

# Lead Score - Case Study

## Problem Statement

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

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

There are a lot of leads generated in the initial stage, but only a few of them come out as paying customers. In the middle stage, you need to nurture the potential leads well (i.e. educating the leads about the product, constantly communicating etc. ) in order to get a higher lead conversion.

X Education has appointed you to help them select the most promising leads, i.e. the leads that are most likely to convert into paying customers. The company requires you to **build a model wherein you need to assign a lead score to each of the leads such that the customers with higher lead score have a higher conversion chance and the customers with lower lead score have a lower conversion chance**. The CEO, in particular, has given a ballpark of the target lead conversion rate to be around 80%.

## Goals of the Case Study

- Build a **logistic regression model** to assign a lead score between 0 and 100 to each of the leads which can be used by the company to target potential leads. A higher score would mean that the lead is hot, i.e. is most likely to convert whereas a lower score would mean that the lead is cold and will mostly not get converted.

*All the outcomes and understandings are written in BLUE*

```
# Suppress Warnings
import warnings
warnings.filterwarnings('ignore')
#Importing required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

# 1: Loading and Cleaning Data

## 1.1 Import Data

```
# Loading the data using Pandas
```

```
df = pd.read_csv('C:\Data science Project\Lead+Scoring+Case+Study\Lead  
Scoring Assignment\Leads.csv')
```

```
df
```

	Prospect ID	Lead Number \
0	7927b2df-8bba-4d29-b9a2-b6e0beafe620	660737
1	2a272436-5132-4136-86fa-dcc88c88f482	660728
2	8cc8c611-a219-4f35-ad23-fdfd2656bd8a	660727
3	0cc2df48-7cf4-4e39-9de9-19797f9b38cc	660719
4	3256f628-e534-4826-9d63-4a8b88782852	660681
5	2058ef08-2858-443e-a01f-a9237db2f5ce	660680
6	9fae7df4-169d-489b-afe4-0f3d752542ed	660673
7	20ef72a2-fb3b-45e0-924e-551c5fa59095	660664
8	cfa0128c-a0da-4656-9d47-0aa4e67bf690	660624
9	af465dfc-7204-4130-9e05-33231863c4b5	660616
10	2a369e35-ca95-4ca9-9e4f-9d27175aa320	660608
11	9bc8ce93-6144-49e0-9f9d-080fc980f83c	660570
12	8bf76a52-2478-476b-8618-1688e07874ad	660562
13	88867067-3750-4753-8d33-1c7d1db53b5e	660558
14	a8531c22-fcf1-48f8-a711-fb5abf98ad87	660553
15	25f4ac14-ff4b-4cd2-9c61-b44c85e19c8f	660547
16	3abb7c77-1634-4083-9a9f-861068220611	660540
17	e5c3beca-a0b6-4b3f-8c01-0919fb9ca3f2	660534
18	82cb5fb0-2d97-4a39-a630-ab5fe2e7f18c	660522
19	4512c16a-e96a-4459-b9ec-c7d8fe8c4880	660509
20	c4419c99-b002-408b-a6fd-fa100716592c	660479
21	fd71ab5b-53b8-4105-9960-efedc44962fa	660478
22	8fd38b83-5c32-4277-bcfb-499f34a01c56	660471
23	ecbc6e69-29a9-44bf-804a-13079ef301bc	660461
24	ecd117ca-375f-49ea-afd6-b52b84d00c69	660458
25	31c326f0-4a9b-43a6-9006-99d3830fbcae	660447
26	c494aca4-8c8e-4081-9784-41eb6346015e	660432
27	6d143c0e-abae-425f-a2c0-52c2946cbd45	660424
28	8247051c-f838-4a41-b39c-1f0b44c3d5e6	660423
29	b3455e2e-8236-478a-b1aa-666ad3381722	660410
...	...	...
9210	14ac6418-af18-4acd-b464-02f6e0fefaf1c	579833
9211	8458b410-48fe-4bcd-aecf-5813b6006ee2	579832
9212	0c15052a-9f8a-47c4-9fc3-eb20c84ffd74	579830
9213	d4587acb-02d1-4c5e-9110-6032d829bac1	579822
9214	479a8b1c-d410-4220-a24f-854a376be43d	579808
9215	06334ac1-64a8-444c-92a7-117dcd26dea5	579802
9216	6da5be9f-3f34-4dc7-9e30-7c26d030372e	579799
9217	b8872c12-7534-498d-8f4a-e79a19516db1	579786

9218	eee466be-b98c-4126-9220-fc406093b9ce	579784
9219	9c970d5c-2748-4f61-90a6-eafd9ad5a242	579778
9220	679ab5f9-0f85-4f16-a903-821ecd82e731	579769
9221	b92509cd-7f4c-414e-a8af-eb9cf0c89da7	579767
9222	68e53bdc-b66d-48ef-8592-973a8a65377e	579764
9223	c55de92b-9295-40e1-90e8-a628c349c292	579755
9224	18930f11-41cd-42d1-96d7-34ac870174cb	579753
9225	787ab5f4-6f09-41c0-b083-55521ca23f8a	579744
9226	c3bb1471-53d5-4244-b2e5-4bbb543835c1	579735
9227	ac95586a-506a-4222-9967-17dfe9f82524	579728
9228	40d3b3cf-d939-49ff-bea5-60e8d4025104	579717
9229	5cfdd915-d5a0-4976-b38d-e5f72ec55526	579712
9230	d11c15b7-8056-45a6-8954-771c0d0495fe	579701
9231	4aeae36b-2b57-494f-bdab-dd58844286b4	579697
9232	2d0109e9-dfb2-4664-83de-c2ea75ec7516	579642
9233	3f715465-2546-47cd-afa8-8b8dc63b8b43	579622
9234	c0b25922-511f-4c56-852e-ced210a45447	579615
9235	19d6451e-fcd6-407c-b83b-48e1af805ea9	579564
9236	82a7005b-7196-4d56-95ce-a79f937a158d	579546
9237	aac550fe-a586-452d-8d3c-f1b62c94e02c	579545
9238	5330a7d1-2f2b-4df4-85d6-64ca2f6b95b9	579538
9239	571b5c8e-a5b2-4d57-8574-f2ffb06fdeff	579533

	Lead Origin	Lead Source	Do Not Email	Do Not Call
\				
0	API	Olark Chat	No	No
1	API	Organic Search	No	No
2	Landing Page Submission	Direct Traffic	No	No
3	Landing Page Submission	Direct Traffic	No	No
4	Landing Page Submission	Google	No	No
5	API	Olark Chat	No	No
6	Landing Page Submission	Google	No	No
7	API	Olark Chat	No	No
8	Landing Page Submission	Direct Traffic	No	No
9	API	Google	No	No
10	Landing Page Submission	Organic Search	No	No
11	Landing Page Submission	Direct Traffic	No	No
12	API	Organic Search	No	No

13	Landing Page Submission	Organic Search	No	No
14	Landing Page Submission	Direct Traffic	Yes	No
15	API	Organic Search	No	No
16	API	Olark Chat	No	No
17	API	Referral Sites	No	No
18	Landing Page Submission	Google	No	No
19	API	Organic Search	No	No
20	Landing Page Submission	Google	No	No
21	API	Google	No	No
22	Landing Page Submission	Google	No	No
23	Landing Page Submission	Google	No	No
24	API	Google	No	No
25	Landing Page Submission	Google	No	No
26	Landing Page Submission	Organic Search	No	No
27	Landing Page Submission	Google	No	No
28	Landing Page Submission	Direct Traffic	No	No
29	API	Google	No	No
...	...	...	...	...
9210	Landing Page Submission	Direct Traffic	No	No
9211	Landing Page Submission	Direct Traffic	No	No
9212	Landing Page Submission	Google	Yes	No
9213	Landing Page Submission	Direct Traffic	Yes	No
9214	API	Organic Search	No	No
9215	Landing Page Submission	Organic Search	No	No
9216	Landing Page Submission	Direct Traffic	Yes	No
9217	API	Olark Chat	No	No

9218	Landing Page Submission	Google	Yes	No
9219	Landing Page Submission	Direct Traffic	No	No
9220	Landing Page Submission	Direct Traffic	No	No
9221	Landing Page Submission	Google	No	No
9222	API	Google	No	No
9223	API	Organic Search	No	No
9224	Landing Page Submission	Google	No	No
9225	Landing Page Submission	Direct Traffic	Yes	No
9226	API	Olark Chat	No	No
9227	Landing Page Submission	Google	No	No
9228	Landing Page Submission	Google	No	No
9229	Landing Page Submission	Organic Search	No	No
9230	Landing Page Submission	Google	No	No
9231	Landing Page Submission	Google	No	No
9232	Landing Page Submission	Direct Traffic	No	No
9233	API	Direct Traffic	No	No
9234	Landing Page Submission	Direct Traffic	No	No
9235	Landing Page Submission	Direct Traffic	Yes	No
9236	Landing Page Submission	Direct Traffic	No	No
9237	Landing Page Submission	Direct Traffic	Yes	No
9238	Landing Page Submission	Google	No	No
9239	Landing Page Submission	Direct Traffic	No	No
	Converted	TotalVisits	Total Time Spent on Website \	
0	0	0.0	0	
1	0	5.0	674	
2	1	2.0	1532	
3	0	1.0	305	
4	1	2.0	1428	

5	0	0.0	0
6	1	2.0	1640
7	0	0.0	0
8	0	2.0	71
9	0	4.0	58
10	1	8.0	1351
11	1	8.0	1343
12	1	11.0	1538
13	0	5.0	170
14	0	1.0	481
15	1	6.0	1012
16	0	0.0	0
17	0	6.0	973
18	1	6.0	1688
19	0	3.0	98
20	0	1.0	233
21	0	4.0	377
22	1	1.0	1013
23	0	4.0	771
24	1	6.0	1137
25	1	3.0	1068
26	1	4.0	1000
27	1	6.0	1315
28	0	5.0	182
29	1	3.0	78
...	...	...	...
9210	1	4.0	927
9211	1	4.0	1112
9212	0	5.0	78
9213	0	5.0	234
9214	1	2.0	881
9215	0	8.0	397
9216	0	6.0	1679
9217	0	0.0	0
9218	0	1.0	149
9219	1	6.0	1389
9220	0	5.0	20
9221	0	4.0	1347
9222	0	6.0	228
9223	0	7.0	142
9224	0	4.0	455
9225	0	2.0	74
9226	0	0.0	0
9227	1	5.0	1283
9228	1	4.0	1944
9229	1	13.0	1226
9230	0	2.0	870
9231	1	8.0	1016
9232	0	2.0	1770

9233	1	13.0	1409
9234	1	5.0	210
9235	1	8.0	1845
9236	0	2.0	238
9237	0	2.0	199
9238	1	3.0	499
9239	1	6.0	1279

Page Views Per Visit			...	Get updates on DM
Content \				
0		0.00	...	
No				
1		2.50	...	
No				
2		2.00	...	
No				
3		1.00	...	
No				
4		1.00	...	
No				
5		0.00	...	
No				
6		2.00	...	
No				
7		0.00	...	
No				
8		2.00	...	
No				
9		4.00	...	
No				
10		8.00	...	
No				
11		2.67	...	
No				
12		11.00	...	
No				
13		5.00	...	
No				
14		1.00	...	
No				
15		6.00	...	
No				
16		0.00	...	
No				
17		6.00	...	
No				
18		3.00	...	
No				
19		3.00	...	

No		
20	1.00	...
No		
21	1.33	...
No		
22	1.00	...
No		
23	4.00	...
No		
24	1.50	...
No		
25	3.00	...
No		
26	2.00	...
No		
27	6.00	...
No		
28	5.00	...
No		
29	3.00	...
No		
...	...	...
...		
9210	4.00	...
No		
9211	4.00	...
No		
9212	5.00	...
No		
9213	2.50	...
No		
9214	2.00	...
No		
9215	8.00	...
No		
9216	6.00	...
No		
9217	0.00	...
No		
9218	1.00	...
No		
9219	6.00	...
No		
9220	2.50	...
No		
9221	2.00	...
No		
9222	6.00	...
No		



9223	7.00	...
No		
9224	4.00	...
No		
9225	2.00	...
No		
9226	0.00	...
No		
9227	1.67	...
No		
9228	2.00	...
No		
9229	6.50	...
No		
9230	2.00	...
No		
9231	4.00	...
No		
9232	2.00	...
No		
9233	2.60	...
No		
9234	2.50	...
No		
9235	2.67	...
No		
9236	2.00	...
No		
9237	2.00	...
No		
9238	3.00	...
No		
9239	3.00	...
No		

Index	Lead Profile	City Asymetrique Activity	
	\		
0	Select	Select	02.Medium
1	Select	Select	02.Medium
2	Potential Lead	Mumbai	02.Medium
3	Select	Mumbai	02.Medium
4	Select	Mumbai	02.Medium
5	NaN	NaN	01.High
6	Potential Lead	Mumbai	02.Medium

7		NaN	NaN	02.Medium
8		NaN	Thane & Outskirts	02.Medium
9		NaN	Mumbai	02.Medium
10		Select	Other Metro Cities	02.Medium
11		Select	Thane & Outskirts	02.Medium
12	Potential Lead		Select	01.High
13		Select	Thane & Outskirts	02.Medium
14		Select	Select	01.High
15		Select	Select	02.Medium
16		NaN	NaN	01.High
17		Select	Select	02.Medium
18		Select	Mumbai	02.Medium
19		Select	Select	02.Medium
20		Select	Mumbai	02.Medium
21	Potential Lead		Select	02.Medium
22	Potential Lead		Mumbai	02.Medium
23		Select	Mumbai	02.Medium
24	Potential Lead		Mumbai	02.Medium
25		Select	Mumbai	02.Medium
26	Potential Lead		Other Cities	03.Low
27	Potential Lead		Mumbai	02.Medium
28		Select	Mumbai	02.Medium
29	Potential Lead		Mumbai	01.High
...	...		...	...
9210	Potential Lead		Mumbai	02.Medium
9211	Other Leads		Mumbai	02.Medium

9212	Potential Lead	Mumbai	02.Medium
9213	NaN	Mumbai	01.High
9214	NaN	NaN	02.Medium
9215	NaN	Thane & Outskirts	02.Medium
9216	Other Leads	Mumbai	01.High
9217	Potential Lead	Select	02.Medium
9218	NaN	Mumbai	02.Medium
9219	Potential Lead	Other Metro Cities	02.Medium
9220	Potential Lead	Thane & Outskirts	02.Medium
9221	Select	Mumbai	NaN
9222	Potential Lead	Other Cities	02.Medium
9223	Potential Lead	Mumbai	02.Medium
9224	Potential Lead	Mumbai	03.Low
9225	Potential Lead	Mumbai	03.Low
9226	Select	Select	01.High
9227	Potential Lead	Mumbai	02.Medium
9228	Select	Mumbai	NaN
9229	Potential Lead	Mumbai	02.Medium
9230	Potential Lead	Mumbai	02.Medium
9231	Potential Lead	Mumbai	02.Medium
9232	Potential Lead	Mumbai	02.Medium
9233	Select	Select	NaN
9234	Potential Lead	Mumbai	02.Medium
9235	Potential Lead	Mumbai	02.Medium
9236	Potential Lead	Mumbai	02.Medium
9237	Potential Lead	Mumbai	02.Medium

9238	NaN	Other Metro Cities	02.Medium
9239	Potential Lead	Other Cities	02.Medium
	Asymmetrique Profile Index	Asymmetrique Activity Score	\
0	02.Medium	15.0	
1	02.Medium	15.0	
2	01.High	14.0	
3	01.High	13.0	
4	01.High	15.0	
5	02.Medium	17.0	
6	01.High	14.0	
7	02.Medium	15.0	
8	02.Medium	14.0	
9	02.Medium	13.0	
10	02.Medium	15.0	
11	01.High	14.0	
12	02.Medium	16.0	
13	01.High	14.0	
14	01.High	16.0	
15	02.Medium	14.0	
16	02.Medium	17.0	
17	02.Medium	13.0	
18	01.High	15.0	
19	02.Medium	14.0	
20	01.High	13.0	
21	02.Medium	15.0	
22	01.High	15.0	
23	01.High	14.0	
24	01.High	14.0	
25	02.Medium	14.0	
26	01.High	11.0	
27	01.High	15.0	
28	01.High	13.0	
29	01.High	16.0	
...	...	...	
9210	01.High	14.0	
9211	02.Medium	15.0	
9212	01.High	13.0	
9213	02.Medium	17.0	
9214	02.Medium	15.0	
9215	01.High	13.0	
9216	01.High	16.0	
9217	02.Medium	15.0	
9218	01.High	13.0	
9219	01.High	15.0	
9220	01.High	13.0	
9221	NaN	NaN	

9222	02.Medium	15.0
9223	01.High	13.0
9224	01.High	12.0
9225	01.High	12.0
9226	02.Medium	16.0
9227	01.High	15.0
9228	NaN	NaN
9229	01.High	15.0
9230	01.High	13.0
9231	01.High	15.0
9232	01.High	14.0
9233	NaN	NaN
9234	01.High	14.0
9235	01.High	15.0
9236	01.High	14.0
9237	01.High	13.0
9238	02.Medium	15.0
9239	01.High	15.0

Asymmetrique Profile Score I agree to pay the amount through  
cheque \

0	15.0
No	
1	15.0
No	
2	20.0
No	
3	17.0
No	
4	18.0
No	
5	15.0
No	
6	20.0
No	
7	15.0
No	
8	14.0
No	
9	16.0
No	
10	14.0
No	
11	17.0
No	
12	16.0
No	
13	17.0
No	

14	17.0
No	
15	15.0
No	
16	15.0
No	
17	13.0
No	
18	18.0
No	
19	15.0
No	
20	17.0
No	
21	16.0
No	
22	20.0
No	
23	18.0
No	
24	18.0
No	
25	16.0
No	
26	18.0
No	
27	19.0
No	
28	18.0
No	
29	18.0
No	
...	...
..	
9210	20.0
No	
9211	15.0
No	
9212	20.0
No	
9213	15.0
No	
9214	15.0
No	
9215	17.0
No	
9216	18.0
No	
9217	16.0

No	
9218	18.0
No	
9219	18.0
No	
9220	19.0
No	
9221	NaN
No	
9222	16.0
No	
9223	18.0
No	
9224	20.0
No	
9225	20.0
No	
9226	15.0
No	
9227	20.0
No	
9228	NaN
No	
9229	20.0
No	
9230	20.0
No	
9231	20.0
No	
9232	20.0
No	
9233	NaN
No	
9234	20.0
No	
9235	17.0
No	
9236	19.0
No	
9237	20.0
No	
9238	16.0
No	
9239	18.0
No	

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

2	Yes	Email Opened
3	No	Modified
4	No	Modified
5	No	Modified
6	No	Modified
7	No	Modified
8	Yes	Email Opened
9	No	Email Opened
10	Yes	Email Opened
11	Yes	Page Visited on Website
12	No	Modified
13	Yes	Email Opened
14	No	Email Bounced
15	No	Email Opened
16	No	Modified
17	No	Modified
18	No	Page Visited on Website
19	No	Modified
20	No	Modified
21	No	Modified
22	No	Modified
23	No	Email Link Clicked
24	Yes	Email Opened
25	No	Modified
26	Yes	Email Opened
27	No	Email Opened
28	No	Email Opened
29	No	Unreachable
...	...	...
9210	No	Modified
9211	No	SMS Sent
9212	Yes	Unsubscribed
9213	No	Modified
9214	No	SMS Sent
9215	Yes	Email Opened
9216	Yes	Modified
9217	No	SMS Sent
9218	No	Modified
9219	Yes	Email Opened
9220	Yes	Modified
9221	Yes	SMS Sent
9222	No	Modified
9223	Yes	Modified
9224	No	Modified
9225	Yes	Modified
9226	No	Modified
9227	No	Email Opened
9228	Yes	Modified
9229	Yes	Modified



9230	No	Email Opened
9231	No	Email Opened
9232	Yes	SMS Sent
9233	No	SMS Sent
9234	No	Modified
9235	No	Email Marked Spam
9236	Yes	SMS Sent
9237	Yes	SMS Sent
9238	No	SMS Sent
9239	Yes	Modified

[9240 rows x 37 columns]

## 1.2 Inspect the dataframe

This helps to give a good idea of the dataframes.

*# The .info() code gives almost the entire information that needs to be inspected, so let's start from there*

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 9240 entries, 0 to 9239
```

```
Data columns (total 37 columns):
```

Prospect ID	9240	non-null	object
Lead Number	9240	non-null	int64
Lead Origin	9240	non-null	object
Lead Source	9204	non-null	object
Do Not Email	9240	non-null	object
Do Not Call	9240	non-null	object
Converted	9240	non-null	int64
TotalVisits	9103	non-null	float64
Total Time Spent on Website	9240	non-null	int64
Page Views Per Visit	9103	non-null	float64
Last Activity	9137	non-null	object
Country	6779	non-null	object
Specialization	7802	non-null	object
How did you hear about X Education	7033	non-null	object
What is your current occupation	6550	non-null	object
What matters most to you in choosing a course	6531	non-null	object
Search	9240	non-null	object
Magazine	9240	non-null	object
Newspaper Article	9240	non-null	object
X Education Forums	9240	non-null	object
Newspaper	9240	non-null	object
Digital Advertisement	9240	non-null	object
Through Recommendations	9240	non-null	object
Receive More Updates About Our Courses	9240	non-null	object
Tags	5887	non-null	object

```

Lead Quality                                4473 non-null object
Update me on Supply Chain Content          9240 non-null object
Get updates on DM Content                  9240 non-null object
Lead Profile                              6531 non-null object
City                                       7820 non-null object
Asymmetrique Activity Index              5022 non-null object
Asymmetrique Profile Index               5022 non-null object
Asymmetrique Activity Score              5022 non-null float64
Asymmetrique Profile Score               5022 non-null float64
I agree to pay the amount through cheque  9240 non-null object
A free copy of Mastering The Interview    9240 non-null object
Last Notable Activity                    9240 non-null object
dtypes: float64(4), int64(3), object(30)
memory usage: 2.6+ MB

```

*#To get the idea of how the table looks like we can use .head() or .tail() command*  
df.head()

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

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

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

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

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

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

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

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

[5 rows x 37 columns]

*# The .shape code gives the no. of rows and columns*

df.shape

(9240, 37)

*#To get an idea of the numeric values, use .describe()*

df.describe()

	Lead Number	Converted	TotalVisits	Total Time Spent on Website \
count	9240.000000	9240.000000	9103.000000	9240.000000

mean	617188.435606	0.385390	3.445238
std	23405.995698	0.486714	4.854853
min	579533.000000	0.000000	0.000000
25%	596484.500000	0.000000	1.000000
50%	615479.000000	0.000000	3.000000
75%	637387.250000	1.000000	5.000000
max	660737.000000	1.000000	251.000000

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

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

## 1.3 Cleaning the dataframe

```
# Converting all the values to lower case
df = df.applymap(lambda s:s.lower() if type(s) == str else s)

# Replacing 'Select' with NaN (Since it means no option is selected)
df = df.replace('select',np.nan)

# Checking if there are columns with one unique value since it won't
affect our analysis
df.nunique()
```

Prospect ID	9240
Lead Number	9240
Lead Origin	5

Lead Source	20
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	18
How did you hear about X Education	9
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	5
City	6
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	

*# Dropping unique valued columns*

```
df1= df.drop(['Magazine','Receive More Updates About Our Courses','I agree to pay the amount through cheque','Get updates on DM Content','Update me on Supply Chain Content'],axis=1)
```

*# Checking the percentage of missing values*

```
round(100*(df1.isnull().sum()/len(df1.index)), 2)
```

Prospect ID	0.00
Lead Number	0.00
Lead Origin	0.00
Lead Source	0.39
Do Not Email	0.00
Do Not Call	0.00

Converted	0.00
TotalVisits	1.48
Total Time Spent on Website	0.00
Page Views Per Visit	1.48
Last Activity	1.11
Country	26.63
Specialization	36.58
How did you hear about X Education	78.46
What is your current occupation	29.11
What matters most to you in choosing a course	29.32
Search	0.00
Newspaper Article	0.00
X Education Forums	0.00
Newspaper	0.00
Digital Advertisement	0.00
Through Recommendations	0.00
Tags	36.29
Lead Quality	51.59
Lead Profile	74.19
City	39.71
Asymmetrique Activity Index	45.65
Asymmetrique Profile Index	45.65
Asymmetrique Activity Score	45.65
Asymmetrique Profile Score	45.65
A free copy of Mastering The Interview	0.00
Last Notable Activity	0.00
dtype: float64	

*# Removing all the columns that are no required and have 35% null values*

```
df2 = df1.drop(['Asymmetrique Profile Index','Asymmetrique Activity Index','Asymmetrique Activity Score','Asymmetrique Profile Score','Lead Profile','Tags','Lead Quality','How did you hear about X Education','City','Lead Number'],axis=1)
df2.head()
```

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

	Lead Source	Do Not Email	Do Not Call	Converted	TotalVisits \
0	olark chat	no	no	0	0.0
1	organic search	no	no	0	5.0
2	direct traffic	no	no	1	2.0
3	direct traffic	no	no	0	1.0
4	google	no	no	1	2.0

Total Time Spent on Website		Page Views Per Visit		Last
Activity \				
0	0	0.0	page visited on	
website				
1	674	2.5	email	
opened				
2	1532	2.0	email	
opened				
3	305	1.0		
unreachable				
4	1428	1.0	converted	
to lead				
What is your current occupation \				
0	...	unemployed		
1	...	unemployed		
2	...	student		
3	...	unemployed		
4	...	unemployed		
What matters most to you in choosing a course		Search Newspaper		
Article \				
0	better career prospects	no		
no				
1	better career prospects	no		
no				
2	better career prospects	no		
no				
3	better career prospects	no		
no				
4	better career prospects	no		
no				
X Education Forums Newspaper Digital Advertisement Through		Recommendations \		
0	no	no	no	
no				
1	no	no	no	
no				
2	no	no	no	
no				
3	no	no	no	
no				
4	no	no	no	
no				
A free copy of Mastering The Interview		Last Notable Activity		
0	no	modified		
1	no	email opened		
2	yes	email opened		

3	no	modified
4	no	modified

[5 rows x 22 columns]

```
# Rechecking the percentage of missing values
round(100*(df2.isnull().sum()/len(df2.index)), 2)
```

Prospect ID	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	36.58
What is your current occupation	29.11
What matters most to you in choosing a course	29.32
Search	0.00
Newspaper Article	0.00
X Education Forums	0.00
Newspaper	0.00
Digital Advertisement	0.00
Through Recommendations	0.00
A free copy of Mastering The Interview	0.00
Last Notable Activity	0.00
dtype: float64	

***There is a huge value of null variables in 4 columns as seen above. But removing the rows with the null value will cost us a lot of data and they are important columns. So, instead we are going to replace the NaN values with 'not provided'. This way we have all the data and almost no null values. In case these come up in the model, it will be of no use and we can drop it off then.***

```
df2['Specialization'] = df2['Specialization'].fillna('not provided')
df2['What matters most to you in choosing a course'] = df2['What
matters most to you in choosing a course'].fillna('not provided')
df2['Country'] = df2['Country'].fillna('not provided')
df2['What is your current occupation'] = df2['What is your current
occupation'].fillna('not provided')
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9240 entries, 0 to 9239
Data columns (total 22 columns):
Prospect ID                9240 non-null object
```



Lead Origin	9240	non-null	object
Lead Source	9204	non-null	object
Do Not Email	9240	non-null	object
Do Not Call	9240	non-null	object
Converted	9240	non-null	int64
TotalVisits	9103	non-null	float64
Total Time Spent on Website	9240	non-null	int64
Page Views Per Visit	9103	non-null	float64
Last Activity	9137	non-null	object
Country	9240	non-null	object
Specialization	9240	non-null	object
What is your current occupation	9240	non-null	object
What matters most to you in choosing a course	9240	non-null	object
Search	9240	non-null	object
Newspaper Article	9240	non-null	object
X Education Forums	9240	non-null	object
Newspaper	9240	non-null	object
Digital Advertisement	9240	non-null	object
Through Recommendations	9240	non-null	object
A free copy of Mastering The Interview	9240	non-null	object
Last Notable Activity	9240	non-null	object

dtypes: float64(2), int64(2), object(18)  
memory usage: 1.6+ MB

*# Rechecking the percentage of missing values*  
`round(100*(df2.isnull().sum()/len(df2.index)), 2)`

Prospect ID	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	0.00
Specialization	0.00
What is your current occupation	0.00
What matters most to you in choosing a course	0.00
Search	0.00
Newspaper Article	0.00
X Education Forums	0.00
Newspaper	0.00
Digital Advertisement	0.00
Through Recommendations	0.00
A free copy of Mastering The Interview	0.00
Last Notable Activity	0.00

dtype: float64

```
df2["Country"].value_counts()
```

```
india          6492
not provided    2461
united states   69
united arab emirates  53
singapore       24
saudi arabia    21
united kingdom  15
australia       13
qatar           10
bahrain         7
hong kong       7
france          6
oman            6
unknown         5
nigeria         4
south africa    4
kuwait          4
germany         4
canada          4
sweden          3
bangladesh      2
belgium         2
philippines     2
ghana           2
netherlands     2
italy           2
china           2
asia/pacific region  2
uganda          2
tanzania        1
denmark         1
switzerland     1
malaysia        1
russia          1
sri lanka       1
vietnam         1
kenya           1
liberia         1
indonesia       1
Name: Country, dtype: int64
```

```
def slots(x):
    category = ""
    if x == "india":
        category = "india"
    elif x == "not provided":
        category = "not provided"
    else:
```

```

        category = "outside india"
    return category

df2['Country'] = df2.apply(lambda x:slots(x['Country']), axis = 1)
df2['Country'].value_counts()

india          6492
not provided    2461
outside india    287
Name: Country, dtype: int64

# Rechecking the percentage of missing values
round(100*(df2.isnull().sum()/len(df2.index)), 2)

Prospect ID          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              0.00
Specialization        0.00
What is your current occupation 0.00
What matters most to you in choosing a course 0.00
Search               0.00
Newspaper Article    0.00
X Education Forums   0.00
Newspaper            0.00
Digital Advertisement 0.00
Through Recommendations 0.00
A free copy of Mastering The Interview 0.00
Last Notable Activity 0.00
dtype: float64

# Checking the percent of lose if the null values are removed
round(100*(sum(df2.isnull().sum(axis=1) > 1)/df2.shape[0]),2)

1.48

df3 = df2[df2.isnull().sum(axis=1) <1]

# Code for checking number of rows left in percent
round(100*(df3.shape[0])/(df.shape[0]),2)

98.2

```

```
# Rechecking the percentage of missing values
round(100*(df3.isnull().sum()/len(df3.index)), 2)
```

```
Prospect ID          0.0
Lead Origin          0.0
Lead Source          0.0
Do Not Email        0.0
Do Not Call         0.0
Converted           0.0
TotalVisits         0.0
Total Time Spent on Website 0.0
Page Views Per Visit 0.0
Last Activity       0.0
Country            0.0
Specialization      0.0
What is your current occupation 0.0
What matters most to you in choosing a course Search 0.0
Newspaper Article   0.0
X Education Forums  0.0
Newspaper           0.0
Digital Advertisement 0.0
Through Recommendations 0.0
A free copy of Mastering The Interview 0.0
Last Notable Activity 0.0
dtype: float64
```

```
# To familiarize all the categorical values
```

```
for column in df3:
    print(df3[column].astype('category').value_counts())
```

```
print('-----')
print('-----')
```

```
ffffb0e5e-9f92-4017-9f42-781a69da4154    1
539366d9-f633-455a-99e4-dbc5907db28e    1
53ac14bd-2bb2-4315-a21c-94562d1b6b2d    1
53aabd84-5dcc-4299-bbe3-62f3764b07b1    1
539ffa32-1be7-4fe1-b04c-faf1bab763cf    1
539eb309-df36-4a89-ac58-6d3651393910    1
5398e7ff-74db-4074-89fb-4fd9a603f521    1
53953744-234a-4cb9-9af4-bcc47eb472f4    1
5390c5fe-b12c-4f6e-ae92-908672abb0a1    1
53dbb914-71e7-458a-9749-cfb4d655eac2    1
5379ee79-64b7-44f8-8c56-0e1ca2d5b887    1
537963c8-22d9-459d-8aae-ddac40580ffb    1
53744d5a-0483-42c0-80b0-8990a4d2356d    1
53715ab1-2106-4c4e-8493-81cc465eb9ce    1
536cdc6b-f4c1-449d-bfd8-9ef0ac912dbb    1
53690d88-52f0-4ce5-b6b8-a13570a6db35    1
```

53c4e210-3344-4737-813f-74ef9a747ab6	1
53dd16bd-8201-448d-8e20-97de1cf44a7f	1
5464e56f-d39b-49a4-881c-8c6f75f2bbc7	1
54170a0f-0470-4612-b284-3ea12d3a9ea0	1
543892e8-5b9a-4552-99b9-87d57f40552a	1
5434ccf3-9de6-4c72-8dd6-66c2829d0ee2	1
542a0891-2e52-40ba-ab42-e468b9636322	1
54238b21-65ce-4304-98c6-0f8a6b9671e3	1
5420238f-2224-4472-8041-d127c8a5533f	1
5418151f-a055-4e26-b56f-6f1726638b68	1
541325bd-15bb-4b52-8ad9-3fdf3cb1dd55	1
53e64fef-c5c6-4d03-b07a-8ccde69a6218	1
54113bf6-465b-4f6c-b0ee-2a582d37323e	1
540e2e23-517c-4470-b163-6ad9e89b8890	1
..	
aa503b9c-f853-497f-a1cc-97d6b13312d1	1
aa4f0ba5-5985-469f-8cd7-98f7b20d27ea	1
aa4180a5-84f1-4e67-8d90-0c8403070a59	1
aa405742-17ac-4c65-b19e-ab91c241cc53	1
aa27a0af-eeab-4007-a770-fa8a93fa53c8	1
aabadcb8-fe4f-4456-b3b5-16e937cef311	1
aa1edcad-f74f-426c-881a-5bbaa5ce717d	1
aa02cd65-92f9-447c-8cc2-44b7b6f817fe	1
a9fab024-c486-4a99-a05d-aba8c6252dc8	1
a9f12b1c-c158-4347-a695-9565a947fd55	1
a9ecd64e-dc3e-4058-8637-fefd2cd72768	1
a9ea3237-c91c-4a93-b7e8-f6550511bff1	1
aa5fb614-bf24-408d-9c89-e97b91d9479d	1
aa5ff9e9-bd5c-4a6e-bc03-e19552725635	1
aa613715-ff22-429d-9fbb-92da56b827aa	1
aa6fc8ca-ae09-4c9e-bae0-0427f5f56a70	1
aa708f29-9cb7-4959-a251-8aff9613b024	1
aa7e4871-e2f5-4c6a-887a-040c3a7b80bb	1
aa7f5fc5-f49a-44a7-b870-e7abfbd0fe76	1
aa897134-688c-45b9-ba5c-33c952dc0199	1
aa978022-96be-45b7-bf9c-e00fec32734e	1
aa994ac7-bf38-4b47-85cd-afbdd9c556b8	1
aa9b208a-31f7-456f-8968-beee2b2ab2c7	1
aaa762ef-af82-45b3-aa72-279403f1dbfd	1
aaa8345c-314b-4a24-aafb-aeb28f65c7ad	1
aaaaf89c-20bc-4974-8d0d-e31f1dc4f562	1
aab11d65-90a3-4f8a-98ac-58cfa19475ba	1
aab516e2-9881-4f4f-901a-cde597f7f9e9	1
aab6143a-424d-4a19-993e-03065412c420	1
000104b9-23e4-4ddc-8caa-8629fe8ad7f4	1
Name: Prospect ID, Length: 9074, dtype: int64	

```
api 3578
lead add form 581
lead import 30
Name: Lead Origin, dtype: int64
```

---

```
google 2873
direct traffic 2543
olark chat 1753
organic search 1154
reference 443
welingak website 129
referral sites 125
facebook 31
bing 6
click2call 4
press_release 2
social media 2
live chat 2
pay per click ads 1
nc_edm 1
testone 1
welearn 1
welearnblog_home 1
blog 1
youtubechannel 1
Name: Lead Source, dtype: int64
```

---

```
no 8358
yes 716
Name: Do Not Email, dtype: int64
```

---

```
no 9072
yes 2
Name: Do Not Call, dtype: int64
```

---

```
0 5639
1 3435
Name: Converted, dtype: int64
```

---

```
0.0 2161
2.0 1679
3.0 1306
4.0 1120
5.0 783
```

6.0	466
1.0	395
7.0	309
8.0	224
9.0	164
10.0	114
11.0	86
13.0	48
12.0	45
14.0	36
16.0	21
15.0	18
17.0	16
18.0	15
20.0	12
19.0	9
21.0	6
23.0	6
24.0	5
25.0	5
27.0	5
22.0	3
29.0	2
26.0	2
28.0	2
43.0	1
115.0	1
74.0	1
55.0	1
54.0	1
141.0	1
42.0	1
41.0	1
32.0	1
30.0	1
251.0	1

Name: TotalVisits, dtype: int64

-----

0	2165
60	19
127	18
75	18
234	17
87	17
74	17
62	17
157	17
69	16

213	16
32	16
96	16
12	15
176	15
68	15
94	15
71	15
33	15
247	15
78	14
63	14
139	14
49	14
36	14
2	14
129	14
151	14
14	14
100	14
...	
546	1
544	1
1214	1
460	1
1253	1
1251	1
1249	1
468	1
1235	1
1233	1
483	1
484	1
1229	1
486	1
495	1
509	1
1193	1
511	1
512	1
513	1
514	1
1206	1
522	1
523	1
524	1
528	1
530	1
1197	1



```
532      1
2272     1
Name: Total Time Spent on Website, Length: 1717, dtype: int64
```

```
-----
-----
0.00      2161
2.00      1794
3.00      1196
4.00       896
1.00       651
5.00       517
1.50       306
6.00       244
2.50       241
7.00       133
3.50        94
8.00        86
1.33        66
1.67        60
2.33        59
2.67        54
9.00        45
4.50        43
1.75        28
3.33        27
10.00       25
1.25        23
5.50        21
2.25        19
11.00       18
3.67        16
6.50        13
1.80        13
2.75        12
1.40        11
...
1.31        1
1.27        1
1.21        1
8.21        1
1.63        1
3.91        1
4.17        1
2.63        1
24.00       1
2.57        1
2.56        1
2.86        1
2.45        1
```

2.90	1
2.38	1
3.17	1
2.29	1
3.29	1
3.38	1
3.43	1
2.14	1
2.13	1
3.57	1
2.08	1
1.93	1
1.86	1
3.80	1
3.82	1
3.83	1
55.00	1

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

email opened	3432
sms sent	2716
olark chat conversation	972
page visited on website	640
converted to lead	428
email bounced	312
email link clicked	267
form submitted on website	116
unreachable	90
unsubscribed	59
had a phone conversation	25
view in browser link clicked	6
approached upfront	5
email marked spam	2
email received	2
resubscribed to emails	1
visited booth in tradeshow	1

Name: Last Activity, dtype: int64

india	6491
not provided	2296
outside india	287

Name: Country, dtype: int64

not provided	3282
finance management	959
human resource management	837

marketing management	823
operations management	499
business administration	399
it projects management	366
supply chain management	346
banking, investment and insurance	335
media and advertising	202
travel and tourism	202
international business	176
healthcare management	156
hospitality management	111
e-commerce	111
retail management	100
rural and agribusiness	73
e-business	57
services excellence	40

Name: Specialization, dtype: int64

unemployed	5476
not provided	2683
working professional	677
student	206
other	15
housewife	9
businessman	8

Name: What is your current occupation, dtype: int64

better career prospects	6370
not provided	2702
other	1
flexibility & convenience	1

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

no	9060
yes	14

Name: Search, dtype: int64

no	9072
yes	2

Name: Newspaper Article, dtype: int64

no	9073
yes	1

Name: X Education Forums, dtype: int64

```
-----  
no      9073  
yes      1  
Name: Newspaper, dtype: int64  
-----
```

```
-----  
no      9070  
yes      4  
Name: Digital Advertisement, dtype: int64  
-----
```

```
-----  
no      9067  
yes      7  
Name: Through Recommendations, dtype: int64  
-----
```

```
-----  
no      6186  
yes      2888  
Name: A free copy of Mastering The Interview, dtype: int64  
-----
```

```
-----  
modified      3267  
email opened  2823  
sms sent      2152  
page visited on website  318  
olark chat conversation  183  
email link clicked      173  
email bounced           60  
unsubscribed            45  
unreachable             32  
had a phone conversation  14  
email marked spam        2  
view in browser link clicked  1  
resubscribed to emails      1  
form submitted on website   1  
email received            1  
approached upfront         1  
Name: Last Notable Activity, dtype: int64  
-----  
-----
```

```
# Removing Id values since they are unique for everyone  
df_final = df3.drop('Prospect ID',1)  
df_final.shape  
  
(9074, 21)
```

## 2. EDA

### 2.1. Univariate Analysis

#### 2.1.1. Categorical Variables

```
df_final.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 9074 entries, 0 to 9239
Data columns (total 21 columns):
Lead Origin                9074 non-null object
Lead Source                9074 non-null object
Do Not Email              9074 non-null object
Do Not Call               9074 non-null object
Converted                 9074 non-null int64
TotalVisits               9074 non-null float64
Total Time Spent on Website 9074 non-null int64
Page Views Per Visit      9074 non-null float64
Last Activity             9074 non-null object
Country                   9074 non-null object
Specialization             9074 non-null object
What is your current occupation 9074 non-null object
What matters most to you in choosing a course 9074 non-null object
Search                    9074 non-null object
Newspaper Article         9074 non-null object
X Education Forums        9074 non-null object
Newspaper                 9074 non-null object
Digital Advertisement     9074 non-null object
Through Recommendations   9074 non-null object
A free copy of Mastering The Interview 9074 non-null object
Last Notable Activity     9074 non-null object
dtypes: float64(2), int64(2), object(17)
memory usage: 1.5+ MB

plt.figure(figsize = (20,40))

plt.subplot(6,2,1)
sns.countplot(df_final['Lead Origin'])
plt.title('Lead Origin')

plt.subplot(6,2,2)
sns.countplot(df_final['Do Not Email'])
plt.title('Do Not Email')

plt.subplot(6,2,3)
sns.countplot(df_final['Do Not Call'])
plt.title('Do Not Call')

plt.subplot(6,2,4)
```

```
sns.countplot(df_final['Country'])
plt.title('Country')

plt.subplot(6,2,5)
sns.countplot(df_final['Search'])
plt.title('Search')

plt.subplot(6,2,6)
sns.countplot(df_final['Newspaper Article'])
plt.title('Newspaper Article')

plt.subplot(6,2,7)
sns.countplot(df_final['X Education Forums'])
plt.title('X Education Forums')

plt.subplot(6,2,8)
sns.countplot(df_final['Newspaper'])
plt.title('Newspaper')

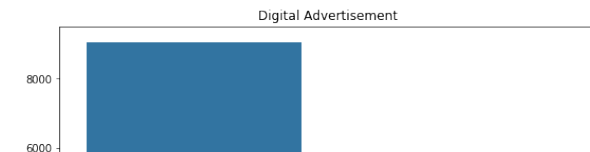
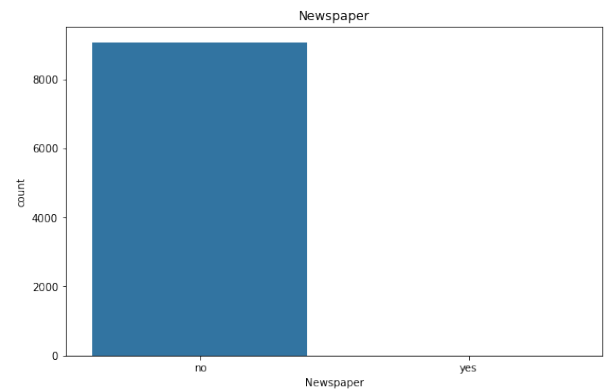
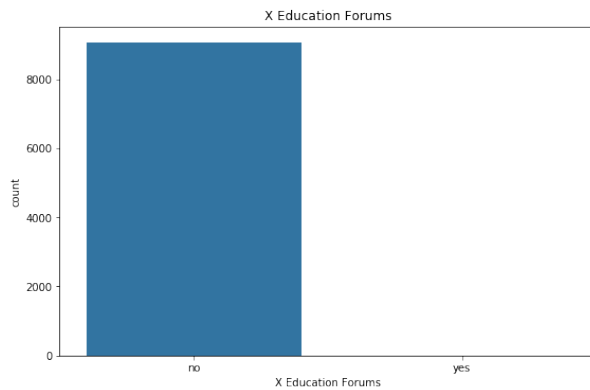
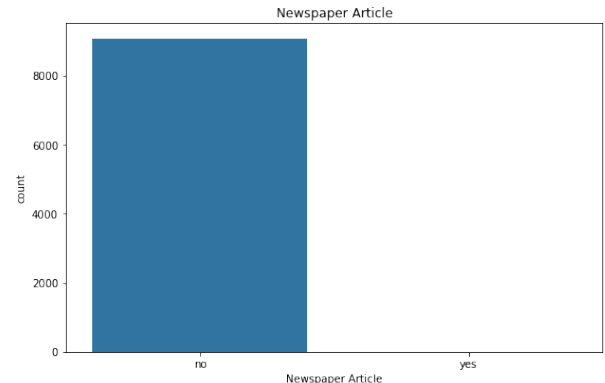
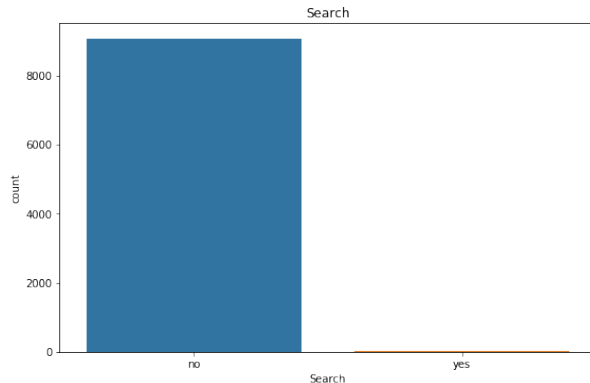
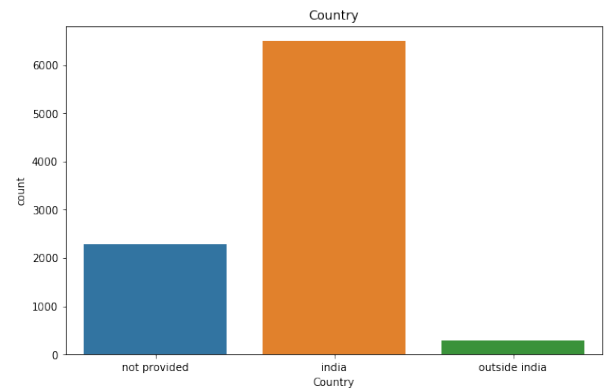
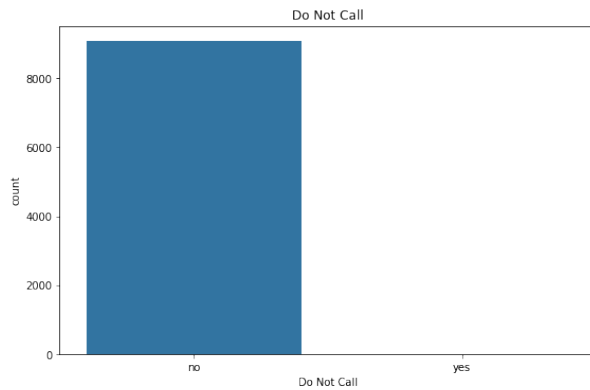
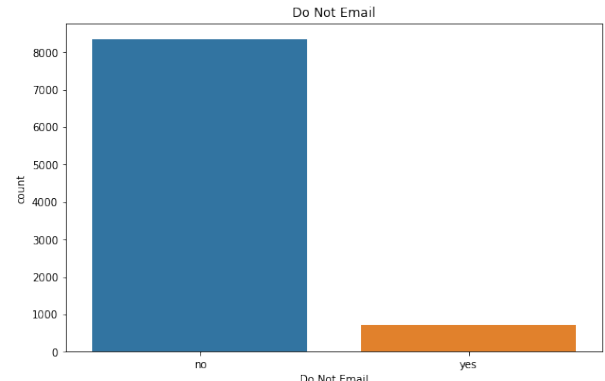
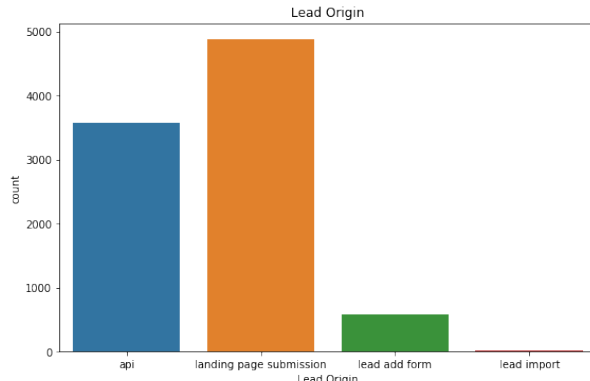
plt.subplot(6,2,9)
sns.countplot(df_final['Digital Advertisement'])
plt.title('Digital Advertisement')

plt.subplot(6,2,10)
sns.countplot(df_final['Through Recommendations'])
plt.title('Through Recommendations')

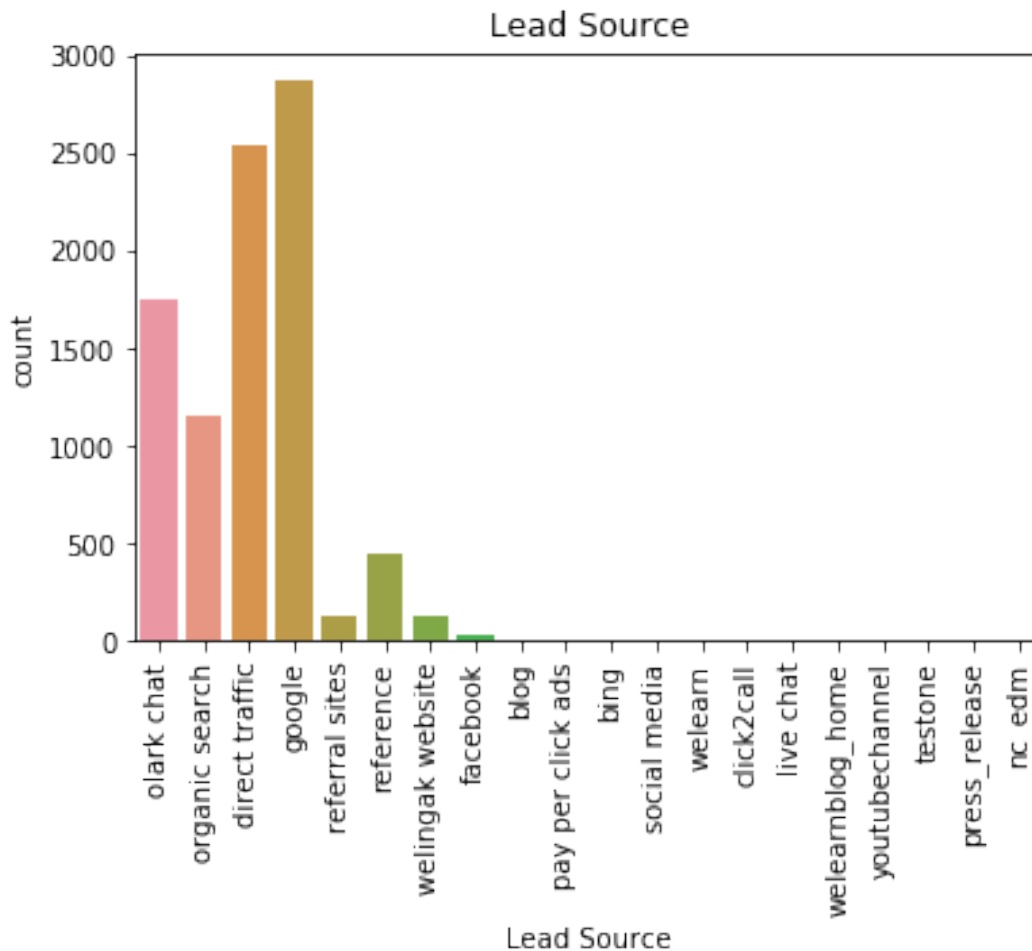
plt.subplot(6,2,11)
sns.countplot(df_final['A free copy of Mastering The Interview'])
plt.title('A free copy of Mastering The Interview')

plt.subplot(6,2,12)
sns.countplot(df_final['Last Notable Activity']).tick_params(axis='x',
rotation = 90)
plt.title('Last Notable Activity')

plt.show()
```



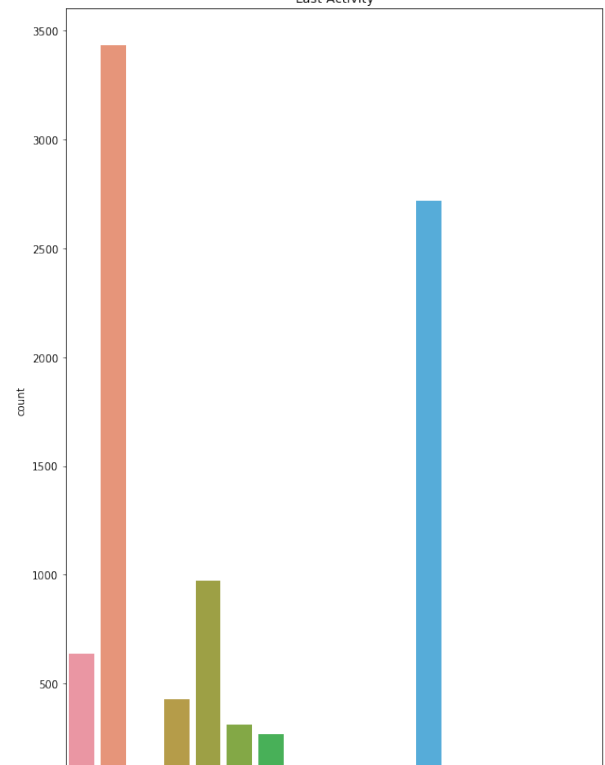
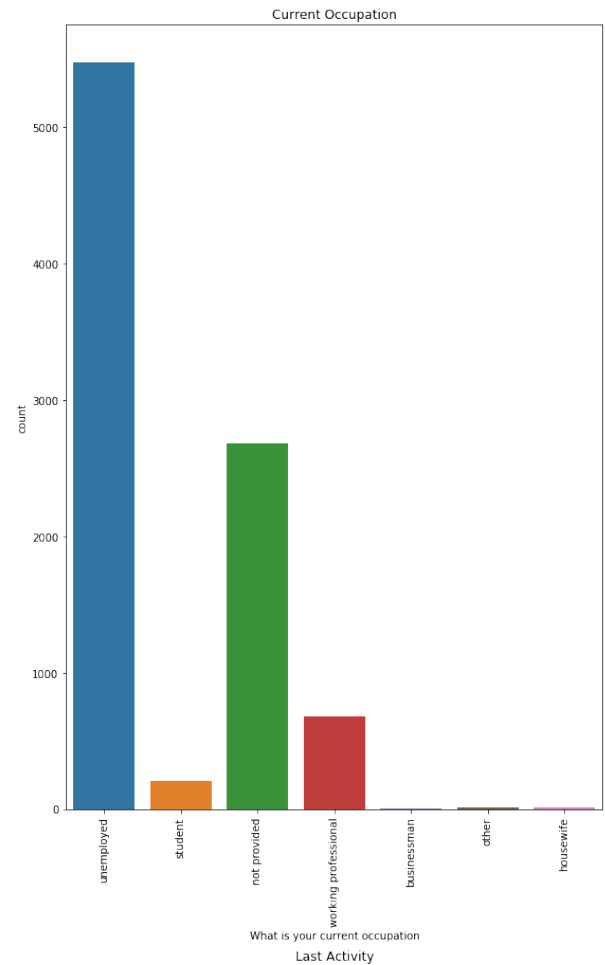
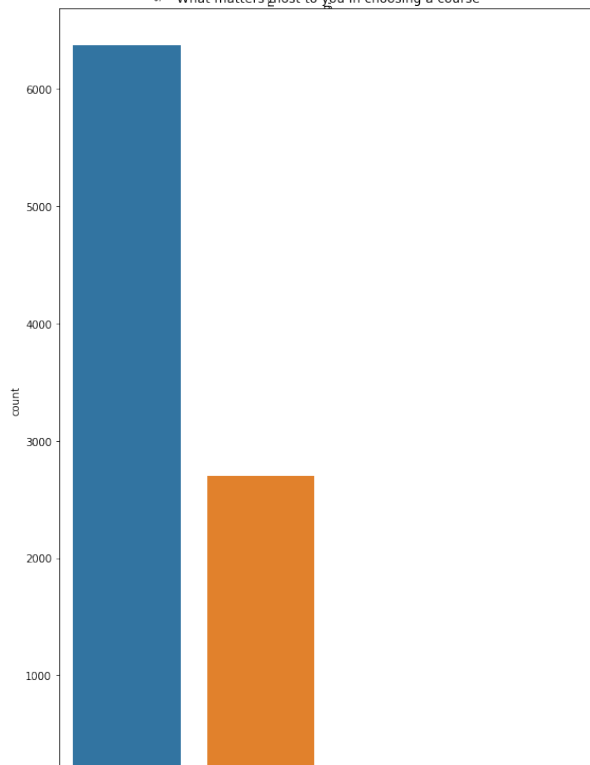
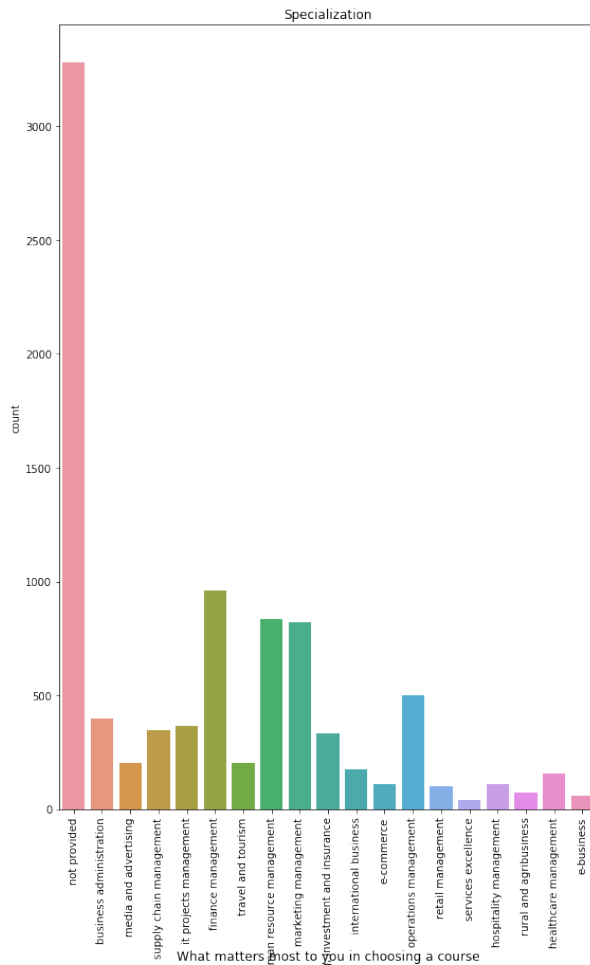
```
sns.countplot(df_final['Lead Source']).tick_params(axis='x', rotation
= 90)
plt.title('Lead Source')
plt.show()
```



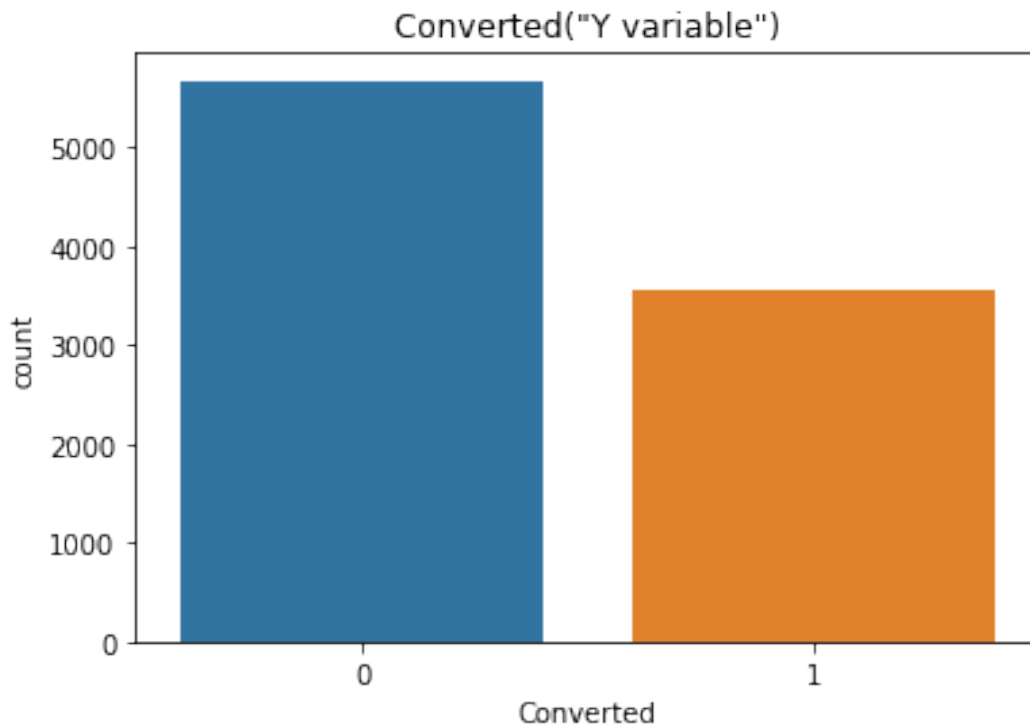
```
plt.figure(figsize = (20,30))
plt.subplot(2,2,1)
sns.countplot(df_final['Specialization']).tick_params(axis='x',
rotation = 90)
plt.title('Specialization')
plt.subplot(2,2,2)
sns.countplot(df_final['What is your current
occupation']).tick_params(axis='x', rotation = 90)
plt.title('Current Occupation')
plt.subplot(2,2,3)
sns.countplot(df_final['What matters most to you in choosing a
course']).tick_params(axis='x', rotation = 90)
plt.title('What matters most to you in choosing a course')
plt.subplot(2,2,4)
```



```
sns.countplot(df_final['Last Activity']).tick_params(axis='x',  
rotation = 90)  
plt.title('Last Activity')  
plt.show()
```



```
sns.countplot(df['Converted'])
plt.title('Converted("Y variable")')
plt.show()
```



### 2.1.1. Numerical Variables

```
df_final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9074 entries, 0 to 9239
Data columns (total 21 columns):
Lead Origin                9074 non-null object
Lead Source                9074 non-null object
Do Not Email              9074 non-null object
Do Not Call               9074 non-null object
Converted                 9074 non-null int64
TotalVisits               9074 non-null float64
Total Time Spent on Website 9074 non-null int64
Page Views Per Visit      9074 non-null float64
Last Activity             9074 non-null object
Country                   9074 non-null object
Specialization             9074 non-null object
What is your current occupation 9074 non-null object
What matters most to you in choosing a course 9074 non-null object
Search                    9074 non-null object
Newspaper Article         9074 non-null object
X Education Forums        9074 non-null object
```

Newspaper	9074 non-null object
Digital Advertisement	9074 non-null object
Through Recommendations	9074 non-null object
A free copy of Mastering The Interview	9074 non-null object
Last Notable Activity	9074 non-null object

dtypes: float64(2), int64(2), object(17)

memory usage: 1.8+ MB

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

```
plt.subplot(221)
```

```
plt.hist(df_final['TotalVisits'], bins = 200)
```

```
plt.title('Total Visits')
```

```
plt.xlim(0,25)
```

```
plt.subplot(222)
```

```
plt.hist(df_final['Total Time Spent on Website'], bins = 10)
```

```
plt.title('Total Time Spent on Website')
```

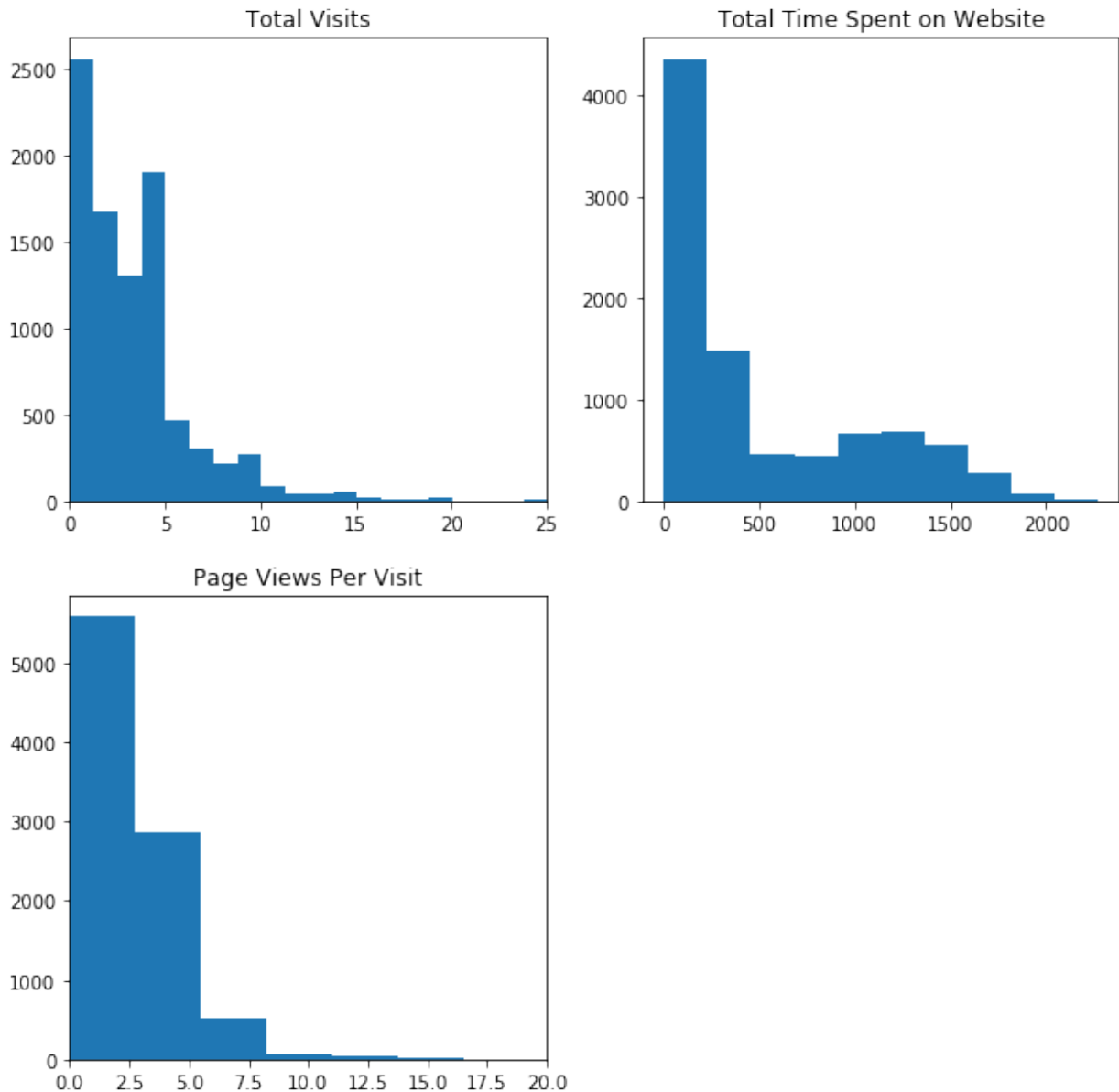
```
plt.subplot(223)
```

```
plt.hist(df_final['Page Views Per Visit'], bins = 20)
```

```
plt.title('Page Views Per Visit')
```

```
plt.xlim(0,20)
```

```
plt.show()
```

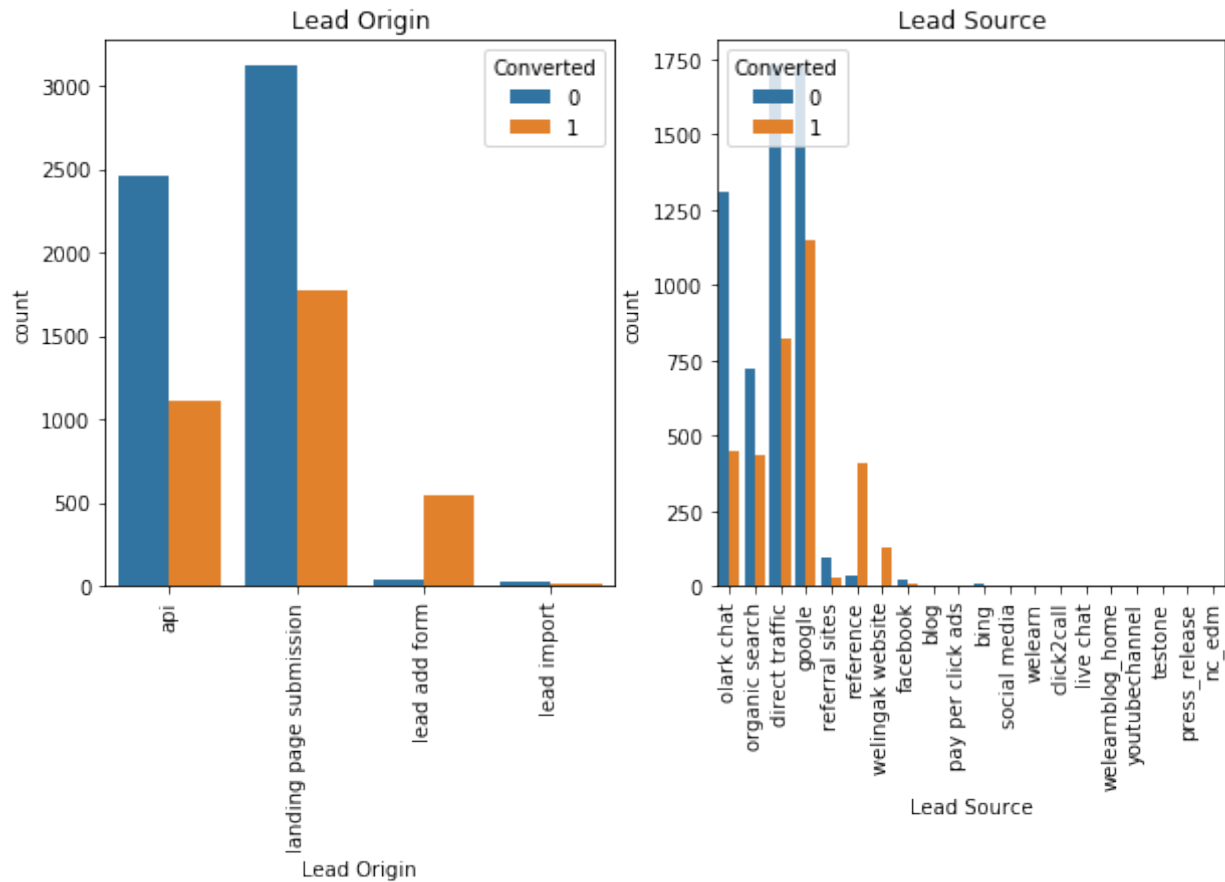


## 2.1. Relating all the categorical variables to Converted

```
plt.figure(figsize = (10,5))

plt.subplot(1,2,1)
sns.countplot(x='Lead Origin', hue='Converted', data=
df_final).tick_params(axis='x', rotation = 90)
plt.title('Lead Origin')

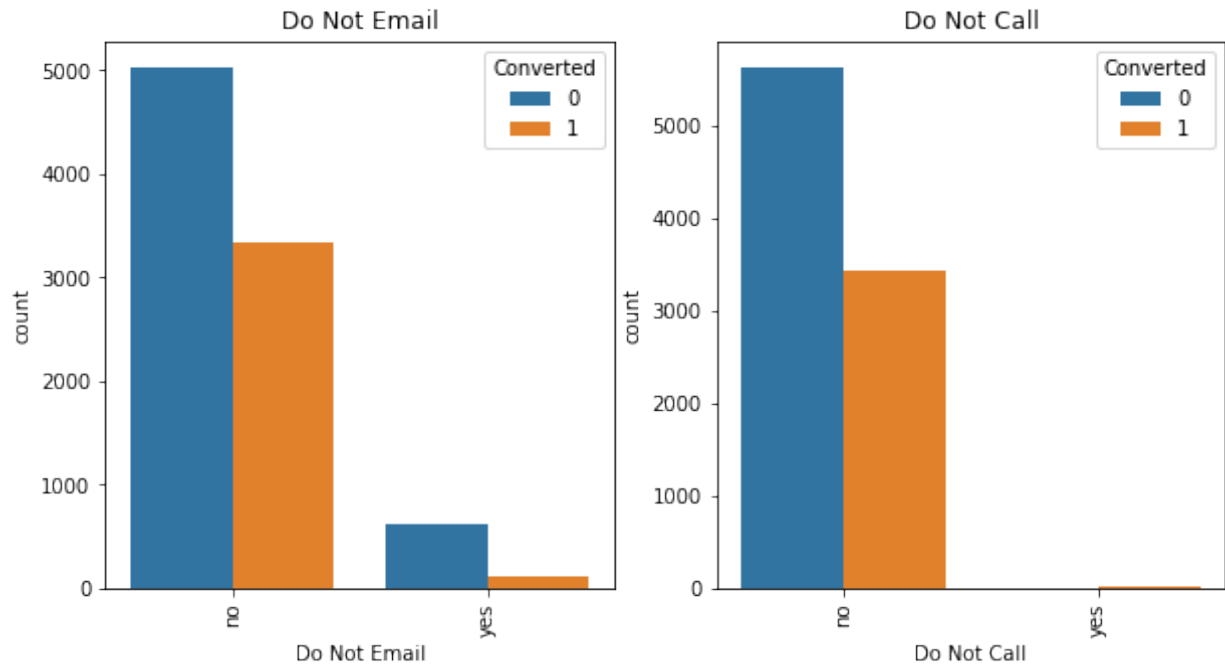
plt.subplot(1,2,2)
sns.countplot(x='Lead Source', hue='Converted', data=
df_final).tick_params(axis='x', rotation = 90)
plt.title('Lead Source')
plt.show()
```



```
plt.figure(figsize = (10,5))

plt.subplot(1,2,1)
sns.countplot(x='Do Not Email', hue='Converted', data=
df_final).tick_params(axis='x', rotation = 90)
plt.title('Do Not Email')

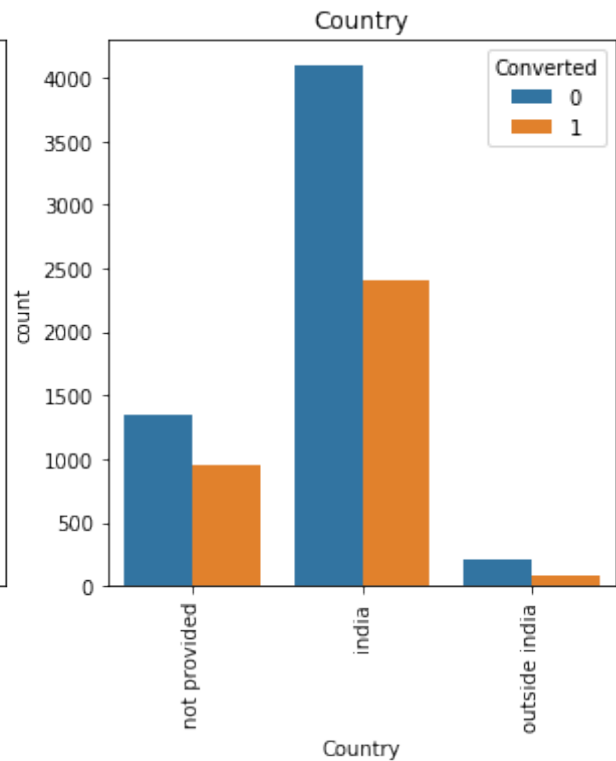
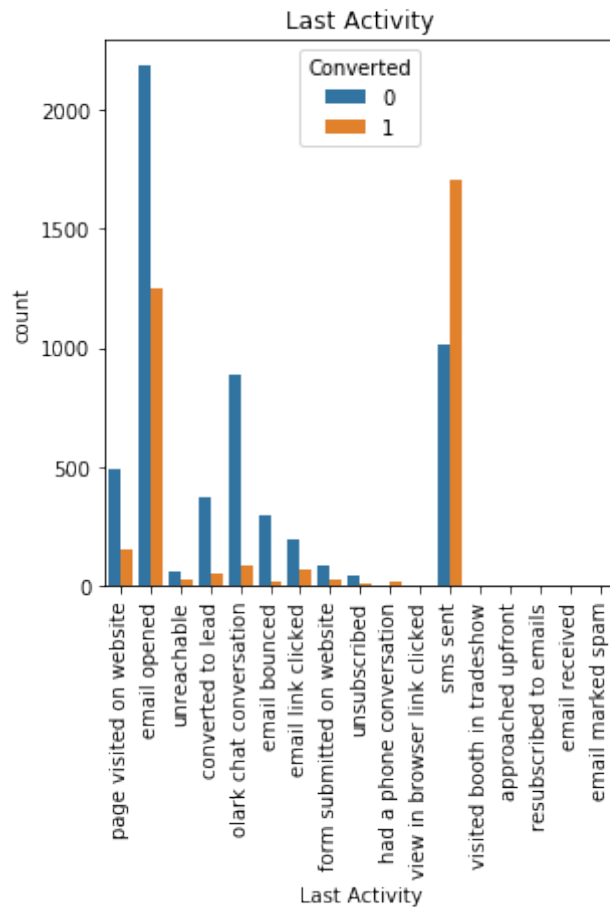
plt.subplot(1,2,2)
sns.countplot(x='Do Not Call', hue='Converted', data=
df_final).tick_params(axis='x', rotation = 90)
plt.title('Do Not Call')
plt.show()
```



```
plt.figure(figsize = (10,5))

plt.subplot(1,2,1)
sns.countplot(x='Last Activity', hue='Converted', data=
df_final).tick_params(axis='x', rotation = 90)
plt.title('Last Activity')

plt.subplot(1,2,2)
sns.countplot(x='Country', hue='Converted', data=
df_final).tick_params(axis='x', rotation = 90)
plt.title('Country')
plt.show()
```

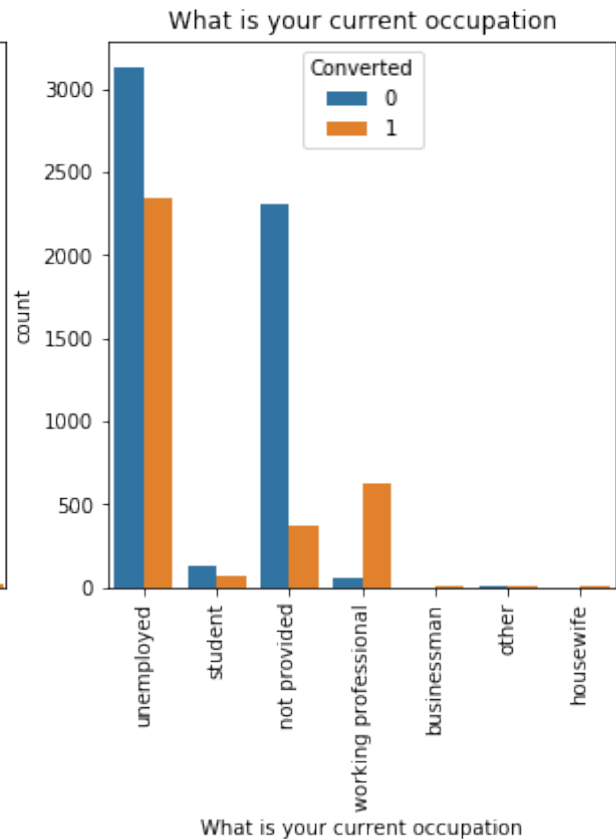
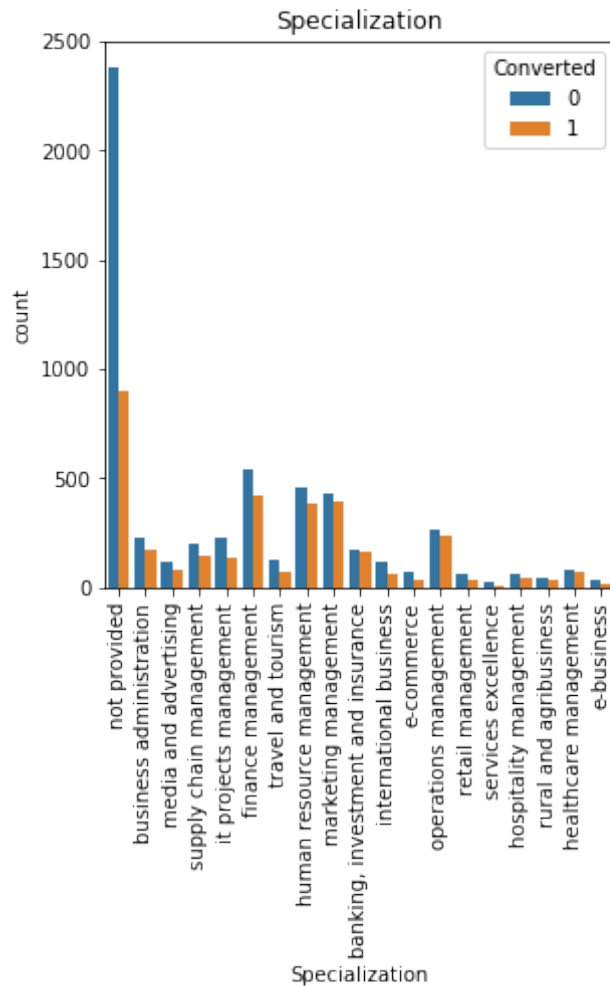


```
plt.figure(figsize = (10,5))

plt.subplot(1,2,1)
sns.countplot(x='Specialization', hue='Converted', data=
df_final).tick_params(axis='x', rotation = 90)
plt.title('Specialization')

plt.subplot(1,2,2)
sns.countplot(x='What is your current occupation', hue='Converted',
data= df_final).tick_params(axis='x', rotation = 90)
plt.title('What is your current occupation')
plt.show()
```

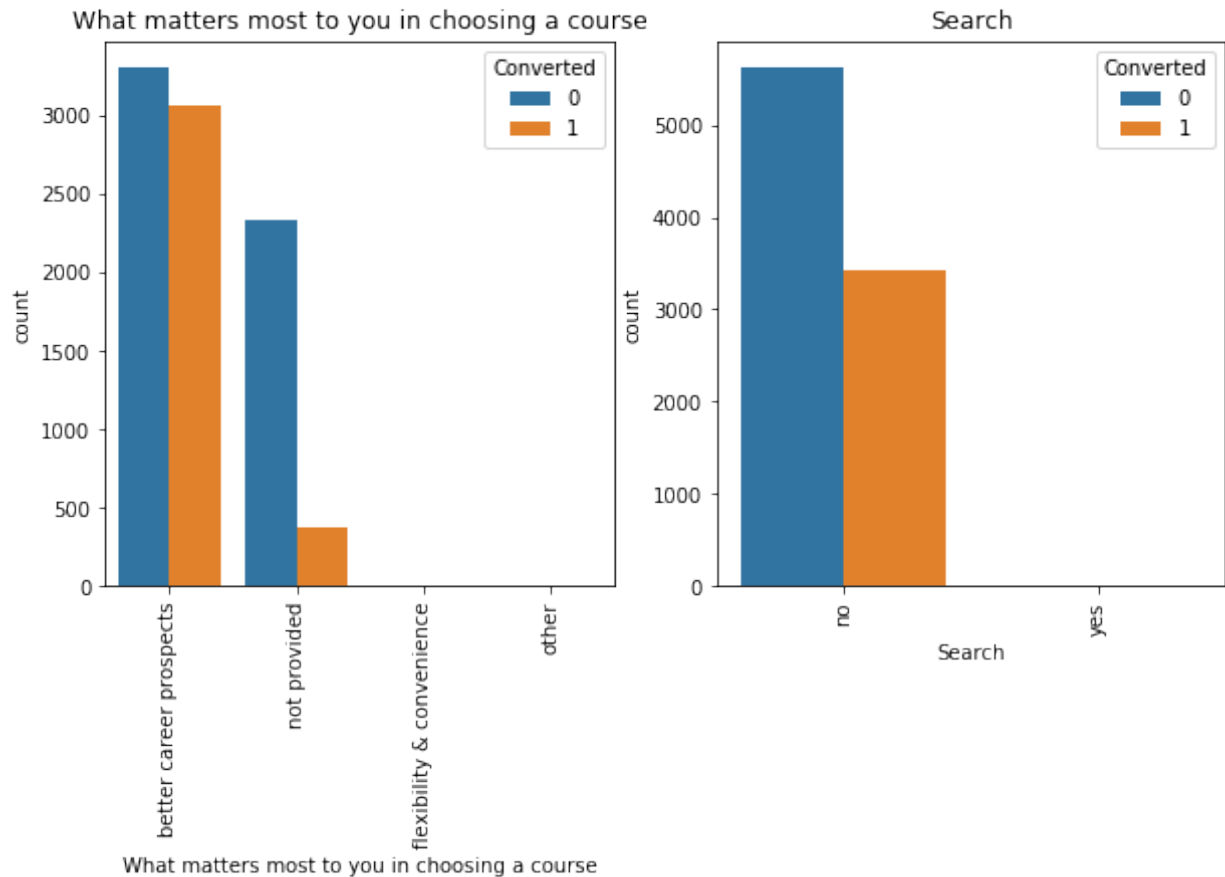




```
plt.figure(figsize = (10,5))

plt.subplot(1,2,1)
sns.countplot(x='What matters most to you in choosing a course',
hue='Converted', data= df_final).tick_params(axis='x', rotation = 90)
plt.title('What matters most to you in choosing a course')

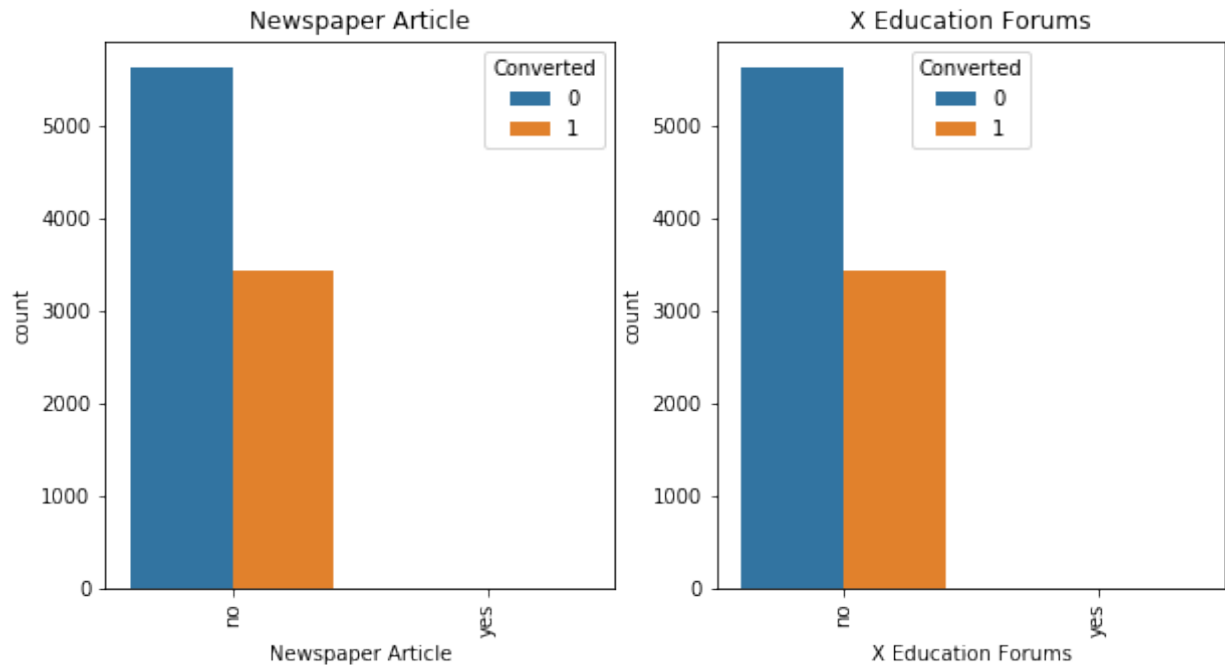
plt.subplot(1,2,2)
sns.countplot(x='Search', hue='Converted', data=
df_final).tick_params(axis='x', rotation = 90)
plt.title('Search')
plt.show()
```



```
plt.figure(figsize = (10,5))

plt.subplot(1,2,1)
sns.countplot(x='Newspaper Article', hue='Converted', data=
df_final).tick_params(axis='x', rotation = 90)
plt.title('Newspaper Article')

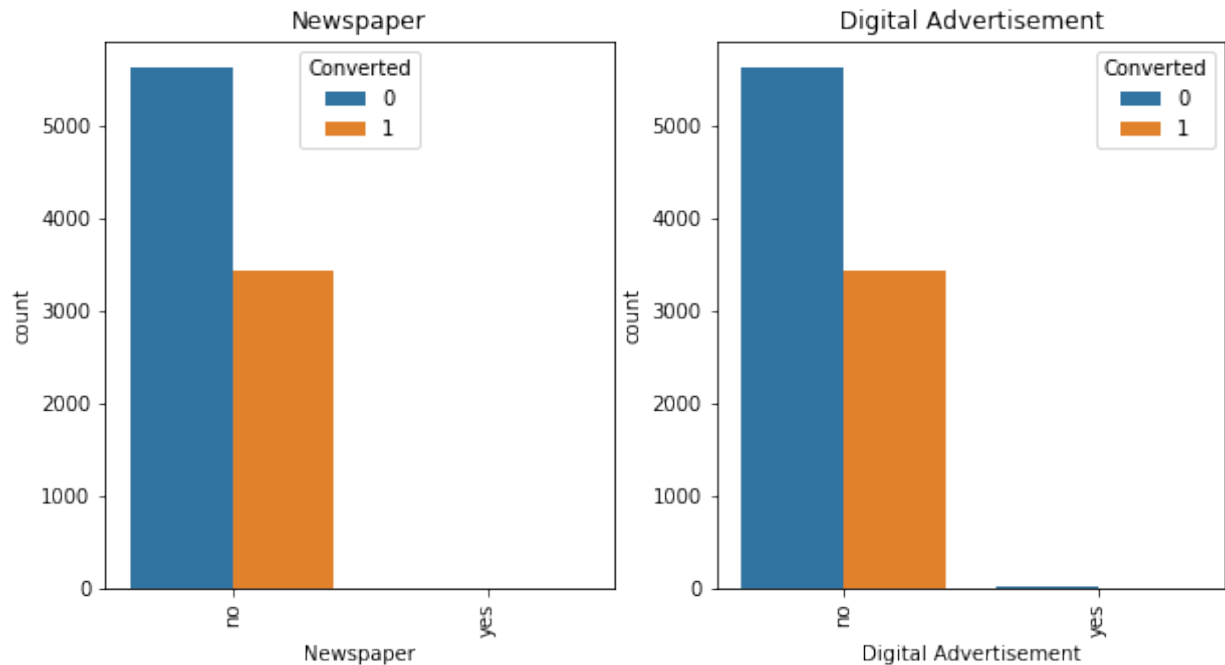
plt.subplot(1,2,2)
sns.countplot(x='X Education Forums', hue='Converted', data=
df_final).tick_params(axis='x', rotation = 90)
plt.title('X Education Forums')
plt.show()
```



```
plt.figure(figsize = (10,5))

plt.subplot(1,2,1)
sns.countplot(x='Newspaper', hue='Converted', data=
df_final).tick_params(axis='x', rotation = 90)
plt.title('Newspaper')

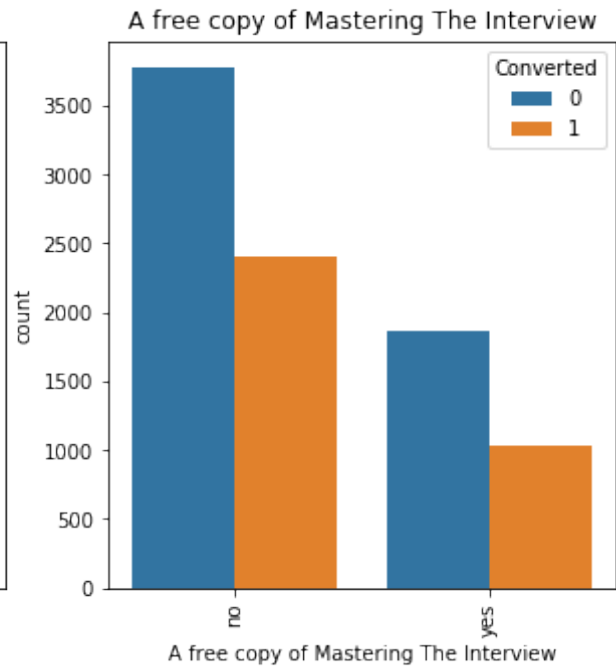
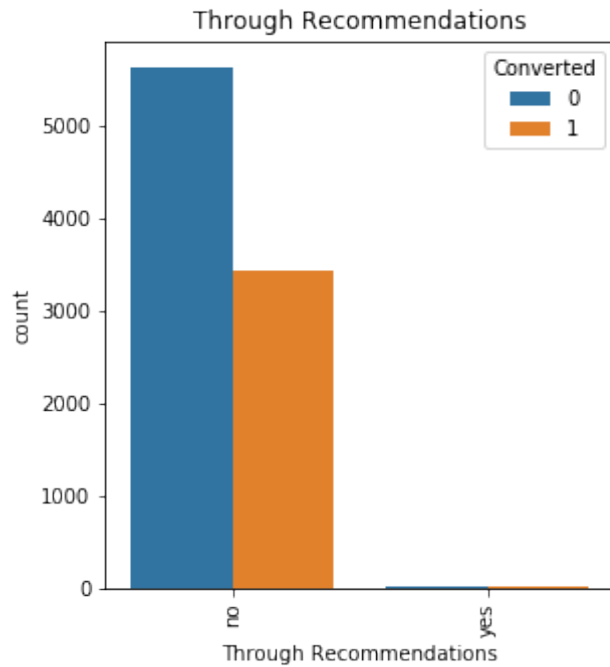
plt.subplot(1,2,2)
sns.countplot(x='Digital Advertisement', hue='Converted', data=
df_final).tick_params(axis='x', rotation = 90)
plt.title('Digital Advertisement')
plt.show()
```



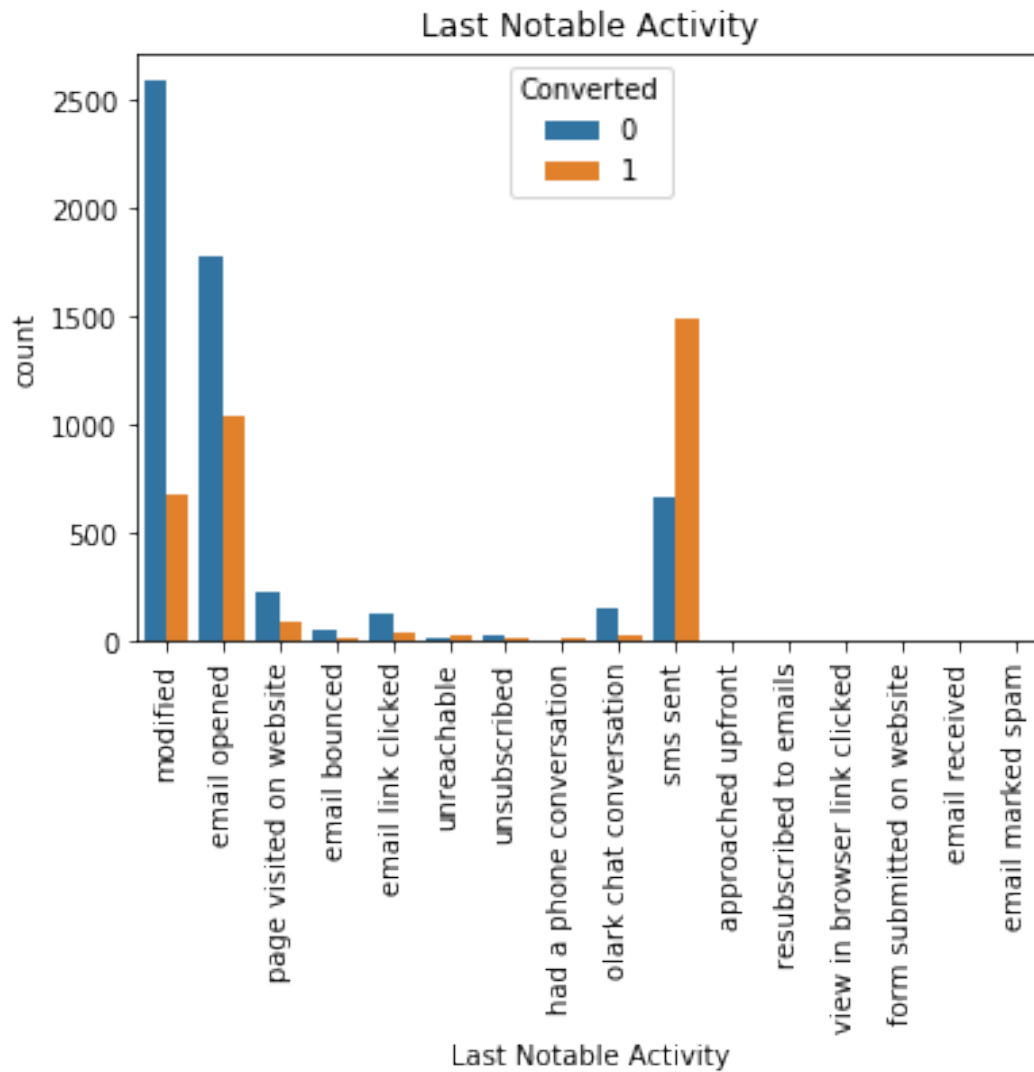
```
plt.figure(figsize = (10,5))

plt.subplot(1,2,1)
sns.countplot(x='Through Recommendations', hue='Converted', data=
df_final).tick_params(axis='x', rotation = 90)
plt.title('Through Recommendations')

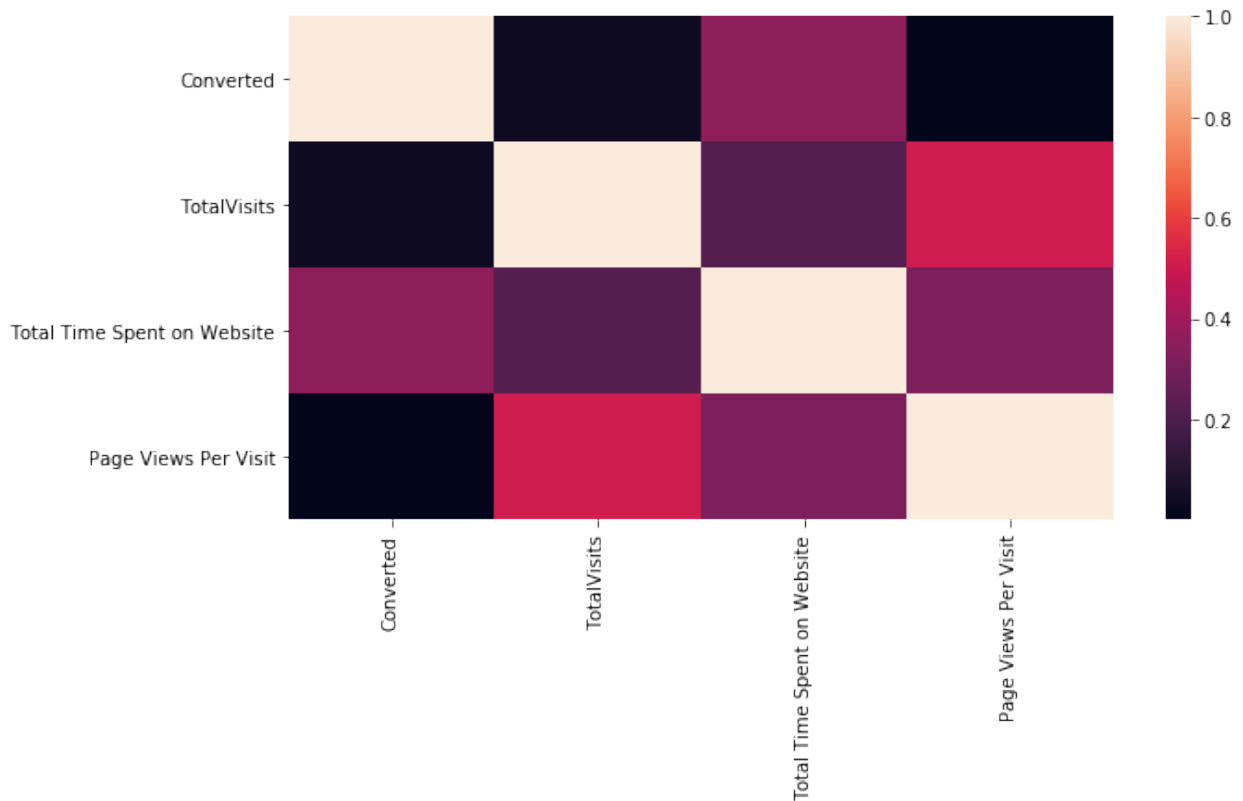
plt.subplot(1,2,2)
sns.countplot(x='A free copy of Mastering The Interview',
hue='Converted', data= df_final).tick_params(axis='x', rotation = 90)
plt.title('A free copy of Mastering The Interview')
plt.show()
```



```
sns.countplot(x='Last Notable Activity', hue='Converted', data=
df_final).tick_params(axis='x', rotation = 90)
plt.title('Last Notable Activity')
plt.show()
```



```
# To check the correlation among variables  
plt.figure(figsize=(10,5))  
sns.heatmap(df_final.corr())  
plt.show()
```



*It is understandable from the above EDA that there are many elements that have very little data and so will be of less relevance to our analysis.*

```
numeric = df_final[['TotalVisits', 'Total Time Spent on Website', 'Page Views Per Visit']]
numeric.describe(percentiles=[0.25, 0.5, 0.75, 0.9, 0.99])
```

	TotalVisits	Total Time Spent on Website	Page Views Per Visit
count	9074.000000	9074.000000	9074.000000
mean	3.456028	482.887481	2.370151
std	4.858802	545.256560	2.160871
min	0.000000	0.000000	0.000000
25%	1.000000	11.000000	1.000000
50%	3.000000	246.000000	2.000000
75%	5.000000	922.750000	3.200000
90%	7.000000	1373.000000	5.000000
99%	17.000000	1839.000000	9.000000
max	251.000000	2272.000000	55.000000

*There aren't any major outliers, so moving on to analysis*

### 3. Dummy Variables

```
df_final.info()
```

```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 9074 entries, 0 to 9239
Data columns (total 21 columns):
Lead Origin                9074 non-null object
Lead Source                9074 non-null object
Do Not Email              9074 non-null object
Do Not Call               9074 non-null object
Converted                 9074 non-null int64
TotalVisits               9074 non-null float64
Total Time Spent on Website 9074 non-null int64
Page Views Per Visit      9074 non-null float64
Last Activity             9074 non-null object
Country                   9074 non-null object
Specialization             9074 non-null object
What is your current occupation 9074 non-null object
What matters most to you in choosing a course 9074 non-null object
Search                    9074 non-null object
Newspaper Article         9074 non-null object
X Education Forums        9074 non-null object
Newspaper                 9074 non-null object
Digital Advertisement     9074 non-null object
Through Recommendations   9074 non-null object
A free copy of Mastering The Interview 9074 non-null object
Last Notable Activity     9074 non-null object
dtypes: float64(2), int64(2), object(17)
memory usage: 1.8+ MB

df_final.loc[:, df_final.dtypes == 'object'].columns

Index(['Lead Origin', 'Lead Source', 'Do Not Email', 'Do Not Call',
      'Last Activity', 'Country', 'Specialization',
      'What is your current occupation',
      'What matters most to you in choosing a course', 'Search',
      'Newspaper Article', 'X Education Forums', 'Newspaper',
      'Digital Advertisement', 'Through Recommendations',
      'A free copy of Mastering The Interview', 'Last Notable
Activity'],
      dtype='object')

# Create dummy variables using the 'get_dummies'
dummy = pd.get_dummies(df_final[['Lead Origin', 'Specialization', 'Lead
Source', 'Do Not Email', 'Last Activity', 'What is your current
occupation', 'A free copy of Mastering The Interview', 'Last Notable
Activity']], drop_first=True)
# Add the results to the master dataframe
df_final_dum = pd.concat([df_final, dummy], axis=1)
df_final_dum

```

	Lead Origin	Lead Source	Do Not Email	Do Not Call
\				



0		api	olark chat	no	no
1		api	organic search	no	no
2	landing page submission		direct traffic	no	no
3	landing page submission		direct traffic	no	no
4	landing page submission		google	no	no
5		api	olark chat	no	no
6	landing page submission		google	no	no
7		api	olark chat	no	no
8	landing page submission		direct traffic	no	no
9		api	google	no	no
10	landing page submission		organic search	no	no
11	landing page submission		direct traffic	no	no
12		api	organic search	no	no
13	landing page submission		organic search	no	no
14	landing page submission		direct traffic	yes	no
15		api	organic search	no	no
16		api	olark chat	no	no
17		api	referral sites	no	no
18	landing page submission		google	no	no
19		api	organic search	no	no
20	landing page submission		google	no	no
21		api	google	no	no
22	landing page submission		google	no	no
23	landing page submission		google	no	no
24		api	google	no	no
25	landing page submission		google	no	no

26	landing page submission	organic search	no	no
27	landing page submission	google	no	no
28	landing page submission	direct traffic	no	no
29	api	google	no	no
...	...	...	...	...
9210	landing page submission	direct traffic	no	no
9211	landing page submission	direct traffic	no	no
9212	landing page submission	google	yes	no
9213	landing page submission	direct traffic	yes	no
9214	api	organic search	no	no
9215	landing page submission	organic search	no	no
9216	landing page submission	direct traffic	yes	no
9217	api	olark chat	no	no
9218	landing page submission	google	yes	no
9219	landing page submission	direct traffic	no	no
9220	landing page submission	direct traffic	no	no
9221	landing page submission	google	no	no
9222	api	google	no	no
9223	api	organic search	no	no
9224	landing page submission	google	no	no
9225	landing page submission	direct traffic	yes	no
9226	api	olark chat	no	no
9227	landing page submission	google	no	no
9228	landing page submission	google	no	no
9229	landing page submission	organic search	no	no
9230	landing page submission	google	no	no

9231	landing page submission	google	no	no
9232	landing page submission	direct traffic	no	no
9233	api	direct traffic	no	no
9234	landing page submission	direct traffic	no	no
9235	landing page submission	direct traffic	yes	no
9236	landing page submission	direct traffic	no	no
9237	landing page submission	direct traffic	yes	no
9238	landing page submission	google	no	no
9239	landing page submission	direct traffic	no	no

	Converted	TotalVisits	Total Time Spent on Website \
0	0	0.0	0
1	0	5.0	674
2	1	2.0	1532
3	0	1.0	305
4	1	2.0	1428
5	0	0.0	0
6	1	2.0	1640
7	0	0.0	0
8	0	2.0	71
9	0	4.0	58
10	1	8.0	1351
11	1	8.0	1343
12	1	11.0	1538
13	0	5.0	170
14	0	1.0	481
15	1	6.0	1012
16	0	0.0	0
17	0	6.0	973
18	1	6.0	1688
19	0	3.0	98
20	0	1.0	233
21	0	4.0	377
22	1	1.0	1013
23	0	4.0	771
24	1	6.0	1137
25	1	3.0	1068
26	1	4.0	1000
27	1	6.0	1315
28	0	5.0	182
29	1	3.0	78

...	...	...	...
9210	1	4.0	927
9211	1	4.0	1112
9212	0	5.0	78
9213	0	5.0	234
9214	1	2.0	881
9215	0	8.0	397
9216	0	6.0	1679
9217	0	0.0	0
9218	0	1.0	149
9219	1	6.0	1389
9220	0	5.0	20
9221	0	4.0	1347
9222	0	6.0	228
9223	0	7.0	142
9224	0	4.0	455
9225	0	2.0	74
9226	0	0.0	0
9227	1	5.0	1283
9228	1	4.0	1944
9229	1	13.0	1226
9230	0	2.0	870
9231	1	8.0	1016
9232	0	2.0	1770
9233	1	13.0	1409
9234	1	5.0	210
9235	1	8.0	1845
9236	0	2.0	238
9237	0	2.0	199
9238	1	3.0	499
9239	1	6.0	1279

Country \	Page Views	Per Visit	Last Activity	
0		0.00	page visited on website	not provided
1		2.50	email opened	india
2		2.00	email opened	india
3		1.00	unreachable	india
4		1.00	converted to lead	india
5		0.00	olark chat conversation	not provided
6		2.00	email opened	india
7		0.00	olark chat conversation	not provided

8	2.00	email opened	india
9	4.00	email opened	india
10	8.00	email opened	india
11	2.67	page visited on website	india
12	11.00	email opened	india
13	5.00	email opened	india
14	1.00	email bounced	outside india
15	6.00	email opened	india
16	0.00	olark chat conversation	not provided
17	6.00	email link clicked	india
18	3.00	page visited on website	india
19	3.00	page visited on website	india
20	1.00	unreachable	india
21	1.33	page visited on website	india
22	1.00	converted to lead	india
23	4.00	email link clicked	india
24	1.50	email opened	india
25	3.00	form submitted on website	india
26	2.00	email opened	india
27	6.00	email opened	india
28	5.00	email opened	india
29	3.00	unreachable	india
...	...	...	...
9210	4.00	email link clicked	india
9211	4.00	sms sent	india
9212	5.00	unsubscribed	india

9213	2.50	page visited on website	india
9214	2.00	sms sent	india
9215	8.00	email opened	india
9216	6.00	page visited on website	india
9217	0.00	sms sent	not provided
9218	1.00	email bounced	india
9219	6.00	email opened	india
9220	2.50	sms sent	india
9221	2.00	sms sent	india
9222	6.00	sms sent	india
9223	7.00	email opened	india
9224	4.00	form submitted on website	india
9225	2.00	email bounced	outside india
9226	0.00	sms sent	not provided
9227	1.67	email opened	india
9228	2.00	sms sent	india
9229	6.50	sms sent	india
9230	2.00	email opened	india
9231	4.00	email opened	india
9232	2.00	sms sent	india
9233	2.60	sms sent	india
9234	2.50	sms sent	india
9235	2.67	email marked spam	outside india
9236	2.00	sms sent	india
9237	2.00	sms sent	india
9238	3.00	sms sent	india

9239	3.00	sms sent	outside india
------	------	----------	---------------

	...	\
0	...	
1	...	
2	...	
3	...	
4	...	
5	...	
6	...	
7	...	
8	...	
9	...	
10	...	
11	...	
12	...	
13	...	
14	...	
15	...	
16	...	
17	...	
18	...	
19	...	
20	...	
21	...	
22	...	
23	...	
24	...	
25	...	
26	...	
27	...	
28	...	
29	...	
...	...	
9210	...	
9211	...	
9212	...	
9213	...	
9214	...	
9215	...	
9216	...	
9217	...	
9218	...	
9219	...	
9220	...	
9221	...	
9222	...	
9223	...	

9224	...
9225	...
9226	...
9227	...
9228	...
9229	...
9230	...
9231	...
9232	...
9233	...
9234	...
9235	...
9236	...
9237	...
9238	...
9239	...

Last Notable Activity_form submitted on website \	
0	0
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0
10	0
11	0
12	0
13	0
14	0
15	0
16	0
17	0
18	0
19	0
20	0
21	0
22	0
23	0
24	0
25	0
26	0
27	0
28	0
29	0
...	...



9210	0
9211	0
9212	0
9213	0
9214	0
9215	0
9216	0
9217	0
9218	0
9219	0
9220	0
9221	0
9222	0
9223	0
9224	0
9225	0
9226	0
9227	0
9228	0
9229	0
9230	0
9231	0
9232	0
9233	0
9234	0
9235	0
9236	0
9237	0
9238	0
9239	0

	Last Notable Activity_had a phone conversation \
0	0
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0
10	0
11	0
12	0
13	0
14	0
15	0
16	0

17	0
18	0
19	0
20	0
21	0
22	0
23	0
24	0
25	0
26	0
27	0
28	0
29	0
...	...
9210	0
9211	0
9212	0
9213	0
9214	0
9215	0
9216	0
9217	0
9218	0
9219	0
9220	0
9221	0
9222	0
9223	0
9224	0
9225	0
9226	0
9227	0
9228	0
9229	0
9230	0
9231	0
9232	0
9233	0
9234	0
9235	0
9236	0
9237	0
9238	0
9239	0

Last Notable Activity_modified \	
0	1
1	0
2	0
3	1

4	1
5	1
6	1
7	1
8	0
9	0
10	0
11	0
12	1
13	0
14	0
15	0
16	1
17	1
18	0
19	1
20	1
21	1
22	1
23	0
24	0
25	1
26	0
27	0
28	0
29	0
...	...
9210	1
9211	0
9212	0
9213	1
9214	0
9215	0
9216	1
9217	0
9218	1
9219	0
9220	1
9221	0
9222	1
9223	1
9224	1
9225	1
9226	1
9227	0
9228	1
9229	1
9230	0
9231	0

9232	0
9233	0
9234	1
9235	0
9236	0
9237	0
9238	0
9239	1

	Last Notable Activity_olark chat conversation \
0	0
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0
10	0
11	0
12	0
13	0
14	0
15	0
16	0
17	0
18	0
19	0
20	0
21	0
22	0
23	0
24	0
25	0
26	0
27	0
28	0
29	0
...	...
9210	0
9211	0
9212	0
9213	0
9214	0
9215	0
9216	0
9217	0

9218	0
9219	0
9220	0
9221	0
9222	0
9223	0
9224	0
9225	0
9226	0
9227	0
9228	0
9229	0
9230	0
9231	0
9232	0
9233	0
9234	0
9235	0
9236	0
9237	0
9238	0
9239	0

Last Notable Activity_page visited on website \	
0	0
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0
10	0
11	1
12	0
13	0
14	0
15	0
16	0
17	0
18	1
19	0
20	0
21	0
22	0
23	0
24	0

25	0
26	0
27	0
28	0
29	0
...	...
9210	0
9211	0
9212	0
9213	0
9214	0
9215	0
9216	0
9217	0
9218	0
9219	0
9220	0
9221	0
9222	0
9223	0
9224	0
9225	0
9226	0
9227	0
9228	0
9229	0
9230	0
9231	0
9232	0
9233	0
9234	0
9235	0
9236	0
9237	0
9238	0
9239	0

	Last Notable Activity_resubscribed to emails \
0	0
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0
10	0

11	0
12	0
13	0
14	0
15	0
16	0
17	0
18	0
19	0
20	0
21	0
22	0
23	0
24	0
25	0
26	0
27	0
28	0
29	0
...	...
9210	0
9211	0
9212	0
9213	0
9214	0
9215	0
9216	0
9217	0
9218	0
9219	0
9220	0
9221	0
9222	0
9223	0
9224	0
9225	0
9226	0
9227	0
9228	0
9229	0
9230	0
9231	0
9232	0
9233	0
9234	0
9235	0
9236	0
9237	0
9238	0

9239

0

Last Notable Activity_sms sent		Last Notable Activity_unreachable	
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
5	0	0	0
6	0	0	0
7	0	0	0
8	0	0	0
9	0	0	0
10	0	0	0
11	0	0	0
12	0	0	0
13	0	0	0
14	0	0	0
15	0	0	0
16	0	0	0
17	0	0	0
18	0	0	0
19	0	0	0
20	0	0	0
21	0	0	0
22	0	0	0
23	0	0	0



24	0	0
25	0	0
26	0	0
27	0	0
28	0	0
29	0	1
...	...	...
9210	0	0
9211	1	0
9212	0	0
9213	0	0
9214	1	0
9215	0	0
9216	0	0
9217	1	0
9218	0	0
9219	0	0
9220	0	0
9221	1	0
9222	0	0
9223	0	0
9224	0	0
9225	0	0
9226	0	0
9227	0	0
9228	0	0

9229	0	0
9230	0	0
9231	0	0
9232	1	0
9233	1	0
9234	0	0
9235	0	0
9236	1	0
9237	1	0
9238	1	0
9239	0	0

	Last Notable Activity_unsubscribed \
0	0
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0
10	0
11	0
12	0
13	0
14	0
15	0
16	0
17	0
18	0
19	0
20	0
21	0
22	0
23	0
24	0
25	0

26	0
27	0
28	0
29	0
...	...
9210	0
9211	0
9212	1
9213	0
9214	0
9215	0
9216	0
9217	0
9218	0
9219	0
9220	0
9221	0
9222	0
9223	0
9224	0
9225	0
9226	0
9227	0
9228	0
9229	0
9230	0
9231	0
9232	0
9233	0
9234	0
9235	0
9236	0
9237	0
9238	0
9239	0

	Last Notable Activity_view in browser link clicked	
0		0
1		0
2		0
3		0
4		0
5		0
6		0
7		0
8		0
9		0
10		0
11		0

12	0
13	0
14	0
15	0
16	0
17	0
18	0
19	0
20	0
21	0
22	0
23	0
24	0
25	0
26	0
27	0
28	0
29	0
...	...
9210	0
9211	0
9212	0
9213	0
9214	0
9215	0
9216	0
9217	0
9218	0
9219	0
9220	0
9221	0
9222	0
9223	0
9224	0
9225	0
9226	0
9227	0
9228	0
9229	0
9230	0
9231	0
9232	0
9233	0
9234	0
9235	0
9236	0
9237	0
9238	0
9239	0

```
[9074 rows x 100 columns]
```

```
df_final_dum = df_final_dum.drop(['What is your current occupation_not  
provided', 'Lead Origin', 'Lead Source', 'Do Not Email', 'Do Not  
Call', 'Last Activity', 'Country', 'Specialization',  
'Specialization_not provided', 'What is your current occupation', 'What  
matters most to you in choosing a course', 'Search', 'Newspaper  
Article', 'X Education Forums', 'Newspaper', 'Digital Advertisement',  
'Through Recommendations', 'A free copy of Mastering The Interview',  
'Last Notable Activity'], 1)  
df_final_dum
```

	Converted	TotalVisits	Total Time Spent on Website \
0	0	0.0	0
1	0	5.0	674
2	1	2.0	1532
3	0	1.0	305
4	1	2.0	1428
5	0	0.0	0
6	1	2.0	1640
7	0	0.0	0
8	0	2.0	71
9	0	4.0	58
10	1	8.0	1351
11	1	8.0	1343
12	1	11.0	1538
13	0	5.0	170
14	0	1.0	481
15	1	6.0	1012
16	0	0.0	0
17	0	6.0	973
18	1	6.0	1688
19	0	3.0	98
20	0	1.0	233
21	0	4.0	377
22	1	1.0	1013
23	0	4.0	771
24	1	6.0	1137
25	1	3.0	1068
26	1	4.0	1000
27	1	6.0	1315
28	0	5.0	182
29	1	3.0	78
...	...	...	...
9210	1	4.0	927
9211	1	4.0	1112
9212	0	5.0	78
9213	0	5.0	234
9214	1	2.0	881

9215	0	8.0	397
9216	0	6.0	1679
9217	0	0.0	0
9218	0	1.0	149
9219	1	6.0	1389
9220	0	5.0	20
9221	0	4.0	1347
9222	0	6.0	228
9223	0	7.0	142
9224	0	4.0	455
9225	0	2.0	74
9226	0	0.0	0
9227	1	5.0	1283
9228	1	4.0	1944
9229	1	13.0	1226
9230	0	2.0	870
9231	1	8.0	1016
9232	0	2.0	1770
9233	1	13.0	1409
9234	1	5.0	210
9235	1	8.0	1845
9236	0	2.0	238
9237	0	2.0	199
9238	1	3.0	499
9239	1	6.0	1279

	Page Views	Per Visit	Lead Origin_landing page submission \
0		0.00	0
1		2.50	0
2		2.00	1
3		1.00	1
4		1.00	1
5		0.00	0
6		2.00	1
7		0.00	0
8		2.00	1
9		4.00	0
10		8.00	1
11		2.67	1
12		11.00	0
13		5.00	1
14		1.00	1
15		6.00	0
16		0.00	0
17		6.00	0
18		3.00	1
19		3.00	0
20		1.00	1
21		1.33	0

22	1.00	1
23	4.00	1
24	1.50	0
25	3.00	1
26	2.00	1
27	6.00	1
28	5.00	1
29	3.00	0
...	...	...
9210	4.00	1
9211	4.00	1
9212	5.00	1
9213	2.50	1
9214	2.00	0
9215	8.00	1
9216	6.00	1
9217	0.00	0
9218	1.00	1
9219	6.00	1
9220	2.50	1
9221	2.00	1
9222	6.00	0
9223	7.00	0
9224	4.00	1
9225	2.00	1
9226	0.00	0
9227	1.67	1
9228	2.00	1
9229	6.50	1
9230	2.00	1
9231	4.00	1
9232	2.00	1
9233	2.60	0
9234	2.50	1
9235	2.67	1
9236	2.00	1
9237	2.00	1
9238	3.00	1
9239	3.00	1

	Lead Origin_lead add form	Lead Origin_lead import \
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
5	0	0
6	0	0
7	0	0

8	0	0
9	0	0
10	0	0
11	0	0
12	0	0
13	0	0
14	0	0
15	0	0
16	0	0
17	0	0
18	0	0
19	0	0
20	0	0
21	0	0
22	0	0
23	0	0
24	0	0
25	0	0
26	0	0
27	0	0
28	0	0
29	0	0
...	...	...
9210	0	0
9211	0	0
9212	0	0
9213	0	0
9214	0	0
9215	0	0
9216	0	0
9217	0	0
9218	0	0
9219	0	0
9220	0	0
9221	0	0
9222	0	0
9223	0	0
9224	0	0
9225	0	0
9226	0	0
9227	0	0
9228	0	0
9229	0	0
9230	0	0
9231	0	0
9232	0	0
9233	0	0
9234	0	0
9235	0	0



9236	0	0
9237	0	0
9238	0	0
9239	0	0

Specialization_business	administration	Specialization_e-
business \		
0	0	
0		
1	0	
0		
2	1	
0		
3	0	
0		
4	0	
0		
5	0	
0		
6	0	
0		
7	0	
0		
8	0	
0		
9	0	
0		
10	0	
0		
11	0	
0		
12	0	
0		
13	1	
0		
14	1	
0		
15	0	
0		
16	0	
0		
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9216	1	
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9239		0
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Specialization\_e-commerce \

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Last Notable Activity_form submitted on website \	
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9230	0
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9239	0

Last Notable Activity\_had a phone conversation \

0	0
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9210	0
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9239	0

Last Notable Activity_modified \	
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9	0



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9210	1
9211	0
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9215	0
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9221	0
9222	1
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9224	1
9225	1
9226	1
9227	0
9228	1
9229	1
9230	0
9231	0
9232	0
9233	0
9234	1
9235	0
9236	0
9237	0

9238	0
9239	1

	Last Notable Activity_olark chat conversation \
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9210	0
9211	0
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9239	0

	Last Notable Activity_page visited on website \
0	0
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8	0
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10	0
11	1
12	0
13	0
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17	0
18	1
19	0
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21	0
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9210	0
9211	0
9212	0
9213	0
9214	0
9215	0
9216	0
9217	0
9218	0
9219	0
9220	0
9221	0
9222	0
9223	0
9224	0
9225	0
9226	0
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9229	0
9230	0
9231	0
9232	0
9233	0
9234	0
9235	0
9236	0
9237	0
9238	0
9239	0

	Last Notable Activity_resubscribed to emails \
0	0
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9210	0
9211	0
9212	0
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9218	0
9219	0
9220	0
9221	0
9222	0
9223	0
9224	0
9225	0
9226	0
9227	0
9228	0
9229	0
9230	0
9231	0
9232	0
9233	0
9234	0
9235	0
9236	0
9237	0
9238	0
9239	0

Last Notable Activity_sms sent	Last Notable Activity_unreachable \
0	0
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1		0
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2		0
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3		0
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4		0
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5		0
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6		0
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26		0
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9210		0
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9211		1
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9212		0
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9213		0
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9214		1
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9215		0
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9216		0
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9217		1
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9218		0
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9219		0
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9220		0
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9221		1
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9222		0
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9223		0
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9224		0
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9225		0
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9226		0
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9227		0
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9228		0
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9229	0
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9230	0
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9231	0
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9232	1
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9233	1
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9234	0
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9235	0
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9236	1
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9237	1
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9238	1
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9239	0
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	Last Notable Activity_unsubscribed \
0	0
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0
10	0
11	0
12	0
13	0
14	0
15	0
16	0
17	0
18	0
19	0
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21	0
22	0
23	0
24	0



25	0
26	0
27	0
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29	0
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9210	0
9211	0
9212	1
9213	0
9214	0
9215	0
9216	0
9217	0
9218	0
9219	0
9220	0
9221	0
9222	0
9223	0
9224	0
9225	0
9226	0
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9230	0
9231	0
9232	0
9233	0
9234	0
9235	0
9236	0
9237	0
9238	0
9239	0

Last Notable Activity\_view in browser link clicked

0	0
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0
10	0

11	0
12	0
13	0
14	0
15	0
16	0
17	0
18	0
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21	0
22	0
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9210	0
9211	0
9212	0
9213	0
9214	0
9215	0
9216	0
9217	0
9218	0
9219	0
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9221	0
9222	0
9223	0
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9225	0
9226	0
9227	0
9228	0
9229	0
9230	0
9231	0
9232	0
9233	0
9234	0
9235	0
9236	0
9237	0
9238	0
9239	0

[9074 rows x 81 columns]

## 4. Test-Train Split

```
# Import the required library
from sklearn.model_selection import train_test_split
```

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

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

	Lead Origin_landing page submission	Lead Origin_lead add form	\
0	0	0	
1	0	0	
2	1	0	
3	1	0	
4	1	0	

	Lead Origin_lead import	Specialization_business administration	\
0	0	0	
1	0	0	
2	0	1	
3	0	0	
4	0	0	

	Specialization_e-business	Specialization_e-commerce	\
0	0	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	

	Specialization_finance management	\
0	0	
1	0	
2	0	
3	0	
4	0	

	...	\
0	...	
1	...	
2	...	

3 ...  
4 ...

	Last Notable Activity_form submitted on website \
0	0
1	0
2	0
3	0
4	0

	Last Notable Activity_had a phone conversation \
0	0
1	0
2	0
3	0
4	0

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

	Last Notable Activity_olark chat conversation \
0	0
1	0
2	0
3	0
4	0

	Last Notable Activity_page visited on website \
0	0
1	0
2	0
3	0
4	0

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

	Last Notable Activity_sms sent	Last Notable Activity_unreachable \
0	0	0
1	0	0

2	0	0
3	0	0
4	0	0

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

	Last Notable Activity_view in browser link clicked
0	0
1	0
2	0
3	0
4	0

[5 rows x 80 columns]

*# Putting the target variable in y*

```
y = df_final_dum['Converted']
y.head()
```

0	0
1	0
2	1
3	0
4	1

Name: Converted, dtype: int64

*# Split the dataset into 70% and 30% for train and test respectively*

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
train_size=0.7, test_size=0.3, random_state=10)
```

*# Import MinMax scaler*

```
from sklearn.preprocessing import MinMaxScaler
```

*# Scale the three numeric features*

```
scaler = MinMaxScaler()
```

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

```
X_train.head()
```

	TotalVisits	Total Time Spent on Website	Page Views Per Visit
1289	0.014184	0.612676	0.083333

3604	0.000000	0.000000	0.000000
5584	0.042553	0.751761	0.250000
7679	0.000000	0.000000	0.000000
7563	0.014184	0.787852	0.083333

	Lead Origin_landing page submission	Lead Origin_lead add
form \		
1289	1	0
3604	0	0
5584	1	0
7679	0	0
7563	1	0

	Lead Origin_lead import	Specialization_business administration
\		
1289	0	0
3604	0	0
5584	0	0
7679	0	0
7563	0	0

	Specialization_e-business	Specialization_e-commerce	\
1289	0	0	
3604	0	0	
5584	0	0	
7679	0	0	
7563	0	0	

	Specialization_finance management	\
1289	1	
3604	0	
5584	0	
7679	0	
7563	0	

... \

1289	...
3604	...
5584	...
7679	...
7563	...

	Last Notable Activity_form submitted on website \
1289	0
3604	0
5584	0
7679	0
7563	0

	Last Notable Activity_had a phone conversation \
1289	0
3604	0
5584	0
7679	0
7563	0

	Last Notable Activity_modified \
1289	0
3604	0
5584	0
7679	0
7563	1

	Last Notable Activity_olark chat conversation \
1289	0
3604	0
5584	0
7679	0
7563	0

	Last Notable Activity_page visited on website \
1289	0
3604	1
5584	0
7679	0
7563	0

	Last Notable Activity_resubscribed to emails \
1289	0
3604	0
5584	0
7679	0
7563	0

	Last Notable Activity_sms sent	Last Notable Activity_unreachable \
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1289	0
0	
3604	0
0	
5584	0
0	
7679	0
0	
7563	0
0	

	Last Notable Activity_unsubscribed \
1289	0
3604	0
5584	0
7679	0
7563	0

	Last Notable Activity_view in browser link clicked
1289	0
3604	0
5584	0
7679	0
7563	0

[5 rows x 80 columns]

```
# To check the correlation among variables
plt.figure(figsize=(20,30))
sns.heatmap(X_train.corr())
plt.show()
```





*Since there are a lot of variables it is difficult to drop variable. We'll do it after RFE*

## 5. Model Building

```
# Import 'LogisticRegression'
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()

# Import RFE
from sklearn.feature_selection import RFE

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

# Features that have been selected by RFE
list(zip(X_train.columns, rfe.support_, rfe.ranking_))

[('TotalVisits', True, 1),
 ('Total Time Spent on Website', True, 1),
 ('Page Views Per Visit', False, 6),
 ('Lead Origin_landing page submission', False, 26),
 ('Lead Origin_lead add form', True, 1),
 ('Lead Origin_lead import', False, 46),
 ('Specialization_business administration', False, 33),
 ('Specialization_e-business', False, 32),
 ('Specialization_e-commerce', False, 23),
 ('Specialization_finance management', False, 30),
 ('Specialization_healthcare management', False, 25),
 ('Specialization_hospitality management', False, 43),
 ('Specialization_human resource management', False, 31),
 ('Specialization_international business', False, 37),
 ('Specialization_it projects management', False, 28),
 ('Specialization_marketing management', False, 22),
 ('Specialization_media and advertising', False, 40),
 ('Specialization_operations management', False, 27),
 ('Specialization_retail management', False, 63),
 ('Specialization_rural and agribusiness', False, 24),
 ('Specialization_services excellence', False, 21),
 ('Specialization_supply chain management', False, 29),
 ('Specialization_travel and tourism', False, 35),
 ('Lead Source_blog', False, 41),
 ('Lead Source_click2call', False, 61),
 ('Lead Source_direct traffic', True, 1),
 ('Lead Source_facebook', False, 45),
 ('Lead Source_google', True, 1),
 ('Lead Source_live chat', False, 48),
 ('Lead Source_nc_edm', False, 64),
 ('Lead Source_olark chat', False, 19),
 ('Lead Source_organic search', True, 1),
 ('Lead Source_pay per click ads', False, 65),
```

```
(
    'Lead Source_press_release', False, 51),
    ('Lead Source_reference', False, 18),
    ('Lead Source_referral sites', False, 4),
    ('Lead Source_social media', False, 20),
    ('Lead Source_testone', False, 42),
    ('Lead Source_welearn', False, 49),
    ('Lead Source_welearnblog_home', False, 44),
    ('Lead Source_welingak website', True, 1),
    ('Lead Source_youtubechannel', False, 47),
    ('Do Not Email_yes', True, 1),
    ('Last Activity_converted to lead', False, 14),
    ('Last Activity_email bounced', False, 11),
    ('Last Activity_email link clicked', False, 54),
    ('Last Activity_email marked spam', False, 39),
    ('Last Activity_email opened', False, 58),
    ('Last Activity_email received', False, 56),
    ('Last Activity_form submitted on website', False, 36),
    ('Last Activity_had a phone conversation', False, 5),
    ('Last Activity_olark chat conversation', True, 1),
    ('Last Activity_page visited on website', False, 16),
    ('Last Activity_resubscribed to emails', False, 15),
    ('Last Activity_sms sent', True, 1),
    ('Last Activity_unreachable', False, 17),
    ('Last Activity_unsubscribed', False, 52),
    ('Last Activity_view in browser link clicked', False, 53),
    ('Last Activity_visited booth in tradeshow', False, 55),
    ('What is your current occupation_housewife', True, 1),
    ('What is your current occupation_other', True, 1),
    ('What is your current occupation_student', False, 2),
    ('What is your current occupation_unemployed', False, 3),
    ('What is your current occupation_working professional', True, 1),
    ('A free copy of Mastering The Interview_yes', False, 59),
    ('Last Notable Activity_email bounced', False, 50),
    ('Last Notable Activity_email link clicked', False, 10),
    ('Last Notable Activity_email marked spam', False, 34),
    ('Last Notable Activity_email opened', False, 13),
    ('Last Notable Activity_email received', False, 60),
    ('Last Notable Activity_form submitted on website', False, 57),
    ('Last Notable Activity_had a phone conversation', True, 1),
    ('Last Notable Activity_modified', False, 7),
    ('Last Notable Activity_olark chat conversation', False, 9),
    ('Last Notable Activity_page visited on website', False, 12),
    ('Last Notable Activity_resubscribed to emails', False, 8),
    ('Last Notable Activity_sms sent', False, 62),
    ('Last Notable Activity_unreachable', True, 1),
    ('Last Notable Activity_unsubscribed', False, 38),
    ('Last Notable Activity_view in browser link clicked', False, 66)]
```

```
# Put all the columns selected by RFE in the variable 'col'
col = X_train.columns[rfe.support_]
```

*All the variables selected by RFE, next statistics part (p-values and the VIFs).*

```
# Selecting columns selected by RFE
X_train = X_train[col]

# Importing statsmodels
import statsmodels.api as sm

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

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

Dep. Variable:	Converted	No. Observations:
6351		
Model:	GLM	Df Residuals:
6335		
Model Family:	Binomial	Df Model:
15		
Link Function:	logit	Scale:
1.0000		
Method:	IRLS	Log-Likelihood:
-2741.3		
Date:	Mon, 10 Jun 2019	Deviance:
5482.6		
Time:	17:10:21	Pearson chi2:
6.64e+03		
No. Iterations:	22	Covariance Type:
nonrobust		

=====

					coef	std
err	z	P> z	[0.025	0.975]		
-----						
const					-1.2524	
0.081	-15.450	0.000	-1.411	-1.094		
TotalVisits					4.5519	
1.398	3.256	0.001	1.812	7.292		
Total Time Spent on Website					4.5660	
0.162	28.101	0.000	4.248	4.884		
Lead Origin_lead add form					2.6773	
0.225	11.916	0.000	2.237	3.118		
Lead Source_direct traffic					-1.4795	

0.114	-12.979	0.000	-1.703	-1.256	
Lead Source_google					-1.1705
0.109	-10.690	0.000	-1.385	-0.956	
Lead Source_organic search					-1.2823
0.134	-9.541	0.000	-1.546	-1.019	
Lead Source_welingak website					2.5984
1.033	2.515	0.012	0.573	4.624	
Do Not Email_yes					-1.4076
0.168	-8.387	0.000	-1.737	-1.079	
Last Activity_olark chat conversation					-1.4678
0.165	-8.874	0.000	-1.792	-1.144	
Last Activity_sms sent					1.3213
0.073	18.222	0.000	1.179	1.463	
What is your current occupation_housewife					24.4759
3.07e+04	0.001	0.999	-6.01e+04	6.01e+04	
What is your current occupation_other					1.4134
0.760	1.859	0.063	-0.077	2.904	
What is your current occupation_working professional					2.8071
0.193	14.509	0.000	2.428	3.186	
Last Notable Activity_had a phone conversation					24.2053
2.18e+04	0.001	0.999	-4.28e+04	4.28e+04	
Last Notable Activity_unreachable					1.7029
0.610	2.790	0.005	0.507	2.899	

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

```
# Importing 'variance_inflation_factor'
from statsmodels.stats.outliers_influence import
variance_inflation_factor

# Make a VIF dataframe for all the variables present
vif = pd.DataFrame()
vif['Features'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X_train.values, i) for i in
range(X_train.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

	Features	VIF
1	Total Time Spent on Website	2.34
0	TotalVisits	2.28
4	Lead Source_google	2.04
3	Lead Source_direct traffic	1.91
5	Lead Source_organic search	1.60
9	Last Activity_sms sent	1.49
2	Lead Origin_lead add form	1.47
6	Lead Source_welingak website	1.31
12	What is your current occupation_working profes...	1.17

7		Do Not Email_yes	1.10
8	Last Activity_olark	chat conversation	1.02
11	What is your current occupation_other		1.01
14	Last Notable Activity_unreachable		1.01
10	What is your current occupation_housewife		1.00
13	Last Notable Activity_had a phone conversation		1.00

*The VIF values seem fine but the p-values aren't. So removing 'Last Notable Activity had a phone conversation'*

```
X_train.drop('Last Notable Activity_had a phone conversation', axis =
1, inplace = True)
```

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

```
X_train_sm = sm.add_constant(X_train)
```

```
logm2 = sm.GLM(y_train, X_train_sm, family = sm.families.Binomial())
```

```
res = logm2.fit()
```

```
res.summary()
```

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

```
"""
```

# Generalized Linear Model Regression Results

```
=====
```

```
=====
```

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

```
6351
```

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

```
6336
```

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

```
14
```

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

```
1.0000
```

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

```
-2749.9
```

```
Date:                   Mon, 10 Jun 2019    Deviance:
```

```
5499.7
```

```
Time:                   17:10:22    Pearson chi2:
```

```
6.64e+03
```

```
No. Iterations:          20    Covariance Type:
```

```
nonrobust
```

```
=====
```

```
=====
```

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

```
-----
```

```
-----
```

```
const          -1.2492
```

```
0.081          -15.422          0.000          -1.408          -1.090
```

TotalVisits					4.7231
1.410	3.349	0.001	1.959	7.488	
Total Time Spent on Website					4.5511
0.162	28.089	0.000	4.234	4.869	
Lead Origin_lead add form					2.6773
0.225	11.918	0.000	2.237	3.118	
Lead Source_direct traffic					-1.4795
0.114	-12.987	0.000	-1.703	-1.256	
Lead Source_google					-1.1600
0.109	-10.611	0.000	-1.374	-0.946	
Lead Source_organic search					-1.2778
0.134	-9.510	0.000	-1.541	-1.014	
Lead Source_welingak website					2.5990
1.033	2.515	0.012	0.574	4.624	
Do Not Email_yes					-1.4113
0.168	-8.413	0.000	-1.740	-1.083	
Last Activity_olark chat conversation					-1.4730
0.165	-8.908	0.000	-1.797	-1.149	
Last Activity_sms sent					1.3132
0.072	18.136	0.000	1.171	1.455	
What is your current occupation_housewife					22.4667
1.13e+04	0.002	0.998	-2.21e+04	2.21e+04	
What is your current occupation_other					1.4049
0.760	1.848	0.065	-0.085	2.895	
What is your current occupation_working professional					2.8013
0.193	14.487	0.000	2.422	3.180	
Last Notable Activity_unreachable					1.6925
0.610	2.774	0.006	0.497	2.888	

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

*# Make a VIF dataframe for all the variables present*

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

	Features	VIF
1	Total Time Spent on Website	2.34
0	TotalVisits	2.28
4	Lead Source_google	2.04
3	Lead Source_direct traffic	1.91
5	Lead Source_organic search	1.60
9	Last Activity_sms sent	1.49
2	Lead Origin_lead add form	1.47
6	Lead Source_welingak website	1.31

12	What is your current occupation_working profes...	1.17
7	Do Not Email_yes	1.10
8	Last Activity_olark chat conversation	1.02
11	What is your current occupation_other	1.01
13	Last Notable Activity_unreachable	1.01
10	What is your current occupation_housewife	1.00

*The VIF values seem fine but the p-values aren't. So removing 'What is your current occupation housewife'*

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

# Refit the model with the new set of features
X_train_sm = sm.add_constant(X_train)
logm3 = sm.GLM(y_train, X_train_sm, family = sm.families.Binomial())
res = logm3.fit()
res.summary()
```

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

# Generalized Linear Model Regression Results

```
=====
=====
Dep. Variable:          Converted    No. Observations:
6351
Model:                  GLM    Df Residuals:
6337
Model Family:          Binomial    Df Model:
13
Link Function:          logit    Scale:
1.0000
Method:                 IRLS    Log-Likelihood:
-2755.4
Date:                   Mon, 10 Jun 2019    Deviance:
5510.8
Time:                   17:10:22    Pearson chi2:
6.65e+03
No. Iterations:         7    Covariance Type:
nonrobust
=====
=====
```

					coef	std
err	z	P> z	[0.025	0.975]		
-----						
const					-1.2461	
0.081	-15.396	0.000	-1.405	-1.087		



TotalVisits					4.6490
1.403	3.314	0.001	1.899	7.399	
Total Time Spent on Website					4.5480
0.162	28.098	0.000	4.231	4.865	
Lead Origin_lead add form					2.6841
0.224	11.957	0.000	2.244	3.124	
Lead Source_direct traffic					-1.4736
0.114	-12.954	0.000	-1.697	-1.251	
Lead Source_google					-1.1551
0.109	-10.580	0.000	-1.369	-0.941	
Lead Source_organic search					-1.2633
0.134	-9.426	0.000	-1.526	-1.001	
Lead Source_welingak website					2.5921
1.033	2.509	0.012	0.567	4.617	
Do Not Email_yes					-1.4146
0.168	-8.437	0.000	-1.743	-1.086	
Last Activity_olark chat conversation					-1.4765
0.165	-8.932	0.000	-1.800	-1.152	
Last Activity_sms sent					1.3072
0.072	18.070	0.000	1.165	1.449	
What is your current occupation_other					1.4003
0.760	1.842	0.066	-0.090	2.890	
What is your current occupation_working professional					2.7968
0.193	14.467	0.000	2.418	3.176	
Last Notable Activity_unreachable					1.6871
0.610	2.766	0.006	0.492	2.883	

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

*# Make a VIF dataframe for all the variables present*

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

	Features	VIF
1	Total Time Spent on Website	2.34
0	TotalVisits	2.28
4	Lead Source_google	2.04
3	Lead Source_direct traffic	1.91
5	Lead Source_organic search	1.60
9	Last Activity_sms sent	1.49
2	Lead Origin_lead add form	1.47
6	Lead Source_welingak website	1.31
11	What is your current occupation_working profes...	1.17
7	Do Not Email_yes	1.10

8	Last Activity_olark chat conversation	1.02
10	What is your current occupation_other	1.01
12	Last Notable Activity_unreachable	1.01

*The VIF values seem fine but the p-values aren't. So removing 'What is your current occupation other'*

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

# Refit the model with the new set of features
X_train_sm = sm.add_constant(X_train)
logm4 = sm.GLM(y_train, X_train_sm, family = sm.families.Binomial())
res = logm4.fit()
res.summary()
```

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

# Generalized Linear Model Regression Results

```
=====
=====
Dep. Variable:          Converted    No. Observations:
6351
Model:                  GLM        Df Residuals:
6338
Model Family:           Binomial    Df Model:
12
Link Function:           logit       Scale:
1.0000
Method:                  IRLS       Log-Likelihood:
-2757.3
Date:                   Mon, 10 Jun 2019    Deviance:
5514.5
Time:                   17:10:22    Pearson chi2:
6.65e+03
No. Iterations:          7    Covariance Type:
nonrobust
=====
=====
```

					coef	std
err	z	P> z	[0.025	0.975]		
-----						
const					-1.2466	
0.081	-15.398	0.000	-1.405	-1.088		
TotalVisits					4.7586	
1.410	3.375	0.001	1.995	7.522		
Total Time Spent on Website					4.5539	

0.162	28.136	0.000	4.237	4.871	
Lead Origin_lead add form					2.6860
0.224	11.966	0.000	2.246	3.126	
Lead Source_direct traffic					-1.4706
0.114	-12.929	0.000	-1.694	-1.248	
Lead Source_google					-1.1564
0.109	-10.588	0.000	-1.370	-0.942	
Lead Source_organic search					-1.2631
0.134	-9.416	0.000	-1.526	-1.000	
Lead Source_welingak website					2.5923
1.033	2.509	0.012	0.567	4.617	
Do Not Email_yes					-1.4186
0.168	-8.461	0.000	-1.747	-1.090	
Last Activity_olark chat conversation					-1.4717
0.165	-8.909	0.000	-1.796	-1.148	
Last Activity_sms sent					1.3038
0.072	18.031	0.000	1.162	1.445	
What is your current occupation_working professional					2.7934
0.193	14.449	0.000	2.414	3.172	
Last Notable Activity_unreachable					1.6837
0.610	2.761	0.006	0.488	2.879	

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

```
# Make a VIF dataframe for all the variables present
vif = pd.DataFrame()
vif['Features'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X_train.values, i) for i in
range(X_train.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

	Features	VIF
1	Total Time Spent on Website	2.33
0	TotalVisits	2.28
4	Lead Source_google	2.04
3	Lead Source_direct traffic	1.91
5	Lead Source_organic search	1.60
9	Last Activity_sms sent	1.49
2	Lead Origin_lead add form	1.47
6	Lead Source_welingak website	1.31
10	What is your current occupation_working profes...	1.17
7	Do Not Email_yes	1.10
8	Last Activity_olark chat conversation	1.02
11	Last Notable Activity_unreachable	1.01

***All the VIF values are good and all the p-values are below 0.05. So we can fix model.***

## 6. Creating Prediction

```
# Predicting the probabilities on the train set
```

```
y_train_pred = res.predict(X_train_sm)
```

```
y_train_pred[:10]
```

```
1289    0.611739
3604    0.223294
5584    0.425011
7679    0.223294
7563    0.432202
7978    0.732762
7780    0.130274
7863    0.982565
838     0.779231
708     0.132990
dtype: float64
```

```
# Reshaping to an array
```

```
y_train_pred = y_train_pred.values.reshape(-1)
```

```
y_train_pred[:10]
```

```
array([0.61173868, 0.22329356, 0.42501069, 0.22329356, 0.43220183,
       0.73276232, 0.13027447, 0.9825646 , 0.77923117, 0.13298976])
```

```
# Data frame with given conversion rate and probability of predicted ones
```

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

```
y_train_pred_final.head()
```

	Converted	Conversion_Prob
0	1	0.611739
1	0	0.223294
2	0	0.425011
3	0	0.223294
4	0	0.432202

```
# Substituting 0 or 1 with the cut off as 0.5
```

```
y_train_pred_final['Predicted'] =
```

```
y_train_pred_final.Conversion_Prob.map(lambda x: 1 if x > 0.5 else 0)
```

```
y_train_pred_final.head()
```

	Converted	Conversion_Prob	Predicted
0	1	0.611739	1
1	0	0.223294	0
2	0	0.425011	0
3	0	0.223294	0
4	0	0.432202	0

## 7. Model Evaluation

```
# Importing metrics from sklearn for evaluation
from sklearn import metrics

# Creating confusion matrix
confusion = metrics.confusion_matrix(y_train_pred_final.Converted,
y_train_pred_final.Predicted )
confusion

array([[3403,  492],
       [ 729, 1727]], dtype=int64)

# Predicted      not_churn    churn
# Actual
# not_churn      3403        492
# churn          729        1727

# Check the overall accuracy
metrics.accuracy_score(y_train_pred_final.Converted,
y_train_pred_final.Predicted)

0.807746811525744
```

*That's around 81% accuracy with is a very good value*

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

# Calculating the sensitivity
TP/(TP+FN)

0.7031758957654723

# Calculating the specificity
TN/(TN+FP)

0.8736842105263158
```

*With the current cut off as 0.5 we have around 81% accuracy, sensitivity of around 70% and specificity of around 87%.*

## 7. Optimise Cut off (ROC Curve)

The previous cut off was randomly selected. Now to find the optimum one

```

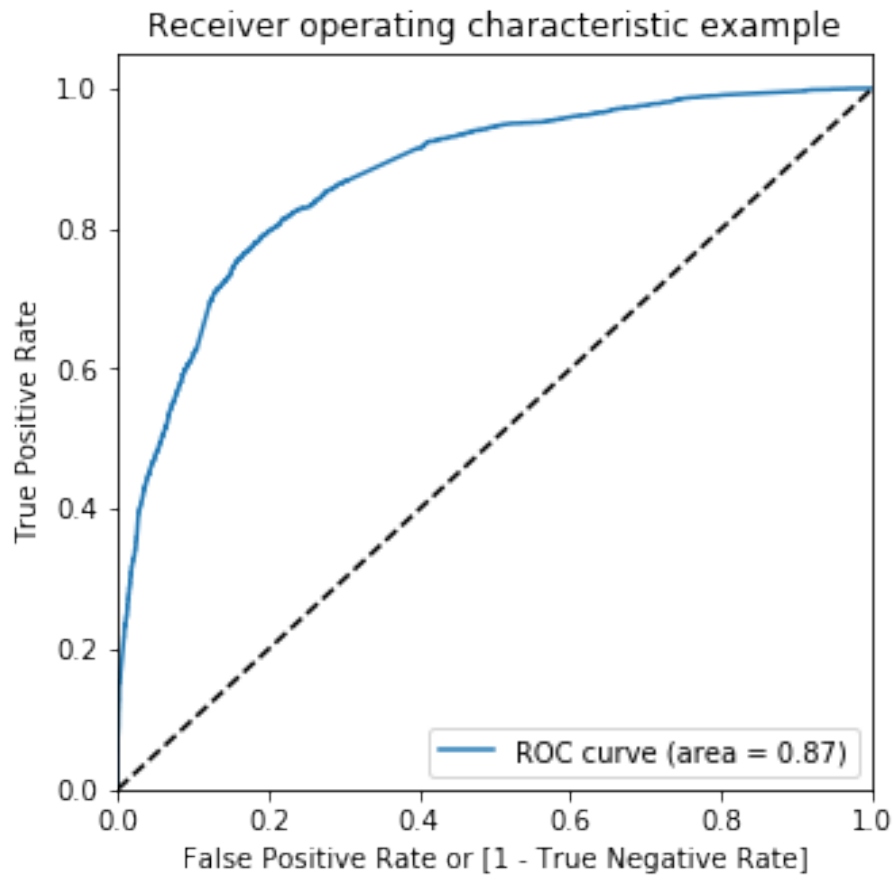
# ROC function
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
                                              drop_intermediate =
False )
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(5, 5))
    plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % auc_score )
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()

    return None

fpr, tpr, thresholds =
metrics.roc_curve( y_train_pred_final.Converted,
y_train_pred_final.Conversion_Prob, drop_intermediate = False )

# Call the ROC function
draw_roc(y_train_pred_final.Converted,
y_train_pred_final.Conversion_Prob)

```



*The area under ROC curve is 0.87 which is a very good value.*

```
# Creating columns with different probability cutoffs
numbers = [float(x)/10 for x in range(10)]
for i in numbers:
    y_train_pred_final[i]=
y_train_pred_final.Conversion_Prob.map(lambda x: 1 if x > i else 0)
y_train_pred_final.head()
```

	Converted	Conversion_Prob	Predicted	0.0	0.1	0.2	0.3	0.4	0.5
0.6 \									
0	1	0.611739	1	1	1	1	1	1	1
1									
1	0	0.223294	0	1	1	1	0	0	0
0									
2	0	0.425011	0	1	1	1	1	1	0
0									
3	0	0.223294	0	1	1	1	0	0	0
0									
4	0	0.432202	0	1	1	1	1	1	0
0									
	0.7	0.8	0.9						

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

*# Creating a dataframe to see the values of accuracy, sensitivity, and specificity at different values of probability cutoffs*

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

*# Making confusing matrix to find values of sensitivity, accuracy and specificity for each level of probability*

```
from sklearn.metrics import confusion_matrix
```

```
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]
```

```
cutoff_df
```

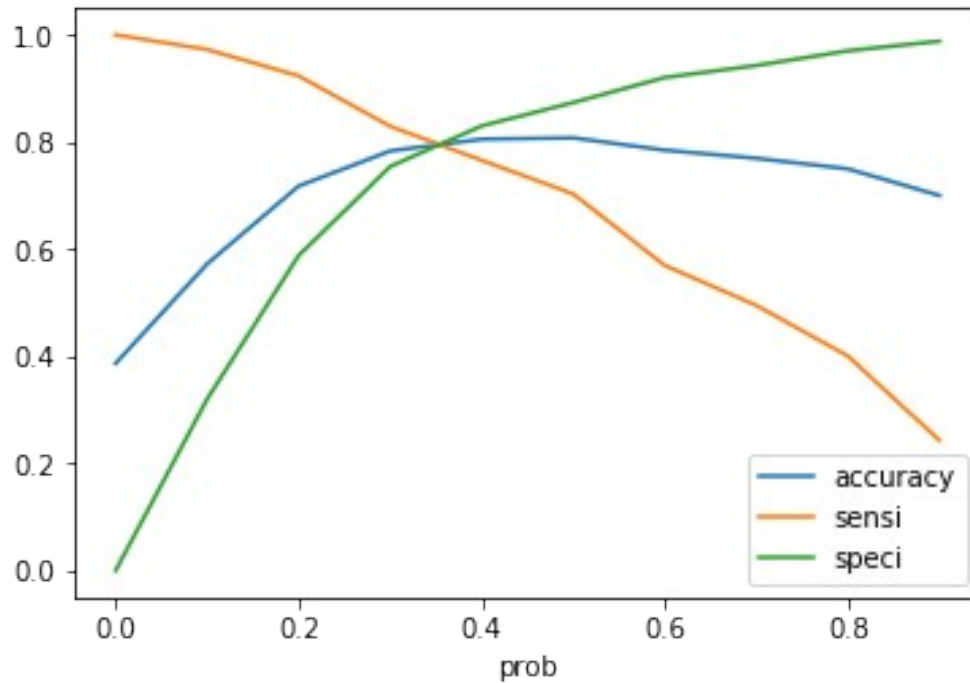
	prob	accuracy	sensi	speci
0.0	0.0	0.386711	1.000000	0.000000
0.1	0.1	0.572508	0.972720	0.320154
0.2	0.2	0.717840	0.923453	0.588190
0.3	0.3	0.783341	0.829397	0.754300
0.4	0.4	0.805228	0.765879	0.830039
0.5	0.5	0.807747	0.703176	0.873684
0.6	0.6	0.784758	0.569625	0.920411
0.7	0.7	0.769643	0.495114	0.942747
0.8	0.8	0.749961	0.400651	0.970218
0.9	0.9	0.700205	0.243485	0.988190

*# Plotting it*

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

```
plt.show()
```





*From the graph it is visible that the optimal cut off is at 0.35.*

```
y_train_pred_final['final_predicted'] =
y_train_pred_final.Conversion_Prob.map( lambda x: 1 if x > 0.35 else
0)
y_train_pred_final.head()
```

	Converted	Conversion_Prob	Predicted	0.0	0.1	0.2	0.3	0.4	0.5
0.6	\								
0	1	0.611739	1	1	1	1	1	1	1
1									
1	0	0.223294	0	1	1	1	0	0	0
0									
2	0	0.425011	0	1	1	1	1	1	0
0									
3	0	0.223294	0	1	1	1	0	0	0
0									
4	0	0.432202	0	1	1	1	1	1	0
0									

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

```

# Check the overall accuracy
metrics.accuracy_score(y_train_pred_final.Converted,
y_train_pred_final.final_predicted)

0.7967249252086286

# Creating confusion matrix
confusion2 = metrics.confusion_matrix(y_train_pred_final.Converted,
y_train_pred_final.final_predicted )
confusion2

array([[3097,  798],
       [ 493, 1963]], dtype=int64)

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

# Calculating the sensitivity
TP/(TP+FN)

0.7992671009771987

# Calculating the specificity
TN/(TN+FP)

0.7951219512195122

```

***With the current cut off as 0.35 we have accuracy, sensitivity and specificity of around 80%.***

## 8. Prediction on Test set

```

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

# Substituting all the columns in the final train model
col = X_train.columns

# Select the columns in X_train for X_test as well
X_test = X_test[col]
# Add a constant to X_test
X_test_sm = sm.add_constant(X_test[col])
X_test_sm
X_test_sm

```

	const	TotalVisits	Total Time Spent on Website \
8308	1.0	0.035461	0.416813
7212	1.0	0.028369	0.001320
2085	1.0	0.000000	0.000000
4048	1.0	0.028369	0.617077
4790	1.0	0.028369	0.005282
8552	1.0	0.063830	0.552817
2232	1.0	0.021277	0.496919
5259	1.0	0.000000	0.000000
2399	1.0	0.028369	0.639085
8018	1.0	0.000000	0.000000
3221	1.0	0.014184	0.394366
1226	1.0	0.000000	0.000000
8914	1.0	0.014184	0.000880
765	1.0	0.007092	0.041373
2973	1.0	0.028369	0.199384
3917	1.0	0.021277	0.615757
2201	1.0	0.035461	0.056778
8088	1.0	0.000000	0.000000
3192	1.0	0.014184	0.462588
6636	1.0	0.035461	0.745599
2542	1.0	0.035461	0.532130
6095	1.0	0.028369	0.783011
9217	1.0	0.000000	0.000000
5664	1.0	0.035461	0.700704
4967	1.0	0.014184	0.097271
5889	1.0	0.063830	0.437940
4758	1.0	0.028369	0.476232
4999	1.0	0.028369	0.134243
2734	1.0	0.000000	0.000000
653	1.0	0.028369	0.093750
...	...	...	...
124	1.0	0.028369	0.720951
2172	1.0	0.085106	0.365317
8016	1.0	0.049645	0.042254
1681	1.0	0.000000	0.000000
1593	1.0	0.014184	0.641725
7103	1.0	0.000000	0.000000
2603	1.0	0.028369	0.552377
8331	1.0	0.007092	0.068662
2711	1.0	0.021277	0.224472
3141	1.0	0.000000	0.000000
3847	1.0	0.049645	0.478433
301	1.0	0.028369	0.261884
7883	1.0	0.014184	0.308099
4182	1.0	0.014184	0.227113
3071	1.0	0.028369	0.204225
6790	1.0	0.078014	0.140405
5404	1.0	0.021277	0.132042
1411	1.0	0.028369	0.555018

2141	1.0	0.014184	0.190581
97	1.0	0.000000	0.000000
7796	1.0	0.035461	0.100352
2453	1.0	0.035461	0.169014
8639	1.0	0.035461	0.084067
4039	1.0	0.000000	0.000000
7311	1.0	0.014184	0.186180
3261	1.0	0.000000	0.000000
8179	1.0	0.170213	0.148768
6236	1.0	0.000000	0.000000
5240	1.0	0.078014	0.458627
7243	1.0	0.035461	0.499560

	Lead Origin_lead add form	Lead Source_direct traffic \
8308	0	1
7212	0	0
2085	1	0
4048	0	1
4790	0	1
8552	0	1
2232	0	0
5259	0	0
2399	0	0
8018	0	0
3221	0	0
1226	0	0
8914	0	1
765	0	0
2973	0	1
3917	0	0
2201	0	1
8088	1	0
3192	0	0
6636	0	1
2542	0	0
6095	0	0
9217	0	0
5664	0	0
4967	0	0
5889	0	0
4758	0	0
4999	0	0
2734	1	0
653	0	0
...	...	...
124	0	0
2172	0	0
8016	0	0
1681	0	0
1593	0	0

7103	0	0
2603	0	0
8331	0	1
2711	0	0
3141	0	0
3847	0	0
301	0	0
7883	0	0
4182	0	1
3071	0	0
6790	0	0
5404	0	1
1411	0	0
2141	0	0
97	0	0
7796	0	0
2453	0	0
8639	0	0
4039	0	0
7311	0	1
3261	0	0
8179	0	0
6236	0	0
5240	0	0
7243	0	0

	Lead Source_google	Lead Source_organic search \
8308	0	0
7212	0	1
2085	0	0
4048	0	0
4790	0	0
8552	0	0
2232	0	1
5259	0	0
2399	1	0
8018	0	0
3221	1	0
1226	0	0
8914	0	0
765	1	0
2973	0	0
3917	1	0
2201	0	0
8088	0	0
3192	1	0
6636	0	0
2542	1	0
6095	1	0
9217	0	0

5664	1	0
4967	1	0
5889	0	1
4758	0	1
4999	1	0
2734	0	0
653	0	0
...	...	...
124	1	0
2172	1	0
8016	0	1
1681	0	0
1593	1	0
7103	0	0
2603	0	1
8331	0	0
2711	1	0
3141	0	0
3847	0	1
301	1	0
7883	1	0
4182	0	0
3071	1	0
6790	0	1
5404	0	0
1411	1	0
2141	1	0
97	0	0
7796	1	0
2453	1	0
8639	1	0
4039	0	0
7311	0	0
3261	0	0
8179	1	0
6236	0	0
5240	1	0
7243	0	1
Lead Source_welingak website Do Not Email_yes \		
8308	0	0
7212	0	0
2085	1	0
4048	0	0
4790	0	0
8552	0	0
2232	0	1
5259	0	0
2399	0	1
8018	0	0

3221	0	0
1226	0	0
8914	0	0
765	0	0
2973	0	0
3917	0	0
2201	0	0
8088	0	0
3192	0	0
6636	0	0
2542	0	0
6095	0	0
9217	0	0
5664	0	0
4967	0	0
5889	0	0
4758	0	0
4999	0	0
2734	0	0
653	0	0
...	...	...
124	0	0
2172	0	0
8016	0	0
1681	0	0
1593	0	0
7103	0	0
2603	0	0
8331	0	1
2711	0	0
3141	0	0
3847	0	0
301	0	0
7883	0	0
4182	0	0
3071	0	0
6790	0	1
5404	0	1
1411	0	0
2141	0	0
97	0	0
7796	0	1
2453	0	0
8639	0	0
4039	0	0
7311	0	0
3261	0	0
8179	0	0
6236	0	0
5240	0	0

7243	0	0
	Last Activity_olark chat conversation	Last Activity_sms sent \
8308	0	0
7212	0	1
2085	0	0
4048	0	1
4790	0	0
8552	0	1
2232	0	0
5259	0	0
2399	0	1
8018	1	0
3221	0	1
1226	1	0
8914	0	0
765	0	0
2973	0	0
3917	0	1
2201	1	0
8088	0	1
3192	0	0
6636	0	0
2542	0	0
6095	0	0
9217	0	1
5664	0	1
4967	1	0
5889	0	0
4758	0	0
4999	0	0
2734	0	0
653	0	0
...	...	...
124	0	0
2172	0	0
8016	0	1
1681	0	0
1593	0	0
7103	0	0
2603	0	1
8331	0	0
2711	0	0
3141	0	0
3847	0	1
301	0	0
7883	0	0
4182	0	0
3071	0	1
6790	0	0



5404	0	1
1411	0	0
2141	0	0
97	1	0
7796	0	1
2453	0	0
8639	0	0
4039	0	0
7311	0	0
3261	1	0
8179	0	1
6236	0	0
5240	0	1
7243	0	0

	What is your current occupation_working professional \
8308	0
7212	1
2085	0
4048	0
4790	0
8552	0
2232	0
5259	0
2399	0
8018	0
3221	0
1226	0
8914	0
765	0
2973	0
3917	0
2201	0
8088	1
3192	1
6636	0
2542	1
6095	0
9217	0
5664	0
4967	1
5889	0
4758	0
4999	0
2734	0
653	0
...	...
124	0
2172	0
8016	0

1681	0
1593	0
7103	0
2603	0
8331	0
2711	0
3141	0
3847	0
301	0
7883	1
4182	1
3071	0
6790	0
5404	0
1411	0
2141	0
97	0
7796	0
2453	0
8639	0
4039	0
7311	0
3261	0
8179	0
6236	0
5240	0
7243	0

#### Last Notable Activity\_unreachable

8308	0
7212	0
2085	0
4048	0
4790	0
8552	0
2232	0
5259	0
2399	0
8018	0
3221	0
1226	0
8914	0
765	0
2973	0
3917	0
2201	0
8088	0
3192	0
6636	0
2542	0

6095	0
9217	0
5664	0
4967	0
5889	0
4758	0
4999	0
2734	0
653	0
...	...
124	0
2172	0
8016	0
1681	0
1593	0
7103	0
2603	0
8331	0
2711	0
3141	0
3847	0
301	0
7883	0
4182	0
3071	0
6790	0
5404	0
1411	0
2141	0
97	0
7796	0
2453	0
8639	0
4039	0
7311	0
3261	0
8179	0
6236	0
5240	0
7243	0

[2723 rows x 13 columns]

```

# Storing prediction of test set in the variable 'y_test_pred'
y_test_pred = res.predict(X_test_sm)
# Converting it to df
y_pred_df = pd.DataFrame(y_test_pred)
# Converting y_test to dataframe
y_test_df = pd.DataFrame(y_test)
# Remove index for both dataframes to append them side by side

```

```

y_pred_df.reset_index(drop=True, inplace=True)
y_test_df.reset_index(drop=True, inplace=True)
# Append y_test_df and y_pred_df
y_pred_final = pd.concat([y_test_df, y_pred_df],axis=1)
# Renaming column
y_pred_final= y_pred_final.rename(columns = {0 : 'Conversion_Prob'})
y_pred_final.head()

```

	Converted	Conversion_Prob
0	0	0.342925
1	1	0.849219
2	1	0.982565
3	1	0.822258
4	0	0.071883

```

# Making prediction using cut off 0.35
y_pred_final['final_predicted'] =
y_pred_final.Conversion_Prob.map(lambda x: 1 if x > 0.35 else 0)
y_pred_final

```

	Converted	Conversion_Prob	final_predicted
0	0	0.342925	0
1	1	0.849219	1
2	1	0.982565	1
3	1	0.822258	1
4	0	0.071883	0
5	1	0.803423	1
6	0	0.173071	0
7	1	0.223294	0
8	1	0.628924	1
9	0	0.061901	0
10	1	0.682271	1
11	0	0.061901	0
12	0	0.066257	0
13	0	0.101488	0
14	0	0.157866	0
15	1	0.858899	1
16	0	0.022718	0
17	1	0.996075	1
18	1	0.928541	1
19	1	0.699933	1
20	1	0.951774	1
21	1	0.785467	1
22	0	0.514295	1
23	0	0.905554	1
24	0	0.361032	1
25	1	0.447308	1
26	1	0.448702	1
27	0	0.160215	0
28	1	0.808364	1

29	0	0.335224	0
...	...	...	...
2693	0	0.734036	1
2694	1	0.417184	1
2695	0	0.314921	0
2696	0	0.223294	0
2697	0	0.642657	1
2698	0	0.223294	0
2699	0	0.809167	1
2700	0	0.022112	0
2701	0	0.217639	0
2702	0	0.223294	0
2703	1	0.770143	1
2704	1	0.254385	0
2705	1	0.865408	1
2706	0	0.764576	1
2707	0	0.491460	1
2708	0	0.051292	0
2709	0	0.106272	0
2710	1	0.564526	1
2711	0	0.187313	0
2712	0	0.061901	0
2713	0	0.131017	0
2714	0	0.187775	0
2715	0	0.135711	0
2716	0	0.223294	0
2717	0	0.141629	0
2718	1	0.061901	0
2719	0	0.595864	1
2720	0	0.223294	0
2721	1	0.795858	1
2722	1	0.483521	1

[2723 rows x 3 columns]

*# Check the overall accuracy*

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

0.8005875872199779

*# Creating confusion matrix*

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

```
array([[1394, 350],
       [ 193, 786]], dtype=int64)
```

```

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

# Calculating the sensitivity
TP/(TP+FN)

0.8028600612870276

# Calculating the specificity
TN/(TN+FP)

0.7993119266055045

```

***With the current cut off as 0.35 we have accuracy, sensitivity and specificity of around 80%.***

## 9. Precision-Recall

```

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

array([[3403,  492],
       [ 729, 1727]], dtype=int64)

# Precision = TP / TP + FP
confusion[1,1]/(confusion[0,1]+confusion[1,1])

0.7782785038305543

#Recall = TP / TP + FN
confusion[1,1]/(confusion[1,0]+confusion[1,1])

0.7031758957654723

```

***With the current cut off as 0.35 we have Precision around 78% and Recall around 70%***

### 9.1. Precision and recall tradeoff

```

from sklearn.metrics import precision_recall_curve
y_train_pred_final.Converted, y_train_pred_final.Predicted

(0      1
 1      0
 2      0
 3      0

```

4	0
5	1
6	1
7	1
8	1
9	0
10	1
11	1
12	1
13	0
14	1
15	0
16	0
17	1
18	1
19	0
20	1
21	1
22	0
23	1
24	0
25	0
26	1
27	0
28	0
29	0
	..
6321	1
6322	1
6323	0
6324	0
6325	0
6326	0
6327	0
6328	1
6329	1
6330	1
6331	1
6332	0
6333	0
6334	1
6335	0
6336	0
6337	1
6338	0
6339	0
6340	1
6341	0
6342	0

```
6343    0
6344    1
6345    1
6346    0
6347    0
6348    0
6349    0
6350    1
Name: Converted, Length: 6351, dtype: int64, 0    1
1        0
2        0
3        0
4        0
5        1
6        0
7        1
8        1
9        0
10       1
11       1
12       0
13       0
14       0
15       0
16       0
17       1
18       0
19       0
20       0
21       1
22       0
23       0
24       0
25       0
26       1
27       0
28       0
29       0
..
6321    1
6322    1
6323    0
6324    0
6325    0
6326    0
6327    0
6328    0
6329    0
6330    0
```



```

6331    0
6332    0
6333    0
6334    1
6335    0
6336    0
6337    1
6338    0
6339    0
6340    1
6341    0
6342    0
6343    0
6344    0
6345    1
6346    0
6347    0
6348    0
6349    0
6350    0
Name: Predicted, Length: 6351, dtype: int64)

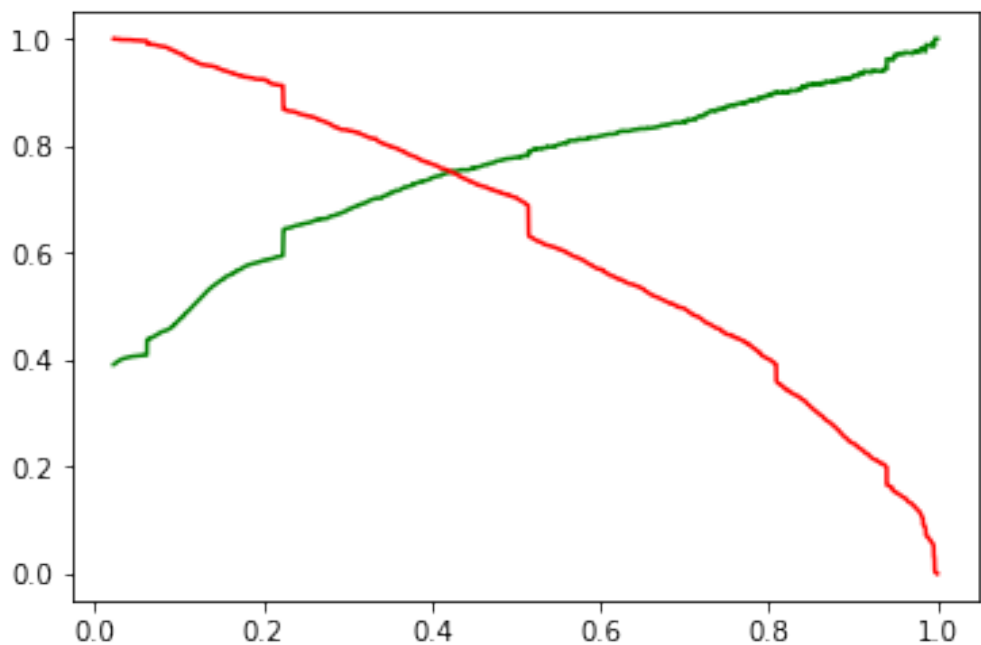
```

```

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

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

```



```
y_train_pred_final['final_predicted'] =
y_train_pred_final.Conversion_Prob.map(lambda x: 1 if x > 0.41 else 0)
y_train_pred_final.head()
```

	Converted	Conversion_Prob	Predicted	0.0	0.1	0.2	0.3	0.4	0.5
0.6 \									
0	1	0.611739	1	1	1	1	1	1	1
1									
1	0	0.223294	0	1	1	1	0	0	0
0									
2	0	0.425011	0	1	1	1	1	1	0
0									
3	0	0.223294	0	1	1	1	0	0	0
0									
4	0	0.432202	0	1	1	1	1	1	0
0									

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

*# Accuracy*

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

0.8060148008187688

*# Creating confusion matrix again*

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

```
array([[3256, 639],
       [ 593, 1863]], dtype=int64)
```

*# Substituting the value of true positive*

```
TP = confusion2[1,1]
```

*# Substituting the value of true negatives*

```
TN = confusion2[0,0]
```

*# Substituting the value of false positives*

```
FP = confusion2[0,1]
```

*# Substituting the value of false negatives*

```
FN = confusion2[1,0]
```

*# Precision = TP / TP + FP*

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

0.7446043165467626

```
#Recall = TP / TP + FN  
TP / (TP + FN)
```

```
0.7585504885993485
```

*With the current cut off as 0.41 we have Precision around 74% and Recall around 76%*

## 10. Prediction on Test set

```
# Storing prediction of test set in the variable 'y_test_pred'  
y_test_pred = res.predict(X_test_sm)  
# Converting it to df  
y_pred_df = pd.DataFrame(y_test_pred)  
# Converting y_test to dataframe  
y_test_df = pd.DataFrame(y_test)  
# Remove index for both dataframes to append them side by side  
y_pred_df.reset_index(drop=True, inplace=True)  
y_test_df.reset_index(drop=True, inplace=True)  
# Append y_test_df and y_pred_df  
y_pred_final = pd.concat([y_test_df, y_pred_df], axis=1)  
# Renaming column  
y_pred_final = y_pred_final.rename(columns = {0 : 'Conversion_Prob'})  
y_pred_final.head()
```

	Converted	Conversion_Prob
0	0	0.342925
1	1	0.849219
2	1	0.982565
3	1	0.822258
4	0	0.071883

```
# Making prediction using cut off 0.41  
y_pred_final['final_predicted'] =  
y_pred_final.Conversion_Prob.map(lambda x: 1 if x > 0.41 else 0)  
y_pred_final
```

	Converted	Conversion_Prob	final_predicted
0	0	0.342925	0
1	1	0.849219	1
2	1	0.982565	1
3	1	0.822258	1
4	0	0.071883	0
5	1	0.803423	1
6	0	0.173071	0
7	1	0.223294	0
8	1	0.628924	1
9	0	0.061901	0
10	1	0.682271	1
11	0	0.061901	0
12	0	0.066257	0

13	0	0.101488	0
14	0	0.157866	0
15	1	0.858899	1
16	0	0.022718	0
17	1	0.996075	1
18	1	0.928541	1
19	1	0.699933	1
20	1	0.951774	1
21	1	0.785467	1
22	0	0.514295	1
23	0	0.905554	1
24	0	0.361032	0
25	1	0.447308	1
26	1	0.448702	1
27	0	0.160215	0
28	1	0.808364	1
29	0	0.335224	0
...	...	...	...
2693	0	0.734036	1
2694	1	0.417184	1
2695	0	0.314921	0
2696	0	0.223294	0
2697	0	0.642657	1
2698	0	0.223294	0
2699	0	0.809167	1
2700	0	0.022112	0
2701	0	0.217639	0
2702	0	0.223294	0
2703	1	0.770143	1
2704	1	0.254385	0
2705	1	0.865408	1
2706	0	0.764576	1
2707	0	0.491460	1
2708	0	0.051292	0
2709	0	0.106272	0
2710	1	0.564526	1
2711	0	0.187313	0
2712	0	0.061901	0
2713	0	0.131017	0
2714	0	0.187775	0
2715	0	0.135711	0
2716	0	0.223294	0
2717	0	0.141629	0
2718	1	0.061901	0
2719	0	0.595864	1
2720	0	0.223294	0
2721	1	0.795858	1
2722	1	0.483521	1

```

[2723 rows x 3 columns]

# Check the overall accuracy
metrics.accuracy_score(y_pred_final['Converted'],
y_pred_final.final_predicted)

0.808666911494675

# Creating confusion matrix
confusion2 = metrics.confusion_matrix(y_pred_final['Converted'],
y_pred_final.final_predicted )
confusion2

array([[1465, 279],
       [ 242, 737]], dtype=int64)

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

# Precision = TP / TP + FP
TP / (TP + FP)

0.7253937007874016

#Recall = TP / TP + FN
TP / (TP + FN)

0.7528089887640449

```

***With the current cut off as 0.41 we have Precision around 73% and Recall around 75%***

## Conclusion

It was found that the variables that mattered the most in the potential buyers are (In descending order):

1. The total time spend on the Website.
2. Total number of visits.
3. When the lead source was:
  - a. Google
  - b. Direct traffic
  - c. Organic search

d. Welingak website

1. When the last activity was:

a. SMS

b. Olark chat conversation

1. When the lead origin is Lead add format.
2. When their current occupation is as a working professional. Keeping these in mind the X Education can flourish as they have a very high chance to get almost all the potential buyers to change their mind and buy their courses.