LEAD SCORING CASE STUDY

In [1]:
```
#importing libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')

from sklearn.preprocessing import StandardScaler
```

In [2]:
```
#importing dataset to csv

leads=pd.read_csv("Leads.csv")
```

In [3]:
```
# Looking at first few entries

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
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	660737	API	Olark Chat	No	No	0	0.0	0	0.0
1	2a272436-5132-4136-86fa-dcc88c88f482	660728	API	Organic Search	No	No	0	5.0	674	2.5
2	8cc8c611-a219-4f35-ad23-fdfd2656bd8a	660727	Landing Page Submission	Direct Traffic	No	No	1	2.0	1532	2.0
3	0cc2df48-7cf4-4e39-9de9-19797f9b38cc	660719	Landing Page Submission	Direct Traffic	No	No	0	1.0	305	1.0
4	3256f628-e534-4826-9d63-4a8b88782852	660681	Landing Page Submission	Google	No	No	1	2.0	1428	1.0

5 rows × 37 columns

In [4]:
```
#checking total rows and cols in dataset
leads.shape
```

Out[4]: (9240, 37)

This dataset has:

- 9240 rows,
- 37 columns

In [5]:
```python
#basic data check
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 [6]:
```python
leads.describe()
```

Out[6]:

	Lead Number	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Asymmetrique Activity Score	Asymmetriq Profile Sc
count	9240.000000	9240.000000	9103.000000	9240.000000	9103.000000	5022.000000	5022.000
mean	617188.435606	0.385390	3.445238	487.698268	2.362820	14.306252	16.3448
std	23405.995698	0.486714	4.854853	548.021466	2.161418	1.386694	1.811
min	579533.000000	0.000000	0.000000	0.000000	0.000000	7.000000	11.0000
25%	596484.500000	0.000000	1.000000	12.000000	1.000000	14.000000	15.0000
50%	615479.000000	0.000000	3.000000	248.000000	2.000000	14.000000	16.0000
75%	637387.250000	1.000000	5.000000	936.000000	3.000000	15.000000	18.0000
max	660737.000000	1.000000	251.000000	2272.000000	55.000000	18.000000	20.0000

In [7]:

```
#check for duplicates
sum(leads.duplicated(subset = 'Prospect ID')) == 0
```

Out[7]: True

No duplicate values in Prospect ID

In [8]:

```
#check for duplicates
sum(leads.duplicated(subset = 'Lead Number')) == 0
```

Out[8]: True

No duplicate values in Lead Number

Clearly Prospect ID & Lead Number are two variables that are just indicative of the ID number of the Contacted People & can be dropped.

EXPLORATORY DATA ANALYSIS

Data Cleaning & Treatment:

In [9]:

```
#dropping Lead Number and Prospect ID since they have all unique values

leads.drop(['Prospect ID', 'Lead Number'], 1, inplace = True)
```

In [10]:

```
#Converting 'Select' values to NaN.

leads = leads.replace('Select', np.nan)
```

In [11]:

```
#checking null values in each rows

leads.isnull().sum()
```

Out[11]:

```
Lead Origin                                         0
Lead Source                                        36
Do Not Email                                        0
Do Not Call                                         0
Converted                                           0
TotalVisits                                       137
Total Time Spent on Website                         0
Page Views Per Visit                              137
Last Activity                                     103
Country                                          2461
Specialization                                   3380
How did you hear about X Education               7250
What is your current occupation                  2690
What matters most to you in choosing a course    2709
Search                                              0
Magazine                                            0
Newspaper Article                                   0
X Education Forums                                  0
Newspaper                                           0
Digital Advertisement                               0
Through Recommendations                             0
Receive More Updates About Our Courses              0
Tags                                             3353
Lead Quality                                     4767
Update me on Supply Chain Content                   0
Get updates on DM Content                           0
Lead Profile                                     6855
City                                             3669
Asymmetrique Activity Index                      4218
Asymmetrique Profile Index                       4218
Asymmetrique Activity Score                      4218
Asymmetrique Profile Score                       4218
I agree to pay the amount through cheque            0
A free copy of Mastering The Interview              0
Last Notable Activity                               0
dtype: int64
```

In [12]:

```
#checking percentage of null values in each column

leads.isnull().mean()*100
```

Out[12]:
```
Lead Origin                                       0.000000
Lead Source                                       0.389610
Do Not Email                                      0.000000
Do Not Call                                       0.000000
Converted                                         0.000000
TotalVisits                                       1.482684
Total Time Spent on Website                       0.000000
Page Views Per Visit                              1.482684
Last Activity                                     1.114719
Country                                          26.634199
Specialization                                   36.580087
How did you hear about X Education               78.463203
What is your current occupation                  29.112554
What matters most to you in choosing a course    29.318182
Search                                            0.000000
Magazine                                          0.000000
Newspaper Article                                 0.000000
X Education Forums                                0.000000
Newspaper                                         0.000000
Digital Advertisement                             0.000000
Through Recommendations                           0.000000
Receive More Updates About Our Courses            0.000000
Tags                                             36.287879
Lead Quality                                     51.590909
Update me on Supply Chain Content                 0.000000
Get updates on DM Content                         0.000000
Lead Profile                                     74.188312
City                                             39.707792
Asymmetrique Activity Index                      45.649351
Asymmetrique Profile Index                       45.649351
Asymmetrique Activity Score                      45.649351
Asymmetrique Profile Score                       45.649351
I agree to pay the amount through cheque          0.000000
A free copy of Mastering The Interview            0.000000
Last Notable Activity                             0.000000
dtype: float64
```

In [13]:
```python
#dropping cols with more than 40% missing values

cols=leads.columns


for i in cols:
    if((leads[i].isnull().mean()*100) >= 40):
        leads.drop(i, 1, inplace = True)
```

In [14]:
```python
#checking null values percentage

leads.isnull().mean()*100
```

Out[14]:
```
Lead Origin                                       0.000000
Lead Source                                       0.389610
Do Not Email                                      0.000000
Do Not Call                                       0.000000
Converted                                         0.000000
TotalVisits                                       1.482684
Total Time Spent on Website                       0.000000
Page Views Per Visit                              1.482684
Last Activity                                     1.114719
Country                                          26.634199
Specialization                                   36.580087
What is your current occupation                  29.112554
What matters most to you in choosing a course    29.318182
Search                                            0.000000
Magazine                                          0.000000
Newspaper Article                                 0.000000
X Education Forums                                0.000000
Newspaper                                         0.000000
Digital Advertisement                             0.000000
Through Recommendations                           0.000000
Receive More Updates About Our Courses            0.000000
Tags                                             36.287879
Update me on Supply Chain Content                 0.000000
Get updates on DM Content                         0.000000
City                                             39.707792
I agree to pay the amount through cheque          0.000000
A free copy of Mastering The Interview            0.000000
Last Notable Activity                             0.000000
dtype: float64
```

Categorical Attributes Analysis:

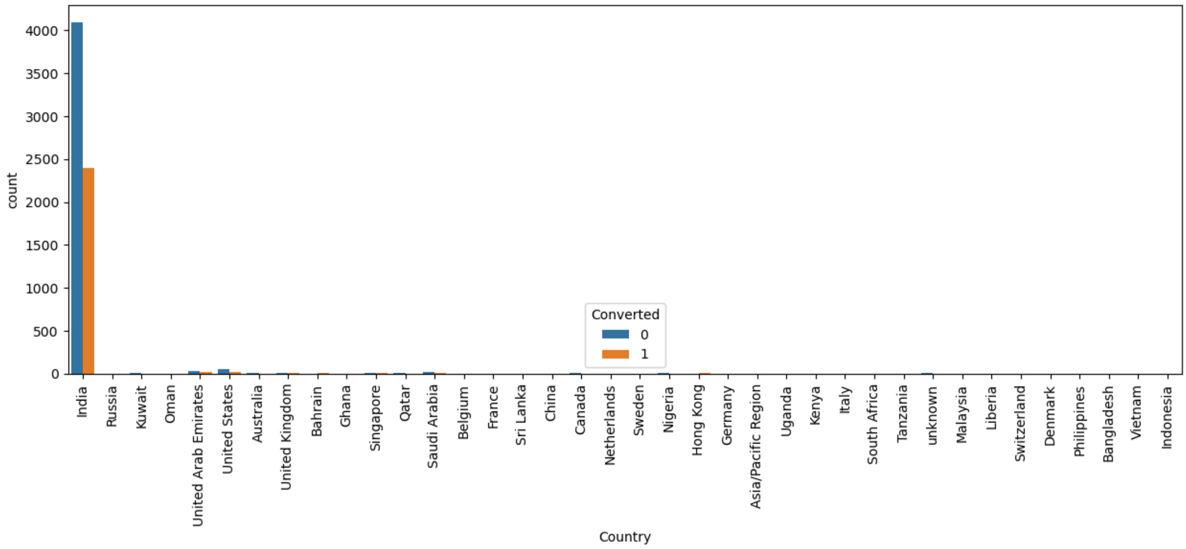
In [15]:
```
#checking value counts of Country column

leads['Country'].value_counts(dropna=False)
```

Out[15]:

```
India                   6492
NaN                     2461
United States             69
United Arab Emirates      53
Singapore                 24
Saudi Arabia              21
United Kingdom            15
Australia                 13
Qatar                     10
Bahrain                    7
Hong Kong                  7
Oman                       6
France                     6
unknown                    5
Kuwait                     4
South Africa               4
Canada                     4
Nigeria                    4
Germany                    4
Sweden                     3
Philippines                2
Uganda                     2
Italy                      2
Bangladesh                 2
Netherlands                2
Asia/Pacific Region        2
China                      2
Belgium                    2
Ghana                      2
Kenya                      1
Sri Lanka                  1
Tanzania                   1
Malaysia                   1
Liberia                    1
Switzerland                1
Denmark                    1
Russia                     1
Vietnam                    1
Indonesia                  1
Name: Country, dtype: int64
```

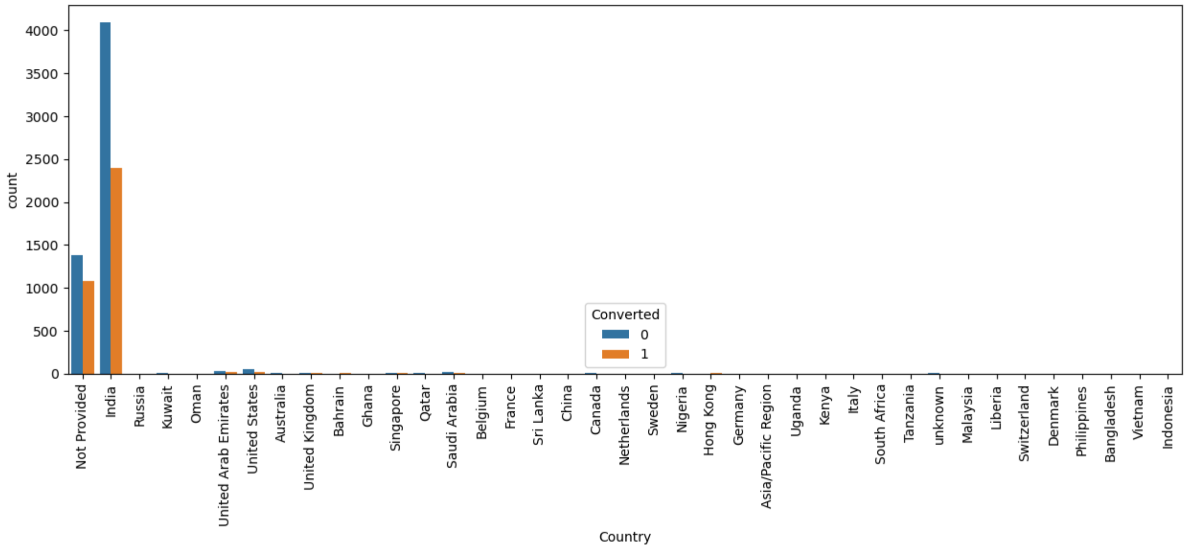
In [16]:

```python
#plotting spread of Country columnn
plt.figure(figsize=(15,5))
s1=sns.countplot(leads.Country, hue=leads.Converted)
s1.set_xticklabels(s1.get_xticklabels(),rotation=90)
plt.show()
```



In [17]:
```
# # Imputing missing values in Country column with "'not provided"

leads['Country'] = leads['Country'].replace(np.nan,'Not Provided')
```

In [18]:
```
#plotting spread of Country columnn after replacing NaN values

plt.figure(figsize=(15,5))
s1=sns.countplot(leads.Country, hue=leads.Converted)
s1.set_xticklabels(s1.get_xticklabels(),rotation=90)
plt.show()
```



As we can see the Number of Values for India are quite high (nearly 97% of the Data), this column can be dropped

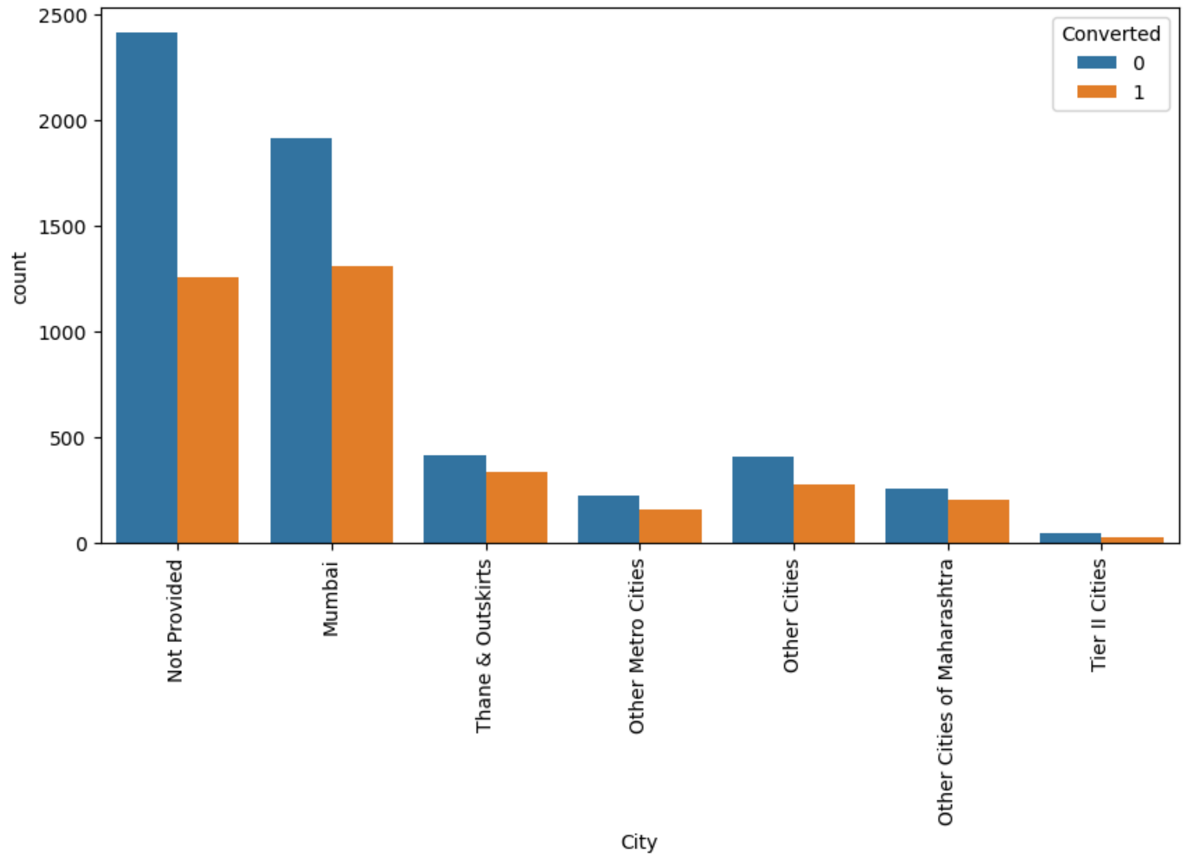
In [19]:
```
#creating a list of columns to be droppped

cols_to_drop=['Country']
```

In [20]:
```
#checking value counts of "City" column

leads['City'].value_counts(dropna=False)
```

Out[20]:
```
NaN                            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 [21]:
```
leads['City'] = leads['City'].replace(np.nan,'Not Provided')
```

In [22]:
```
#plotting spread of City columnn after replacing NaN values

plt.figure(figsize=(10,5))
s1=sns.countplot(leads.City, hue=leads.Converted)
s1.set_xticklabels(s1.get_xticklabels(),rotation=90)
plt.show()
```



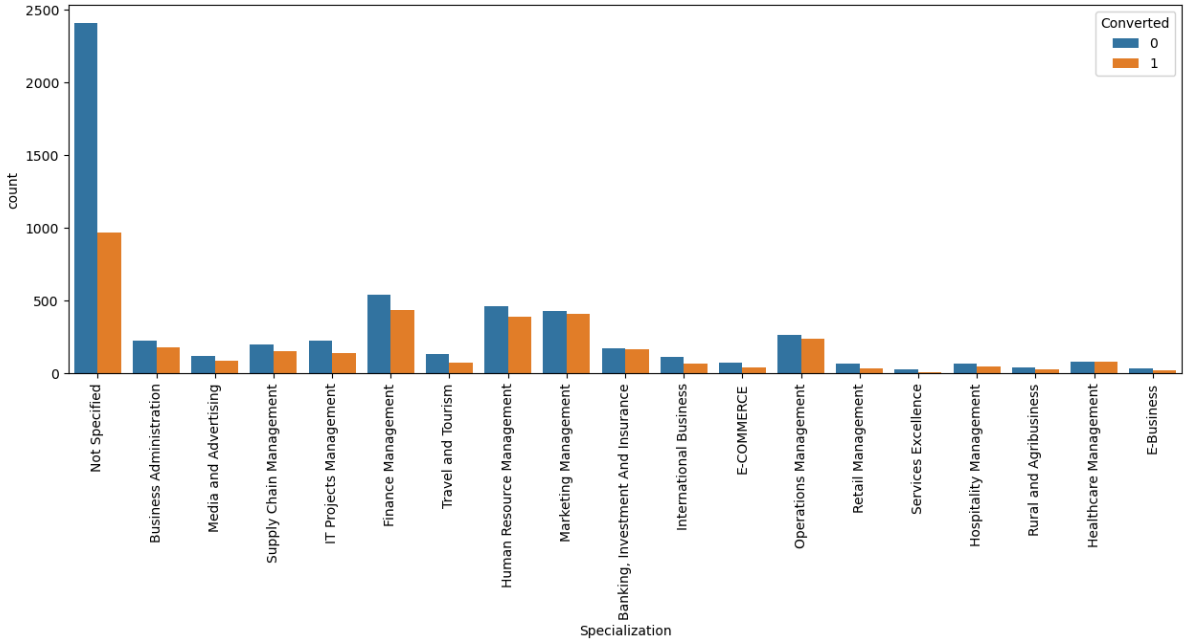
In [23]:
```
#checking value counts of Specialization column

leads['Specialization'].value_counts(dropna=False)
```

Out[23]:
```
NaN                                  3380
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 [24]:
```
# Lead may not have mentioned specialization because it was not in the list or maybe
# and don't have a specialization yet. So we will replace NaN values here with 'Not :

leads['Specialization'] = leads['Specialization'].replace(np.nan, 'Not Specified')
```

In [25]:
```
#plotting spread of Specialization columnn

plt.figure(figsize=(15,5))
s1=sns.countplot(leads.Specialization, hue=leads.Converted)
```

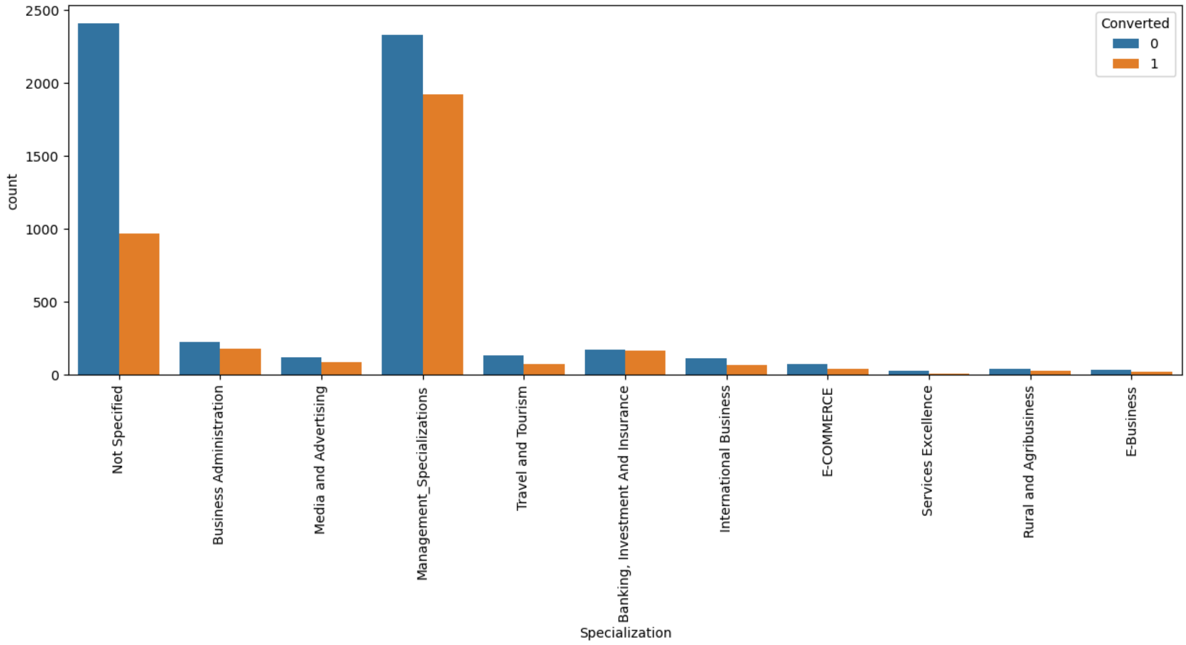
```
s1.set_xticklabels(s1.get_xticklabels(),rotation=90)
plt.show()
```



We see that specialization with **Management** in them have higher number of leads as well as leads converted. So this is definitely a significant variable and should not be dropped.

In [26]:
```
#combining Management Specializations because they show similar trends

leads['Specialization'] = leads['Specialization'].replace(['Finance Management','Huma
                                                            'Marketing Management','Op
                                                            'IT Projects Management',
                                                     'Healthcare Management','Hospital
                                                            'Retail Management'] ,'Man
```

In [27]:
```
#visualizing count of Variable based on Converted value


plt.figure(figsize=(15,5))
s1=sns.countplot(leads.Specialization, hue=leads.Converted)
s1.set_xticklabels(s1.get_xticklabels(),rotation=90)
plt.show()
```



In [28]:
```
#What is your current occupation

leads['What is your current occupation'].value_counts(dropna=False)
```

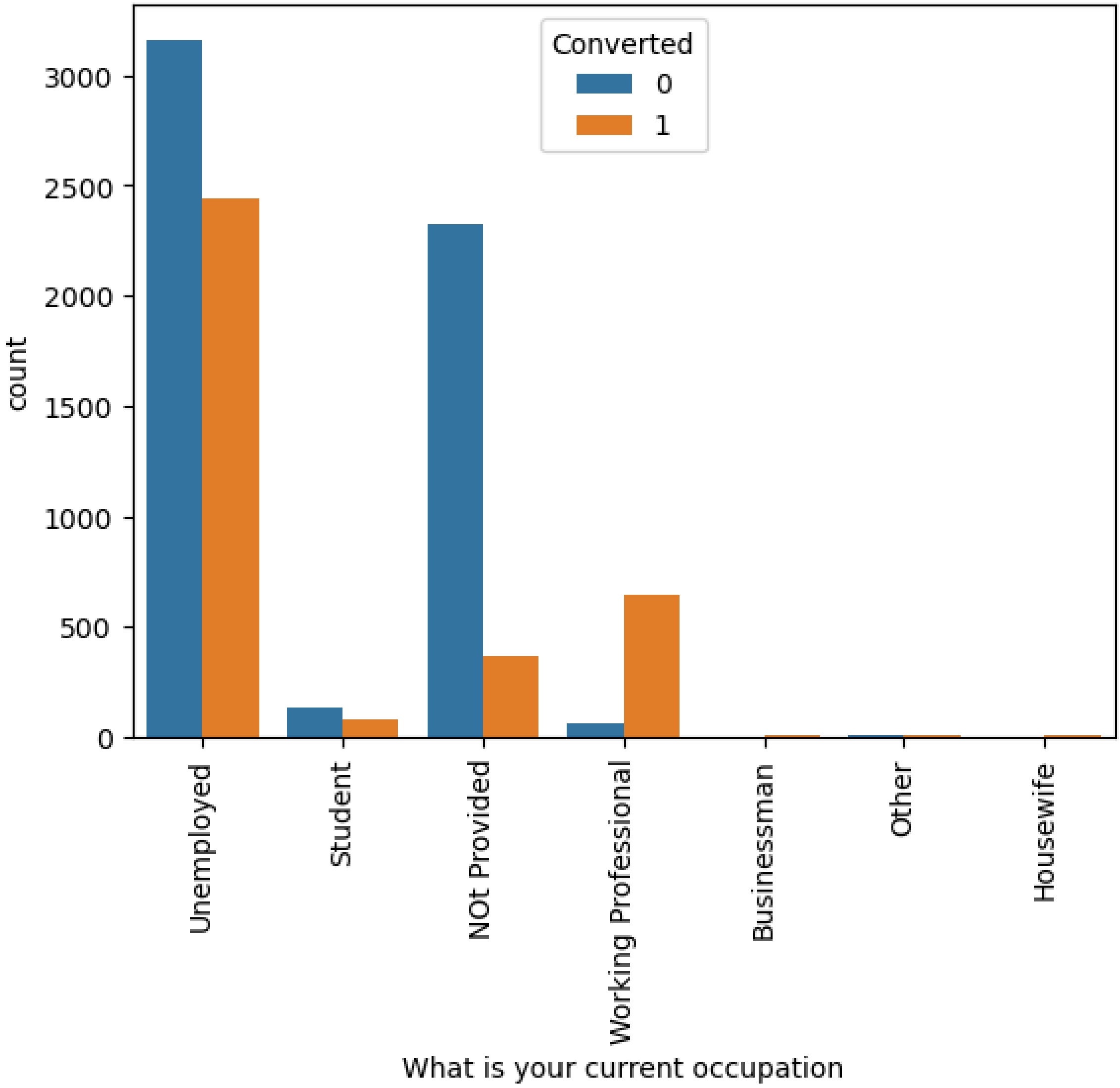
Out[28]:
```
Unemployed              5600
NaN                     2690
Working Professional     706
Student                  210
Other                     16
Housewife                 10
Businessman                8
Name: What is your current occupation, dtype: int64
```

In [29]:
```
#imputing Nan values with mode "Unemployed"

leads['What is your current occupation'] = leads['What is your current occupation'].
```

In [30]:
```
#checking count of values
leads['What is your current occupation'].value_counts(dropna=False)
```

Out[30]:
```
Unemployed              5600
NOt Provided            2690
Working Professional     706
Student                  210
Other                     16
Housewife                 10
Businessman                8
Name: What is your current occupation, dtype: int64
```

In [31]:
```
#visualizing count of Variable based on Converted value

s1=sns.countplot(leads['What is your current occupation'], hue=leads.Converted)
s1.set_xticklabels(s1.get_xticklabels(),rotation=90)
plt.show()
```



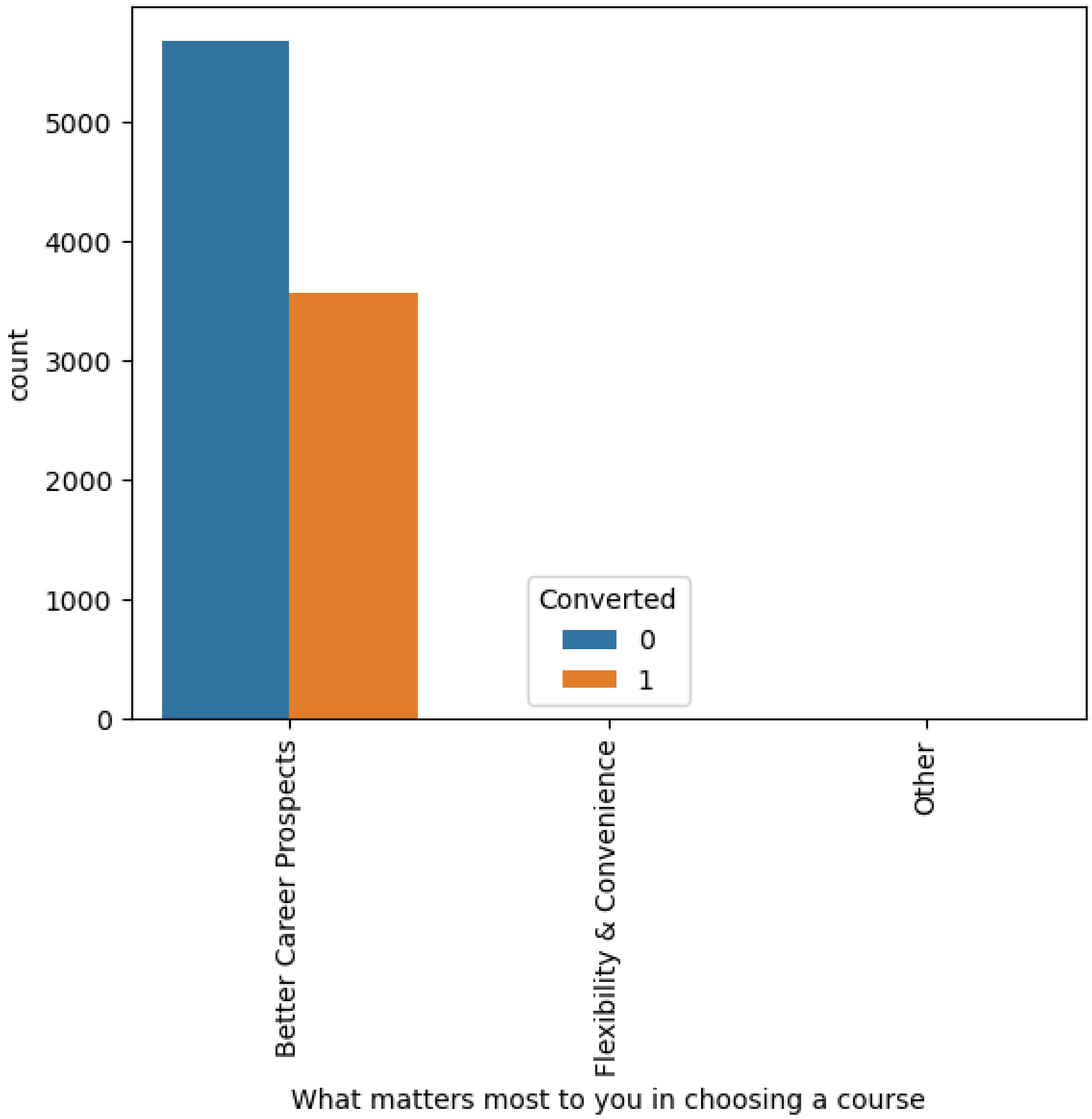
- Working Professionals going for the course have high chances of joining it.
- Unemployed leads are the most in terms of Absolute numbers.

In [32]:
```
#checking value counts

leads['What matters most to you in choosing a course'].value_counts(dropna=False)
```

Out[32]:
```
Better Career Prospects      6528
NaN                          2709
Flexibility & Convenience       2
Other                           1
Name: What matters most to you in choosing a course, dtype: int64
```

In [33]:
```
#replacing Nan values with Mode "Better Career Prospects"

leads['What matters most to you in choosing a course'] = leads['What matters most to
```

In [34]:
```
#visualizing count of Variable based on Converted value

s1=sns.countplot(leads['What matters most to you in choosing a course'], hue=leads.C
s1.set_xticklabels(s1.get_xticklabels(),rotation=90)
plt.show()
```



In [35]:
```
#checking value counts of variable
leads['What matters most to you in choosing a course'].value_counts(dropna=False)
```

Out[35]:
```
Better Career Prospects      9237
Flexibility & Convenience       2
Other                           1
Name: What matters most to you in choosing a course, dtype: int64
```

In [36]:
```
#Here again we have another Column that is worth Dropping. So we Append to the cols_
cols_to_drop.append('What matters most to you in choosing a course')
cols_to_drop
```

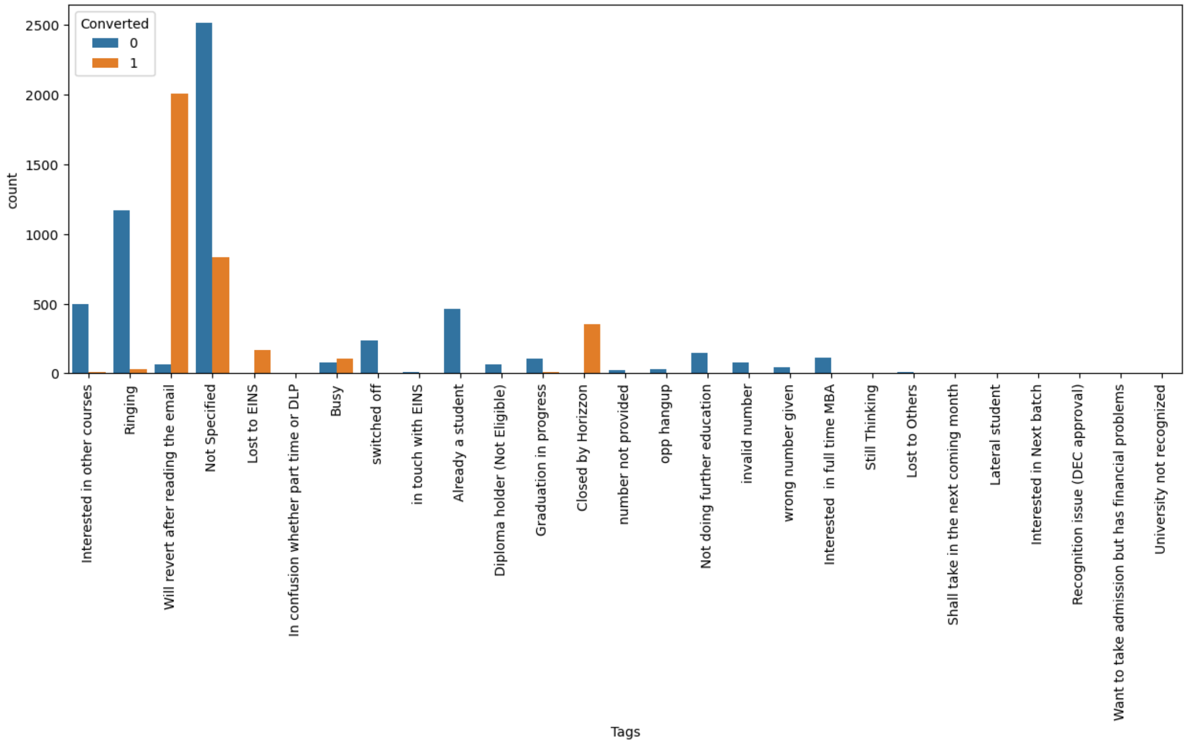
Out[36]:
```
['Country', 'What matters most to you in choosing a course']
```

In [37]:
```
#checking value counts of Tag variable
leads['Tags'].value_counts(dropna=False)
```

Out[37]:
```
NaN                                                  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 [38]:
```
#replacing Nan values with "Not Specified"
leads['Tags'] = leads['Tags'].replace(np.nan,'Not Specified')
```

In [39]:
```
#visualizing count of Variable based on Converted value

plt.figure(figsize=(15,5))
s1=sns.countplot(leads['Tags'], hue=leads.Converted)
s1.set_xticklabels(s1.get_xticklabels(),rotation=90)
plt.show()
```



In [40]:

```
#replacing tags with low frequency with "Other Tags"
leads['Tags'] = leads['Tags'].replace(['In confusion whether part time or DLP', 'in 
                                      'Approached upfront','Graduation in progress','
                                     'Lost to Others','Shall take in the next coming 
                                     'Recognition issue (DEC approval)','Want to take
                                     'University not recognized'], 'Other_Tags')

leads['Tags'] = leads['Tags'].replace(['switched off',
                                       'Already a student',
                                        'Not doing further education',
                                        'invalid number',
                                        'wrong number given',
                                        'Interested  in full time MBA'] , 'Other_Tags
```

In [41]:

```
#checking percentage of missing values
leads.isnull().mean()*100
```

Out[41]:

```
Lead Origin                                      0.000000
Lead Source                                      0.389610
Do Not Email                                     0.000000
Do Not Call                                      0.000000
Converted                                        0.000000
TotalVisits                                      1.482684
Total Time Spent on Website                      0.000000
Page Views Per Visit                             1.482684
Last Activity                                    1.114719
Country                                          0.000000
Specialization                                   0.000000
What is your current occupation                  0.000000
What matters most to you in choosing a course    0.000000
Search                                           0.000000
Magazine                                         0.000000
Newspaper Article                                0.000000
X Education Forums                               0.000000
Newspaper                                        0.000000
Digital Advertisement                            0.000000
Through Recommendations                          0.000000
Receive More Updates About Our Courses           0.000000
Tags                                             0.000000
Update me on Supply Chain Content                0.000000
Get updates on DM Content                        0.000000
City                                             0.000000
I agree to pay the amount through cheque         0.000000
A free copy of Mastering The Interview           0.000000
Last Notable Activity                            0.000000
dtype: float64
```

In [42]:

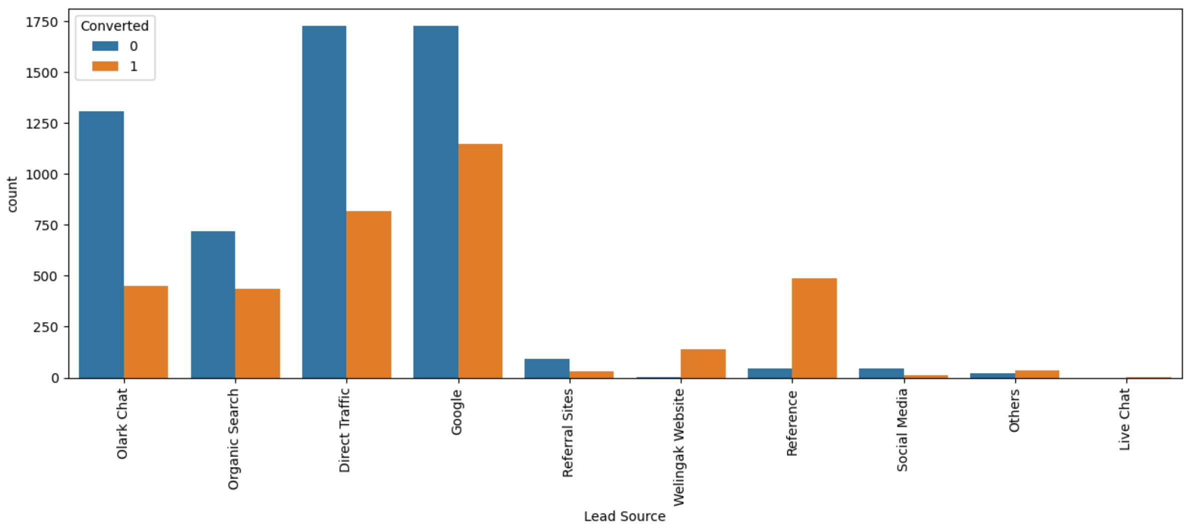
```
#checking value counts of Lead Source column

leads['Lead Source'].value_counts(dropna=False)
```

```
Out[42]: Google               2868
         Direct Traffic       2543
         Olark Chat           1755
         Organic Search       1154
         Reference             534
         Welingak Website      142
         Referral Sites        125
         Facebook               55
         NaN                    36
         bing                    6
         google                  5
         Click2call              4
         Press_Release           2
         Social Media            2
         Live Chat               2
         youtubechannel          1
         testone                 1
         Pay per Click Ads       1
         welearnblog_Home        1
         WeLearn                 1
         blog                    1
         NC_EDM                  1
         Name: Lead Source, dtype: int64
```

```
In [43]: #replacing Nan Values and combining low frequency values
leads['Lead Source'] = leads['Lead Source'].replace(np.nan,'Others')
leads['Lead Source'] = leads['Lead Source'].replace('google','Google')
leads['Lead Source'] = leads['Lead Source'].replace('Facebook','Social Media')
leads['Lead Source'] = leads['Lead Source'].replace(['bing','Click2call','Press_Relea
                                                      'youtubechannel','welearnblog_Ho
                                                      'WeLearn','blog','Pay per Click
                                                     'testone','NC_EDM'] ,'Others')
```

We can group some of the lower frequency occuring labels under a common label 'Others'

```
In [44]: #visualizing count of Variable based on Converted value
plt.figure(figsize=(15,5))
s1=sns.countplot(leads['Lead Source'], hue=leads.Converted)
s1.set_xticklabels(s1.get_xticklabels(),rotation=90)
plt.show()
```



Inference

- Maximum number of leads are generated by Google and Direct traffic.
- Conversion Rate of reference leads and leads through welingak website is high.

- To improve overall lead conversion rate, focus should be on improving lead converion of olark chat, organic search, direct traffic, and google leads and generate more leads from reference and welingak website.

In [45]:
```
# Last Activity:

leads['Last Activity'].value_counts(dropna=False)
```

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
NaN                              103
Unreachable                       93
Unsubscribed                      61
Had a Phone Conversation          30
Approached upfront                 9
View in browser link Clicked       6
Email Received                     2
Email Marked Spam                  2
Visited Booth in Tradeshow         1
Resubscribed to emails             1
Name: Last Activity, dtype: int64
```

In [46]:
```
#replacing Nan Values and combining low frequency values

leads['Last Activity'] = leads['Last Activity'].replace(np.nan,'Others')
leads['Last Activity'] = leads['Last Activity'].replace(['Unreachable','Unsubscribed
                                                        'Had a Phone Conversation',
                                                        'Approached upfront',
                                                        'View in browser link Clicke
                                                        'Email Marked Spam',
                                                        'Email Received','Resubscrib
                                                         'Visited Booth in Tradeshow
```

In [47]:
```
# Last Activity:

leads['Last Activity'].value_counts(dropna=False)
```

Out[47]:
```
Email Opened                 3437
SMS Sent                     2745
Olark Chat Conversation       973
Page Visited on Website       640
Converted to Lead             428
Email Bounced                 326
Others                        308
Email Link Clicked            267
Form Submitted on Website     116
Name: Last Activity, dtype: int64
```

In [48]:
```
#Check the Null Values in All Columns:
leads.isnull().mean()*100
```

Out[48]:
```
Lead Origin                                      0.000000
Lead Source                                      0.000000
Do Not Email                                     0.000000
Do Not Call                                      0.000000
Converted                                        0.000000
TotalVisits                                      1.482684
Total Time Spent on Website                      0.000000
Page Views Per Visit                             1.482684
Last Activity                                    0.000000
Country                                          0.000000
Specialization                                   0.000000
What is your current occupation                  0.000000
What matters most to you in choosing a course    0.000000
Search                                           0.000000
Magazine                                         0.000000
Newspaper Article                                0.000000
X Education Forums                               0.000000
Newspaper                                        0.000000
Digital Advertisement                            0.000000
Through Recommendations                          0.000000
Receive More Updates About Our Courses           0.000000
Tags                                             0.000000
Update me on Supply Chain Content                0.000000
Get updates on DM Content                        0.000000
City                                             0.000000
I agree to pay the amount through cheque         0.000000
A free copy of Mastering The Interview           0.000000
Last Notable Activity                            0.000000
dtype: float64
```

In [49]:
```
#Drop all rows which have Nan Values. Since the number of Dropped rows is less than .
leads = leads.dropna()
```

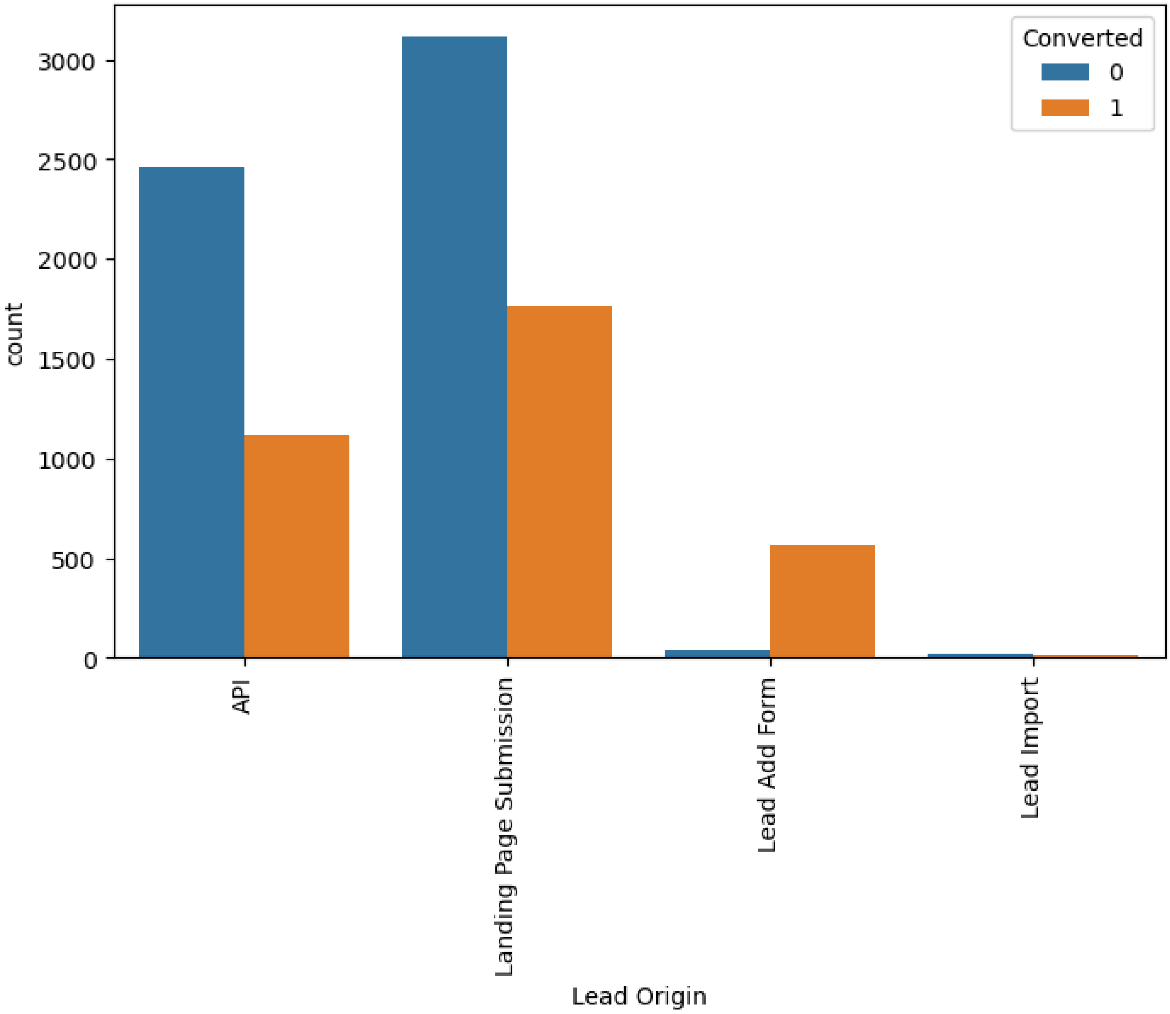
In [50]:
```
#Checking percentage of Null Values in All Columns:
leads.isnull().mean()*100
```

Out[50]:
```
Lead Origin                                      0.0
Lead Source                                      0.0
Do Not Email                                     0.0
Do Not Call                                      0.0
Converted                                        0.0
TotalVisits                                      0.0
Total Time Spent on Website                      0.0
Page Views Per Visit                             0.0
Last Activity                                    0.0
Country                                          0.0
Specialization                                   0.0
What is your current occupation                  0.0
What matters most to you in choosing a course    0.0
Search                                           0.0
Magazine                                         0.0
Newspaper Article                                0.0
X Education Forums                               0.0
Newspaper                                        0.0
Digital Advertisement                            0.0
Through Recommendations                          0.0
Receive More Updates About Our Courses           0.0
Tags                                             0.0
Update me on Supply Chain Content                0.0
Get updates on DM Content                        0.0
City                                             0.0
I agree to pay the amount through cheque         0.0
A free copy of Mastering The Interview           0.0
Last Notable Activity                            0.0
dtype: float64
```

In [51]:
```
#Lead Origin
leads['Lead Origin'].value_counts(dropna=False)
```

Out[51]:
```
Landing Page Submission    4886
API                        3578
Lead Add Form               608
Lead Import                  31
Name: Lead Origin, dtype: int64
```

In [52]:
```
#visualizing count of Variable based on Converted value

plt.figure(figsize=(8,5))
s1=sns.countplot(leads['Lead Origin'], hue=leads.Converted)
s1.set_xticklabels(s1.get_xticklabels(),rotation=90)
plt.show()
```

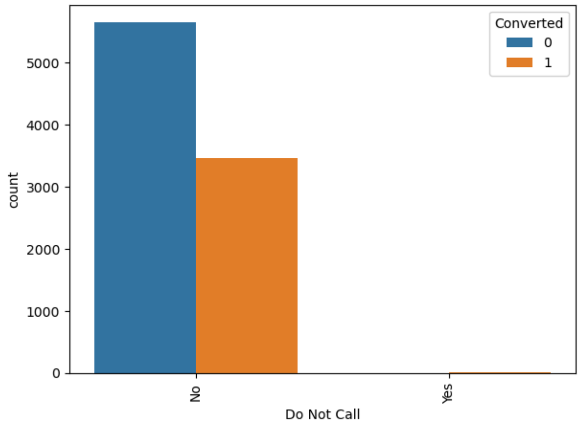


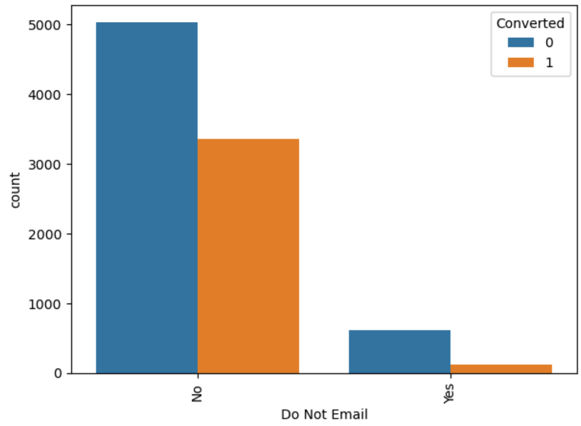
Inference

- API and Landing Page Submission bring higher number of leads as well as conversion.
- Lead Add Form has a very high conversion rate but count of leads are not very high.
- Lead Import and Quick Add Form get very few leads.
- In order to improve overall lead conversion rate, we have to improve lead converion of API and Landing Page Submission origin and generate more leads from Lead Add Form.

In [53]:

```
#Do Not Email & Do Not Call
#visualizing count of Variable based on Converted value

plt.figure(figsize=(15,5))

ax1=plt.subplot(1, 2, 1)
ax1=sns.countplot(leads['Do Not Call'], hue=leads.Converted)
ax1.set_xticklabels(ax1.get_xticklabels(),rotation=90)

ax2=plt.subplot(1, 2, 2)
ax2=sns.countplot(leads['Do Not Email'], hue=leads.Converted)
ax2.set_xticklabels(ax2.get_xticklabels(),rotation=90)
plt.show()
```





In [54]:
```
#checking value counts for Do Not Call
leads['Do Not Call'].value_counts(dropna=False)
```
Out[54]:
```
No     9101
Yes       2
Name: Do Not Call, dtype: int64
```

In [55]:
```
#checking value counts for Do Not Email
leads['Do Not Email'].value_counts(dropna=False)
```
Out[55]:
```
No     8379
Yes     724
Name: Do Not Email, dtype: int64
```

We Can append the **Do Not Call** Column to the list of Columns to be Dropped since > 90% is of only one Value

In [56]:
```
cols_to_drop.append('Do Not Call')
cols_to_drop
```
Out[56]:
```
['Country', 'What matters most to you in choosing a course', 'Do Not Call']
```

In [57]:
```
# IMBALANCED VARIABLES THAT CAN BE DROPPED
```

In [58]:
```
leads.Search.value_counts(dropna=False)
```
Out[58]:
```
No     9089
Yes      14
Name: Search, dtype: int64
```

In [59]:
```
leads.Magazine.value_counts(dropna=False)
```
Out[59]:
```
No    9103
Name: Magazine, dtype: int64
```

In [60]:
```
leads['Newspaper Article'].value_counts(dropna=False)
```
Out[60]:
```
No     9101
Yes       2
Name: Newspaper Article, dtype: int64
```

In [61]:
```
leads['X Education Forums'].value_counts(dropna=False)
```
Out[61]:
```
No     9102
Yes       1
Name: X Education Forums, dtype: int64
```

In [62]:
```
leads['Newspaper'].value_counts(dropna=False)
```

Out[62]:
```
No     9102
Yes       1
Name: Newspaper, dtype: int64
```

In [63]:
```
leads['Digital Advertisement'].value_counts(dropna=False)
```

Out[63]:
```
No     9099
Yes       4
Name: Digital Advertisement, dtype: int64
```

In [64]:
```
leads['Through Recommendations'].value_counts(dropna=False)
```

Out[64]:
```
No     9096
Yes       7
Name: Through Recommendations, dtype: int64
```

In [65]:
```
leads['Receive More Updates About Our Courses'].value_counts(dropna=False)
```

Out[65]:
```
No    9103
Name: Receive More Updates About Our Courses, dtype: int64
```

In [66]:
```
leads['Update me on Supply Chain Content'].value_counts(dropna=False)
```

Out[66]:
```
No    9103
Name: Update me on Supply Chain Content, dtype: int64
```

In [67]:
```
leads['Get updates on DM Content'].value_counts(dropna=False)
```

Out[67]:
```
No    9103
Name: Get updates on DM Content, dtype: int64
```

In [68]:
```
leads['I agree to pay the amount through cheque'].value_counts(dropna=False)
```

Out[68]:
```
No    9103
Name: I agree to pay the amount through cheque, dtype: int64
```

In [69]:
```
leads['A free copy of Mastering The Interview'].value_counts(dropna=False)
```

Out[69]:
```
No     6215
Yes    2888
Name: A free copy of Mastering The Interview, dtype: int64
```

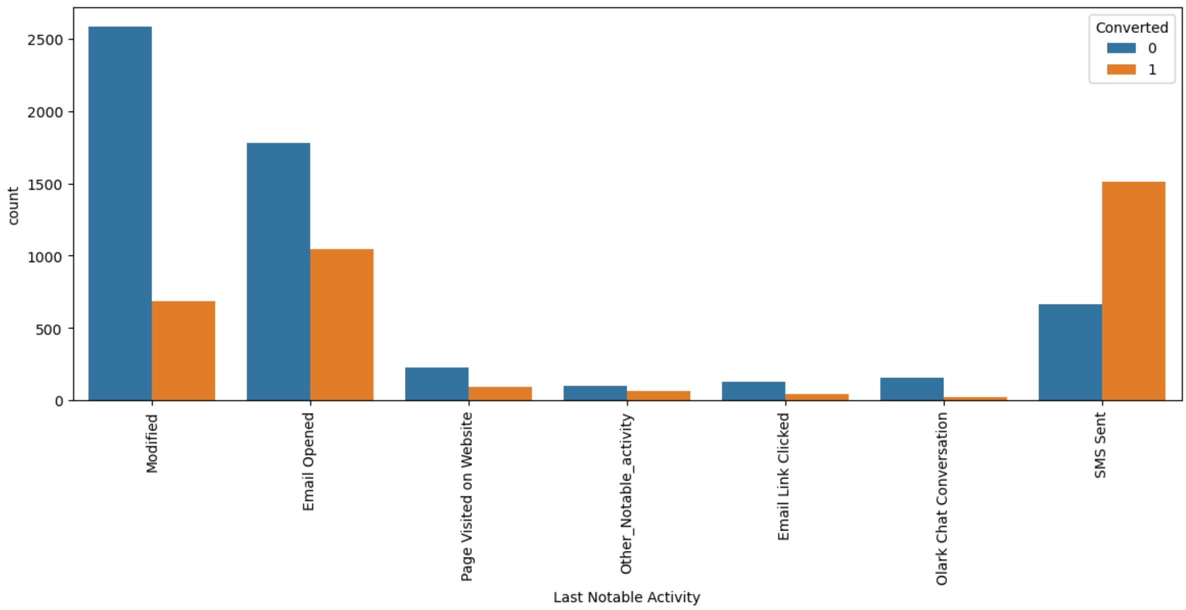
In [70]:
```
#adding imbalanced columns to the list of columns to be dropped

cols_to_drop.extend(['Search','Magazine','Newspaper Article','X Education Forums','Ne
                 'Digital Advertisement','Through Recommendations','Receive More Upda
                 'Update me on Supply Chain Content',
                 'Get updates on DM Content','I agree to pay the amount through chequ
```

In [71]:
```
#checking value counts of last Notable Activity
leads['Last Notable Activity'].value_counts()
```

```
Out[71]: Modified                       3270
Email Opened                   2827
SMS Sent                       2172
Page Visited on Website         318
Olark Chat Conversation         183
Email Link Clicked              173
Email Bounced                    60
Unsubscribed                     47
Unreachable                      32
Had a Phone Conversation         14
Email Marked Spam                 2
Approached upfront                1
Resubscribed to emails            1
View in browser link Clicked      1
Form Submitted on Website         1
Email Received                    1
Name: Last Notable Activity, dtype: int64
```

```
In [72]: #clubbing lower frequency values

leads['Last Notable Activity'] = leads['Last Notable Activity'].replace(['Had a Phon
                                                                       'Email Marked
                                                                         'Unreachabl
                                                                         'Unsubscrib
                                                                         'Email Boun
                                                                       'Resubscribed
                                                                       'View in brow
                                                                       'Approached u
                                                                       'Form Submitt
                                                                       'Email Receiv
```

```
In [73]: #visualizing count of Variable based on Converted value

plt.figure(figsize = (14,5))
ax1=sns.countplot(x = "Last Notable Activity", hue = "Converted", data = leads)
ax1.set_xticklabels(ax1.get_xticklabels(),rotation=90)
plt.show()
```




```
In [74]: #checking value counts for variable

leads['Last Notable Activity'].value_counts()
```

Out[74]:
```
Modified                    3270
Email Opened                2827
SMS Sent                    2172
Page Visited on Website      318
Olark Chat Conversation      183
Email Link Clicked           173
Other_Notable_activity       160
Name: Last Notable Activity, dtype: int64
```

In [75]:
```
#list of columns to be dropped
cols_to_drop
```

Out[75]:
```
['Country',
 'What matters most to you in choosing a course',
 'Do Not Call',
 'Search',
 'Magazine',
 'Newspaper Article',
 'X Education Forums',
 'Newspaper',
 'Digital Advertisement',
 'Through Recommendations',
 'Receive More Updates About Our Courses',
 'Update me on Supply Chain Content',
 'Get updates on DM Content',
 'I agree to pay the amount through cheque']
```

In [76]:
```
#dropping columns
leads = leads.drop(cols_to_drop,1)
leads.info()
```

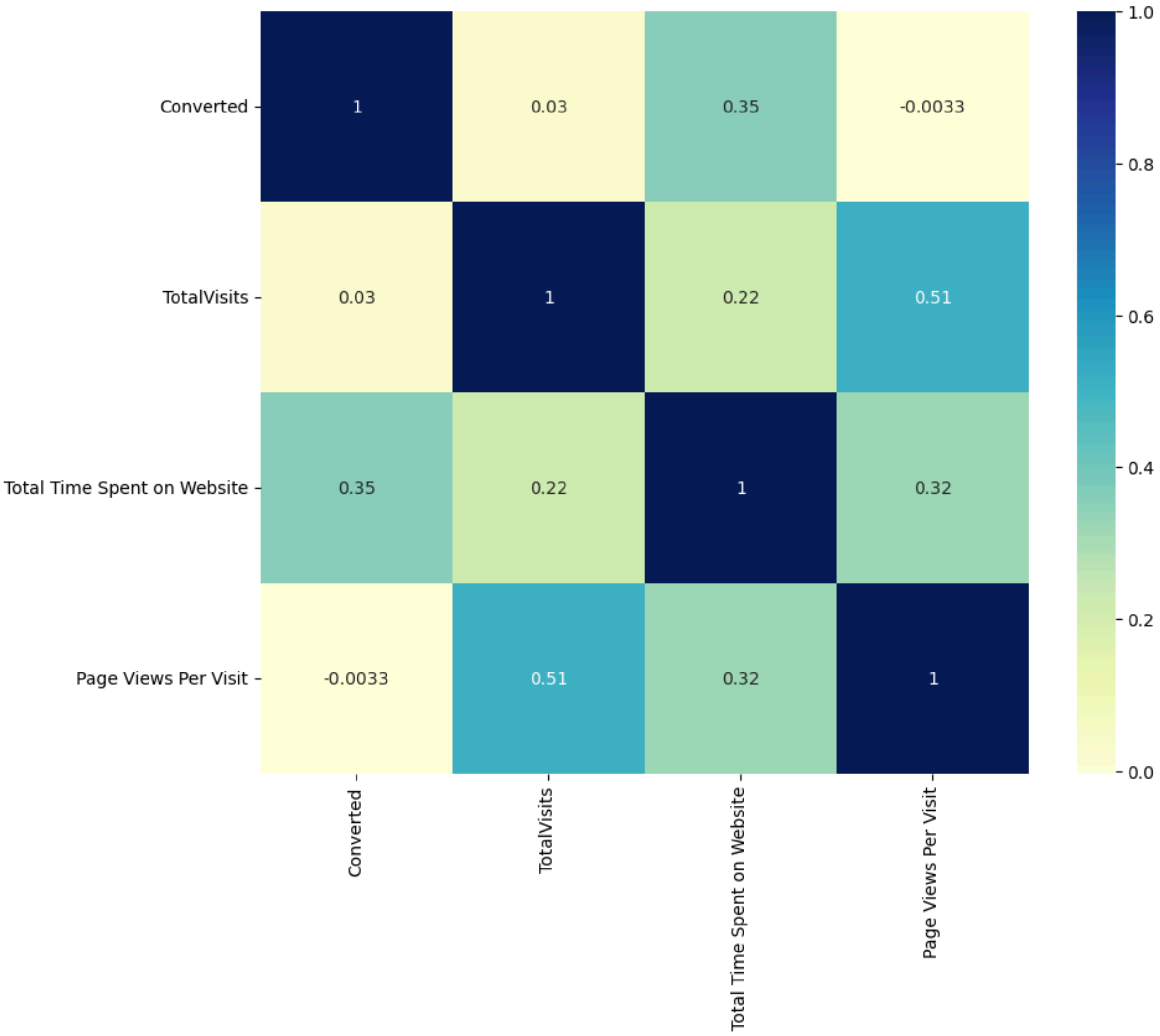
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9103 entries, 0 to 9239
Data columns (total 14 columns):
 #   Column                                  Non-Null Count  Dtype  
---  ------                                  --------------  -----  
 0   Lead Origin                             9103 non-null   object 
 1   Lead Source                             9103 non-null   object 
 2   Do Not Email                            9103 non-null   object 
 3   Converted                               9103 non-null   int64  
 4   TotalVisits                             9103 non-null   float64
 5   Total Time Spent on Website             9103 non-null   int64  
 6   Page Views Per Visit                    9103 non-null   float64
 7   Last Activity                           9103 non-null   object 
 8   Specialization                          9103 non-null   object 
 9   What is your current occupation         9103 non-null   object 
 10  Tags                                    9103 non-null   object 
 11  City                                    9103 non-null   object 
 12  A free copy of Mastering The Interview  9103 non-null   object 
 13  Last Notable Activity                   9103 non-null   object 
dtypes: float64(2), int64(2), object(10)
memory usage: 1.0+ MB
```

Numerical Attributes Analysis:

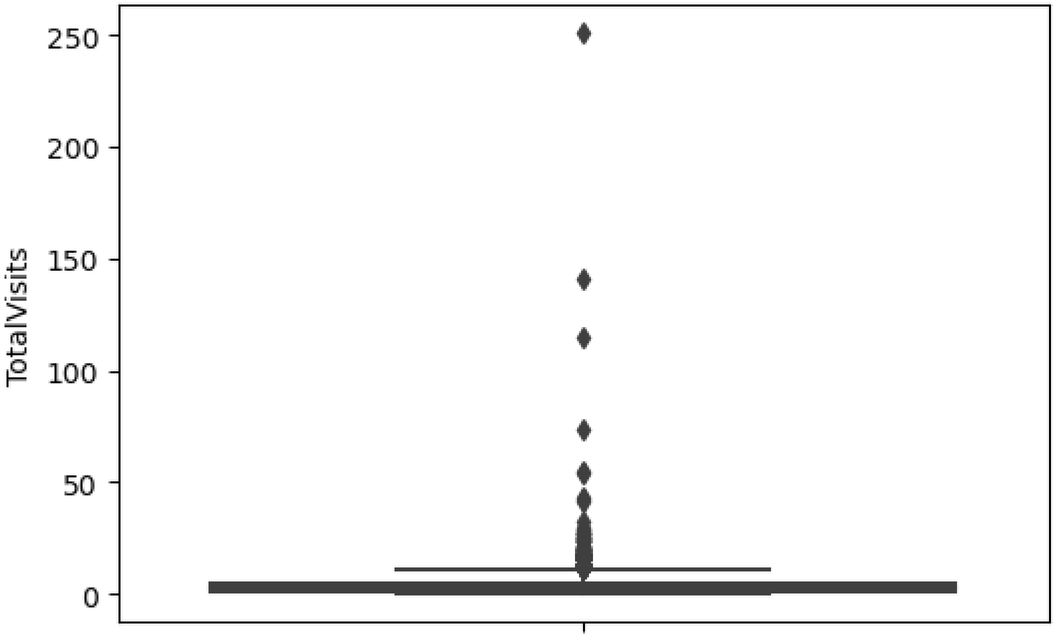
In [77]:
```
#Check the % of Data that has Converted Values = 1:

Converted = (sum(leads['Converted'])/len(leads['Converted'].index))*100
Converted
```

Out[77]:
```
38.02043282434362
```

In [78]:
```
#Checking correlations of numeric values
# figure size
plt.figure(figsize=(10,8))

# heatmap
sns.heatmap(leads.corr(), cmap="YlGnBu", annot=True)
plt.show()
```



In [79]:
```
#Total Visits
#visualizing spread of variable

plt.figure(figsize=(6,4))
sns.boxplot(y=leads['TotalVisits'])
plt.show()
```

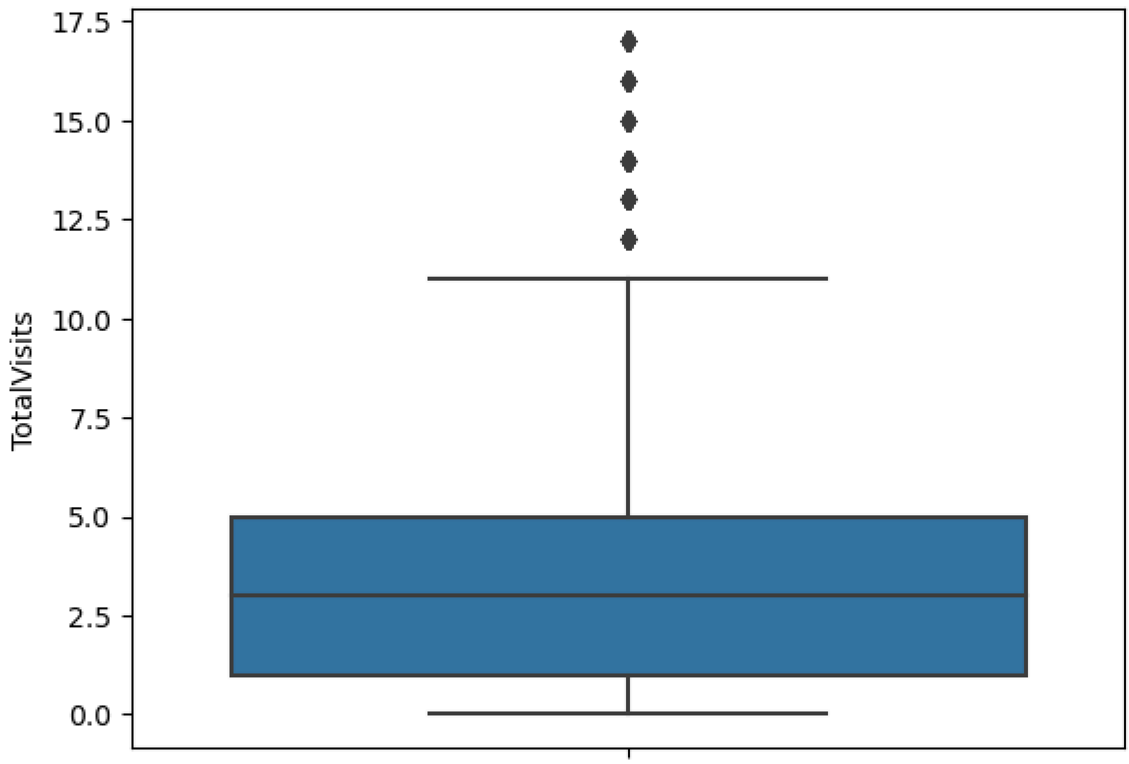


We can see presence of outliers here

In [80]:
```
#checking percentile values for "Total Visits"

leads['TotalVisits'].describe(percentiles=[0.05,.25, .5, .75, .90, .95, .99])
```

Out[80]:
```
count    9103.000000
mean        3.445238
std         4.854853
min         0.000000
5%          0.000000
25%         1.000000
50%         3.000000
75%         5.000000
90%         7.000000
95%        10.000000
99%        17.000000
max       251.000000
Name: TotalVisits, dtype: float64
```

In [81]:
```
#Outlier Treatment: Remove top & bottom 1% of the Column Outlier values

Q3 = leads.TotalVisits.quantile(0.99)
leads = leads[(leads.TotalVisits <= Q3)]
Q1 = leads.TotalVisits.quantile(0.01)
leads = leads[(leads.TotalVisits >= Q1)]
sns.boxplot(y=leads['TotalVisits'])
plt.show()
```



In [82]:
```
leads.shape
```

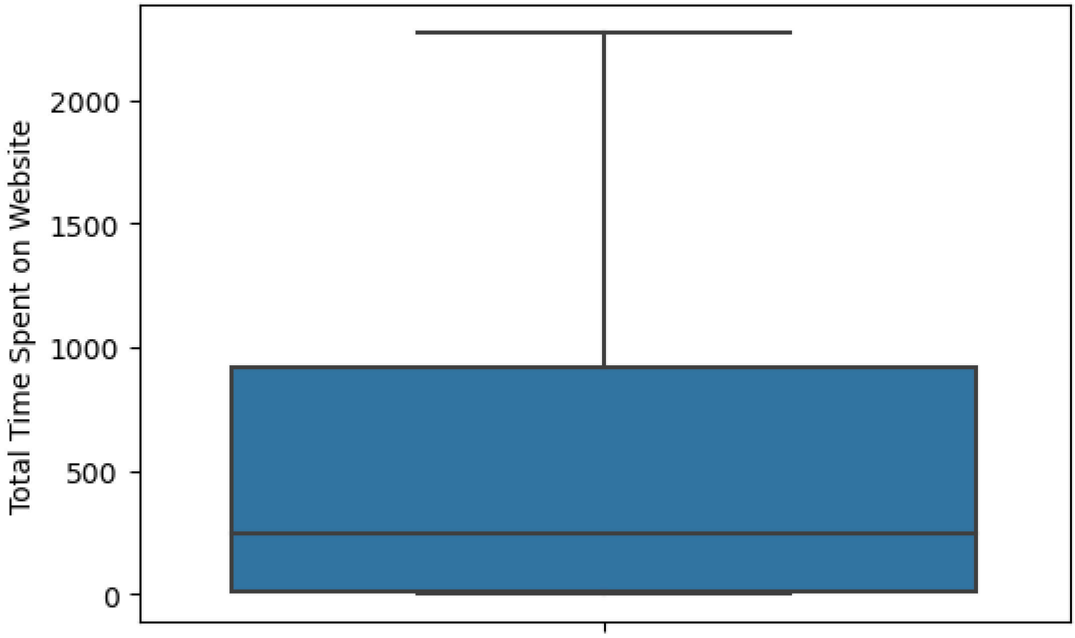
Out[82]:
```
(9020, 14)
```

Check for the Next Numerical Column:

In [83]:
```
#checking percentiles for "Total Time Spent on Website"

leads['Total Time Spent on Website'].describe(percentiles=[0.05,.25, .5, .75, .90, .
```

Out[83]:
```
count    9020.000000
mean      479.759534
std       544.688157
min         0.000000
5%          0.000000
25%         7.000000
50%       243.000000
75%       915.250000
90%      1371.000000
95%      1554.050000
99%      1836.620000
max      2272.000000
Name: Total Time Spent on Website, dtype: float64
```

In [84]:
```
#visualizing spread of numeric variable

plt.figure(figsize=(6,4))
sns.boxplot(y=leads['Total Time Spent on Website'])
plt.show()
```



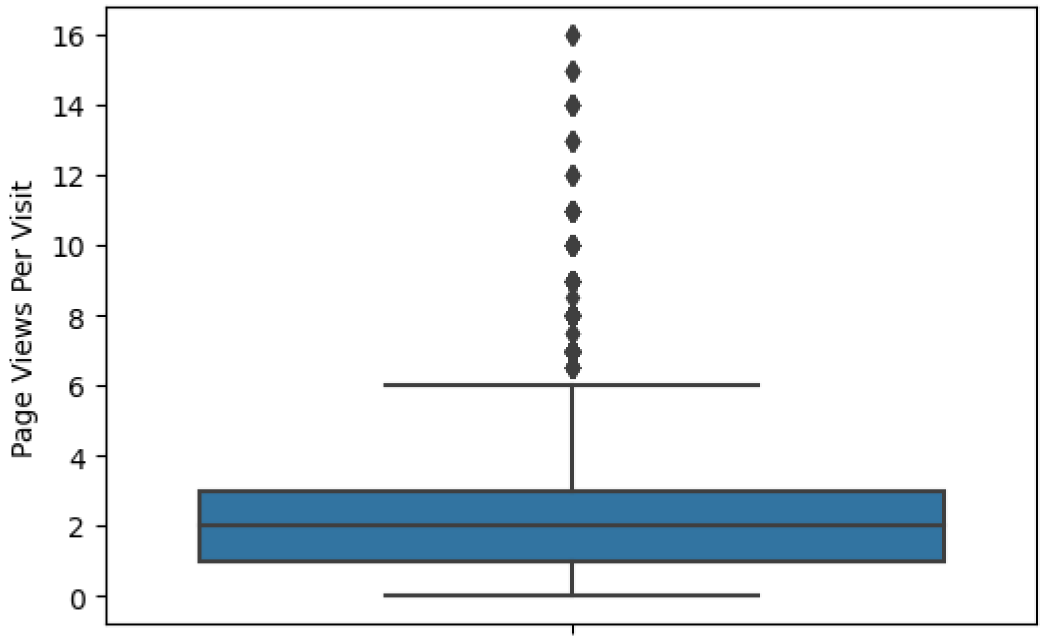
Since there are no major Outliers for the above variable we don't do any Outlier Treatment for this above Column

Check for Page Views Per Visit:

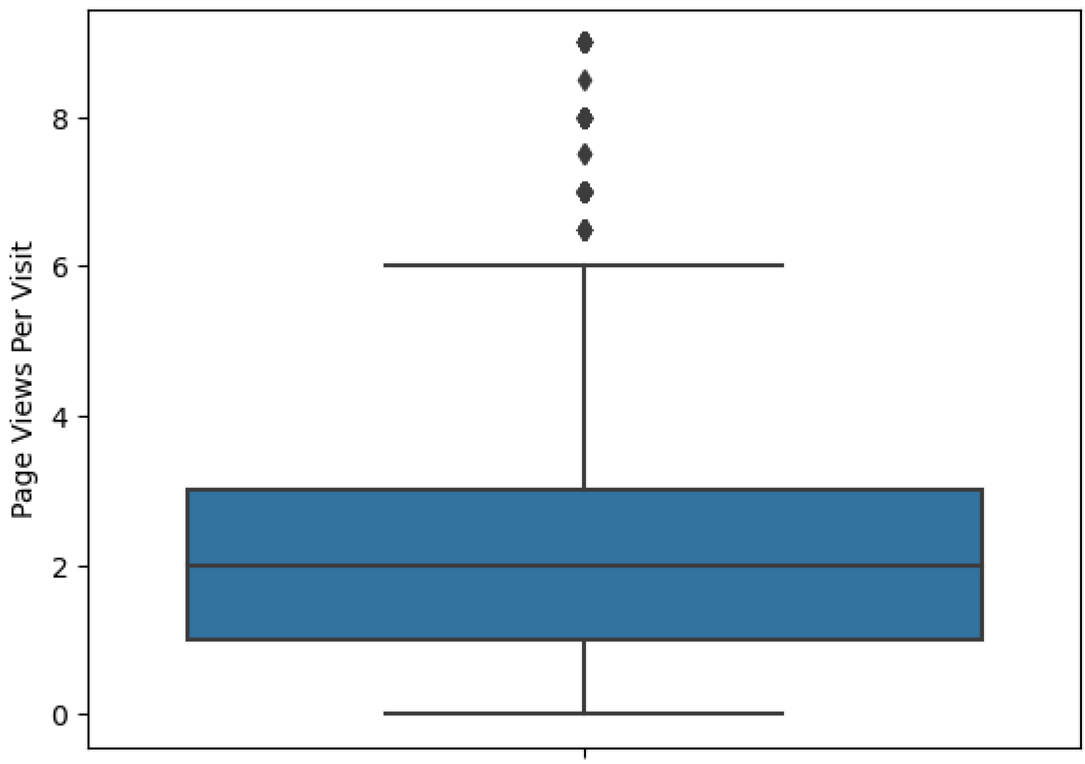
In [85]:
```
#checking spread of "Page Views Per Visit"

leads['Page Views Per Visit'].describe()
```

Out[85]:
```
count    9020.000000
mean        2.337271
std         2.062363
min         0.000000
25%         1.000000
50%         2.000000
75%         3.000000
max        16.000000
Name: Page Views Per Visit, dtype: float64
```

In [86]:
```
#visualizing spread of numeric variable

plt.figure(figsize=(6,4))
sns.boxplot(y=leads['Page Views Per Visit'])
plt.show()
```



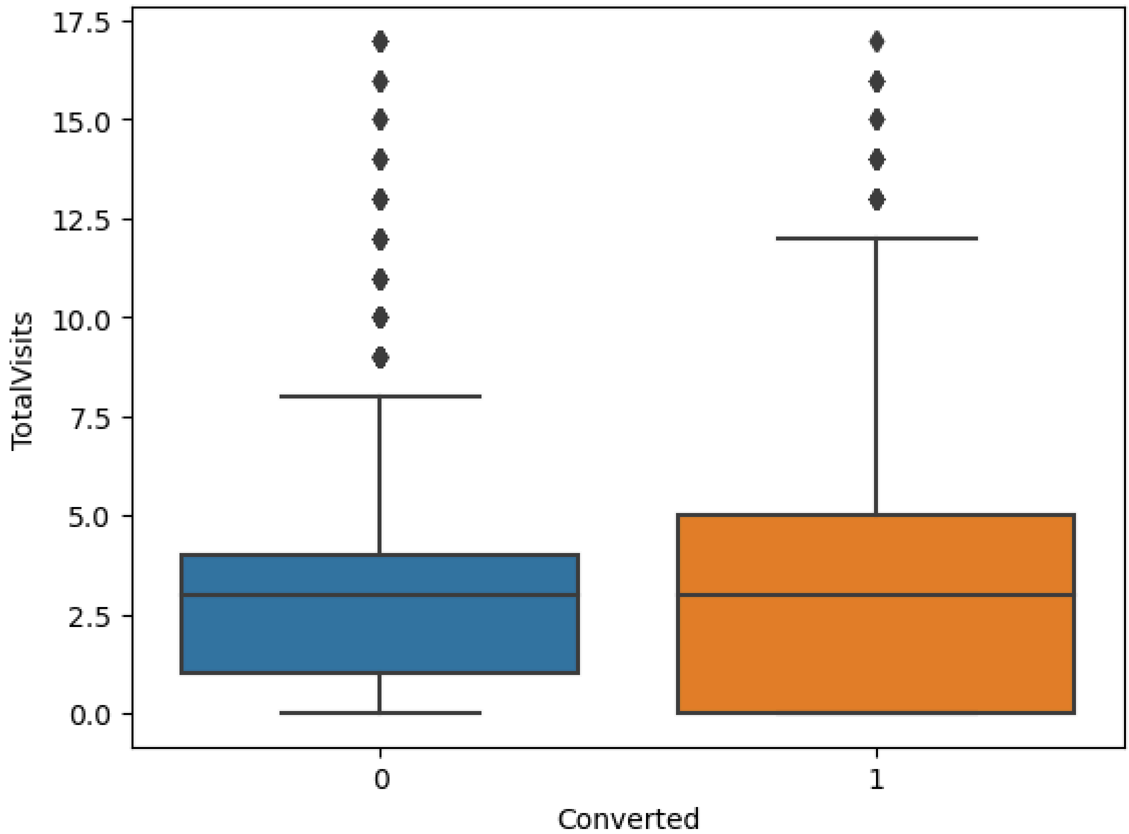
In [87]:
```
#Outlier Treatment: Remove top & bottom 1%

Q3 = leads['Page Views Per Visit'].quantile(0.99)
leads = leads[leads['Page Views Per Visit'] <= Q3]
Q1 = leads['Page Views Per Visit'].quantile(0.01)
leads = leads[leads['Page Views Per Visit'] >= Q1]
sns.boxplot(y=leads['Page Views Per Visit'])
plt.show()
```



In [88]:
```
leads.shape
```

Out[88]:
```
(8953, 14)
```

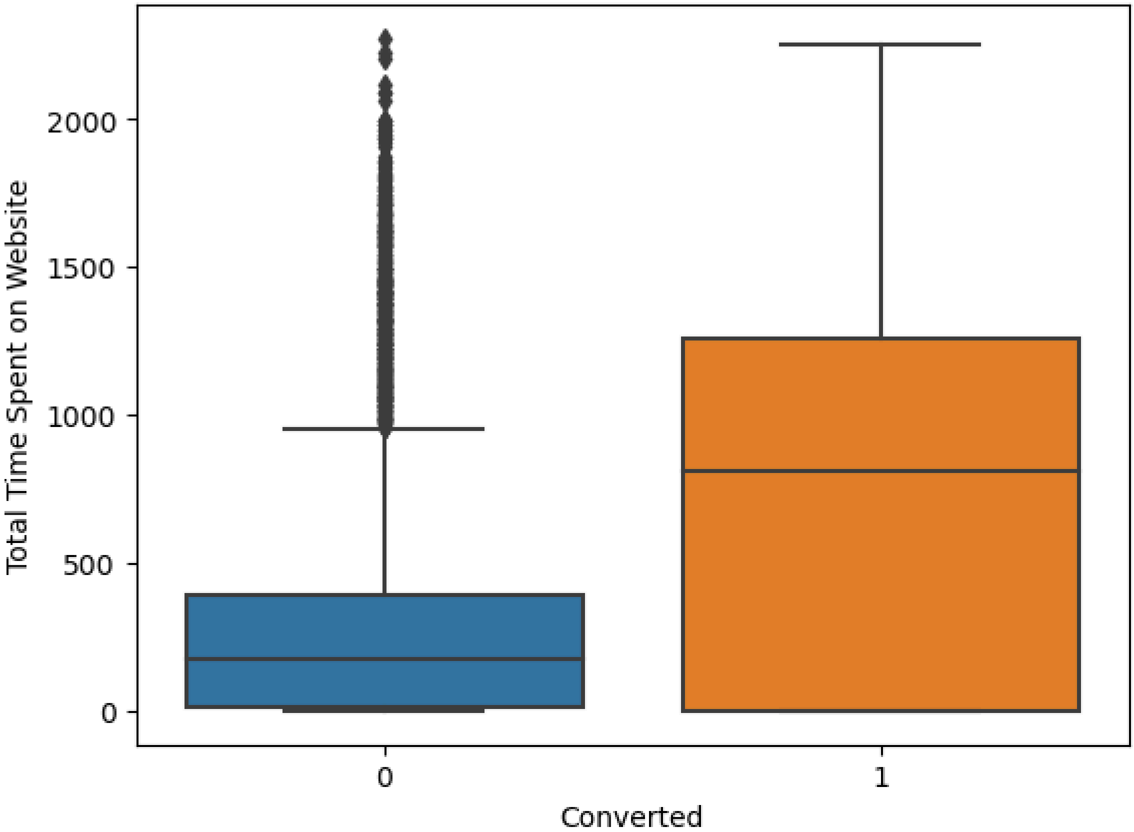
In [89]:
```
#checking Spread of "Total Visits" vs Converted variable
sns.boxplot(y = 'TotalVisits', x = 'Converted', data = leads)
plt.show()
```



Inference

- Median for converted and not converted leads are the close.
- Nothng conclusive can be said on the basis of Total Visits

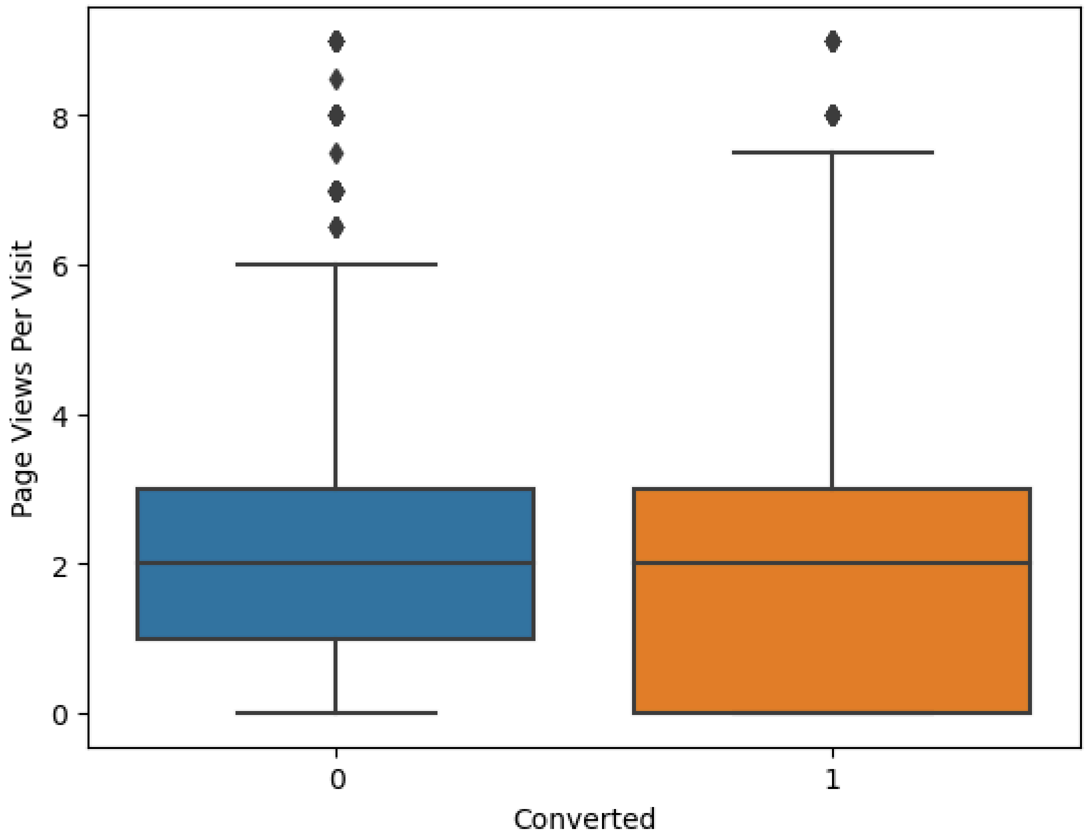
In [90]:
```
#checking Spread of "Total Time Spent on Website" vs Converted variable

sns.boxplot(x=leads.Converted, y=leads['Total Time Spent on Website'])
plt.show()
```



Inference

- Leads spending more time on the website are more likely to be converted.
- Website should be made more engaging to make leads spend more time.

In [91]:
```
#checking Spread of "Page Views Per Visit" vs Converted variable

sns.boxplot(x=leads.Converted,y=leads['Page Views Per Visit'])
plt.show()
```



Inference

- Median for converted and unconverted leads is the same.
- Nothing can be said specifically for lead conversion from Page Views Per Visit

In [92]:
```
#checking missing values in leftover columns/

leads.isnull().mean()*100
```

Out[92]:
```
Lead Origin                                 0.0
Lead Source                                 0.0
Do Not Email                                0.0
Converted                                   0.0
TotalVisits                                 0.0
Total Time Spent on Website                 0.0
Page Views Per Visit                        0.0
Last Activity                               0.0
Specialization                              0.0
What is your current occupation             0.0
Tags                                        0.0
City                                        0.0
A free copy of Mastering The Interview      0.0
Last Notable Activity                       0.0
dtype: float64
```

There are no missing values in the columns to be analyzed further

Dummy Variable Creation:

In [93]:
```
#getting a list of categorical columns

cat_cols= leads.select_dtypes(include=['object']).columns
cat_cols
```

Out[93]:
```
Index(['Lead Origin', 'Lead Source', 'Do Not Email', 'Last Activity',
       'Specialization', 'What is your current occupation', 'Tags', 'City',
       'A free copy of Mastering The Interview', 'Last Notable Activity'],
      dtype='object')
```

In [94]:
```
# List of variables to map

varlist =  ['A free copy of Mastering The Interview','Do Not Email']

# 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)
```

In [95]:
```
#getting dummies and dropping the first column and adding the results to the master (
dummy = pd.get_dummies(leads[['Lead Origin','What is your current occupation',
                              'City']], drop_first=True)

leads = pd.concat([leads,dummy],1)
```

In [96]:
```
dummy = pd.get_dummies(leads['Specialization'], prefix  = 'Specialization')
dummy = dummy.drop(['Specialization_Not Specified'], 1)

leads = pd.concat([leads, dummy], axis = 1)
```

In [97]:
```
dummy = pd.get_dummies(leads['Lead Source'], prefix  = 'Lead Source')
dummy = dummy.drop(['Lead Source_Others'], 1)

leads = pd.concat([leads, dummy], axis = 1)
```

In [98]:
```
dummy = pd.get_dummies(leads['Last Activity'], prefix  = 'Last Activity')
dummy = dummy.drop(['Last Activity_Others'], 1)

leads = pd.concat([leads, dummy], axis = 1)
```

In [99]:
```
dummy = pd.get_dummies(leads['Last Notable Activity'], prefix  = 'Last Notable Activi
dummy = dummy.drop(['Last Notable Activity_Other_Notable_activity'], 1)

leads = pd.concat([leads, dummy], axis = 1)
```

In [100]:
```
dummy = pd.get_dummies(leads['Tags'], prefix  = 'Tags')
dummy = dummy.drop(['Tags_Not Specified'], 1)

leads = pd.concat([leads, dummy], axis = 1)
```

In [101]:
```
#dropping the original columns after dummy variable creation

leads.drop(cat_cols,1,inplace = True)
```

In [102]:
```
leads.head()
```

Out[102]:

	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Lead Origin_Landing Page Submission	Lead Origin_Lead Add Form	Lead Origin_Lead Import	What is your occupation_Ho
0	0	0.0	0	0.0	0	0	0	
1	0	5.0	674	2.5	0	0	0	
2	1	2.0	1532	2.0	1	0	0	
3	0	1.0	305	1.0	1	0	0	
4	1	2.0	1428	1.0	1	0	0	

5 rows × 59 columns

Train-Test Split & Logistic Regression Model Building:

In [103]:
```
from sklearn.model_selection import train_test_split

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

y.head()

X=leads.drop('Converted', axis=1)
```

In [104]:
```
# 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=(
```

In [105]:
```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6267 entries, 9196 to 5825
Data columns (total 58 columns):
 #   Column                                          Non-Null Count  Dtype  
---  ------                                          --------------  -----  
 0   TotalVisits                                     6267 non-null   float64
 1   Total Time Spent on Website                     6267 non-null   int64  
 2   Page Views Per Visit                            6267 non-null   float64
 3   Lead Origin_Landing Page Submission             6267 non-null   uint8  
 4   Lead Origin_Lead Add Form                       6267 non-null   uint8  
 5   Lead Origin_Lead Import                         6267 non-null   uint8  
 6   What is your current occupation_Housewife       6267 non-null   uint8  
 7   What is your current occupation_NOt Provided    6267 non-null   uint8  
 8   What is your current occupation_Other           6267 non-null   uint8  
 9   What is your current occupation_Student         6267 non-null   uint8  
 10  What is your current occupation_Unemployed      6267 non-null   uint8  
 11  What is your current occupation_Working Professional  6267 non-null   uint8  
 12  City_Not Provided                               6267 non-null   uint8  
 13  City_Other Cities                               6267 non-null   uint8  
 14  City_Other Cities of Maharashtra                6267 non-null   uint8  
 15  City_Other Metro Cities                         6267 non-null   uint8  
 16  City_Thane & Outskirts                          6267 non-null   uint8  
 17  City_Tier II Cities                             6267 non-null   uint8  
 18  Specialization_Banking, Investment And Insurance  6267 non-null   uint8  
 19  Specialization_Business Administration          6267 non-null   uint8  
 20  Specialization_E-Business                       6267 non-null   uint8  
 21  Specialization_E-COMMERCE                       6267 non-null   uint8  
 22  Specialization_International Business           6267 non-null   uint8  
 23  Specialization_Management_Specializations       6267 non-null   uint8  
 24  Specialization_Media and Advertising            6267 non-null   uint8  
 25  Specialization_Rural and Agribusiness           6267 non-null   uint8  
 26  Specialization_Services Excellence              6267 non-null   uint8  
 27  Specialization_Travel and Tourism               6267 non-null   uint8  
 28  Lead Source_Direct Traffic                      6267 non-null   uint8  
 29  Lead Source_Google                              6267 non-null   uint8  
 30  Lead Source_Live Chat                           6267 non-null   uint8  
 31  Lead Source_Olark Chat                          6267 non-null   uint8  
 32  Lead Source_Organic Search                      6267 non-null   uint8  
 33  Lead Source_Reference                           6267 non-null   uint8  
 34  Lead Source_Referral Sites                      6267 non-null   uint8  
 35  Lead Source_Social Media                        6267 non-null   uint8  
 36  Lead Source_Welingak Website                    6267 non-null   uint8  
 37  Last Activity_Converted to Lead                 6267 non-null   uint8  
 38  Last Activity_Email Bounced                     6267 non-null   uint8  
 39  Last Activity_Email Link Clicked                6267 non-null   uint8  
 40  Last Activity_Email Opened                      6267 non-null   uint8  
 41  Last Activity_Form Submitted on Website         6267 non-null   uint8  
 42  Last Activity_Olark Chat Conversation           6267 non-null   uint8  
 43  Last Activity_Page Visited on Website           6267 non-null   uint8  
 44  Last Activity_SMS Sent                          6267 non-null   uint8  
 45  Last Notable Activity_Email Link Clicked        6267 non-null   uint8  
 46  Last Notable Activity_Email Opened              6267 non-null   uint8  
 47  Last Notable Activity_Modified                  6267 non-null   uint8  
 48  Last Notable Activity_Olark Chat Conversation   6267 non-null   uint8  
 49  Last Notable Activity_Page Visited on Website   6267 non-null   uint8  
 50  Last Notable Activity_SMS Sent                  6267 non-null   uint8  
 51  Tags_Busy                                       6267 non-null   uint8  
 52  Tags_Closed by Horizzon                         6267 non-null   uint8  
 53  Tags_Interested in other courses                6267 non-null   uint8  
 54  Tags_Lost to EINS                               6267 non-null   uint8  
 55  Tags_Other_Tags                                 6267 non-null   uint8  
 56  Tags_Ringing                                    6267 non-null   uint8  
 57  Tags_Will revert after reading the email        6267 non-null   uint8  
```

```
dtypes: float64(2), int64(1), uint8(55)
memory usage: 532.5 KB
```

Scaling of Data:

In [106]:
```
#scaling numeric columns

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

num_cols=X_train.select_dtypes(include=['float64', 'int64']).columns

X_train[num_cols] = scaler.fit_transform(X_train[num_cols])

X_train.head()
```

Out[106]:

	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Lead Origin_Landing Page Submission	Lead Origin_Lead Add Form	Lead Origin_Lead Import	What is your curre occupation_Housew
9196	0.668862	1.848117	1.455819	1	0	0	
4696	-0.030697	-0.037832	0.399961	1	0	0	
3274	0.319082	-0.642138	-0.127967	1	0	0	
2164	-0.380477	-0.154676	-0.127967	0	0	0	
1667	0.319082	1.258415	-0.481679	0	0	0	

5 rows × 58 columns

Model Building using Stats Model & RFE:

In [107]:
```
import statsmodels.api as sm
```

In [108]:
```
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()

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

In [109]:
```
rfe.support_
```

Out[109]:
```
array([False,  True, False, False,  True, False, False,  True, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False,  True,  True, False, False,  True, False,  True, False,
        True, False,  True, False, False, False, False, False,  True,
        True, False,  True,  True, False, False,  True,  True,  True,
        True,  True,  True,  True])
```

In [110]:
```
list(zip(X_train.columns, rfe.support_, rfe.ranking_))
```

```
Out[110]: [('TotalVisits', False, 21),
 ('Total Time Spent on Website', True, 1),
 ('Page Views Per Visit', False, 20),
 ('Lead Origin_Landing Page Submission', False, 10),
 ('Lead Origin_Lead Add Form', True, 1),
 ('Lead Origin_Lead Import', False, 39),
 ('What is your current occupation_Housewife', False, 14),
 ('What is your current occupation_NOt Provided', True, 1),
 ('What is your current occupation_Other', False, 31),
 ('What is your current occupation_Student', False, 17),
 ('What is your current occupation_Unemployed', False, 15),
 ('What is your current occupation_Working Professional', False, 7),
 ('City_Not Provided', False, 36),
 ('City_Other Cities', False, 19),
 ('City_Other Cities of Maharashtra', False, 26),
 ('City_Other Metro Cities', False, 37),
 ('City_Thane & Outskirts', False, 34),
 ('City_Tier II Cities', False, 13),
 ('Specialization_Banking, Investment And Insurance', False, 9),
 ('Specialization_Business Administration', False, 33),
 ('Specialization_E-Business', False, 28),
 ('Specialization_E-COMMERCE', False, 25),
 ('Specialization_International Business', False, 27),
 ('Specialization_Management_Specializations', False, 29),
 ('Specialization_Media and Advertising', False, 22),
 ('Specialization_Rural and Agribusiness', False, 32),
 ('Specialization_Services Excellence', False, 24),
 ('Specialization_Travel and Tourism', False, 4),
 ('Lead Source_Direct Traffic', True, 1),
 ('Lead Source_Google', True, 1),
 ('Lead Source_Live Chat', False, 38),
 ('Lead Source_Olark Chat', False, 16),
 ('Lead Source_Organic Search', True, 1),
 ('Lead Source_Reference', False, 23),
 ('Lead Source_Referral Sites', True, 1),
 ('Lead Source_Social Media', False, 5),
 ('Lead Source_Welingak Website', True, 1),
 ('Last Activity_Converted to Lead', False, 8),
 ('Last Activity_Email Bounced', True, 1),
 ('Last Activity_Email Link Clicked', False, 30),
 ('Last Activity_Email Opened', False, 12),
 ('Last Activity_Form Submitted on Website', False, 18),
 ('Last Activity_Olark Chat Conversation', False, 3),
 ('Last Activity_Page Visited on Website', False, 6),
 ('Last Activity_SMS Sent', True, 1),
 ('Last Notable Activity_Email Link Clicked', True, 1),
 ('Last Notable Activity_Email Opened', False, 11),
 ('Last Notable Activity_Modified', True, 1),
 ('Last Notable Activity_Olark Chat Conversation', True, 1),
 ('Last Notable Activity_Page Visited on Website', False, 35),
 ('Last Notable Activity_SMS Sent', False, 2),
 ('Tags_Busy', True, 1),
 ('Tags_Closed by Horizzon', True, 1),
 ('Tags_Interested in other courses', True, 1),
 ('Tags_Lost to EINS', True, 1),
 ('Tags_Other_Tags', True, 1),
 ('Tags_Ringing', True, 1),
 ('Tags_Will revert after reading the email', True, 1)]
```

In [111]:

```
#list of RFE supported columns
col = X_train.columns[rfe.support_]
col
```

Out[111]:
```
Index(['Total Time Spent on Website', 'Lead Origin_Lead Add Form',
       'What is your current occupation_NOt Provided',
       'Lead Source_Direct Traffic', 'Lead Source_Google',
       'Lead Source_Organic Search', 'Lead Source_Referral Sites',
       'Lead Source_Welingak Website', 'Last Activity_Email Bounced',
       'Last Activity_SMS Sent', 'Last Notable Activity_Email Link Clicked',
       'Last Notable Activity_Modified',
       'Last Notable Activity_Olark Chat Conversation', 'Tags_Busy',
       'Tags_Closed by Horizzon', 'Tags_Interested in other courses',
       'Tags_Lost to EINS', 'Tags_Other_Tags', 'Tags_Ringing',
       'Tags_Will revert after reading the email'],
      dtype='object')
```

In [112]:
```
X_train.columns[~rfe.support_]
```

Out[112]:
```
Index(['TotalVisits', 'Page Views Per Visit',
       'Lead Origin_Landing Page Submission', 'Lead Origin_Lead Import',
       'What is your current occupation_Housewife',
       'What is your current occupation_Other',
       'What is your current occupation_Student',
       'What is your current occupation_Unemployed',
       'What is your current occupation_Working Professional',
       'City_Not Provided', 'City_Other Cities',
       'City_Other Cities of Maharashtra', 'City_Other Metro Cities',
       'City_Thane & Outskirts', 'City_Tier II Cities',
       'Specialization_Banking, Investment And Insurance',
       'Specialization_Business Administration', 'Specialization_E-Business',
       'Specialization_E-COMMERCE', 'Specialization_International Business',
       'Specialization_Management_Specializations',
       'Specialization_Media and Advertising',
       'Specialization_Rural and Agribusiness',
       'Specialization_Services Excellence',
       'Specialization_Travel and Tourism', 'Lead Source_Live Chat',
       'Lead Source_Olark Chat', 'Lead Source_Reference',
       'Lead Source_Social Media', 'Last Activity_Converted to Lead',
       'Last Activity_Email Link Clicked', 'Last Activity_Email Opened',
       'Last Activity_Form Submitted on Website',
       'Last Activity_Olark Chat Conversation',
       'Last Activity_Page Visited on Website',
       'Last Notable Activity_Email Opened',
       'Last Notable Activity_Page Visited on Website',
       'Last Notable Activity_SMS Sent'],
      dtype='object')
```

In [113]:
```
#BUILDING MODEL #1

X_train_sm = sm.add_constant(X_train[col])
logm1 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm1.fit()
res.summary()
```

Out[113]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6267
Model:	GLM	**Df Residuals:**	6246
Model Family:	Binomial	**Df Model:**	20
Link Function:	Logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1094.9
Date:	Mon, 17 Feb 2025	**Deviance:**	2189.9
Time:	21:41:38	**Pearson chi2:**	9.17e+03
No. Iterations:	8	**Pseudo R-squ. (CS):**	0.6244
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	1.1637	0.167	6.977	0.000	0.837	1.491
Total Time Spent on Website	1.0704	0.065	16.494	0.000	0.943	1.198
Lead Origin_Lead Add Form	0.7656	0.478	1.601	0.109	-0.172	1.703
What is your current occupation_NOt Provided	-2.4331	0.160	-15.236	0.000	-2.746	-2.120
Lead Source_Direct Traffic	-1.4597	0.188	-7.772	0.000	-1.828	-1.092
Lead Source_Google	-0.9336	0.172	-5.424	0.000	-1.271	-0.596
Lead Source_Organic Search	-0.9830	0.216	-4.548	0.000	-1.407	-0.559
Lead Source_Referral Sites	-0.9687	0.497	-1.949	0.051	-1.943	0.005
Lead Source_Welingak Website	2.7132	1.124	2.413	0.016	0.509	4.917
Last Activity_Email Bounced	-1.2093	0.452	-2.678	0.007	-2.095	-0.324
Last Activity_SMS Sent	2.0629	0.129	16.037	0.000	1.811	2.315
Last Notable Activity_Email Link Clicked	-1.2555	0.507	-2.478	0.013	-2.248	-0.263
Last Notable Activity_Modified	-1.4286	0.133	-10.751	0.000	-1.689	-1.168
Last Notable Activity_Olark Chat Conversation	-2.3959	0.541	-4.433	0.000	-3.455	-1.336
Tags_Busy	-1.1713	0.263	-4.454	0.000	-1.687	-0.656
Tags_Closed by Horizzon	5.5504	1.029	5.396	0.000	3.534	7.566
Tags_Interested in other courses	-3.8144	0.429	-8.894	0.000	-4.655	-2.974
Tags_Lost to EINS	4.9972	0.631	7.916	0.000	3.760	6.234
Tags_Other_Tags	-4.0446	0.247	-16.370	0.000	-4.529	-3.560
Tags_Ringing	-5.1361	0.276	-18.621	0.000	-5.677	-4.596
Tags_Will revert after reading the email	2.8699	0.221	12.960	0.000	2.436	3.304

In [114]:

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


# Create a dataframe that will contain the names of all the feature variables and the
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in range(X_tra
vif['VIF'] = round(vif['VIF'], 2)
```

```
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[114]:

	Features	VIF
4	Lead Source_Google	2.67
3	Lead Source_Direct Traffic	2.56
2	What is your current occupation_NOt Provided	2.41
19	Tags_Will revert after reading the email	2.26
1	Lead Origin_Lead Add Form	1.97
17	Tags_Other_Tags	1.97
11	Last Notable Activity_Modified	1.93
18	Tags_Ringing	1.78
5	Lead Source_Organic Search	1.65
9	Last Activity_SMS Sent	1.64
0	Total Time Spent on Website	1.44
15	Tags_Interested in other courses	1.38
7	Lead Source_Welingak Website	1.37
14	Tags_Closed by Horizzon	1.33
13	Tags_Busy	1.13
8	Last Activity_Email Bounced	1.10
16	Tags_Lost to EINS	1.09
6	Lead Source_Referral Sites	1.08
12	Last Notable Activity_Olark Chat Conversation	1.07
10	Last Notable Activity_Email Link Clicked	1.05

p-value of variable Lead Source_Referral Sites is high, so we can drop it.

In [115]:
```
#dropping column with high p-value

col = col.drop('Lead Origin_Lead Add Form',1)
```

In [116]:
```
#BUILDING MODEL #2

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[116]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6267
Model:	GLM	**Df Residuals:**	6247
Model Family:	Binomial	**Df Model:**	19
Link Function:	Logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1096.3
Date:	Mon, 17 Feb 2025	**Deviance:**	2192.6
Time:	21:42:12	**Pearson chi2:**	9.22e+03
No. Iterations:	8	**Pseudo R-squ. (CS):**	0.6242
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	1.2111	0.164	7.369	0.000	0.889	1.533
Total Time Spent on Website	1.0716	0.065	16.460	0.000	0.944	1.199
What is your current occupation_NOt Provided	-2.4402	0.160	-15.292	0.000	-2.753	-2.127
Lead Source_Direct Traffic	-1.5237	0.184	-8.286	0.000	-1.884	-1.163
Lead Source_Google	-0.9897	0.169	-5.870	0.000	-1.320	-0.659
Lead Source_Organic Search	-1.0421	0.213	-4.883	0.000	-1.460	-0.624
Lead Source_Referral Sites	-1.0233	0.498	-2.054	0.040	-2.000	-0.047
Lead Source_Welingak Website	3.4325	1.030	3.334	0.001	1.414	5.451
Last Activity_Email Bounced	-1.2169	0.454	-2.681	0.007	-2.107	-0.327
Last Activity_SMS Sent	2.0770	0.128	16.189	0.000	1.826	2.328
Last Notable Activity_Email Link Clicked	-1.2696	0.504	-2.520	0.012	-2.257	-0.282
Last Notable Activity_Modified	-1.4414	0.133	-10.850	0.000	-1.702	-1.181
Last Notable Activity_Olark Chat Conversation	-2.4231	0.541	-4.479	0.000	-3.483	-1.363
Tags_Busy	-1.1697	0.263	-4.444	0.000	-1.686	-0.654
Tags_Closed by Horizzon	5.8192	1.018	5.715	0.000	3.823	7.815
Tags_Interested in other courses	-3.8096	0.430	-8.868	0.000	-4.652	-2.968
Tags_Lost to EINS	5.0213	0.631	7.958	0.000	3.785	6.258
Tags_Other_Tags	-4.0334	0.247	-16.333	0.000	-4.517	-3.549
Tags_Ringing	-5.1153	0.275	-18.570	0.000	-5.655	-4.575
Tags_Will revert after reading the email	2.9394	0.217	13.518	0.000	2.513	3.366

Since 'All' the p-values are less we can check the Variance Inflation Factor to see if there is any correlation between the variables

In [117]:

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

Out[117]:

	Features	VIF
3	Lead Source_Google	2.49
2	Lead Source_Direct Traffic	2.39
1	What is your current occupation_NOt Provided	2.35
10	Last Notable Activity_Modified	1.93
16	Tags_Other_Tags	1.92
18	Tags_Will revert after reading the email	1.86
17	Tags_Ringing	1.73
8	Last Activity_SMS Sent	1.60
4	Lead Source_Organic Search	1.58
0	Total Time Spent on Website	1.41
14	Tags_Interested in other courses	1.36
12	Tags_Busy	1.13
13	Tags_Closed by Horizzon	1.12
7	Last Activity_Email Bounced	1.10
15	Tags_Lost to EINS	1.08
5	Lead Source_Referral Sites	1.07
11	Last Notable Activity_Olark Chat Conversation	1.06
6	Lead Source_Welingak Website	1.05
9	Last Notable Activity_Email Link Clicked	1.05

There is a high correlation between two variables so we drop the variable with the higher valued VIF value

In [118]:

```
#dropping variable with high VIF

col = col.drop('Lead Source_Referral Sites',1)
```

In [119]:

```
#BUILDING MODEL #3
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[119]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6267
Model:	GLM	**Df Residuals:**	6248
Model Family:	Binomial	**Df Model:**	18
Link Function:	Logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1098.6
Date:	Mon, 17 Feb 2025	**Deviance:**	2197.2
Time:	21:42:59	**Pearson chi2:**	9.25e+03
No. Iterations:	8	**Pseudo R-squ. (CS):**	0.6240
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	1.1476	0.161	7.114	0.000	0.831	1.464
Total Time Spent on Website	1.0547	0.065	16.335	0.000	0.928	1.181
What is your current occupation_NOt Provided	-2.4564	0.159	-15.418	0.000	-2.769	-2.144
Lead Source_Direct Traffic	-1.4455	0.180	-8.027	0.000	-1.798	-1.093
Lead Source_Google	-0.9097	0.164	-5.532	0.000	-1.232	-0.587
Lead Source_Organic Search	-0.9623	0.210	-4.580	0.000	-1.374	-0.551
Lead Source_Welingak Website	3.4778	1.029	3.378	0.001	1.460	5.495
Last Activity_Email Bounced	-1.2051	0.454	-2.654	0.008	-2.095	-0.315
Last Activity_SMS Sent	2.0859	0.128	16.284	0.000	1.835	2.337
Last Notable Activity_Email Link Clicked	-1.2699	0.510	-2.489	0.013	-2.270	-0.270
Last Notable Activity_Modified	-1.4313	0.133	-10.789	0.000	-1.691	-1.171
Last Notable Activity_Olark Chat Conversation	-2.4336	0.542	-4.487	0.000	-3.497	-1.371
Tags_Busy	-1.1905	0.262	-4.539	0.000	-1.705	-0.676
Tags_Closed by Horizzon	5.8283	1.018	5.725	0.000	3.833	7.824
Tags_Interested in other courses	-3.8911	0.434	-8.974	0.000	-4.741	-3.041
Tags_Lost to EINS	5.0308	0.631	7.977	0.000	3.795	6.267
Tags_Other_Tags	-4.0453	0.247	-16.401	0.000	-4.529	-3.562
Tags_Ringing	-5.1188	0.275	-18.610	0.000	-5.658	-4.580
Tags_Will revert after reading the email	2.9211	0.217	13.486	0.000	2.497	3.346

In [131]:

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

Out[131]:

	Features	VIF
3	Lead Source_Google	2.40
2	Lead Source_Direct Traffic	2.32
1	What is your current occupation_NOt Provided	2.23
8	Last Notable Activity_Modified	1.90
14	Tags_Other_Tags	1.85
16	Tags_Will revert after reading the email	1.81
15	Tags_Ringing	1.68
7	Last Activity_SMS Sent	1.59
4	Lead Source_Organic Search	1.54
0	Total Time Spent on Website	1.39
12	Tags_Interested in other courses	1.31
10	Tags_Busy	1.12
6	Last Activity_Email Bounced	1.10
11	Tags_Closed by Horizzon	1.10
13	Tags_Lost to EINS	1.07
9	Last Notable Activity_Olark Chat Conversation	1.06
5	Lead Source_Welingak Website	1.05

In [120]:

```
#dropping variable with high VIF

col = col.drop('Last Notable Activity_Email Link Clicked',1)
```

In [121]:

```
#BUILDING MODEL #4
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[121]: Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6267
Model:	GLM	**Df Residuals:**	6249
Model Family:	Binomial	**Df Model:**	17
Link Function:	Logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1102.2
Date:	Mon, 17 Feb 2025	**Deviance:**	2204.3
Time:	21:44:40	**Pearson chi2:**	9.21e+03
No. Iterations:	8	**Pseudo R-squ. (CS):**	0.6235
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	1.0980	0.160	6.880	0.000	0.785	1.411
Total Time Spent on Website	1.0602	0.065	16.412	0.000	0.934	1.187
What is your current occupation_NOt Provided	-2.4599	0.159	-15.501	0.000	-2.771	-2.149
Lead Source_Direct Traffic	-1.4379	0.180	-7.988	0.000	-1.791	-1.085
Lead Source_Google	-0.8941	0.164	-5.448	0.000	-1.216	-0.572
Lead Source_Organic Search	-0.9492	0.210	-4.522	0.000	-1.361	-0.538
Lead Source_Welingak Website	3.4581	1.028	3.365	0.001	1.444	5.472
Last Activity_Email Bounced	-1.1791	0.454	-2.598	0.009	-2.069	-0.289
Last Activity_SMS Sent	2.1180	0.128	16.585	0.000	1.868	2.368
Last Notable Activity_Modified	-1.4004	0.132	-10.596	0.000	-1.659	-1.141
Last Notable Activity_Olark Chat Conversation	-2.3921	0.543	-4.406	0.000	-3.456	-1.328
Tags_Busy	-1.1788	0.262	-4.493	0.000	-1.693	-0.665
Tags_Closed by Horizzon	5.7930	1.018	5.689	0.000	3.797	7.789
Tags_Interested in other courses	-3.8893	0.434	-8.970	0.000	-4.739	-3.039
Tags_Lost to EINS	5.0192	0.631	7.948	0.000	3.782	6.257
Tags_Other_Tags	-4.0527	0.246	-16.467	0.000	-4.535	-3.570
Tags_Ringing	-5.1135	0.275	-18.595	0.000	-5.653	-4.575
Tags_Will revert after reading the email	2.9135	0.216	13.507	0.000	2.491	3.336

In [123]:

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

Out[123]:

	Features	VIF
3	Lead Source_Google	2.40
2	Lead Source_Direct Traffic	2.32
1	What is your current occupation_NOt Provided	2.23
8	Last Notable Activity_Modified	1.90
14	Tags_Other_Tags	1.85
16	Tags_Will revert after reading the email	1.81
15	Tags_Ringing	1.68
7	Last Activity_SMS Sent	1.59
4	Lead Source_Organic Search	1.54
0	Total Time Spent on Website	1.39
12	Tags_Interested in other courses	1.31
10	Tags_Busy	1.12
6	Last Activity_Email Bounced	1.10
11	Tags_Closed by Horizzon	1.10
13	Tags_Lost to EINS	1.07
9	Last Notable Activity_Olark Chat Conversation	1.06
5	Lead Source_Welingak Website	1.05

So the Values all seem to be in order so now, Moving on to derive the Probabilities, Lead Score, Predictions on Train Data:

In [124]:
```
# Getting the Predicted values on the train set
y_train_pred = res.predict(X_train_sm)
y_train_pred[:10]
```

Out[124]:
```
9196    0.303204
4696    0.033072
3274    0.306033
2164    0.005222
1667    0.988475
7024    0.543223
8018    0.009206
778     0.092466
6942    0.005068
4440    0.041033
dtype: float64
```

In [125]:
```
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]
```

Out[125]:
```
array([0.30320369, 0.03307186, 0.30603259, 0.0052217 , 0.98847546,
       0.54322336, 0.00920607, 0.09246557, 0.00506774, 0.04103274])
```

In [126]:
```
y_train_pred_final = pd.DataFrame({'Converted':y_train.values, 'Converted_prob':y_tra
y_train_pred_final['Prospect ID'] = y_train.index
y_train_pred_final.head()
```

Out[126]:

	Converted	Converted_prob	Prospect ID
0	1	0.303204	9196
1	0	0.033072	4696
2	0	0.306033	3274
3	0	0.005222	2164
4	1	0.988475	1667

In [127]:

```
y_train_pred_final['Predicted'] = y_train_pred_final.Converted_prob.map(lambda x: 1 :

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

Out[127]:

	Converted	Converted_prob	Prospect ID	Predicted
0	1	0.303204	9196	0
1	0	0.033072	4696	0
2	0	0.306033	3274	0
3	0	0.005222	2164	0
4	1	0.988475	1667	1

In [128]:

```
from sklearn import metrics

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

```
[[3723  159]
 [ 248 2137]]
```

In [129]:

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

```
0.9350566459230892
```

In [130]:

```
TP = confusion[1,1] # true positive
TN = confusion[0,0] # true negatives
FP = confusion[0,1] # false positives
FN = confusion[1,0] # false negatives
```

In [131]:

```
# Let's see the sensitivity of our logistic regression model
TP / float(TP+FN)
```

Out[131]:

```
0.8960167714884696
```

In [132]:

```
# Let us calculate specificity
TN / float(TN+FP)
```

Out[132]:

```
0.9590417310664606
```

In [133]:

```
# Calculate False Postive Rate - predicting conversion when customer does not have co
print(FP/ float(TN+FP))
```

```
0.04095826893353941
```

In [134]:
```
# positive predictive value
print (TP / float(TP+FP))
```

0.9307491289198606

In [135]:
```
# Negative predictive value
print (TN / float(TN+ FN))
```

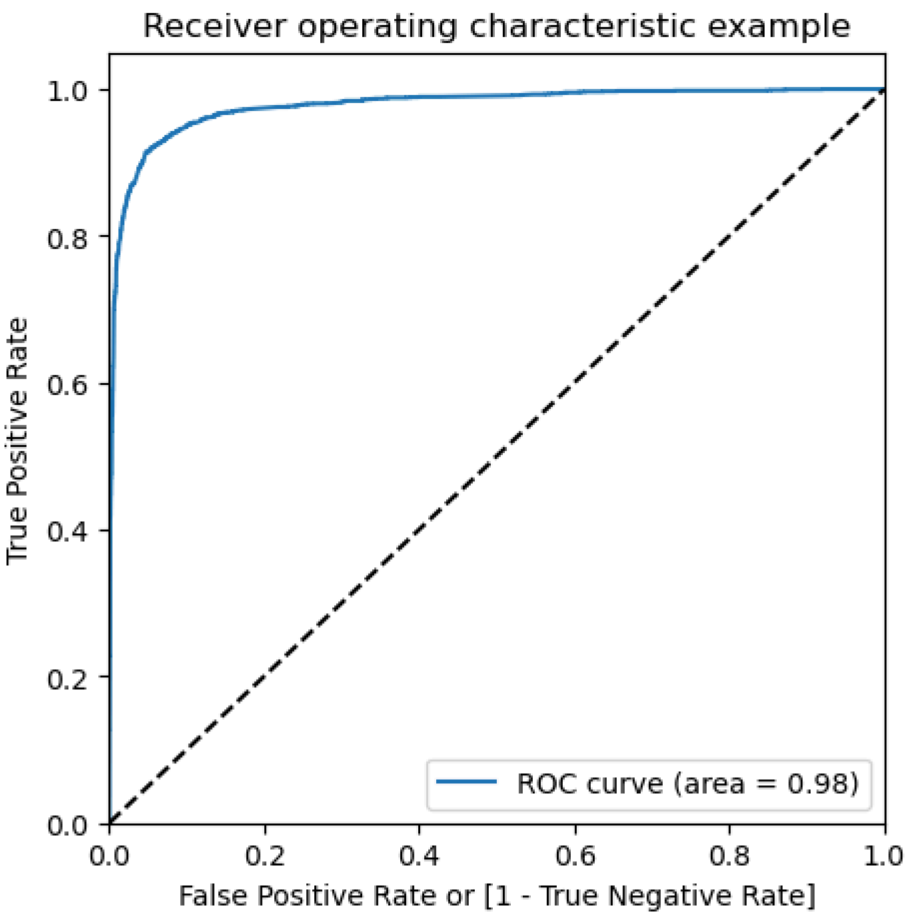
0.9375472173256106

PLOTTING ROC CURVE

In [136]:
```
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 None
```

In [137]:
```
fpr, tpr, thresholds = metrics.roc_curve( y_train_pred_final.Converted, y_train_pred_
```

In [138]:
```
draw_roc(y_train_pred_final.Converted, y_train_pred_final.Converted_prob)
```



The ROC Curve should be a value close to 1. We are getting a good value of 0.97 indicating a good predictive model.

Finding Optimal Cutoff Point

Above we had chosen an arbitrary cut-off value of 0.5. We need to determine the best cut-off value and the below section deals with that:

In [139]:
```
# Let's create columns with different probability cutoffs
numbers = [float(x)/10 for x in range(10)]
for i in numbers:
    y_train_pred_final[i]= y_train_pred_final.Converted_prob.map(lambda x: 1 if x > 
y_train_pred_final.head()
```

Out[139]:

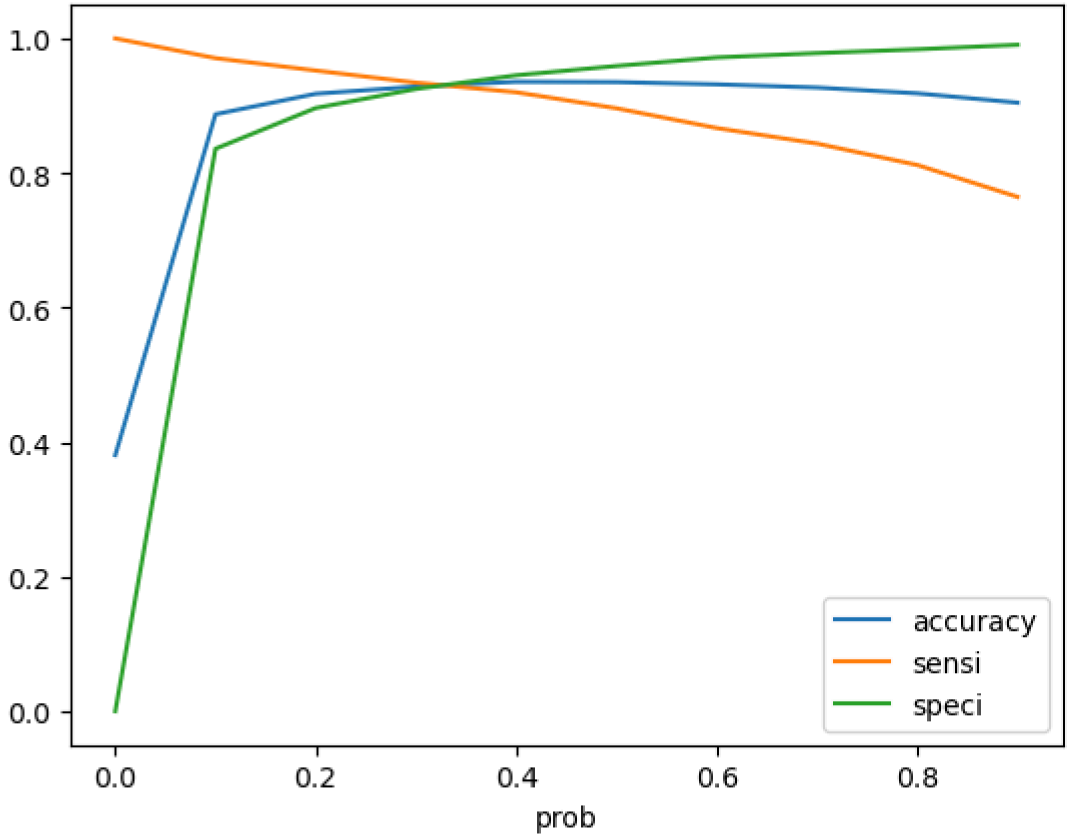
	Converted	Converted_prob	Prospect ID	Predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.
0	1	0.303204	9196	0	1	1	1	1	0	0	0	0	0	
1	0	0.033072	4696	0	1	0	0	0	0	0	0	0	0	
2	0	0.306033	3274	0	1	1	1	1	0	0	0	0	0	
3	0	0.005222	2164	0	1	0	0	0	0	0	0	0	0	
4	1	0.988475	1667	1	1	1	1	1	1	1	1	1	1	

In [140]:
```
# Now let's calculate accuracy sensitivity and specificity for various probability c
cutoff_df = pd.DataFrame( columns = ['prob','accuracy','sensi','speci'])
from sklearn.metrics import confusion_matrix

# TP = confusion[1,1] # true positive
# TN = confusion[0,0] # true negatives
# FP = confusion[0,1] # false positives
# FN = confusion[1,0] # false negatives

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[
    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  0.380565  1.000000  0.000000
0.1   0.1  0.887187  0.970650  0.835909
0.2   0.2  0.917664  0.952201  0.896445
0.3   0.3  0.928355  0.934172  0.924781
0.4   0.4  0.935535  0.919916  0.945131
0.5   0.5  0.935057  0.896017  0.959042
0.6   0.6  0.931706  0.866667  0.971664
0.7   0.7  0.926919  0.843606  0.978104
0.8   0.8  0.918302  0.811740  0.983771
0.9   0.9  0.904420  0.764361  0.990469
```

In [141]:

```
# Let's plot accuracy sensitivity and specificity for various probabilities.
cutoff_df.plot.line(x='prob', y=['accuracy','sensi','speci'])
plt.show()
```



In [142]:

```
#### From the curve above, 0.3 is the optimum point to take it as a cutoff probabili

y_train_pred_final['final_Predicted'] = y_train_pred_final.Converted_prob.map( lambda

y_train_pred_final.head()
```

Out[142]:

	Converted	Converted_prob	Prospect ID	Predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.
0	1	0.303204	9196	0	1	1	1	1	0	0	0	0	0	
1	0	0.033072	4696	0	1	0	0	0	0	0	0	0	0	
2	0	0.306033	3274	0	1	1	1	1	0	0	0	0	0	
3	0	0.005222	2164	0	1	0	0	0	0	0	0	0	0	
4	1	0.988475	1667	1	1	1	1	1	1	1	1	1	1	

In [143]:

```
y_train_pred_final['Lead_Score'] = y_train_pred_final.Converted_prob.map( lambda x: r

y_train_pred_final[['Converted','Converted_prob','Prospect ID','final_Predicted','Lea
```

Out[143]:

	Converted	Converted_prob	Prospect ID	final_Predicted	Lead_Score
0	1	0.303204	9196	1	30
1	0	0.033072	4696	0	3
2	0	0.306033	3274	1	31
3	0	0.005222	2164	0	1
4	1	0.988475	1667	1	99

In [144]:
```
# Let's check the overall accuracy.
metrics.accuracy_score(y_train_pred_final.Converted, y_train_pred_final.final_Predic
```
Out[144]:
```
0.9283548747407053
```

In [145]:
```
confusion2 = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_fina
confusion2
```
Out[145]:
```
array([[3590,  292],
       [ 157, 2228]], dtype=int64)
```

In [146]:
```
TP = confusion2[1,1] # true positive
TN = confusion2[0,0] # true negatives
FP = confusion2[0,1] # false positives
FN = confusion2[1,0] # false negatives
```

In [147]:
```
# Let's see the sensitivity of our logistic regression model
TP / float(TP+FN)
```
Out[147]:
```
0.9341719077568135
```

In [148]:
```
# Let us calculate specificity
TN / float(TN+FP)
```
Out[148]:
```
0.9247810407006698
```

Observation:

So as we can see above the model seems to be performing well. The ROC curve has a value of 0.97, which is very good. We have the following values for the Train Data:

- Accuracy : 92.29%
- Sensitivity : 91.70%
- Specificity : 92.66%

Some of the other Stats are derived below, indicating the False Positive Rate, Positive Predictive Value,Negative Predictive Values, Precision & Recall.

In [149]:
```
# Calculate False Postive Rate - predicting conversion when customer does not have c
print(FP/ float(TN+FP))
```
```
0.07521895929933024
```

In [150]:
```
# Positive predictive value
print (TP / float(TP+FP))
```
```
0.8841269841269841
```

In [151]:
```
# Negative predictive value
print (TN / float(TN+ FN))
```

```
0.9580998131838805
```

In [152]:
```
#Looking at the confusion matrix again

confusion = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_fina
confusion
```

Out[152]:
```
array([[3590,  292],
       [ 157, 2228]], dtype=int64)
```

In [153]:
```
##### Precision
TP / TP + FP

confusion[1,1]/(confusion[0,1]+confusion[1,1])
```

Out[153]:
```
0.8841269841269841
```

In [154]:
```
##### Recall
TP / TP + FN

confusion[1,1]/(confusion[1,0]+confusion[1,1])
```

Out[154]:
```
0.9341719077568135
```

In [155]:
```
from sklearn.metrics import precision_score, recall_score
```

In [156]:
```
precision_score(y_train_pred_final.Converted , y_train_pred_final.final_Predicted)
```

Out[156]:
```
0.8841269841269841
```

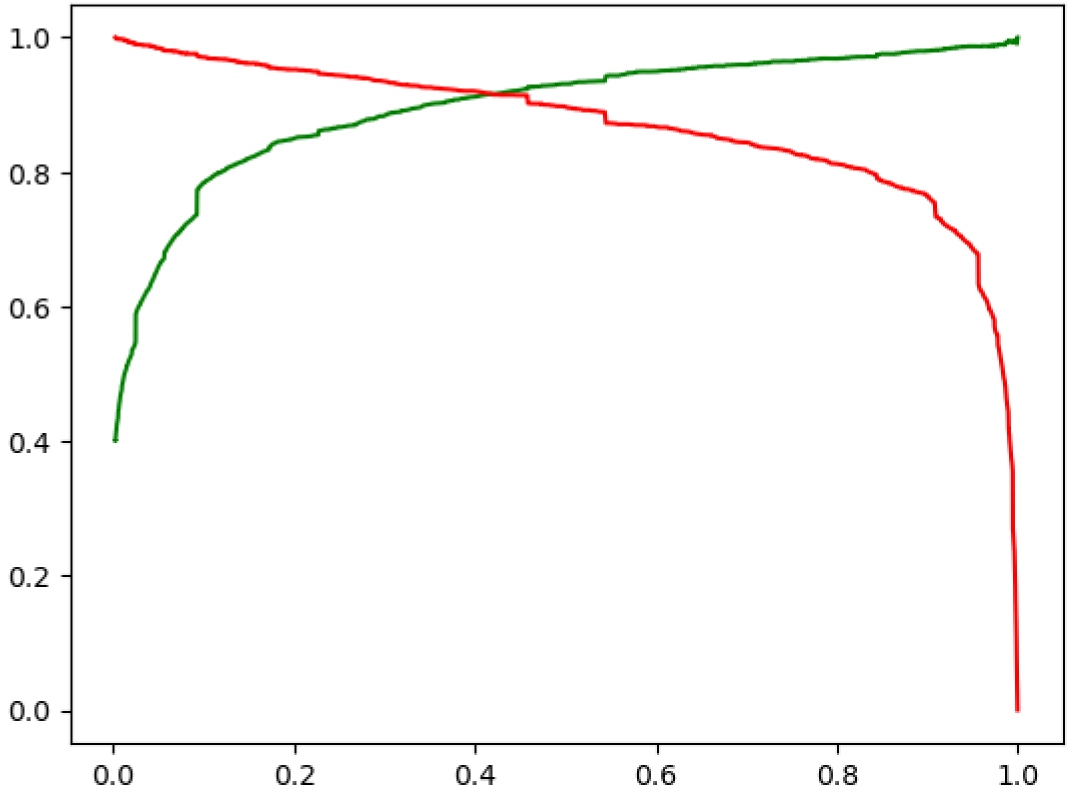
In [157]:
```
recall_score(y_train_pred_final.Converted, y_train_pred_final.final_Predicted)
```

Out[157]:
```
0.9341719077568135
```

In [158]:
```
from sklearn.metrics import precision_recall_curve
```

In [159]:
```
y_train_pred_final.Converted, y_train_pred_final.final_Predicted
p, r, thresholds = precision_recall_curve(y_train_pred_final.Converted, y_train_pred_
```

In [160]:
```
plt.plot(thresholds, p[:-1], "g-")
plt.plot(thresholds, r[:-1], "r-")
plt.show()
```



In [161]:

```
#scaling test set

num_cols=X_test.select_dtypes(include=['float64', 'int64']).columns

X_test[num_cols] = scaler.fit_transform(X_test[num_cols])

X_test.head()
```

Out[161]:

	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Lead Origin_Landing Page Submission	Lead Origin_Lead Add Form	Lead Origin_Lead Import	What is your curre occupation_Housew
7681	0.575687	-0.311318	0.092860	1	0	0	
984	-0.090676	-0.550262	0.356568	1	0	0	
8135	-0.423857	0.812462	-0.170849	1	0	0	
6915	0.242505	-0.628665	-0.170849	1	0	0	
2712	-0.090676	-0.421456	0.356568	0	0	0	

5 rows × 58 columns

In [162]:

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

Out[162]:

	Total Time Spent on Website	What is your current occupation_NOt Provided	Lead Source_Direct Traffic	Lead Source_Google	Lead Source_Organic Search	Lead Source_Welingak Website
7681	-0.311318	0	1	0	0	0
984	-0.550262	0	0	0	1	0
8135	0.812462	1	1	0	0	0
6915	-0.628665	0	0	1	0	0
2712	-0.421456	0	0	1	0	0

In [163]:

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

PREDICTIONS ON TEST SET

In [164]:

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

In [165]:

```
y_test_pred[:10]
```

Out[165]:

```
7681    0.024955
984     0.022540
8135    0.544807
6915    0.003773
2712    0.935270
244     0.002161
4698    0.009019
8287    0.023944
6791    0.978512
8970    0.004523
dtype: float64
```

In [166]:

```
# Converting y_pred to a dataframe which is an array
y_pred_1 = pd.DataFrame(y_test_pred)
```

In [167]:

```
# Let's see the head
y_pred_1.head()
```

Out[167]:

	0
7681	0.024955
984	0.022540
8135	0.544807
6915	0.003773
2712	0.935270

In [168]:

```
# Converting y_test to dataframe
y_test_df = pd.DataFrame(y_test)
```

In [169]:

```
# Putting CustID to index
y_test_df['Prospect ID'] = y_test_df.index
```

In [170]:
```
# Removing index for both dataframes to append them side by side
y_pred_1.reset_index(drop=True, inplace=True)
y_test_df.reset_index(drop=True, inplace=True)
```

In [171]:
```
# Appending y_test_df and y_pred_1
y_pred_final = pd.concat([y_test_df, y_pred_1],axis=1)
```

In [172]:
```
y_pred_final.head()
```

Out[172]:

	Converted	Prospect ID	0
0	0	7681	0.024955
1	0	984	0.022540
2	0	8135	0.544807
3	0	6915	0.003773
4	1	2712	0.935270

In [173]:
```
# Renaming the column
y_pred_final= y_pred_final.rename(columns={ 0 : 'Converted_prob'})
```

In [174]:
```
y_pred_final.head()
```

Out[174]:

	Converted	Prospect ID	Converted_prob
0	0	7681	0.024955
1	0	984	0.022540
2	0	8135	0.544807
3	0	6915	0.003773
4	1	2712	0.935270

In [175]:
```
# Rearranging the columns
y_pred_final = y_pred_final[['Prospect ID','Converted','Converted_prob']]
y_pred_final['Lead_Score'] = y_pred_final.Converted_prob.map( lambda x: round(x*100)
```

In [176]:
```
# Let's see the head of y_pred_final
y_pred_final.head()
```

Out[176]:

	Prospect ID	Converted	Converted_prob	Lead_Score
0	7681	0	0.024955	2
1	984	0	0.022540	2
2	8135	0	0.544807	54
3	6915	0	0.003773	0
4	2712	1	0.935270	94

In [177]:
```
y_pred_final['final_Predicted'] = y_pred_final.Converted_prob.map(lambda x: 1 if x >
```

In [178]:
```
y_pred_final.head()
```

Out[178]:

	Prospect ID	Converted	Converted_prob	Lead_Score	final_Predicted
0	7681	0	0.024955	2	0
1	984	0	0.022540	2	0
2	8135	0	0.544807	54	1
3	6915	0	0.003773	0	0
4	2712	1	0.935270	94	1

In [179]:

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

Out[179]:

```
0.9381980640357409
```

In [180]:

```
confusion2 = metrics.confusion_matrix(y_pred_final.Converted, y_pred_final.final_Pre
confusion2
```

Out[180]:

```
array([[1563,  113],
       [  53,  957]], dtype=int64)
```

In [181]:

```
TP = confusion2[1,1] # true positive
TN = confusion2[0,0] # true negatives
FP = confusion2[0,1] # false positives
FN = confusion2[1,0] # false negatives
```

In [182]:

```
# Let's see the sensitivity of our logistic regression model
TP / float(TP+FN)
```

Out[182]:

```
0.9475247524752475
```

In [183]:

```
# Let us calculate specificity
TN / float(TN+FP)
```

Out[183]:

```
0.9325775656324582
```

In [184]:

```
precision_score(y_pred_final.Converted , y_pred_final.final_Predicted)
```

Out[184]:

```
0.8943925233644859
```

In [185]:

```
recall_score(y_pred_final.Converted, y_pred_final.final_Predicted)
```

Out[185]:

```
0.9475247524752475
```

Observation:

After running the model on the Test Data these are the figures we obtain:

- Accuracy : 92.78%
- Sensitivity : 91.98%
- Specificity : 93.26%

Final Observation:

Let us compare the values obtained for Train & Test:

Train Data:

- Accuracy : 92.29%
- Sensitivity : 91.70%
- Specificity : 92.66%

Test Data:

- Accuracy : 92.78%
- Sensitivity : 91.98%
- Specificity : 93.26%

In [ ]:
```

```