



# LEAD SCORING CASE STUDY

BY: SHUBHANG SINGH AND SANDEEP  
CHALLA

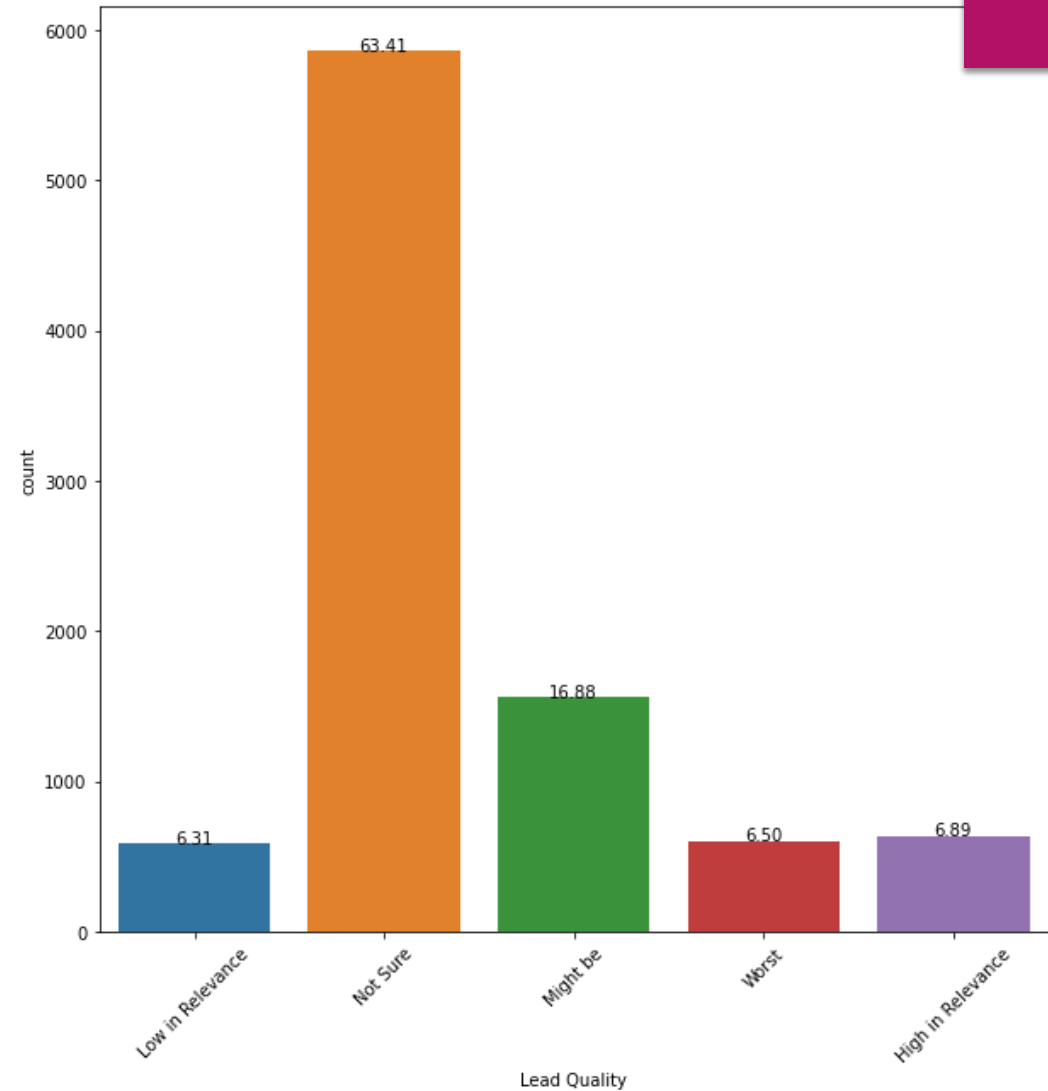
# PROBLEM STATEMENT

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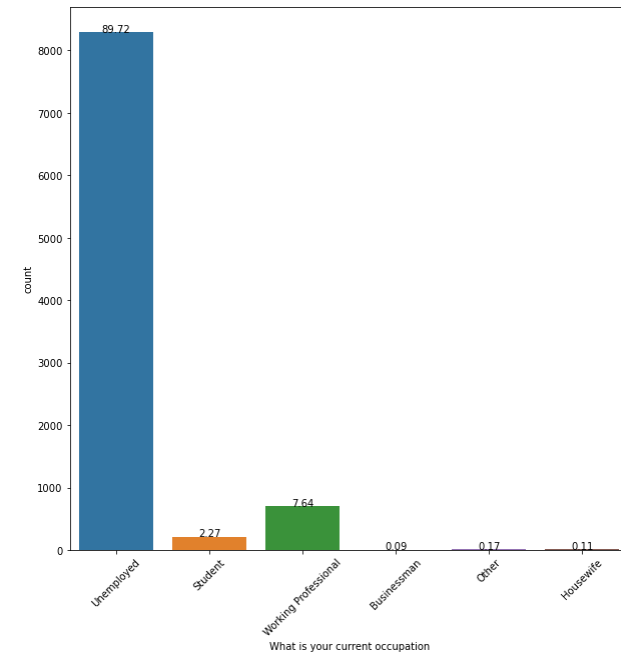
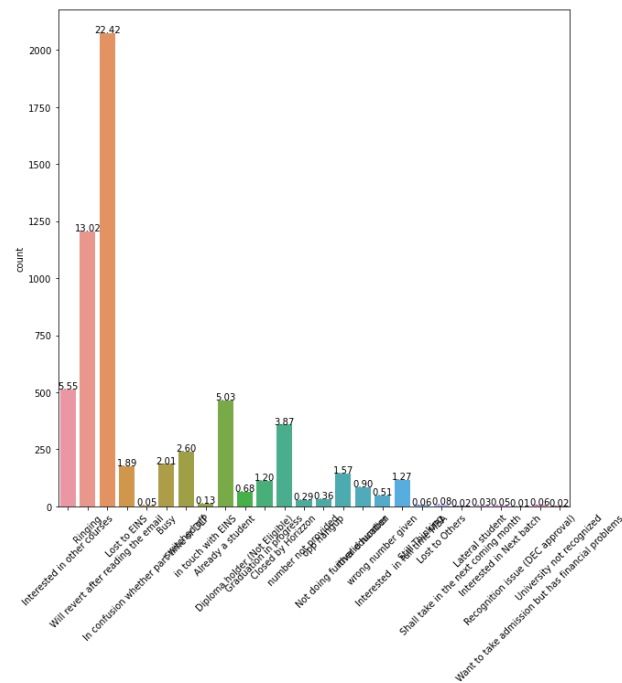
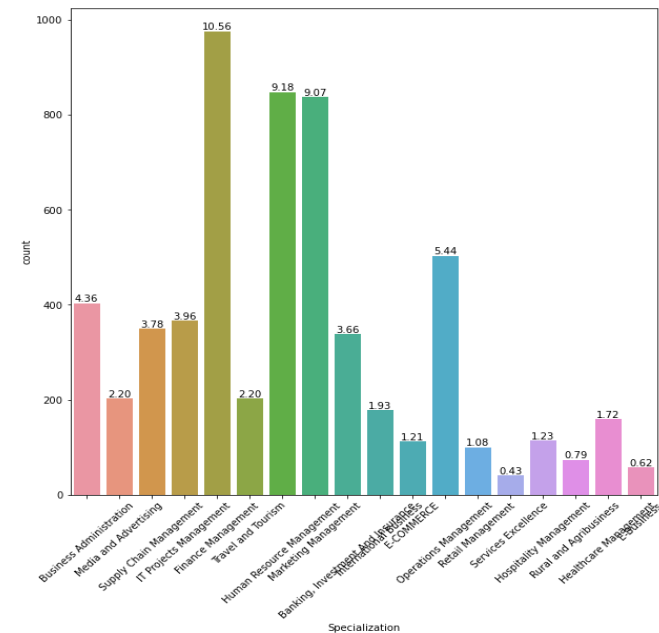
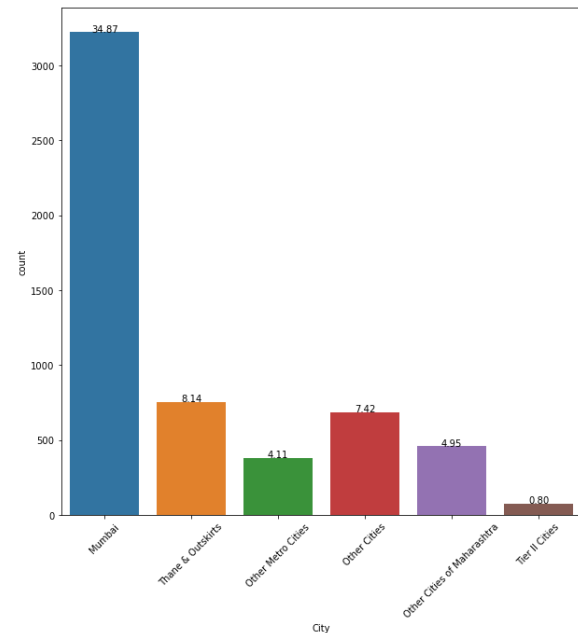
- Create a model in such a way that the customers with high lead score have higher conversion chance and low leads score have lower conversion chance. The ballpark of the target lead conversion rate is around 80%
- Also, the model should be able to adjust if the company's requirement changes in near future.

# Approach of the analysis

- ▶ We started our analysis by reading and understanding the data. Finding the numerical and categorical variables and also looking at the number of null values in each of them.
- ▶ Then we went on with data cleaning in which we dropped the columns having null percentage greater than 50%.

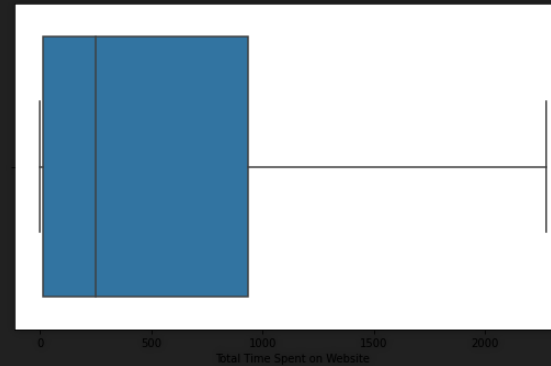


# EDA: EXPLORATORY DATA ANALYSIS





# Outlier Treatment



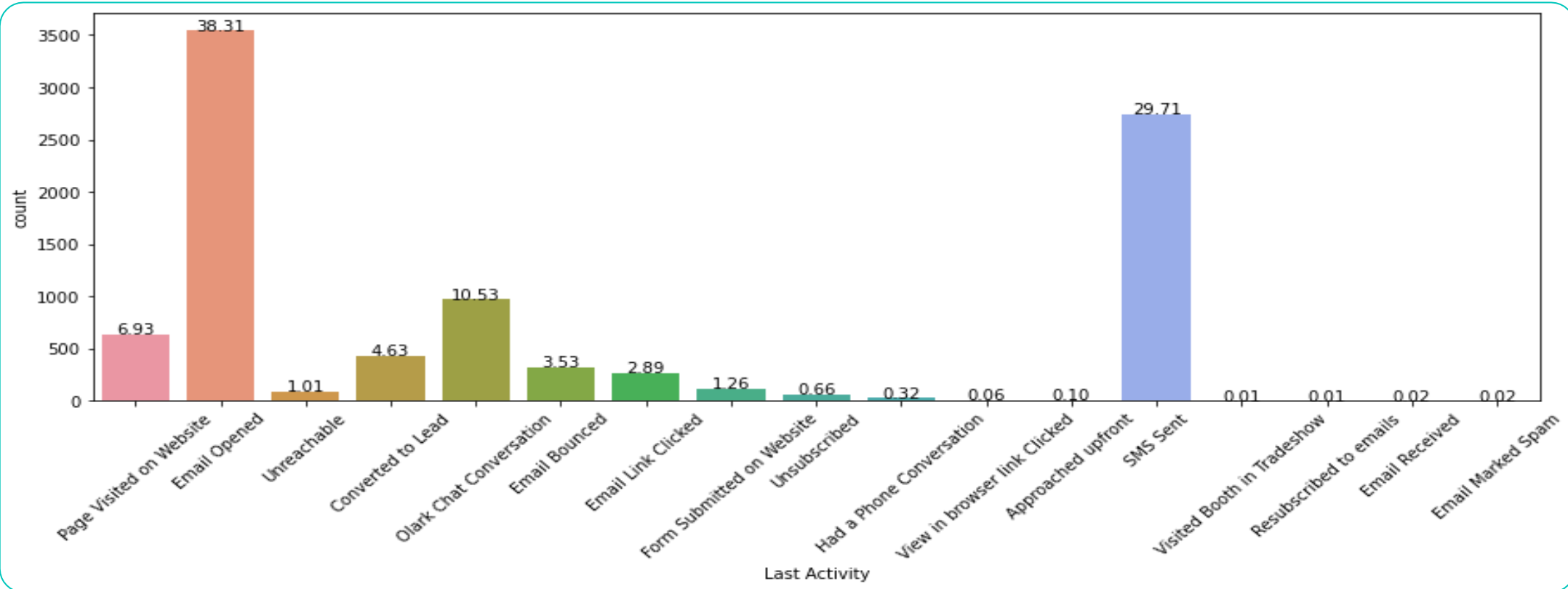
- There are lot of outliers in **TotalVisits** and **Page Views per Visit**.

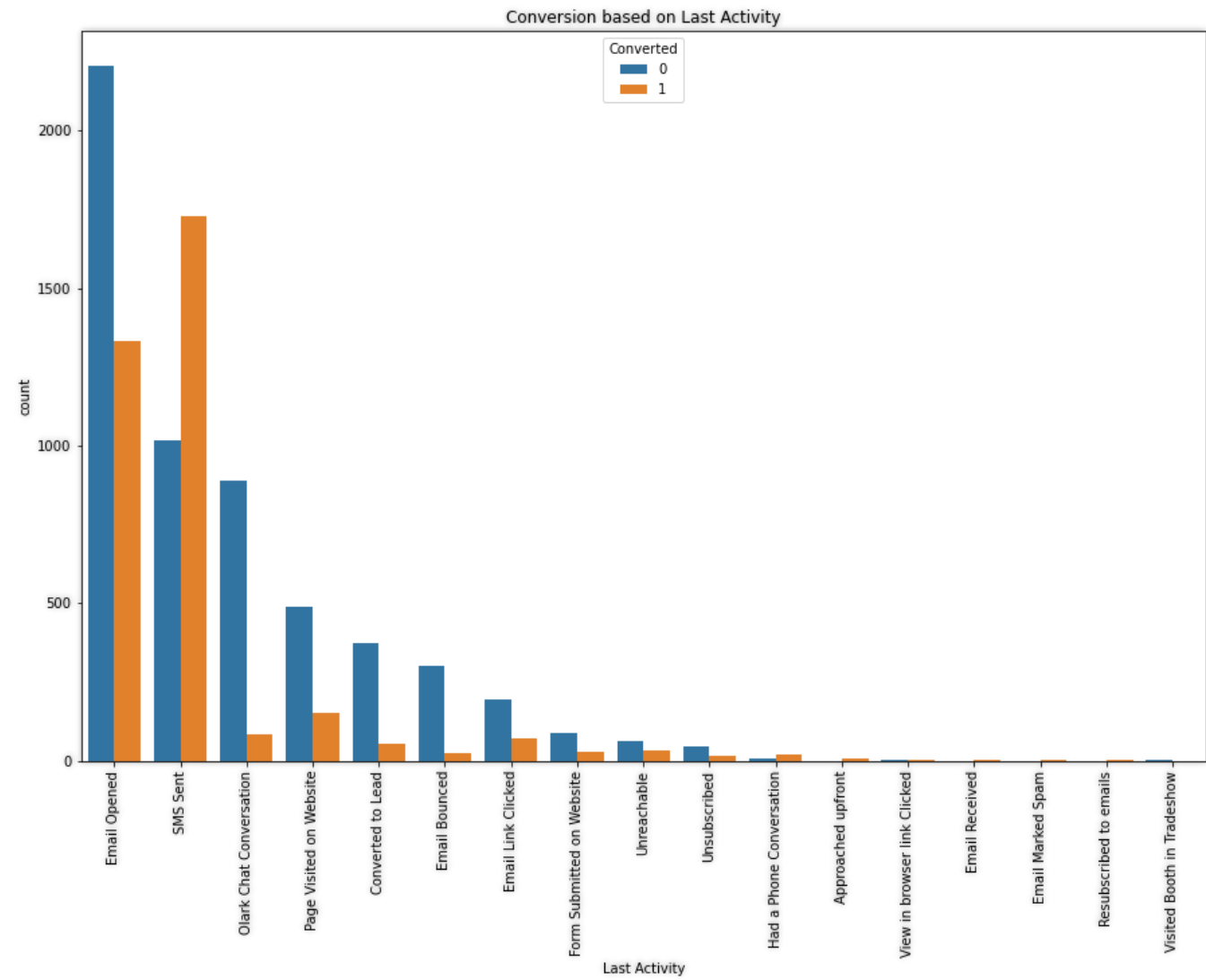
# Univariate and Bivariate Analysis

## Observations:

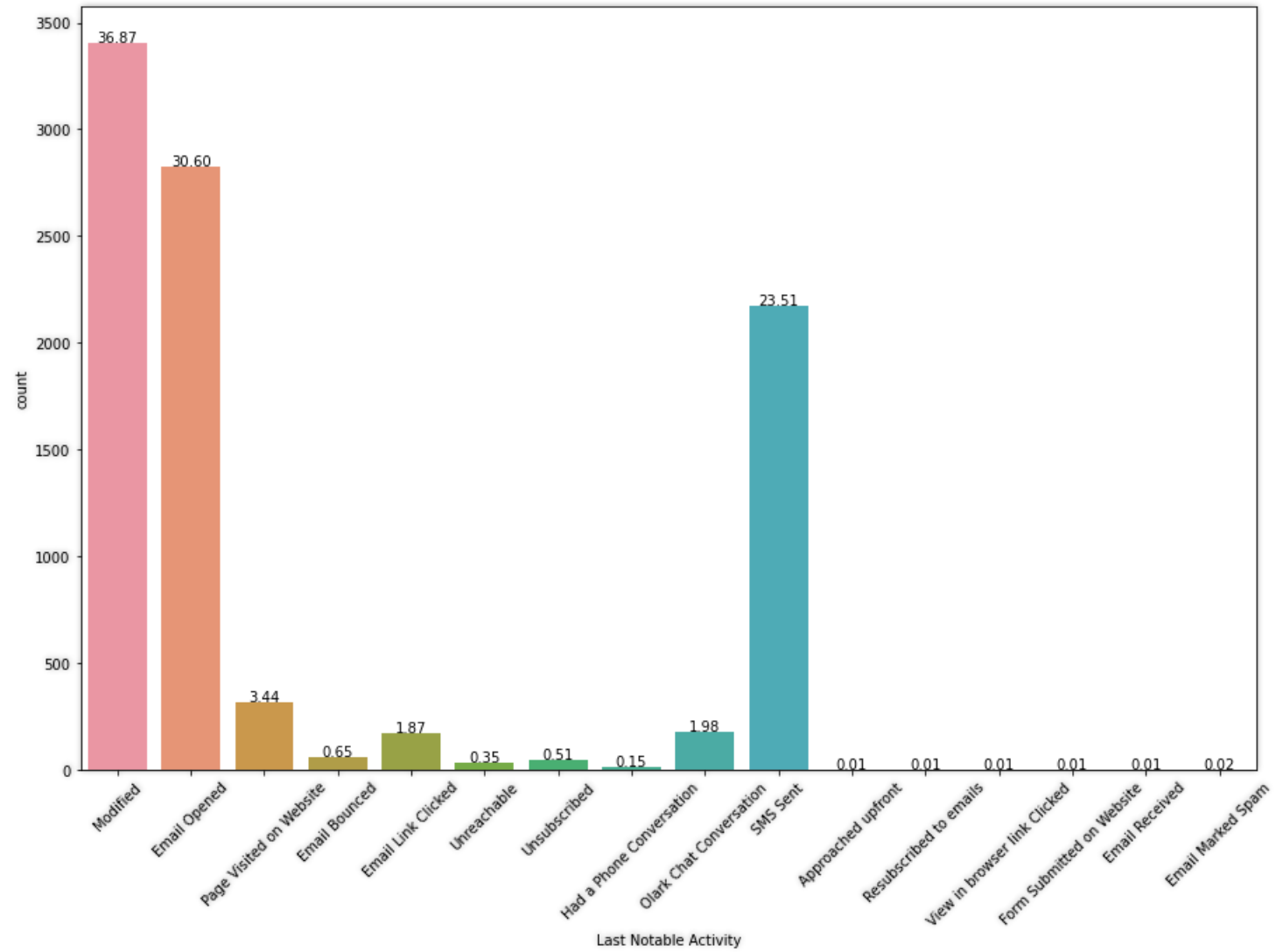
1. Lead Add Form has the highest conversion rate at 92%
2. Quick Add Form has 100% conversion rate but it has only one entry, so not a reliable factor
3. API has the least amount of conversions.
4. Most student found X education via Google Search. But most leads were not converted to actual students.
5. Reference had the highest number of conversions at 92%
6. No conversions were made through Youtube channel, blog, press releases.

# Bar Plots

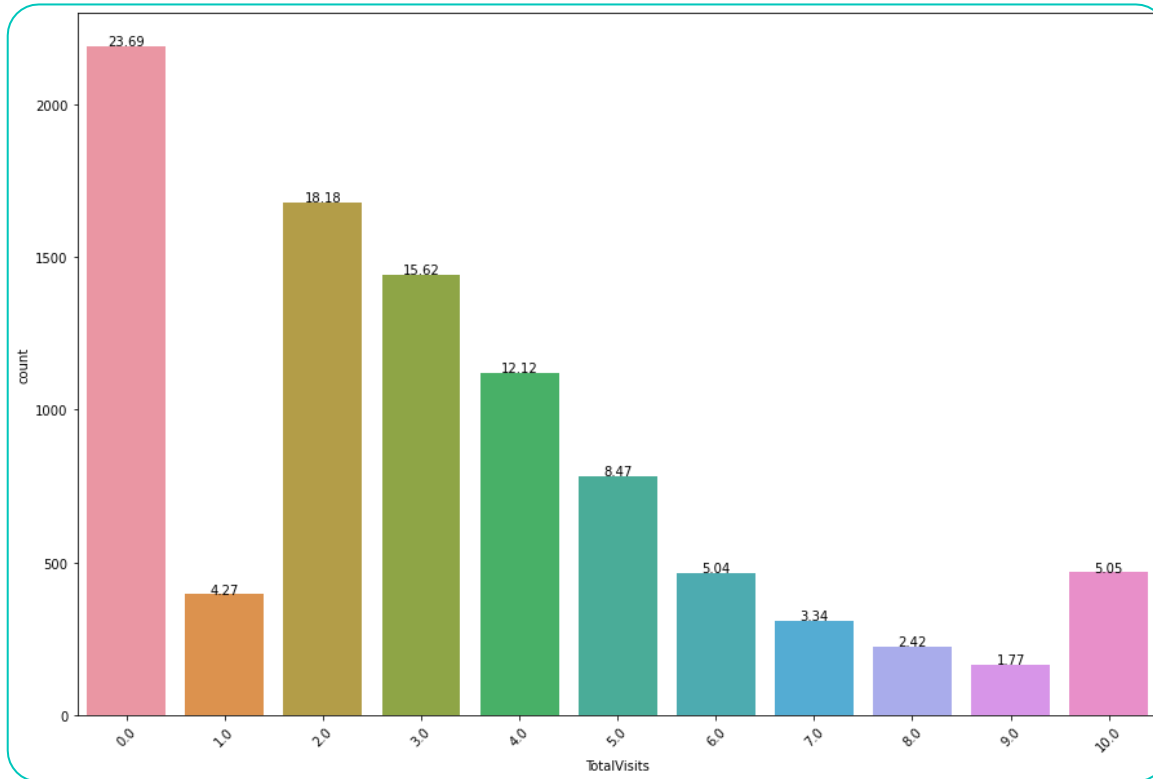






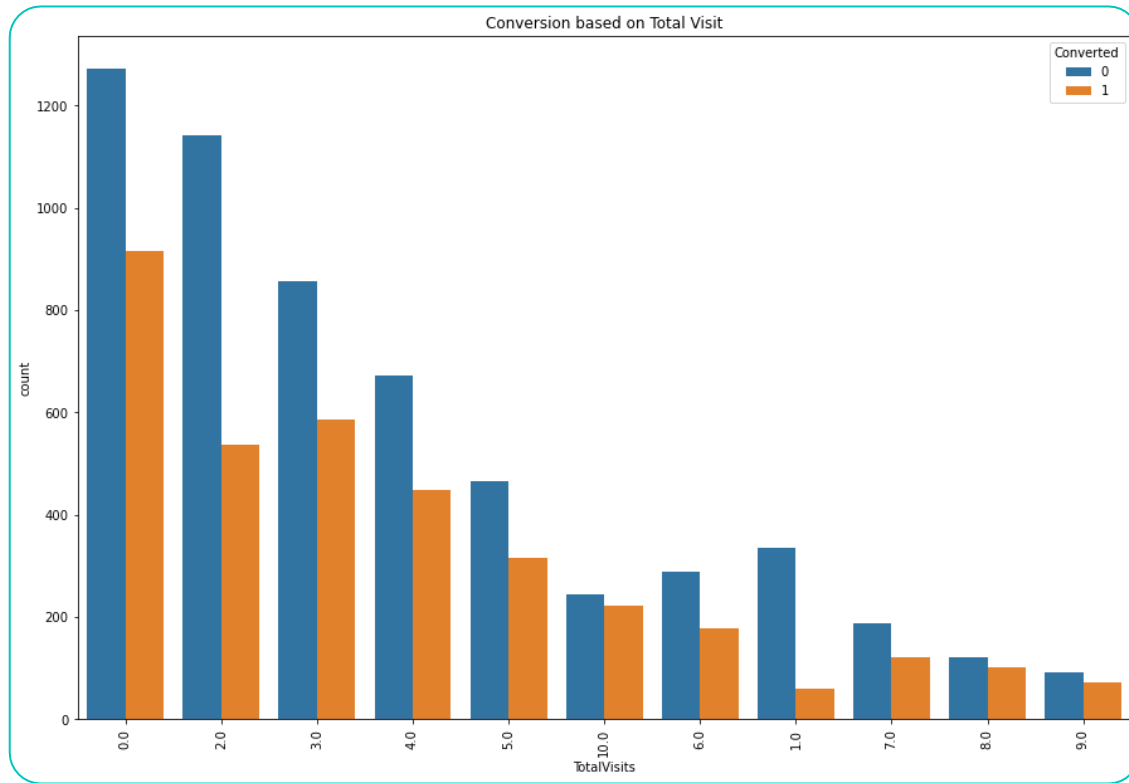


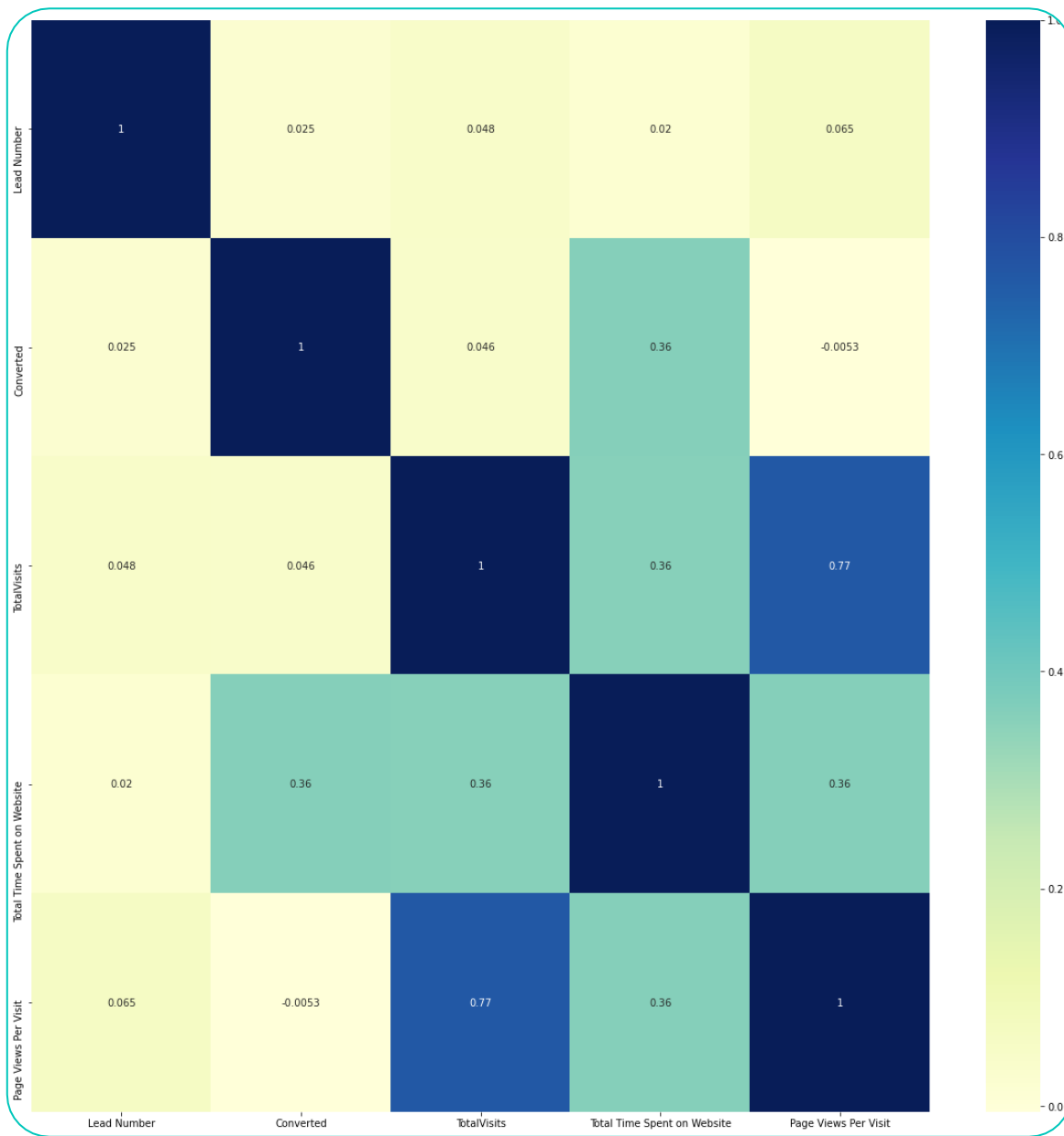
# Continuous Variable Bar Plots



For Total  
Visit

# Total Visits vs Conversion based on Total Visits





Checking  
Correlation  
b/w  
Variables

# Data Preparation

- Creating dummy variables.
- Performing Train-Test Split
- Scaling

# Modelling

- Creating a Logistic Regression Model.
- Feature Selection using RFE
- Assessing the model with StatsModels api
- Recalibrating the model again and again till we reach a point where all the variables are significant and the VIF values are less than 5 to reduce multi-collinearity.

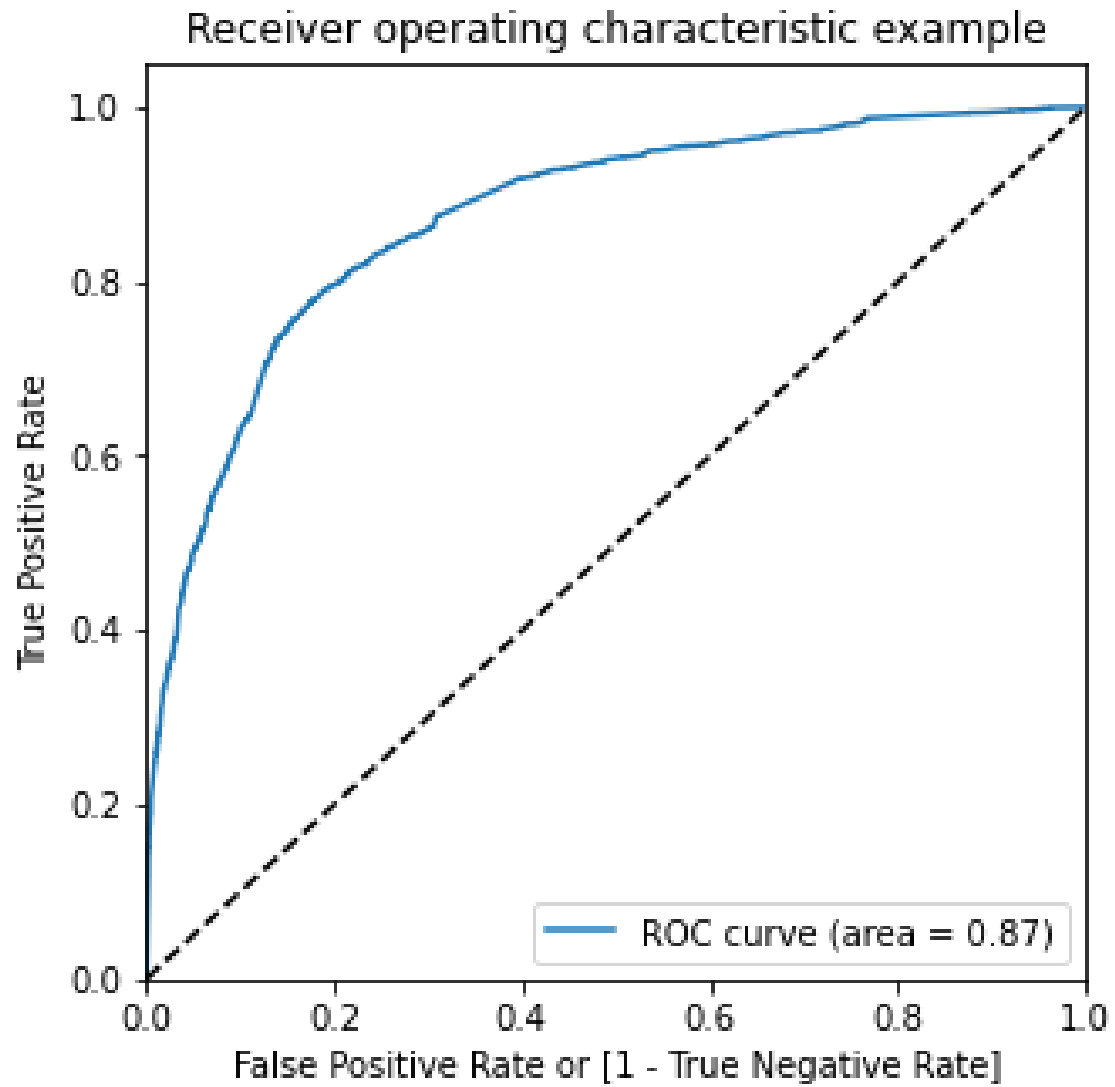


# Final Model Visualization with VIF

<b>Dep. Variable:</b>	Converted	<b>No. Observations:</b>	6468
<b>Model:</b>	GLM	<b>Df Residuals:</b>	6455
<b>Model Family:</b>	Binomial	<b>Df Model:</b>	12
<b>Link Function:</b>	logit	<b>Scale:</b>	1.0000
<b>Method:</b>	IRLS	<b>Log-Likelihood:</b>	-2799.5
<b>Date:</b>	Sun, 07 Feb 2021	<b>Deviance:</b>	5599.0
<b>Time:</b>	13:58:35	<b>Pearson chi2:</b>	9.11e+03
<b>No. Iterations:</b>	7		
<b>Covariance Type:</b>	nonrobust		

	coef	std err	z	P> z	[0.025	0.975]
<b>const</b>	1.3837	0.179	7.726	0.000	1.033	1.735
<b>Total Time Spent on Website</b>	1.0659	0.038	27.980	0.000	0.991	1.141
<b>Lead Source_Olark chat</b>	1.1280	0.100	11.322	0.000	0.933	1.323
<b>Lead Source_Reference</b>	3.5984	0.201	17.914	0.000	3.205	3.992
<b>Lead Source_Welingak website</b>	5.4963	0.727	7.556	0.000	4.071	6.922
<b>Last Activity_Converted to Lead</b>	-1.2127	0.217	-5.585	0.000	-1.638	-0.787
<b>Last Activity_Email Bounced</b>	-1.7984	0.282	-6.383	0.000	-2.351	-1.246
<b>Last Activity_Had a Phone Conversation</b>	2.1604	0.652	3.314	0.001	0.883	3.438
<b>Last Activity_Olark Chat Conversation</b>	-1.4009	0.162	-8.624	0.000	-1.719	-1.083
<b>Last Activity_SMS Sent</b>	1.1884	0.072	16.449	0.000	1.047	1.330
<b>What is your current occupation_Other</b>	-2.8435	0.819	-3.471	0.001	-4.449	-1.238
<b>What is your current occupation_Student</b>	-2.3752	0.286	-8.313	0.000	-2.935	-1.815
<b>What is your current occupation_Unemployed</b>	-2.7984	0.180	-15.540	0.000	-3.151	-2.445

	Features	VIF
11	What is your current occupation_Unemployed	2.01
1	Lead Source_Olark chat	1.73
8	Last Activity_SMS Sent	1.50
7	Last Activity_Olark Chat Conversation	1.43
0	Total Time Spent on Website	1.21
2	Lead Source_Reference	1.09
4	Last Activity_Converted to Lead	1.09
5	Last Activity_Email Bounced	1.07
3	Lead Source_Welingak website	1.04
10	What is your current occupation_Student	1.03
6	Last Activity_Had a Phone Conversation	1.01
9	What is your current occupation_Other	1.00



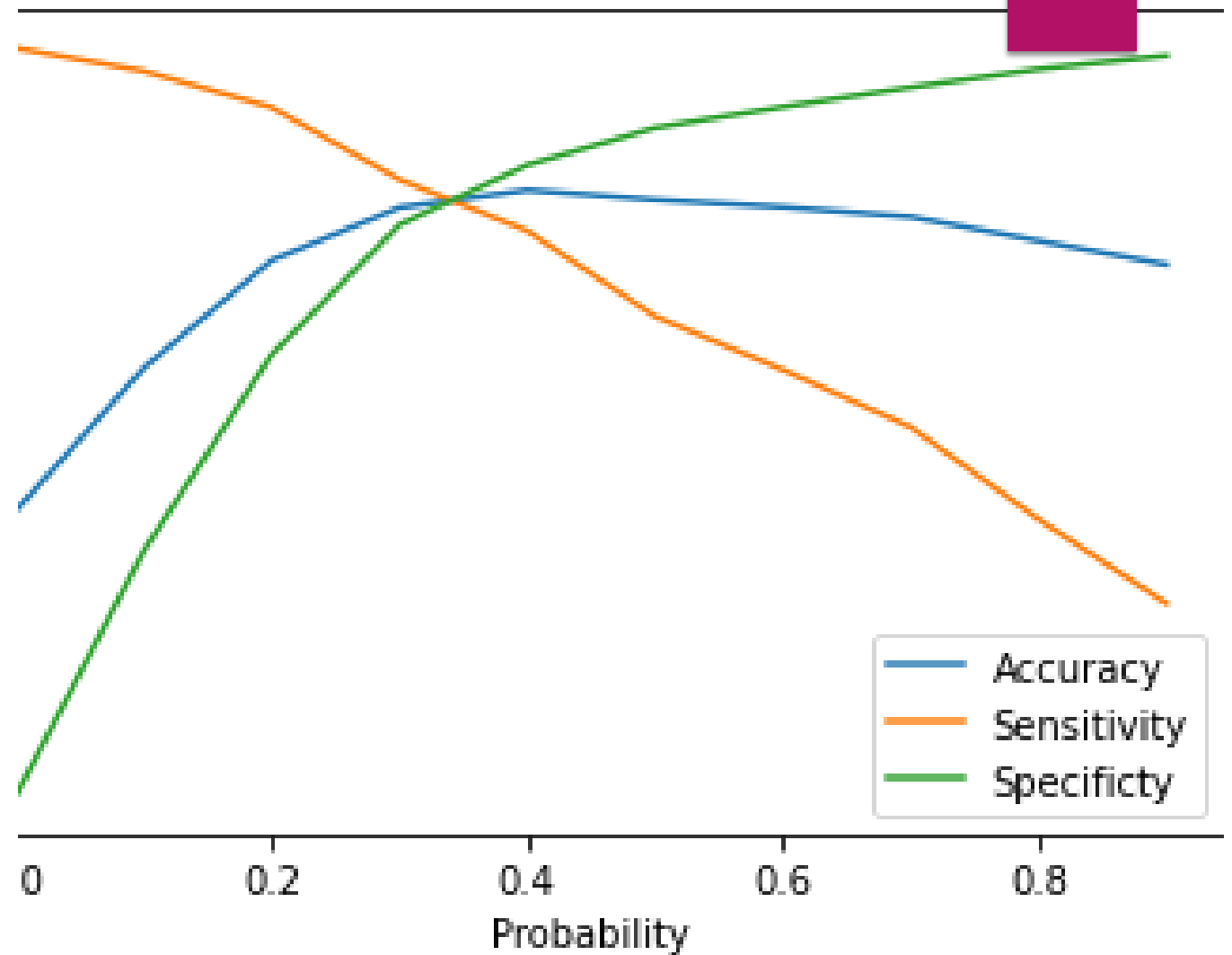
## Plotting the ROC curve

Observation:  
From the ROC curve we can say that the model will be able to provide us with a good result overall.

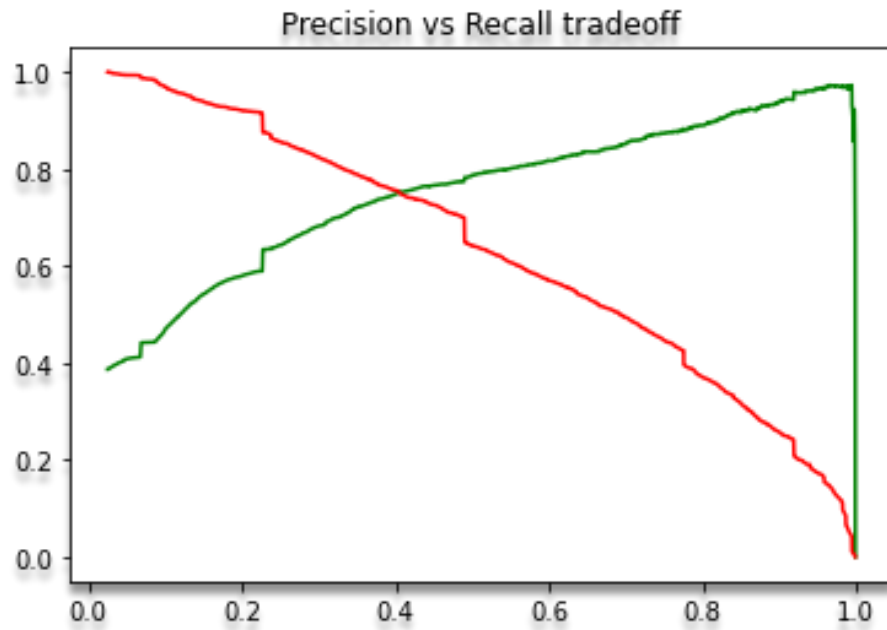
# Finding Optimal Cut off point

## ► Observation:

From the curve we can see that the optimal cut off is at 0.33. This is the point where all the parameters are equally balanced.



# Precision and Recall Curve



- ▶ From the scores we note that our model has a good overall relevancy, defined by Precision at 70% and a great return of relevant results, defined by Recall at 80%.
- ▶ The precision vs recall tradeoff value from the graph is at 0.4
- ▶ Comparing it with the F1 score we can say that our model is fairly accurate.

# Final Model Reporting and Equation

- ▶ **log odds = 1.3837 +(1.0659 Total Time Spent on Website) + (1.1280 Lead Source\_Olark chat) + (3.5984 Lead Source\_Reference) + (5.4963 Lead Source\_Welingak website) + (-1.2127 Last Activity\_Converted to Lead) + (-1.7984 Last Activity\_Email Bounced) + (2.1604 Last Activity\_Had a Phone Conversation) + (-1.4009 Last Activity\_Olark Chat Conversation) + (1.1884 Last Activity\_SMS Sent)+(-2.8435 What is your current occupation\_Other)+(-2.3752 What is your current occupation\_Student)+(-2.7984 \* What is your current occupation\_Unemployed)**

# Insights

- ▶ Hot Leads are identified as Customers having lead score of 33 or above.
- ▶ Sales Team of the company should first focus on the “Hot Leads”.
- ▶ Higher the Lead score, higher the chances of conversion of “Hot Leads” into “Paying Customers”
- ▶ The “Cold Leads should be focused after the Sales Team is done with the “Hot Leads”.