X Education: Hot Leads for a focussed sales follow-up.

Problem Statement:

X Education gets a lot of leads, but their lead conversion rate is poor.

Solution Statement:

Many leads in sales funnel are not actual potential students but some of them are very potential leads.
Solution is to identify the high potential prospective students and focus the sales follow-up activities on pursuing these hot leads.

Task:

Identify the potential leads from the response and sales activity data and score them accordingly.
The driving questions are:

1. Which responses are significant in predicting whether the lead will convert to a sale or not?
2. Generate a score for the convertible leads based on the probability of how potential a lead each of them could be.
3. Find who are the Hot Leads based on the above score so that the sales team can focus their effort on those leads.

Solution

Step 1: Import and Inspect Data

In [1]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
import pandas as pd
import numpy as np
```

In [3]:
```
data=pd.read_csv('Leads.csv')
pd.set_option('max_columns',None)
```

In [4]:
```
data.head()
```

Out[4]:

	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
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	660737	API	Olark Chat	No	No	0	0.0	0	0.0	Page Visited on Website	NaN	Select
1	2a272436-5132-4136-86fa-dcc88c88f482	660728	API	Organic Search	No	No	0	5.0	674	2.5	Email Opened	India	Select
2	8cc8c611-a219-4f35-ad23-fdfd2656bd8a	660727	Landing Page Submission	Direct Traffic	No	No	1	2.0	1532	2.0	Email Opened	India	Business Administration
3	0cc2df48-7cf4-4e39-9de9-19797f9b38cc	660719	Landing Page Submission	Direct Traffic	No	No	0	1.0	305	1.0	Unreachable	India	Media and Advertising
4	3256f628-e534-4826-9d63-4a8b88782852	660681	Landing Page Submission	Google	No	No	1	2.0	1428	1.0	Converted to Lead	India	Select

In [5]:
```
data.columns
```

Out[5]:
```
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')
```

In [6]:
```
data.shape
```

Out[6]:
```
(9240, 37)
```

Inspecting Missing Values

In [7]:
```
data.isna().sum()
```

Out[7]:
```
Prospect ID                                         0
Lead Number                                         0
Lead Origin                                         0
Lead Source                                        36
Do Not Email                                        0
Do Not Call                                         0
Converted                                           0
TotalVisits                                       137
Total Time Spent on Website                         0
Page Views Per Visit                              137
Last Activity                                     103
Country                                          2461
Specialization                                   1438
How did you hear about X Education               2207
What is your current occupation                  2690
What matters most to you in choosing a course    2709
Search                                              0
Magazine                                            0
Newspaper Article                                   0
X Education Forums                                  0
Newspaper                                           0
Digital Advertisement                               0
Through Recommendations                             0
Receive More Updates About Our Courses              0
Tags                                             3353
Lead Quality                                     4767
Update me on Supply Chain Content                   0
Get updates on DM Content                           0
Lead Profile                                     2709
City                                             1420
Asymmetrique Activity Index                      4218
Asymmetrique Profile Index                       4218
Asymmetrique Activity Score                      4218
Asymmetrique Profile Score                       4218
I agree to pay the amount through cheque            0
A free copy of Mastering The Interview              0
Last Notable Activity                               0
dtype: int64
```

Checking percentage of missing values

In [8]:
```
round(100*(data.isna().sum()/len(data.index)), 2)
```

Out[8]:
```
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
Country                                          26.63
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
Tags                                             36.29
Lead Quality                                     51.59
Update me on Supply Chain Content                 0.00
Get updates on DM Content                         0.00
Lead Profile                                     29.32
City                                             15.37
Asymmetrique Activity Index                      45.65
Asymmetrique Profile Index                       45.65
Asymmetrique Activity Score                      45.65
Asymmetrique Profile Score                       45.65
I agree to pay the amount through cheque          0.00
A free copy of Mastering The Interview            0.00
Last Notable Activity                             0.00
dtype: float64
```

Descriptive statistics

In [9]:
```
data.describe()
```

Out[9]:

	Lead Number	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Asymmetrique Activity Score	Asymmetrique Profile Score
count	9240.000000	9240.000000	9103.000000	9240.000000	9103.000000	5022.000000	5022.000000
mean	617188.435606	0.385390	3.445238	487.698268	2.362820	14.306252	16.344883
std	23405.995698	0.486714	4.854853	548.021466	2.161418	1.386694	1.811395
min	579533.000000	0.000000	0.000000	0.000000	0.000000	7.000000	11.000000
25%	596484.500000	0.000000	1.000000	12.000000	1.000000	14.000000	15.000000
50%	615479.000000	0.000000	3.000000	248.000000	2.000000	14.000000	16.000000
75%	637387.250000	1.000000	5.000000	936.000000	3.000000	15.000000	18.000000
max	660737.000000	1.000000	251.000000	2272.000000	55.000000	18.000000	20.000000

Inspect Data

In [10]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9240 entries, 0 to 9239
Data columns (total 37 columns):
 #   Column                                         Non-Null Count  Dtype
---  ------                                         --------------  -----
 0   Prospect ID                                    9240 non-null   object
 1   Lead Number                                    9240 non-null   int64
 2   Lead Origin                                    9240 non-null   object
 3   Lead Source                                    9204 non-null   object
 4   Do Not Email                                   9240 non-null   object
 5   Do Not Call                                    9240 non-null   object
 6   Converted                                      9240 non-null   int64
 7   TotalVisits                                    9103 non-null   float64
 8   Total Time Spent on Website                    9240 non-null   int64
 9   Page Views Per Visit                           9103 non-null   float64
 10  Last Activity                                  9137 non-null   object
 11  Country                                        6779 non-null   object
 12  Specialization                                 7802 non-null   object
 13  How did you hear about X Education             7033 non-null   object
 14  What is your current occupation                6550 non-null   object
 15  What matters most to you in choosing a course  6531 non-null   object
 16  Search                                         9240 non-null   object
 17  Magazine                                       9240 non-null   object
 18  Newspaper Article                              9240 non-null   object
 19  X Education Forums                             9240 non-null   object
 20  Newspaper                                      9240 non-null   object
 21  Digital Advertisement                          9240 non-null   object
 22  Through Recommendations                        9240 non-null   object
 23  Receive More Updates About Our Courses         9240 non-null   object
 24  Tags                                           5887 non-null   object
 25  Lead Quality                                   4473 non-null   object
 26  Update me on Supply Chain Content              9240 non-null   object
 27  Get updates on DM Content                      9240 non-null   object
 28  Lead Profile                                   6531 non-null   object
 29  City                                           7820 non-null   object
 30  Asymmetrique Activity Index                    5022 non-null   object
 31  Asymmetrique Profile Index                     5022 non-null   object
 32  Asymmetrique Activity Score                    5022 non-null   float64
 33  Asymmetrique Profile Score                     5022 non-null   float64
 34  I agree to pay the amount through cheque       9240 non-null   object
 35  A free copy of Mastering The Interview         9240 non-null   object
 36  Last Notable Activity                          9240 non-null   object
dtypes: float64(4), int64(3), object(30)
memory usage: 2.6+ MB
```

Step 2: Data Preparation (Missing Values, Insignificant Columns, Categorical Variables, Outliers etc)

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

In [11]:
```
## The following columns are Binary Variables:
# Do Not Email, 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 chequ
e,
# A free copy of Mastering The Interview

varlist=["Do Not Email","Do Not Call", "Search", "Magazine", "Newspaper Article", "X Education Forums",
 "Newspaper", "Digital Advertisement", "Through Recommendations", "Receive More Updates About Our Cours
es", "Update me on Supply Chain Content", "Get updates on DM Content", "I agree to pay the amount throu
gh cheque", "A free copy of Mastering The Interview"]
def binary_map(x):
    return x.map({'Yes':1,'No':0})
data[varlist]=data[varlist].apply(binary_map)

data.head()
```

Out[11]:

	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
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	660737	API	Olark Chat	0	0	0	0.0	0	0.0	Page Visited on Website	NaN	Select
1	2a272436-5132-4136-86fa-dcc88c88f482	660728	API	Organic Search	0	0	0	5.0	674	2.5	Email Opened	India	Select
2	8cc8c611-a219-4f35-ad23-fdfd2656bd8a	660727	Landing Page Submission	Direct Traffic	0	0	1	2.0	1532	2.0	Email Opened	India	Business Administration
3	0cc2df48-7cf4-4e39-9de9-19797f9b38cc	660719	Landing Page Submission	Direct Traffic	0	0	0	1.0	305	1.0	Unreachable	India	Media and Advertising
4	3256f628-e534-4826-9d63-4a8b88782852	660681	Landing Page Submission	Google	0	0	1	2.0	1428	1.0	Converted to Lead	India	Select

Categorical Variables

One of the following strategies are used:

1. Drop missing/unanswered
2. Impute with modes
3. Drop columns having a significant number of same responses
4. Reduce number of levels (to optimize on the dummy variables)

1. Lead Source

In [12]:
```
data['Lead Source'].value_counts()
```

Out[12]:
```
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
Social Media            2
Live Chat               2
Press_Release           2
welearnblog_Home        1
Pay per Click Ads       1
blog                    1
WeLearn                 1
youtubechannel          1
NC_EDM                  1
testone                 1
Name: Lead Source, dtype: int64
```

In [13]:
```
source=['Facebook','bing','google','Click2call','Press_Release','Live Chat','Social Media','welearnblog
_Home','blog','WeLearn','testone','Pay per Click Ads','youtubechannel','NC_EDM']
```

In [14]:
```
data['Lead Source']=data['Lead Source'].apply(lambda x: 'Others' if x in source else x)
```

In [15]:
```
data['Lead Source'].value_counts()
```

Out[15]:
```
Google              2868
Direct Traffic      2543
Olark Chat          1755
Organic Search      1154
Reference            534
Welingak Website     142
Referral Sites       125
Others                83
Name: Lead Source, dtype: int64
```

In [16]:
```
data['Lead Source'].fillna(data['Lead Source'].mode()[0],inplace=True)
```

In [17]:
```
data['Lead Source'].isnull().sum()
```

Out[17]:
```
0
```

2. Total Visits

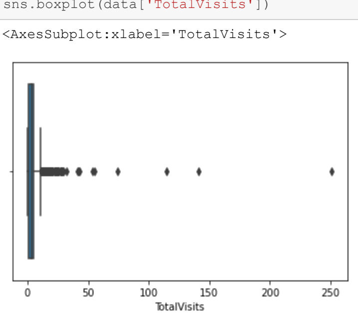
In [18]:
```
data['TotalVisits'].describe()
```

Out[18]:
```
count    9103.000000
mean        3.445238
std         4.854853
min         0.000000
25%         1.000000
50%         3.000000
75%         5.000000
max       251.000000
Name: TotalVisits, dtype: float64
```

In [19]:
```
import seaborn as sns
```

In [20]:
```
sns.boxplot(data['TotalVisits'])
```

Out[20]:
```
<AxesSubplot:xlabel='TotalVisits'>
```



In [21]:
```
data['TotalVisits'].fillna(data['TotalVisits'].mode()[0],inplace=True)
```

3. Country and Specialization

In [22]:
```
data['Country'].value_counts()
```

Out[22]:
```
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
South Africa               4
Canada                     4
Kuwait                     4
Nigeria                    4
Sweden                     3
Philippines                2
Uganda                     2
Belgium                    2
Ghana                      2
Asia/Pacific Region        2
China                      2
Bangladesh                 2
Italy                      2
Netherlands                2
Liberia                    1
Vietnam                    1
Sri Lanka                  1
Tanzania                   1
Indonesia                  1
Denmark                    1
Malaysia                   1
Switzerland                1
Russia                     1
Kenya                      1
Name: Country, dtype: int64
```

In [23]:
```
data['Country'].fillna(data['Country'].mode()[0],inplace=True)
```

In [24]:
```
data['Specialization'].value_counts()
```

Out[24]:
```
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
```

In [25]:
```
data.shape
```

Out[25]:
```
(9240, 37)
```

In [26]:
```
data['Specialization'].fillna(data['Specialization'].mode()[0],inplace=True)
```

4. 'How did you hear about X Education'

In [27]:
```
data['How did you hear about X Education'].value_counts()
```

Out[27]:
```
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 [28]:
```
data['How did you hear about X Education'].fillna(data['How did you hear about X Education'].mode()[0],
inplace=True)
```

Note:
A Large percentage of students has not choosen this option So column can be dropped

In [29]:
```
data.drop('How did you hear about X Education',1,inplace=True)
```

5. 'What is your current occupation'

In [30]:
```
data['What is your current occupation'].value_counts()
```

Out[30]:
```
Unemployed              5600
Working Professional     706
Student                  210
Other                     16
Housewife                 10
Businessman                8
Name: What is your current occupation, dtype: int64
```

In [31]:
```
data['What is your current occupation'].fillna(data['What is your current occupation'].mode()[0],inplac
e=True)
```

In [32]:
```
data['What is your current occupation']=data['What is your current occupation'].apply(lambda x: 'Unempl
oyed' if x in['Student','Other','Housewife','Businessman'] else x)
```

In [33]:
```
data['What is your current occupation'].value_counts()
```

Out[33]:
```
Unemployed              8534
Working Professional     706
Name: What is your current occupation, dtype: int64
```

6. 'What matters most to you in choosing a course'

In [34]:
```
data['What matters most to you in choosing a course'].value_counts()
```

Out[34]:
```
Better Career Prospects      6528
Flexibility & Convenience       2
Other                           1
Name: What matters most to you in choosing a course, dtype: int64
```

In [35]:
```
data['What matters most to you in choosing a course'].fillna(data['What matters most to you in choosing
 a course'].mode()[0],inplace=True)
```

In [36]:
```
data['Better Career Prospects']=data['What matters most to you in choosing a course'].apply(lambda x: 1
 if x=='Better Career Prospects' else 0)
```

In [37]:
```
data['Better Career Prospects'].value_counts()
```

Out[37]:
```
1    9237
0       3
Name: Better Career Prospects, dtype: int64
```

Note:

> For the variable **'What matters most to you in choosing a course'**, almost all of the values is 'Better Career Prospects'.
> This means the variable is not going to vary its effect in the model significantly for different prospects.
> While this possibly could be a crucial business insight, this will be insignificant for the model. Thus dropping this column

In [38]:
```
data.drop('What matters most to you in choosing a course',1,inplace=True)
```

7. Tags

By data dictionary, this column is filled by the sales person after making a call. This could be a potentially significant column

In [39]:
```
data['Tags'].value_counts()
```

Out[39]:
```
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
In confusion whether part time or DLP                   5
Interested in Next batch                                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
```

In [40]:
```
data['Tags'].isnull().sum()
```

Out[40]:
```
3353
```

In [41]:
```
data['Tags'].fillna(data['Tags'].mode()[0],inplace=True)
```

Tags are having too many levels. These are binned into three broad categories:

1. *Tags_DeadEnd*: Possible Dead-End calls as tagged by the sales people.

   > Not doing further education, invalid number, wrong number given, Diploma holder (Not Eligible),'opp hangup','number not provided','Lost to Others','Closed by Horizzon'

2. *Tags_UnclearLeads*: Calls with no clear idea as tagged by the sales people.

   > ringing,switched off,busy,Lost to EINS, in touch with EINS,'Graduation in progress','Lateral student','Recognition issue (DEC approval)','University not recognised'

3. *Tags_ReasonedLeads*: Calls where some reason was provided by the leads tagged by the sales people.

   > 'Will Revert after reading the email','Interested in other courses','Already a student','Interested in full time MBA','Still Thinking','Want to take admission but has financial problems','Interested in Next batch','In confusion wheather part time or DLP','Shall take in next coming month'

In [42]:
```
tags_0=['Not doing further education', 'invalid number', 'wrong number given','Diploma holder (Not Elig
ible)','opp hangup','number not provided','Lost to Others','Closed by Horizzon']
tags_1=['ringing','switched off','busy','Lost to EINS', 'in touch with EINS','Graduation in progress',
'Lateral student','Recognition issue (DEC approval)','University not recognised']
tags_2=['Will Revert after reading the email','Interested in other courses','Already a student','Intere
sted in full time MBA','Still Thinking','Want to take admission but has financial problems','Interested
 in Next batch','In confusion wheather part time or DLP','Shall take in next coming month']
```

In [43]:
```
data['Tags_DeadEnd']=data['Tags'].apply(lambda x: 1 if x in tags_0 else 0)
```

In [44]:
```
data['Tags_UnclearLeads']=data['Tags'].apply(lambda x: 1 if x in tags_1 else 0)
data['Tags_ReasonedLeads']=data['Tags'].apply(lambda x: 1 if x in tags_2 else 0)
```

In [45]:
```
data.drop('Tags',1,inplace=True)
```

8. Lead Quality, 'Lead Profile'

In [46]:
```
data['Lead Quality'].value_counts()
```

Out[46]:
```
Might be             1560
Not Sure             1092
High in Relevance     637
Worst                 601
Low in Relevance      583
Name: Lead Quality, dtype: int64
```

In [47]:
```
data['Lead Quality'].fillna(data['Lead Quality'].mode()[0],inplace=True)
```

In [48]:
```
data['Lead Quality']=data['Lead Quality'].apply(lambda x: 'Not Sure_Low Rel' if x in ['Not Sure','Low i
n Relevance'] else x)
```

In [49]:
```
data['Lead Quality'].value_counts()
```

Out[49]:
```
Might be             6327
Not Sure_Low Rel     1675
High in Relevance     637
Worst                 601
Name: Lead Quality, dtype: int64
```

In [50]:
```
data['Lead Profile'].value_counts()
```

Out[50]:
```
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 [51]:
```
data['Lead Profile'].fillna(data['Lead Profile'].mode()[0],inplace=True)
```

In [52]:
```
data['Lead Profile']=data['Lead Profile'].apply(lambda x: 'Other Leads' if x in ['Student of SomeSchoo
l','Lateral Student','Dual Specialization Student','Select'] else x)
```

In [53]:
```
data['Lead Profile'].value_counts()
```

Out[53]:
```
Other Leads       7627
Potential Lead    1613
Name: Lead Profile, dtype: int64
```

9. City, 'Asymmetrique Activity Index', 'Asymmetrique Activity Score'

In [54]:
```
data['City'].value_counts()
```

Out[54]:
```
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
```

In [55]:
```
data['City'].fillna(data['City'].mode()[0],inplace=True)
```

In [56]:
```
data['City']=data['City'].apply(lambda x: data['City'].mode()[0] if x=='Select' else x)
```

In [57]:
```
data['City'].value_counts()
```

Out[57]:
```
Mumbai                         6891
Thane & Outskirts               752
Other Cities                    686
Other Cities of Maharashtra     457
Other Metro Cities              380
Tier II Cities                   74
Name: City, dtype: int64
```

In [58]:
```
data['Asymmetrique Activity Index'].value_counts()
```

Out[58]:
```
02.Medium    3839
01.High       821
03.Low        362
Name: Asymmetrique Activity Index, dtype: int64
```

In [59]:
```
data['Asymmetrique Activity Index'].fillna(data['Asymmetrique Activity Index'].mode()[0],inplace=True)
```

In [60]:
```
data['Asymmetrique Profile Index'].value_counts()
```

Out[60]:
```
02.Medium    2788
01.High      2203
03.Low         31
Name: Asymmetrique Profile Index, dtype: int64
```

In [61]:
```
data['Asymmetrique Activity Index'].fillna(data['Asymmetrique Activity Index'].mode()[0],inplace=True)
```

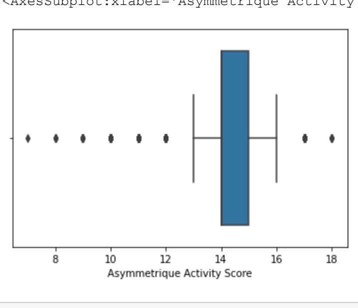
In [62]:
```
data['Asymmetrique Activity Score'].describe()
```

Out[62]:
```
count    5022.000000
mean       14.306252
std         1.386694
min         7.000000
25%        14.000000
50%        14.000000
75%        15.000000
max        18.000000
Name: Asymmetrique Activity Score, dtype: float64
```

Checking for Outliers

In [63]:
```
sns.boxplot(data['Asymmetrique Activity Score'])
```

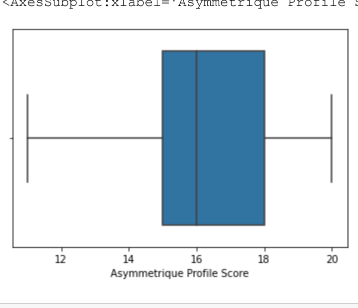
Out[63]:
```
<AxesSubplot:xlabel='Asymmetrique Activity Score'>
```



In [64]:
```
data['Asymmetrique Activity Score'].fillna(data['Asymmetrique Activity Score'].mean(),inplace=True)
```

In [65]:
```
sns.boxplot(data['Asymmetrique Profile Score'])
```

Out[65]:
```
<AxesSubplot:xlabel='Asymmetrique Profile Score'>
```

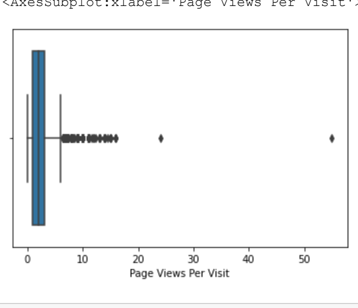


In [66]:
```
data['Asymmetrique Profile Score'].fillna(data['Asymmetrique Profile Score'].mean(),inplace=True)
```

In [67]:
```
data['Page Views Per Visit'].describe()
```

Out[67]:
```
count    9103.000000
mean        2.362820
std         2.161418
min         0.000000
25%         1.000000
50%         2.000000
75%         3.000000
max        55.000000
Name: Page Views Per Visit, dtype: float64
```

In [68]:
```
sns.boxplot(data['Page Views Per Visit'])
```
Out[68]: <AxesSubplot:xlabel='Page Views Per Visit'>



In [69]:
```
data['Page Views Per Visit'].fillna(data['Page Views Per Visit'].mode()[0],inplace=True)
```

In [70]:
```
data['Last Activity'].value_counts()
```
Out[70]:
```
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
Visited Booth in Tradeshow         1
Resubscribed to emails             1
Name: Last Activity, dtype: int64
```

In [71]:
```
data['Last Activity'].fillna(data['Last Activity'].mode()[0],inplace=True)
```

In [72]:
```
data['Asymmetrique Profile Index'].value_counts()
```
Out[72]:
```
02.Medium    2788
01.High      2203
03.Low         31
Name: Asymmetrique Profile Index, dtype: int64
```

In [73]:
```
data['Asymmetrique Profile Index'].fillna(data['Asymmetrique Profile Index'].mode()[0],inplace=True)
```

In [74]:
```
data.isna().sum()
```
Out[74]:
```
Prospect ID                                    0
Lead Number                                    0
Lead Origin                                    0
Lead Source                                    0
Do Not Email                                   0
Do Not Call                                    0
Converted                                      0
TotalVisits                                    0
Total Time Spent on Website                    0
Page Views Per Visit                           0
Last Activity                                  0
Country                                        0
Specialization                                 0
What is your current occupation                0
Search                                         0
Magazine                                       0
Newspaper Article                              0
X Education Forums                             0
Newspaper                                      0
Digital Advertisement                          0
Through Recommendations                        0
Receive More Updates About Our Courses         0
Lead Quality                                   0
Update me on Supply Chain Content              0
Get updates on DM Content                      0
Lead Profile                                   0
City                                           0
Asymmetrique Activity Index                    0
Asymmetrique Profile Index                     0
Asymmetrique Activity Score                    0
Asymmetrique Profile Score                     0
I agree to pay the amount through cheque       0
A free copy of Mastering The Interview         0
Last Notable Activity                          0
Better Career Prospects                        0
Tags_DeadEnd                                   0
Tags_UnclearLeads                              0
Tags_ReasonedLeads                             0
dtype: int64
```

In [75]:
```
data.head()
```
Out[75]:

	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
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	660737	API	Olark Chat	0	0	0	0.0	0	0.0	Page Visited on Website	India	Select
1	2a272436-5132-4136-86fa-dcc88c88f482	660728	API	Organic Search	0	0	0	5.0	674	2.5	Email Opened	India	Select
2	8cc8c611-a219-4f35-ad23-fdfd2656bd8a	660727	Landing Page Submission	Direct Traffic	0	0	1	2.0	1532	2.0	Email Opened	India	Business Administration
3	0cc2df48-7cf4-4e39-9de9-19797f9b38cc	660719	Landing Page Submission	Direct Traffic	0	0	0	1.0	305	1.0	Unreachable	India	Media and Advertising
4	3256f628-e534-4826-9d63-4a8b88782852	660681	Landing Page Submission	Google	0	0	1	2.0	1428	1.0	Converted to Lead	India	Select

In [76]:
```
data['Country'].value_counts()
```
Out[76]:
```
India                   8953
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
South Africa               4
Canada                     4
Kuwait                     4
Nigeria                    4
Sweden                     3
Philippines                2
Uganda                     2
Belgium                    2
Ghana                      2
Asia/Pacific Region        2
China                      2
Bangladesh                 2
Italy                      2
Netherlands                2
Liberia                    1
Vietnam                    1
Sri Lanka                  1
Tanzania                   1
Indonesia                  1
Denmark                    1
Malaysia                   1
Switzerland                1
Russia                     1
Kenya                      1
Name: Country, dtype: int64
```

In [77]:
```
data['Country_India']=data['Country'].apply(lambda x: 1 if x=='India' else 0)
```

In [78]:
```
data.drop('Country',inplace=True,axis=1)
```

In [79]:
```
data.head()
```
Out[79]:

	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	Specialization	What yo curr occupati
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	660737	API	Olark Chat	0	0	0	0.0	0	0.0	Page Visited on Website	Select	Unemploy
1	2a272436-5132-4136-86fa-dcc88c88f482	660728	API	Organic Search	0	0	0	5.0	674	2.5	Email Opened	Select	Unemploy
2	8cc8c611-a219-4f35-ad23-fdfd2656bd8a	660727	Landing Page Submission	Direct Traffic	0	0	1	2.0	1532	2.0	Email Opened	Business Administration	Unemploy
3	0cc2df48-7cf4-4e39-9de9-19797f9b38cc	660719	Landing Page Submission	Direct Traffic	0	0	0	1.0	305	1.0	Unreachable	Media and Advertising	Unemploy
4	3256f628-e534-4826-9d63-4a8b88782852	660681	Landing Page Submission	Google	0	0	1	2.0	1428	1.0	Converted to Lead	Select	Unemploy

For categorical variables with multiple levels, create dummy features (one-hot encoded)

In [80]:
```
dummy1=pd.get_dummies(data[['Lead Origin','Lead Source','What is your current occupation','Better Caree
r Prospects','Lead Quality','Asymmetrique Activity Index','Asymmetrique Profile Index','Lead Profile',
'City']],drop_first=True)
```

In [81]:
```
#'Last Activity',,'Lead Profile','Tags','Specialization',
```

In [82]:
```
dummy1.head()
```
Out[82]:

	Better Career Prospects	Lead Origin_Landing Page Submission	Lead Origin_Lead Add Form	Lead Origin_Lead Import	Lead Origin_Quick Add Form	Lead Source_Google	Lead Source_Olark Chat	Lead Source_Organic Search	Lead Source_Others	Sc
0	1	0	0	0	0	0	1	0	0	
1	1	0	0	0	0	0	0	1	0	
2	1	1	0	0	0	0	0	0	0	
3	1	1	0	0	0	0	0	0	0	
4	1	1	0	0	0	1	0	0	0	

In [83]:
```
data=pd.concat([data,dummy1],axis=1)
```

In [84]:
```
data.head()
```
Out[84]:

	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	Specialization	What yo curr occupati
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	660737	API	Olark Chat	0	0	0	0.0	0	0.0	Page Visited on Website	Select	Unemploy
1	2a272436-5132-4136-86fa-dcc88c88f482	660728	API	Organic Search	0	0	0	5.0	674	2.5	Email Opened	Select	Unemploy
2	8cc8c611-a219-4f35-ad23-fdfd2656bd8a	660727	Landing Page Submission	Direct Traffic	0	0	1	2.0	1532	2.0	Email Opened	Business Administration	Unemploy
3	0cc2df48-7cf4-4e39-9de9-19797f9b38cc	660719	Landing Page Submission	Direct Traffic	0	0	0	1.0	305	1.0	Unreachable	Media and Advertising	Unemploy
4	3256f628-e534-4826-9d63-4a8b88782852	660681	Landing Page Submission	Google	0	0	1	2.0	1428	1.0	Converted to Lead	Select	Unemploy

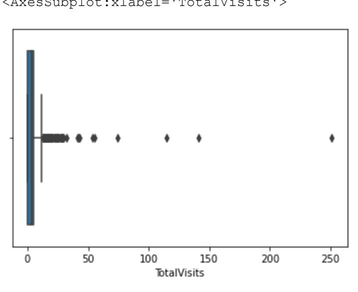
In [85]:
```
#### Dropping the repeated variables
data.drop(['Lead Origin','Lead Source','What is your current occupation','Better Career Prospects','Lea
d Quality'],1,inplace=True)
```

In [86]:
```
data.isna().sum()
```
Out[86]:
```
Prospect ID                                              0
Lead Number                                              0
Do Not Email                                             0
Do Not Call                                              0
Converted                                                0
TotalVisits                                              0
Total Time Spent on Website                              0
Page Views Per Visit                                     0
Last Activity                                            0
Specialization                                           0
Search                                                   0
Magazine                                                 0
Newspaper Article                                        0
X Education Forums                                       0
Newspaper                                                0
Digital Advertisement                                    0
Through Recommendations                                  0
Receive More Updates About Our Courses                   0
Update me on Supply Chain Content                        0
Get updates on DM Content                                0
Lead Profile                                             0
City                                                     0
Asymmetrique Activity Index                              0
Asymmetrique Profile Index                               0
Asymmetrique Activity Score                              0
Asymmetrique Profile Score                               0
I agree to pay the amount through cheque                 0
A free copy of Mastering The Interview                   0
Last Notable Activity                                    0
Tags_DeadEnd                                             0
Tags_UnclearLeads                                        0
Tags_ReasonedLeads                                       0
Country_India                                            0
Lead Origin_Landing Page Submission                      0
Lead Origin_Lead Add Form                                0
Lead Origin_Lead Import                                  0
Lead Origin_Quick Add Form                               0
Lead Source_Google                                       0
Lead Source_Olark Chat                                   0
Lead Source_Organic Search                               0
Lead Source_Others                                       0
Lead Source_Reference                                    0
Lead Source_Referral Sites                               0
Lead Source_Welingak Website                             0
What is your current occupation_Working Professional     0
Lead Quality_Might be                                    0
Lead Quality_Not Sure_Low Rel                            0
Lead Quality_Worst                                       0
Asymmetrique Activity Index_02.Medium                    0
Asymmetrique Activity Index_03.Low                       0
Asymmetrique Profile Index_02.Medium                     0
Asymmetrique Profile Index_03.Low                        0
Lead Profile_Potential Lead                              0
City_Other Cities                                        0
City_Other Cities of Maharashtra                         0
City_Other Metro Cities                                  0
City_Thane & Outskirts                                   0
City_Tier II Cities                                      0
dtype: int64
```

In [87]:
```
data.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9240 entries, 0 to 9239
Data columns (total 58 columns):
 #   Column                                                Non-Null Count  Dtype
---  ------                                                --------------  -----
 0   Prospect ID                                           9240 non-null   object
 1   Lead Number                                           9240 non-null   int64
 2   Do Not Email                                          9240 non-null   int64
 3   Do Not Call                                           9240 non-null   int64
 4   Converted                                             9240 non-null   int64
 5   TotalVisits                                           9240 non-null   float64
 6   Total Time Spent on Website                           9240 non-null   int64
 7   Page Views Per Visit                                  9240 non-null   float64
 8   Last Activity                                         9240 non-null   object
 9   Specialization                                        9240 non-null   object
 10  Search                                                9240 non-null   int64
 11  Magazine                                              9240 non-null   int64
 12  Newspaper Article                                     9240 non-null   int64
 13  X Education Forums                                    9240 non-null   int64
 14  Newspaper                                             9240 non-null   int64
 15  Digital Advertisement                                 9240 non-null   int64
 16  Through Recommendations                               9240 non-null   int64
 17  Receive More Updates About Our Courses                9240 non-null   int64
 18  Update me on Supply Chain Content                     9240 non-null   int64
 19  Get updates on DM Content                             9240 non-null   int64
 20  Lead Profile                                          9240 non-null   object
 21  City                                                  9240 non-null   object
 22  Asymmetrique Activity Index                           9240 non-null   object
 23  Asymmetrique Profile Index                            9240 non-null   object
 24  Asymmetrique Activity Score                           9240 non-null   float64
 25  Asymmetrique Profile Score                            9240 non-null   float64
 26  I agree to pay the amount through cheque              9240 non-null   int64
 27  A free copy of Mastering The Interview                9240 non-null   int64
 28  Last Notable Activity                                 9240 non-null   object
 29  Tags_DeadEnd                                          9240 non-null   int64
 30  Tags_UnclearLeads                                     9240 non-null   int64
 31  Tags_ReasonedLeads                                    9240 non-null   int64
 32  Country_India                                         9240 non-null   int64
 33  Lead Origin_Landing Page Submission                   9240 non-null   uint8
 34  Lead Origin_Lead Add Form                             9240 non-null   uint8
 35  Lead Origin_Lead Import                               9240 non-null   uint8
 36  Lead Origin_Quick Add Form                            9240 non-null   uint8
 37  Lead Source_Google                                    9240 non-null   uint8
 38  Lead Source_Olark Chat                                9240 non-null   uint8
 39  Lead Source_Organic Search                            9240 non-null   uint8
 40  Lead Source_Others                                    9240 non-null   uint8
 41  Lead Source_Reference                                 9240 non-null   uint8
 42  Lead Source_Referral Sites                            9240 non-null   uint8
 43  Lead Source_Welingak Website                          9240 non-null   uint8
 44  What is your current occupation_Working Professional  9240 non-null   uint8
 45  Lead Quality_Might be                                 9240 non-null   uint8
 46  Lead Quality_Not Sure_Low Rel                         9240 non-null   uint8
 47  Lead Quality_Worst                                    9240 non-null   uint8
 48  Asymmetrique Activity Index_02.Medium                 9240 non-null   uint8
 49  Asymmetrique Activity Index_03.Low                    9240 non-null   uint8
 50  Asymmetrique Profile Index_02.Medium                  9240 non-null   uint8
 51  Asymmetrique Profile Index_03.Low                     9240 non-null   uint8
 52  Lead Profile_Potential Lead                           9240 non-null   uint8
 53  City_Other Cities                                     9240 non-null   uint8
 54  City_Other Cities of Maharashtra                      9240 non-null   uint8
 55  City_Other Metro Cities                               9240 non-null   uint8
 56  City_Thane & Outskirts                                9240 non-null   uint8
 57  City_Tier II Cities                                   9240 non-null   uint8
dtypes: float64(4), int64(21), object(8), uint8(25)
memory usage: 2.5+ MB
```

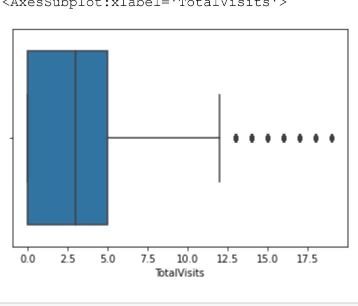
In [88]:
```
data.select_dtypes(include=np.number).columns
```
Out[88]:
```
Index(['Lead Number', 'Do Not Email', 'Do Not Call', 'Converted',
       'TotalVisits', 'Total Time Spent on Website', 'Page Views Per Visit',
       'Search', 'Magazine', 'Newspaper Article', 'X Education Forums',
       'Newspaper', 'Digital Advertisement', 'Through Recommendations',
       'Receive More Updates About Our Courses',
       'Update me on Supply Chain Content', 'Get updates on DM Content',
       'Asymmetrique Activity Score', 'Asymmetrique Profile Score',
       'I agree to pay the amount through cheque',
       'A free copy of Mastering The Interview', 'Tags_DeadEnd',
       'Tags_UnclearLeads', 'Tags_ReasonedLeads', 'Country_India',
       'Lead Origin_Landing Page Submission', 'Lead Origin_Lead Add Form',
       'Lead Origin_Lead Import', 'Lead Origin_Quick Add Form',
       'Lead Source_Google', 'Lead Source_Olark Chat',
       'Lead Source_Organic Search', 'Lead Source_Others',
       'Lead Source_Reference', 'Lead Source_Referral Sites',
       'Lead Source_Welingak Website',
       'What is your current occupation_Working Professional',
       'Lead Quality_Might be', 'Lead Quality_Not Sure_Low Rel',
       'Lead Quality_Worst', 'Asymmetrique Activity Index_02.Medium',
       'Asymmetrique Activity Index_03.Low',
       'Asymmetrique Profile Index_02.Medium',
       'Asymmetrique Profile Index_03.Low', 'Lead Profile_Potential Lead',
       'City_Other Cities', 'City_Other Cities of Maharashtra',
       'City_Other Metro Cities', 'City_Thane & Outskirts',
       'City_Tier II Cities'],
      dtype='object')
```

In [89]:
```
sns.boxplot(data['TotalVisits'])
```
Out[89]: <AxesSubplot:xlabel='TotalVisits'>



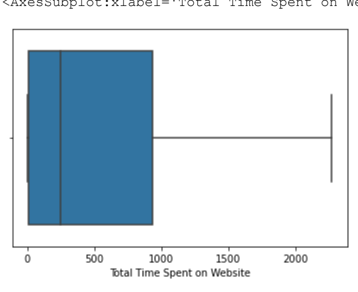
In [90]:
```
data=data[data['TotalVisits']<20]
```

In [91]:
```
sns.boxplot(data['TotalVisits'])
```
Out[91]: <AxesSubplot:xlabel='TotalVisits'>

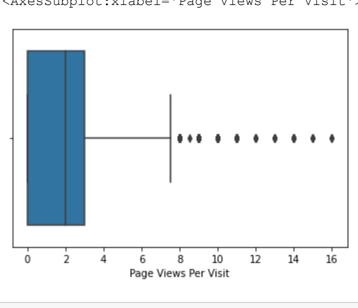


In [92]:
```
data.shape
```
Out[92]: (9181, 58)

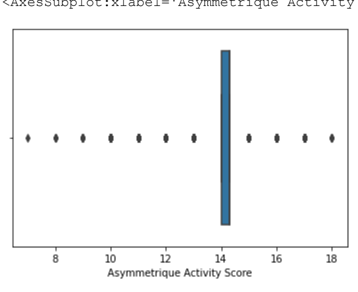
In [93]:
```
sns.boxplot(data['Total Time Spent on Website'])
```
Out[93]: <AxesSubplot:xlabel='Total Time Spent on Website'>



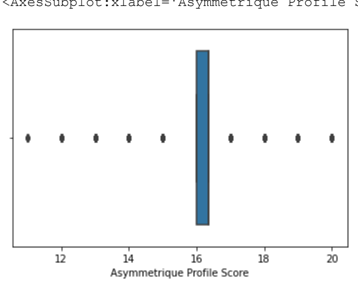
In [94]:
```
sns.boxplot(data['Page Views Per Visit'])
```
Out[94]: <AxesSubplot:xlabel='Page Views Per Visit'>



In [95]:
```
sns.boxplot(data['Asymmetrique Activity Score'])
```
Out[95]: <AxesSubplot:xlabel='Asymmetrique Activity Score'>



In [96]:
```
sns.boxplot(data['Asymmetrique Profile Score'])
```
Out[96]: <AxesSubplot:xlabel='Asymmetrique Profile Score'>



In [97]:
```
data.columns
```
Out[97]:
```
Index(['Prospect ID', 'Lead Number', 'Do Not Email', 'Do Not Call',
       'Converted', 'TotalVisits', 'Total Time Spent on Website',
       'Page Views Per Visit', 'Last Activity', 'Specialization', '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',
       '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',
       'Tags_DeadEnd', 'Tags_UnclearLeads', 'Tags_ReasonedLeads',
       'Country_India', 'Lead Origin_Landing Page Submission',
       'Lead Origin_Lead Add Form', 'Lead Origin_Lead Import',
       'Lead Origin_Quick Add Form', 'Lead Source_Google',
       'Lead Source_Olark Chat', 'Lead Source_Organic Search',
       'Lead Source_Others', 'Lead Source_Reference',
       'Lead Source_Referral Sites', 'Lead Source_Welingak Website',
       'What is your current occupation_Working Professional',
       'Lead Quality_Might be', 'Lead Quality_Not Sure_Low Rel',
       'Lead Quality_Worst', 'Asymmetrique Activity Index_02.Medium',
       'Asymmetrique Activity Index_03.Low',
       'Asymmetrique Profile Index_02.Medium',
       'Asymmetrique Profile Index_03.Low', 'Lead Profile_Potential Lead',
       'City_Other Cities', 'City_Other Cities of Maharashtra',
       'City_Other Metro Cities', 'City_Thane & Outskirts',
       'City_Tier II Cities'],
      dtype='object')
```

In [98]:
```
data['Last Notable Activity'].value_counts()
```
Out[98]:
```
Modified                        3394
Email Opened                    2813
SMS Sent                        2163
Page Visited on Website          298
Olark Chat Conversation          182
Email Link Clicked               172
Email Bounced                     59
Unsubscribed                      47
Unreachable                       32
Had a Phone Conversation          14
Email Marked Spam                  2
Form Submitted on Website          1
Email Received                     1
View in browser link Clicked       1
Approached upfront                 1
Resubscribed to emails             1
Name: Last Notable Activity, dtype: int64
```

In [99]:
```
data['Last Activity'].value_counts()
```
Out[99]:
```
Email Opened                    3524
SMS Sent                        2733
Olark Chat Conversation          972
Page Visited on Website          614
Converted to Lead                428
Email Bounced                    325
Email Link Clicked               266
Form Submitted on Website        115
Unreachable                       93
Unsubscribed                      61
Had a Phone Conversation          30
Approached upfront                 9
View in browser link Clicked       5
Email Received                     2
Email Marked Spam                  2
Visited Booth in Tradeshow         1
Resubscribed to emails             1
Name: Last Activity, dtype: int64
```

In [100]:
```
data.drop(['Prospect ID','Lead Number','Last Activity','Specialization','Last Activity','Last Notable A
ctivity','Lead Profile','Asymmetrique Activity Index','Asymmetrique Profile Index','City'],1,inplace=Tr
ue)
```

In [101]:
```
converted=(sum(data['Converted'])/len(data['Converted'].index))*100
```

In [102]:
```
converted
```
Out[102]: 38.52521511817885

Step 3: Model Fitment and Tuning

In [103]:
```
from sklearn.model_selection import train_test_split
```

In [104]:
```
data.head()
```
Out[104]:

	Do Not Email	Do Not Call	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Search	Magazine	Newspaper Article	X Education Forums	Newspaper	Digital Advertisement	T Recommen
0	0	0	0	0.0	0	0.0	0	0	0	0	0	0	
1	0	0	0	5.0	674	2.5	0	0	0	0	0	0	
2	0	0	1	2.0	1532	2.0	0	0	0	0	0	0	
3	0	0	0	1.0	305	1.0	0	0	0	0	0	0	
4	0	0	1	2.0	1428	1.0	0	0	0	0	0	0	

In [105]:
```
data.shape
```
Out[105]: (9181, 49)

In [106]:
```
y=data.pop('Converted')
```

Test/Train split

In [107]:
```
X_train,X_test,y_train,y_test=train_test_split(data,y,train_size=0.7,test_size=0.3,random_state=100)
```

In [108]:
```
from sklearn.preprocessing import StandardScaler
```

In [109]:
```
scaler=StandardScaler()
X_train[['Total Time Spent on Website','Page Views Per Visit','TotalVisits','Asymmetrique Activity Scor
e','Asymmetrique Profile Score']]=scaler.fit_transform(X_train[['Total Time Spent on Website','Page Vie
ws Per Visit','TotalVisits','Asymmetrique Activity Score','Asymmetrique Profile Score']])
```

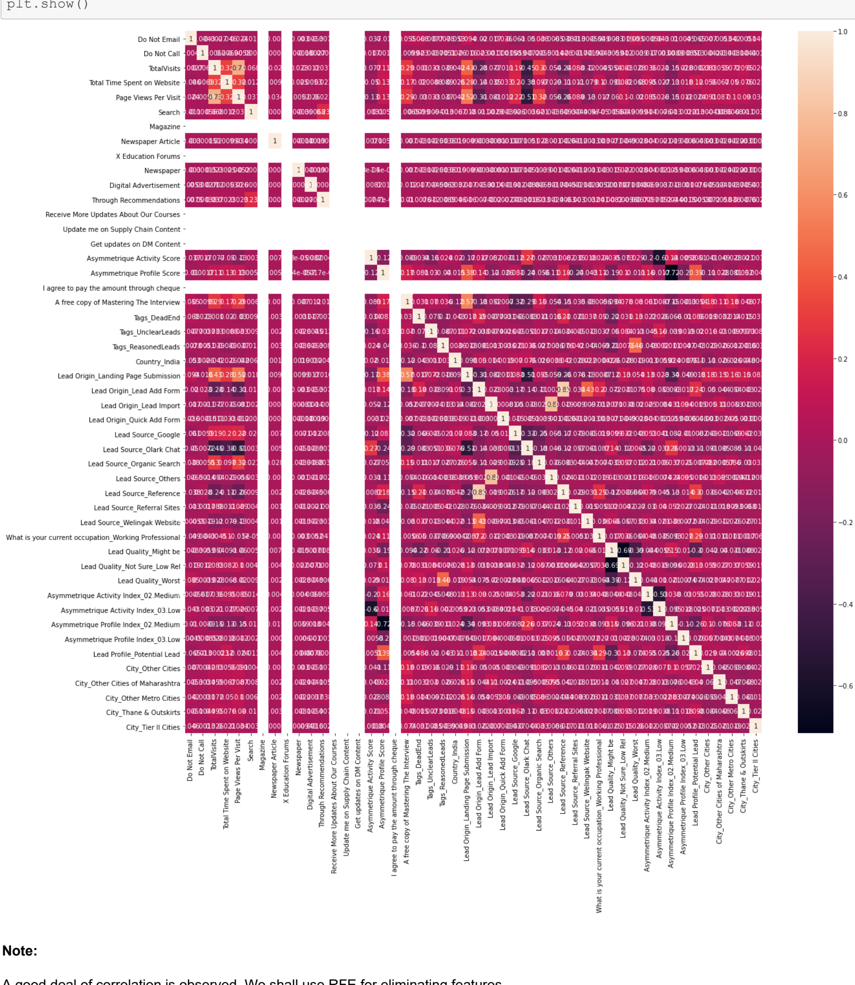
In [110]:
```
X_train.head()
```
Out[110]:

	Do Not Email	Do Not Call	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Search	Magazine	Newspaper Article	X Education Forums	Newspaper	Digital Advertisement	Throu Recommendati
3555	0	0	-1.037750	0.256903	-1.121918	0	0	0	0	0	0	
8055	0	0	-1.037750	-0.895640	-1.121918	0	0	0	0	0	0	
1843	0	0	-0.392819	-0.527769	-0.153998	0	0	0	0	0	0	
1763	0	0	-0.070354	-0.404541	0.329962	0	0	0	0	0	0	
3017	0	0	0.252111	1.230040	0.813922	0	0	0	0	0	0	

Looking at Correlations

In [111]:
```
import matplotlib.pyplot as plt
```

In [112]:
```
plt.figure(figsize = (20,20))
sns.heatmap(data.corr(),annot = True)
plt.show()
```



Note:

A good deal of correlation is observed. We shall use RFE for eliminating features

Quick glance at the model appeal

In [113]:
```
import statsmodels.api as sm
```

In [114]:
```
logm1=sm.GLM(y_train,(sm.add_constant(X_train)),family=sm.families.Binomial())
```

In [115]:
```
logm1.fit().summary()
```

Out[115]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6426
Model:	GLM	**Df Residuals:**	6383
Model Family:	Binomial	**Df Model:**	42
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2349.4
Date:	Tue, 10 Aug 2021	**Deviance:**	4698.7
Time:	22:02:16	**Pearson chi2:**	7.87e+03
No. Iterations:	33		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.7391	0.438	-1.686	0.092	-1.598	0.120
Do Not Email	-1.2084	0.170	-7.104	0.000	-1.542	-0.875
Do Not Call	19.1621	3.13e+04	0.001	1.000	-6.14e+04	6.14e+04
TotalVisits	0.1495	0.054	2.788	0.005	0.044	0.255
Total Time Spent on Website	1.1209	0.044	25.486	0.000	1.035	1.207
Page Views Per Visit	-0.0926	0.059	-1.570	0.116	-0.208	0.023
Search	-1.2150	0.915	-1.328	0.184	-3.008	0.578
Magazine	-2.101e-07	0.104	-2.03e-06	1.000	-0.203	0.203
Newspaper Article	27.2962	6.97e+05	3.92e-05	1.000	-1.37e+06	1.37e+06
X Education Forums	4.694e-08	0.029	1.6e-06	1.000	-0.057	0.057
Newspaper	-26.3961	1.21e+05	-0.000	1.000	-2.38e+05	2.38e+05
Digital Advertisement	-0.9596	2.410	-0.398	0.690	-5.683	3.763
Through Recommendations	0.7937	2.225	0.357	0.721	-3.567	5.155
Receive More Updates About Our Courses	5.893e-08	0.018	3.24e-06	1.000	-0.036	0.036
Update me on Supply Chain Content	2.022e-07	0.090	2.24e-06	1.000	-0.177	0.177
Get updates on DM Content	2.777e-07	0.131	2.12e-06	1.000	-0.257	0.257
Asymmetrique Activity Score	1.0689	0.084	12.692	0.000	0.904	1.234
Asymmetrique Profile Score	-0.0248	0.074	-0.337	0.736	-0.169	0.120
I agree to pay the amount through cheque	-1.365e-07	0.063	-2.16e-06	1.000	-0.124	0.124
A free copy of Mastering The Interview	0.0944	0.114	0.826	0.409	-0.129	0.318
Tags_DeadEnd	-0.5330	0.172	-3.102	0.002	-0.870	-0.196
Tags_UnclearLeads	0.1530	0.151	1.014	0.311	-0.143	0.449
Tags_ReasonedLeads	-3.8616	0.305	-12.665	0.000	-4.459	-3.264
Country_India	0.4102	0.234	1.751	0.080	-0.049	0.869
Lead Origin_Landing Page Submission	-0.2279	0.130	-1.753	0.080	-0.483	0.027
Lead Origin_Lead Add Form	2.8333	0.505	5.611	0.000	1.844	3.823
Lead Origin_Lead Import	0.3325	0.882	0.377	0.706	-1.397	2.062
Lead Origin_Quick Add Form	32.7674	1.58e+07	2.07e-06	1.000	-3.1e+07	3.1e+07
Lead Source_Google	0.2983	0.122	2.454	0.014	0.060	0.537
Lead Source_Olark Chat	0.6734	0.169	3.973	0.000	0.341	1.006
Lead Source_Organic Search	0.0255	0.140	0.183	0.855	-0.248	0.299
Lead Source_Others	-0.7190	0.665	-1.082	0.279	-2.022	0.584
Lead Source_Reference	0.1964	0.555	0.354	0.724	-0.892	1.285
Lead Source_Referral Sites	-0.1024	0.382	-0.268	0.788	-0.850	0.645
Lead Source_Welingak Website	3.3011	0.890	3.710	0.000	1.557	5.045
What is your current occupation_Working Professional	2.7037	0.213	12.665	0.000	2.285	3.122
Lead Quality_Might be	-2.9822	0.282	-10.566	0.000	-3.535	-2.429
Lead Quality_Not Sure_Low Rel	-2.7064	0.285	-9.495	0.000	-3.265	-2.148
Lead Quality_Worst	-4.5922	0.451	-10.181	0.000	-5.476	-3.708
Asymmetrique Activity Index_02.Medium	2.3820	0.227	10.507	0.000	1.938	2.826
Asymmetrique Activity Index_03.Low	2.6596	0.512	5.194	0.000	1.656	3.663
Asymmetrique Profile Index_02.Medium	-0.1043	0.145	-0.720	0.472	-0.388	0.180
Asymmetrique Profile Index_03.Low	0.8664	0.674	1.286	0.199	-0.455	2.187
Lead Profile_Potential Lead	1.6254	0.137	11.859	0.000	1.357	1.894
City_Other Cities	0.0129	0.152	0.085	0.932	-0.284	0.310
City_Other Cities of Maharashtra	0.1773	0.178	0.997	0.319	-0.171	0.526
City_Other Metro Cities	0.0867	0.187	0.463	0.644	-0.281	0.454
City_Thane & Outskirts	-0.1179	0.147	-0.803	0.422	-0.406	0.170
City_Tier II Cities	-0.0072	0.426	-0.017	0.987	-0.842	0.828

In [116]:
```
from sklearn.linear_model import LogisticRegression
logreg=LogisticRegression()
```

Feature Selection Using RFE

In [117]:
```
from sklearn.feature_selection import RFE
rfe=RFE(logreg,15)
rfe=rfe.fit(X_train,y_train)
```

In [118]:
```
rfe.support_
```

Out[118]:
```
array([ True, False, False,  True, False, False, False, False, False,
        True, False, False, False, False, False,  True, False, False,
       False, False, False,  True, False, False,  True, False, False,
       False, False, False, False, False, False,  True,  True,  True,
        True,  True,  True,  True, False,  True,  True, False, False,
       False, False, False])
```

In [119]:
```
list(zip(X_train.columns, rfe.support_, rfe.ranking_))
```

Out[119]:
```
[('Do Not Email', True, 1),
 ('Do Not Call', False, 23),
 ('TotalVisits', False, 17),
 ('Total Time Spent on Website', True, 1),
 ('Page Views Per Visit', False, 19),
 ('Search', False, 2),
 ('Magazine', False, 32),
 ('Newspaper Article', False, 7),
 ('X Education Forums', False, 29),
 ('Newspaper', True, 1),
 ('Digital Advertisement', False, 13),
 ('Through Recommendations', False, 24),
 ('Receive More Updates About Our Courses', False, 34),
 ('Update me on Supply Chain Content', False, 30),
 ('Get updates on DM Content', False, 31),
 ('Asymmetrique Activity Score', True, 1),
 ('Asymmetrique Profile Score', False, 26),
 ('I agree to pay the amount through cheque', False, 33),
 ('A free copy of Mastering The Interview', False, 21),
 ('Tags_DeadEnd', False, 5),
 ('Tags_UnclearLeads', False, 14),
 ('Tags_ReasonedLeads', True, 1),
 ('Country_India', False, 6),
 ('Lead Origin_Landing Page Submission', False, 9),
 ('Lead Origin_Lead Add Form', True, 1),
 ('Lead Origin_Lead Import', False, 22),
 ('Lead Origin_Quick Add Form', False, 10),
 ('Lead Source_Google', False, 8),
 ('Lead Source_Olark Chat', False, 3),
 ('Lead Source_Organic Search', False, 27),
 ('Lead Source_Others', False, 4),
 ('Lead Source_Reference', False, 12),
 ('Lead Source_Referral Sites', False, 15),
 ('Lead Source_Welingak Website', True, 1),
 ('What is your current occupation_Working Professional', True, 1),
 ('Lead Quality_Might be', True, 1),
 ('Lead Quality_Not Sure_Low Rel', True, 1),
 ('Lead Quality_Worst', True, 1),
 ('Asymmetrique Activity Index_02.Medium', True, 1),
 ('Asymmetrique Activity Index_03.Low', True, 1),
 ('Asymmetrique Profile Index_02.Medium', False, 20),
 ('Asymmetrique Profile Index_03.Low', True, 1),
 ('Lead Profile_Potential Lead', True, 1),
 ('City_Other Cities', False, 25),
 ('City_Other Cities of Maharashtra', False, 11),
 ('City_Other Metro Cities', False, 18),
 ('City_Thane & Outskirts', False, 16),
 ('City_Tier II Cities', False, 28)]
```

RFE results feature-wise list along with their ranks

In [120]:
```
rfe_df = pd.DataFrame(list(zip(X_train.columns, rfe.support_, rfe.ranking_)))
rfe_df.rename(columns={0: 'features', 1:'rfe_support', 2:'rfe_ranking'}, inplace = True)
rfe_df.sort_values('rfe_ranking')
```

Out[120]:

	features	rfe_support	rfe_ranking
0	Do Not Email	True	1
24	Lead Origin_Lead Add Form	True	1
15	Asymmetrique Activity Score	True	1
33	Lead Source_Welingak Website	True	1
34	What is your current occupation_Working Profes...	True	1
35	Lead Quality_Might be	True	1
9	Newspaper	True	1
37	Lead Quality_Worst	True	1
36	Lead Quality_Not Sure_Low Rel	True	1
38	Asymmetrique Activity Index_02.Medium	True	1
39	Asymmetrique Activity Index_03.Low	True	1
3	Total Time Spent on Website	True	1
41	Asymmetrique Profile Index_03.Low	True	1
42	Lead Profile_Potential Lead	True	1
21	Tags_ReasonedLeads	True	1
5	Search	False	2
28	Lead Source_Olark Chat	False	3
30	Lead Source_Others	False	4
19	Tags_DeadEnd	False	5
22	Country_India	False	6
7	Newspaper Article	False	7
27	Lead Source_Google	False	8
23	Lead Origin_Landing Page Submission	False	9
26	Lead Origin_Quick Add Form	False	10
44	City_Other Cities of Maharashtra	False	11
31	Lead Source_Reference	False	12
10	Digital Advertisement	False	13
20	Tags_UnclearLeads	False	14
32	Lead Source_Referral Sites	False	15
46	City_Thane & Outskirts	False	16
2	TotalVisits	False	17
45	City_Other Metro Cities	False	18
4	Page Views Per Visit	False	19
40	Asymmetrique Profile Index_02.Medium	False	20
18	A free copy of Mastering The Interview	False	21
25	Lead Origin_Lead Import	False	22
1	Do Not Call	False	23
11	Through Recommendations	False	24
43	City_Other Cities	False	25
16	Asymmetrique Profile Score	False	26
29	Lead Source_Organic Search	False	27
47	City_Tier II Cities	False	28
8	X Education Forums	False	29
13	Update me on Supply Chain Content	False	30
14	Get updates on DM Content	False	31
6	Magazine	False	32
17	I agree to pay the amount through cheque	False	33
12	Receive More Updates About Our Courses	False	34

Columns Selected after RFE

In [121]:
```
col = X_train.columns[rfe.support_]
```

In [122]:
```
col
```

Out[122]:
```
Index(['Do Not Email', 'Total Time Spent on Website', 'Newspaper',
       'Asymmetrique Activity Score', 'Tags_ReasonedLeads',
       'Lead Origin_Lead Add Form', 'Lead Source_Welingak Website',
       'What is your current occupation_Working Professional',
       'Lead Quality_Might be', 'Lead Quality_Not Sure_Low Rel',
       'Lead Quality_Worst', 'Asymmetrique Activity Index_02.Medium',
       'Asymmetrique Activity Index_03.Low',
       'Asymmetrique Profile Index_03.Low', 'Lead Profile_Potential Lead'],
      dtype='object')
```

Step 4: Model Fitment

In [123]:
```
X_train_sm = sm.add_constant(X_train[col])
logm2 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm2.fit()
```

In [124]:
```
res.summary()
```

Out[124]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6426
Model:	GLM	**Df Residuals:**	6410
Model Family:	Binomial	**Df Model:**	15
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2388.4
Date:	Tue, 10 Aug 2021	**Deviance:**	4776.8
Time:	22:02:20	**Pearson chi2:**	7.79e+03
No. Iterations:	19		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.3235	0.338	-0.956	0.339	-0.986	0.339
Do Not Email	-1.3152	0.164	-8.006	0.000	-1.637	-0.993
Total Time Spent on Website	1.0302	0.039	26.720	0.000	0.955	1.106
Newspaper	-22.3305	1.77e+04	-0.001	0.999	-3.48e+04	3.47e+04
Asymmetrique Activity Score	1.1230	0.081	13.866	0.000	0.964	1.282
Tags_ReasonedLeads	-3.7638	0.301	-12.488	0.000	-4.355	-3.173
Lead Origin_Lead Add Form	2.7571	0.213	12.935	0.000	2.339	3.175
Lead Source_Welingak Website	3.0526	0.762	4.004	0.000	1.558	4.547
What is your current occupation_Working Professional	2.6380	0.212	12.472	0.000	2.223	3.053
Lead Quality_Might be	-2.7735	0.275	-10.099	0.000	-3.312	-2.235
Lead Quality_Not Sure_Low Rel	-2.6147	0.279	-9.379	0.000	-3.161	-2.068
Lead Quality_Worst	-4.7379	0.444	-10.672	0.000	-5.608	-3.868
Asymmetrique Activity Index_02.Medium	2.2340	0.218	10.247	0.000	1.807	2.661
Asymmetrique Activity Index_03.Low	2.7708	0.502	5.522	0.000	1.787	3.754
Asymmetrique Profile Index_03.Low	1.1803	0.581	2.032	0.042	0.042	2.319
Lead Profile_Potential Lead	1.6380	0.125	13.108	0.000	1.393	1.883

In [125]:
```
X_train=X_train[col]
```

In [126]:
```
X_train_1=X_train.drop('Newspaper',1)
```

In [127]:
```
X_train_sm=sm.add_constant(X_train_1)
logm3=sm.GLM(y_train,X_train_sm,family=sm.families.Binomial())
res1=logm3.fit()
res1.summary()
```

Out[127]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6426
Model:	GLM	**Df Residuals:**	6411
Model Family:	Binomial	**Df Model:**	14
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2390.3
Date:	Tue, 10 Aug 2021	**Deviance:**	4780.6
Time:	22:02:20	**Pearson chi2:**	7.79e+03
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.3235	0.338	-0.957	0.339	-0.986	0.339
Do Not Email	-1.3134	0.164	-7.998	0.000	-1.635	-0.992
Total Time Spent on Website	1.0275	0.039	26.685	0.000	0.952	1.103
Asymmetrique Activity Score	1.1216	0.081	13.856	0.000	0.963	1.280
Tags_ReasonedLeads	-3.7610	0.301	-12.481	0.000	-4.352	-3.170
Lead Origin_Lead Add Form	2.7554	0.213	12.930	0.000	2.338	3.173
Lead Source_Welingak Website	3.0510	0.762	4.003	0.000	1.557	4.545
What is your current occupation_Working Professional	2.6383	0.211	12.477	0.000	2.224	3.053
Lead Quality_Might be	-2.7709	0.275	-10.094	0.000	-3.309	-2.233
Lead Quality_Not Sure_Low Rel	-2.6177	0.279	-9.393	0.000	-3.164	-2.072
Lead Quality_Worst	-4.7346	0.444	-10.669	0.000	-5.604	-3.865
Asymmetrique Activity Index_02.Medium	2.2314	0.218	10.239	0.000	1.804	2.659
Asymmetrique Activity Index_03.Low	2.7673	0.502	5.517	0.000	1.784	3.750
Asymmetrique Profile Index_03.Low	1.1818	0.581	2.036	0.042	0.044	2.320
Lead Profile_Potential Lead	1.6403	0.125	13.131	0.000	1.395	1.885

In [128]:
```
X_train_1.shape
```

Out[128]:
```
(6426, 14)
```

Checking VIFs

In [129]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Features'] = X_train_1.columns
vif['VIF'] = [variance_inflation_factor(X_train_1.values, i) for i in range(X_train_1.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[129]:

	Features	VIF
10	Asymmetrique Activity Index_02.Medium	11.40
7	Lead Quality_Might be	8.28
11	Asymmetrique Activity Index_03.Low	3.01
8	Lead Quality_Not Sure_Low Rel	2.90
2	Asymmetrique Activity Score	2.40
9	Lead Quality_Worst	2.06
4	Lead Origin_Lead Add Form	1.63
13	Lead Profile_Potential Lead	1.60
3	Tags_ReasonedLeads	1.41
5	Lead Source_Welingak Website	1.30
6	What is your current occupation_Working Profes...	1.26
0	Do Not Email	1.11
1	Total Time Spent on Website	1.10
12	Asymmetrique Profile Index_03.Low	1.01

In [130]:
```
#Asymmetrique Activity Index_02.Medium has a very high VIF
X_train_2=X_train_1.drop('Asymmetrique Activity Index_02.Medium',1)
```

In [131]:
```
X_train_sm=sm.add_constant(X_train_2)
logm3=sm.GLM(y_train,X_train_sm,family=sm.families.Binomial())
res1=logm3.fit()
res1.summary()
```

Out[131]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6426
Model:	GLM	**Df Residuals:**	6412
Model Family:	Binomial	**Df Model:**	13
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2446.2
Date:	Tue, 10 Aug 2021	**Deviance:**	4892.5
Time:	22:02:21	**Pearson chi2:**	7.86e+03
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	1.7599	0.267	6.598	0.000	1.237	2.283
Do Not Email	-1.2582	0.163	-7.721	0.000	-1.578	-0.939
Total Time Spent on Website	1.0277	0.038	27.029	0.000	0.953	1.102
Asymmetrique Activity Score	0.4550	0.043	10.607	0.000	0.371	0.539
Tags_ReasonedLeads	-3.7884	0.300	-12.648	0.000	-4.375	-3.201
Lead Origin_Lead Add Form	2.8427	0.209	13.585	0.000	2.433	3.253
Lead Source_Welingak Website	3.0052	0.753	3.991	0.000	1.529	4.481
What is your current occupation_Working Professional	2.6296	0.208	12.666	0.000	2.223	3.037
Lead Quality_Might be	-2.7488	0.268	-10.259	0.000	-3.274	-2.224
Lead Quality_Not Sure_Low Rel	-2.5620	0.272	-9.419	0.000	-3.095	-2.029
Lead Quality_Worst	-4.6588	0.437	-10.671	0.000	-5.514	-3.803
Asymmetrique Activity Index_03.Low	-1.1361	0.330	-3.439	0.001	-1.784	-0.489
Asymmetrique Profile Index_03.Low	0.9772	0.576	1.697	0.090	-0.151	2.106
Lead Profile_Potential Lead	1.6000	0.121	13.208	0.000	1.363	1.837

In [132]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Features'] = X_train_2.columns
vif['VIF'] = [variance_inflation_factor(X_train_1.values, i) for i in range(X_train_2.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[132]:

	Features	VIF
10	Asymmetrique Activity Index_03.Low	11.40
7	Lead Quality_Might be	8.28
11	Asymmetrique Profile Index_03.Low	3.01
8	Lead Quality_Not Sure_Low Rel	2.90
2	Asymmetrique Activity Score	2.40
9	Lead Quality_Worst	2.06
4	Lead Origin_Lead Add Form	1.63
3	Tags_ReasonedLeads	1.41
5	Lead Source_Welingak Website	1.30
6	What is your current occupation_Working Profes...	1.26
0	Do Not Email	1.11
1	Total Time Spent on Website	1.10
12	Lead Profile_Potential Lead	1.01

In [133]:
```
#Asymmetrique Asymmetrique Activity Index_03.Low also has a very high VIF
X_train_3=X_train_2.drop('Asymmetrique Activity Index_03.Low',1)
```

In [134]:
```
X_train_sm=sm.add_constant(X_train_3)
logm3=sm.GLM(y_train,X_train_sm,family=sm.families.Binomial())
res1=logm3.fit()
res1.summary()
```

Out[134]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6426
Model:	GLM	**Df Residuals:**	6413
Model Family:	Binomial	**Df Model:**	12
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2453.1
Date:	Tue, 10 Aug 2021	**Deviance:**	4906.1
Time:	22:02:21	**Pearson chi2:**	7.64e+03
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	1.6900	0.263	6.427	0.000	1.175	2.205
Do Not Email	-1.2572	0.163	-7.727	0.000	-1.576	-0.938
Total Time Spent on Website	1.0327	0.038	27.233	0.000	0.958	1.107
Asymmetrique Activity Score	0.5213	0.038	13.631	0.000	0.446	0.596
Tags_ReasonedLeads	-3.7835	0.298	-12.692	0.000	-4.368	-3.199
Lead Origin_Lead Add Form	2.8775	0.209	13.745	0.000	2.467	3.288
Lead Source_Welingak Website	2.9362	0.748	3.927	0.000	1.471	4.401
What is your current occupation_Working Professional	2.6094	0.205	12.745	0.000	2.208	3.011
Lead Quality_Might be	-2.7097	0.265	-10.242	0.000	-3.228	-2.191
Lead Quality_Not Sure_Low Rel	-2.5132	0.269	-9.354	0.000	-3.040	-1.987
Lead Quality_Worst	-4.6494	0.435	-10.684	0.000	-5.502	-3.796
Asymmetrique Profile Index_03.Low	0.9633	0.574	1.678	0.093	-0.162	2.088
Lead Profile_Potential Lead	1.6025	0.121	13.276	0.000	1.366	1.839

In [135]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Features'] = X_train_3.columns
vif['VIF'] = [variance_inflation_factor(X_train_3.values, i) for i in range(X_train_3.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[135]:

	Features	VIF
4	Lead Origin_Lead Add Form	1.55
3	Tags_ReasonedLeads	1.41
11	Lead Profile_Potential Lead	1.39
9	Lead Quality_Worst	1.37
5	Lead Source_Welingak Website	1.30
6	What is your current occupation_Working Profes...	1.25
7	Lead Quality_Might be	1.22
8	Lead Quality_Not Sure_Low Rel	1.15
0	Do Not Email	1.11
1	Total Time Spent on Website	1.08
2	Asymmetrique Activity Score	1.01
10	Asymmetrique Profile Index_03.Low	1.01

In [136]:
```
#Asymmetrique Asymmetrique Profile Index_03.Low also and Assymmetrique Activity Score have identiical V
IF
X_train_4=X_train_3.drop('Asymmetrique Profile Index_03.Low',1)
```

In [137]:
```
X_train_sm=sm.add_constant(X_train_4)
logm3=sm.GLM(y_train,X_train_sm,family=sm.families.Binomial())
res1=logm3.fit()
res1.summary()
```

Out[137]:

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6426
Model:	GLM	**Df Residuals:**	6414
Model Family:	Binomial	**Df Model:**	11
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2454.5
Date:	Tue, 10 Aug 2021	**Deviance:**	4909.0
Time:	22:02:22	**Pearson chi2:**	7.63e+03
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	1.6921	0.263	6.435	0.000	1.177	2.207
Do Not Email	-1.2493	0.162	-7.705	0.000	-1.567	-0.932
Total Time Spent on Website	1.0332	0.038	27.254	0.000	0.959	1.108
Asymmetrique Activity Score	0.5222	0.038	13.647	0.000	0.447	0.597
Tags_ReasonedLeads	-3.7824	0.298	-12.681	0.000	-4.367	-3.198
Lead Origin_Lead Add Form	2.8737	0.209	13.732	0.000	2.464	3.284
Lead Source_Welingak Website	2.9354	0.748	3.927	0.000	1.470	4.401
What is your current occupation_Working Professional	2.6170	0.204	12.801	0.000	2.216	3.018
Lead Quality_Might be	-2.7085	0.265	-10.238	0.000	-3.227	-2.190
Lead Quality_Not Sure_Low Rel	-2.5105	0.269	-9.344	0.000	-3.037	-1.984
Lead Quality_Worst	-4.6526	0.435	-10.691	0.000	-5.506	-3.800
Lead Profile_Potential Lead	1.5982	0.121	13.242	0.000	1.362	1.835

Task 1: Responses that are significant in predicting whether the lead will convert to a sale.

In [138]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Features'] = X_train_4.columns
vif['VIF'] = [variance_inflation_factor(X_train_4.values, i) for i in range(X_train_4.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[138]:

	Features	VIF
4	Lead Origin_Lead Add Form	1.55
3	Tags_ReasonedLeads	1.41
10	Lead Profile_Potential Lead	1.39
9	Lead Quality_Worst	1.37
5	Lead Source_Welingak Website	1.30
6	What is your current occupation_Working Profes...	1.25
7	Lead Quality_Might be	1.21
8	Lead Quality_Not Sure_Low Rel	1.15
0	Do Not Email	1.11
1	Total Time Spent on Website	1.08
2	Asymmetrique Activity Score	1.01

Top Responses significant predicting whether the lead will be converting to a scale.

In [139]:
```
coefs = res1.params
coefs
```

Out[139]:
```
const                                                   1.692078
Do Not Email                                           -1.249291
Total Time Spent on Website                             1.033217
Asymmetrique Activity Score                             0.522155
Tags_ReasonedLeads                                     -3.782388
Lead Origin_Lead Add Form                               2.873692
Lead Source_Welingak Website                            2.935398
What is your current occupation_Working Professional    2.617035
Lead Quality_Might be                                  -2.708540
Lead Quality_Not Sure_Low Rel                          -2.510515
Lead Quality_Worst                                     -4.652646
Lead Profile_Potential Lead                             1.598161
dtype: float64
```

Top Contributing Variables

In [140]:
```
coefs.abs().sort_values(ascending = False)
```

Out[140]:
```
Lead Quality_Worst                                      4.652646
Tags_ReasonedLeads                                      3.782388
Lead Source_Welingak Website                            2.935398
Lead Origin_Lead Add Form                               2.873692
Lead Quality_Might be                                   2.708540
What is your current occupation_Working Professional    2.617035
Lead Quality_Not Sure_Low Rel                           2.510515
const                                                   1.692078
Lead Profile_Potential Lead                             1.598161
Do Not Email                                            1.249291
Total Time Spent on Website                             1.033217
Asymmetrique Activity Score                             0.522155
dtype: float64
```

Top Focus Variables

In [141]:
```
coefs.sort_values(ascending = False)
```

Out[141]:
```
Lead Source_Welingak Website                            2.935398
Lead Origin_Lead Add Form                               2.873692
What is your current occupation_Working Professional    2.617035
const                                                   1.692078
Lead Profile_Potential Lead                             1.598161
Total Time Spent on Website                             1.033217
Asymmetrique Activity Score                             0.522155
Do Not Email                                           -1.249291
Lead Quality_Not Sure_Low Rel                          -2.510515
Lead Quality_Might be                                  -2.708540
Tags_ReasonedLeads                                     -3.782388
Lead Quality_Worst                                     -4.652646
dtype: float64
```

Task 2: Scoring for the convertible leads based on the probability of how potential a lead, each of them, could be.

In [142]:
```
y_train_pred = res1.predict(X_train_sm).values.reshape(-1)
```

In [143]:
```
y_train_pred_final = pd.DataFrame({'Converted':y_train, 'Converted_Prob':y_train_pred})

y_train_pred_final.head()
```

Out[143]:

	Converted	Converted_Prob
3555	1	0.980599
8055	1	0.993261
1843	0	0.152428
1763	0	0.007727
3017	1	0.564242

Task 3: Predicting Hot Leads

In [144]:
```
y_train_pred_final['predicted'] = y_train_pred_final.Converted_Prob.map(lambda x: 1 if x > 0.5 else 0)

y_train_pred_final.head()
```

Out[144]:

	Converted	Converted_Prob	predicted
3555	1	0.980599	1
8055	1	0.993261	1
1843	0	0.152428	0
1763	0	0.007727	0
3017	1	0.564242	1

Confusion Matrix

In [145]:
```
from sklearn import metrics
```

In [146]:
```
confusion = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final.predicted )
print(confusion)
```

```
[[3541  385]
 [ 677 1823]]
```

In [147]:
```
print(metrics.accuracy_score(y_train_pred_final.Converted, y_train_pred_final.predicted))
```

```
0.834733893557423
```

In [148]:
```
TP = confusion[1,1] # true positive
TN = confusion[0,0] # true negatives
FP = confusion[0,1] # false positives
FN = confusion[1,0] # false negatives
```

In [149]:
```
TP / float(TP+FN)
```

Out[149]:
```
0.7292
```

In [150]:
```
TN / float(TN+FP)
```

Out[150]:
```
0.9019358125318391
```

In [151]:
```
print(FP/ float(TN+FP))
```

```
0.09806418746816098
```

In [152]:
```
print (TP / float(TP+FP))
```

```
0.8256340579710145
```

In [153]:
```
print (TN / float(TN+ FN))
```

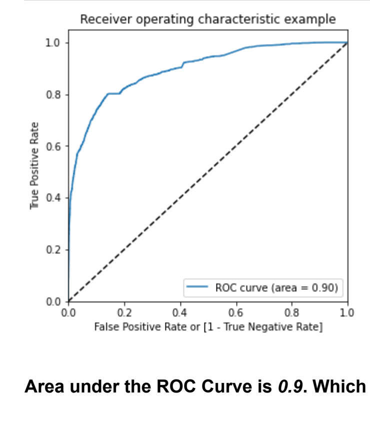
```
0.8394973921289711
```

Step 5: Model Evaluation and Optimization

In [154]:
```
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
```

In [155]:
```
fpr, tpr, thresholds = metrics.roc_curve( y_train_pred_final.Converted, y_train_pred_final.Converted_Pr
ob, drop_intermediate = False )
```

In [156]:
```
draw_roc(y_train_pred_final.Converted, y_train_pred_final.Converted_Prob)
```



Area under the ROC Curve is *0.9*. Which means this is *a good model*.

In [157]:

```python
numbers = [float(x)/10 for x in range(10)]
for i in numbers:
    y_train_pred_final[i]= y_train_pred_final.Converted_Prob.map(lambda x: 1 if x > i else 0)
y_train_pred_final.head()
```

Out[157]:

	Converted	Converted_Prob	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
3555	1	0.980599	1	1	1	1	1	1	1	1	1	1	1
8055	1	0.993261	1	1	1	1	1	1	1	1	1	1	1
1843	0	0.152428	0	1	1	0	0	0	0	0	0	0	0
1763	0	0.007727	0	1	0	0	0	0	0	0	0	0	0
3017	1	0.564242	1	1	1	1	1	1	1	0	0	0	0

Determining optimum probability cut-off

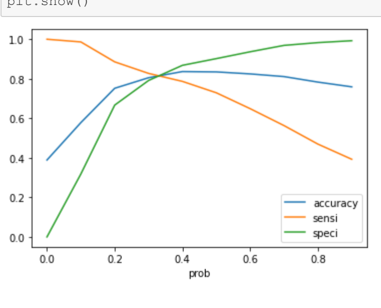
In [158]:

```python
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  0.389045  1.0000  0.000000
0.1   0.1  0.578120  0.9864  0.318136
0.2   0.2  0.751945  0.8856  0.666836
0.3   0.3  0.805322  0.8272  0.791391
0.4   0.4  0.836446  0.7868  0.868059
0.5   0.5  0.834734  0.7292  0.901936
0.6   0.6  0.824619  0.6488  0.936577
0.7   0.7  0.811080  0.5632  0.968925
0.8   0.8  0.783224  0.4696  0.982934
0.9   0.9  0.759259  0.3928  0.992613
```

In [159]:

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



Note:

At the Probability of **approx. 0.3**, the sensitivity and specificity curves cross each other. This gives us the optimum cut-off point. We can proceed calculating the metrics at this point.

In [160]:

```python
y_train_pred_final['final_predicted'] = y_train_pred_final.Converted_Prob.map( lambda x: 1 if x > 0.3 else 0)

y_train_pred_final.head()
```

Out[160]:

	Converted	Converted_Prob	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	final_predicted
3555	1	0.980599	1	1	1	1	1	1	1	1	1	1	1	1
8055	1	0.993261	1	1	1	1	1	1	1	1	1	1	1	1
1843	0	0.152428	0	1	1	0	0	0	0	0	0	0	0	0
1763	0	0.007727	0	1	0	0	0	0	0	0	0	0	0	0
3017	1	0.564242	1	1	1	1	1	1	1	0	0	0	0	1

In [161]:

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

Out[161]: 0.8053221288515406

In [162]:

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

Out[162]:

```
array([[3107,  819],
       [ 432, 2068]], dtype=int64)
```

In [163]:

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

In [164]:

```python
# Sensitivity
TP / float(TP+FN)
```

Out[164]: 0.8272

In [165]:

```python
# Specificity
TN / float(TN+FP)
```

Out[165]: 0.7913907284768212

In [166]:

```python
print(FP/ float(TN+FP))
```

0.20860927152317882

In [167]:

```python
print (TP / float(TP+FP))
```

0.7163145133356426

In [168]:

```python
print (TN / float(TN+ FN))
```

0.8779316191014411

In [169]:

```python
# Precision
confusion2[1,1]/(confusion2[0,1]+confusion2[1,1])
```

Out[169]: 0.7163145133356426

In [170]:

```python
# Recall
confusion2[1,1]/(confusion2[1,0]+confusion2[1,1])
```

Out[170]: 0.8272

In [171]:

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

In [172]:

```python
precision_score(y_train_pred_final.Converted, y_train_pred_final.final_predicted)
```

Out[172]: 0.7163145133356426

In [173]:

```python
recall_score(y_train_pred_final.Converted, y_train_pred_final.final_predicted)
```

Out[173]: 0.8272

In [174]:

```python
X_test[['Total Time Spent on Website','Page Views Per Visit','TotalVisits','Asymmetrique Activity Score','Asymmetrique Profile Score']]=scaler.transform(X_test[['Total Time Spent on Website','Page Views Per Visit','TotalVisits','Asymmetrique Activity Score','Asymmetrique Profile Score']])
```

In [175]:

```python
X_test=X_test[X_train_4.columns]
```

In [176]:

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

In [177]:

```python
y_test_pred=res1.predict(X_test_sm)
```

Task 2: Probability Score for the potential leads

In [178]:

```python
y_test_pred_final=pd.DataFrame({'Converted':y_test,'Converted_prob':y_test_pred})
y_test_pred_final
```

Out[178]:

	Converted	Converted_prob
6187	0	0.569190
7610	0	0.178430
7084	0	0.254505
491	0	0.143002
4222	0	0.728445
...	...	...
7246	0	0.094872
2727	1	0.995274
501	0	0.129145
8330	1	0.999239
506	0	0.071211

2755 rows × 2 columns

Task 3: Hot Leads among the potential leads

In [179]:

```python
y_test_pred_final['final_predicted'] = y_test_pred_final.Converted_prob.map(lambda x: 1 if x > 0.3 else 0)
```

In [180]:

```python
y_test_pred_final
```

Out[180]:

	Converted	Converted_prob	final_predicted
6187	0	0.569190	1
7610	0	0.178430	0
7084	0	0.254505	0
491	0	0.143002	0
4222	0	0.728445	1
...	...	...	...
7246	0	0.094872	0
2727	1	0.995274	1
501	0	0.129145	0
8330	1	0.999239	1
506	0	0.071211	0

2755 rows × 3 columns

In [181]:

```python
## Accuracy
metrics.accuracy_score(y_test_pred_final.Converted, y_test_pred_final.final_predicted)
```

Out[181]: 0.8010889292196007

In [182]:

```python
confusion2 = metrics.confusion_matrix(y_test_pred_final.Converted, y_test_pred_final.final_predicted )
confusion2
```

Out[182]:

```
array([[1362,  356],
       [ 192,  845]], dtype=int64)
```

In [183]:

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

In [184]:

```python
# Sensitivity
TP / float(TP+FN)
```

Out[184]: 0.8148505303760849

In [185]:

```python
# Specificity
TN / float(TN+FP)
```

Out[185]: 0.7927823050058207

In [186]:

```python
precision_score(y_test_pred_final.Converted, y_test_pred_final.final_predicted)
```

Out[186]: 0.7035803497085762

In [187]:

```python
recall_score(y_train_pred_final.Converted, y_train_pred_final.final_predicted)
```

Out[187]: 0.8272

Assignent Subjective Questions:

1. Which are the top three variables in your model which contribute most towards the probability of a lead getting converted?

> **Lead Source_Welingak Website**
> **Lead Origin_Lead Add Form**
> **What is your current occupation_Working Professional**

1. What are the top 3 categorical/dummy variables in the model which should be focused the most on in order to increase the probability of lead conversion?

> **Lead Source_Welingak Website**
> **Lead Origin_Lead Add Form**
> **What is your current occupation_Working Professional**

1. X Education has a period of 2 months every year during which they hire some interns. The sales team, in particular, has around 10 interns allotted to them. So during this phase, they wish to make the lead conversion more aggressive. So they want almost all of the potential leads (i.e. the customers who have been predicted as 1 by the model) to be converted and hence, want to make phone calls to as much of such people as possible. Suggest a good strategy they should employ at this stage.

> This is essentially a peak calling season for X Education and thus to enhance as much mileage as possible and maximize on the caller availability, all the people have been predicted by the model (probability > 0.3) can be called.
> To increase probability of getting conversions early-on in the process, the list can be prioritized based on the scores and can be called in the descending order of scores.

1. Similarly, at times, the company reaches its target for a quarter before the deadline. During this time, the company wants the sales team to focus on some new work as well. So during this time, the company's aim is to not make phone calls unless it's extremely necessary, i.e. they want to minimize the rate of useless phone calls. Suggest a strategy they should employ at this stage.

> This is a sensitive calling season for X Education and thus to be as efficient as possible by maximizing the conversion rate, the callers can be asked to focus on people with most contributions.
> Based on domain knowledge, we can focus on top 3 or top 5 people. As a matter of fact, The model has identified 3 specific types of Leads:
>
> 1. Leads who have come from the Welingak website, **Lead Source_Welingak Website**
> 2. Leads who have been identified as a lead by triggering the 'Lead Add Form' user action, **Lead Origin_Lead Add Form**
> 3. Leads who are working professionals and possibly have a specific reason in their minds for the course and perhaps lesser monetary challenges in taking up a course. **What is your current occupation_Working Professional**
>
> The actual focus group of leads for the callers can be decided based on a detailed business discussion backed by the model statistics and business accumen.

Note:

The below three variables are the most significant influencers for the model.

> **Lead Quality_Worst**
> **Tags_ReasonedLeads** (These are leads whom the sales people have tagged as have been reasoned by the lead during a sales call)
> **Lead Source_Welingak Website**

We have to note that the first two are negatively inlfuencing the conversion. Essentially, these are people who are more likely will not convert.