Lead Case Study

```
An education company named X Education sells online courses to industry professionals. On
any given day, many professionals who are interested in the courses land on their website
and browse for courses.

The company markets its courses on several websites and search engines like Google. Once
these people land on the website, they might browse the courses or fill up a form for the
course or watch some videos. When these people fill up a form providing their email
address or phone number, they are classified to be a lead. Moreover, the company also
gets leads through past referrals. Once these leads are acquired, employees from the
sales team start making calls, writing emails, etc. Through this process, some of the
leads get converted while most do not. The typical lead conversion rate at X education is
around 30%.

There are a lot of leads generated in the initial stage, but only a few of them come out
as paying customers. In the middle stage, you need to nurture the potential leads well
(i.e. educating the leads about the product, constantly communicating etc. ) in order to
get a higher lead conversion.

X Education has appointed you to help them select the most promising leads, i.e. the
leads that are most likely to convert into paying customers. The company requires you to
build a model wherein you need to assign a lead score to each of the leads such that the
customers with higher lead score have a higher conversion chance and the customers with
lower lead score have a lower conversion chance. The CEO, in particular, has given a
ballpark of the target lead conversion rate to be around 80%.
```

In [1]:

```python
#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]:

```
lead=pd.read_csv('D:/task/Leads.csv')
lead.head()
```

Out[2]:

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

5 rows × 37 columns

In [4]:

```
#checking total rows and cols in dataset
lead.shape
```

Out[4]:

```
(9240, 37)
```

In [5]:

```
#basic data check
lead.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]:

```
lead.describe()
```

Out[6]:

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

In [7]:

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

Out[7]:

True

In [8]:

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

Out[8]:

True

Data Cleaning

In [9]:

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

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

In [10]:

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

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

In [11]:

```
#checking null values in each rows

lead.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

round(100*(lead.isnull().sum()/len(lead.index)), 2)
```

Out[12]:

```
Lead Origin                                       0.00
Lead Source                                       0.39
Do Not Email                                      0.00
Do Not Call                                       0.00
Converted                                         0.00
TotalVisits                                       1.48
Total Time Spent on Website                       0.00
Page Views Per Visit                              1.48
Last Activity                                     1.11
Country                                          26.63
Specialization                                   36.58
How did you hear about X Education               78.46
What is your current occupation                  29.11
What matters most to you in choosing a course    29.32
Search                                            0.00
Magazine                                          0.00
Newspaper Article                                 0.00
X Education Forums                                0.00
Newspaper                                         0.00
Digital Advertisement                             0.00
Through Recommendations                           0.00
Receive More Updates About Our Courses            0.00
Tags                                             36.29
Lead Quality                                     51.59
Update me on Supply Chain Content                 0.00
Get updates on DM Content                         0.00
Lead Profile                                     74.19
City                                             39.71
Asymmetrique Activity Index                      45.65
Asymmetrique Profile Index                       45.65
Asymmetrique Activity Score                      45.65
Asymmetrique Profile Score                       45.65
I agree to pay the amount through cheque          0.00
A free copy of Mastering The Interview            0.00
Last Notable Activity                             0.00
dtype: float64
```

In [13]:

```
#dropping cols with more than 45% missing values

cols=lead.columns

for i in cols:
    if((100*(lead[i].isnull().sum()/len(lead.index))) >= 45):
        lead.drop(i, 1, inplace = True)
```

In [14]:

```
#checking null values percentage

round(100*(lead.isnull().sum()/len(lead.index)), 2)
```

Out[14]:

```
Lead Origin                                      0.00
Lead Source                                      0.39
Do Not Email                                     0.00
Do Not Call                                      0.00
Converted                                        0.00
TotalVisits                                      1.48
Total Time Spent on Website                      0.00
Page Views Per Visit                             1.48
Last Activity                                    1.11
Country                                         26.63
Specialization                                  36.58
What is your current occupation                 29.11
What matters most to you in choosing a course   29.32
Search                                           0.00
Magazine                                         0.00
Newspaper Article                                0.00
X Education Forums                               0.00
Newspaper                                        0.00
Digital Advertisement                            0.00
Through Recommendations                          0.00
Receive More Updates About Our Courses           0.00
Tags                                            36.29
Update me on Supply Chain Content                0.00
Get updates on DM Content                        0.00
City                                            39.71
I agree to pay the amount through cheque         0.00
A free copy of Mastering The Interview           0.00
Last Notable Activity                            0.00
dtype: float64
```

Categorial value

In [15]:

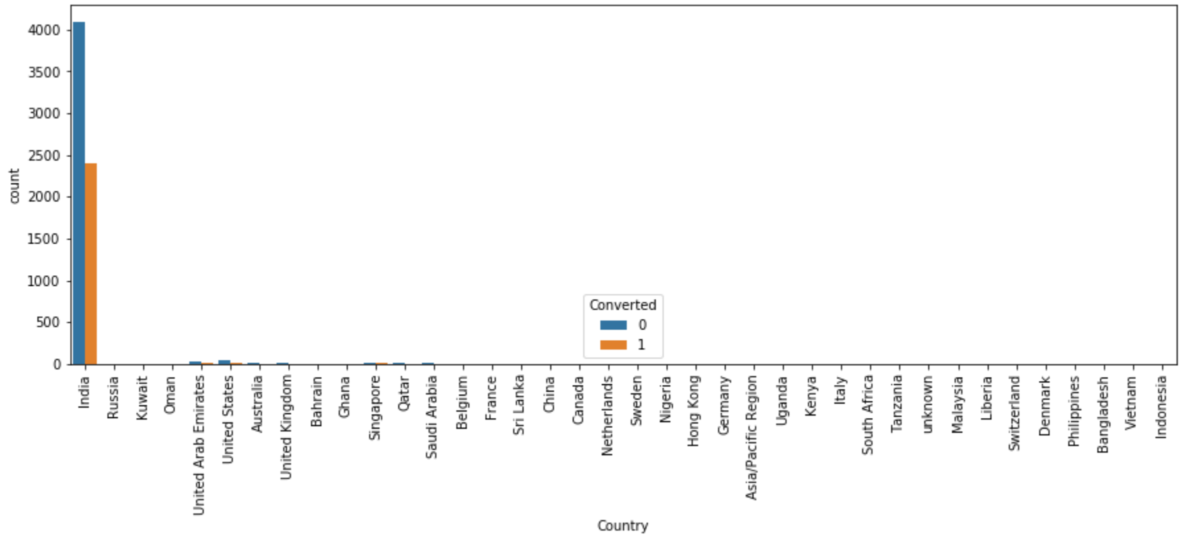
```
#checking value counts of Country column

lead['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
Hong Kong                  7
Bahrain                    7
Oman                       6
France                     6
unknown                    5
Nigeria                    4
South Africa               4
Kuwait                     4
Canada                     4
Germany                    4
Sweden                     3
Uganda                     2
Philippines                2
Netherlands                2
China                      2
Ghana                      2
Italy                      2
Bangladesh                 2
Asia/Pacific Region        2
Belgium                    2
Indonesia                  1
Kenya                      1
Denmark                    1
Switzerland                1
Liberia                    1
Tanzania                   1
Vietnam                    1
Sri Lanka                  1
Russia                     1
Malaysia                   1
Name: Country, dtype: int64
```

In [16]:

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

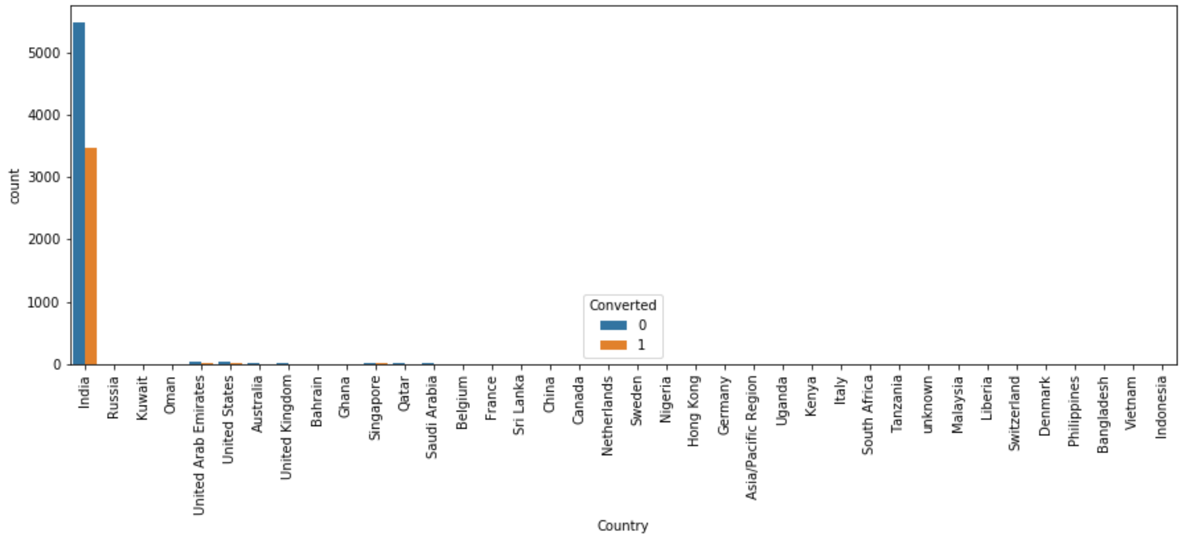


In [17]:

```
# Since India is the most common occurence among the non-missing values we can impute all m

lead['Country'] = lead['Country'].replace(np.nan,'India')
```

In [18]:

```
#plotting spread of Country columnn after replacing NaN values

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



In [19]:

```
#creating a list of columns to be droppped

cols_to_drop=['Country']
```

In [20]:

```
#checking value counts of "City" column

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

Out[20]:

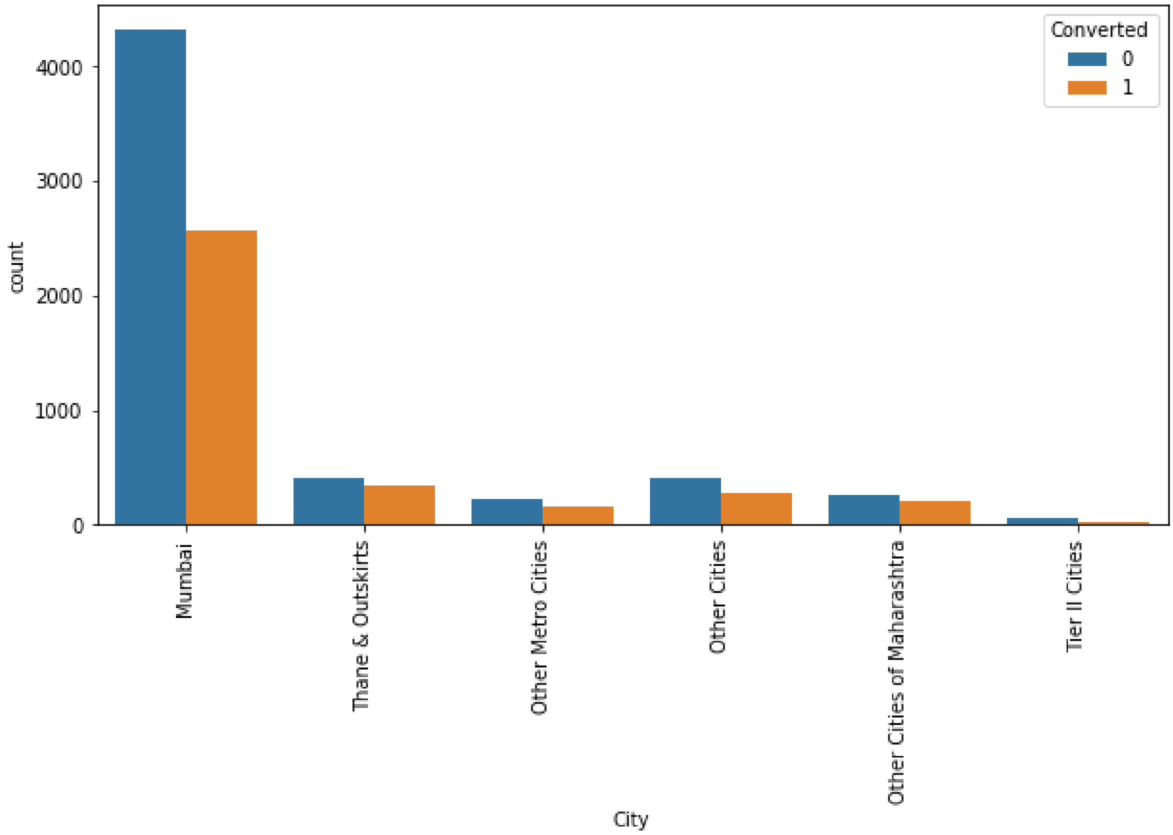
```
NaN                            3669
Mumbai                         3222
Thane & Outskirts               752
Other Cities                    686
Other Cities of Maharashtra     457
Other Metro Cities              380
Tier II Cities                   74
Name: City, dtype: int64
```

In [21]:

```
lead['City'] = lead['City'].replace(np.nan,'Mumbai')
```

In [22]:

```
#plotting spread of City columnn after replacing NaN values

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



In [23]:

```
#checking value counts of Specialization column

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

Out[23]:

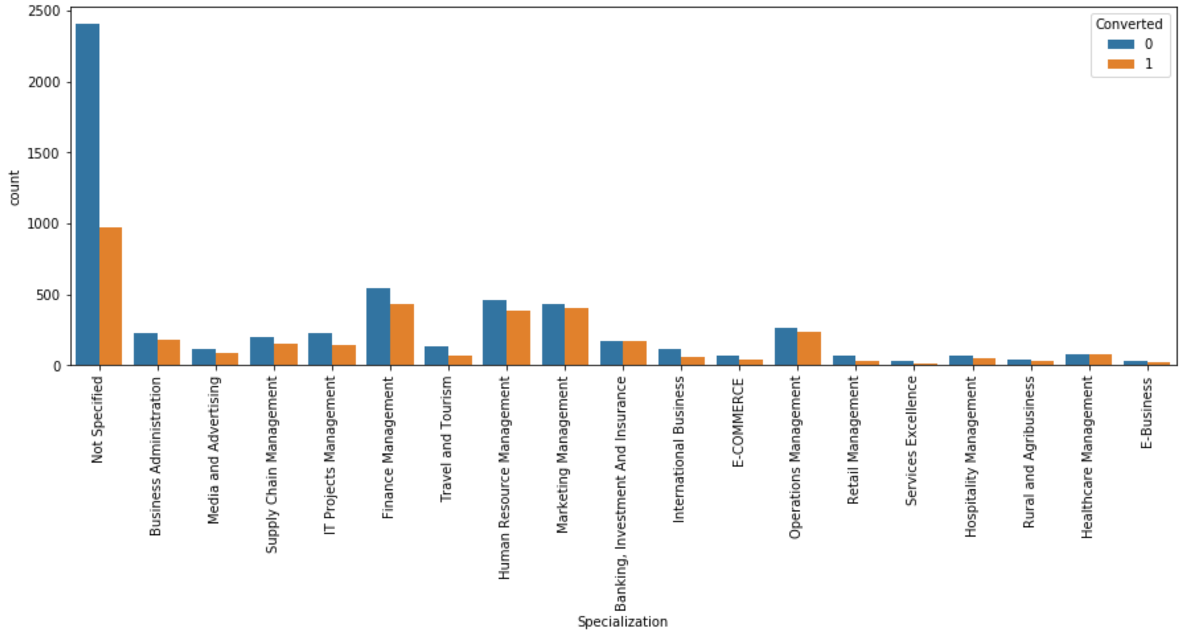
```
NaN                                  3380
Finance Management                    976
Human Resource Management             848
Marketing Management                  838
Operations Management                 503
Business Administration               403
IT Projects Management                366
Supply Chain Management               349
Banking, Investment And Insurance     338
Media and Advertising                 203
Travel and Tourism                    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 they a
# and don't have a specialization yet. So we will replace NaN values here with 'Not Specifi

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

In [25]:

```
#plotting spread of Specialization columnn

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

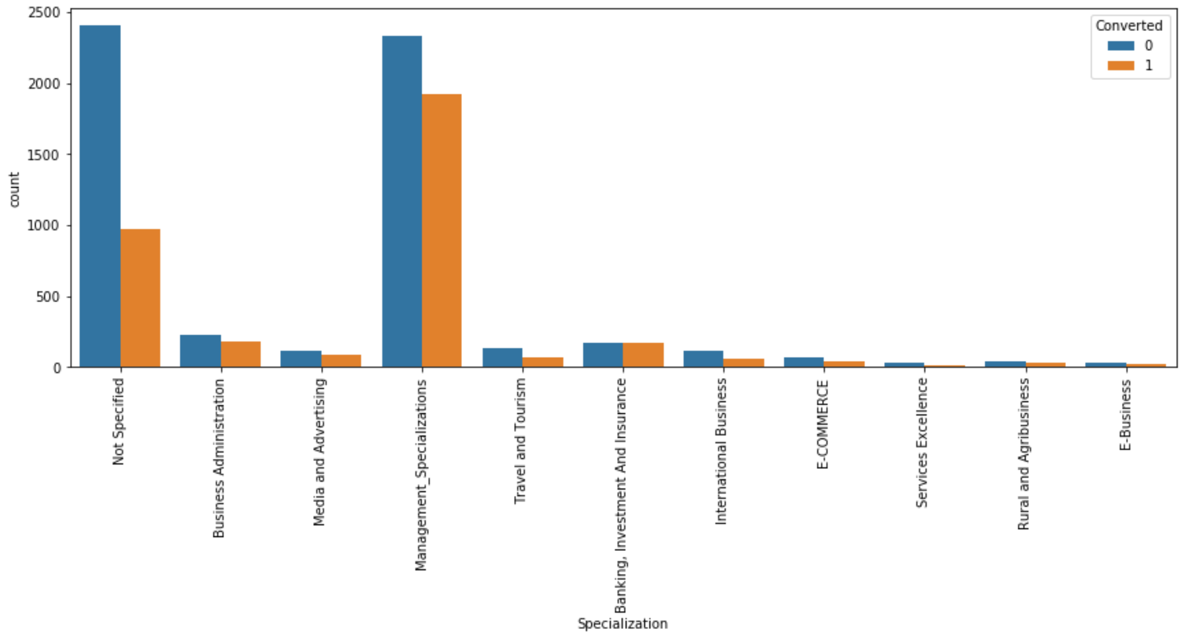


In [26]:

```
#combining Management Specializations because they show similar trends

lead['Specialization'] = lead['Specialization'].replace(['Finance Management','Human Resour
                                                          'Marketing Management','Operatio
                                                          'IT Projects Management','Supply
                                                   'Healthcare Management','Hospitality Ma
                                                          'Retail Management'] ,'Managemen
```

In [27]:

```
#visualizing count of Variable based on Converted value


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



In [28]:

```
#What is your current occupation

lead['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"

lead['What is your current occupation'] = lead['What is your current occupation'].replace(n
```

In [30]:

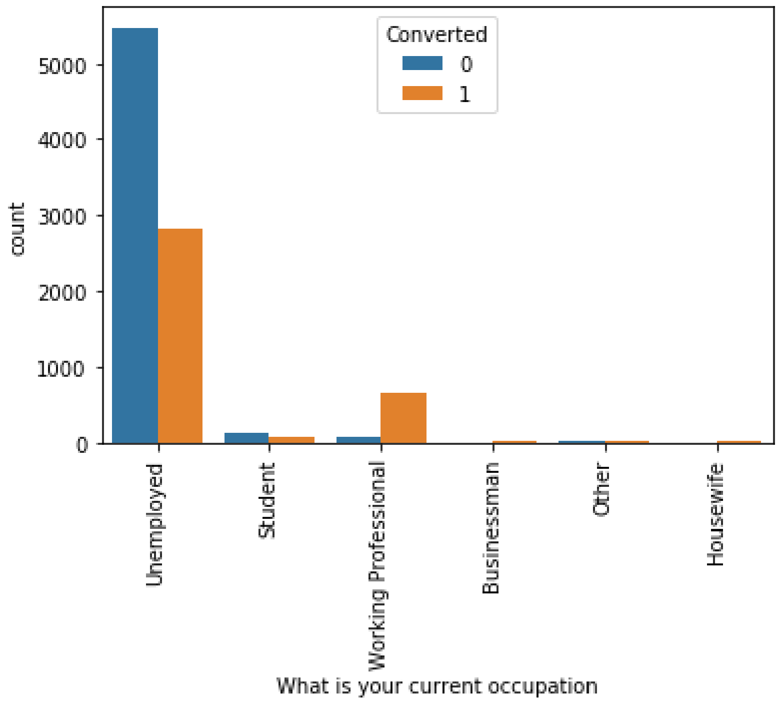
```
#checking count of values
lead['What is your current occupation'].value_counts(dropna=False)
```

Out[30]:

```
Unemployed              8290
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

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



In [32]:

```
#checking value counts

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

Out[32]:

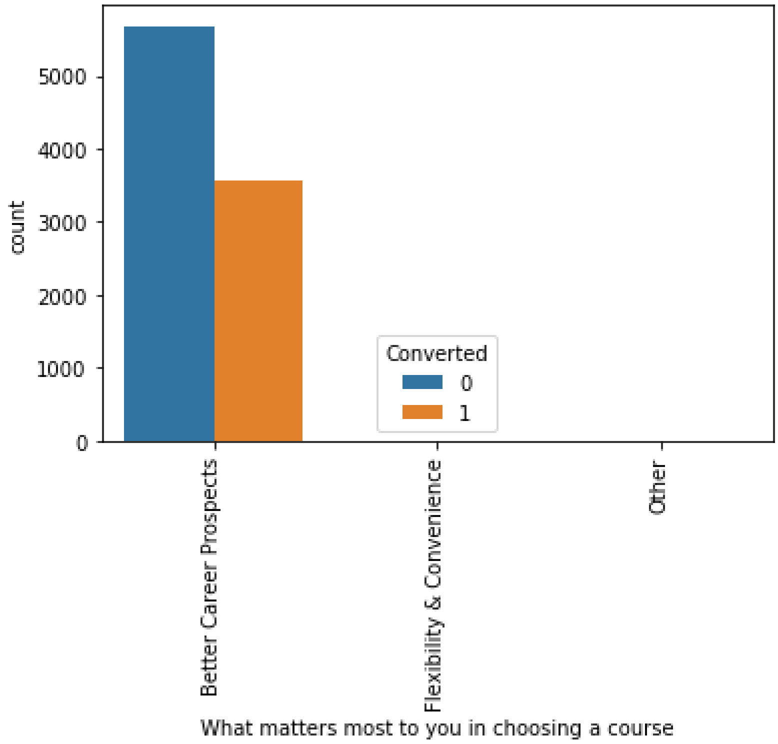
```
Better Career Prospects      6528
NaN                          2709
Flexibility & Convenience       2
Other                           1
Name: What matters most to you in choosing a course, dtype: int64
```

In [33]:

```
#replacing Nan values with Mode "Better Career Prospects"

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

In [34]:

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



In [35]:

```
#checking value counts of variable
lead['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_to_drop
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
lead['Tags'].value_counts(dropna=False)
```

Out[37]:

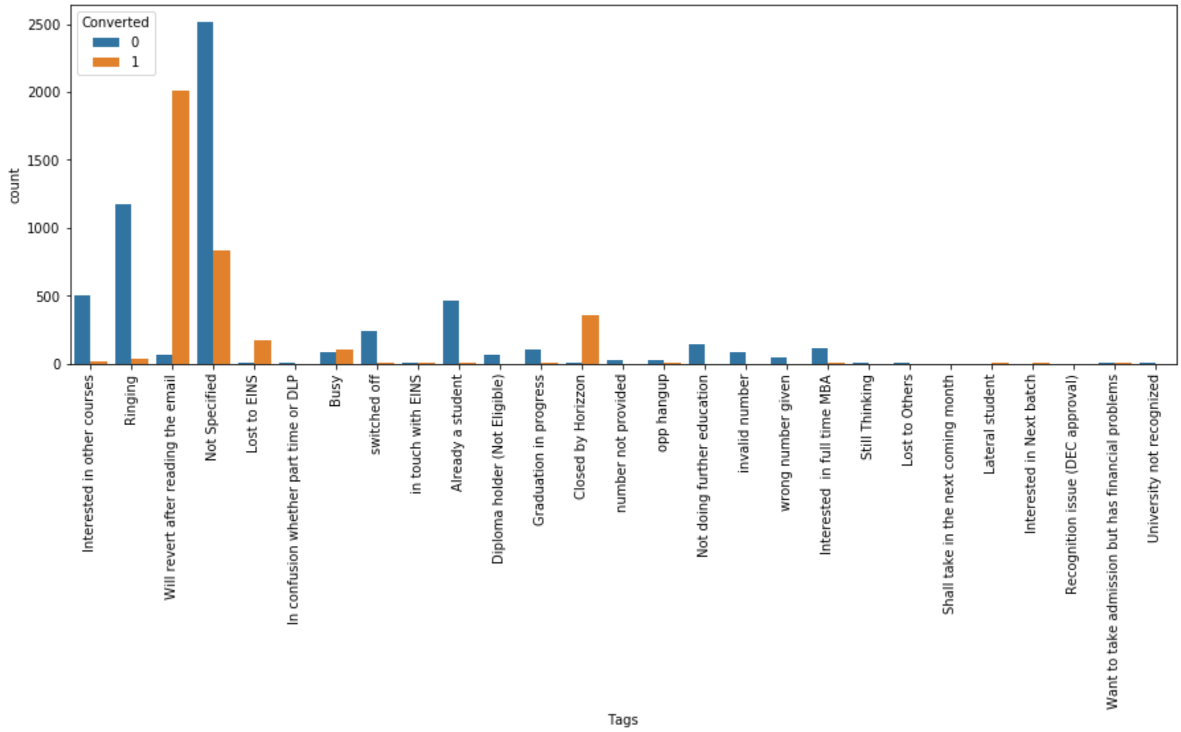
```
NaN                                                  3353
Will revert after reading the email                  2072
Ringing                                              1203
Interested in other courses                           513
Already a student                                     465
Closed 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
Want to take admission but has financial problems       6
Still Thinking                                          6
Interested in Next batch                                5
In confusion whether part time or DLP                   5
Lateral student                                         3
University not recognized                               2
Shall take in the next coming month                     2
Recognition issue (DEC approval)                        1
Name: Tags, dtype: int64
```

In [38]:

```
#replacing Nan values with "Not Specified"
lead['Tags'] = lead['Tags'].replace(np.nan,'Not Specified')
```

In [39]:

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



In [40]:

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

lead['Tags'] = lead['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
round(100*(lead.isnull().sum()/len(lead.index)), 2)
```

Out[41]:

```
Lead Origin                                      0.00
Lead Source                                      0.39
Do Not Email                                     0.00
Do Not Call                                      0.00
Converted                                        0.00
TotalVisits                                      1.48
Total Time Spent on Website                      0.00
Page Views Per Visit                             1.48
Last Activity                                    1.11
Country                                          0.00
Specialization                                   0.00
What is your current occupation                  0.00
What matters most to you in choosing a course    0.00
Search                                           0.00
Magazine                                         0.00
Newspaper Article                                0.00
X Education Forums                               0.00
Newspaper                                        0.00
Digital Advertisement                            0.00
Through Recommendations                          0.00
Receive More Updates About Our Courses           0.00
Tags                                             0.00
Update me on Supply Chain Content                0.00
Get updates on DM Content                        0.00
City                                             0.00
I agree to pay the amount through cheque         0.00
A free copy of Mastering The Interview           0.00
Last Notable Activity                            0.00
dtype: float64
```

In [42]:

```
#checking value counts of Lead Source column

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

Out[42]:

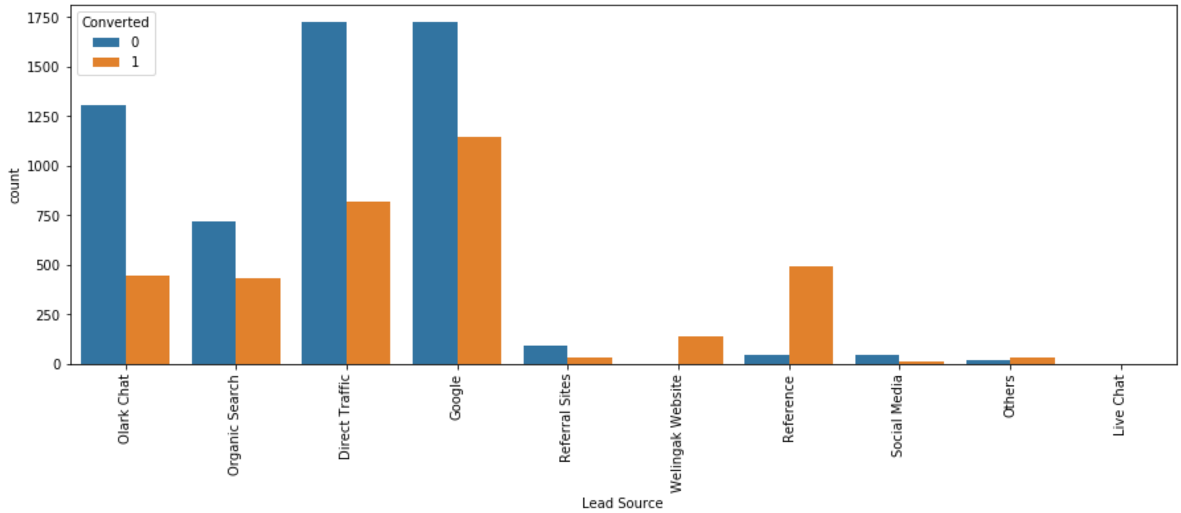
```
Google               2868
Direct Traffic       2543
Olark Chat           1755
Organic Search       1154
Reference             534
Welingak Website      142
Referral Sites        125
Facebook               55
NaN                    36
bing                    6
google                  5
Click2call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

In [43]:

```
#replacing Nan Values and combining low frequency values
lead['Lead Source'] = lead['Lead Source'].replace(np.nan,'Others')
lead['Lead Source'] = lead['Lead Source'].replace('google','Google')
lead['Lead Source'] = lead['Lead Source'].replace('Facebook','Social Media')
lead['Lead Source'] = lead['Lead Source'].replace(['bing','Click2call','Press_Release',
                                                     'youtubechannel','welearnblog_Home',
                                                     'WeLearn','blog','Pay per Click Ads',
                                                    'testone','NC_EDM'] ,'Others')
```

In [44]:

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



In [45]:

```
# Last Activity:

lead['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
Resubscribed to emails             1
Visited Booth in Tradeshow         1
Name: Last Activity, dtype: int64
```

In [46]:

```
#replacing Nan Values and combining low frequency values

lead['Last Activity'] = lead['Last Activity'].replace(np.nan,'Others')
lead['Last Activity'] = lead['Last Activity'].replace(['Unreachable','Unsubscribed',
                                                        'Had a Phone Conversation',
                                                        'Approached upfront',
                                                        'View in browser link Clicked',
                                                        'Email Marked Spam',
                                                        'Email Received','Resubscribed to e
                                                         'Visited Booth in Tradeshow'],'Oth
```

In [47]:

```
# Last Activity:

lead['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:
round(100*(lead.isnull().sum()/len(lead.index)), 2)
```

Out[48]:

```
Lead Origin                                      0.00
Lead Source                                      0.00
Do Not Email                                     0.00
Do Not Call                                      0.00
Converted                                        0.00
TotalVisits                                      1.48
Total Time Spent on Website                      0.00
Page Views Per Visit                             1.48
Last Activity                                    0.00
Country                                          0.00
Specialization                                   0.00
What is your current occupation                  0.00
What matters most to you in choosing a course    0.00
Search                                           0.00
Magazine                                         0.00
Newspaper Article                                0.00
X Education Forums                               0.00
Newspaper                                        0.00
Digital Advertisement                            0.00
Through Recommendations                          0.00
Receive More Updates About Our Courses           0.00
Tags                                             0.00
Update me on Supply Chain Content                0.00
Get updates on DM Content                        0.00
City                                             0.00
I agree to pay the amount through cheque         0.00
A free copy of Mastering The Interview           0.00
Last Notable Activity                            0.00
dtype: float64
```

In [49]:

```
#Drop all rows which have Nan Values. Since the number of Dropped rows is less than 2%, it
lead = lead.dropna()
```

In [50]:

```
#Checking percentage of Null Values in All Columns:
round(100*(lead.isnull().sum()/len(lead.index)), 2)
```

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]:

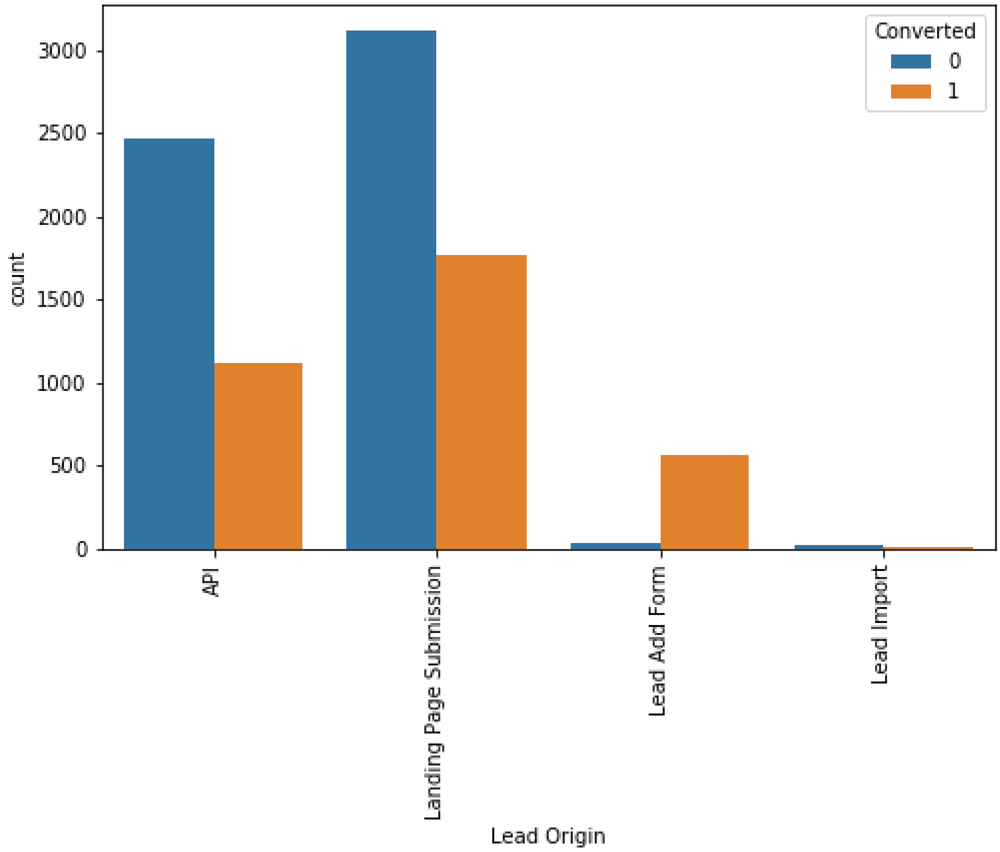
```
#Lead Origin
lead['Lead Origin'].value_counts(dropna=False)
```

Out[51]:

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

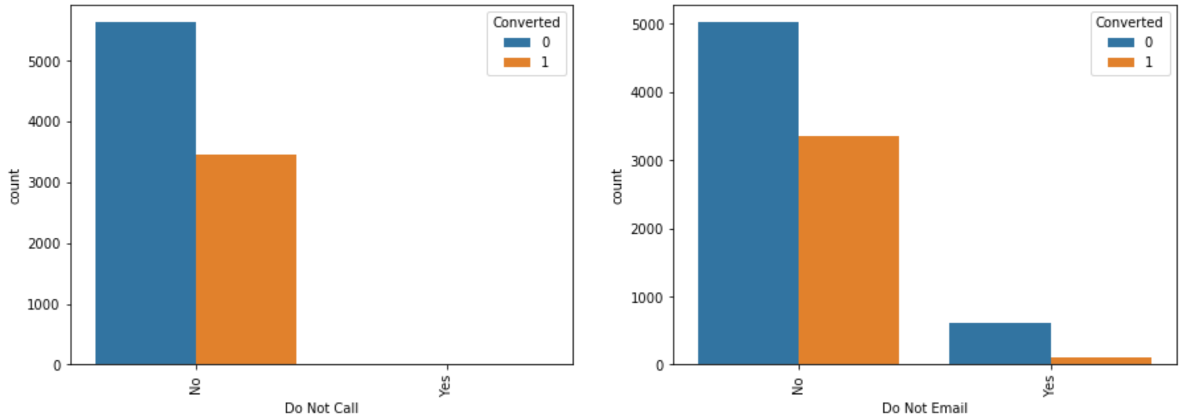
In [52]:

```
#visualizing count of Variable based on Converted value

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



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(lead['Do Not Call'], hue=lead.Converted)
ax1.set_xticklabels(ax1.get_xticklabels(),rotation=90)

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



In [54]:

```
#checking value counts for Do Not Call
lead['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
lead['Do Not Email'].value_counts(dropna=False)
```

Out[55]:

```
No     8379
Yes     724
Name: Do Not Email, dtype: int64
```

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]:

```
lead.Search.value_counts(dropna=False)
```

Out[57]:

```
No     9089
Yes      14
Name: Search, dtype: int64
```

In [58]:

```
lead.Magazine.value_counts(dropna=False)
```

Out[58]:

```
No    9103
Name: Magazine, dtype: int64
```

In [59]:

```
lead['Newspaper Article'].value_counts(dropna=False)
```

Out[59]:

```
No     9101
Yes       2
Name: Newspaper Article, dtype: int64
```

In [60]:

```
lead['X Education Forums'].value_counts(dropna=False)
```

Out[60]:

```
No     9102
Yes       1
Name: X Education Forums, dtype: int64
```

In [61]:

```
lead['Newspaper'].value_counts(dropna=False)
```

Out[61]:

```
No     9102
Yes       1
Name: Newspaper, dtype: int64
```

In [62]:

```
lead['Digital Advertisement'].value_counts(dropna=False)
```

Out[62]:

```
No     9099
Yes       4
Name: Digital Advertisement, dtype: int64
```

In [63]:

```
lead['Through Recommendations'].value_counts(dropna=False)
```

Out[63]:

```
No     9096
Yes       7
Name: Through Recommendations, dtype: int64
```

In [64]:

```
lead['Receive More Updates About Our Courses'].value_counts(dropna=False)
```

Out[64]:

```
No    9103
Name: Receive More Updates About Our Courses, dtype: int64
```

In [65]:

```
lead['Update me on Supply Chain Content'].value_counts(dropna=False)
```

Out[65]:

```
No    9103
Name: Update me on Supply Chain Content, dtype: int64
```

In [66]:

```
lead['Get updates on DM Content'].value_counts(dropna=False)
```

Out[66]:

```
No    9103
Name: Get updates on DM Content, dtype: int64
```

In [67]:

```
lead['I agree to pay the amount through cheque'].value_counts(dropna=False)
```

Out[67]:

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

In [68]:

```
lead['A free copy of Mastering The Interview'].value_counts(dropna=False)
```

Out[68]:

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

In [69]:

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

In [70]:

```
#checking value counts of last Notable Activity
lead['Last Notable Activity'].value_counts()
```

Out[70]:

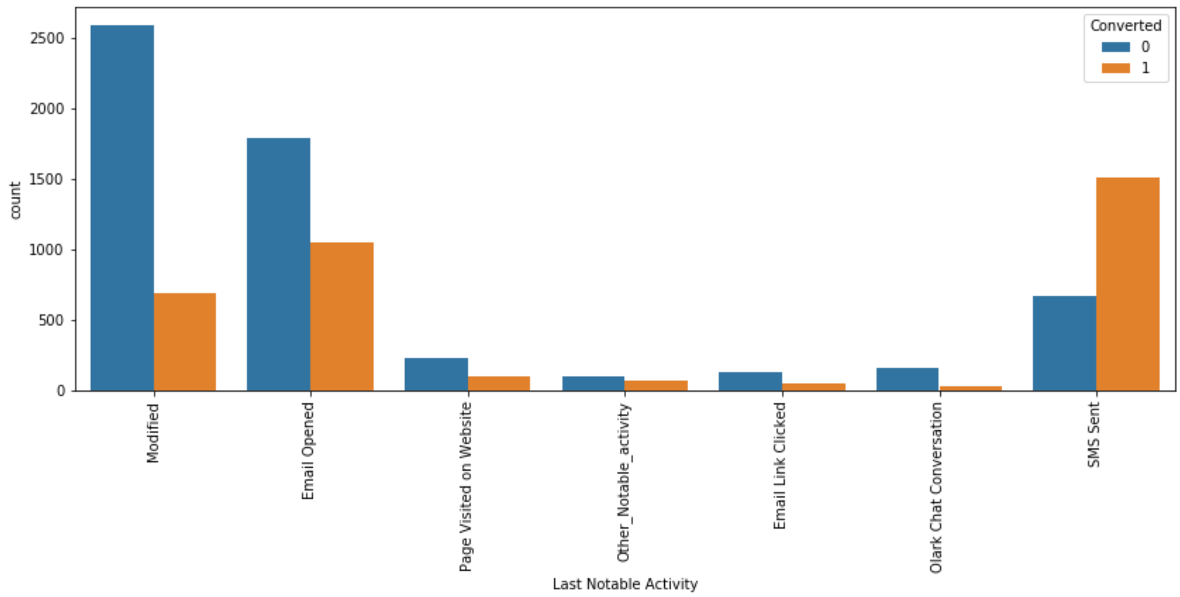
```
Modified                        3270
Email Opened                    2827
SMS Sent                        2172
Page Visited on Website          318
Olark Chat Conversation          183
Email Link Clicked               173
Email Bounced                     60
Unsubscribed                      47
Unreachable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

In [72]:

```
#clubbing lower frequency values

lead['Last Notable Activity'] = lead['Last Notable Activity'].replace(['Had a Phone Convers
                                                                        'Email Marked Spam',
                                                                          'Unreachable',
                                                                          'Unsubscribed',
                                                                          'Email Bounced',
                                                                        'Resubscribed to ema
                                                                        'View in browser lin
                                                                        'Approached upfront'
                                                                        'Form Submitted on W
                                                                        'Email Received'],'O
```

In [73]:

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



In [74]:

```
#checking value counts for variable

lead['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
lead = lead.drop(cols_to_drop,1)
lead.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: 1.4+ MB
```

Numerical Attributes

In [77]:

```
#Check the % of Data that has Converted Values = 1:

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

Out[77]:

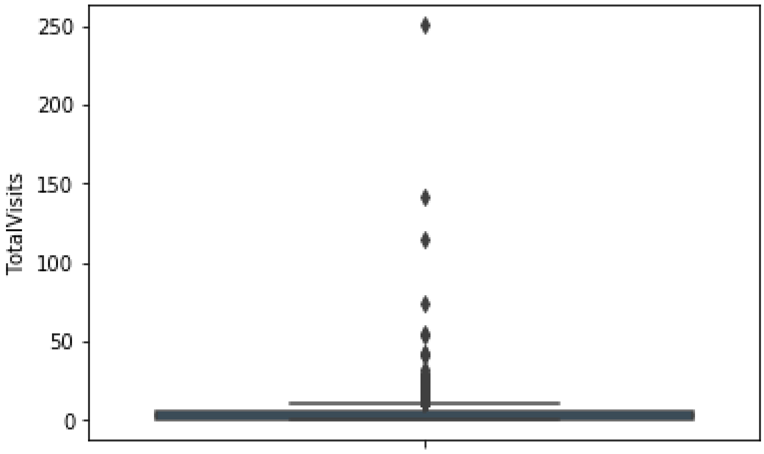
38.02043282434362

In [78]:

```
#Checking correlations of numeric values
# figure size
plt.figure(figsize=(10,8))

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

In [79]:

```
#visualizing spread of variable

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



In [80]:

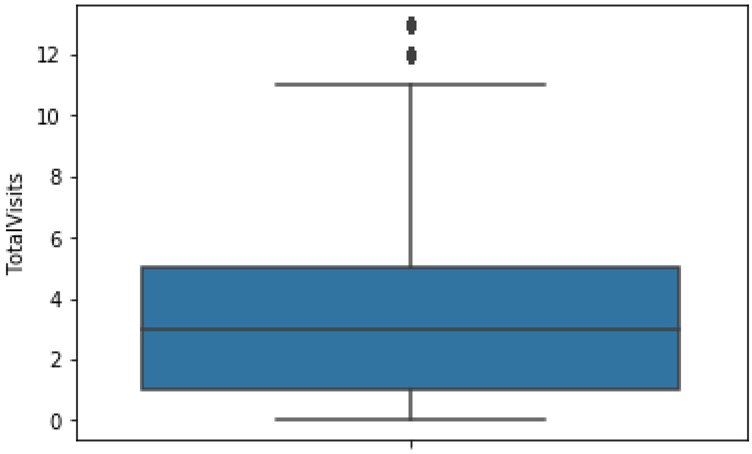
```
lead['TotalVisits'].describe(percentiles=[0.05,.25, .5, .75, .90, .95, .99])
```

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 [82]:

```
#Outlier Treatment: Remove top & bottom 1% of the Column Outlier values

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



In [86]:

```
lead.shape
```

Out[86]:

```
(8929, 14)
```

In [87]:

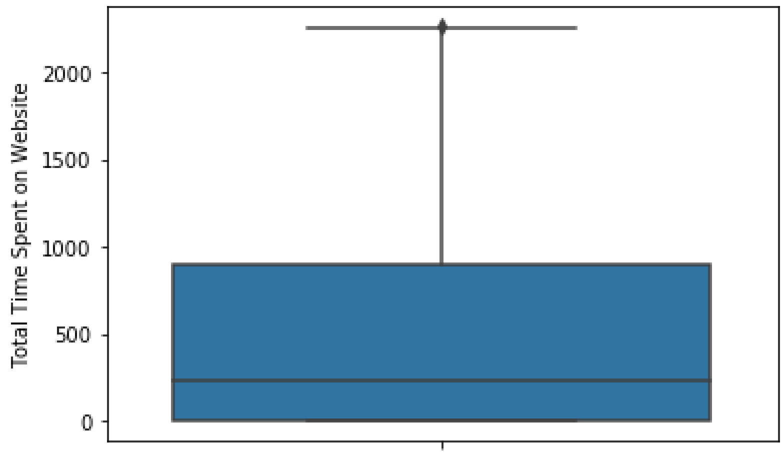
```
#checking percentiles for "Total Time Spent on Website"

lead['Total Time Spent on Website'].describe(percentiles=[0.05,.25, .5, .75, .90, .95, .99]
```

Out[87]:

```
count    8929.000000
mean      476.246612
std       543.335243
min         0.000000
5%          0.000000
25%         4.000000
50%       239.000000
75%       905.000000
90%      1368.000000
95%      1552.000000
99%      1836.440000
max      2272.000000
Name: Total Time Spent on Website, dtype: float64
```

In [88]:

```
#visualizing spread of numeric variable

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



In [89]:

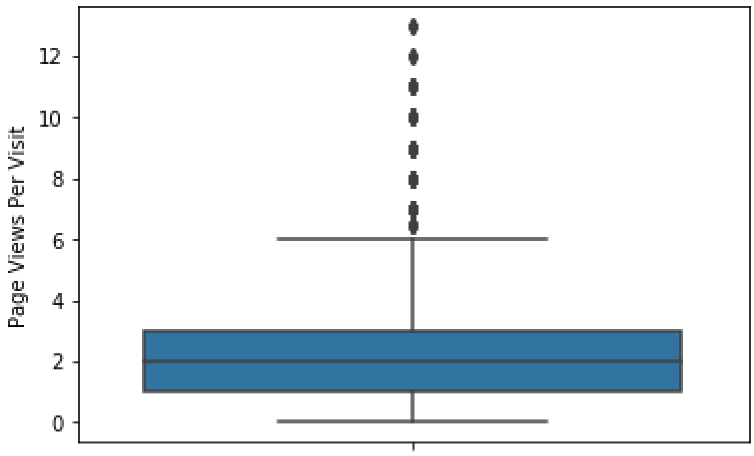
```
#checking spread of "Page Views Per Visit"

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

Out[89]:

```
count    8929.000000
mean        2.303194
std         1.993860
min         0.000000
25%         1.000000
50%         2.000000
75%         3.000000
max        13.000000
Name: Page Views Per Visit, dtype: float64
```

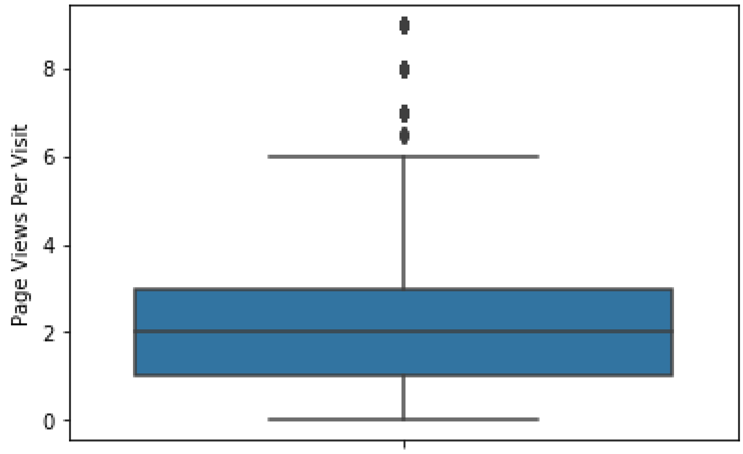
In [90]:

```
#visualizing spread of numeric variable

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



In [92]:

```
#Outlier Treatment: Remove top & bottom 1%

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



In [93]:

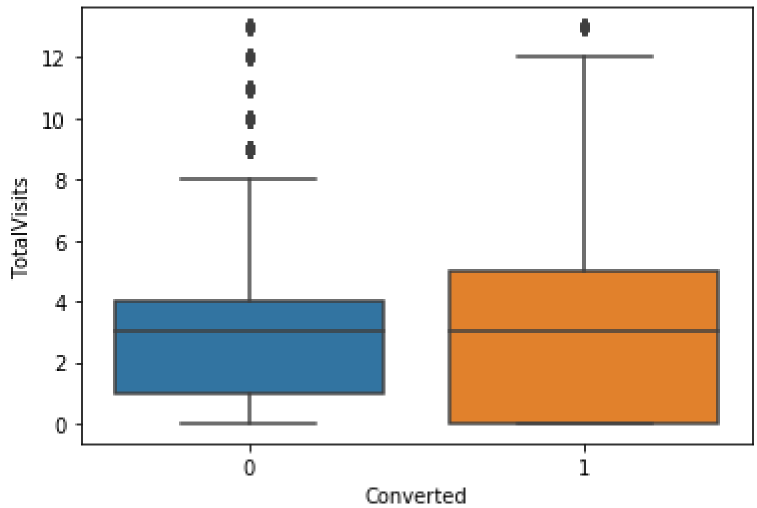
```
lead.shape
```

Out[93]:

```
(8878, 14)
```

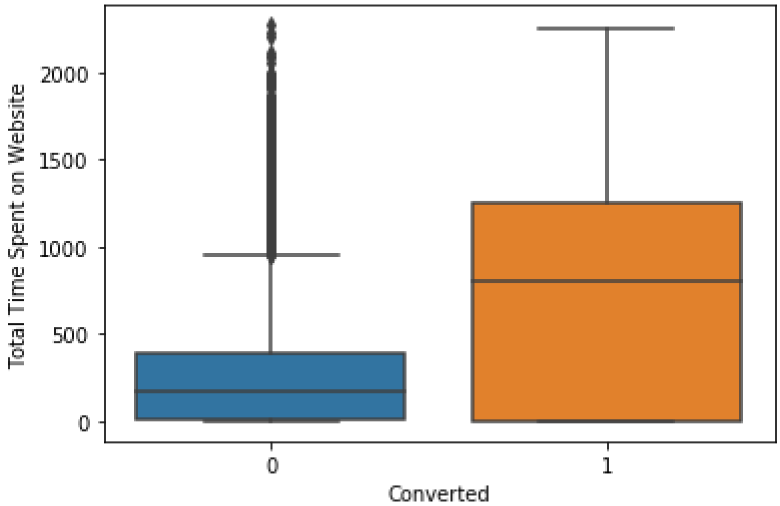
In [94]:

```
#checking Spread of "Total Visits" vs Converted variable
sns.boxplot(y = 'TotalVisits', x = 'Converted', data = lead)
plt.show()
```



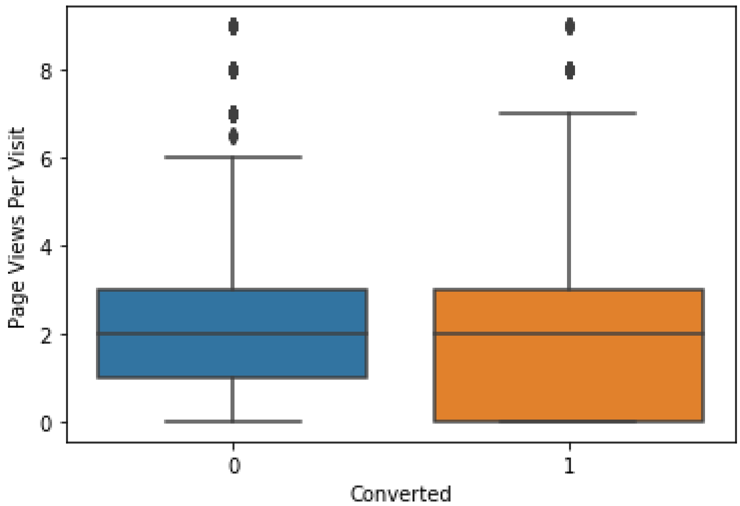
In [95]:

```
#checking Spread of "Total Time Spent on Website" vs Converted variable

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



In [96]:

```
#checking Spread of "Page Views Per Visit" vs Converted variable

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



In [97]:

```
round(100*(lead.isnull().sum()/len(lead.index)),2)
```

Out[97]:

```
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
```

Dummy Variables

In [99]:

```
#getting a list of categorical columns

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

Out[99]:

```
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 [100]:

```
# 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
lead[varlist] = lead[varlist].apply(binary_map)
```

In [102]:

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

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

In [103]:

```
dummy = pd.get_dummies(lead['Specialization'], prefix  = 'Specialization')
dummy = dummy.drop(['Specialization_Not Specified'], 1)
lead = pd.concat([lead, dummy], axis = 1)
```

In [104]:

```
dummy = pd.get_dummies(lead['Lead Source'], prefix  = 'Lead Source')
dummy = dummy.drop(['Lead Source_Others'], 1)
lead = pd.concat([lead, dummy], axis = 1)
```

In [105]:

```
dummy = pd.get_dummies(lead['Last Activity'], prefix  = 'Last Activity')
dummy = dummy.drop(['Last Activity_Others'], 1)
lead = pd.concat([lead, dummy], axis = 1)
```

In [106]:

```
dummy = pd.get_dummies(lead['Last Notable Activity'], prefix  = 'Last Notable Activity')
dummy = dummy.drop(['Last Notable Activity_Other_Notable_activity'], 1)
lead = pd.concat([lead, dummy], axis = 1)
```

In [107]:

```
dummy = pd.get_dummies(lead['Tags'], prefix  = 'Tags')
dummy = dummy.drop(['Tags_Not Specified'], 1)
lead = pd.concat([lead, dummy], axis = 1)
```

In [108]:

```
#dropping the original columns after dummy variable creation

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

In [109]:

```
lead.head()
```

Out[109]:

	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 occupatio
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 × 57 columns

Train Test

In [110]:

```
from sklearn.model_selection import train_test_split

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

y.head()

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

In [111]:

```
# 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, ra
```

In [112]:

```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6214 entries, 1233 to 5879
Data columns (total 56 columns):
 #   Column                                          Non-Null Count  D
type
---  ------                                          --------------  -
----
 0   TotalVisits                                     6214 non-null   f
loat64
 1   Total Time Spent on Website                     6214 non-null   i
nt64
 2   Page Views Per Visit                            6214 non-null   f
loat64
 3   Lead Origin_Landing Page Submission             6214 non-null   u
int8
 4   Lead Origin_Lead Add Form                       6214 non-null   u
int8
 5   Lead Origin_Lead Import                         6214 non-null   u
int8
 6   What is your current occupation_Housewife       6214 non-null   u
int8
 7   What is your current occupation_Other           6214 non-null   u
int8
 8   What is your current occupation_Student         6214 non-null   u
int8
 9   What is your current occupation_Unemployed      6214 non-null   u
int8
 10  What is your current occupation_Working Professional  6214 non-null   u
int8
 11  City_Other Cities                               6214 non-null   u
int8
 12  City_Other Cities of Maharashtra                6214 non-null   u
int8
 13  City_Other Metro Cities                         6214 non-null   u
int8
 14  City_Thane & Outskirts                          6214 non-null   u
int8
 15  City_Tier II Cities                             6214 non-null   u
int8
 16  Specialization_Banking, Investment And Insurance  6214 non-null   u
int8
 17  Specialization_Business Administration          6214 non-null   u
int8
 18  Specialization_E-Business                       6214 non-null   u
int8
 19  Specialization_E-COMMERCE                       6214 non-null   u
int8
 20  Specialization_International Business           6214 non-null   u
int8
 21  Specialization_Management_Specializations       6214 non-null   u
int8
 22  Specialization_Media and Advertising            6214 non-null   u
int8
 23  Specialization_Rural and Agribusiness           6214 non-null   u
int8
 24  Specialization_Services Excellence              6214 non-null   u
int8
```

```
 25  Specialization_Travel and Tourism                      6214 non-null   u
int8
 26  Lead Source_Direct Traffic                             6214 non-null   u
int8
 27  Lead Source_Google                                     6214 non-null   u
int8
 28  Lead Source_Live Chat                                  6214 non-null   u
int8
 29  Lead Source_Olark Chat                                 6214 non-null   u
int8
 30  Lead Source_Organic Search                             6214 non-null   u
int8
 31  Lead Source_Reference                                  6214 non-null   u
int8
 32  Lead Source_Referral Sites                             6214 non-null   u
int8
 33  Lead Source_Social Media                               6214 non-null   u
int8
 34  Lead Source_Welingak Website                           6214 non-null   u
int8
 35  Last Activity_Converted to Lead                        6214 non-null   u
int8
 36  Last Activity_Email Bounced                            6214 non-null   u
int8
 37  Last Activity_Email Link Clicked                       6214 non-null   u
int8
 38  Last Activity_Email Opened                             6214 non-null   u
int8
 39  Last Activity_Form Submitted on Website                6214 non-null   u
int8
 40  Last Activity_Olark Chat Conversation                  6214 non-null   u
int8
 41  Last Activity_Page Visited on Website                  6214 non-null   u
int8
 42  Last Activity_SMS Sent                                 6214 non-null   u
int8
 43  Last Notable Activity_Email Link Clicked               6214 non-null   u
int8
 44  Last Notable Activity_Email Opened                     6214 non-null   u
int8
 45  Last Notable Activity_Modified                         6214 non-null   u
int8
 46  Last Notable Activity_Olark Chat Conversation          6214 non-null   u
int8
 47  Last Notable Activity_Page Visited on Website          6214 non-null   u
int8
 48  Last Notable Activity_SMS Sent                         6214 non-null   u
int8
 49  Tags_Busy                                              6214 non-null   u
int8
 50  Tags_Closed by Horizzon                                6214 non-null   u
int8
 51  Tags_Interested in other courses                       6214 non-null   u
int8
 52  Tags_Lost to EINS                                      6214 non-null   u
int8
 53  Tags_Other_Tags                                        6214 non-null   u
int8
 54  Tags_Ringing                                           6214 non-null   u
int8
 55  Tags_Will revert after reading the email               6214 non-null   u
```

```
int8
dtypes: float64(2), int64(1), uint8(53)
memory usage: 515.8 KB
```

Scaling

In [113]:

```
#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[113]:

	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 you occupation_H
1233	-1.130693	-0.871154	-1.193107	0	0	0	
6078	-1.130693	-0.871154	-1.193107	0	0	0	
6404	-0.010992	-0.743835	0.402109	1	0	0	
4409	-1.130693	-0.871154	-1.193107	0	1	0	
1927	-1.130693	-0.871154	-1.193107	0	0	0	

5 rows × 56 columns

Model Building

In [114]:

```
import statsmodels.api as sm
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()

from sklearn.feature_selection import RFE
rfe = RFE(logreg, 15)             # running RFE with 15 variables as output
rfe = rfe.fit(X_train, y_train)
```

In [115]:

```
rfe.support_
```

Out[115]:

```
array([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, False, False,
       False, False,  True, False, False, False, False,  True, False,
       False, False, False, False,  True, False,  True,  True, False,
        True, False, False,  True, False,  True,  True,  True,  True,
        True,  True])
```

In [116]:

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

Out[116]:

```
[('TotalVisits', False, 22),
 ('Total Time Spent on Website', True, 1),
 ('Page Views Per Visit', False, 21),
 ('Lead Origin_Landing Page Submission', False, 2),
 ('Lead Origin_Lead Add Form', True, 1),
 ('Lead Origin_Lead Import', False, 25),
 ('What is your current occupation_Housewife', False, 23),
 ('What is your current occupation_Other', False, 29),
 ('What is your current occupation_Student', False, 7),
 ('What is your current occupation_Unemployed', False, 6),
 ('What is your current occupation_Working Professional', False, 16),
 ('City_Other Cities', False, 33),
 ('City_Other Cities of Maharashtra', False, 38),
 ('City_Other Metro Cities', False, 31),
 ('City_Thane & Outskirts', False, 41),
 ('City_Tier II Cities', False, 26),
 ('Specialization_Banking, Investment And Insurance', False, 30),
 ('Specialization_Business Administration', False, 40),
 ('Specialization_E-Business', False, 37),
 ('Specialization_E-COMMERCE', False, 34),
 ('Specialization_International Business', False, 17),
 ('Specialization_Management_Specializations', False, 35),
 ('Specialization_Media and Advertising', False, 36),
 ('Specialization_Rural and Agribusiness', False, 32),
 ('Specialization_Services Excellence', False, 15),
 ('Specialization_Travel and Tourism', False, 14),
 ('Lead Source_Direct Traffic', False, 11),
 ('Lead Source_Google', False, 13),
 ('Lead Source_Live Chat', False, 42),
 ('Lead Source_Olark Chat', True, 1),
 ('Lead Source_Organic Search', False, 12),
 ('Lead Source_Reference', False, 9),
 ('Lead Source_Referral Sites', False, 10),
 ('Lead Source_Social Media', False, 24),
 ('Lead Source_Welingak Website', True, 1),
 ('Last Activity_Converted to Lead', False, 27),
 ('Last Activity_Email Bounced', False, 4),
 ('Last Activity_Email Link Clicked', False, 18),
 ('Last Activity_Email Opened', False, 20),
 ('Last Activity_Form Submitted on Website', False, 19),
 ('Last Activity_Olark Chat Conversation', True, 1),
 ('Last Activity_Page Visited on Website', False, 28),
 ('Last Activity_SMS Sent', True, 1),
 ('Last Notable Activity_Email Link Clicked', True, 1),
 ('Last Notable Activity_Email Opened', False, 39),
 ('Last Notable Activity_Modified', True, 1),
 ('Last Notable Activity_Olark Chat Conversation', False, 5),
 ('Last Notable Activity_Page Visited on Website', False, 8),
 ('Last Notable Activity_SMS Sent', True, 1),
 ('Tags_Busy', False, 3),
 ('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 [117]:

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

Out[117]:

```
Index(['Total Time Spent on Website', 'Lead Origin_Lead Add Form',
       'Lead Source_Olark Chat', 'Lead Source_Welingak Website',
       'Last Activity_Olark Chat Conversation', 'Last Activity_SMS Sent',
       'Last Notable Activity_Email Link Clicked',
       'Last Notable Activity_Modified', 'Last Notable Activity_SMS Sent',
       '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 [118]:

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

Out[118]:

```
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_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-Busines
s',
       '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_Direct Traffic',
       'Lead Source_Google', 'Lead Source_Live Chat',
       'Lead Source_Organic Search', 'Lead Source_Reference',
       'Lead Source_Referral Sites', 'Lead Source_Social Media',
       'Last Activity_Converted to Lead', 'Last Activity_Email Bounced',
       'Last Activity_Email Link Clicked', 'Last Activity_Email Opened',
       'Last Activity_Form Submitted on Website',
       'Last Activity_Page Visited on Website',
       'Last Notable Activity_Email Opened',
       'Last Notable Activity_Olark Chat Conversation',
       'Last Notable Activity_Page Visited on Website', 'Tags_Busy'],
      dtype='object')
```

In [119]:

```
#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[119]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6214
Model:	GLM	**Df Residuals:**	6198
Model Family:	Binomial	**Df Model:**	15
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1222.7
Date:	Tue, 12 May 2020	**Deviance:**	2445.3
Time:	11:47:07	**Pearson chi2:**	8.75e+03
No. Iterations:	24		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.7560	0.100	-17.622	0.000	-1.951	-1.561
Total Time Spent on Website	1.0556	0.061	17.441	0.000	0.937	1.174
Lead Origin_Lead Add Form	1.8910	0.425	4.446	0.000	1.057	2.725
Lead Source_Olark Chat	1.4277	0.149	9.558	0.000	1.135	1.720
Lead Source_Welingak Website	24.7394	1.8e+04	0.001	0.999	-3.53e+04	3.54e+04
Last Activity_Olark Chat Conversation	-0.7773	0.229	-3.388	0.001	-1.227	-0.328
Last Activity_SMS Sent	1.4249	0.230	6.187	0.000	0.974	1.876
Last Notable Activity_Email Link Clicked	-1.0993	0.427	-2.573	0.010	-1.937	-0.262
Last Notable Activity_Modified	-1.2409	0.161	-7.704	0.000	-1.557	-0.925
Last Notable Activity_SMS Sent	0.7837	0.261	2.998	0.003	0.271	1.296
Tags_Closed by Horizzon	7.0777	1.023	6.920	0.000	5.073	9.082
Tags_Interested in other courses	-1.8582	0.405	-4.585	0.000	-2.653	-1.064
Tags_Lost to EINS	5.5441	0.604	9.172	0.000	4.359	6.729
Tags_Other_Tags	-2.6260	0.228	-11.533	0.000	-3.072	-2.180
Tags_Ringing	-3.5673	0.243	-14.661	0.000	-4.044	-3.090
Tags_Will revert after reading the email	4.5287	0.192	23.572	0.000	4.152	4.905

In [121]:

```
#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[121]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6214
Model:	GLM	**Df Residuals:**	6198
Model Family:	Binomial	**Df Model:**	15
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1222.7
Date:	Tue, 12 May 2020	**Deviance:**	2445.3
Time:	11:49:07	**Pearson chi2:**	8.75e+03
No. Iterations:	24		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.7560	0.100	-17.622	0.000	-1.951	-1.561
Total Time Spent on Website	1.0556	0.061	17.441	0.000	0.937	1.174
Lead Origin_Lead Add Form	1.8910	0.425	4.446	0.000	1.057	2.725
Lead Source_Olark Chat	1.4277	0.149	9.558	0.000	1.135	1.720
Lead Source_Welingak Website	24.7394	1.8e+04	0.001	0.999	-3.53e+04	3.54e+04
Last Activity_Olark Chat Conversation	-0.7773	0.229	-3.388	0.001	-1.227	-0.328
Last Activity_SMS Sent	1.4249	0.230	6.187	0.000	0.974	1.876
Last Notable Activity_Email Link Clicked	-1.0993	0.427	-2.573	0.010	-1.937	-0.262
Last Notable Activity_Modified	-1.2409	0.161	-7.704	0.000	-1.557	-0.925
Last Notable Activity_SMS Sent	0.7837	0.261	2.998	0.003	0.271	1.296
Tags_Closed by Horizzon	7.0777	1.023	6.920	0.000	5.073	9.082
Tags_Interested in other courses	-1.8582	0.405	-4.585	0.000	-2.653	-1.064
Tags_Lost to EINS	5.5441	0.604	9.172	0.000	4.359	6.729
Tags_Other_Tags	-2.6260	0.228	-11.533	0.000	-3.072	-2.180
Tags_Ringing	-3.5673	0.243	-14.661	0.000	-4.044	-3.090
Tags_Will revert after reading the email	4.5287	0.192	23.572	0.000	4.152	4.905

In [122]:

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

In [124]:

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

Out[124]:

	Features	VIF
8	Last Notable Activity_SMS Sent	6.55
5	Last Activity_SMS Sent	6.44
7	Last Notable Activity_Modified	2.07
1	Lead Origin_Lead Add Form	1.83
2	Lead Source_Olark Chat	1.66
14	Tags_Will revert after reading the email	1.62
4	Last Activity_Olark Chat Conversation	1.59
0	Total Time Spent on Website	1.43
3	Lead Source_Welingak Website	1.30
9	Tags_Closed by Horizzon	1.24
12	Tags_Other_Tags	1.17
10	Tags_Interested in other courses	1.13
13	Tags_Ringing	1.12
11	Tags_Lost to EINS	1.05
6	Last Notable Activity_Email Link Clicked	1.04

In [125]:

```
col = col.drop('Last Notable Activity_SMS Sent',1)
```

In [126]:

```
#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[126]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6214
Model:	GLM	**Df Residuals:**	6199
Model Family:	Binomial	**Df Model:**	14
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1227.2
Date:	Tue, 12 May 2020	**Deviance:**	2454.4
Time:	11:51:22	**Pearson chi2:**	9.04e+03
No. Iterations:	24		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.7021	0.097	-17.532	0.000	-1.892	-1.512
Total Time Spent on Website	1.0529	0.060	17.441	0.000	0.935	1.171
Lead Origin_Lead Add Form	1.8664	0.428	4.360	0.000	1.027	2.705
Lead Source_Olark Chat	1.4306	0.148	9.642	0.000	1.140	1.721
Lead Source_Welingak Website	24.7531	1.79e+04	0.001	0.999	-3.51e+04	3.51e+04
Last Activity_Olark Chat Conversation	-0.6650	0.227	-2.928	0.003	-1.110	-0.220
Last Activity_SMS Sent	2.0193	0.118	17.096	0.000	1.788	2.251
Last Notable Activity_Email Link Clicked	-1.1785	0.431	-2.737	0.006	-2.022	-0.335
Last Notable Activity_Modified	-1.5512	0.129	-12.010	0.000	-1.804	-1.298
Tags_Closed by Horizzon	7.2593	1.023	7.094	0.000	5.254	9.265
Tags_Interested in other courses	-1.8069	0.406	-4.452	0.000	-2.602	-1.011
Tags_Lost to EINS	5.6750	0.606	9.360	0.000	4.487	6.863
Tags_Other_Tags	-2.5775	0.225	-11.433	0.000	-3.019	-2.136
Tags_Ringing	-3.4728	0.239	-14.534	0.000	-3.941	-3.005
Tags_Will revert after reading the email	4.6031	0.194	23.734	0.000	4.223	4.983

In [127]:

```
# Create a dataframe that will contain the names of all the feature variables and their res
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]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[127]:

	Features	VIF
1	Lead Origin_Lead Add Form	1.83
2	Lead Source_Olark Chat	1.65
7	Last Notable Activity_Modified	1.64
13	Tags_Will revert after reading the email	1.56
4	Last Activity_Olark Chat Conversation	1.55
5	Last Activity_SMS Sent	1.50
0	Total Time Spent on Website	1.43
3	Lead Source_Welingak Website	1.30
8	Tags_Closed by Horizzon	1.23
11	Tags_Other_Tags	1.15
9	Tags_Interested in other courses	1.11
12	Tags_Ringing	1.10
10	Tags_Lost to EINS	1.05
6	Last Notable Activity_Email Link Clicked	1.03

In [128]:

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

Out[128]:

```
1233    0.060663
6078    0.060663
6404    0.045500
4409    0.014404
1927    0.979818
1969    0.696494
7413    0.113653
7097    0.005548
327     0.978739
6215    0.203400
dtype: float64
```

In [129]:

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

Out[129]:

```
array([0.06066318, 0.06066318, 0.04550008, 0.01440366, 0.97981785,
       0.69649364, 0.11365324, 0.00554797, 0.97873938, 0.20339953])
```

In [130]:

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

Out[130]:

	Converted	Converted_prob	Prospect ID
0	0	0.060663	1233
1	0	0.060663	6078
2	0	0.045500	6404
3	0	0.014404	4409
4	1	0.979818	1927

In [131]:

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

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

Out[131]:

	Converted	Converted_prob	Prospect ID	Predicted
0	0	0.060663	1233	0
1	0	0.060663	6078	0
2	0	0.045500	6404	0
3	0	0.014404	4409	0
4	1	0.979818	1927	1

In [132]:

```
from sklearn import metrics

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

```
[[3715  157]
 [ 304 2038]]
```

In [133]:

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

0.9258126810428066

In [134]:

```
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 [135]:

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

Out[135]:

0.8701964133219471

In [136]:

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

Out[136]:

0.9594524793388429

In [137]:

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

0.04054752066115702

In [138]:

```
# positive predictive value
print (TP / float(TP+FP))
```

0.9284738041002278

In [139]:

```
# Negative predictive value
print (TN / float(TN+ FN))
```

0.9243592933565563

Plotting ROC Curve

In [141]:

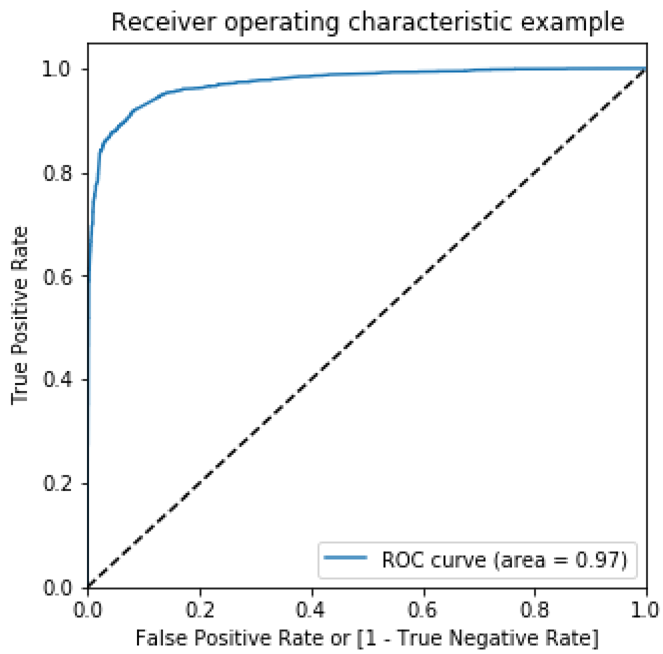
```
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
                                              drop_intermediate = False )
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(5, 5))
    plt.plot( fpr, tpr, label='ROC curve (area = %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 [142]:

```
fpr, tpr, thresholds = metrics.roc_curve( y_train_pred_final.Converted, y_train_pred_final.
```

In [143]:

```
draw_roc(y_train_pred_final.Converted, y_train_pred_final.Converted_prob)
```



In [144]:

```
# 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 > i else
y_train_pred_final.head()
```

Out[144]:

	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	0.060663	1233	0	1	0	0	0	0	0	0	0	0	
1	0	0.060663	6078	0	1	0	0	0	0	0	0	0	0	
2	0	0.045500	6404	0	1	0	0	0	0	0	0	0	0	
3	0	0.014404	4409	0	1	0	0	0	0	0	0	0	0	
4	1	0.979818	1927	1	1	1	1	1	1	1	1	1	1	

Optimal cutoff

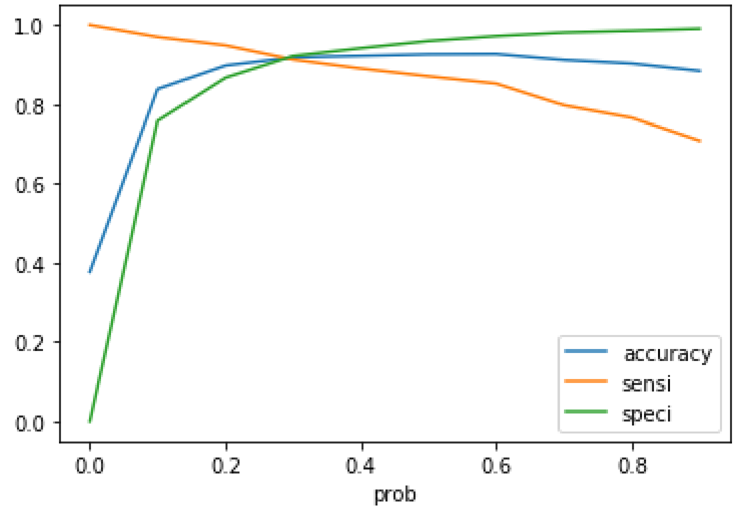
In [146]:

```
# Now let's calculate accuracy sensitivity and specificity for various probability cutoffs.
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[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  0.376891  1.000000  0.000000
0.1   0.1  0.837947  0.969684  0.758264
0.2   0.2  0.897490  0.948335  0.866736
0.3   0.3  0.918249  0.912468  0.921746
0.4   0.4  0.921950  0.889838  0.941374
0.5   0.5  0.925813  0.870196  0.959452
0.6   0.6  0.926617  0.851836  0.971849
0.7   0.7  0.911651  0.797182  0.980888
0.8   0.8  0.902639  0.766012  0.985279
0.9   0.9  0.883972  0.707942  0.990444
```

In [147]:

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



In [148]:

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

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

y_train_pred_final.head()
```

Out[148]:

	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	0.060663	1233	0	1	0	0	0	0	0	0	0	0	
1	0	0.060663	6078	0	1	0	0	0	0	0	0	0	0	
2	0	0.045500	6404	0	1	0	0	0	0	0	0	0	0	
3	0	0.014404	4409	0	1	0	0	0	0	0	0	0	0	
4	1	0.979818	1927	1	1	1	1	1	1	1	1	1	1	

In [149]:

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

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

Out[149]:

	Converted	Converted_prob	Prospect ID	final_Predicted	Lead_Score
0	0	0.060663	1233	0	6
1	0	0.060663	6078	0	6
2	0	0.045500	6404	0	5
3	0	0.014404	4409	0	1
4	1	0.979818	1927	1	98

In [150]:

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

Out[150]:

```
0.9182491149018346
```

In [151]:

```
confusion2 = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final.fina
confusion2
```

Out[151]:

```
array([[3569,  303],
       [ 205, 2137]], dtype=int64)
```

In [152]:

```
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 [153]:

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

Out[153]:

```
0.912467976088813
```

In [154]:

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

Out[154]:

```
0.921745867768595
```

In [155]:

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

```
0.07825413223140495
```

In [156]:

```
# Positive predictive value
print (TP / float(TP+FP))
```

```
0.8758196721311475
```

In [157]:

```
# Negative predictive value
print (TN / float(TN+ FN))
```

```
0.9456809750927399
```

In [158]:

```
#Looking at the confusion matrix again

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

Out[158]:

```
array([[3569,  303],
       [ 205, 2137]], dtype=int64)
```

In [159]:

```
##### Precision
TP / TP + FP

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

Out[159]:

```
0.8758196721311475
```

In [160]:

```
##### Recall
TP / TP + FN

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

Out[160]:

```
0.912467976088813
```

In [161]:

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

In [162]:

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

Out[162]:

```
0.8758196721311475
```

In [163]:

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

Out[163]:

```
0.912467976088813
```

In [164]:

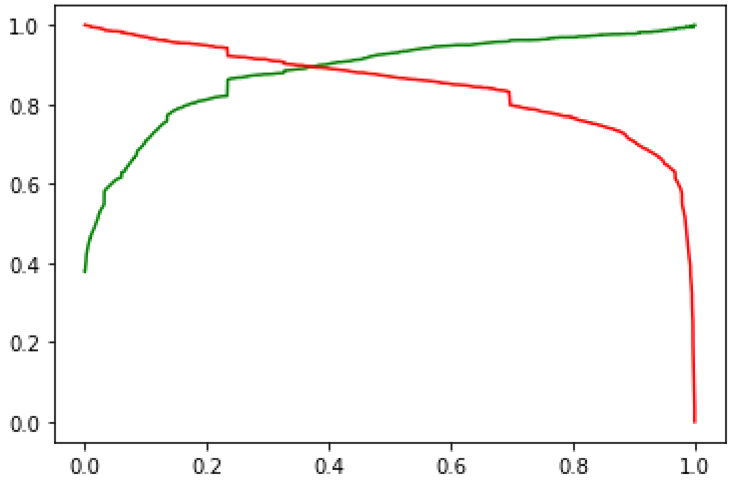
```
from sklearn.metrics import precision_recall_curve
```

In [165]:

```
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_final.
```

In [166]:

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



In [167]:

```
#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[167]:

	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 you occupation_H
1103	0.713461	1.713072	1.424441	1	0	0	
3775	-1.130765	-0.881876	-1.192363	0	0	0	
3228	0.344615	1.528111	0.901080	1	0	0	
5575	-1.130765	-0.881876	-1.192363	0	1	0	
3871	-1.130765	-0.881876	-1.192363	0	0	0	

5 rows × 56 columns

In [169]:

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

Out[169]:

	Total Time Spent on Website	Lead Origin_Lead Add Form	Lead Source_Olark Chat	Lead Source_Welingak Website	Last Activity_Olark Chat Conversation	Last Activity_SMS Sent	L Act L
1103	1.713072	0	0	0	0	1	
3775	-0.881876	0	1	0	1	0	
3228	1.528111	0	0	0	0	1	
5575	-0.881876	1	0	0	0	0	
3871	-0.881876	0	1	0	0	0	

In [170]:

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

predictions of test

In [171]:

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

In [172]:

```
y_test_pred[:10]
```

Out[172]:

```
1103    0.998800
3775    0.005362
3228    0.872815
5575    0.034166
3871    0.231487
948     0.976854
8836    0.056412
8512    0.005362
8548    0.016591
2126    0.992924
dtype: float64
```

In [173]:

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

In [174]:

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

Out[174]:

	0
1103	0.998800
3775	0.005362
3228	0.872815
5575	0.034166
3871	0.231487

In [175]:

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

In [176]:

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

In [177]:

```
# 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 [178]:

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

In [179]:

```
y_pred_final.head()
```

Out[179]:

	Converted	Prospect ID	0
0	1	1103	0.998800
1	0	3775	0.005362
2	0	3228	0.872815
3	0	5575	0.034166
4	0	3871	0.231487

In [180]:

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

In [181]:

```
y_pred_final.head()
```

Out[181]:

	Converted	Prospect ID	Converted_prob
0	1	1103	0.998800
1	0	3775	0.005362
2	0	3228	0.872815
3	0	5575	0.034166
4	0	3871	0.231487

In [182]:

```
# 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 [183]:

```
# Let's see the head of y_pred_final
y_pred_final.head()
```

Out[183]:

	Prospect ID	Converted	Converted_prob	Lead_Score
0	1103	1	0.998800	100
1	3775	0	0.005362	1
2	3228	0	0.872815	87
3	5575	0	0.034166	3
4	3871	0	0.231487	23

In [184]:

```
y_pred_final['final_Predicted'] = y_pred_final.Converted_prob.map(lambda x: 1 if x > 0.3 el
```

In [185]:

```
y_pred_final.head()
```

Out[185]:

	Prospect ID	Converted	Converted_prob	Lead_Score	final_Predicted
0	1103	1	0.998800	100	1
1	3775	0	0.005362	1	0
2	3228	0	0.872815	87	1
3	5575	0	0.034166	3	0
4	3871	0	0.231487	23	0

In [186]:

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

Out[186]:

```
0.926051051051051
```

In [187]:

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

Out[187]:

```
array([[1524,  120],
       [  77,  943]], dtype=int64)
```

In [188]:

```
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 [189]:

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

Out[189]:

```
0.927007299270073
```

In [190]:

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

Out[190]:

```
0.8871119473189087
```

In [191]:

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

Out[191]:

```
0.9245098039215687
```

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

Accuracy : 92% Sensitivity : 91% Specificity : 93%

observation

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

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

Train Accuracy : 92% Sensitivity : 91% Specificity : 92%

```
Test Accuracy : 92% Sensitivity : 91% Specificity : 93%
```

#test Accuracy : 92.78% Sensitivity : 91.98% Specificity : 93.26%

The Model seems to predict the Conversion Rate very well and we should be able to give the CEO confidence in making good calls based on this model