Lead Scoring Case Study

Importing all necessary libraries

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Reading CSV file

In [2]:

```
Lead_scoring_df = pd.read_csv("Leads.csv")
Lead_scoring_df.head()
```

Out[2]:

	Prospect ID	Lead Number	Lead Origin	Lead Source	Do Not Email	Do Not Call	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	...	Get updates on DM Content	Lead Profile	City	Asymmetrique Activity Index	Asym Pro
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	660737	API	Olark Chat	No	No	0	0.0	0	0.0	...	No	Select	Select	02.Medium	0
1	2a272436-5132-4136-86fa-dcc88c88f482	660728	API	Organic Search	No	No	0	5.0	674	2.5	...	No	Select	Select	02.Medium	0
2	8cc8c611-a219-4f35-ad23-fdfd2656bd8a	660727	Landing Page Submission	Direct Traffic	No	No	1	2.0	1532	2.0	...	No	Potential Lead	Mumbai	02.Medium	

	Prospect ID	Lead Number	Lead Origin	Lead Source	Do Not Email	Do Not Call	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	...	Get updates on DM Content	Lead Profile	City	Asymmetrique Activity Index	Asym Pro
3	0cc2df48-7cf4-4e39-9de9-19797f9b38cc	660719	Landing Page Submission	Direct Traffic	No	No	0	1.0	305	1.0	...	No	Select	Mumbai	02.Medium	
4	3256f628-e534-4826-9d63-4a8b88782852	660681	Landing Page Submission	Google	No	No	1	2.0	1428	1.0	...	No	Select	Mumbai	02.Medium	

5 rows × 37 columns

In [3]:

```
Lead_scoring_df.shape
```

Out[3]:

```
(9240, 37)
```

In [4]:

```
Lead_scoring_df.describe()
```

Out[4]:

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

	Lead Number	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Asymmetrique Activity Score	Asymmetrique Profile Score
75%	637387.250000	1.000000	5.000000	936.000000	3.000000	15.000000	18.000000
max	660737.000000	1.000000	251.000000	2272.000000	55.000000	18.000000	20.000000

In [5]:

```
Lead_scoring_df.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
```

Data Cleaning

In [6]:

```
Lead_scoring_df_null_Percentage = ((Lead_scoring_df.isnull().sum()/len(Lead_scoring_df))*100)
Lead_scoring_df_null_Percentage
```

Out[6]:

```
Prospect ID                                       0.000000
Lead Number                                       0.000000
Lead Origin                                       0.000000
Lead Source                                       0.389610
Do Not Email                                      0.000000
Do Not Call                                       0.000000
Converted                                         0.000000
TotalVisits                                       1.482684
Total Time Spent on Website                       0.000000
Page Views Per Visit                              1.482684
Last Activity                                     1.114719
Country                                          26.634199
Specialization                                   15.562771
How did you hear about X Education               23.885281
What is your current occupation                  29.112554
What matters most to you in choosing a course    29.318182
Search                                            0.000000
Magazine                                          0.000000
Newspaper Article                                 0.000000
X Education Forums                                0.000000
Newspaper                                         0.000000
Digital Advertisement                             0.000000
Through Recommendations                           0.000000
Receive More Updates About Our Courses            0.000000
Tags                                             36.287879
```

```
Lead Quality                                     51.590909
Update me on Supply Chain Content                 0.000000
Get updates on DM Content                         0.000000
Lead Profile                                     29.318182
City                                             15.367965
Asymmetrique Activity Index                      45.649351
Asymmetrique Profile Index                       45.649351
Asymmetrique Activity Score                      45.649351
Asymmetrique Profile Score                       45.649351
I agree to pay the amount through cheque          0.000000
A free copy of Mastering The Interview            0.000000
Last Notable Activity                             0.000000
dtype: float64
```

In [7]:

```
# Dropping redundant columns
Lead_scoring_df = Lead_scoring_df.drop(['Prospect ID', 'Lead Number', 'Country', 'Receive More Updates About Our Courses',
              'Update me on Supply Chain Content', 'Get updates on DM Content', 'City',
              'I agree to pay the amount through cheque','Magazine'], axis = 1 )
```

In [8]:

```
Lead_scoring_df.shape
```

Out[8]:

```
(9240, 28)
```

now we have noticed that there are columns which have 'select' category which means customer did not select any of the options. they eventually act as null values, thus we will make them null.

In [9]:

```
Column_have_select = []
for i in Lead_scoring_df.columns:
    if len(Lead_scoring_df[i].isin(['Select']).unique())>1:
        Column_have_select.append(i)

Column_have_select
```

Out[9]:

```
['Specialization', 'How did you hear about X Education', 'Lead Profile']
```

In [10]:

```
# chsnge Select to NAN
for i in Column_have_select:
    Lead_scoring_df[i] = Lead_scoring_df[i].replace('Select',np.NaN)
```

```
Lead_scoring_df.head()
```

Out[10]:

	Lead Origin	Lead Source	Do Not Email	Do Not Call	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Last Activity	Specialization	...	Through Recommendations	Tags	Lead Quality	L Pro
0	API	Olark Chat	No	No	0	0.0	0	0.0	Page Visited on Website	NaN	...	No	Interested in other courses	Low in Relevance	N
1	API	Organic Search	No	No	0	5.0	674	2.5	Email Opened	NaN	...	No	Ringing	NaN	N
2	Landing Page Submission	Direct Traffic	No	No	1	2.0	1532	2.0	Email Opened	Business Administration	...	No	Will revert after reading the email	Might be	Poter L
3	Landing Page Submission	Direct Traffic	No	No	0	1.0	305	1.0	Unreachable	Media and Advertising	...	No	Ringing	Not Sure	N
4	Landing Page Submission	Google	No	No	1	2.0	1428	1.0	Converted to Lead	NaN	...	No	Will revert after reading the email	Might be	N

5 rows × 28 columns

In [11]:

```
Lead_scoring_df_null_Percentage = round(((Lead_scoring_df.isnull().sum()/len(Lead_scoring_df))*100),2)
Lead_scoring_df_null_Percentage
```

Out[11]:

```
Lead Origin                                      0.00
Lead Source                                      0.39
Do Not Email                                     0.00
Do Not Call                                      0.00
Converted                                        0.00
TotalVisits                                      1.48
```

```
Total Time Spent on Website                       0.00
Page Views Per Visit                              1.48
Last Activity                                     1.11
Specialization                                   36.58
How did you hear about X Education               78.46
What is your current occupation                  29.11
What matters most to you in choosing a course    29.32
Search                                            0.00
Newspaper Article                                 0.00
X Education Forums                                0.00
Newspaper                                         0.00
Digital Advertisement                             0.00
Through Recommendations                           0.00
Tags                                             36.29
Lead Quality                                     51.59
Lead Profile                                     74.19
Asymmetrique Activity Index                      45.65
Asymmetrique Profile Index                       45.65
Asymmetrique Activity Score                      45.65
Asymmetrique Profile Score                       45.65
A free copy of Mastering The Interview            0.00
Last Notable Activity                             0.00
dtype: float64
```

from above we see there are columns having more than 40% missing values, so it is better to remove these columns as it imputing them could lead to bias predictions.

dropping columns having missing values above 40%

In [12]:

```
#dropping columns having missing values more than 40%
above_40 = list(Lead_scoring_df_null_Percentage[Lead_scoring_df_null_Percentage > 40].index)
Lead_scoring_df = Lead_scoring_df.drop(above_40, axis =1)
Lead_scoring_df.head()
```

Out[12]:

	Lead Origin	Lead Source	Do Not Email	Do Not Call	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Last Activity	Specialization	...	What matters most to you in choosing a course	Search	Newspaper Article	X Education Forums	Ne

	Lead Origin	Lead Source	Do Not Email	Do Not Call	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Last Activity	Specialization	...	What matters most to you in choosing a course	Search	Newspaper Article	X Education Forums	Ne
0	API	Olark Chat	No	No	0	0.0	0	0.0	Page Visited on Website	NaN	...	Better Career Prospects	No	No	No	
1	API	Organic Search	No	No	0	5.0	674	2.5	Email Opened	NaN	...	Better Career Prospects	No	No	No	
2	Landing Page Submission	Direct Traffic	No	No	1	2.0	1532	2.0	Email Opened	Business Administration	...	Better Career Prospects	No	No	No	
3	Landing Page Submission	Direct Traffic	No	No	0	1.0	305	1.0	Unreachable	Media and Advertising	...	Better Career Prospects	No	No	No	
4	Landing Page Submission	Google	No	No	1	2.0	1428	1.0	Converted to Lead	NaN	...	Better Career Prospects	No	No	No	

5 rows × 21 columns

In [13]:

```
Lead_scoring_df_null_Percentage = round((((Lead_scoring_df.isnull().sum()/len(Lead_scoring_df))*100),2)
Lead_scoring_df_null_Percentage
```

Out[13]:

```
Lead Origin                                  0.00
Lead Source                                  0.39
Do Not Email                                 0.00
Do Not Call                                  0.00
Converted                                    0.00
TotalVisits                                  1.48
Total Time Spent on Website                  0.00
```

```
Page Views Per Visit                              1.48
Last Activity                                     1.11
Specialization                                   36.58
What is your current occupation                  29.11
What matters most to you in choosing a course    29.32
Search                                            0.00
Newspaper Article                                 0.00
X Education Forums                                0.00
Newspaper                                         0.00
Digital Advertisement                             0.00
Through Recommendations                           0.00
Tags                                             36.29
A free copy of Mastering The Interview            0.00
Last Notable Activity                             0.00
dtype: float64
```

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

In [14]:

```
Column_have_yes_no = []
for i in Lead_scoring_df.columns:
    if len(Lead_scoring_df[i].isin(['No']).unique())>1:
        Column_have_yes_no.append(i)

Column_have_yes_no
```

Out[14]:

```
['Do Not Email',
 'Do Not Call',
 'Search',
 'Newspaper Article',
 'X Education Forums',
 'Newspaper',
 'Digital Advertisement',
 'Through Recommendations',
 'A free copy of Mastering The Interview']
```

In [15]:

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

# Applying the function in Column_have_yes_no
Lead_scoring_df[Column_have_yes_no] = Lead_scoring_df[Column_have_yes_no].apply(binary_map)
```

In [16]:

```
Lead_scoring_df.head()
```

Out[16]:

	Lead Origin	Lead Source	Do Not Email	Do Not Call	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Last Activity	Specialization	...	What matters most to you in choosing a course	Search	Newspaper Article	X Education Forums	Ne
0	API	Olark Chat	0	0	0	0.0	0	0.0	Page Visited on Website	NaN	...	Better Career Prospects	0	0	0	
1	API	Organic Search	0	0	0	5.0	674	2.5	Email Opened	NaN	...	Better Career Prospects	0	0	0	
2	Landing Page Submission	Direct Traffic	0	0	1	2.0	1532	2.0	Email Opened	Business Administration	...	Better Career Prospects	0	0	0	
3	Landing Page Submission	Direct Traffic	0	0	0	1.0	305	1.0	Unreachable	Media and Advertising	...	Better Career Prospects	0	0	0	
4	Landing Page Submission	Google	0	0	1	2.0	1428	1.0	Converted to Lead	NaN	...	Better Career Prospects	0	0	0	

5 rows × 21 columns

In [17]:

```
Lead_scoring_df.isna().sum()
```

Out[17]:

```
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
Specialization                                   3380
What is your current occupation                  2690
What matters most to you in choosing a course    2709
Search                                              0
Newspaper Article                                   0
X Education Forums                                  0
Newspaper                                           0
Digital Advertisement                               0
Through Recommendations                             0
Tags                                             3353
A free copy of Mastering The Interview              0
Last Notable Activity                               0
dtype: int64
```

In [18]:

```
Lead_scoring_df['Lead Source'].value_counts()
```

Out[18]:

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

data is skwed, we are going to replace these labels (Facebook, bing, Click2call, Live Chat,Press_Release, Social Media, testone, WeLearn, blog, Pay per

Click Ads, welearnblog_Home, youtubechannel, NC_EDM) in one label as 'Others'. we will deal with missing values by imputing missing values with max occuring label

In [19]:

```
Lead_scoring_df['Lead Source'] = Lead_scoring_df['Lead Source'].replace(['Facebook', 'bing', 'Click2call', 'Live Chat','Press_Rele
                          'testone', 'WeLearn', 'blog','Pay per Click Ads', 'welearnblog_Home',
                          'youtubechannel', 'NC_EDM','Welingak Website','Referral Sites'],'Other')
Lead_scoring_df['Lead Source'] = Lead_scoring_df['Lead Source'].replace('google','Google')

Lead_scoring_df['Lead Source'].value_counts()
```

Out[19]:

```
Google            2873
Direct Traffic    2543
Olark Chat        1755
Organic Search    1154
Reference          534
Other              345
Name: Lead Source, dtype: int64
```

In [20]:

```
# imputing missing values to max occuring label i.e. Google

Lead_scoring_df['Lead Source'] = Lead_scoring_df['Lead Source'].replace(np.NaN,'Google')
```

In [21]:

```
Lead_scoring_df['What is your current occupation'].value_counts()
```

Out[21]:

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

In [22]:

```
# imputing missing values to max occuring label i.e. Unemployed

Lead_scoring_df['What is your current occupation'] = Lead_scoring_df['What is your current occupation'].replace(np.NaN,'Unemployed
```

In [23]:

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

Out[23]:

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

We see that there is no meaning of this column so we will drop it

In [24]:

```
Lead_scoring_df=Lead_scoring_df.drop('What matters most to you in choosing a course',axis=1)
```

In [25]:

```
Lead_scoring_df['Specialization'].value_counts()
```

Out[25]:

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

here also we will create another category for missing values as the count is very high and imputing missing values with median can lead to misleading results.

In [26]:

```
# replacing missing values with label 'Missing'

Lead_scoring_df['Specialization'] = Lead_scoring_df['Specialization'].replace(np.NaN,'Missing')
```

In [27]:

```
Lead_scoring_df['TotalVisits'].value_counts()
```

Out[27]:
```
0.0      2189
2.0      1680
3.0      1306
4.0      1120
5.0       783
6.0       466
1.0       395
7.0       309
8.0       224
9.0       164
10.0      114
11.0       86
13.0       48
12.0       45
14.0       36
16.0       21
15.0       18
17.0       16
18.0       15
20.0       12
19.0        9
21.0        6
23.0        6
24.0        5
25.0        5
27.0        5
22.0        3
29.0        2
28.0        2
26.0        2
141.0       1
55.0        1
30.0        1
43.0        1
74.0        1
41.0        1
54.0        1
115.0       1
251.0       1
32.0        1
42.0        1
Name: TotalVisits, dtype: int64
```

In [28]:

```
# imputing all the missing values with label having max occurences
miss_max = ['TotalVisits','Page Views Per Visit','Last Activity','Total Time Spent on Website','Tags']
for i in Lead_scoring_df[miss_max].columns:
    max_str = Lead_scoring_df[i].value_counts()[Lead_scoring_df[i].value_counts() == Lead_scoring_df[i].value_counts().max()].inde
    Lead_scoring_df[i] = Lead_scoring_df[i].fillna(value=max_str)
```

In [29]:

```
Lead_scoring_df.isna().sum()
```

Out[29]:

```
Lead Origin                               0
Lead Source                               0
Do Not Email                              0
Do Not Call                               0
Converted                                 0
TotalVisits                               0
Total Time Spent on Website               0
Page Views Per Visit                      0
Last Activity                             0
Specialization                            0
What is your current occupation           0
Search                                    0
Newspaper Article                         0
X Education Forums                        0
Newspaper                                 0
Digital Advertisement                     0
Through Recommendations                   0
Tags                                      0
A free copy of Mastering The Interview    0
Last Notable Activity                     0
dtype: int64
```

Handling Outliers

In [30]:

```
# checking the statistical data
Lead_scoring_df.describe(percentiles=[0.25,0.50,0.75,0.90,0.95,0.97,0.99])
```

Out[30]:

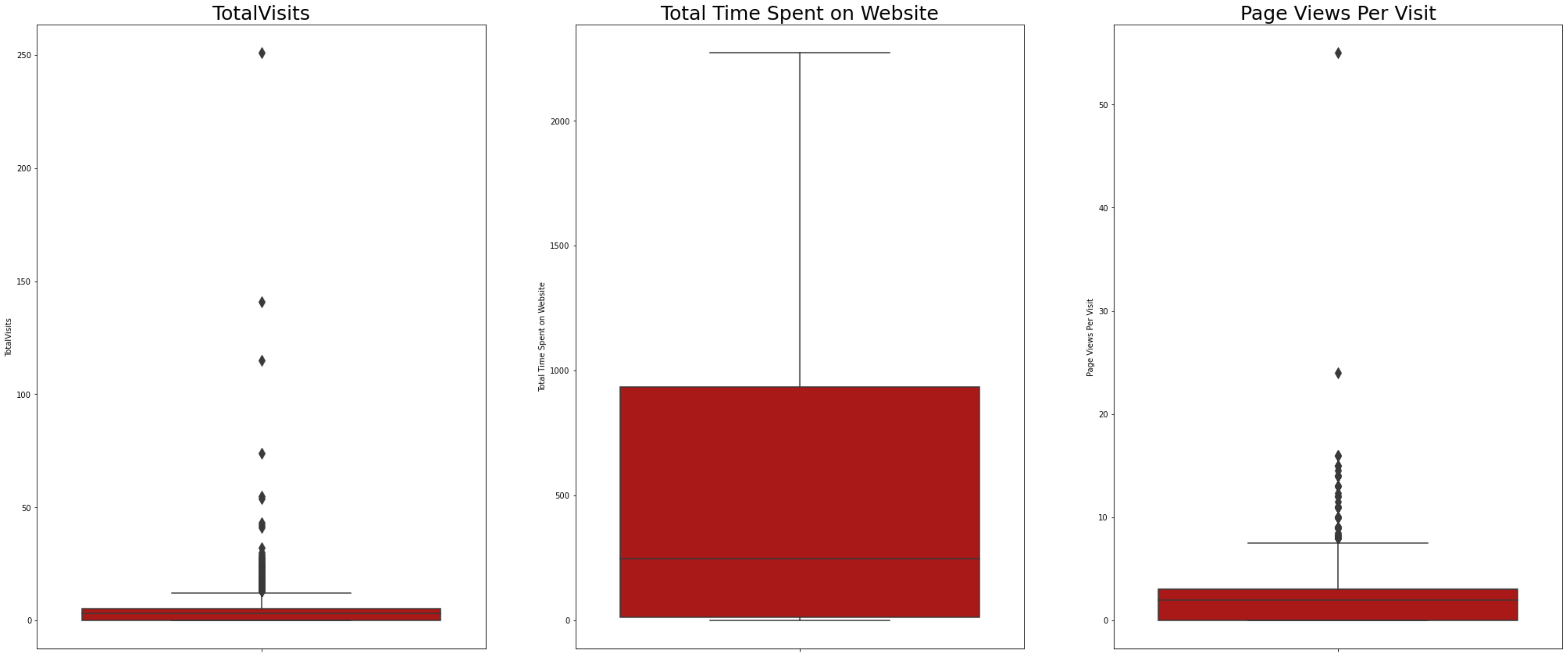
	Do Not Email	Do Not Call	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Search	Newspaper Article	X Education Forums	Newspaper	Digital Advertisement

	Do Not Email	Do Not Call	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Search	Newspaper Article	X Education Forums	Newspaper	Digital Advertisement
count	9240.000000	9240.000000	9240.000000	9240.000000	9240.000000	9240.000000	9240.000000	9240.000000	9240.000000	9240.000000	9240.000000
mean	0.079437	0.000216	0.385390	3.394156	487.698268	2.327787	0.001515	0.000216	0.000108	0.000108	0.000433
std	0.270435	0.014711	0.486714	4.836682	548.021466	2.164258	0.038898	0.014711	0.010403	0.010403	0.020803
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	12.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	3.000000	248.000000	2.000000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	1.000000	5.000000	936.000000	3.000000	0.000000	0.000000	0.000000	0.000000	0.000000
90%	0.000000	0.000000	1.000000	7.000000	1380.000000	5.000000	0.000000	0.000000	0.000000	0.000000	0.000000
95%	1.000000	0.000000	1.000000	10.000000	1562.000000	6.000000	0.000000	0.000000	0.000000	0.000000	0.000000
97%	1.000000	0.000000	1.000000	11.000000	1660.000000	7.000000	0.000000	0.000000	0.000000	0.000000	0.000000
99%	1.000000	0.000000	1.000000	17.000000	1840.610000	9.000000	0.000000	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	251.000000	2272.000000	55.000000	1.000000	1.000000	1.000000	1.000000	1.000000

As we can see there are outliers in 2 variables 'TotalVisits' and 'Page Views Per Visit'.

In [31]:

```
plt.figure(figsize=(35,50))

# Title names for the columns in the dataset

col_title={0:'TotalVisits',1:'Total Time Spent on Website',2:'Page Views Per Visit'}

# Visualising the outliers with boxplot for all the variables

for i in range(3):
    plt.subplot(3,3,i+1)
    plt.title(col_title[i],fontsize=25)
    sns.boxplot(y=Lead_scoring_df[col_title[i]],data=Lead_scoring_df,palette='gist_heat',fliersize=10)
```



From the above boxplots we can now confirm that we have two outlier variables in our dataset ('TotalVisits' and 'Page Views Per Visit'). Now as per business requirement we cannot drop these outliers because it may impact our analysis/model so we will create bins for these two outliers

In [32]:

```
# For 'TotalVisits' variable

# As we have range from 0 to 251 for'TotalVisits' variable

ranges_total_visits={'TotalVisits_0_50': 50,'TotalVisits_50_100': 100,'TotalVisits_100_150': 150,
                     'TotalVisits_150_200' : 200,'TotalVisits_200_250': 250,'TotalVisits_250_300': 300}

# Assigning '1' or '0' to each bins

for i in range(len(list(ranges_total_visits.keys()))):
    Lead_scoring_df[list(ranges_total_visits.keys())[i]]=Lead_scoring_df['TotalVisits'].map(lambda x: 1 if (x < list(ranges_total_
```

In [33]:

```
# For 'Page Views Per Visit' variable

# As we have range from 0 to 55 for'Page Views Per Visit' variable

ranges_total_visits_1={'Page Views Per Visit_0_10': 10,'Page Views Per Visit_10_20': 20,'Page Views Per Visit_20_30': 30,
                     'Page Views Per Visit_30_40' : 40,'Page Views Per Visit_40_50': 50,'Page Views Per Visit_50_60': 60}

# Assigning '1' or '0' to each bins

for i in range(len(list(ranges_total_visits_1.keys()))):
    Lead_scoring_df[list(ranges_total_visits_1.keys())[i]]=Lead_scoring_df['Page Views Per Visit'].map(lambda x: 1 if (x < list(ra
```

In [34]:

```
redundant=['TotalVisits','Page Views Per Visit','TotalVisits_150_200','TotalVisits_200_250','Page Views Per Visit_30_40','Page Vie

Lead_scoring_df=Lead_scoring_df.drop(redundant,axis=1)

Lead_scoring_df.head()
```

Out[34]:

	Lead Origin	Lead Source	Do Not Email	Do Not Call	Converted	Total Time Spent on Website	Last Activity	Specialization	What is your current occupation	Search	...	A free copy of Mastering The Interview	Last Notable Activity	TotalVisits_0_50	Total
0	API	Olark Chat	0	0	0	0	Page Visited on Website	Missing	Unemployed	0	...	0	Modified	1	
1	API	Organic Search	0	0	0	674	Email Opened	Missing	Unemployed	0	...	0	Email Opened	1	
2	Landing Page Submission	Direct Traffic	0	0	1	1532	Email Opened	Business Administration	Student	0	...	1	Email Opened	1	
3	Landing Page Submission	Direct Traffic	0	0	0	305	Unreachable	Media and Advertising	Unemployed	0	...	0	Modified	1	
4	Landing Page Submission	Google	0	0	1	1428	Converted to Lead	Missing	Unemployed	0	...	0	Modified	1	

5 rows × 26 columns

After creating bins we removed the outliers and are now good to go. Before creating the dummy variables let's remove redundant columns/varaibles.

Also from above we know columns : 'Last Activity', 'Tags', 'Last Notable Activity' activity columns came from sales team, thus we will drop these redundant columns.

In [35]:

```
# dropping redundant column

redundant=['Last Activity', 'Tags', 'Last Notable Activity']

Lead_scoring_df=Lead_scoring_df.drop(redundant,axis=1)

Lead_scoring_df.head()
```

Out[35]:

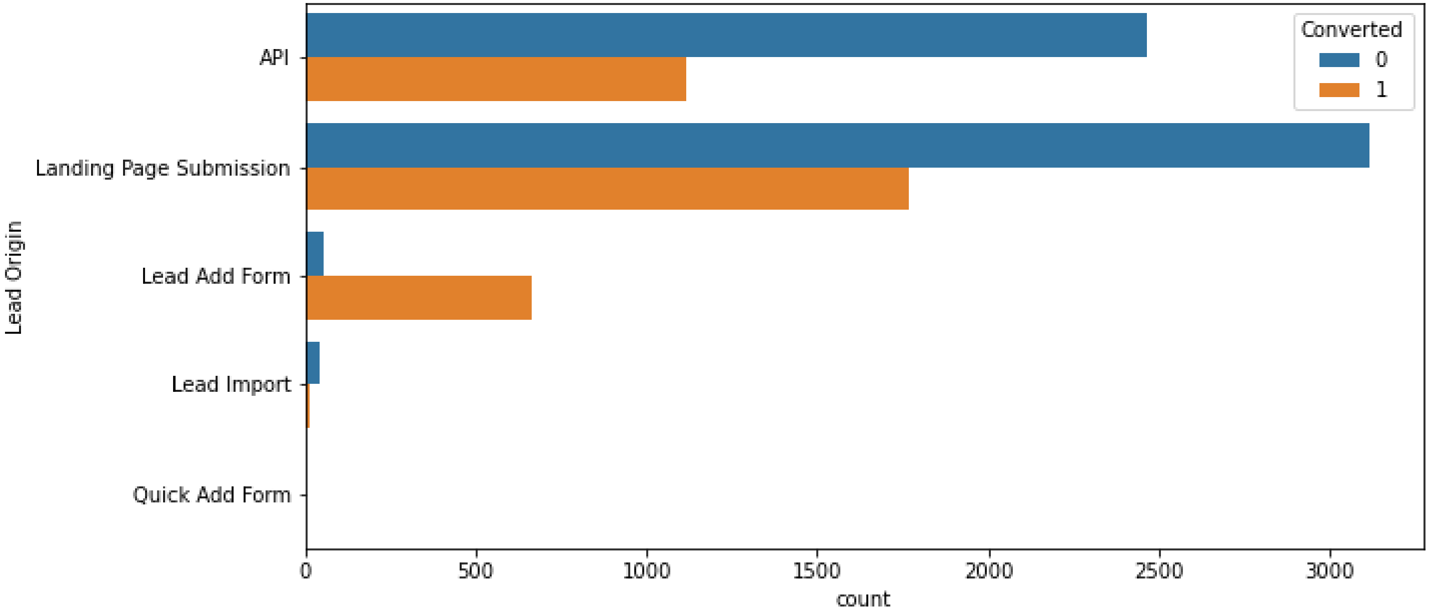
	Lead Origin	Lead Source	Do Not Email	Do Not Call	Converted	Total Time Spent on Website	Specialization	What is your current occupation	Search	Newspaper Article	...	Through Recommendations	A free copy of Mastering The Interview	TotalVisits_0_
0	API	Olark Chat	0	0	0	0	Missing	Unemployed	0	0	...	0	0	
1	API	Organic Search	0	0	0	674	Missing	Unemployed	0	0	...	0	0	
2	Landing Page Submission	Direct Traffic	0	0	1	1532	Business Administration	Student	0	0	...	0	1	
3	Landing Page Submission	Direct Traffic	0	0	0	305	Media and Advertising	Unemployed	0	0	...	0	0	
4	Landing Page Submission	Google	0	0	1	1428	Missing	Unemployed	0	0	...	0	0	

5 rows × 23 columns

Exploratory Data Analysis

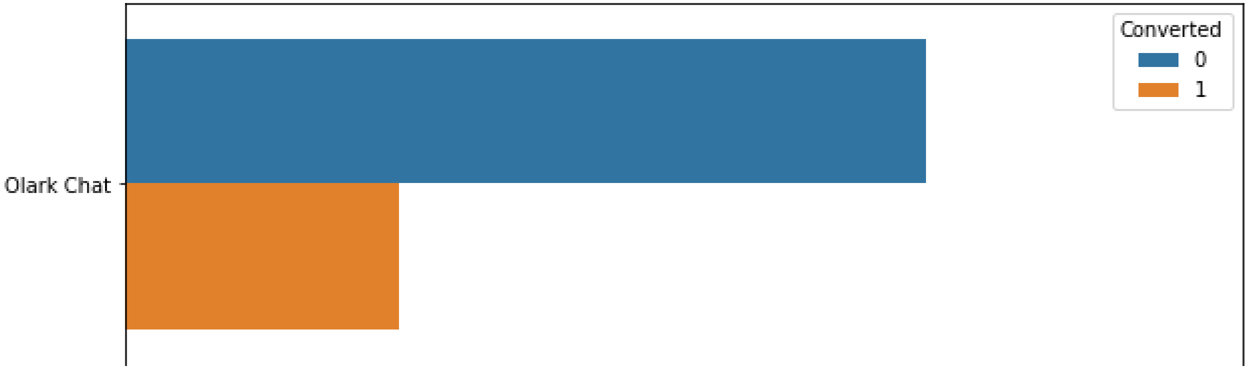
In [36]:

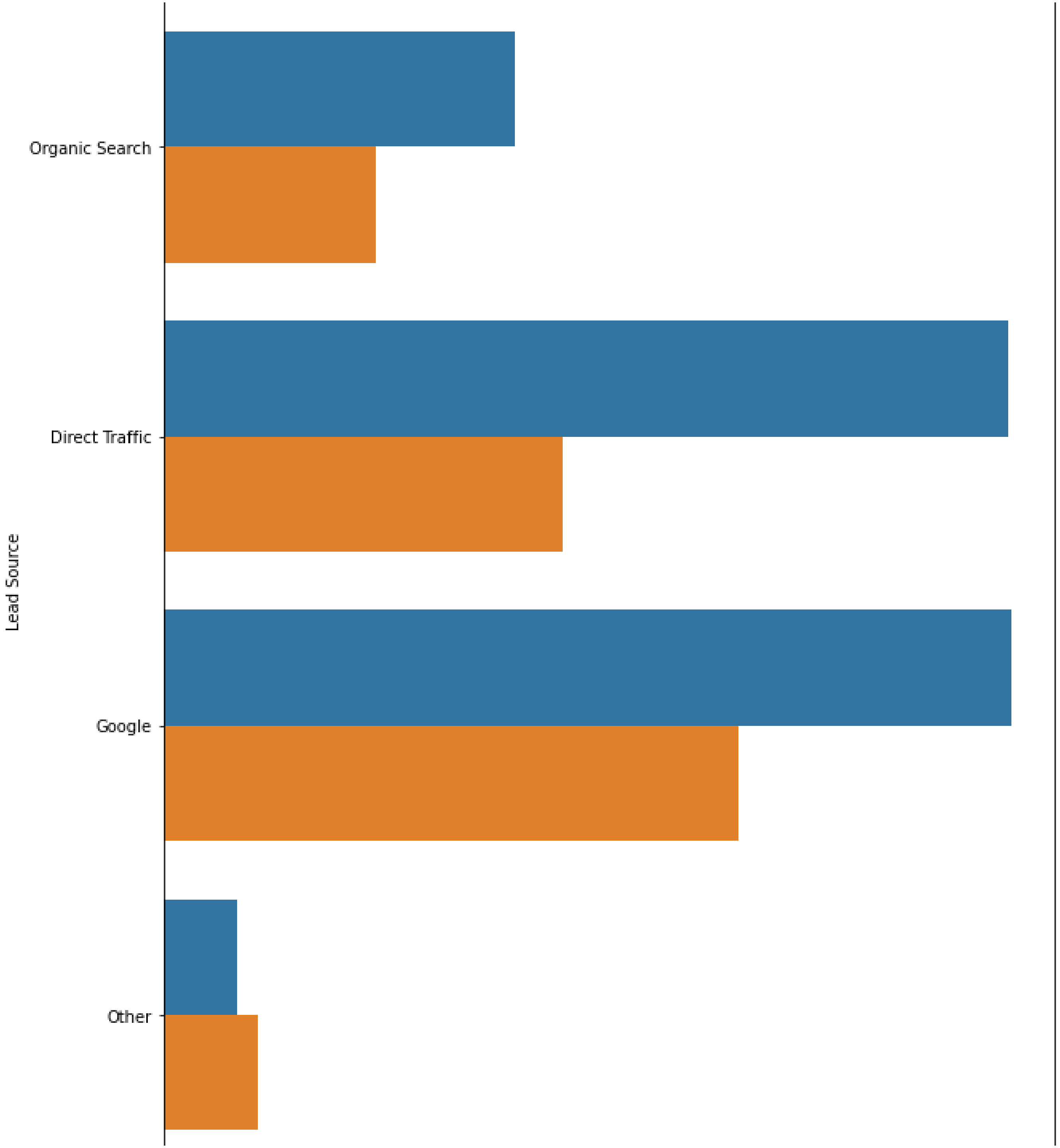
```
plt.figure(figsize=(10, 5))
sns.countplot(y="Lead Origin", hue="Converted", data=Lead_scoring_df)
plt.show()
```

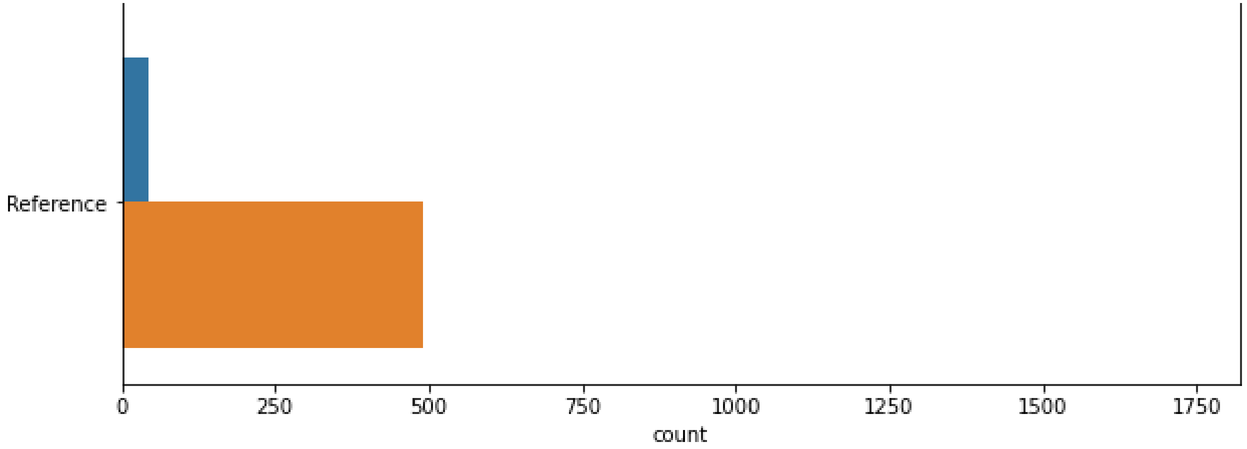


In [37]:

```
plt.figure(figsize=(10, 20))
sns.countplot(y="Lead Source", hue="Converted", data=Lead_scoring_df)
plt.show()
```

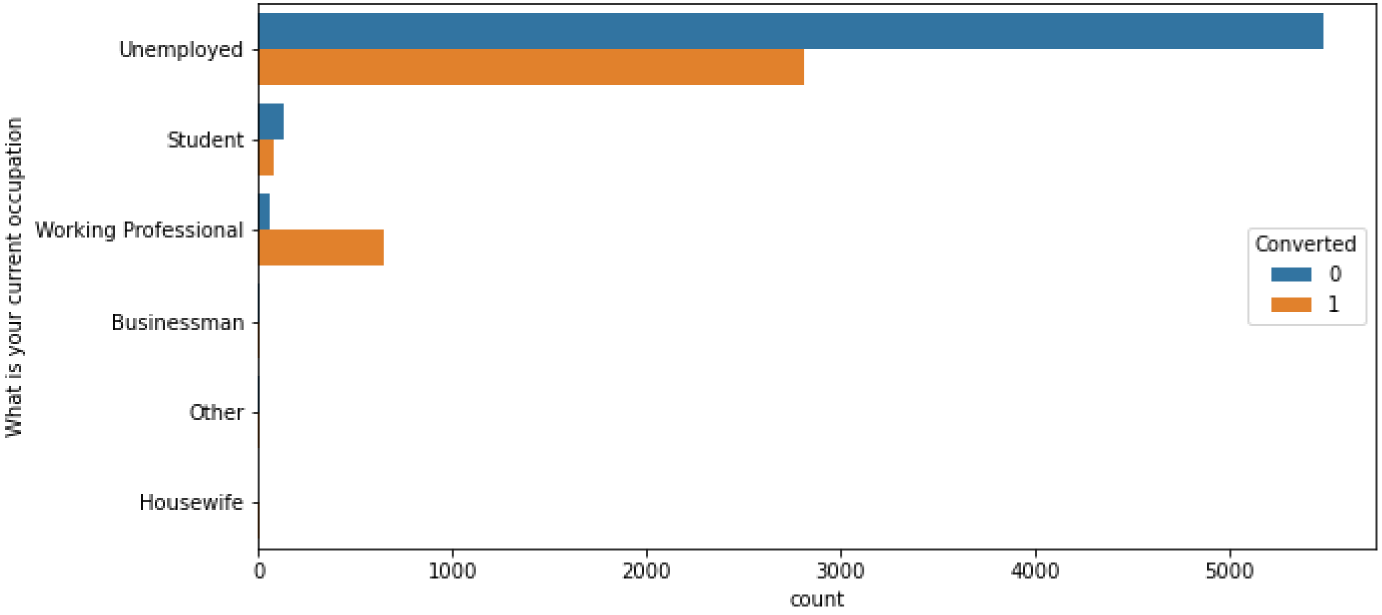



Organic Search
Direct Traffic
Google
Other
Lead Source



In [38]:

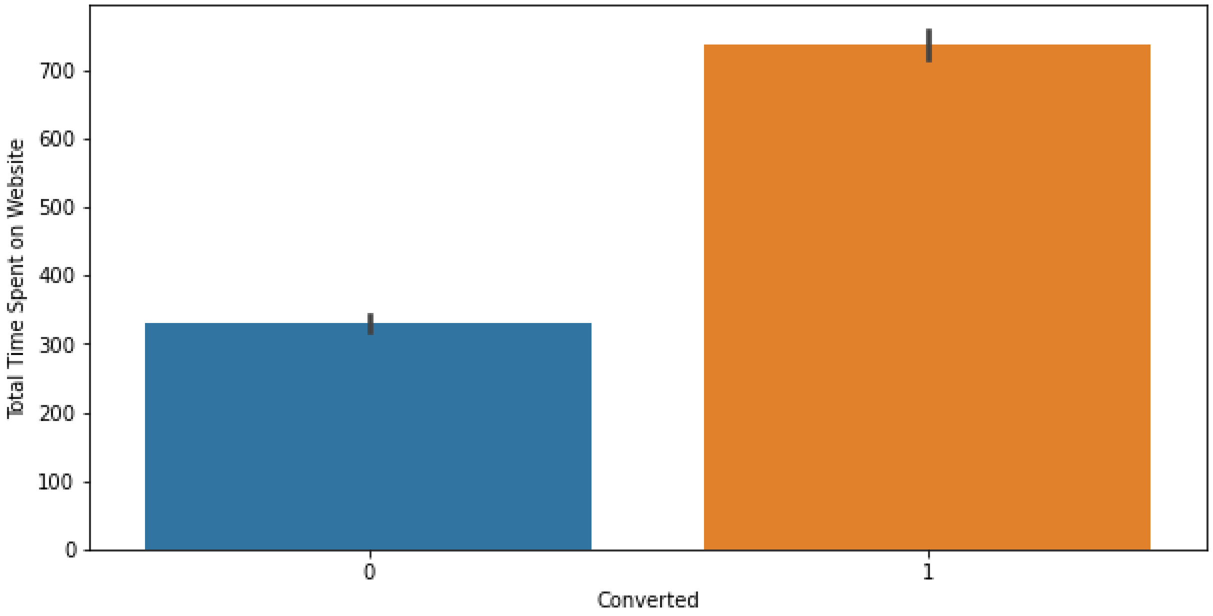
```
plt.figure(figsize=(10, 5))
sns.countplot(y="What is your current occupation", hue="Converted", data=Lead_scoring_df)
plt.show()
```



In [39]:

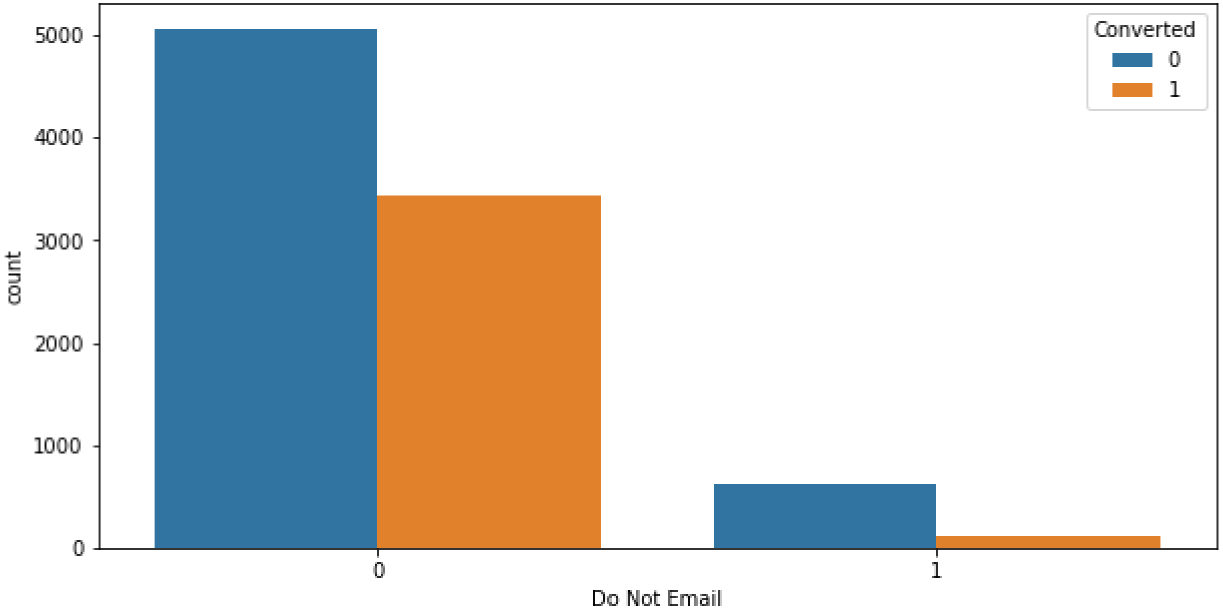
```
plt.figure(figsize=(10, 5))
sns.barplot(x = 'Converted', y = 'Total Time Spent on Website',data = Lead_scoring_df)
```

```
plt.show()
```



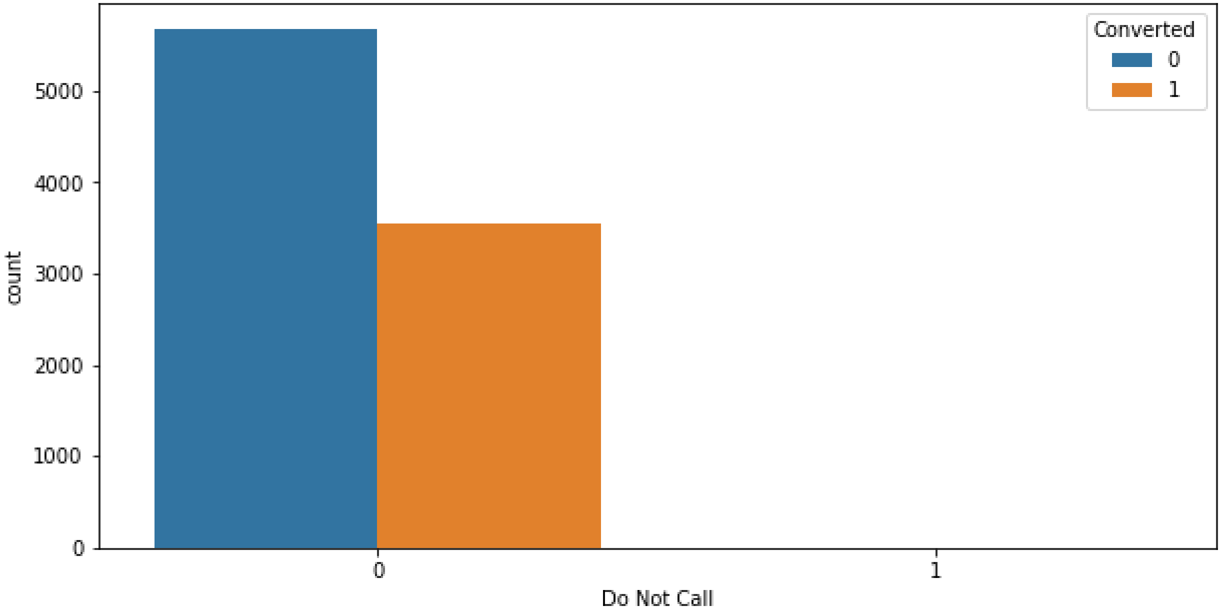
In [40]:

```
plt.figure(figsize=(10, 5))
sns.countplot(x="Do Not Email", hue="Converted", data=Lead_scoring_df)
plt.show()
```



In [41]:

```
plt.figure(figsize=(10, 5))
sns.countplot(x="Do Not Call", hue="Converted", data=Lead_scoring_df)
plt.show()
```



Observations from EDA Process -

- Maximum lead conversion happened from Landing Page Submission.
- Major lead conversion in the lead source is from 'Google'
- Major lead conversion is from the Unemployed Group
- Major lead conversion from Total Time Spent on Website
- Major conversion has happened from the emails that have been sent

Creating Dummy Variables

In [42]:

```
#Creating a dummy variables for 4 categories and dropping the first level.

cat = ['Lead Origin', 'Lead Source','Specialization','What is your current occupation']

#creating dummy variables data set
dummy = pd.get_dummies(Lead_scoring_df[cat], drop_first=True)

# Adding these dummies to our original dataset
Lead_scoring_df = pd.concat([Lead_scoring_df,dummy],axis=1)
```

```
#dropping the duplicate columns
Lead_scoring_df = Lead_scoring_df.drop(cat, axis=1)

#viewing the dataset
Lead_scoring_df.head()
```

Out[42]:

	Do Not Email	Do Not Call	Converted	Total Time Spent on Website	Search	Newspaper Article	X Education Forums	Newspaper	Digital Advertisement	Through Recommendations	...	Specialization_Retail Management	Specialization and Agribu
0	0	0	0	0	0	0	0	0	0	0	...	0	
1	0	0	0	674	0	0	0	0	0	0	...	0	
2	0	0	1	1532	0	0	0	0	0	0	...	0	
3	0	0	0	305	0	0	0	0	0	0	...	0	
4	0	0	1	1428	0	0	0	0	0	0	...	0	

5 rows × 51 columns

In [43]:

```
Lead_scoring_df.shape
```

Out[43]:

```
(9240, 51)
```

In [44]:

```
Lead_scoring_df.describe()
```

Out[44]:

	Do Not Email	Do Not Call	Converted	Total Time Spent on Website	Search	Newspaper Article	X Education Forums	Newspaper	Digital Advertisement	Through Recommendations	...	Sp
count	9240.000000	9240.000000	9240.000000	9240.000000	9240.000000	9240.000000	9240.000000	9240.000000	9240.000000	9240.000000	...	
mean	0.079437	0.000216	0.385390	487.698268	0.001515	0.000216	0.000108	0.000108	0.000433	0.000758	...	
std	0.270435	0.014711	0.486714	548.021466	0.038898	0.014711	0.010403	0.010403	0.020803	0.027515	...	

	Do Not Email	Do Not Call	Converted	Total Time Spent on Website	Search	Newspaper Article	X Education Forums	Newspaper	Digital Advertisement	Through Recommendations	...	Sp
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	
25%	0.000000	0.000000	0.000000	12.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	
50%	0.000000	0.000000	0.000000	248.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	
75%	0.000000	0.000000	1.000000	936.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	
max	1.000000	1.000000	1.000000	2272.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	...	

8 rows × 51 columns

Normalising continuous features

In [45]:

```
normalized_df=(Lead_scoring_df['Total Time Spent on Website']-Lead_scoring_df['Total Time Spent on Website'].max())/(Lead_scoring_
Lead_scoring_df = Lead_scoring_df.drop(['Total Time Spent on Website'], 1)
Lead_scoring_df = pd.concat([Lead_scoring_df,normalized_df],axis=1)
Lead_scoring_df.head()
```

Out[45]:

	Do Not Email	Do Not Call	Converted	Search	Newspaper Article	X Education Forums	Newspaper	Digital Advertisement	Through Recommendations	A free copy of Mastering The Interview	...	Specialization_Rural and Agribusiness	Specializatic
0	0	0	0	0	0	0	0	0	0	0	...	0	
1	0	0	0	0	0	0	0	0	0	0	...	0	
2	0	0	1	0	0	0	0	0	0	1	...	0	
3	0	0	0	0	0	0	0	0	0	0	...	0	
4	0	0	1	0	0	0	0	0	0	0	...	0	

5 rows × 51 columns

Model Building

Let's start by splitting our data into a training set and a test set.

In [46]:

```
from sklearn.model_selection import train_test_split

# Putting feature variable to X
X = Lead_scoring_df.drop(['Converted'],axis=1)

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

y.head()
```

Out[46]:

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

In [47]:

```
# 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=51)
```

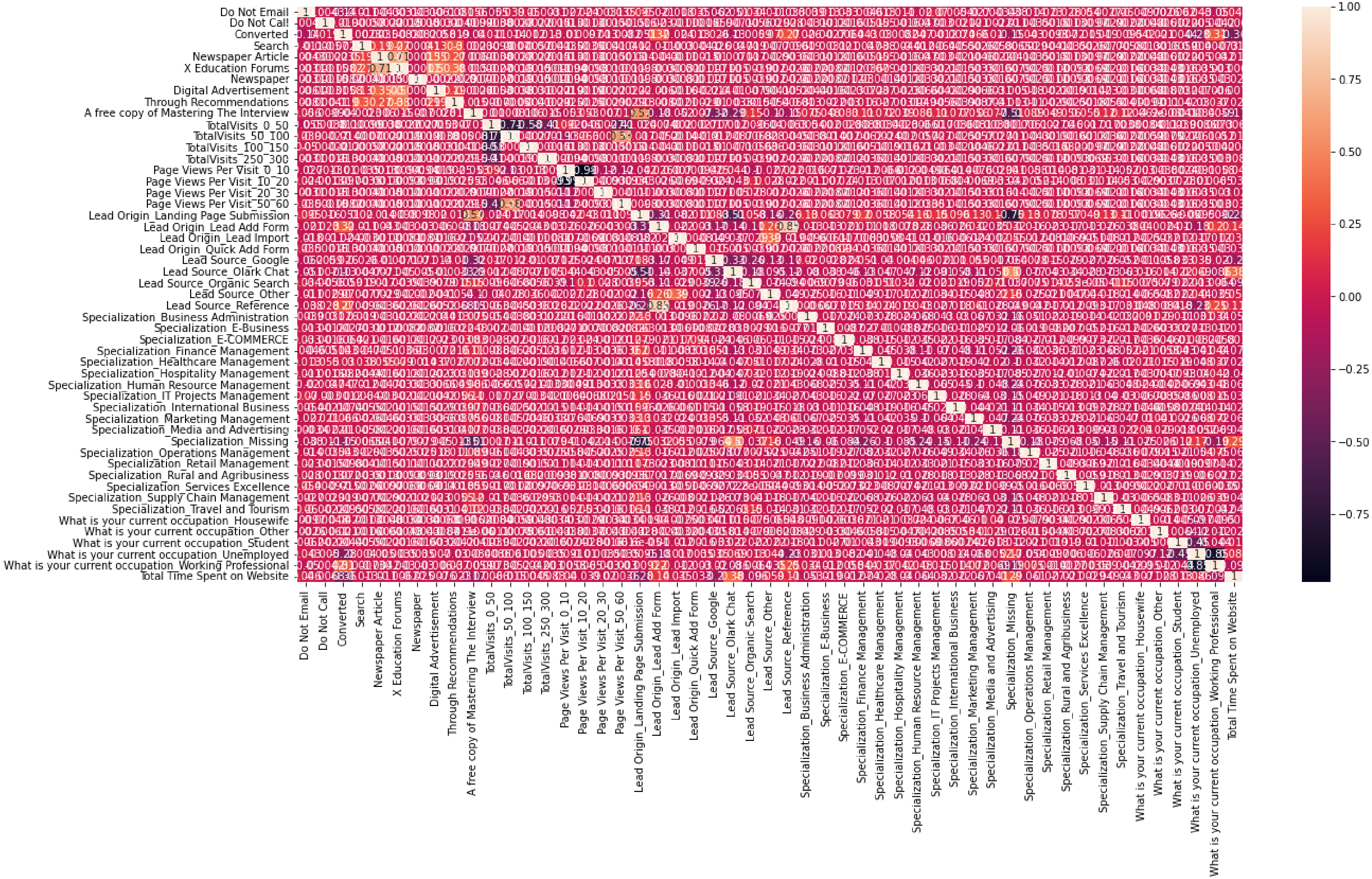
Correlation Matrix

In [48]:

```
plt.figure(figsize = (20,10))
sns.heatmap(Lead_scoring_df.corr(),annot = True)
```

Out[48]:

```
<AxesSubplot:>
```



we see lot of coorelation is there in df

PCA on the data

```
In [49]:
```

```
from sklearn.decomposition import PCA
```

In [50]:

```
pca = PCA(random_state=51)
```

In [51]:

```
pca.fit(X_train)
```

Out[51]:

```
PCA(random_state=51)
```

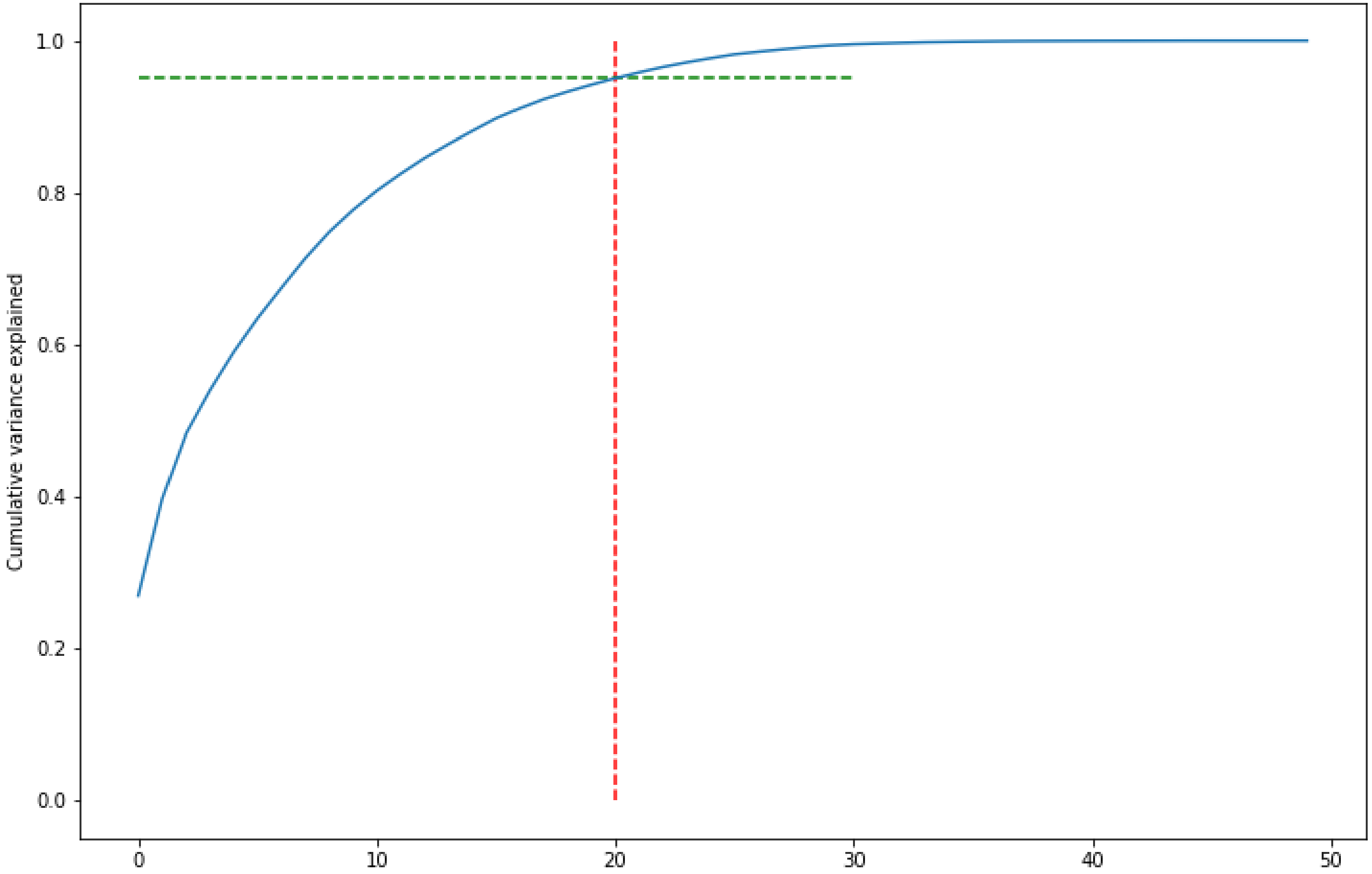
Making a scree plot for the explained variance

In [52]:

```
var_cumu = np.cumsum(pca.explained_variance_ratio_)
```

In [53]:

```
fig = plt.figure(figsize=[12,8])
plt.plot(var_cumu)
plt.vlines(x=20, ymax=1, ymin=0, colors="r", linestyles="--")
plt.hlines(y=0.95, xmax=30, xmin=0, colors="g", linestyles="--")
plt.ylabel("Cumulative variance explained")
plt.show()
```



Perform PCA with 20 components for which includes 95% of data variance

In [54]:
```
from sklearn.decomposition import IncrementalPCA
```

In [55]:
```
pca_final = IncrementalPCA(n_components=20)
```

In [56]:
```
df_train_pca = pca_final.fit_transform(X_train)
```

In [57]:
```
df_train_pca.shape
```

Out[57]:
```
(6468, 20)
```

In [58]:
```
corrmat = np.corrcoef(df_train_pca.transpose())
```

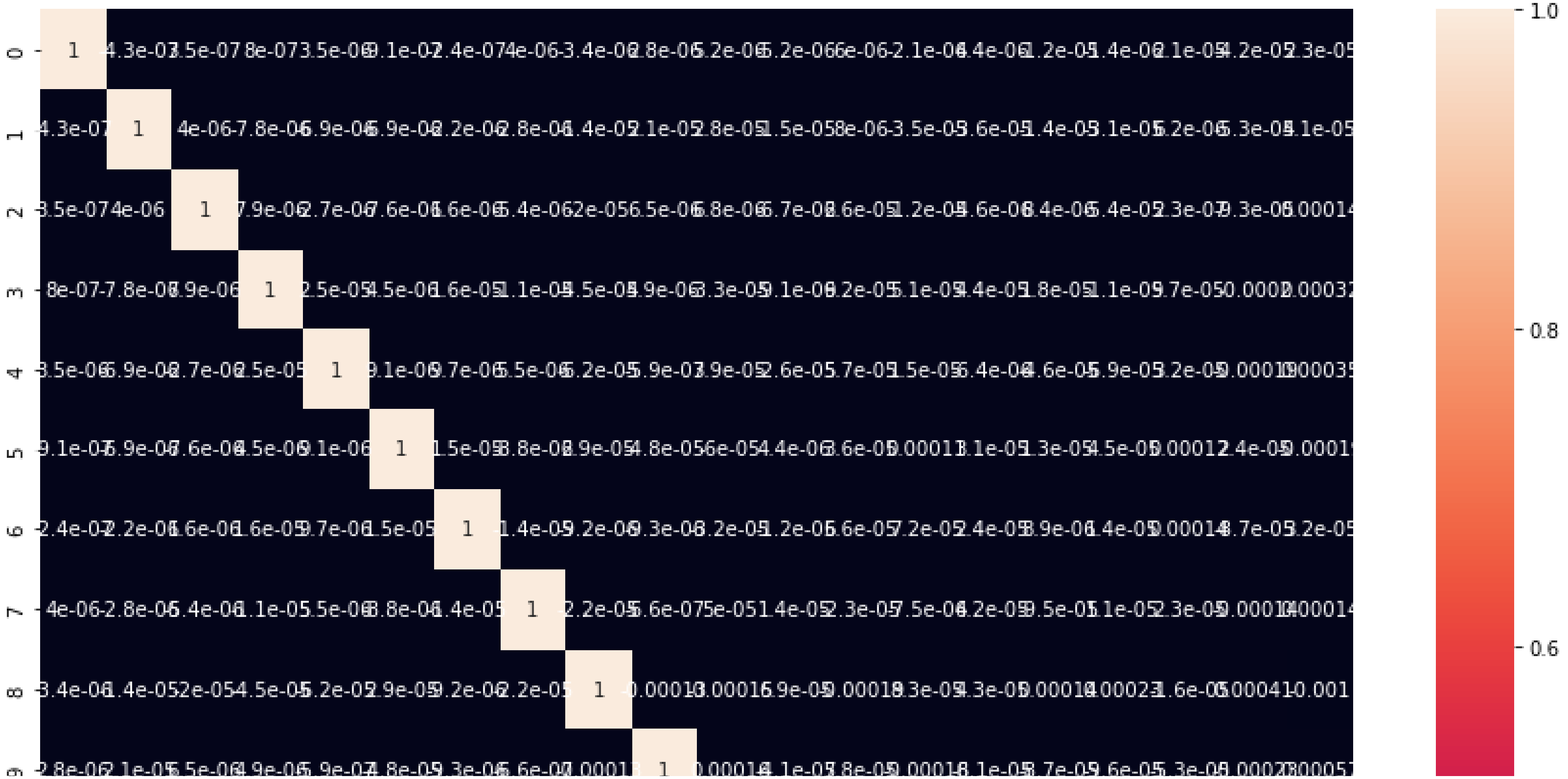
In [59]:
```
corrmat.shape
```

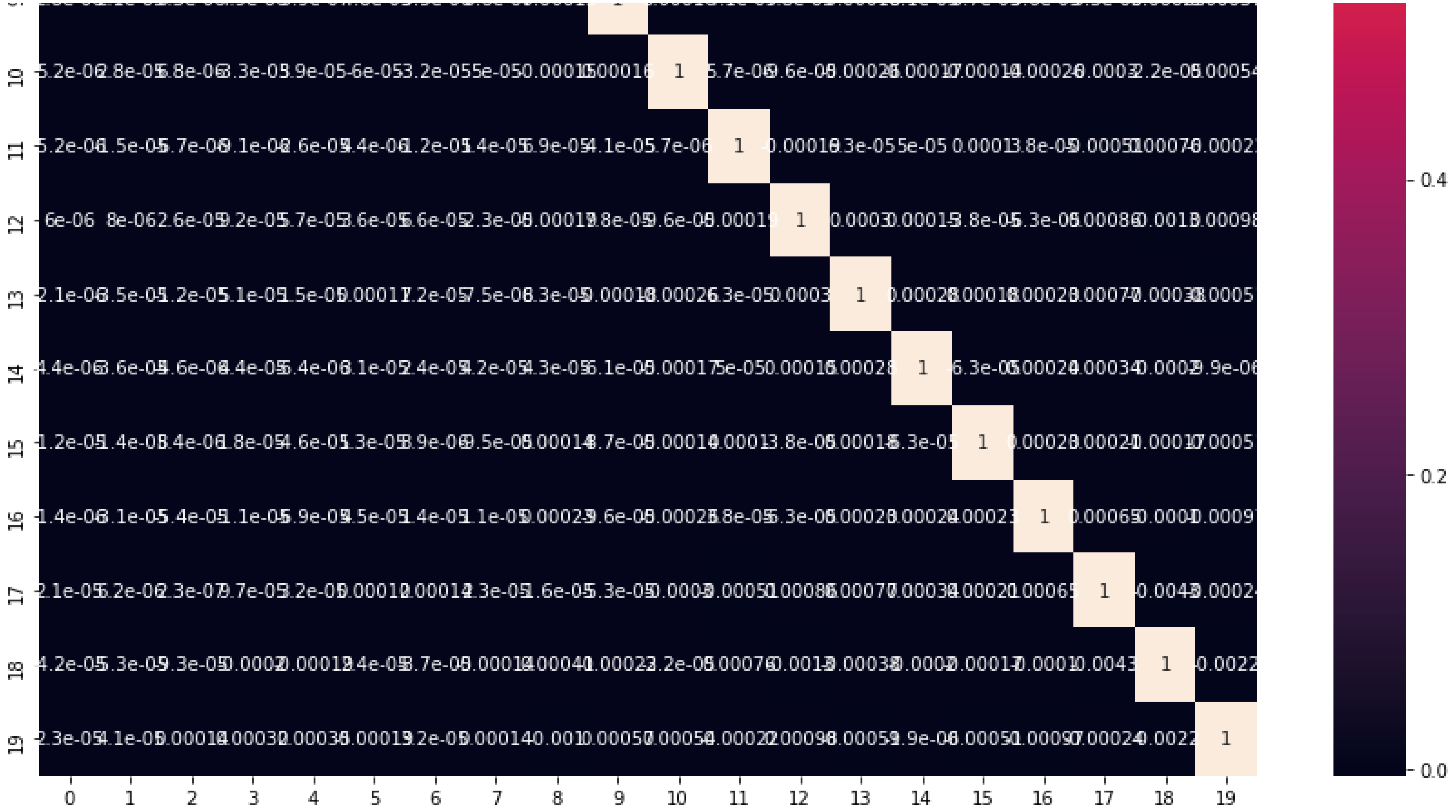
Out[59]:
```
(20, 20)
```

Plotting the heatmap of the corr matrix

In [60]:
```
plt.figure(figsize=[15,15])
sns.heatmap(corrmat, annot=True)
```

Out[60]:
```
<AxesSubplot:>
```





Applying the transformation on the test set

In [61]:

```
df_test_pca = pca_final.transform(X_test)
df_test_pca.shape
```

Out[61]:

```
(2772, 20)
```

Applying logistic regression on the data on our Principal components

In [62]:

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

In [63]:

```
learner_pca = LogisticRegression()
```

In [64]:

```
model_pca = learner_pca.fit(df_train_pca, y_train)
```

Making predictions on the test set

In [65]:

```
pred_probs_test = model_pca.predict_proba(df_test_pca)[:,1]
```

In [66]:

```
pred_probs_test
```

Out[66]:

```
array([0.67123312, 0.76832954, 0.41432273, ..., 0.2000577 , 0.46122542,
       0.09388255])
```

In [67]:

```
"{:2.2}".format(metrics.roc_auc_score(y_test, pred_probs_test))
```

Out[67]:

```
'0.84'
```

In [68]:

```
y_test_pred_final=pd.DataFrame({'Converted':y_test.values,'Converted_Probability':pred_probs_test,'ID':y_test.index})
```

In [69]:

```
y_test_pred_final.head()
```

Out[69]:

	Converted	Converted_Probability	ID
0	0	0.671233	979
1	1	0.768330	7039
2	0	0.414323	3864
3	1	0.648865	2746
4	0	0.232230	7384

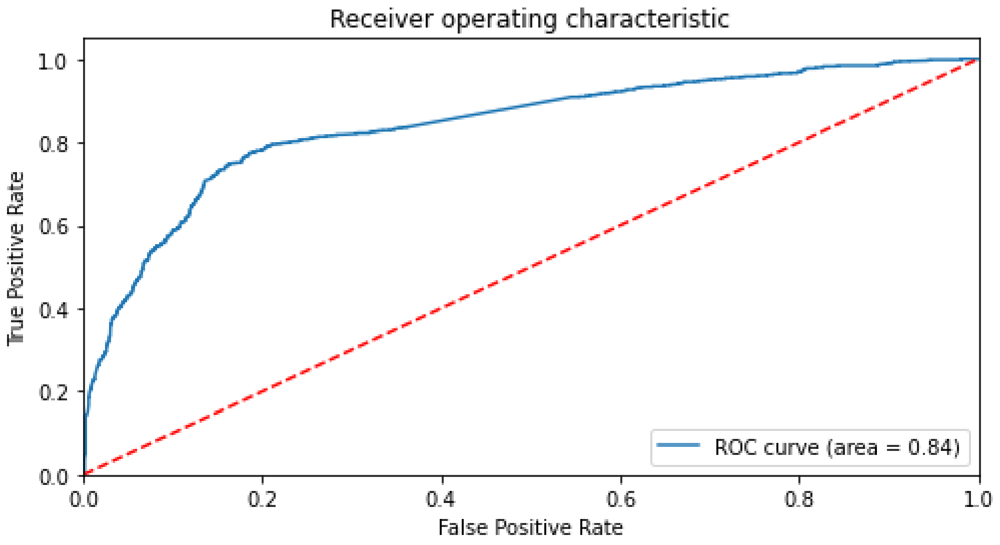
ROC Curve Plotting

In [70]:

```
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score


def edu_roc( real, probability ):
    fpr, tpr, thresholds = roc_curve( real, probability,drop_intermediate = False )
    auc_score = roc_auc_score( real, probability )
    plt.figure(figsize=(8, 4))
    plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % auc_score )
    plt.plot([0, 1], [0, 1], 'r--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic')
    plt.legend(loc="lower right")
    plt.show()
    return None
```

In [71]:

```
edu_roc(y_test_pred_final.Converted, y_test_pred_final.Converted_Probability)
```



Points to be concluded from above roc curve -

- The curve is closer to the left side of the border than to the right side hence our model is having great accuracy.

- The area under the curve is 84% of the total area.

Model Evaluation

Finding Optimal Cutoff Point

In [72]:

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

Out[72]:

	Converted	Converted_Probability	ID	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	0	0.671233	979	1	1	1	1	1	1	1	0	0	0
1	1	0.768330	7039	1	1	1	1	1	1	1	1	0	0
2	0	0.414323	3864	1	1	1	1	1	0	0	0	0	0
3	1	0.648865	2746	1	1	1	1	1	1	1	0	0	0
4	0	0.232230	7384	1	1	1	0	0	0	0	0	0	0

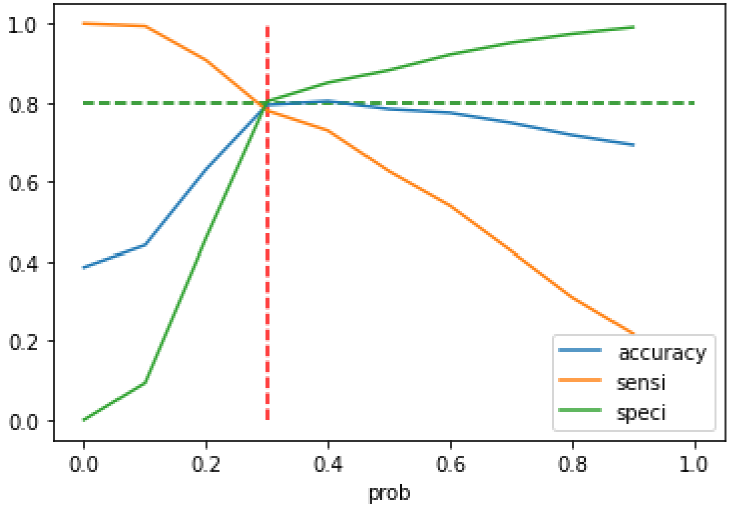
In [73]:

```
# 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_test_pred_final.Converted, y_test_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  0.385281  1.000000  0.000000
0.1   0.1  0.440115  0.993446  0.093310
0.2   0.2  0.631313  0.907303  0.458333
0.3   0.3  0.794012  0.779963  0.802817
0.4   0.4  0.803752  0.729401  0.850352
0.5   0.5  0.783550  0.626404  0.882042
0.6   0.6  0.774170  0.539326  0.921362
0.7   0.7  0.748918  0.426030  0.951291
0.8   0.8  0.717893  0.309925  0.973592
0.9   0.9  0.693001  0.218165  0.990610
```

In [74]:

```
# Let's plot accuracy sensitivity and specificity for various probabilities.
cutoff_df.plot.line(x='prob', y=['accuracy','sensi','speci'])
plt.vlines(x=0.3, ymax=1, ymin=0, colors="r", linestyles="--")
plt.hlines(y=0.8, xmax=1, xmin=0, colors="g", linestyles="--")
plt.show()
```



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

In [75]:

```
# Predicting the outcomes with probability cutoff as 0.3 by creating new columns in the final test dataset
y_test_pred_final['Predicted']=y_test_pred_final['Converted_Probability'].map(lambda x:1 if x >0.3 else 0 )
```

```
y_test_pred_final.head()
```

Out[75]:

	Converted	Converted_Probability	ID	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	Predicted
0	0	0.671233	979	1	1	1	1	1	1	1	0	0	0	1
1	1	0.768330	7039	1	1	1	1	1	1	1	1	0	0	1
2	0	0.414323	3864	1	1	1	1	1	0	0	0	0	0	1
3	1	0.648865	2746	1	1	1	1	1	1	1	0	0	0	1
4	0	0.232230	7384	1	1	1	0	0	0	0	0	0	0	0

In [76]:

```
print('Accuracy score in predicting test dataset :',metrics.accuracy_score(y_test_pred_final.Converted, y_test_pred_final.Predicte

print('Precision score in predicting test dataset:',precision_score(y_test_pred_final.Converted, y_test_pred_final.Predicted))

print('Recall score in predicting test dataset:',recall_score(y_test_pred_final.Converted, y_test_pred_final.Predicted))
```

```
Accuracy score in predicting test dataset : 0.7940115440115441
Precision score in predicting test dataset: 0.7125748502994012
Recall score in predicting test dataset: 0.7799625468164794
```

Lead Score assigning

In [77]:

```
# Creating new columns for lead number and lead score
# Dropping unwanted columns
L = [0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9]
y_test_pred_final=y_test_pred_final.drop(L,1)
y_test_pred_final['Lead Score']=y_test_pred_final['Converted_Probability'].apply(lambda x:round(x*100))


y_test_pred_final.head()
```

Out[77]:

	Converted	Converted_Probability	ID	Predicted	Lead Score
0	0	0.671233	979	1	67
1	1	0.768330	7039	1	77

	Converted	Converted_Probability	ID	Predicted	Lead Score
2	0	0.414323	3864	1	41
3	1	0.648865	2746	1	65
4	0	0.232230	7384	0	23

Conclusion

Valuable Insights -

- The Sensitivity and Specificity, Accuracy, Precision and Recall score we got from test set are almost accurate.
- We have high recall score than precision score which is a sign of good model.
- In business terms, this model has an ability to adjust with the company’s requirements in coming future.
- This concludes that the model is in stable state.
- Important features responsible for good conversion rate or the ones' which contributes more towards the probability of a lead getting converted are :
    - **Lead Origin_Lead Add Form**
    - **Total Time Spent on Website**
    - **What is your current occupation_Working Professional**

In [ ]: