Lead case Study Assignment

Step1:Reading and Understanding the data

In [1]:

```
#Supressing the warnings
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
#Importing the Numpy and Pandas
import numpy as np
import pandas as pd
```

In [3]:

```
#Importing the data
lead=pd.read_csv("S:/ds/Logistic Regression/Assignment/Leads.csv")
lead.head()
```

Out[3]:

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

5 rows × 37 columns

In [4]:

```
#Let's check the dimensions of our dataframe
lead.shape
```

Out[4]:

```
(9240, 37)
```

In [5]:

```
#Let's look at the sttistical aspects of our dataframe
lead.describe()
```

Out[5]:

	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

In [6]:

```
#Let's see the type of each column
lead.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9240 entries, 0 to 9239
Data columns (total 37 columns):
Prospect ID                                      9240 non-null object
Lead Number                                      9240 non-null int64
Lead Origin                                      9240 non-null object
Lead Source                                      9204 non-null object
Do Not Email                                     9240 non-null object
Do Not Call                                      9240 non-null object
Converted                                        9240 non-null int64
TotalVisits                                      9103 non-null float64
Total Time Spent on Website                      9240 non-null int64
Page Views Per Visit                             9103 non-null float64
Last Activity                                    9137 non-null object
Country                                          6779 non-null object
Specialization                                   7802 non-null object
How did you hear about X Education               7033 non-null object
What is your current occupation                  6550 non-null object
What matters most to you in choosing a course    6531 non-null object
Search                                           9240 non-null object
Magazine                                         9240 non-null object
Newspaper Article                                9240 non-null object
X Education Forums                               9240 non-null object
Newspaper                                        9240 non-null object
Digital Advertisement                            9240 non-null object
Through Recommendations                          9240 non-null object
Receive More Updates About Our Courses           9240 non-null object
Tags                                             5887 non-null object
Lead Quality                                     4473 non-null object
Update me on Supply Chain Content                9240 non-null object
Get updates on DM Content                        9240 non-null object
Lead Profile                                     6531 non-null object
City                                             7820 non-null object
Asymmetrique Activity Index                      5022 non-null object
Asymmetrique Profile Index                       5022 non-null object
Asymmetrique Activity Score                      5022 non-null float64
Asymmetrique Profile Score                       5022 non-null float64
I agree to pay the amount through cheque         9240 non-null object
A free copy of Mastering The Interview           9240 non-null object
Last Notable Activity                            9240 non-null object
dtypes: float64(4), int64(3), object(30)
memory usage: 2.6+ MB
```

In [7]:

```
# To check the sum of missing values
lead.isnull().sum()
```

Out[7]:

```
Prospect ID                                          0
```

```
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                                   1438
How did you hear about X Education               2207
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                                     2709
City                                             1420
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
```

Step2:Data Cleaning

In [8]:

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

In [9]:

```
#Adding up the missing values(Column wise)
lead.isnull().sum()
```

Out[9]:

```
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
```

```
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 [10]:

```
#Checking the percentage of missing values
round(100*(lead.isnull().sum()/len(lead.index)),2)
```

Out[10]:

```
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
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 [11]:

```
#Dropping the column which has 70% greater than the nan values i.e. Lead Profile
lead=lead.drop('Lead Profile',1)
```

In [12]:

```
lead=lead.drop('How did you hear about X Education',1)
```

In [13]:

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

In [14]:

```python
lead['Country'].describe()
```

Out[14]:

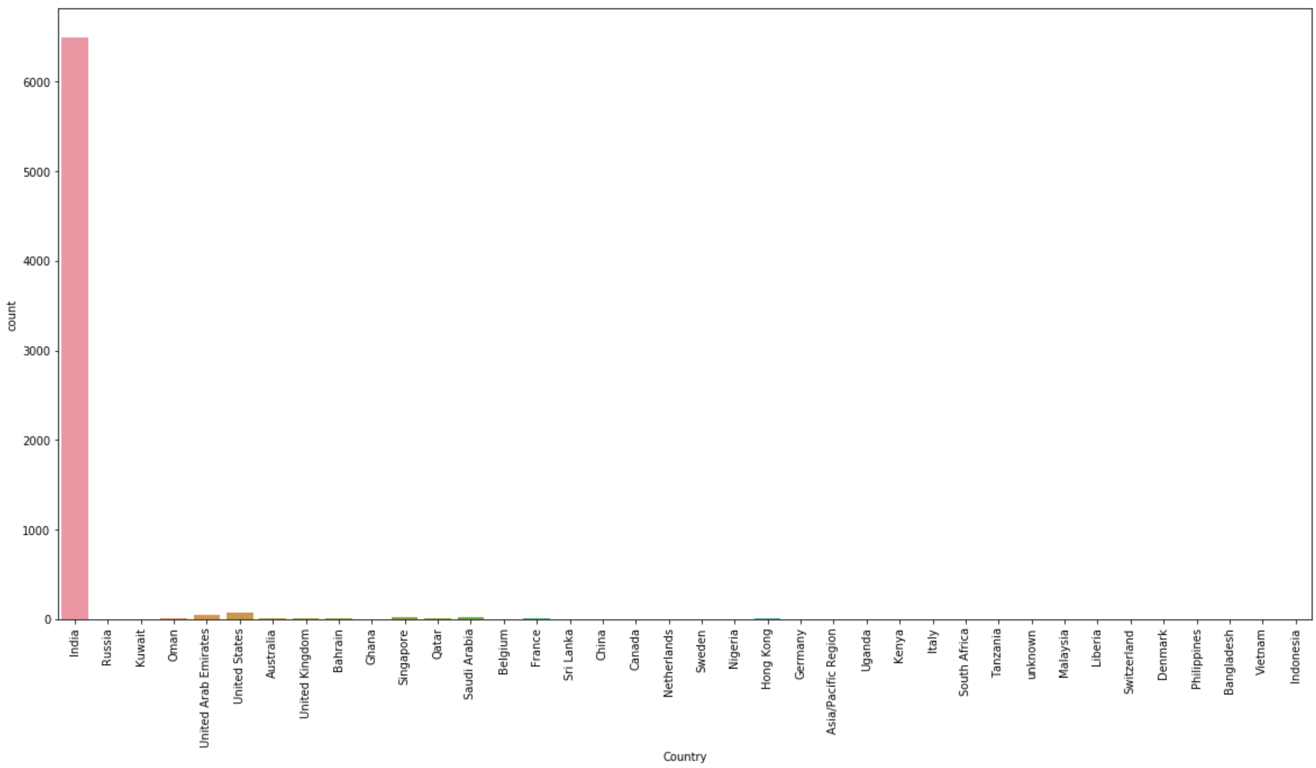
```
count      6779
unique       38
top       India
freq       6492
Name: Country, dtype: object
```

In [15]:

```python
plt.figure(figsize=(20,10))
sns.countplot(lead['Country'])
plt.xticks(rotation=90)
```

Out[15]:

```
(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, 26, 27, 28, 29, 30, 31, 32, 33,
        34, 35, 36, 37]), <a list of 38 Text xticklabel objects>)
```



In [16]:

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

In [17]:

```python
lead['Specialization'].describe()
```

Out[17]:

```
count                    5860
unique                     18
top          Finance Management
```

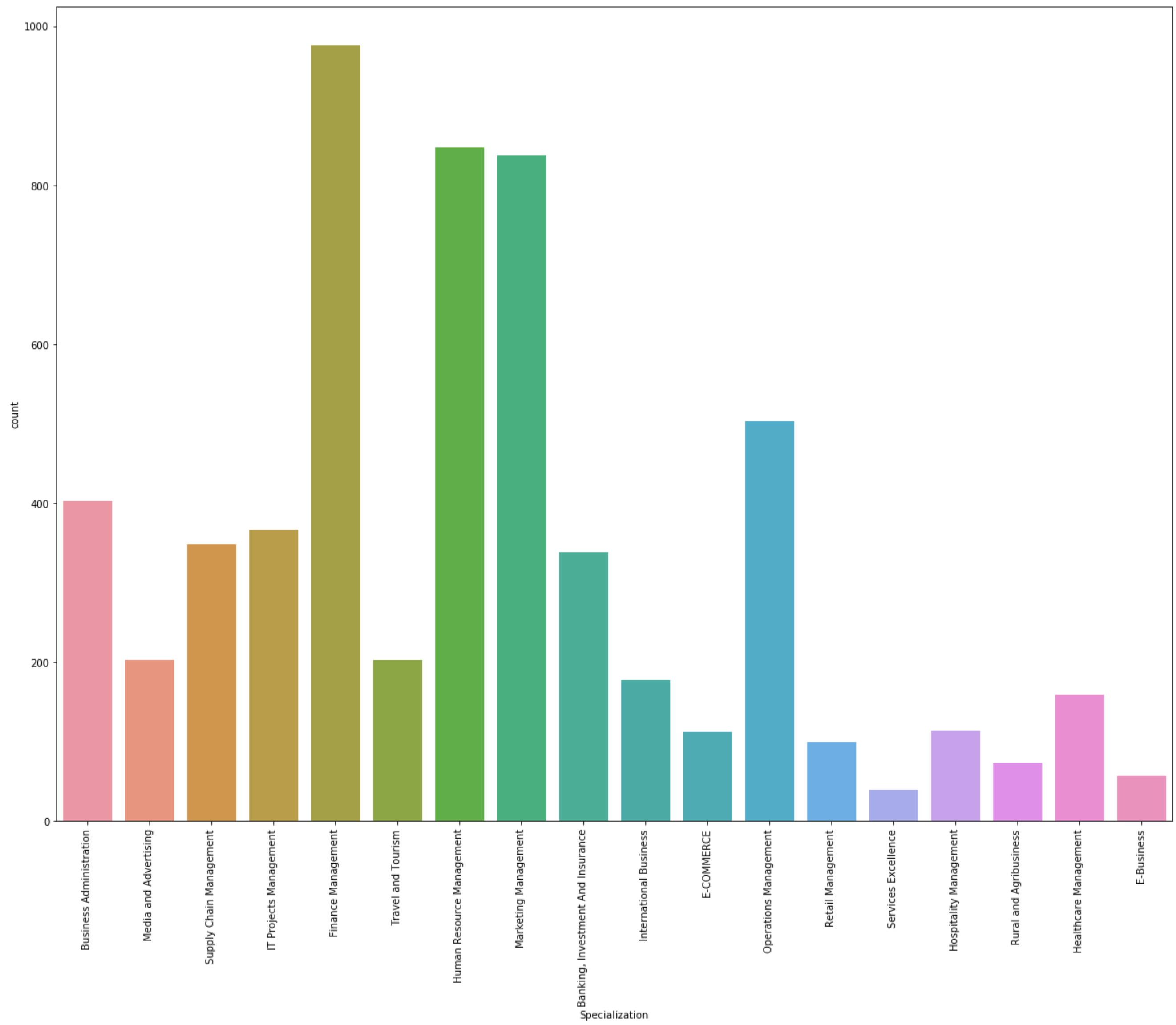
```
top         Finance Management
freq                       976
Name: Specialization, dtype: object
```

In [18]:

```
plt.figure(figsize=(20,15))
sns.countplot(lead['Specialization'])
plt.xticks(rotation=90)
```

Out[18]:

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



In [19]:

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

In [20]:

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

Out[20]:

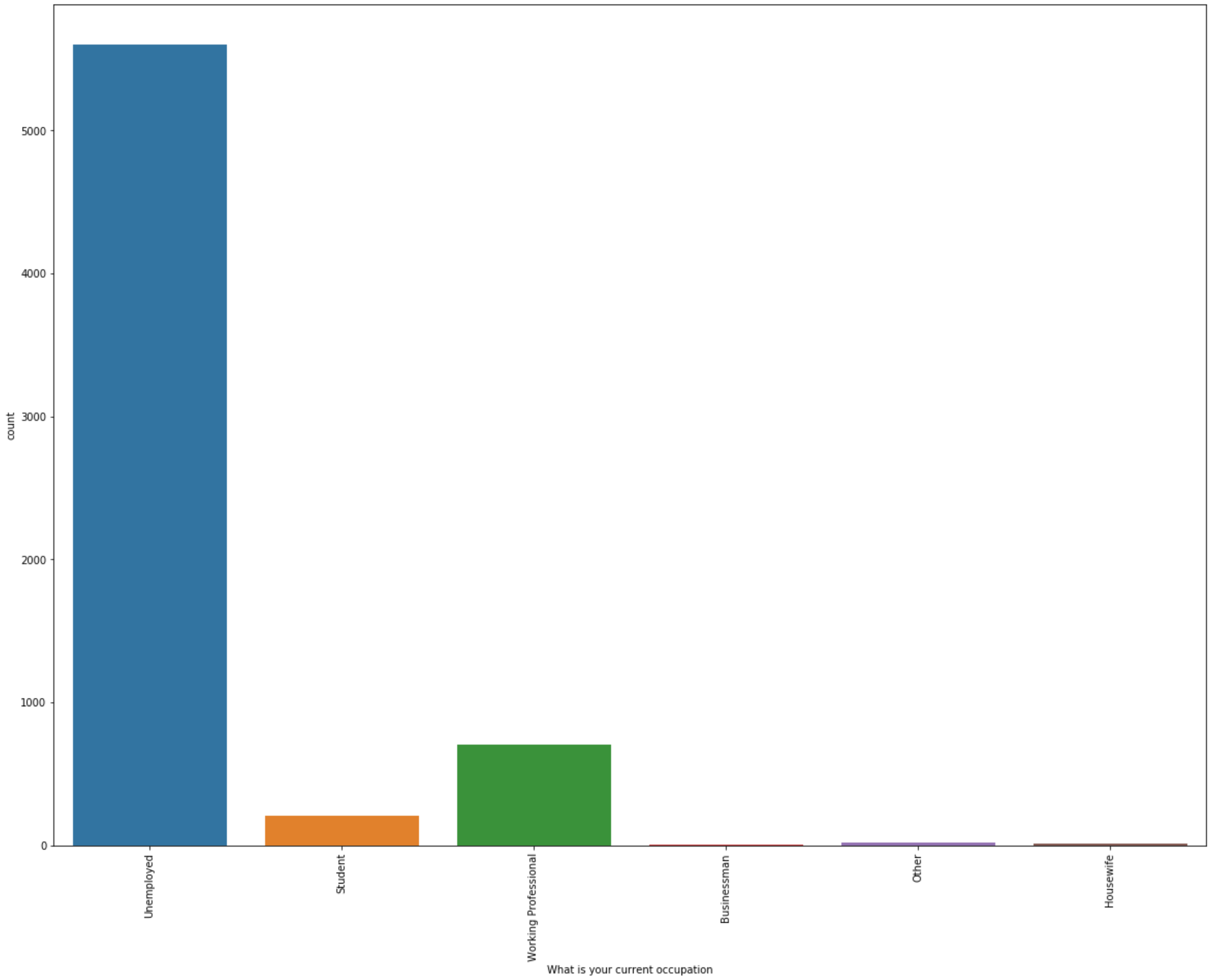
```
count             6550
unique               6
top         Unemployed
freq              5600
Name: What is your current occupation, dtype: object
```

In [21]:

```
plt.figure(figsize=(20,15))
sns.countplot(lead['What is your current occupation'])
plt.xticks(rotation=90)
```

Out[21]:

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



In [22]:

```
lead['What is your current occupation']=lead['What is your current occupation'].replace(np.nan,'Un
employed')
```

In [23]:

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

Out[23]:

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

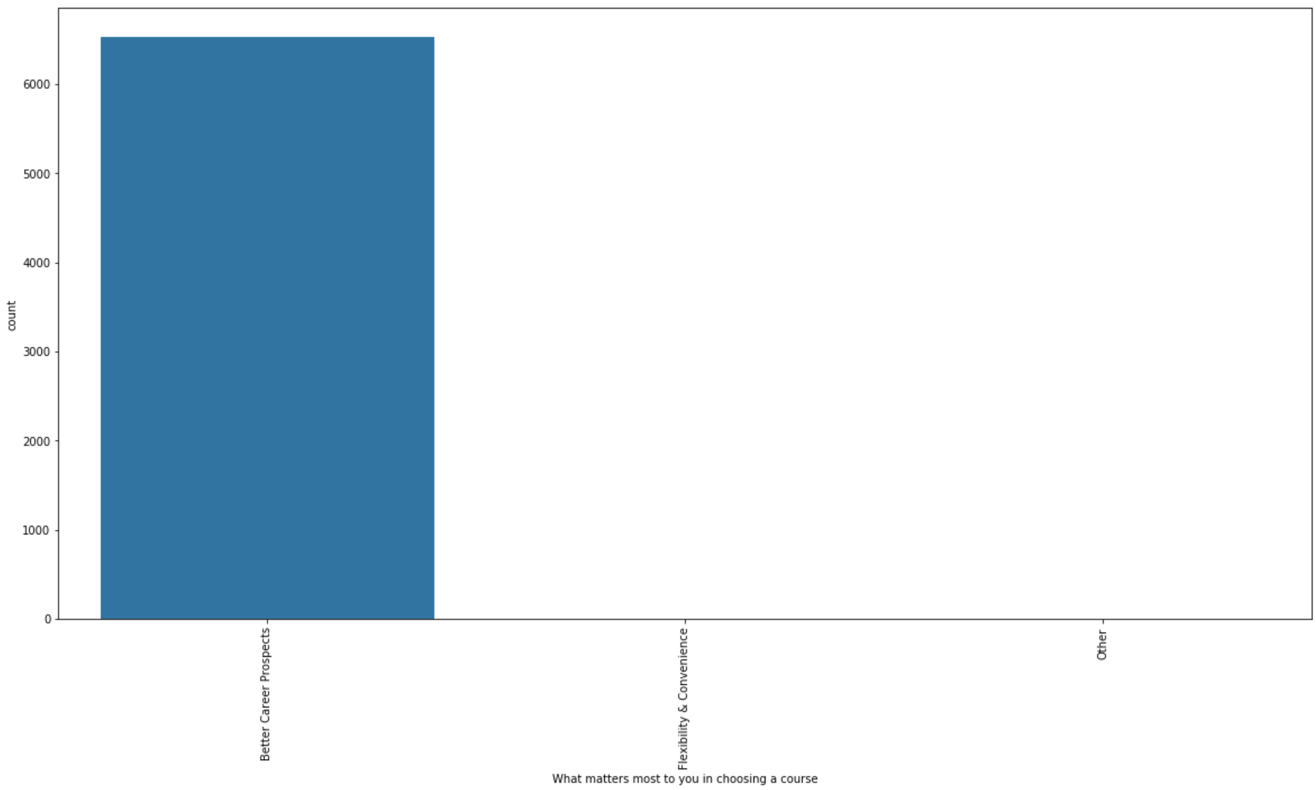
In [24]:

```
plt.figure(figsize=(20,10))
```

```
sns.countplot(lead['What matters most to you in choosing a course'])
plt.xticks(rotation=90)
```

Out[24]:

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



In [25]:

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

In [26]:

```
lead['Tags'].describe()
```

Out[26]:

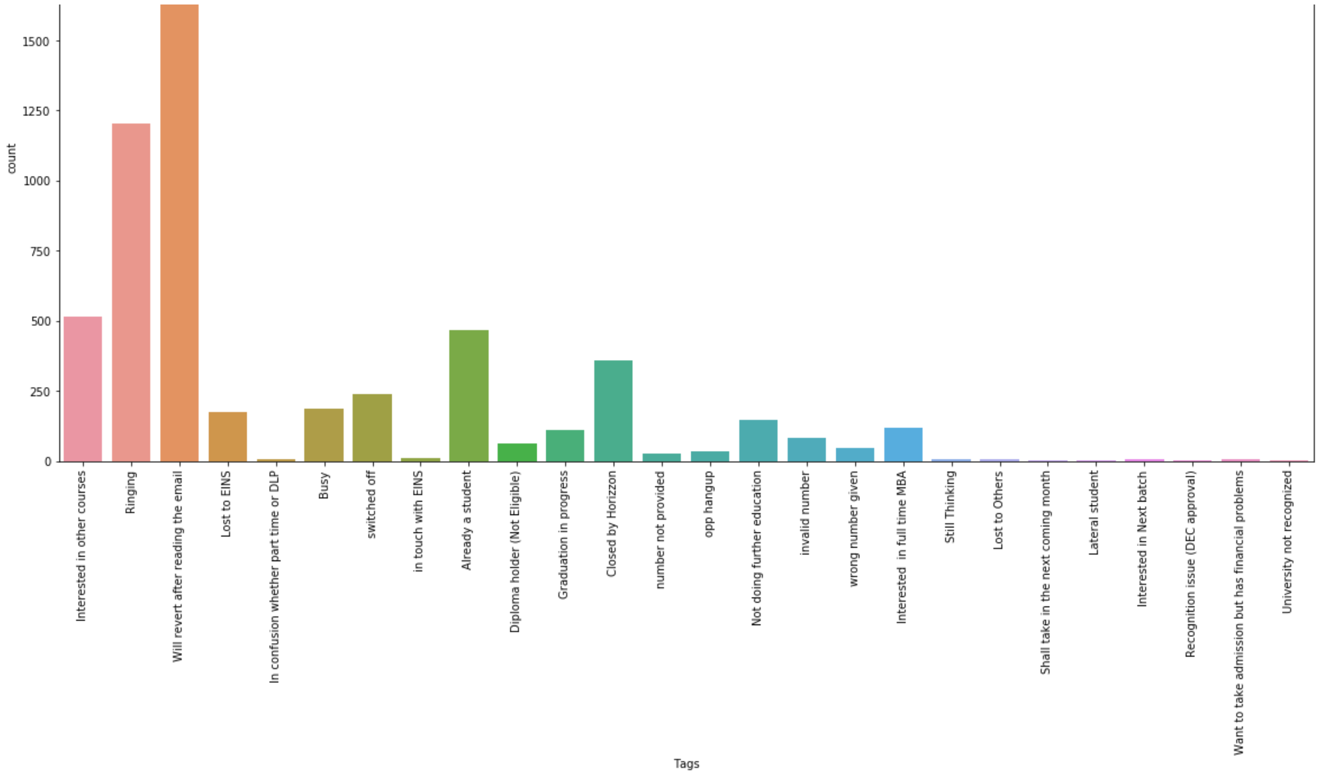
```
count                                5887
unique                                 26
top        Will revert after reading the email
freq                                 2072
Name: Tags, dtype: object
```

In [27]:

```
plt.figure(figsize=(20,10))
sns.countplot(lead['Tags'])
plt.xticks(rotation=90)
```

Out[27]:

```
(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 xticklabel objects>)
```



In [28]:

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

In [29]:

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

Out[29]:

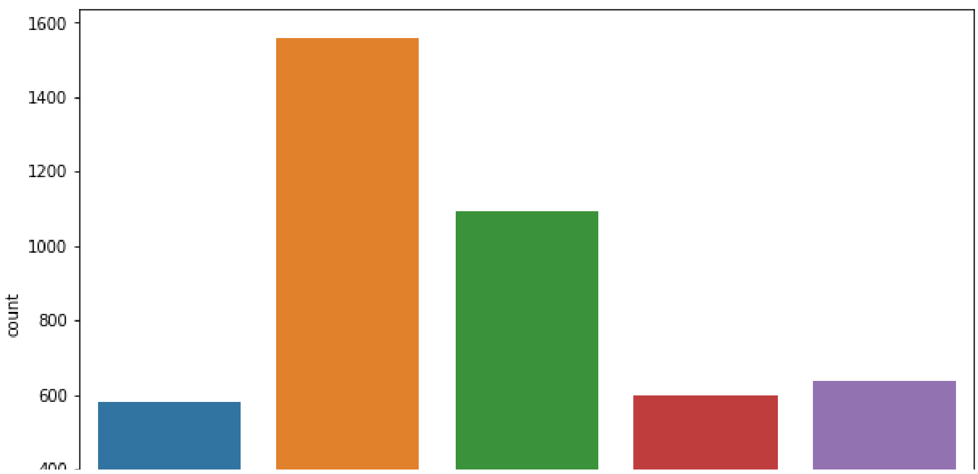
```
count          4473
unique            5
top        Might be
freq           1560
Name: Lead Quality, dtype: object
```

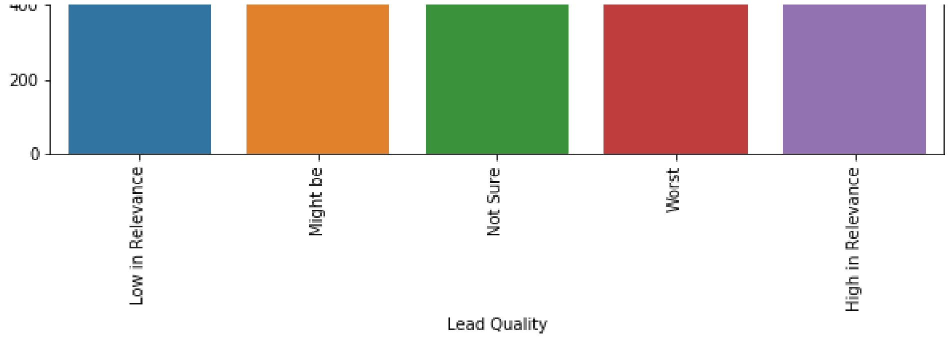
In [30]:

```
plt.figure(figsize=(10,7))
sns.countplot(lead['Lead Quality'])
plt.xticks(rotation=90)
```

Out[30]:

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





In [31]:

```
lead['Lead Quality']=lead['Lead Quality'].replace(np.nan,'Not Sure')
```

In [32]:

```
lead['City'].describe()
```

Out[32]:

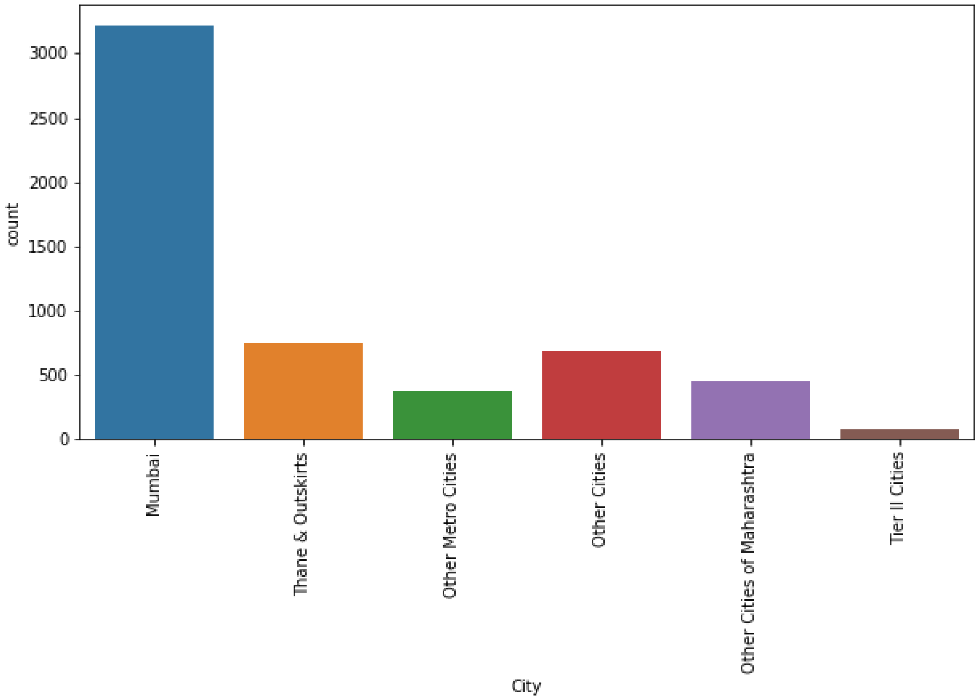
```
count       5571
unique         6
top       Mumbai
freq        3222
Name: City, dtype: object
```

In [33]:

```
plt.figure(figsize=(10,5))
sns.countplot(lead['City'])
plt.xticks(rotation=90)
```

Out[33]:

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



In [34]:

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

In [35]:

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

Out[35]:

```
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                                      0.00
Update me on Supply Chain Content                 0.00
Get updates on DM Content                         0.00
City                                              0.00
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 [36]:

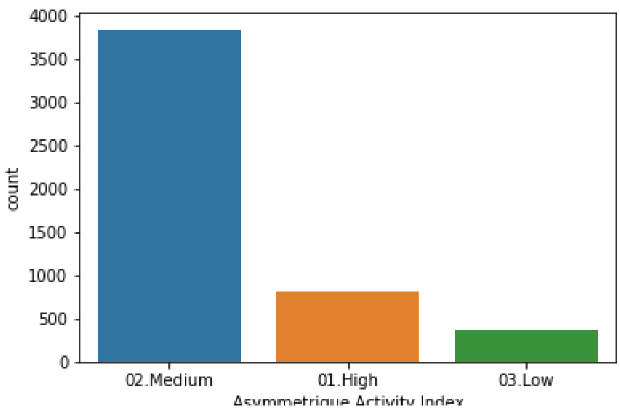
```
lead['Asymmetrique Activity Index'].describe()
```

Out[36]:

```
count          5022
unique            3
top       02.Medium
freq           3839
Name: Asymmetrique Activity Index, dtype: object
```

In [37]:

```
plt1=sns.countplot(lead['Asymmetrique Activity Index'])
```



Asymmetrique Activity Index

In [38]:

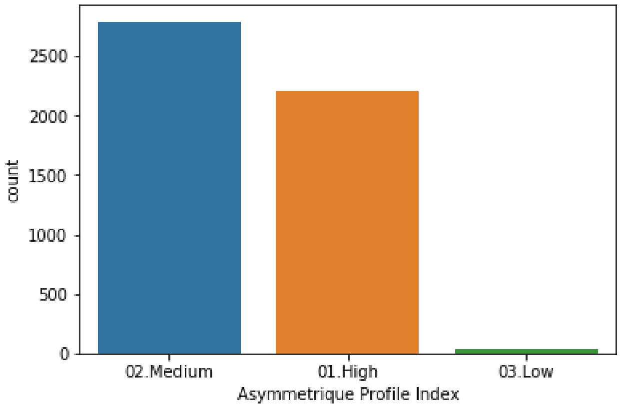
```
lead['Asymmetrique Profile Index'].describe()
```

Out[38]:

```
count          5022
unique            3
top       02.Medium
freq           2788
Name: Asymmetrique Profile Index, dtype: object
```

In [39]:

```
plt2=sns.countplot(lead['Asymmetrique Profile Index'])
```



In [40]:

```
lead['Asymmetrique Activity Score'].describe()
```

Out[40]:

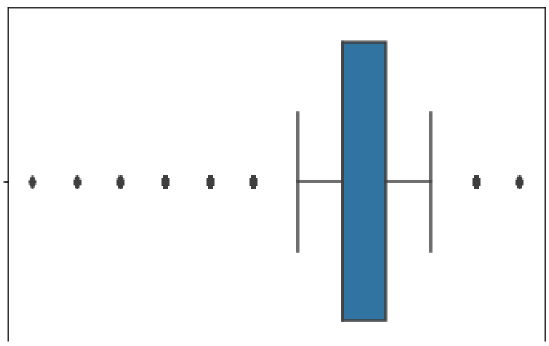
```
count    5022.000000
mean       14.306252
std         1.386694
min         7.000000
25%        14.000000
50%        14.000000
75%        15.000000
max        18.000000
Name: Asymmetrique Activity Score, dtype: float64
```

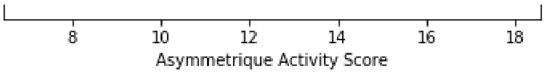
In [41]:

```
sns.boxplot(lead['Asymmetrique Activity Score'])
```

Out[41]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d37bc04d30>
```





In [42]:

```
lead['Asymmetrique Profile Score'].describe()
```

Out[42]:

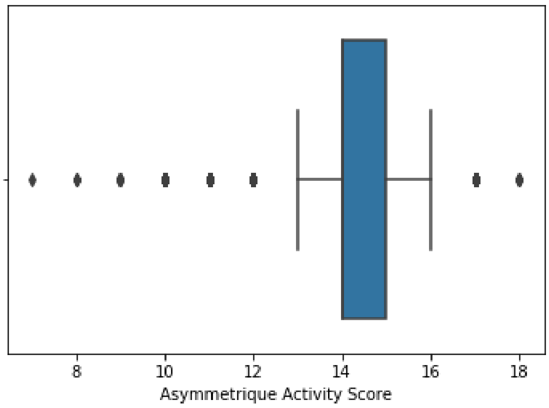
```
count    5022.000000
mean       16.344883
std         1.811395
min        11.000000
25%        15.000000
50%        16.000000
75%        18.000000
max        20.000000
Name: Asymmetrique Profile Score, dtype: float64
```

In [43]:

```
sns.boxplot(lead['Asymmetrique Activity Score'])
```

Out[43]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d37bc4aef0>
```



In [44]:

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

In [45]:

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

Out[45]:

```
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                                     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 [46]:

```
lead.dropna(inplace=True)
```

In [47]:

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

Out[47]:

```
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 [48]:

```
lead.shape
```

Out[48]:

```
(9074, 31)
```

Step3:Analyzing the Data

In [49]:

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

Out[49]:

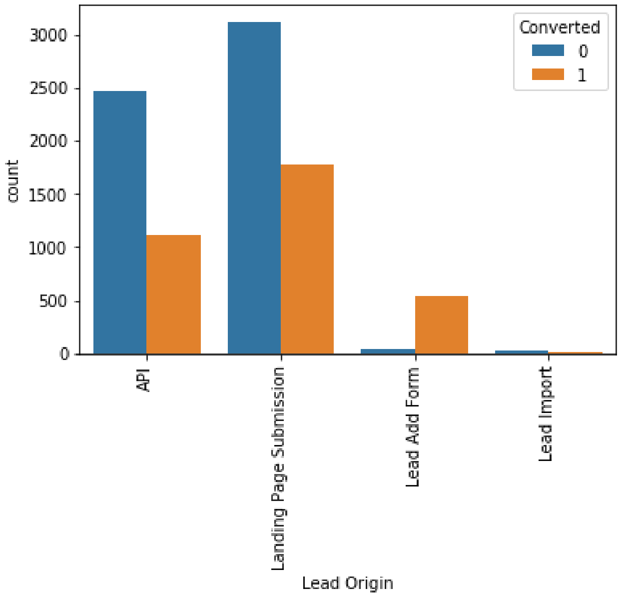
```
37.85541106458012
```

In [50]:

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

Out[50]:

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

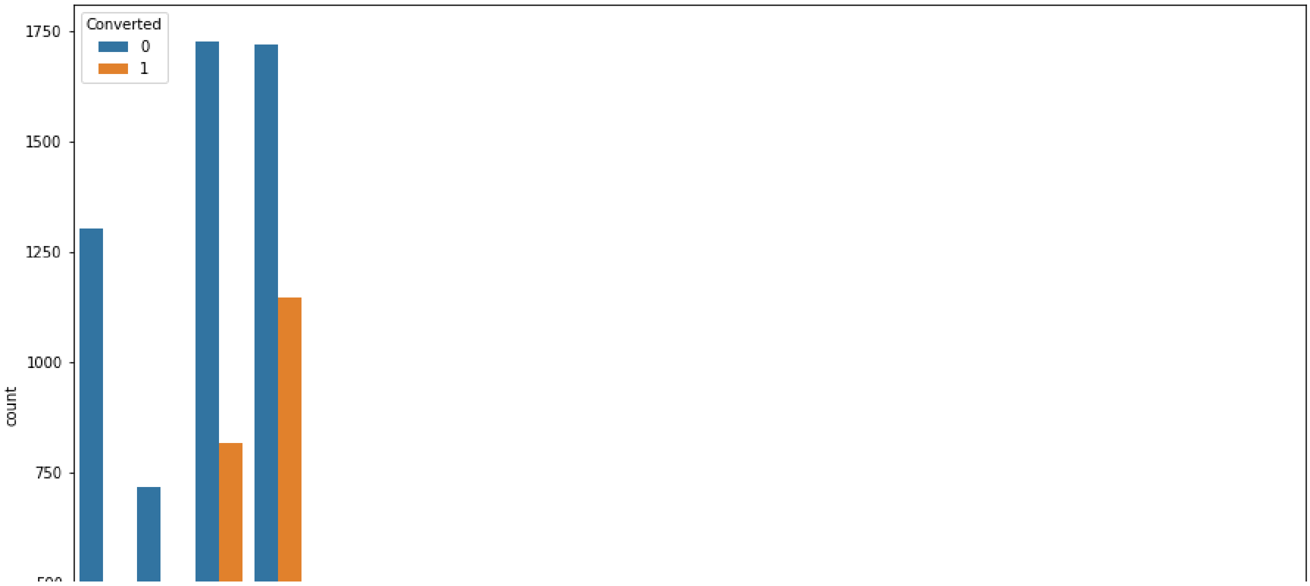


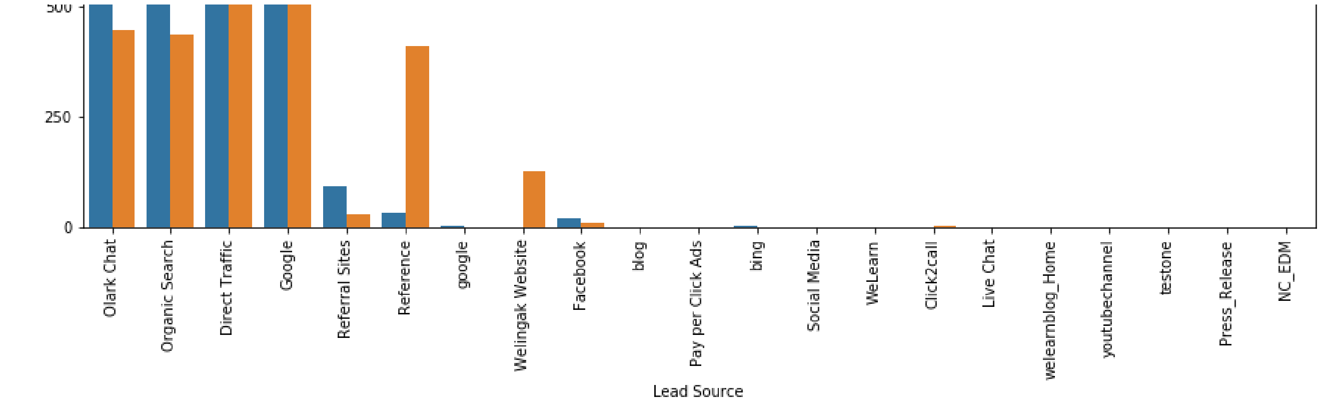
In [51]:

```
plt.figure(figsize=(15,10))
sns.countplot(x='Lead Source',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[51]:

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





In [52]:

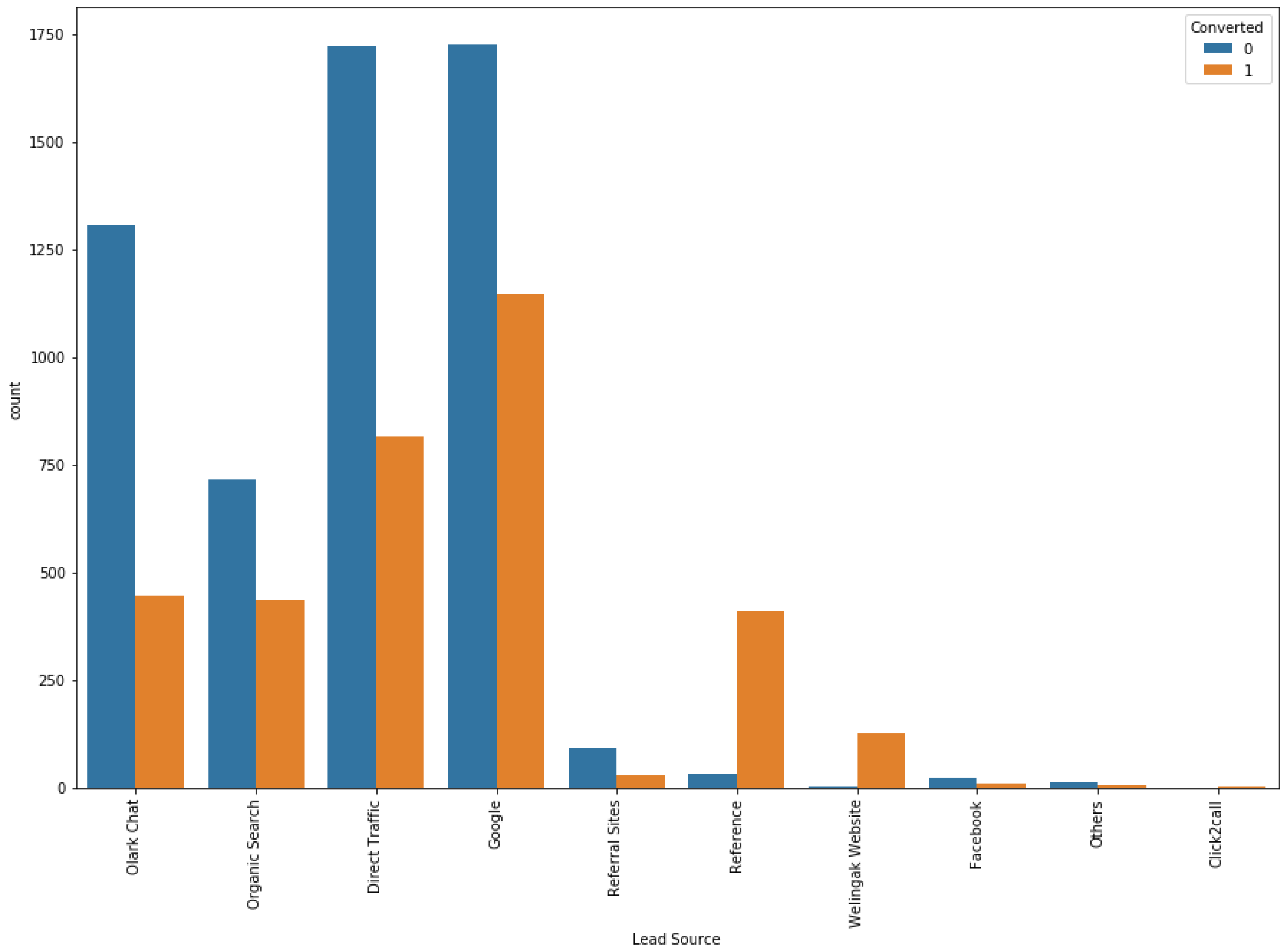
```
lead['Lead Source']=lead['Lead Source'].replace(['google'],'Google')
lead['Lead Source']=lead['Lead Source'].replace(['blog','Pay per Click Ads','bing','Social Media',
'WeLearn','Click2cal','Live Chat','welearnblog_Home','youtubechannel','testone','Press_Release','N
C_EDM'],'Others')
```

In [53]:

```
plt.figure(figsize=(15,10))
sns.countplot(x='Lead Source',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[53]:

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

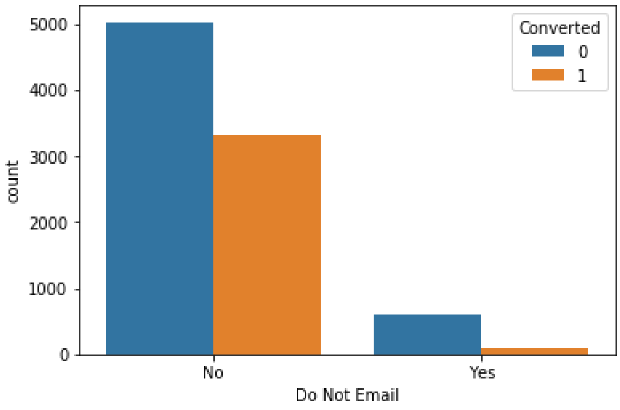


In [54]:

```
sns.countplot(x='Do Not Email',hue='Converted',data=lead)
```

Out[54]:

<matplotlib.axes._subplots.AxesSubplot at 0x1d37c4a4a90>

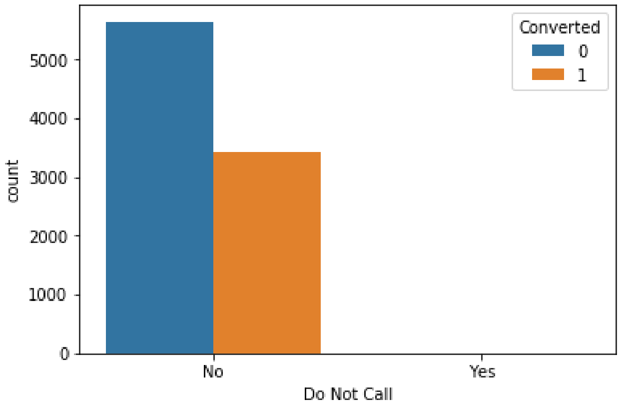


In [55]:

```
sns.countplot(x='Do Not Call',hue='Converted',data=lead)
```

Out[55]:

<matplotlib.axes._subplots.AxesSubplot at 0x1d37c502160>



In [56]:

```
lead['TotalVisits'].describe(percentiles=(.05,.10,.25,.50,.75,.90,.95,.99))
```

Out[56]:

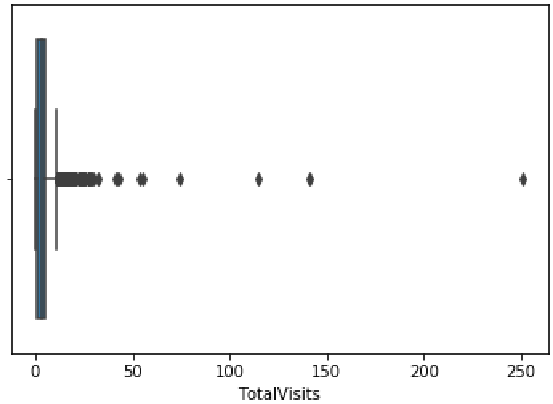
```
count    9074.000000
mean        3.456028
std         4.858802
min         0.000000
5%          0.000000
10%         0.000000
25%         1.000000
50%         3.000000
75%         5.000000
90%         7.000000
95%        10.000000
99%        17.000000
max       251.000000
Name: TotalVisits, dtype: float64
```

In [57]:

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

Out[57]:

<matplotlib.axes._subplots.AxesSubplot at 0x1d37c5646d8>



In [58]:

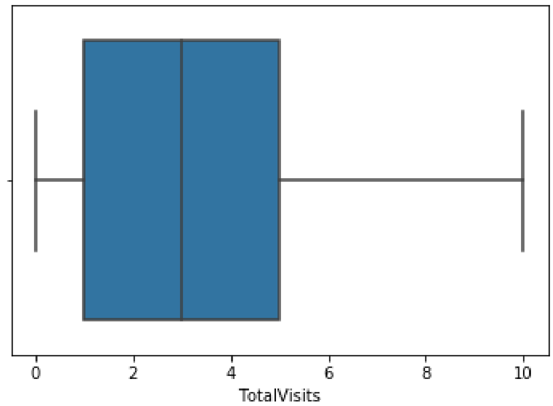
```
percentiles=lead['TotalVisits'].quantile([0.05,0.95]).values
lead['TotalVisits'][lead['TotalVisits']<=percentiles[0]]=percentiles[0]
lead['TotalVisits'][lead['TotalVisits']>=percentiles[1]]=percentiles[1]
```

In [59]:

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

Out[59]:

<matplotlib.axes._subplots.AxesSubplot at 0x1d37c5aca90>

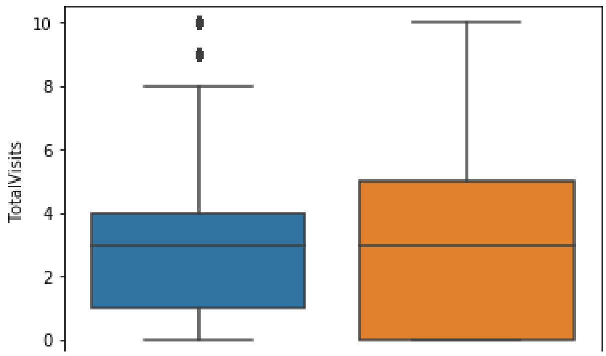


In [60]:

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

Out[60]:

<matplotlib.axes._subplots.AxesSubplot at 0x1d37c617cc0>



In [61]:

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

Out[61]:

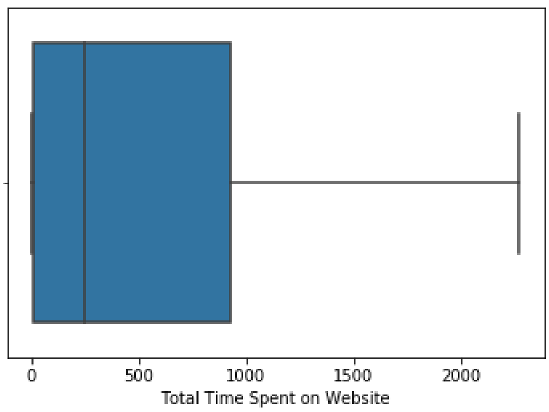
```
count    9074.000000
mean      482.887481
std       545.256560
min         0.000000
25%        11.000000
50%       246.000000
75%       922.750000
max      2272.000000
Name: Total Time Spent on Website, dtype: float64
```

In [62]:

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

Out[62]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d37d6cdef0>
```

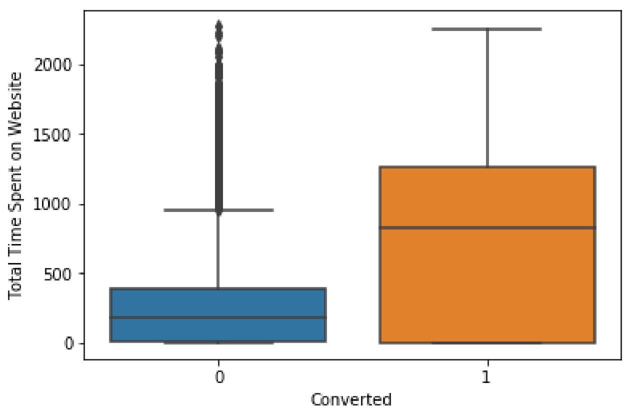


In [63]:

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

Out[63]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d37d720c18>
```



In [64]:

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

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

Out[64]:

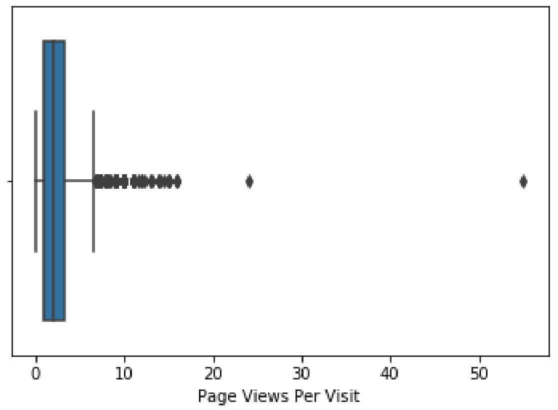
```
count    9074.000000
mean        2.370151
std         2.160871
min         0.000000
25%         1.000000
50%         2.000000
75%         3.200000
max        55.000000
Name: Page Views Per Visit, dtype: float64
```

In [65]:

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

Out[65]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d37d782208>
```



In [66]:

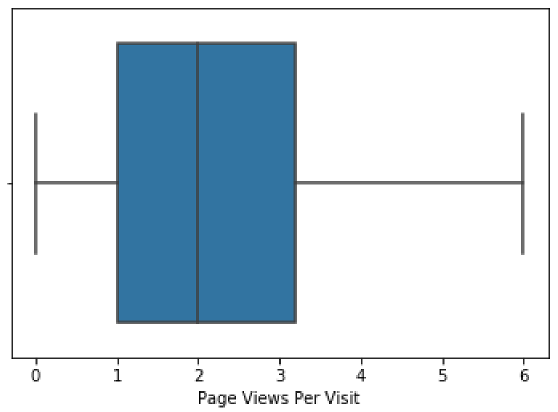
```
percentiles=lead['Page Views Per Visit'].quantile([0.05,0.95]).values
lead['Page Views Per Visit'][lead['Page Views Per Visit']<=percentiles[0]]=percentiles[0]
lead['Page Views Per Visit'][lead['Page Views Per Visit']>=percentiles[1]]=percentiles[1]
```

In [67]:

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

Out[67]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d37d7d7da0>
```



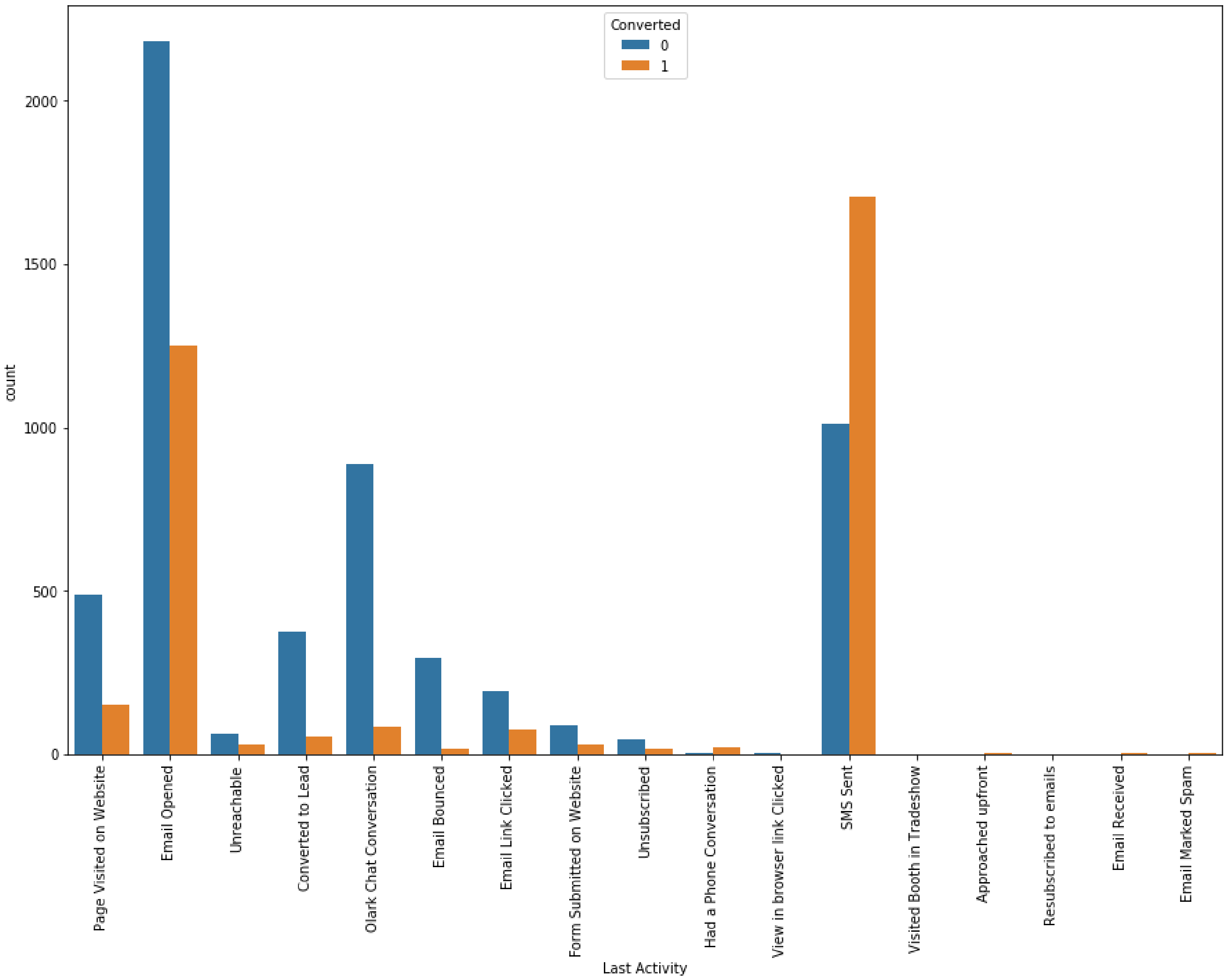
In [68]:

```
plt.figure(figsize=(15,10))
```

```
plt.figure(figsize=(15,10))
sns.countplot(x='Last Activity',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[68]:

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



In [69]:

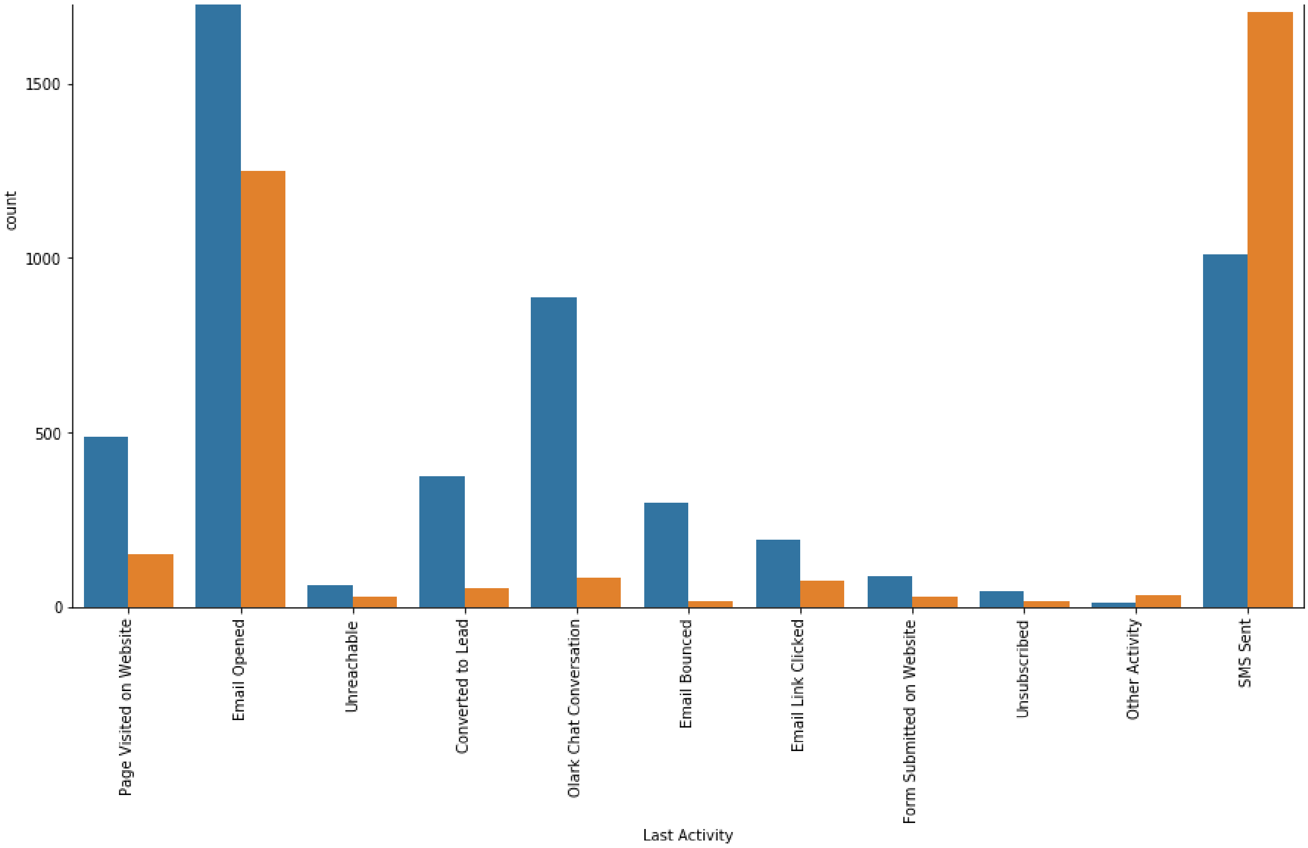
```
lead['Last Activity']=lead['Last Activity'].replace(['Had a Phone Conversation','View in browser l
ink Clicked','Visited Booth in Tradeshow','Approached upfront','Resubscribed to emails','Email
Received','Email Marked Spam'],'Other Activity')
```

In [70]:

```
plt.figure(figsize=(15,10))
sns.countplot(x='Last Activity',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[70]:

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

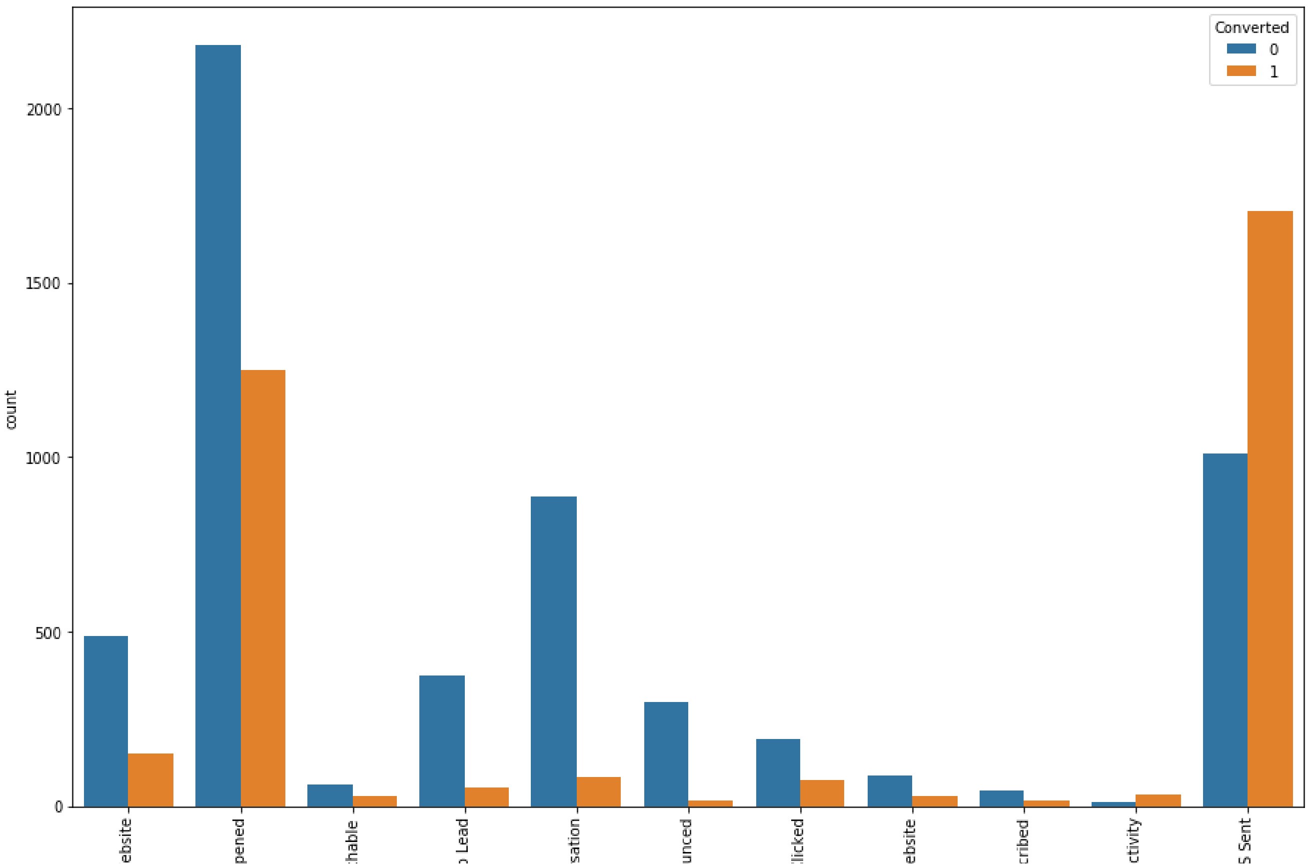


In [71]:

```
plt.figure(figsize=(15,10))
sns.countplot(x='Last Activity',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[71]:

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

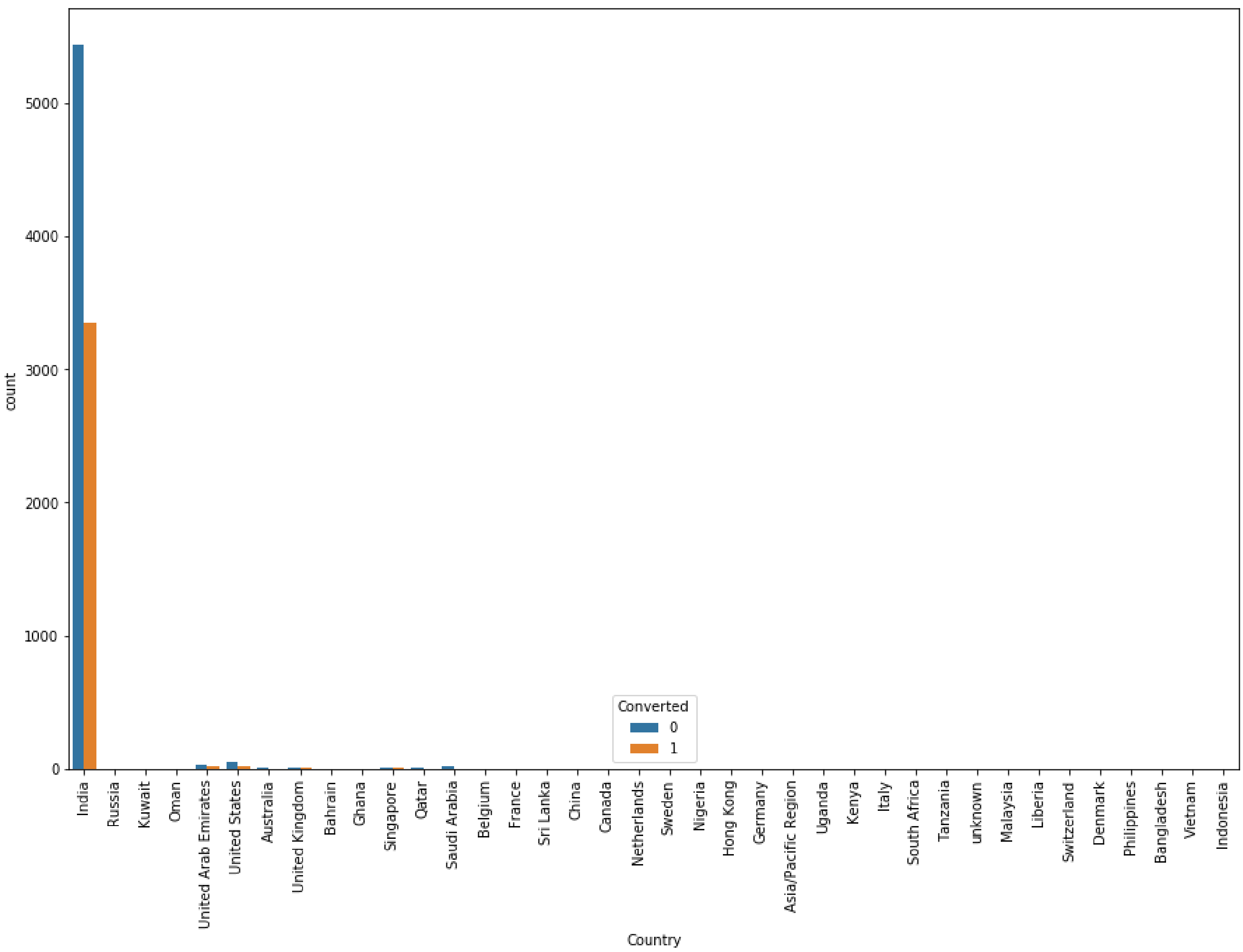


In [72]:

```
plt.figure(figsize=(15,10))
sns.countplot(x='Country',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[72]:

```
(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, 26, 27, 28, 29, 30, 31, 32, 33,
        34, 35, 36, 37]), <a list of 38 Text xticklabel objects>)
```



In [73]:

```
lead['Country']=lead['Country'].replace(['Russia','Kuwait','Oman','Bahrain','Ghana','Belgium','Fra
nce','Sri Lanka','China','Canada','Netherlands','Sweden','Nigeria','Hong
Kong','Germany','Asia/Pacific Region','Uganda','Kenya','Italy','South Africa','Tanzania','unknown'
,'Malaysia','Liberia','Switzerland','Denmark','Philippines','Bangladesh','Vietnam','Indonesia'],'O
ther countries')
```

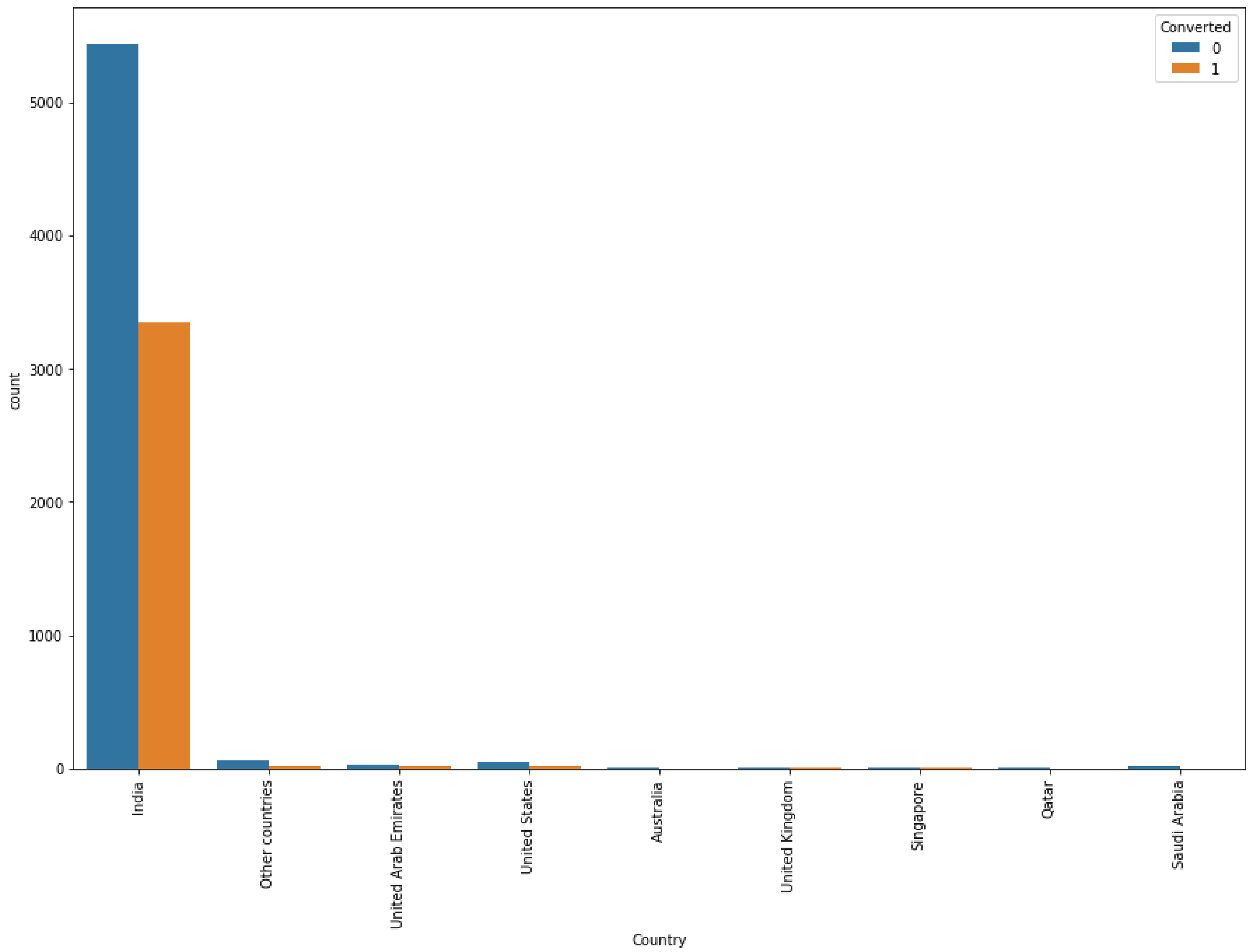
In [74]:

```
plt.figure(figsize=(15,10))
sns.countplot(x='Country',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[74]:

Out[74]:

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



In [75]:

```
lead['Specialization'].describe()
```

Out[75]:

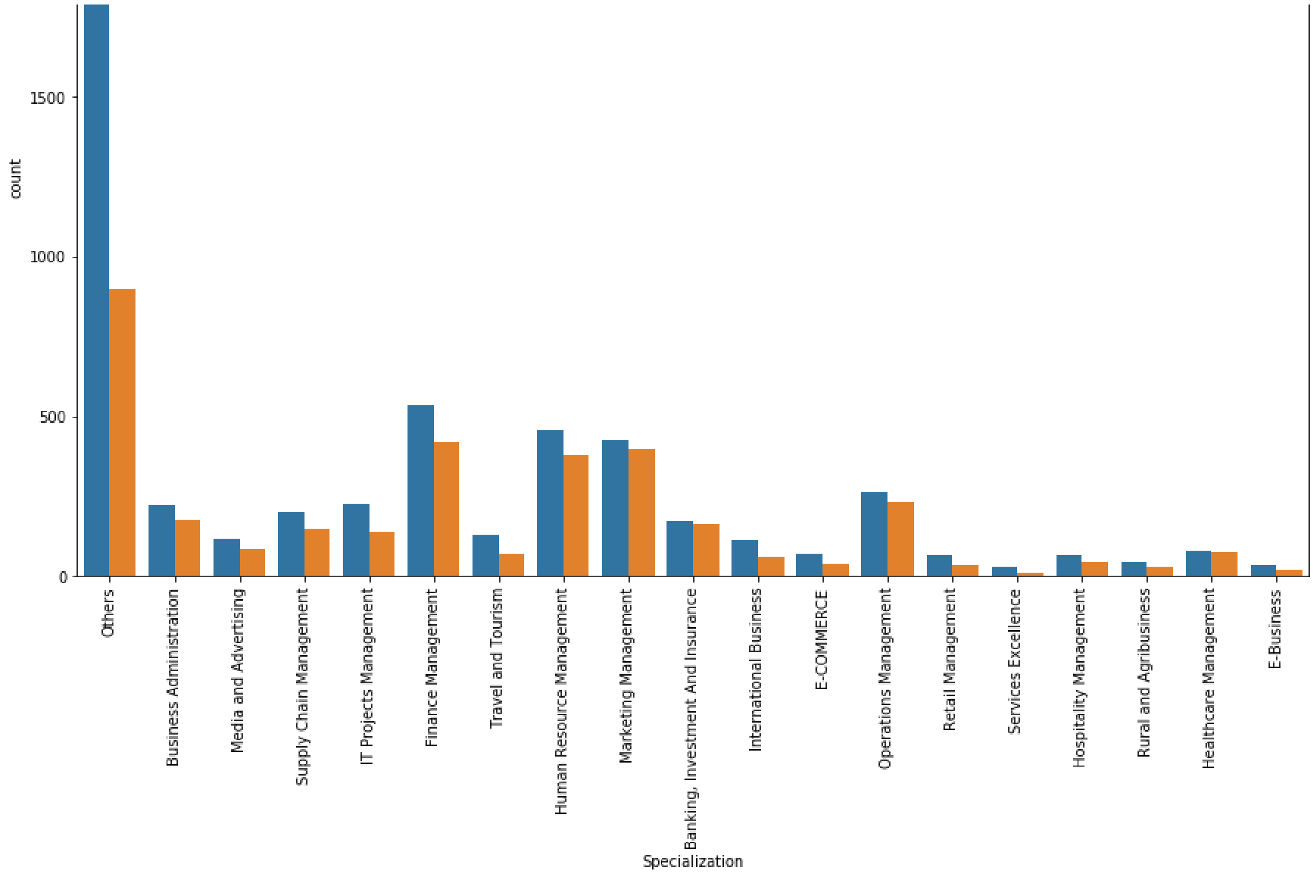
```
count        9074
unique         19
top        Others
freq         3282
Name: Specialization, dtype: object
```

In [76]:

```
plt.figure(figsize=(15,10))
sns.countplot(x='Specialization',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[76]:

```
(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 xticklabel objects>)
```



In [77]:

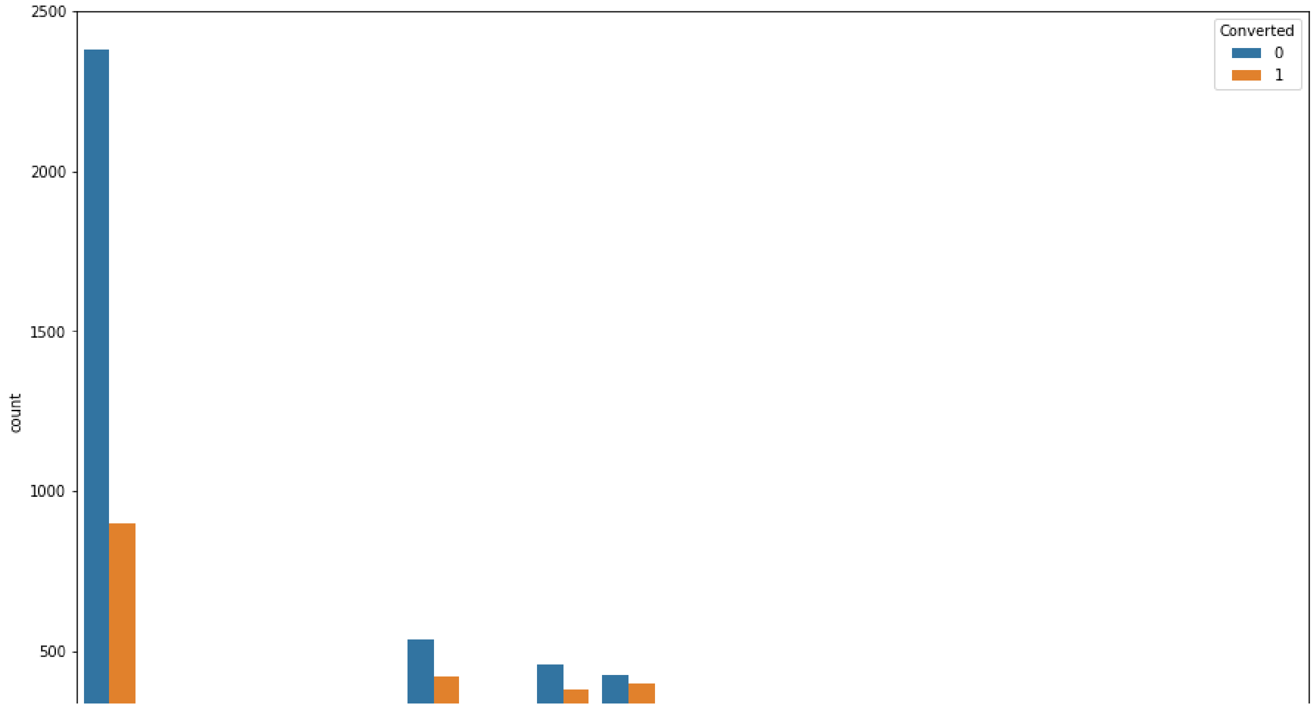
```
lead['Specialization']=lead['Specialization'].replace('Others','Other Specialization')
```

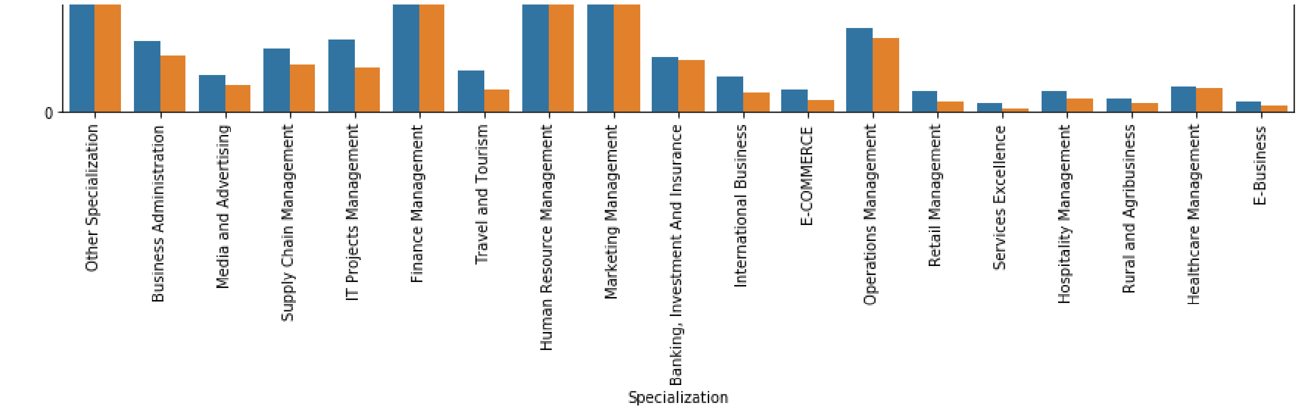
In [78]:

```
plt.figure(figsize=(15,10))
sns.countplot(x='Specialization',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[78]:

```
(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 xticklabel objects>)
```





In [79]:

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

Out[79]:

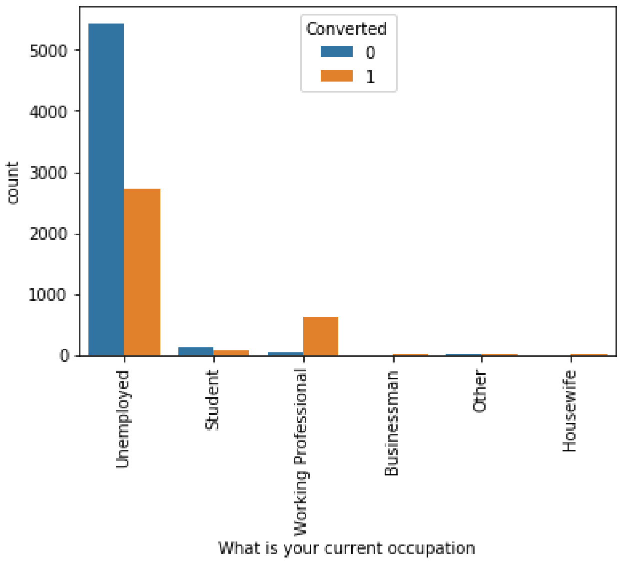
```
count            9074
unique              6
top        Unemployed
freq             8159
Name: What is your current occupation, dtype: object
```

In [80]:

```
sns.countplot(x='What is your current occupation',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[80]:

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



In [81]:

```
lead['What is your current occupation']=lead['What is your current occupation'].replace('Other','O
ther Occupation')
```

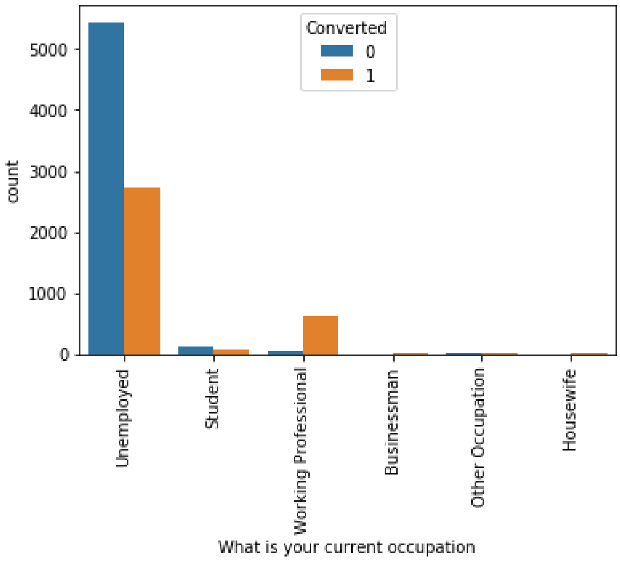
In [82]:

```
sns.countplot(x='What is your current occupation',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[82]:

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

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



In [83]:

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

Out[83]:

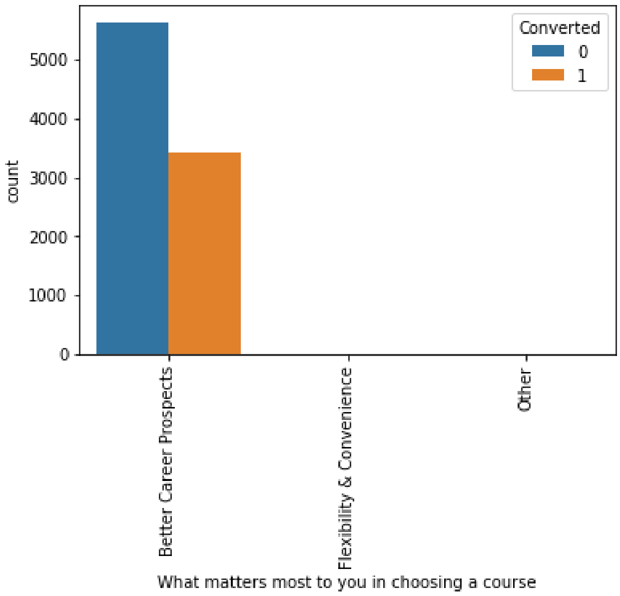
```
count                         9074
unique                           3
top       Better Career Prospects
freq                          9072
Name: What matters most to you in choosing a course, dtype: object
```

In [84]:

```
sns.countplot(x='What matters most to you in choosing a course',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[84]:

(array([0, 1, 2]), <a list of 3 Text xticklabel objects>)



In [85]:

```
lead['Search'].describe()
```

Out[85]:

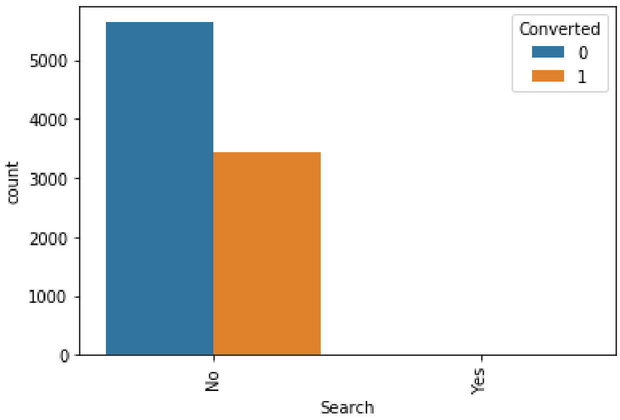
```
count      9074
unique        2
top          No
freq       9060
Name: Search, dtype: object
```

In [86]:

```
sns.countplot(x='Search',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[86]:

```
(array([0, 1]), <a list of 2 Text xticklabel objects>)
```



In [87]:

```
lead['Magazine'].describe()
```

Out[87]:

```
count      9074
unique        1
top          No
freq       9074
Name: Magazine, dtype: object
```

In [88]:

```
lead['Newspaper Article'].describe()
```

Out[88]:

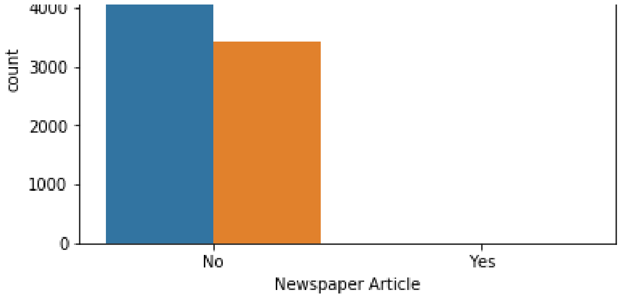
```
count      9074
unique        2
top          No
freq       9072
Name: Newspaper Article, dtype: object
```

In [89]:

```
sns.countplot(x='Newspaper Article',hue='Converted',data=lead)
```

Out[89]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d300688ef0>
```



In [90]:

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

Out[90]:

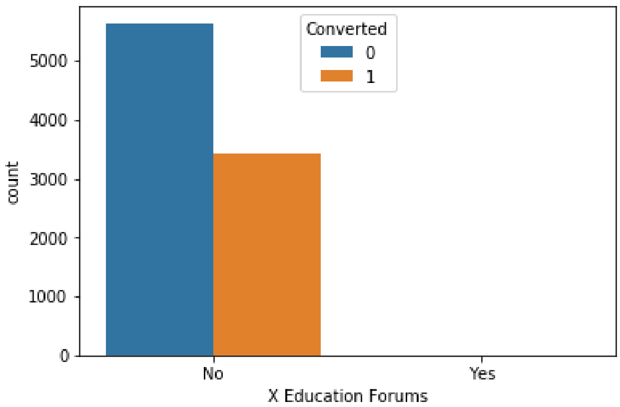
```
count      9074
unique        2
top          No
freq       9073
Name: X Education Forums, dtype: object
```

In [91]:

```
sns.countplot(x='X Education Forums',hue='Converted',data=lead)
```

Out[91]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d3006f3940>
```



In [92]:

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

Out[92]:

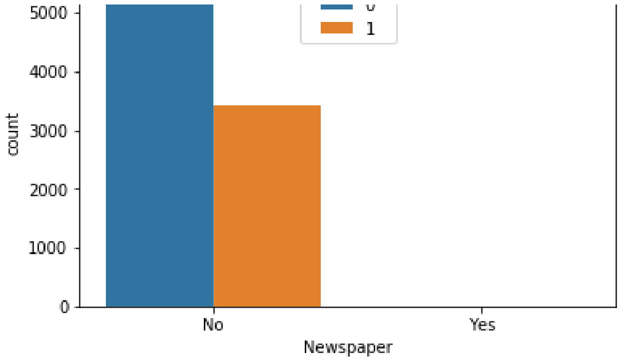
```
count      9074
unique        2
top          No
freq       9073
Name: Newspaper, dtype: object
```

In [93]:

```
sns.countplot(x='Newspaper',hue='Converted',data=lead)
```

Out[93]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d3007443c8>
```



In [94]:

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

Out[94]:

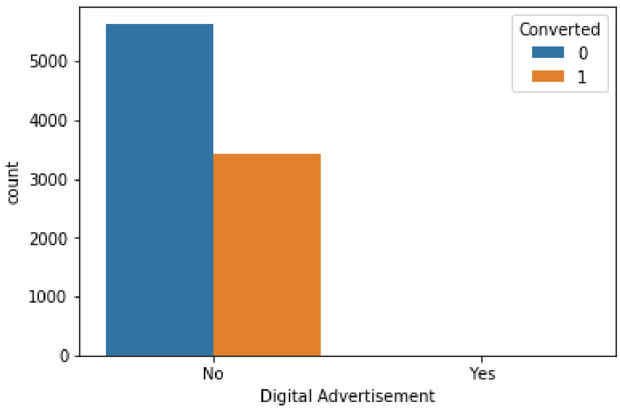
```
count      9074
unique        2
top          No
freq       9070
Name: Digital Advertisement, dtype: object
```

In [95]:

```
sns.countplot(x='Digital Advertisement',hue='Converted',data=lead)
```

Out[95]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d300797320>
```



In [96]:

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

Out[96]:

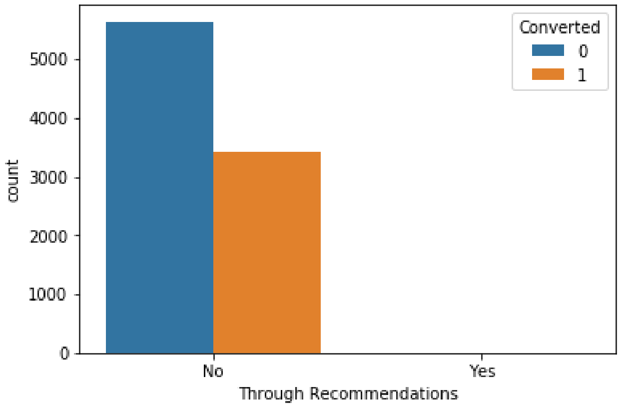
```
count      9074
unique        2
top          No
freq       9067
Name: Through Recommendations, dtype: object
```

In [97]:

```
sns.countplot(x='Through Recommendations',hue='Converted',data=lead)
```

Out[97]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d3008029b0>
```



In [98]:

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

Out[98]:

```
count      9074
unique        1
top          No
freq       9074
Name: Receive More Updates About Our Courses, dtype: object
```

In [99]:

```
lead['Tags'].describe()
```

Out[99]:

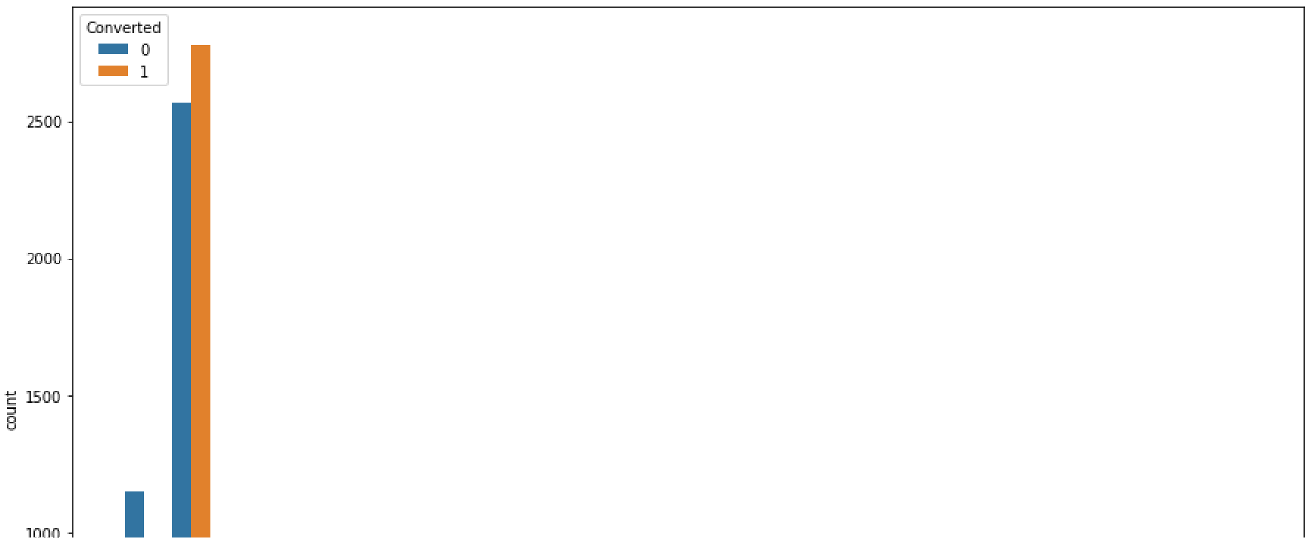
```
count                                 9074
unique                                  26
top       Will revert after reading the email
freq                                  5343
Name: Tags, dtype: object
```

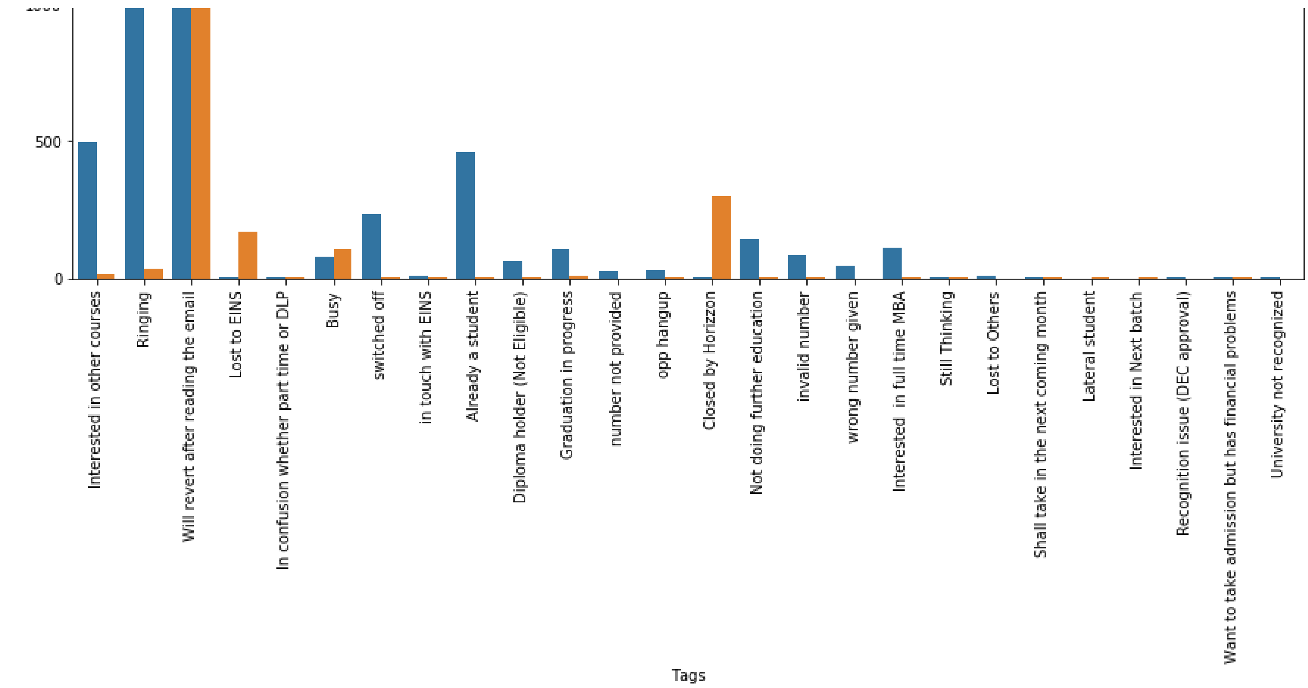
In [100]:

```
plt.figure(figsize=(15,10))
sns.countplot(x='Tags',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[100]:

```
(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 xticklabel objects>)
```





In [101]:

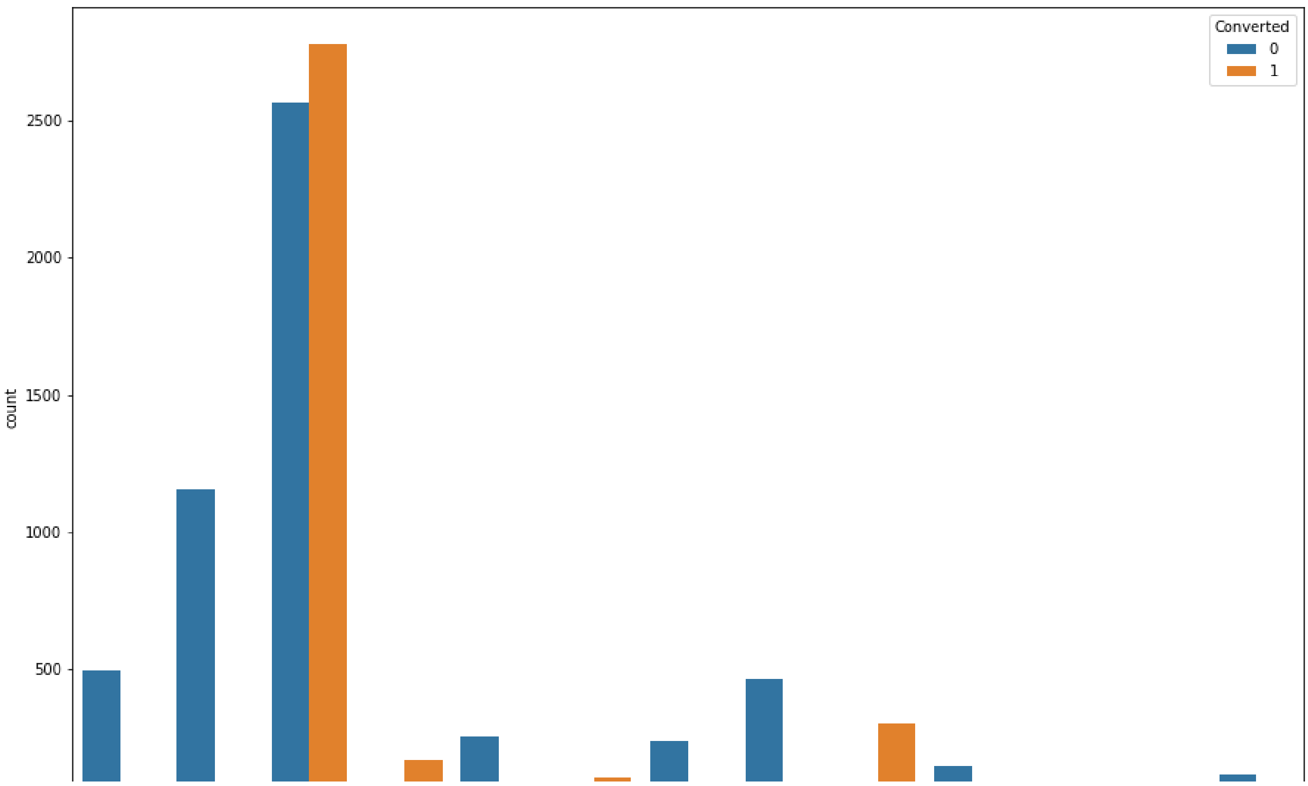
```
lead['Tags']=lead['Tags'].replace(['In confusion whether part time or DLP','in touch with EINS','Diploma holder (Not Eligible)','Graduation in progress','number not provided','opp hangup','Still Thinking','Lost to Others','Shall take in the next coming month','Lateral student','Interested in Next batch','Recognition issue (DEC approval)','Want to take admission but has financial problems','University not recognized'],'Other Tags')
```

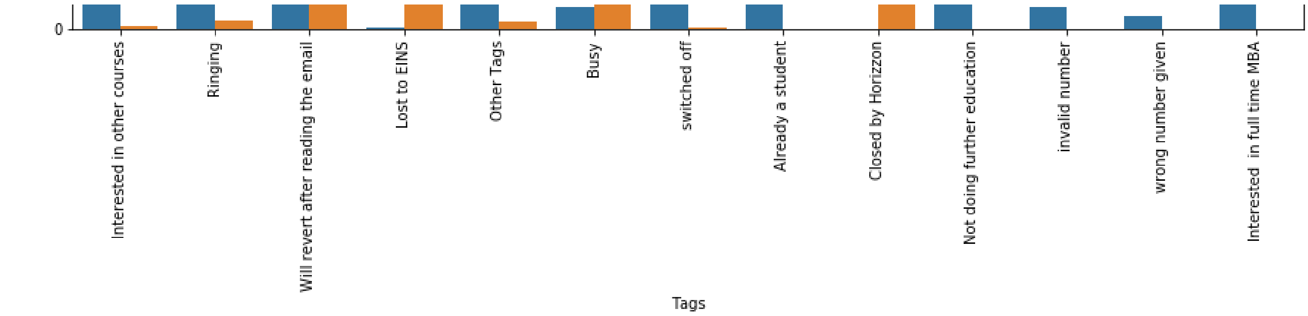
In [102]:

```
plt.figure(figsize=(15,10))
sns.countplot(x='Tags',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[102]:

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





In [103]:

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

Out[103]:

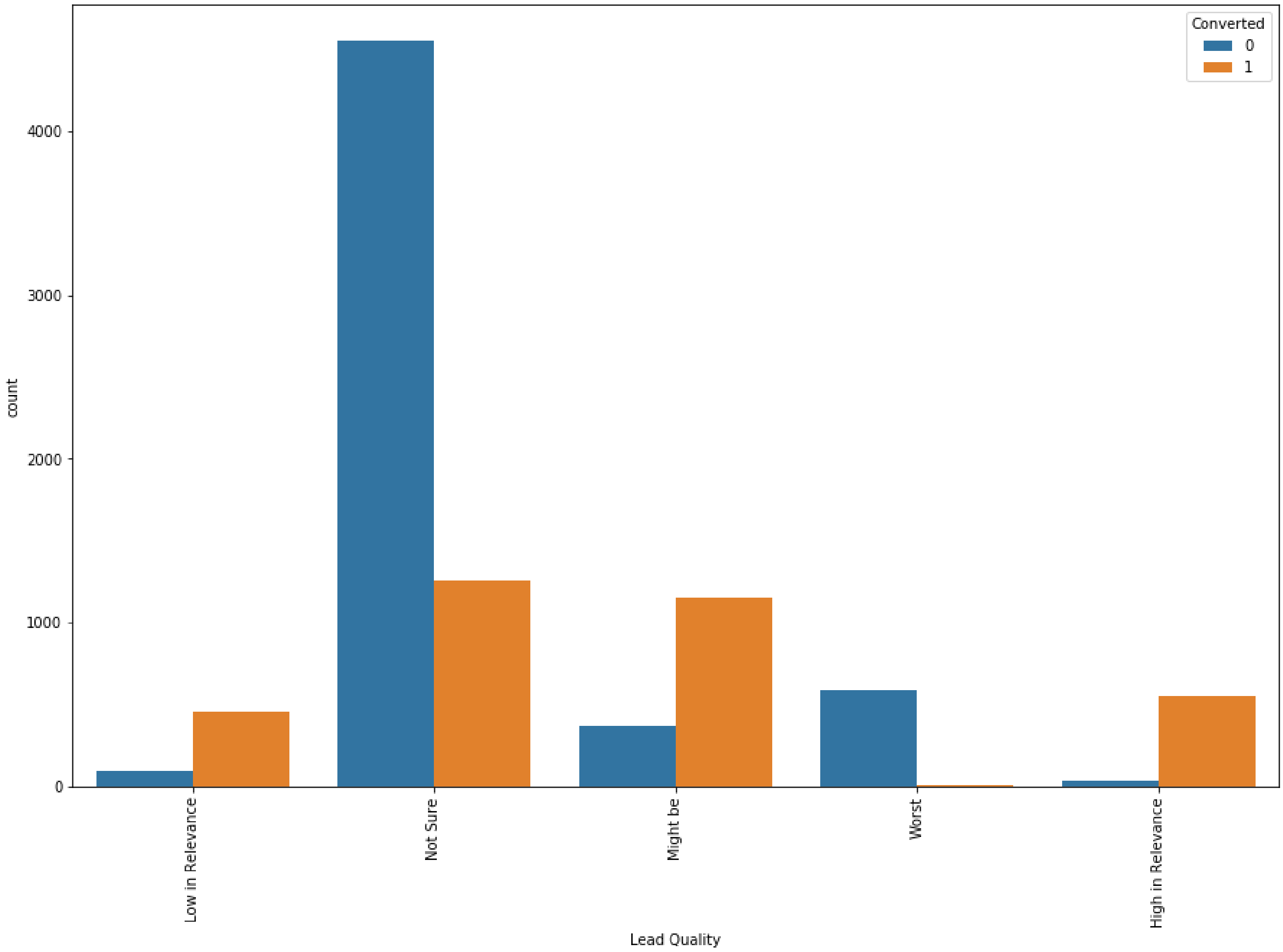
```
count          9074
unique            5
top        Not Sure
freq           5806
Name: Lead Quality, dtype: object
```

In [104]:

```
plt.figure(figsize=(15,10))
sns.countplot(x='Lead Quality',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[104]:

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



In [105]:

In [105]:

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

Out[105]:

```
count      9074
unique        1
top          No
freq       9074
Name: Update me on Supply Chain Content, dtype: object
```

In [106]:

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

Out[106]:

```
count      9074
unique        1
top          No
freq       9074
Name: Get updates on DM Content, dtype: object
```

In [107]:

```
lead['City'].describe()
```

Out[107]:

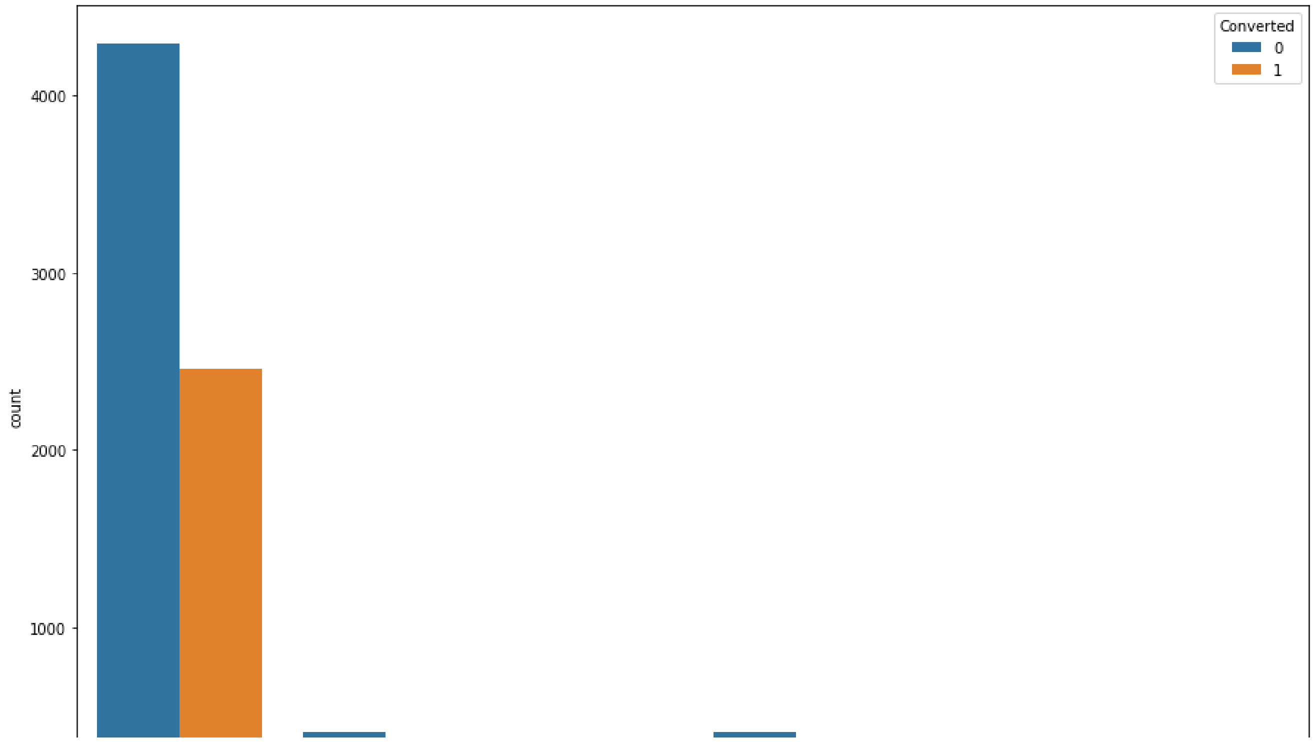
```
count        9074
unique          6
top        Mumbai
freq         6752
Name: City, dtype: object
```

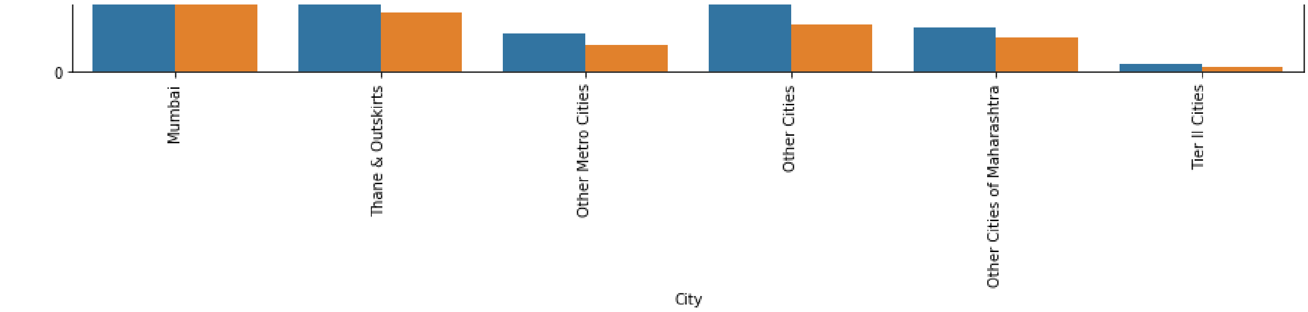
In [108]:

```
plt.figure(figsize=(15,10))
sns.countplot(x='City',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[108]:

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





In [109]:

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

Out[109]:

```
count      9074
unique        1
top          No
freq       9074
Name: I agree to pay the amount through cheque, dtype: object
```

In [110]:

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

Out[110]:

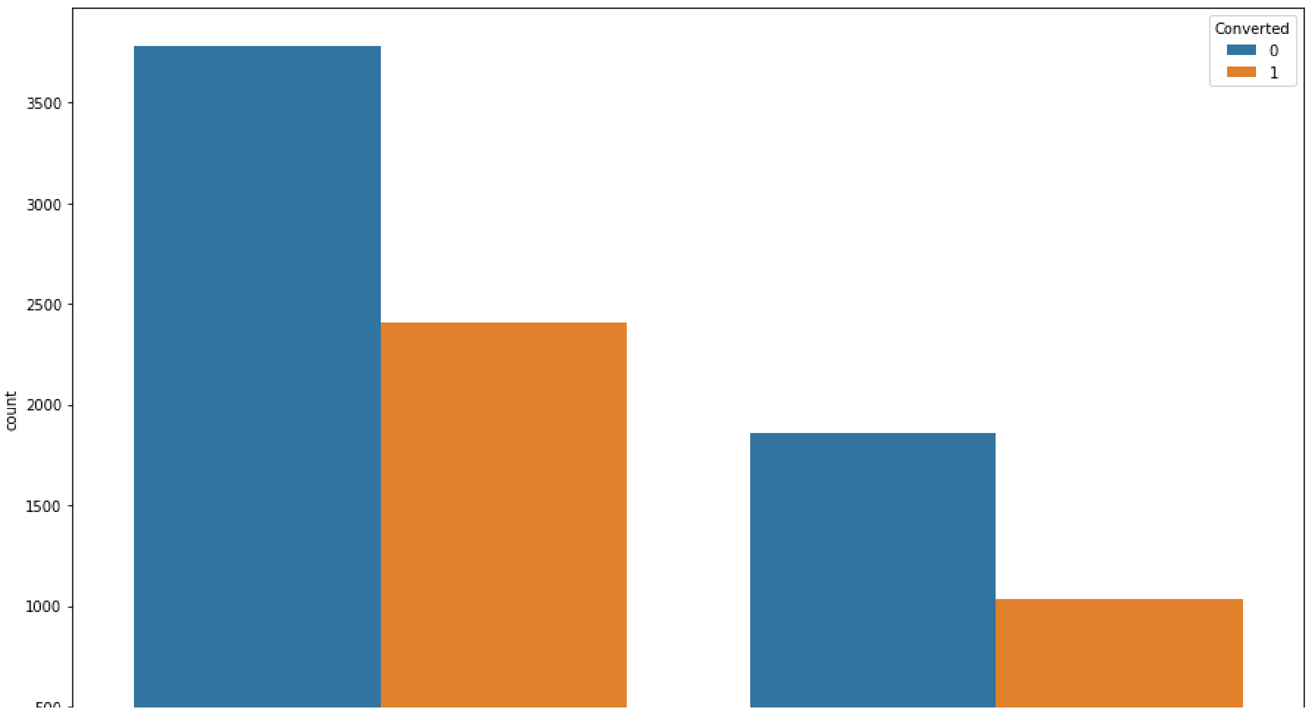
```
count      9074
unique        2
top          No
freq       6186
Name: A free copy of Mastering The Interview, dtype: object
```

In [111]:

```
plt.figure(figsize=(15,10))
sns.countplot(x='A free copy of Mastering The Interview',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[111]:

```
(array([0, 1]), <a list of 2 Text xticklabel objects>)
```



In [112]:

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

Out[112]:

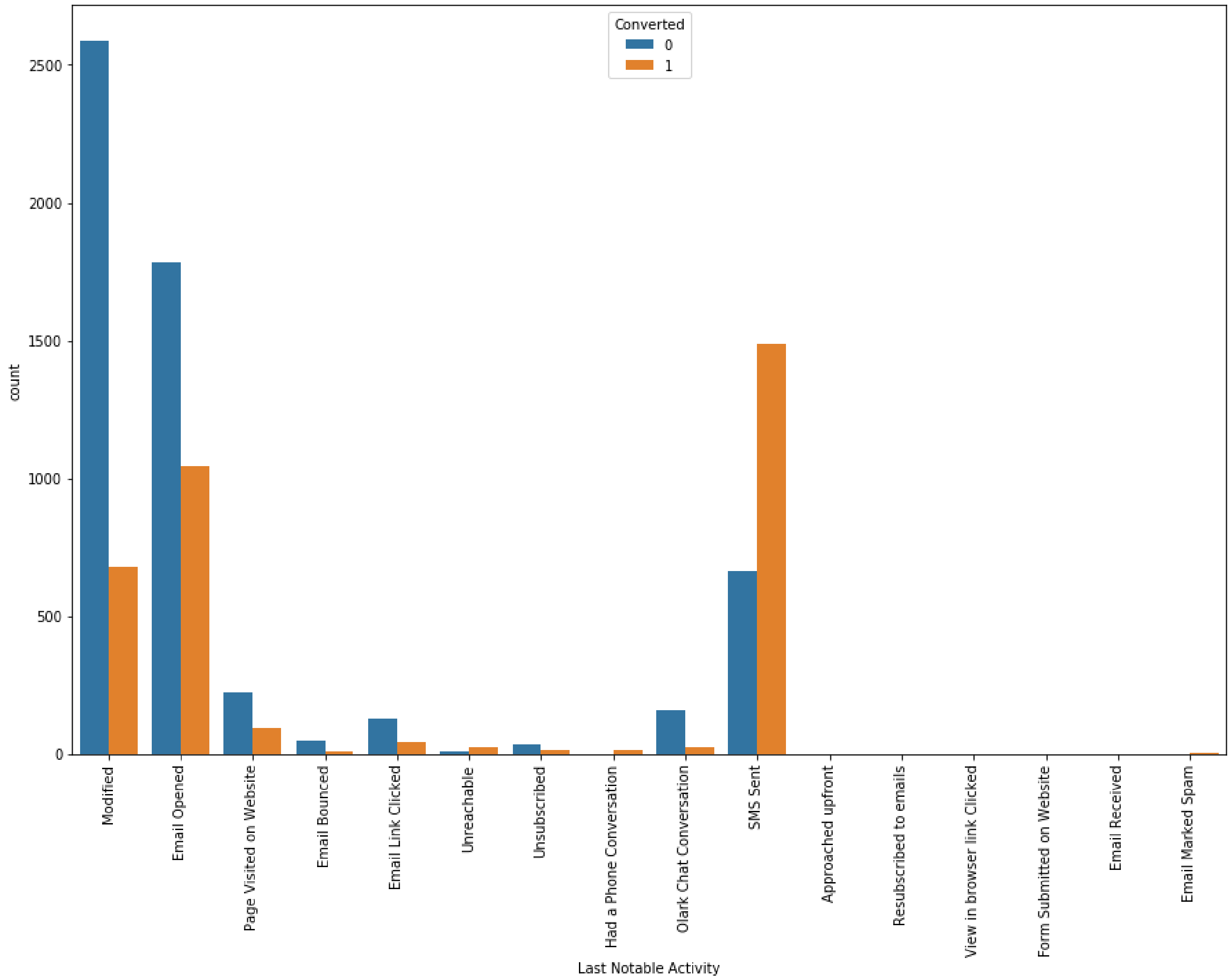
```
count          9074
unique           16
top        Modified
freq           3267
Name: Last Notable Activity, dtype: object
```

In [113]:

```
plt.figure(figsize=(15,10))
sns.countplot(x='Last Notable Activity',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[113]:

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



In [114]:

```
lead['Last Notable Activity']=lead['Last Notable Activity'].replace(['Approached
```

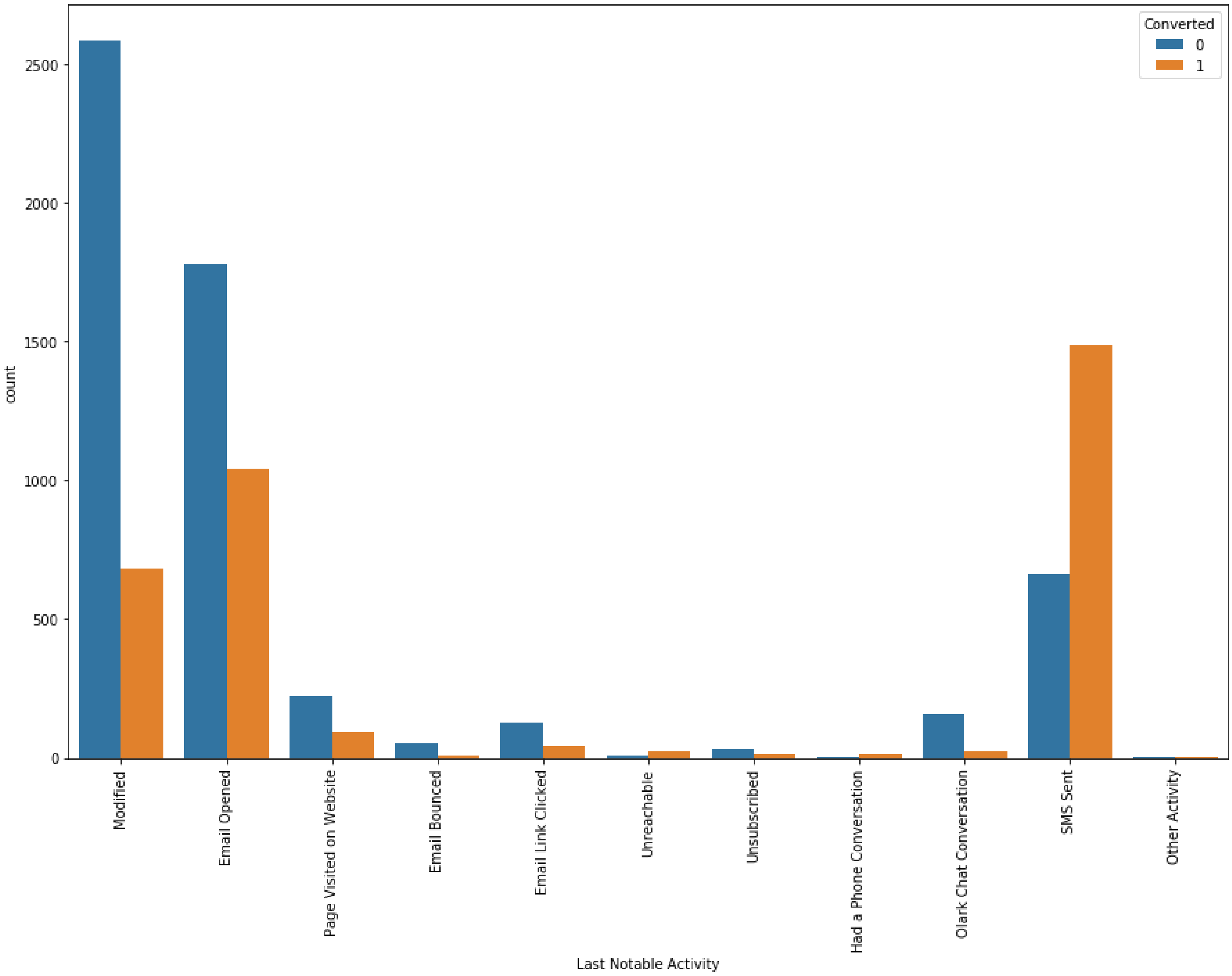
```
upfront','Resubscribed to emails','View in browser link Clicked','Form Submitted on Website','Emai
l Received','Email Marked Spam'],'Other Activity')
```

In [115]:

```
plt.figure(figsize=(15,10))
sns.countplot(x='Last Notable Activity',hue='Converted',data=lead)
plt.xticks(rotation=90)
```

Out[115]:

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



In [116]:

```
lead=lead.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 Courses','Update me on Supply Chain Content','Get
updates on DM Content','Country','I agree to pay the amount through cheque','A free copy of Master
ing The Interview'],1)
```

In [117]:

```
lead.shape
```

Out[117]:

```
(9074, 16)
```

In [118]:

```
lead.head()
```

Out[118]:

	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 is your current occupation	
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	API	Olark Chat	No	No	0	0.0	0	0.0	Page Visited on Website	Other Specialization	Unemployed	In
1	2a272436-5132-4136-86fa-dcc88c88f482	API	Organic Search	No	No	0	5.0	674	2.5	Email Opened	Other Specialization	Unemployed	
2	8cc8c611-a219-4f35-ad23-fdfd2656bd8a	Landing Page Submission	Direct Traffic	No	No	1	2.0	1532	2.0	Email Opened	Business Administration	Student	W th
3	0cc2df48-7cf4-4e39-9de9-19797f9b38cc	Landing Page Submission	Direct Traffic	No	No	0	1.0	305	1.0	Unreachable	Media and Advertising	Unemployed	
4	3256f628-e534-4826-9d63-4a8b88782852	Landing Page Submission	Google	No	No	1	2.0	1428	1.0	Converted to Lead	Other Specialization	Unemployed	W th

Data Preparation

In [119]:

```
# Convert the Binary variables(yes/no) into 0 and 1
varlist=['Do Not Email','Do Not Call']
def binary_map(x):
    return x.map({'Yes':1,'No':0})
lead[varlist]=lead[varlist].apply(binary_map)
```

In [120]:

```
lead.head()
```

Out[120]:

	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 is your current occupation	
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	API	Olark Chat	0	0	0	0.0	0	0.0	Page Visited on Website	Other Specialization	Unemployed	In
1	2a272436-5132-4136-86fa-dcc88c88f482	API	Organic Search	0	0	0	5.0	674	2.5	Email Opened	Other Specialization	Unemployed	
2	8cc8c611-a219-4f35-ad23-fdfd2656bd8a	Landing Page Submission	Direct Traffic	0	0	1	2.0	1532	2.0	Email Opened	Business Administration	Student	W th
3	0cc2df48-7cf4-4e39-9de9-19797f9b38cc	Landing Page Submission	Direct Traffic	0	0	0	1.0	305	1.0	Unreachable	Media and Advertising	Unemployed	
4	3256f628-e534-4826-9d63-4a8b88782852	Landing Page Submission	Google	0	0	1	2.0	1428	1.0	Converted to Lead	Other Specialization	Unemployed	W th

In [121]:

```
lead.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9074 entries, 0 to 9239
Data columns (total 16 columns):
Prospect ID                        9074 non-null object
Lead Origin                        9074 non-null object
Lead Source                        9074 non-null object
Do Not Email                       9074 non-null int64
Do Not Call                        9074 non-null int64
Converted                          9074 non-null int64
TotalVisits                        9074 non-null float64
Total Time Spent on Website        9074 non-null int64
Page Views Per Visit               9074 non-null float64
Last Activity                      9074 non-null object
Specialization                     9074 non-null object
What is your current occupation    9074 non-null object
Tags                               9074 non-null object
Lead Quality                       9074 non-null object
City                               9074 non-null object
Last Notable Activity              9074 non-null object
dtypes: float64(2), int64(4), object(10)
memory usage: 1.5+ MB
```

In [122]:

```
#Creating dummy variables for some of the categorical variables
dummy=pd.get_dummies(lead[['Lead Origin','Lead Source','Last Activity','Specialization','What is y
our current occupation','Tags','Lead Quality','Last Notable Activity','City']],drop_first=True)
lead=pd.concat([lead,dummy],axis=1)
```

In [123]:

```
lead.head()
```

Out[123]:

	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	...	Last Notable Activity_Other Activity	Last Notab Activity_Pa Visited Websi
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	API	Olark Chat	0	0	0	0.0	0	0.0	Page Visited on Website	...	0	
1	2a272436-5132-4136-86fa-dcc88c88f482	API	Organic Search	0	0	0	5.0	674	2.5	Email Opened	...	0	
2	8cc8c611-a219-4f35-ad23-fdfd2656bd8a	Landing Page Submission	Direct Traffic	0	0	1	2.0	1532	2.0	Email Opened	...	0	
3	0cc2df48-7cf4-4e39-9de9-19797f9b38cc	Landing Page Submission	Direct Traffic	0	0	0	1.0	305	1.0	Unreachable	...	0	
4	3256f628-e534-4826-9d63-4a8b88782852	Landing Page Submission	Google	0	0	1	2.0	1428	1.0	Converted to Lead	...	0	

5 rows × 92 columns

In [124]:

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

In [125]:

```
lead.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9074 entries, 0 to 9239
Data columns (total 83 columns):
Prospect ID                                             9074 non-null object
Do Not Email                                            9074 non-null int64
Do Not Call                                             9074 non-null int64
Converted                                               9074 non-null int64
TotalVisits                                             9074 non-null float64
Total Time Spent on Website                             9074 non-null int64
Page Views Per Visit                                    9074 non-null float64
Lead Origin_Landing Page Submission                     9074 non-null uint8
Lead Origin_Lead Add Form                               9074 non-null uint8
Lead Origin_Lead Import                                 9074 non-null uint8
Lead Source_Direct Traffic                              9074 non-null uint8
Lead Source_Facebook                                    9074 non-null uint8
Lead Source_Google                                      9074 non-null uint8
Lead Source_Olark Chat                                  9074 non-null uint8
Lead Source_Organic Search                              9074 non-null uint8
Lead Source_Others                                      9074 non-null uint8
Lead Source_Reference                                   9074 non-null uint8
Lead Source_Referral Sites                              9074 non-null uint8
Lead Source_Welingak Website                            9074 non-null uint8
Last Activity_Email Bounced                             9074 non-null uint8
Last Activity_Email Link Clicked                        9074 non-null uint8
Last Activity_Email Opened                              9074 non-null uint8
Last Activity_Form Submitted on Website                 9074 non-null uint8
Last Activity_Olark Chat Conversation                   9074 non-null uint8
Last Activity_Other Activity                            9074 non-null uint8
Last Activity_Page Visited on Website                   9074 non-null uint8
Last Activity_SMS Sent                                  9074 non-null uint8
Last Activity_Unreachable                               9074 non-null uint8
Last Activity_Unsubscribed                              9074 non-null uint8
Specialization_Business Administration                  9074 non-null uint8
Specialization_E-Business                               9074 non-null uint8
Specialization_E-COMMERCE                               9074 non-null uint8
Specialization_Finance Management                       9074 non-null uint8
Specialization_Healthcare Management                    9074 non-null uint8
Specialization_Hospitality Management                   9074 non-null uint8
Specialization_Human Resource Management                9074 non-null uint8
Specialization_IT Projects Management                   9074 non-null uint8
Specialization_International Business                   9074 non-null uint8
Specialization_Marketing Management                     9074 non-null uint8
Specialization_Media and Advertising                    9074 non-null uint8
Specialization_Operations Management                    9074 non-null uint8
Specialization_Other Specialization                     9074 non-null uint8
Specialization_Retail Management                        9074 non-null uint8
Specialization_Rural and Agribusiness                   9074 non-null uint8
Specialization_Services Excellence                      9074 non-null uint8
Specialization_Supply Chain Management                  9074 non-null uint8
Specialization_Travel and Tourism                       9074 non-null uint8
What is your current occupation_Housewife               9074 non-null uint8
What is your current occupation_Other Occupation        9074 non-null uint8
What is your current occupation_Student                 9074 non-null uint8
What is your current occupation_Unemployed              9074 non-null uint8
What is your current occupation_Working Professional    9074 non-null uint8
Tags_Busy                                               9074 non-null uint8
Tags_Closed by Horizzon                                 9074 non-null uint8
Tags_Interested  in full time MBA                       9074 non-null uint8
Tags_Interested in other courses                        9074 non-null uint8
Tags_Lost to EINS                                       9074 non-null uint8
Tags_Not doing further education                        9074 non-null uint8
Tags_Other Tags                                         9074 non-null uint8
Tags_Ringing                                            9074 non-null uint8
Tags_Will revert after reading the email                9074 non-null uint8
Tags_invalid number                                     9074 non-null uint8
Tags_switched off                                       9074 non-null uint8
Tags_wrong number given                                 9074 non-null uint8
Lead Quality_Low in Relevance                           9074 non-null uint8
Lead Quality_Might be                                   9074 non-null uint8
Lead Quality_Not Sure                                   9074 non-null uint8
Lead Quality_Worst                                      9074 non-null uint8
Last Notable Activity_Email Link Clicked                9074 non-null uint8
Last Notable Activity_Email Opened                      9074 non-null uint8
Last Notable Activity_Had a Phone Conversation          9074 non-null uint8
```

```
Last Notable Activity_Modified                        9074 non-null uint8
Last Notable Activity_Olark Chat Conversation         9074 non-null uint8
Last Notable Activity_Other Activity                  9074 non-null uint8
Last Notable Activity_Page Visited on Website         9074 non-null uint8
Last Notable Activity_SMS Sent                        9074 non-null uint8
Last Notable Activity_Unreachable                     9074 non-null uint8
Last Notable Activity_Unsubscribed                    9074 non-null uint8
City_Other Cities                                     9074 non-null uint8
City_Other Cities of Maharashtra                      9074 non-null uint8
City_Other Metro Cities                               9074 non-null uint8
City_Thane & Outskirts                                9074 non-null uint8
City_Tier II Cities                                   9074 non-null uint8
dtypes: float64(2), int64(4), object(1), uint8(76)
memory usage: 1.5+ MB
```

In [126]:

```
lead.shape
```

Out[126]:

```
(9074, 83)
```

In [127]:

```
lead.head()
```

Out[127]:

	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	...	Last Notable Activity_Other Activity
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	0	0	0	0.0	0	0.0	0	0	0	...	0
1	2a272436-5132-4136-86fa-dcc88c88f482	0	0	0	5.0	674	2.5	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

5 rows × 83 columns

In [128]:

```
lead.isnull().sum()
```

Out[128]:

```
Prospect ID                                    0
Do Not Email                                   0
Do Not Call                                    0
Converted                                      0
TotalVisits                                    0
Total Time Spent on Website                    0
Page Views Per Visit                           0
Lead Origin_Landing Page Submission            0
Lead Origin_Lead Add Form                      0
Lead Origin_Lead Import                        0
Lead Source_Direct Traffic                     0
```

```
Lead Source_Direct Traffic                                0
Lead Source_Facebook                                      0
Lead Source_Google                                        0
Lead Source_Olark Chat                                    0
Lead Source_Organic Search                                0
Lead Source_Others                                        0
Lead Source_Reference                                     0
Lead Source_Referral Sites                                0
Lead Source_Welingak Website                              0
Last Activity_Email Bounced                               0
Last Activity_Email Link Clicked                          0
Last Activity_Email Opened                                0
Last Activity_Form Submitted on Website                   0
Last Activity_Olark Chat Conversation                     0
Last Activity_Other Activity                              0
Last Activity_Page Visited on Website                     0
Last Activity_SMS Sent                                    0
Last Activity_Unreachable                                 0
Last Activity_Unsubscribed                                0
Specialization_Business Administration                    0
                                                         ..
Tags_Closed by Horizzon                                   0
Tags_Interested  in full time MBA                         0
Tags_Interested in other courses                          0
Tags_Lost to EINS                                         0
Tags_Not doing further education                          0
Tags_Other Tags                                           0
Tags_Ringing                                              0
Tags_Will revert after reading the email                  0
Tags_invalid number                                       0
Tags_switched off                                         0
Tags_wrong number given                                   0
Lead Quality_Low in Relevance                             0
Lead Quality_Might be                                     0
Lead Quality_Not Sure                                     0
Lead Quality_Worst                                        0
Last Notable Activity_Email Link Clicked                  0
Last Notable Activity_Email Opened                        0
Last Notable Activity_Had a Phone Conversation            0
Last Notable Activity_Modified                            0
Last Notable Activity_Olark Chat Conversation             0
Last Notable Activity_Other Activity                      0
Last Notable Activity_Page Visited on Website             0
Last Notable Activity_SMS Sent                            0
Last Notable Activity_Unreachable                         0
Last Notable Activity_Unsubscribed                        0
City_Other Cities                                         0
City_Other Cities of Maharashtra                          0
City_Other Metro Cities                                   0
City_Thane & Outskirts                                    0
City_Tier II Cities                                       0
Length: 83, dtype: int64
```

Step4:Split the data into test and train data

In [129]:

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

In [130]:

```
X=lead.drop(['Prospect ID','Converted'],axis=1)
```

In [131]:

```
X.head()
```

Out[131]:

	Do Not	Do Not	TotalVisits	Total Time Spent	Page Views Per	Lead Origin_Landing Page	Lead Origin_Lead	Lead Origin_Lead	Lead Source_Direct	Lead Source_Facebook	...	Last Not Activity_O

	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_Direct Traffic	Lead Source_Facebook	...	Last Notable Activity_O Act
0	0	0	0.0	0	0.0	0	0	0	0	0	...	
1	0	0	5.0	674	2.5	0	0	0	0	0	...	
2	0	0	2.0	1532	2.0	1	0	0	1	0	...	
3	0	0	1.0	305	1.0	1	0	0	1	0	...	
4	0	0	2.0	1428	1.0	1	0	0	0	0	...	

5 rows × 81 columns

In [132]:

```
y=lead['Converted']
```

In [133]:

```
y.head()
```

Out[133]:

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

In [134]:

```
X_train,X_test,y_train,y_test=train_test_split(X,y,train_size=0.7,test_size=0.3,random_state=100)
```

Step5:Feature Scaling

In [135]:

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

In [136]:

```
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()
```

```
C:\Users\DELL\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645:
DataConversionWarning: Data with input dtype int64, float64 were all converted to float64 by
StandardScaler.
  return self.partial_fit(X, y)
C:\Users\DELL\Anaconda3\lib\site-packages\sklearn\base.py:464: DataConversionWarning: Data with in
put dtype int64, float64 were all converted to float64 by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

Out[136]:

	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_Direct Traffic	Lead Source_Facebook	...	L Act
3009	0	0	-0.432779	-0.160255	-0.155018	1	0	0	1	0	...	
1012	1	0	-0.432779	-0.540048	-0.155018	1	0	0	1	0	...	
9226	0	0	-1.150329	-0.888650	-1.265540	0	0	0	0	0	...	

	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_Direct Traffic	Lead Source_Facebook	...	L Act
4750	0	0	-0.432779	1.643304	0.15[illegible]	1	0	0	1	0	...	
7987	0	0	0.643547	2.017593	-0.122613	1	0	0	1	0	...	

5 rows × 81 columns

In [137]:

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

Out[137]:

```
37.85541106458012
```

The data has almost 38% of converted rate

Step6:Model Building

In [138]:

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

In [140]:

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

Out[140]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6351
Model:	GLM	**Df Residuals:**	6269
Model Family:	Binomial	**Df Model:**	81
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1250.3
Date:	Sun, 10 May 2020	**Deviance:**	2500.5
Time:	19:42:24	**Pearson chi2:**	3.89e+04
No. Iterations:	24	**Covariance Type:**	nonrobust

	coef	std err	z	P>|z|	[0.025	0.975]
const	3.5822	3.090	1.159	0.246	-2.475	9.639
Do Not Email	-1.3798	0.326	-4.229	0.000	-2.019	-0.740
Do Not Call	23.7111	1.37e+05	0.000	1.000	-2.68e+05	2.68e+05
TotalVisits	0.1814	0.087	2.090	0.037	0.011	0.351
Total Time Spent on Website	1.1463	0.064	17.923	0.000	1.021	1.272
Page Views Per Visit	-0.3272	0.099	-3.309	0.001	-0.521	-0.133
Lead Origin_Landing Page Submission	-0.9782	0.221	-4.426	0.000	-1.411	-0.545
Lead Origin_Lead Add Form	-0.3545	1.528	-0.232	0.817	-3.350	2.641
Lead Origin_Lead Import	29.7283	2.16e+05	0.000	1.000	-4.23e+05	4.23e+05
Lead Source_Direct Traffic	-0.5886	2.384	-0.247	0.805	-5.261	4.083
Lead Source_Facebook	-29.2165	2.16e+05	-0.000	1.000	-4.23e+05	4.23e+05
Lead Source_Google	-0.3859	2.381	-0.162	0.871	-5.053	4.281
Lead Source_Olark Chat	0.2759	2.380	0.116	0.908	-4.389	4.941
Lead Source_Organic Search	-0.3600	2.387	-0.151	0.880	-5.039	4.319
Lead Source_Others	0.1822	2.378	0.077	0.939	-4.478	4.842

Lead Source_Reference	1.1350	1.864	0.609	0.543	-2.519	4.789
Lead Source_Referral Sites	-0.6808	2.427	-0.280	0.779	-5.438	4.076
Lead Source_Welingak Website	4.8221	1.975	2.441	0.015	0.951	8.693
Last Activity_Email Bounced	-0.5569	0.870	-0.640	0.522	-2.262	1.148
Last Activity_Email Link Clicked	0.8426	0.644	1.309	0.191	-0.419	2.105
Last Activity_Email Opened	0.0002	0.385	0.000	1.000	-0.754	0.754
Last Activity_Form Submitted on Website	0.1085	0.591	0.184	0.854	-1.050	1.268
Last Activity_Olark Chat Conversation	-0.5465	0.392	-1.395	0.163	-1.315	0.222
Last Activity_Other Activity	1.5856	1.150	1.378	0.168	-0.669	3.840
Last Activity_Page Visited on Website	0.5048	0.456	1.107	0.268	-0.389	1.398
Last Activity_SMS Sent	1.1277	0.360	3.130	0.002	0.421	1.834
Last Activity_Unreachable	0.6472	0.840	0.770	0.441	-1.000	2.294
Last Activity_Unsubscribed	0.8287	1.571	0.528	0.598	-2.250	3.907
Specialization_Business Administration	-0.2248	0.392	-0.573	0.566	-0.993	0.544
Specialization_E-Business	-0.3581	0.715	-0.501	0.616	-1.759	1.043
Specialization_E-COMMERCE	0.5866	0.587	0.999	0.318	-0.564	1.737
Specialization_Finance Management	-0.4382	0.345	-1.269	0.205	-1.115	0.239
Specialization_Healthcare Management	-0.5121	0.510	-1.004	0.315	-1.512	0.488
Specialization_Hospitality Management	-0.1619	0.544	-0.297	0.766	-1.229	0.905
Specialization_Human Resource Management	-0.2797	0.347	-0.806	0.420	-0.960	0.400
Specialization_IT Projects Management	-0.0082	0.411	-0.020	0.984	-0.813	0.796
Specialization_International Business	-0.8327	0.460	-1.812	0.070	-1.734	0.068
Specialization_Marketing Management	0.0474	0.348	0.136	0.892	-0.635	0.730
Specialization_Media and Advertising	-0.5371	0.488	-1.101	0.271	-1.493	0.419
Specialization_Operations Management	-0.1253	0.392	-0.320	0.749	-0.894	0.643
Specialization_Other Specialization	-0.7930	0.358	-2.212	0.027	-1.496	-0.090
Specialization_Retail Management	-0.2317	0.562	-0.412	0.680	-1.333	0.870
Specialization_Rural and Agribusiness	0.0877	0.688	0.127	0.899	-1.261	1.436
Specialization_Services Excellence	-0.0492	0.971	-0.051	0.960	-1.952	1.854
Specialization_Supply Chain Management	-0.4315	0.426	-1.013	0.311	-1.266	0.403
Specialization_Travel and Tourism	-0.7776	0.511	-1.520	0.128	-1.780	0.225
What is your current occupation_Housewife	20.5948	7.16e+04	0.000	1.000	-1.4e+05	1.4e+05
What is your current occupation_Other Occupation	-0.7597	2.038	-0.373	0.709	-4.754	3.234
What is your current occupation_Student	-1.3241	1.550	-0.854	0.393	-4.362	1.714
What is your current occupation_Unemployed	-2.1162	1.448	-1.462	0.144	-4.954	0.721
What is your current occupation_Working Professional	-0.8050	1.484	-0.542	0.588	-3.714	2.104
Tags_Busy	3.9283	0.849	4.628	0.000	2.265	5.592
Tags_Closed by Horizzon	8.8779	1.138	7.801	0.000	6.647	11.108
Tags_Interested in full time MBA	0.3603	1.227	0.294	0.769	-2.044	2.765
Tags_Interested in other courses	0.2368	0.888	0.267	0.790	-1.503	1.976
Tags_Lost to EINS	9.7406	1.087	8.962	0.000	7.610	11.871
Tags_Not doing further education	-0.0870	1.504	-0.058	0.954	-3.034	2.860
Tags_Other Tags	1.0409	0.864	1.204	0.228	-0.653	2.735
Tags_Ringing	-1.1040	0.857	-1.289	0.197	-2.783	0.575
Tags_Will revert after reading the email	4.1820	0.811	5.155	0.000	2.592	5.772
Tags_invalid number	-22.5256	2.22e+04	-0.001	0.999	-4.35e+04	4.34e+04
Tags_switched off	-1.8107	1.014	-1.786	0.074	-3.798	0.177
Tags_wrong number given	-22.7925	3.02e+04	-0.001	0.999	-5.92e+04	5.92e+04
Lead Quality_Low in Relevance	-0.6414	0.434	-1.477	0.140	-1.492	0.210
Lead Quality_Might be	-1.3395	0.395	-3.394	0.001	-2.113	-0.566

Lead Quality_Not Sure	-4.1181	0.378	-10.885	0.000	-4.860	-3.377
Lead Quality_Worst	-4.8069	1.016	-4.730	0.000	-6.799	-2.815
Last Notable Activity_Email Link Clicked	-3.0417	1.201	-2.532	0.011	-5.396	-0.687
Last Notable Activity_Email Opened	-1.3443	1.017	-1.322	0.186	-3.337	0.648
Last Notable Activity_Had a Phone Conversation	-1.6149	1.993	-0.810	0.418	-5.521	2.291
Last Notable Activity_Modified	-2.5848	0.989	-2.612	0.009	-4.524	-0.645
Last Notable Activity_Olark Chat Conversation	-2.6371	1.093	-2.414	0.016	-4.779	-0.496
Last Notable Activity_Other Activity	-1.7492	2.518	-0.695	0.487	-6.685	3.187
Last Notable Activity_Page Visited on Website	-2.4235	1.083	-2.238	0.025	-4.546	-0.301
Last Notable Activity_SMS Sent	-0.0792	1.010	-0.078	0.938	-2.059	1.901
Last Notable Activity_Unreachable	-0.9994	1.381	-0.724	0.469	-3.706	1.708
Last Notable Activity_Unsubscribed	-1.2165	1.966	-0.619	0.536	-5.071	2.637
City_Other Cities	-0.2033	0.224	-0.908	0.364	-0.642	0.235
City_Other Cities of Maharashtra	-0.0101	0.261	-0.039	0.969	-0.521	0.501
City_Other Metro Cities	0.1117	0.287	0.389	0.697	-0.451	0.674
City_Thane & Outskirts	-0.1072	0.218	-0.493	0.622	-0.534	0.319
City_Tier II Cities	0.9194	0.654	1.407	0.160	-0.362	2.201

Feature Scaling using RFE

In [142]:

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

In [143]:

```
from sklearn.feature_selection import RFE
rfe=RFE(logreg,15)
rfe=rfe.fit(X_train,y_train)
```

In [144]:

```
rfe.support_
```

Out[144]:

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

In [145]:

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

Out[145]:

```
[('Do Not Email', True, 1),
 ('Do Not Call', False, 31),
 ('TotalVisits', False, 44),
 ('Total Time Spent on Website', False, 3),
 ('Page Views Per Visit', False, 40),
 ('Lead Origin_Landing Page Submission', False, 16),
 ('Lead Origin_Lead Add Form', True, 1),
 ('Lead Origin_Lead Import', False, 2),
 ('Lead Source_Direct Traffic', False, 38),
```

```
 ('Lead Source_Facebook', False, 39),
 ('Lead Source_Google', False, 42),
 ('Lead Source_Olark Chat', False, 5),
 ('Lead Source_Organic Search', False, 43),
 ('Lead Source_Others', False, 58),
 ('Lead Source_Reference', False, 52),
 ('Lead Source_Referral Sites', False, 33),
 ('Lead Source_Welingak Website', True, 1),
 ('Last Activity_Email Bounced', False, 50),
 ('Last Activity_Email Link Clicked', False, 35),
 ('Last Activity_Email Opened', False, 57),
 ('Last Activity_Form Submitted on Website', False, 61),
 ('Last Activity_Olark Chat Conversation', False, 13),
 ('Last Activity_Other Activity', False, 8),
 ('Last Activity_Page Visited on Website', False, 37),
 ('Last Activity_SMS Sent', False, 7),
 ('Last Activity_Unreachable', False, 14),
 ('Last Activity_Unsubscribed', False, 17),
 ('Specialization_Business Administration', False, 64),
 ('Specialization_E-Business', False, 67),
 ('Specialization_E-COMMERCE', False, 15),
 ('Specialization_Finance Management', False, 45),
 ('Specialization_Healthcare Management', False, 41),
 ('Specialization_Hospitality Management', False, 65),
 ('Specialization_Human Resource Management', False, 55),
 ('Specialization_IT Projects Management', False, 47),
 ('Specialization_International Business', False, 21),
 ('Specialization_Marketing Management', False, 30),
 ('Specialization_Media and Advertising', False, 34),
 ('Specialization_Operations Management', False, 59),
 ('Specialization_Other Specialization', False, 20),
 ('Specialization_Retail Management', False, 60),
 ('Specialization_Rural and Agribusiness', False, 46),
 ('Specialization_Services Excellence', False, 54),
 ('Specialization_Supply Chain Management', False, 48),
 ('Specialization_Travel and Tourism', False, 24),
 ('What is your current occupation_Housewife', False, 32),
 ('What is your current occupation_Other Occupation', False, 25),
 ('What is your current occupation_Student', False, 36),
 ('What is your current occupation_Unemployed', False, 19),
 ('What is your current occupation_Working Professional', True, 1),
 ('Tags_Busy', True, 1),
 ('Tags_Closed by Horizzon', True, 1),
 ('Tags_Interested  in full time MBA', False, 18),
 ('Tags_Interested in other courses', False, 10),
 ('Tags_Lost to EINS', True, 1),
 ('Tags_Not doing further education', False, 11),
 ('Tags_Other Tags', False, 28),
 ('Tags_Ringing', True, 1),
 ('Tags_Will revert after reading the email', True, 1),
 ('Tags_invalid number', True, 1),
 ('Tags_switched off', True, 1),
 ('Tags_wrong number given', True, 1),
 ('Lead Quality_Low in Relevance', False, 56),
 ('Lead Quality_Might be', False, 9),
 ('Lead Quality_Not Sure', True, 1),
 ('Lead Quality_Worst', True, 1),
 ('Last Notable Activity_Email Link Clicked', False, 12),
 ('Last Notable Activity_Email Opened', False, 63),
 ('Last Notable Activity_Had a Phone Conversation', False, 27),
 ('Last Notable Activity_Modified', False, 6),
 ('Last Notable Activity_Olark Chat Conversation', False, 4),
 ('Last Notable Activity_Other Activity', False, 66),
 ('Last Notable Activity_Page Visited on Website', False, 22),
 ('Last Notable Activity_SMS Sent', True, 1),
 ('Last Notable Activity_Unreachable', False, 26),
 ('Last Notable Activity_Unsubscribed', False, 29),
 ('City_Other Cities', False, 49),
 ('City_Other Cities of Maharashtra', False, 62),
 ('City_Other Metro Cities', False, 53),
 ('City_Thane & Outskirts', False, 51),
 ('City_Tier II Cities', False, 23)]
```

In [146]:

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

In [147]:

```
col
```

Out[147]:

```
Index(['Do Not Email', 'Lead Origin_Lead Add Form',
       'Lead Source_Welingak Website',
       'What is your current occupation_Working Professional', 'Tags_Busy',
       'Tags_Closed by Horizzon', 'Tags_Lost to EINS', 'Tags_Ringing',
       'Tags_Will revert after reading the email', 'Tags_invalid number',
       'Tags_switched off', 'Tags_wrong number given', 'Lead Quality_Not Sure',
       'Lead Quality_Worst', 'Last Notable Activity_SMS Sent'],
      dtype='object')
```

In [148]:

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

Out[148]:

```
Index(['Do Not Call', 'TotalVisits', 'Total Time Spent on Website',
       'Page Views Per Visit', 'Lead Origin_Landing Page Submission',
       'Lead Origin_Lead Import', 'Lead Source_Direct Traffic',
       'Lead Source_Facebook', 'Lead Source_Google', 'Lead Source_Olark Chat',
       'Lead Source_Organic Search', 'Lead Source_Others',
       'Lead Source_Reference', 'Lead Source_Referral Sites',
       '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_SMS Sent',
       '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',
       'Tags_Interested  in full time MBA', 'Tags_Interested in other courses',
       'Tags_Not doing further education', 'Tags_Other Tags',
       'Lead Quality_Low in Relevance', 'Lead Quality_Might be',
       'Last Notable Activity_Email Link Clicked',
       'Last Notable Activity_Email Opened',
       'Last Notable Activity_Had a Phone Conversation',
       'Last Notable Activity_Modified',
       'Last Notable Activity_Olark Chat Conversation',
       'Last Notable Activity_Other Activity',
       'Last Notable Activity_Page Visited on Website',
       'Last Notable Activity_Unreachable',
       'Last Notable Activity_Unsubscribed', 'City_Other Cities',
       'City_Other Cities of Maharashtra', 'City_Other Metro Cities',
       'City_Thane & Outskirts', 'City_Tier II Cities'],
      dtype='object')
```

In [150]:

```
# Assigning the model with StatsModel
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[150]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6351
Model:	GLM	**Df Residuals:**	6335
Model Family:	Binomial	**Df Model:**	15
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1580.6
Date:	Sun, 10 May 2020	**Deviance:**	3161.3
Time:	19:59:54	**Pearson chi2:**	3.11e+04
No. Iterations:	24	**Covariance Type:**	nonrobust

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-1.8547	0.215	-8.636	0.000	-2.276	-1.434
Do Not Email	-1.3106	0.213	-6.154	0.000	-1.728	-0.893
Lead Origin_Lead Add Form	1.0452	0.360	2.900	0.004	0.339	1.752
Lead Source_Welingak Website	3.4638	0.817	4.238	0.000	1.862	5.066
What is your current occupation_Working Professional	1.2843	0.287	4.476	0.000	0.722	1.847
Tags_Busy	3.5477	0.332	10.680	0.000	2.897	4.199
Tags_Closed by Horizzon	7.7377	0.762	10.152	0.000	6.244	9.231
Tags_Lost to EINS	8.9540	0.753	11.887	0.000	7.478	10.430
Tags_Ringing	-1.9696	0.340	-5.800	0.000	-2.635	-1.304
Tags_Will revert after reading the email	3.7332	0.228	16.340	0.000	3.285	4.181
Tags_invalid number	-23.4649	2.21e+04	-0.001	0.999	-4.34e+04	4.33e+04
Tags_switched off	-2.5711	0.589	-4.367	0.000	-3.725	-1.417
Tags_wrong number given	-23.0779	3.17e+04	-0.001	0.999	-6.21e+04	6.2e+04
Lead Quality_Not Sure	-3.3496	0.129	-26.033	0.000	-3.602	-3.097
Lead Quality_Worst	-3.7672	0.848	-4.445	0.000	-5.428	-2.106
Last Notable Activity_SMS Sent	2.7931	0.122	22.838	0.000	2.553	3.033

In [151]:

```
col1=col.drop('Tags_invalid number',1)
```

In [152]:

```
col1
```

Out[152]:

```
Index(['Do Not Email', 'Lead Origin_Lead Add Form',
       'Lead Source_Welingak Website',
       'What is your current occupation_Working Professional', '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_Not Sure',
       'Lead Quality_Worst', 'Last Notable Activity_SMS Sent'],
      dtype='object')
```

In [153]:

```
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[153]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6351
Model:	GLM	**Df Residuals:**	6336
Model Family:	Binomial	**Df Model:**	14
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1586.7
Date:	Sun, 10 May 2020	**Deviance:**	3173.3
Time:	20:03:11	**Pearson chi2:**	3.07e+04
No. Iterations:	22	**Covariance Type:**	nonrobust

	coef	std err	z	P>|z|	[0.025	0.975]
const	-2.0195	0.217	-9.308	0.000	-2.445	-1.594
Do Not Email	-1.3018	0.212	-6.130	0.000	-1.718	-0.886
Lead Origin_Lead Add Form	1.0769	0.362	2.974	0.003	0.367	1.787
Lead Source_Welingak Website	3.4268	0.818	4.190	0.000	1.824	5.030
What is your current occupation_Working Professional	1.3240	0.290	4.567	0.000	0.756	1.892
Tags_Busy	3.7300	0.331	11.270	0.000	3.081	4.379
Tags_Closed by Horizzon	7.8904	0.763	10.345	0.000	6.396	9.385
Tags_Lost to EINS	9.1124	0.754	12.086	0.000	7.635	10.590
Tags_Ringing	-1.7713	0.338	-5.244	0.000	-2.433	-1.109
Tags_Will revert after reading the email	3.8970	0.230	16.954	0.000	3.446	4.348
Tags_switched off	-2.3666	0.588	-4.028	0.000	-3.518	-1.215
Tags_wrong number given	-20.8825	1.17e+04	-0.002	0.999	-2.29e+04	2.28e+04
Lead Quality_Not Sure	-3.3417	0.128	-26.020	0.000	-3.593	-3.090
Lead Quality_Worst	-3.7822	0.848	-4.462	0.000	-5.444	-2.121
Last Notable Activity_SMS Sent	2.7503	0.120	22.841	0.000	2.514	2.986

In [155]:

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

In [156]:

```
col2
```

Out[156]:

```
Index(['Do Not Email', 'Lead Origin_Lead Add Form',
       'Lead Source_Welingak Website',
       'What is your current occupation_Working Professional', 'Tags_Busy',
       'Tags_Closed by Horizzon', 'Tags_Lost to EINS', 'Tags_Ringing',
       'Tags_Will revert after reading the email', 'Tags_switched off',
       'Lead Quality_Not Sure', 'Lead Quality_Worst',
       'Last Notable Activity_SMS Sent'],
      dtype='object')
```

In [157]:

```
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()
```

```
res.summary()
```

Out[157]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6351
Model:	GLM	**Df Residuals:**	6337
Model Family:	Binomial	**Df Model:**	13
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1588.8
Date:	Sun, 10 May 2020	**Deviance:**	3177.6
Time:	20:07:13	**Pearson chi2:**	3.08e+04
No. Iterations:	8	**Covariance Type:**	nonrobust

	coef	std err	z	P>|z|	[0.025	0.975]
const	-2.0888	0.216	-9.654	0.000	-2.513	-1.665
Do Not Email	-1.3012	0.212	-6.134	0.000	-1.717	-0.885
Lead Origin_Lead Add Form	1.0894	0.363	3.001	0.003	0.378	1.801
Lead Source_Welingak Website	3.4138	0.818	4.173	0.000	1.810	5.017
What is your current occupation_Working Professional	1.3403	0.291	4.602	0.000	0.769	1.911
Tags_Busy	3.8040	0.330	11.532	0.000	3.157	4.450
Tags_Closed by Horizzon	7.9562	0.763	10.433	0.000	6.461	9.451
Tags_Lost to EINS	9.1785	0.754	12.177	0.000	7.701	10.656
Tags_Ringing	-1.6947	0.337	-5.036	0.000	-2.354	-1.035
Tags_Will revert after reading the email	3.9665	0.229	17.311	0.000	3.517	4.416
Tags_switched off	-2.2882	0.587	-3.900	0.000	-3.438	-1.138
Lead Quality_Not Sure	-3.3406	0.128	-26.026	0.000	-3.592	-3.089
Lead Quality_Worst	-3.7624	0.850	-4.426	0.000	-5.428	-2.096
Last Notable Activity_SMS Sent	2.7406	0.120	22.847	0.000	2.506	2.976

In [158]:

```
# Getting predicted values on the train set

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

Out[158]:

```
3009    0.188037
1012    0.194070
9226    0.000805
4750    0.782077
7987    0.977003
1281    0.990228
2880    0.188037
4971    0.753104
7536    0.867357
1248    0.000805
dtype: float64
```

In [159]:

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

Out[159]:

```
array([1.88037158e-01, 1.94070077e-01, 8.04879357e-04, 7.82076694e-01,
       9.77003470e-01, 9.90227993e-01, 1.88037158e-01, 7.53103755e-01,
```

```
        8.67356930e-01, 8.04879357e-04])
```

In [161]:

```
# creating a dataframe with the actual churn and the predicted probabilities

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[161]:

	Converted	Converted_prob	Prospect ID
0	0	0.188037	3009
1	0	0.194070	1012
2	0	0.000805	9226
3	1	0.782077	4750
4	1	0.977003	7987

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

In [162]:

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

y_train_pred_final.head()
```

Out[162]:

	Converted	Converted_prob	Prospect ID	predicted
0	0	0.188037	3009	0
1	0	0.194070	1012	0
2	0	0.000805	9226	0
3	1	0.782077	4750	1
4	1	0.977003	7987	1

In [164]:

```
from sklearn import metrics

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

```
[[3756  149]
 [ 363 2083]]
```

In [165]:

```
# Total Accuracy

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

```
0.9193827743662415
```

Step 7:Checking VIFs

In [166]:

```
#checking for the VIF values of the feature variables.

from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [167]:

```
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[167]:

	Features	VIF
8	Tags_Will revert after reading the email	2.89
12	Last Notable Activity_SMS Sent	2.85
1	Lead Origin_Lead Add Form	1.62
7	Tags_Ringing	1.56
2	Lead Source_Welingak Website	1.36
3	What is your current occupation_Working Profes...	1.26
5	Tags_Closed by Horizzon	1.15
0	Do Not Email	1.11
4	Tags_Busy	1.11
10	Lead Quality_Not Sure	1.11
6	Tags_Lost to EINS	1.05
9	Tags_switched off	1.04
11	Lead Quality_Worst	1.02

Step8: Metrics beyond simply accuracy

In [168]:

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

In [169]:

```
# sensitivity of our logistic regression model

TP/float(TP+FN)
```

Out[169]:

0.8515944399018807

In [170]:

```
# specificity

TN/float(TN+FP)
```

Out[170]:

0.9618437900128041

In [171]:

```
# false positive rate

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

0.038156209987195905

In [172]:

```
#positive predictive value

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

0.9332437275985663

In [173]:

```
#negative predictive value

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

0.9118718135469774

Step 9:Plotting the ROC curve

In [174]:

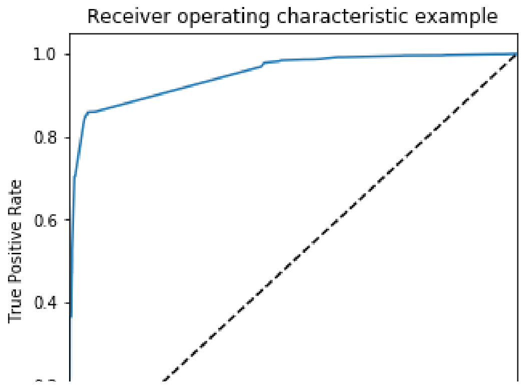
```
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
                                              drop_intermediate = False )
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(5, 5))
    plt.plot( fpr, tpr, label='ROC curve (area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

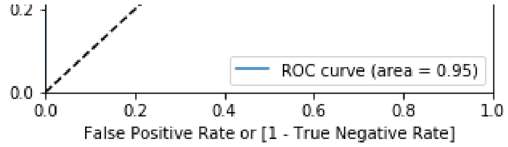
In [175]:

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

In [176]:

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





Step 10:Finding Optimal Cutoff point

In [177]:

```
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[177]:

	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	0	0.188037	3009	0	1	1	0	0	0	0	0	0	0	0
1	0	0.194070	1012	0	1	1	0	0	0	0	0	0	0	0
2	0	0.000805	9226	0	1	0	0	0	0	0	0	0	0	0
3	1	0.782077	4750	1	1	1	1	1	1	1	1	1	0	0
4	1	0.977003	7987	1	1	1	1	1	1	1	1	1	1	1

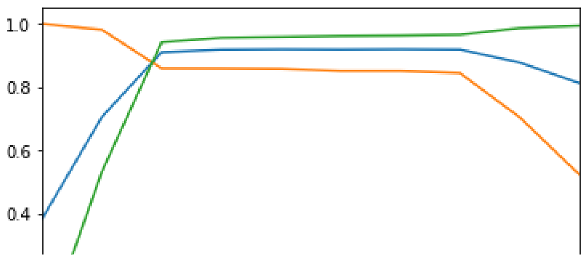
In [178]:

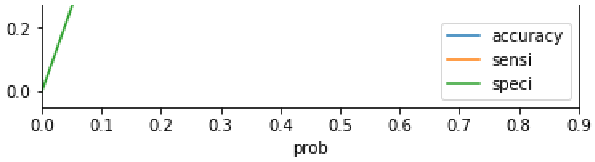
```
cutoff_df = pd.DataFrame( columns = ['prob','accuracy','sensi','speci'])
from sklearn.metrics import confusion_matrix

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  0.385136  1.000000  0.000000
0.1   0.1  0.705873  0.981603  0.533163
0.2   0.2  0.910408  0.859771  0.942125
0.3   0.3  0.918910  0.859362  0.956210
0.4   0.4  0.920013  0.858136  0.958771
0.5   0.5  0.919383  0.851594  0.961844
0.6   0.6  0.920170  0.851594  0.963124
0.7   0.7  0.919225  0.845053  0.965685
0.8   0.8  0.878287  0.705233  0.986684
0.9   0.9  0.813258  0.524530  0.994110
```

In [181]:

```
cutoff_df.plot.line(x='prob', y=['accuracy','sensi','speci'])
plt.show()
```





In [182]:

```
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[182]:

	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	0	0.188037	3009	0	1	1	0	0	0	0	0	0	0	0	0
1	0	0.194070	1012	0	1	1	0	0	0	0	0	0	0	0	0
2	0	0.000805	9226	0	1	0	0	0	0	0	0	0	0	0	0
3	1	0.782077	4750	1	1	1	1	1	1	1	1	1	0	0	1
4	1	0.977003	7987	1	1	1	1	1	1	1	1	1	1	1	1

assigning lead score

In [183]:

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

y_train_pred_final.head()
```

Out[183]:

	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	0	0.188037	3009	0	1	1	0	0	0	0	0	0	0	0	0	19
1	0	0.194070	1012	0	1	1	0	0	0	0	0	0	0	0	0	19
2	0	0.000805	9226	0	1	0	0	0	0	0	0	0	0	0	0	0
3	1	0.782077	4750	1	1	1	1	1	1	1	1	1	0	0	1	78
4	1	0.977003	7987	1	1	1	1	1	1	1	1	1	1	1	1	98

In [184]:

```
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 [185]:

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

Out[185]:

```
0.8597710547833197
```

In [186]:

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

Out[186]:

```
0.9421254801536492
```

In [187]:

```
#false positive rate
print(FP/float(TN/FP))
```

```
13.88312041315575
```

In [188]:

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

```
0.9029626449119794
```

In [189]:

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

```
0.9147190452511188
```

Precision and Recall

In [191]:

```
# looking at confusion matrix again

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

Out[191]:

```
array([[3756,  149],
       [ 363, 2083]], dtype=int64)
```

In [192]:

```
#precision
TP/TP+FP

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

Out[192]:

```
0.9332437275985663
```

In [193]:

```
#recall
TP/TP+FN

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

Out[193]:

```
0.8515944399018807
```

In [194]:

```
### Using sklearn utilities for the same
```

In [195]:

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

In [196]:

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

Out[196]:

```
0.9332437275985663
```

In [197]:

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

Out[197]:

```
0.8515944399018807
```

Precision and recall tradeoff

In [198]:

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

In [199]:

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

Out[199]:

```
(0        0
 1        0
 2        0
 3        1
 4        1
 5        1
 6        0
 7        1
 8        1
 9        0
 10       0
 11       0
 12       0
 13       1
 14       1
 15       1
 16       0
 17       0
 18       0
 19       0
 20       1
 21       0
 22       0
 23       0
 24       1
 25       0
 26       1
 27       1
 28       0
 29       1
         ..
 6321     0
 6322     1
 6323     0
```

```
6323    0
6324    1
6325    0
6326    0
6327    0
6328    1
6329    1
6330    1
6331    0
6332    0
6333    0
6334    0
6335    0
6336    0
6337    0
6338    0
6339    0
6340    0
6341    0
6342    1
6343    0
6344    1
6345    1
6346    0
6347    1
6348    0
6349    0
6350    0
Name: Converted, Length: 6351, dtype: int64, 0       0
1       0
2       0
3       1
4       1
5       1
6       0
7       1
8       1
9       0
10      0
11      0
12      0
13      1
14      1
15      1
16      0
17      0
18      0
19      0
20      1
21      0
22      0
23      0
24      1
25      0
26      0
27      1
28      0
29      1
       ..
6321    0
6322    1
6323    0
6324    1
6325    0
6326    0
6327    0
6328    1
6329    0
6330    1
6331    0
6332    0
6333    0
6334    0
6335    0
6336    0
6337    0
6338    0
6339    0
```

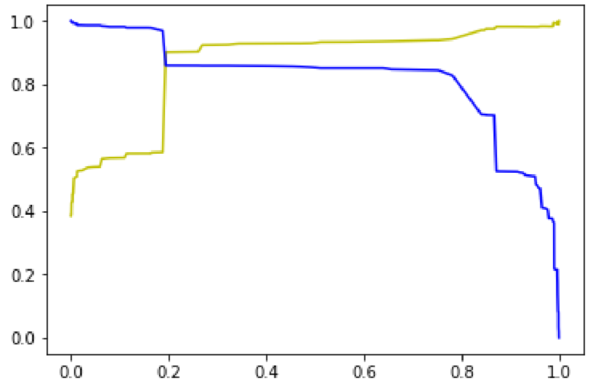
```
6339    0
6340    0
6341    0
6342    1
6343    0
6344    1
6345    1
6346    0
6347    1
6348    0
6349    0
6350    0
Name: predicted, Length: 6351, dtype: int64)
```

In [200]:

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

In [204]:

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



making predictions on the test set

In [205]:

```
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()
```

```
C:\Users\DELL\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645:
DataConversionWarning: Data with input dtype int64, float64 were all converted to float64 by
StandardScaler.
  return self.partial_fit(X, y)
C:\Users\DELL\Anaconda3\lib\site-packages\sklearn\base.py:464: DataConversionWarning: Data with in
put dtype int64, float64 were all converted to float64 by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

Out[205]:

	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_Direct Traffic	Lead Source_Facebook	...	L Act
3009	0	0	-0.432779	-0.160255	-0.155018	1	0	0	1	0	...	
1012	1	0	-0.432779	-0.540048	-0.155018	1	0	0	1	0	...	
9226	0	0	-1.150329	[illegible]	[illegible]	0	0	0	0	0	...	

	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_Direct Traffic	Lead Source_Facebook	...	L Act
				0.888650	1.265540							
4750	0	0	-0.432779	1.643304	[illegible]	1	0	0	1	0	...	
7987	0	0	0.643547	2.017593	0.122613	1	0	0	1	0	...	

5 rows × 81 columns

In [206]:

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

Out[206]:

	Do Not Email	Lead Origin_Lead Add Form	Lead Source_Welingak Website	What is your current occupation_Working Professional	Tags_Busy	Tags_Closed by Horizzon	Tags_Lost to EINS	Tags_Ringing	Tags_Will revert after reading the email	Tags
3271	0	0	0	0	0	0	0	0	1	
1490	0	0	0	1	0	0	0	0	1	
7936	0	0	0	0	0	0	0	0	1	
4216	0	1	0	0	0	1	0	0	0	
3830	0	0	0	0	0	0	0	0	1	

In [207]:

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

In [208]:

```
#making predictiond on the test set

y_test_pred=res.predict(X_test_sm)
```

In [209]:

```
y_test_pred[:10]
```

Out[209]:

```
3271    0.188037
1490    0.961508
7936    0.188037
4216    0.999049
3830    0.188037
1800    0.961508
6507    0.012329
4821    0.000445
4223    0.996691
4714    0.188037
dtype: float64
```

In [210]:

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

In [211]:

```
y_pred_1.head()
```

Out[211]:

	0
3271	0.188037

	0
1490	0.961508
7936	0.188037
4216	0.999049
3830	0.188037

In [212]:

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

In [213]:

```
y_test_df['Prospect ID'] = y_test_df.index
```

In [214]:

```
y_pred_1.reset_index(drop=True, inplace=True)
y_test_df.reset_index(drop=True, inplace=True)
```

In [215]:

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

In [216]:

```
y_pred_final.head()
```

Out[216]:

	Converted	Prospect ID	0
0	0	3271	0.188037
1	1	1490	0.961508
2	0	7936	0.188037
3	1	4216	0.999049
4	0	3830	0.188037

In [217]:

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

In [218]:

```
#rearranging the columns
y_pred_final = y_pred_final.reindex_axis(['Prospect ID','Converted','Converted_prob'], axis=1)
```

In [219]:

```
y_pred_final.head()
```

Out[219]:

	Prospect ID	Converted	Converted_prob
0	3271	0	0.188037
1	1490	1	0.961508
2	7936	0	0.188037
3	4216	1	0.999049
4	3830	0	0.188037

In [220]:

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

In [221]:

```
y_pred_final.head()
```

Out[221]:

	Prospect ID	Converted	Converted_prob	final_predicted
0	3271	0	0.188037	0
1	1490	1	0.961508	1
2	7936	0	0.188037	0
3	4216	1	0.999049	1
4	3830	0	0.188037	0

In [222]:

```
# overall accuracy
metrics.accuracy_score(y_pred_final.Converted, y_pred_final.final_predicted)
```

Out[222]:

```
0.906720528828498
```

In [223]:

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

Out[223]:

```
array([[1635,   99],
       [ 155,  834]], dtype=int64)
```

In [224]:

```
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 [225]:

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

Out[225]:

```
0.8432760364004045
```

In [226]:

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

Out[226]:

```
0.9429065743944637
```

In [ ]:

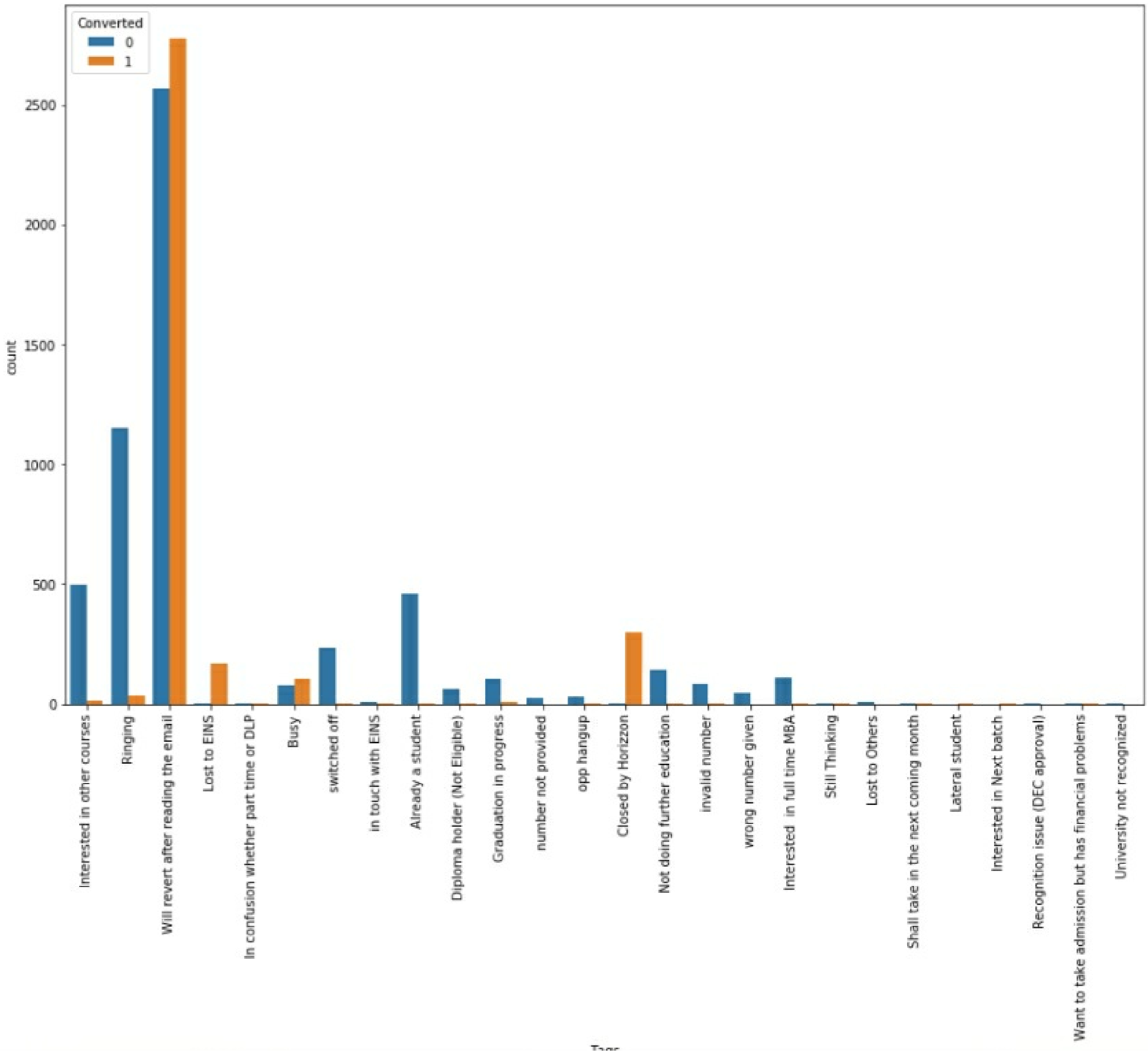
```
# Questions and Answers
```

```
# Questions and Answers
```

1. Which are the top three variables in your model that contribute most towards the probability of a lead getting converted?

Ans:

The features used to build the model have been represented below based on their importance in lead conversion as per their coefficient values.



As per the above diagram,the top 3 variables that contribute most towards the probability of a lead getting converted are:

1. Will revert after reading the email
2. Closed by Horizzon
3. Lost to EINS

2. What are the top 3 categorical/dummy variables in the model which get maximum focus in order to increase the probability of lead conversion?

Ans:

As per the above diagram, the top 3 categorical/dummy variables that contribute the most towards the probability of a lead getting converted are also :

1. Will revert after reading the email
2. Closed by Horizzon
3. Lost to EINS

3. X Education has a period of 2 months every year during which they hire few interns. The sales team, in particular, has

around 10 interns allotted to them. So, during this phase, they wish to make the lead conversion more aggressive. So they want almost all of the potential leads (i.e. the customers who have been predicted as 1 by the model) to be converted and hence, want to make phone calls to as much of such people as possible. Suggest a good strategy they should employ at this stage.

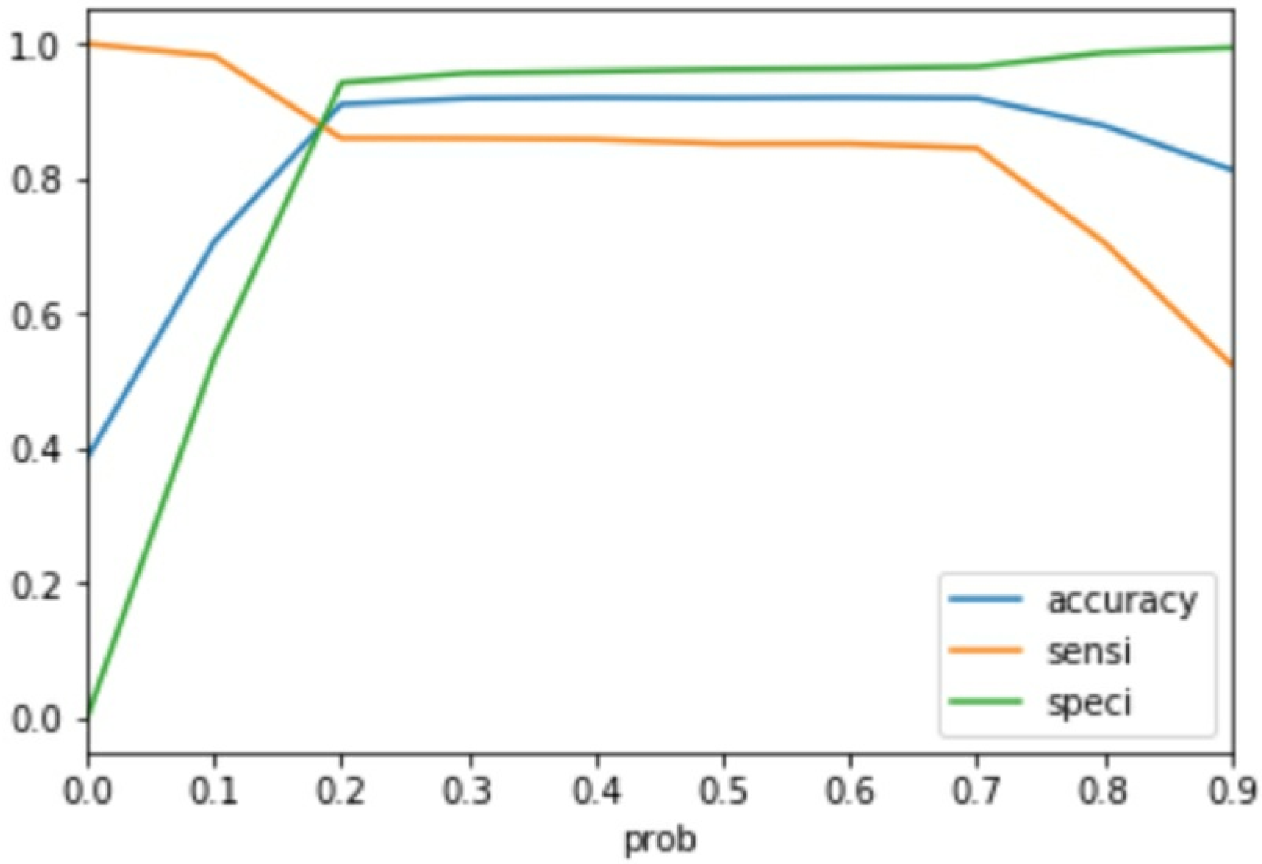
Ans:

Sensitivity with respect to our model can be defined as the ratio of total number of actual Conversions correctly predicted to the total no of actual Conversions.

Similarly, Specificity can be defined as the ratio of total no of actual non-Conversions correctly predicted to the total number of actual non-Conversions.

For a particular model, as one increases, the other decreases and vice versa. Different values of the sensitivity and specificity can be achieved for the same model by changing the Conversion Probability cutoff threshold value.

For our model, the below graph shows how the Sensitivity and Specificity rating changes with change in the threshold value



When the probability thresholds are very low, the sensitivity is very high and specificity is very low. Similarly, for larger probability thresholds, the sensitivity values are very low but the specificity values are very high.

High sensitivity implies that our model will correctly identify almost all leads who are likely to Convert. It will do that by over-estimating the Conversion likelihood, i.e. it will misclassify some non-Conversion cases as Conversions.

Now, since X Education has more man-power for these 2 months and they wish to make the lead conversion more aggressive by wanting almost all of the potential leads, we can choose a lower threshold value for Conversion Probability.

This will ensure the Sensitivity rating is very high which in turn will make sure almost all leads who are likely to Convert are identified correctly and the agents can make phone calls to as much of such people as possible.

4. Similarly, at times, the company reaches its target for a quarter before the deadline. During this time, the company wants the sales team to focus on some new work as well. So during this time, the company's aim is to not make phone calls unless it's extremely necessary, i.e. they want to minimize the rate of useless phone calls. Suggest a strategy they should employ at this stage.

Ans:

Following the similar logic and context from the previous question, High Specificity implies that our model will correctly identify almost all leads who are not likely to Convert. It will do that at the cost of losing out some low Conversion rate risky leads to the competition, i.e. it will misclassify some Conversion cases as non-Conversions.

Therefore, since X Education has already reached its target for a quarter and doesn’t want to make phone calls unless it’s extremely necessary, i.e. they want to minimize the rate of useless phone calls, we can choose a higher threshold value for Conversion Probability.

This will ensure the Specificity rating is very high, which in turn will make sure almost all leads who are on the brink of the probability of getting Converted or not are not selected. As a result the agents won’t have to make unnecessary phone calls and can focus on some new work.

In [ ]:

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