Lead Scoring Case Study

The study is conducted for X Education in an effort to increase the number of customers visiting their site enrolled in their courses. It aims to build an analytical model that can estimate the lead score for the new customer based on learning from past data.

Data

For the construction of the analytical model, a dataset of historical leads including around 9000 data points is supplied. In this instance, the target variable is the column 'Converted,' which indicates whether a previous lead was converted or not.

In [1]:

```
from matplotlib import pyplot as plt
import seaborn as sns
import pandas as pd
from sklearn.preprocessing import PowerTransformer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFE
from sklearn import metrics
from sklearn.metrics import precision_recall_curve
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [2]:

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

Out[2]:

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

5 rows × 37 columns

In [3]:

```
leads.shape
```

Out[3]:

```
(9240, 37)
```

In [4]:

```
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
```

In [5]:

```
plt.title("Distribution of data between target classes")
leads.Converted.value_counts().plot.bar()
```

Out[5]:

```
<AxesSubplot:title={'center':'Distribution of data between target classes'}>
```

In [6]:

```
leads.describe(include="all")
```

Out[6]:

	Prospect ID	Lead Number	Lead Origin	Lead Source	Do Not Email	Do Not Call	Converted	TotalVisit
count	9240	9240.000000	9240	9204	9240	9240	9240.000000	9103.00000
unique	9240	NaN	5	21	2	2	NaN	Nal
top	7e2819e8-97f0-416b-bcb6-45ef14f0e11a	NaN	Landing Page Submission	Google	No	No	NaN	Nal
freq	1	NaN	4886	2868	8506	9238	NaN	Nal
mean	NaN	617188.435606	NaN	NaN	NaN	NaN	0.385390	3.44523
std	NaN	23405.995698	NaN	NaN	NaN	NaN	0.486714	4.85485
min	NaN	579533.000000	NaN	NaN	NaN	NaN	0.000000	0.00000
25%	NaN	596484.500000	NaN	NaN	NaN	NaN	0.000000	1.00000
50%	NaN	615479.000000	NaN	NaN	NaN	NaN	0.000000	3.00000
75%	NaN	637387.250000	NaN	NaN	NaN	NaN	1.000000	5.00000
max	NaN	660737.000000	NaN	NaN	NaN	NaN	1.000000	251.00000

11 rows × 37 columns

Data Cleaning

Check constants and uniques

In [7]:

```
leads.nunique()
```

Out[7]:

```
Prospect ID                                    9240
Lead Number                                    9240
Lead Origin                                       5
Lead Source                                      21
Do Not Email                                      2
Do Not Call                                       2
Converted                                         2
TotalVisits                                      41
Total Time Spent on Website                    1731
Page Views Per Visit                            114
Last Activity                                    17
Country                                          38
Specialization                                   19
How did you hear about X Education               10
What is your current occupation                   6
What matters most to you in choosing a course     3
Search                                            2
Magazine                                          1
Newspaper Article                                 2
X Education Forums                                2
Newspaper                                         2
Digital Advertisement                             2
Through Recommendations                           2
Receive More Updates About Our Courses            1
Tags                                             26
Lead Quality                                      5
Update me on Supply Chain Content                 1
Get updates on DM Content                         1
Lead Profile                                      6
City                                              7
Asymmetrique Activity Index                       3
Asymmetrique Profile Index                        3
Asymmetrique Activity Score                      12
Asymmetrique Profile Score                       10
I agree to pay the amount through cheque          1
A free copy of Mastering The Interview            2
Last Notable Activity                            16
dtype: int64
```

Remove columns with unique values

In [8]:

```
leads = leads.drop(columns = ["Prospect ID", "Lead Number"])
```

Remove columns with constant values

In [9]:

```
constants = leads.nunique()[leads.nunique() == 1]
print(constants)
leads = leads.drop(columns = constants.index)
```

```
Magazine                                      1
Receive More Updates About Our Courses        1
Update me on Supply Chain Content             1
Get updates on DM Content                     1
I agree to pay the amount through cheque      1
dtype: int64
```

Check the number of unique categories in each categorical column

Check columns with more number of constant values and highly imbalanced categorical group

In [10]:

```
leads["Do Not Call"].value_counts()
```

Out[10]:

```
No     9238
Yes       2
Name: Do Not Call, dtype: int64
```

In [11]:

```
leads["Search"].value_counts()
```

Out[11]:

```
No     9226
Yes      14
Name: Search, dtype: int64
```

In [12]:

```
leads["Newspaper Article"].value_counts()
```

Out[12]:

```
No     9238
Yes       2
Name: Newspaper Article, dtype: int64
```

In [13]:

```
leads["Newspaper"].value_counts()
```

Out[13]:

```
No     9239
Yes       1
Name: Newspaper, dtype: int64
```

In [14]:

```
leads["X Education Forums"].value_counts()
```

Out[14]:

```
No     9239
Yes       1
Name: X Education Forums, dtype: int64
```

In [15]:

```
leads["A free copy of Mastering The Interview"].value_counts()
```

Out[15]:

```
No     6352
Yes    2888
Name: A free copy of Mastering The Interview, dtype: int64
```

In [16]:

```
leads["Digital Advertisement"].value_counts()
```

Out[16]:

```
No     9236
Yes       4
Name: Digital Advertisement, dtype: int64
```

In [17]:

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

Out[17]:

```
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
Resubscribed to emails             1
Approached upfront                 1
Email Received                     1
Form Submitted on Website          1
View in browser link Clicked       1
Name: Last Notable Activity, dtype: int64
```

In [18]:

```
leads["Through Recommendations"].value_counts()
```

Out[18]:

```
No     9233
Yes       7
Name: Through Recommendations, dtype: int64
```

The value counts of most the above columns ('Do Not Call', 'Search', 'Newspaper Article', 'X Education Forums', 'Newspaper', 'Digital Advertisement', 'Through Recommendations'), there were a few columns in which only one value was significantly present for all of the data points, making them useless to the analysis, therefore we should eliminate them.

In [19]:

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

Out[19]:

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

In [20]:

```
leads = leads.drop(columns=['Do Not Call', 'Search', 'Newspaper Article', 'X Education Foru
            'Digital Advertisement', 'Through Recommendations', 'What matters most to you i
```

In [21]:

```
leads["Tags"].value_counts()
```

Out[21]:

```
Will revert after reading the email                2072
Ringing                                            1203
Interested in other courses                         513
Already a student                                   465
Closed by Horizzon                                  358
switched off                                        240
Busy                                                186
Lost to EINS                                        175
Not doing further education                         145
Interested  in full time MBA                        117
Graduation in progress                              111
invalid number                                       83
Diploma holder (Not Eligible)                        63
wrong number given                                   47
opp hangup                                           33
number not provided                                  27
in touch with EINS                                   12
Lost to Others                                        7
Want to take admission but has financial problems     6
Still Thinking                                        6
Interested in Next batch                              5
In confusion whether part time or DLP                 5
Lateral student                                       3
Shall take in the next coming month                   2
University not recognized                             2
Recognition issue (DEC approval)                      1
Name: Tags, dtype: int64
```

The column has a greater number of categories, making it harder to utilise in the study; also, the column does not seem to have much relevance, so we may remove it.

In [22]:

```
leads = leads.drop(columns="Tags")
```

Identify missing values

In [23]:

```
null_counts = (leads.isnull().sum() / len(leads)) * 100
null_counts
```

Out[23]:

```
Lead Origin                                    0.000000
Lead Source                                    0.389610
Do Not Email                                   0.000000
Converted                                      0.000000
TotalVisits                                    1.482684
Total Time Spent on Website                    0.000000
Page Views Per Visit                           1.482684
Last Activity                                  1.114719
Country                                       26.634199
Specialization                                15.562771
How did you hear about X Education            23.885281
What is your current occupation               29.112554
Lead Quality                                  51.590909
Lead Profile                                  29.318182
City                                          15.367965
Asymmetrique Activity Index                   45.649351
Asymmetrique Profile Index                    45.649351
Asymmetrique Activity Score                   45.649351
Asymmetrique Profile Score                    45.649351
A free copy of Mastering The Interview         0.000000
Last Notable Activity                          0.000000
dtype: float64
```

Check values that are potentially missing in categorical variable

In [24]:

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

Out[24]:

```
Select                         4146
Potential Lead                 1613
Other Leads                     487
Student of SomeSchool           241
Lateral Student                  24
Dual Specialization Student      20
Name: Lead Profile, dtype: int64
```

In [25]:

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

Out[25]:

```
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
```

In [26]:

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

Out[26]:

```
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
```

Notably, the variables Lead Profile and How did you hear about X Education contain a large number of rows with the value Select, which is useless to the analysis, therefore we should remove them.

In [27]:

```
leads = leads.drop(columns = ['Lead Profile', 'How did you hear about X Education'])
```

Drop columns having high percentage of missing values

In [28]:

```
high_missings = null_counts[null_counts>45]
high_missings
```

Out[28]:

```
Lead Quality                   51.590909
Asymmetrique Activity Index    45.649351
Asymmetrique Profile Index     45.649351
Asymmetrique Activity Score    45.649351
Asymmetrique Profile Score     45.649351
dtype: float64
```

In [29]:

```
leads = leads.drop(columns = high_missings.index)
```

In [30]:

```
leads.shape
```

Out[30]:

```
(9240, 14)
```

In [31]:

```
leads["City"].value_counts()
```

Out[31]:

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

As we can see, we don't have much information on the city, and the majority of the values are Other, thus we can remove the column.

In [32]:

```
leads = leads.drop(columns = "City")
```

In [33]:

```
leads["Country"].value_counts()
```

Out[33]:

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

Similarly, the country column has almost all of the values to India and very few distributed across several other countries. Also consideribng the high number of missing values it is good to drop the column.

In [34]:

```
leads = leads.drop(columns = "Country")
```

Impute columns with less percentage of missing values

In [35]:

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

Out[35]:

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

We can simply remove the rows that have a small number of null values in the columns. And assuming that the inference inputs will have the values in real-time.

In [36]:

```
leads = leads[~leads["TotalVisits"].isnull()]
```

In [37]:

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

In [38]:

```
leads.isnull().sum()[leads.isnull().sum()>0]
```

Out[38]:

```
Specialization                    1431
What is your current occupation   2683
dtype: int64
```

In [39]:

```
leads["What is your current occupation"].value_counts()
```

Out[39]:

```
Unemployed              5476
Working Professional     677
Student                  206
Other                     15
Housewife                  9
Businessman                8
Name: What is your current occupation, dtype: int64
```

Though the column What is your current occupation contains more number of missing values, it is more relevent to the business. So, it is better to drop the rows where the values are null for that column and keep the rest for analysis.

In [40]:

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

In [41]:

```
leads.isnull().sum()[leads.isnull().sum()>0]
```

Out[41]:

```
Specialization    18
dtype: int64
```

In [42]:

```
leads = leads[~leads["Specialization"].isnull()]
```

Check the records retained in data cleaning process

In [43]:

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

Out[43]:

```
0
```

In [44]:

```
leads.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6373 entries, 0 to 9239
Data columns (total 12 columns):
 #   Column                                  Non-Null Count  Dtype  
---  ------                                  --------------  -----  
 0   Lead Origin                             6373 non-null   object 
 1   Lead Source                             6373 non-null   object 
 2   Do Not Email                            6373 non-null   object 
 3   Converted                               6373 non-null   int64  
 4   TotalVisits                             6373 non-null   float64
 5   Total Time Spent on Website             6373 non-null   int64  
 6   Page Views Per Visit                    6373 non-null   float64
 7   Last Activity                           6373 non-null   object 
 8   Specialization                          6373 non-null   object 
 9   What is your current occupation         6373 non-null   object 
 10  A free copy of Mastering The Interview  6373 non-null   object 
 11  Last Notable Activity                   6373 non-null   object 
dtypes: float64(2), int64(2), object(8)
memory usage: 647.3+ KB
```

In [45]:

```
leads.head()
```

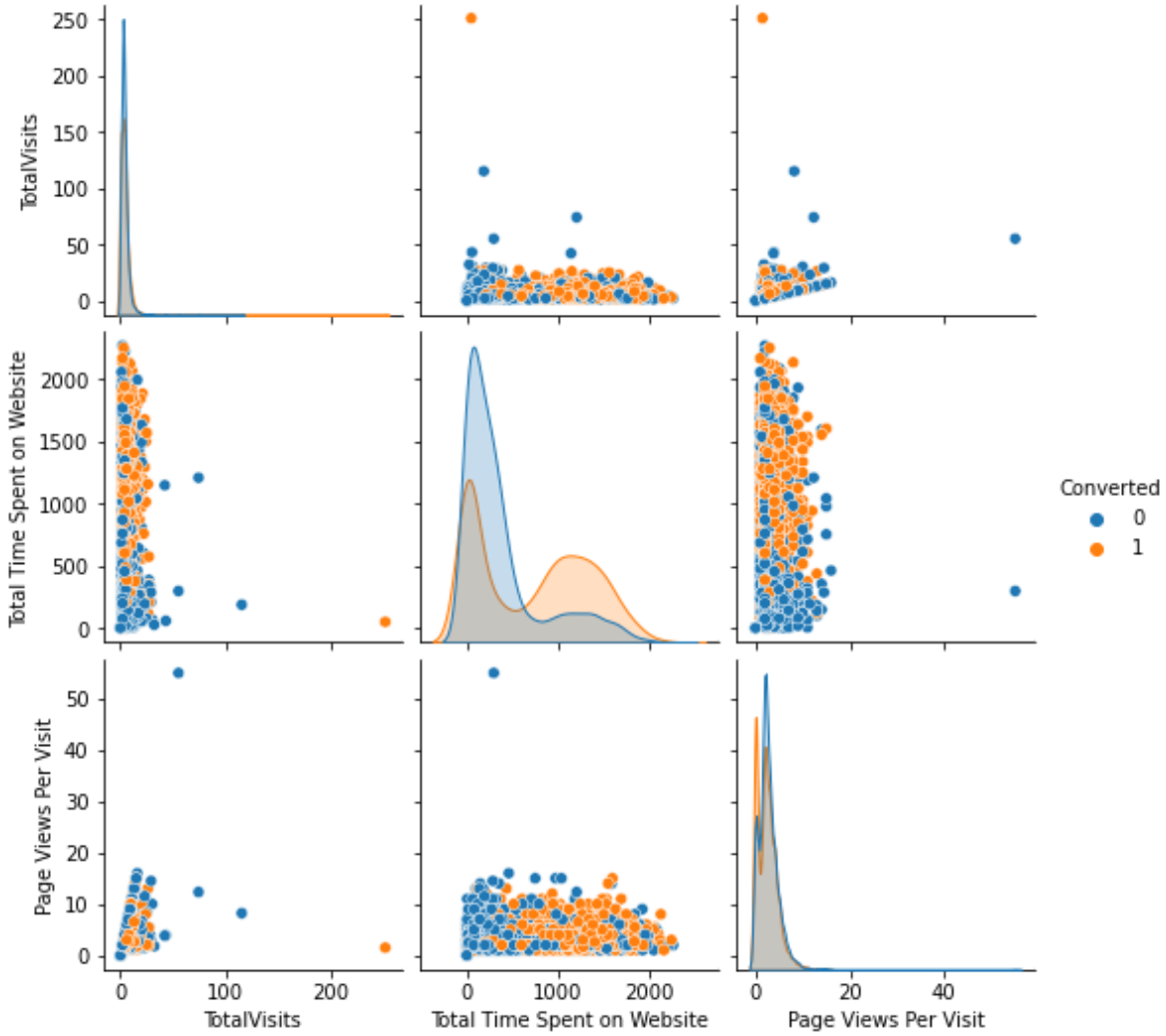
Out[45]:

	Lead Origin	Lead Source	Do Not Email	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Last Activity	Specializati
0	API	Olark Chat	No	0	0.0	0	0.0	Page Visited on Website	Sele
1	API	Organic Search	No	0	5.0	674	2.5	Email Opened	Sele
2	Landing Page Submission	Direct Traffic	No	1	2.0	1532	2.0	Email Opened	Busine Administrati
3	Landing Page Submission	Direct Traffic	No	0	1.0	305	1.0	Unreachable	Media a Advertisi
4	Landing Page Submission	Google	No	1	2.0	1428	1.0	Converted to Lead	Sele

Data Preparation

In [46]:

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



In [47]:

```
pt = PowerTransformer()
transformed_vals = pd.DataFrame(pt.fit_transform(leads[numeric_vars]))
transformed_vals.columns = numeric_vars
transformed_vals.head()
```

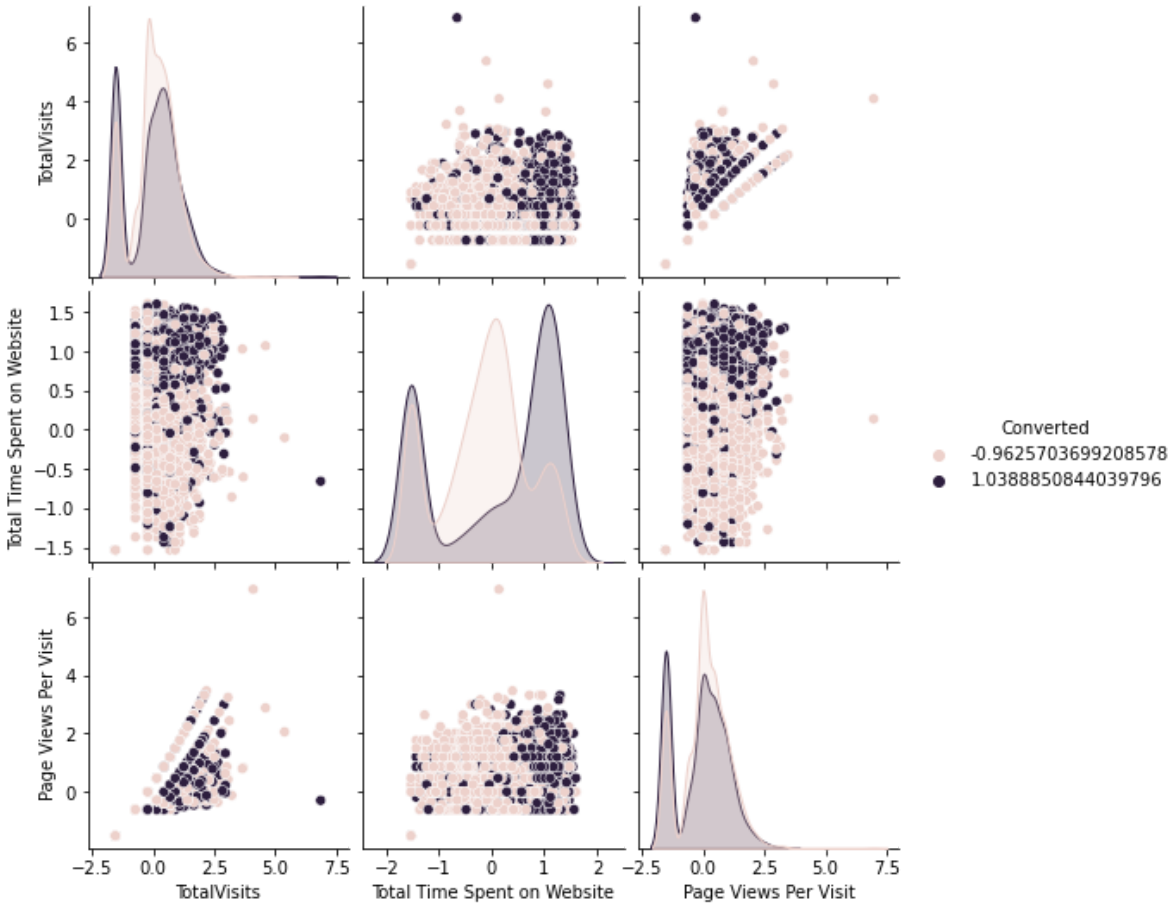
Out[47]:

	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Converted
0	-1.539988	-1.532509	-1.534722	-0.962570
1	0.690854	0.641870	0.230818	-0.962570
2	-0.219742	1.262512	-0.019004	1.038885
3	-0.723932	0.153656	-0.629842	-0.962570
4	-0.219742	1.204175	-0.629842	1.038885

The range of the numerical variables are wide which can make the vizualizationdifficult. Hence the power transformation is applied.

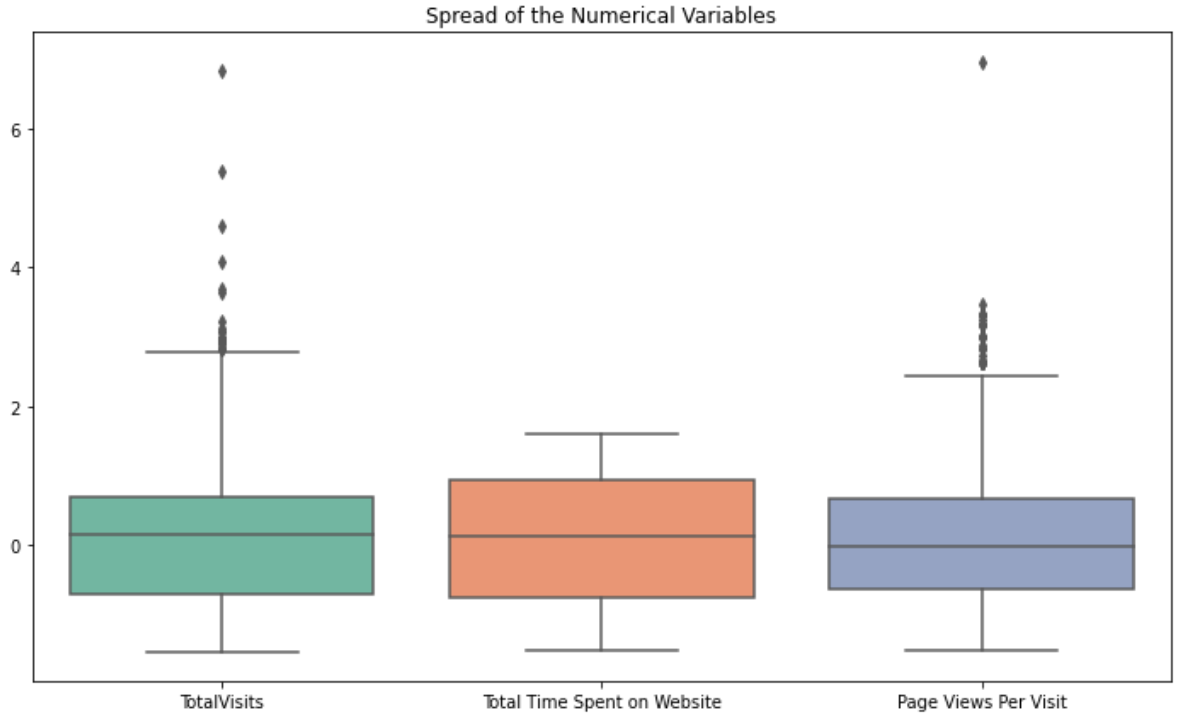
In [48]:

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



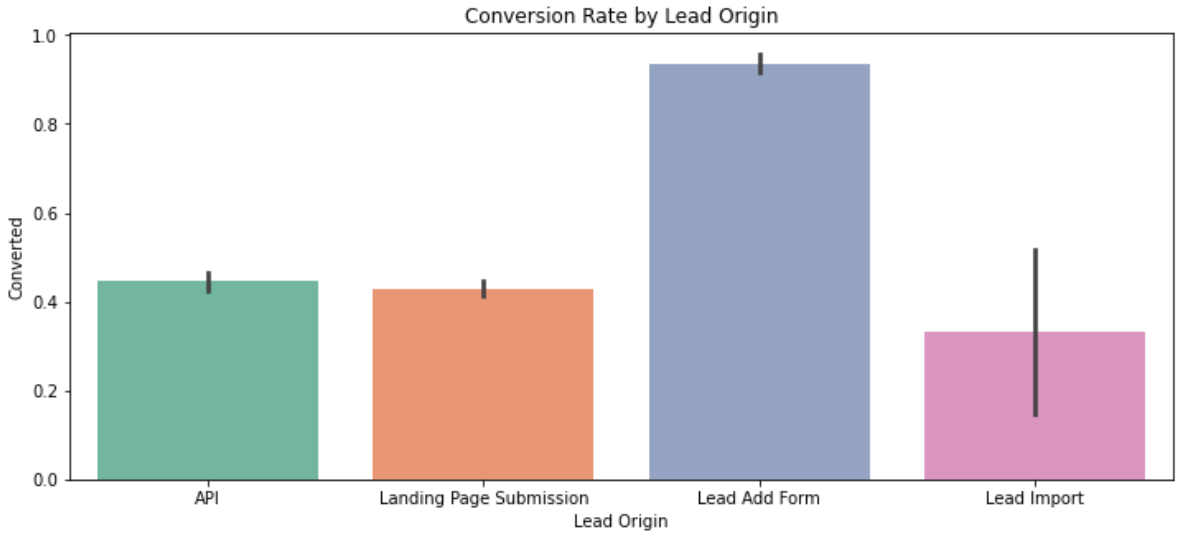
In [49]:

```
plt.figure(figsize=(12, 7))
plt.title("Spread of the Numerical Variables")
sns.boxplot(data=transformed_vals.drop(columns = "Converted"), palette="Set2")
plt.show()
```



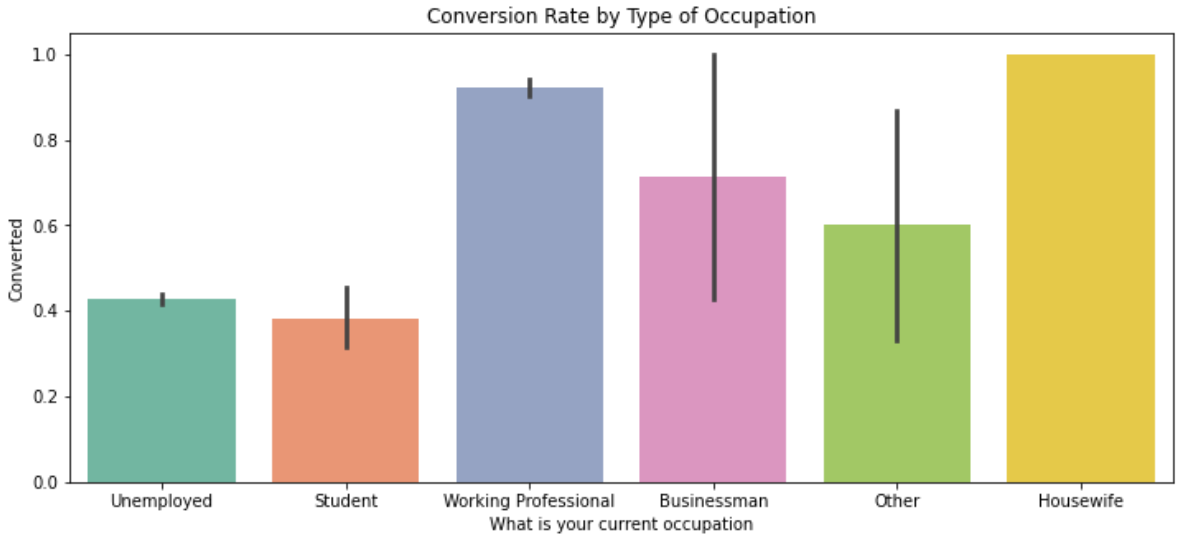
In [50]:

```
plt.figure(figsize=(12, 5))
plt.title("Conversion Rate by Lead Origin")
sns.barplot(data=leads, x="Lead Origin", y="Converted", palette="Set2")
plt.show()
```



In [51]:

```
plt.figure(figsize=(12, 5))
plt.title("Conversion Rate by Type of Occupation")
sns.barplot(data=leads, x="What is your current occupation", y="Converted", palette="Set2")
plt.show()
```



Group Categories having less number of values

In [52]:

```
leads.nunique()
```

Out[52]:

```
Lead Origin                                 4
Lead Source                                16
Do Not Email                                2
Converted                                   2
TotalVisits                                38
Total Time Spent on Website              1613
Page Views Per Visit                      107
Last Activity                              16
Specialization                             19
What is your current occupation             6
A free copy of Mastering The Interview      2
Last Notable Activity                      14
dtype: int64
```

In [53]:

```
lead_source_val_counts = leads["Lead Source"].value_counts()
lead_source_val_counts
```

Out[53]:

```
Google               2048
Direct Traffic       1873
Olark Chat            892
Organic Search        870
Reference             443
Welingak Website      129
Referral Sites         75
Facebook               28
Click2call              4
bing                    3
Live Chat               2
Social Media            2
testone                 1
Pay per Click Ads       1
Press_Release           1
WeLearn                 1
Name: Lead Source, dtype: int64
```

In [54]:

```
leads["Lead Source"] = leads["Lead Source"].apply(lambda x: "Other" if x in lead_source_val
```

In [55]:

```
leads["Lead Source"].value_counts()
```

Out[55]:

```
Google              2048
Direct Traffic      1873
Olark Chat           892
Organic Search       870
Reference            443
Welingak Website     129
Referral Sites        75
Other                 43
Name: Lead Source, dtype: int64
```

In [56]:

```
# Cannot be grouped since categories are too unique to group
leads["Last Activity"].value_counts()
```

Out[56]:

```
Email Opened                    2455
SMS Sent                        2189
Olark Chat Conversation          428
Page Visited on Website          427
Converted to Lead                292
Email Link Clicked               178
Email Bounced                    175
Form Submitted on Website         81
Unreachable                       71
Unsubscribed                      40
Had a Phone Conversation          23
Approached upfront                 5
View in browser link Clicked       4
Email Received                     2
Email Marked Spam                  2
Visited Booth in Tradeshow         1
Name: Last Activity, dtype: int64
```

In [57]:

```
# Cannot be grouped since categories are too unique to group
leads["Last Notable Activity"].value_counts()
```

Out[57]:

```
Email Opened                    2038
Modified                        1947
SMS Sent                        1869
Page Visited on Website          213
Email Link Clicked               110
Olark Chat Conversation           76
Email Bounced                     49
Unsubscribed                      31
Unreachable                       22
Had a Phone Conversation          13
Email Marked Spam                  2
Approached upfront                 1
Email Received                     1
View in browser link Clicked       1
Name: Last Notable Activity, dtype: int64
```

Encode categorical variables

In [58]:

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

Out[58]:

```
Select                               1838
Finance Management                    745
Human Resource Management             665
Marketing Management                  663
Operations Management                 391
Business Administration               310
IT Projects Management                278
Supply Chain Management               275
Banking, Investment And Insurance     266
Media and Advertising                 161
Travel and Tourism                    149
International Business                136
Healthcare Management                 122
Hospitality Management                 90
E-COMMERCE                             80
Retail Management                      78
Rural and Agribusiness                 58
E-Business                             43
Services Excellence                    25
Name: Specialization, dtype: int64
```

In [59]:

```
# Creating a dummy variable for the variable 'Specialization' since it has the level 'Selec
# therefore we remove it directly.

dummy_specialization = pd.get_dummies(leads["Specialization"], prefix="Specialization")
dummy_specialization = dummy_specialization.drop(columns=["Specialization_Select"])

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

In [60]:

```
# Create dummy variables for rest of the categorical varaibles

dummy = pd.get_dummies(leads[['Lead Origin', 'Lead Source', 'Do Not Email', 'Last Activity'
                              'What is your current occupation','A free copy of Mastering T
                              'Last Notable Activity']], drop_first=True)

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

In [61]:

```
# Remove the variables for which dummy variables were generated.

leads = leads.drop(columns = ['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'])
```

In [62]:

```
leads.head()
```

Out[62]:

	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Specialization_Banking, Investment And Insurance	Specialization_Business Administration	Spe
0	0	0.0	0	0.0	0	0	
1	0	5.0	674	2.5	0	0	
2	1	2.0	1532	2.0	0	1	
3	0	1.0	305	1.0	0	0	
4	1	2.0	1428	1.0	0	0	

5 rows × 67 columns

In [63]:

```
leads.shape
```

Out[63]:

```
(6373, 67)
```

Train Test Split

In [64]:

```
# Split the dataset into train and test sets in 7:3 ratio

X_train, X_test, y_train, y_test = train_test_split(leads.drop(columns="Converted"),
                                                    leads["Converted"],
                                                    train_size=0.7,
                                                    test_size=0.3,
                                                    random_state=100)
```

In [65]:

```
print("X Train:", X_train.shape)
print("y Train:", y_train.shape)
print("X Test:", X_test.shape)
print("y Test:", y_test.shape)
```

```
X Train: (4461, 66)
y Train: (4461,)
X Test: (1912, 66)
y Test: (1912,)
```

Normalization

In [66]:

```
# Since the dummies are already in a 0 and 1 range, scale the other numeric variables

scaler = MinMaxScaler()

num_vars = ['TotalVisits', 'Page Views Per Visit', 'Total Time Spent on Website']

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

X_train.head()
```

Out[66]:

	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Specialization_Banking, Investment And Insurance	Specialization_Business Administration	Specializatic Bus
8003	0.015936	0.029489	0.125	0	0	
218	0.015936	0.082306	0.250	0	0	
4171	0.023904	0.034331	0.375	0	0	
4037	0.000000	0.000000	0.000	0	0	
3660	0.000000	0.000000	0.000	0	0	

5 rows × 66 columns

In [67]:

```
X_train.isnull().sum().sum()
```

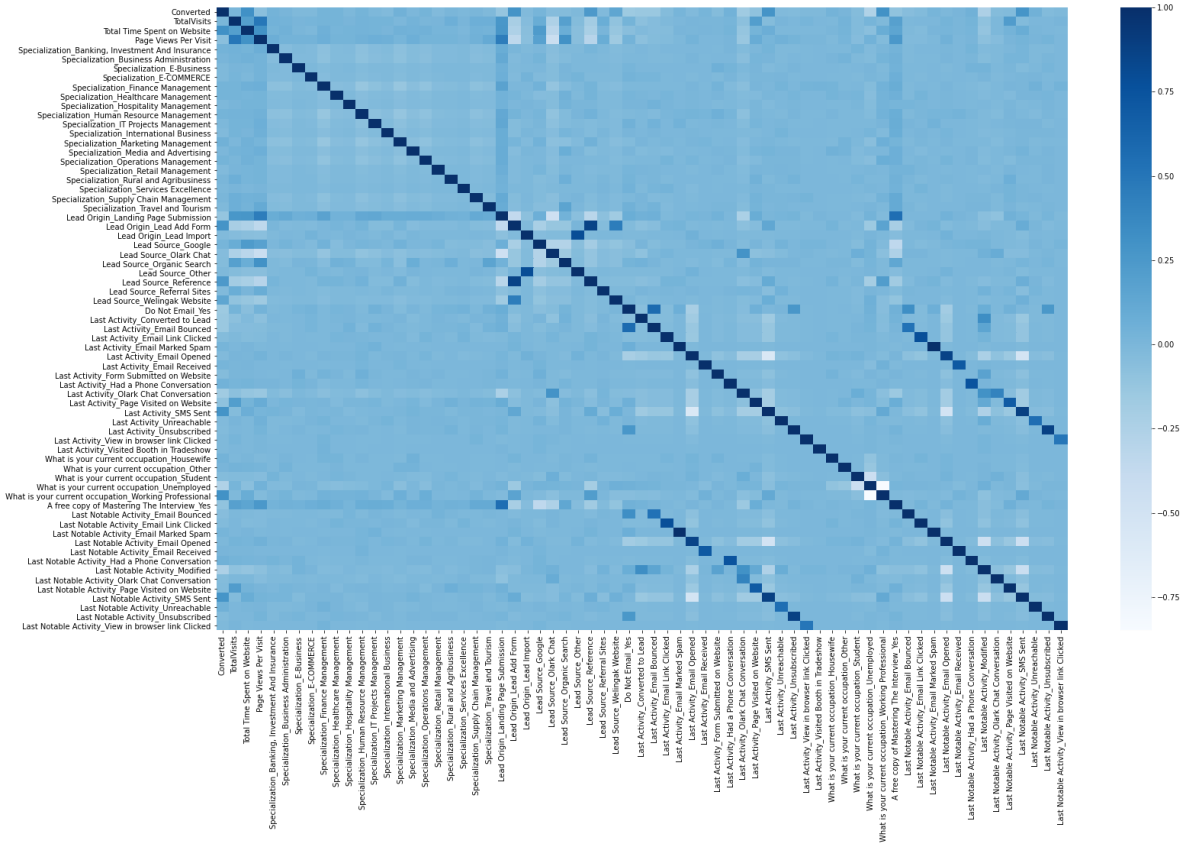
Out[67]:

```
0
```

Observe Corelation

In [68]:

```
plt.figure(figsize = (25,15))
sns.heatmap(leads.corr(), cmap="Blues")
plt.show()
```



We could see there is comparitively strong colurs on the top left corner of the heatmap, which indcates the numeric variables have better correlation with the target.

Model Building

Feature Selection

Since there are many features in the dataset it is not convenient to select them manually, hence in the first level the Recursive Feature Elimination technique is used. We will use the sklearn RFE class to automatically do the feature selection.

In [69]:

```
rfe = RFE(LogisticRegression(), n_features_to_select = 15)
rfe = rfe.fit(X_train, y_train)
```

In [70]:

```
def rfe_result(X_train, y_train, n_features_to_select):
    lm = LogisticRegression()
    lm.fit(X_train, y_train)
    rfe = RFE(lm, n_features_to_select = n_features_to_select)
    rfe = rfe.fit(X_train, y_train)
    return pd.DataFrame({"Feature":X_train.columns, "Support":rfe.support_, "Rank":rfe.rank
```

In [71]:

```
def rfe_rejects(X_train, y_train, n_features_to_select):
    rfe_df = rfe_result(X_train, y_train, n_features_to_select)
    return rfe_df[rfe_df.Support==False].sort_values(by="Rank", ascending=False)
```

In [72]:

```
# List of features rejected by RFE
rfe_rejs = rfe_rejects(X_train, y_train, n_features_to_select = 15)
rfe_rejs
```

Out[72]:

	Feature	Support	Rank
35	Last Activity_Email Marked Spam	False	52
57	Last Notable Activity_Email Received	False	51
55	Last Notable Activity_Email Marked Spam	False	50
9	Specialization_Hospitality Management	False	49
18	Specialization_Services Excellence	False	48
37	Last Activity_Email Received	False	47
27	Lead Source_Other	False	46
34	Last Activity_Email Link Clicked	False	45
46	Last Activity_Visited Booth in Tradeshow	False	44
48	What is your current occupation_Other	False	43
52	A free copy of Mastering The Interview_Yes	False	42
43	Last Activity_Unreachable	False	41
62	Last Notable Activity_SMS Sent	False	40
36	Last Activity_Email Opened	False	39
44	Last Activity_Unsubscribed	False	38
64	Last Notable Activity_Unsubscribed	False	37
45	Last Activity_View in browser link Clicked	False	36
60	Last Notable Activity_Olark Chat Conversation	False	35
61	Last Notable Activity_Page Visited on Website	False	34
16	Specialization_Retail Management	False	33
26	Lead Source_Organic Search	False	32
29	Lead Source_Referral Sites	False	31
24	Lead Source_Google	False	30
23	Lead Origin_Lead Import	False	29
65	Last Notable Activity_View in browser link Cli...	False	28
38	Last Activity_Form Submitted on Website	False	27
56	Last Notable Activity_Email Opened	False	26
41	Last Activity_Page Visited on Website	False	25
12	Specialization_International Business	False	24
14	Specialization_Media and Advertising	False	23
2	Page Views Per Visit	False	22
32	Last Activity_Converted to Lead	False	21
54	Last Notable Activity_Email Link Clicked	False	20

	Feature	Support	Rank
15	Specialization_Operations Management	False	19
11	Specialization_IT Projects Management	False	18
20	Specialization_Travel and Tourism	False	17
10	Specialization_Human Resource Management	False	16
4	Specialization_Business Administration	False	15
7	Specialization_Finance Management	False	14
19	Specialization_Supply Chain Management	False	13
13	Specialization_Marketing Management	False	12
5	Specialization_E-Business	False	11
8	Specialization_Healthcare Management	False	10
6	Specialization_E-COMMERCE	False	9
21	Lead Origin_Landing Page Submission	False	8
17	Specialization_Rural and Agribusiness	False	7
3	Specialization_Banking, Investment And Insurance	False	6
40	Last Activity_Olark Chat Conversation	False	5
33	Last Activity_Email Bounced	False	4
53	Last Notable Activity_Email Bounced	False	3
59	Last Notable Activity_Modified	False	2

In [73]:

```
# Choose only the columns selected by RFE

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

Now that we have all the RFE-selected variables, let's utilise them to develop a logistic regression model using statsmodels.

In [74]:

```
X_train_sm = sm.add_constant(X_train)
logmodel1 = sm.GLM(y_train, X_train_sm, family=sm.families.Binomial())
logmodel1 = logmodel1.fit()
logmodel1.summary()
```

Out[74]:

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:	Tue, 12 Jul 2022	**Deviance:**	4145.5
Time:	00:31:01	**Pearson chi2:**	4.84e+03
No. Iterations:	22		
Covariance Type:	nonrobust		

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

Many variables have p-values above.05. They'll represent a challenge. Let's look at VIFs then.

In [75]:

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

In [76]:

```
vif_result(X_train)
```

Out[76]:

	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 Profes...	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

Clearly, three features have a high vif value.

Let's drop Lead Source Reference, which has a high p-value and VIF.

In [77]:

```
X_train = X_train.drop(columns = "Lead Source_Reference")
```

In [78]:

```
logmodel2 = sm.GLM(y_train, sm.add_constant(X_train), family=sm.families.Binomial())
logmodel2 = logmodel2.fit()
logmodel2.summary()
```

Out[78]:

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:	Tue, 12 Jul 2022	**Deviance:**	4146.5
Time:	00:31:01	**Pearson chi2:**	4.82e+03
No. Iterations:	22		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.0057	0.600	-1.677	0.094	-2.181	0.170
TotalVisits	11.3428	2.682	4.229	0.000	6.086	16.599
Total Time Spent on Website	4.4312	0.185	23.924	0.000	4.068	4.794
Lead Origin_Lead Add Form	4.2084	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

In [79]:

```
vif_result(X_train)
```

Out[79]:

	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 Profes...	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

Droping the What is your current occupation_Housewife column based on p-value since vif is decent for all the features

In [80]:

```
X_train = X_train.drop(columns = "What is your current occupation_Housewife")
```

In [81]:

```
logmodel3 = sm.GLM(y_train, sm.add_constant(X_train), family=sm.families.Binomial())
logmodel3 = logmodel3.fit()
logmodel3.summary()
```

Out[81]:

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:**	-2075.5
Date:	Tue, 12 Jul 2022	**Deviance:**	4150.9
Time:	00:31:01	**Pearson chi2:**	4.82e+03
No. Iterations:	21		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.4519	0.554	-0.816	0.414	-1.537	0.633
TotalVisits	11.1469	2.667	4.179	0.000	5.919	16.375
Total Time Spent on Website	4.4291	0.185	23.922	0.000	4.066	4.792
Lead Origin_Lead Add Form	4.2058	0.258	16.275	0.000	3.699	4.712
Lead Source_Olark Chat	1.4532	0.122	11.932	0.000	1.215	1.692
Lead Source_Welingak Website	2.1542	1.037	2.078	0.038	0.122	4.186
Do Not Email_Yes	-1.5061	0.194	-7.783	0.000	-1.885	-1.127
Last Activity_Had a Phone Conversation	1.0400	0.983	1.058	0.290	-0.886	2.966
Last Activity_SMS Sent	1.1824	0.082	14.360	0.000	1.021	1.344
What is your current occupation_Student	-1.7030	0.588	-2.894	0.004	-2.856	-0.550
What is your current occupation_Unemployed	-1.8892	0.550	-3.437	0.001	-2.967	-0.812
What is your current occupation_Working Professional	0.7255	0.581	1.249	0.212	-0.413	1.864
Last Notable Activity_Had a Phone Conversation	22.1951	1.26e+04	0.002	0.999	-2.47e+04	2.48e+04
Last Notable Activity_Unreachable	2.7844	0.807	3.449	0.001	1.202	4.367

In [82]:

```
vif_result(X_train)
```

Out[82]:

	Features	VIF
9	What is your current occupation_Unemployed	3.64
6	Last Activity_Had a Phone Conversation	2.44
11	Last Notable Activity_Had a Phone Conversation	2.43
1	Total Time Spent on Website	2.37
2	Lead Origin_Lead Add Form	1.70
0	TotalVisits	1.62
7	Last Activity_SMS Sent	1.59
10	What is your current occupation_Working Profes...	1.56
3	Lead Source_Olark Chat	1.44
4	Lead Source_Welingak Website	1.33
5	Do Not Email_Yes	1.09
8	What is your current occupation_Student	1.09
12	Last Notable Activity_Unreachable	1.01

Drop the column Last Notable Activity_Had a Phone Conversation which has a high p-value

In [83]:

```
X_train = X_train.drop(columns = "Last Notable Activity_Had a Phone Conversation")
```

In [84]:

```
logmodel4 = sm.GLM(y_train, sm.add_constant(X_train), family=sm.families.Binomial())
logmodel4 = logmodel4.fit()
logmodel4.summary()
```

Out[84]:

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:	Tue, 12 Jul 2022	**Deviance:**	4156.7
Time:	00:31:01	**Pearson chi2:**	4.83e+03
No. Iterations:	7		
Covariance Type:	nonrobust		

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

In [85]:

```
vif_result(X_train)
```

Out[85]:

	Features	VIF
9	What is your current occupation_Unemployed	3.64
1	Total Time Spent on Website	2.37
2	Lead Origin_Lead Add Form	1.70
0	TotalVisits	1.62
7	Last Activity_SMS Sent	1.59
10	What is your current occupation_Working Profes...	1.56
3	Lead Source_Olark Chat	1.44
4	Lead Source_Welingak Website	1.33
5	Do Not Email_Yes	1.09
8	What is your current occupation_Student	1.09
6	Last Activity_Had a Phone Conversation	1.01
11	Last Notable Activity_Unreachable	1.01

Drop the column What is your current occupation_Working Professional which has a high p-value

In [86]:

```
X_train = X_train.drop(columns = "What is your current occupation_Working Professional")
```

In [87]:

```
logmodel5 = sm.GLM(y_train, sm.add_constant(X_train), family=sm.families.Binomial())
logmodel5 = logmodel5.fit()
logmodel5.summary()
```

Out[87]:

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:	Tue, 12 Jul 2022	**Deviance:**	4158.1
Time:	00:31:02	**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_Olark 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

In [88]:

```
vif_result(X_train)
```

Out[88]:

	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_Olark 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

Now, the p-values and VIFs seem to be acceptable for all variables.

Model Evaluation

Predict y_train

In [89]:

```
y_train_pred = logmodel5.predict(sm.add_constant(X_train))
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]
```

Out[89]:

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

Bind actual output and the predicted probability

In [90]:

```
# Establish a new dataframe with the conversion flag and estimated probabilities.

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

Out[90]:

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

1 in 'Predicted' if Paid Prob > 0.5 otherwise 0

In [91]:

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

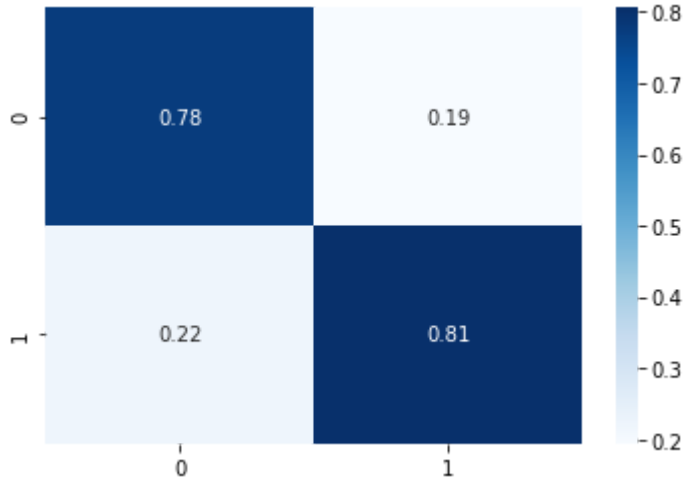
Out[91]:

	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

Confusion Matrix

In [92]:

```
confusion = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final.Predi
sns.heatmap(confusion / sum(confusion), annot=True, cmap="Blues")
plt.show()
```



In [93]:

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

Check the overall accuracy

In [94]:

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

Out[94]:

```
0.7886124187401928
```

Check Sensitivity/Recall

In [95]:

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

Out[95]:

```
0.739413680781759
```

Check Specificity

In [96]:

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

Out[96]:

```
0.8343425605536332
```

Check Precision

In [97]:

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

Out[97]:

```
0.8057809330628803
```

Find the Optimal Probability Cutoff

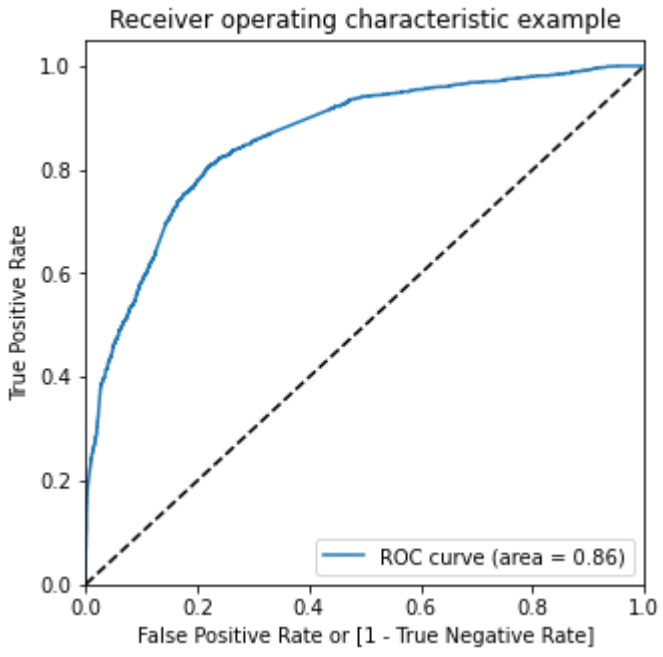
To get better performance, we must optimise the threshold. Let's start by plotting a ROC curve to check what AUC we receive.

In [98]:

```
def Plot_roc_curve( 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()
```

In [99]:

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



The area under the curve is good. Let's also look at the sensitivity vs. specificity tradeoff to determine the best cutoff point.

In [100]:

```
for i in [n/10 for n in range(10)]:
    y_train_pred_final[i]= y_train_pred_final.Conversion_Prob.map(lambda x: 1 if x > i else
y_train_pred_final.head()
```

Out[100]:

	Converted	Conversion_Prob	Predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	0	0.300117	0	1	1	1	1	0	0	0	0	0	0
1	0	0.142002	0	1	1	0	0	0	0	0	0	0	0
2	1	0.127629	0	1	1	0	0	0	0	0	0	0	0
3	1	0.291558	0	1	1	1	0	0	0	0	0	0	0
4	1	0.954795	1	1	1	1	1	1	1	1	1	1	1

In [101]:

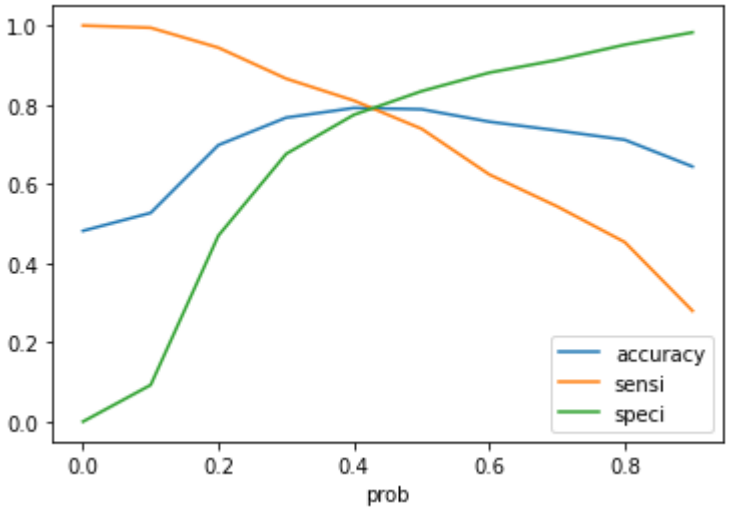
```
cutoff_df = pd.DataFrame( columns=['prob','accuracy','sensi','speci'])

for i in [n/10 for n in range(10)]:
    cm = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final[i])
    total=sum(sum(cm))
    accuracy = (cm[0,0]+cm[1,1])/total

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

cutoff_df
```

Out[101]:

	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

In [102]:

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



Let's choose 0.42 as our cutoff value, since the best values for the three measures occur about 0.42.

In [103]:

```
y_train_pred_final['final_predicted'] = y_train_pred_final.Conversion_Prob.map(lambda x: 1
y_train_pred_final.head()
```

Out[103]:

	Converted	Conversion_Prob	Predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	final_
0	0	0.300117	0	1	1	1	1	0	0	0	0	0	0	
1	0	0.142002	0	1	1	0	0	0	0	0	0	0	0	
2	1	0.127629	0	1	1	0	0	0	0	0	0	0	0	
3	1	0.291558	0	1	1	1	0	0	0	0	0	0	0	
4	1	0.954795	1	1	1	1	1	1	1	1	1	1	1	

In [104]:

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

Out[104]:

```
0.7908540685944856
```

In [105]:

```
confusion = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final.final
confusion
```

Out[105]:

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

In [106]:

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

Sensitivity for P=4.2

In [107]:

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

Out[107]:

```
0.793392275476966
```

Specificity for P=4.2

In [108]:

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

Out[108]:

```
0.7884948096885813
```

Test perfomance using Test Dataset

Apply necessary transformation to the test data set

In [109]:

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

In [110]:

```
X_test_sm = sm.add_constant(X_test[X_train.columns])
X_test_sm.head()
```

Out[110]:

	const	TotalVisits	Total Time Spent on Website	Lead Origin_Lead Add Form	Lead Source_Olark Chat	Lead Source_Welingak Website	Do Not Email_Yes	A Co
4771	1.0	0.000000	0.000000	1	0	0	0	
6122	1.0	0.027888	0.029049	0	0	0	0	
9202	1.0	0.015936	0.416813	0	0	0	0	
6570	1.0	0.011952	0.378961	0	0	0	1	
2668	1.0	0.031873	0.395246	0	0	0	0	

Make predictions on the test Data set

In [111]:

```
y_test_pred = pd.DataFrame(y_test)
y_test_pred["Conversion_Prob"] = logmodel5.predict(X_test_sm)
y_test_pred['final_predicted'] = y_test_pred.Conversion_Prob.map(lambda x: 1 if x > 0.42 el
y_test_pred.head()
```

Out[111]:

	Converted	Conversion_Prob	final_predicted
4771	1	0.996296	1
6122	0	0.129992	0
9202	0	0.703937	1
6570	1	0.299564	0
2668	1	0.720796	1

In [112]:

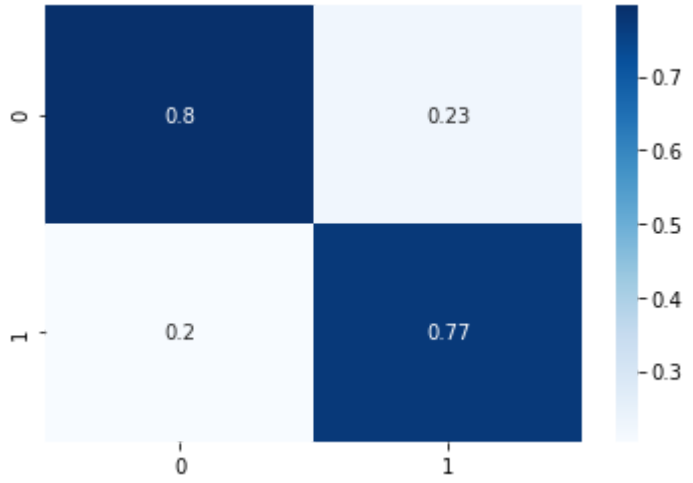
```
metrics.accuracy_score(y_test_pred['Converted'], y_test_pred.final_predicted)
```

Out[112]:

```
0.7845188284518828
```

In [113]:

```
confusion = metrics.confusion_matrix(y_test_pred.Converted, y_test_pred.final_predicted )
sns.heatmap(confusion / sum(confusion), annot=True, cmap="Blues")
plt.show()
```



In [114]:

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

Sensitivity

In [115]:

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

Out[115]:

```
0.7794759825327511
```

Specificity

In [116]:

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

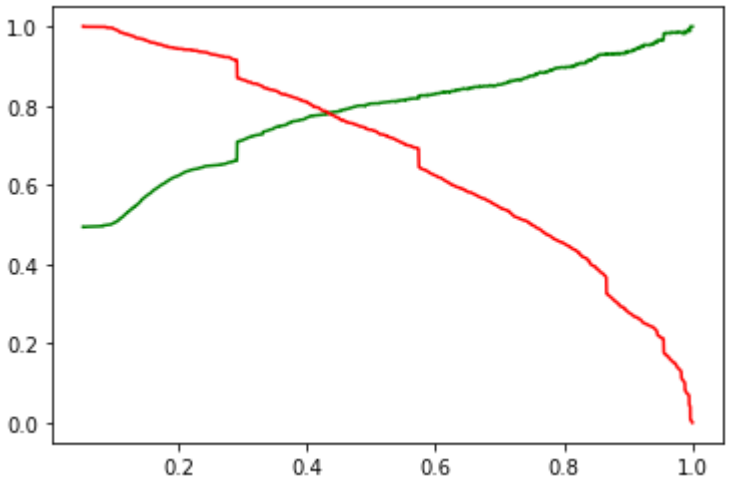
Out[116]:

```
0.7891566265060241
```

Precision-Recall Score

In [117]:

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



We will fix the probability threshold to same 4.2, since the precision-recall curve also gives a cut-off aroung 4.2 but in other cases we could go ahead and test the new thresholds.

Feature Importance

In [118]:

```
feature_imp = pd.DataFrame(logmodel5.params.reset_index())
feature_imp.columns = ["Feature", "Coefficient"]
feature_imp
```

Out[118]:

	Feature	Coefficient
0	const	0.204037
1	TotalVisits	11.148912
2	Total Time Spent on Website	4.422291
3	Lead Origin_Lead Add Form	4.205123
4	Lead Source_Olark Chat	1.452589
5	Lead Source_Welingak Website	2.152559
6	Do Not Email_Yes	-1.503680
7	Last Activity_Had a Phone Conversation	2.755220
8	Last Activity_SMS Sent	1.185594
9	What is your current occupation_Student	-2.357784
10	What is your current occupation_Unemployed	-2.544455
11	Last Notable Activity_Unreachable	2.784594

In [119]:

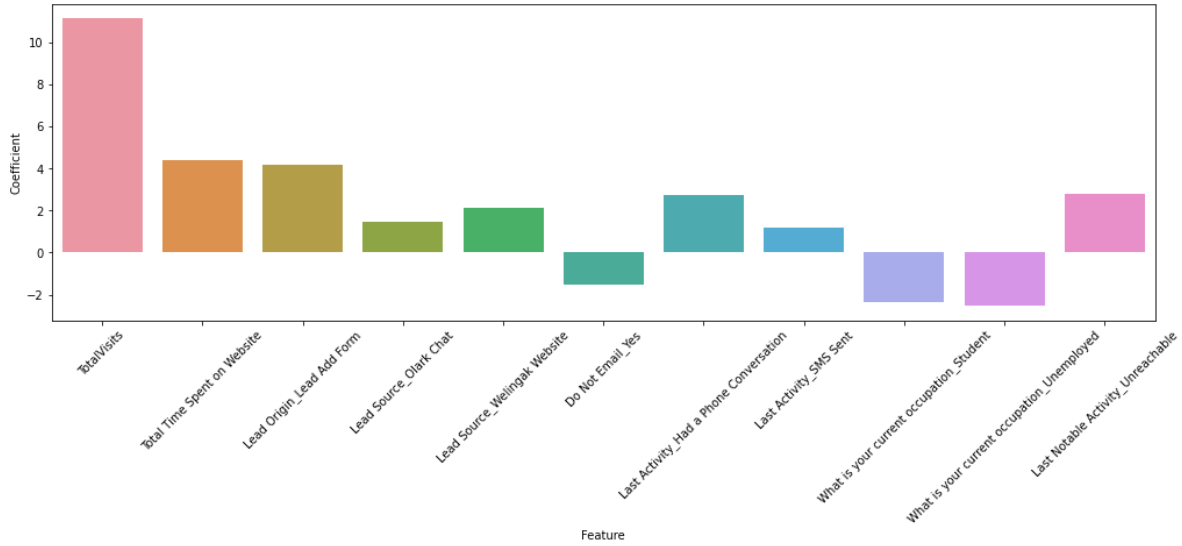
```
feature_imp[feature_imp.Feature != "const"].sort_values(by="Coefficient", ascending=False)
```

Out[119]:

	Feature	Coefficient
1	TotalVisits	11.148912
2	Total Time Spent on Website	4.422291
3	Lead Origin_Lead Add Form	4.205123
11	Last Notable Activity_Unreachable	2.784594
7	Last Activity_Had a Phone Conversation	2.755220
5	Lead Source_Welingak Website	2.152559
4	Lead Source_Olark Chat	1.452589
8	Last Activity_SMS Sent	1.185594
6	Do Not Email_Yes	-1.503680
9	What is your current occupation_Student	-2.357784
10	What is your current occupation_Unemployed	-2.544455

In [120]:

```
plt.figure(figsize=(17, 5))
plot = sns.barplot(data = feature_imp[feature_imp.Feature != "const"], x="Feature", y="Coef
plt.xticks(rotation=45)
plt.show()
```



Results

Three features that contribute the most to the lead conversion probability

1. Total Visits
2. Total Time Spent on Website
3. Lead Origin Lead Add Form

Two features that negatively influence the likelihood of a lead conversion

1. What is your current occupation Student
2. What is your current occupation Unemployed