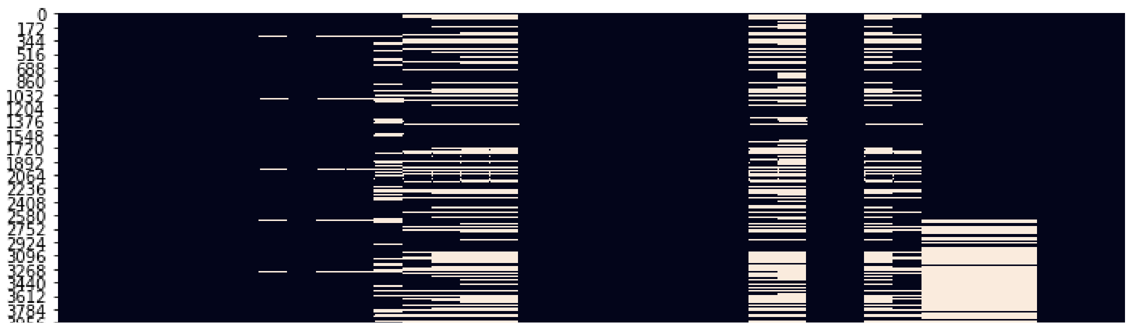
	Total	Percentage
Lead Quality	4767	51.59
Asymmetrique Profile Score	4218	45.65
Asymmetrique Activity Score	4218	45.65
Asymmetrique Profile Index	4218	45.65

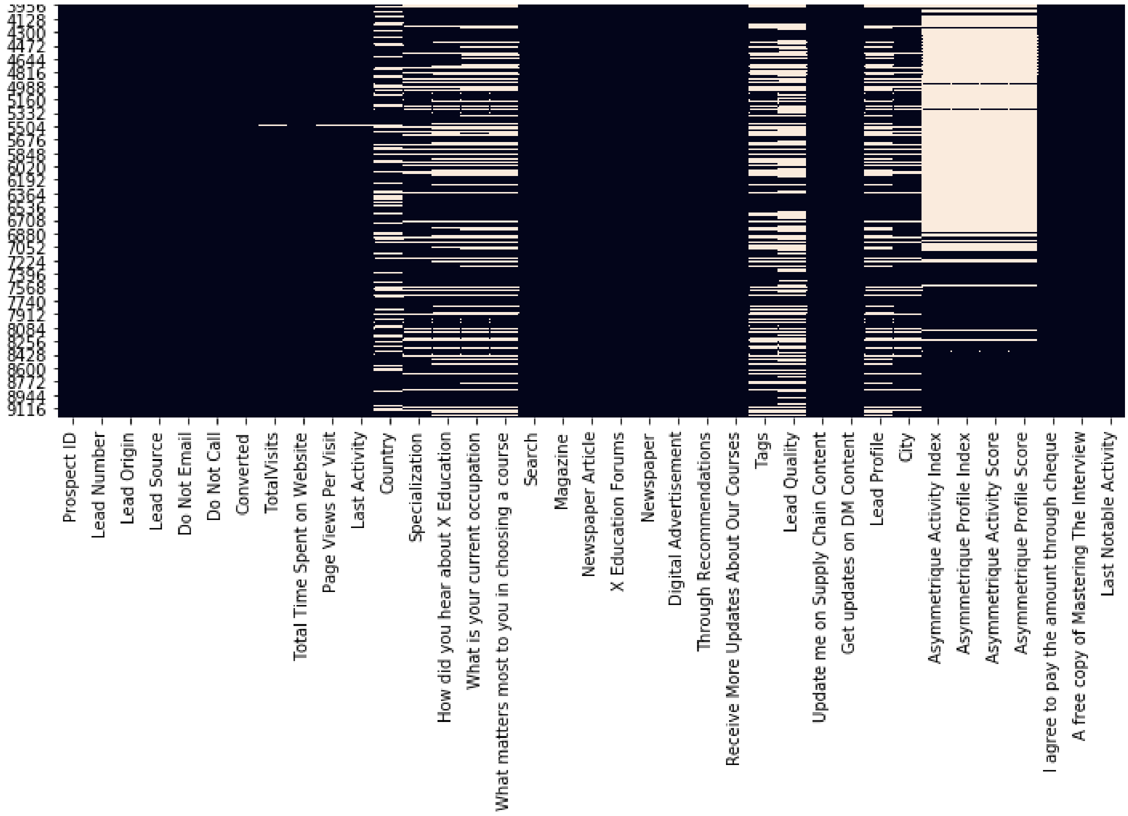
	Total	Percentage
Asymmetrique Activity Index	4218	45.65
Tags	3353	36.29
What matters most to you in choosing a course	2709	29.32
Lead Profile	2709	29.32
What is your current occupation	2690	29.11
Country	2461	26.63
How did you hear about X Education	2207	23.89
Specialization	1438	15.56
City	1420	15.37
TotalVisits	137	1.48
Page Views Per Visit	137	1.48
Last Activity	103	1.11
Lead Source	36	0.39
Do Not Email	0	0.00
Do Not Call	0	0.00
Converted	0	0.00
Total Time Spent on Website	0	0.00
Lead Origin	0	0.00
Lead Number	0	0.00
Last Notable Activity	0	0.00
Newspaper Article	0	0.00
Search	0	0.00
Magazine	0	0.00
A free copy of Mastering The Interview	0	0.00
X Education Forums	0	0.00
Newspaper	0	0.00
Digital Advertisement	0	0.00
Through Recommendations	0	0.00
Receive More Updates About Our Courses	0	0.00
Update me on Supply Chain Content	0	0.00
Get updates on DM Content	0	0.00
I agree to pay the amount through cheque	0	0.00
Prospect ID	0	0.00

Visualizing occurence of Null values in the columns based on rows

In [10]:

```
import matplotlib.pyplot as plt,seaborn as sns
plt.figure(figsize=(10,10))
sns.heatmap(leads.isnull(), cbar=False)

plt.tight_layout()
plt.show()
```





Dropping Unnecessary Columns

In [11]:

```
# Identifying if any column exists with only null values
leads.isnull().all(axis=0).any()
```

Out[11]:

```
False
```

In [12]:

```
# Dropping all columns with only 0 values
leads.loc[:, (leads != 0).any(axis=0)]
leads.shape
```

Out[12]:

```
(9240, 37)
```

In [13]:

```
leads= leads.loc[:,leads.nunique()!=1]
leads.shape
```

Out[13]:

```
(9240, 32)
```

In [14]:

```
# Deleting the columns 'Asymmetrique Activity Score' & 'Asymmetrique Profile Score'
# as they will be represented by their corresponding index columns
leads = leads.drop('Asymmetrique Activity Score', axis=1)
leads = leads.drop('Asymmetrique Profile Score', axis=1)
leads.shape
```

Out[14]:

```
(9240, 30)
```

(9240, 30)

In [15]:

```
# Deleting the columns 'Prospect ID' as it will not have any effect in the predicting model
leads = leads.drop('Prospect ID', axis=1)
#leads = leads.drop('Lead Number', axis=1)
leads.shape
```

Out[15]:

```
(9240, 29)
```

In [16]:

```
#Deleting the columns 'What matters most to you in choosing a course' as it mostly has unique valu
es and some null values.
leads = leads.drop('What matters most to you in choosing a course', axis=1)
leads.shape
```

Out[16]:

```
(9240, 28)
```

In [17]:

```
# Deleting the columns 'How did you hear about X Education' as it mostly has null values or 'Selec
t' values
# that contribute to the 'Converted' percentage.
leads = leads.drop('How did you hear about X Education', axis=1)
leads.shape
```

Out[17]:

```
(9240, 27)
```

Imputing with Median values because the continuous variables have outliers

In [18]:

```
leads['TotalVisits'].replace(np.NaN, leads['TotalVisits'].median(), inplace =True)
```

In [19]:

```
leads['Page Views Per Visit'].replace(np.NaN, leads['Page Views Per Visit'].median(), inplace
=True)
```

In [20]:

```
leads['Country'].mode()
```

Out[20]:

```
0    India
dtype: object
```

In [21]:

```
leads.loc[pd.isnull(leads['Country']), ['Country']] = 'India'
```

In [22]:

```
leads['Country'] = leads['Country'].apply(lambda x: 'India' if x=='India' else 'Outside India')
leads['Country'].value_counts()
```

Out[22]:

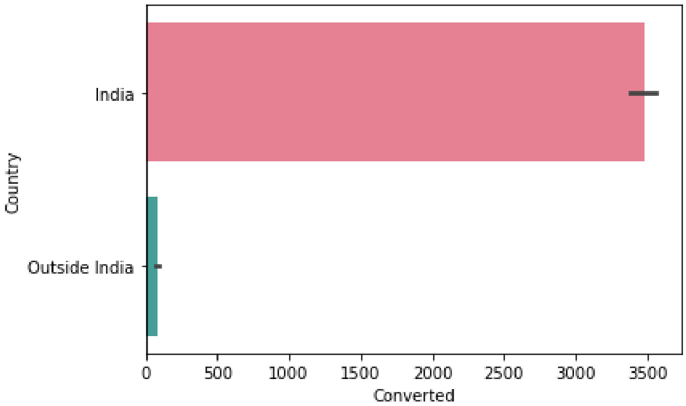
```
India             8953
Outside India      287
Name: Country, dtype: int64
```

In [23]:

```
sns.barplot(y='Country', x='Converted', palette='husl', data=leads, estimator=np.sum)
```

Out[23]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2520b86ecd0>
```



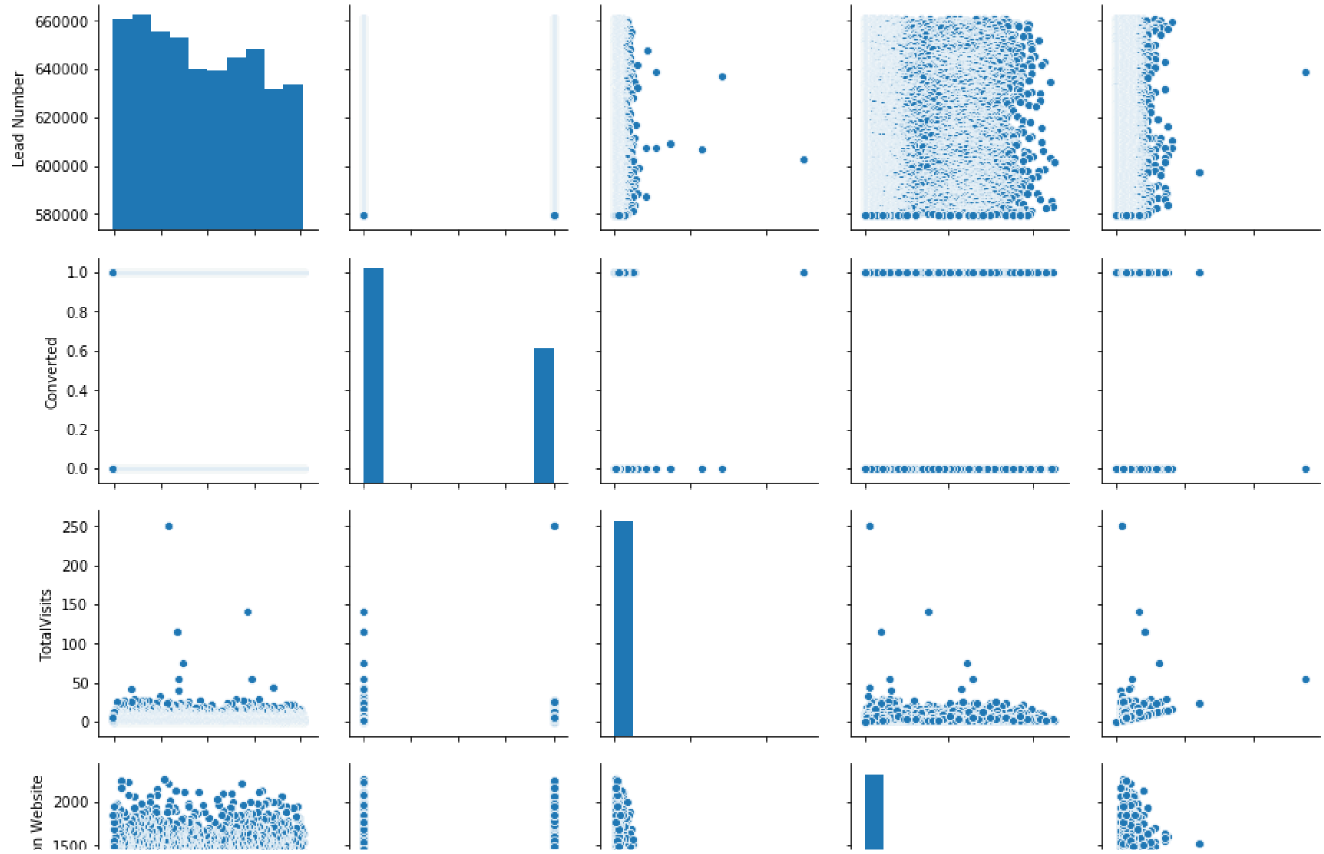
visulaizations

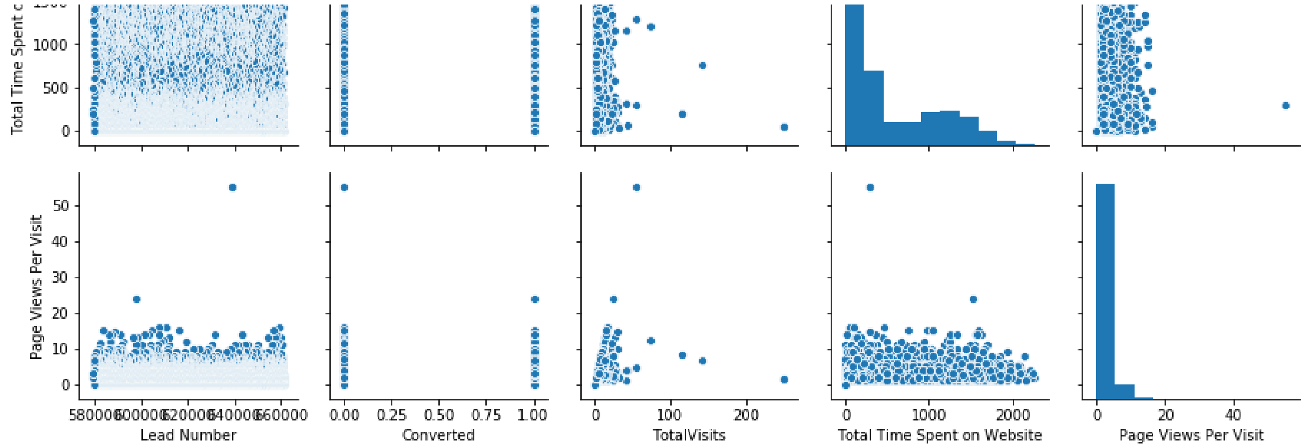
In [24]:

```
import matplotlib.pyplot as plt,seaborn as sns
```

In [25]:

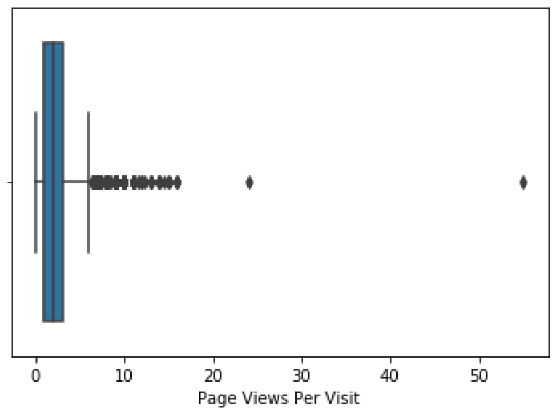
```
sns.pairplot(leads)
plt.show()
```





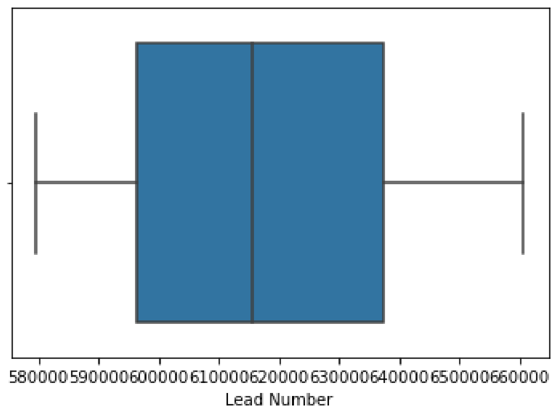
In [26]:

```
sns.boxplot(leads['Page Views Per Visit'])
plt.show()
```



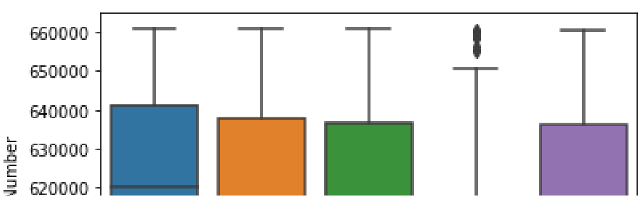
In [27]:

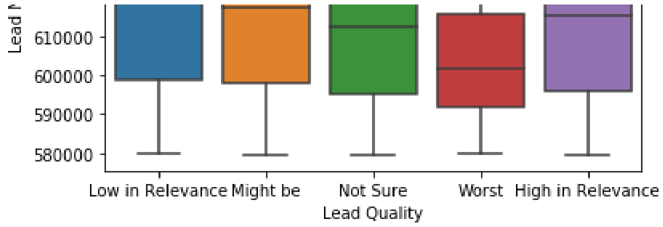
```
sns.boxplot(leads['Lead Number'])
plt.show()
```



In [28]:

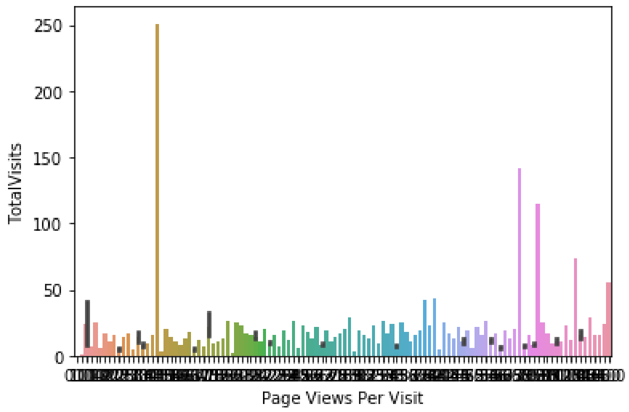
```
sns.boxplot(leads['Lead Quality'],leads['Lead Number'])
plt.show()
```





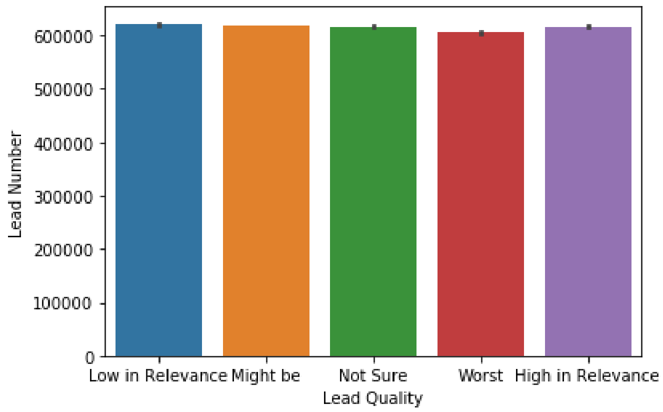
In [29]:

```
sns.barplot(x='Page Views Per Visit',y='TotalVisits',data=leads)
plt.show()
```



In [30]:

```
sns.barplot(x='Lead Quality',y='Lead Number',data=leads)
plt.show()
```



Creating a new category consisting on NULL/Select values for the field Asymmetrique Profile Index

In [31]:

```
leads['Lead Quality'].value_counts()
```

Out[31]:

```
Might be              1560
Not Sure              1092
High in Relevance      637
Worst                  601
Low in Relevance       583
Name: Lead Quality, dtype: int64
```

In [32]:

```
leads['Lead Quality'].isnull().sum()
```

Out[32]:

```
4767
```

In [33]:

```
leads['Lead Quality'].fillna("Unknown", inplace = True)
leads['Lead Quality'].value_counts()
```

Out[33]:

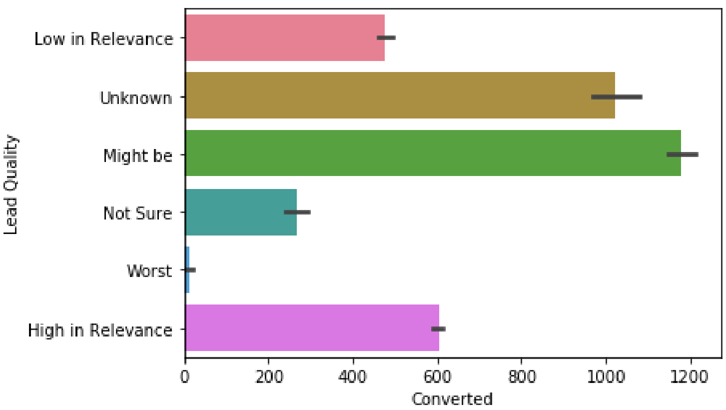
```
Unknown                 4767
Might be                1560
Not Sure                1092
High in Relevance        637
Worst                    601
Low in Relevance         583
Name: Lead Quality, dtype: int64
```

In [34]:

```
sns.barplot(y='Lead Quality', x='Converted', palette='husl', data=leads, estimator=np.sum)
```

Out[34]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x25216ba2760>
```



In [35]:

```
leads['Asymmetrique Profile Index'].value_counts()
```

Out[35]:

```
02.Medium     2788
01.High       2203
03.Low          31
Name: Asymmetrique Profile Index, dtype: int64
```

In [36]:

```
leads['Asymmetrique Profile Index'].isnull().sum()
```

Out[36]:

```
4218
```

In [37]:

```
leads['Asymmetrique Profile Index'].fillna("Unknown", inplace = True)
leads['Asymmetrique Profile Index'].value_counts()
```

Out[37]:

```
Unknown       4218
```

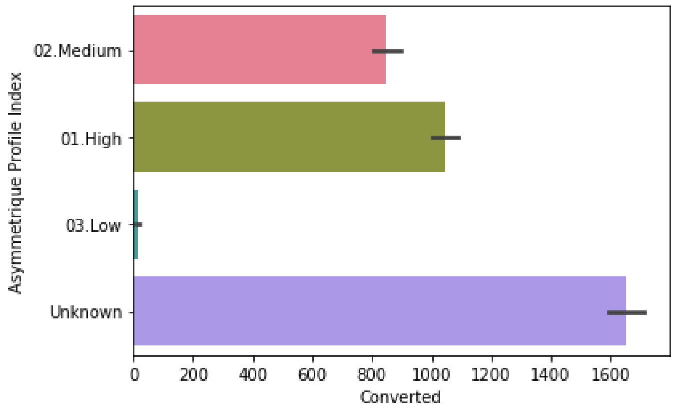
```
Unknown      4218
02.Medium    2788
01.High      2203
03.Low         31
Name: Asymmetrique Profile Index, dtype: int64
```

In [38]:

```
sns.barplot(y='Asymmetrique Profile Index', x='Converted', palette='husl', data=leads, estimator=np
.sum)
```

Out[38]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x25216a80bb0>
```



In [39]:

```
#for Asymmetrique Activity Index
```

In [40]:

```
leads['Asymmetrique Activity Index'].value_counts()
leads['Asymmetrique Activity Index'].isnull().sum()
leads['Asymmetrique Activity Index'].fillna("Unknown", inplace = True)
leads['Asymmetrique Activity Index'].value_counts()
```

Out[40]:

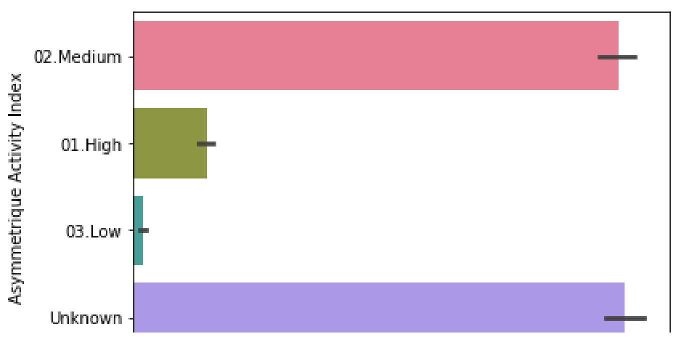
```
Unknown      4218
02.Medium    3839
01.High       821
03.Low        362
Name: Asymmetrique Activity Index, dtype: int64
```

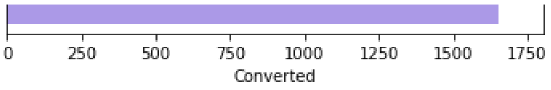
In [41]:

```
sns.barplot(y='Asymmetrique Activity Index', x='Converted', palette='husl', data=leads, estimator=n
p.sum)
```

Out[41]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x252167f8520>
```





In [42]:

```
#for City
```

In [43]:

```
leads['City'].isnull().sum()
leads['City'].fillna("Unknown", inplace = True)
leads['City'].value_counts()
leads['City'].replace('Select', 'Unknown', inplace =True)
leads['City'].value_counts()
```

Out[43]:

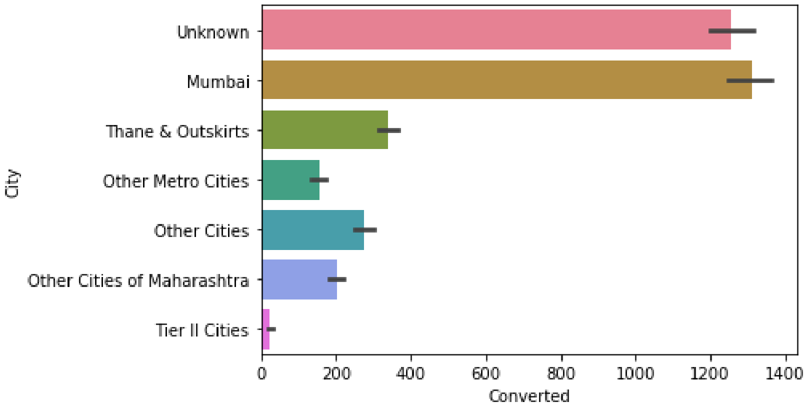
```
Unknown                        3669
Mumbai                         3222
Thane & Outskirts               752
Other Cities                    686
Other Cities of Maharashtra     457
Other Metro Cities              380
Tier II Cities                   74
Name: City, dtype: int64
```

In [44]:

```
sns.barplot(y='City', x='Converted', palette='husl', data=leads, estimator=np.sum)
```

Out[44]:

```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x252177c4eb0&gt;
```



In [45]:

```
#for last activity
leads['Last Activity'].value_counts()
leads['Last Activity'].isnull().sum()
leads['Last Activity'].fillna("Unknown", inplace = True)
leads['Last Activity'].value_counts()
```

Out[45]:

```
Email Opened                 3437
SMS Sent                     2745
Olark Chat Conversation       973
Page Visited on Website       640
Converted to Lead             428
Email Bounced                 326
Email Link Clicked            267
Form Submitted on Website     116
Unknown                       103
Unreachable                    93
```

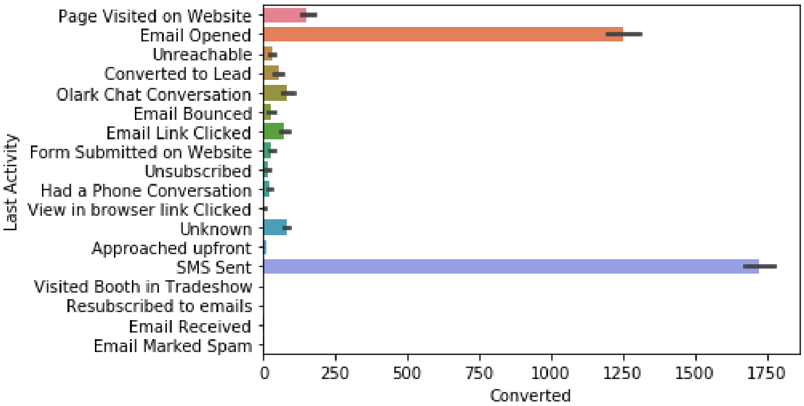
```
Unsubscribed                    61
Had a Phone Conversation        30
Approached upfront               9
View in browser link Clicked     6
Email Marked Spam                2
Email Received                   2
Resubscribed to emails           1
Visited Booth in Tradeshow       1
Name: Last Activity, dtype: int64
```

In [46]:

```
sns.barplot(y='Last Activity', x='Converted', palette='husl', data=leads, estimator=np.sum)
```

Out[46]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x25216be9a30>
```



In [47]:

```
leads['What is your current occupation'].value_counts()
leads['What is your current occupation'].isnull().sum()
leads['What is your current occupation'].fillna("Unknown", inplace = True)
leads['What is your current occupation'].value_counts()
```

Out[47]:

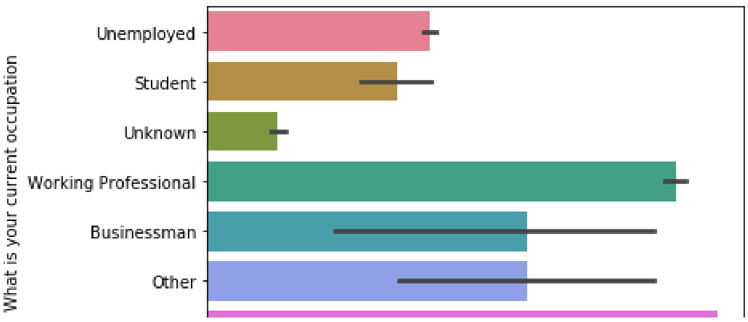
```
Unemployed              5600
Unknown                 2690
Working Professional     706
Student                  210
Other                     16
Housewife                 10
Businessman                8
Name: What is your current occupation, dtype: int64
```

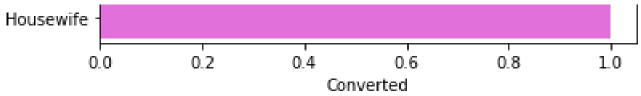
In [48]:

```
sns.barplot(y='What is your current occupation', x='Converted', palette='husl', data=leads)
```

Out[48]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x25216ae2520>
```





In [49]:

```
# for lead profile
leads['Lead Profile'].value_counts()
leads['Lead Profile'].isnull().sum()
leads['Lead Profile'].fillna("Unknown", inplace = True)
leads['Lead Profile'].value_counts()
```

Out[49]:

```
Select                         4146
Unknown                        2709
Potential Lead                 1613
Other Leads                     487
Student of SomeSchool           241
Lateral Student                  24
Dual Specialization Student      20
Name: Lead Profile, dtype: int64
```

In [50]:

```
leads['Lead Profile'].replace('Select', 'Unknown', inplace =True)
leads['Lead Profile'].value_counts()
```

Out[50]:

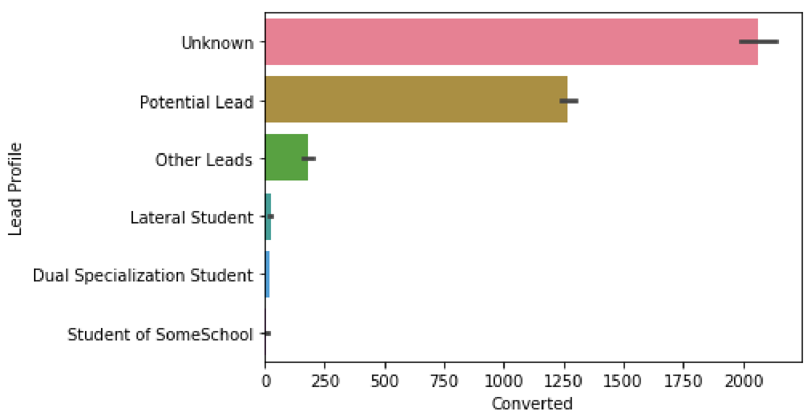
```
Unknown                        6855
Potential Lead                 1613
Other Leads                     487
Student of SomeSchool           241
Lateral Student                  24
Dual Specialization Student      20
Name: Lead Profile, dtype: int64
```

In [51]:

```
sns.barplot(y='Lead Profile', x='Converted', palette='husl', data=leads, estimator=np.sum)
```

Out[51]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x252185ea820>
```



In [52]:

```
# for tags
leads['Tags'].value_counts()
leads['Tags'].isnull().sum()
leads['Tags'].fillna("Unknown", inplace = True)
leads['Tags'].value_counts()
```

Out[52]:

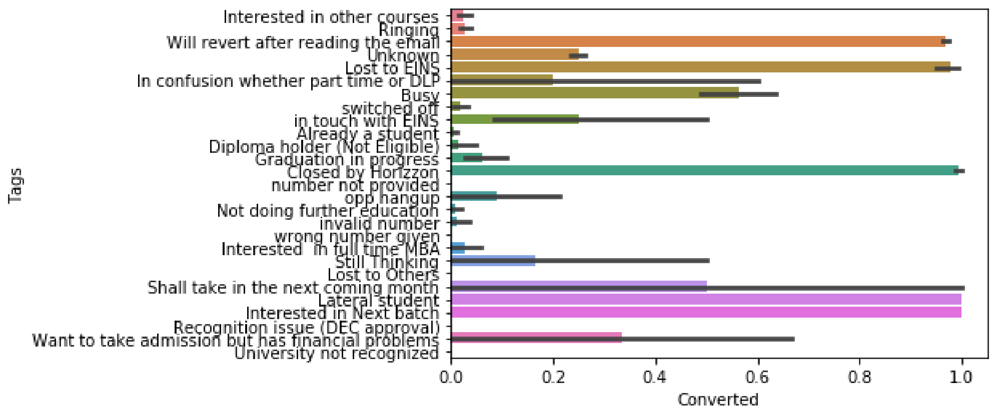
```
Unknown                                              3353
Will revert after reading the email                  2072
Ringing                                              1203
Interested in other courses                           513
Already a student                                     465
Closed by Horizzon                                    358
switched off                                          240
Busy                                                  186
Lost to EINS                                          175
Not doing further education                           145
Interested  in full time MBA                          117
Graduation in progress                                111
invalid number                                         83
Diploma holder (Not Eligible)                          63
wrong number given                                     47
opp hangup                                             33
number not provided                                    27
in touch with EINS                                     12
Lost to Others                                          7
Still Thinking                                          6
Want to take admission but has financial problems       6
In confusion whether part time or DLP                   5
Interested in Next batch                                5
Lateral student                                         3
Shall take in the next coming month                     2
University not recognized                               2
Recognition issue (DEC approval)                        1
Name: Tags, dtype: int64
```

In [53]:

```
sns.barplot(y='Tags', x='Converted', palette='husl', data=leads)
```

Out[53]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x25216b8f5e0>
```



In [54]:

```
leads['Specialization'].value_counts()
leads['Specialization'].isnull().sum()
leads['Specialization'].fillna("Unknown", inplace = True)
leads['Specialization'].value_counts()
```

Out[54]:

```
Select                               1942
Unknown                              1438
Finance Management                    976
Human Resource Management             848
Marketing Management                  838
Operations Management                 503
Business Administration               403
IT Projects Management                366
Supply Chain Management               349
Banking, Investment And Insurance     338
```

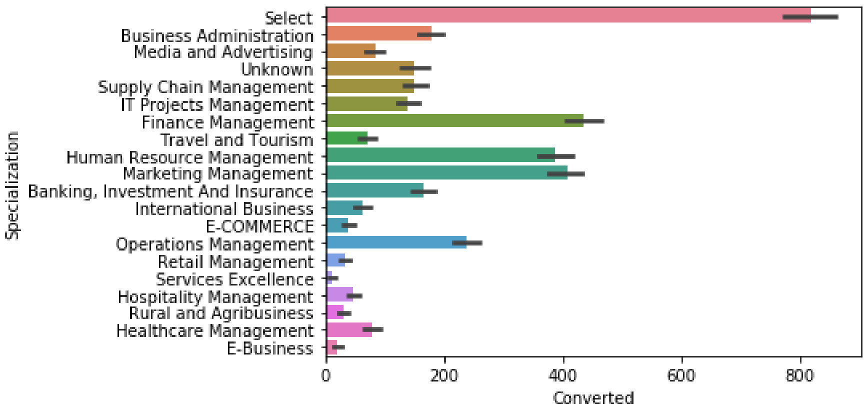
```
Travel and Tourism                   203
Media and Advertising                203
International Business               178
Healthcare Management                159
Hospitality Management               114
E-COMMERCE                           112
Retail Management                    100
Rural and Agribusiness                73
E-Business                            57
Services Excellence                   40
Name: Specialization, dtype: int64
```

In [55]:

```
sns.barplot(y='Specialization', x='Converted', palette='husl', data=leads, estimator=np.sum)
```

Out[55]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x252170b30a0>
```



In [56]:

```
leads['Lead Quality'].value_counts()
leads['Lead Quality'].isnull().sum()
leads['Lead Quality'].fillna("Unknown", inplace = True)
leads['Lead Quality'].value_counts()
```

Out[56]:

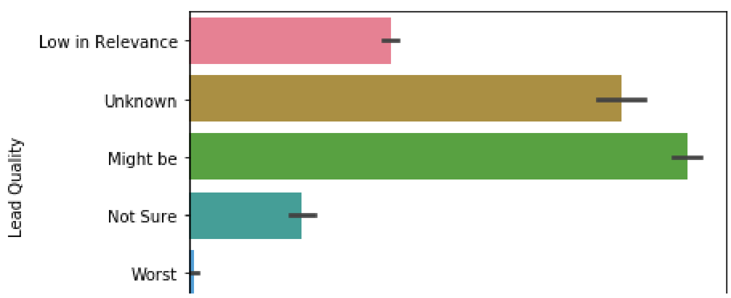
```
Unknown              4767
Might be             1560
Not Sure             1092
High in Relevance     637
Worst                 601
Low in Relevance      583
Name: Lead Quality, dtype: int64
```

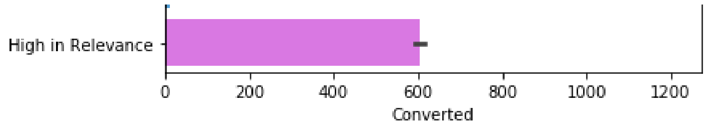
In [57]:

```
sns.barplot(y='Lead Quality', x='Converted', palette='husl', data=leads, estimator=np.sum)
```

Out[57]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x25216bc6520>
```





Reinspecting Null Values

In [58]:

```
# Checking for total count and percentage of null values in all columns of the dataframe.

total = pd.DataFrame(leads.isnull().sum().sort_values(ascending=False), columns=['Total'])
percentage = pd.DataFrame(round(100*(leads.isnull().sum()/leads.shape[0]),2).sort_values(ascending=
False)\
                          ,columns=['Percentage'])
pd.concat([total, percentage], axis = 1).head()
```

Out[58]:

	Total	Percentage
Lead Source	36	0.39
Last Notable Activity	0	0.00
What is your current occupation	0	0.00
Lead Origin	0	0.00
Do Not Email	0	0.00

Checking for Outliers

In [59]:

```
# Checking outliers at 25%,50%,75%,90%,95% and 99%
leads.describe(percentiles=[.25,.5,.75,.90,.95,.99]).T
```

Out[59]:

	count	mean	std	min	25%	50%	75%	90%	95%	99%	max
Lead Number	9240.0	617188.435606	23405.995698	579533.0	596484.5	615479.0	637387.25	650506.1	655404.05	659592.98	660737.0
Converted	9240.0	0.385390	0.486714	0.0	0.0	0.0	1.00	1.0	1.00	1.00	1.0
TotalVisits	9240.0	3.438636	4.819024	0.0	1.0	3.0	5.00	7.0	10.00	17.00	251.0
Total Time Spent on Website	9240.0	487.698268	548.021466	0.0	12.0	248.0	936.00	1380.0	1562.00	1840.61	2272.0
Page Views Per Visit	9240.0	2.357440	2.145781	0.0	1.0	2.0	3.00	5.0	6.00	9.00	55.0

In [60]:

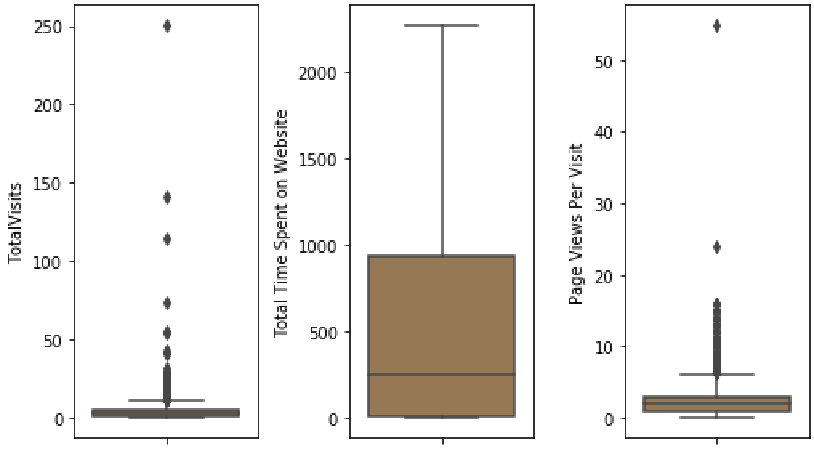
```
numeric_variables = ['TotalVisits','Total Time Spent on Website','Page Views Per Visit']
print(numeric_variables)
```

```
['TotalVisits', 'Total Time Spent on Website', 'Page Views Per Visit']
```

In [61]:

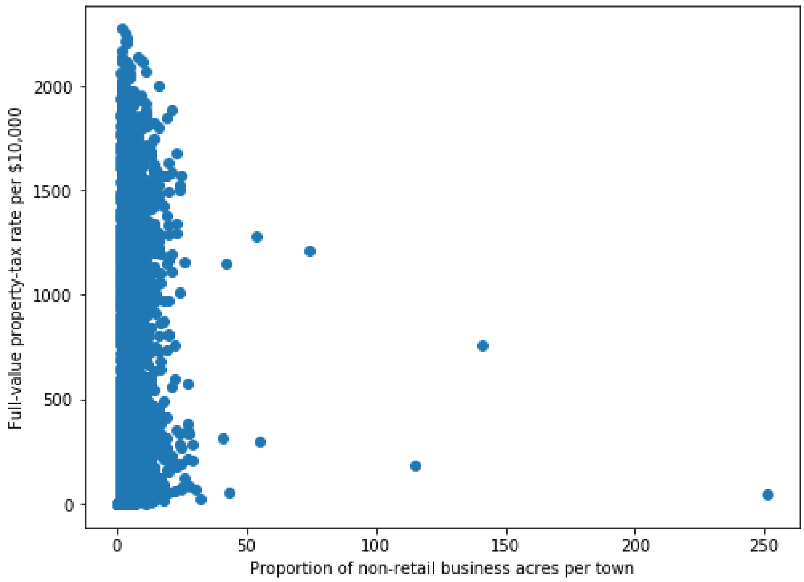
```
numeric_variables = ['TotalVisits','Total Time Spent on Website','Page Views Per Visit']
def boxplot(var_list):
    plt.figure(figsize=(12,8))
    for var in var_list:
        plt.subplot(2,5,var_list.index(var)+1)
        #plt.boxplot(country[var])
        sns.boxplot(y=var,palette='cubehelix', data=leads)
```

```
    # Automatically adjust subplot params so that the subplotS fits in to the figure area.
    plt.tight_layout()
    # display the plot
    plt.show()

boxplot(numeric_variables)
```



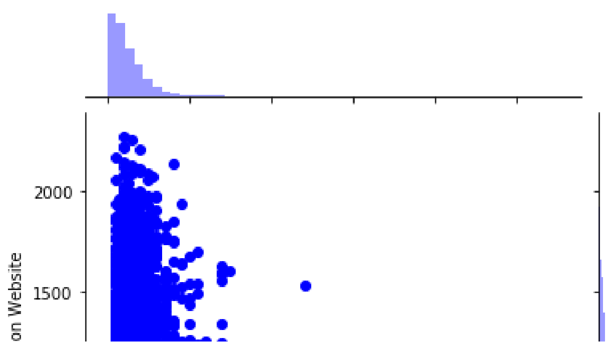
In [62]:

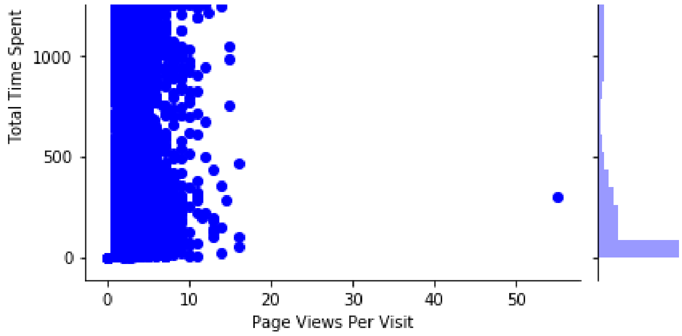
```
fig, ax = plt.subplots(figsize=(8,6))
ax.scatter(leads['TotalVisits'], leads['Total Time Spent on Website'])
ax.set_xlabel('Proportion of non-retail business acres per town')
ax.set_ylabel('Full-value property-tax rate per $10,000')
plt.show()
```



In [63]:

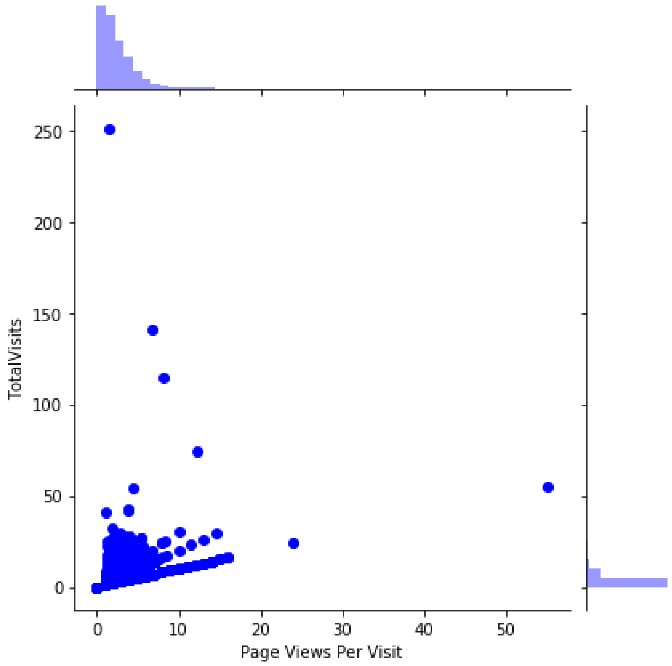
```
sns.jointplot(leads['Page Views Per Visit'],leads['Total Time Spent on Website'], color="b")
plt.show()
```





In [64]:

```
sns.jointplot(leads['Page Views Per Visit'],leads['TotalVisits'], color="b")
plt.show()
```



Removing outlier values based on the Interquartile distance

In [65]:

```
Q1 = leads['TotalVisits'].quantile(0.25)
Q3 = leads['TotalVisits'].quantile(0.75)
IQR = Q3 - Q1
leads=leads.loc[(leads['TotalVisits'] >= Q1 - 1.5*IQR) & (leads['TotalVisits'] <= Q3 + 1.4*IQR)]

Q1 = leads['Page Views Per Visit'].quantile(0.25)
Q3 = leads['Page Views Per Visit'].quantile(0.75)
IQR = Q3 - Q1
leads=leads.loc[(leads['Page Views Per Visit'] >= Q1 - 1.5*IQR) & (leads['Page Views Per Visit'] <=
Q3 + 1.5*IQR)]

leads.shape
```

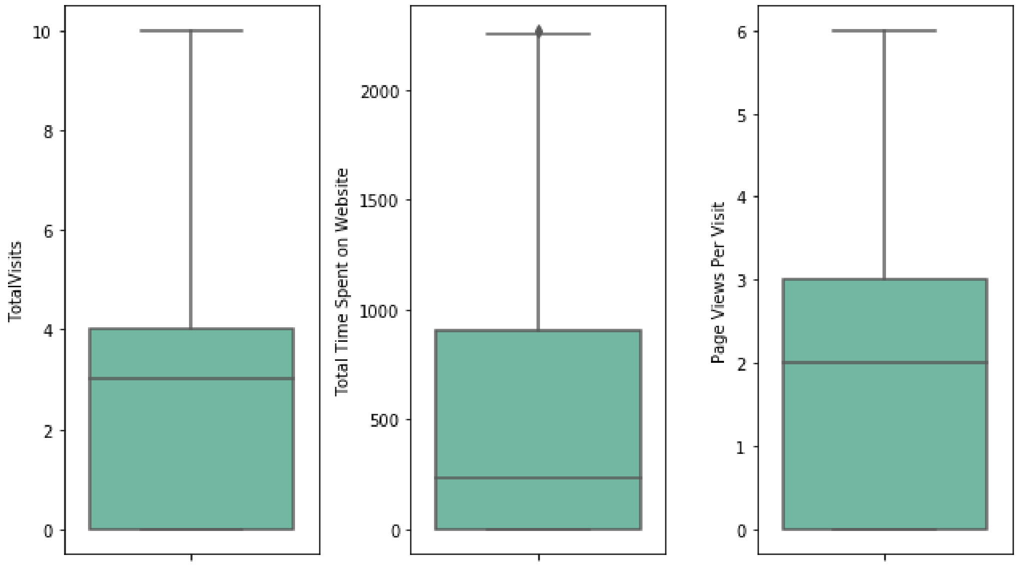
Out[65]:

```
(8611, 27)
```

In [66]:

```
def boxplot(var_list):
    plt.figure(figsize=(15,10))
    for var in var_list:
        plt.subplot(2,5,var_list.index(var)+1)
```

```
        #plt.boxplot(country[var])
        sns.boxplot(y=var,palette='BuGn_r', data=leads)
    # Automatically adjust subplot params so that the subplotS fits in to the figure area.
    plt.tight_layout()
    # display the plot
    plt.show()

boxplot(numeric_variables)
```



In [67]:

```
leads.shape
```

Out[67]:

```
(8611, 27)
```

Converting some binary variables (Yes/No) to 0/1

In [68]:

```
# List of variables to map

varlist =  ['Search','Do Not Email', 'Do Not Call', 'Newspaper Article', 'X Education Forums',
'Newspaper',
            'Digital Advertisement','Through Recommendations','A free copy of Mastering The Intervi
ew']

# Defining the map function
def binary_map(x):
    return x.map({'Yes': 1, "No": 0})

# Applying the function to the housing list
leads[varlist] = leads[varlist].apply(binary_map)
leads.head()
```

Out[68]:

	Lead Number	Lead Origin	Lead Source	Do Not Email	Do Not Call	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Last Activity	...	Digital Advertisement	Throug Recommendation
0	660737	API	Olark Chat	0	0	0	0.0	0	0.0	Page Visited on Website	...	0	
1	660728	API	Organic Search	0	0	0	5.0	674	2.5	Email Opened	...	0	
2	660727	Landing Page	Direct Traffic	0	0	1	2.0	1532	2.0	Email Opened	...	0	

	Lead Number	Lead Origin	Lead Source	Do Not Email	Do Not Call	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Last Activity	...	Digital Advertisement	Through Recommendation
		Submission	Traffic							Opened			
3	660719	Landing Page Submission	Direct Traffic	0	0	0	1.0	305	1.0	Unreachable	...	0	
4	660681	Landing Page Submission	Google	0	0	1	2.0	1428	1.0	Converted to Lead	...	0	

5 rows × 27 columns

For categorical variables with multiple levels, creating dummy features

In [69]:

```
# Creating a dummy variable for some of the categorical variables and dropping the first one.
dummy1 = pd.get_dummies(leads[['Country', 'Lead Source','Lead Origin','Last Notable Activity']],
drop_first=True)

# Adding the results to the master dataframe
leads = pd.concat([leads, dummy1], axis=1)
leads.shape
```

Out[69]:

```
(8611, 67)
```

In [70]:

```
# Creating dummy variables for the remaining categorical variables and
# dropping the level called 'Unknown' which represents null/select values.

# Creating dummy variables for the variable 'Lead Quality'
ml = pd.get_dummies(leads['Lead Quality'], prefix='Lead Quality')
# Dropping the level called 'Unknown' which represents null/select values
ml1 = ml.drop(['Lead Quality_Unknown'], 1)
#Adding the results to the master dataframe
leads = pd.concat([leads,ml1], axis=1)
#-------------------------------------------------------------------------------------
# Creating dummy variables for the variable 'Asymmetrique Profile Index'
ml = pd.get_dummies(leads['Asymmetrique Profile Index'], prefix='Asymmetrique Profile Index')
# Dropping the level called 'Unknown' which represents null/select values
ml1 = ml.drop(['Asymmetrique Profile Index_Unknown'], 1)
#Adding the results to the master dataframe
leads = pd.concat([leads,ml1], axis=1)
#-------------------------------------------------------------------------------------
# Creating dummy variables for the variable 'Asymmetrique Activity Index'
ml = pd.get_dummies(leads['Asymmetrique Activity Index'], prefix='Asymmetrique Activity Index')
# Dropping the level called 'Unknown' which represents null/select values
ml1 = ml.drop(['Asymmetrique Activity Index_Unknown'], 1)
#Adding the results to the master dataframe
leads = pd.concat([leads,ml1], axis=1)
#-------------------------------------------------------------------------------------
# Creating dummy variables for the variable 'Tags'
ml = pd.get_dummies(leads['Tags'], prefix='Tags')
# Dropping the level called 'Unknown' which represents null/select values
ml1 = ml.drop(['Tags_Unknown'], 1)
#Adding the results to the master dataframe
leads = pd.concat([leads,ml1], axis=1)
#-------------------------------------------------------------------------------------
# Creating dummy variables for the variable 'Lead Profile'
ml = pd.get_dummies(leads['Lead Profile'], prefix='Lead Profile')
# Dropping the level called 'Unknown' which represents null/select values
ml1 = ml.drop(['Lead Profile_Unknown'], 1)
#Adding the results to the master dataframe
leads = pd.concat([leads,ml1], axis=1)
#-------------------------------------------------------------------------------------
# Creating dummy variables for the variable 'What is your current occupation'
ml = pd.get_dummies(leads['What is your current occupation'], prefix='What is your current
occupation')
# Dropping the level called 'Unknown' which represents null/select values
ml1 = ml.drop(['What is your current occupation_Unknown'], 1)
#Adding the results to the master dataframe
```

```
leads = pd.concat([leads,ml1], axis=1)
#-------------------------------------------------------------------------------
# Creating dummy variables for the variable 'Specialization'
ml = pd.get_dummies(leads['Specialization'], prefix='Specialization')
# Dropping the level called 'Unknown' which represents null/select values
ml1 = ml.drop(['Specialization_Unknown'], 1)
#Adding the results to the master dataframe
leads = pd.concat([leads,ml1], axis=1)
#-------------------------------------------------------------------------------
# Creating dummy variables for the variable 'City'
ml = pd.get_dummies(leads['City'], prefix='City')
# Dropping the level called 'Unknown' which represents null/select values
ml1 = ml.drop(['City_Unknown'], 1)
#Adding the results to the master dataframe
leads = pd.concat([leads,ml1], axis=1)
#-------------------------------------------------------------------------------
# Creating dummy variables for the variable 'Last Activity'
ml = pd.get_dummies(leads['Last Activity'], prefix='Last Activity')
# Dropping the level called 'Unknown' which represents null/select values
ml1 = ml.drop(['Last Activity_Unknown'], 1)
#Adding the results to the master dataframe
leads = pd.concat([leads,ml1], axis=1)
#-------------------------------------------------------------------------------
leads.shape
```

Out[70]:

```
(8611, 157)
```

Dropping the repeated variables

In [71]:

```
leads = leads.drop(['Lead Quality','Asymmetrique Profile Index','Asymmetrique Activity Index','Tag
s','Lead Profile',
                    'Lead Origin','What is your current occupation', 'Specialization', 'City','Last
Activity', 'Country',
                    'Lead Source','Last Notable Activity'], 1)
leads.shape
```

Out[71]:

```
(8611, 144)
```

In [72]:

```
leads.head()
```

Out[72]:

	Lead Number	Do Not Email	Do Not Call	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Search	Newspaper Article	X Education Forums	...	Last Activity_Form Submitted on Website	Last Activity_Had a Phone Conversation	Acti Cor
0	660737	0	0	0	0.0	0	0.0	0	0	0	...	0	0	
1	660728	0	0	0	5.0	674	2.5	0	0	0	...	0	0	
2	660727	0	0	1	2.0	1532	2.0	0	0	0	...	0	0	
3	660719	0	0	0	1.0	305	1.0	0	0	0	...	0	0	
4	660681	0	0	1	2.0	1428	1.0	0	0	0	...	0	0	

5 rows × 144 columns

In [73]:

```
# Ensuring there are no categorical columns left in the dataframe
cols = leads.columns
num_cols = leads._get_numeric_data().columns
list(set(cols) - set(num_cols))
```

Out[73]:

```
[]
```

In [74]:

```
# Creating a copy of this origial variable in case if needed later on
original_leads = leads.copy()
print(original_leads.shape)
print(leads.shape)
```

```
(8611, 144)
(8611, 144)
```

Step 4: Test-Train Split

In [75]:

```
from sklearn.model_selection import train_test_split
```

In [76]:

```
# Putting feature variable to X
X = leads.drop(['Converted','Lead Number'], axis=1)

X.head()
```

Out[76]:

	Do Not Email	Do Not Call	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Search	Newspaper Article	X Education Forums	Newspaper	Digital Advertisement	...	Last Activity_Form Submitted on Website	Last Activity_Ha a Phon Conversatio
0	0	0	0.0	0	0.0	0	0	0	0	0	...	0	
1	0	0	5.0	674	2.5	0	0	0	0	0	...	0	
2	0	0	2.0	1532	2.0	0	0	0	0	0	...	0	
3	0	0	1.0	305	1.0	0	0	0	0	0	...	0	
4	0	0	2.0	1428	1.0	0	0	0	0	0	...	0	

5 rows × 142 columns

In [77]:

```
# Putting response variable to y
y = leads['Converted']

y.head()
```

Out[77]:

```
0    0
1    0
2    1
3    0
4    1
Name: Converted, dtype: int64
```

In [78]:

```
# Splitting the data into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, test_size=0.3,
random_state=100)
```

Step 5: Feature Scaling

In [79]:

```
from sklearn.preprocessing import StandardScaler
```

In [80]:

```
scaler = StandardScaler()

X_train[['TotalVisits','Total Time Spent on Website','Page Views Per Visit']] =
scaler.fit_transform(X_train[['TotalVisits','Total Time Spent on Website','Page Views Per Visit']]
)

X_train.head()
```

Out[80]:

	Do Not Email	Do Not Call	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Search	Newspaper Article	X Education Forums	Newspaper	Digital Advertisement	...	Last Activity_Form Submitted on Website	Activ Conv
532	0	0	0.106035	-0.442813	0.569927	0	0	0	0	0	...	0	
7273	0	0	1.834432	2.375255	-0.407388	0	0	0	0	0	...	0	
4998	0	0	-1.190262	-0.870128	-1.262538	0	0	0	0	0	...	0	
6668	0	0	0.106035	-0.247575	0.569927	0	0	0	0	0	...	0	
2917	0	0	-1.190262	-0.870128	-1.262538	0	0	0	0	0	...	0	

5 rows × 142 columns

In [81]:

```
X_train.describe()
```

Out[81]:

	Do Not Email	Do Not Call	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Search	Newspaper Article	X Education Forums	Newspaper	Advertis
count	6027.000000	6027.000000	6.027000e+03	6.027000e+03	6.027000e+03	6027.000000	6027.0	6027.0	6027.0	6027.(
mean	0.081467	0.000166	-6.719916e-17	-1.532613e-17	-4.244158e-17	0.000996	0.0	0.0	0.0	0.(
std	0.273573	0.012881	1.000083e+00	1.000083e+00	1.000083e+00	0.031539	0.0	0.0	0.0	0.(
min	0.000000	0.000000	-1.190262e+00	-8.701282e-01	-1.262538e+00	0.000000	0.0	0.0	0.0	0.(
25%	0.000000	0.000000	-1.190262e+00	-8.701282e-01	-1.262538e+00	0.000000	0.0	0.0	0.0	0.(
50%	0.000000	0.000000	1.060353e-01	-4.372877e-01	-4.089475e-02	0.000000	0.0	0.0	0.0	0.(
75%	0.000000	0.000000	5.381345e-01	7.654565e-01	5.699270e-01	0.000000	0.0	0.0	0.0	0.(
max	1.000000	1.000000	3.130729e+00	3.279615e+00	2.402392e+00	1.000000	0.0	0.0	0.0	1.(

8 rows × 142 columns

Checking the Lead Conversion Rate

In [82]:

In [82]:

```
### Checking the Lead Conversion Rate
converted = (sum(leads['Converted'])/len(leads['Converted'].index))*100
converted
```

Out[82]:

```
38.2185576588085
```

We have almost 38% lead conversion rate

Step 6: Model Building

Running Your First Training Model

In [83]:

```
import statsmodels.api as sm
```

In [84]:

```
# Logistic regression model
logm1 = sm.GLM(y_train,(sm.add_constant(X_train)), family = sm.families.Binomial())
logm1.fit().summary()
```

Out[84]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6027
Model:	GLM	**Df Residuals:**	5897
Model Family:	Binomial	**Df Model:**	129
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	nan
Date:	Tue, 12 May 2020	**Deviance:**	nan
Time:	14:09:10	**Pearson chi2:**	2.76e+18
No. Iterations:	100		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	1.156e+15	3.61e+07	3.2e+07	0.000	1.16e+15	1.16e+15
Do Not Email	-6.185e+14	4.68e+06	-1.32e+08	0.000	-6.18e+14	-6.18e+14
Do Not Call	1.557e+15	6.81e+07	2.29e+07	0.000	1.56e+15	1.56e+15
TotalVisits	7.196e+13	1.5e+06	4.79e+07	0.000	7.2e+13	7.2e+13
Total Time Spent on Website	3.989e+14	1.07e+06	3.74e+08	0.000	3.99e+14	3.99e+14
Page Views Per Visit	-1.283e+14	1.63e+06	-7.88e+07	0.000	-1.28e+14	-1.28e+14
Search	2.424e+14	2.86e+07	8.48e+06	0.000	2.42e+14	2.42e+14
Newspaper Article	-5.9463	4.05e-07	-1.47e+07	0.000	-5.946	-5.946
X Education Forums	-15.4848	5.73e-07	-2.7e+07	0.000	-15.485	-15.485
Newspaper	8.8602	6.58e-07	1.35e+07	0.000	8.860	8.860
Digital Advertisement	2.29e+14	4.84e+07	4.73e+06	0.000	2.29e+14	2.29e+14
Through Recommendations	6.835e+14	4.02e+07	1.7e+07	0.000	6.83e+14	6.83e+14
A free copy of Mastering The Interview	-1.25e+14	2.93e+06	-4.27e+07	0.000	-1.25e+14	-1.25e+14
Country_Outside India	1.204e+14	5.19e+06	2.32e+07	0.000	1.2e+14	1.2e+14
Lead Source_Direct Traffic	-9.692e+14	3.71e+07	-2.61e+07	0.000	-9.69e+14	-9.69e+14
Lead Source_Facebook	-3.394e+15	5.27e+07	-6.45e+07	0.000	-3.39e+15	-3.39e+15
Lead Source_Google	-9.231e+14	3.71e+07	-2.49e+07	0.000	-9.23e+14	-9.23e+14

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Lead Source_Live Chat	3.227e+15	4.94e+07	6.53e+07	0.000	3.23e+15	3.23e+15
Lead Source_NC_EDM	1.969e+15	7.69e+07	2.56e+07	0.000	1.97e+15	1.97e+15
Lead Source_Olark Chat	-6.961e+14	3.7e+07	-1.88e+07	0.000	-6.96e+14	-6.96e+14
Lead Source_Organic Search	-8.926e+14	3.72e+07	-2.4e+07	0.000	-8.93e+14	-8.93e+14
Lead Source_Pay per Click Ads	-2.463e+15	7.69e+07	-3.2e+07	0.000	-2.46e+15	-2.46e+15
Lead Source_Press_Release	-1.222e+15	7.75e+07	-1.58e+07	0.000	-1.22e+15	-1.22e+15
Lead Source_Reference	-6.647e+14	1.39e+07	-4.8e+07	0.000	-6.65e+14	-6.65e+14
Lead Source_Referral Sites	-1.011e+15	3.79e+07	-2.67e+07	0.000	-1.01e+15	-1.01e+15
Lead Source_Social Media	-6.075e+14	7.92e+07	-7.67e+06	0.000	-6.08e+14	-6.08e+14
Lead Source_WeLearn	-27.7316	2.52e-07	-1.1e+08	0.000	-27.732	-27.732
Lead Source_Welingak Website	4.169e+15	1.5e+07	2.79e+08	0.000	4.17e+15	4.17e+15
Lead Source_bing	-3.701e+14	4.62e+07	-8e+06	0.000	-3.7e+14	-3.7e+14
Lead Source_blog	9.1873	3.99e-07	2.3e+07	0.000	9.187	9.187
Lead Source_google	-4.405e+15	6.08e+07	-7.24e+07	0.000	-4.4e+15	-4.4e+15
Lead Source_testone	-4.097e+15	7.73e+07	-5.3e+07	0.000	-4.1e+15	-4.1e+15
Lead Source_welearnblog_Home	12.1421	3.07e-07	3.95e+07	0.000	12.142	12.142
Lead Source_youtubechannel	-5.185e+15	7.8e+07	-6.64e+07	0.000	-5.19e+15	-5.19e+15
Lead Origin_Landing Page Submission	-1.048e+14	4.24e+06	-2.47e+07	0.000	-1.05e+14	-1.05e+14
Lead Origin_Lead Add Form	-4.396e+14	3.67e+07	-1.2e+07	0.000	-4.4e+14	-4.4e+14
Lead Origin_Lead Import	2.027e+15	5.24e+07	3.86e+07	0.000	2.03e+15	2.03e+15
Lead Origin_Quick Add Form	3.376e+15	7.77e+07	4.34e+07	0.000	3.38e+15	3.38e+15
Last Notable Activity_Email Bounced	-2.794e+14	1.42e+07	-1.96e+07	0.000	-2.79e+14	-2.79e+14
Last Notable Activity_Email Link Clicked	-9.328e+14	1.34e+07	-6.98e+07	0.000	-9.33e+14	-9.33e+14
Last Notable Activity_Email Marked Spam	1.72e+15	2.38e+07	7.23e+07	0.000	1.72e+15	1.72e+15
Last Notable Activity_Email Opened	-6.302e+14	1.01e+07	-6.24e+07	0.000	-6.3e+14	-6.3e+14
Last Notable Activity_Email Received	-1.334e+15	8.8e+07	-1.52e+07	0.000	-1.33e+15	-1.33e+15
Last Notable Activity_Form Submitted on Website	3.3288	2e-07	1.66e+07	0.000	3.329	3.329
Last Notable Activity_Had a Phone Conversation	5.612e+15	3.54e+07	1.59e+08	0.000	5.61e+15	5.61e+15
Last Notable Activity_Modified	-9.107e+14	9.5e+06	-9.59e+07	0.000	-9.11e+14	-9.11e+14
Last Notable Activity_Olark Chat Conversation	-1.272e+15	1.13e+07	-1.12e+08	0.000	-1.27e+15	-1.27e+15
Last Notable Activity_Page Visited on Website	-7.5e+14	1.16e+07	-6.46e+07	0.000	-7.5e+14	-7.5e+14
Last Notable Activity_Resubscribed to emails	1.137e+15	3.3e+07	3.44e+07	0.000	1.14e+15	1.14e+15
Last Notable Activity_SMS Sent	1.219e+14	1.02e+07	1.2e+07	0.000	1.22e+14	1.22e+14
Last Notable Activity_Unreachable	-8.203e+14	1.88e+07	-4.37e+07	0.000	-8.2e+14	-8.2e+14
Last Notable Activity_Unsubscribed	-5.052e+14	2.49e+07	-2.03e+07	0.000	-5.05e+14	-5.05e+14
Last Notable Activity_View in browser link Clicked	0.1942	2.08e-07	9.35e+05	0.000	0.194	0.194
Lead Quality_High in Relevance	1.245e+12	5.53e+06	2.25e+05	0.000	1.24e+12	1.24e+12
Lead Quality_Low in Relevance	-5.385e+13	5.38e+06	-1e+07	0.000	-5.38e+13	-5.38e+13
Lead Quality_Might be	-1.548e+14	4.01e+06	-3.86e+07	0.000	-1.55e+14	-1.55e+14
Lead Quality_Not Sure	3.556e+14	3.69e+06	9.65e+07	0.000	3.56e+14	3.56e+14
Lead Quality_Worst	-3.588e+14	5.65e+06	-6.35e+07	0.000	-3.59e+14	-3.59e+14
Asymmetrique Profile Index_01.High	-1.077e+14	3.85e+06	-2.8e+07	0.000	-1.08e+14	-1.08e+14
Asymmetrique Profile Index_02.Medium	-9.874e+13	3.32e+06	-2.97e+07	0.000	-9.87e+13	-9.87e+13
Asymmetrique Profile Index_03.Low	-7.681e+13	1.44e+07	-5.34e+06	0.000	-7.68e+13	-7.68e+13
Asymmetrique Activity Index_01.High	-1.104e+13	4.13e+06	-2.67e+06	0.000	-1.1e+13	-1.1e+13
Asymmetrique Activity Index_02.Medium	1.253e+14	3.33e+06	3.77e+07	0.000	1.25e+14	1.25e+14
Asymmetrique Activity Index_03.Low	-3.976e+14	5e+06	-7.95e+07	0.000	-3.98e+14	-3.98e+14
Tags_Already a student	-6.267e+13	6.54e+06	-9.58e+06	0.000	-6.27e+13	-6.27e+13
Tags_Busy	1.605e+15	7.4e+06	2.17e+08	0.000	1.6e+15	1.6e+15
Tags_Closed by Horizzon	1.606e+15	6.85e+06	2.34e+08	0.000	1.61e+15	1.61e+15

Tags_Diploma holder (Not Eligible)	-1.792e+15	1.08e+07	-1.66e+08	0.000	-1.79e+15	-1.79e+15
Tags_Graduation in progress	6.651e+14	9.32e+06	7.13e+07	0.000	6.65e+14	6.65e+14
Tags_In confusion whether part time or DLP	-3.731e+15	3.39e+07	-1.1e+08	0.000	-3.73e+15	-3.73e+15
Tags_Interested in full time MBA	4.243e+13	8.88e+06	4.78e+06	0.000	4.24e+13	4.24e+13
Tags_Interested in Next batch	3.904e+15	3.41e+07	1.14e+08	0.000	3.9e+15	3.9e+15
Tags_Interested in other courses	6.568e+13	5.12e+06	1.28e+07	0.000	6.57e+13	6.57e+13
Tags_Lateral student	5.082e+15	4.78e+07	1.06e+08	0.000	5.08e+15	5.08e+15
Tags_Lost to EINS	1.773e+15	7.03e+06	2.52e+08	0.000	1.77e+15	1.77e+15
Tags_Lost to Others	-1.353e+15	2.62e+07	-5.16e+07	0.000	-1.35e+15	-1.35e+15
Tags_Not doing further education	2.747e+14	8.11e+06	3.39e+07	0.000	2.75e+14	2.75e+14
Tags_Recognition issue (DEC approval)	-4.164e+15	6.91e+07	-6.03e+07	0.000	-4.16e+15	-4.16e+15
Tags_Ringing	-7.029e+14	4.31e+06	-1.63e+08	0.000	-7.03e+14	-7.03e+14
Tags_Shall take in the next coming month	-1.386e+15	4.78e+07	-2.9e+07	0.000	-1.39e+15	-1.39e+15
Tags_Still Thinking	-3.871e+15	4.84e+07	-8e+07	0.000	-3.87e+15	-3.87e+15
Tags_University not recognized	8.864e+14	6.8e+07	1.3e+07	0.000	8.86e+14	8.86e+14
Tags_Want to take admission but has financial problems	8.449e+14	3.96e+07	2.14e+07	0.000	8.45e+14	8.45e+14
Tags_Will revert after reading the email	1.025e+15	4.95e+06	2.07e+08	0.000	1.03e+15	1.03e+15
Tags_in touch with EINS	1.194e+15	2.28e+07	5.24e+07	0.000	1.19e+15	1.19e+15
Tags_invalid number	-3.392e+15	1.07e+07	-3.18e+08	0.000	-3.39e+15	-3.39e+15
Tags_number not provided	-2.815e+15	1.78e+07	-1.58e+08	0.000	-2.82e+15	-2.82e+15
Tags_opp hangup	-4.173e+14	1.5e+07	-2.79e+07	0.000	-4.17e+14	-4.17e+14
Tags_switched off	-6.546e+14	6.57e+06	-9.97e+07	0.000	-6.55e+14	-6.55e+14
Tags_wrong number given	-2.368e+15	1.31e+07	-1.81e+08	0.000	-2.37e+15	-2.37e+15
Lead Profile_Dual Specialization Student	2.013e+15	1.98e+07	1.02e+08	0.000	2.01e+15	2.01e+15
Lead Profile_Lateral Student	1.7e+15	1.85e+07	9.19e+07	0.000	1.7e+15	1.7e+15
Lead Profile_Other Leads	3.806e+14	4.72e+06	8.06e+07	0.000	3.81e+14	3.81e+14
Lead Profile_Potential Lead	2.747e+14	3.31e+06	8.31e+07	0.000	2.75e+14	2.75e+14
Lead Profile_Student of SomeSchool	-1.712e+14	8.49e+06	-2.02e+07	0.000	-1.71e+14	-1.71e+14
What is your current occupation_Businessman	-1.879e+15	3.94e+07	-4.77e+07	0.000	-1.88e+15	-1.88e+15
What is your current occupation_Housewife	3.39e+15	2.81e+07	1.21e+08	0.000	3.39e+15	3.39e+15
What is your current occupation_Other	-1.775e+14	2.2e+07	-8.07e+06	0.000	-1.77e+14	-1.77e+14
What is your current occupation_Student	-5.603e+14	7.31e+06	-7.67e+07	0.000	-5.6e+14	-5.6e+14
What is your current occupation_Unemployed	-6.18e+14	4.2e+06	-1.47e+08	0.000	-6.18e+14	-6.18e+14
What is your current occupation_Working Professional	-5.58e+14	5.63e+06	-9.91e+07	0.000	-5.58e+14	-5.58e+14
Specialization_Banking, Investment And Insurance	3.793e+14	6.85e+06	5.54e+07	0.000	3.79e+14	3.79e+14
Specialization_Business Administration	3.388e+14	6.61e+06	5.13e+07	0.000	3.39e+14	3.39e+14
Specialization_E-Business	3.985e+14	1.28e+07	3.11e+07	0.000	3.98e+14	3.98e+14
Specialization_E-COMMERCE	6.38e+14	9.59e+06	6.65e+07	0.000	6.38e+14	6.38e+14
Specialization_Finance Management	1.588e+14	5.77e+06	2.75e+07	0.000	1.59e+14	1.59e+14
Specialization_Healthcare Management	2.622e+14	9.07e+06	2.89e+07	0.000	2.62e+14	2.62e+14
Specialization_Hospitality Management	1.8e+14	9.34e+06	1.93e+07	0.000	1.8e+14	1.8e+14
Specialization_Human Resource Management	2.464e+14	5.8e+06	4.25e+07	0.000	2.46e+14	2.46e+14
Specialization_IT Projects Management	3.386e+14	6.86e+06	4.94e+07	0.000	3.39e+14	3.39e+14
Specialization_International Business	3.924e+13	8.13e+06	4.83e+06	0.000	3.92e+13	3.92e+13
Specialization_Marketing Management	3.104e+14	5.67e+06	5.47e+07	0.000	3.1e+14	3.1e+14
Specialization_Media and Advertising	-9.269e+13	8.04e+06	-1.15e+07	0.000	-9.27e+13	-9.27e+13
Specialization_Operations Management	2.929e+14	6.26e+06	4.68e+07	0.000	2.93e+14	2.93e+14
Specialization_Retail Management	1.539e+14	1.03e+07	1.5e+07	0.000	1.54e+14	1.54e+14
Specialization_Rural and Agribusiness	5.052e+13	1.16e+07	4.36e+06	0.000	5.05e+13	5.05e+13
Specialization_Select	1.247e+14	4.15e+06	3e+07	0.000	1.25e+14	1.25e+14

Specialization_Services Excellence	7.193e+14	1.52e+07	4.72e+07	0.000	7.19e+14	7.19e+14
Specialization_Supply Chain Management	-6.971e+13	6.9e+06	-1.01e+07	0.000	-6.97e+13	-6.97e+13
Specialization_Travel and Tourism	1.102e+14	8.34e+06	1.32e+07	0.000	1.1e+14	1.1e+14
City_Mumbai	-1.493e+14	4.68e+06	-3.19e+07	0.000	-1.49e+14	-1.49e+14
City_Other Cities	-3.896e+13	5.49e+06	-7.1e+06	0.000	-3.9e+13	-3.9e+13
City_Other Cities of Maharashtra	-9.99e+13	6.07e+06	-1.65e+07	0.000	-9.99e+13	-9.99e+13
City_Other Metro Cities	-8.16e+13	6.28e+06	-1.3e+07	0.000	-8.16e+13	-8.16e+13
City_Thane & Outskirts	-1.486e+14	5.28e+06	-2.81e+07	0.000	-1.49e+14	-1.49e+14
City_Tier II Cities	-3.927e+13	1.05e+07	-3.75e+06	0.000	-3.93e+13	-3.93e+13
Last Activity_Approached upfront	1.845e+15	2.91e+07	6.34e+07	0.000	1.85e+15	1.85e+15
Last Activity_Converted to Lead	-6.011e+13	1.03e+07	-5.83e+06	0.000	-6.01e+13	-6.01e+13
Last Activity_Email Bounced	2.651e+14	1.14e+07	2.33e+07	0.000	2.65e+14	2.65e+14
Last Activity_Email Link Clicked	3.035e+14	1.21e+07	2.5e+07	0.000	3.03e+14	3.03e+14
Last Activity_Email Marked Spam	1.72e+15	2.38e+07	7.23e+07	0.000	1.72e+15	1.72e+15
Last Activity_Email Opened	1.705e+14	9.68e+06	1.76e+07	0.000	1.71e+14	1.71e+14
Last Activity_Email Received	4.438e+15	6.8e+07	6.53e+07	0.000	4.44e+15	4.44e+15
Last Activity_Form Submitted on Website	1.599e+14	1.2e+07	1.33e+07	0.000	1.6e+14	1.6e+14
Last Activity_Had a Phone Conversation	-9.268e+14	2.31e+07	-4.01e+07	0.000	-9.27e+14	-9.27e+14
Last Activity_Olark Chat Conversation	1.663e+13	9.84e+06	1.69e+06	0.000	1.66e+13	1.66e+13
Last Activity_Page Visited on Website	1.353e+14	1.04e+07	1.3e+07	0.000	1.35e+14	1.35e+14
Last Activity_Resubscribed to emails	1.137e+15	3.3e+07	3.44e+07	0.000	1.14e+15	1.14e+15
Last Activity_SMS Sent	5.358e+14	9.72e+06	5.51e+07	0.000	5.36e+14	5.36e+14
Last Activity_Unreachable	3.613e+14	1.39e+07	2.6e+07	0.000	3.61e+14	3.61e+14
Last Activity_Unsubscribed	7.594e+14	2.36e+07	3.22e+07	0.000	7.59e+14	7.59e+14
Last Activity_View in browser link Clicked	-4.255e+14	4.86e+07	-8.75e+06	0.000	-4.26e+14	-4.26e+14
Last Activity_Visited Booth in Tradeshow	0	0	nan	nan	0	0

Step 7: Feature Selection Using RFE

In [85]:

```
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
```

In [86]:

```
from sklearn.feature_selection import RFE
rfe = RFE(logreg, 20)             # running RFE with 20 variables as output
rfe = rfe.fit(X_train, y_train)
```

In [87]:

```
rfe.support_
```

Out[87]:

```
array([False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False,  True,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False,  True, False, False, False, False, False,  True,
        True, False,  True,  True, False, False,  True, False,  True,
       False,  True, False,  True, False,  True, False, False, False,
       False,  True, False,  True,  True,  True,  True,  True, False,
       False, False, False, False, False, False, False, False,  True,
        True, False, False, False, False, False, False, False, False,
```

```
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False,  True, False, False, False, False])
```

In [88]:

```python
list(zip(X_train.columns, rfe.support_, rfe.ranking_))
```

Out[88]:

```
[('Do Not Email', False, 5),
 ('Do Not Call', False, 75),
 ('TotalVisits', False, 58),
 ('Total Time Spent on Website', False, 9),
 ('Page Views Per Visit', False, 55),
 ('Search', False, 22),
 ('Newspaper Article', False, 117),
 ('X Education Forums', False, 116),
 ('Newspaper', False, 122),
 ('Digital Advertisement', False, 91),
 ('Through Recommendations', False, 98),
 ('A free copy of Mastering The Interview', False, 62),
 ('Country_Outside India', False, 84),
 ('Lead Source_Direct Traffic', False, 41),
 ('Lead Source_Facebook', False, 25),
 ('Lead Source_Google', False, 44),
 ('Lead Source_Live Chat', False, 110),
 ('Lead Source_NC_EDM', False, 19),
 ('Lead Source_Olark Chat', False, 8),
 ('Lead Source_Organic Search', False, 42),
 ('Lead Source_Pay per Click Ads', False, 111),
 ('Lead Source_Press_Release', False, 114),
 ('Lead Source_Reference', False, 17),
 ('Lead Source_Referral Sites', False, 43),
 ('Lead Source_Social Media', False, 109),
 ('Lead Source_WeLearn', False, 115),
 ('Lead Source_Welingak Website', True, 1),
 ('Lead Source_bing', False, 90),
 ('Lead Source_blog', False, 118),
 ('Lead Source_google', False, 70),
 ('Lead Source_testone', False, 105),
 ('Lead Source_welearnblog_Home', False, 119),
 ('Lead Source_youtubechannel', False, 81),
 ('Lead Origin_Landing Page Submission', False, 101),
 ('Lead Origin_Lead Add Form', False, 7),
 ('Lead Origin_Lead Import', False, 50),
 ('Lead Origin_Quick Add Form', False, 53),
 ('Last Notable Activity_Email Bounced', False, 47),
 ('Last Notable Activity_Email Link Clicked', False, 26),
 ('Last Notable Activity_Email Marked Spam', False, 80),
 ('Last Notable Activity_Email Opened', False, 103),
 ('Last Notable Activity_Email Received', False, 107),
 ('Last Notable Activity_Form Submitted on Website', False, 120),
 ('Last Notable Activity_Had a Phone Conversation', False, 27),
 ('Last Notable Activity_Modified', False, 2),
 ('Last Notable Activity_Olark Chat Conversation', False, 4),
 ('Last Notable Activity_Page Visited on Website', False, 79),
 ('Last Notable Activity_Resubscribed to emails', False, 93),
 ('Last Notable Activity_SMS Sent', False, 21),
 ('Last Notable Activity_Unreachable', False, 71),
 ('Last Notable Activity_Unsubscribed', False, 46),
 ('Last Notable Activity_View in browser link Clicked', False, 121),
 ('Lead Quality_High in Relevance', False, 52),
 ('Lead Quality_Low in Relevance', False, 85),
 ('Lead Quality_Might be', False, 18),
 ('Lead Quality_Not Sure', False, 106),
 ('Lead Quality_Worst', True, 1),
 ('Asymmetrique Profile Index_01.High', False, 76),
 ('Asymmetrique Profile Index_02.Medium', False, 89),
 ('Asymmetrique Profile Index_03.Low', False, 88),
 ('Asymmetrique Activity Index_01.High', False, 59),
 ('Asymmetrique Activity Index_02.Medium', False, 72),
 ('Asymmetrique Activity Index_03.Low', True, 1),
 ('Tags_Already a student', True, 1),
```

```
('Tags_Busy', False, 34),
('Tags_Closed by Horizzon', True, 1),
('Tags_Diploma holder (Not Eligible)', True, 1),
('Tags_Graduation in progress', False, 11),
('Tags_In confusion whether part time or DLP', False, 10),
('Tags_Interested  in full time MBA', True, 1),
('Tags_Interested in Next batch', False, 49),
('Tags_Interested in other courses', True, 1),
('Tags_Lateral student', False, 45),
('Tags_Lost to EINS', True, 1),
('Tags_Lost to Others', False, 33),
('Tags_Not doing further education', True, 1),
('Tags_Recognition issue (DEC approval)', False, 32),
('Tags_Ringing', True, 1),
('Tags_Shall take in the next coming month', False, 113),
('Tags_Still Thinking', False, 36),
('Tags_University not recognized', False, 82),
('Tags_Want to take admission but has financial problems', False, 48),
('Tags_Will revert after reading the email', True, 1),
('Tags_in touch with EINS', False, 104),
('Tags_invalid number', True, 1),
('Tags_number not provided', True, 1),
('Tags_opp hangup', True, 1),
('Tags_switched off', True, 1),
('Tags_wrong number given', True, 1),
('Lead Profile_Dual Specialization Student', False, 40),
('Lead Profile_Lateral Student', False, 15),
('Lead Profile_Other Leads', False, 37),
('Lead Profile_Potential Lead', False, 23),
('Lead Profile_Student of SomeSchool', False, 60),
('What is your current occupation_Businessman', False, 35),
('What is your current occupation_Housewife', False, 16),
('What is your current occupation_Other', False, 12),
('What is your current occupation_Student', False, 3),
('What is your current occupation_Unemployed', True, 1),
('What is your current occupation_Working Professional', True, 1),
('Specialization_Banking, Investment And Insurance', False, 54),
('Specialization_Business Administration', False, 63),
('Specialization_E-Business', False, 67),
('Specialization_E-COMMERCE', False, 29),
('Specialization_Finance Management', False, 78),
('Specialization_Healthcare Management', False, 87),
('Specialization_Hospitality Management', False, 68),
('Specialization_Human Resource Management', False, 61),
('Specialization_IT Projects Management', False, 56),
('Specialization_International Business', False, 31),
('Specialization_Marketing Management', False, 66),
('Specialization_Media and Advertising', False, 20),
('Specialization_Operations Management', False, 69),
('Specialization_Retail Management', False, 65),
('Specialization_Rural and Agribusiness', False, 112),
('Specialization_Select', False, 24),
('Specialization_Services Excellence', False, 64),
('Specialization_Supply Chain Management', False, 14),
('Specialization_Travel and Tourism', False, 97),
('City_Mumbai', False, 86),
('City_Other Cities', False, 77),
('City_Other Cities of Maharashtra', False, 102),
('City_Other Metro Cities', False, 108),
('City_Thane & Outskirts', False, 83),
('City_Tier II Cities', False, 96),
('Last Activity_Approached upfront', False, 73),
('Last Activity_Converted to Lead', False, 30),
('Last Activity_Email Bounced', False, 38),
('Last Activity_Email Link Clicked', False, 39),
('Last Activity_Email Marked Spam', False, 74),
('Last Activity_Email Opened', False, 95),
('Last Activity_Email Received', False, 100),
('Last Activity_Form Submitted on Website', False, 94),
('Last Activity_Had a Phone Conversation', False, 6),
('Last Activity_Olark Chat Conversation', False, 28),
('Last Activity_Page Visited on Website', False, 57),
('Last Activity_Resubscribed to emails', False, 92),
('Last Activity_SMS Sent', True, 1),
('Last Activity_Unreachable', False, 51),
('Last Activity_Unsubscribed', False, 13),
('Last Activity_View in browser link Clicked', False, 99),
```

```
('Last Activity_Visited Booth in Tradeshow', False, 123)]
```

In [89]:

```
col = X_train.columns[rfe.support_]
col
```

Out[89]:

```
Index(['Lead Source_Welingak Website', 'Lead Quality_Worst',
       'Asymmetrique Activity Index_03.Low', 'Tags_Already a student',
       'Tags_Closed by Horizzon', 'Tags_Diploma holder (Not Eligible)',
       'Tags_Interested  in full time MBA', 'Tags_Interested in other courses',
       'Tags_Lost to EINS', 'Tags_Not doing further education', 'Tags_Ringing',
       'Tags_Will revert after reading the email', 'Tags_invalid number',
       'Tags_number not provided', 'Tags_opp hangup', 'Tags_switched off',
       'Tags_wrong number given', 'What is your current occupation_Unemployed',
       'What is your current occupation_Working Professional',
       'Last Activity_SMS Sent'],
      dtype='object')
```

In [90]:

```
X_train.columns[~rfe.support_]
```

Out[90]:

```
Index(['Do Not Email', 'Do Not Call', 'TotalVisits',
       'Total Time Spent on Website', 'Page Views Per Visit', 'Search',
       'Newspaper Article', 'X Education Forums', 'Newspaper',
       'Digital Advertisement',
       ...
       'Last Activity_Email Received',
       'Last Activity_Form Submitted on Website',
       'Last Activity_Had a Phone Conversation',
       'Last Activity_Olark Chat Conversation',
       'Last Activity_Page Visited on Website',
       'Last Activity_Resubscribed to emails', 'Last Activity_Unreachable',
       'Last Activity_Unsubscribed',
       'Last Activity_View in browser link Clicked',
       'Last Activity_Visited Booth in Tradeshow'],
      dtype='object', length=122)
```

In [91]:

```
X_train_sm = sm.add_constant(X_train[col])
logm2 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm2.fit()
res.summary()
```

Out[91]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6027
Model:	GLM	**Df Residuals:**	6006
Model Family:	Binomial	**Df Model:**	20
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1191.8
Date:	Tue, 12 May 2020	**Deviance:**	2383.6
Time:	14:10:26	**Pearson chi2:**	8.66e+03
No. Iterations:	24		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-2.7110	0.096	-28.118	0.000	-2.900	-2.522
Lead Source_Welingak Website	24.4713	1.82e+04	0.001	0.999	-3.57e+04	3.57e+04

Lead Quality_Worst	-2.5401	0.781	-3.254	0.001	-4.070	-1.010
Asymmetrique Activity Index_03.Low	-2.1743	0.364	-5.969	0.000	-2.888	-1.460
Tags_Already a student	-3.8715	0.729	-5.312	0.000	-5.300	-2.443
Tags_Closed by Horizzon	5.3108	0.723	7.343	0.000	3.893	6.728
Tags_Diploma holder (Not Eligible)	-24.4842	2.88e+04	-0.001	0.999	-5.64e+04	5.64e+04
Tags_Interested in full time MBA	-3.7801	1.031	-3.667	0.000	-5.801	-1.760
Tags_Interested in other courses	-3.0495	0.346	-8.818	0.000	-3.727	-2.372
Tags_Lost to EINS	6.5069	0.810	8.035	0.000	4.920	8.094
Tags_Not doing further education	-3.7519	1.034	-3.627	0.000	-5.779	-1.725
Tags_Ringing	-4.6608	0.279	-16.682	0.000	-5.208	-4.113
Tags_Will revert after reading the email	3.6081	0.192	18.807	0.000	3.232	3.984
Tags_invalid number	-25.6820	2.91e+04	-0.001	0.999	-5.7e+04	5.69e+04
Tags_number not provided	-26.2965	4.89e+04	-0.001	1.000	-9.58e+04	9.58e+04
Tags_opp hangup	-3.5660	1.064	-3.352	0.001	-5.651	-1.481
Tags_switched off	-4.9004	0.600	-8.171	0.000	-6.076	-3.725
Tags_wrong number given	-26.2116	3.61e+04	-0.001	0.999	-7.08e+04	7.07e+04
What is your current occupation_Unemployed	2.2356	0.121	18.461	0.000	1.998	2.473
What is your current occupation_Working Professional	2.0585	0.343	5.994	0.000	1.385	2.732
Last Activity_SMS Sent	2.2508	0.118	19.100	0.000	2.020	2.482

In [92]:

```
# Getting the predicted values on the train set
y_train_pred = res.predict(X_train_sm)
y_train_pred[:10]
```

Out[92]:

```
532     0.000526
7273    0.218047
4998    0.062329
6668    0.005846
2917    0.021581
1668    0.005846
8738    0.066012
1474    0.005846
4583    0.386943
1786    0.855130
dtype: float64
```

In [93]:

```
# reshaping the numpy array containing predicted values
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]
```

Out[93]:

```
array([5.25830490e-04, 2.18047166e-01, 6.23292574e-02, 5.84604584e-03,
       2.15805406e-02, 5.84604584e-03, 6.60121891e-02, 5.84604584e-03,
       3.86943418e-01, 8.55130457e-01])
```

Creating a dataframe with the actual churn flag and the predicted probabilities

In [94]:

```
y_train_pred_final = pd.DataFrame({'Converted':y_train.values, 'Conversion_Prob':y_train_pred})
y_train_pred_final['LeadID'] = y_train.index
y_train_pred_final.head()
```

Out[94]:

	Converted	Conversion_Prob	LeadID
0	0	0.000526	532
1	1	0.218047	7273
2	0	0.062329	4998
3	0	0.005846	6668
4	0	0.021581	2917

Creating new column 'predicted' with 1 if Churn_Prob > 0.5 else 0

In [95]:

```
y_train_pred_final['predicted'] = y_train_pred_final.Conversion_Prob.map(lambda x: 1 if x > 0.5 els
e 0)

# Let's see the head
y_train_pred_final.head()
```

Out[95]:

	Converted	Conversion_Prob	LeadID	predicted
0	0	0.000526	532	0
1	1	0.218047	7273	0
2	0	0.062329	4998	0
3	0	0.005846	6668	0
4	0	0.021581	2917	0

In [96]:

```
from sklearn import metrics
```

Creating Confusion Metrics

In [97]:

```
# Confusion matrix
confusion = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final.predicted )
print(confusion)
```

```
[[3659   85]
 [ 379 1904]]
```

In [98]:

```
# Let's check the overall accuracy.
print(metrics.accuracy_score(y_train_pred_final.Converted, y_train_pred_final.predicted))
```

```
0.9230131076820972
```

Checking VIFs

In [99]:

```
# Check for the VIF values of the feature variables.
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [100]:

```
vif = pd.DataFrame()
```

```
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in range(X_train[col].shape[1
])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

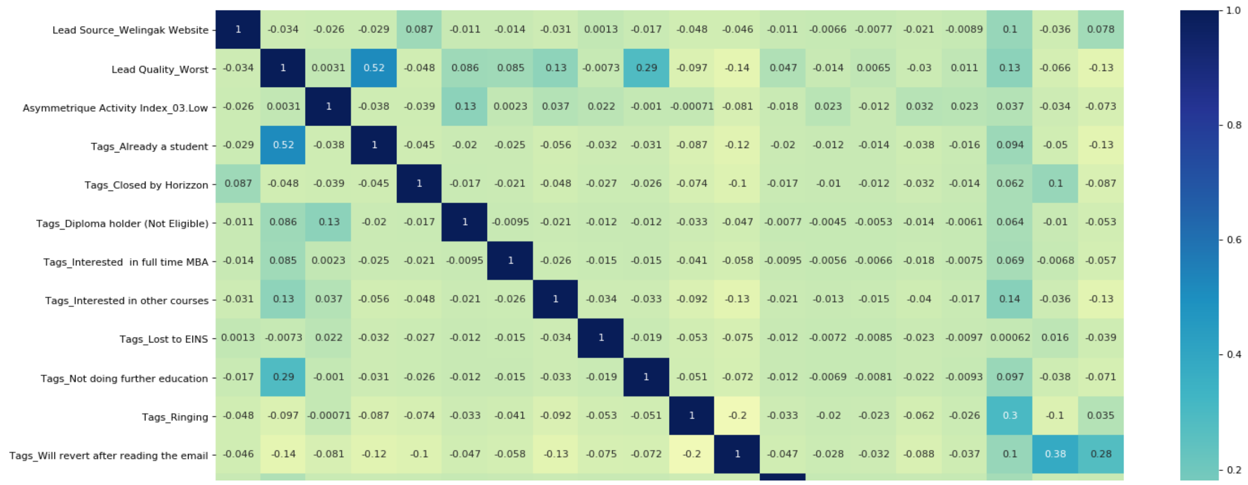
Out[100]:

	Features	VIF
9	Tags_Not doing further education	1.30
4	Tags_Closed by Horizzon	1.28
15	Tags_switched off	1.19
6	Tags_Interested in full time MBA	1.11
0	Lead Source_Welingak Website	1.09
5	Tags_Diploma holder (Not Eligible)	1.09
2	Asymmetrique Activity Index_03.Low	1.07
8	Tags_Lost to EINS	1.07
12	Tags_invalid number	1.07
16	Tags_wrong number given	1.04
14	Tags_opp hangup	1.03
13	Tags_number not provided	1.02
18	What is your current occupation_Working Profes...	0.76
10	Tags_Ringing	0.62
1	Lead Quality_Worst	0.62
7	Tags_Interested in other courses	0.35
3	Tags_Already a student	0.27
11	Tags_Will revert after reading the email	0.13
17	What is your current occupation_Unemployed	0.05
19	Last Activity_SMS Sent	0.01

Clearly there is not much multicollinearity present in our model among the selected features as per their VIF values.

In [101]:

```
# Slightly alter the figure size to make it more horizontal.
plt.figure(figsize=(20,15), dpi=80, facecolor='w', edgecolor='k', frameon='True')

cor = X_train[col].corr()
sns.heatmap(cor, annot=True, cmap="YlGnBu")

plt.tight_layout()
plt.show()
```



Dropping the Variable and Updating the Model

In [102]:

```
col = col.drop('Tags_number not provided', 1)
col
```

Out[102]:

```
Index(['Lead Source_Welingak Website', 'Lead Quality_Worst',
       'Asymmetrique Activity Index_03.Low', 'Tags_Already a student',
       'Tags_Closed by Horizzon', 'Tags_Diploma holder (Not Eligible)',
       'Tags_Interested  in full time MBA', 'Tags_Interested in other courses',
       'Tags_Lost to EINS', 'Tags_Not doing further education', 'Tags_Ringing',
       'Tags_Will revert after reading the email', 'Tags_invalid number',
       'Tags_opp hangup', 'Tags_switched off', 'Tags_wrong number given',
       'What is your current occupation_Unemployed',
       'What is your current occupation_Working Professional',
       'Last Activity_SMS Sent'],
      dtype='object')
```

In [103]:

```
X_train_sm = sm.add_constant(X_train[col])
logm3 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm3.fit()
res.summary()
```

Out[103]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6027
Model:	GLM	**Df Residuals:**	6007
Model Family:	Binomial	**Df Model:**	19
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1207.1
Date:	Tue, 12 May 2020	**Deviance:**	2414.1
Time:	14:10:49	**Pearson chi2:**	8.41e+03
No. Iterations:	24		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-2.6970	0.096	-28.194	0.000	-2.884	-2.510
Lead Source_Welingak Website	24.5357	1.82e+04	0.001	0.999	-3.56e+04	3.57e+04

Lead Source_Welingak Website	24.5557	1.82e+04	0.001	0.999	-3.56e+04	3.57e+04
Lead Quality_Worst	-2.5132	0.781	-3.217	0.001	-4.044	-0.982
Asymmetrique Activity Index_03.Low	-2.1501	0.363	-5.918	0.000	-2.862	-1.438
Tags_Already a student	-3.8057	0.728	-5.224	0.000	-5.233	-2.378
Tags_Closed by Horizzon	5.3495	0.723	7.402	0.000	3.933	6.766
Tags_Diploma holder (Not Eligible)	-24.4179	2.88e+04	-0.001	0.999	-5.65e+04	5.65e+04
Tags_Interested in full time MBA	-3.7095	1.030	-3.602	0.000	-5.728	-1.691
Tags_Interested in other courses	-2.9795	0.345	-8.637	0.000	-3.656	-2.303
Tags_Lost to EINS	6.4945	0.808	8.037	0.000	4.911	8.078
Tags_Not doing further education	-3.6806	1.033	-3.562	0.000	-5.706	-1.655
Tags_Ringing	-4.5710	0.278	-16.432	0.000	-5.116	-4.026
Tags_Will revert after reading the email	3.6473	0.191	19.098	0.000	3.273	4.022
Tags_invalid number	-25.6008	2.91e+04	-0.001	0.999	-5.71e+04	5.7e+04
Tags_opp hangup	-3.4805	1.063	-3.276	0.001	-5.563	-1.398
Tags_switched off	-4.8088	0.599	-8.027	0.000	-5.983	-3.635
Tags_wrong number given	-26.1228	3.61e+04	-0.001	0.999	-7.09e+04	7.08e+04
What is your current occupation_Unemployed	2.1601	0.120	18.073	0.000	1.926	2.394
What is your current occupation_Working Professional	2.0128	0.343	5.863	0.000	1.340	2.686
Last Activity_SMS Sent	2.2159	0.116	19.029	0.000	1.988	2.444

In [104]:

```
# Getting the predicted values on the train set
y_train_pred = res.predict(X_train_sm)
y_train_pred[:10]
```

Out[104]:

```
532     0.000555
7273    0.231508
4998    0.063150
6668    0.006013
2917    0.021590
1668    0.006013
8738    0.063748
1474    0.006013
4583    0.381987
1786    0.842772
dtype: float64
```

In [105]:

```
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]
```

Out[105]:

```
array([5.55160193e-04, 2.31508255e-01, 6.31503774e-02, 6.01278867e-03,
       2.15896301e-02, 6.01278867e-03, 6.37483580e-02, 6.01278867e-03,
       3.81986714e-01, 8.42772091e-01])
```

In [106]:

```
y_train_pred_final = pd.DataFrame({'Converted':y_train.values, 'Conversion_Prob':y_train_pred})
y_train_pred_final['LeadID'] = y_train.index
y_train_pred_final.head()
```

Out[106]:

	Converted	Conversion_Prob	LeadID
0	0	0.000555	532

	Converted	Conversion_Prob	LeadID
1	1	0.231508	7273
2	0	0.063150	4998
3	0	0.006013	6668
4	0	0.021590	2917

In [107]:

```
y_train_pred_final['predicted'] = y_train_pred_final.Conversion_Prob.map(lambda x: 1 if x > 0.5 els
e 0)

# Let's see the head
y_train_pred_final.head()
```

Out[107]:

	Converted	Conversion_Prob	LeadID	predicted
0	0	0.000555	532	0
1	1	0.231508	7273	0
2	0	0.063150	4998	0
3	0	0.006013	6668	0
4	0	0.021590	2917	0

In [108]:

```
from sklearn import metrics
```

In [109]:

```
# Confusion matrix
confusion = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final.predicted )
print(confusion)
```

```
[[3653   91]
 [ 379 1904]]
```

In [110]:

```
# checking accuracy
print(metrics.accuracy_score(y_train_pred_final.Converted, y_train_pred_final.predicted))
```

```
0.922017587522814
```

In [111]:

```
#checking VIFS
```

In [112]:

```
# Check for the VIF values of the feature variables.
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [113]:

```
# Check for the VIF values of the feature variables.
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [114]:

```
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in range(X_train[col].shape[1
])]
```

```
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[114]:

	Features	VIF
9	Tags_Not doing further education	1.30
4	Tags_Closed by Horizzon	1.27
14	Tags_switched off	1.19
6	Tags_Interested in full time MBA	1.11
5	Tags_Diploma holder (Not Eligible)	1.09
0	Lead Source_Welingak Website	1.09
8	Tags_Lost to EINS	1.07
12	Tags_invalid number	1.07
2	Asymmetrique Activity Index_03.Low	1.07
15	Tags_wrong number given	1.04
13	Tags_opp hangup	1.03
17	What is your current occupation_Working Profes...	0.76
1	Lead Quality_Worst	0.62
10	Tags_Ringing	0.62
7	Tags_Interested in other courses	0.35
3	Tags_Already a student	0.27
11	Tags_Will revert after reading the email	0.13
16	What is your current occupation_Unemployed	0.05
18	Last Activity_SMS Sent	0.01

Dropping the Variable and Updating the Model

In [115]:

```
col = col.drop('Tags_wrong number given', 1)
col
```

Out[115]:

```
Index(['Lead Source_Welingak Website', 'Lead Quality_Worst',
       'Asymmetrique Activity Index_03.Low', 'Tags_Already a student',
       'Tags_Closed by Horizzon', 'Tags_Diploma holder (Not Eligible)',
       'Tags_Interested  in full time MBA', 'Tags_Interested in other courses',
       'Tags_Lost to EINS', 'Tags_Not doing further education', 'Tags_Ringing',
       'Tags_Will revert after reading the email', 'Tags_invalid number',
       'Tags_opp hangup', 'Tags_switched off',
       'What is your current occupation_Unemployed',
       'What is your current occupation_Working Professional',
       'Last Activity_SMS Sent'],
      dtype='object')
```

In [116]:

```
X_train_sm = sm.add_constant(X_train[col])
logm4 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm4.fit()
res.summary()
```

Out[116]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6027

Model:	GLM	**Df Residuals:**	6008
Model Family:	Binomial	**Df Model:**	18
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1231.5
Date:	Tue, 12 May 2020	**Deviance:**	2463.0
Time:	14:11:06	**Pearson chi2:**	8.27e+03
No. Iterations:	24		
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-2.6743	0.094	-28.305	0.000	-2.860	-2.489
Lead Source_Welingak Website	24.6354	1.81e+04	0.001	0.999	-3.55e+04	3.56e+04
Lead Quality_Worst	-2.7836	0.746	-3.731	0.000	-4.246	-1.321
Asymmetrique Activity Index_03.Low	-2.1120	0.363	-5.822	0.000	-2.823	-1.401
Tags_Already a student	-3.6755	0.726	-5.061	0.000	-5.099	-2.252
Tags_Closed by Horizzon	5.4132	0.722	7.499	0.000	3.998	6.828
Tags_Diploma holder (Not Eligible)	-24.2953	2.87e+04	-0.001	0.999	-5.64e+04	5.63e+04
Tags_Interested in full time MBA	-3.5914	1.029	-3.492	0.000	-5.607	-1.576
Tags_Interested in other courses	-2.8655	0.344	-8.340	0.000	-3.539	-2.192
Tags_Lost to EINS	6.5838	0.821	8.020	0.000	4.975	8.193
Tags_Not doing further education	-3.5410	1.032	-3.432	0.001	-5.563	-1.519
Tags_Ringing	-4.4302	0.276	-16.035	0.000	-4.972	-3.889
Tags_Will revert after reading the email	3.7114	0.190	19.555	0.000	3.339	4.083
Tags_invalid number	-25.4580	2.91e+04	-0.001	0.999	-5.7e+04	5.7e+04
Tags_opp hangup	-3.3387	1.061	-3.146	0.002	-5.418	-1.259
Tags_switched off	-4.6642	0.598	-7.799	0.000	-5.836	-3.492
What is your current occupation_Unemployed	2.0429	0.117	17.435	0.000	1.813	2.273
What is your current occupation_Working Professional	1.9381	0.343	5.648	0.000	1.266	2.611
Last Activity_SMS Sent	2.1585	0.114	18.900	0.000	1.935	2.382

In [117]:

```
# Getting the predicted values on the train set
y_train_pred = res.predict(X_train_sm)
y_train_pred[:10]
```

Out[117]:

```
532     0.000606
7273    0.254467
4998    0.064504
6668    0.006295
2917    0.015951
1668    0.006295
8738    0.060456
1474    0.006295
4583    0.373826
1786    0.821572
dtype: float64
```

In [118]:

```
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]
```

Out[118]:

```
array([6.06178975e-04, 2.54466917e-01, 6.45040056e-02, 6.29484356e-03,
```

```
1.59513246e-02, 6.29484356e-03, 6.04559779e-02, 6.29484356e-03,
3.73826433e-01, 8.21571534e-01])
```

Creating a dataframe with the actual churn flag and the predicted probabilities

In [119]:

```
y_train_pred_final = pd.DataFrame({'Converted':y_train.values, 'Conversion_Prob':y_train_pred})
y_train_pred_final['LeadID'] = y_train.index
y_train_pred_final.head()
```

Out[119]:

	Converted	Conversion_Prob	LeadID
0	0	0.000606	532
1	1	0.254467	7273
2	0	0.064504	4998
3	0	0.006295	6668
4	0	0.015951	2917

In [120]:

```
y_train_pred_final['predicted'] = y_train_pred_final.Conversion_Prob.map(lambda x: 1 if x > 0.5 els
e 0)

# Let's see the head
y_train_pred_final.head()
```

Out[120]:

	Converted	Conversion_Prob	LeadID	predicted
0	0	0.000606	532	0
1	1	0.254467	7273	0
2	0	0.064504	4998	0
3	0	0.006295	6668	0
4	0	0.015951	2917	0

In [121]:

```
from sklearn import metrics
```

In [122]:

```
# Confusion matrix
confusion = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final.predicted )
print(confusion)
```

```
[[3643  101]
 [ 379 1904]]
```

In [123]:

```
print(metrics.accuracy_score(y_train_pred_final.Converted, y_train_pred_final.predicted))
```

```
0.920358387257342
```

In [124]:

```
# checking VIFs
```

In [125]:

```
# Check for the VIF values of the feature variables.
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [126]:

```
# Create a dataframe that will contain the names of all the feature variables and their respective
VIFs
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in range(X_train[col].shape[1
])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[126]:

	Features	VIF
9	Tags_Not doing further education	1.29
4	Tags_Closed by Horizzon	1.27
14	Tags_switched off	1.18
6	Tags_Interested in full time MBA	1.10
5	Tags_Diploma holder (Not Eligible)	1.09
0	Lead Source_Welingak Website	1.09
8	Tags_Lost to EINS	1.07
2	Asymmetrique Activity Index_03.Low	1.07
12	Tags_invalid number	1.06
13	Tags_opp hangup	1.03
16	What is your current occupation_Working Profes...	0.75
1	Lead Quality_Worst	0.62
10	Tags_Ringing	0.61
7	Tags_Interested in other courses	0.34
3	Tags_Already a student	0.27
11	Tags_Will revert after reading the email	0.13
15	What is your current occupation_Unemployed	0.05
17	Last Activity_SMS Sent	0.01

Dropping the Variable and Updating the Model

In [127]:

```
col = col.drop('Tags_Diploma holder (Not Eligible)', 1)
col
```

Out[127]:

```
Index(['Lead Source_Welingak Website', 'Lead Quality_Worst',
       'Asymmetrique Activity Index_03.Low', 'Tags_Already a student',
       'Tags_Closed by Horizzon', 'Tags_Interested  in full time MBA',
       'Tags_Interested in other courses', 'Tags_Lost to EINS',
       'Tags_Not doing further education', 'Tags_Ringing',
       'Tags_Will revert after reading the email', 'Tags_invalid number',
       'Tags_opp hangup', 'Tags_switched off',
       'What is your current occupation_Unemployed',
       'What is your current occupation_Working Professional',
       'Last Activity_SMS Sent'],
      dtype='object')
```

In [128]:

```
X_train_sm = sm.add_constant(X_train[col])
logm5 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm5.fit()
res.summary()
```

Out[128]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6027
Model:	GLM	**Df Residuals:**	6009
Model Family:	Binomial	**Df Model:**	17
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1242.1
Date:	Tue, 12 May 2020	**Deviance:**	2484.2
Time:	14:11:21	**Pearson chi2:**	8.44e+03
No. Iterations:	24		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-2.6894	0.095	-28.372	0.000	-2.875	-2.504
Lead Source_Welingak Website	24.6893	1.8e+04	0.001	0.999	-3.53e+04	3.54e+04
Lead Quality_Worst	-2.9241	0.719	-4.066	0.000	-4.334	-1.515
Asymmetrique Activity Index_03.Low	-2.1621	0.358	-6.044	0.000	-2.863	-1.461
Tags_Already a student	-3.5997	0.726	-4.959	0.000	-5.022	-2.177
Tags_Closed by Horizzon	5.4708	0.721	7.583	0.000	4.057	6.885
Tags_Interested in full time MBA	-3.5260	1.029	-3.427	0.001	-5.543	-1.509
Tags_Interested in other courses	-2.8012	0.344	-8.153	0.000	-3.475	-2.128
Tags_Lost to EINS	6.6867	0.828	8.077	0.000	5.064	8.309
Tags_Not doing further education	-3.4678	1.032	-3.360	0.001	-5.491	-1.445
Tags_Ringing	-4.3795	0.276	-15.870	0.000	-4.920	-3.839
Tags_Will revert after reading the email	3.7670	0.189	19.900	0.000	3.396	4.138
Tags_invalid number	-25.3999	2.91e+04	-0.001	0.999	-5.7e+04	5.7e+04
Tags_opp hangup	-3.2823	1.062	-3.091	0.002	-5.364	-1.201
Tags_switched off	-4.6146	0.598	-7.717	0.000	-5.787	-3.443
What is your current occupation_Unemployed	1.9864	0.116	17.063	0.000	1.758	2.215
What is your current occupation_Working Professional	1.8979	0.343	5.539	0.000	1.226	2.569
Last Activity_SMS Sent	2.1844	0.114	19.196	0.000	1.961	2.407

In [129]:

```
y_train_pred = res.predict(X_train_sm)
y_train_pred[:10]
```

Out[129]:

```
532     0.000564
7273    0.252655
4998    0.063603
6668    0.006166
2917    0.014149
1668    0.006166
8738    0.053905
1474    0.006166
4583    0.376377
1786    0.814791
dtype: float64
```

In [130]:

```
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]
```

Out[130]:

```
array([5.64116029e-04, 2.52654814e-01, 6.36031744e-02, 6.16642865e-03,
       1.41488237e-02, 6.16642865e-03, 5.39050207e-02, 6.16642865e-03,
       3.76377353e-01, 8.14791052e-01])
```

Creating a dataframe with the actual churn flag and the predicted probabilities

In [131]:

```
y_train_pred_final = pd.DataFrame({'Converted':y_train.values, 'Conversion_Prob':y_train_pred})
y_train_pred_final['LeadID'] = y_train.index
y_train_pred_final.head()
```

Out[131]:

	Converted	Conversion_Prob	LeadID
0	0	0.000564	532
1	1	0.252655	7273
2	0	0.063603	4998
3	0	0.006166	6668
4	0	0.014149	2917

In [132]:

```
y_train_pred_final['predicted'] = y_train_pred_final.Conversion_Prob.map(lambda x: 1 if x > 0.5 els
e 0)

# Let's see the head
y_train_pred_final.head()
```

Out[132]:

	Converted	Conversion_Prob	LeadID	predicted
0	0	0.000564	532	0
1	1	0.252655	7273	0
2	0	0.063603	4998	0
3	0	0.006166	6668	0
4	0	0.014149	2917	0

In [133]:

```
from sklearn import metrics
```

In [134]:

```
# Confusion matrix
confusion = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final.predicted )
print(confusion)
```

```
[[3642  102]
 [ 379 1904]]
```

In [135]:

```
print(metrics.accuracy_score(y_train_pred_final.Converted, y_train_pred_final.predicted))
```

```
0.9201924672307947
```

In [136]:

```
# checking VIFs
```

In [137]:

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [138]:

```
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in range(X_train[col].shape[1
])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[138]:

	Features	VIF
8	Tags_Not doing further education	1.27
4	Tags_Closed by Horizzon	1.26
13	Tags_switched off	1.17
5	Tags_Interested in full time MBA	1.10
0	Lead Source_Welingak Website	1.09
7	Tags_Lost to EINS	1.07
11	Tags_invalid number	1.06
2	Asymmetrique Activity Index_03.Low	1.06
12	Tags_opp hangup	1.03
15	What is your current occupation_Working Profes...	0.74
1	Lead Quality_Worst	0.61
9	Tags_Ringing	0.59
6	Tags_Interested in other courses	0.34
3	Tags_Already a student	0.27
10	Tags_Will revert after reading the email	0.12
14	What is your current occupation_Unemployed	0.05
16	Last Activity_SMS Sent	0.01

Dropping the Variable and Updating the Model

In [139]:

```
col = col.drop('Tags_invalid number', 1)
col
```

Out[139]:

```
Index(['Lead Source_Welingak Website', 'Lead Quality_Worst',
       'Asymmetrique Activity Index_03.Low', 'Tags_Already a student',
       'Tags_Closed by Horizzon', 'Tags_Interested  in full time MBA',
       'Tags_Interested in other courses', 'Tags_Lost to EINS',
       'Tags_Not doing further education', 'Tags_Ringing',
       'Tags_Will revert after reading the email', 'Tags_opp hangup',
       'Tags_switched off', 'What is your current occupation_Unemployed',
       'What is your current occupation_Working Professional',
       'Last Activity_SMS Sent'],
      dtype='object')
```

In [140]:

```
X_train_sm = sm.add_constant(X_train[col])
logm6 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm6.fit()
res.summary()
```

Out[140]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6027
Model:	GLM	**Df Residuals:**	6010
Model Family:	Binomial	**Df Model:**	16
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1265.8
Date:	Tue, 12 May 2020	**Deviance:**	2531.7
Time:	14:11:33	**Pearson chi2:**	8.61e+03
No. Iterations:	24		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-2.6909	0.094	-28.496	0.000	-2.876	-2.506
Lead Source_Welingak Website	24.7961	1.79e+04	0.001	0.999	-3.51e+04	3.51e+04
Lead Quality_Worst	-3.2138	0.684	-4.697	0.000	-4.555	-1.873
Asymmetrique Activity Index_03.Low	-2.0944	0.360	-5.812	0.000	-2.801	-1.388
Tags_Already a student	-3.4637	0.725	-4.776	0.000	-4.885	-2.042
Tags_Closed by Horizzon	5.5620	0.721	7.716	0.000	4.149	6.975
Tags_Interested in full time MBA	-3.4031	1.029	-3.308	0.001	-5.419	-1.387
Tags_Interested in other courses	-2.6811	0.343	-7.820	0.000	-3.353	-2.009
Tags_Lost to EINS	6.8217	0.844	8.078	0.000	5.167	8.477
Tags_Not doing further education	-3.3294	1.032	-3.226	0.001	-5.352	-1.307
Tags_Ringing	-4.2552	0.275	-15.492	0.000	-4.794	-3.717
Tags_Will revert after reading the email	3.8503	0.188	20.450	0.000	3.481	4.219
Tags_opp hangup	-3.1537	1.062	-2.970	0.003	-5.235	-1.072
Tags_switched off	-4.4896	0.597	-7.516	0.000	-5.660	-3.319
What is your current occupation_Unemployed	1.8699	0.114	16.332	0.000	1.645	2.094
What is your current occupation_Working Professional	1.8215	0.343	5.307	0.000	1.149	2.494
Last Activity_SMS Sent	2.1762	0.112	19.402	0.000	1.956	2.396

In [141]:

```
y_train_pred = res.predict(X_train_sm)
y_train_pred[:10]
```

Out[141]:

```
532     0.000608
7273    0.281919
4998    0.063514
6668    0.006205
2917    0.010564
1668    0.006205
8738    0.051400
1474    0.006205
4583    0.374088
1786    0.794975
dtype: float64
```

In [142]:

```
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]
```

Out[142]:

```
array([6.07886214e-04, 2.81918507e-01, 6.35140356e-02, 6.20488694e-03,
       1.05638139e-02, 6.20488694e-03, 5.14002613e-02, 6.20488694e-03,
       3.74087585e-01, 7.94974829e-01])
```

In [143]:

```
y_train_pred_final = pd.DataFrame({'Converted':y_train.values, 'Conversion_Prob':y_train_pred})
y_train_pred_final['LeadID'] = y_train.index
y_train_pred_final.head()
```

Out[143]:

	Converted	Conversion_Prob	LeadID
0	0	0.000608	532
1	1	0.281919	7273
2	0	0.063514	4998
3	0	0.006205	6668
4	0	0.010564	2917

In [144]:

```
y_train_pred_final['predicted'] = y_train_pred_final.Conversion_Prob.map(lambda x: 1 if x > 0.5 els
e 0)

# Let's see the head
y_train_pred_final.head()
```

Out[144]:

	Converted	Conversion_Prob	LeadID	predicted
0	0	0.000608	532	0
1	1	0.281919	7273	0
2	0	0.063514	4998	0
3	0	0.006205	6668	0
4	0	0.010564	2917	0

In [145]:

```
from sklearn import metrics
```

In [146]:

```
confusion = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final.predicted )
print(confusion)
```

```
[[3636  108]
 [ 379 1904]]
```

In [147]:

```
print(metrics.accuracy_score(y_train_pred_final.Converted, y_train_pred_final.predicted))
```

```
0.9191969470715116
```

In [148]:

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [149]:

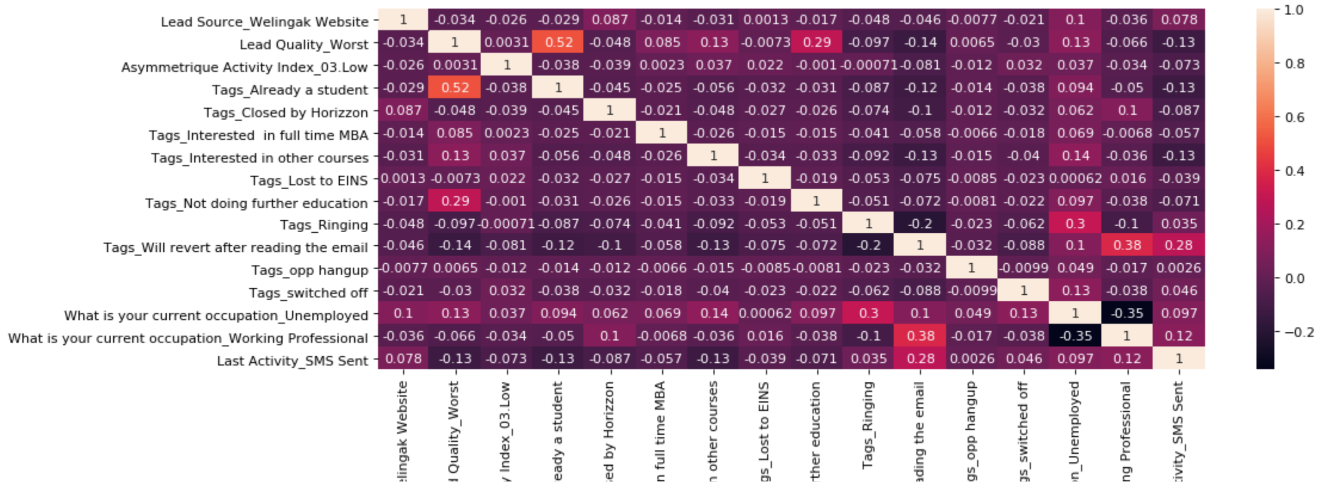
```
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in range(X_train[col].shape[1
])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

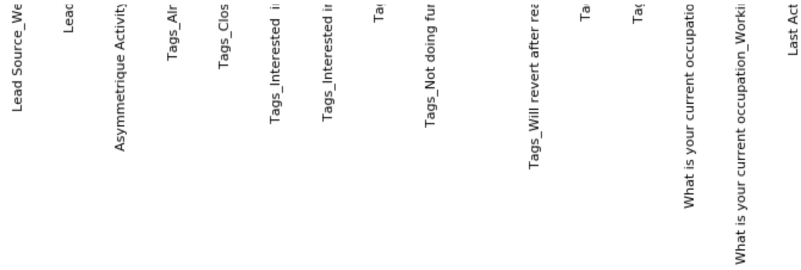
Out[149]:

	Features	VIF
8	Tags_Not doing further education	1.26
4	Tags_Closed by Horizzon	1.25
12	Tags_switched off	1.17
5	Tags_Interested in full time MBA	1.09
0	Lead Source_Welingak Website	1.08
7	Tags_Lost to EINS	1.06
2	Asymmetrique Activity Index_03.Low	1.05
11	Tags_opp hangup	1.02
14	What is your current occupation_Working Profes...	0.73
1	Lead Quality_Worst	0.61
9	Tags_Ringing	0.58
6	Tags_Interested in other courses	0.33
3	Tags_Already a student	0.26
10	Tags_Will revert after reading the email	0.12
13	What is your current occupation_Unemployed	0.05
15	Last Activity_SMS Sent	0.01

In [150]:

```
plt.figure(figsize=(15,8), dpi=80, facecolor='w', edgecolor='k', frameon='True')

cor = X_train[col].corr()
sns.heatmap(cor, annot=True)

plt.tight_layout()
plt.show()
```





Step 8: Calculating Metrics beyond Accuracy

In [151]:

```
TP = confusion[1,1]
TN = confusion[0,0]
FP = confusion[0,1]
FN = confusion[1,0]
```

In [152]:

```
TP / float(TP+FN)
```

Out[152]:

```
0.8339903635567236
```

In [153]:

```
TN / float(TN+FP)
```

Out[153]:

```
0.9711538461538461
```

In [154]:

```
print(FP/ float(TN+FP))
print (TP / float(TP+FP))
print (TN / float(TN+ FN))
```

```
0.028846153846153848
0.9463220675944334
0.9056039850560399
```

Step 9: Plotting the ROC Curve

It shows the tradeoff between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in specificity).

The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test.

The closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test.

In [155]:

```
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
                                              drop_intermediate = False )
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(5, 5))
    plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % auc_score )
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
```

```
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()

    return fpr,tpr, thresholds
```

In [156]:

```
fpr, tpr, thresholds = metrics.roc_curve( y_train_pred_final.Converted, y_train_pred_final.Conversi
on_Prob, drop_intermediate = False )
```

draw_roc(y_train_pred_final.Converted, y_train_pred_final.Conversion_Prob)

Calculating the area under the curve

In [157]:

```
def auc_val(fpr,tpr):
    AreaUnderCurve = 0.
    for i in range(len(fpr)-1):
        AreaUnderCurve += (fpr[i+1]-fpr[i]) * (tpr[i+1]+tpr[i])
    AreaUnderCurve *= 0.5
    return AreaUnderCurve
```

In [158]:

```
auc = auc_val(fpr,tpr)
auc
```

Out[158]:

```
0.9668445421566313
```

Step 10: Finding Optimal Cutoff Point

optimal cutoff meand the probability of sensitivity and specificity

In [159]:

```
numbers = [float(x)/10 for x in range(10)]
for i in numbers:
    y_train_pred_final[i]= y_train_pred_final.Conversion_Prob.map(lambda x: 1 if x > i else 0)
y_train_pred_final.head()
```

Out[159]:

	Converted	Conversion_Prob	LeadID	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	0	0.000608	532	0	1	0	0	0	0	0	0	0	0	0
1	1	0.281919	7273	0	1	1	1	0	0	0	0	0	0	0
2	0	0.063514	4998	0	1	0	0	0	0	0	0	0	0	0
3	0	0.006205	6668	0	1	0	0	0	0	0	0	0	0	0
4	0	0.010564	2917	0	1	0	0	0	0	0	0	0	0	0

In [160]:

```
cutoff_df = pd.DataFrame( columns = ['prob','accuracy','sensi','speci'])
from sklearn.metrics import confusion_matrix
```

In [161]:

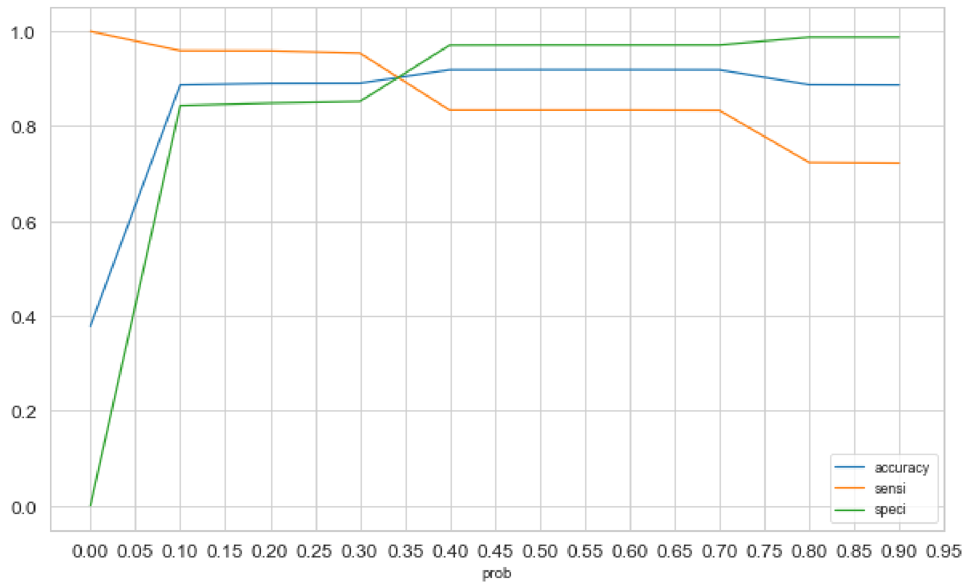
```
num = [0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9]
for i in num:
    cm1 = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final[i] )
```

```
    cm1 = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final[i] )
    total1=sum(sum(cm1))
    accuracy = (cm1[0,0]+cm1[1,1])/total1

    speci = cm1[0,0]/(cm1[0,0]+cm1[0,1])
    sensi = cm1[1,1]/(cm1[1,0]+cm1[1,1])
    cutoff_df.loc[i] =[ i ,accuracy,sensi,speci]
print(cutoff_df)
```

```
     prob  accuracy     sensi     speci
0.0   0.0  0.378795  1.000000  0.000000
0.1   0.1  0.887340  0.959264  0.843483
0.2   0.2  0.890493  0.958826  0.848825
0.3   0.3  0.890825  0.954008  0.852297
0.4   0.4  0.919031  0.833990  0.970887
0.5   0.5  0.919197  0.833990  0.971154
0.6   0.6  0.919197  0.833990  0.971154
0.7   0.7  0.919031  0.833552  0.971154
0.8   0.8  0.887672  0.723609  0.987714
0.9   0.9  0.887174  0.722295  0.987714
```

In [162]:

```
sns.set_style("whitegrid") # white/whitegrid/dark/ticks
sns.set_context("paper") # talk/poster
cutoff_df.plot.line(x='prob', y=['accuracy','sensi','speci'], figsize=(10,6))
# plot x axis limits
plt.xticks(np.arange(0, 1, step=0.05), size = 12)
plt.yticks(size = 12)
plt.show()
```



In [163]:

```
y_train_pred_final.head()
```

Out[163]:

	Converted	Conversion_Prob	LeadID	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	0	0.000608	532	0	1	0	0	0	0	0	0	0	0	0
1	1	0.281919	7273	0	1	1	1	0	0	0	0	0	0	0
2	0	0.063514	4998	0	1	0	0	0	0	0	0	0	0	0
3	0	0.006205	6668	0	1	0	0	0	0	0	0	0	0	0
4	0	0.010564	2917	0	1	0	0	0	0	0	0	0	0	0

In [164]:

```
y_train_pred_final['final_predicted'] = y_train_pred_final.Conversion_Prob.map( lambda x: 1 if x >
```

```
y_train_pred_final['final_predicted'] = y_train_pred_final.Conversion_Prob.map( lambda x: 1 if x > 0.33 else 0)

y_train_pred_final.head()
```

Out[164]:

	Converted	Conversion_Prob	LeadID	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	final_predicted
0	0	0.000608	532	0	1	0	0	0	0	0	0	0	0	0	0
1	1	0.281919	7273	0	1	1	1	0	0	0	0	0	0	0	0
2	0	0.063514	4998	0	1	0	0	0	0	0	0	0	0	0	0
3	0	0.006205	6668	0	1	0	0	0	0	0	0	0	0	0	0
4	0	0.010564	2917	0	1	0	0	0	0	0	0	0	0	0	0

In [165]:

```
# Let's check the overall accuracy.
metrics.accuracy_score(y_train_pred_final.Converted, y_train_pred_final.final_predicted)
```

Out[165]:

```
0.9080803052928489
```

In [166]:

```
confusion1 = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final.final_predicted)
confusion1
```

Out[166]:

```
array([[3433,  311],
       [ 243, 2040]], dtype=int64)
```

In [167]:

```
TP = confusion1[1,1]
TN = confusion1[0,0]
FP = confusion1[0,1]
FN = confusion1[1,0]
```

In [168]:

```
TP / float(TP+FN)
```

Out[168]:

```
0.8935611038107752
```

In [169]:

```
TP / float(TP+FN)
```

Out[169]:

```
0.8935611038107752
```

In [170]:

```
print(FP/ float(TN+FP))
```

```
0.08306623931623931
```

In [171]:

```python
print (TP / float(TP+FP))
```

```
0.8677158655891111
```

In [172]:

```python
print (TN / float(TN+ FN))
```

```
0.9338955386289445
```

Step 11: Precision and Recall

Precision TP / TP + FP

In [173]:

```python
precision = confusion1[1,1]/(confusion1[0,1]+confusion1[1,1])
precision
```

Out[173]:

```
0.8677158655891111
```

Recall TP / TP + FN

In [174]:

```python
recall = confusion1[1,1]/(confusion1[1,0]+confusion1[1,1])
recall
```

Out[174]:

```
0.8935611038107752
```

In [175]:

```python
from sklearn.metrics import precision_score, recall_score
```

In [176]:

```python
precision_score(y_train_pred_final.Converted, y_train_pred_final.final_predicted)
```

Out[176]:

```
0.8677158655891111
```

In [177]:

```python
recall_score(y_train_pred_final.Converted, y_train_pred_final.final_predicted)
```

Out[177]:

```
0.8935611038107752
```

Precision and recall tradeoff

In [178]:

```python
from sklearn.metrics import precision_recall_curve
```

In [179]:

```
y_train_pred_final.Converted, y_train_pred_final.final_predicted
```

Out[179]:

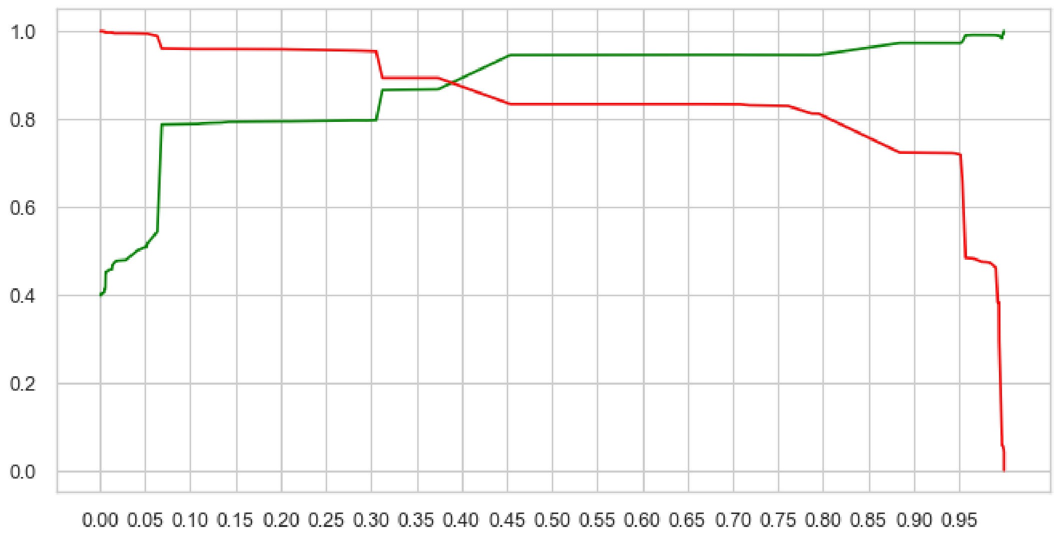
```
(0       0
 1       1
 2       0
 3       0
 4       0
        ..
 6022    0
 6023    0
 6024    0
 6025    0
 6026    1
 Name: Converted, Length: 6027, dtype: int64,
 0       0
 1       0
 2       0
 3       0
 4       0
        ..
 6022    0
 6023    0
 6024    1
 6025    0
 6026    0
 Name: final_predicted, Length: 6027, dtype: int64)
```

In [180]:

```
p, r, thresholds = precision_recall_curve(y_train_pred_final.Converted, y_train_pred_final.Conversi
on_Prob)
```

In [181]:

```
plt.figure(figsize=(8, 4), dpi=100, facecolor='w', edgecolor='k', frameon='True')
plt.plot(thresholds, p[:-1], "g-")
plt.plot(thresholds, r[:-1], "r-")
plt.xticks(np.arange(0, 1, step=0.05))
plt.show()
```



From the precision-recall graph above, we get the optical threshold value as close to .37. However our business requirement here is to have Lead Conversion Rate around 80%

Calculating the F1 score

In [182]:

```
F1 = 2*(precision*recall)/(precision+recall)
```

```
F1 = 2*(precision*recall)/(precision+recall)
F1
```

Out[182]:

0.8804488562796721

Step 12: Making predictions on the test set

In [183]:

```
X_test[['TotalVisits','Total Time Spent on Website','Page Views Per Visit']] = scaler.transform(X_
test[['TotalVisits','Total Time Spent on Website','Page Views Per Visit']])
X_test.head()
```

Out[183]:

	Do Not Email	Do Not Call	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Search	Newspaper Article	X Education Forums	Newspaper	Digital Advertisement	...	Last Activity_Form Submitted on Website	Acti Conv
376	0	0	0.538134	-0.184951	1.180749	0	0	0	0	0	...	0	
8914	0	0	-0.326064	-0.866444	-0.040895	0	0	0	0	0	...	0	
7331	0	0	0.106035	-0.210737	0.569927	0	0	0	0	0	...	0	
6344	0	0	-0.326064	1.124622	-0.040895	0	0	0	0	0	...	0	
3783	0	0	2.698630	-0.126011	0.569927	0	0	0	0	0	...	0	

5 rows × 142 columns

In [184]:

```
X_test = X_test[col]
X_test.head()
```

Out[184]:

	Lead Source_Welingak Website	Lead Quality_Worst	Asymmetrique Activity Index_03.Low	Tags_Already a student	Tags_Closed by Horizzon	Tags_Interested in full time MBA	Tags_Interested in other courses	Tags_Lost to EINS	Tags d fu educa
376	0	0	0	0	0	0	0	0	
8914	0	1	0	1	0	0	0	0	
7331	0	0	0	0	0	0	0	0	
6344	0	0	0	0	0	0	0	0	
3783	0	0	0	0	0	0	0	0	

In [185]:

```
X_test_sm = sm.add_constant(X_test)
```

In [186]:

```
y_test_pred = res.predict(X_test_sm)
```

In [187]:

```
y_test_pred[:10]
```

Out[187]:

```
376     0.063514
8914    0.000554
7331    0.006205
6344    0.063514
3783    0.305557
4783    0.006205
3789    0.997529
185     0.029253
4116    0.951703
8622    0.984185
dtype: float64
```

In [188]:

```
y_pred_1 = pd.DataFrame(y_test_pred)
y_pred_1.head()
```

Out[188]:

	0
376	0.063514
8914	0.000554
7331	0.006205
6344	0.063514
3783	0.305557

In [189]:

```
y_test_df = pd.DataFrame(y_test)
y_test_df['LeadID'] = y_test_df.index
y_pred_1.reset_index(drop=True, inplace=True)
y_test_df.reset_index(drop=True, inplace=True)
y_pred_final = pd.concat([y_test_df, y_pred_1],axis=1)
y_pred_final.head()
```

Out[189]:

	Converted	LeadID	0
0	0	376	0.063514
1	0	8914	0.000554
2	0	7331	0.006205
3	1	6344	0.063514
4	0	3783	0.305557

In [190]:

```
y_pred_final= y_pred_final.rename(columns={ 0 : 'Conversion_Prob'})
```

In [191]:

```
y_pred_final.head()
```

Out[191]:

	Converted	LeadID	Conversion_Prob
0	0	376	0.063514
1	0	8914	0.000554
2	0	7331	0.006205
3	1	6344	0.063514

	Converted	LeadID	Conversion_Prob
4	0	3783	0.305557

In [192]:

```
y_pred_final.shape
```

Out[192]:

```
(2584, 3)
```

In [193]:

```
y_pred_final['final_predicted'] = y_pred_final.Conversion_Prob.map(lambda x: 1 if x > 0.33 else 0)
```

In [194]:

```
y_pred_final.head()
```

Out[194]:

	Converted	LeadID	Conversion_Prob	final_predicted
0	0	376	0.063514	0
1	0	8914	0.000554	0
2	0	7331	0.006205	0
3	1	6344	0.063514	0
4	0	3783	0.305557	0

In [195]:

```
acc_score=metrics.accuracy_score(y_pred_final.Converted, y_pred_final.final_predicted)
acc_score
```

Out[195]:

```
0.8947368421052632
```

In [196]:

```
confusion_test = metrics.confusion_matrix(y_pred_final.Converted, y_pred_final.final_predicted )
print(confusion_test)
```

```
[[1434  142]
 [ 130  878]]
```

Confusion Matrix in Visuals

In [197]:

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import metrics
```

In [198]:

```
TP / float(TP+FN)
```

Out[198]:

```
0.8935611038107752
```

Specificity TN / TN + FP

Specificity TN / TN + FP

In [199]:

```
TN / float(TN+FP)
```

Out[199]:

```
0.9169337606837606
```

False Postive Rate FP / TN + FP

In [200]:

```
print(FP/ float(TN+FP))
```

```
0.08306623931623931
```

Positive Predictive Value TP / TP + FP

In [201]:

```
print (TP / float(TP+FP))
```

```
0.8677158655891111
```

Negative Predictive Value TN / TN + FN

In [202]:

```
print (TN / float(TN+ FN))
```

```
0.9338955386289445
```

Precision TP / TP + FP

In [203]:

```
Precision = confusion_test[1,1]/(confusion_test[0,1]+confusion_test[1,1])
Precision
```

Out[203]:

```
0.8607843137254902
```

Recall TP / TP + FN

In [204]:

```
Recall = confusion_test[1,1]/(confusion_test[1,0]+confusion_test[1,1])
Recall
```

Out[204]:

```
0.871031746031746
```

In [205]:

```
F1 = 2*(Precision*Recall)/(Precision+Recall)
F1
```

Out[205]:

```
0.8658777120315583
```

In [206]:

```
from sklearn.metrics import classification_report
print(classification_report(y_pred_final.Converted, y_pred_final.final_predicted))
```

```
              precision    recall  f1-score   support

           0       0.92      0.91      0.91      1576
           1       0.86      0.87      0.87      1008

    accuracy                           0.89      2584
   macro avg       0.89      0.89      0.89      2584
weighted avg       0.89      0.89      0.89      2584
```

In [207]:

```
from sklearn.model_selection import cross_val_score

lr = LogisticRegression(solver = 'lbfgs')
scores = cross_val_score(lr, X, y, cv=10)
scores.sort()
accuracy = scores.mean()

print(scores)
print(accuracy)
```

```
[0.84320557 0.90940767 0.91521487 0.91637631 0.92450639 0.92682927
 0.92799071 0.92799071 0.93271462 0.93379791]
0.9158034013220477
```

Plotting the ROC Curve for Test Dataset

In [208]:

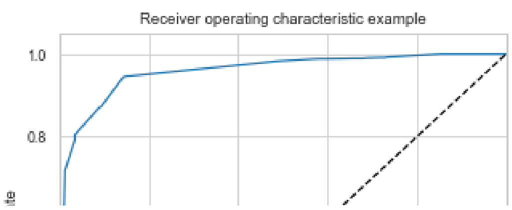
```
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
                                              drop_intermediate = False )
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(5, 5))
    plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % auc_score )
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()

    return fpr,tpr, thresholds
```

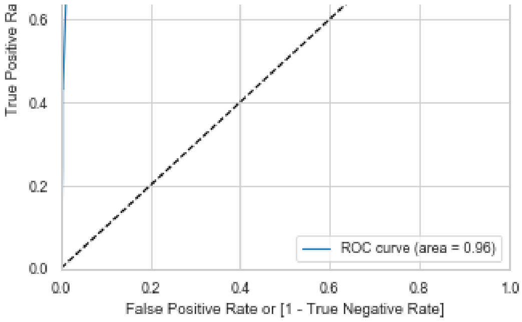
In [209]:

```
fpr, tpr, thresholds = metrics.roc_curve( y_pred_final.Converted, y_pred_final.Conversion_Prob, dro
p_intermediate = False )
```

In [210]:

```
draw_roc(y_pred_final.Converted, y_pred_final.Conversion_Prob)
```





Out[210]:

```
(array([0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
        0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 6.34517766e-04,
        1.26903553e-03, 1.26903553e-03, 1.26903553e-03, 1.26903553e-03,
        1.26903553e-03, 1.26903553e-03, 1.26903553e-03, 1.26903553e-03,
        3.17258883e-03, 3.17258883e-03, 3.17258883e-03, 3.17258883e-03,
        3.17258883e-03, 4.44162437e-03, 4.44162437e-03, 4.44162437e-03,
        4.44162437e-03, 1.14213198e-02, 1.26903553e-02, 1.26903553e-02,
        1.26903553e-02, 1.26903553e-02, 3.48984772e-02, 3.48984772e-02,
        3.48984772e-02, 3.55329949e-02, 9.01015228e-02, 9.32741117e-02,
        1.43401015e-01, 1.44670051e-01, 1.48477157e-01, 1.49746193e-01,
        1.52918782e-01, 1.54822335e-01, 1.55456853e-01, 1.56725888e-01,
        1.57360406e-01, 4.87944162e-01, 5.62182741e-01, 5.81852792e-01,
        5.82487310e-01, 6.00253807e-01, 6.57994924e-01, 6.59898477e-01,
        6.60532995e-01, 6.63071066e-01, 6.63705584e-01, 6.72588832e-01,
        6.77664975e-01, 6.78299492e-01, 6.89086294e-01, 7.16370558e-01,
        7.17005076e-01, 7.17639594e-01, 7.27791878e-01, 7.30964467e-01,
        8.54695431e-01, 8.55964467e-01, 8.56598985e-01, 8.79441624e-01,
        8.80710660e-01, 8.84517766e-01, 8.91497462e-01, 8.92766497e-01,
        8.95939086e-01, 8.96573604e-01, 8.97208122e-01, 8.98477157e-01,
        9.10532995e-01, 9.11802030e-01, 9.17512690e-01, 9.18147208e-01,
        9.18781726e-01, 9.27030457e-01, 9.28934010e-01, 9.37182741e-01,
        9.37817259e-01, 9.70812183e-01, 9.71446701e-01, 9.72081218e-01,
        9.72715736e-01, 9.73350254e-01, 9.98096447e-01, 9.98730964e-01,
        1.00000000e+00]),
 array([0.        , 0.00198413, 0.00496032, 0.00595238, 0.00694444,
        0.00992063, 0.01289683, 0.02678571, 0.02678571, 0.04166667,
        0.04861111, 0.05257937, 0.05456349, 0.05555556, 0.07142857,
        0.07440476, 0.23710317, 0.33531746, 0.39186508, 0.41964286,
        0.43253968, 0.43253968, 0.44047619, 0.44146825, 0.44246032,
        0.64781746, 0.71130952, 0.71428571, 0.7172619 , 0.71825397,
        0.79265873, 0.79464286, 0.80357143, 0.80555556, 0.87103175,
        0.87202381, 0.94444444, 0.94444444, 0.94543651, 0.94543651,
        0.94642857, 0.94642857, 0.94642857, 0.94642857, 0.94642857,
        0.98214286, 0.98710317, 0.98809524, 0.98809524, 0.98809524,
        0.9890873 , 0.9890873 , 0.9890873 , 0.9890873 , 0.9890873 ,
        0.9890873 , 0.9890873 , 0.9890873 , 0.99007937, 0.99107143,
        0.99107143, 0.99107143, 0.99107143, 0.99206349, 1.        ,
        1.        , 1.        , 1.        , 1.        , 1.        ,
        1.        , 1.        , 1.        , 1.        , 1.        ,
        1.        , 1.        , 1.        , 1.        , 1.        ,
        1.        , 1.        , 1.        , 1.        , 1.        ,
        1.        , 1.        , 1.        , 1.        , 1.        ,
        1.        , 1.        , 1.        ]),
 array([2.00000000e+00, 1.00000000e+00, 1.00000000e+00, 1.00000000e+00,
        1.00000000e+00, 1.00000000e+00, 1.00000000e+00, 1.00000000e+00,
        1.00000000e+00, 1.00000000e+00, 9.99719004e-01, 9.99010342e-01,
        9.98961300e-01, 9.98179808e-01, 9.97529193e-01, 9.97406945e-01,
        9.94543382e-01, 9.94274254e-01, 9.91345706e-01, 9.90920303e-01,
        9.84184743e-01, 9.80283161e-01, 9.65628663e-01, 9.57347735e-01,
        9.55326467e-01, 9.53880451e-01, 9.51703160e-01, 9.46399659e-01,
        9.41967221e-01, 9.33803563e-01, 7.94974829e-01, 7.86971038e-01,
        7.61224263e-01, 7.18075047e-01, 3.74087585e-01, 3.23181172e-01,
        3.05556643e-01, 2.95381286e-01, 2.09833944e-01, 1.42036002e-01,
        1.34866719e-01, 1.21934972e-01, 1.14265160e-01, 1.08273458e-01,
        6.85557694e-02, 6.35140356e-02, 5.21515492e-02, 5.14002613e-02,
        4.98095777e-02, 4.17106455e-02, 2.92531129e-02, 2.79091642e-02,
        1.88360902e-02, 1.84397507e-02, 1.79618660e-02, 1.73826077e-02,
        1.55138616e-02, 1.47915048e-02, 1.44280338e-02, 1.35911431e-02,
        1.29571336e-02, 1.05638139e-02, 8.28292349e-03, 6.73012293e-03,
        6.20488694e-03, 5.91337130e-03, 5.33158085e-03, 4.91495057e-03,
        4.85792696e-03, 4.62345903e-03, 3.69730101e-03, 2.25140418e-03,
        2.17376615e-03, 2.11929386e-03, 2.07124438e-03, 1.79955032e-03,
```

```
       1.21008480e-03, 1.15296081e-03, 7.68299662e-04, 7.54719839e-04,
       7.32015561e-04, 6.33156141e-04, 6.07886214e-04, 5.88218736e-04,
       5.71687484e-04, 5.53648448e-04, 2.50959471e-04, 1.86712801e-04,
       9.76465739e-05, 9.07127898e-05, 8.53789975e-05, 7.24753523e-05,
       6.82138240e-05]))
```

In [211]:

```
def auc_val(fpr,tpr):
    AreaUnderCurve = 0.
    for i in range(len(fpr)-1):
        AreaUnderCurve += (fpr[i+1]-fpr[i]) * (tpr[i+1]+tpr[i])
    AreaUnderCurve *= 0.5
    return AreaUnderCurve
```

In [212]:

```
auc = auc_val(fpr,tpr)
auc
```

Out[212]:

```
0.957425935158327
```

Step 13: Calculating Lead score for the entire dataset

In [213]:

```
leads_test_pred = y_pred_final.copy()
leads_test_pred.head()
```

Out[213]:

	Converted	LeadID	Conversion_Prob	final_predicted
0	0	376	0.063514	0
1	0	8914	0.000554	0
2	0	7331	0.006205	0
3	1	6344	0.063514	0
4	0	3783	0.305557	0

In [214]:

```
leads_train_pred = y_train_pred_final.copy()
leads_train_pred.head()
```

Out[214]:

	Converted	Conversion_Prob	LeadID	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	final_predicted
0	0	0.000608	532	0	1	0	0	0	0	0	0	0	0	0	0
1	1	0.281919	7273	0	1	1	1	0	0	0	0	0	0	0	0
2	0	0.063514	4998	0	1	0	0	0	0	0	0	0	0	0	0
3	0	0.006205	6668	0	1	0	0	0	0	0	0	0	0	0	0
4	0	0.010564	2917	0	1	0	0	0	0	0	0	0	0	0	0

In [215]:

```
leads_train_pred = leads_train_pred[['LeadID','Converted','Conversion_Prob','final_predicted']]
leads_train_pred.head()
```

Out[215]:

	LeadID	Converted	Conversion_Prob	final_predicted
0	532	0	0.000608	0
1	7273	1	0.281919	0
2	4998	0	0.063514	0
3	6668	0	0.006205	0
4	2917	0	0.010564	0

In [216]:

```
lead_full_pred = leads_train_pred.append(leads_test_pred)
lead_full_pred.head()
```

Out[216]:

	LeadID	Converted	Conversion_Prob	final_predicted
0	532	0	0.000608	0
1	7273	1	0.281919	0
2	4998	0	0.063514	0
3	6668	0	0.006205	0
4	2917	0	0.010564	0

In [217]:

```
print(leads_train_pred.shape)
print(leads_test_pred.shape)
print(lead_full_pred.shape)
```

```
(6027, 4)
(2584, 4)
(8611, 4)
```

In [218]:

```
len(lead_full_pred['LeadID'].unique().tolist())
```

Out[218]:

```
8611
```

In [219]:

```
lead_full_pred['Lead_Score'] = lead_full_pred['Conversion_Prob'].apply(lambda x : round(x*100))
lead_full_pred.head()
```

Out[219]:

	LeadID	Converted	Conversion_Prob	final_predicted	Lead_Score
0	532	0	0.000608	0	0
1	7273	1	0.281919	0	28
2	4998	0	0.063514	0	6
3	6668	0	0.006205	0	1
4	2917	0	0.010564	0	1

In [220]:

```
lead_full_pred.LeadID.max()
```

Out[220]:

```
9239
```

In [221]:

```
lead_full_pred = lead_full_pred.set_index('LeadID').sort_index(axis = 0, ascending = True)
lead_full_pred.head()
```

Out[221]:

LeadID	Converted	Conversion_Prob	final_predicted	Lead_Score
0	0	0.029253	0	3
1	0	0.006205	0	1
2	1	0.761224	1	76
3	0	0.006205	0	1
4	1	0.953880	1	95

In [222]:

```
original_leads = original_leads[['Lead Number']]
original_leads.head()
```

Out[222]:

	Lead Number
0	660737
1	660728
2	660727
3	660719
4	660681

In [223]:

```
leads_with_score = pd.concat([original_leads, lead_full_pred], axis=1)
leads_with_score.head(10)
```

Out[223]:

	Lead Number	Converted	Conversion_Prob	final_predicted	Lead_Score
0	660737	0	0.029253	0	3
1	660728	0	0.006205	0	1
2	660727	1	0.761224	1	76
3	660719	0	0.006205	0	1
4	660681	1	0.953880	1	95
5	660680	0	0.063514	0	6
6	660673	1	0.953880	1	95
7	660664	0	0.063514	0	6
8	660624	0	0.063514	0	6
9	660616	0	0.063514	0	6

In [224]:

```
leads_with_score.shape
```

Out[224]:

```
(8611, 5)
```

In [225]:

```
total = pd.DataFrame(leads_with_score.isnull().sum().sort_values(ascending=False),
columns=['Total'])
percentage = pd.DataFrame(round(100*(leads_with_score.isnull().sum()/leads_with_score.shape[0]),2).
sort_values(ascending=False)\
                          ,columns=['Percentage'])
pd.concat([total, percentage], axis = 1)
```

Out[225]:

	Total	Percentage
Lead_Score	0	0.0
final_predicted	0	0.0
Conversion_Prob	0	0.0
Converted	0	0.0
Lead Number	0	0.0

Step 14: Determining Feature Importance

Selecting the coefficients of the selected features from our final model excluding the intercept

In [226]:

```
pd.options.display.float_format = '{:.2f}'.format
new_params = res.params[1:]
new_params
```

Out[226]:

```
Lead Source_Welingak Website                           24.80
Lead Quality_Worst                                     -3.21
Asymmetrique Activity Index_03.Low                     -2.09
Tags_Already a student                                 -3.46
Tags_Closed by Horizzon                                 5.56
Tags_Interested  in full time MBA                      -3.40
Tags_Interested in other courses                       -2.68
Tags_Lost to EINS                                       6.82
Tags_Not doing further education                       -3.33
Tags_Ringing                                           -4.26
Tags_Will revert after reading the email                3.85
Tags_opp hangup                                        -3.15
Tags_switched off                                      -4.49
What is your current occupation_Unemployed              1.87
What is your current occupation_Working Professional    1.82
Last Activity_SMS Sent                                  2.18
dtype: float64
```

Getting a relative coeffient value for all the features wrt the feature with the highest coefficient

In [227]:

```
#feature_importance = abs(new_params)
feature_importance = new_params
feature_importance = 100.0 * (feature_importance / feature_importance.max())
feature_importance
```

Out[227]:

```
Lead Source_Welingak Website                           100.00
Lead Quality_Worst                                     -12.96
Asymmetrique Activity Index_03.Low                      -8.45
Tags_Already a student                                 -13.97
Tags_Closed by Horizzon                                 22.43
Tags_Interested  in full time MBA                      -13.72
```

```
Tags_Interested in other courses                     -10.81
Tags_Lost to EINS                                     27.51
Tags_Not doing further education                     -13.43
Tags_Ringing                                         -17.16
Tags_Will revert after reading the email              15.53
Tags_opp hangup                                      -12.72
Tags_switched off                                    -18.11
What is your current occupation_Unemployed             7.54
What is your current occupation_Working Professional   7.35
Last Activity_SMS Sent                                 8.78
dtype: float64
```

Sorting the feature variables based on their relative coefficient values

In [228]:

```python
sorted_idx = np.argsort(feature_importance,kind='quicksort',order='list of str')
sorted_idx
##
```

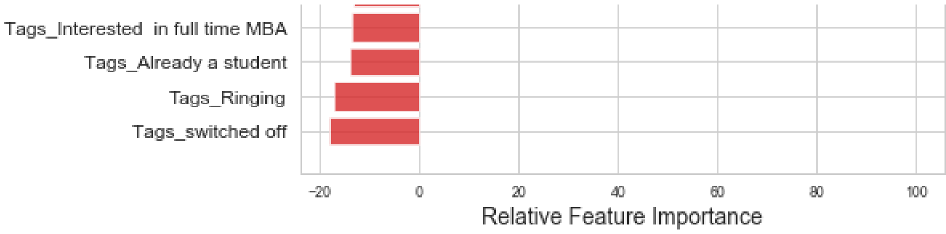
Out[228]:

```
Lead Source_Welingak Website                          12
Lead Quality_Worst                                     9
Asymmetrique Activity Index_03.Low                     3
Tags_Already a student                                 5
Tags_Closed by Horizzon                                8
Tags_Interested  in full time MBA                      1
Tags_Interested in other courses                      11
Tags_Lost to EINS                                      6
Tags_Not doing further education                       2
Tags_Ringing                                          14
Tags_Will revert after reading the email              13
Tags_opp hangup                                       15
Tags_switched off                                     10
What is your current occupation_Unemployed             4
What is your current occupation_Working Professional   7
Last Activity_SMS Sent                                 0
dtype: int64
```

Plot showing the feature variables based on their relative coefficient values

In [229]:

```python
pos = np.arange(sorted_idx.shape[0]) + .5

featfig = plt.figure(figsize=(10,6))
featax = featfig.add_subplot(1, 1, 1)
featax.barh(pos, feature_importance[sorted_idx], align='center', color = 'tab:red',alpha=0.8)
featax.set_yticks(pos)
featax.set_yticklabels(np.array(X_train[col].columns)[sorted_idx], fontsize=12)
featax.set_xlabel('Relative Feature Importance', fontsize=14)

plt.tight_layout()
plt.show()
```



Selecting Top 3 features which contribute most towards the probability of a lead getting converted

In [230]:

```
pd.DataFrame(feature_importance).reset_index().sort_values(by=0,ascending=False).head(3)
```

Out[230]:

	index	0
0	Lead Source_Welingak Website	100.00
7	Tags_Lost to EINS	27.51
4	Tags_Closed by Horizzon	22.43

Step 15: Conclusion

After trying several models, we finally chose a model with the following characteristics: 1 All variables have p-value < 0.05. All the features have very low VIF values, meaning, there is hardly any muliticollinearity among the features. This is also evident from the heat map. The overall accuracy of 0.9056 at a probability threshold of 0.33 on the heat map.

In [ ]: