

LEAD SCORING CASE STUDY

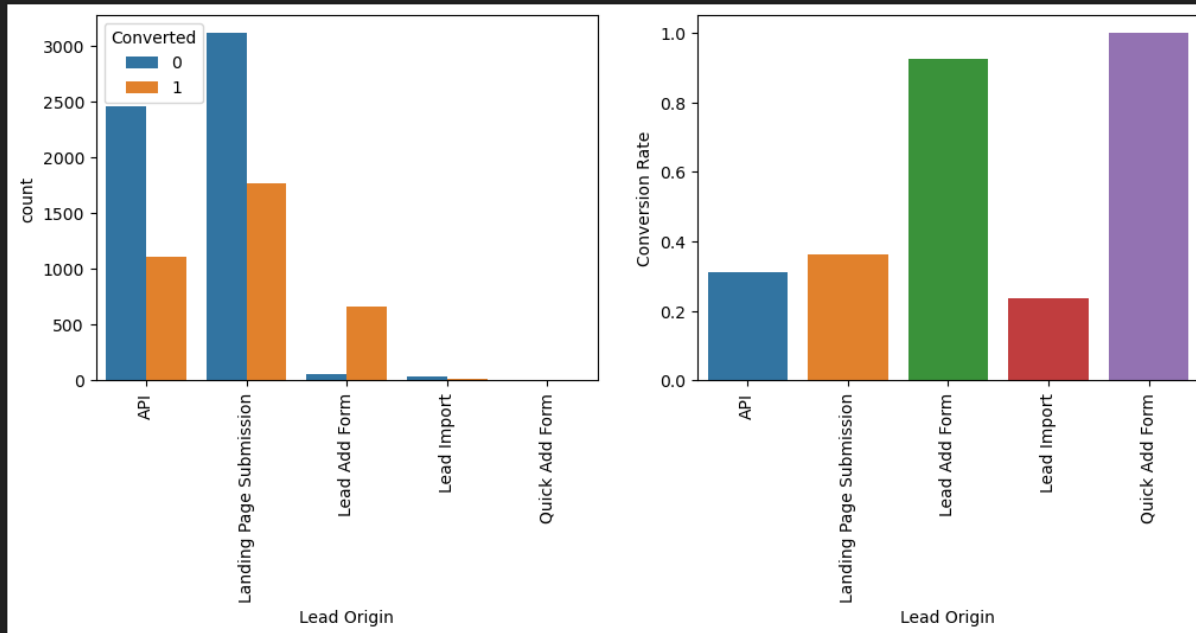
PHAM LAM PHONG

1. Problem Statement

- Problem Statement: Although X Education gets a lot of leads, its lead conversion rate is very poor. To make the process more efficient, the lead conversion rate should go up as the sales team will now be focusing more on communicating with the potential leads rather than making calls to everyone.
- Data science problem: 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.

Categorical Attributes Analysis

Lead Source

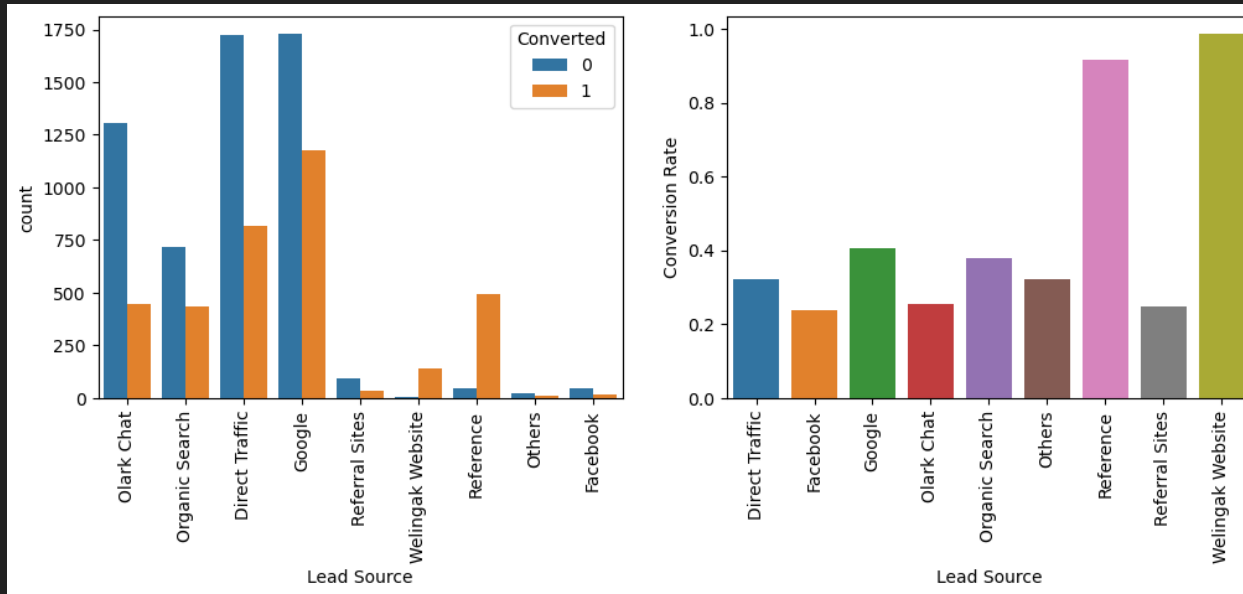


Inference:

- Although the main source of customers come from API and Landing Page Submissions, the conversion rate of 'Lead Add Form' is the highest over 90%.
- Quick add form' has only 1 observation, therefore it has no statistical significance.

Categorical Attributes Analysis

Lead Origin

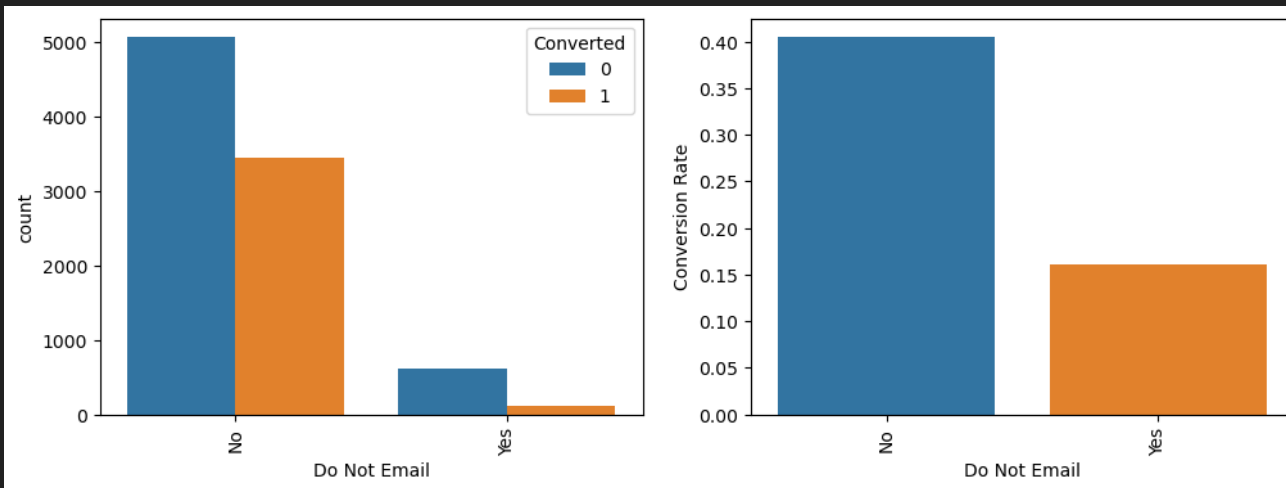


Inference:

- Welingak website' and 'Reference' are two lead sources that have significantly higher conversion rates than the other lead sources

Categorical Attributes Analysis

Do not email

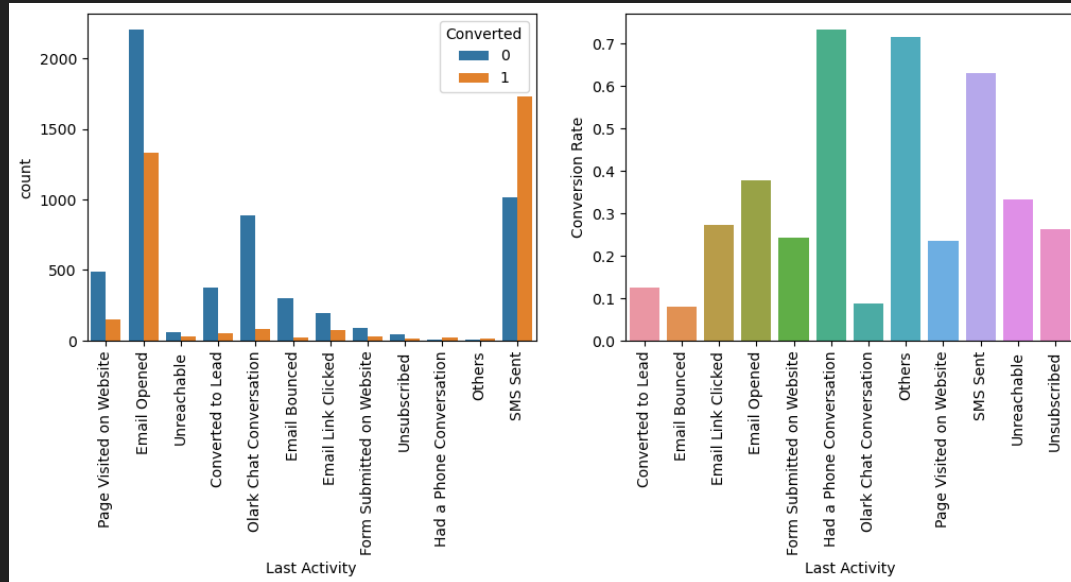


Inference:

- We can easily observe that customers who don't send email ad have a significantly lower conversion rate

Categorical Attributes Analysis

Last Activity

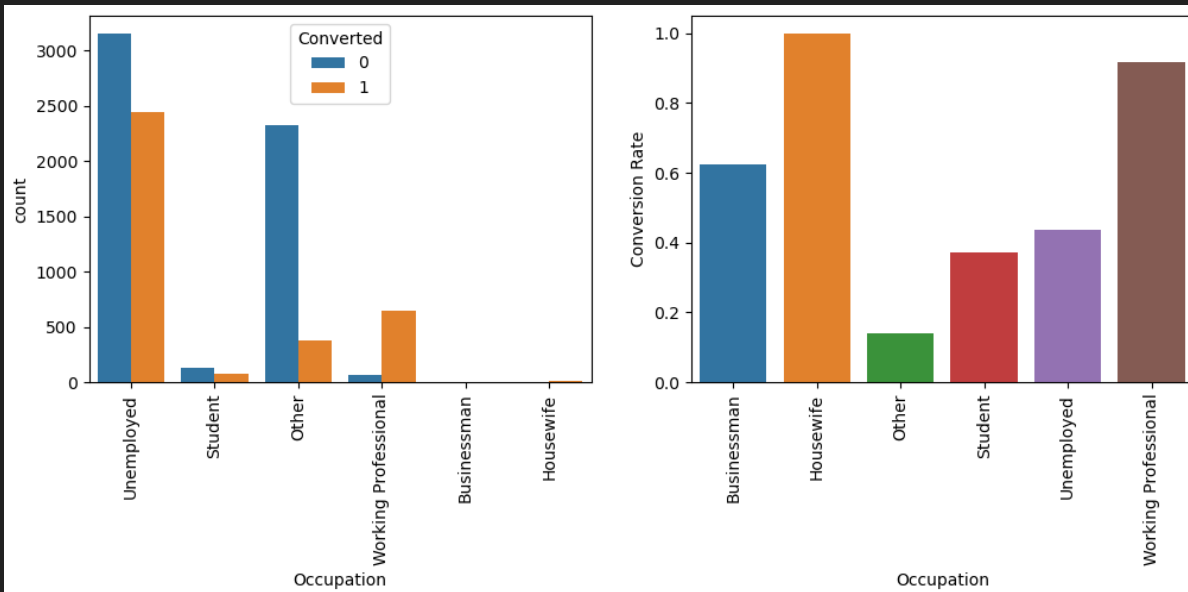


Inference:

- Customers who were last contacted via phone consultation or text message tend to have a higher conversion rate than other types of activities.
- Although 'others' activities also have high conversion rates, they have a small number of observations and many activities are grouped together, so they are not statistically significant

Categorical Attributes Analysis

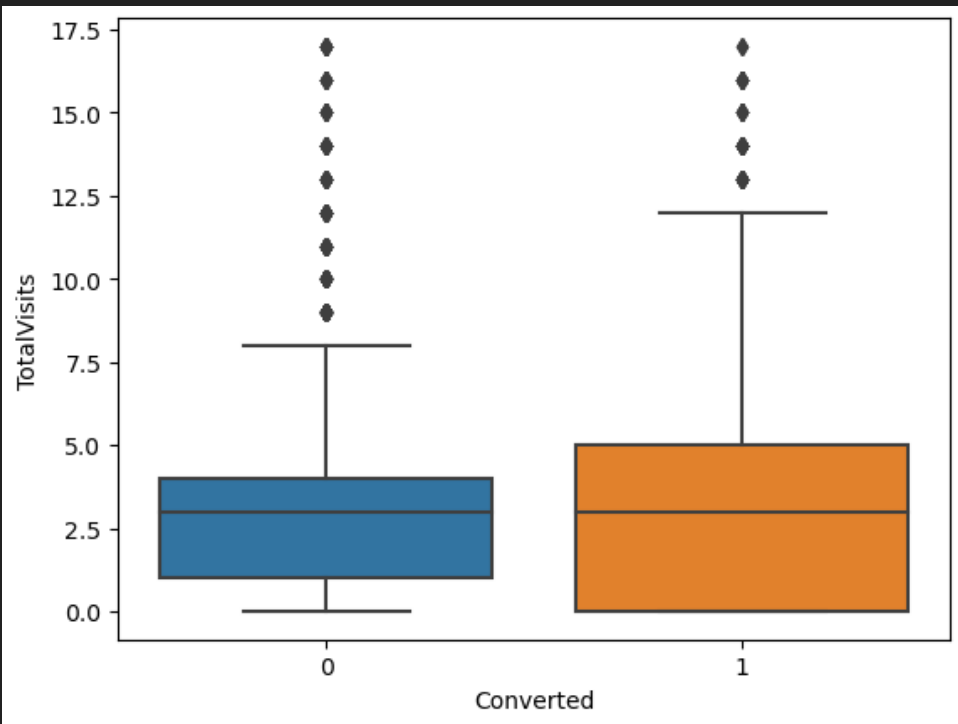
Occupation



Inference:

- Professional workers typically have a significantly higher course enrollment rate than other types of occupations

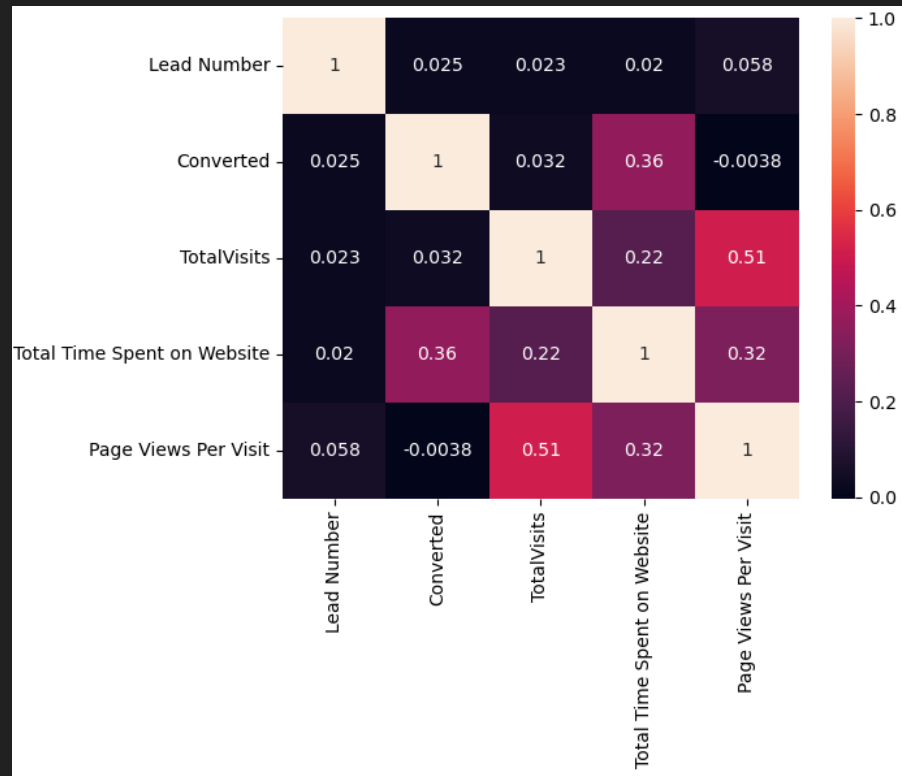
Numerical Attributes Analysis



Inference:

- Based on the graph, we can only predict that customers who are converted to lead tend to have higher total visit numbers

Numerical Attributes Analysis



Inference:

- We can see that Total Time spend on website seems to have high correction than others features

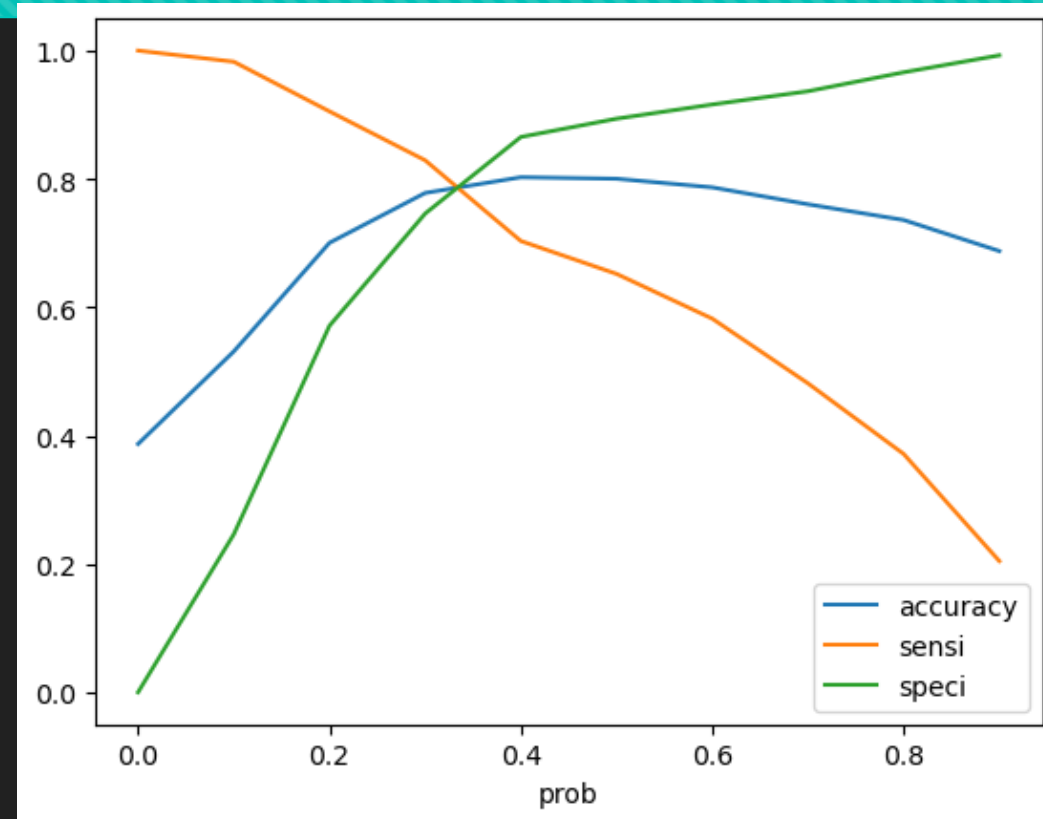
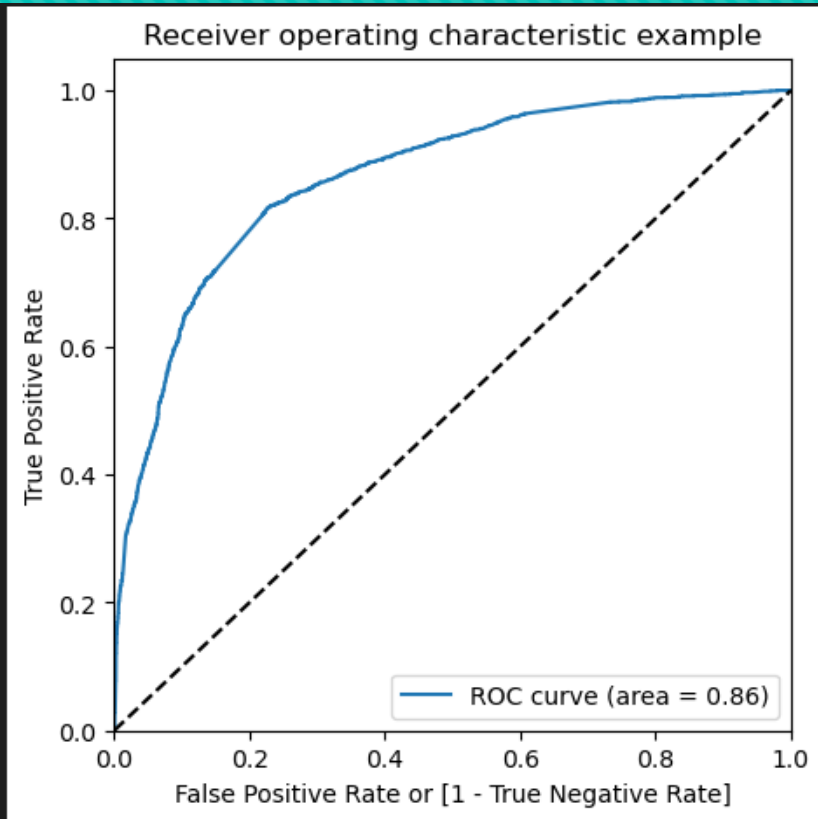
Model Building

Generalized Linear Model Regression Results							
Dep. Variable:		Converted	No. Observations:		6409		
Model:		GLM	Df Residuals:		6398		
Model Family:		Binomial	Df Model:		10		
Link Function:		Logit	Scale:		1.0000		
Method:		IRLS	Log-Likelihood:		-2877.1		
Date:	Tue, 07 Mar 2023		Deviance:		5754.2		
Time:	23:30:29		Pearson chi2:		7.37e+03		
No. Iterations:		7	Pseudo R-squ. (CS):		0.3540		
Covariance Type:		nonrobust					
		coef	std err	z	P> z	[0.025	0.975]
	const	0.5052	0.890	0.567	0.570	-1.240	2.250
	Do Not Email	-0.3252	0.042	-7.763	0.000	-0.407	-0.243
	Total Time Spent on Website	1.1343	0.039	29.079	0.000	1.058	1.211
	Lead Origin_Lead Add Form	3.6918	0.198	18.650	0.000	3.304	4.080
	Lead Source_Google	0.3091	0.076	4.079	0.000	0.161	0.458
	Lead Source_Olark Chat	1.2831	0.101	12.727	0.000	1.086	1.481
	Lead Source_Welingak Website	2.0024	0.743	2.694	0.007	0.546	3.459
	Occupation_Other	-2.8474	0.892	-3.191	0.001	-4.597	-1.098
	Occupation_Student	-1.8400	0.912	-2.018	0.044	-3.627	-0.053
	Occupation_Unemployed	-1.4604	0.890	-1.641	0.101	-3.205	0.284
	Occupation_Working Professional	0.8887	0.905	0.982	0.326	-0.885	2.663

Using RFE technique to remove attributes and build a model for the remaining attributes.

Making the model stable by using StatsModels library

Model Building



- Performing is quite well with above model. The ROC curve has a value of 0,86 which is good.
- From the curve above, 0.2 is the optimum point to take it as a cutoff probability.
- Accuracy : 76.38% ◦ Sensitivity :83.06% ◦ Specificity : 72.28%