LEAD SCORING CASE STUDY

Problem Statement

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

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

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

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

Goals of the Case Study

- Build a **logistic regression model** to assign a lead score between 0 and 100 to each of the leads which can be used by the company to target potential leads. A higher score would mean that the lead is hot, i.e. is most likely to convert whereas a lower score would mean that the lead is cold and will mostly not get converted.

```
#importing libraries

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

import warnings
warnings.filterwarnings('ignore')

from sklearn.preprocessing import StandardScaler


# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load in

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# Any results you write to the current directory are saved as output.
```

```
/kaggle/input/leads-dataset/Leads Data Dictionary.xlsx
/kaggle/input/leads-dataset/Leads.csv
/kaggle/input/leads-dataset/image.jpg
```

```
#importing dataset to csv

leads=pd.read_csv("/kaggle/input/leads-dataset/Leads.csv")
leads.head()
```

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

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

```
(9240, 37)
```

This dataset has:

- 9240 rows,
- 37 columns

```
#basic data check
leads.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
```

```
leads.describe()
```

	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

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

```
True
```

No duplicate values in Prospect ID

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

```
True
```

No duplicate values in Lead Number

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

EXPLORATORY DATA ANALYSIS

Data Cleaning & Treatment:

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

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

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

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

```
#checking null values in each rows

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

```
Lead Origin                                         0
Lead Source                                        36
Do Not Email                                        0
Do Not Call                                         0
Converted                                           0
TotalVisits                                       137
Total Time Spent on Website                         0
Page Views Per Visit                              137
Last Activity                                     103
Country                                          2461
Specialization                                   3380
How did you hear about X Education               7250
What is your current occupation                  2690
What matters most to you in choosing a course    2709
Search                                              0
Magazine                                            0
Newspaper Article                                   0
X Education Forums                                  0
Newspaper                                           0
Digital Advertisement                               0
Through Recommendations                             0
Receive More Updates About Our Courses              0
Tags                                             3353
Lead Quality                                     4767
Update me on Supply Chain Content                   0
Get updates on DM Content                           0
Lead Profile                                     6855
```

```
City                                             3669
Asymmetrique Activity Index                      4218
Asymmetrique Profile Index                       4218
Asymmetrique Activity Score                      4218
Asymmetrique Profile Score                       4218
I agree to pay the amount through cheque            0
A free copy of Mastering The Interview              0
Last Notable Activity                               0
dtype: int64
```

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

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

```
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
```

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

cols=leads.columns

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

```
#checking null values percentage

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

```
Lead Origin                                       0.00
Lead Source                                       0.39
Do Not Email                                      0.00
Do Not Call                                       0.00
Converted                                         0.00
TotalVisits                                       1.48
Total Time Spent on Website                       0.00
Page Views Per Visit                              1.48
Last Activity                                     1.11
Country                                          26.63
Specialization                                   36.58
What is your current occupation                  29.11
What matters most to you in choosing a course    29.32
Search                                            0.00
Magazine                                          0.00
Newspaper Article                                 0.00
X Education Forums                                0.00
Newspaper                                         0.00
Digital Advertisement                             0.00
Through Recommendations                           0.00
Receive More Updates About Our Courses            0.00
Tags                                             36.29
Update me on Supply Chain Content                 0.00
```

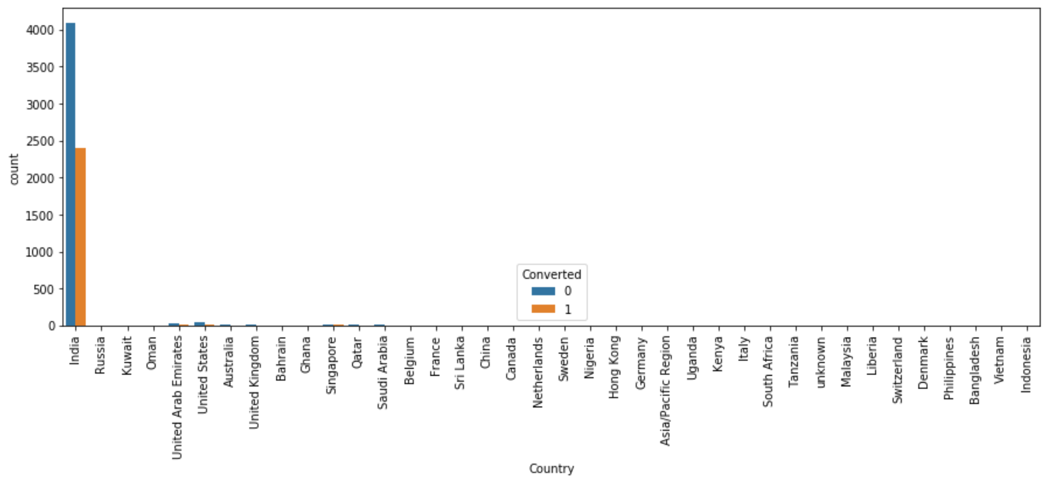
```
Get updates on DM Content                          0.00
City                                              39.71
I agree to pay the amount through cheque           0.00
A free copy of Mastering The Interview             0.00
Last Notable Activity                              0.00
dtype: float64
```

Categorical Attributes Analysis:

```
#checking value counts of Country column

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

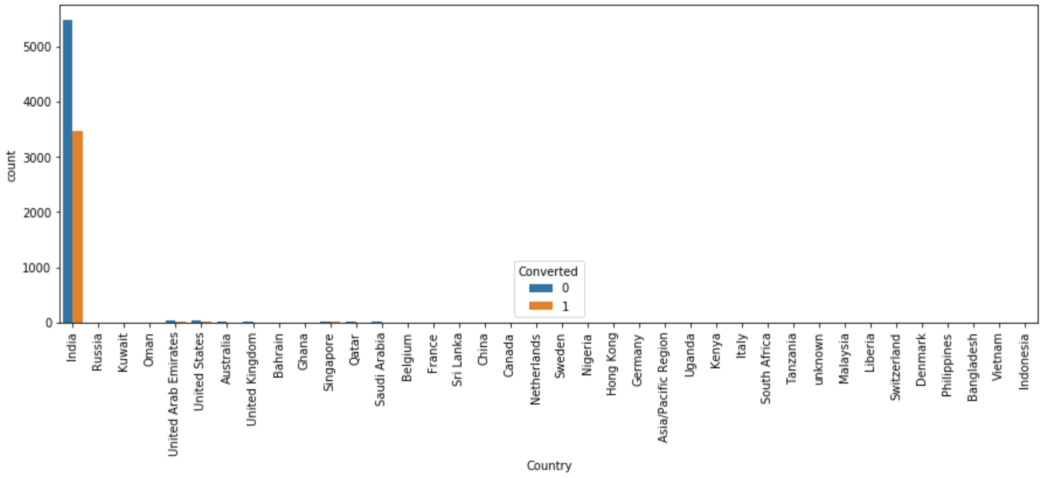
```
India                   6492
NaN                     2461
United States             69
United Arab Emirates      53
Singapore                 24
Saudi Arabia              21
United Kingdom            15
Australia                 13
Qatar                     10
Bahrain                    7
Hong Kong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

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



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

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

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

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



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

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

cols_to_drop=['Country']
```

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

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

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

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

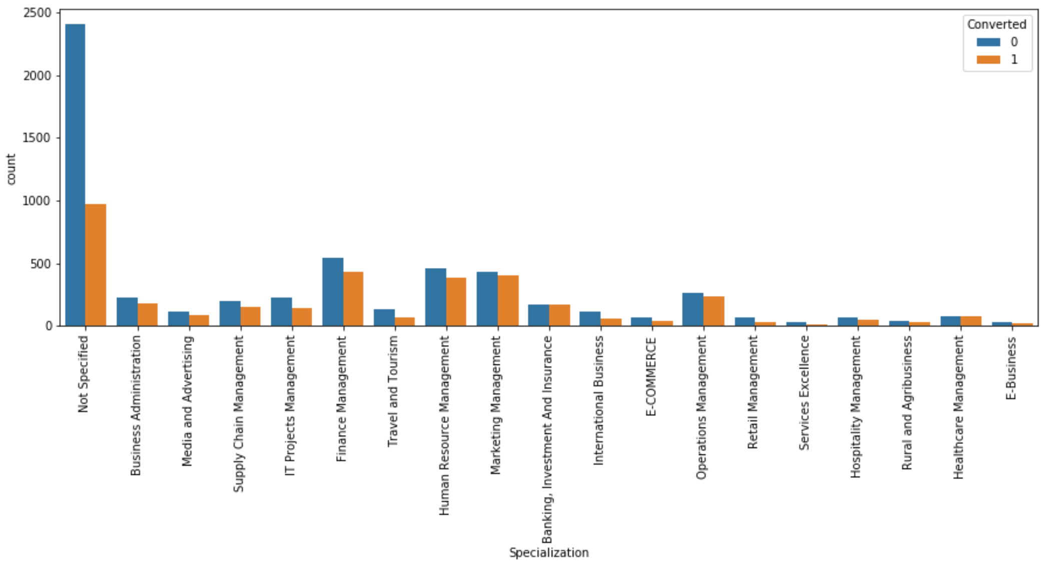
```
#plotting spread of City columnn after replacing NaN values

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


```
#checking value counts of Specialization column

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

```
NaN                                  3380
Finance Management                    976
Human Resource Management             848
Marketing Management                  838
Operations Management                 503
Business Administration               403
IT Projects Management                366
Supply Chain Management               349
Banking, Investment And Insurance     338
Media and Advertising                 203
Travel and Tourism                    203
International Business                178
Healthcare Management                 159
Hospitality Management                114
E-COMMERCE                            112
Retail Management                     100
Rural and Agribusiness                 73
E-Business                             57
Services Excellence                    40
Name: Specialization, dtype: int64
```

```
# Lead may not have mentioned specialization because it was not in the list or maybe they are a students
# and don't have a specialization yet. So we will replace NaN values here with 'Not Specified'

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

```
#plotting spread of Specialization columnn

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

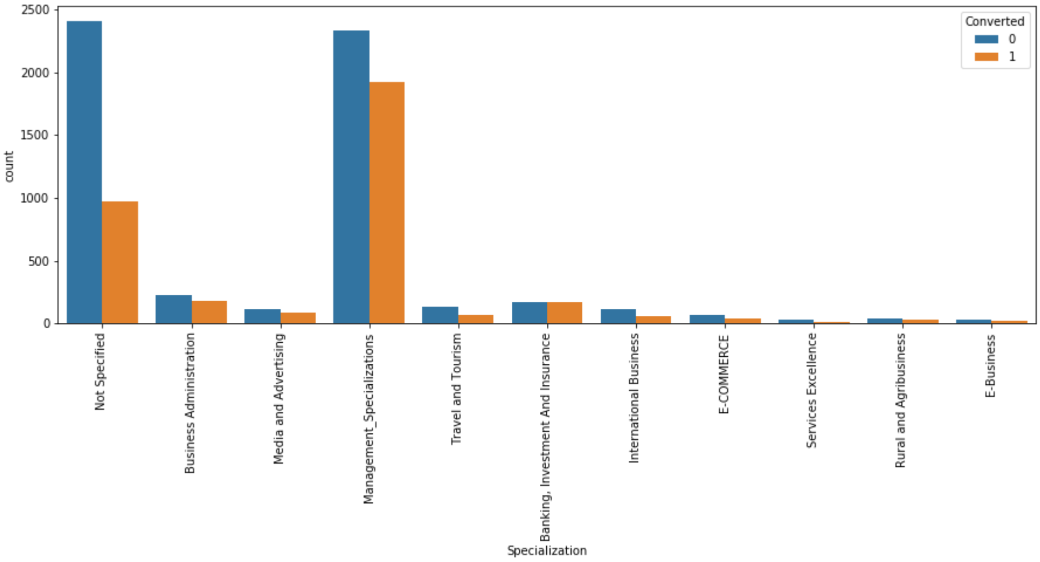


We see that specialization with **Management** in them have higher number of leads as well as leads converted. So this is definitely a significant variable and should not be dropped.

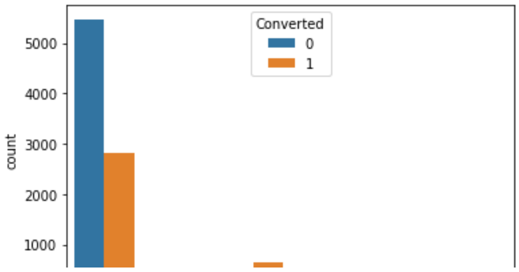
```
#combining Management Specializations because they show similar trends

leads['Specialization'] = leads['Specialization'].replace(['Finance Management','Human Resource Management',
                                                           'Marketing Management','Operations Management',
                                                           'IT Projects Management','Supply Chain Management',
```

```
                                                  'Healthcare Management','Hospitality Management',
                                                        'Retail Management'] ,'Management_Specializations')
```

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


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




```
#What is your current occupation

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

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


#imputing Nan values with mode "Unemployed"

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


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

    Unemployed              8290
    Working Professional     706
    Student                  210
    Other                     16
    Housewife                 10
    Businessman                8
    Name: What is your current occupation, dtype: int64


#visualizing count of Variable based on Converted value

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



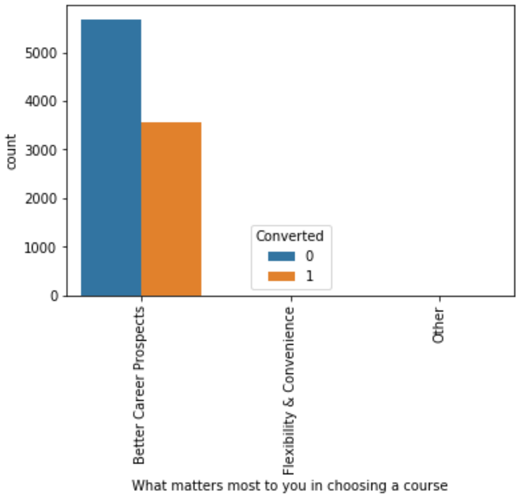
- Working Professionals going for the course have high chances of joining it.
- Unemployed leads are the most in terms of Absolute numbers.

```
#checking value counts

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

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

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

leads['What matters most to you in choosing a course'] = leads['What matters most to you in choosing a course'].replace(np.nan,'Better Ca
```

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

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




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

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

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

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

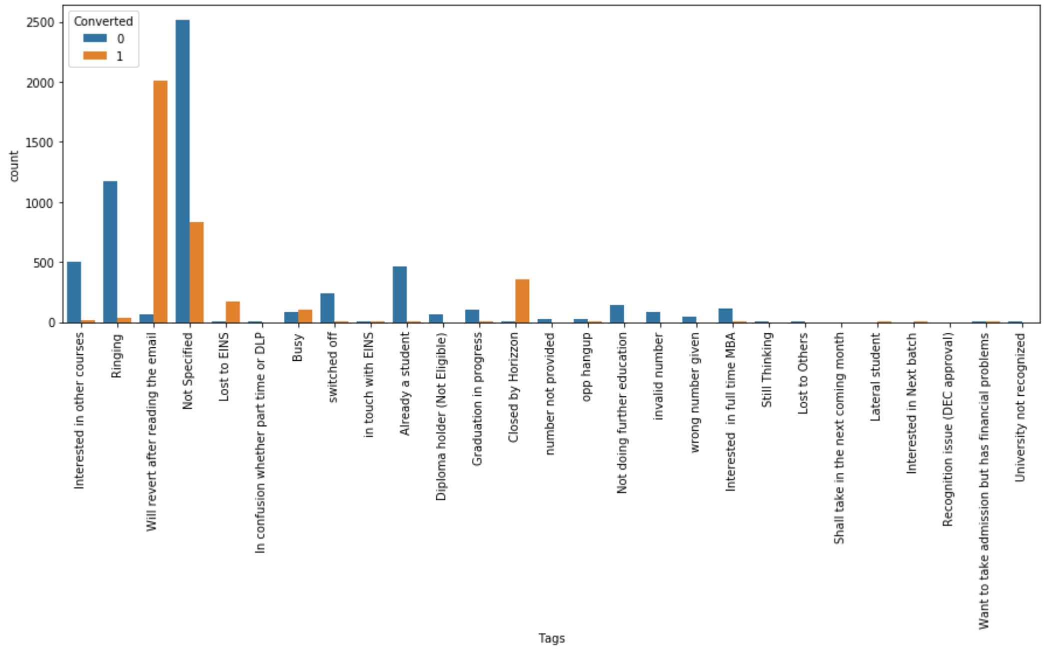
```
#checking value counts of Tag variable
leads['Tags'].value_counts(dropna=False)
```

```
NaN                                                  3353
Will revert after reading the email                  2072
Ringing                                              1203
Interested in other courses                           513
Already a student                                     465
Closed by Horizzon                                    358
```

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

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

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

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




```
#replacing tags with low frequency with "Other Tags"
leads['Tags'] = leads['Tags'].replace(['In confusion whether part time or DLP', 'in touch with EINS','Diploma holder (Not Eligible)',
                                     'Approached upfront','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')

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

```
#checking percentage of missing values
round(100*(leads.isnull().sum()/len(leads.index)), 2)
```

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

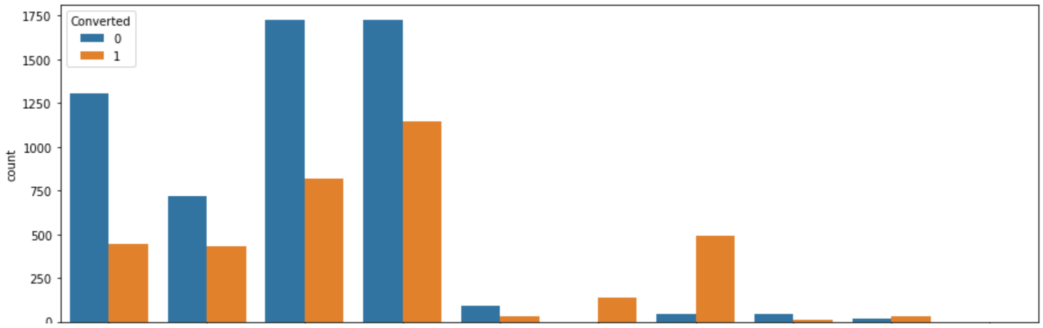
```
#checking value counts of Lead Source column

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

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

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

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

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



- Inference
  - Maximum number of leads are generated by Google and Direct traffic.
  - Conversion Rate of reference leads and leads through welingak website is high.
  - To improve overall lead conversion rate, focus should be on improving lead converion of olark chat, organic search, direct traffic, and google leads and generate more leads from reference and welingak website.

```
# Last Activity:

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

```
Email Opened                   3437
SMS Sent                       2745
Olark Chat Conversation         973
Page Visited on Website         640
Converted to Lead               428
Email Bounced                   326
Email Link Clicked              267
Form Submitted on Website       116
NaN                             103
Unreachable                      93
Unsubscribed                     61
Had a Phone Conversation         30
Approached upfront                9
View in browser link Clicked      6
Email Marked Spam                 2
Email Received                    2
Visited Booth in Tradeshow        1
Resubscribed to emails            1
Name: Last Activity, dtype: int64
```

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

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

```
# Last Activity:

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

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

```
#Check the Null Values in All Columns:
round(100*(leads.isnull().sum()/len(leads.index)), 2)
```

```
Lead Origin                                    0.00
Lead Source                                    0.00
Do Not Email                                   0.00
Do Not Call                                    0.00
Converted                                      0.00
TotalVisits                                    1.48
Total Time Spent on Website                    0.00
```

```
Page Views Per Visit                             1.48
Last Activity                                    0.00
Country                                          0.00
Specialization                                   0.00
What is your current occupation                  0.00
What matters most to you in choosing a course    0.00
Search                                           0.00
Magazine                                         0.00
Newspaper Article                                0.00
X Education Forums                               0.00
Newspaper                                        0.00
Digital Advertisement                            0.00
Through Recommendations                          0.00
Receive More Updates About Our Courses           0.00
Tags                                             0.00
Update me on Supply Chain Content                0.00
Get updates on DM Content                        0.00
City                                             0.00
I agree to pay the amount through cheque         0.00
A free copy of Mastering The Interview           0.00
Last Notable Activity                            0.00
dtype: float64
```

```
#Drop all rows which have Nan Values. Since the number of Dropped rows is less than 2%, it will not affect the model
leads = leads.dropna()
```

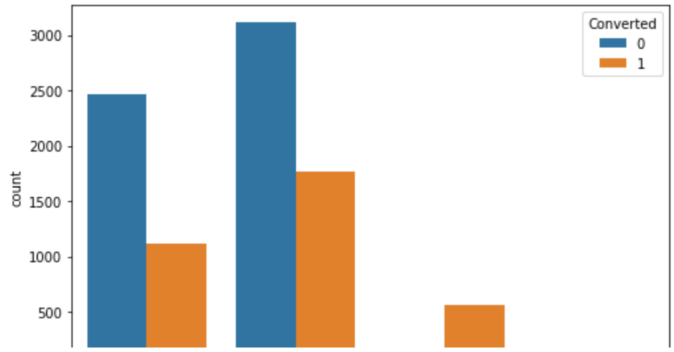
```
#Checking percentage of Null Values in All Columns:
round(100*(leads.isnull().sum()/len(leads.index)), 2)
```

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

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

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

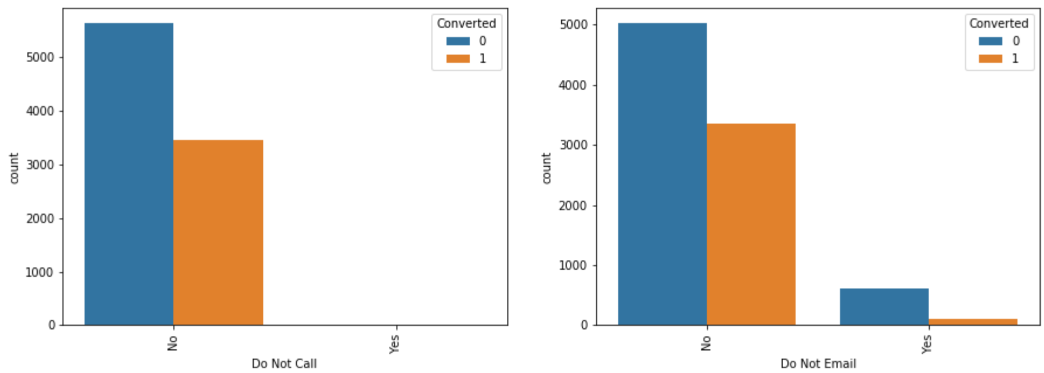
```
#visualizing count of Variable based on Converted value

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



Inference

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

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

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

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

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




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

```
No     9101
Yes       2
Name: Do Not Call, dtype: int64
```

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

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

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

```
cols_to_drop.append('Do Not Call')
cols_to_drop
```

```
['Country', 'What matters most to you in choosing a course', 'Do Not Call']
```

```
# IMBALANCED VARIABLES THAT CAN BE DROPPED
```

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

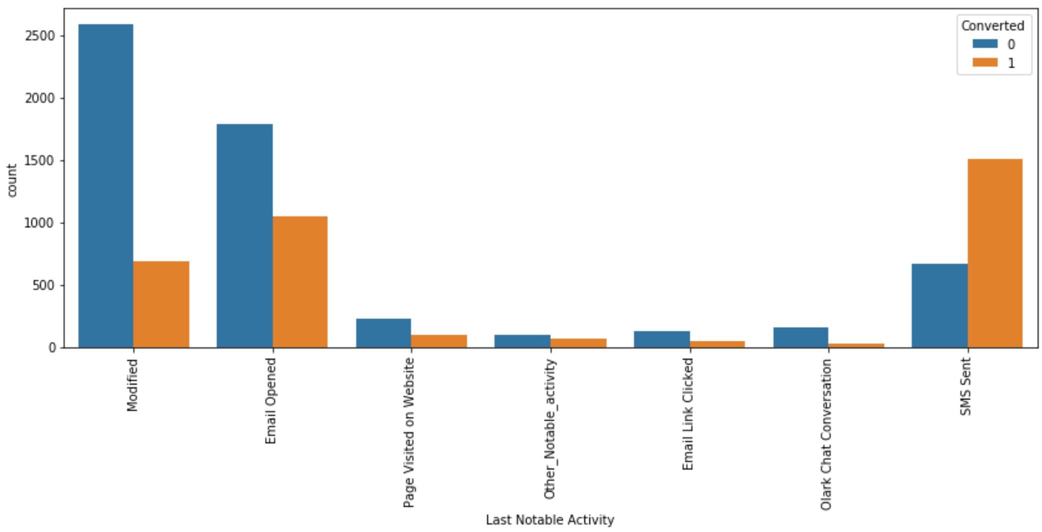
```
#adding imbalanced columns to the list of columns to be dropped

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

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

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

```
#clubbing lower frequency values

leads['Last Notable Activity'] = leads['Last Notable Activity'].replace(['Had a Phone Conversation',
                                                                        'Email Marked Spam',
                                                                          'Unreachable',
                                                                          'Unsubscribed',
                                                                          'Email Bounced',
                                                                        'Resubscribed to emails',
                                                                        'View in browser link Clicked',
                                                                        'Approached upfront',
                                                                        'Form Submitted on Website',
                                                                        'Email Received'],'Other_Notable_activity')
```

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

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




```
#checking value counts for variable

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

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

```
#list of columns to be dropped
cols_to_drop
```

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

```
#dropping columns
leads = leads.drop(cols_to_drop,1)
leads.info()
```

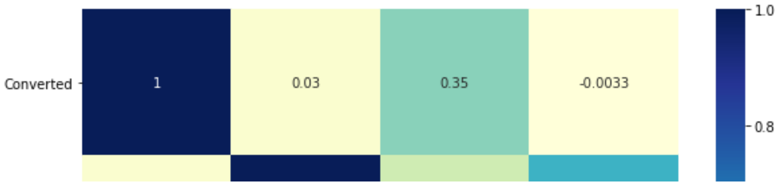
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9103 entries, 0 to 9239
Data columns (total 14 columns):
Lead Origin                               9103 non-null object
Lead Source                               9103 non-null object
Do Not Email                              9103 non-null object
Converted                                 9103 non-null int64
TotalVisits                               9103 non-null float64
Total Time Spent on Website               9103 non-null int64
Page Views Per Visit                      9103 non-null float64
Last Activity                             9103 non-null object
Specialization                            9103 non-null object
What is your current occupation           9103 non-null object
Tags                                      9103 non-null object
City                                      9103 non-null object
A free copy of Mastering The Interview    9103 non-null object
Last Notable Activity                     9103 non-null object
dtypes: float64(2), int64(2), object(10)
memory usage: 1.4+ MB
```

Numerical Attributes Analysis:

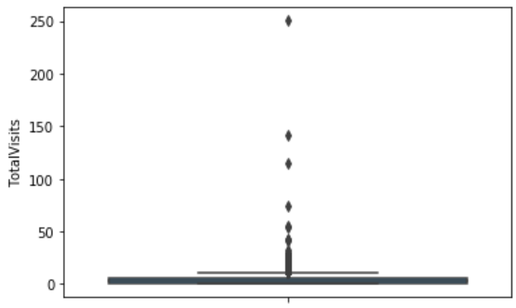
```
#Check the % of Data that has Converted Values = 1:

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

```
38.02043282434362
```

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

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




```
#Total Visits
#visualizing spread of variable

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

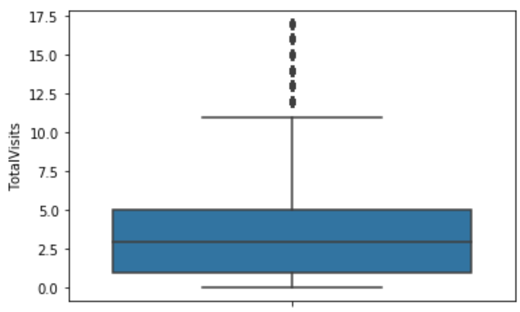


We can see presence of outliers here

```
#checking percentile values for "Total Visits"

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

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

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

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




```
leads.shape
```

```
(9020, 14)
```

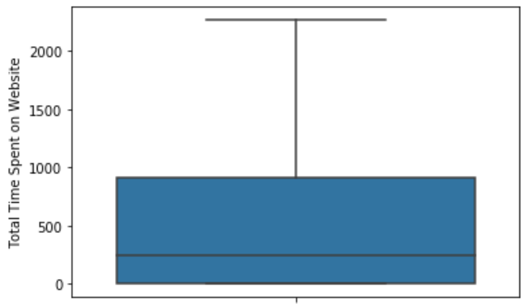
Check for the Next Numerical Column:

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

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

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

```
#visualizing spread of numeric variable

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



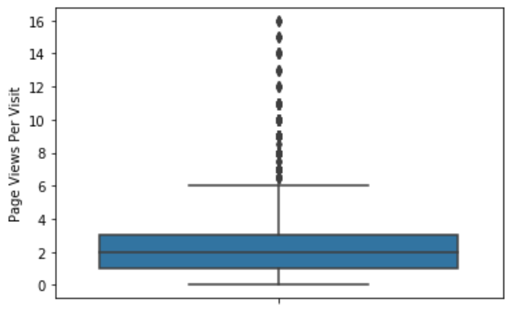
Since there are no major Outliers for the above variable we don't do any Outlier Treatment for this above Column

Check for Page Views Per Visit:

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

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

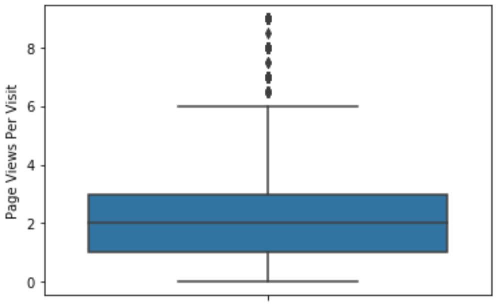
```
count    9020.000000
mean        2.337271
std         2.062363
min         0.000000
25%         1.000000
50%         2.000000
75%         3.000000
max        16.000000
Name: Page Views Per Visit, dtype: float64
```

```
#visualizing spread of numeric variable

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




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

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

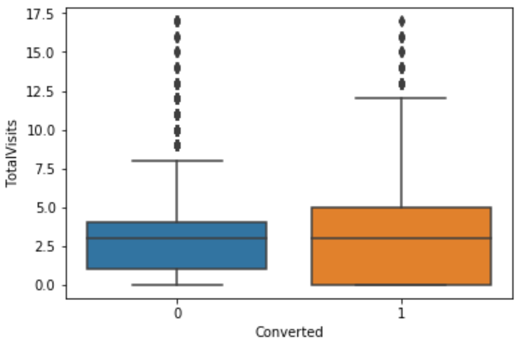
```
sns.boxplot(y=leads['Page Views Per Visit'])
plt.show()
```




```
leads.shape
```

    (8953, 14)

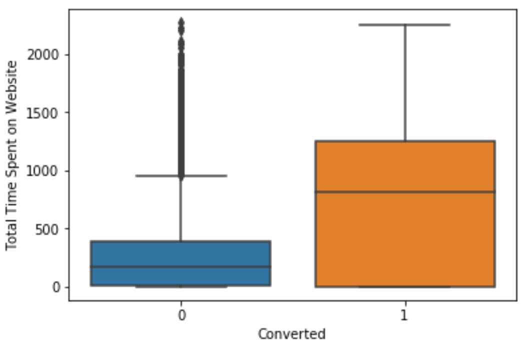
```
#checking Spread of "Total Visits" vs Converted variable
sns.boxplot(y = 'TotalVisits', x = 'Converted', data = leads)
plt.show()
```



Inference

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

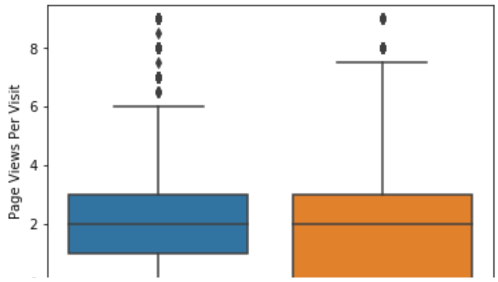
```
#checking Spread of "Total Time Spent on Website" vs Converted variable

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



Inference

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

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

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



Inference

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

```
#checking missing values in leftover columns/

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

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

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

Dummy Variable Creation:

```
#getting a list of categorical columns

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

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

```
# List of variables to map

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

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

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

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

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

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

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

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


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


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


#dropping the original columns after dummy variable creation

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


leads.head()
```

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

5 rows × 57 columns

Train-Test Split & Logistic Regression Model Building:

```
from sklearn.model_selection import train_test_split

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

y.head()

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


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


X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6267 entries, 9196 to 5825
Data columns (total 56 columns):
TotalVisits                                          6267 non-null float64
Total Time Spent on Website                          6267 non-null int64
Page Views Per Visit                                 6267 non-null float64
Lead Origin_Landing Page Submission                  6267 non-null uint8
Lead Origin_Lead Add Form                            6267 non-null uint8
Lead Origin_Lead Import                              6267 non-null uint8
What is your current occupation_Housewife            6267 non-null uint8
What is your current occupation_Other                6267 non-null uint8
What is your current occupation_Student              6267 non-null uint8
What is your current occupation_Unemployed           6267 non-null uint8
What is your current occupation_Working Professional    6267 non-null uint8
City_Other Cities                                    6267 non-null uint8
City_Other Cities of Maharashtra                     6267 non-null uint8
City_Other Metro Cities                              6267 non-null uint8
City_Thane & Outskirts                               6267 non-null uint8
City_Tier II Cities                                  6267 non-null uint8
Specialization_Banking, Investment And Insurance     6267 non-null uint8
Specialization_Business Administration               6267 non-null uint8
Specialization_E-Business                            6267 non-null uint8
Specialization_E-COMMERCE                            6267 non-null uint8
Specialization_International Business                6267 non-null uint8
Specialization_Management_Specializations            6267 non-null uint8
Specialization_Media and Advertising                 6267 non-null uint8
```

```
Specialization_Rural and Agribusiness                  6267 non-null uint8
Specialization_Services Excellence                     6267 non-null uint8
Specialization_Travel and Tourism                      6267 non-null uint8
Lead Source_Direct Traffic                             6267 non-null uint8
Lead Source_Google                                     6267 non-null uint8
Lead Source_Live Chat                                  6267 non-null uint8
Lead Source_Olark Chat                                 6267 non-null uint8
Lead Source_Organic Search                             6267 non-null uint8
Lead Source_Reference                                  6267 non-null uint8
Lead Source_Referral Sites                             6267 non-null uint8
Lead Source_Social Media                               6267 non-null uint8
Lead Source_Welingak Website                           6267 non-null uint8
Last Activity_Converted to Lead                        6267 non-null uint8
Last Activity_Email Bounced                            6267 non-null uint8
Last Activity_Email Link Clicked                       6267 non-null uint8
Last Activity_Email Opened                             6267 non-null uint8
Last Activity_Form Submitted on Website                6267 non-null uint8
Last Activity_Olark Chat Conversation                  6267 non-null uint8
Last Activity_Page Visited on Website                  6267 non-null uint8
Last Activity_SMS Sent                                 6267 non-null uint8
Last Notable Activity_Email Link Clicked               6267 non-null uint8
Last Notable Activity_Email Opened                     6267 non-null uint8
Last Notable Activity_Modified                         6267 non-null uint8
Last Notable Activity_Olark Chat Conversation          6267 non-null uint8
Last Notable Activity_Page Visited on Website          6267 non-null uint8
Last Notable Activity_SMS Sent                         6267 non-null uint8
Tags_Busy                                              6267 non-null uint8
Tags_Closed by Horizzon                                6267 non-null uint8
Tags_Interested in other courses                       6267 non-null uint8
Tags_Lost to EINS                                      6267 non-null uint8
Tags_Other_Tags                                        6267 non-null uint8
```

Scaling of Data:

```
#scaling numeric columns

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

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

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

X_train.head()
```

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

5 rows × 56 columns

Model Building using Stats Model & RFE:

```
import statsmodels.api as sm


from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()

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


rfe.support_
```

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

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

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

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

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

```
Index(['Total Time Spent on Website', 'Lead Origin_Lead Add Form',
       'Lead Source_Direct Traffic', 'Lead Source_Referral Sites',
       'Lead Source_Welingak Website', 'Last Activity_SMS Sent',
       'Last Notable Activity_Modified',
       'Last Notable Activity_Olark Chat Conversation',
       'Last Notable Activity_SMS Sent', 'Tags_Closed by Horizzon',
       'Tags_Interested in other courses', 'Tags_Lost to EINS',
       'Tags_Other_Tags', 'Tags_Ringing',
       'Tags_Will revert after reading the email'],
      dtype='object')
```

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

```
Index(['TotalVisits', 'Page Views Per Visit',
       'Lead Origin_Landing Page Submission', 'Lead Origin_Lead Import',
       'What is your current occupation_Housewife',
       'What is your current occupation_Other',
       'What is your current occupation_Student',
       'What is your current occupation_Unemployed',
```

```
        'What is your current occupation_Working Professional',
        'City_Other Cities', 'City_Other Cities of Maharashtra',
        'City_Other Metro Cities', 'City_Thane & Outskirts',
        'City_Tier II Cities',
        'Specialization_Banking, Investment And Insurance',
        'Specialization_Business Administration', 'Specialization_E-Business',
        'Specialization_E-COMMERCE', 'Specialization_International Business',
        'Specialization_Management_Specializations',
        'Specialization_Media and Advertising',
        'Specialization_Rural and Agribusiness',
        'Specialization_Services Excellence',
        'Specialization_Travel and Tourism', 'Lead Source_Google',
        'Lead Source_Live Chat', 'Lead Source_Olark Chat',
        'Lead Source_Organic Search', 'Lead Source_Reference',
        'Lead Source_Social Media', 'Last Activity_Converted to Lead',
        'Last Activity_Email Bounced', 'Last Activity_Email Link Clicked',
        'Last Activity_Email Opened', 'Last Activity_Form Submitted on Website',
        'Last Activity_Olark Chat Conversation',
        'Last Activity_Page Visited on Website',
        'Last Notable Activity_Email Link Clicked',
        'Last Notable Activity_Email Opened',
        'Last Notable Activity_Page Visited on Website', 'Tags_Busy'],
       dtype='object')
```

```
#BUILDING MODEL #1

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

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6267
Model:	GLM	**Df Residuals:**	6251
Model Family:	Binomial	**Df Model:**	15
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1254.7
Date:	Tue, 03 Sep 2019	**Deviance:**	2509.3
Time:	13:06:29	**Pearson chi2:**	8.34e+03
No. Iterations:	8		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.1899	0.088	-13.480	0.000	-1.363	-1.017
Total Time Spent on Website	0.8970	0.053	16.999	0.000	0.794	1.000
Lead Origin_Lead Add Form	1.6712	0.450	3.714	0.000	0.789	2.553
Lead Source_Direct Traffic	-0.8320	0.129	-6.471	0.000	-1.084	-0.580
Lead Source_Referral Sites	-0.5284	0.465	-1.138	0.255	-1.439	0.382
Lead Source_Welingak Website	3.9043	1.110	3.518	0.000	1.729	6.079
Last Activity_SMS Sent	1.2373	0.223	5.555	0.000	0.801	1.674
Last Notable Activity_Modified	-1.2839	0.150	-8.532	0.000	-1.579	-0.989
Last Notable Activity_Olark Chat Conversation	-1.7123	0.490	-3.496	0.000	-2.672	-0.752
Last Notable Activity_SMS Sent	1.0151	0.257	3.943	0.000	0.511	1.520
Tags_Closed by Horizzon	6.9834	1.019	6.853	0.000	4.986	8.981
Tags_Interested in other courses	-2.1641	0.407	-5.321	0.000	-2.961	-1.367
Tags_Lost to EINS	5.7302	0.608	9.419	0.000	4.538	6.923
Tags_Other_Tags	-2.4417	0.210	-11.633	0.000	-2.853	-2.030
Tags_Ringing	-3.5858	0.243	-14.752	0.000	-4.062	-3.109
Tags_Will revert after reading the email	4.4263	0.185	23.989	0.000	4.065	4.788

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

```
#dropping column with high p-value

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

```
#BUILDING MODEL #2

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

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6267
Model:	GLM	**Df Residuals:**	6252
Model Family:	Binomial	**Df Model:**	14
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1255.3
Date:	Tue, 03 Sep 2019	**Deviance:**	2510.7
Time:	13:06:29	**Pearson chi2:**	8.34e+03
No. Iterations:	8		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.2029	0.088	-13.729	0.000	-1.375	-1.031
Total Time Spent on Website	0.8963	0.053	16.979	0.000	0.793	1.000
Lead Origin_Lead Add Form	1.6795	0.450	3.735	0.000	0.798	2.561
Lead Source_Direct Traffic	-0.8224	0.128	-6.409	0.000	-1.074	-0.571
Lead Source_Welingak Website	3.9060	1.110	3.520	0.000	1.731	6.081
Last Activity_SMS Sent	1.2437	0.223	5.584	0.000	0.807	1.680
Last Notable Activity_Modified	-1.2791	0.150	-8.501	0.000	-1.574	-0.984
Last Notable Activity_Olark Chat Conversation	-1.7079	0.489	-3.491	0.000	-2.667	-0.749
Last Notable Activity_SMS Sent	1.0150	0.257	3.943	0.000	0.510	1.520

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

Tags_Lost to EINS 5.7337 0.608 9.426 0.000 4.541 6.926

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

Tags_Will revert after reading the email 4.4234 0.184 23.993 0.000 4.062 4.785

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

	Features	VIF
7	Last Notable Activity_SMS Sent	6.22
4	Last Activity_SMS Sent	6.12
1	Lead Origin_Lead Add Form	1.82
5	Last Notable Activity_Modified	1.69
13	Tags_Will revert after reading the email	1.61
2	Lead Source_Direct Traffic	1.38
3	Lead Source_Welingak Website	1.34
11	Tags_Other_Tags	1.26
0	Total Time Spent on Website	1.22
8	Tags_Closed by Horizzon	1.21
12	Tags_Ringing	1.18
9	Tags_Interested in other courses	1.13
10	Tags_Lost to EINS	1.06
6	Last Notable Activity_Olark Chat Conversation	1.01

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

```
#dropping variable with high VIF

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

```
#BUILDING MODEL #3
X_train_sm = sm.add_constant(X_train[col])
logm3 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm3.fit()
res.summary()
```

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6267
Model:	GLM	**Df Residuals:**	6253
Model Family:	Binomial	**Df Model:**	13
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1263.3
Date:	Tue, 03 Sep 2019	**Deviance:**	2526.6
Time:	13:06:30	**Pearson chi2:**	8.51e+03
No. Iterations:	8		
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-1.1179	0.084	-13.382	0.000	-1.282	-0.954
Total Time Spent on Website	0.8896	0.053	16.907	0.000	0.786	0.993
Lead Origin_Lead Add Form	1.6630	0.455	3.657	0.000	0.772	2.554
Lead Source_Direct Traffic	-0.8212	0.127	-6.471	0.000	-1.070	-0.572
Lead Source_Welingak Website	3.8845	1.114	3.488	0.000	1.701	6.068
Last Activity_SMS Sent	1.9981	0.113	17.718	0.000	1.777	2.219
Last Notable Activity_Modified	-1.6525	0.124	-13.279	0.000	-1.896	-1.409
Last Notable Activity_Olark Chat Conversation	-1.8023	0.491	-3.669	0.000	-2.765	-0.839
Tags_Closed by Horizzon	7.1955	1.020	7.053	0.000	5.196	9.195
Tags_Interested in other courses	-2.1318	0.406	-5.253	0.000	-2.927	-1.336

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

	Features	VIF
1	Lead Origin_Lead Add Form	1.82
12	Tags_Will revert after reading the email	1.56
4	Last Activity_SMS Sent	1.46
5	Last Notable Activity_Modified	1.40
2	Lead Source_Direct Traffic	1.38
3	Lead Source_Welingak Website	1.34
10	Tags_Other_Tags	1.25
0	Total Time Spent on Website	1.22
7	Tags_Closed by Horizzon	1.21
11	Tags_Ringing	1.16
8	Tags_Interested in other courses	1.12
9	Tags_Lost to EINS	1.06
6	Last Notable Activity_Olark Chat Conversation	1.01

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

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

```
9196    0.283149
4696    0.031440
3274    0.576636
2164    0.006433
1667    0.989105
7024    0.130813
8018    0.024219
778     0.205594
6942    0.002678
4440    0.096716
dtype: float64
```

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

```
array([0.28314859, 0.0314396 , 0.57663553, 0.00643284, 0.98910464,
       0.13081306, 0.02421913, 0.20559401, 0.00267787, 0.09671623])
```

```
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()
```

	Converted	Converted_prob	Prospect ID
0	1	0.283149	9196
1	0	0.031440	4696
2	0	0.576636	3274
3	0	0.006433	2164
4	1	0.989105	1667

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

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

	Converted	Converted_prob	Prospect ID	Predicted
0	1	0.283149	9196	0
1	0	0.031440	4696	0
2	0	0.576636	3274	1
3	0	0.006433	2164	0
4	1	0.989105	1667	1

```
from sklearn import metrics

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

```
[[3693  189]
 [ 281 2104]]
```

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

```
0.9250039891495133
```

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

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

```
0.8821802935010482
```

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

```
0.9513137557959814
```

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

```
0.04868624420401855
```

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

```
0.9175752289576974
```

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

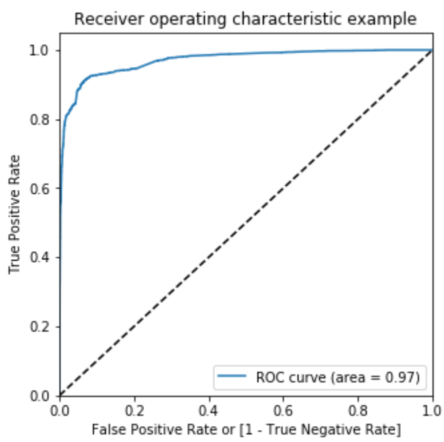
```
0.9292903875188727
```

PLOTTING ROC CURVE

```
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
```

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

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



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

Finding Optimal Cutoff Point

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

```
# Let's create columns with different probability cutoffs
numbers = [float(x)/10 for x in range(10)]
for i in numbers:
    y_train_pred_final[i]= y_train_pred_final.Converted_prob.map(lambda x: 1 if x > i else 0)
y_train_pred_final.head()
```

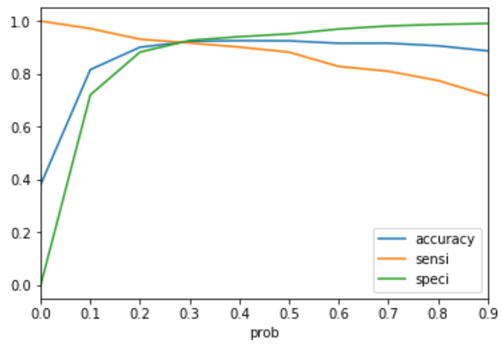
	Converted	Converted_prob	Prospect ID	Predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	1	0.283149	9196	0	1	1	1	0	0	0	0	0	0	0
1	0	0.031440	4696	0	1	0	0	0	0	0	0	0	0	0
2	0	0.576636	3274	1	1	1	1	1	1	1	0	0	0	0
3	0	0.006433	2164	0	1	0	0	0	0	0	0	0	0	0
4	1	0.989105	1667	1	1	1	1	1	1	1	1	1	1	1

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

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

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

```
    total1=sum(sum(cm1))
    accuracy = (cm1[0,0]+cm1[1,1])/total1

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

```
     prob  accuracy     sensi     speci
0.0   0.0  0.380565  1.000000  0.000000
0.1   0.1  0.816180  0.971488  0.720762
0.2   0.2  0.901069  0.931237  0.882535
0.3   0.3  0.922930  0.916981  0.926584
0.4   0.4  0.925802  0.901468  0.940752
0.5   0.5  0.925004  0.882180  0.951314
0.6   0.6  0.915909  0.828092  0.969861
0.7   0.7  0.916228  0.810063  0.981453
0.8   0.8  0.906335  0.774843  0.987120
0.9   0.9  0.887027  0.718239  0.990726
```

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




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

y_train_pred_final['final_Predicted'] = y_train_pred_final.Converted_prob.map( lambda x: 1 if x > 0.3 else 0)

y_train_pred_final.head()
```

	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	fin
0	1	0.283149	9196	0	1	1	1	0	0	0	0	0	0	0	
1	0	0.031440	4696	0	1	0	0	0	0	0	0	0	0	0	
2	0	0.576636	3274	1	1	1	1	1	1	1	0	0	0	0	
3	0	0.006433	2164	0	1	0	0	0	0	0	0	0	0	0	
4	1	0.989105	1667	1	1	1	1	1	1	1	1	1	1	1	

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

y_train_pred_final[['Converted','Converted_prob','Prospect ID','final_Predicted','Lead_Score']].head()
```

	Converted	Converted_prob	Prospect ID	final_Predicted	Lead_Score
0	1	0.283149	9196	0	28
1	0	0.031440	4696	0	3
2	0	0.576636	3274	1	58
3	0	0.006433	2164	0	1
4	1	0.989105	1667	1	99

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

```
0.922929631402585
```

```
confusion2 = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final.final_Predicted )
confusion2
```

```
array([[3597,  285],
       [ 198, 2187]])
```

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

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

```
0.9169811320754717
```

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

```
0.9265842349304482
```

Observation:

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

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

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

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

```
0.07341576506955177
```

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

```
0.8847087378640777
```

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

```
0.9478260869565217
```

```
#Looking at the confusion matrix again

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

```
array([[3597,  285],
       [ 198, 2187]])
```

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

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

```
0.8847087378640777
```

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

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

```
0.9169811320754717
```

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

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

```
0.8847087378640777
```

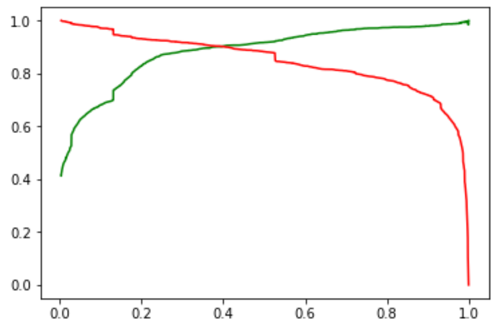
```
recall_score(y_train_pred_final.Converted, y_train_pred_final.final_Predicted)
```

    0.9169811320754717

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

```
y_train_pred_final.Converted, y_train_pred_final.final_Predicted
p, r, thresholds = precision_recall_curve(y_train_pred_final.Converted, y_train_pred_final.Converted_prob)
```

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




```
#scaling test set
```

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

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

```
X_test.head()
```

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

5 rows × 56 columns

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

	Total Time Spent on Website	Lead Origin_Lead Add Form	Lead Source_Direct Traffic	Lead Source_Welingak Website	Last Activity_SMS Sent	Last Notable Activity_Modified	Last Nc Activity_ Convers
7681	-0.311318	0	1	0	1	0	
984	-0.550262	0	0	0	1	1	
8135	0.812462	0	1	0	1	0	
6915	-0.628665	0	0	0	0	0	
2712	-0.421456	0	0	0	0	0	

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

PREDICTIONS ON TEST SET

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

```
y_test_pred[:10]
```

```
7681    0.024819
984     0.025692
8135    0.686054
6915    0.005880
2712    0.953208
244     0.002398
4698    0.014697
8287    0.027549
6791    0.981608
8970    0.005703
dtype: float64
```

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

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

	0
7681	0.024819
984	0.025692
8135	0.686054
6915	0.005880
2712	0.953208

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

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

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

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

```
y_pred_final.head()
```

	Converted	Prospect ID	0
0	0	7681	0.024819
1	0	984	0.025692
2	0	8135	0.686054
3	0	6915	0.005880
4	1	2712	0.953208

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

```
y_pred_final.head()
```

	Converted	Prospect ID	Converted_prob
0	0	7681	0.024819
1	0	984	0.025692
2	0	8135	0.686054
3	0	6915	0.005880
4	1	2712	0.953208

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

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

	Prospect ID	Converted	Converted_prob	Lead_Score
0	7681	0	0.024819	2
1	984	0	0.025692	3
2	8135	0	0.686054	69
3	6915	0	0.005880	1
4	2712	1	0.953208	95

```
y_pred_final['final_Predicted'] = y_pred_final.Converted_prob.map(lambda x: 1 if x > 0.3 else 0)
```

```
y_pred_final.head()
```

	Prospect ID	Converted	Converted_prob	Lead_Score	final_Predicted
0	7681	0	0.024819	2	0
1	984	0	0.025692	3	0
2	8135	0	0.686054	69	1
3	6915	0	0.005880	1	0
4	2712	1	0.953208	95	1

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

```
0.9277736411020104
```

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

```
array([[1563,  113],
       [  81,  929]])
```

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

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

```
0.9198019801980198
```

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

```
0.9325775656324582
```

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

```
0.8915547024952015
```

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

```
0.9198019801980198
```

Observation:

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

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

Final Observation:

Let us compare the values obtained for Train & Test:

Train Data:

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

Test Data:

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

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