# Lead Scoring Case Study

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### Problem Statement

On any given day, several people end up on the website of X Education.
Every person who lands on the website is a potential lead.

 It is important to identify which such leads may be accidental / not-so-interested and which ones might actually buy a course.

 Based on characteristics, such as number of visits to the website, number of hours spent on the website, and lead occupation, we must construct a logistic regression model.

Load and read the Leads.csv file.

 Check the data types and missing values and remove columns with over 3000 null values.

 'Select' value present in various columns can also be assumed to be a null value.

 Remove columns with singular values and index-like columns which are not useful for the analysis.

• Perform data visualization and exploratory data analysis.

 For all the categorical variables, create dummy variables for logistic regression modelling.

Use MinMaxScaler to standardize the continuous variables.

Using test\_train\_split from the sklearn library, split the dataset into 70% training and 30% testing sets.

 Perform logistic regression modelling and remove non-significant features by checking the p-value and VIF.

 Use a preliminary conversion probability (0.5) and compute the confusion matrix and the relevant metrics, i.e. accuracy, sensitivity, specificity, precision, and recall.

 Check the area under the ROC curve to check goodness of model predictions; area should be closer to 1.

 Using a range of conversion probabilities (0.0-0.9), find the optimal sensitivity-specificity and precision-recall values.

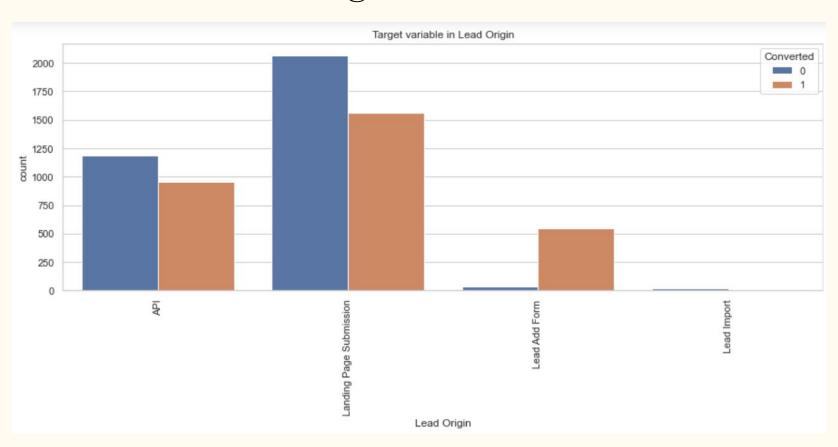
 Apply the best model on the test set, and for the optimal conversion probability, compute and compare the previously mentioned metrics.

# Data Analysis

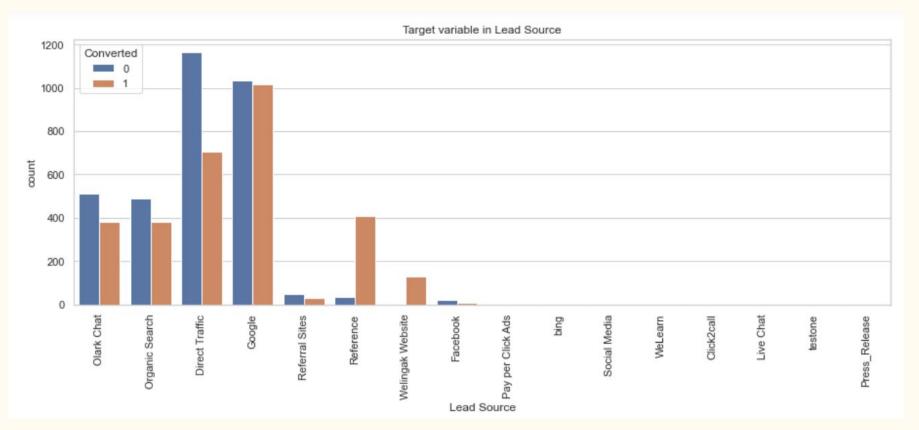
# Balance of Target Data

 With a ~ 52-48 split, the converted column did not have a huge data imbalance.

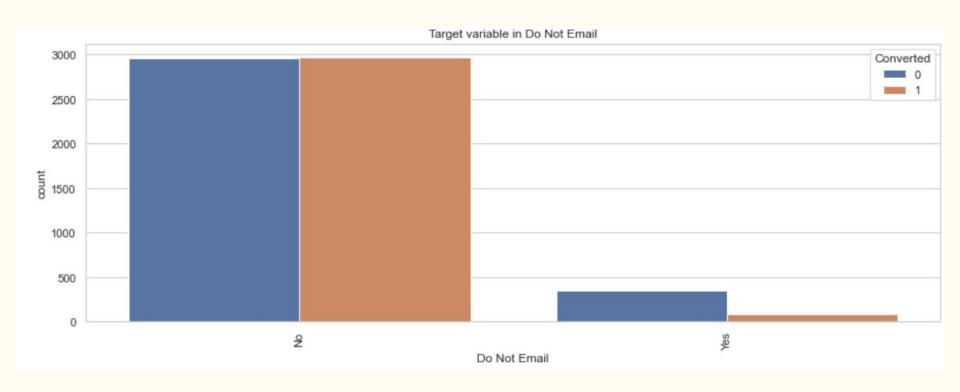
# Lead origin vs Converted



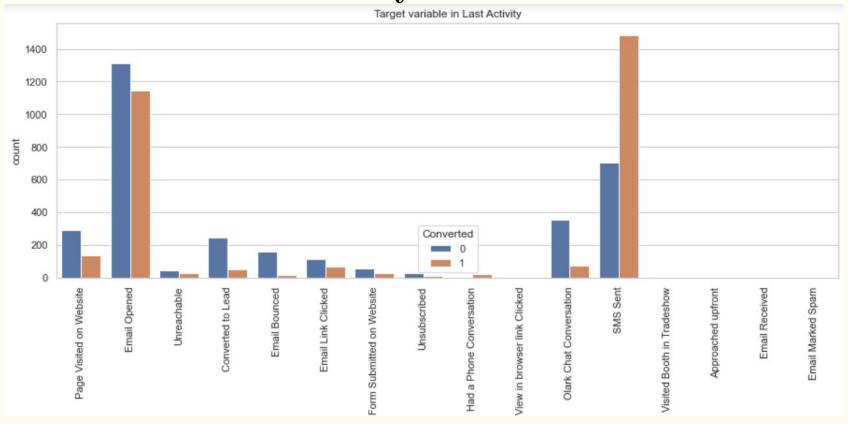
### Lead source vs Converted



## Lead source vs Converted



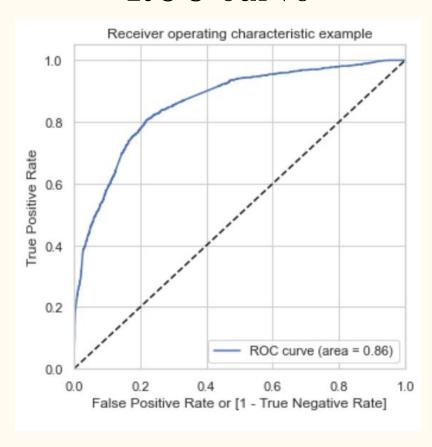
# Last activity vs Converted



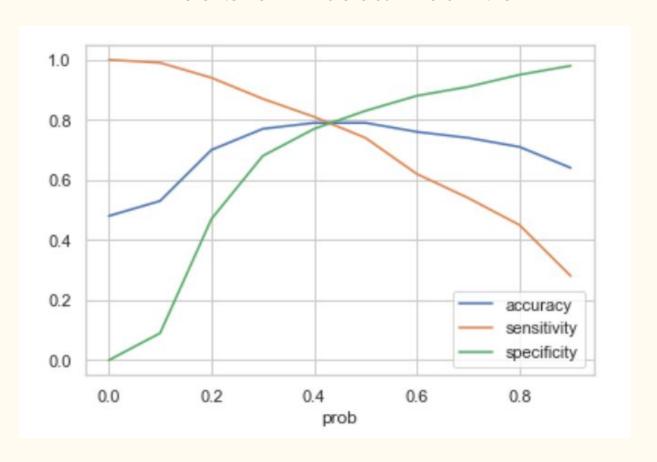
## Final Feature Set

	coef	std err	z	P> z	[0.025	0.975]
const	0.2040	0.196	1.043	0.297	-0.179	0.587
TotalVisits	11.1489	2.665	4.184	0.000	5.926	16.371
Total Time Spent on Website	4.4223	0.185	23.899	0.000	4.060	4.785
Lead Origin_Lead Add Form	4.2051	0.258	16.275	0.000	3.699	4.712
Lead Source_Olark Chat	1.4526	0.122	11.934	0.000	1.214	1.691
Lead Source_Welingak Website	2.1526	1.037	2.076	0.038	0.121	4.185
Do Not Email_Yes	-1.5037	0.193	<b>-</b> 7.774	0.000	-1.883	-1.125
Last Activity_Had a Phone Conversation	2.7552	0.802	3.438	0.001	1.184	4.326
Last Activity_SMS Sent	1.1856	0.082	14.421	0.000	1.024	1.347
What is your current occupation_Student	-2.3578	0.281	-8.392	0.000	<b>-</b> 2.908	-1.807
What is your current occupation_Unemployed	-2.5445	0.186	-13.699	0.000	-2.908	-2.180
Last Notable Activity_Unreachable	2.7846	0.807	3.449	0.001	1.202	4.367

## ROC curve



## Precision-Recall curve



#### Conclusions

- We noted that the total time spent and the total number of visits to the X Education website are the two most important features.
- 1-3 visits may account accidental clicks but people visiting the website more than thrice and interact with the chatbot are more likely to be convertible leads.
- Such leads must be targeted appropriately through phone calls and emails.
- They should be notified of lean options, discounts, and referral bonuses.
- If they lead needs more convincing, they can be offered trial classes and short calls with successful alums instead of just marketing personnel.
- Unemployed leads and people looking for career transitions should also be focussed upon.
- Spending should be focussed on Google ads as they seem to bring in the most convertible leads.
- Follow-up calls should only be made after sufficient time in order to not alienate the potential customer.