Logistic Regression Case Study on -

Lead Scoring

Problem Statement

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

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

Now, although X Education gets a lot of leads, its lead conversion rate is very poor. For example, if, say, they acquire 100 leads in a day, only about 30 of them are converted. To make this process more efficient, **the company wishes to identify the most potential leads, also known as 'Hot Leads'**. If they successfully identify this set of leads, the lead conversion rate should go up as the sales team will now be focusing more on communicating with the potential leads rather than making calls to everyone. A typical lead conversion process can be represented using the following funnel:

`Lead Conversion Process - Demonstrated as a funnel`

As you can see, there are a lot of leads generated in the initial stage (top) but only a few of them come out as paying customers from the bottom. 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%.**

Data

You have been provided with a leads dataset from the past with around 9000 data points. This dataset consists of various attributes such as Lead Source, Total Time Spent on Website, Total Visits, Last Activity, etc. which may or may not be useful in ultimately deciding whether a lead will be converted or not. The target variable, in this case, is the column ‘Converted’ which tells whether a past lead was converted or not wherein 1 means it was converted and 0 means it wasn’t converted.

Another thing that you also need to check out for are the levels present in the categorical variables.

Many of the categorical variables have a level called 'Select' which needs to be handled because it is as good as a null value.

Goal

There are quite a few goals for this 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.**

```
# Suppressing Warnings
import warnings
warnings.filterwarnings('ignore')

# Importing Pandas and NumPy
import pandas as pd, numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

# Importing lead dataset
lead_data = pd.read_csv("Leads.csv")
lead_data.head()
```

```
                            Prospect ID  Lead Number              Lead
Origin  \
0  7927b2df-8bba-4d29-b9a2-b6e0beafe620       660737
API
1  2a272436-5132-4136-86fa-dcc88c88f482       660728
API
2  8cc8c611-a219-4f35-ad23-fdfd2656bd8a       660727  Landing Page
Submission
3  0cc2df48-7cf4-4e39-9de9-19797f9b38cc       660719  Landing Page
Submission
4  3256f628-e534-4826-9d63-4a8b88782852       660681  Landing Page
Submission

      Lead Source Do Not Email Do Not Call  Converted  TotalVisits  \
0      Olark Chat           No          No          0          0.0
1  Organic Search           No          No          0          5.0
2  Direct Traffic           No          No          1          2.0
3  Direct Traffic           No          No          0          1.0
4          Google           No          No          1          2.0
```

```
   Total Time Spent on Website  Page Views Per Visit  ...  \
0                            0                   0.0  ...
1                          674                   2.5  ...
2                         1532                   2.0  ...
3                          305                   1.0  ...
4                         1428                   1.0  ...

  Get updates on DM Content    Lead Profile    City  \
0                        No          Select  Select
1                        No          Select  Select
2                        No  Potential Lead  Mumbai
3                        No          Select  Mumbai
4                        No          Select  Mumbai

  Asymmetrique Activity Index Asymmetrique Profile Index  \
0                   02.Medium                  02.Medium
1                   02.Medium                  02.Medium
2                   02.Medium                    01.High
3                   02.Medium                    01.High
4                   02.Medium                    01.High

  Asymmetrique Activity Score Asymmetrique Profile Score  \
0                        15.0                       15.0
1                        15.0                       15.0
2                        14.0                       20.0
3                        13.0                       17.0
4                        15.0                       18.0

  I agree to pay the amount through cheque  \
0                                       No
1                                       No
2                                       No
3                                       No
4                                       No

  A free copy of Mastering The Interview Last Notable Activity
0                                     No             Modified
1                                     No         Email Opened
2                                    Yes         Email Opened
3                                     No             Modified
4                                     No             Modified

[5 rows x 37 columns]
```

Data Inspection

```
# checking the shape of the data
lead_data.shape
```

```
(9240, 37)
```

We have 9240 rows and 37 columns in our leads dataset.

```
# checking non null count and datatype of the variables
lead_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9240 entries, 0 to 9239
Data columns (total 37 columns):
 #   Column                                        Non-Null Count
Dtype
---  ------                                        --------------
-----
 0   Prospect ID                                   9240 non-null
object
 1   Lead Number                                   9240 non-null
int64
 2   Lead Origin                                   9240 non-null
object
 3   Lead Source                                   9204 non-null
object
 4   Do Not Email                                  9240 non-null
object
 5   Do Not Call                                   9240 non-null
object
 6   Converted                                     9240 non-null
int64
 7   TotalVisits                                   9103 non-null
float64
 8   Total Time Spent on Website                   9240 non-null
int64
 9   Page Views Per Visit                          9103 non-null
float64
 10  Last Activity                                 9137 non-null
object
 11  Country                                       6779 non-null
object
 12  Specialization                                7802 non-null
object
 13  How did you hear about X Education            7033 non-null
object
 14  What is your current occupation               6550 non-null
object
 15  What matters most to you in choosing a course  6531 non-null
object
 16  Search                                        9240 non-null
object
 17  Magazine                                      9240 non-null
object
 18  Newspaper Article                             9240 non-null
object
 19  X Education Forums                            9240 non-null
```

```
object
 20  Newspaper                                      9240 non-null
object
 21  Digital Advertisement                          9240 non-null
object
 22  Through Recommendations                        9240 non-null
object
 23  Receive More Updates About Our Courses         9240 non-null
object
 24  Tags                                           5887 non-null
object
 25  Lead Quality                                   4473 non-null
object
 26  Update me on Supply Chain Content              9240 non-null
object
 27  Get updates on DM Content                      9240 non-null
object
 28  Lead Profile                                   6531 non-null
object
 29  City                                           7820 non-null
object
 30  Asymmetrique Activity Index                    5022 non-null
object
 31  Asymmetrique Profile Index                     5022 non-null
object
 32  Asymmetrique Activity Score                    5022 non-null
float64
 33  Asymmetrique Profile Score                     5022 non-null
float64
 34  I agree to pay the amount through cheque       9240 non-null
object
 35  A free copy of Mastering The Interview         9240 non-null
object
 36  Last Notable Activity                          9240 non-null
object
dtypes: float64(4), int64(3), object(30)
memory usage: 2.6+ MB
```

All the dataypes of the variables are in correct format.

```
# Describing data
lead_data.describe()
```

```
         Lead Number    Converted  TotalVisits  Total Time Spent on
Website  \
count    9240.000000  9240.000000  9103.000000
9240.000000
mean   617188.435606     0.385390     3.445238
487.698268
std     23405.995698     0.486714     4.854853
548.021466
```

```
min    579533.000000     0.000000     0.000000
0.000000
25%    596484.500000     0.000000     1.000000
12.000000
50%    615479.000000     0.000000     3.000000
248.000000
75%    637387.250000     1.000000     5.000000
936.000000
max    660737.000000     1.000000   251.000000
2272.000000

       Page Views Per Visit  Asymmetrique Activity Score  \
count           9103.000000                  5022.000000
mean               2.362820                    14.306252
std                2.161418                     1.386694
min                0.000000                     7.000000
25%                1.000000                    14.000000
50%                2.000000                    14.000000
75%                3.000000                    15.000000
max               55.000000                    18.000000

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

From above description about counts, we can see that there are missing values present in our data.

Data Cleaning

1)Handling the 'Select' level that is present in many of the categorical variables.

We observe that there are 'Select' values in many columns.It may be because the customer did not select any option from the list, hence it shows 'Select'.'Select' values are as good as NULL. So we can convert these values to null values.

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

```
# checking the columns for null values
lead_data.isnull().sum()
```

```
Prospect ID                                         0
Lead Number                                         0
Lead Origin                                         0
```

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

```
# Finding the null percentages across columns
round(lead_data.isnull().sum()/len(lead_data.index),2)*100
```

```
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                                      1.0
Total Time Spent on Website                      0.0
Page Views Per Visit                             1.0
Last Activity                                    1.0
Country                                         27.0
```

```
Specialization                                   37.0
How did you hear about X Education               78.0
What is your current occupation                  29.0
What matters most to you in choosing a course    29.0
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                                             36.0
Lead Quality                                     52.0
Update me on Supply Chain Content                 0.0
Get updates on DM Content                         0.0
Lead Profile                                     74.0
City                                             40.0
Asymmetrique Activity Index                      46.0
Asymmetrique Profile Index                       46.0
Asymmetrique Activity Score                      46.0
Asymmetrique Profile Score                       46.0
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
```

We see that for some columns we have high percentage of missing values. We can drop the columns with missing values greater than 40% .

```
# dropping the columns with missing values greater than or equal to 40% .
lead_data=lead_data.drop(columns=['How did you hear about X Education','Lead Quality','Lead Profile',
                                  'Asymmetrique Activity Index','Asymmetrique Profile Index','Asymmetrique Activity Score',
                                 'Asymmetrique Profile Score'])
```

```
# Finding the null percentages across columns after removing the above columns
round(lead_data.isnull().sum()/len(lead_data.index),2)*100
```

```
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                                       1.0
Total Time Spent on Website                       0.0
```

```
Page Views Per Visit                              1.0
Last Activity                                     1.0
Country                                          27.0
Specialization                                   37.0
What is your current occupation                  29.0
What matters most to you in choosing a course    29.0
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                                             36.0
Update me on Supply Chain Content                 0.0
Get updates on DM Content                         0.0
City                                             40.0
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
```

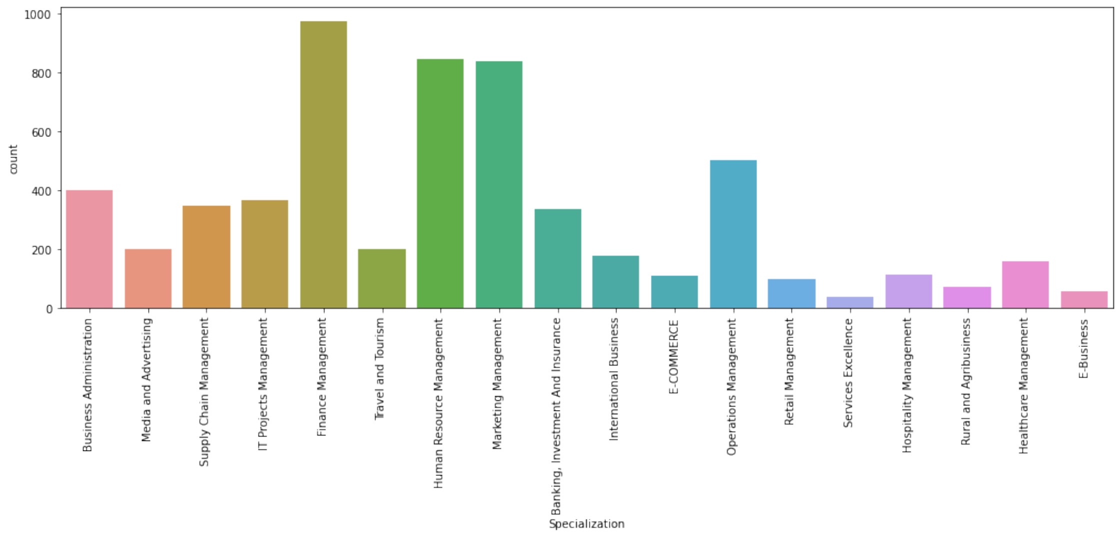
1) Column: 'Specialization'

This column has 37% missing values

```
plt.figure(figsize=(17,5))
sns.countplot(lead_data['Specialization'])
plt.xticks(rotation=90)
```

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14,
15, 16,
        17]),
 [Text(0, 0, 'Business Administration'),
  Text(1, 0, 'Media and Advertising'),
  Text(2, 0, 'Supply Chain Management'),
  Text(3, 0, 'IT Projects Management'),
  Text(4, 0, 'Finance Management'),
  Text(5, 0, 'Travel and Tourism'),
  Text(6, 0, 'Human Resource Management'),
  Text(7, 0, 'Marketing Management'),
  Text(8, 0, 'Banking, Investment And Insurance'),
  Text(9, 0, 'International Business'),
  Text(10, 0, 'E-COMMERCE'),
  Text(11, 0, 'Operations Management'),
  Text(12, 0, 'Retail Management'),
  Text(13, 0, 'Services Excellence'),
  Text(14, 0, 'Hospitality Management'),
  Text(15, 0, 'Rural and Agribusiness'),
```

```
 Text(16, 0, 'Healthcare Management'),
 Text(17, 0, 'E-Business')])
```



There is 37% missing values present in the Specialization column .It may be possible that the lead may leave this column blank if he may be a student or not having any specialization or his specialization is not there in the options given. So we can create a another category 'Others' for this.

```
# Creating a separate category called 'Others' for this
lead_data['Specialization'] =
lead_data['Specialization'].replace(np.nan, 'Others')
```

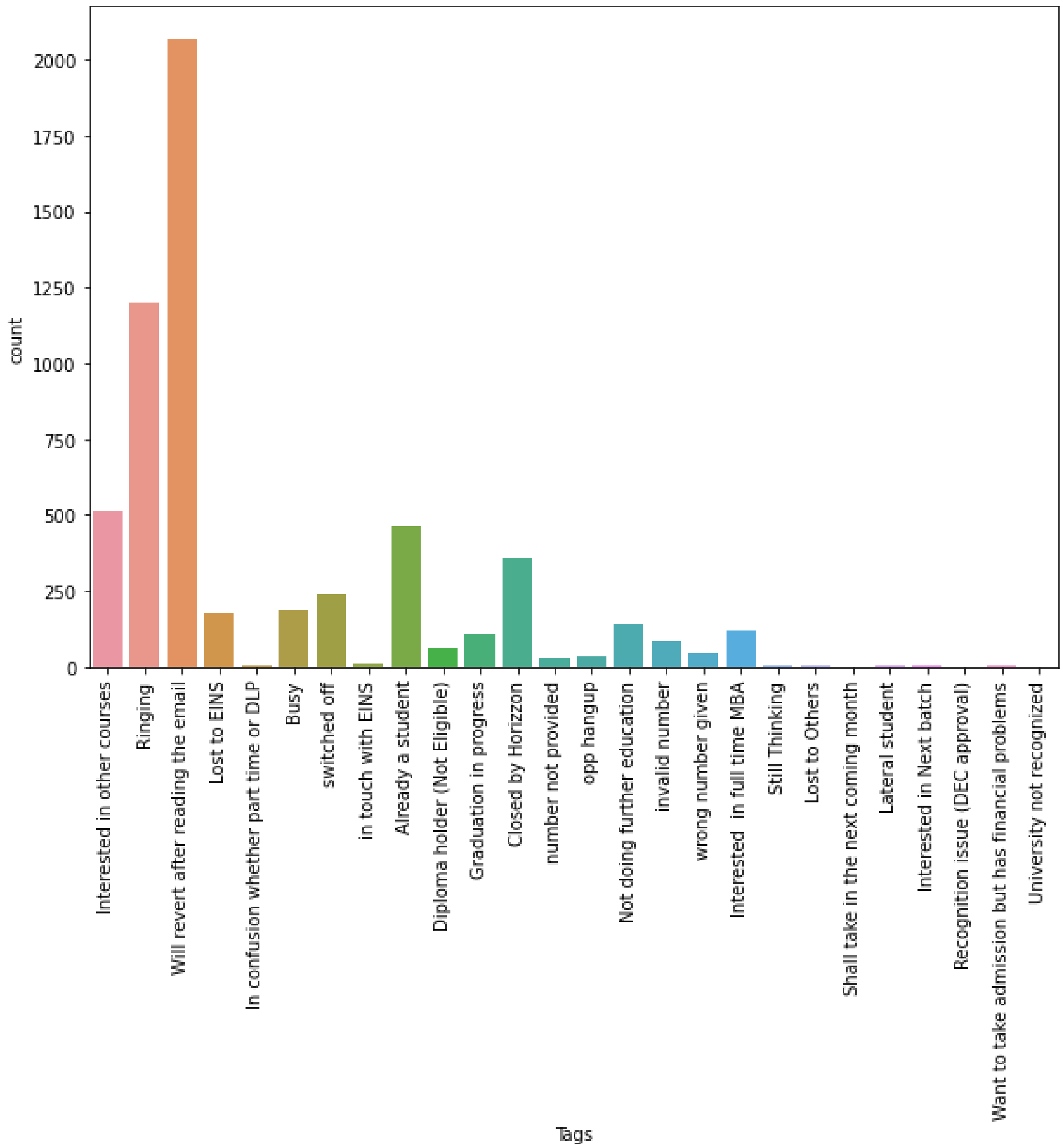
2) Tags column

'Tags' column has 36% missing values

```
# Visualizing Tags column
plt.figure(figsize=(10,7))
sns.countplot(lead_data['Tags'])
plt.xticks(rotation=90)
```

```
(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]),
 [Text(0, 0, 'Interested in other courses'),
  Text(1, 0, 'Ringing'),
  Text(2, 0, 'Will revert after reading the email'),
  Text(3, 0, 'Lost to EINS'),
  Text(4, 0, 'In confusion whether part time or DLP'),
  Text(5, 0, 'Busy'),
  Text(6, 0, 'switched off'),
  Text(7, 0, 'in touch with EINS'),
  Text(8, 0, 'Already a student'),
  Text(9, 0, 'Diploma holder (Not Eligible)'),
  Text(10, 0, 'Graduation in progress'),
```

```
Text(11, 0, 'Closed by Horizzon'),
Text(12, 0, 'number not provided'),
Text(13, 0, 'opp hangup'),
Text(14, 0, 'Not doing further education'),
Text(15, 0, 'invalid number'),
Text(16, 0, 'wrong number given'),
Text(17, 0, 'Interested  in full time MBA'),
Text(18, 0, 'Still Thinking'),
Text(19, 0, 'Lost to Others'),
Text(20, 0, 'Shall take in the next coming month'),
Text(21, 0, 'Lateral student'),
Text(22, 0, 'Interested in Next batch'),
Text(23, 0, 'Recognition issue (DEC approval)'),
Text(24, 0, 'Want to take admission but has financial problems'),
Text(25, 0, 'University not recognized')])
```



Since most values are 'Will revert after reading the email' , we can impute missing values in this column with this value.

```
# Imputing the missing data in the tags column with 'Will revert after reading the email'
lead_data['Tags']=lead_data['Tags'].replace(np.nan,'Will revert after reading the email')
```

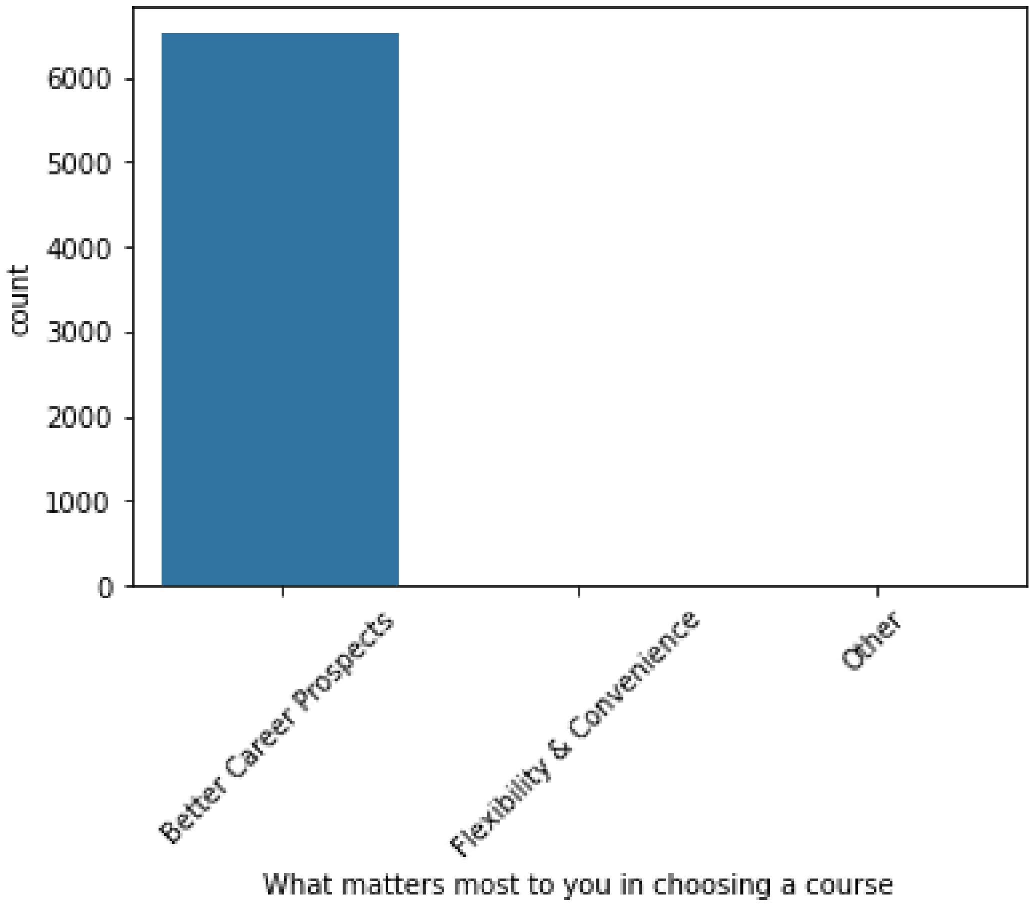
3) Column: 'What matters most to you in choosing a course'

this column has 29% missing values

```
# Visualizing this column
sns.countplot(lead_data['What matters most to you in choosing a
```

```
course'])
plt.xticks(rotation=45)
```

```
(array([0, 1, 2]),
 [Text(0, 0, 'Better Career Prospects'),
  Text(1, 0, 'Flexibility & Convenience'),
  Text(2, 0, 'Other')])
```




```
# Finding the percentage of the different categories of this column:
round(lead_data['What matters most to you in choosing a
course'].value_counts(normalize=True),2)*100
```

```
Better Career Prospects      100.0
Flexibility & Convenience      0.0
Other                          0.0
Name: What matters most to you in choosing a course, dtype: float64
```

We can see that this is highly skewed column so we can remove this column.

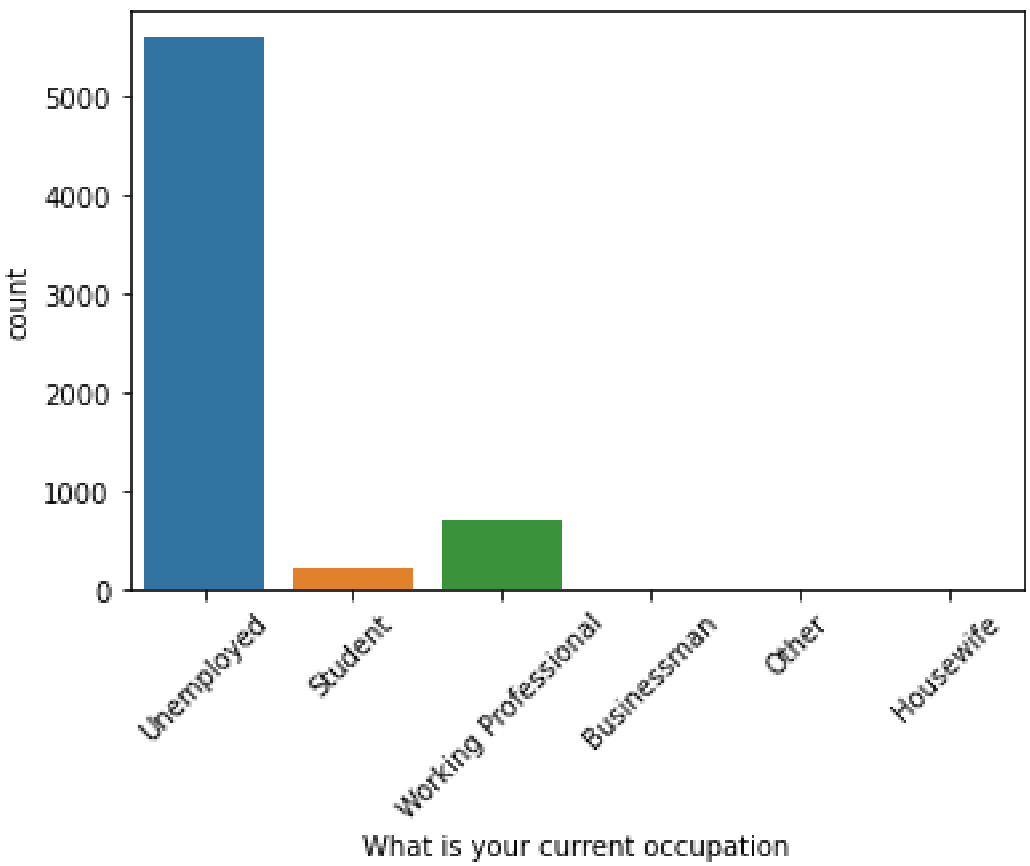
```
# Dropping this column
lead_data=lead_data.drop('What matters most to you in choosing a
course',axis=1)
```

4) Column: 'What is your current occupation'

this column has 29% missing values

```
sns.countplot(lead_data['What is your current occupation'])
plt.xticks(rotation=45)
```

```
(array([0, 1, 2, 3, 4, 5]),
 [Text(0, 0, 'Unemployed'),
  Text(1, 0, 'Student'),
  Text(2, 0, 'Working Professional'),
  Text(3, 0, 'Businessman'),
  Text(4, 0, 'Other'),
  Text(5, 0, 'Housewife')])
```




```
# Finding the percentage of the different categories of this column:
round(lead_data['What is your current
occupation'].value_counts(normalize=True),2)*100
```

```
Unemployed              85.0
Working Professional    11.0
Student                  3.0
Other                    0.0
Housewife                0.0
```

```
Businessman                0.0
Name: What is your current occupation, dtype: float64
```

Since the most values are 'Unemployed' , we can impute missing values in this column with this value.

```
# Imputing the missing data in the 'What is your current occupation'
column with 'Unemployed'
lead_data['What is your current occupation']=lead_data['What is your
current occupation'].replace(np.nan,'Unemployed')
```

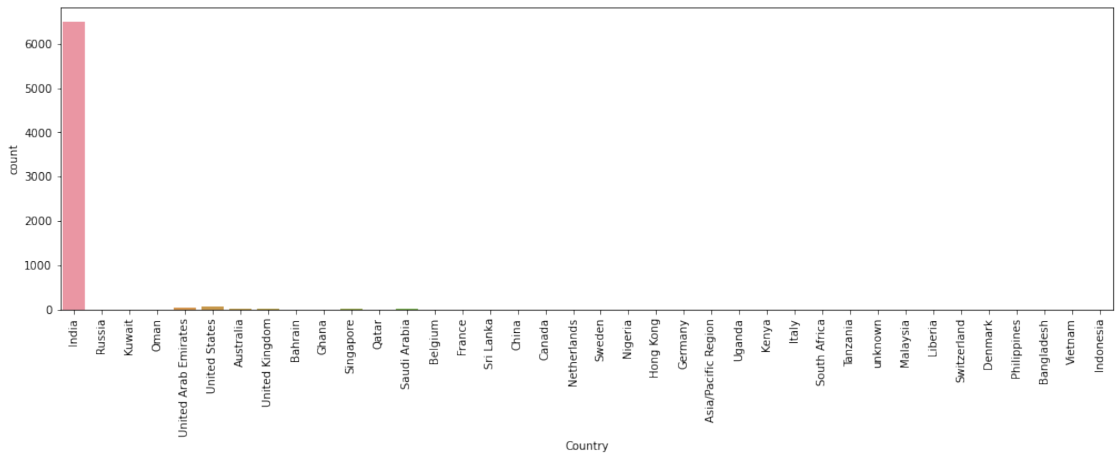
5) Column: 'Country'

This column has 27% missing values

```
plt.figure(figsize=(17,5))
sns.countplot(lead_data['Country'])
plt.xticks(rotation=90)
```

```
(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]),
 [Text(0, 0, 'India'),
  Text(1, 0, 'Russia'),
  Text(2, 0, 'Kuwait'),
  Text(3, 0, 'Oman'),
  Text(4, 0, 'United Arab Emirates'),
  Text(5, 0, 'United States'),
  Text(6, 0, 'Australia'),
  Text(7, 0, 'United Kingdom'),
  Text(8, 0, 'Bahrain'),
  Text(9, 0, 'Ghana'),
  Text(10, 0, 'Singapore'),
  Text(11, 0, 'Qatar'),
  Text(12, 0, 'Saudi Arabia'),
  Text(13, 0, 'Belgium'),
  Text(14, 0, 'France'),
  Text(15, 0, 'Sri Lanka'),
  Text(16, 0, 'China'),
  Text(17, 0, 'Canada'),
  Text(18, 0, 'Netherlands'),
  Text(19, 0, 'Sweden'),
  Text(20, 0, 'Nigeria'),
  Text(21, 0, 'Hong Kong'),
  Text(22, 0, 'Germany'),
  Text(23, 0, 'Asia/Pacific Region'),
  Text(24, 0, 'Uganda'),
  Text(25, 0, 'Kenya'),
  Text(26, 0, 'Italy'),
```

```
  Text(27, 0, 'South Africa'),
  Text(28, 0, 'Tanzania'),
  Text(29, 0, 'unknown'),
  Text(30, 0, 'Malaysia'),
  Text(31, 0, 'Liberia'),
  Text(32, 0, 'Switzerland'),
  Text(33, 0, 'Denmark'),
  Text(34, 0, 'Philippines'),
  Text(35, 0, 'Bangladesh'),
  Text(36, 0, 'Vietnam'),
  Text(37, 0, 'Indonesia')])
```



We can see that this is highly skewed column but it is an important information w.r.t. to the lead. Since most values are 'India' , we can impute missing values in this column with this value.

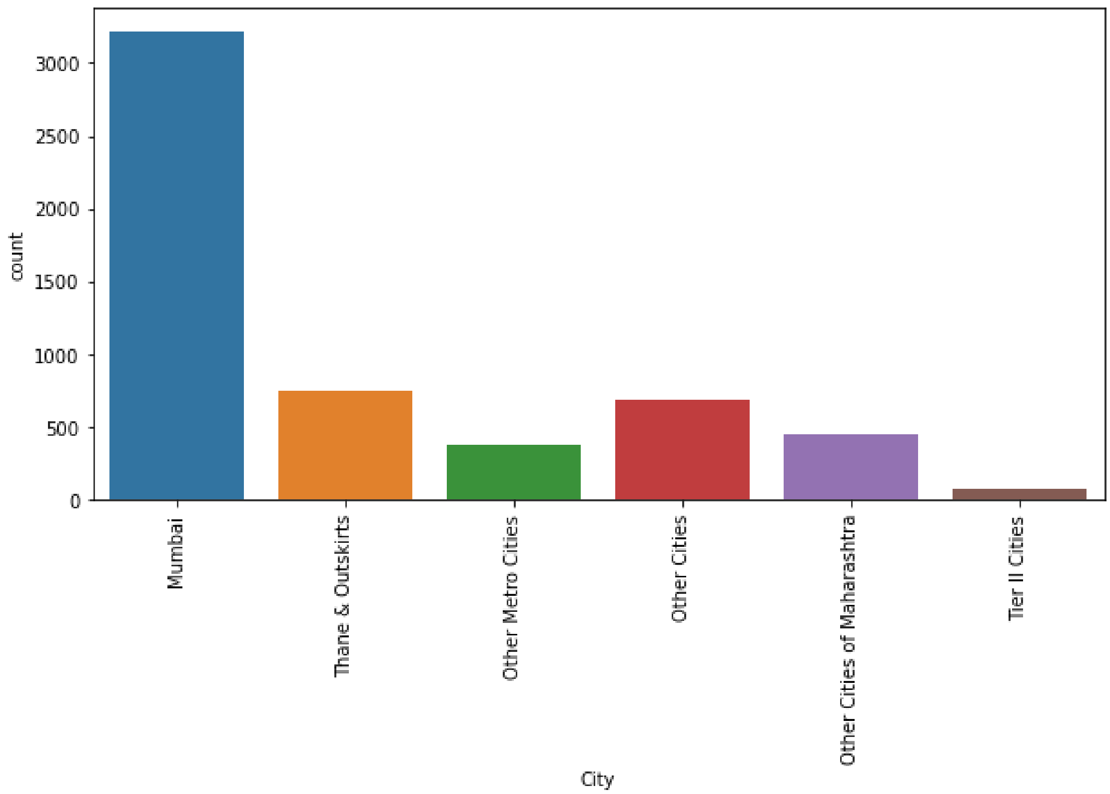
```
# Imputing the missing data in the 'Country' column with 'India'
lead_data['Country']=lead_data['Country'].replace(np.nan,'India')
```

6) Column: 'City'

This column has 40% missing values

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

```
(array([0, 1, 2, 3, 4, 5]),
 [Text(0, 0, 'Mumbai'),
  Text(1, 0, 'Thane & Outskirts'),
  Text(2, 0, 'Other Metro Cities'),
  Text(3, 0, 'Other Cities'),
  Text(4, 0, 'Other Cities of Maharashtra'),
  Text(5, 0, 'Tier II Cities')])
```




```
# Finding the percentage of the different categories of this column:
round(lead_data['City'].value_counts(normalize=True),2)*100
```

```
Mumbai                          58.0
Thane & Outskirts               13.0
Other Cities                    12.0
Other Cities of Maharashtra      8.0
Other Metro Cities               7.0
Tier II Cities                   1.0
Name: City, dtype: float64
```

Since most values are 'Mumbai' , we can impute missing values in this column with this value.

```
# Imputing the missing data in the 'City' column with 'Mumbai'
lead_data['City']=lead_data['City'].replace(np.nan,'Mumbai')
```

```
# Finding the null percentages across columns after removing the above
columns
round(lead_data.isnull().sum()/len(lead_data.index),2)*100
```

```
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                                    1.0
Total Time Spent on Website                    0.0
Page Views Per Visit                           1.0
Last Activity                                  1.0
Country                                        0.0
Specialization                                 0.0
What is your current occupation                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
```

Rest missing values are under 2% so we can drop these rows.

```
# Dropping the rows with null values
lead_data.dropna(inplace = True)

# Finding the null percentages across columns after removing the above columns
round(lead_data.isnull().sum()/len(lead_data.index),2)*100
```

```
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
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
```

Now we don't have any missing value in the dataset.

We can find the percentage of rows retained.

```
# Percentage of rows retained
(len(lead_data.index)/9240)*100
```

```
98.2034632034632
```

We have retained 98% of the rows after cleaning the data .

Exploratory Data Anaysis

Checking for duplicates:

```
lead_data[lead_data.duplicated()]
```

```
Empty DataFrame
Columns: [Prospect ID, Lead Number, Lead Origin, Lead Source, Do Not
Email, Do Not Call, Converted, TotalVisits, Total Time Spent on
Website, Page Views Per Visit, Last Activity, Country, Specialization,
What is your current occupation, Search, Magazine, Newspaper Article,
X Education Forums, Newspaper, Digital Advertisement, Through
Recommendations, Receive More Updates About Our Courses, Tags, Update
me on Supply Chain Content, Get updates on DM Content, City, I agree
to pay the amount through cheque, A free copy of Mastering The
Interview, Last Notable Activity]
Index: []

[0 rows x 29 columns]
```

We see there are no duplicate records in our lead dataset.

Univariate Analysis and Bivariate Analysis

1) Converted

Converted is the target variable, Indicates whether a lead has been successfully converted (1) or not (0)

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

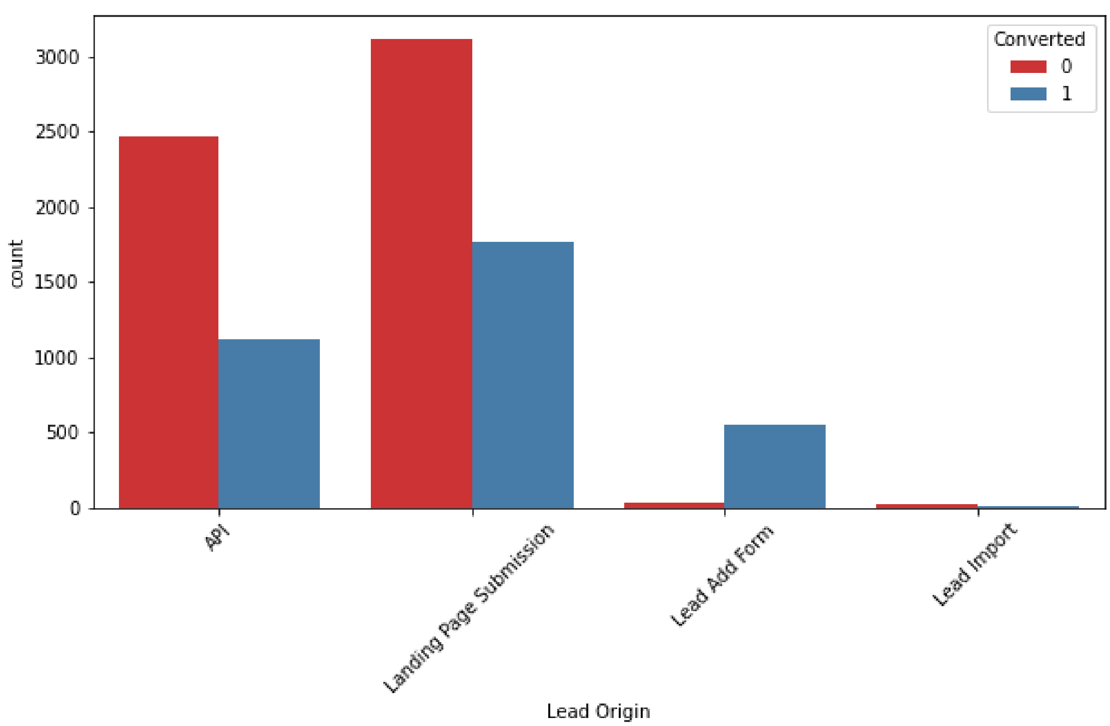
```
37.85541106458012
```

The lead conversion rate is 38%.

2) Lead Origin

```
plt.figure(figsize=(10,5))
sns.countplot(x = "Lead Origin", hue = "Converted", data =
lead_data,palette='Set1')
plt.xticks(rotation = 45)
```

```
(array([0, 1, 2, 3]),
 [Text(0, 0, 'API'),
  Text(1, 0, 'Landing Page Submission'),
  Text(2, 0, 'Lead Add Form'),
  Text(3, 0, 'Lead Import')])
```



Inference :

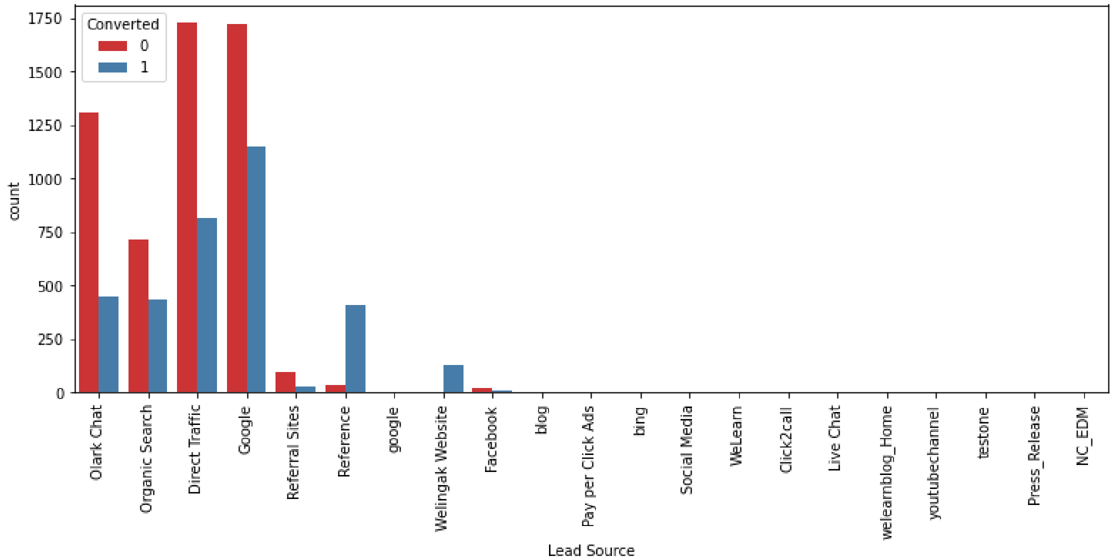
1. API and Landing Page Submission have 30-35% conversion rate but count of lead originated from them are considerable.
2. Lead Add Form has more than 90% conversion rate but count of lead are not very high.
3. Lead Import are very less in count.

To improve overall lead conversion rate, we need to focus more on improving lead converion of API and Landing Page Submission origin and generate more leads from Lead Add Form.

3) Lead Source

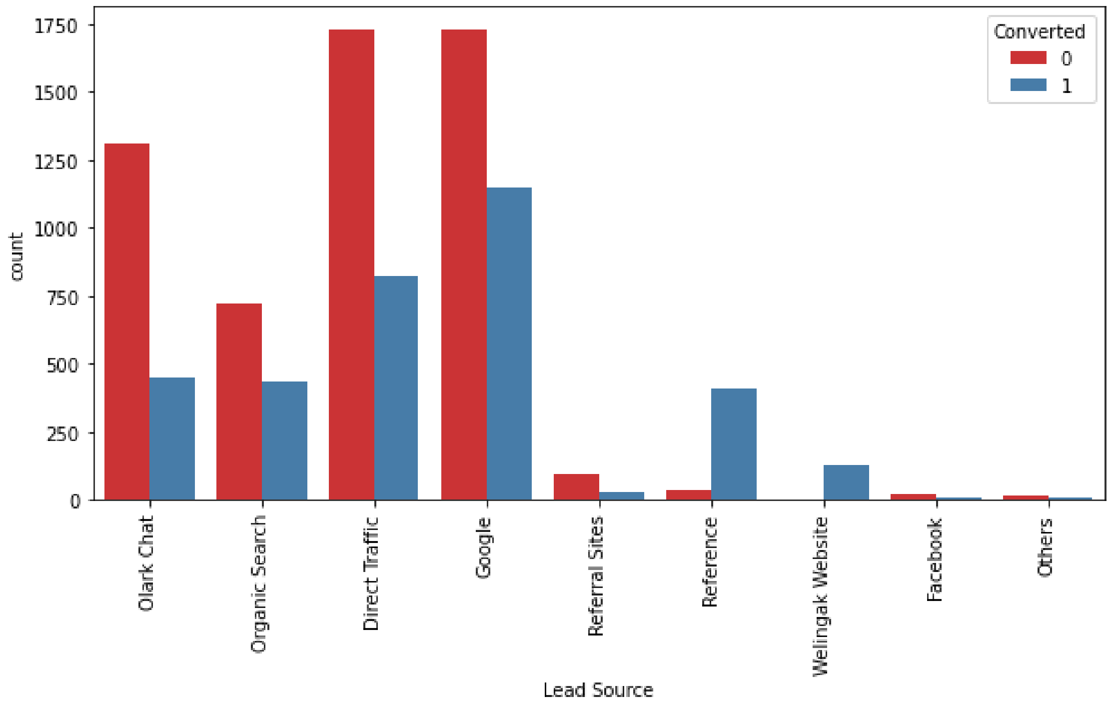
```
plt.figure(figsize=(13,5))
sns.countplot(x = "Lead Source", hue = "Converted", data = lead_data,
palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14,
15, 16,
        17, 18, 19, 20]),
 [Text(0, 0, 'Olark Chat'),
  Text(1, 0, 'Organic Search'),
  Text(2, 0, 'Direct Traffic'),
  Text(3, 0, 'Google'),
  Text(4, 0, 'Referral Sites'),
  Text(5, 0, 'Reference'),
  Text(6, 0, 'google'),
  Text(7, 0, 'Welingak Website'),
  Text(8, 0, 'Facebook'),
  Text(9, 0, 'blog'),
  Text(10, 0, 'Pay per Click Ads'),
  Text(11, 0, 'bing'),
  Text(12, 0, 'Social Media'),
  Text(13, 0, 'WeLearn'),
  Text(14, 0, 'Click2call'),
  Text(15, 0, 'Live Chat'),
  Text(16, 0, 'welearnblog_Home'),
  Text(17, 0, 'youtubechannel'),
  Text(18, 0, 'testone'),
  Text(19, 0, 'Press_Release'),
  Text(20, 0, 'NC_EDM')])
```




```
# Need to replace 'google' with 'Google'
lead_data['Lead Source'] = lead_data['Lead
Source'].replace(['google'], 'Google')

# Creating a new category 'Others' for some of the Lead Sources which
do not have much values.
lead_data['Lead Source'] = lead_data['Lead
Source'].replace(['Click2call', 'Live Chat', 'NC_EDM', 'Pay per Click
Ads', 'Press_Release',
  'Social Media', 'WeLearn', 'bing', 'blog', 'testone',
'welearnblog_Home', 'youtubechannel'], 'Others')

# Visualizing again
plt.figure(figsize=(10,5))
sns.countplot(x = "Lead Source", hue = "Converted", data =
lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8]),
 [Text(0, 0, 'Olark Chat'),
  Text(1, 0, 'Organic Search'),
  Text(2, 0, 'Direct Traffic'),
  Text(3, 0, 'Google'),
  Text(4, 0, 'Referral Sites'),
  Text(5, 0, 'Reference'),
  Text(6, 0, 'Welingak Website'),
  Text(7, 0, 'Facebook'),
  Text(8, 0, 'Others')])
```



Inference

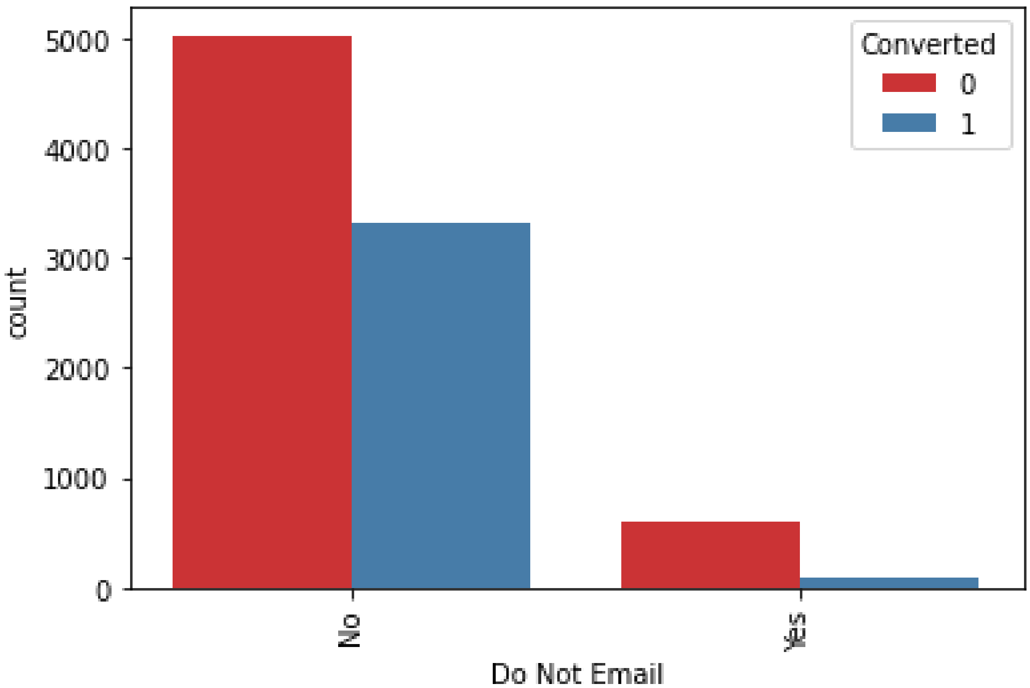
1. Google and Direct traffic generates maximum number of leads.
2. Conversion Rate of reference leads and leads through welingak website is high.

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.

4) Do not Email

```
sns.countplot(x = "Do Not Email", hue = "Converted", data =
lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0, 1]), [Text(0, 0, 'No'), Text(1, 0, 'Yes')])
```



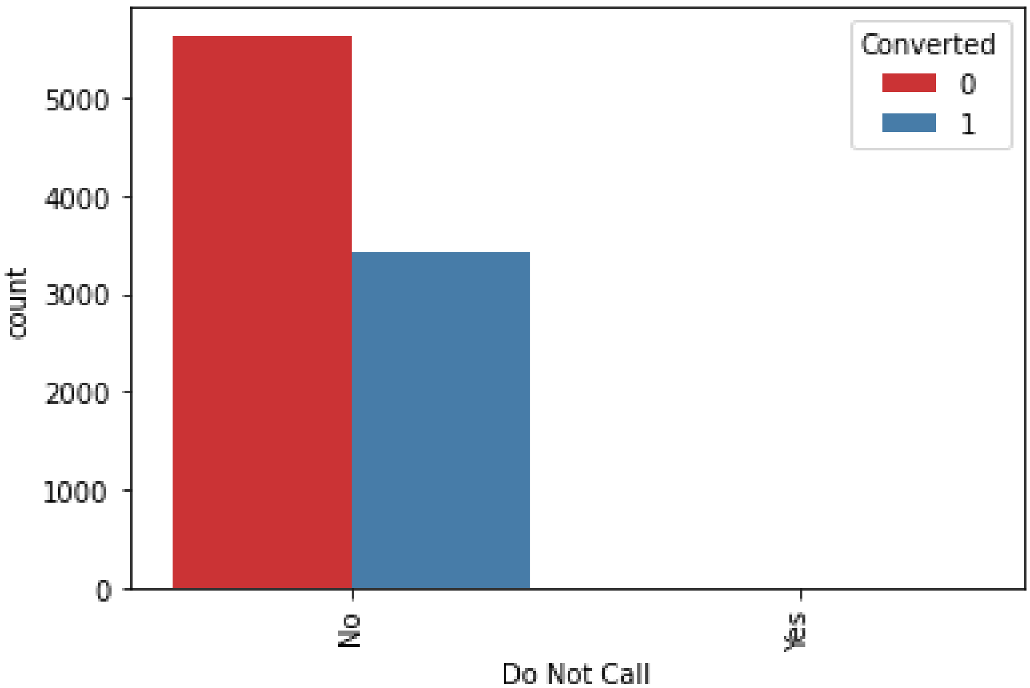
Inference

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

5) Do not call

```
sns.countplot(x = "Do Not Call", hue = "Converted", data =
lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0, 1]), [Text(0, 0, 'No'), Text(1, 0, 'Yes')])
```



Inference

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

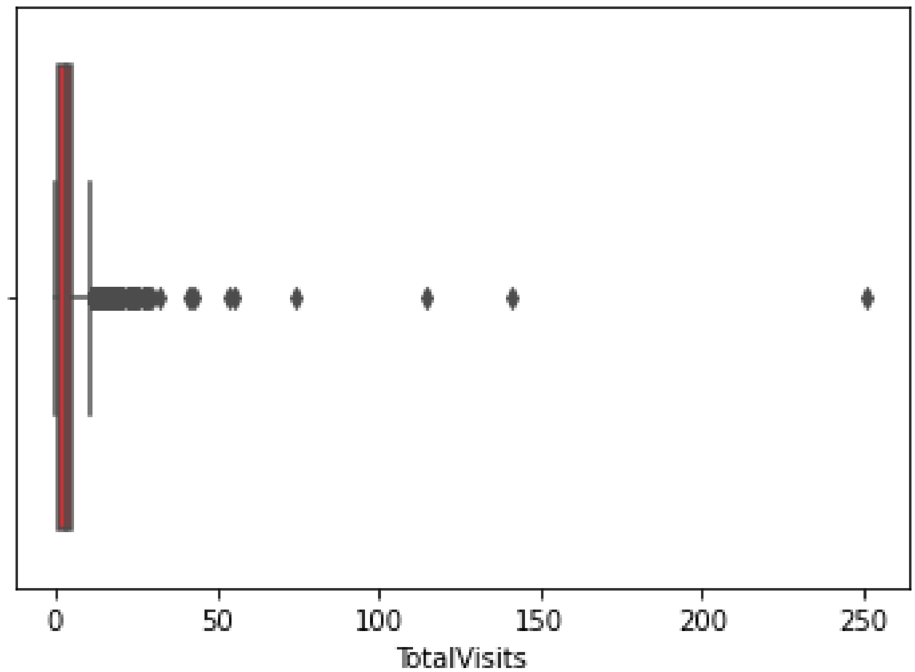
6) TotalVisits

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

```
count    9074.000000
mean        3.456028
std         4.858802
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
```

```
sns.boxplot(lead_data['TotalVisits'],orient='vert',palette='Set1')
```

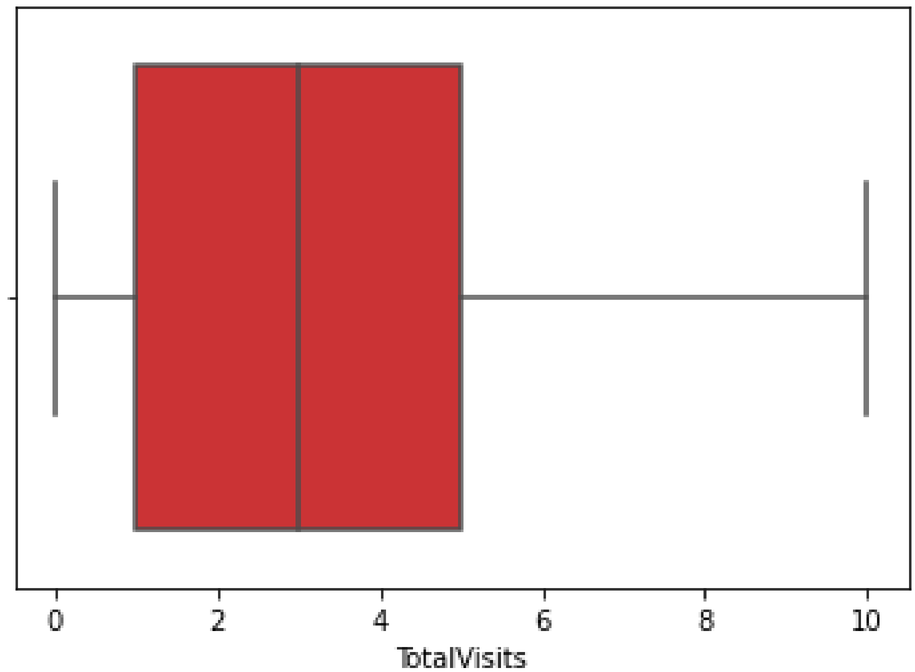
```
<AxesSubplot:xlabel='TotalVisits'>
```



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

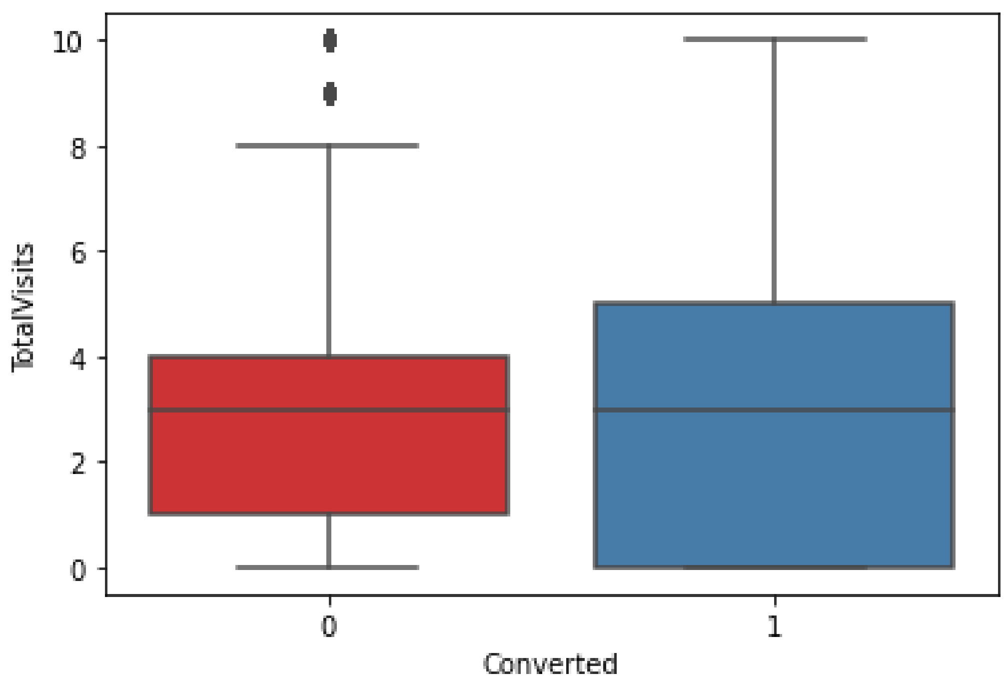
```
percentiles = lead_data['TotalVisits'].quantile([0.05,0.95]).values
lead_data['TotalVisits'][lead_data['TotalVisits'] <= percentiles[0]] =
percentiles[0]
lead_data['TotalVisits'][lead_data['TotalVisits'] >= percentiles[1]] =
percentiles[1]

# Visualizing again
sns.boxplot(lead_data['TotalVisits'],orient='vert',palette='Set1')
```

```
<AxesSubplot:xlabel='TotalVisits'>
```




```
sns.boxplot(y = 'TotalVisits', x = 'Converted', data =
lead_data,palette='Set1')
```

```
<AxesSubplot:xlabel='Converted', ylabel='TotalVisits'>
```



Inference

- Median for converted and not converted leads are the same.

Nothing can be concluded on the basis of Total Visits.

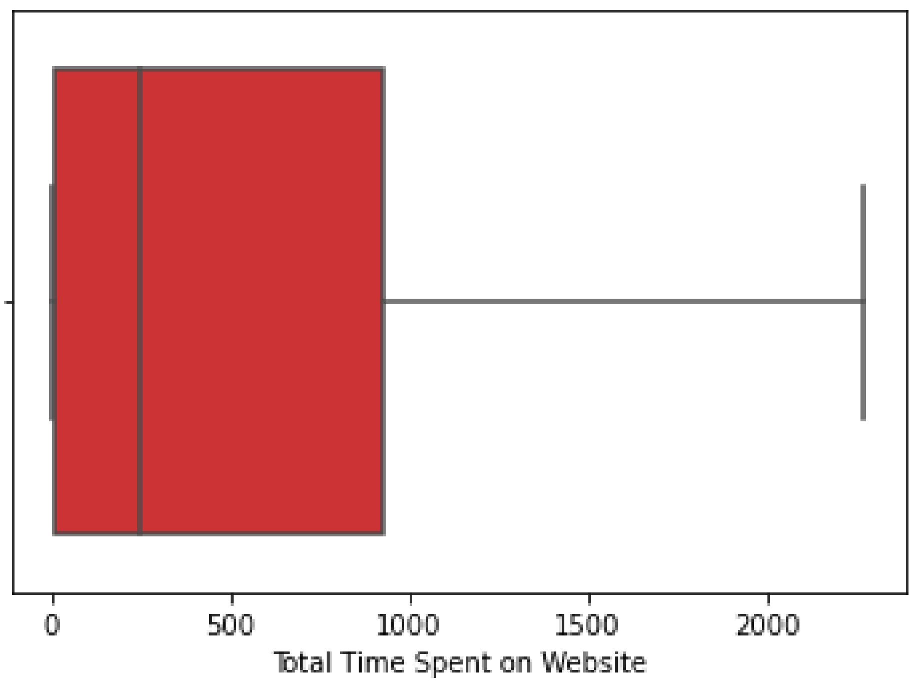
7) Total Time Spent on Website

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

```
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
```

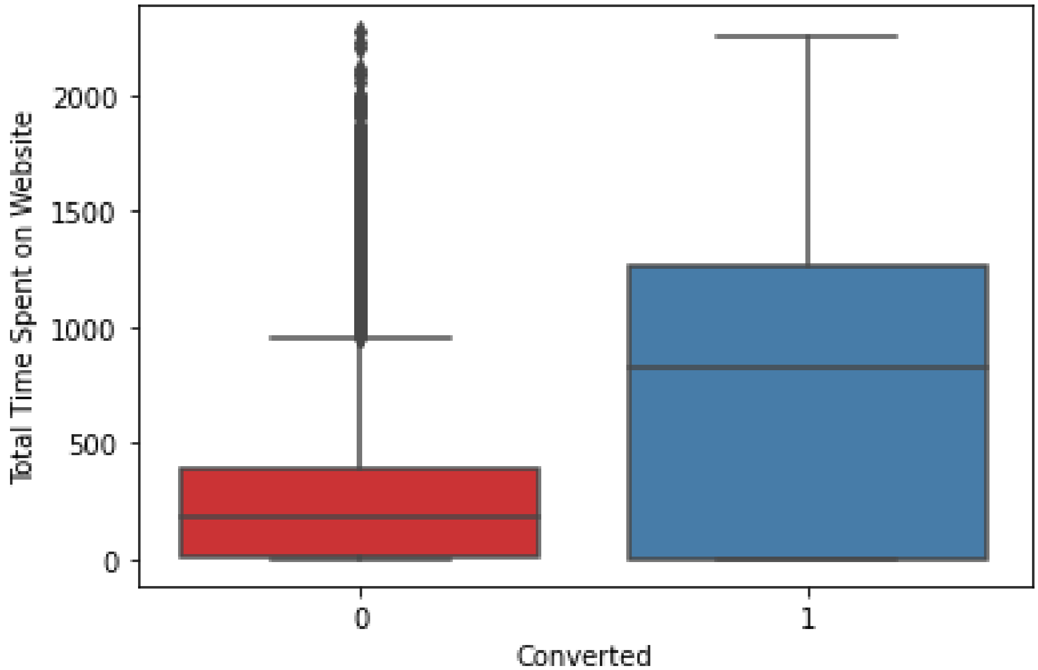
```
sns.boxplot(lead_data['Total Time Spent on
Website'],orient='vert',palette='Set1')
```

```
<AxesSubplot:xlabel='Total Time Spent on Website'>
```




```
sns.boxplot(y = 'Total Time Spent on Website', x = 'Converted', data =
lead_data,palette='Set1')
```

```
<AxesSubplot:xlabel='Converted', ylabel='Total Time Spent on Website'>
```



Inference

- Leads spending more time on the weblise are more likely to be converted.

Website should be made more engaging to make leads spend more time.

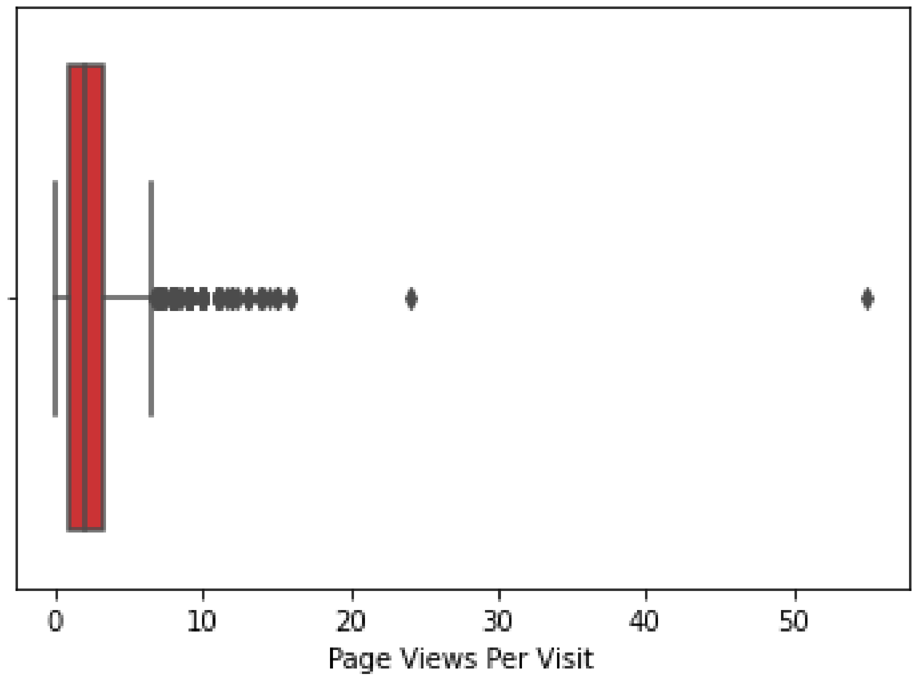
8) Page Views Per Visit

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

```
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
```

```
sns.boxplot(lead_data['Page Views Per
Visit'],orient='vert',palette='Set1')
```

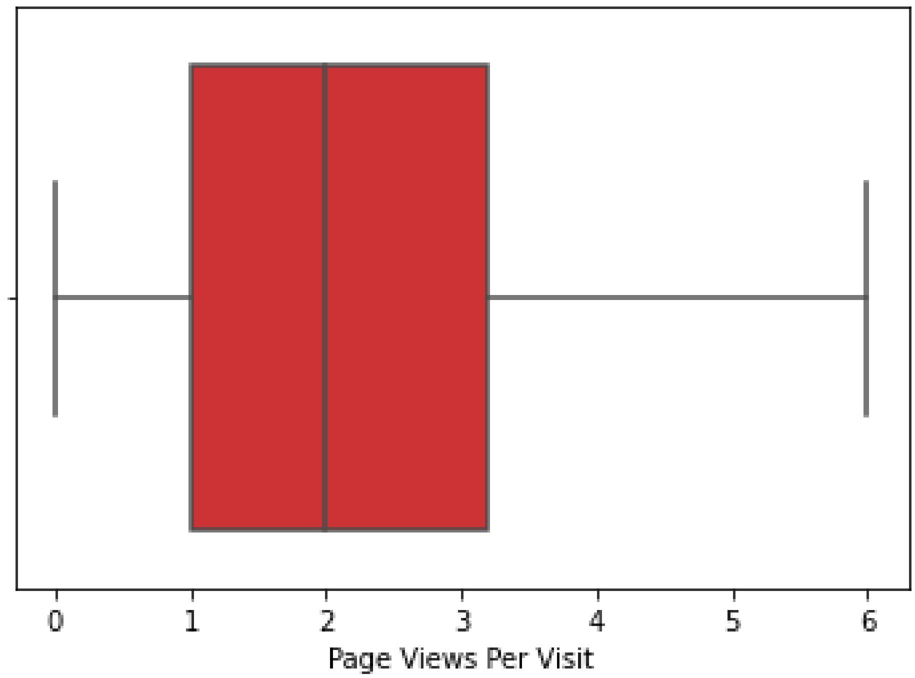
```
<AxesSubplot:xlabel='Page Views Per Visit'>
```



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

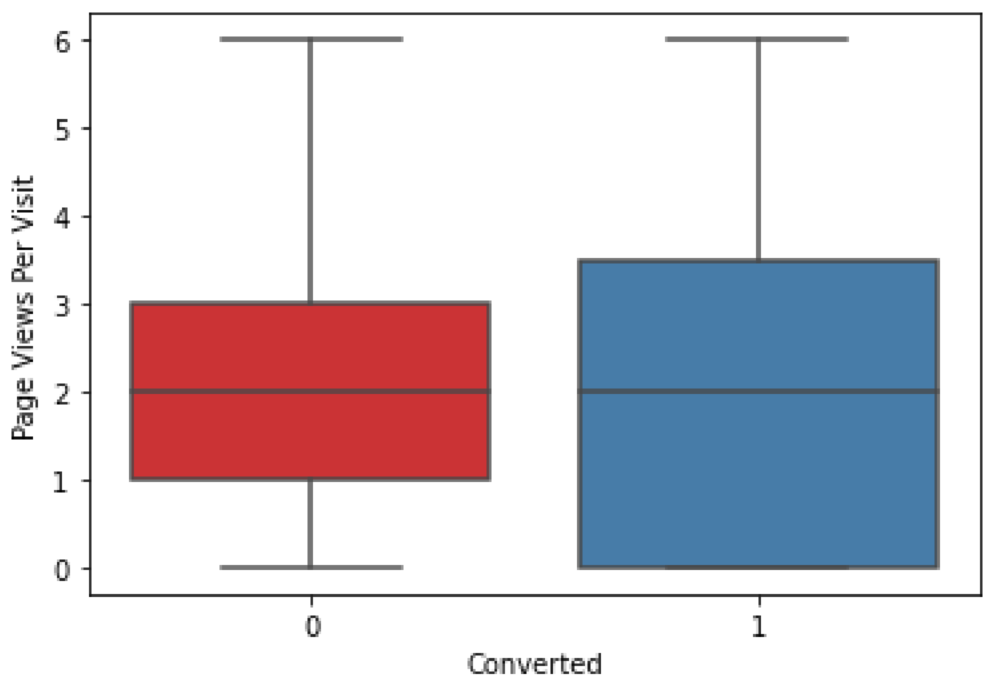
```
percentiles = lead_data['Page Views Per
Visit'].quantile([0.05,0.95]).values
lead_data['Page Views Per Visit'][lead_data['Page Views Per Visit'] <=
percentiles[0]] = percentiles[0]
lead_data['Page Views Per Visit'][lead_data['Page Views Per Visit'] >=
percentiles[1]] = percentiles[1]

# Visualizing again
sns.boxplot(lead_data['Page Views Per
Visit'],palette='Set1',orient='vert')
```

```
<AxesSubplot:xlabel='Page Views Per Visit'>
```




```
sns.boxplot(y = 'Page Views Per Visit', x = 'Converted', data
=lead_data,palette='Set1')
```

```
<AxesSubplot:xlabel='Converted', ylabel='Page Views Per Visit'>
```



Inference

- Median for converted and unconverted leads is the same.

Nothing can be said specifically for lead conversion from Page Views Per Visit

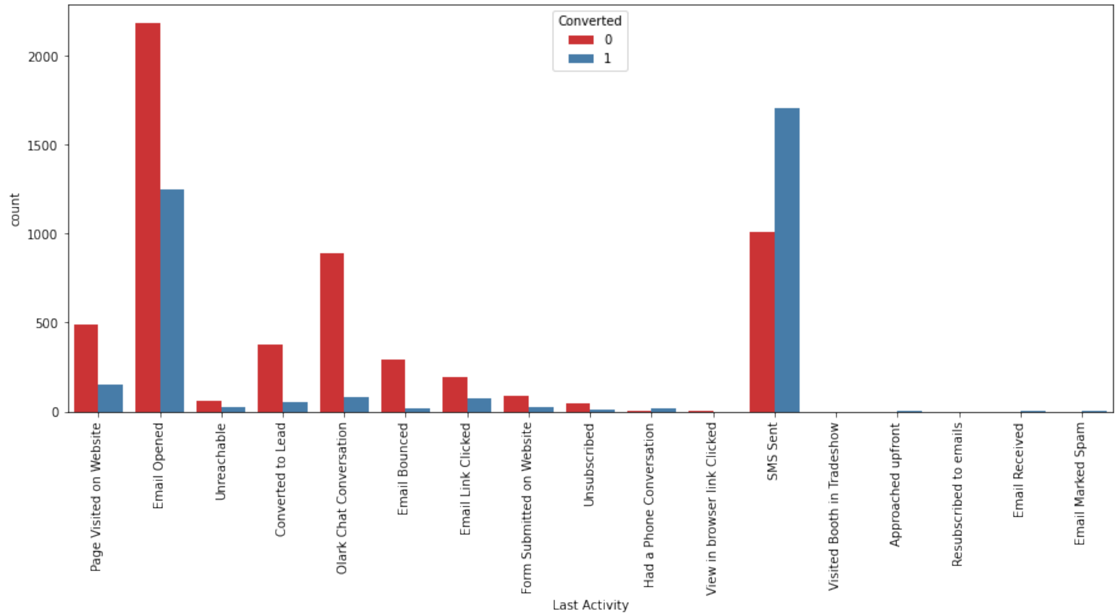
9) Last Activity

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

```
count             9074
unique              17
top       Email Opened
freq              3432
Name: Last Activity, dtype: object
```

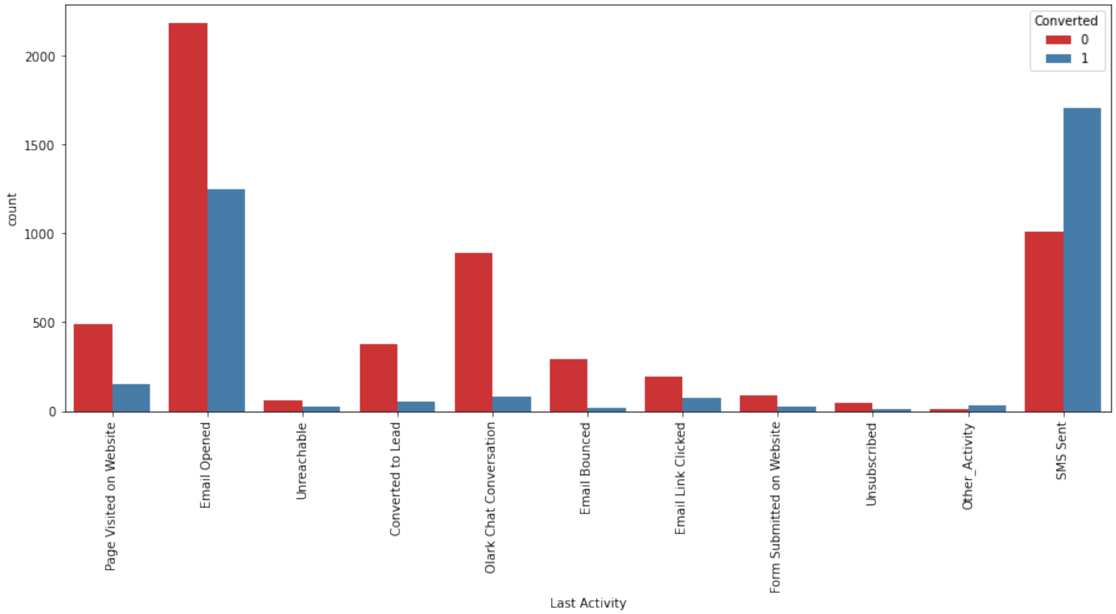
```
plt.figure(figsize=(15,6))
sns.countplot(x = "Last Activity", hue = "Converted", data =
lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14,
15, 16]),
 [Text(0, 0, 'Page Visited on Website'),
  Text(1, 0, 'Email Opened'),
  Text(2, 0, 'Unreachable'),
  Text(3, 0, 'Converted to Lead'),
  Text(4, 0, 'Olark Chat Conversation'),
  Text(5, 0, 'Email Bounced'),
  Text(6, 0, 'Email Link Clicked'),
  Text(7, 0, 'Form Submitted on Website'),
  Text(8, 0, 'Unsubscribed'),
  Text(9, 0, 'Had a Phone Conversation'),
  Text(10, 0, 'View in browser link Clicked'),
  Text(11, 0, 'SMS Sent'),
  Text(12, 0, 'Visited Booth in Tradeshow'),
  Text(13, 0, 'Approached upfront'),
  Text(14, 0, 'Resubscribed to emails'),
  Text(15, 0, 'Email Received'),
  Text(16, 0, 'Email Marked Spam')])
```




```
# We can club the last activities to "Other_Activity" which are having
less data.
lead_data['Last Activity'] = lead_data['Last Activity'].replace(['Had
a Phone Conversation', 'View in browser link Clicked',
                                                        'Visited Booth
in Tradeshow', 'Approached upfront',
                                                        'Resubscribed
to emails','Email Received', 'Email Marked Spam'], 'Other_Activity')

# Visualizing again
plt.figure(figsize=(15,6))
sns.countplot(x = "Last Activity", hue = "Converted", data =
lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10]),
 [Text(0, 0, 'Page Visited on Website'),
  Text(1, 0, 'Email Opened'),
  Text(2, 0, 'Unreachable'),
  Text(3, 0, 'Converted to Lead'),
  Text(4, 0, 'Olark Chat Conversation'),
  Text(5, 0, 'Email Bounced'),
  Text(6, 0, 'Email Link Clicked'),
  Text(7, 0, 'Form Submitted on Website'),
  Text(8, 0, 'Unsubscribed'),
  Text(9, 0, 'Other_Activity'),
  Text(10, 0, 'SMS Sent')])
```



Inference

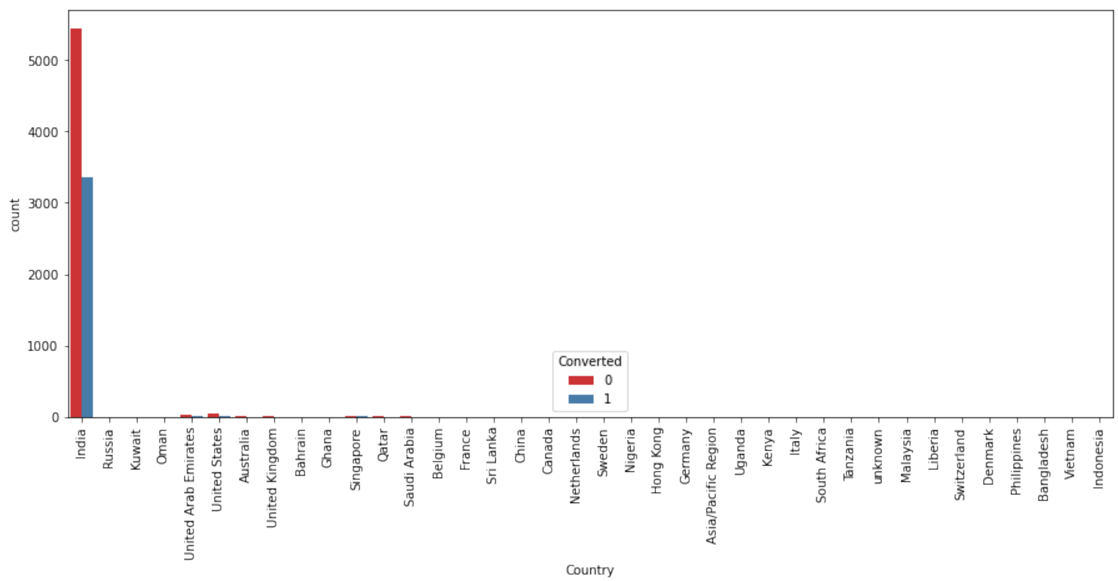
1. Most of the lead have their Email opened as their last activity.
2. Conversion rate for leads with last activity as SMS Sent is almost 60%.

10) Country

```
plt.figure(figsize=(15,6))
sns.countplot(x = "Country", hue = "Converted", data =
lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(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]),
 [Text(0, 0, 'India'),
  Text(1, 0, 'Russia'),
  Text(2, 0, 'Kuwait'),
  Text(3, 0, 'Oman'),
  Text(4, 0, 'United Arab Emirates'),
  Text(5, 0, 'United States'),
  Text(6, 0, 'Australia'),
  Text(7, 0, 'United Kingdom'),
  Text(8, 0, 'Bahrain'),
  Text(9, 0, 'Ghana'),
  Text(10, 0, 'Singapore'),
  Text(11, 0, 'Qatar'),
  Text(12, 0, 'Saudi Arabia'),
  Text(13, 0, 'Belgium'),
  Text(14, 0, 'France'),
  Text(15, 0, 'Sri Lanka'),
```

```
 Text(16, 0, 'China'),
 Text(17, 0, 'Canada'),
 Text(18, 0, 'Netherlands'),
 Text(19, 0, 'Sweden'),
 Text(20, 0, 'Nigeria'),
 Text(21, 0, 'Hong Kong'),
 Text(22, 0, 'Germany'),
 Text(23, 0, 'Asia/Pacific Region'),
 Text(24, 0, 'Uganda'),
 Text(25, 0, 'Kenya'),
 Text(26, 0, 'Italy'),
 Text(27, 0, 'South Africa'),
 Text(28, 0, 'Tanzania'),
 Text(29, 0, 'unknown'),
 Text(30, 0, 'Malaysia'),
 Text(31, 0, 'Liberia'),
 Text(32, 0, 'Switzerland'),
 Text(33, 0, 'Denmark'),
 Text(34, 0, 'Philippines'),
 Text(35, 0, 'Bangladesh'),
 Text(36, 0, 'Vietnam'),
 Text(37, 0, 'Indonesia')])
```



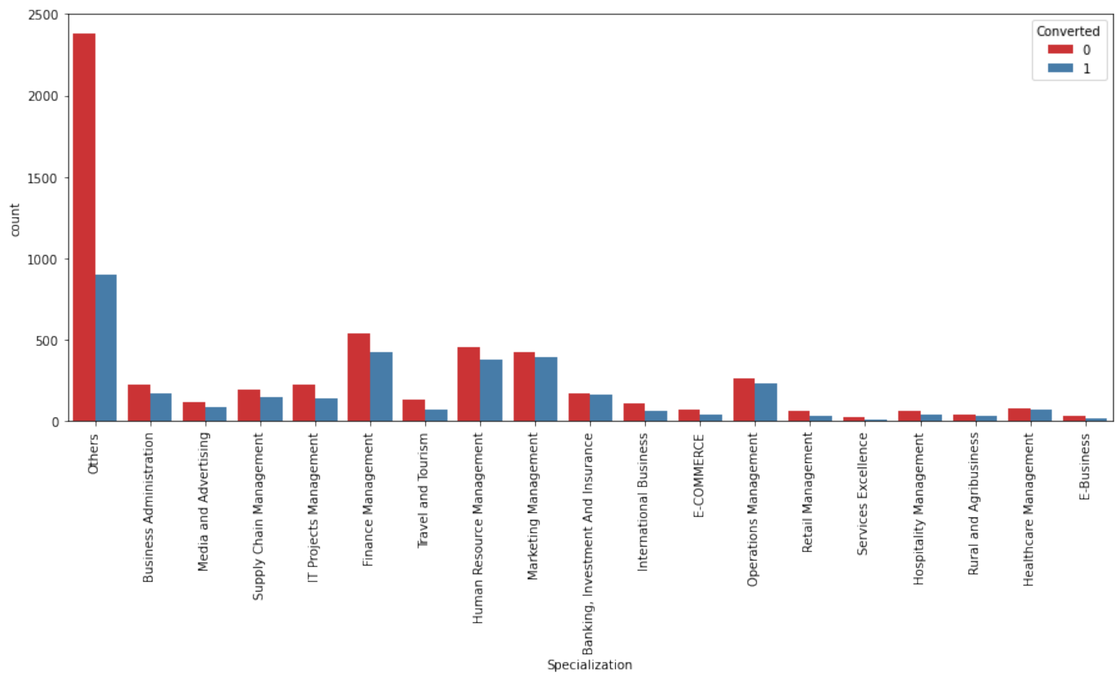
Inference

Most values are 'India' no such inference can be drawn

11) Specialization

```
plt.figure(figsize=(15,6))
sns.countplot(x = "Specialization", hue = "Converted", data = 
lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14,
15, 16,
        17, 18]),
 [Text(0, 0, 'Others'),
  Text(1, 0, 'Business Administration'),
  Text(2, 0, 'Media and Advertising'),
  Text(3, 0, 'Supply Chain Management'),
  Text(4, 0, 'IT Projects Management'),
  Text(5, 0, 'Finance Management'),
  Text(6, 0, 'Travel and Tourism'),
  Text(7, 0, 'Human Resource Management'),
  Text(8, 0, 'Marketing Management'),
  Text(9, 0, 'Banking, Investment And Insurance'),
  Text(10, 0, 'International Business'),
  Text(11, 0, 'E-COMMERCE'),
  Text(12, 0, 'Operations Management'),
  Text(13, 0, 'Retail Management'),
  Text(14, 0, 'Services Excellence'),
  Text(15, 0, 'Hospitality Management'),
  Text(16, 0, 'Rural and Agribusiness'),
  Text(17, 0, 'Healthcare Management'),
  Text(18, 0, 'E-Business')])
```



Inference

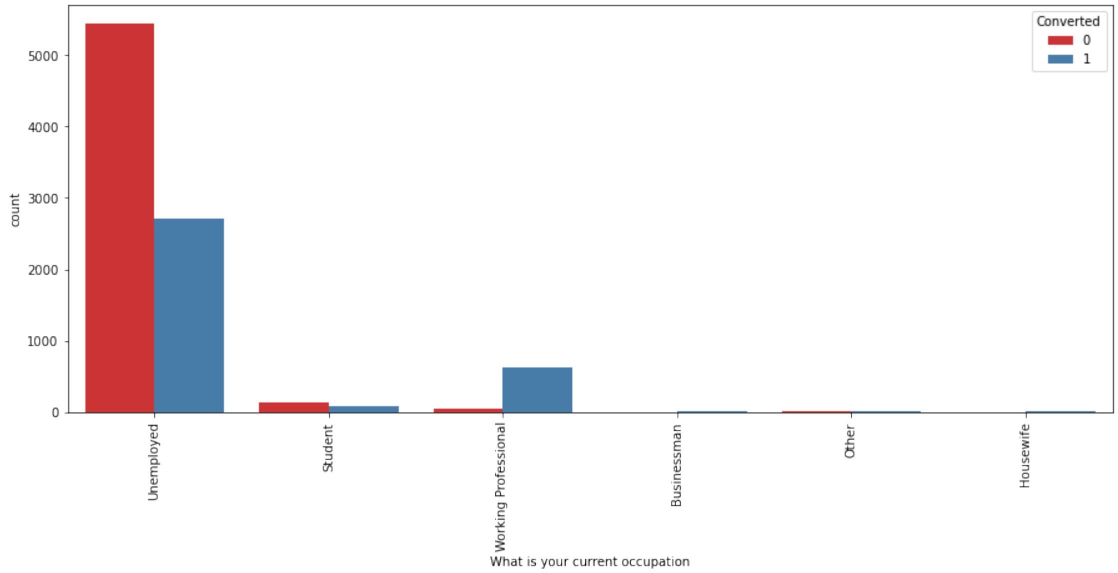
Focus should be more on the Specialization with high conversion rate.

12) What is your current occupation

```
plt.figure(figsize=(15,6))
sns.countplot(x = "What is your current occupation", hue =
```

```
"Converted", data = lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0, 1, 2, 3, 4, 5]),
 [Text(0, 0, 'Unemployed'),
  Text(1, 0, 'Student'),
  Text(2, 0, 'Working Professional'),
  Text(3, 0, 'Businessman'),
  Text(4, 0, 'Other'),
  Text(5, 0, 'Housewife')])
```



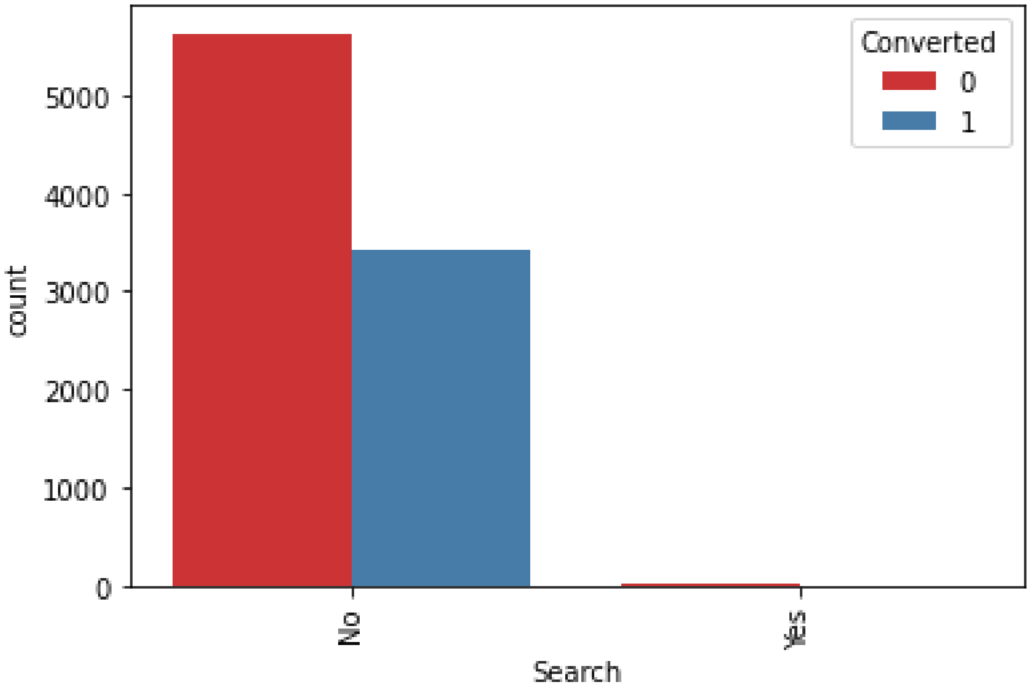
Inference

1. Working Professionals going for the course have high chances of joining it.
2. Unemployed leads are the most in numbers but has around 30-35% conversion rate.

13) Search

```
sns.countplot(x = "Search", hue = "Converted", data =
lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0, 1]), [Text(0, 0, 'No'), Text(1, 0, 'Yes')])
```



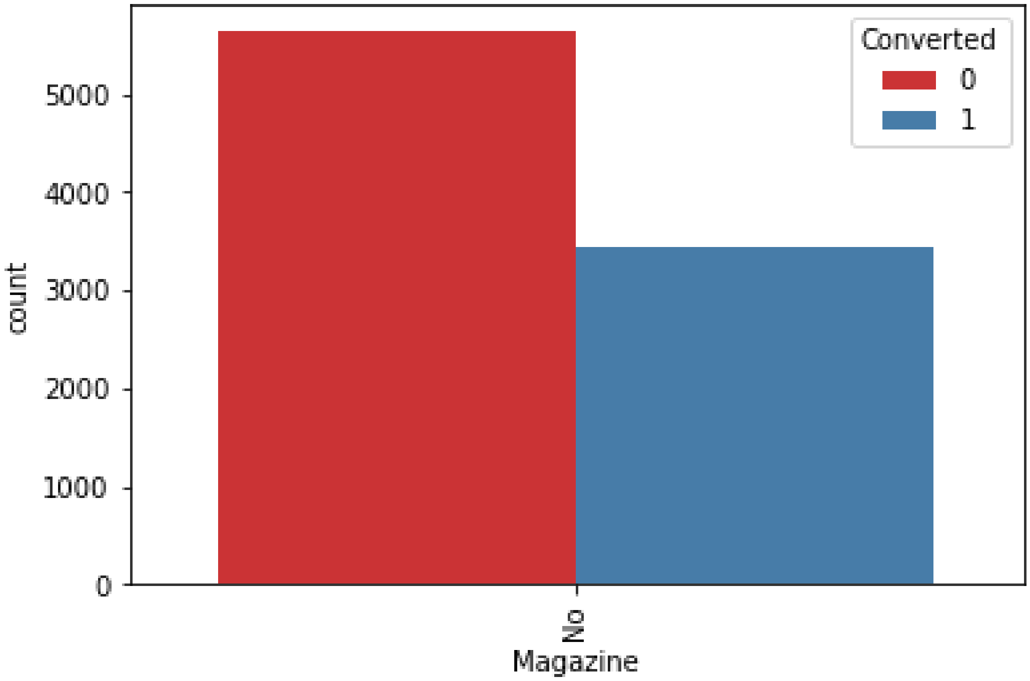
Inference

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

14) Magazine

```
sns.countplot(x = "Magazine", hue = "Converted", data =
lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0]), [Text(0, 0, 'No')])
```



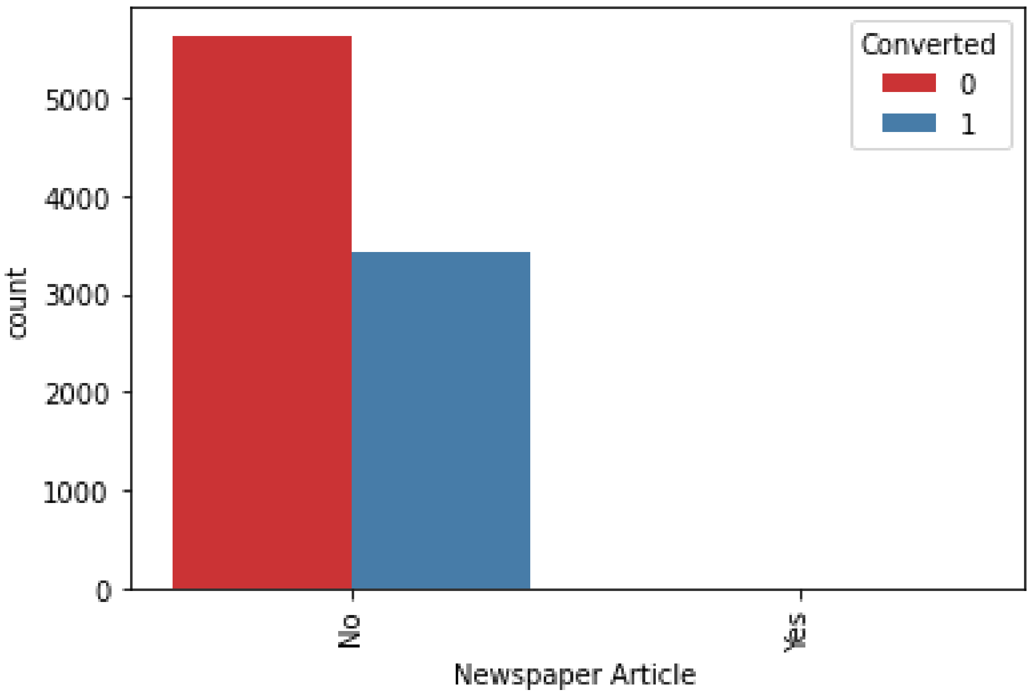
Inference

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

15) Newspaper Article

```
sns.countplot(x = "Newspaper Article", hue = "Converted", data =
lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0, 1]), [Text(0, 0, 'No'), Text(1, 0, 'Yes')])
```



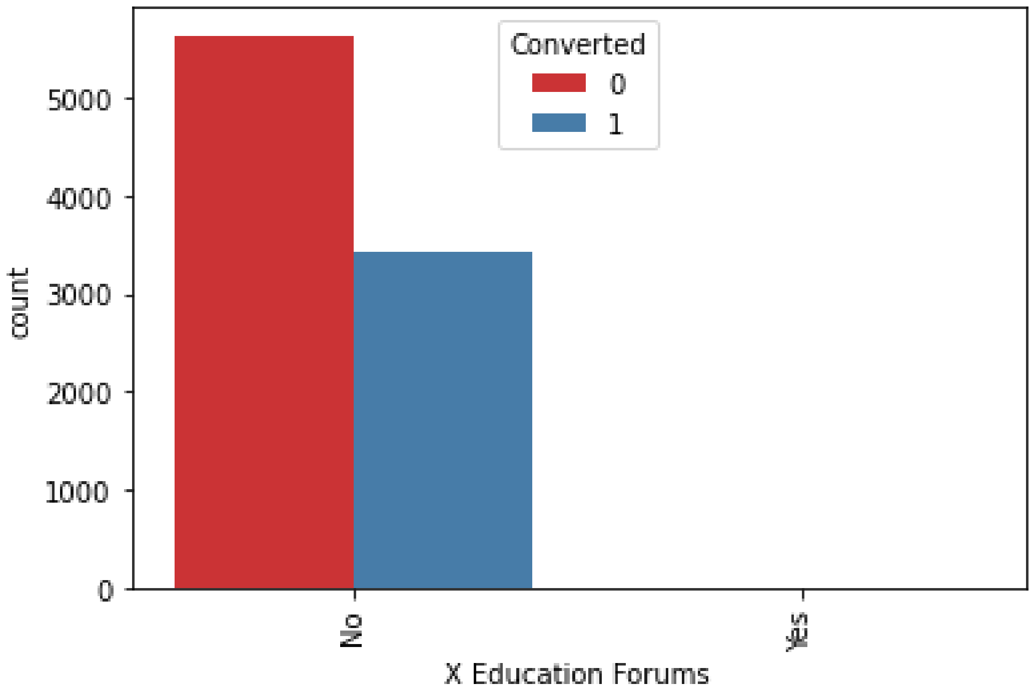
Inference

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

16) X Education Forums

```
sns.countplot(x = "X Education Forums", hue = "Converted", data =
lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0, 1]), [Text(0, 0, 'No'), Text(1, 0, 'Yes')])
```



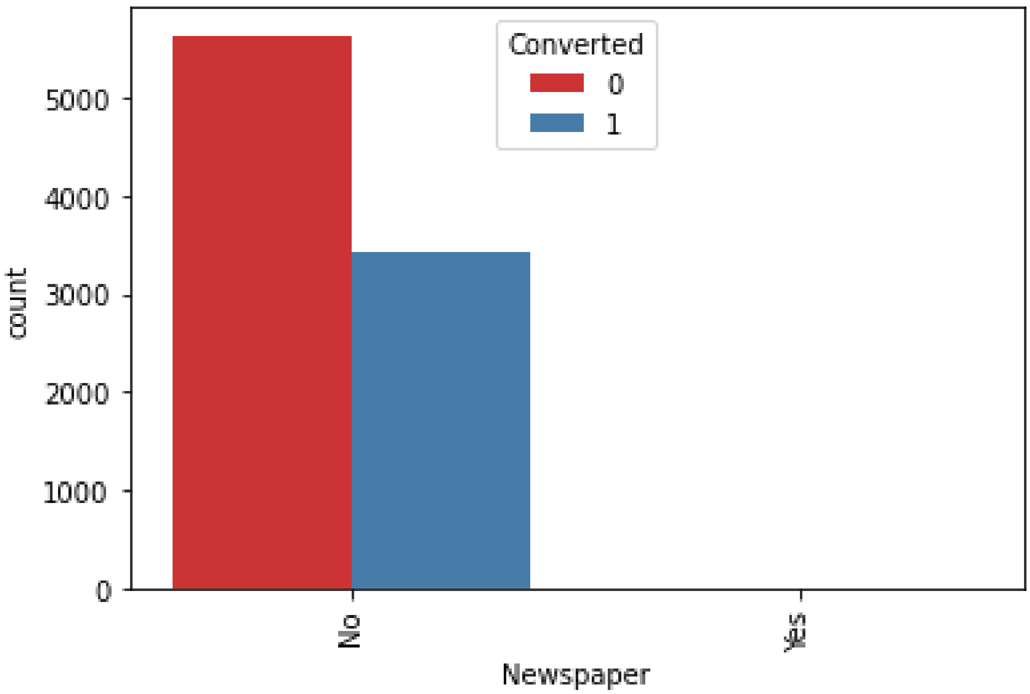
Inference

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

17) Newspaper

```
sns.countplot(x = "Newspaper", hue = "Converted", data =
lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0, 1]), [Text(0, 0, 'No'), Text(1, 0, 'Yes')])
```



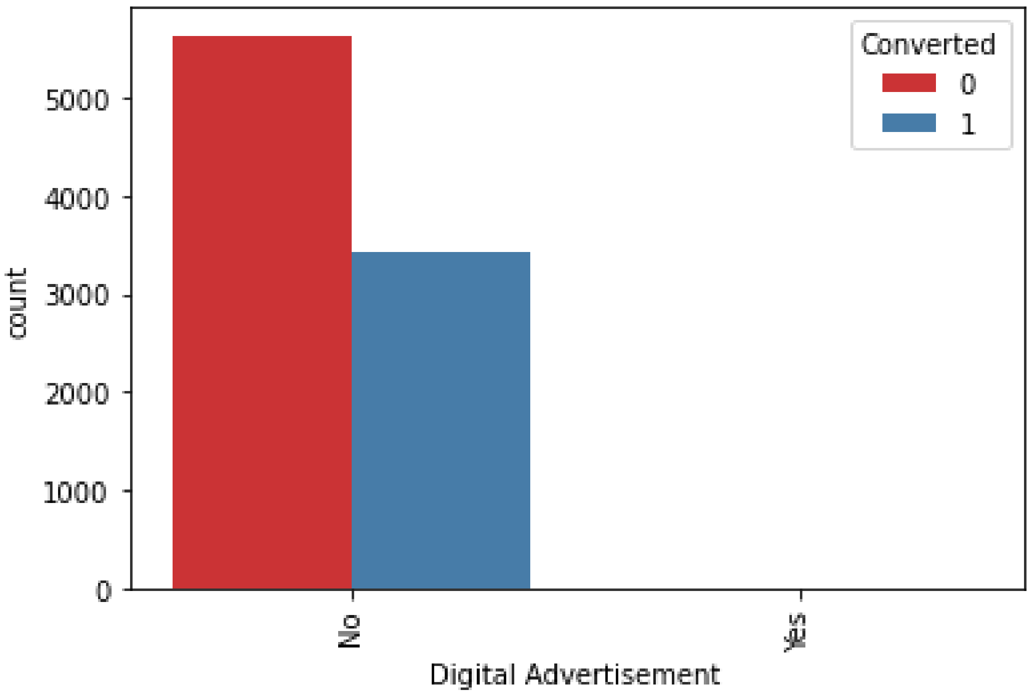
Inference

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

18) Digital Advertisement

```
sns.countplot(x = "Digital Advertisement", hue = "Converted", data = lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0, 1]), [Text(0, 0, 'No'), Text(1, 0, 'Yes')])
```



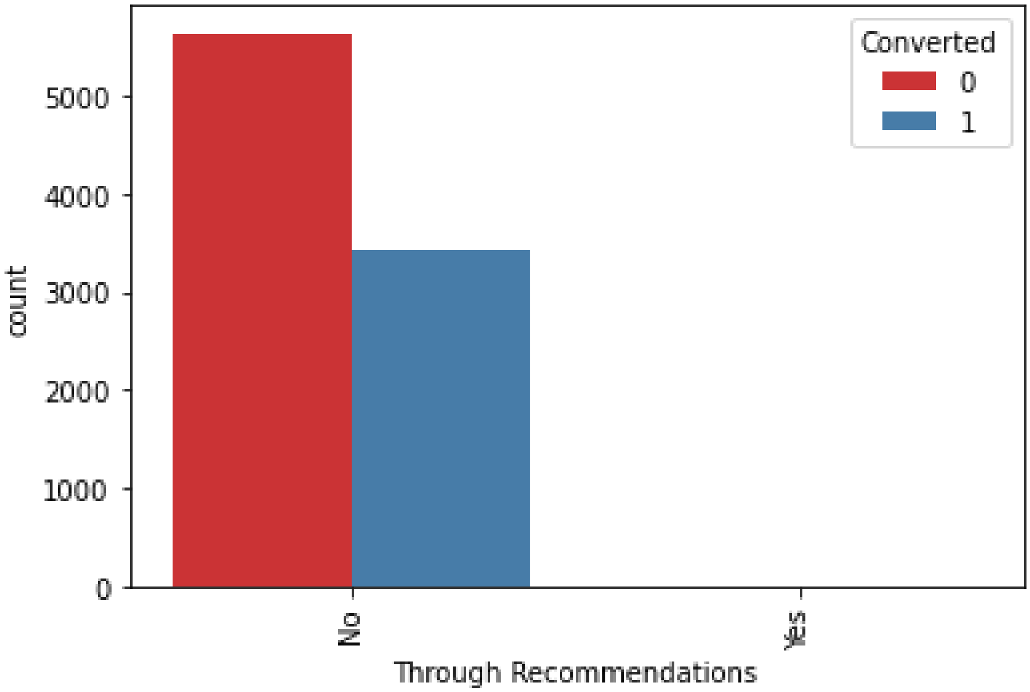
Inference

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

19) Through Recommendations

```
sns.countplot(x = "Through Recommendations", hue = "Converted", data =
lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0, 1]), [Text(0, 0, 'No'), Text(1, 0, 'Yes')])
```



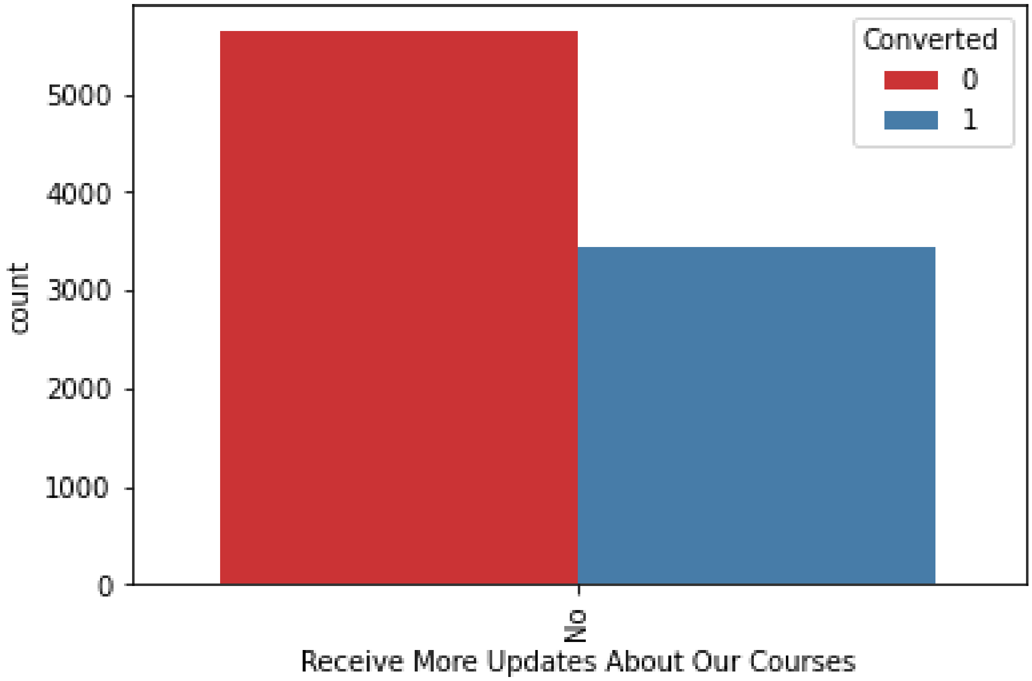
Inference

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

20) Receive More Updates About Our Courses

```
sns.countplot(x = "Receive More Updates About Our Courses", hue =
"Converted", data = lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0]), [Text(0, 0, 'No')])
```



Inference

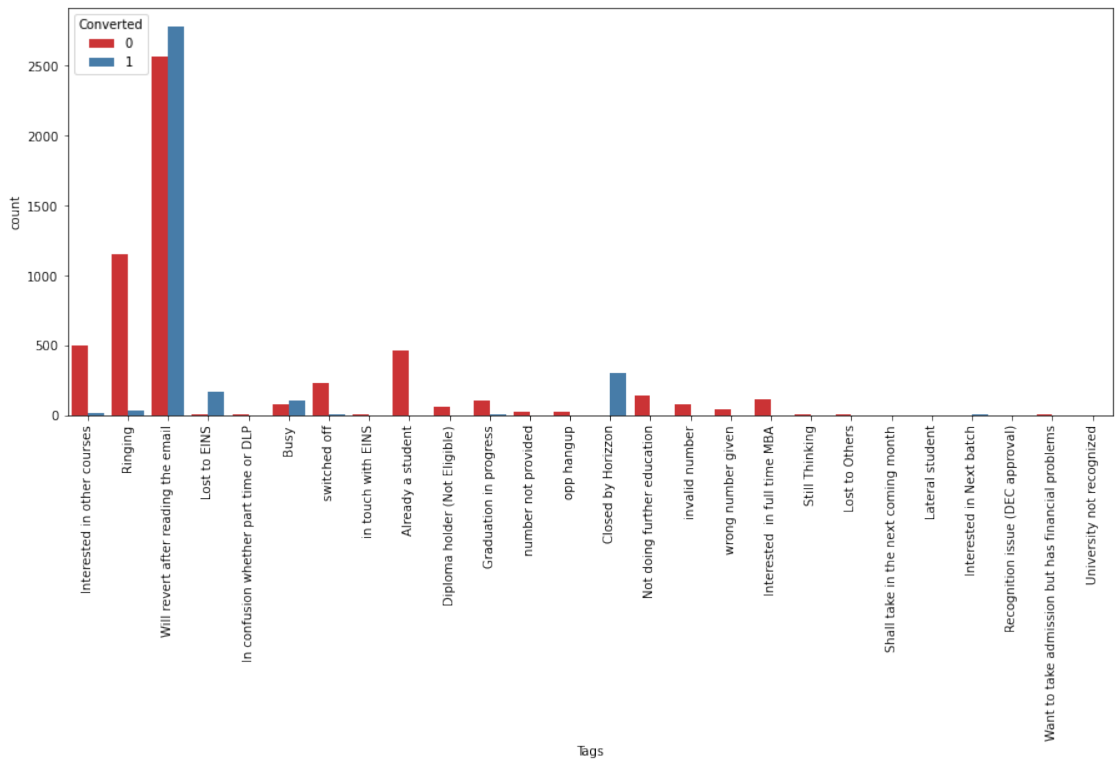
Most entries are 'No'. No Inference can be drawn with this parameter.

21) Tags

```
plt.figure(figsize=(15,6))
sns.countplot(x = "Tags", hue = "Converted", data =
lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(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]),
 [Text(0, 0, 'Interested in other courses'),
  Text(1, 0, 'Ringing'),
  Text(2, 0, 'Will revert after reading the email'),
  Text(3, 0, 'Lost to EINS'),
  Text(4, 0, 'In confusion whether part time or DLP'),
  Text(5, 0, 'Busy'),
  Text(6, 0, 'switched off'),
  Text(7, 0, 'in touch with EINS'),
  Text(8, 0, 'Already a student'),
  Text(9, 0, 'Diploma holder (Not Eligible)'),
  Text(10, 0, 'Graduation in progress'),
  Text(11, 0, 'number not provided'),
  Text(12, 0, 'opp hangup'),
  Text(13, 0, 'Closed by Horizzon'),
  Text(14, 0, 'Not doing further education'),
  Text(15, 0, 'invalid number'),
```

```
 Text(16, 0, 'wrong number given'),
 Text(17, 0, 'Interested  in full time MBA'),
 Text(18, 0, 'Still Thinking'),
 Text(19, 0, 'Lost to Others'),
 Text(20, 0, 'Shall take in the next coming month'),
 Text(21, 0, 'Lateral student'),
 Text(22, 0, 'Interested in Next batch'),
 Text(23, 0, 'Recognition issue (DEC approval)'),
 Text(24, 0, 'Want to take admission but has financial problems'),
 Text(25, 0, 'University not recognized')])
```



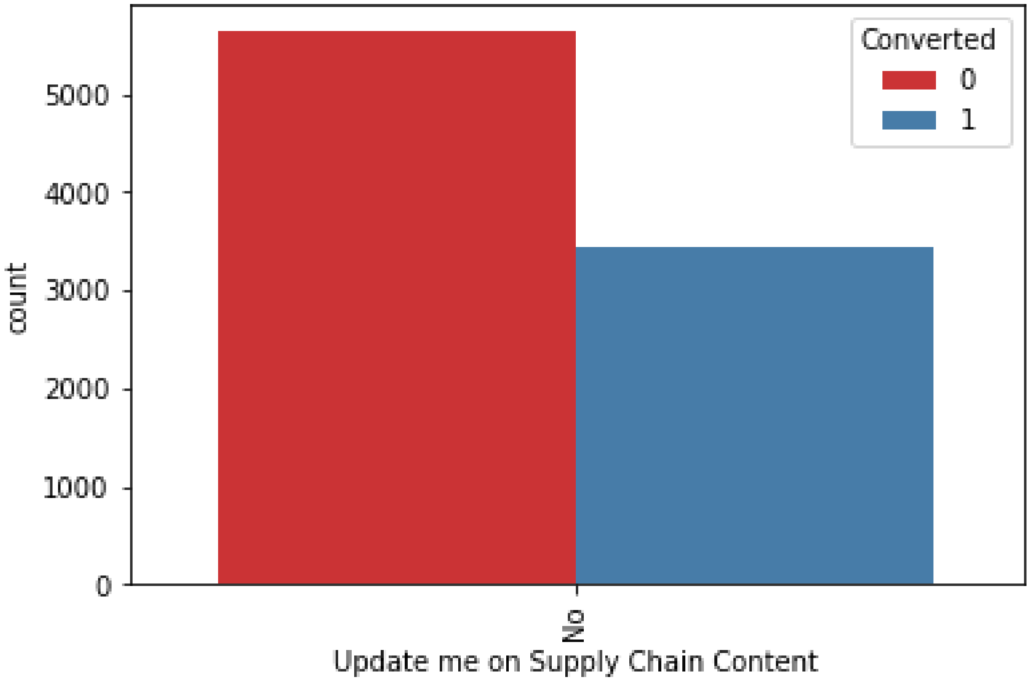
Inference

Since this is a column which is generated by the sales team for their analysis , so this is not available for model building . So we will need to remove this column before building the model.

22) Update me on Supply Chain Content

```
sns.countplot(x = "Update me on Supply Chain Content", hue = "Converted", data = lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0]), [Text(0, 0, 'No')])
```



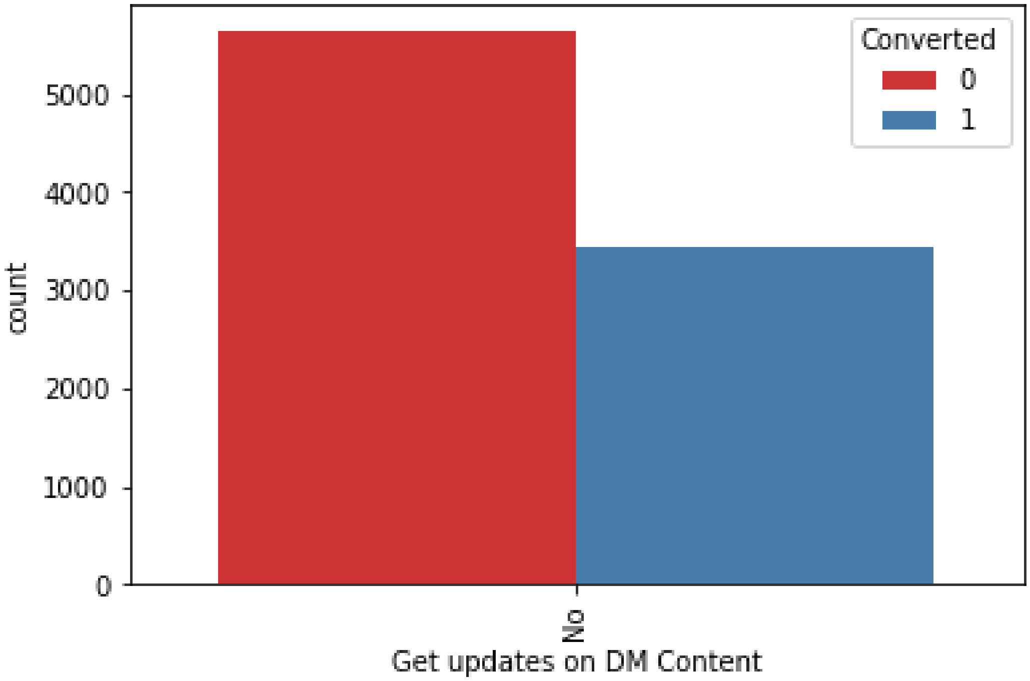
Inference

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

23) Get updates on DM Content

```
sns.countplot(x = "Get updates on DM Content", hue = "Converted", data
= lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0]), [Text(0, 0, 'No')])
```



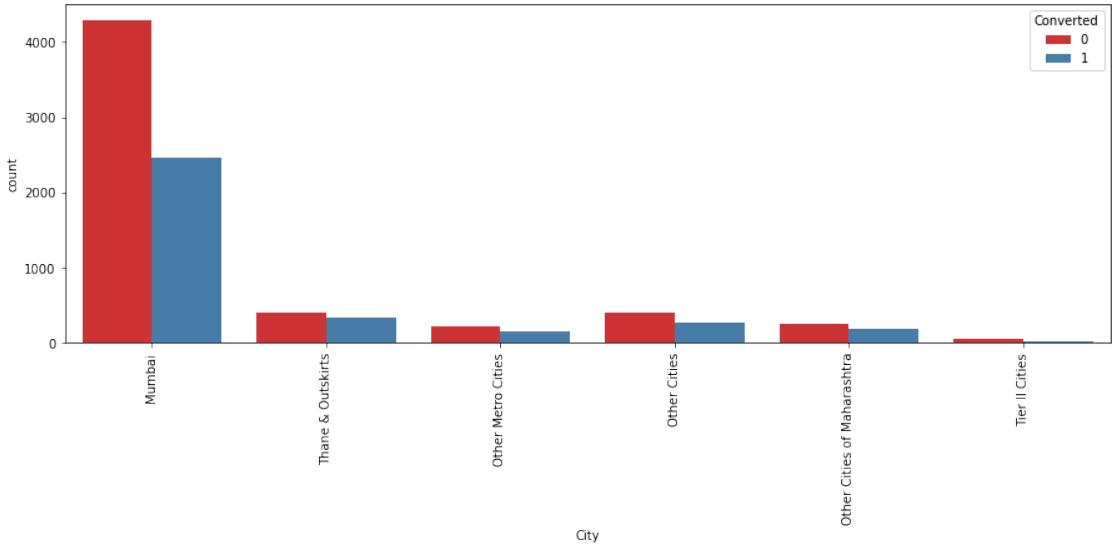
Inference

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

24) City

```
plt.figure(figsize=(15,5))
sns.countplot(x = "City", hue = "Converted", data =
lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0, 1, 2, 3, 4, 5]),
 [Text(0, 0, 'Mumbai'),
  Text(1, 0, 'Thane & Outskirts'),
  Text(2, 0, 'Other Metro Cities'),
  Text(3, 0, 'Other Cities'),
  Text(4, 0, 'Other Cities of Maharashtra'),
  Text(5, 0, 'Tier II Cities')])
```



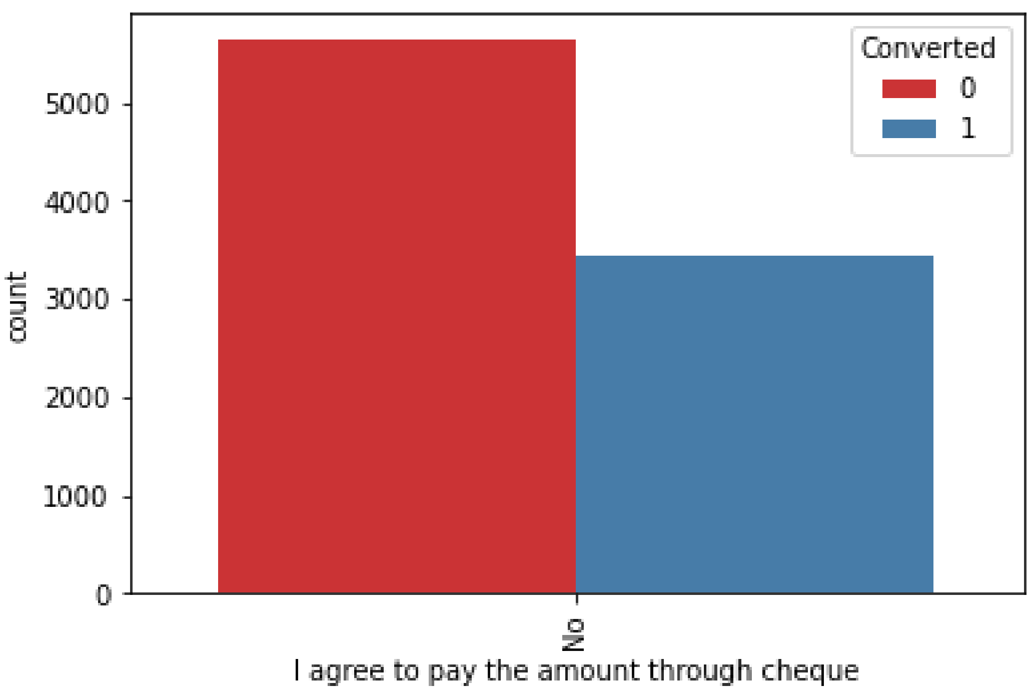
Inference

Most leads are from mumbai with around 50% conversion rate.

25) I agree to pay the amount through cheque

```
sns.countplot(x = "I agree to pay the amount through cheque", hue =
"Converted", data = lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0]), [Text(0, 0, 'No')])
```



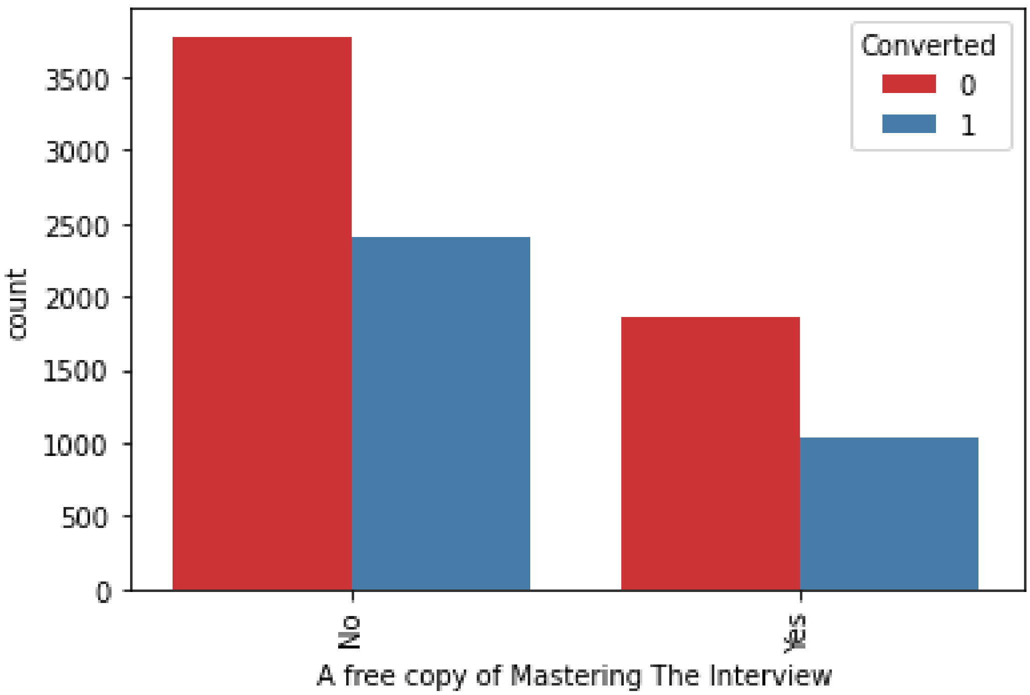
Inference

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

26) A free copy of Mastering The Interview

```
sns.countplot(x = "A free copy of Mastering The Interview", hue =
"Converted", data = lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([0, 1]), [Text(0, 0, 'No'), Text(1, 0, 'Yes')])
```



Inference

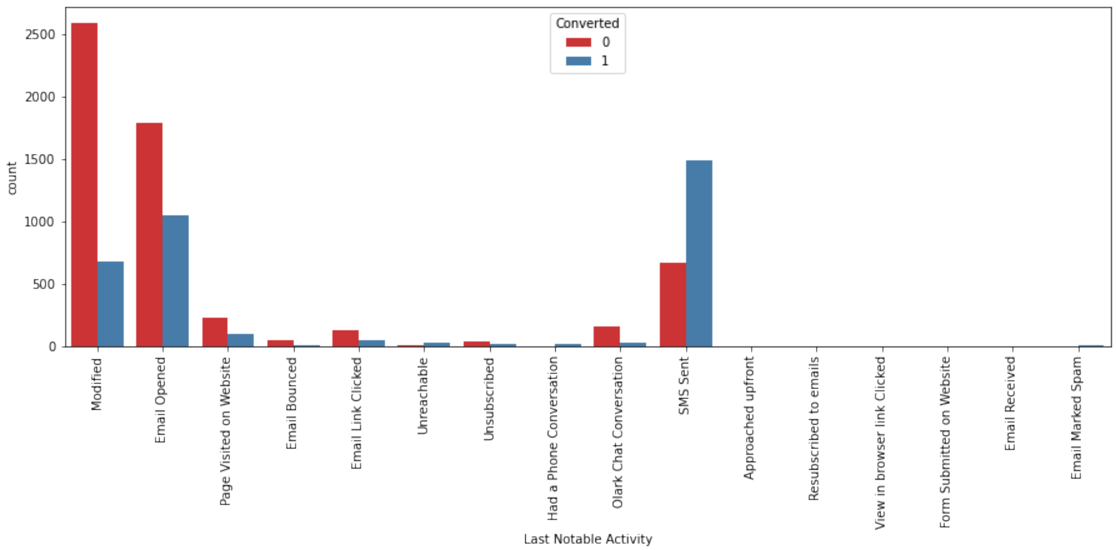
Most entries are 'No'. No Inference can be drawn with this parameter.

27) Last Notable Activity

```
plt.figure(figsize=(15,5))
sns.countplot(x = "Last Notable Activity", hue = "Converted", data =
lead_data,palette='Set1')
plt.xticks(rotation = 90)
```

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14,
15]),
 [Text(0, 0, 'Modified'),
  Text(1, 0, 'Email Opened'),
  Text(2, 0, 'Page Visited on Website'),
  Text(3, 0, 'Email Bounced'),
  Text(4, 0, 'Email Link Clicked'),
  Text(5, 0, 'Unreachable'),
```

```
 Text(6, 0, 'Unsubscribed'),
 Text(7, 0, 'Had a Phone Conversation'),
 Text(8, 0, 'Olark Chat Conversation'),
 Text(9, 0, 'SMS Sent'),
 Text(10, 0, 'Approached upfront'),
 Text(11, 0, 'Resubscribed to emails'),
 Text(12, 0, 'View in browser link Clicked'),
 Text(13, 0, 'Form Submitted on Website'),
 Text(14, 0, 'Email Received'),
 Text(15, 0, 'Email Marked Spam')])
```



Results

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

```
lead_data = lead_data.drop(['Lead Number','Tags','Country','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',
                            'A free copy of Mastering The Interview'],1)
```

```
lead_data.shape
```

```
(9074, 14)
```

```
lead_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9074 entries, 0 to 9239
Data columns (total 14 columns):
 #   Column                                  Non-Null Count  Dtype  
---  ------                                  --------------  -----  
 0   Prospect ID                             9074 non-null   object 
 1   Lead Origin                             9074 non-null   object 
 2   Lead Source                             9074 non-null   object 
 3   Do Not Email                            9074 non-null   object 
 4   Do Not Call                             9074 non-null   object 
 5   Converted                               9074 non-null   int64  
 6   TotalVisits                             9074 non-null   float64
 7   Total Time Spent on Website             9074 non-null   int64  
 8   Page Views Per Visit                    9074 non-null   float64
 9   Last Activity                           9074 non-null   object 
 10  Specialization                          9074 non-null   object 
 11  What is your current occupation  9074 non-null   object 
 12  City                                    9074 non-null   object 
 13  Last Notable Activity                   9074 non-null   object 
dtypes: float64(2), int64(2), object(10)
memory usage: 1.4+ MB
```

Data Preparation

1) Converting some binary variables (Yes/No) to 1/0

```
vars =  ['Do Not Email', 'Do Not Call']

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

lead_data[vars] = lead_data[vars].apply(binary_map)
```

2) Creating Dummy variables for the categorical features:

'Lead Origin', 'Lead Source', 'Last Activity', 'Specialization','What is your current occupation','City','Last Notable Activity'

```
# Creating a dummy variable for the categorical variables and dropping
the first one.
dummy_data = pd.get_dummies(lead_data[['Lead Origin', 'Lead Source',
'Last Activity', 'Specialization','What is your current occupation',
                             'City','Last Notable Activity']],
drop_first=True)
dummy_data.head()
```

```
   Lead Origin_Landing Page Submission  Lead Origin_Lead Add Form  \
0                                    0                          0   
1                                    0                          0   
2                                    1                          0   
3                                    1                          0   
4                                    1                          0   
```

```
   Lead Origin_Lead Import  Lead Source_Facebook  Lead 
Source_Google  \
0                        0                     0                    0   

1                        0                     0                    0   

2                        0                     0                    0   

3                        0                     0                    0   

4                        0                     0                    1   


   Lead Source_Olark Chat  Lead Source_Organic Search  Lead 
Source_Others  \
0                       1                           0
0   
1                       0                           1
0   
2                       0                           0
0   
3                       0                           0
0   
4                       0                           0
0   

   Lead Source_Reference  Lead Source_Referral Sites  ...  \
0                      0                           0  ...   
1                      0                           0  ...   
2                      0                           0  ...   
3                      0                           0  ...   
4                      0                           0  ...   

   Last Notable Activity_Form Submitted on Website  \
0                                                0   
1                                                0   
2                                                0   
3                                                0   
4                                                0   

   Last Notable Activity_Had a Phone Conversation  \
0                                               0   
1                                               0   
2                                               0   
3                                               0   
4                                               0   

   Last Notable Activity_Modified  \
```

```
0                               1
1                               0
2                               0
3                               1
4                               1

   Last Notable Activity_Olark Chat Conversation  \
0                                              0
1                                              0
2                                              0
3                                              0
4                                              0

   Last Notable Activity_Page Visited on Website  \
0                                              0
1                                              0
2                                              0
3                                              0
4                                              0

   Last Notable Activity_Resubscribed to emails  \
0                                             0
1                                             0
2                                             0
3                                             0
4                                             0

   Last Notable Activity_SMS Sent  Last Notable 
Activity_Unreachable  \
0                               0                                   0

1                               0                                   0

2                               0                                   0

3                               0                                   0

4                               0                                   0


   Last Notable Activity_Unsubscribed  \
0                                   0
1                                   0
2                                   0
3                                   0
4                                   0

   Last Notable Activity_View in browser link Clicked
0                                                  0
```

```
1                                                   0
2                                                   0
3                                                   0
4                                                   0

[5 rows x 64 columns]
```

```
# Concatenating the dummy_data to the lead_data dataframe
lead_data = pd.concat([lead_data, dummy_data], axis=1)
lead_data.head()
```

```
                            Prospect ID              Lead Origin  \
0  7927b2df-8bba-4d29-b9a2-b6e0beafe620                      API
1  2a272436-5132-4136-86fa-dcc88c88f482                      API
2  8cc8c611-a219-4f35-ad23-fdfd2656bd8a  Landing Page Submission
3  0cc2df48-7cf4-4e39-9de9-19797f9b38cc  Landing Page Submission
4  3256f628-e534-4826-9d63-4a8b88782852  Landing Page Submission

      Lead Source  Do Not Email  Do Not Call  Converted
TotalVisits  \
0      Olark Chat             0            0          0          0.0

1  Organic Search             0            0          0          5.0

2  Direct Traffic             0            0          1          2.0

3  Direct Traffic             0            0          0          1.0

4          Google             0            0          1          2.0


   Total Time Spent on Website  Page Views Per Visit            Last
Activity  \
0                            0                   0.0  Page Visited on
Website
1                          674                   2.5            Email
Opened
2                         1532                   2.0            Email
Opened
3                          305                   1.0
Unreachable
4                         1428                   1.0        Converted
to Lead

   ... Last Notable Activity_Form Submitted on Website  \
0  ...                                                0
1  ...                                                0
2  ...                                                0
3  ...                                                0
4  ...                                                0
```

```
  Last Notable Activity_Had a Phone Conversation  \
0                                               0
1                                               0
2                                               0
3                                               0
4                                               0

  Last Notable Activity_Modified  \
0                              1
1                              0
2                              0
3                              1
4                              1

  Last Notable Activity_Olark Chat Conversation  \
0                                              0
1                                              0
2                                              0
3                                              0
4                                              0

   Last Notable Activity_Page Visited on Website  \
0                                               0
1                                               0
2                                               0
3                                               0
4                                               0

   Last Notable Activity_Resubscribed to emails  \
0                                              0
1                                              0
2                                              0
3                                              0
4                                              0

   Last Notable Activity_SMS Sent  Last Notable
Activity_Unreachable  \
0                               0                                  0

1                               0                                  0

2                               0                                  0

3                               0                                  0

4                               0                                  0
```

```
   Last Notable Activity_Unsubscribed  \
0                                    0
1                                    0
2                                    0
3                                    0
4                                    0

   Last Notable Activity_View in browser link Clicked
0                                                   0
1                                                   0
2                                                   0
3                                                   0
4                                                   0

[5 rows x 78 columns]
```

Dropping the columns for which dummies were created

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

lead_data.head()

                            Prospect ID  Do Not Email  Do Not Call
Converted  \
0  7927b2df-8bba-4d29-b9a2-b6e0beafe620             0            0
0
1  2a272436-5132-4136-86fa-dcc88c88f482             0            0
0
2  8cc8c611-a219-4f35-ad23-fdfd2656bd8a             0            0
1
3  0cc2df48-7cf4-4e39-9de9-19797f9b38cc             0            0
0
4  3256f628-e534-4826-9d63-4a8b88782852             0            0
1

   TotalVisits  Total Time Spent on Website  Page Views Per Visit  \
0          0.0                            0                   0.0
1          5.0                          674                   2.5
2          2.0                         1532                   2.0
3          1.0                          305                   1.0
4          2.0                         1428                   1.0

   Lead Origin_Landing Page Submission  Lead Origin_Lead Add Form  \
0                                    0                          0
1                                    0                          0
2                                    1                          0
3                                    1                          0
4                                    1                          0
```

```
   Lead Origin_Lead Import  ...  \
0                        0  ...   
1                        0  ...   
2                        0  ...   
3                        0  ...   
4                        0  ...   

   Last Notable Activity_Form Submitted on Website  \
0                                                0   
1                                                0   
2                                                0   
3                                                0   
4                                                0   

   Last Notable Activity_Had a Phone Conversation  \
0                                               0   
1                                               0   
2                                               0   
3                                               0   
4                                               0   

   Last Notable Activity_Modified  \
0                               1   
1                               0   
2                               0   
3                               1   
4                               1   

   Last Notable Activity_Olark Chat Conversation  \
0                                              0   
1                                              0   
2                                              0   
3                                              0   
4                                              0   

   Last Notable Activity_Page Visited on Website  \
0                                              0   
1                                              0   
2                                              0   
3                                              0   
4                                              0   

   Last Notable Activity_Resubscribed to emails  \
0                                             0   
1                                             0   
2                                             0   
3                                             0   
4                                             0   
```

```
   Last Notable Activity_SMS Sent  Last Notable
Activity_Unreachable  \
0                               0                                  0

1                               0                                  0

2                               0                                  0

3                               0                                  0

4                               0                                  0


   Last Notable Activity_Unsubscribed  \
0                                   0
1                                   0
2                                   0
3                                   0
4                                   0

   Last Notable Activity_View in browser link Clicked
0                                                  0
1                                                  0
2                                                  0
3                                                  0
4                                                  0

[5 rows x 71 columns]
```

3) Splitting the data into train and test set.

```
from sklearn.model_selection import train_test_split

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

```
   Do Not Email  Do Not Call  TotalVisits  Total Time Spent on Website
\
0             0            0          0.0                            0

1             0            0          5.0                          674

2             0            0          2.0                         1532

3             0            0          1.0                          305

4             0            0          2.0                         1428
```

```
   Page Views Per Visit  Lead Origin_Landing Page Submission  \
0                   0.0                                    0
1                   2.5                                    0
2                   2.0                                    1
3                   1.0                                    1
4                   1.0                                    1

   Lead Origin_Lead Add Form  Lead Origin_Lead Import  Lead
Source_Facebook  \
0                          0                        0
0
1                          0                        0
0
2                          0                        0
0
3                          0                        0
0
4                          0                        0
0

   Lead Source_Google  ...  Last Notable Activity_Form Submitted on
Website  \
0                   0  ...
0
1                   0  ...
0
2                   0  ...
0
3                   0  ...
0
4                   1  ...
0

   Last Notable Activity_Had a Phone Conversation  \
0                                               0
1                                               0
2                                               0
3                                               0
4                                               0

   Last Notable Activity_Modified  \
0                               1
1                               0
2                               0
3                               1
4                               1

   Last Notable Activity_Olark Chat Conversation  \
0                                              0
```

```
1                                               0
2                                               0
3                                               0
4                                               0

   Last Notable Activity_Page Visited on Website  \
0                                               0
1                                               0
2                                               0
3                                               0
4                                               0

   Last Notable Activity_Resubscribed to emails  \
0                                              0
1                                              0
2                                              0
3                                              0
4                                              0

   Last Notable Activity_SMS Sent  Last Notable
Activity_Unreachable  \
0                               0                                   0

1                               0                                   0

2                               0                                   0

3                               0                                   0

4                               0                                   0


   Last Notable Activity_Unsubscribed  \
0                                    0
1                                    0
2                                    0
3                                    0
4                                    0

   Last Notable Activity_View in browser link Clicked
0                                                   0
1                                                   0
2                                                   0
3                                                   0
4                                                   0

[5 rows x 69 columns]
```

```
# Putting target variable to y
y = lead_data['Converted']

y.head()
```

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

```
# 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)
```

4) Scaling the features

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

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

X_train.head()
```

```
      Do Not Email  Do Not Call  TotalVisits  Total Time Spent on
Website  \
3009             0            0    -0.432779                    -
0.160255
1012             1            0    -0.432779                    -
0.540048
9226             0            0    -1.150329                    -
0.888650
4750             0            0    -0.432779
1.643304
7987             0            0     0.643547
2.017593

      Page Views Per Visit  Lead Origin_Landing Page Submission  \
3009             -0.155018                                    1
1012             -0.155018                                    1
9226             -1.265540                                    0
4750             -0.155018                                    1
7987              0.122613                                    1

      Lead Origin_Lead Add Form  Lead Origin_Lead Import  \
3009                          0                        0
1012                          0                        0
```

```
9226                          0                        0
4750                          0                        0
7987                          0                        0

      Lead Source_Facebook  Lead Source_Google  ...  \
3009                     0                   0  ...
1012                     0                   0  ...
9226                     0                   0  ...
4750                     0                   0  ...
7987                     0                   0  ...

      Last Notable Activity_Form Submitted on Website  \
3009                                                0
1012                                                0
9226                                                0
4750                                                0
7987                                                0

      Last Notable Activity_Had a Phone Conversation  \
3009                                               0
1012                                               0
9226                                               0
4750                                               0
7987                                               0

      Last Notable Activity_Modified  \
3009                               0
1012                               0
9226                               1
4750                               0
7987                               1

      Last Notable Activity_Olark Chat Conversation  \
3009                                              0
1012                                              0
9226                                              0
4750                                              0
7987                                              0

      Last Notable Activity_Page Visited on Website  \
3009                                              0
1012                                              0
9226                                              0
4750                                              0
7987                                              0

      Last Notable Activity_Resubscribed to emails  \
3009                                             0
1012                                             0
```

```
9226                                               0
4750                                               0
7987                                               0

      Last Notable Activity_SMS Sent  Last Notable
Activity_Unreachable  \
3009                           0
0
1012                           0
0
9226                           0
0
4750                           1
0
7987                           0
0

      Last Notable Activity_Unsubscribed  \
3009                               0
1012                               0
9226                               0
4750                               0
7987                               0

      Last Notable Activity_View in browser link Clicked
3009                                                0
1012                                                0
9226                                                0
4750                                                0
7987                                                0

[5 rows x 69 columns]
```

```
# Checking the Lead Conversion rate
Converted =
(sum(lead_data['Converted'])/len(lead_data['Converted'].index))*100
Converted
```

```
37.85541106458012
```

We have almost 38% lead conversion rate.

Feature Selection Using RFE

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

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

```
rfe.support_
```

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

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

```
[('Do Not Email', True, 1),
 ('Do Not Call', False, 9),
 ('TotalVisits', False, 21),
 ('Total Time Spent on Website', True, 1),
 ('Page Views Per Visit', False, 20),
 ('Lead Origin_Landing Page Submission', True, 1),
 ('Lead Origin_Lead Add Form', True, 1),
 ('Lead Origin_Lead Import', True, 1),
 ('Lead Source_Facebook', False, 24),
 ('Lead Source_Google', False, 25),
 ('Lead Source_Olark Chat', True, 1),
 ('Lead Source_Organic Search', False, 36),
 ('Lead Source_Others', False, 28),
 ('Lead Source_Reference', True, 1),
 ('Lead Source_Referral Sites', False, 48),
 ('Lead Source_Welingak Website', True, 1),
 ('Last Activity_Email Bounced', False, 19),
 ('Last Activity_Email Link Clicked', False, 13),
 ('Last Activity_Email Opened', False, 7),
 ('Last Activity_Form Submitted on Website', False, 35),
 ('Last Activity_Olark Chat Conversation', True, 1),
 ('Last Activity_Other_Activity', True, 1),
 ('Last Activity_Page Visited on Website', False, 12),
 ('Last Activity_SMS Sent', True, 1),
 ('Last Activity_Unreachable', False, 11),
 ('Last Activity_Unsubscribed', True, 1),
 ('Specialization_Business Administration', False, 30),
 ('Specialization_E-Business', False, 23),
 ('Specialization_E-COMMERCE', False, 32),
 ('Specialization_Finance Management', False, 44),
 ('Specialization_Healthcare Management', False, 39),
 ('Specialization_Hospitality Management', False, 10),
 ('Specialization_Human Resource Management', False, 43),
 ('Specialization_IT Projects Management', False, 47),
 ('Specialization_International Business', False, 26),
 ('Specialization_Marketing Management', False, 34),
 ('Specialization_Media and Advertising', False, 22),
 ('Specialization_Operations Management', False, 41),
```

```
 ('Specialization_Others', True, 1),
 ('Specialization_Retail Management', False, 27),
 ('Specialization_Rural and Agribusiness', False, 38),
 ('Specialization_Services Excellence', False, 18),
 ('Specialization_Supply Chain Management', False, 46),
 ('Specialization_Travel and Tourism', False, 33),
 ('What is your current occupation_Housewife', True, 1),
 ('What is your current occupation_Other', False, 31),
 ('What is your current occupation_Student', True, 1),
 ('What is your current occupation_Unemployed', True, 1),
 ('What is your current occupation_Working Professional', True, 1),
 ('City_Other Cities', False, 42),
 ('City_Other Cities of Maharashtra', False, 45),
 ('City_Other Metro Cities', False, 40),
 ('City_Thane & Outskirts', False, 50),
 ('City_Tier II Cities', False, 8),
 ('Last Notable Activity_Email Bounced', False, 16),
 ('Last Notable Activity_Email Link Clicked', False, 4),
 ('Last Notable Activity_Email Marked Spam', False, 29),
 ('Last Notable Activity_Email Opened', False, 6),
 ('Last Notable Activity_Email Received', False, 49),
 ('Last Notable Activity_Form Submitted on Website', False, 37),
 ('Last Notable Activity_Had a Phone Conversation', True, 1),
 ('Last Notable Activity_Modified', True, 1),
 ('Last Notable Activity_Olark Chat Conversation', False, 2),
 ('Last Notable Activity_Page Visited on Website', False, 5),
 ('Last Notable Activity_Resubscribed to emails', False, 17),
 ('Last Notable Activity_SMS Sent', False, 15),
 ('Last Notable Activity_Unreachable', True, 1),
 ('Last Notable Activity_Unsubscribed', False, 14),
 ('Last Notable Activity_View in browser link Clicked', False, 3)]
```

```
# Viewing columns selected by RFE
cols = X_train.columns[rfe.support_]
cols
```

```
Index(['Do Not Email', 'Total Time Spent on Website',
       'Lead Origin_Landing Page Submission', 'Lead Origin_Lead Add
Form',
       'Lead Origin_Lead Import', 'Lead Source_Olark Chat',
       'Lead Source_Reference', 'Lead Source_Welingak Website',
       'Last Activity_Olark Chat Conversation', 'Last
Activity_Other_Activity',
       'Last Activity_SMS Sent', 'Last Activity_Unsubscribed',
       'Specialization_Others', 'What is your current
occupation_Housewife',
       'What is your current occupation_Student',
       'What is your current occupation_Unemployed',
       'What is your current occupation_Working Professional',
       'Last Notable Activity_Had a Phone Conversation',
       'Last Notable Activity_Modified', 'Last Notable
```

```
Activity_Unreachable'],
      dtype='object')
```

Model Building

Assessing the model with StatsModels

Model-1

```
import statsmodels.api as sm

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

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                 Generalized Linear Model Regression Results

======================================================================
========
Dep. Variable:              Converted   No. Observations:
6351
Model:                            GLM   Df Residuals:
6330
Model Family:                Binomial   Df Model:
20
Link Function:                  logit   Scale:
1.0000
Method:                          IRLS   Log-Likelihood:
-2590.3
Date:                Wed, 22 Mar 2023   Deviance:
5180.6
Time:                        09:09:05   Pearson chi2:
6.52e+03
No. Iterations:                    21

Covariance Type:            nonrobust

======================================================================
==================================================
                                                        coef    std
err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------
--------------------------------------------------
const                                                 0.8338
0.637      1.309      0.190      -0.414       2.082
Do Not Email                                         -1.6759
0.191     -8.796      0.000      -2.049      -1.302
Total Time Spent on Website                           1.1081
```

```
0.041     27.194      0.000       1.028       1.188
Lead Origin_Landing Page Submission                          -1.1219
0.130     -8.663      0.000      -1.376      -0.868
Lead Origin_Lead Add Form                                     1.6019
0.915      1.751      0.080      -0.191       3.395
Lead Origin_Lead Import                                       0.9059
0.480      1.888      0.059      -0.035       1.846
Lead Source_Olark Chat                                        1.1250
0.124      9.082      0.000       0.882       1.368
Lead Source_Reference                                         1.7697
0.938      1.887      0.059      -0.069       3.608
Lead Source_Welingak Website                                  4.2961
1.165      3.687      0.000       2.012       6.580
Last Activity_Olark Chat Conversation                        -0.9504
0.172     -5.531      0.000      -1.287      -0.614
Last Activity_Other_Activity                                  1.8717
0.537      3.483      0.000       0.818       2.925
Last Activity_SMS Sent                                        1.3454
0.076     17.766      0.000       1.197       1.494
Last Activity_Unsubscribed                                    1.4083
0.483      2.917      0.004       0.462       2.355
Specialization_Others                                        -1.1410
0.126     -9.052      0.000      -1.388      -0.894
What is your current occupation_Housewife                    21.7588
1.53e+04      0.001       0.999   -2.99e+04    2.99e+04
What is your current occupation_Student                      -0.5518
0.673     -0.820      0.412      -1.871       0.767
What is your current occupation_Unemployed                   -1.0059
0.634     -1.587      0.113      -2.248       0.236
What is your current occupation_Working Professional          1.6281
0.660      2.466      0.014       0.334       2.922
Last Notable Activity_Had a Phone Conversation                1.4204
1.223      1.161      0.246      -0.978       3.818
Last Notable Activity_Modified                               -0.8675
0.082    -10.620      0.000      -1.028      -0.707
Last Notable Activity_Unreachable                             1.5785
0.476      3.316      0.001       0.645       2.512
======================================================================
==================================================
"""
```

Since Pvalue of 'What is your current occupation_Housewife' is very high, we can drop this column.

```
# Dropping the column 'What is your current occupation_Housewife'
col1 = cols.drop('What is your current occupation_Housewife')
```

Model-2

```
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()

<class 'statsmodels.iolib.summary.Summary'>
"""
                 Generalized Linear Model Regression Results

==============================================================================
========
Dep. Variable:              Converted   No. Observations:
6351
Model:                            GLM   Df Residuals:
6331
Model Family:                Binomial   Df Model:
19
Link Function:                  logit   Scale:
1.0000
Method:                          IRLS   Log-Likelihood:
-2592.3
Date:                Wed, 22 Mar 2023   Deviance:
5184.5
Time:                        09:09:05   Pearson chi2:
6.53e+03
No. Iterations:                     7

Covariance Type:            nonrobust

==============================================================================
==================================================
                                                                  coef    std
err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
--------------------------------------------------
const                                                           1.3160
0.590      2.230      0.026       0.159       2.473
Do Not Email                                                   -1.6800
0.191     -8.812      0.000      -2.054      -1.306
Total Time Spent on Website                                     1.1069
0.041     27.184      0.000       1.027       1.187
Lead Origin_Landing Page Submission                            -1.1154
0.129     -8.621      0.000      -1.369      -0.862
Lead Origin_Lead Add Form                                       1.6044
0.915      1.754      0.079      -0.189       3.397
Lead Origin_Lead Import                                         0.9081
0.480      1.893      0.058      -0.032       1.848
Lead Source_Olark Chat                                          1.1254
0.124      9.085      0.000       0.883       1.368
Lead Source_Reference                                           1.7729
0.938      1.890      0.059      -0.066       3.611
Lead Source_Welingak Website                                    4.2952
```

```
1.165      3.685      0.000       2.011       6.579
Last Activity_Olark Chat Conversation                      -0.9512
0.172     -5.531      0.000      -1.288      -0.614
Last Activity_Other_Activity                                1.8733
0.537      3.486      0.000       0.820       2.927
Last Activity_SMS Sent                                      1.3445
0.076     17.756      0.000       1.196       1.493
Last Activity_Unsubscribed                                  1.4117
0.483      2.924      0.003       0.466       2.358
Specialization_Others                                      -1.1373
0.126     -9.031      0.000      -1.384      -0.890
What is your current occupation_Student                    -1.0384
0.627     -1.656      0.098      -2.268       0.191
What is your current occupation_Unemployed                 -1.4919
0.585     -2.550      0.011      -2.638      -0.345
What is your current occupation_Working Professional        1.1419
0.613      1.862      0.063      -0.060       2.344
Last Notable Activity_Had a Phone Conversation              1.4165
1.223      1.158      0.247      -0.981       3.814
Last Notable Activity_Modified                             -0.8703
0.082    -10.657      0.000      -1.030      -0.710
Last Notable Activity_Unreachable                           1.5745
0.476      3.305      0.001       0.641       2.508
======================================================================
==================================================
"""
```

Since Pvalue of 'Last Notable Activity_Had a Phone Conversation' is very high, we can drop this column.

```
col1 = col1.drop('Last Notable Activity_Had a Phone Conversation')
```

Model-3

```
X_train_sm = sm.add_constant(X_train[col1])
logm3 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm3.fit()
res.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                 Generalized Linear Model Regression Results

======================================================================
========
Dep. Variable:              Converted   No. Observations:
6351
Model:                            GLM   Df Residuals:
6332
Model Family:                Binomial   Df Model:
18
Link Function:                  logit   Scale:
```

```
1.0000
Method:                          IRLS   Log-Likelihood:
-2593.1
Date:                Wed, 22 Mar 2023   Deviance:
5186.1
Time:                        09:09:05   Pearson chi2:
6.53e+03
No. Iterations:                     7

Covariance Type:            nonrobust

======================================================================
==================================================
                                                          coef    std
err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------
--------------------------------------------------
const                                                   1.3199
0.590      2.235      0.025       0.163       2.477
Do Not Email                                           -1.6826
0.191     -8.816      0.000      -2.057      -1.308
Total Time Spent on Website                             1.1059
0.041     27.170      0.000       1.026       1.186
Lead Origin_Landing Page Submission                    -1.1158
0.129     -8.626      0.000      -1.369      -0.862
Lead Origin_Lead Add Form                               1.6034
0.915      1.753      0.080      -0.190       3.396
Lead Origin_Lead Import                                 0.9065
0.480      1.890      0.059      -0.034       1.847
Lead Source_Olark Chat                                  1.1230
0.124      9.064      0.000       0.880       1.366
Lead Source_Reference                                   1.7724
0.938      1.889      0.059      -0.066       3.611
Lead Source_Welingak Website                            4.2977
1.165      3.688      0.000       2.013       6.582
Last Activity_Olark Chat Conversation                  -0.9462
0.172     -5.503      0.000      -1.283      -0.609
Last Activity_Other_Activity                            2.2308
0.463      4.820      0.000       1.324       3.138
Last Activity_SMS Sent                                  1.3440
0.076     17.751      0.000       1.196       1.492
Last Activity_Unsubscribed                              1.4134
0.483      2.928      0.003       0.467       2.360
Specialization_Others                                  -1.1413
0.126     -9.063      0.000      -1.388      -0.895
What is your current occupation_Student                -1.0390
0.627     -1.656      0.098      -2.269       0.191
What is your current occupation_Unemployed             -1.4916
0.585     -2.549      0.011      -2.639      -0.345
What is your current occupation_Working Professional     1.1383
```

```
0.614      1.855      0.064      -0.064       2.341
Last Notable Activity_Modified                               -0.8767
0.082    -10.750      0.000      -1.037      -0.717
Last Notable Activity_Unreachable                             1.5719
0.476      3.299      0.001       0.638       2.506
======================================================================
==================================================
"""
```

Since Pvalue of 'What is your current occupation_Student' is very high, we can drop this column.

```
col1 = col1.drop('What is your current occupation_Student')
```

Model-4

```
X_train_sm = sm.add_constant(X_train[col1])
logm4 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm4.fit()
res.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                 Generalized Linear Model Regression Results

======================================================================
========
Dep. Variable:               Converted   No. Observations:
6351
Model:                             GLM   Df Residuals:
6333
Model Family:                 Binomial   Df Model:
17
Link Function:                   logit   Scale:
1.0000
Method:                           IRLS   Log-Likelihood:
-2594.5
Date:                 Wed, 22 Mar 2023   Deviance:
5189.0
Time:                         09:09:06   Pearson chi2:
6.53e+03
No. Iterations:                      7

Covariance Type:             nonrobust

======================================================================
==================================================
                                                                coef    std
err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------
--------------------------------------------------
```

```
const                                                     0.4409
0.240      1.836      0.066      -0.030       0.912
Do Not Email                                             -1.6789
0.191     -8.807      0.000      -2.053      -1.305
Total Time Spent on Website                               1.1067
0.041     27.196      0.000       1.027       1.186
Lead Origin_Landing Page Submission                      -1.1290
0.129     -8.745      0.000      -1.382      -0.876
Lead Origin_Lead Add Form                                 1.5974
0.914      1.747      0.081      -0.195       3.390
Lead Origin_Lead Import                                   0.8993
0.480      1.874      0.061      -0.041       1.840
Lead Source_Olark Chat                                    1.1178
0.124      9.029      0.000       0.875       1.360
Lead Source_Reference                                     1.7790
0.938      1.897      0.058      -0.059       3.617
Lead Source_Welingak Website                              4.3023
1.165      3.693      0.000       2.019       6.586
Last Activity_Olark Chat Conversation                    -0.9478
0.172     -5.518      0.000      -1.284      -0.611
Last Activity_Other_Activity                              2.2295
0.463      4.816      0.000       1.322       3.137
Last Activity_SMS Sent                                    1.3427
0.076     17.728      0.000       1.194       1.491
Last Activity_Unsubscribed                                1.4093
0.483      2.919      0.004       0.463       2.356
Specialization_Others                                    -1.1534
0.126     -9.171      0.000      -1.400      -0.907
What is your current occupation_Unemployed               -0.6003
0.213     -2.818      0.005      -1.018      -0.183
What is your current occupation_Working Professional      2.0282
0.283      7.161      0.000       1.473       2.583
Last Notable Activity_Modified                           -0.8740
0.081    -10.725      0.000      -1.034      -0.714
Last Notable Activity_Unreachable                         1.5774
0.475      3.318      0.001       0.646       2.509
======================================================================
==================================================
"""
```

Since Pvalue of 'Lead Origin_Lead Add Form' is very high, we can drop this column.

```
col1 = col1.drop('Lead Origin_Lead Add Form')
```

Model-5

```
X_train_sm = sm.add_constant(X_train[col1])
logm5 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm5.fit()
res.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                 Generalized Linear Model Regression Results

======================================================================
========
Dep. Variable:             Converted   No. Observations:
6351
Model:                           GLM   Df Residuals:
6334
Model Family:               Binomial   Df Model:
16
Link Function:                 logit   Scale:
1.0000
Method:                         IRLS   Log-Likelihood:
-2596.2
Date:               Wed, 22 Mar 2023   Deviance:
5192.3
Time:                       09:09:06   Pearson chi2:
6.54e+03
No. Iterations:                    7

Covariance Type:           nonrobust

======================================================================
==================================================
                                                                coef    std
err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------
--------------------------------------------------
const                                                         0.4578
0.240      1.907      0.056      -0.013       0.928
Do Not Email                                                 -1.6806
0.191     -8.816      0.000      -2.054      -1.307
Total Time Spent on Website                                   1.1047
0.041     27.190      0.000       1.025       1.184
Lead Origin_Landing Page Submission                          -1.1473
0.129     -8.907      0.000      -1.400      -0.895
Lead Origin_Lead Import                                       0.8826
0.480      1.838      0.066      -0.059       1.824
Lead Source_Olark Chat                                        1.1108
0.124      8.993      0.000       0.869       1.353
Lead Source_Reference                                         3.3614
0.243     13.840      0.000       2.885       3.837
Lead Source_Welingak Website                                  5.8902
0.730      8.073      0.000       4.460       7.320
Last Activity_Olark Chat Conversation                        -0.9522
0.172     -5.544      0.000      -1.289      -0.616
Last Activity_Other_Activity                                  2.2254
0.463      4.808      0.000       1.318       3.133
```

```
Last Activity_SMS Sent                                     1.3427
0.076     17.732      0.000       1.194       1.491
Last Activity_Unsubscribed                                 1.4077
0.483      2.916      0.004       0.462       2.354
Specialization_Others                                     -1.1652
0.126     -9.273      0.000      -1.411      -0.919
What is your current occupation_Unemployed                -0.5974
0.213     -2.804      0.005      -1.015      -0.180
What is your current occupation_Working Professional       2.0280
0.283      7.158      0.000       1.473       2.583
Last Notable Activity_Modified                            -0.8745
0.081    -10.736      0.000      -1.034      -0.715
Last Notable Activity_Unreachable                          1.5728
0.475      3.308      0.001       0.641       2.505
======================================================================
==================================================
"""
```

Checking for VIF values:

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

# Create a dataframe that will contain the names of all the feature
variables and their respective VIFs
vif = pd.DataFrame()
vif['Features'] = X_train[col1].columns
vif['VIF'] = [variance_inflation_factor(X_train[col1].values, i) for i
in range(X_train[col1].shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

	Features	VIF
12	What is your current occupation_Unemployed	9.72
2	Lead Origin_Landing Page Submission	5.74
11	Specialization_Others	3.99
4	Lead Source_Olark Chat	2.24
14	Last Notable Activity_Modified	1.86
13	What is your current occupation_Working Profes...	1.66
9	Last Activity_SMS Sent	1.63
7	Last Activity_Olark Chat Conversation	1.59
5	Lead Source_Reference	1.46
1	Total Time Spent on Website	1.32
0	Do Not Email	1.21
6	Lead Source_Welingak Website	1.11
10	Last Activity_Unsubscribed	1.08
3	Lead Origin_Lead Import	1.03
8	Last Activity_Other_Activity	1.01
15	Last Notable Activity_Unreachable	1.01

```
# Dropping the column  'What is your current occupation_Unemployed' 
because it has high VIF
col1 = col1.drop('What is your current occupation_Unemployed')
```

Model-6

```
X_train_sm = sm.add_constant(X_train[col1])
logm5 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm5.fit()
res.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                 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:                
-2600.0
Date:                Wed, 22 Mar 2023   Deviance:                       
5200.0
Time:                        09:09:07   Pearson chi2:                   
6.54e+03
No. Iterations:                     7                                         

Covariance Type:            nonrobust                                         

======================================================================
==================================================
                                                           coef    std 
err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------
--------------------------------------------------
const                                                   -0.1106      
0.127     -0.868      0.385      -0.361       0.139
Do Not Email                                            -1.6767      
0.191     -8.786      0.000      -2.051      -1.303
Total Time Spent on Website                              1.1047      
0.041     27.207      0.000       1.025       1.184
Lead Origin_Landing Page Submission                     -1.1519      
0.129     -8.935      0.000      -1.405      -0.899
Lead Origin_Lead Import                                  0.8640      
0.480      1.799      0.072      -0.077       1.805
```

```
Lead Source_Olark Chat                                      1.1164
0.124      9.037      0.000       0.874       1.359
Lead Source_Reference                                       3.3731
0.243     13.906      0.000       2.898       3.848
Lead Source_Welingak Website                                5.8819
0.730      8.063      0.000       4.452       7.312
Last Activity_Olark Chat Conversation                      -0.9437
0.172     -5.502      0.000      -1.280      -0.608
Last Activity_Other_Activity                                2.2075
0.463      4.767      0.000       1.300       3.115
Last Activity_SMS Sent                                      1.3276
0.075     17.609      0.000       1.180       1.475
Last Activity_Unsubscribed                                  1.3822
0.483      2.863      0.004       0.436       2.328
Specialization_Others                                      -1.1774
0.126     -9.356      0.000      -1.424      -0.931
What is your current occupation_Working Professional     2.6063
0.195     13.382      0.000       2.225       2.988
Last Notable Activity_Modified                             -0.8814
0.081    -10.826      0.000      -1.041      -0.722
Last Notable Activity_Unreachable                           1.5571
0.474      3.284      0.001       0.628       2.486
======================================================================
==================================================
"""
```

```
# Dropping the column  'Lead Origin_Lead Import' because it has high Pvalue
col1 = col1.drop('Lead Origin_Lead Import')
```

Model-7

```
X_train_sm = sm.add_constant(X_train[col1])
logm5 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm5.fit()
res.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                 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:
```

```
-2601.5
Date:                Wed, 22 Mar 2023   Deviance:
5203.0
Time:                        09:09:07   Pearson chi2:
6.54e+03
No. Iterations:                     7

Covariance Type:            nonrobust

======================================================================
==================================================
                                                           coef    std
err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------
--------------------------------------------------
const                                                   -0.0717
0.126     -0.570      0.569      -0.318       0.175
Do Not Email                                            -1.6783
0.191     -8.798      0.000      -2.052      -1.304
Total Time Spent on Website                              1.0976
0.040     27.211      0.000       1.019       1.177
Lead Origin_Landing Page Submission                     -1.1863
0.128     -9.291      0.000      -1.437      -0.936
Lead Source_Olark Chat                                   1.0915
0.123      8.905      0.000       0.851       1.332
Lead Source_Reference                                    3.3401
0.242     13.812      0.000       2.866       3.814
Lead Source_Welingak Website                             5.8588
0.729      8.033      0.000       4.429       7.288
Last Activity_Olark Chat Conversation                   -0.9485
0.171     -5.531      0.000      -1.285      -0.612
Last Activity_Other_Activity                             2.1988
0.463      4.752      0.000       1.292       3.106
Last Activity_SMS Sent                                   1.3250
0.075     17.587      0.000       1.177       1.473
Last Activity_Unsubscribed                               1.3784
0.482      2.858      0.004       0.433       2.324
Specialization_Others                                   -1.1983
0.126     -9.536      0.000      -1.445      -0.952
What is your current occupation_Working Professional     2.6064
0.195     13.389      0.000       2.225       2.988
Last Notable Activity_Modified                          -0.8816
0.081    -10.833      0.000      -1.041      -0.722
Last Notable Activity_Unreachable                        1.5470
0.474      3.264      0.001       0.618       2.476
======================================================================
==================================================
"""
```

Checking for VIF values:

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

# Create a dataframe that will contain the names of all the feature
variables and their respective VIFs
vif = pd.DataFrame()
vif['Features'] = X_train[col1].columns
vif['VIF'] = [variance_inflation_factor(X_train[col1].values, i) for i
in range(X_train[col1].shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

```
                                                Features   VIF
10                                Specialization_Others  2.17
3                                  Lead Source_Olark Chat  2.03
12                          Last Notable Activity_Modified  1.79
2                      Lead Origin_Landing Page Submission  1.70
6                    Last Activity_Olark Chat Conversation  1.59
8                                  Last Activity_SMS Sent  1.57
1                             Total Time Spent on Website  1.29
4                                 Lead Source_Reference  1.24
0                                          Do Not Email  1.21
11  What is your current occupation_Working Profes...  1.19
5                            Lead Source_Welingak Website  1.09
9                           Last Activity_Unsubscribed  1.08
7                           Last Activity_Other_Activity  1.01
13                    Last Notable Activity_Unreachable  1.01
```

```
# Dropping the column  'Last Activity_Unsubscribed' to reduce the
variables
col1 = col1.drop('Last Activity_Unsubscribed')
```

Model-8

```
X_train_sm = sm.add_constant(X_train[col1])
logm5 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm5.fit()
res.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                 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:
-2605.1
Date:                Wed, 22 Mar 2023   Deviance:
5210.2
Time:                        09:09:08   Pearson chi2:
6.54e+03
No. Iterations:                     7

Covariance Type:            nonrobust

======================================================================
==================================================
                                                               coef    std
err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------
--------------------------------------------------
const                                                       -0.0616
0.126     -0.490      0.624      -0.308       0.185
Do Not Email                                                -1.5192
0.177     -8.594      0.000      -1.866      -1.173
Total Time Spent on Website                                  1.0988
0.040     27.251      0.000       1.020       1.178
Lead Origin_Landing Page Submission                         -1.1893
0.128     -9.313      0.000      -1.440      -0.939
Lead Source_Olark Chat                                       1.0922
0.123      8.915      0.000       0.852       1.332
Lead Source_Reference                                        3.3284
0.241     13.787      0.000       2.855       3.802
Lead Source_Welingak Website                                 5.8242
0.728      7.999      0.000       4.397       7.251
Last Activity_Olark Chat Conversation                       -0.9545
0.171     -5.568      0.000      -1.290      -0.619
Last Activity_Other_Activity                                 2.1869
0.463      4.725      0.000       1.280       3.094
Last Activity_SMS Sent                                       1.3094
0.075     17.459      0.000       1.162       1.456
Specialization_Others                                       -1.1991
0.126     -9.547      0.000      -1.445      -0.953
What is your current occupation_Working Professional     2.6072
0.194     13.433      0.000       2.227       2.988
Last Notable Activity_Modified                              -0.8886
0.081    -10.930      0.000      -1.048      -0.729
Last Notable Activity_Unreachable                            1.5360
0.473      3.245      0.001       0.608       2.464
======================================================================
```

```
================================================================
"""
```

Checking for VIF values:

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

# Create a dataframe that will contain the names of all the feature
variables and their respective VIFs
vif = pd.DataFrame()
vif['Features'] = X_train[col1].columns
vif['VIF'] = [variance_inflation_factor(X_train[col1].values, i) for i
in range(X_train[col1].shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif

                                             Features   VIF
9                               Specialization_Others  2.17
3                              Lead Source_Olark Chat  2.03
11                     Last Notable Activity_Modified  1.78
2                  Lead Origin_Landing Page Submission  1.70
6                Last Activity_Olark Chat Conversation  1.59
8                              Last Activity_SMS Sent  1.57
1                         Total Time Spent on Website  1.29
4                               Lead Source_Reference  1.24
10  What is your current occupation_Working Profes...  1.19
0                                        Do Not Email  1.13
5                         Lead Source_Welingak Website  1.09
7                         Last Activity_Other_Activity  1.01
12                  Last Notable Activity_Unreachable  1.01

# Dropping the column  'Last Notable Activity_Unreachable' to reduce
the variables
col1 = col1.drop('Last Notable Activity_Unreachable')
```

Model-9

```
X_train_sm = sm.add_constant(X_train[col1])
logm5 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm5.fit()
res.summary()

<class 'statsmodels.iolib.summary.Summary'>
"""
                 Generalized Linear Model Regression Results

======================================================================
========
Dep. Variable:              Converted   No. Observations:
6351
```

```
Model:                            GLM   Df Residuals:
6338
Model Family:                Binomial   Df Model:
12
Link Function:                  logit   Scale:
1.0000
Method:                          IRLS   Log-Likelihood:
-2610.5
Date:                Wed, 22 Mar 2023   Deviance:
5221.0
Time:                        09:09:08   Pearson chi2:
6.53e+03
No. Iterations:                     7

Covariance Type:            nonrobust

======================================================================
==================================================
                                                            coef    std
err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------
--------------------------------------------------
const                                                    -0.0376
0.125     -0.300      0.764      -0.283       0.208
Do Not Email                                             -1.5218
0.177     -8.611      0.000      -1.868      -1.175
Total Time Spent on Website                               1.0954
0.040     27.225      0.000       1.017       1.174
Lead Origin_Landing Page Submission                      -1.1940
0.128     -9.360      0.000      -1.444      -0.944
Lead Source_Olark Chat                                    1.0819
0.122      8.847      0.000       0.842       1.322
Lead Source_Reference                                     3.3166
0.241     13.747      0.000       2.844       3.789
Lead Source_Welingak Website                              5.8115
0.728      7.981      0.000       4.384       7.239
Last Activity_Olark Chat Conversation                    -0.9613
0.171     -5.610      0.000      -1.297      -0.625
Last Activity_Other_Activity                              2.1751
0.463      4.699      0.000       1.268       3.082
Last Activity_SMS Sent                                    1.2942
0.075     17.308      0.000       1.148       1.441
Specialization_Others                                    -1.2025
0.125     -9.582      0.000      -1.448      -0.957
What is your current occupation_Working Professional     2.6083
0.194     13.454      0.000       2.228       2.988
Last Notable Activity_Modified                           -0.9004
0.081    -11.097      0.000      -1.059      -0.741
======================================================================
```

```
==================================================
"""
```

Checking for VIF values:

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

# Create a dataframe that will contain the names of all the feature
variables and their respective VIFs
vif = pd.DataFrame()
vif['Features'] = X_train[col1].columns
vif['VIF'] = [variance_inflation_factor(X_train[col1].values, i) for i
in range(X_train[col1].shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

	Features	VIF
9	Specialization_Others	2.16
3	Lead Source_Olark Chat	2.03
11	Last Notable Activity_Modified	1.78
2	Lead Origin_Landing Page Submission	1.69
6	Last Activity_Olark Chat Conversation	1.59
8	Last Activity_SMS Sent	1.56
1	Total Time Spent on Website	1.29
4	Lead Source_Reference	1.24
10	What is your current occupation_Working Profes...	1.18
0	Do Not Email	1.13
5	Lead Source_Welingak Website	1.09
7	Last Activity_Other_Activity	1.01

Since the Pvalues of all variables is 0 and VIF values are low for all the variables, model-9 is our final model. We have 12 variables in our final model.

Making Prediction on the Train set

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

```
3009    0.196697
1012    0.125746
9226    0.323477
4750    0.865617
7987    0.797752
1281    0.744001
2880    0.100027
4971    0.965845
7536    0.854512
1248    0.768071
dtype: float64
```

```python
# Reshaping into an array
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]
```

```
array([0.19669707, 0.12574636, 0.32347712, 0.86561739, 0.79775204,
       0.74400101, 0.10002735, 0.96584525, 0.85451189, 0.76807088])
```

Creating a dataframe with the actual Converted flag and the predicted probabilities

```python
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	0	0.196697	3009
1	0	0.125746	1012
2	0	0.323477	9226
3	1	0.865617	4750
4	1	0.797752	7987

Choosing an arbitrary cut-off probability point of 0.5 to find the predicted labels

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

```python
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	0	0.196697	3009	0
1	0	0.125746	1012	0
2	0	0.323477	9226	0
3	1	0.865617	4750	1
4	1	0.797752	7987	1

Making the Confusion matrix

```python
from sklearn import metrics

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

```
[[3461  444]
 [ 719 1727]]
```

```python
# The confusion matrix indicates as below
# Predicted     not_converted    converted
# Actual
```

```
# not_converted        3461      444
# converted            719       1727

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

```
Accuracy : 0.8168792316170682
```

Metrics beyond simply accuracy

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

# Sensitivity of our logistic regression model
print("Sensitivity : ",TP / float(TP+FN))
```

```
Sensitivity :  0.7060506950122649
```

```
# Let us calculate specificity
print("Specificity : ",TN / float(TN+FP))
```

```
Specificity :  0.8862996158770806
```

```
# Calculate false postive rate - predicting converted lead when the
lead actually was not converted
print("False Positive Rate :",FP/ float(TN+FP))
```

```
False Positive Rate : 0.11370038412291933
```

```
# positive predictive value
print("Positive Predictive Value :",TP / float(TP+FP))
```

```
Positive Predictive Value : 0.7954859511745739
```

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

```
Negative predictive value : 0.8279904306220096
```

We found out that our specificity was good (~88%) but our sensitivity was only 70%. Hence, this needed to be taken care of.

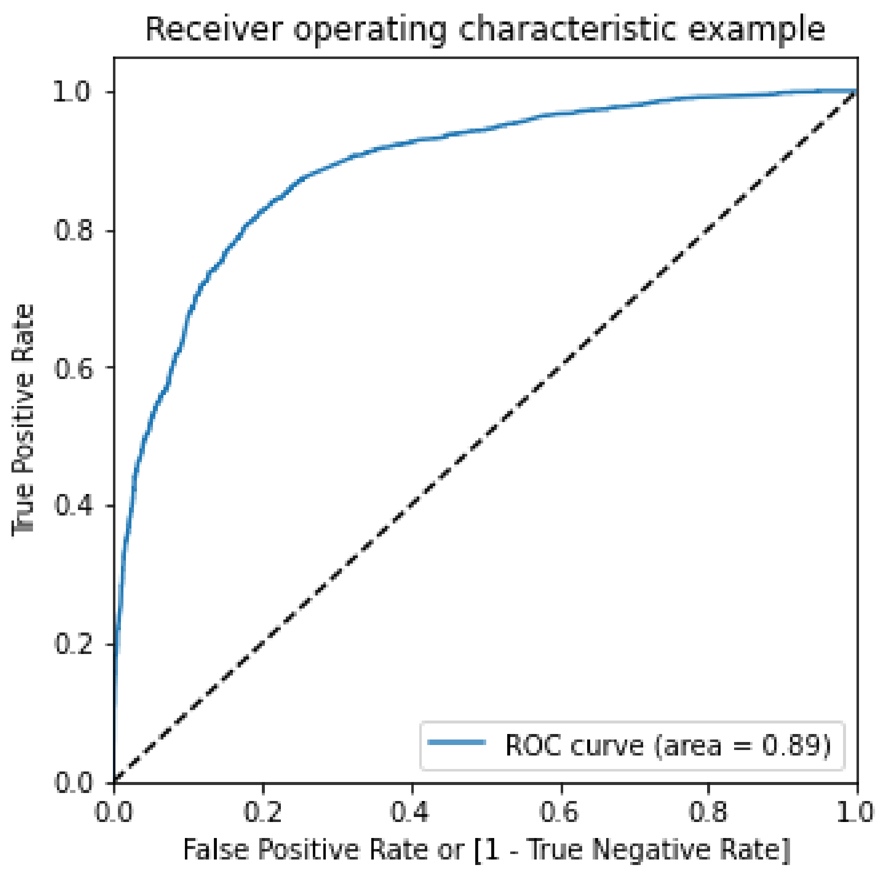
We have got sensitivity of 70% and this was mainly because of the cut-off point of 0.5 that we had arbitrarily chosen. Now, this cut-off point had to be optimised in order to get a decent value of sensitivity and for this we will use the ROC curve.

Plotting the ROC Curve

An ROC curve demonstrates several things:

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

```
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)
```



Since we have higher (0.89) area under the ROC curve , therefore our model is a good one.

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

```
# 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          0        0.196697         3009          0    1    1    0
0    0
1          0        0.125746         1012          0    1    1    0
0    0
2          0        0.323477         9226          0    1    1    1
1    0
```

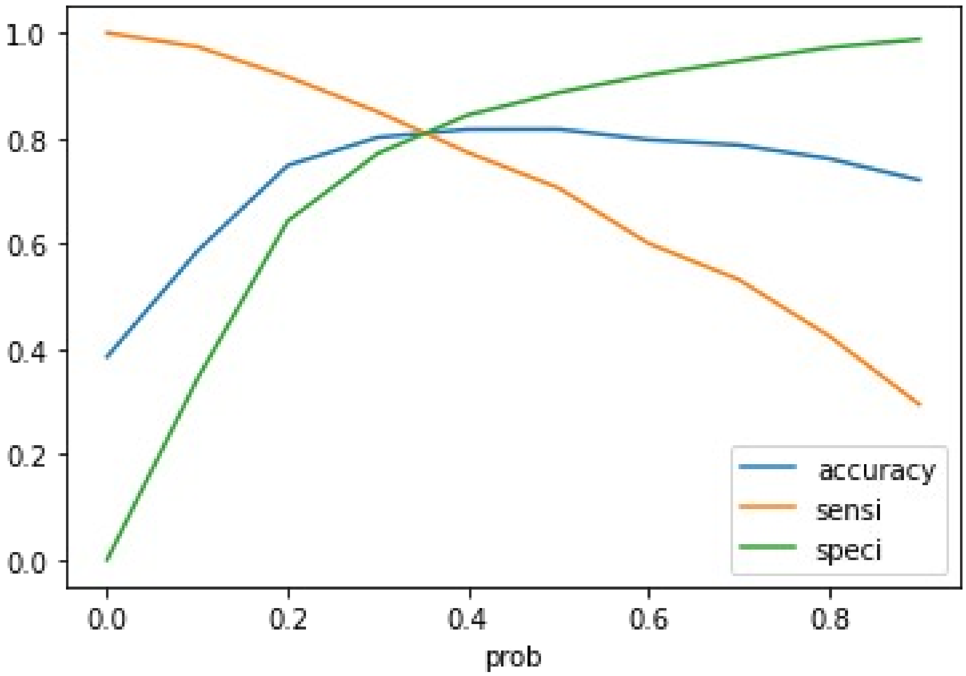
```
3          1        0.865617        4750          1    1    1    1
1    1
4          1        0.797752        7987          1    1    1    1
1    1

   0.5  0.6  0.7  0.8  0.9
0    0    0    0    0    0
1    0    0    0    0    0
2    0    0    0    0    0
3    1    1    1    1    0
4    1    1    1    0    0
```

```
# 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  0.385136  1.000000  0.000000
0.1   0.1  0.586049  0.973426  0.343406
0.2   0.2  0.748386  0.916599  0.643022
0.3   0.3  0.801449  0.849959  0.771063
0.4   0.4  0.816564  0.772690  0.844046
0.5   0.5  0.816879  0.706051  0.886300
0.6   0.6  0.797040  0.600572  0.920102
0.7   0.7  0.786963  0.531889  0.946735
0.8   0.8  0.761297  0.424775  0.972087
0.9   0.9  0.720831  0.294767  0.987708
```

```
# 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, 0.34 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 > 0.34 else 0)

y_train_pred_final.head()

   Converted  Converted_prob  Prospect ID  predicted  0.0  0.1  0.2
0.3  0.4  \
0          0        0.196697         3009          0    1    1    0
0    0
1          0        0.125746         1012          0    1    1    0
0    0
2          0        0.323477         9226          0    1    1    1
1    0
3          1        0.865617         4750          1    1    1    1
1    1
4          1        0.797752         7987          1    1    1    1
1    1

   0.5  0.6  0.7  0.8  0.9  final_predicted
0    0    0    0    0    0                0
1    0    0    0    0    0                0
2    0    0    0    0    0                0
3    1    1    1    1    0                1
4    1    1    1    0    0                1
```

Assigning Lead Score to the Training data

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

y_train_pred_final.head()
```

```
   Converted  Converted_prob  Prospect ID  predicted  0.0  0.1  0.2
0.3  0.4  \
0          0        0.196697         3009          0    1    1    0
0    0
1          0        0.125746         1012          0    1    1    0
0    0
2          0        0.323477         9226          0    1    1    1
1    0
3          1        0.865617         4750          1    1    1    1
1    1
4          1        0.797752         7987          1    1    1    1
1    1

   0.5  0.6  0.7  0.8  0.9  final_predicted  Lead_Score
0    0    0    0    0    0                0          20
1    0    0    0    0    0                0          13
2    0    0    0    0    0                0          32
3    1    1    1    1    0                1          87
4    1    1    1    0    0                1          80
```

Model Evaluation

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

```
Accuracy : 0.8108959219020627
```

```
# Confusion matrix
confusion2 = metrics.confusion_matrix(y_train_pred_final.Converted,
y_train_pred_final.final_predicted )
confusion2
```

```
array([[3151,  754],
       [ 447, 1999]], dtype=int64)
```

```
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
print("Sensitivity : ",TP / float(TP+FN))
```

```
Sensitivity :  0.8172526573998364
```

```python
# Let us calculate specificity
print("Specificity :",TN / float(TN+FP))
```

```
Specificity : 0.8069142125480153
```

```python
# Calculate false postive rate - predicting converted lead when the lead was actually not have converted
print("False Positive rate : ",FP/ float(TN+FP))
```

```
False Positive rate :  0.19308578745198463
```

```python
# Positive predictive value
print("Positive Predictive Value :",TP / float(TP+FP))
```

```
Positive Predictive Value : 0.7261169633127498
```

```python
# Negative predictive value
print("Negative Predictive Value : ",TN / float(TN+ FN))
```

```
Negative Predictive Value :  0.8757643135075042
```

Precision and Recall

- **Precision = Also known as Positive Predictive Value, it refers to the percentage of the results which are relevant.**
- **Recall = Also known as Sensitivity , it refers to the percentage of total relevant results correctly classified by the algorithm.**

```python
#Looking at the confusion matrix again

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

```
array([[3461,  444],
       [ 719, 1727]], dtype=int64)
```

```python
# Precision
TP / TP + FP

print("Precision : ",confusion[1,1]/(confusion[0,1]+confusion[1,1]))
```

```
Precision :  0.7954859511745739
```

```python
# Recall
TP / TP + FN

print("Recall :",confusion[1,1]/(confusion[1,0]+confusion[1,1]))
```

```
Recall : 0.7060506950122649
```

Using sklearn utilities for the same

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

```python
print("Precision :",precision_score(y_train_pred_final.Converted , 
y_train_pred_final.predicted))
```

```
Precision : 0.7954859511745739
```

```python
print("Recall :",recall_score(y_train_pred_final.Converted, 
y_train_pred_final.predicted))
```

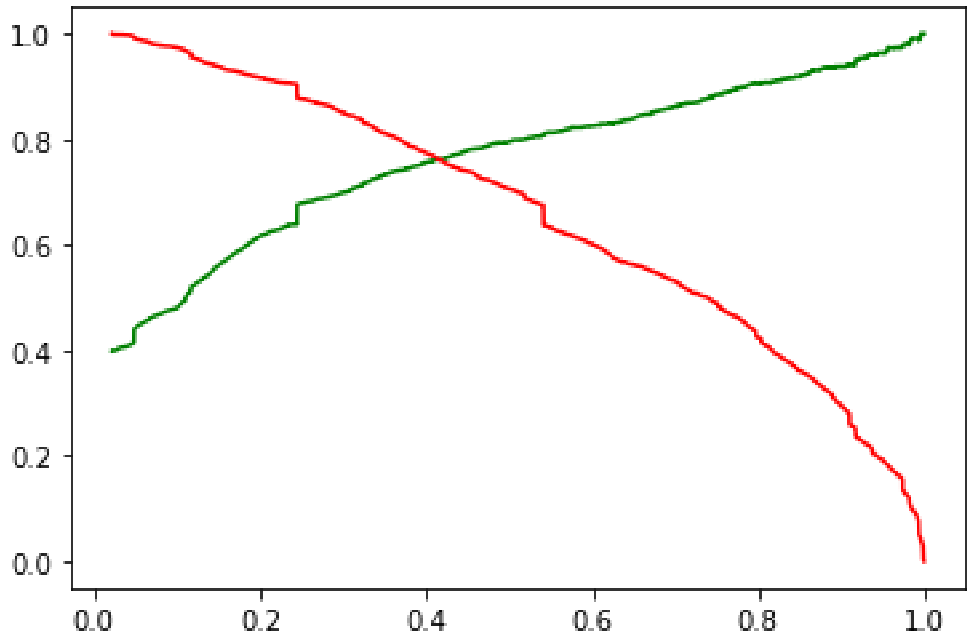
```
Recall : 0.7060506950122649
```

Precision and recall tradeoff¶

```python
from sklearn.metrics import precision_recall_curve

y_train_pred_final.Converted, y_train_pred_final.predicted
```

```
(0       0
 1       0
 2       0
 3       1
 4       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
        ..
 6346    0
 6347    1
 6348    1
 6349    0
 6350    0
 Name: predicted, Length: 6351, dtype: int64)
```

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

# plotting a trade-off curve between precision and recall
plt.plot(thresholds, p[:-1], "g-")
plt.plot(thresholds, r[:-1], "r-")
plt.show()
```



**The above graph shows the trade-off between the Precision and Recall .

Making predictions on the test set

Scaling the test data

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

'Total Time Spent on Website',

'Page Views Per Visit']])

# Assigning the columns selected by the final model to the X_test
X_test = X_test[col1]
X_test.head()
```

```
      Do Not Email  Total Time Spent on Website  \
3271             0                    -0.600595
1490             0                     1.887326
7936             0                    -0.752879
4216             0                    -0.888650
3830             0                    -0.587751

      Lead Origin_Landing Page Submission  Lead Source_Olark Chat  \
3271                                    0                       0
1490                                    1                       0
7936                                    0                       0
4216                                    0                       0
3830                                    1                       0
```

```
      Lead Source_Reference  Lead Source_Welingak Website  \
3271                      0                             0
1490                      0                             0
7936                      0                             0
4216                      1                             0
3830                      0                             0

      Last Activity_Olark Chat Conversation  Last
Activity_Other_Activity  \
3271                                      0
0
1490                                      0
0
7936                                      0
0
4216                                      0
0
3830                                      0
0

      Last Activity_SMS Sent  Specialization_Others  \
3271                       0                      1
1490                       0                      0
7936                       0                      1
4216                       0                      0
3830                       0                      0

      What is your current occupation_Working Professional  \
3271                                                     0
1490                                                     1
7936                                                     0
4216                                                     0
3830                                                     0

      Last Notable Activity_Modified
3271                               0
1490                               0
7936                               0
4216                               1
3830                               0
```

```
# Adding a const
X_test_sm = sm.add_constant(X_test)

# Making predictions on the test set
y_test_pred = res.predict(X_test_sm)
y_test_pred[:10]
```

```
3271    0.130342
1490    0.969057
```

```
7936    0.112570
4216    0.802999
3830    0.132924
1800    0.635544
6507    0.342648
4821    0.302742
4223    0.916621
4714    0.323477
dtype: float64
```

```
# Converting y_test_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
3271  0.130342
1490  0.969057
7936  0.112570
4216  0.802999
3830  0.132924
```

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

# Putting Prospect ID 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         3271  0.130342
1          1         1490  0.969057
2          0         7936  0.112570
3          1         4216  0.802999
4          0         3830  0.132924
```

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

# Rearranging the columns
y_pred_final = y_pred_final.reindex(columns=['Prospect
ID','Converted','Converted_prob'])
```

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

```
   Prospect ID  Converted  Converted_prob
0         3271          0        0.130342
1         1490          1        0.969057
2         7936          0        0.112570
3         4216          1        0.802999
4         3830          0        0.132924
```

```python
y_pred_final['final_predicted'] =
y_pred_final.Converted_prob.map(lambda x: 1 if x > 0.34 else 0)
```

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

```
   Prospect ID  Converted  Converted_prob  final_predicted
0         3271          0        0.130342                0
1         1490          1        0.969057                1
2         7936          0        0.112570                0
3         4216          1        0.802999                1
4         3830          0        0.132924                0
```

```python
# Let's check the overall accuracy.
print("Accuracy :",metrics.accuracy_score(y_pred_final.Converted,
y_pred_final.final_predicted))
```

```
Accuracy : 0.8049944913698127
```

```python
# Making the confusion matrix
confusion2 = metrics.confusion_matrix(y_pred_final.Converted,
y_pred_final.final_predicted )
confusion2
```

```
array([[1396,  338],
       [ 193,  796]], dtype=int64)
```

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

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

```
Sensitivity : 0.8048533872598584
```

```python
# Let us calculate specificity
print("Specificity :",TN / float(TN+FP))
```

```
Specificity : 0.8050749711649365
```

Assigning Lead Score to the Testing data

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

y_pred_final.head()
```

```
   Prospect ID  Converted  Converted_prob  final_predicted  Lead_Score
0         3271          0        0.130342                0          13
1         1490          1        0.969057                1          97
2         7936          0        0.112570                0          11
3         4216          1        0.802999                1          80
4         3830          0        0.132924                0          13
```

Observations:

After running the model on the Test Data , we obtain:

- **Accuracy : 80.4 %**
- **Sensitivity : 80.4 %**
- **Specificity : 80.5 %**

Results :

1) Comparing the values obtained for Train & Test:

Train Data:

- **Accuracy : 81.0 %**
- **Sensitivity : 81.7 %**
- **Specificity : 80.6 %**

Test Data:

- **Accuracy : 80.4 %**
- **Sensitivity : 80.4 %**
- **Specificity : 80.5 %**

Thus we have achieved our goal of getting a ballpark of the target lead conversion rate to be around 80% . 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 to get a higher lead conversion rate of 80%.

2) Finding out the leads which should be contacted:

The customers which should be contacted are the customers whose "Lead Score" is equal to or greater than 85. They can be termed as 'Hot Leads'.

```
hot_leads=y_pred_final.loc[y_pred_final["Lead_Score"]>=85]
hot_leads
```

```
      Prospect ID  Converted  Converted_prob  final_predicted
Lead_Score
```

```
1             1490          1        0.969057                1
97
8             4223          1        0.916621                1
92
16            1946          1        0.924467                1
92
21            2461          1        0.992551                1
99
23            5822          1        0.997991                1
100
...            ...        ...             ...              ...
...
2694          1566          1        0.947723                1
95
2699          6461          1        0.961562                1
96
2703          5741          1        0.908283                1
91
2715          6299          1        0.871977                1
87
2720          6501          1        0.854745                1
85

[368 rows x 5 columns]
```

So there are 368 leads which can be contacted and have a high chance of getting converted. The Prospect ID of the customers to be contacted are :

```
print("The Prospect ID of the customers which should be contacted
are :")

hot_leads_ids = hot_leads["Prospect ID"].values.reshape(-1)
hot_leads_ids
```

```
The Prospect ID of the customers which should be contacted are :

array([1490, 4223, 1946, 2461, 5822, 2684, 2010, 4062, 7696, 9049,
1518,
       4543, 4830, 4365, 3542, 2504, 7674, 8596, 4003, 4963, 6947,
4807,
        446,  789, 8372, 5805, 3758, 1561, 5367,  737, 6423, 8286,
7174,
       4461, 1436, 7552, 3932, 4080, 1475, 5785, 2860, 7253, 4297,
5490,
       1995, 4498, 5797, 8687,  831, 7653, 2018, 6743, 3976, 5769,
1051,
       1663, 3288, 8959, 7521, 8282, 8213, 9063, 5292, 6913, 1481,
785,
       3265, 3285, 7433, 3858, 3810, 2009, 8106,  373, 7417, 4179,
8568,
       7268, 6784, 6754, 7236, 2960, 7753, 3983,  802, 8745, 4717,
```

```
505,
       8509, 6094, 4992, 7036, 2680, 7065,  112, 6149, 7157, 7175,
1675,
       6999, 5826, 8492, 6499, 2481, 3439, 4612, 7129, 4793, 4837,
2495,
        822, 8111, 2378, 5075, 7699, 5638, 2342, 8077, 2727,  720,
7489,
       2961, 1542, 5656, 2630, 6728, 8205, 6332, 8461, 2427, 5087,
174,
       2674, 8065, 2095, 1568, 8597, 4865, 3535, 4708, 1304, 6066,
6538,
       5700, 1388, 5815, 7970, 7902, 5804, 7805, 5042, 4081, 6684,
5440,
       1927, 5032, 5824,   64, 2650, 5808, 4578, 4803, 1470, 5810,
2473,
       2584, 2578, 7259, 3727, 1454, 6064, 3150, 2118, 4403, 3194,
8475,
       1200, 2575, 1299, 1525, 4613, 4909, 8204, 4772, 1374, 8888,
8082,
       4862, 1595, 8942, 1899, 8474, 3463, 2022, 7893, 3248, 6486,
1729,
       8620, 1190, 2486, 2158, 3355, 5353, 2994, 4559, 8521,  973,
7168,
       4677, 7537,  493, 1563, 4860, 9076, 2153, 5389, 1783, 2105,
1578,
       6729, 1263, 2011, 4330, 6252, 1820, 6760, 3015, 2285, 7091,
2598,
       7018, 6290, 5061,  356, 8271, 4285, 8540, 2854, 8375, 4310,
4505,
       1979, 3532, 1444, 4934, 8804, 1416, 7334, 2652, 7057, 5525,
2560,
       3085, 7445, 3396, 9062, 2943, 7690, 8198, 4233, 8265, 7750,
353,
       8088, 7193, 7978, 8928, 6685, 4378, 5455, 5363, 2354, 2714,
718,
       2559, 5000, 2664, 6040, 4068, 3570, 9043, 8090, 2483, 3762,
4112,
       1407, 6740, 6892, 5175,  662, 8452, 7304, 3207, 8505, 6175,
5561,
       5633, 8415, 3660, 3770,  220, 6994, 4253, 1112, 3723, 6725,
746,
       8592, 3496, 5502, 4241, 6933, 4388, 7021, 3097, 3836, 4116,
6314,
       8322, 3165, 6723, 3817, 1534, 1360, 7053, 6944, 4671, 5877,
2673,
       3146,  745, 1950, 4382, 2174, 1682, 7240, 6375, 7941, 5293,
3736,
       7450, 2617, 6127, 4371, 1026, 8113, 6242, 1089, 2841, 7136,
3477,
       2763, 6890, 4734, 7823, 2870, 5337, 4879, 1467, 3942, 8343,
```

```
8052,
       1566, 6461, 5741, 6299, 6501], dtype=int64)
```

3) Finding out the Important Features from our final model:

```
res.params.sort_values(ascending=False)
```

```
Lead Source_Welingak Website                            5.811465
Lead Source_Reference                                   3.316598
What is your current occupation_Working Professional    2.608292
Last Activity_Other_Activity                            2.175096
Last Activity_SMS Sent                                  1.294180
Total Time Spent on Website                             1.095412
Lead Source_Olark Chat                                  1.081908
const                                                  -0.037565
Last Notable Activity_Modified                         -0.900449
Last Activity_Olark Chat Conversation                  -0.961276
Lead Origin_Landing Page Submission                    -1.193957
Specialization_Others                                  -1.202474
Do Not Email                                           -1.521825
dtype: float64
```

Recommendations:

- The company **should make calls** to the leads coming from the `lead sources` `"Welingak Websites"` and `"Reference"` as these are more likely to get converted.
- The company **should make calls** to the leads who are the `"working professionals"` as they are more likely to get converted.
- The company **should make calls** to the leads who spent `"more time on the websites"` as these are more likely to get converted.
- The company **should make calls** to the leads coming from the `lead sources` `"Olark Chat"` as these are more likely to get converted.
- The company **should make calls** to the leads whose `last activity` was `SMS Sent` as they are more likely to get converted.
- The company **should not make calls** to the leads whose `last activity` was `"Olark Chat Conversation"` as they are not likely to get converted.
- The company **should not make calls** to the leads whose `lead origin` is `"Landing Page Submission"` as they are not likely to get converted.
- The company **should not make calls** to the leads whose `Specialization` was `"Others"` as they are not likely to get converted.
- The company **should not make calls** to the leads who chose the option of `"Do not Email" as "yes"` as they are not likely to get converted.