

```

# Suppress unnecessary warnings

import warnings
warnings.filterwarnings('ignore')

# Importing the NumPy and Pandas packages

import numpy as np
import pandas as pd

#import visualization libraries
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style="whitegrid")

#import stats library
from scipy import stats
import statsmodels.api as sm

#import sklearn libraries
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFE
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn import metrics
from sklearn.metrics import classification_report, recall_score, roc_auc_score, roc_curve, accuracy_score, precision_score, precision_recall_curve, confusion_matrix
from sklearn.preprocessing import LabelEncoder

#import miscellaneous libraries
pd.set_option("display.max_columns", None)
pd.set_option("display.max_colwidth", 200)

```

Importing the "Leads" Dataset

```

# Read the dataset
leads = pd.read_csv("Leads.csv")

leads.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	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

	Country	Specialization	How did you hear about X Education \
0	NaN	Select	Select
1	India	Select	Select
2	India	Business Administration	Select
3	India	Media and Advertising	Word Of Mouth
4	India	Select	Other

	What is your current occupation \
0	Unemployed
1	Unemployed
2	Student
3	Unemployed
4	Unemployed

	What matters most to you in choosing a course	Search Magazine \
0	Better Career Prospects	No No
1	Better Career Prospects	No No

2		Better Career Prospects	No	No
3		Better Career Prospects	No	No
4		Better Career Prospects	No	No
Newspaper Article X Education Forums Newspaper Digital Advertisement				
\				
0	No	No	No	No
1	No	No	No	No
2	No	No	No	No
3	No	No	No	No
4	No	No	No	No
Through Recommendations Receive More Updates About Our Courses \				
0	No			No
1	No			No
2	No			No
3	No			No
4	No			No
Tags Lead Quality \				
0	Interested in other courses	Low in Relevance		
1	Ringling	NaN		
2	Will revert after reading the email	Might be		
3	Ringling	Not Sure		
4	Will revert after reading the email	Might be		
Update me on Supply Chain Content Get updates on DM Content Lead Profile \				
0		No		No
Select				
1		No		No
Select				
2		No		No
Potential Lead				
3		No		No
Select				
4		No		No
Select				
City Asymmetrique Activity Index Asymmetrique Profile Index \				
0	Select	02.Medium		02.Medium
1	Select	02.Medium		02.Medium
2	Mumbai	02.Medium		01.High
3	Mumbai	02.Medium		01.High
4	Mumbai	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

#Checking the Shape of dataset

leads.shape

(9240, 37)

Inspecting the different columns in the dataset

leads.columns

```
Index(['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', 'How did you hear about X
Education',
      'What is your current occupation',
      'What matters most to you in choosing a course', 'Search',
'Magazine',
      'Newspaper Article', 'X Education Forums', 'Newspaper',
      'Digital Advertisement', 'Through Recommendations',
      'Receive More Updates About Our Courses', 'Tags', 'Lead
Quality',
      'Update me on Supply Chain Content', 'Get updates on DM
Content',
      'Lead Profile', 'City', 'Asymmetrique Activity Index',
      'Asymmetrique Profile Index', 'Asymmetrique Activity Score',
      'Asymmetrique Profile Score',
      'I agree to pay the amount through cheque',
      'A free copy of Mastering The Interview', 'Last Notable
```

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

```
# Checking the summary of the dataset  
leads.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

```
# Checking the info to see the types of the feature variables and the  
null values present  
leads.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

```

As it seems that there are quite a few categorical variables present in this dataset for which we will need to create dummy variables. Also, there are a lot of null values present as well, so we will need to treat them accordingly.

Step 1: Data Cleaning and Preparation

```

# Checking the number of missing values in each column
leads.isnull().sum().sort_values(ascending=False)

Lead Quality          4767
Asymmetrique Activity Index  4218
Asymmetrique Profile Score  4218
Asymmetrique Activity Score  4218
Asymmetrique Profile Index  4218
Tags                  3353

```

Lead Profile	2709
What matters most to you in choosing a course	2709
What is your current occupation	2690
Country	2461
How did you hear about X Education	2207
Specialization	1438
City	1420
Page Views Per Visit	137
TotalVisits	137
Last Activity	103
Lead Source	36
Receive More Updates About Our Courses	0
I agree to pay the amount through cheque	0
Get updates on DM Content	0
Update me on Supply Chain Content	0
A free copy of Mastering The Interview	0
Prospect ID	0
Newspaper Article	0
Through Recommendations	0
Digital Advertisement	0
Newspaper	0
X Education Forums	0
Lead Number	0
Magazine	0
Search	0
Total Time Spent on Website	0
Converted	0
Do Not Call	0
Do Not Email	0
Lead Origin	0
Last Notable Activity	0
dtype: int64	

As it is clearly seen there are a lot of columns which have high number of missing values. Clearly, these columns are not useful. Since, there are 9000 datapoints in our dataframe, let's eliminate the columns having greater than 3000 missing values as they are of no use to us.

```
# Dropping all the columns in which greater than
for c in leads.columns:
    if leads[c].isnull().sum()>3000:
        leads.drop(c, axis=1,inplace=True)

leads.isnull().sum().sort_values(ascending=False)
```

What matters most to you in choosing a course	2709
Lead Profile	2709
What is your current occupation	2690
Country	2461
How did you hear about X Education	2207

Specialization	1438
City	1420
Page Views Per Visit	137
TotalVisits	137
Last Activity	103
Lead Source	36
Get updates on DM Content	0
Newspaper	0
I agree to pay the amount through cheque	0
A free copy of Mastering The Interview	0
Update me on Supply Chain Content	0
Receive More Updates About Our Courses	0
Through Recommendations	0
Digital Advertisement	0
Prospect ID	0
X Education Forums	0
Newspaper Article	0
Magazine	0
Search	0
Lead Number	0
Total Time Spent on Website	0
Converted	0
Do Not Call	0
Do Not Email	0
Lead Origin	0
Last Notable Activity	0
dtype: int64	

```
#checking value counts of "City" column
leads['City'].value_counts(dropna=False)
```

Mumbai	3222
Select	2249
NaN	1420
Thane & Outskirts	752
Other Cities	686
Other Cities of Maharashtra	457
Other Metro Cities	380
Tier II Cities	74
Name: City, dtype: int64	

Mumbai has highest numbers of leads

As you might be able to interpret, the variable City won't be of any use in our analysis. So it's best that we drop it.

```
# dropping the "City" feature
leads.drop(['City'], axis = 1, inplace = True)
```

```
#checking value counts of "Country" column  
leads['Country'].value_counts(dropna=False)
```

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

Name: Country, dtype: int64

Highest number of leads from INDIA

```
# dropping the "Country" feature  
leads.drop(['Country'], axis = 1, inplace = True)
```

#Now checking the percentage of missing values in each column

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

Prospect ID	0.00
Lead Number	0.00
Lead Origin	0.00
Lead Source	0.39
Do Not Email	0.00
Do Not Call	0.00
Converted	0.00
TotalVisits	1.48
Total Time Spent on Website	0.00
Page Views Per Visit	1.48
Last Activity	1.11
Specialization	15.56
How did you hear about X Education	23.89
What is your current occupation	29.11
What matters most to you in choosing a course	29.32
Search	0.00
Magazine	0.00
Newspaper Article	0.00
X Education Forums	0.00
Newspaper	0.00
Digital Advertisement	0.00
Through Recommendations	0.00
Receive More Updates About Our Courses	0.00
Update me on Supply Chain Content	0.00
Get updates on DM Content	0.00
Lead Profile	29.32
I agree to pay the amount through cheque	0.00
A free copy of Mastering The Interview	0.00
Last Notable Activity	0.00
dtype:	float64

Checking the number of null values again

```
leads.isnull().sum().sort_values(ascending=False)
```

What matters most to you in choosing a course	2709
Lead Profile	2709
What is your current occupation	2690
How did you hear about X Education	2207
Specialization	1438
TotalVisits	137
Page Views Per Visit	137
Last Activity	103
Lead Source	36
Get updates on DM Content	0
Update me on Supply Chain Content	0
X Education Forums	0

I agree to pay the amount through cheque	0
A free copy of Mastering The Interview	0
Receive More Updates About Our Courses	0
Through Recommendations	0
Digital Advertisement	0
Newspaper	0
Prospect ID	0
Newspaper Article	0
Magazine	0
Search	0
Lead Number	0
Total Time Spent on Website	0
Converted	0
Do Not Call	0
Do Not Email	0
Lead Origin	0
Last Notable Activity	0
dtype: int64	

Visualizing the features with Select values

```
def countplot(x, fig):
    plt.subplot(2,2, fig)
    sns.countplot(leads[x])
    plt.title('Count across'+ ' ' + x, size = 16)
    plt.xlabel(x,size = 14)
    plt.xticks(rotation = 90)

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

countplot('How did you hear about X Education',1)
countplot('Lead Profile',2)
countplot('Specialization',3)
```

```
plt.tight_layout()
```

```
-----
-----
ValueError                                Traceback (most recent call
last)
d:\Users\hp\Downloads\Lead Scoring Case Study SR_HN_JJ (1).ipynb Cell
26 line 1
      <a href='vscode-notebook-cell:/d%3A/Users/hp/Downloads/Lead
%20Scoring%20Case%20Study%20SR_HN_JJ%20%281%29.ipynb#X34sZmlsZQ%3D%3D?
line=5'>6</a>      plt.xticks(rotation = 90)
      <a href='vscode-notebook-cell:/d%3A/Users/hp/Downloads/Lead
%20Scoring%20Case%20Study%20SR_HN_JJ%20%281%29.ipynb#X34sZmlsZQ%3D%3D?
line=7'>8</a>  plt.figure(figsize=(15,10))
```

```

--> <a href='vscode-notebook-cell:/d%3A/Users/hp/Downloads/Lead
%20Scoring%20Case%20Study%20SR_HN_JJ%20%281%29.ipynb#X34sZmlsZQ%3D%3D?
line=9'>10</a> countplot('How did you hear about X Education',1)
    <a href='vscode-notebook-cell:/d%3A/Users/hp/Downloads/Lead
%20Scoring%20Case%20Study%20SR_HN_JJ%20%281%29.ipynb#X34sZmlsZQ%3D%3D?
line=10'>11</a> countplot('Lead Profile',2)
    <a href='vscode-notebook-cell:/d%3A/Users/hp/Downloads/Lead
%20Scoring%20Case%20Study%20SR_HN_JJ%20%281%29.ipynb#X34sZmlsZQ%3D%3D?
line=11'>12</a> countplot('Specialization',3)

```

d:\Users\hp\Downloads\Lead Scoring Case Study SR_HN_JJ (1).ipynb Cell
26 line 3

```

    <a href='vscode-notebook-cell:/d%3A/Users/hp/Downloads/Lead
%20Scoring%20Case%20Study%20SR_HN_JJ%20%281%29.ipynb#X34sZmlsZQ%3D%3D?
line=0'>1</a> def countplot(x, fig):
    <a href='vscode-notebook-cell:/d%3A/Users/hp/Downloads/Lead
%20Scoring%20Case%20Study%20SR_HN_JJ%20%281%29.ipynb#X34sZmlsZQ%3D%3D?
line=1'>2</a>     plt.subplot(2,2, fig)
----> <a href='vscode-notebook-cell:/d%3A/Users/hp/Downloads/Lead
%20Scoring%20Case%20Study%20SR_HN_JJ%20%281%29.ipynb#X34sZmlsZQ%3D%3D?
line=2'>3</a>     sns.countplot(leads[x])
    <a href='vscode-notebook-cell:/d%3A/Users/hp/Downloads/Lead
%20Scoring%20Case%20Study%20SR_HN_JJ%20%281%29.ipynb#X34sZmlsZQ%3D%3D?
line=3'>4</a>     plt.title('Count across'+ ' ' + x, size = 16)
    <a href='vscode-notebook-cell:/d%3A/Users/hp/Downloads/Lead
%20Scoring%20Case%20Study%20SR_HN_JJ%20%281%29.ipynb#X34sZmlsZQ%3D%3D?
line=4'>5</a>     plt.xlabel(x,size = 14)

```

File c:\Users\hp\anaconda3\Lib\site-packages\seaborn\categorical.py:2943, in countplot(data, x, y, hue, order, hue_order, orient, color, palette, saturation, width, dodge, ax, **kwargs)

```

    2940 elif x is not None and y is not None:
    2941     raise ValueError("Cannot pass values for both `x` and
`y`")

```

```

-> 2943 plotter = _CountPlotter(
    2944     x, y, hue, data, order, hue_order,
    2945     estimator, errorbar, n_boot, units, seed,
    2946     orient, color, palette, saturation,
    2947     width, errcolor, errwidth, capsize, dodge
    2948 )
    2950 plotter.value_label = "count"
    2952 if ax is None:

```

File c:\Users\hp\anaconda3\Lib\site-packages\seaborn\categorical.py:1530, in _BarPlotter.__init__(self, x, y, hue, data, order, hue_order, estimator, errorbar, n_boot, units, seed, orient, color, palette, saturation, width, errcolor, errwidth, capsize, dodge)

```

    1525 def __init__(self, x, y, hue, data, order, hue_order,
    1526               estimator, errorbar, n_boot, units, seed,
    1527               orient, color, palette, saturation, width,

```

```

1528         errcolor, errwidth, capsize, dodge):
1529     """Initialize the plotter."""
-> 1530     self.establish_variables(x, y, hue, data, orient,
1531                             order, hue_order, units)
1532     self.establish_colors(color, palette, saturation)
1533     self.estimate_statistic(estimator, errorbar, n_boot, seed)

```

File c:\Users\hp\anaconda3\Lib\site-packages\seaborn\categorical.py:516, in _CategoricalPlotter.establish_variables(self, x, y, hue, data, orient, order, hue_order, units)

```

513     plot_data = data
515     # Convert to a list of arrays, the common representation
-> 516 plot_data = [np.asarray(d, float) for d in plot_data]
518     # The group names will just be numeric indices
519     group_names = list(range(len(plot_data)))

```

File c:\Users\hp\anaconda3\Lib\site-packages\seaborn\categorical.py:516, in <listcomp>(.0)

```

513     plot_data = data
515     # Convert to a list of arrays, the common representation
-> 516 plot_data = [np.asarray(d, float) for d in plot_data]
518     # The group names will just be numeric indices
519     group_names = list(range(len(plot_data)))

```

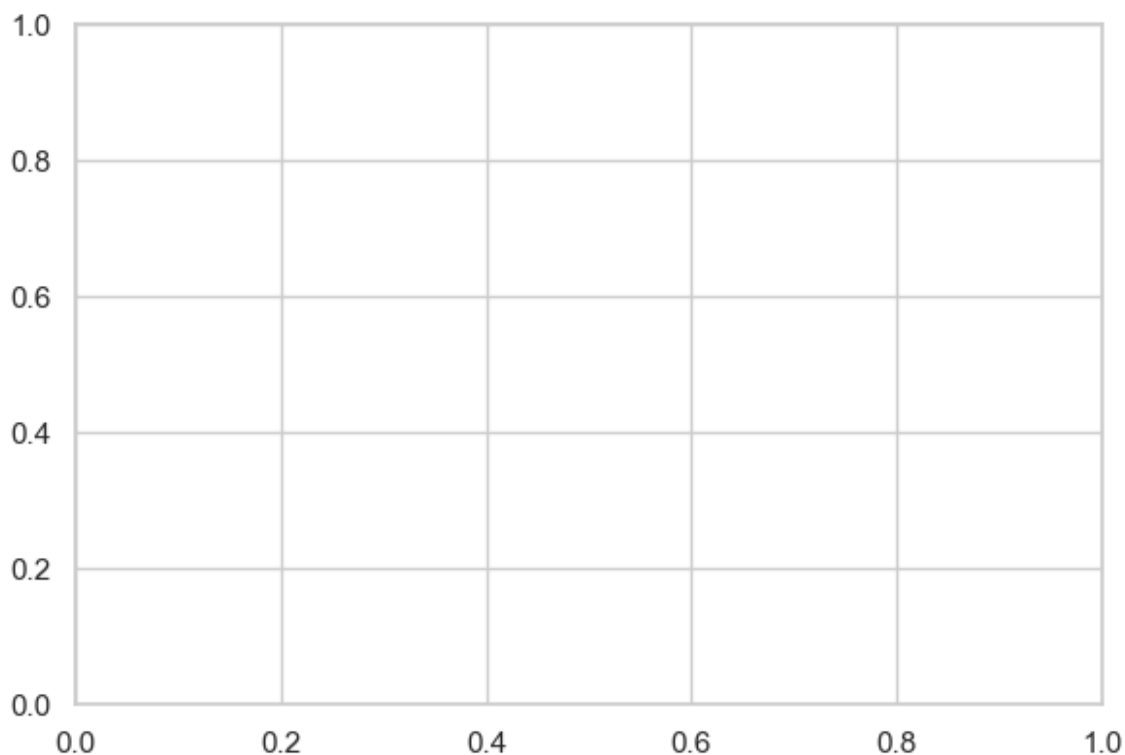
File c:\Users\hp\anaconda3\Lib\site-packages\pandas\core\series.py:893, in Series.__array__(self, dtype)

```

846 def __array__(self, dtype: npt.DTypeLike | None = None) ->
np.ndarray:
847     """
848     Return the values as a NumPy array.
849
850     (...)
891     dtype='datetime64[ns]')
892     """
-> 893     return np.asarray(self._values, dtype)

```

ValueError: could not convert string to float: 'Select'



there are a few columns in which there is a level called 'Select' which basically means that the student had not selected the option for that particular column which is why it shows 'Select'. These values are as good as missing values and hence we need to identify the value counts of the level 'Select' in all the columns that it is present.

```
# checking the value counts of all the columns
```

```
for c in leads:
    print(leads[c].astype('category').value_counts())
    print('_____')
```

```
000104b9-23e4-4ddc-8caa-8629fe8ad7f4    1
a7a319ea-b6ae-4c6b-afc5-183b933d10b5    1
aa27a0af-eeab-4007-a770-fa8a93fa53c8    1
aa30ebb2-8476-41ce-9258-37cc025110d3    1
aa405742-17ac-4c65-b19e-ab91c241cc53    1
..
539eb309-df36-4a89-ac58-6d3651393910    1
539ffa32-1be7-4fe1-b04c-faf1bab763cf    1
53aabd84-5dcc-4299-bbe3-62f3764b07b1    1
53ac14bd-2bb2-4315-a21c-94562d1b6b2d    1
ffffb0e5e-9f92-4017-9f42-781a69da4154    1
Name: Prospect ID, Length: 9240, dtype: int64
```

```
579533    1
629593    1
```

630390 1
630403 1
630405 1

..
602534 1
602540 1
602557 1
602561 1
660737 1

Name: Lead Number, Length: 9240, dtype: int64

Landing Page Submission	4886
API	3580
Lead Add Form	718
Lead Import	55
Quick Add Form	1

Name: Lead Origin, dtype: int64

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
WeLearn	1
Pay per Click Ads	1
NC_EDM	1
blog	1
testone	1
welearnblog_Home	1
youtubechannel	1

Name: Lead Source, dtype: int64

No	8506
Yes	734

Name: Do Not Email, dtype: int64

No	9238
Yes	2

Name: Do Not Call, dtype: int64

```
0    5679
1    3561
Name: Converted, dtype: int64
```

```
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
23.0      6
21.0      6
24.0      5
25.0      5
27.0      5
22.0      3
26.0      2
28.0      2
29.0      2
54.0      1
141.0     1
115.0     1
74.0      1
55.0      1
30.0      1
43.0      1
42.0      1
41.0      1
32.0      1
251.0     1
```

```
Name: TotalVisits, dtype: int64
```

```
0    2193
60    19
```

75	18
74	18
127	18

...

1091	1
1088	1
1085	1
1084	1
2272	1

Name: Total Time Spent on Website, Length: 1731, dtype: int64

0.0	2189
2.0	1795
3.0	1196
4.0	896
1.0	651

...

3.57	1
3.8	1
3.82	1
3.83	1
55.0	1

Name: Page Views Per Visit, Length: 114, dtype: int64

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

Name: Last Activity, dtype: int64

Select	1942
Finance Management	976
Human Resource Management	848
Marketing Management	838
Operations Management	503
Business Administration	403

IT Projects Management	366
Supply Chain Management	349
Banking, Investment And Insurance	338
Media and Advertising	203
Travel and Tourism	203
International Business	178
Healthcare Management	159
Hospitality Management	114
E-COMMERCE	112
Retail Management	100
Rural and Agribusiness	73
E-Business	57
Services Excellence	40

Name: Specialization, dtype: int64

Select	5043
Online Search	808
Word Of Mouth	348
Student of SomeSchool	310
Other	186
Multiple Sources	152
Advertisements	70
Social Media	67
Email	26
SMS	23

Name: How did you hear about X Education, dtype: int64

Unemployed	5600
Working Professional	706
Student	210
Other	16
Housewife	10
Businessman	8

Name: What is your current occupation, dtype: int64

Better Career Prospects	6528
Flexibility & Convenience	2
Other	1

Name: What matters most to you in choosing a course, dtype: int64

No	9226
Yes	14

Name: Search, dtype: int64

No	9240
----	------

Name: Magazine, dtype: int64

No	9238
Yes	2

Name: Newspaper Article, dtype: int64

No 9239

Yes 1

Name: X Education Forums, dtype: int64

No 9239

Yes 1

Name: Newspaper, dtype: int64

No 9236

Yes 4

Name: Digital Advertisement, dtype: int64

No 9233

Yes 7

Name: Through Recommendations, dtype: int64

No 9240

Name: Receive More Updates About Our Courses, dtype: int64

No 9240

Name: Update me on Supply Chain Content, dtype: int64

No 9240

Name: Get updates on DM Content, dtype: int64

Select 4146

Potential Lead 1613

Other Leads 487

Student of SomeSchool 241

Lateral Student 24

Dual Specialization Student 20

Name: Lead Profile, dtype: int64

No 9240

Name: I agree to pay the amount through cheque, dtype: int64

No 6352

Yes 2888

Name: A free copy of Mastering The Interview, dtype: int64

Modified 3407

Email Opened 2827

SMS Sent 2172

Page Visited on Website 318

Olark Chat Conversation 183

Email Link Clicked 173

Email Bounced 60

Unsubscribed	47
Unreachable	32
Had a Phone Conversation	14
Email Marked Spam	2
Approached upfront	1
Email Received	1
Form Submitted on Website	1
Resubscribed to emails	1
View in browser link Clicked	1

Name: Last Notable Activity, dtype: int64

The following three columns now have the level 'Select'. Let's check them once again.

```
leads['Lead Profile'].astype('category').value_counts()
```

Select	4146
Potential Lead	1613
Other Leads	487
Student of SomeSchool	241
Lateral Student	24
Dual Specialization Student	20

Name: Lead Profile, dtype: int64

```
leads['How did you hear about X Education'].value_counts()
```

Select	5043
Online Search	808
Word Of Mouth	348
Student of SomeSchool	310
Other	186
Multiple Sources	152
Advertisements	70
Social Media	67
Email	26
SMS	23

Name: How did you hear about X Education, dtype: int64

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

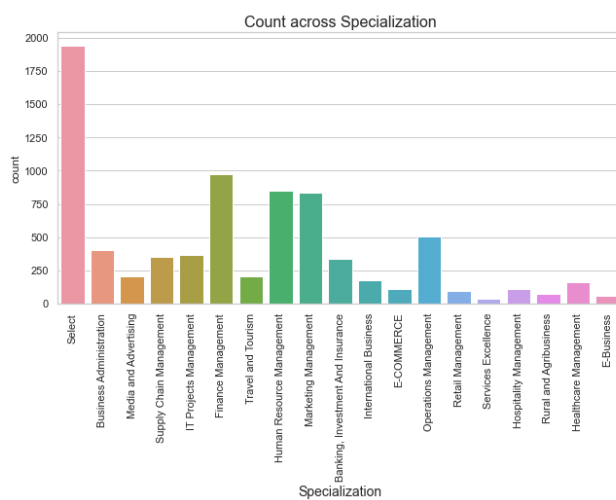
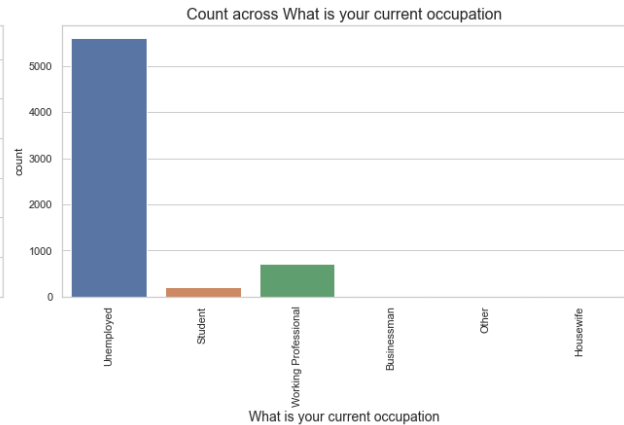
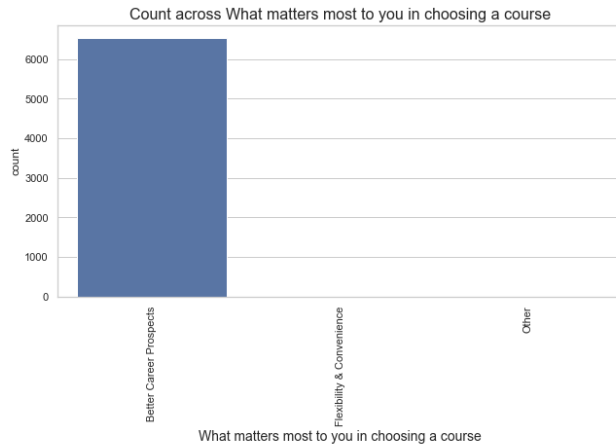
Select	1942
Finance Management	976
Human Resource Management	848
Marketing Management	838
Operations Management	503
Business Administration	403
IT Projects Management	366
Supply Chain Management	349
Banking, Investment And Insurance	338
Travel and Tourism	203

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

Visualizing the features

```
def countplot(x, fig):  
    plt.subplot(4,2, fig)  
    sns.countplot(leads[x])  
    plt.title('Count across'+ ' '+ x, size = 16)  
    plt.xlabel(x,size = 14)  
    plt.xticks(rotation = 90)  
  
plt.figure(figsize=(18,25))  
  
countplot('What matters most to you in choosing a course',1)  
countplot('What is your current occupation',2)  
countplot('Specialization',3)  
  
plt.tight_layout()
```



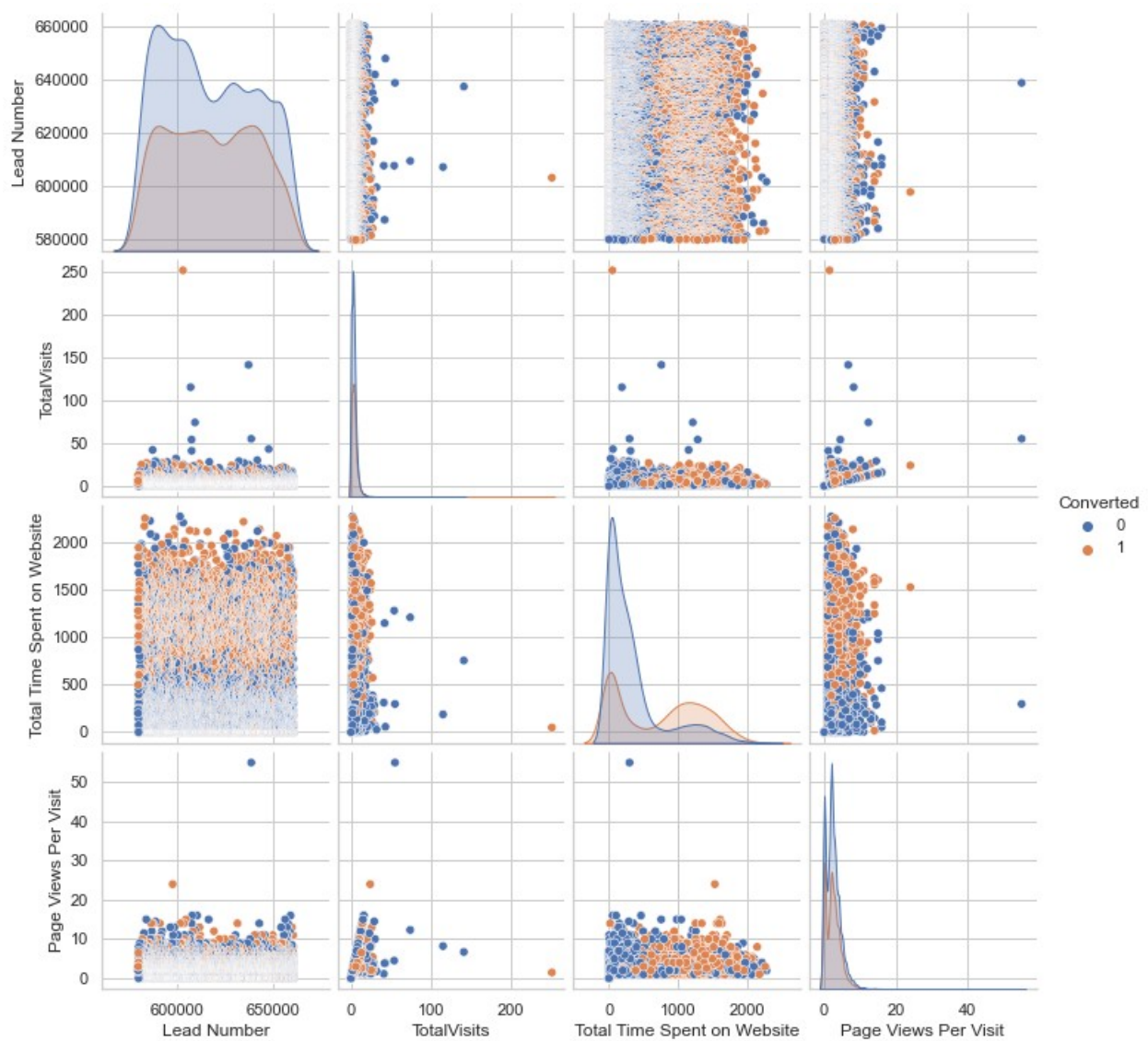
As it can be seen that the levels of "Lead Profile" and "How did you hear about X Education" have a lot of rows which have the value Select which is of no use to the analysis
So it's best that we drop them.

```
# dropping Lead Profile and How did you hear about X Education cols
leads.drop(['Lead Profile', 'How did you hear about X Education'],
axis = 1, inplace = True)
```

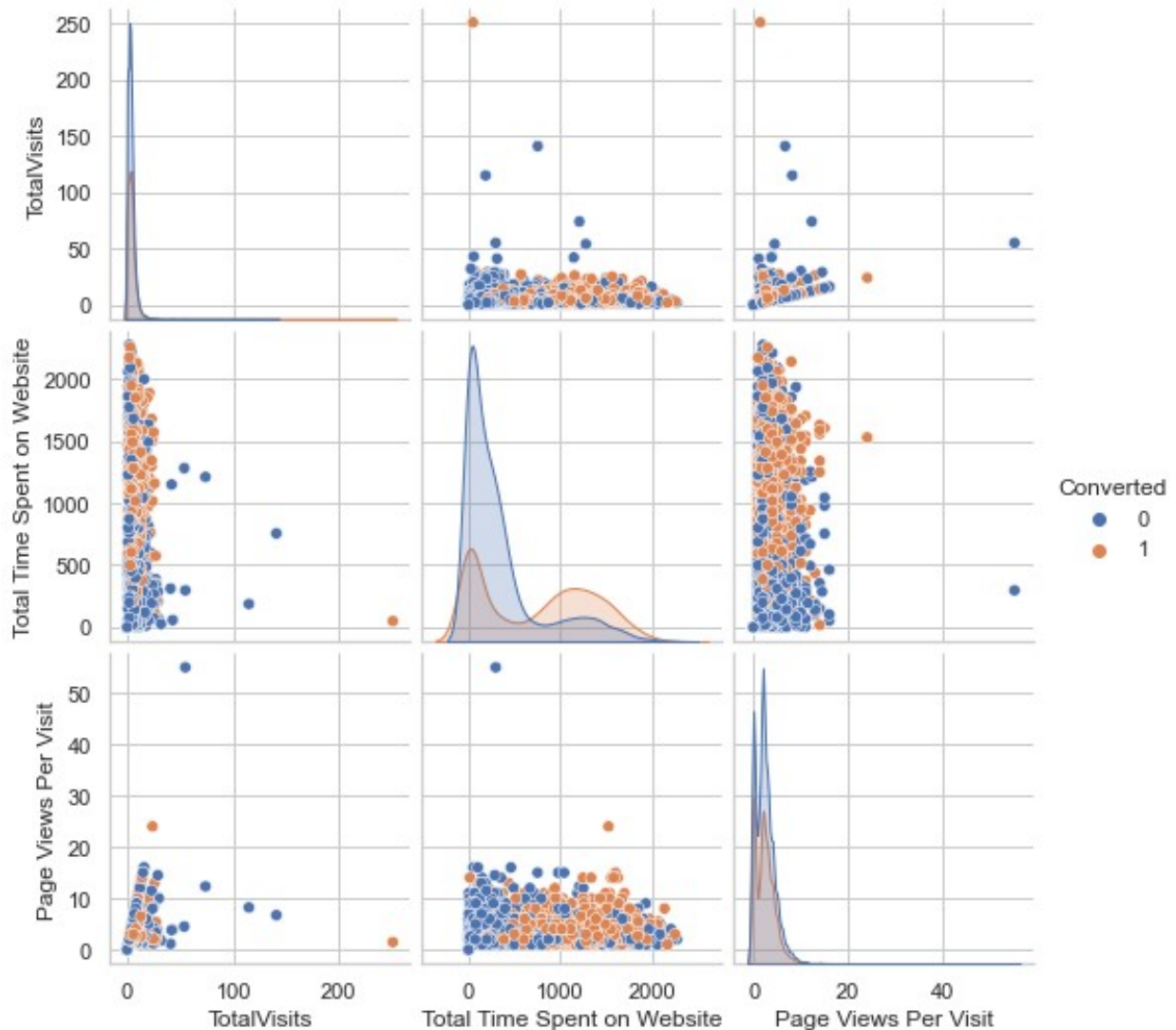
Also we notice that, when we got the value counts of all the columns, there were a few columns in which only one value was majorly present for all the data points. These include Do Not Call, Search, Magazine, Newspaper Article, X Education Forums, Newspaper, Digital Advertisement, Through Recommendations, Receive More Updates About Our Courses, Update me on Supply Chain Content, Get updates on DM Content, I agree to pay the amount through cheque. Since practically all of the values for these variables are No, it's best that we drop these columns as they won't help with our analysis.

```
from matplotlib import pyplot as plt
import seaborn as sns
```

```
sns.pairplot(leads,diag_kind='kde',hue='Converted')
plt.show()
```



```
x_edu = leads[['TotalVisits','Total Time Spent on Website','Page Views  
Per Visit','Converted']]
sns.pairplot(x_edu,diag_kind='kde',hue='Converted')
plt.show()
```

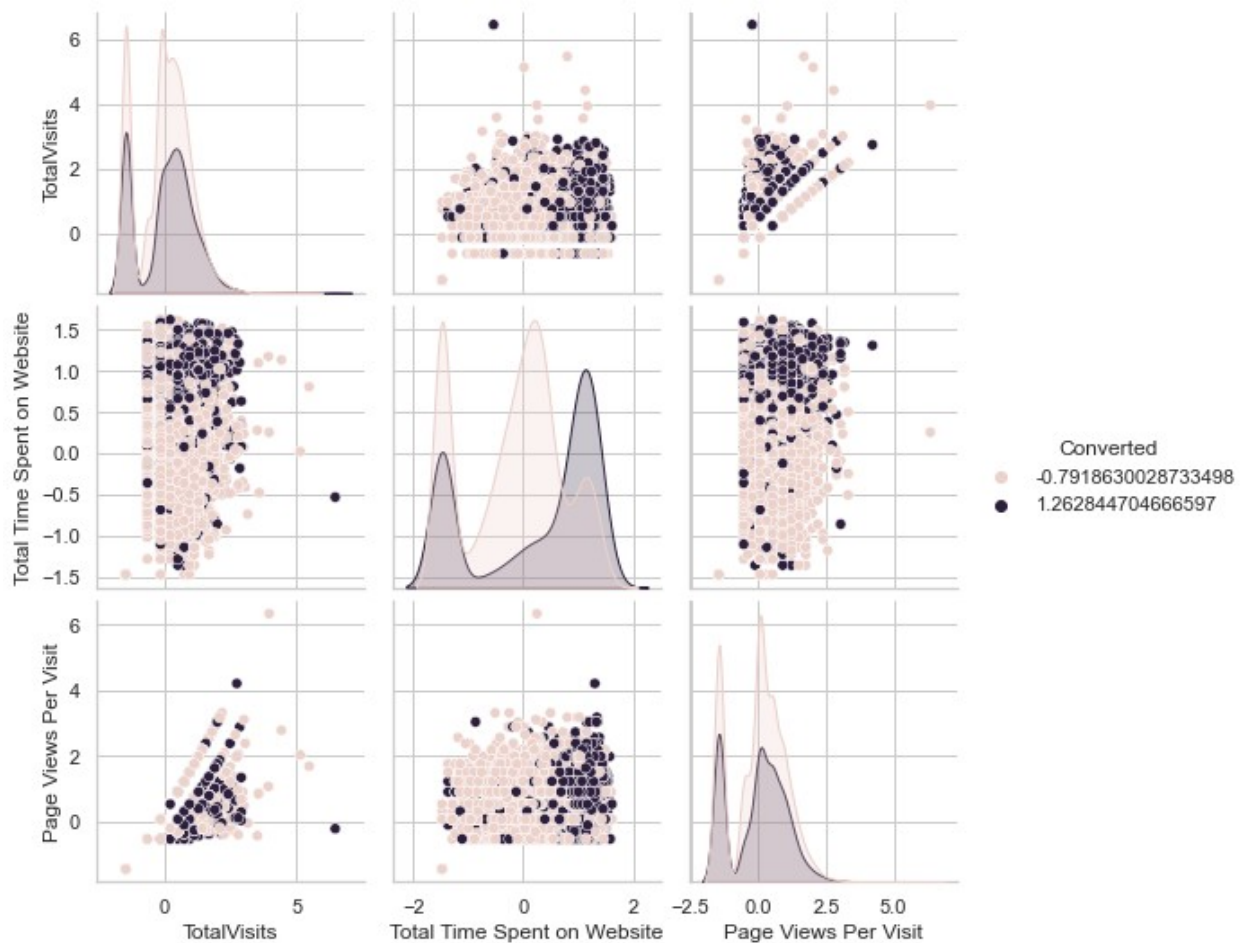



```
from sklearn.preprocessing import PowerTransformer
pt = PowerTransformer()
transformedx_edu = pd.DataFrame(pt.fit_transform(x_edu))
transformedx_edu.columns = x_edu.columns
transformedx_edu.head()
```

	TotalVisits	Total Time Spent on Website	Page Views Per Visit	
Converted				
0	-1.457907	-1.473767	-1.454706	-
0.791863				
1	0.747918	0.729628	0.308534	-
0.791863				
2	-0.141636	1.306093	0.065574	
1.262845				
3	-0.640428	0.264936	-0.536967	-
0.791863				

```
4      -0.141636      1.252499      -0.536967
1.262845
```

```
sns.pairplot(transformedx_edu,diag_kind='kde',hue='Converted')
plt.show()
```



```
# Dropping the above columns
```

```
leads.drop(['Do Not Call', 'Search', 'Magazine', 'Newspaper Article',
            'X Education Forums', 'Newspaper',
            'Digital Advertisement', 'Through Recommendations',
            'Receive More Updates About Our Courses',
            'Update me on Supply Chain Content', 'Get updates on DM
            Content',
            'I agree to pay the amount through cheque'], axis = 1,
inplace = True)
```

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

```
Better Career Prospects      6528
Flexibility & Convenience      2
```

```
Other          1
Name: What matters most to you in choosing a course, dtype: int64
```

The variable `What matters most to you in choosing a course` has the level `Better Career Prospects` 6528 times while the other two levels appear once twice and once respectively.

So we should dropping this column as well.

```
leads.drop(['What matters most to you in choosing a course'], axis =
1, inplace=True)
```

```
# Checking the number of null values again
```

```
leads.isnull().sum().sort_values(ascending=False)
```

```
What is your current occupation    2690
Specialization                    1438
TotalVisits                       137
Page Views Per Visit              137
Last Activity                     103
Lead Source                       36
Prospect ID                       0
Lead Number                       0
Lead Origin                       0
Do Not Email                      0
Converted                        0
Total Time Spent on Website       0
A free copy of Mastering The Interview 0
Last Notable Activity             0
dtype: int64
```

Now, there's the column `What is your current occupation` which has a lot of null values. Now you can drop the entire row but since we have already lost so many feature variables, we choose not to drop it as it might turn out to be significant in the analysis. So let's just drop the null rows for the column `What is your current occupation`.

```
# Dropping the null values rows in the column 'What is your current
occupation'
```

```
leads = leads[~pd.isnull(leads['What is your current occupation'])]
```

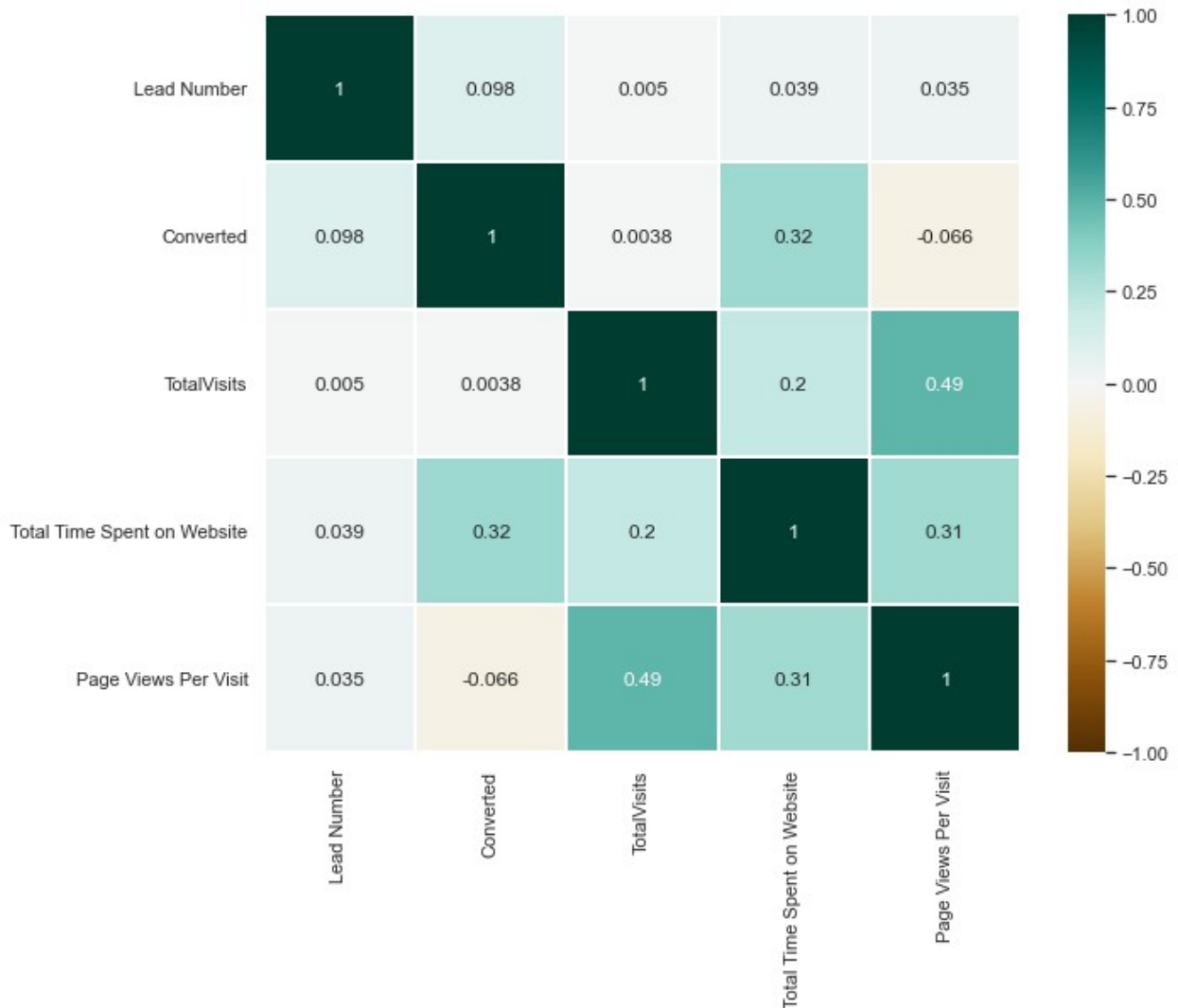
```
# Observing Correlation
```

```
# figure size
```

```
plt.figure(figsize=(10,8))
```

```
# heatmap
```

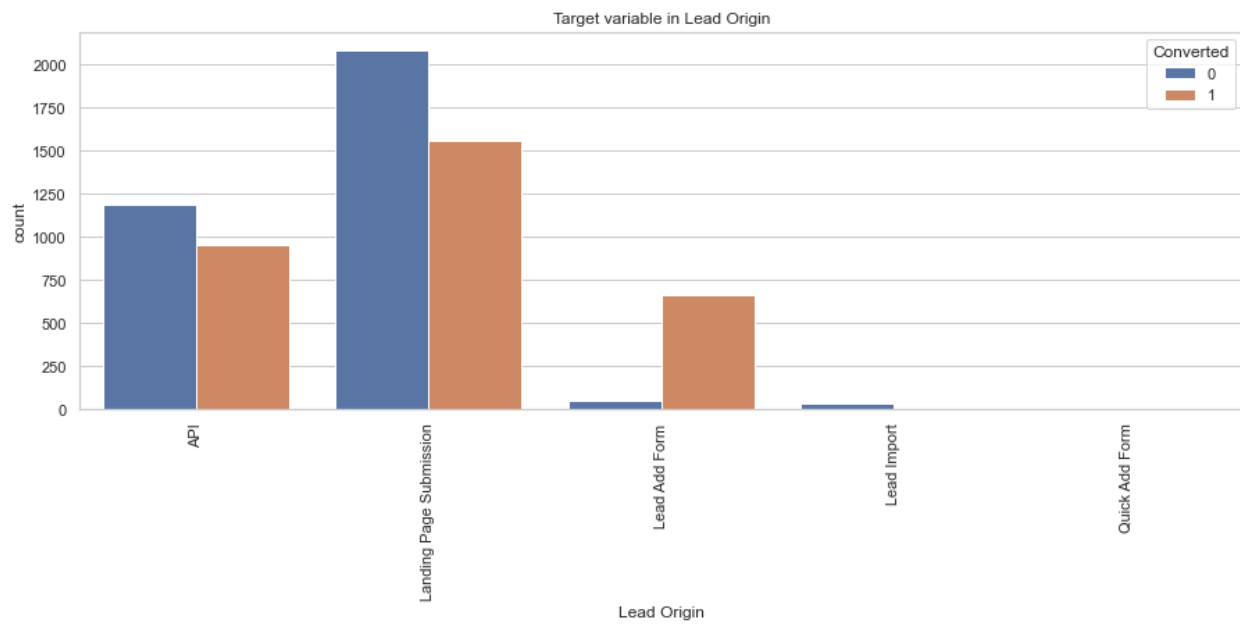
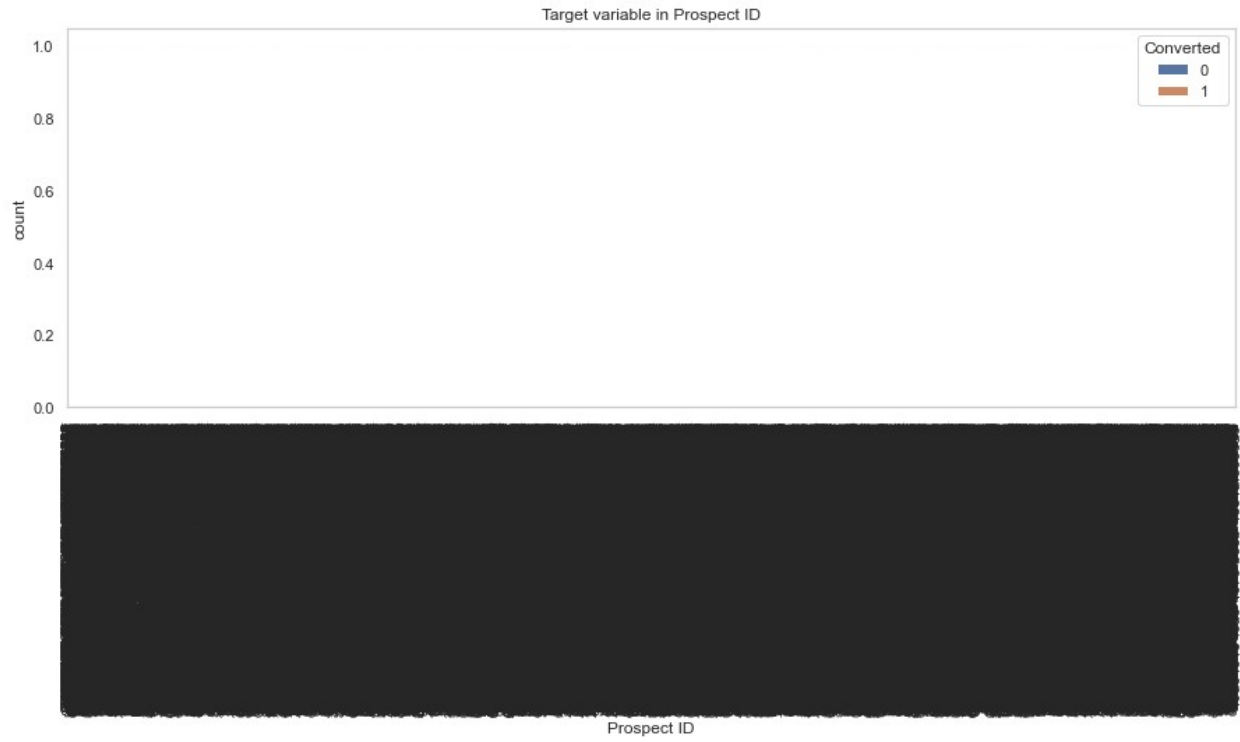
```
sns.heatmap(leads.corr(), annot=True, cmap="BrBG",
robust=True, linewidth=0.1, vmin=-1 )
plt.show()
```

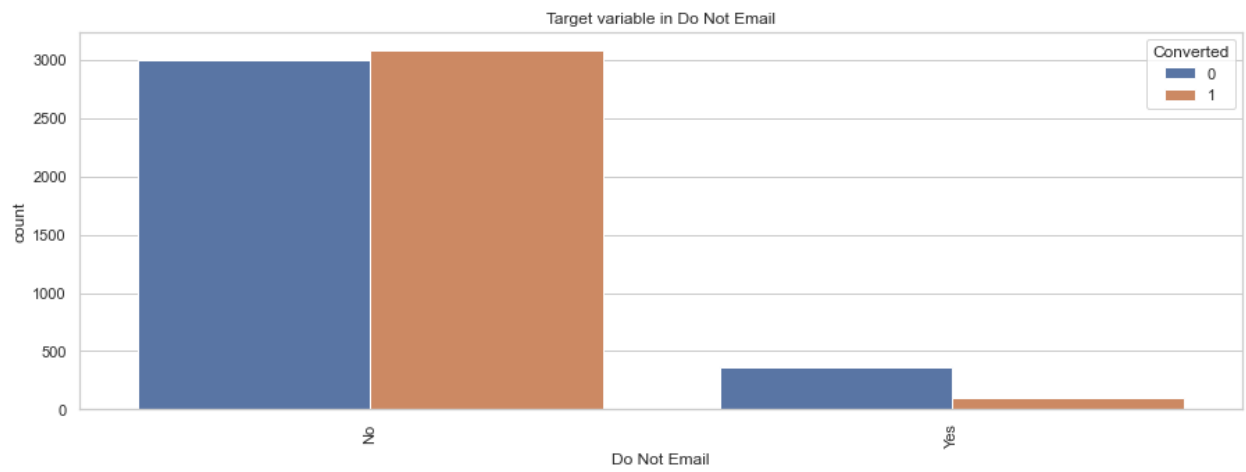
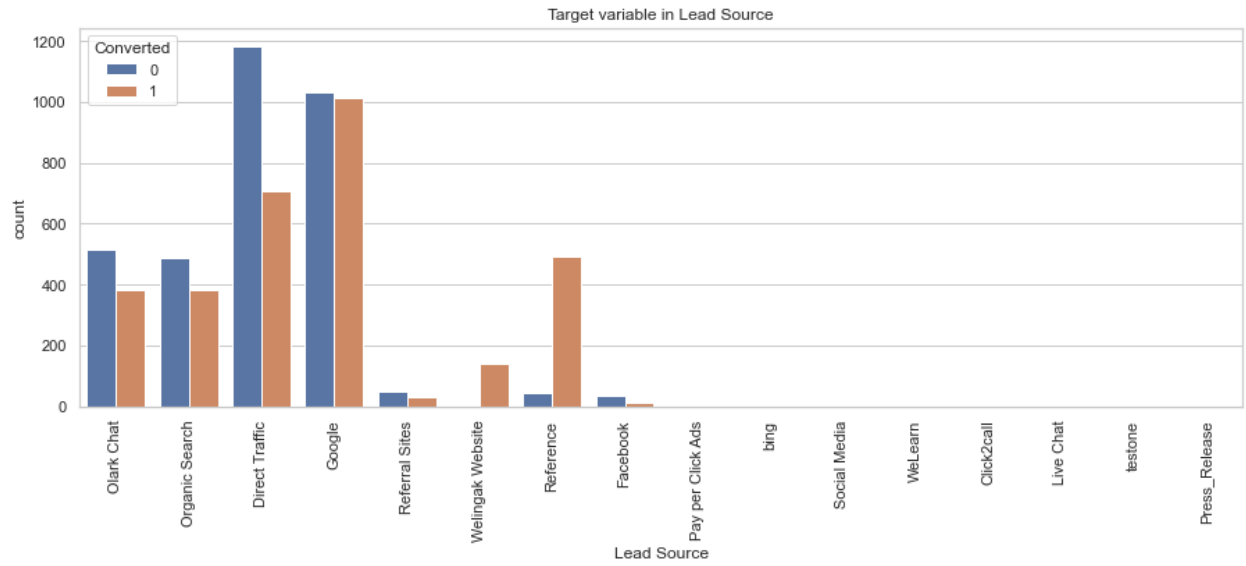


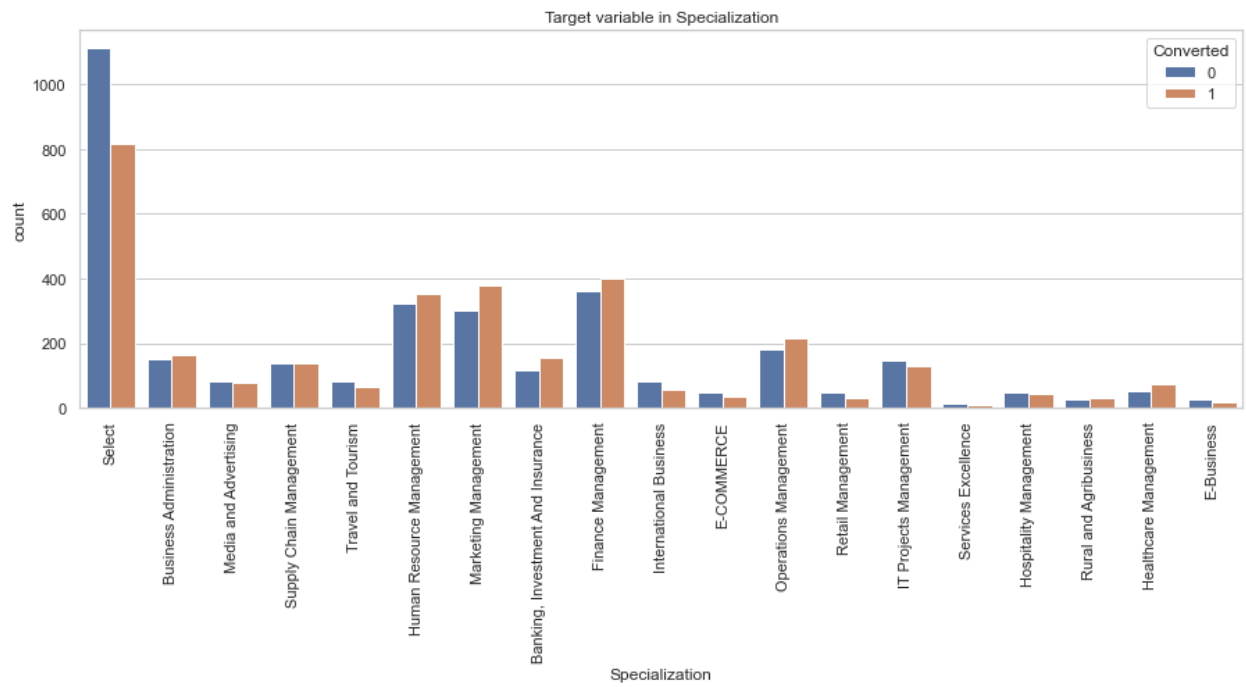
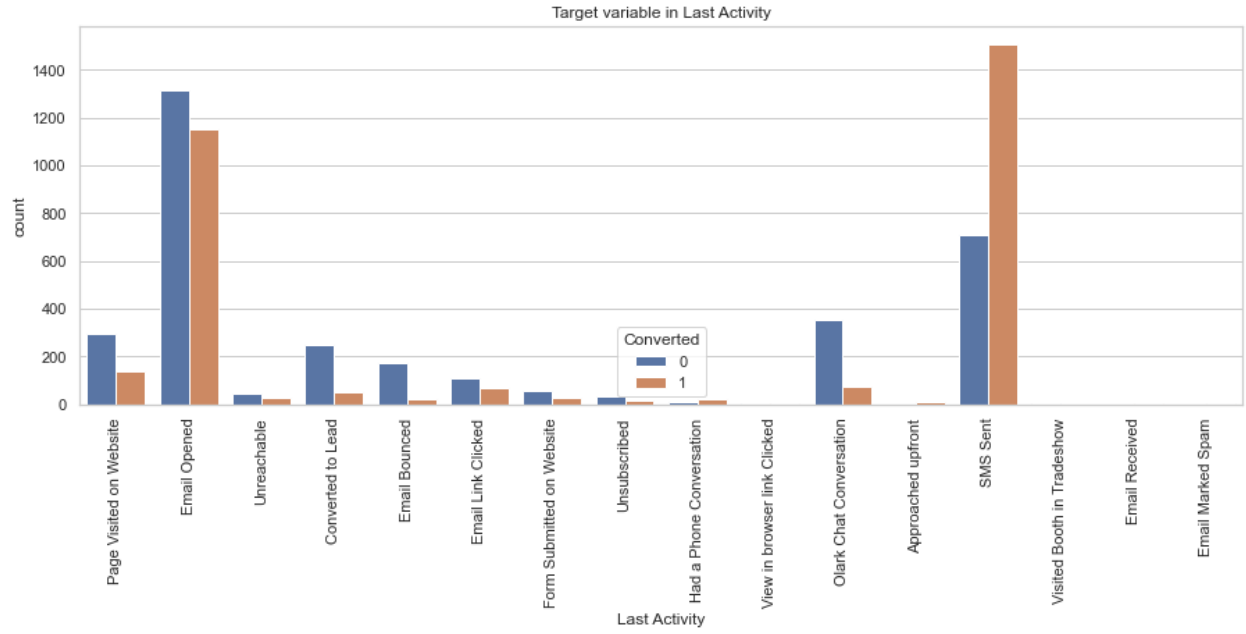
Analysing Categorical features

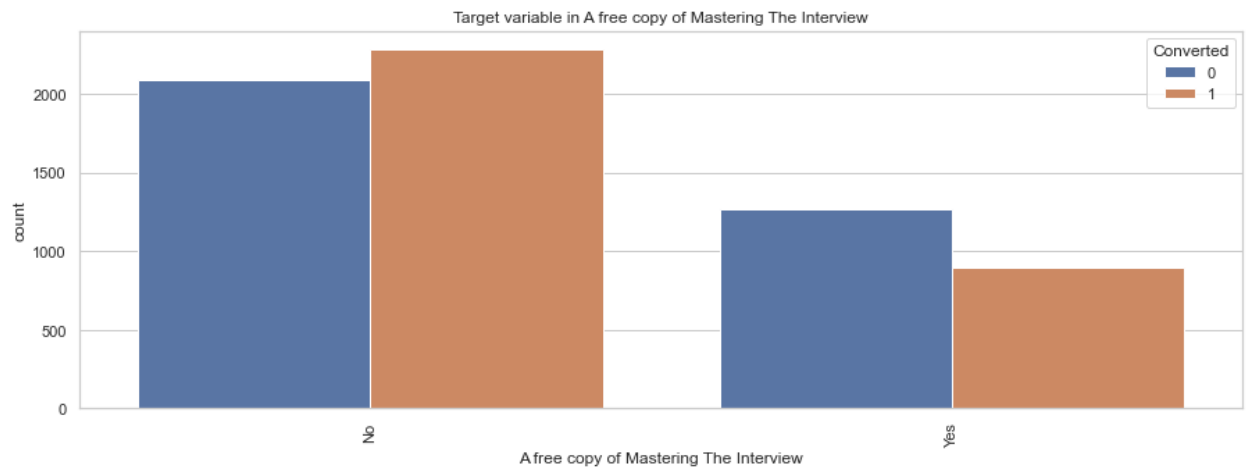
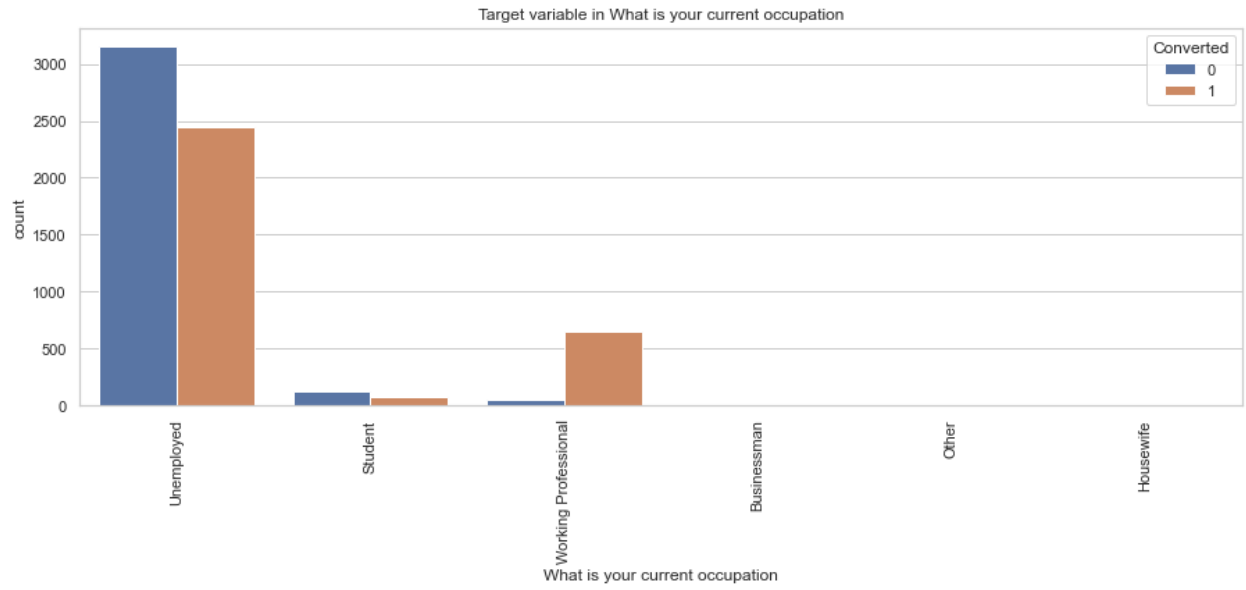
```
conv = leads.select_dtypes(include = "object").columns
for i in conv:

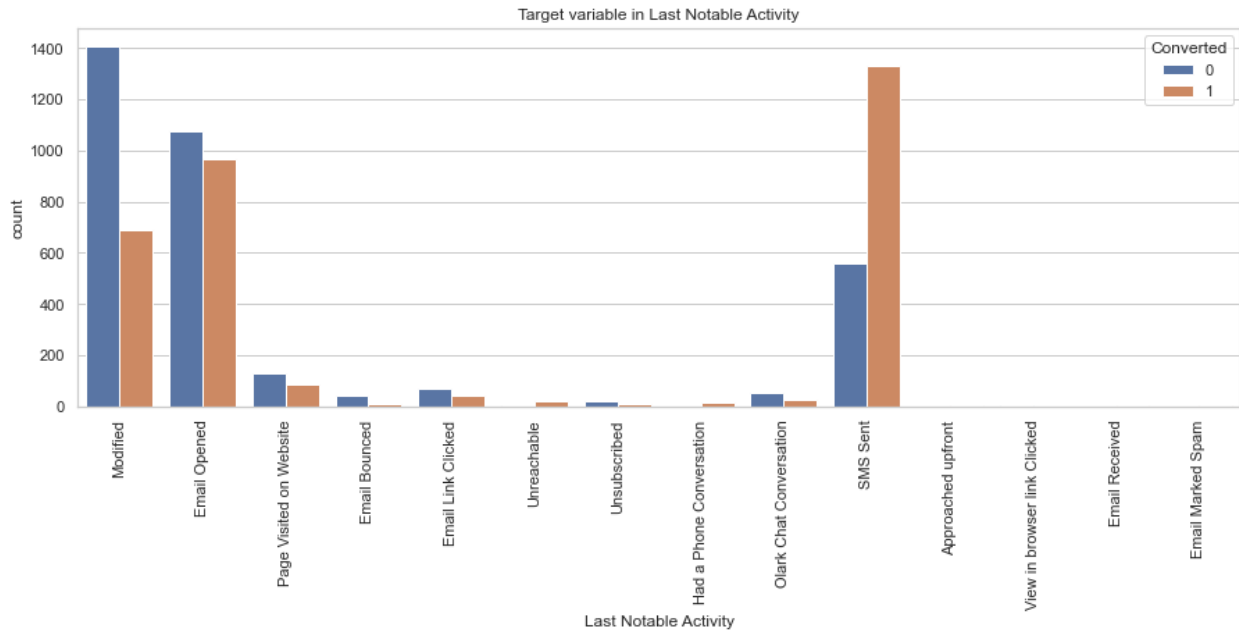
    plt.figure(figsize = (15,5))
    sns.countplot(leads[i], hue=leads.Converted)
    plt.xticks(rotation = 90)
    plt.title('Target variable in'+' '+ i)
    plt.xlabel(i)
    plt.show()
```











```
# Checking the number of null values again
leads.isnull().sum().sort_values(ascending=False)

TotalVisits                130
Page Views Per Visit       130
Last Activity              103
Lead Source                 36
Specialization             18
Prospect ID                 0
Lead Number                 0
Lead Origin                 0
Do Not Email                0
Converted                   0
Total Time Spent on Website 0
What is your current occupation 0
A free copy of Mastering The Interview 0
Last Notable Activity       0
dtype: int64
```

Since now the number of null values present in the columns are quite small we can simply drop the rows in which these null values are present.

```
# Dropping the null values rows in the column 'TotalVisits'

leads = leads[~pd.isnull(leads['TotalVisits'])]

# Checking the number of null values again
leads.isnull().sum().sort_values(ascending=False)
```

Lead Source	29
Specialization	18
Prospect ID	0
Lead Number	0
Lead Origin	0
Do Not Email	0
Converted	0
TotalVisits	0
Total Time Spent on Website	0
Page Views Per Visit	0
Last Activity	0
What is your current occupation	0
A free copy of Mastering The Interview	0
Last Notable Activity	0

dtype: int64

Dropping the null values rows in the column 'Lead Source'

```
leads = leads[~pd.isnull(leads['Lead Source'])]
```

Checking the number of null values again

```
leads.isnull().sum().sort_values(ascending=False)
```

Specialization	18
Prospect ID	0
Lead Number	0
Lead Origin	0
Lead Source	0
Do Not Email	0
Converted	0
TotalVisits	0
Total Time Spent on Website	0
Page Views Per Visit	0
Last Activity	0
What is your current occupation	0
A free copy of Mastering The Interview	0
Last Notable Activity	0

dtype: int64

Drop the null values rows in the column 'Specialization'

```
leads = leads[~pd.isnull(leads['Specialization'])]
```

Checking the number of null values again

```
leads.isnull().sum().sort_values(ascending=False)
```

Prospect ID	0
Lead Number	0
Lead Origin	0
Lead Source	0
Do Not Email	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
A free copy of Mastering The Interview   0
Last Notable Activity                    0
dtype: int64

```

Now your data doesn't have any null values. Let's now check the percentage of rows that we have retained.

```

print(len(leads.index))
print(len(leads.index)/9240)

6373
0.6897186147186147

```

We still have around 69% of the rows which seems good enough.

Let's look at the dataset again

```
leads.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	Converted	TotalVisits	\
0	Olark Chat	No	0	0.0	
1	Organic Search	No	0	5.0	
2	Direct Traffic	No	1	2.0	
3	Direct Traffic	No	0	1.0	
4	Google	No	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				
	Specialization	What is your current occupation	\	
0	Select	Unemployed		
1	Select	Unemployed		
2	Business Administration	Student		
3	Media and Advertising	Unemployed		
4	Select	Unemployed		
	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		

Now, clearly the variables `Prospect ID` and `Lead Number` won't be of any use in the analysis, so it's best that we drop these two variables.

```
# Dropping the "Prospect ID" and "Lead Number"
leads.drop(['Prospect ID', 'Lead Number'], 1, inplace = True)

leads.head()
```

	Lead Origin	Lead Source	Do Not Email	Converted	\
0	API	Olark Chat	No	0	
1	API	Organic Search	No	0	
2	Landing Page Submission	Direct Traffic	No	1	
3	Landing Page Submission	Direct Traffic	No	0	
4	Landing Page Submission	Google	No	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	

	Last Activity	Specialization	\
0	Page Visited on Website	Select	
1	Email Opened	Select	
2	Email Opened	Business Administration	

3	Unreachable	Media and Advertising
4	Converted to Lead	Select

	What is your current occupation	A free copy of Mastering The Interview \
0	Unemployed	No
1	Unemployed	No
2	Student	Yes
3	Unemployed	No
4	Unemployed	No

	Last Notable Activity
0	Modified
1	Email Opened
2	Email Opened
3	Modified
4	Modified

Dummy variable creation

The next step is to dealing with the categorical variables present in the dataset. So first take a look at which variables are actually categorical variables.

```
# Checking the columns which are of type 'object'

temp = leads.loc[:, leads.dtypes == 'object']
temp.columns

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

# Demo Cell
df = pd.DataFrame({'P': ['p', 'q', 'p']})
df

   P
0  p
1  q
2  p

pd.get_dummies(df)
```

	P_p	P_q
0	1	0
1	0	1
2	1	0

```
pd.get_dummies(df, prefix=['coll'])
```

	coll_p	coll_q
0	1	0
1	0	1
2	1	0

```
# Creating dummy variables using the 'get_dummies' command
dummy = pd.get_dummies(leads[['Lead Origin', 'Lead Source', 'Do Not
Email', 'Last Activity',
                                'What is your current occupation','A
free copy of Mastering The Interview',
                                'Last Notable Activity']],
drop_first=True)

# Add the results to the master dataframe
leads = pd.concat([leads, dummy], axis=1)

# Creating dummy variable separately for the variable 'Specialization'
since it has the level 'Select'
# which is useless so we
# drop that level by specifying it explicitly

dummy_spl = pd.get_dummies(leads['Specialization'], prefix =
'Specialization')
dummy_spl = dummy_spl.drop(['Specialization_Select'], 1)
leads = pd.concat([leads, dummy_spl], axis = 1)

# Dropping the variables for which the dummy variables have been
created

leads = leads.drop(['Lead Origin', 'Lead Source', 'Do Not Email',
'Last Activity',
                    'Specialization', 'What is your current
occupation',
                    'A free copy of Mastering The Interview', 'Last
Notable Activity'], 1)

# Let's take a look at the dataset again

leads.head()
```

Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit
0	0	0.0	0
0.0			

1	0	5.0	674
2.5			
2	1	2.0	1532
2.0			
3	0	1.0	305
1.0			
4	1	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	Lead Source_Direct Traffic	Lead Source_Facebook	\
0	0	0		
0				
1	0	0		
0				
2	0	1		
0				
3	0	1		
0				
4	0	0		
0				

	Lead Source_Google Chat	Lead Source_Live Chat	Lead Source_0lark	\
0	0	0	1	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	1	0	0	

	Lead Source_Organic Search	Lead Source_Pay per Click Ads	\
0	0	0	
1	1	0	
2	0	0	
3	0	0	
4	0	0	

Lead Source_Press_Release	Lead Source_Reference	\
---------------------------	-----------------------	---

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

Lead Source_Referral Sites	Lead Source_Social Media	Lead Source_WeLearn \
----------------------------	--------------------------	-----------------------

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

Lead Source_Welingak Website	Lead Source_bing	Lead Source_testone
------------------------------	------------------	---------------------

\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

Do Not Email_Yes	Last Activity_Converted to Lead	\
------------------	---------------------------------	---

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

Last Activity_Email Bounced	Last Activity_Email Link Clicked	\
-----------------------------	----------------------------------	---

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

Last Activity_Email Marked Spam	Last Activity_Email Opened	\
---------------------------------	----------------------------	---

0	0	0
1	0	1
2	0	1

3	0	0
4	0	0

Last Activity_Email Received Last Activity_Form Submitted on Website \

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

Last Activity_Had a Phone Conversation \

0	0
1	0
2	0
3	0
4	0

Last Activity_Olark Chat Conversation \

0	0
1	0
2	0
3	0
4	0

Last Activity_Page Visited on Website Last Activity_SMS Sent \

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

Last Activity_Unreachable Last Activity_Unsubscribed \

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

Last Activity_View in browser link Clicked \

0	0
1	0
2	0
3	0
4	0

	Last Activity_Visited Booth in Tradeshow \
0	0
1	0
2	0
3	0
4	0

	What is your current occupation_Housewife \
0	0
1	0
2	0
3	0
4	0

	What is your current occupation_Other \
0	0
1	0
2	0
3	0
4	0

	What is your current occupation_Student \
0	0
1	0
2	1
3	0
4	0

	What is your current occupation_Unemployed \
0	1
1	1
2	0
3	1
4	1

	What is your current occupation_Working Professional \
0	0
1	0
2	0
3	0
4	0

	A free copy of Mastering The Interview_Yes \
0	0
1	0
2	1
3	0
4	0

	Last Notable Activity_Email Bounced \
0	0
1	0
2	0
3	0
4	0

	Last Notable Activity_Email Link Clicked \
0	0
1	0
2	0
3	0
4	0

	Last Notable Activity_Email Marked Spam \
0	0
1	0
2	0
3	0
4	0

	Last Notable Activity_Email Opened	Last Notable Activity_Email Received \
0	0	
0		
1	1	
0		
2	1	
0		
3	0	
0		
4	0	
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_0lark 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_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

Specialization_Banking, Investment And Insurance \	
0	0
1	0
2	0
3	0
4	0

Specialization_Business Administration Specialization_E-Business \		
0	0	0

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

	Specialization_E-COMMERCE	Specialization_Finance Management	\
0	0	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	

	Specialization_Healthcare Management	\
0	0	
1	0	
2	0	
3	0	
4	0	

	Specialization_Hospitality Management	\
0	0	
1	0	
2	0	
3	0	
4	0	

	Specialization_Human Resource Management	\
0	0	
1	0	
2	0	
3	0	
4	0	

	Specialization_IT Projects Management	\
0	0	
1	0	
2	0	
3	0	
4	0	

	Specialization_International Business Management	Specialization_Marketing	\
0	0		
0			
1	0		
0			

2	0
0	
3	0
0	
4	0
0	

Specialization_Media and Advertising Management \	Specialization_Operations
---------------------------------------------------	---------------------------

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

Specialization_Retail Management Agribusiness \	Specialization_Rural and
-------------------------------------------------	--------------------------

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

Specialization_Services Excellence Management \	Specialization_Supply Chain
-------------------------------------------------	-----------------------------

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

Specialization_Travel and Tourism

0	0
1	0
2	0

3	0
4	0

Test-Train Split

The next step is to splitting the dataset into training an testing sets.

```
# Importing the `train_test_split` library
```

```
# Put all the feature variables in X
```

```
X = leads.drop(['Converted'], 1)
```

```
X.head()
```

	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	Lead Source_Direct Traffic	Lead Source_Facebook	\
0	0	0		
0				
1	0	0		
0				
2	0	1		
0				
3	0	1		
0				
4	0	0		
0				

	Lead Source_Google Chat	Lead Source_Live Chat	Lead Source_Olark	\
0	0	0		1
1	0	0		0
2	0	0		0
3	0	0		0

4	1	0	0
---	---	---	---

	Lead Source_Organic Search	Lead Source_Pay per Click Ads \
0	0	0
1	1	0
2	0	0
3	0	0
4	0	0

	Lead Source_Press_Release	Lead Source_Reference \
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0

	Lead Source_Referral Sites	Lead Source_Social Media	Lead Source_WeLearn \
0	0	0	
0			
1	0	0	
0			
2	0	0	
0			
3	0	0	
0			
4	0	0	
0			

	Lead Source_Welingak Website	Lead Source_bing	Lead Source_testone
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	Do Not Email_Yes	Last Activity_Converted to Lead \
0	0	0
1	0	0
2	0	0
3	0	0
4	0	1

	Last Activity_Email Bounced	Last Activity_Email Link Clicked \
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0

	Last Activity_Email Marked Spam	Last Activity_Email Opened \
0	0	0
1	0	1
2	0	1
3	0	0
4	0	0

	Last Activity_Email Received Website \	Last Activity_Form Submitted on
0	0	
0		
1	0	
0		
2	0	
0		
3	0	
0		
4	0	
0		

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

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

	Last Activity_Page Visited on Website	Last Activity_SMS Sent \
0	1	0
1	0	0
2	0	0
3	0	0
4	0	0

Last Activity_Unreachable Last Activity_Unsubscribed \

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

Last Activity_View in browser link Clicked \

0	0
1	0
2	0
3	0
4	0

Last Activity_Visited Booth in Tradeshow \

0	0
1	0
2	0
3	0
4	0

What is your current occupation_Housewife \

0	0
1	0
2	0
3	0
4	0

What is your current occupation_Other \

0	0
1	0
2	0
3	0
4	0

What is your current occupation_Student \

0	0
1	0
2	1
3	0
4	0

What is your current occupation_Unemployed \

0	1
1	1
2	0
3	1
4	1

What is your current occupation_Working Professional \

0	0
---	---

1	0
2	0
3	0
4	0

A free copy of Mastering The Interview_Yes \	
0	0
1	0
2	1
3	0
4	0

Last Notable Activity_Email Bounced \	
0	0
1	0
2	0
3	0
4	0

Last Notable Activity_Email Link Clicked \	
0	0
1	0
2	0
3	0
4	0

Last Notable Activity_Email Marked Spam \	
0	0
1	0
2	0
3	0
4	0

Last Notable Activity_Email Opened		Last Notable Activity_Email Received \	
0	0	0	0
1	1	0	0
2	1	0	0
3	0	0	0
4	0	0	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_0lark 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_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

	Specialization_Banking, Investment And Insurance \
0	0
1	0
2	0
3	0
4	0

	Specialization_Business Administration \	Specialization_E-Business \
0	0	0
1	0	0
2	1	0
3	0	0
4	0	0

	Specialization_E-COMMERCE	Specialization_Finance Management \
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0

	Specialization_Healthcare Management \
0	0
1	0
2	0
3	0
4	0

	Specialization_Hospitality Management \
0	0
1	0
2	0
3	0
4	0

	Specialization_Human Resource Management \
0	0
1	0
2	0
3	0
4	0

Specialization_IT Projects Management \

0	0
1	0
2	0
3	0
4	0

Specialization_International Business Management \ Specialization_Marketing

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

Specialization_Media and Advertising Management \ Specialization_Operations

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

Specialization_Retail Management Agribusiness \ Specialization_Rural and

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

Specialization_Services Excellence Management \ Specialization_Supply Chain

0	0
0	
1	0

```

0
2
0
3
0
4
0

```

```

Specialization_Travel and Tourism
0
1
2
3
4

```

```
y = leads['Converted']
```

```
y.head()
```

```

0    0
1    0
2    1
3    0
4    1

```

```
Name: Converted, dtype: int64
```

```
# Splitting the dataset into 70% train and 30% 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)
```

```
#lets check the shape
```

```
print("X_train Size", X_train.shape)
```

```
print("y_train Size", y_train.shape)
```

```
X_train Size (4461, 74)
```

```
y_train Size (4461,)
```

Scaling

Now there are a few numeric variables present in the dataset which have different scales. So let's go ahead and scale these variables.

```
# Importing the 'MinMax scaler' Library
```

```
# Scaling the three numeric features present in the dataset
```

```
scaler = MinMaxScaler()
```

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

```
Per Visit', 'Total Time Spent on Website']])
```

```
X_train.head()
```

	TotalVisits	Total Time Spent on Website	Page Views Per
Visit \			
8003	0.015936	0.029489	0.125
218	0.015936	0.082306	0.250
4171	0.023904	0.034331	0.375
4037	0.000000	0.000000	0.000
3660	0.000000	0.000000	0.000

	Lead Origin_Landing Page Submission	Lead Origin_Lead Add
Form \		
8003	1	0
218	1	0
4171	1	0
4037	0	0
3660	0	1

	Lead Origin_Lead Import	Lead Source_Direct Traffic
\		
8003	0	1
218	0	1
4171	0	1
4037	0	0
3660	0	0

	Lead Source_Facebook	Lead Source_Google	Lead Source_Live Chat
\			
8003	0	0	0
218	0	0	0
4171	0	0	0
4037	0	0	0
3660	0	0	0

	Lead Source_0lark Chat	Lead Source_Organic Search
\		

8003	0	0
218	0	0
4171	0	0
4037	1	0
3660	0	0
Lead Source_Pay per Click Ads Lead Source_Press_Release \		
8003	0	0
218	0	0
4171	0	0
4037	0	0
3660	0	0
Lead Source_Reference Lead Source_Referral Sites \		
8003	0	0
218	0	0
4171	0	0
4037	0	0
3660	1	0
Lead Source_Social Media Lead Source_WeLearn \		
8003	0	0
218	0	0
4171	0	0
4037	0	0
3660	0	0
Lead Source_Welingak Website Lead Source_bing Lead Source_testone \		
8003	0	0
0		
218	0	0
0		
4171	0	0
0		
4037	0	0
0		
3660	0	0
0		
Do Not Email_Yes Last Activity_Converted to Lead \		
8003	0	0
218	0	0
4171	0	0
4037	0	0
3660	0	0
Last Activity_Email Bounced Last Activity_Email Link Clicked \		
8003	0	0
218	0	1

4171	0	0
4037	0	0
3660	0	0

	Last Activity_Email Marked Spam	Last Activity_Email Opened \
8003	0	0
218	0	0
4171	0	0
4037	0	1
3660	0	0

	Last Activity_Email Received	Last Activity_Form Submitted on Website \
8003	0	
0		
218	0	
0		
4171	0	
0		
4037	0	
0		
3660	0	
0		

	Last Activity_Had a Phone Conversation \
8003	0
218	0
4171	0
4037	0
3660	0

	Last Activity_Olark Chat Conversation \
8003	0
218	0
4171	0
4037	0
3660	0

	Last Activity_Page Visited on Website	Last Activity_SMS Sent \
8003	0	1
218	0	0
4171	1	0
4037	0	0
3660	0	1

	Last Activity_Unreachable	Last Activity_Unsubscribed \
8003	0	0
218	0	0
4171	0	0
4037	0	0

3660	0	0
Last Activity_View in browser link Clicked \		
8003	0	
218	0	
4171	0	
4037	0	
3660	0	
Last Activity_Visited Booth in Tradeshow \		
8003	0	
218	0	
4171	0	
4037	0	
3660	0	
What is your current occupation_Housewife \		
8003	0	
218	0	
4171	0	
4037	0	
3660	0	
What is your current occupation_Other \		
8003	0	
218	0	
4171	0	
4037	0	
3660	0	
What is your current occupation_Student \		
8003	0	
218	0	
4171	0	
4037	0	
3660	0	
What is your current occupation_Unemployed \		
8003	1	
218	1	
4171	1	
4037	1	
3660	1	
What is your current occupation_Working Professional \		
8003	0	
218	0	
4171	0	
4037	0	
3660	0	

	A free copy of Mastering The Interview_Yes \
8003	1
218	1
4171	1
4037	0
3660	0

	Last Notable Activity_Email Bounced \
8003	0
218	0
4171	0
4037	0
3660	0

	Last Notable Activity_Email Link Clicked \
8003	0
218	0
4171	0
4037	0
3660	0

	Last Notable Activity_Email Marked Spam \
8003	0
218	0
4171	0
4037	0
3660	0

	Last Notable Activity_Email Opened \
8003	0
218	0
4171	0
4037	1
3660	0

	Last Notable Activity_Email Received \
8003	0
218	0
4171	0
4037	0
3660	0

	Last Notable Activity_Had a Phone Conversation \
8003	0
218	0
4171	0
4037	0
3660	0

	Last Notable Activity_Modified \
8003	0
218	1
4171	1
4037	0
3660	0

	Last Notable Activity_Olark Chat Conversation \
8003	0
218	0
4171	0
4037	0
3660	0

	Last Notable Activity_Page Visited on Website \
8003	0
218	0
4171	0
4037	0
3660	0

	Last Notable Activity_SMS Sent	Last Notable Activity_Unreachable \
8003	1	0
218	0	0
4171	0	0
4037	0	0
3660	1	0

	Last Notable Activity_Unsubscribed \
8003	0
218	0
4171	0
4037	0
3660	0

	Last Notable Activity_View in browser link Clicked \
8003	0
218	0
4171	0
4037	0
3660	0

	Specialization_Banking, Investment And Insurance \
8003	0

218	0
4171	0
4037	0
3660	0

Specialization_Business Administration Specialization_E-

Business \

8003	0
0	
218	0
0	
4171	0
0	
4037	0
0	
3660	0
0	

Specialization_E-COMMERCE Specialization_Finance Management \

8003	0	0
218	0	0
4171	0	0
4037	0	0
3660	0	1

Specialization_Healthcare Management \

8003	0
218	0
4171	0
4037	0
3660	0

Specialization_Hospitality Management \

8003	0
218	0
4171	0
4037	0
3660	0

Specialization_Human Resource Management \

8003	0
218	1
4171	0
4037	0
3660	0

Specialization_IT Projects Management \

8003	1
218	0
4171	0

4037	0	
3660	0	
Specialization_International Business \		
8003	0	
218	0	
4171	0	
4037	0	
3660	0	
Specialization_Marketing Management \		
8003	0	
218	0	
4171	0	
4037	0	
3660	0	
Specialization_Media and Advertising \		
8003	0	
218	0	
4171	0	
4037	0	
3660	0	
Specialization_Operations Management		Specialization_Retail
Management \		
8003	0	
0		
218	0	
0		
4171	0	
0		
4037	0	
0		
3660	0	
0		
Specialization_Rural and Agribusiness \		
8003	0	
218	0	
4171	0	
4037	0	
3660	0	
Specialization_Services Excellence \		
8003	0	
218	0	
4171	0	
4037	0	
3660	0	

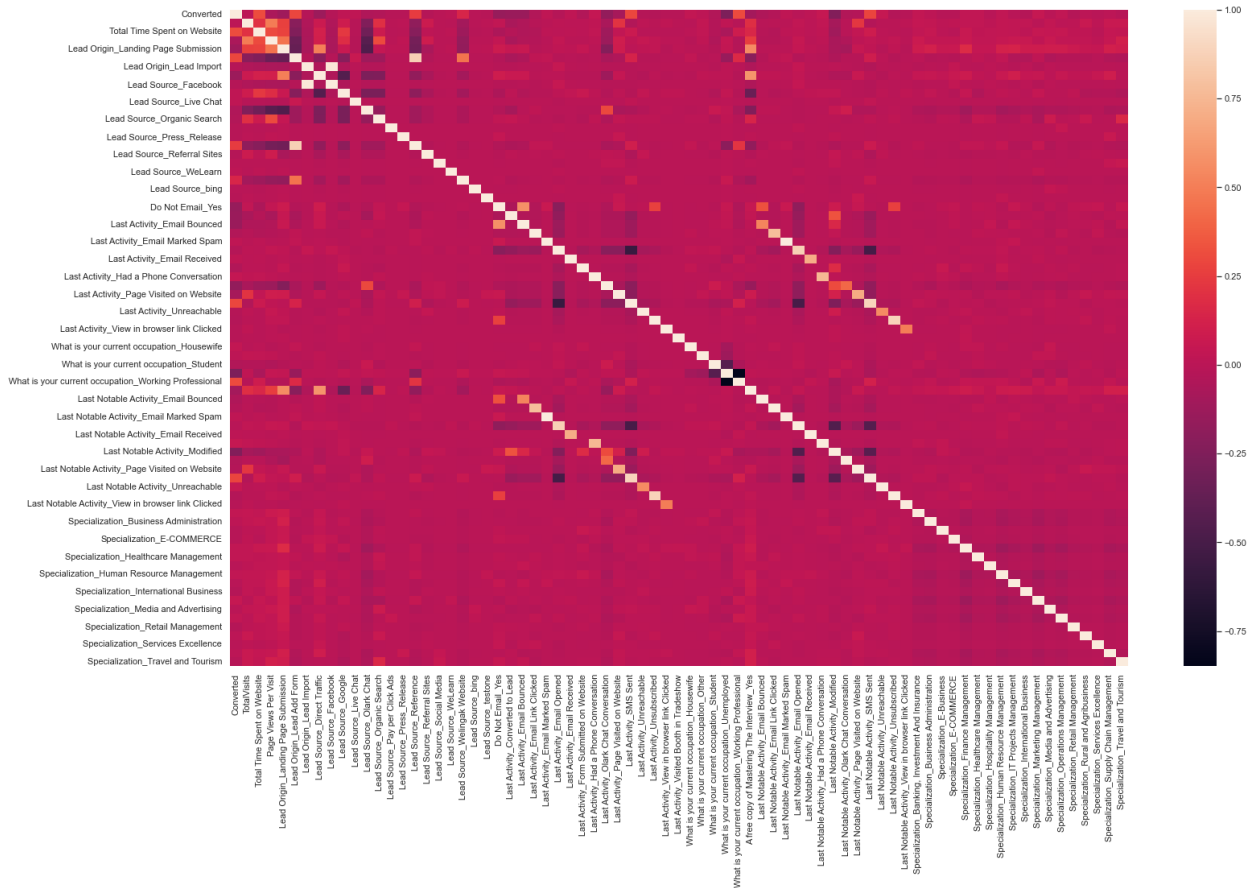
	Specialization_Supply Chain Management \
8003	0
218	0
4171	0
4037	0
3660	0

	Specialization_Travel and Tourism
8003	0
218	0
4171	1
4037	0
3660	0

Looking at the correlations

Let's now look at the correlations. Since the number of variables are pretty high, it's better that we look at the table instead of plotting a heatmap

```
# Looking at the correlation table
plt.figure(figsize = (25,15))
sns.heatmap(leads.corr())
plt.show()
```

Step 2: Model Building

Let's now move to model building. As you can see that there are a lot of variables present in the dataset which we cannot deal with. So the best way to approach this is to select a small set of features from this pool of variables using RFE.

```
# Importing the 'LogisticRegression' and creating a LogisticRegression object
logreg = LogisticRegression()

# Importing the 'RFE' and select 15 variables

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

# Let's take a look at which features have been selected by RFE

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

[('TotalVisits', True, 1),
 ('Total Time Spent on Website', True, 1),
 ('Page Views Per Visit', False, 23),
```

('Lead Origin_Landing Page Submission', False, 8),
('Lead Origin_Lead Add Form', True, 1),
('Lead Origin_Lead Import', False, 52),
('Lead Source_Direct Traffic', False, 24),
('Lead Source_Facebook', False, 51),
('Lead Source_Google', False, 36),
('Lead Source_Live Chat', False, 44),
('Lead Source_Olark Chat', True, 1),
('Lead Source_Organic Search', False, 35),
('Lead Source_Pay per Click Ads', False, 43),
('Lead Source_Press Release', False, 53),
('Lead Source_Reference', True, 1),
('Lead Source_Referral Sites', False, 37),
('Lead Source_Social Media', False, 58),
('Lead Source_WeLearn', False, 42),
('Lead Source_Welingak Website', True, 1),
('Lead Source_bing', False, 33),
('Lead Source_testone', False, 38),
('Do Not Email_Yes', True, 1),
('Last Activity_Converted to Lead', False, 25),
('Last Activity_Email Bounced', False, 4),
('Last Activity_Email Link Clicked', False, 49),
('Last Activity_Email Marked Spam', False, 57),
('Last Activity_Email Opened', False, 41),
('Last Activity_Email Received', False, 54),
('Last Activity_Form Submitted on Website', False, 28),
('Last Activity_Had a Phone Conversation', True, 1),
('Last Activity_Olark Chat Conversation', False, 5),
('Last Activity_Page Visited on Website', False, 26),
('Last Activity_SMS Sent', True, 1),
('Last Activity_Unreachable', False, 47),
('Last Activity_Unsubscribed', False, 40),
('Last Activity_View in browser link Clicked', False, 34),
('Last Activity_Visited Booth in Tradeshow', False, 48),
('What is your current occupation_Housewife', True, 1),
('What is your current occupation_Other', False, 46),
('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),
('A free copy of Mastering The Interview_Yes', False, 50),
('Last Notable Activity_Email Bounced', False, 3),
('Last Notable Activity_Email Link Clicked', False, 20),
('Last Notable Activity_Email Marked Spam', False, 59),
('Last Notable Activity_Email Opened', False, 27),
('Last Notable Activity_Email Received', False, 60),
('Last Notable Activity_Had a Phone Conversation', True, 1),
('Last Notable Activity_Modified', False, 2),
('Last Notable Activity_Olark Chat Conversation', False, 32),
('Last Notable Activity_Page Visited on Website', False, 31),

```
( 'Last Notable Activity_SMS Sent', False, 45),
( 'Last Notable Activity_Unreachable', True, 1),
( 'Last Notable Activity_Unsubscribed', False, 39),
( 'Last Notable Activity_View in browser link Clicked', False, 29),
( 'Specialization_Banking, Investment And Insurance', False, 6),
( 'Specialization_Business Administration', False, 15),
( 'Specialization_E-Business', False, 11),
( 'Specialization_E-COMMERCE', False, 9),
( 'Specialization_Finance Management', False, 14),
( 'Specialization_Healthcare Management', False, 10),
( 'Specialization_Hospitality Management', False, 55),
( 'Specialization_Human Resource Management', False, 16),
( 'Specialization_IT Projects Management', False, 18),
( 'Specialization_International Business', False, 22),
( 'Specialization_Marketing Management', False, 12),
( 'Specialization_Media and Advertising', False, 21),
( 'Specialization_Operations Management', False, 19),
( 'Specialization_Retail Management', False, 30),
( 'Specialization_Rural and Agribusiness', False, 7),
( 'Specialization_Services Excellence', False, 56),
( 'Specialization_Supply Chain Management', False, 13),
( 'Specialization_Travel and Tourism', False, 17)]
```

Putting all the columns selected by RFE in the variable 'col'

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

Now we have all the variables selected by RFE and since we care about the statistics part, i.e. the p-values and the VIFs, let's use these variables to create a logistic regression model using statsmodels.

Select only the columns selected by RFE

```
X_train = X_train[col]
```

Importing 'statsmodels'

Model 1

Fit a logistic Regression model on X_train after adding a constant and output the summary

```
X_train_sm = sm.add_constant(X_train)
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:
4461
Model:                  GLM       Df Residuals:
4445
Model Family:          Binomial   Df Model:
15
Link Function:         logit      Scale:
1.0000
Method:                 IRLS      Log-Likelihood:
-2072.8
Date:                  Sun, 01 Jan 2023   Deviance:
4145.5
Time:                  14:18:37   Pearson chi2:
4.84e+03
No. Iterations:                22

Covariance Type:          nonrobust

```

```

=====
=====
err          z          P>|z|          [0.025          0.975]          coef          std
-----
-----
const                                -1.0061
0.600      -1.677          0.094      -2.182          0.170
TotalVisits                                11.3439
2.682       4.230          0.000       6.088      16.600
Total Time Spent on Website                                4.4312
0.185      23.924          0.000       4.068       4.794
Lead Origin_Lead Add Form                                2.9483
1.191       2.475          0.013       0.614       5.283
Lead Source_0lark Chat                                1.4584
0.122      11.962          0.000       1.219       1.697
Lead Source_Reference                                1.2994
1.214       1.070          0.285      -1.080       3.679
Lead Source_Welingak Website                                3.4159
1.558       2.192          0.028       0.362       6.470
Do Not Email_Yes                                -1.5053
0.193      -7.781          0.000      -1.884      -1.126
Last Activity_Had a Phone Conversation                                1.0397
0.983       1.058          0.290      -0.887       2.966
Last Activity_SMS Sent                                1.1827
0.082      14.362          0.000       1.021       1.344
What is your current occupation_Housewife                                22.6492
2.45e+04       0.001          0.999      -4.8e+04      4.8e+04
What is your current occupation_Student                                -1.1544

```

```

0.630      -1.831      0.067      -2.390      0.081
What is your current occupation_Unemployed      -1.3395
0.594      -2.254      0.024      -2.505      -0.175
What is your current occupation_Working Professional      1.2743
0.623      2.045      0.041      0.053      2.496
Last Notable Activity_Had a Phone Conversation      23.1932
2.08e+04      0.001      0.999      -4.08e+04      4.08e+04
Last Notable Activity_Unreachable      2.7868
0.807      3.453      0.001      1.205      4.369
=====
=====
"""

```

There are quite a few variable which have a p-value greater than 0.05. We will need to take care of them. But first, let's also look at the VIFs.

Checking VIF

```

# Importing the 'variance_inflation_factor' library
# Make a VIF dataframe for all the variables present

vif = pd.DataFrame()
vif['Features'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X_train.values, i) for i in
range(X_train.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif

```

	Features	VIF
2	Lead Origin_Lead Add Form	84.19
4	Lead Source_Reference	65.18
5	Lead Source_Welingak Website	20.03
11	What is your current occupation_Unemployed	3.65
7	Last Activity_Had a Phone Conversation	2.44
13	Last Notable Activity_Had a Phone Conversation	2.43
1	Total Time Spent on Website	2.38
0	TotalVisits	1.62
8	Last Activity_SMS Sent	1.59
12	What is your current occupation_Working Professional	1.56
3	Lead Source_Olark Chat	1.44
6	Do Not Email_Yes	1.09
10	What is your current occupation_Student	1.09
9	What is your current occupation_Housewife	1.01
14	Last Notable Activity_Unreachable	1.01

VIFs seem to be in a decent range except for three variables.

Let's first drop the variable `Lead Source_Reference` since it has a high p-value as well as a high VIF.

```
X_train.drop('Lead Source_Reference', axis = 1, inplace = True)
```

Model 2

```
# Refit the model with the new set of features
```

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

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

```
"""
```

Generalized Linear Model Regression Results

```
=====
```

```
Dep. Variable:          Converted    No. Observations:  
4461
```

```
Model:                  GLM    Df Residuals:  
4446
```

```
Model Family:          Binomial    Df Model:  
14
```

```
Link Function:          logit    Scale:  
1.0000
```

```
Method:                 IRLS    Log-Likelihood:  
-2073.2
```

```
Date:                  Sun, 01 Jan 2023    Deviance:  
4146.5
```

```
Time:                  14:24:01    Pearson chi2:  
4.82e+03
```

```
No. Iterations:          22
```

```
Covariance Type:        nonrobust
```

```
=====
```

```
=====
```

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

```
-----
```

```
const          -1.677          0.094          -2.181          0.170          -1.0057
```

```
0.600          4.229          0.000          6.086          16.599          11.3428
```

```
TotalVisits          0.185          23.924          0.000          4.068          4.794          4.4312
```

```
Total Time Spent on Website          4.2084
```

```
Lead Origin_Lead Add Form
```

0.259	16.277	0.000	3.702	4.715	
Lead Source_Olark Chat					1.4583
0.122	11.960	0.000	1.219	1.697	
Lead Source_Welingak Website					2.1557
1.037	2.079	0.038	0.124	4.188	
Do Not Email_Yes					-1.5036
0.193	-7.779	0.000	-1.882	-1.125	
Last Activity_Had a Phone Conversation					1.0398
0.983	1.058	0.290	-0.887	2.966	
Last Activity_SMS Sent					1.1827
0.082	14.362	0.000	1.021	1.344	
What is your current occupation_Housewife					22.6511
2.45e+04	0.001	0.999	-4.8e+04	4.8e+04	
What is your current occupation_Student					-1.1537
0.630	-1.830	0.067	-2.389	0.082	
What is your current occupation_Unemployed					-1.3401
0.594	-2.255	0.024	-2.505	-0.175	
What is your current occupation_Working Professional					1.2748
0.623	2.046	0.041	0.053	2.496	
Last Notable Activity_Had a Phone Conversation					23.1934
2.08e+04	0.001	0.999	-4.08e+04	4.08e+04	
Last Notable Activity_Unreachable					2.7872
0.807	3.454	0.001	1.205	4.369	

=====

=====

"""

Checking VIF

Make a VIF dataframe for all the variables present

```
vif = pd.DataFrame()
vif['Features'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X_train.values, i) for i in
range(X_train.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

	Features	VIF
10	What is your current occupation_Unemployed	3.65
6	Last Activity_Had a Phone Conversation	2.44
12	Last Notable Activity_Had a Phone Conversation	2.43
1	Total Time Spent on Website	2.38
2	Lead Origin_Lead Add Form	1.71
0	TotalVisits	1.62
7	Last Activity_SMS Sent	1.59
11	What is your current occupation_Working Professional	1.56
3	Lead Source_Olark Chat	1.44
4	Lead Source_Welingak Website	1.33

5		Do Not Email_Yes	1.09
9	What is your current occupation_Student		1.09
8	What is your current occupation_Housewife		1.01
13	Last Notable Activity_Unreachable		1.01

The VIFs are now all less than 5. So let's drop the ones with the high p-values beginning with Last Notable Activity_Had a Phone Conversation.

```
X_train.drop('Last Notable Activity_Had a Phone Conversation', axis =
1, inplace = True)
```

Model 3

```
# Refit the model with the new set of features
```

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

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

```
"""
```

Generalized Linear Model Regression Results

```
=====
```

```
=====
```

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

```
4461
```

```
Model:                  GLM    Df Residuals:
```

```
4447
```

```
Model Family:          Binomial    Df Model:
```

```
13
```

```
Link Function:          logit    Scale:
```

```
1.0000
```

```
Method:                  IRLS    Log-Likelihood:
```

```
-2076.1
```

```
Date:                  Sun, 01 Jan 2023    Deviance:
```

```
4152.2
```

```
Time:                  14:30:54    Pearson chi2:
```

```
4.82e+03
```

```
No. Iterations:          21
```

```
Covariance Type:        nonrobust
```

```
=====
```

```
=====
```

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

```
-----
```

```
-----
```



```

const                                -1.0069
0.600    -1.679    0.093    -2.182    0.168
TotalVisits                            11.4551
2.686    4.265    0.000    6.191    16.720
Total Time Spent on Website            4.4237
0.185    23.900    0.000    4.061    4.787
Lead Origin_Lead Add Form              4.2082
0.259    16.276    0.000    3.701    4.715
Lead Source_0lark Chat                  1.4581
0.122    11.958    0.000    1.219    1.697
Lead Source_Welingak Website            2.1557
1.037    2.079    0.038    0.124    4.188
Do Not Email_Yes                        -1.5037
0.193    -7.780    0.000    -1.882    -1.125
Last Activity_Had a Phone Conversation    2.7502
0.802    3.430    0.001    1.179    4.322
Last Activity_SMS Sent                  1.1826
0.082    14.364    0.000    1.021    1.344
What is your current occupation_Housewife 21.6525
1.49e+04    0.001    0.999    -2.91e+04    2.91e+04
What is your current occupation_Student   -1.1520
0.630    -1.828    0.068    -2.387    0.083
What is your current occupation_Unemployed -1.3385
0.594    -2.253    0.024    -2.503    -0.174
What is your current occupation_Working Professional 1.2743
0.623    2.045    0.041    0.053    2.495
Last Notable Activity_Unreachable        2.7862
0.807    3.453    0.001    1.205    4.368
=====
=====
"""

```

Dropping the `What is your current occupation_Housewife` as having high P value

```

X_train.drop('What is your current occupation_Housewife', axis = 1,
inplace = True)

```

Model 4

```

# Refit the model with the new set of features

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

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

```

```

=====
=====
Dep. Variable:                Converted    No. Observations:
4461
Model:                        GLM          Df Residuals:
4448
Model Family:                Binomial     Df Model:
12
Link Function:                logit        Scale:
1.0000
Method:                       IRLS        Log-Likelihood:
-2078.3
Date:                         Sun, 01 Jan 2023    Deviance:
4156.7
Time:                         14:33:01    Pearson chi2:
4.83e+03
No. Iterations:                7

```

Covariance Type: nonrobust

```

=====
=====
err          z          P>|z|          [0.025          0.975]          coef          std
-----
const                                -0.4528
0.554      -0.818          0.413          -1.538          0.632
TotalVisits                                11.2586
2.672       4.214          0.000           6.023         16.495
Total Time Spent on Website                4.4217
0.185      23.898          0.000           4.059          4.784
Lead Origin_Lead Add Form                4.2057
0.258      16.274          0.000           3.699          4.712
Lead Source_0lark Chat                    1.4530
0.122      11.930          0.000           1.214          1.692
Lead Source_Welingak Website              2.1541
1.037       2.078          0.038           0.122          4.186
Do Not Email_Yes                         -1.5063
0.193      -7.785          0.000          -1.886         -1.127
Last Activity_Had a Phone Conversation      2.7515
0.802       3.432          0.001           1.180          4.323
Last Activity_SMS Sent                    1.1823
0.082      14.362          0.000           1.021          1.344
What is your current occupation_Student    -1.7017
0.588      -2.893          0.004          -2.855         -0.549
What is your current occupation_Unemployed -1.8879
0.550      -3.435          0.001          -2.965         -0.811
What is your current occupation_Working Professional 0.7246

```

```

0.581      1.248      0.212      -0.413      1.862
Last Notable Activity_Unreachable      2.7834
0.807      3.448      0.001      1.201      4.365
=====
=====
"""

```

Drop the variable 'What is your current occupation_Working Professional' as having high P value

```

X_train.drop('What is your current occupation_Working Professional',
axis = 1, inplace = True)

```

Model 4

```

# Refit the model with the new set of features

```

```

logml = sm.GLM(y_train,(sm.add_constant(X_train)), family =
sm.families.Binomial())
res = logml.fit()
res.summary()

```

```

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

```

Generalized Linear Model Regression Results

```

=====
=====
Dep. Variable:          Converted   No. Observations:
4461
Model:                  GLM       Df Residuals:
4449
Model Family:          Binomial   Df Model:
11
Link Function:          logit     Scale:
1.0000
Method:                 IRLS     Log-Likelihood:
-2079.1
Date:                   Sun, 01 Jan 2023   Deviance:
4158.1
Time:                   14:34:05   Pearson chi2:
4.80e+03
No. Iterations:         7

Covariance Type:        nonrobust

=====
=====

```

	coef	std err

z	P> z	[0.025	0.975]			

const				0.2040	0.196	
1.043	0.297	-0.179	0.587			
TotalVisits				11.1489	2.665	
4.184	0.000	5.926	16.371			
Total Time Spent on Website				4.4223	0.185	
23.899	0.000	4.060	4.785			
Lead Origin_Lead Add Form				4.2051	0.258	
16.275	0.000	3.699	4.712			
Lead Source_0lark Chat				1.4526	0.122	
11.934	0.000	1.214	1.691			
Lead Source_Welingak Website				2.1526	1.037	
2.076	0.038	0.121	4.185			
Do Not Email_Yes				-1.5037	0.193	-
7.774	0.000	-1.883	-1.125			
Last Activity_Had a Phone Conversation				2.7552	0.802	
3.438	0.001	1.184	4.326			
Last Activity_SMS Sent				1.1856	0.082	
14.421	0.000	1.024	1.347			
What is your current occupation_Student				-2.3578	0.281	-
8.392	0.000	-2.908	-1.807			
What is your current occupation_Unemployed				-2.5445	0.186	-
13.699	0.000	-2.908	-2.180			
Last Notable Activity_Unreachable				2.7846	0.807	
3.449	0.001	1.202	4.367			
=====						
=====						
"""						

Checking final VIF

```
# Making a VIF dataframe for all the variables present

vif = pd.DataFrame()
vif['Features'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X_train.values, i) for i in
range(X_train.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

	Features	VIF
9	What is your current occupation_Unemployed	2.82
1	Total Time Spent on Website	2.00
0	TotalVisits	1.54
7	Last Activity_SMS Sent	1.51
2	Lead Origin_Lead Add Form	1.45
3	Lead Source_0lark Chat	1.33

4	Lead Source_Welingak Website	1.30
5	Do Not Email_Yes	1.08
8	What is your current occupation_Student	1.06
6	Last Activity_Had a Phone Conversation	1.01
10	Last Notable Activity_Unreachable	1.01

Step 3: Model Evaluation

Now, both the p-values and VIFs seem decent enough for all the variables. So let's go ahead and make predictions using this final set of features.

```
# Use 'predict' to predict the probabilities on the train set

y_train_pred = res.predict(sm.add_constant(X_train))
y_train_pred[:10]

8003    0.300117
218     0.142002
4171    0.127629
4037    0.291558
3660    0.954795
207     0.194426
2044    0.178073
6411    0.949460
6498    0.075995
2085    0.982316
dtype: float64

# Reshaping it into an array

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

array([0.30011695, 0.14200165, 0.12762885, 0.29155814, 0.95479546,
       0.19442563, 0.17807328, 0.94946006, 0.07599465, 0.98231619])
```

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

```
# Creating a new dataframe containing the actual conversion flag and
the probabilities predicted by the model

y_train_pred_final = pd.DataFrame({'Converted':y_train.values,
'Conversion_Prob':y_train_pred})
y_train_pred_final.head()

   Converted  Conversion_Prob
0          0          0.300117
1          0          0.142002
```

2	1	0.127629
3	1	0.291558
4	1	0.954795

Creating new column 'Predicted' with 1 if Paid_Prob > 0.5 else 0

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

Let's see the head

```
y_train_pred_final.head()
```

	Converted	Conversion_Prob	Predicted
0	0	0.300117	0
1	0	0.142002	0
2	1	0.127629	0
3	1	0.291558	0
4	1	0.954795	1

Now that you have the probabilities and have also made conversion predictions using them, it's time to evaluate the model.

```
# Importing the 'metrics' library from sklearn for evaluation
```

Creating the Confusion matrix

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

```
[[1929  383]
 [ 560 1589]]
```

Let's check the overall accuracy

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

```
0.7886124187401928
```

Let's evaluate the other metrics as well

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

Calculating the 'sensitivity'

```
TP/(TP+FN)
```

```
0.739413680781759
```

```
# Calculating the 'specificity'
```

```
TN/(TN+FP)
```

```
0.8343425605536332
```

Finding the Optimal Cutoff

Now 0.5 was just arbitrary to loosely check the model performance. But in order to get good results, you need to optimise the threshold. So first let's plot an ROC curve to see what AUC we get.

```
# ROC function
```

```
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.Conversion_Prob,  
                                          drop_intermediate=False)
```

```
# Importing the 'matplotlib' to plot the ROC curve`
```

```
# Calling the ROC function
```

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


	0.7	0.8	0.9
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	1	1	1

Let's create a dataframe to see the values of accuracy, sensitivity, and specificity at different values of 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

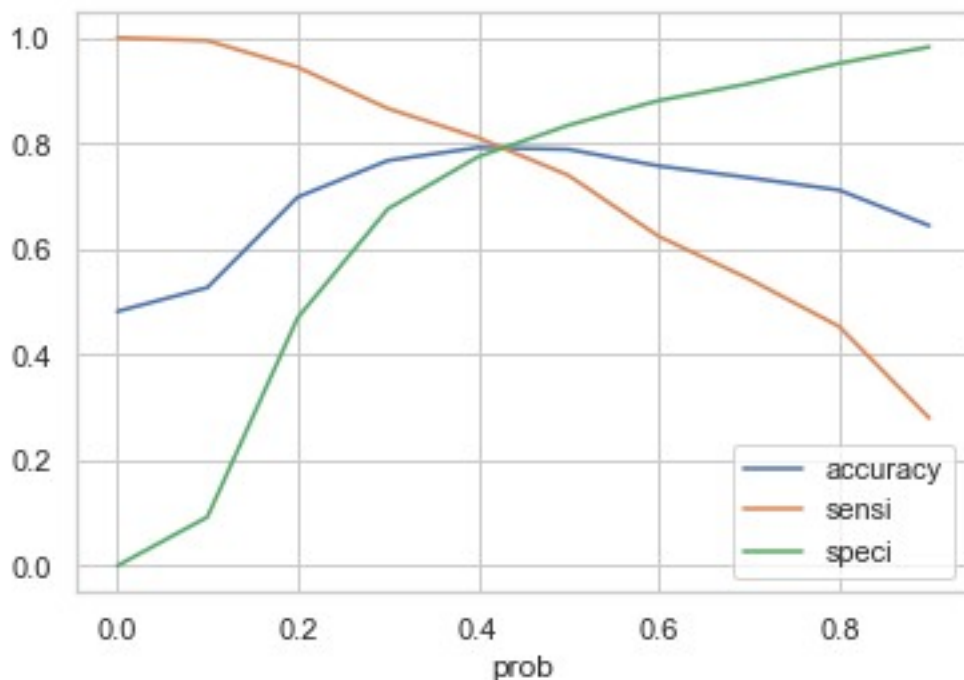
num = [0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9]
for i in num:
    cm1 = metrics.confusion_matrix(y_train_pred_final.Converted,
y_train_pred_final[i] )
    total1=sum(sum(cm1))
    accuracy = (cm1[0,0]+cm1[1,1])/total1

    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	0.481731	1.000000	0.000000
0.1	0.1	0.527012	0.994416	0.092561
0.2	0.2	0.698274	0.944160	0.469723
0.3	0.3	0.767541	0.865984	0.676038
0.4	0.4	0.791975	0.810610	0.774654
0.5	0.5	0.788612	0.739414	0.834343
0.6	0.6	0.757229	0.624011	0.881055
0.7	0.7	0.735037	0.543509	0.913062
0.8	0.8	0.711500	0.453234	0.951557
0.9	0.9	0.644026	0.279665	0.982699

Let's plot it as well

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



As you can see that around 0.42, you get the optimal values of the three metrics. So let's choose 0.42 as our cutoff now.

```
y_train_pred_final['final_predicted'] =
y_train_pred_final.Conversion_Prob.map( lambda x: 1 if x > 0.42 else
0)
```

```
y_train_pred_final.head()
```

	Converted	Conversion_Prob	Predicted	0.0	0.1	0.2	0.3	0.4	0.5
0.6 \									
0	0	0.300117	0	1	1	1	1	0	0
0									
1	0	0.142002	0	1	1	0	0	0	0
0									
2	1	0.127629	0	1	1	0	0	0	0
0									
3	1	0.291558	0	1	1	1	0	0	0
0									
4	1	0.954795	1	1	1	1	1	1	1
1									

	0.7	0.8	0.9	final_predicted
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	1	1	1	1

```

# Let's checking the `accuracy` now

metrics.accuracy_score(y_train_pred_final.Converted,
y_train_pred_final.final_predicted)

0.7908540685944856

# Let's create the confusion matrix once again

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

array([[1823,  489],
       [ 444, 1705]], dtype=int64)

# Let's evaluate the other metrics as well

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

# Calculating the 'Sensitivity'

TP/(TP+FN)

0.793392275476966

# Calculating the 'Specificity'

TN/(TN+FP)

0.7884948096885813

```

This cutoff point seems good to go!

Step 4: Making Predictions on the Test Set

Let's now make predicitons on the test set

```

# Scaling the test set as well using just 'transform'

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

# Selecting the columns in X_train for X_test as well

X_test = X_test[col]
X_test.head()

```

Form	TotalVisits	Total Time Spent on Website	Lead Origin_Lead Add
4771	0.000000	0.000000	
1			
6122	0.027888	0.029049	
0			
9202	0.015936	0.416813	
0			
6570	0.011952	0.378961	
0			
2668	0.031873	0.395246	
0			
Lead Source_0lark Chat	Lead Source_Reference		
4771	0	1	
6122	0	0	
9202	0	0	
6570	0	0	
2668	0	0	
Lead Source_Welingak Website	Do Not Email_Yes		
4771	0	0	
6122	0	0	
9202	0	0	
6570	0	1	
2668	0	0	
Last Activity_Had a Phone Conversation	Last Activity_SMS		
Sent			
4771	0	1	
6122	0	0	
9202	0	1	
6570	0	1	
2668	0	1	
What is your current occupation_Housewife			
4771	0		
6122	0		
9202	0		
6570	0		
2668	0		
What is your current occupation_Student			
4771	0		
6122	0		
9202	0		

6570	0
2668	0

What is your current occupation_Unemployed \	
4771	0
6122	1
9202	1
6570	1
2668	1

What is your current occupation_Working Professional \	
4771	1
6122	0
9202	0
6570	0
2668	0

Last Notable Activity_Had a Phone Conversation \	
4771	0
6122	0
9202	0
6570	0
2668	0

Last Notable Activity_Unreachable	
4771	0
6122	0
9202	0
6570	0
2668	0

Adding a constant to X_test

X_test_sm = sm.add_constant(X_test[col])

Checking X_test_sm

X_test_sm

	const	TotalVisits	Total Time Spent on Website \
4771	1.0	0.000000	0.000000
6122	1.0	0.027888	0.029049
9202	1.0	0.015936	0.416813
6570	1.0	0.011952	0.378961
2668	1.0	0.031873	0.395246
...
5828	1.0	0.011952	0.027289
6583	1.0	0.011952	0.152289
5531	1.0	0.055777	0.702025
3056	1.0	0.011952	0.417694
4088	1.0	0.019920	0.530370

	Lead Origin_Lead Add Form	Lead Source_0lark Chat \
4771	1	0
6122	0	0
9202	0	0
6570	0	0
2668	0	0
...
5828	0	0
6583	0	0
5531	0	0
3056	0	0
4088	0	0

	Lead Source_Reference	Lead Source_Welingak Website	Do Not
Email_Yes \			
4771	1	0	
0			
6122	0	0	
0			
9202	0	0	
0			
6570	0	0	
1			
2668	0	0	
0			
...	
...			
5828	0	0	
0			
6583	0	0	
0			
5531	0	0	
0			
3056	0	0	
1			
4088	0	0	
0			

	Last Activity_Had a Phone Conversation	Last Activity_SMS
Sent \		
4771	0	1
6122	0	0
9202	0	1
6570	0	1
2668	0	1

...
5828	0	1
6583	0	1
5531	0	0
3056	0	1
4088	0	0

What is your current occupation_Housewife \		
4771	0	
6122	0	
9202	0	
6570	0	
2668	0	
...	...	
5828	0	
6583	0	
5531	0	
3056	0	
4088	0	

What is your current occupation_Student \		
4771	0	
6122	0	
9202	0	
6570	0	
2668	0	
...	...	
5828	0	
6583	0	
5531	0	
3056	0	
4088	0	

What is your current occupation_Unemployed \		
4771	0	
6122	1	
9202	1	
6570	1	
2668	1	
...	...	
5828	1	
6583	1	
5531	1	

3056	1
4088	1
What is your current occupation_Working Professional \	
4771	1
6122	0
9202	0
6570	0
2668	0
...	...
5828	0
6583	0
5531	0
3056	0
4088	0

Last Notable Activity_Had a Phone Conversation \	
4771	0
6122	0
9202	0
6570	0
2668	0
...	...
5828	0
6583	0
5531	0
3056	0
4088	0

Last Notable Activity_Unreachable	
4771	0
6122	0
9202	0
6570	0
2668	0
...	...
5828	0
6583	0
5531	0
3056	0
4088	0

[1912 rows x 16 columns]

Dropping the required columns from X_test as well

```
X_test.drop(['Lead Source_Reference', 'What is your current
occupation_Housewife',
            'What is your current occupation_Working Professional',
            'Last Notable Activity_Had a Phone
```



```

Conversation'], 1,
                                inplace = True)

# Make predictions on the test set and store it in the variable
'y_test_pred'

y_test_pred = res.predict(sm.add_constant(X_test))
y_test_pred[:10]
4771    0.996296
6122    0.129992
9202    0.703937
6570    0.299564
2668    0.720796
4233    0.792250
3368    0.704038
9091    0.464521
5972    0.282978
3631    0.786460
dtype: float64

# Converting y_pred to a dataframe
y_pred_1 = pd.DataFrame(y_test_pred)

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

```

	0
4771	0.996296
6122	0.129992
9202	0.703937
6570	0.299564
2668	0.720796

```

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

# Remove 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)

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

```

```
# Check 'y_pred_final'
```

```
y_pred_final.head()
```

	Converted	
0	1	0.996296
1	0	0.129992
2	0	0.703937
3	1	0.299564
4	1	0.720796

```
# Rename the column
```

```
y_pred_final= y_pred_final.rename(columns = {0 : 'Conversion_Prob'})
```

```
# Let's see the head of y_pred_final
```

```
y_pred_final.head()
```

	Converted	Conversion_Prob
0	1	0.996296
1	0	0.129992
2	0	0.703937
3	1	0.299564
4	1	0.720796

```
# Make predictions on the test set using 0.45 as the cutoff
```

```
y_pred_final['final_predicted'] =  
y_pred_final.Conversion_Prob.map(lambda x: 1 if x > 0.42 else 0)
```

```
# Check y_pred_final
```

```
y_pred_final.head()
```

	Converted	Conversion_Prob	final_predicted
0	1	0.996296	1
1	0	0.129992	0
2	0	0.703937	1
3	1	0.299564	0
4	1	0.720796	1

```
# Let's check the overall accuracy
```

```
metrics.accuracy_score(y_pred_final['Converted'],  
y_pred_final.final_predicted)
```

```
0.7845188284518828
```

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

```

array([[786, 210],
       [202, 714]], 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

# Calculating the 'sensitivity'
TP / float(TP+FN)

0.7794759825327511

# Calculating the 'specificity'
TN / float(TN+FP)

0.7891566265060241

```

Precision-Recall View

Let's now also build the training model using the precision-recall view

```

#Looking at the confusion matrix again

confusion = metrics.confusion_matrix(y_train_pred_final.Converted,
y_train_pred_final.Predicted )
confusion

array([[1929, 383],
       [ 560, 1589]], dtype=int64)

```

Precision =

```

TP / TP + FP

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

0.8057809330628803

```

Recall =

```

TP / TP + FN

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

0.739413680781759

```

Precision and recall tradeoff

Importing the `Precision recall curve` library

```
y_train_pred_final.Converted, y_train_pred_final.Predicted
```

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

```
..  
4456    1  
4457    0  
4458    0  
4459    0  
4460    0
```

```
Name: Converted, Length: 4461, dtype: int64,
```

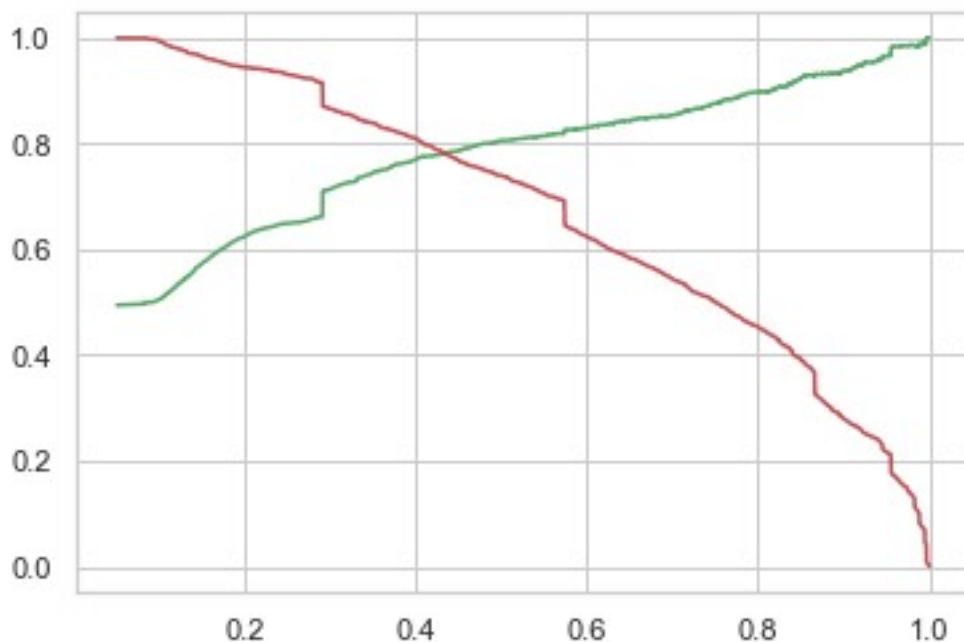
```
0      0  
1      0  
2      0  
3      0  
4      1
```

```
..  
4456    1  
4457    1  
4458    1  
4459    0  
4460    0
```

```
Name: Predicted, Length: 4461, dtype: int64)
```

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

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



```
y_train_pred_final['final_predicted'] =
y_train_pred_final.Conversion_Prob.map(lambda x: 1 if x > 0.44 else 0)
y_train_pred_final.head()
```

	Converted	Conversion_Prob	Predicted	0.0	0.1	0.2	0.3	0.4	0.5
0.6 \									
0	0	0.300117	0	1	1	1	1	0	0
0									
1	0	0.142002	0	1	1	0	0	0	0
0									
2	1	0.127629	0	1	1	0	0	0	0
0									
3	1	0.291558	0	1	1	1	0	0	0
0									
4	1	0.954795	1	1	1	1	1	1	1
1									

	0.7	0.8	0.9	final_predicted
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	1	1	1	1

Let's checking the `accuracy` now

```
metrics.accuracy_score(y_train_pred_final.Converted,
y_train_pred_final.final_predicted)
```

```
0.7895090786819099
```

```
# Let's creating the confusion matrix once again
```

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

```
array([[1852,  460],  
       [ 479, 1670]], dtype=int64)
```

```
# Let's evaluate the other metrics as well
```

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

Precision

```
TP/(TP+FP)
```

```
0.784037558685446
```

Recall

```
TP/(TP+FN)
```

```
0.7771056305258259
```

This cutoff point seems good to go!

Step 5: Making Predictions on the Test Set

Let's now make predicitions on the test set.

```
# Making predictions on the test set and store it in the variable  
'y_test_pred'
```

```
y_test_pred = res.predict(sm.add_constant(X_test))
```

```
y_test_pred[:10]
```

```
4771    0.996296  
6122    0.129992  
9202    0.703937  
6570    0.299564  
2668    0.720796  
4233    0.792250  
3368    0.704038  
9091    0.464521
```

```
5972    0.282978
3631    0.786460
dtype: float64
```

```
# Converting y_pred to a dataframe
```

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

```
# Let's see the head
```

```
y_pred_1.head()
```

```
      0
4771  0.996296
6122  0.129992
9202  0.703937
6570  0.299564
2668  0.720796
```

```
# Converting y_test to dataframe
```

```
y_test_df = pd.DataFrame(y_test)
```

```
# 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)
```

```
# Append y_test_df and y_pred_1
```

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

```
# Checking the 'y_pred_final'
```

```
y_pred_final.head()
```

```
      Converted      0
0             1  0.996296
1             0  0.129992
2             0  0.703937
3             1  0.299564
4             1  0.720796
```

```
# Rename the column
```

```
y_pred_final= y_pred_final.rename(columns = {0 : 'Conversion_Prob'})
```

```
# Let's see the head of y_pred_final
```

```
y_pred_final.head()
```

	Converted	Conversion_Prob
0	1	0.996296
1	0	0.129992
2	0	0.703937
3	1	0.299564
4	1	0.720796

Making predictions on the test set using 0.44 as the cutoff

```
y_pred_final['final_predicted'] =
y_pred_final.Conversion_Prob.map(lambda x: 1 if x > 0.44 else 0)
```

Checking y_pred_final

```
y_pred_final.head()
```

	Converted	Conversion_Prob	final_predicted
0	1	0.996296	1
1	0	0.129992	0
2	0	0.703937	1
3	1	0.299564	0
4	1	0.720796	1

Let's checking the overall accuracy

```
metrics.accuracy_score(y_pred_final['Converted'],
y_pred_final.final_predicted)
```

```
0.7866108786610879
```

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

```
array([[801, 195],
       [213, 703]], 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
```

Calculating the Precision

```
TP/(TP+FP)
```

```
0.7828507795100222
```

Calculating Recall

```
TP/(TP+FN)
```


0.767467248908297