Lead case study

Problem Statement

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%.

Now, although X Education gets a lot of leads, its lead conversion rate is very poor. For example, if, say, they acquire 100 leads in a day, only about 30 of them are converted. To make this process more efficient, the company wishes to identify the most potential leads, also known as ‘Hot Leads’.

If they successfully identify this set of leads, the lead conversion rate should go up as the sales team will now be focusing more on communicating with the potential leads rather than making calls to everyone. A typical lead conversion process can be represented using the following funnel:

In [1]:

```
import warnings
warnings.filterwarnings('ignore')

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

# visulaisation
from matplotlib.pyplot import xticks
%matplotlib inline

# Data display coustomization
pd.set_option('display.max_rows', 100)
pd.set_option('display.max_columns', 100)
```

Data Preparation

In [2]:

```
data = pd.DataFrame(pd.read_csv('E:\dsfw\Leads.csv'))
data.head(5)
```

Out[2]:

	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	Last Activity	Country	Specializati
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	660737	API	Olark Chat	No	No	0	0.0	0	0.0	Page Visited on Website	NaN	Sele
1	2a272436-5132-4136-86fa-dcc88c88f482	660728	API	Organic Search	No	No	0	5.0	674	2.5	Email Opened	India	Sele
	8cc8c611-a219-4f35-		Landing	Direct							Email		Busine

	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	Last Activity	Country	Specializati
2	ad23-fdfd2656bd8a	660727	Page Submission	Traffic	No	No	1	2.0	1532	2.0	Opened	India	Administrati
3	0cc2df48-7cf4-4e39-9de9-19797f9b38cc	660719	Landing Page Submission	Direct Traffic	No	No	0	1.0	305	1.0	Unreachable	India	Media a Advertisi
4	3256f628-e534-4826-9d63-4a8b88782852	660681	Landing Page Submission	Google	No	No	1	2.0	1428	1.0	Converted to Lead	India	Sele

In [3]:

```
#checking duplicates
sum(data.duplicated(subset = 'Prospect ID')) == 0
# No duplicate values
```

Out[3]:

```
True
```

In [4]:

```
data.shape
```

Out[4]:

```
(9240, 37)
```

In [5]:

```
data.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 
```

```
 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: 1.6+ MB
```

In [36]:

```
data.describe()
```

Out[36]:

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

Data Cleaning

In [6]:

```
# As we can observe that there are select values for many column.
#This is because customer did not select any option from the list, hence it shows select.
# Select values are as good as NULL.

# Converting 'Select' values to NaN.
data = data.replace('Select', np.nan)
```

In [7]:

```
data.isnull().sum()
```

Out[7]:

```
Prospect ID                                         0
Lead Number                                         0
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 [28]:

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

Out[28]:

```
Prospect ID                                          0.00
Do Not Email                                         0.00
Do Not Call                                          0.00
Converted                                            0.00
TotalVisits                                          1.48
                                                     ...
Last Notable Activity_Resubscribed to emails         0.00
Last Notable Activity_SMS Sent                       0.00
Last Notable Activity_Unreachable                    0.00
Last Notable Activity_Unsubscribed                   0.00
Last Notable Activity_View in browser link Clicked   0.00
Length: 126, dtype: float64
```

In [8]:

```
# we will drop the columns having more than 70% NA values.
data = data.drop(data.loc[:,list(round(100*(data.isnull().sum()/len(data.index)), 2)>70)].columns,
1)
```

In [9]:

```
data['Lead Quality'].describe()
```

Out[9]:

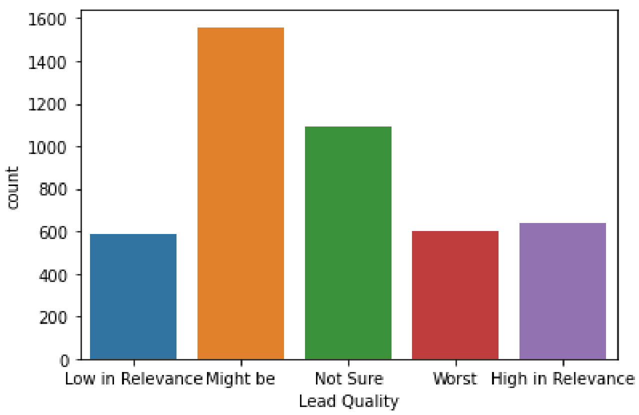
```
count          4473
unique            5
top        Might be
freq           1560
Name: Lead Quality, dtype: object
```

In [10]:

```
sns.countplot(data['Lead Quality'])
```

Out[10]:

```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x123e1868&gt;
```



In [41]:

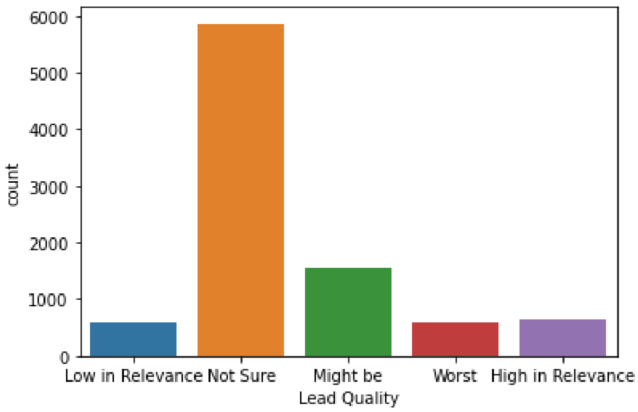
```
# As Lead quality is based on the intution of employee, so if left blank we can impute 'Not Sure'
in NaN safely.
data['Lead Quality'] = data['Lead Quality'].replace(np.nan, 'Not Sure')
```

In [20]:

```
sns.countplot(data['Lead Quality'])
```

Out[20]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x16a9a48>
```

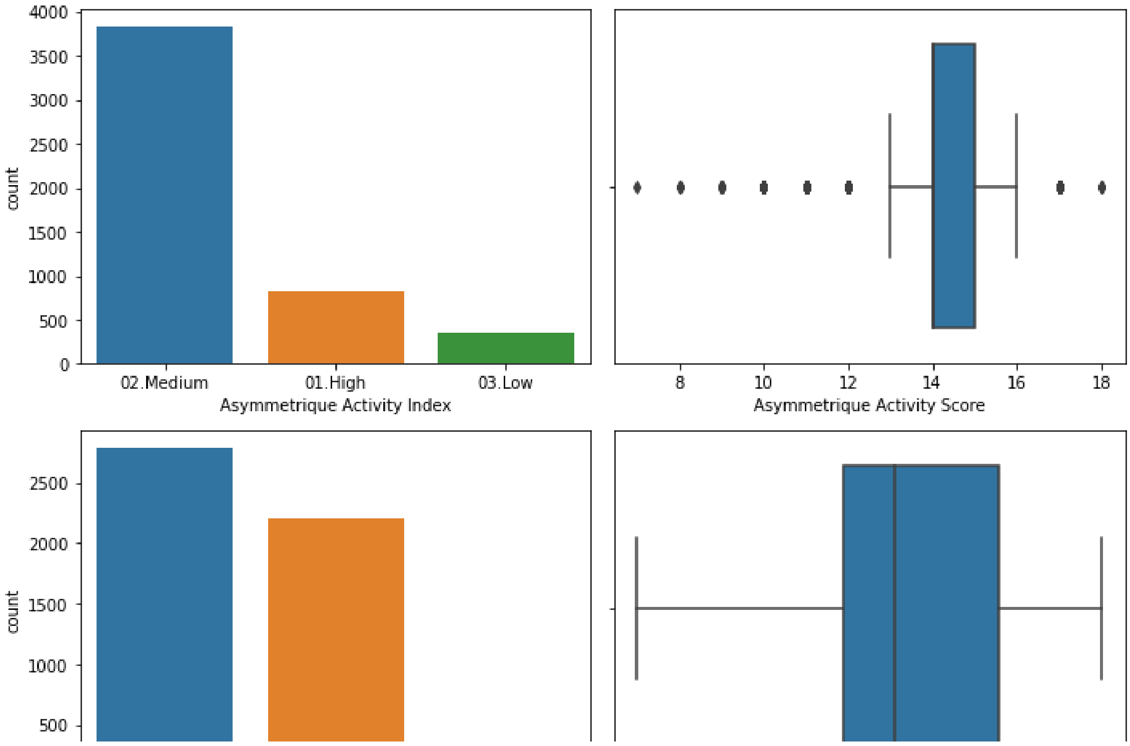


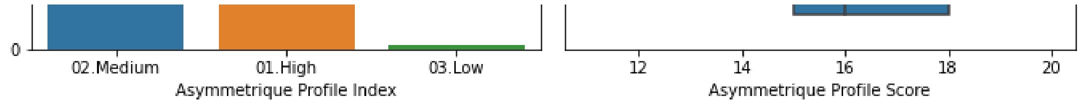
In [11]:

```
## An index and score assigned to each customer based on their activity and their profile
```

In [12]:

```
fig, axs = plt.subplots(2,2, figsize = (10,7.5))
plt1 = sns.countplot(data['Asymmetrique Activity Index'], ax = axs[0,0])
plt2 = sns.boxplot(data['Asymmetrique Activity Score'], ax = axs[0,1])
plt3 = sns.countplot(data['Asymmetrique Profile Index'], ax = axs[1,0])
plt4 = sns.boxplot(data['Asymmetrique Profile Score'], ax = axs[1,1])
plt.tight_layout()
```





In [13]:

```
# There is too much variation in thes parameters so its not reliable to impute any value in it.
# 45% null values means we need to drop these columns.
```

In [14]:

```
data = data.drop(['Asymmetrique Activity Index','Asymmetrique Activity Score','Asymmetrique Profil
e Index','Asymmetrique Profile Score'],1)
```

In [15]:

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

Out[15]:

```
Prospect ID                                       0.00
Lead Number                                       0.00
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
Lead Quality                                     51.59
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
```

In [16]:

```
# City
```

In [17]:

```
data.City.describe()
```

Out[17]:

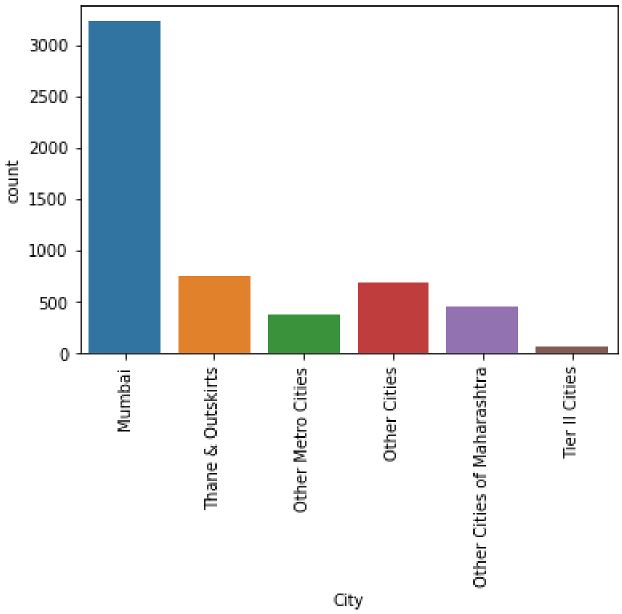
```
count       5571
unique         6
top       Mumbai
freq        3222
Name: City, dtype: object
```

In [18]:

```
sns.countplot(data.City)
xticks(rotation = 90)
```

Out[18]:

```
(array([0, 1, 2, 3, 4, 5]), <a list of 6 Text major ticklabel objects>)
```



In [19]:

```
# Around 60% of the data is Mumbai so we can impute Mumbai in the missing values.
```

In [20]:

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

In [21]:

```
data.Specialization.describe()
```

Out[21]:

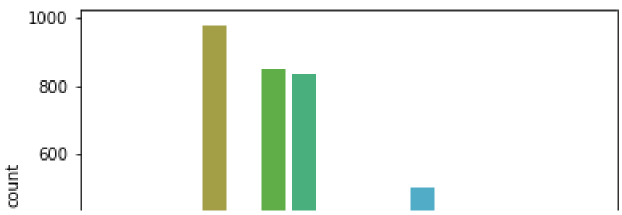
```
count                     5860
unique                      18
top         Finance Management
freq                       976
Name: Specialization, dtype: object
```

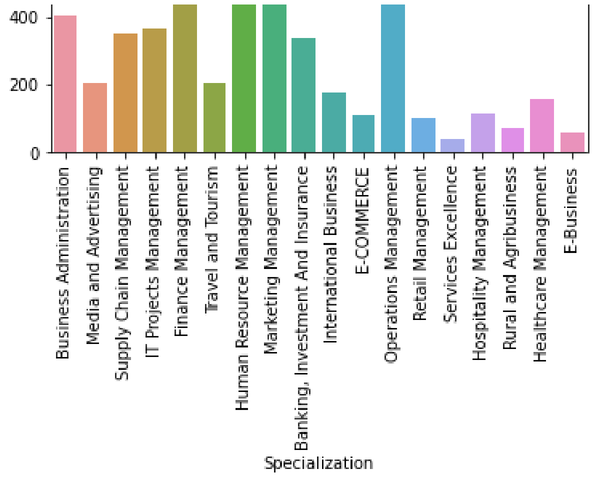
In [22]:

```
sns.countplot(data.Specialization)
xticks(rotation = 90)
```

Out[22]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17]),
 <a list of 18 Text major ticklabel objects>)
```





In [23]:

```
# It maybe the case that lead has not entered any specialization if his/her option is not availabe
on the list,
#  may not have any specialization or is a student.
# Hence we can make a category "Others" for missing values.
```

In [24]:

```
data['Specialization'] = data['Specialization'].replace(np.nan, 'Others')
```

In [25]:

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

Out[25]:

```
Prospect ID                                       0.00
Lead Number                                       0.00
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                                    0.00
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
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 [26]:

```
# Tags
```

In [27]:

```
data.Tags.describe()
```

Out[27]:

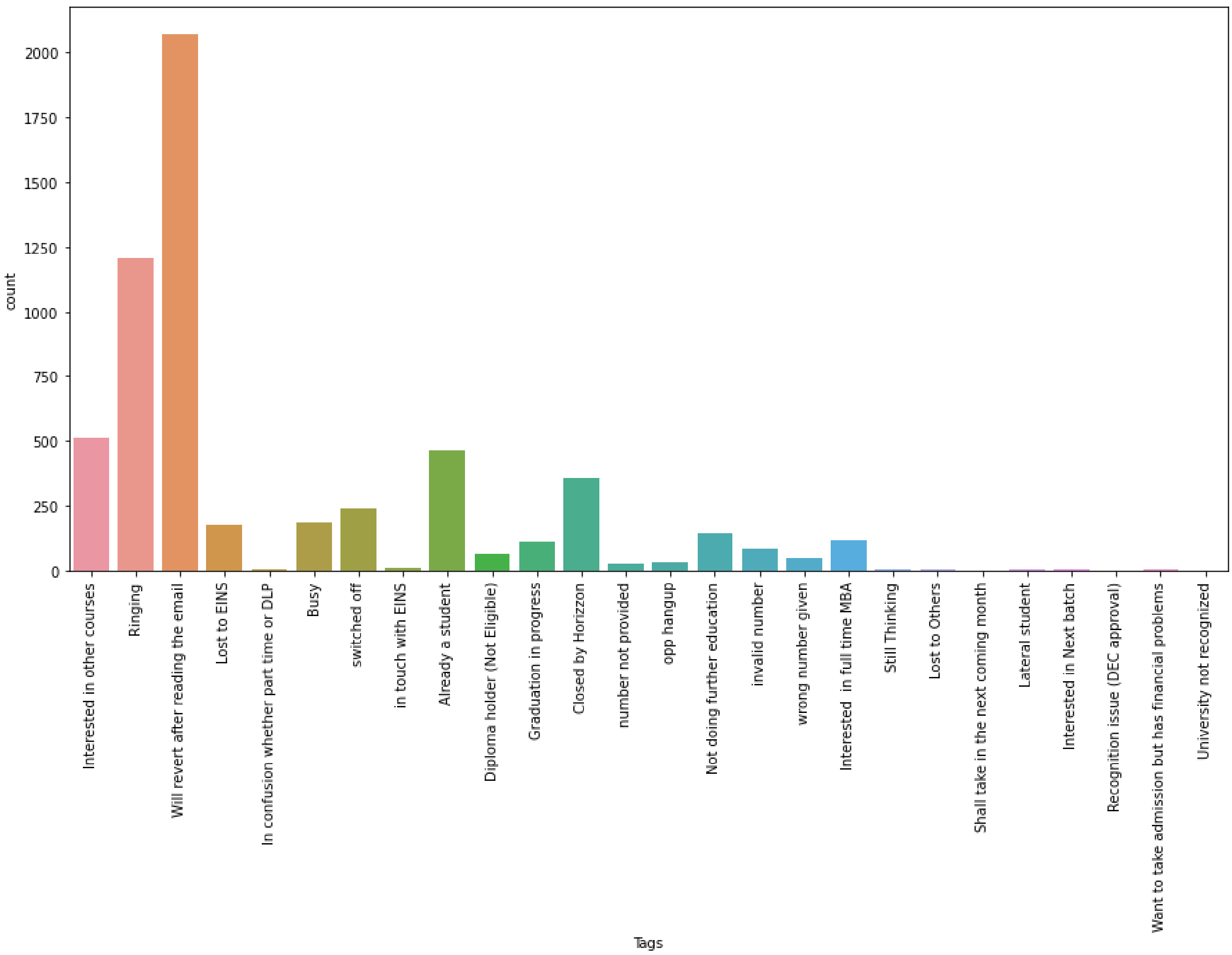
```
count                                     5887
unique                                      26
top          Will revert after reading the email
freq                                      2072
Name: Tags, dtype: object
```

In [28]:

```
fig, axs = plt.subplots(figsize = (15,7.5))
sns.countplot(data.Tags)
xticks(rotation = 90)
```

Out[28]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20, 21, 22, 23, 24, 25]),
 <a list of 26 Text major ticklabel objects>)
```



In [29]:

```
# Blanks in the tag column may be imputed by 'Will revert after reading the email
```

In [30]:

```
data['Tags'] = data['Tags'].replace(np.nan, 'Will revert after reading the email')
```

In [31]:

```
data['What matters most to you in choosing a course'].describe()
```

Out[31]:

```
count                          6531
unique                            3
top       Better Career Prospects
freq                           6528
Name: What matters most to you in choosing a course, dtype: object
```

In [32]:

```
# Blanks in the this column may be imputed by 'Better Career Prospects
```

In [33]:

```
data['What matters most to you in choosing a course'] = data['What matters most to you in choosing a course'].replace(np.nan, 'Better Career Prospects')
```

Occupation

In [34]:

```
data['What is your current occupation'].describe()
```

Out[34]:

```
count            6550
unique              6
top        Unemployed
freq             5600
Name: What is your current occupation, dtype: object
```

In [50]:

```
# 86% entries are of Unemployed so we can impute "Unemployed" in it
```

In [35]:

```
data['What is your current occupation'] = data['What is your current occupation'].replace(np.nan, 'Unemployed')
```

Country

In [36]:

```
# Country is India for most values so let's impute the same in missing values.
data['Country'] = data['Country'].replace(np.nan, 'India')
```

In [37]:

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

Out[37]:

```
Prospect ID                                      0.00
Lead Number                                      0.00
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
Lead Quality                                     51.59
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 [38]:

```
# Rest missing values are under 2% so we can drop these rows.
data.dropna(inplace = True)
```

In [39]:

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

Out[39]:

```
Prospect ID                                      0.0
Lead Number                                      0.0
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
Lead Quality                                     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 [40]:

```
data.to_csv('Leads_cleaned')
```

In [39]:

```
## Now Data is clean and we can start with the analysis part
```

Exploratory Data Analytics

In [41]:

```
# Converted is the target variable, Indicates whether a lead has been successfully converted (1) o
r not (0).
```

In [42]:

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

Out[42]:

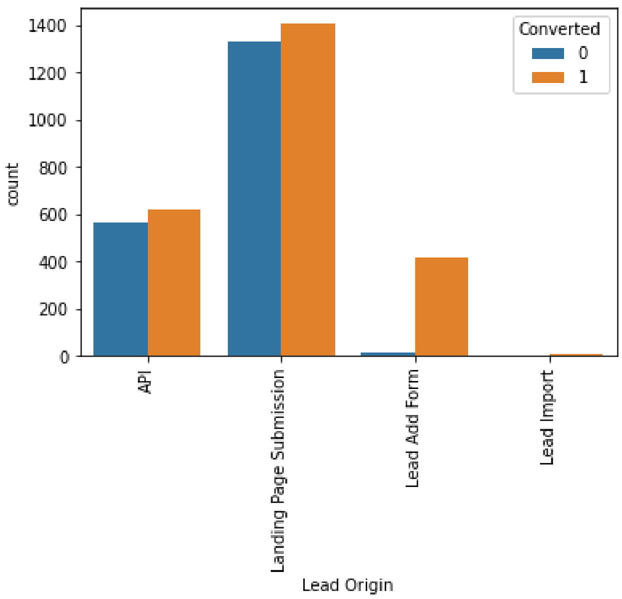
```
56.06338998621957
```

In [43]:

```
sns.countplot(x = "Lead Origin", hue = "Converted", data = data)
xticks(rotation = 90)
```

Out[43]:

```
(array([0, 1, 2, 3]), <a list of 4 Text major ticklabel objects>)
```



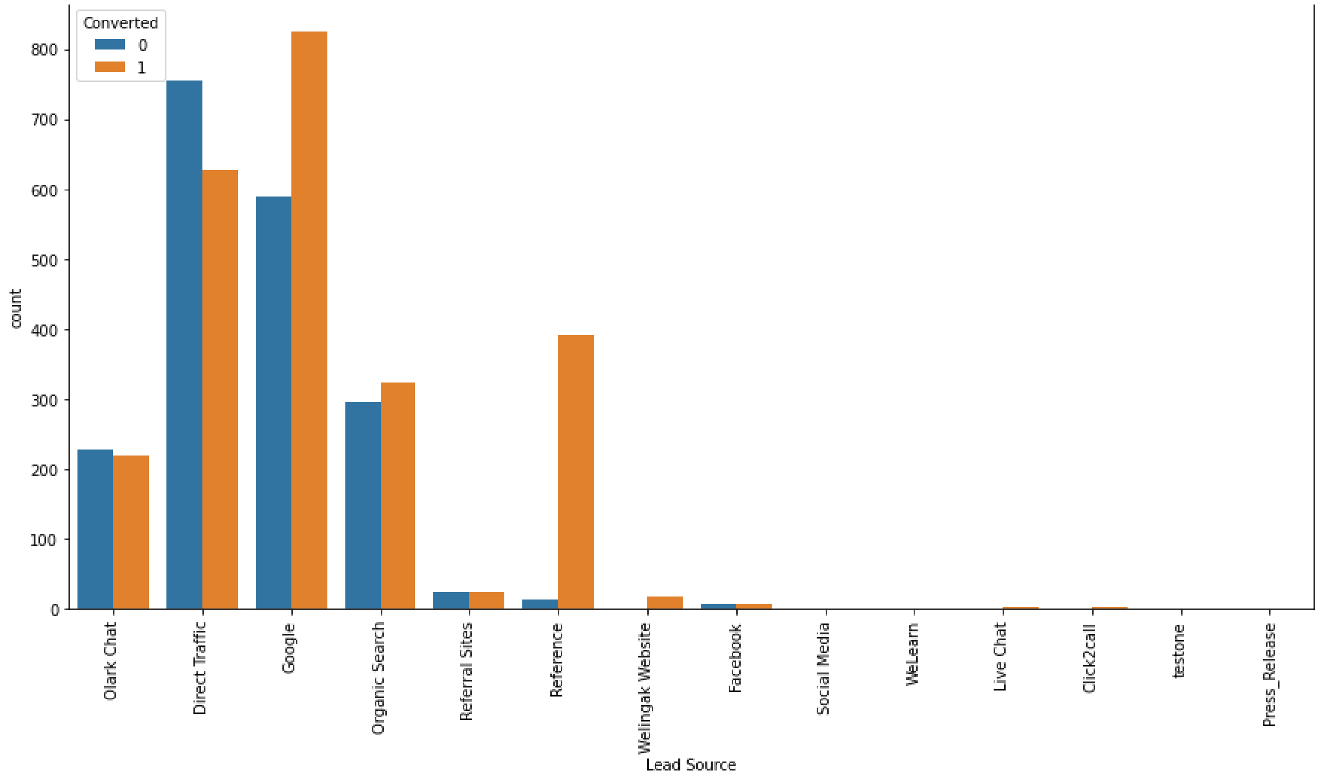
API and Landing Page Submission have 30-35% conversion rate but count of lead originated from them are considerable. Lead Add Form has more than 90% conversion rate but count of lead are not very high. Lead Import are very less in count. To improve overall lead conversion rate, we need to focus more on improving lead converion of API and Landing Page Submission origin and generate more leads from Lead Add Form.

In [44]:

```
fig, axs = plt.subplots(figsize = (15,7.5))
sns.countplot(x = "Lead Source", hue = "Converted", data = data)
xticks(rotation = 90)
```

Out[44]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13]),
 <a list of 14 Text major ticklabel objects>)
```



In [45]:

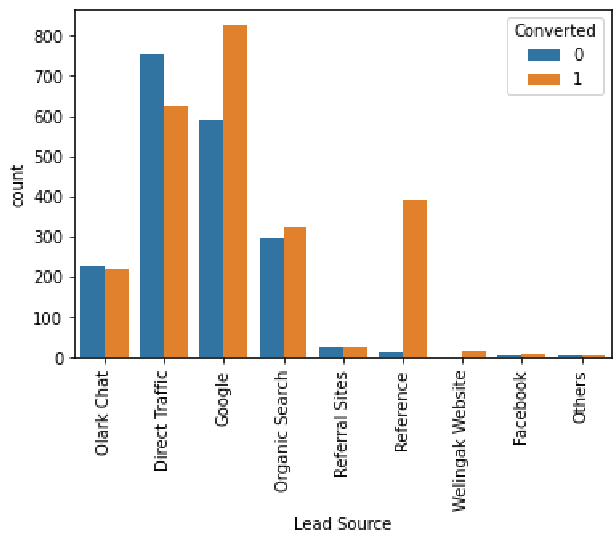
```
data['Lead Source'] = data['Lead Source'].replace(['google'], 'Google')
data['Lead Source'] = data['Lead Source'].replace(['Click2call', 'Live Chat', 'NC_EDM', 'Pay per
Click Ads', 'Press_Release',
  'Social Media', 'WeLearn', 'bing', 'blog', 'testone', 'welearnblog_Home', 'youtubechannel'], 'Oth
ers')
```

In [46]:

```
sns.countplot(x = "Lead Source", hue = "Converted", data = data)
xticks(rotation = 90)
```

Out[46]:

```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8]),
 <a list of 9 Text major ticklabel objects>)
```



Google and Direct traffic generates maximum number of leads. 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.

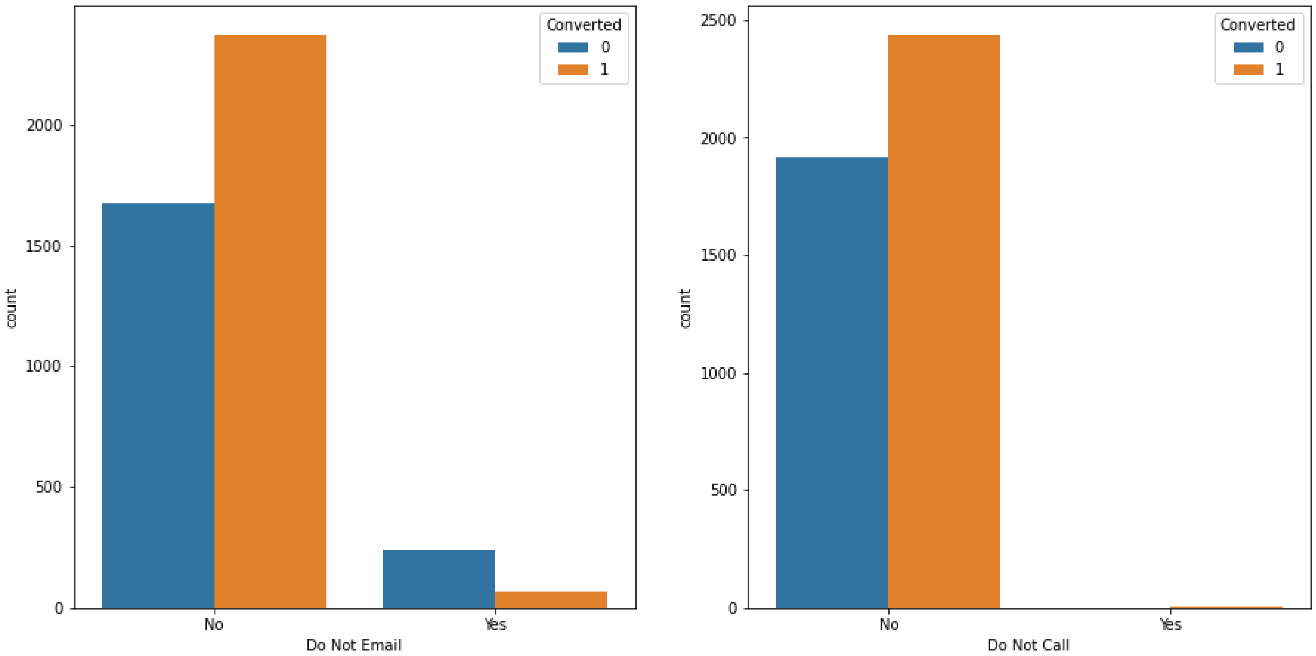
Do Not Email & Do Not Call

In [47]:

```
fig, axs = plt.subplots(1,2,figsize = (15,7.5))
sns.countplot(x = "Do Not Email", hue = "Converted", data = data, ax = axs[0])
sns.countplot(x = "Do Not Call", hue = "Converted", data = data, ax = axs[1])
```

Out[47]:

<matplotlib.axes._subplots.AxesSubplot at 0x58cc490>



Total Visits

In [48]:

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

Out[48]:

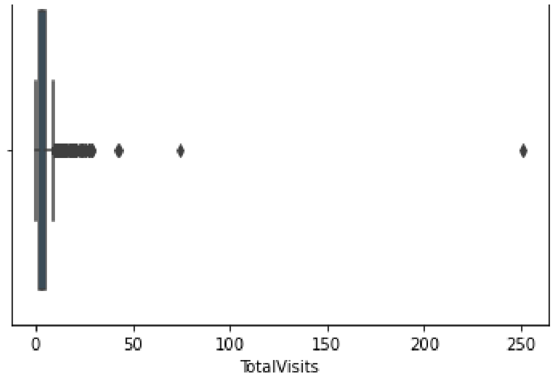
```
count    4354.000000
mean        3.808682
std         5.294923
min         0.000000
5%          0.000000
25%         2.000000
50%         3.000000
75%         5.000000
90%         8.000000
95%        10.000000
99%        18.000000
max       251.000000
Name: TotalVisits, dtype: float64
```

In [49]:

```
sns.boxplot(data['TotalVisits'])
```

Out[49]:

<matplotlib.axes._subplots.AxesSubplot at 0x5918550>



In [50]:

```
# As we can see there are a number of outliers in the data.
# We will cap the outliers to 95% value for analysis.
```

In [51]:

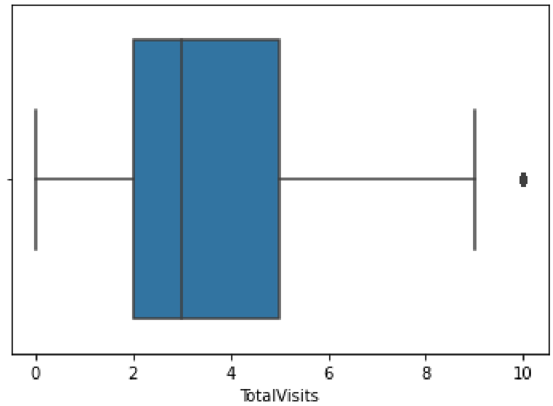
```
percentiles = data['TotalVisits'].quantile([0.05,0.95]).values
data['TotalVisits'][data['TotalVisits'] <= percentiles[0]] = percentiles[0]
data['TotalVisits'][data['TotalVisits'] >= percentiles[1]] = percentiles[1]
```

In [52]:

```
sns.boxplot(data['TotalVisits'])
```

Out[52]:

<matplotlib.axes._subplots.AxesSubplot at 0x12751730>

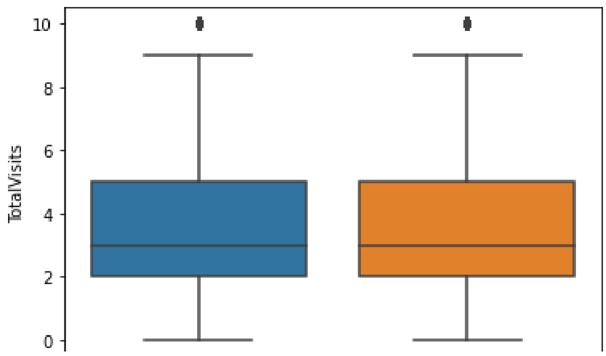


In [53]:

```
sns.boxplot(y = 'TotalVisits', x = 'Converted', data = data)
```

Out[53]:

<matplotlib.axes._subplots.AxesSubplot at 0x1244a4d8>



Inference

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

Total time spent on website

In [54]:

```
data['Total Time Spent on Website'].describe()
```

Out[54]:

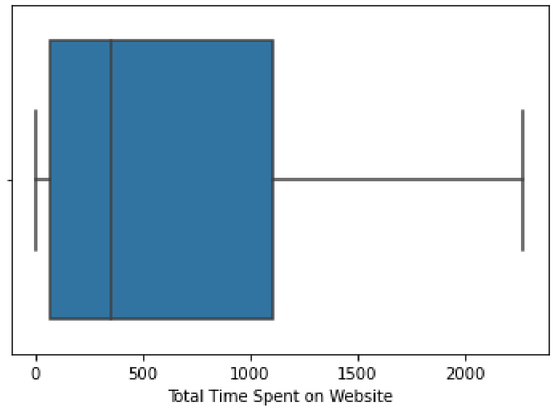
```
count    4354.000000
mean      594.821314
std       579.054824
min         0.000000
25%        66.000000
50%       351.000000
75%      1102.750000
max      2272.000000
Name: Total Time Spent on Website, dtype: float64
```

In [55]:

```
sns.boxplot(data['Total Time Spent on Website'])
```

Out[55]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x589baa8>
```

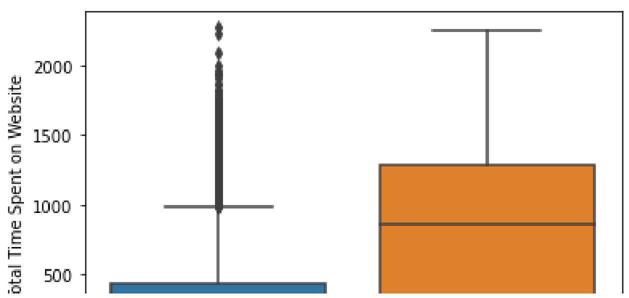


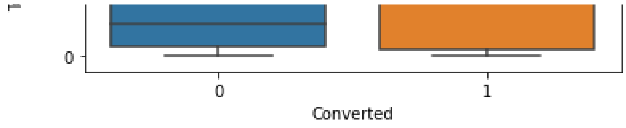
In [56]:

```
sns.boxplot(y = 'Total Time Spent on Website', x = 'Converted', data = data)
```

Out[56]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x13ca0f10>
```





Inference

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

Page views per visit

In [57]:

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

Out[57]:

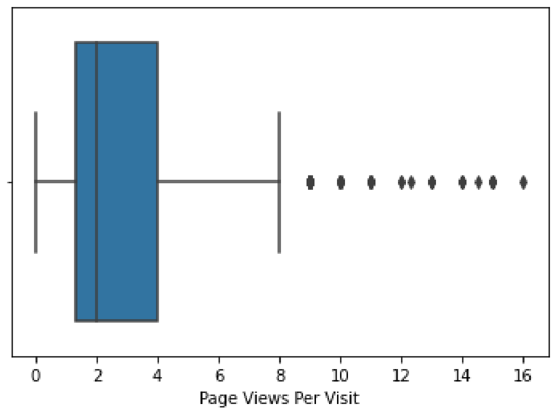
```
count    4354.000000
mean        2.610923
std         2.079434
min         0.000000
25%         1.330000
50%         2.000000
75%         4.000000
max        16.000000
Name: Page Views Per Visit, dtype: float64
```

In [58]:

```
sns.boxplot(data['Page Views Per Visit'])
```

Out[58]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x13cdfe68>
```



In [59]:

```
# As we can see there are a number of outliers in the data.
# We will cap the outliers to 95% value for analysis.
```

In [60]:

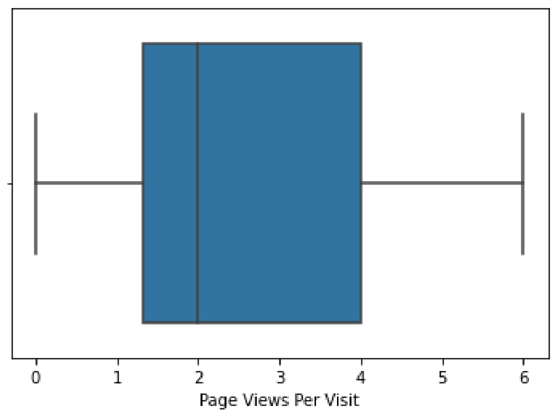
```
percentiles = data['Page Views Per Visit'].quantile([0.05,0.95]).values
data['Page Views Per Visit'][data['Page Views Per Visit'] <= percentiles[0]] = percentiles[0]
data['Page Views Per Visit'][data['Page Views Per Visit'] >= percentiles[1]] = percentiles[1]
```

In [61]:

```
sns.boxplot(data['Page Views Per Visit'])
```

Out[61]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x13d14838>
```

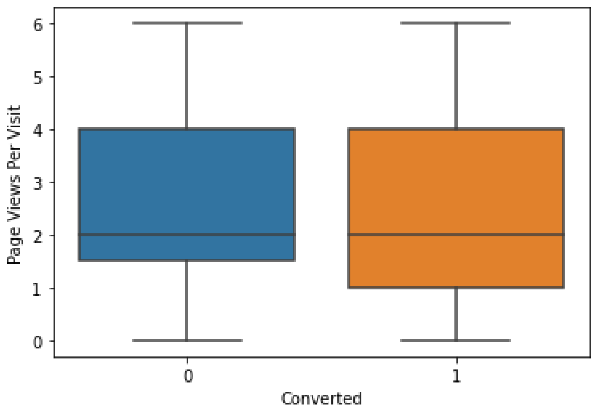


In [62]:

```
sns.boxplot(y = 'Page Views Per Visit', x = 'Converted', data = data)
```

Out[62]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x59187d8>
```



Last Activity

In [63]:

```
data['Last Activity'].describe()
```

Out[63]:

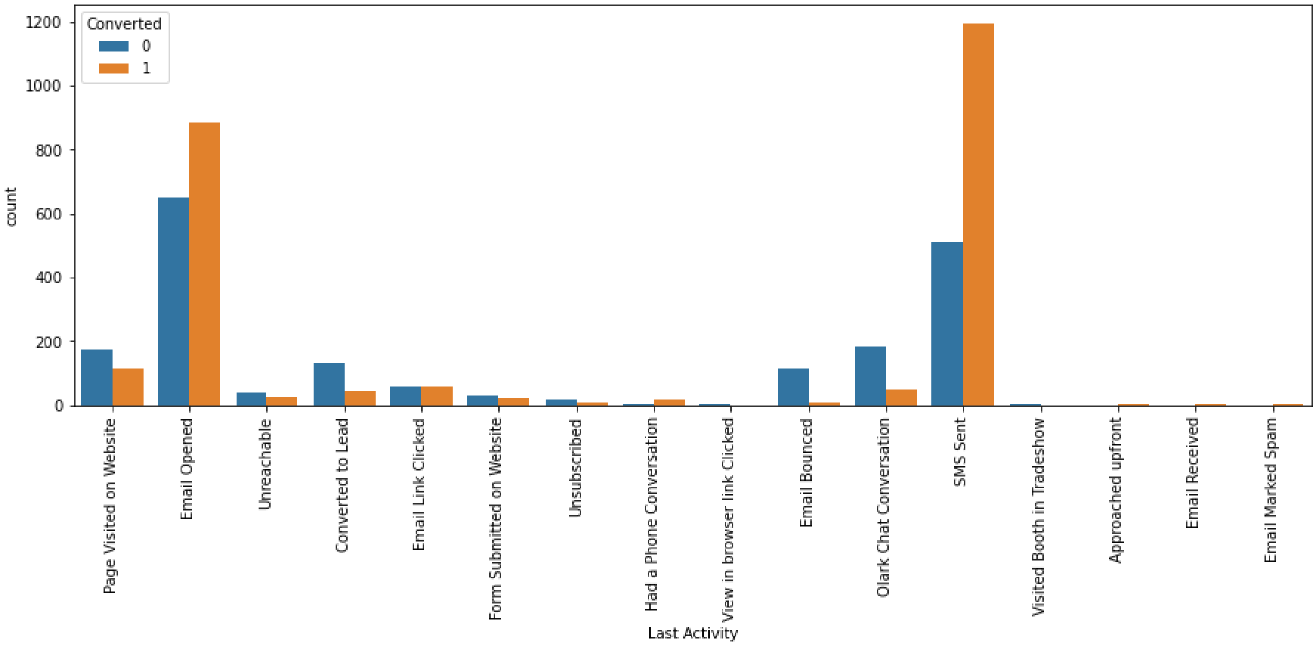
```
count          4354
unique           16
top        SMS Sent
freq           1704
Name: Last Activity, dtype: object
```

In [64]:

```
fig, axs = plt.subplots(figsize = (15,5))
sns.countplot(x = "Last Activity", hue = "Converted", data = data)
xticks(rotation = 90)
```

Out[64]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15]),
 <a list of 16 Text major ticklabel objects>)
```



In [65]:

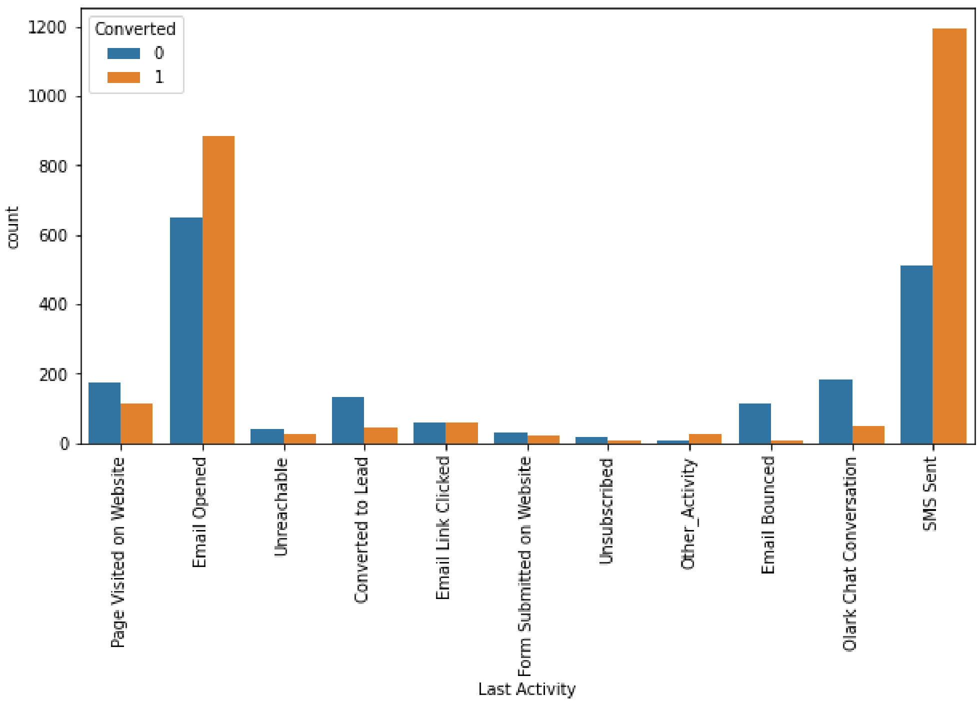
```
# Let's keep considerable last activities as such and club all others to "Other_Activity"
data['Last Activity'] = data['Last Activity'].replace(['Had a Phone Conversation', 'View in
browser link Clicked',
                                                       'Visited Booth in Tradeshow', 'Approached up
ont',
                                                       'Resubscribed to emails','Email Received', '
ail Marked Spam'], 'Other_Activity')
```

In [66]:

```
fig, axs = plt.subplots(figsize = (10,5))
sns.countplot(x = "Last Activity", hue = "Converted", data = data)
xticks(rotation = 90)
```

Out[66]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10]),
 <a list of 11 Text major ticklabel objects>)
```



Most of the lead have their Email opened as their last activity. Conversion rate for leads with last activity as SMS Sent is almost 60%.b

country

In [67]:

```
data.Country.describe()
```

Out[67]:

```
count       4354
unique        28
top        India
freq        4213
Name: Country, dtype: object
```

Specialization

In [68]:

```
data.Specialization.describe()
```

Out[68]:

```
count        4354
unique         19
top        Others
freq          823
Name: Specialization, dtype: object
```

In [69]:

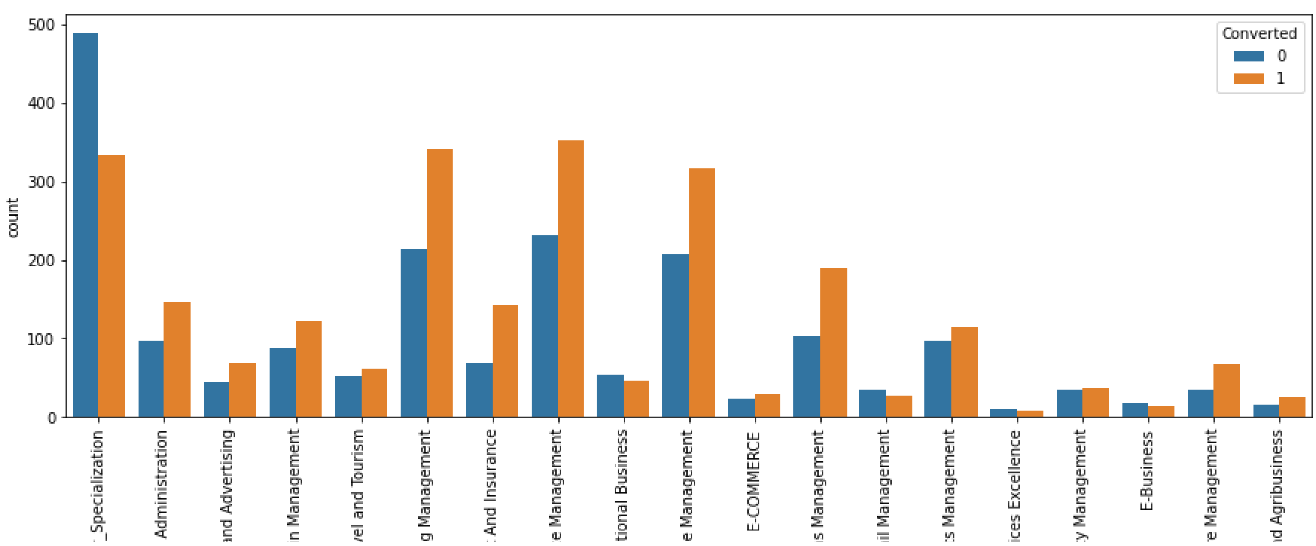
```
data['Specialization'] = data['Specialization'].replace(['Others'], 'Other_Specialization')
```

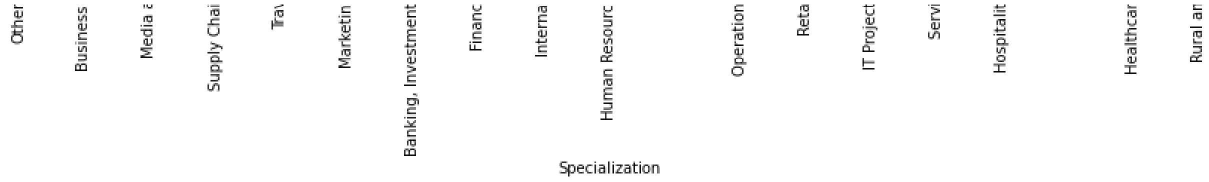
In [70]:

```
fig, axs = plt.subplots(figsize = (15,5))
sns.countplot(x = "Specialization", hue = "Converted", data = data)
xticks(rotation = 90)
```

Out[70]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18]),
 <a list of 19 Text major ticklabel objects>)
```





Focus should be more on the Specialization with high conversion rate.

Occupation

In [71]:

```
data['What is your current occupation'].describe()
```

Out[71]:

```
count              4354
unique                6
top          Unemployed
freq               3483
Name: What is your current occupation, dtype: object
```

In [72]:

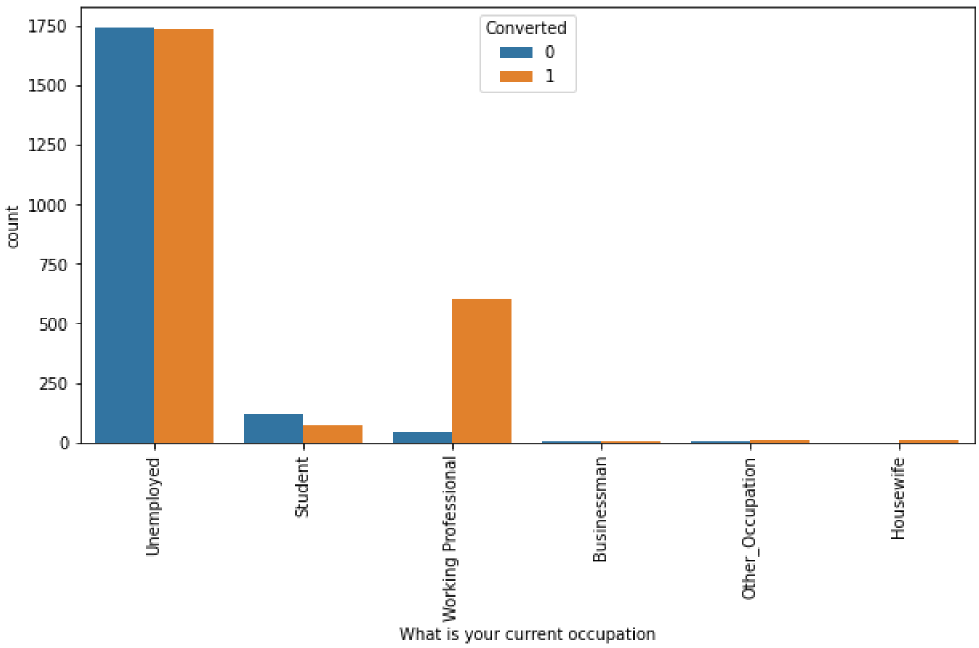
```
data['What is your current occupation'] = data['What is your current occupation'].replace(['Other'
], 'Other_Occupation')
```

In [73]:

```
fig, axs = plt.subplots(figsize = (10,5))
sns.countplot(x = "What is your current occupation", hue = "Converted", data = data)
xticks(rotation = 90)
```

Out[73]:

```
(array([0, 1, 2, 3, 4, 5]), <a list of 6 Text major ticklabel objects>)
```



What matters most to you in choosing a course

In [74]:

```
data['What matters most to you in choosing a course'].describe()
```

Out[74]:

```
count                         4354
unique                           3
top        Better Career Prospects
freq                          4352
Name: What matters most to you in choosing a course, dtype: object
```

Most entries are 'Better Career Prospects'. No Inference can be drawn with this parameter.

Search

In [75]:

```
data.Search.describe()
```

Out[75]:

```
count     4354
unique       2
top         No
freq      4347
Name: Search, dtype: object
```

Most entries are 'No'. No Inference can be drawn with this parameter.

X Education Forums

In [76]:

```
data['X Education Forums'].describe()
```

Out[76]:

```
count     4354
unique       1
top         No
freq      4354
Name: X Education Forums, dtype: object
```

Most entries are 'No'. No Inference can be drawn with this parameter.

Newspaper

In [77]:

```
data['Newspaper'].describe()
```

Out[77]:

```
count     4354
unique       2
top         No
freq      4353
Name: Newspaper, dtype: object
```

Digital Advertisement

In [78]:

```
data['Digital Advertisement'].describe()
```

```
data['Digital Advertisement'].describe()
```

Out[78]:

```
count     4354
unique       2
top         No
freq      4352
Name: Digital Advertisement, dtype: object
```

Through Recommendations

In [79]:

```
data['Through Recommendations'].describe()
```

Out[79]:

```
count     4354
unique       2
top         No
freq      4348
Name: Through Recommendations, dtype: object
```

Receive More Updates About Our Courses

In [80]:

```
data['Receive More Updates About Our Courses'].describe()
```

Out[80]:

```
count     4354
unique       1
top         No
freq      4354
Name: Receive More Updates About Our Courses, dtype: object
```

Tags

In [81]:

```
data.Tags.describe()
```

Out[81]:

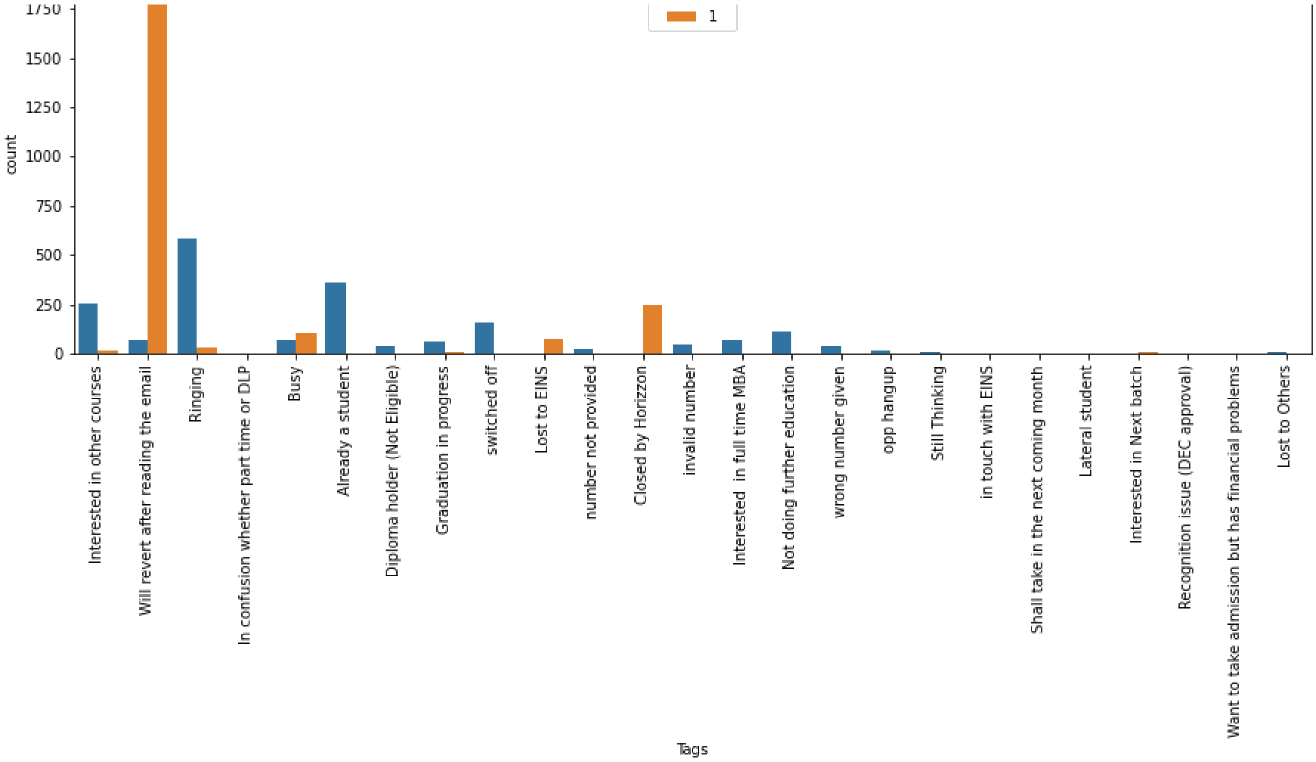
```
count                                  4354
unique                                   25
top       Will revert after reading the email
freq                                   2006
Name: Tags, dtype: object
```

In [82]:

```
fig, axs = plt.subplots(figsize = (15,5))
sns.countplot(x = "Tags", hue = "Converted", data = data)
xticks(rotation = 90)
```

Out[82]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20, 21, 22, 23, 24]),
 <a list of 25 Text major ticklabel objects>)
```



In [83]:

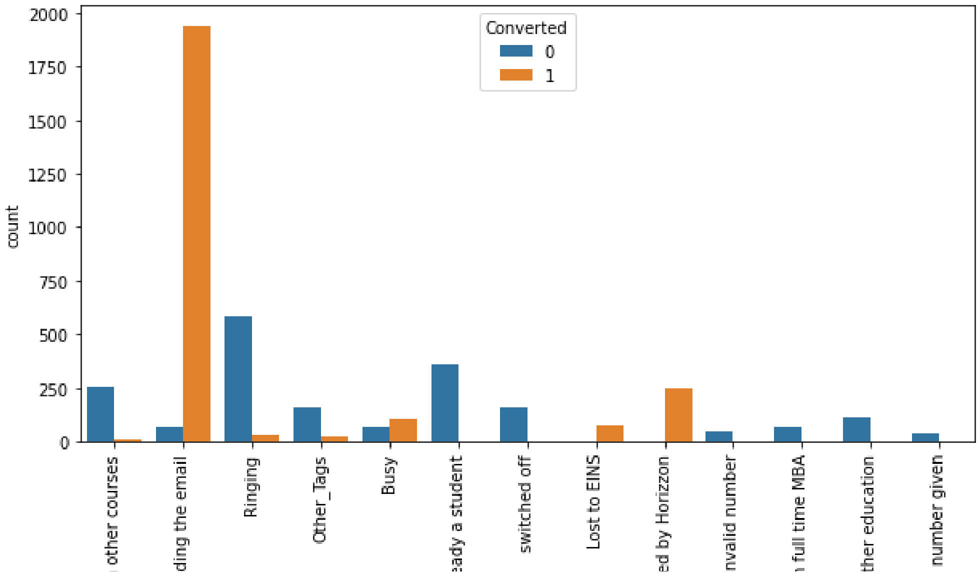
```
# Let's keep considerable last activities as such and club all others to "Other_Activity"
data['Tags'] = data['Tags'].replace(['In confusion whether part time or DLP', 'in touch with EINS',
'Diploma holder (Not Eligible)',
                                     'Approached upfront','Graduation in progress','number not prov
ded', 'opp hangup','Still Thinking',
                                    'Lost to Others','Shall take in the next coming month','Lateral
student','Interested in Next batch',
                                    'Recognition issue (DEC approval)','Want to take admission but
as financial problems',
                                    'University not recognized'], 'Other_Tags')
```

In [84]:

```
fig, axs = plt.subplots(figsize = (10,5))
sns.countplot(x = "Tags", hue = "Converted", data = data)
xticks(rotation = 90)
```

Out[84]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12]),
 <a list of 13 Text major ticklabel objects>)
```



Lead Quality

In [85]:

```
data['Lead Quality'].describe()
```

Out[85]:

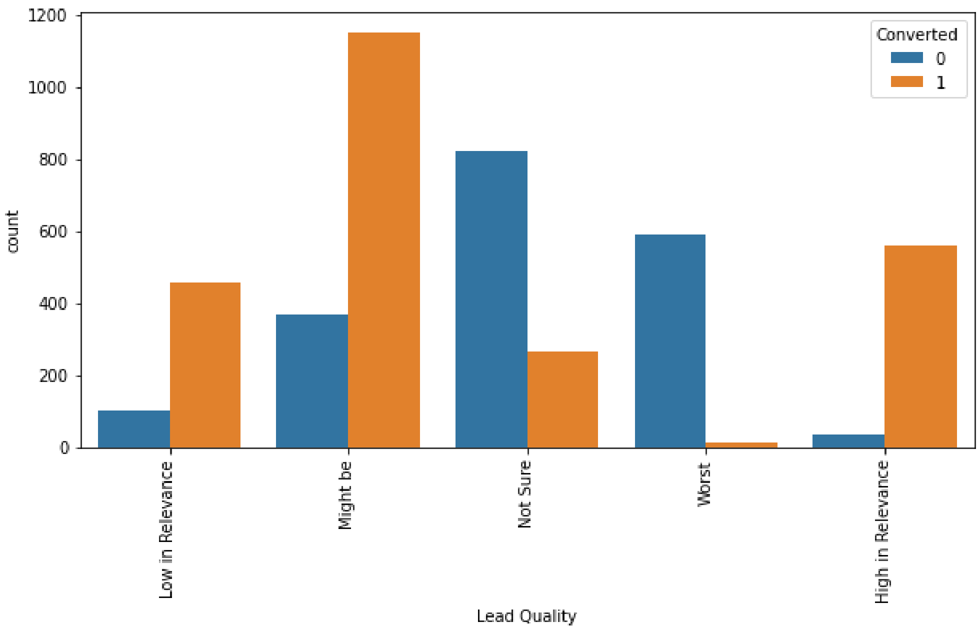
```
count         4354
unique           5
top       Might be
freq          1519
Name: Lead Quality, dtype: object
```

In [86]:

```
fig, axs = plt.subplots(figsize = (10,5))
sns.countplot(x = "Lead Quality", hue = "Converted", data = data)
xticks(rotation = 90)
```

Out[86]:

```
(array([0, 1, 2, 3, 4]), <a list of 5 Text major ticklabel objects>)
```



Update me on Supply Chain Content

In [87]:

```
data['Update me on Supply Chain Content'].describe()
```

Out[87]:

```
count     4354
unique       1
top         No
freq      4354
Name: Update me on Supply Chain Content, dtype: object
```

Get updates on DM Content

In [88]:

```
data['Get updates on DM Content'].describe()
```

Out[88]:

```
count     4354
unique       1
top         No
freq      4354
Name: Get updates on DM Content, dtype: object
```

In [89]:

```
data['I agree to pay the amount through cheque'].describe()
```

Out[89]:

```
count     4354
unique       1
top         No
freq      4354
Name: I agree to pay the amount through cheque, dtype: object
```

In [90]:

```
data['A free copy of Mastering The Interview'].describe()
```

Out[90]:

```
count     4354
unique       2
top         No
freq      2735
Name: A free copy of Mastering The Interview, dtype: object
```

City

In [91]:

```
data.City.describe()
```

Out[91]:

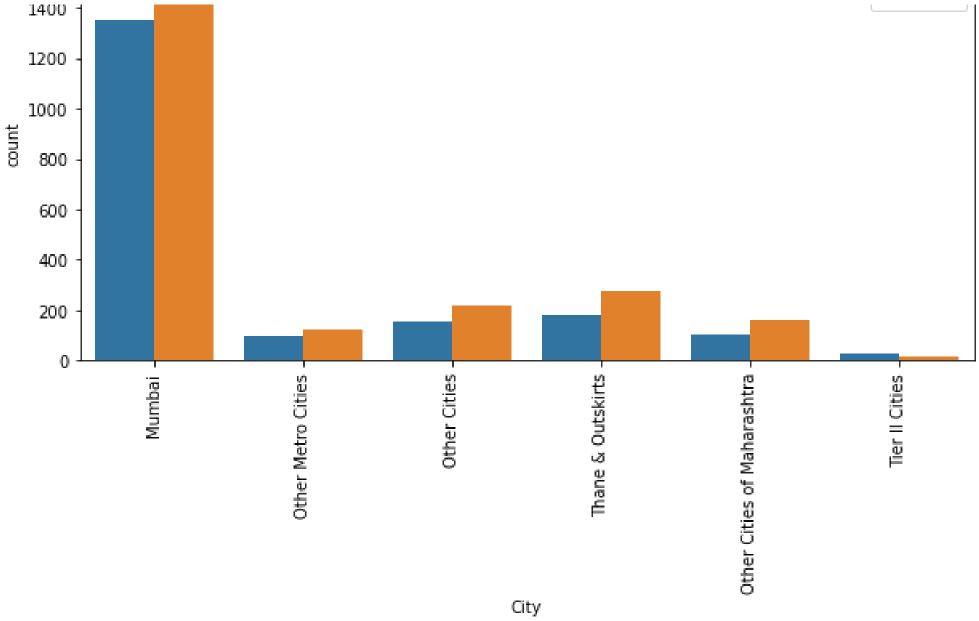
```
count       4354
unique         6
top       Mumbai
freq        2993
Name: City, dtype: object
```

In [92]:

```
fig, axs = plt.subplots(figsize = (10,5))
sns.countplot(x = "City", hue = "Converted", data = data)
xticks(rotation = 90)
```

Out[92]:

```
(array([0, 1, 2, 3, 4, 5]), <a list of 6 Text major ticklabel objects>)
```



Last Notable Activity

In [93]:

```
data['Last Notable Activity'].describe()
```

Out[93]:

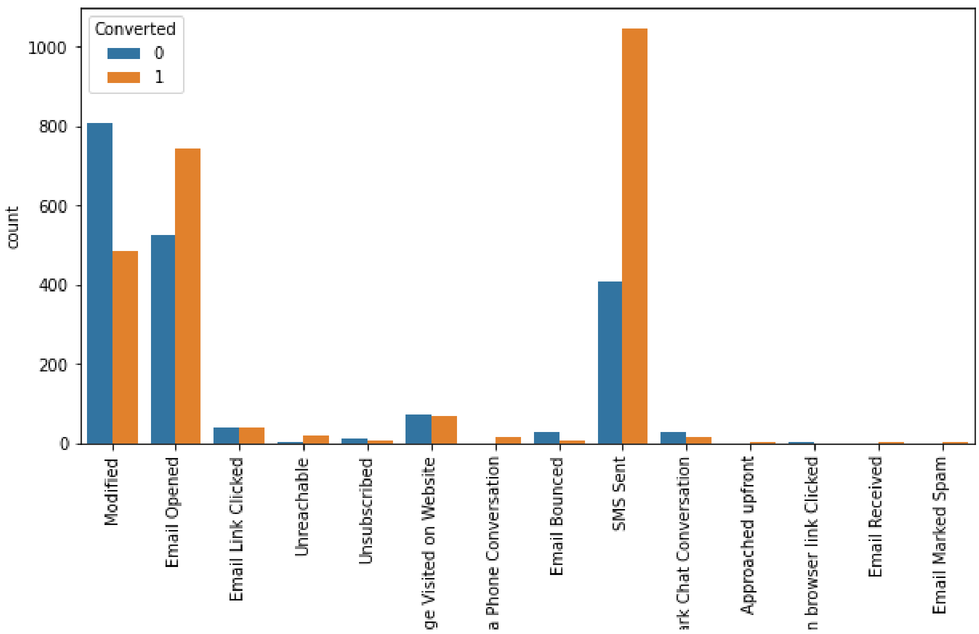
```
count         4354
unique          14
top       SMS Sent
freq          1453
Name: Last Notable Activity, dtype: object
```

In [94]:

```
fig, axs = plt.subplots(figsize = (10,5))
sns.countplot(x = "Last Notable Activity", hue = "Converted", data = data)
xticks(rotation = 90)
```

Out[94]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13]),
 <a list of 14 Text major ticklabel objects>)
```



Results

Based on the univariate analysis we have seen that many columns are not adding any information to the model, heance we can drop them for frther analysis

In [95]:

```
 data= data.drop(['Lead Number','What matters most to you in choosing a
course','Search','Magazine','Newspaper Article','X Education Forums','Newspaper',
           'Digital Advertisement','Through Recommendations','Receive More Updates About Our Course
s','Update me on Supply Chain Content',
           'Get updates on DM Content','I agree to pay the amount through cheque','A free copy of
Mastering The Interview','Country'],1)
```

In [96]:

```
data.shape
```

Out[96]:

```
(4354, 16)
```

In [97]:

```
data.head()
```

Out[97]:

	Prospect ID	Lead Origin	Lead Source	Do Not Email	Do Not Call	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Last Activity	Specialization	What i you currer occupatio
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	API	Olark Chat	No	No	0	0.0	0	0.0	Page Visited on Website	Other_Specialization	Unemploye
2	8cc8c611-a219-4f35-ad23-fdfd2656bd8a	Landing Page Submission	Direct Traffic	No	No	1	2.0	1532	2.0	Email Opened	Business Administration	Studer
3	0cc2df48-7cf4-4e39-9de9-19797f9b38cc	Landing Page Submission	Direct Traffic	No	No	0	1.0	305	1.0	Unreachable	Media and Advertising	Unemploye
4	3256f628-e534-4826-9d63-4a8b88782852	Landing Page Submission	Google	No	No	1	2.0	1428	1.0	Converted to Lead	Other_Specialization	Unemploye
6	9fae7df4-169d-489b-afe4-0f3d752542ed	Landing Page Submission	Google	No	No	1	2.0	1640	2.0	Email Opened	Supply Chain Management	Unemploye

In [98]:

```
# List of variables to map

varlist =  ['Do Not Email', 'Do Not Call']

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

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

In [99]:

```
# Creating a dummy variable for some of the categorical variables and dropping the first one.
dummy1 = pd.get_dummies(data[['Lead Origin', 'Lead Source', 'Last Activity', 'Specialization','What
is your current occupation',
                              'Tags','Lead Quality','City','Last Notable Activity']], drop_first=Tr
e)
dummy1.head()
```

Out[99]:

	Lead Origin_Landing Page Submission	Lead Origin_Lead Add Form	Lead Origin_Lead Import	Lead Source_Facebook	Lead Source_Google	Lead Source_Olark Chat	Lead Source_Organic Search	Lead Source_Others	Sourc
0	0	0	0	0	0	1	0	0	
2	1	0	0	0	0	0	0	0	
3	1	0	0	0	0	0	0	0	
4	1	0	0	0	1	0	0	0	
6	1	0	0	0	1	0	0	0	

In [100]:

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

Out[100]:

	Prospect ID	Lead Origin	Lead Source	Do Not Email	Do Not Call	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Last Activity	Specialization	What i you currer occupatio
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	API	Olark Chat	0	0	0	0.0	0	0.0	Page Visited on Website	Other_Specialization	Unemploye
2	8cc8c611-a219-4f35-ad23-fdfd2656bd8a	Landing Page Submission	Direct Traffic	0	0	1	2.0	1532	2.0	Email Opened	Business Administration	Studer
3	0cc2df48-7cf4-4e39-9de9-19797f9b38cc	Landing Page Submission	Direct Traffic	0	0	0	1.0	305	1.0	Unreachable	Media and Advertising	Unemploye
4	3256f628-e534-4826-9d63-4a8b88782852	Landing Page Submission	Google	0	0	1	2.0	1428	1.0	Converted to Lead	Other_Specialization	Unemploye
6	9fae7df4-169d-489b-afe4-0f3d752542ed	Landing Page Submission	Google	0	0	1	2.0	1640	2.0	Email Opened	Supply Chain Management	Unemploye

In [101]:

```
data = data.drop(['Lead Origin', 'Lead Source', 'Last Activity', 'Specialization','What is your
current occupation','Tags','Lead Quality','City','Last Notable Activity'], axis = 1)
```

In [102]:

```
data.head()
```

Out[102]:

Total

	Prospect ID	Do Not Email	Do Not Call	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	Lead Source_Facebook	Sc
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	0	0	0	0.0	0	0.0	0	0	0	0	
2	8cc8c611-a219-4f35-ad23-fdfd2656bd8a	0	0	1	2.0	1532	2.0	1	0	0	0	
3	0cc2df48-7cf4-4e39-9de9-19797f9b38cc	0	0	0	1.0	305	1.0	1	0	0	0	
4	3256f628-e534-4826-9d63-4a8b88782852	0	0	1	2.0	1428	1.0	1	0	0	0	
6	9fae7df4-169d-489b-afe4-0f3d752542ed	0	0	1	2.0	1640	2.0	1	0	0	0	

In [103]:

```
from sklearn.model_selection import train_test_split

# Putting feature variable to X
X = data.drop(['Prospect ID','Converted'], axis=1)
```

In [104]:

```
X.head()
```

Out[104]:

	Do Not Email	Do Not Call	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Lead Origin_Landing Page Submission	Lead Origin_Lead Add Form	Lead Origin_Lead Import	Lead Source_Facebook	Lead Source_Google	Lead Source_Olar Cha
0	0	0	0.0	0	0.0	0	0	0	0	0	
2	0	0	2.0	1532	2.0	1	0	0	0	0	
3	0	0	1.0	305	1.0	1	0	0	0	0	
4	0	0	2.0	1428	1.0	1	0	0	0	1	
6	0	0	2.0	1640	2.0	1	0	0	0	1	

In [105]:

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

y.head()
```

Out[105]:

```
0    0
2    1
3    0
4    1
6    1
Name: Converted, dtype: int64
```

In [106]:

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

Feature Scaling

In [107]:

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

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

X_train.head()
```

Out[107]:

	Do Not Email	Do Not Call	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Lead Origin_Landing Page Submission	Lead Origin_Lead Add Form	Lead Origin_Lead Import	Lead Source_Facebook	Lead Source_Google	Sourc
4584	0	0	0.888005	0.612028	0.290907	1	0	0	0	0	
5617	0	0	-1.272851	-1.029308	-1.425005	0	0	0	0	0	
1095	0	0	-0.552566	-0.101970	-0.281063	1	0	0	0	1	
3166	0	0	-0.192423	-0.523487	0.290907	1	0	0	0	0	
401	0	0	0.527863	0.866659	1.434849	1	0	0	0	0	

In [108]:

```
# Checking the Churn Rate
Converted = (sum(data['Converted'])/len(data['Converted'].index))*100
Converted
```

Out[108]:

56.06338998621957

Model Building

In [109]:

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

In [110]:

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

Out[110]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	3047
Model:	GLM	**Df Residuals:**	2964
Model Family:	Binomial	**Df Model:**	82
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-384.03

Date:	Tue, 12 May 2020	**Deviance:**	768.06
Time:	08:57:07	**Pearson chi2:**	2.50e+03
No. Iterations:	23		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	17.3425	1.31e+05	0.000	1.000	-2.57e+05	2.57e+05
Do Not Email	-0.9541	0.592	-1.613	0.107	-2.114	0.205
Do Not Call	2.364e-09	1.24e-05	0.000	1.000	-2.42e-05	2.42e-05
TotalVisits	0.4143	0.172	2.411	0.016	0.078	0.751
Total Time Spent on Website	0.9865	0.117	8.414	0.000	0.757	1.216
Page Views Per Visit	-0.3792	0.181	-2.098	0.036	-0.734	-0.025
Lead Origin_Landing Page Submission	0.5456	0.394	1.386	0.166	-0.226	1.317
Lead Origin_Lead Add Form	0.5512	2.541	0.217	0.828	-4.429	5.532
Lead Origin_Lead Import	27.0528	1.31e+05	0.000	1.000	-2.57e+05	2.57e+05
Lead Source_Facebook	-24.8276	1.31e+05	-0.000	1.000	-2.57e+05	2.57e+05
Lead Source_Google	0.4205	0.269	1.560	0.119	-0.108	0.949
Lead Source_Olark Chat	1.7029	0.496	3.431	0.001	0.730	2.676
Lead Source_Organic Search	0.7154	0.367	1.952	0.051	-0.003	1.434
Lead Source_Others	1.6732	2.361	0.709	0.479	-2.955	6.301
Lead Source_Reference	1.8855	2.591	0.728	0.467	-3.193	6.964
Lead Source_Referral Sites	1.2199	0.819	1.490	0.136	-0.385	2.825
Lead Source_Welingak Website	21.9482	3.29e+04	0.001	0.999	-6.45e+04	6.46e+04
Last Activity_Email Bounced	-1.3003	1.276	-1.019	0.308	-3.802	1.201
Last Activity_Email Link Clicked	-1.4290	1.134	-1.260	0.208	-3.652	0.794
Last Activity_Email Opened	-1.6409	0.704	-2.331	0.020	-3.020	-0.261
Last Activity_Form Submitted on Website	-0.7501	0.923	-0.813	0.416	-2.559	1.059
Last Activity_Olark Chat Conversation	-0.9130	0.760	-1.201	0.230	-2.402	0.576
Last Activity_Other_Activity	-2.1750	1.502	-1.448	0.148	-5.119	0.769
Last Activity_Page Visited on Website	-1.1635	0.793	-1.468	0.142	-2.717	0.390
Last Activity_SMS Sent	0.6388	0.662	0.966	0.334	-0.658	1.935
Last Activity_Unreachable	-0.9413	1.170	-0.804	0.421	-3.235	1.352
Last Activity_Unsubscribed	-0.5394	2.424	-0.222	0.824	-5.291	4.212
Specialization_Business Administration	0.0857	0.658	0.130	0.897	-1.205	1.376
Specialization_E-Business	0.5926	1.377	0.430	0.667	-2.106	3.291
Specialization_E-COMMERCE	1.5357	1.165	1.319	0.187	-0.747	3.818
Specialization_Finance Management	-0.5637	0.599	-0.941	0.347	-1.738	0.611
Specialization_Healthcare Management	-0.2858	0.987	-0.290	0.772	-2.219	1.648
Specialization_Hospitality Management	-1.3919	0.883	-1.576	0.115	-3.122	0.339
Specialization_Human Resource Management	-0.5552	0.595	-0.933	0.351	-1.722	0.612
Specialization_IT Projects Management	0.1641	0.741	0.221	0.825	-1.289	1.617
Specialization_International Business	-0.2296	0.918	-0.250	0.802	-2.029	1.570
Specialization_Marketing Management	-0.2624	0.595	-0.441	0.659	-1.428	0.903
Specialization_Media and Advertising	-0.8205	0.797	-1.029	0.303	-2.383	0.742
Specialization_Operations Management	-0.0913	0.662	-0.138	0.890	-1.388	1.206
Specialization_Other_Specialization	-0.0430	0.638	-0.067	0.946	-1.294	1.208
Specialization_Retail Management	-0.6463	0.927	-0.697	0.486	-2.464	1.171
Specialization_Rural and Agribusiness	0.0724	1.270	0.057	0.955	-2.418	2.562
Specialization_Services Excellence	-1.2986	1.748	-0.743	0.458	-4.725	2.128
Specialization_Supply Chain Management	-1.3930	0.658	-2.116	0.034	-2.683	-0.103
Specialization_Travel and Tourism	-0.6480	0.837	-0.774	0.439	-2.288	0.992

What is your current occupation_Housewife	25.8865	5.62e+04	0.000	1.000	-1.1e+05	1.1e+05
What is your current occupation_Other_Occupation	4.6757	2.644	1.768	0.077	-0.507	9.858
What is your current occupation_Student	4.7339	1.911	2.477	0.013	0.988	8.480
What is your current occupation_Unemployed	4.5980	1.771	2.597	0.009	1.127	8.069
What is your current occupation_Working Professional	5.5161	1.807	3.052	0.002	1.974	9.058
Tags_Busy	3.0588	0.857	3.569	0.000	1.379	4.739
Tags_Closed by Horizzon	8.2977	1.454	5.706	0.000	5.448	11.148
Tags_Interested in full time MBA	0.0043	1.391	0.003	0.998	-2.723	2.731
Tags_Interested in other courses	0.3370	0.897	0.376	0.707	-1.421	2.095
Tags_Lost to EINS	7.9796	1.295	6.160	0.000	5.441	10.519
Tags_Not doing further education	-0.3447	1.350	-0.255	0.798	-2.990	2.300
Tags_Other_Tags	1.4014	0.863	1.623	0.105	-0.291	3.094
Tags_Ringing	-0.7264	0.869	-0.835	0.403	-2.430	0.978
Tags_Will revert after reading the email	5.9035	0.836	7.064	0.000	4.266	7.541
Tags_invalid number	-0.0969	1.341	-0.072	0.942	-2.724	2.530
Tags_switched off	-1.1720	1.024	-1.145	0.252	-3.179	0.835
Tags_wrong number given	-21.9687	2.32e+04	-0.001	0.999	-4.55e+04	4.54e+04
Lead Quality_Low in Relevance	-0.8149	0.506	-1.611	0.107	-1.806	0.176
Lead Quality_Might be	-1.4587	0.472	-3.092	0.002	-2.383	-0.534
Lead Quality_Not Sure	-1.4375	0.494	-2.909	0.004	-2.406	-0.469
Lead Quality_Worst	-3.4535	0.831	-4.155	0.000	-5.083	-1.824
City_Other Cities	-0.0803	0.354	-0.227	0.821	-0.774	0.614
City_Other Cities of Maharashtra	-0.2943	0.433	-0.679	0.497	-1.143	0.555
City_Other Metro Cities	-0.4997	0.498	-1.004	0.315	-1.475	0.476
City_Thane & Outskirts	0.1459	0.358	0.408	0.684	-0.556	0.847
City_Tier II Cities	-0.6671	0.905	-0.737	0.461	-2.441	1.107
Last Notable Activity_Email Bounced	-21.4932	1.31e+05	-0.000	1.000	-2.57e+05	2.57e+05
Last Notable Activity_Email Link Clicked	-23.1114	1.31e+05	-0.000	1.000	-2.57e+05	2.57e+05
Last Notable Activity_Email Marked Spam	-0.4887	1.55e+05	-3.16e-06	1.000	-3.03e+05	3.03e+05
Last Notable Activity_Email Opened	-22.8345	1.31e+05	-0.000	1.000	-2.57e+05	2.57e+05
Last Notable Activity_Email Received	-2.9659	1.85e+05	-1.6e-05	1.000	-3.63e+05	3.63e+05
Last Notable Activity_Had a Phone Conversation	0.3539	1.36e+05	2.6e-06	1.000	-2.67e+05	2.67e+05
Last Notable Activity_Modified	-24.2591	1.31e+05	-0.000	1.000	-2.57e+05	2.57e+05
Last Notable Activity_Olark Chat Conversation	-26.2377	1.31e+05	-0.000	1.000	-2.57e+05	2.57e+05
Last Notable Activity_Page Visited on Website	-22.8236	1.31e+05	-0.000	1.000	-2.57e+05	2.57e+05
Last Notable Activity_SMS Sent	-23.6477	1.31e+05	-0.000	1.000	-2.57e+05	2.57e+05
Last Notable Activity_Unreachable	-0.8911	1.34e+05	-6.65e-06	1.000	-2.63e+05	2.63e+05
Last Notable Activity_Unsubscribed	-23.3892	1.31e+05	-0.000	1.000	-2.57e+05	2.57e+05
Last Notable Activity_View in browser link Clicked	-42.2201	1.85e+05	-0.000	1.000	-3.63e+05	3.63e+05

Feature Selection Using RFE

In [111]:

```
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.astype(float), y_train.astype(float))
```

In [112]:

```
rfe.support_
```

Out[112]:

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

In [113]:

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

Out[113]:

```
[('Do Not Email', True, 1),
 ('Do Not Call', False, 69),
 ('TotalVisits', False, 24),
 ('Total Time Spent on Website', True, 1),
 ('Page Views Per Visit', False, 25),
 ('Lead Origin_Landing Page Submission', False, 46),
 ('Lead Origin_Lead Add Form', True, 1),
 ('Lead Origin_Lead Import', False, 33),
 ('Lead Source_Facebook', False, 47),
 ('Lead Source_Google', False, 36),
 ('Lead Source_Olark Chat', True, 1),
 ('Lead Source_Organic Search', False, 27),
 ('Lead Source_Others', False, 44),
 ('Lead Source_Reference', True, 1),
 ('Lead Source_Referral Sites', False, 20),
 ('Lead Source_Welingak Website', False, 22),
 ('Last Activity_Email Bounced', False, 18),
 ('Last Activity_Email Link Clicked', False, 15),
 ('Last Activity_Email Opened', False, 16),
 ('Last Activity_Form Submitted on Website', False, 48),
 ('Last Activity_Olark Chat Conversation', False, 17),
 ('Last Activity_Other_Activity', False, 63),
 ('Last Activity_Page Visited on Website', False, 32),
 ('Last Activity_SMS Sent', True, 1),
 ('Last Activity_Unreachable', False, 56),
 ('Last Activity_Unsubscribed', False, 64),
 ('Specialization_Business Administration', False, 23),
 ('Specialization_E-Business', False, 31),
 ('Specialization_E-COMMERCE', False, 13),
 ('Specialization_Finance Management', False, 42),
 ('Specialization_Healthcare Management', False, 67),
 ('Specialization_Hospitality Management', False, 14),
 ('Specialization_Human Resource Management', False, 43),
 ('Specialization_IT Projects Management', False, 30),
 ('Specialization_International Business', False, 68),
 ('Specialization_Marketing Management', False, 61),
 ('Specialization_Media and Advertising', False, 34),
 ('Specialization_Operations Management', False, 38),
 ('Specialization_Other_Specialization', False, 55),
 ('Specialization_Retail Management', False, 45),
 ('Specialization_Rural and Agribusiness', False, 40),
 ('Specialization_Services Excellence', False, 41),
 ('Specialization_Supply Chain Management', False, 7),
 ('Specialization_Travel and Tourism', False, 26),
 ('What is your current occupation_Housewife', False, 39),
 ('What is your current occupation_Other_Occupation', False, 58),
 ('What is your current occupation_Student', False, 53),
 ('What is your current occupation_Unemployed', False, 51),
 ('What is your current occupation_Working Professional', False, 11),
 ('Tags_Busy', True, 1),
 ('Tags_Closed by Horizzon', True, 1),
 ('Tags_Interested  in full time MBA', False, 10),
 ('Tags_Interested in other courses', False, 2),
```

```
 ('Tags_Lost to EINS', True, 1),
 ('Tags_Not doing further education', False, 3),
 ('Tags_Other_Tags', False, 62),
 ('Tags_Ringing', True, 1),
 ('Tags_Will revert after reading the email', True, 1),
 ('Tags_invalid number', False, 4),
 ('Tags_switched off', True, 1),
 ('Tags_wrong number given', True, 1),
 ('Lead Quality_Low in Relevance', False, 21),
 ('Lead Quality_Might be', False, 9),
 ('Lead Quality_Not Sure', False, 8),
 ('Lead Quality_Worst', True, 1),
 ('City_Other Cities', False, 60),
 ('City_Other Cities of Maharashtra', False, 37),
 ('City_Other Metro Cities', False, 29),
 ('City_Thane & Outskirts', False, 59),
 ('City_Tier II Cities', False, 28),
 ('Last Notable Activity_Email Bounced', False, 19),
 ('Last Notable Activity_Email Link Clicked', False, 49),
 ('Last Notable Activity_Email Marked Spam', False, 54),
 ('Last Notable Activity_Email Opened', False, 57),
 ('Last Notable Activity_Email Received', False, 66),
 ('Last Notable Activity_Had a Phone Conversation', True, 1),
 ('Last Notable Activity_Modified', False, 6),
 ('Last Notable Activity_Olark Chat Conversation', False, 5),
 ('Last Notable Activity_Page Visited on Website', False, 35),
 ('Last Notable Activity_SMS Sent', False, 50),
 ('Last Notable Activity_Unreachable', False, 12),
 ('Last Notable Activity_Unsubscribed', False, 65),
 ('Last Notable Activity_View in browser link Clicked', False, 52)]
```

In [114]:

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

Out[114]:

```
Index(['Do Not Email', 'Total Time Spent on Website',
       'Lead Origin_Lead Add Form', 'Lead Source_Olark Chat',
       'Lead Source_Reference', 'Last Activity_SMS Sent', 'Tags_Busy',
       'Tags_Closed by Horizzon', 'Tags_Lost to EINS', 'Tags_Ringing',
       'Tags_Will revert after reading the email', 'Tags_switched off',
       'Tags_wrong number given', 'Lead Quality_Worst',
       'Last Notable Activity_Had a Phone Conversation'],
      dtype='object')
```

In [115]:

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

Out[115]:

```
Index(['Do Not Call', 'TotalVisits', 'Page Views Per Visit',
       'Lead Origin_Landing Page Submission', 'Lead Origin_Lead Import',
       'Lead Source_Facebook', 'Lead Source_Google',
       'Lead Source_Organic Search', 'Lead Source_Others',
       'Lead Source_Referral Sites', 'Lead Source_Welingak Website',
       'Last Activity_Email Bounced', 'Last Activity_Email Link Clicked',
       'Last Activity_Email Opened', 'Last Activity_Form Submitted on Website',
       'Last Activity_Olark Chat Conversation', 'Last Activity_Other_Activity',
       'Last Activity_Page Visited on Website', 'Last Activity_Unreachable',
       'Last Activity_Unsubscribed', 'Specialization_Business Administration',
       'Specialization_E-Business', 'Specialization_E-COMMERCE',
       'Specialization_Finance Management',
       'Specialization_Healthcare Management',
       'Specialization_Hospitality Management',
       'Specialization_Human Resource Management',
       'Specialization_IT Projects Management',
       'Specialization_International Business',
       'Specialization_Marketing Management',
       'Specialization_Media and Advertising',
       'Specialization_Operations Management',
       'Specialization_Other_Specialization',
```

```
       'Specialization_Retail Management',
       'Specialization_Rural and Agribusiness',
       'Specialization_Services Excellence',
       'Specialization_Supply Chain Management',
       'Specialization_Travel and Tourism',
       'What is your current occupation_Housewife',
       'What is your current occupation_Other_Occupation',
       'What is your current occupation_Student',
       'What is your current occupation_Unemployed',
       'What is your current occupation_Working Professional',
       'Tags_Interested  in full time MBA', 'Tags_Interested in other courses',
       'Tags_Not doing further education', 'Tags_Other_Tags',
       'Tags_invalid number', 'Lead Quality_Low in Relevance',
       'Lead Quality_Might be', 'Lead Quality_Not Sure', 'City_Other Cities',
       'City_Other Cities of Maharashtra', 'City_Other Metro Cities',
       'City_Thane & Outskirts', 'City_Tier II Cities',
       'Last Notable Activity_Email Bounced',
       'Last Notable Activity_Email Link Clicked',
       'Last Notable Activity_Email Marked Spam',
       'Last Notable Activity_Email Opened',
       'Last Notable Activity_Email Received',
       'Last Notable Activity_Modified',
       'Last Notable Activity_Olark Chat Conversation',
       'Last Notable Activity_Page Visited on Website',
       'Last Notable Activity_SMS Sent', 'Last Notable Activity_Unreachable',
       'Last Notable Activity_Unsubscribed',
       'Last Notable Activity_View in browser link Clicked'],
      dtype='object')
```

In [116]:

```
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:**	3047
Model:	GLM	**Df Residuals:**	3031
Model Family:	Binomial	**Df Model:**	15
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-430.53
Date:	Tue, 12 May 2020	**Deviance:**	861.06
Time:	08:58:30	**Pearson chi2:**	2.87e+03
No. Iterations:	22		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-2.7965	0.238	-11.774	0.000	-3.262	-2.331
Do Not Email	-0.7766	0.472	-1.645	0.100	-1.702	0.148
Total Time Spent on Website	0.9288	0.107	8.653	0.000	0.718	1.139
Lead Origin_Lead Add Form	2.2755	1.741	1.307	0.191	-1.138	5.689
Lead Source_Olark Chat	1.0894	0.335	3.253	0.001	0.433	1.746
Lead Source_Reference	-0.0206	1.818	-0.011	0.991	-3.584	3.542
Last Activity_SMS Sent	1.3252	0.212	6.252	0.000	0.910	1.741
Tags_Busy	2.2395	0.310	7.229	0.000	1.632	2.847
Tags_Closed by Horizzon	7.3219	1.035	7.077	0.000	5.294	9.350
Tags_Lost to EINS	6.9987	1.102	6.349	0.000	4.838	9.159
Tags_Ringing	-1.3776	0.343	-4.020	0.000	-2.049	-0.706
Tags_Will revert after reading the email	5.2207	0.262	19.957	0.000	4.708	5.733
Tags_switched off	1.7061	0.638	2.676	0.007	2.956	0.456

Tags_switched off	-1.7061	0.638	-2.676	0.007	-2.956	-0.456
Tags_wrong number given	-21.1873	1.5e+04	-0.001	0.999	-2.95e+04	2.94e+04
Lead Quality_Worst	-2.6317	0.653	-4.028	0.000	-3.912	-1.351
Last Notable Activity_Had a Phone Conversation	24.2845	2.13e+04	0.001	0.999	-4.17e+04	4.17e+04

In [124]:

```
col1 = col.drop('Lead Source_Reference',1)
```

In [125]:

```
col1
```

Out[125]:

```
Index(['Do Not Email', 'Total Time Spent on Website',
       'Lead Origin_Lead Add Form', 'Lead Source_Olark Chat',
       'Last Activity_SMS Sent', 'Tags_Busy', 'Tags_Closed by Horizzon',
       'Tags_Lost to EINS', 'Tags_Ringing',
       'Tags_Will revert after reading the email', 'Tags_switched off',
       'Tags_wrong number given', 'Lead Quality_Worst',
       'Last Notable Activity_Had a Phone Conversation'],
      dtype='object')
```

In [126]:

```
X_train_sm = sm.add_constant(X_train[col1])
logm2 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm2.fit()
res.summary()
```

Out[126]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	3047
Model:	GLM	**Df Residuals:**	3032
Model Family:	Binomial	**Df Model:**	14
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-430.53
Date:	Tue, 12 May 2020	**Deviance:**	861.06
Time:	09:17:30	**Pearson chi2:**	2.87e+03
No. Iterations:	22		
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-2.7964	0.237	-11.780	0.000	-3.262	-2.331
Do Not Email	-0.7766	0.472	-1.646	0.100	-1.702	0.148
Total Time Spent on Website	0.9288	0.107	8.653	0.000	0.718	1.139
Lead Origin_Lead Add Form	2.2568	0.554	4.071	0.000	1.170	3.343
Lead Source_Olark Chat	1.0893	0.335	3.253	0.001	0.433	1.746
Last Activity_SMS Sent	1.3251	0.212	6.254	0.000	0.910	1.740
Tags_Busy	2.2395	0.310	7.229	0.000	1.632	2.847
Tags_Closed by Horizzon	7.3216	1.034	7.079	0.000	5.294	9.349
Tags_Lost to EINS	6.9986	1.102	6.349	0.000	4.838	9.159
Tags_Ringing	-1.3776	0.343	-4.021	0.000	-2.049	-0.706
Tags_Will revert after reading the email	5.2206	0.262	19.964	0.000	4.708	5.733
Tags_switched off	-1.7061	0.638	-2.676	0.007	-2.956	-0.457
Tags_wrong number given	-21.1874	1.5e+04	-0.001	0.999	-2.95e+04	2.94e+04

Lead Quality_Worst	-2.6317	0.653	-4.028	0.000	-3.912	-1.351
Last Notable Activity_Had a Phone Conversation	24.2844	2.13e+04	0.001	0.999	-4.17e+04	4.17e+04

In [127]:

```
col2 = col1.drop('Tags_wrong number given',1)
```

In [128]:

```
col2
```

Out[128]:

```
Index(['Do Not Email', 'Total Time Spent on Website',
       'Lead Origin_Lead Add Form', 'Lead Source_Olark Chat',
       'Last Activity_SMS Sent', 'Tags_Busy', 'Tags_Closed by Horizzon',
       'Tags_Lost to EINS', 'Tags_Ringing',
       'Tags_Will revert after reading the email', 'Tags_switched off',
       'Lead Quality_Worst', 'Last Notable Activity_Had a Phone Conversation'],
      dtype='object')
```

In [129]:

```
X_train_sm = sm.add_constant(X_train[col2])
logm2 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm2.fit()
res.summary()
```

Out[129]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	3047
Model:	GLM	**Df Residuals:**	3033
Model Family:	Binomial	**Df Model:**	13
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-432.76
Date:	Tue, 12 May 2020	**Deviance:**	865.51
Time:	09:18:21	**Pearson chi2:**	2.87e+03
No. Iterations:	21		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-2.8782	0.237	-12.124	0.000	-3.344	-2.413
Do Not Email	-0.8255	0.463	-1.784	0.074	-1.732	0.081
Total Time Spent on Website	0.9302	0.107	8.682	0.000	0.720	1.140
Lead Origin_Lead Add Form	2.2873	0.560	4.088	0.000	1.191	3.384
Lead Source_Olark Chat	1.1162	0.337	3.316	0.001	0.456	1.776
Last Activity_SMS Sent	1.2980	0.210	6.173	0.000	0.886	1.710
Tags_Busy	2.3374	0.307	7.602	0.000	1.735	2.940
Tags_Closed by Horizzon	7.3990	1.034	7.153	0.000	5.372	9.426
Tags_Lost to EINS	7.0451	1.098	6.414	0.000	4.892	9.198
Tags_Ringing	-1.2764	0.340	-3.758	0.000	-1.942	-0.611
Tags_Will revert after reading the email	5.3072	0.261	20.365	0.000	4.796	5.818
Tags_switched off	-1.6023	0.636	-2.520	0.012	-2.848	-0.356
Lead Quality_Worst	-2.5676	0.655	-3.921	0.000	-3.851	-1.284
Last Notable Activity_Had a Phone Conversation	23.3664	1.29e+04	0.002	0.999	-2.53e+04	2.53e+04

In [130]:

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

Out[130]:

```
4584    0.993880
5617    0.930065
1095    0.010197
3166    0.962314
401     0.962134
7113    0.977285
4505    0.993540
7456    0.975896
4532    0.983557
7198    0.001754
dtype: float64
```

In [131]:

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

Out[131]:

```
array([0.99388007, 0.93006544, 0.01019746, 0.96231416, 0.96213386,
       0.97728519, 0.99353982, 0.97589621, 0.98355687, 0.00175408])
```

In [132]:

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

Out[132]:

	Converted	Converted_prob	Prospect ID
0	1	0.993880	4584
1	1	0.930065	5617
2	0	0.010197	1095
3	1	0.962314	3166
4	1	0.962134	401

In [133]:

```
y_train_pred_final['predicted'] = y_train_pred_final.Converted_prob.map(lambda x: 1 if x > 0.5 else
0)

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

Out[133]:

	Converted	Converted_prob	Prospect ID	predicted
0	1	0.993880	4584	1
1	1	0.930065	5617	1
2	0	0.010197	1095	0
3	1	0.962314	3166	1
4	1	0.962134	401	1

In [134]:

```
from sklearn import metrics
```

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

```
[[1293   75]
 [  64 1615]]
```

In [135]:

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

```
0.9543813587134887
```

In [136]:

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

In [137]:

```
# Create a dataframe that will contain the names of all the feature variables and their respective
VIFs
vif = pd.DataFrame()
vif['Features'] = X_train[col2].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in range(X_train[col2].shape[
1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[137]:

	Features	VIF
2	Lead Origin_Lead Add Form	15.99
4	Last Activity_SMS Sent	15.53
10	Tags_switched off	1.98
5	Tags_Busy	1.91
1	Total Time Spent on Website	1.48
3	Lead Source_Olark Chat	1.31
7	Tags_Lost to EINS	1.21
9	Tags_Will revert after reading the email	1.19
0	Do Not Email	1.12
6	Tags_Closed by Horizzon	1.09
11	Lead Quality_Worst	1.06
12	Last Notable Activity_Had a Phone Conversation	1.03
8	Tags_Ringing	1.02

Metrics beyond simply accuracy

In [138]:

```
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 [139]:

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

Out[139]:

```
0.961882072662299
```

In [140]:

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

Out[140]:

```
0.9451754385964912
```

In [141]:

```python
# Calculate false postive rate - predicting churn when customer does not have churned
print(FP/ float(TN+FP))
```

```
0.05482456140350877
```

In [142]:

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

```
0.9556213017751479
```

In [143]:

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

```
0.952837140751658
```

Plotting the ROC Curve

An ROC curve demonstrates several things:

It shows the tradeoff between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in specificity). The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test. The closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test.

In [144]:

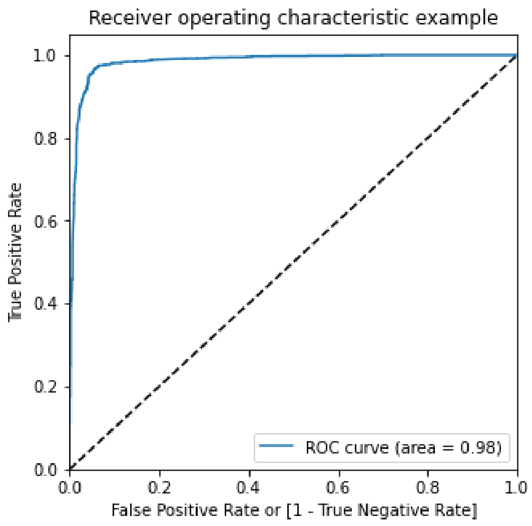
```python
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
                                              drop_intermediate = False )
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(5, 5))
    plt.plot( fpr, tpr, label='ROC curve (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 [145]:

```
fpr, tpr, thresholds = metrics.roc_curve( y_train_pred_final.Converted, y_train_pred_final.Converte
d_prob, drop_intermediate = False )
```

In [146]:

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



Finding Optimal Cutoff Point

Optimal cutoff probability is that prob where we get balanced sensitivity and specificity

In [147]:

```
# 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 0)
y_train_pred_final.head()
```

Out[147]:

	Converted	Converted_prob	Prospect ID	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	1	0.993880	4584	1	1	1	1	1	1	1	1	1	1	1
1	1	0.930065	5617	1	1	1	1	1	1	1	1	1	1	1
2	0	0.010197	1095	0	1	0	0	0	0	0	0	0	0	0
3	1	0.962314	3166	1	1	1	1	1	1	1	1	1	1	1
4	1	0.962134	401	1	1	1	1	1	1	1	1	1	1	1

In [148]:

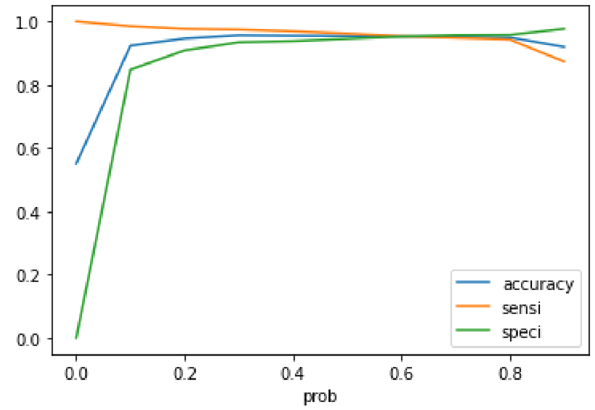
```
# Now let's calculate accuracy sensitivity and specificity for various probability cutoffs.
cutoff_df = pd.DataFrame( columns = ['prob','accuracy','sensi','speci'])
from sklearn.metrics import confusion_matrix

# 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  0.551034  1.000000  0.000000
0.1   0.1  0.923531  0.985110  0.847953
0.2   0.2  0.946177  0.976772  0.908626
0.3   0.3  0.956351  0.974390  0.934211
0.4   0.4  0.955038  0.969029  0.937865
0.5   0.5  0.954381  0.961882  0.945175
0.6   0.6  0.953069  0.953544  0.952485
0.7   0.7  0.952084  0.948183  0.956871
0.8   0.8  0.949458  0.942823  0.957602
0.9   0.9  0.919921  0.873734  0.976608
```

In [149]:

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



In [150]:

```
#### From the curve above, 0.2 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 if x > 0
.2 else 0)

y_train_pred_final.head()
```

Out[150]:

	Converted	Converted_prob	Prospect ID	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	final_predicted
0	1	0.993880	4584	1	1	1	1	1	1	1	1	1	1	1	1
1	1	0.930065	5617	1	1	1	1	1	1	1	1	1	1	1	1
2	0	0.010197	1095	0	1	0	0	0	0	0	0	0	0	0	0
3	1	0.962314	3166	1	1	1	1	1	1	1	1	1	1	1	1
4	1	0.962134	401	1	1	1	1	1	1	1	1	1	1	1	1

In [151]:

```
y_train_pred_final['Lead_Score'] = y_train_pred_final.Converted_prob.map( lambda x: round(x*100))

y_train_pred_final.head()
```

Out[151]:

	Converted	Converted_prob	Prospect ID	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	final_predicted	Lead_Score
0	1	0.993880	4584	1	1	1	1	1	1	1	1	1	1	1	1	99
1	1	0.930065	5617	1	1	1	1	1	1	1	1	1	1	1	1	93
2	0	0.010197	1095	0	1	0	0	0	0	0	0	0	0	0	0	1

	Converted	Converted_prob	Prospect ID	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	final_predicted	Lead_Score
2	0	0.010197	1095	0	1	0	0	0	0	0	0	0	0	0	0	1
3	1	0.962314	3166	1	1	1	1	1	1	1	1	1	1	1	1	96
4	1	0.962134	401	1	1	1	1	1	1	1	1	1	1	1	1	96

In [152]:

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

confusion2 = metrics.confusion_matrix(y_train_pred_final.Converted,
y_train_pred_final.final_predicted )
confusion2

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]:

```
0.9767718880285885
```

In [154]:

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

Out[154]:

```
0.908625730994152
```

In [155]:

```
# Calculate false postive rate - predicting churn when customer does not have churned
print(FP/ float(TN+FP))
```

```
0.09137426900584796
```

In [156]:

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

```
0.9291784702549575
```

In [157]:

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

```
0.9695787831513261
```

In [158]:

```
#Looking at the confusion matrix again

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

Out[158]:

```
array([[1293,   75]
```

```
array([[1295,   75],
       [  64, 1615]], dtype=int64)
```

In [159]:

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

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

Out[159]:

```
0.9556213017751479
```

In [160]:

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

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

Out[160]:

```
0.961882072662299
```

In [161]:

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

In [162]:

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

Out[162]:

```
0.9556213017751479
```

In [163]:

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

Out[163]:

```
0.961882072662299
```

In [164]:

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

In [165]:

```
y_train_pred_final.Converted, y_train_pred_final.predicted
```

Out[165]:

```
(0       1
 1       1
 2       0
 3       1
 4       1
        ..
 3042    1
 3043    1
 3044    1
 3045    1
 3046    1
 Name: Converted, Length: 3047, dtype: int64,
 0       1
 1       1
```

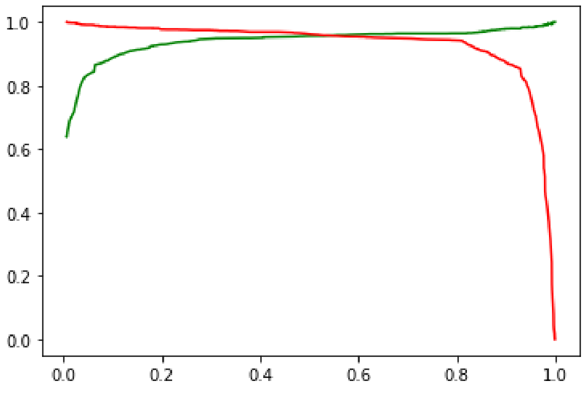
```
2       0
3       1
4       1
        ..
3042    1
3043    1
3044    1
3045    1
3046    1
Name: predicted, Length: 3047, dtype: int64)
```

In [166]:

```
p, r, thresholds = precision_recall_curve(y_train_pred_final.Converted, y_train_pred_final.Converte
d_prob)
```

In [167]:

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



In [168]:

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

X_train.head()
```

Out[168]:

	Do Not Email	Do Not Call	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Lead Origin_Landing Page Submission	Lead Origin_Lead Add Form	Lead Origin_Lead Import	Lead Source_Facebook	Lead Source_Google	Sourc
4584	0	0	0.888005	0.612028	0.290907	1	0	0	0	0	
5617	0	0	-1.272851	-1.029308	-1.425005	0	0	0	0	0	
1095	0	0	-0.552566	-0.101970	-0.281063	1	0	0	0	1	
3166	0	0	-0.192423	-0.523487	0.290907	1	0	0	0	0	
401	0	0	0.527863	0.866659	1.434849	1	0	0	0	0	

In [169]:

```
X_test = X_test[col2]
X_test.head()
```

Out[169]:

	Total		Tags_Will

	Do Not Email	Total Time Spent on Website	Lead Origin_Lead Add Form	Lead Source_Olark Chat	Last Activity_SMS Sent	Tags_Busy	Tags_Closed by Horizzon	Tags_Lost to EINS	Tags_Ringing	Tags_Will revert after reading the email	Tags
4123	0	2.133864	1	0	0	0	1	0	0	0	
4216	0	-1.022917	1	0	0	0	1	0	0	0	
8905	0	-1.022917	0	1	0	0	0	0	0	0	
7971	1	-0.583616	0	0	1	0	0	0	1	0	
964	0	1.663442	0	0	0	0	0	0	0	1	

In [170]:

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

In [171]:

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

In [172]:

```
y_test_pred[:10]
```

Out[172]:

```
4123    0.999848
4216    0.997147
8905    0.005061
7971    0.014415
964     0.981589
6842    0.997897
5991    0.951654
1447    0.986609
2456    0.001475
2629    0.977351
dtype: float64
```

In [177]:

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

In [178]:

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

Out[178]:

	0
4123	0.999848
4216	0.997147
8905	0.005061
7971	0.014415
964	0.981589

In [179]:

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

In [180]:

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

In [181]:

```python
# 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 [182]:

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

In [183]:

```python
y_pred_final.head()
```

Out[183]:

	Converted	Prospect ID	0
0	1	4123	0.999848
1	1	4216	0.997147
2	0	8905	0.005061
3	0	7971	0.014415
4	1	964	0.981589

In [184]:

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

In [186]:

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

Out[186]:

	Converted	Prospect ID	Converted_prob
0	1	4123	0.999848
1	1	4216	0.997147
2	0	8905	0.005061
3	0	7971	0.014415
4	1	964	0.981589

In [187]:

```python
y_pred_final['final_predicted'] = y_pred_final.Converted_prob.map(lambda x: 1 if x > 0.2 else 0)
```

In [188]:

```python
y_pred_final.head()
```

Out[188]:

	Converted	Prospect ID	Converted_prob	final_predicted
0	1	4123	0.999848	1
1	1	4216	0.997147	1

	Converted	Prospect ID	Converted_prob	final_predicted
2	0	8905	0.005061	0
3	0	7971	0.014415	0
4	1	964	0.981589	1

In [189]:

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

Out[189]:

```
0.9502677888293802
```

In [190]:

```
confusion2 = metrics.confusion_matrix(y_pred_final.Converted, y_pred_final.final_predicted )
confusion2
```

Out[190]:

```
array([[495,  50],
       [ 15, 747]], dtype=int64)
```

In [191]:

```
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 [192]:

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

Out[192]:

```
0.9803149606299213
```

In [193]:

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

Out[193]:

```
0.908256880733945
```

In [ ]: