X Education - Lead Scoring Case Study

Detection of Hot Leads to concentrate more of marketing efforts on them, improving conversion rates for X Education.

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Background of X Education Company

- 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.
- 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%.

Problem Statement & Objective of the Study

Problem Statement:

- X Education gets a lot of leads, its lead conversion rate is very poor at around 30%.
- X Education wants to make lead conversion process more efficient by identifying the most potential leads, also known as Hot Leads.
- Their sales team want to know these potential set of leads, which they will be focusing more on communicating rather than making calls to everyone.

Objective of the Study:

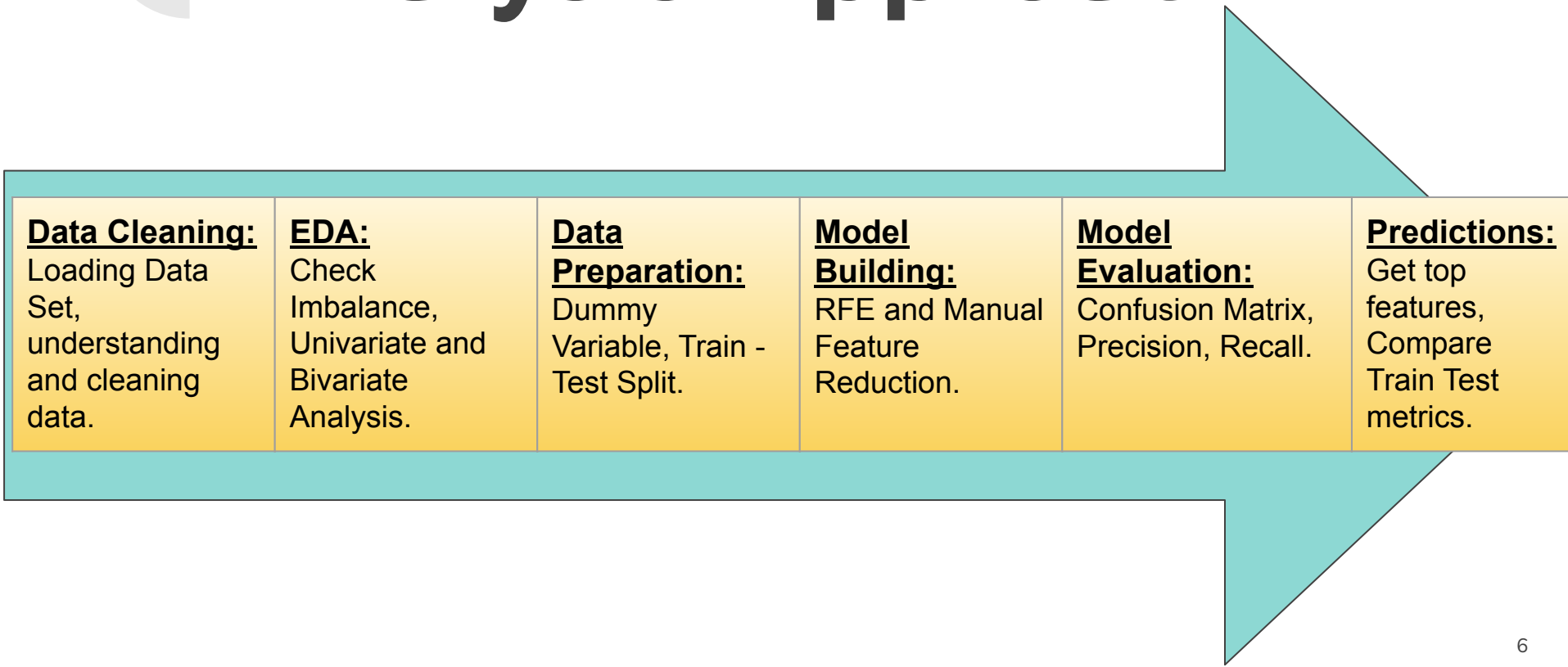
- To help X Education select the most promising leads, i.e., the leads that are most likely to convert into paying customers.
- The company requires to build a model wherein we need to assign a lead score to each of the leads such that the customers with a higher lead score have a higher conversion chance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

Suggested Ideas for Lead Conversion

Leads Grouping	Better Communication	Boost Conversion
• Leads are grouped based on their propensity or likelihood to convert. • This results in a focused group of hot leads.	• We could have a smaller pool of leads to communicate with, which would allow us to have a greater impact.	• We would have a greater conversion rate and be able to hit the 80% objective since we concentrated on hot leads that were more likely to convert.

Since we have a target of 80% conversion rate, we would want to obtain a high sensitivity in obtaining hot leads.

Analysis Approach



Data Cleaning

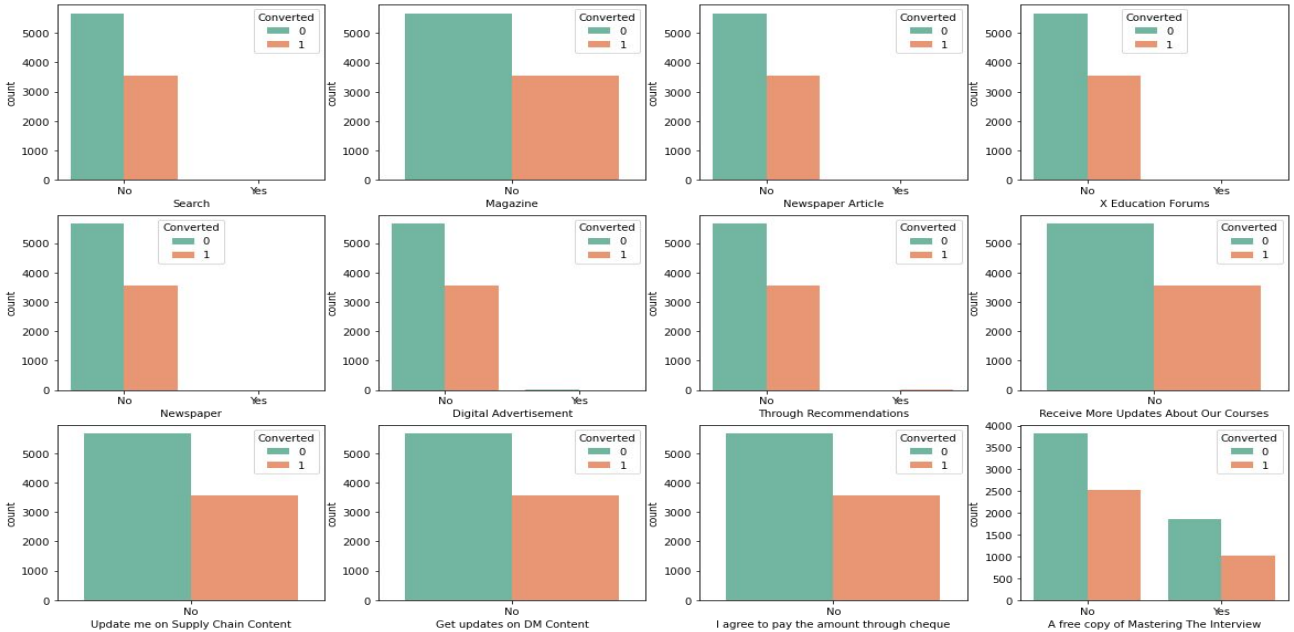
- "Select" level represents null values for some categorical variables, as customers did not choose any option from the list.
- Columns with over 35% null values were dropped.
- Missing values in categorical columns were handled based on value counts and certain considerations.
- Drop columns that don't add any insight or value to the study objective.
- Imputation was used for some categorical variables.
- Additional categories were created for some variables.
- Columns with no use for modeling (Prospect ID, Lead Number) or only one category of response were dropped.
- Numerical data was imputed with mode after checking distribution.

Data Cleaning

- Skewed category columns were checked and dropped to avoid bias in logistic regression models.
- Outliers in TotalVisits and Page Views Per Visit were treated and capped.
- Invalid values were fixed and data was standardized in some columns, such as lead source.
- Low frequency values were grouped together to “Others”.
- Binary categorical variables were mapped.
- Other cleaning activities were performed to ensure data quality and accuracy.
    - Fixed Invalid values & Standardizing Data in columns by checking casing styles, etc. (lead source has Google, google)

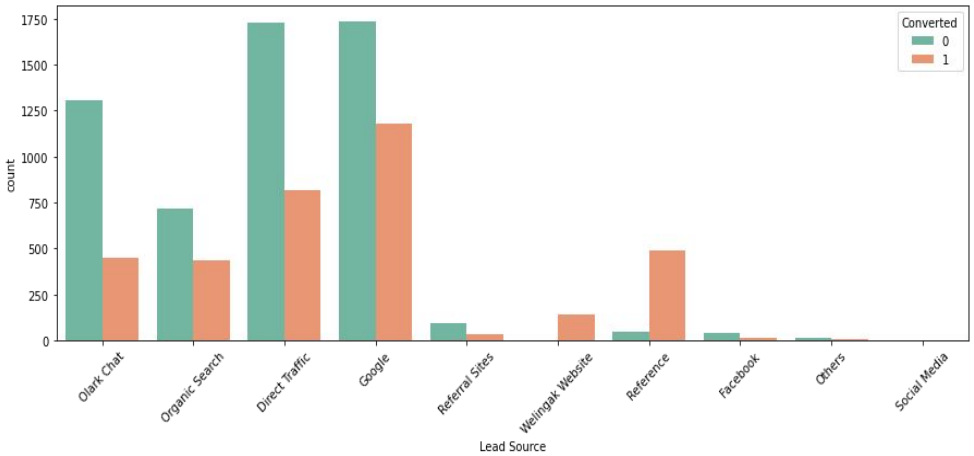
EDA

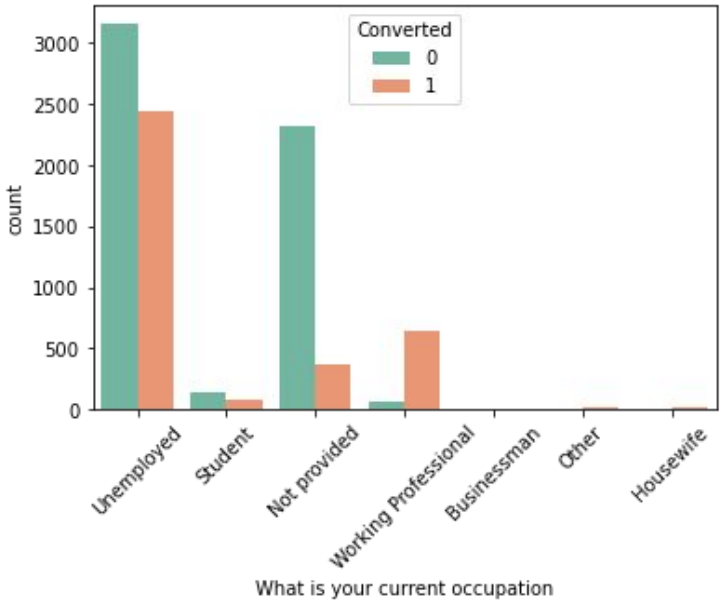
Data is imbalanced while analyzing target variable.



EDA

Univariate Analysis – Categorical Variables.





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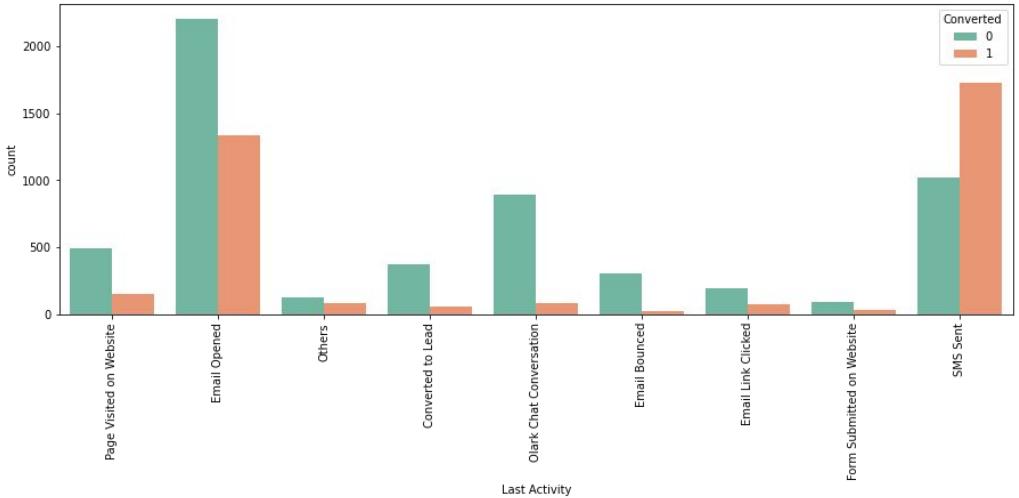
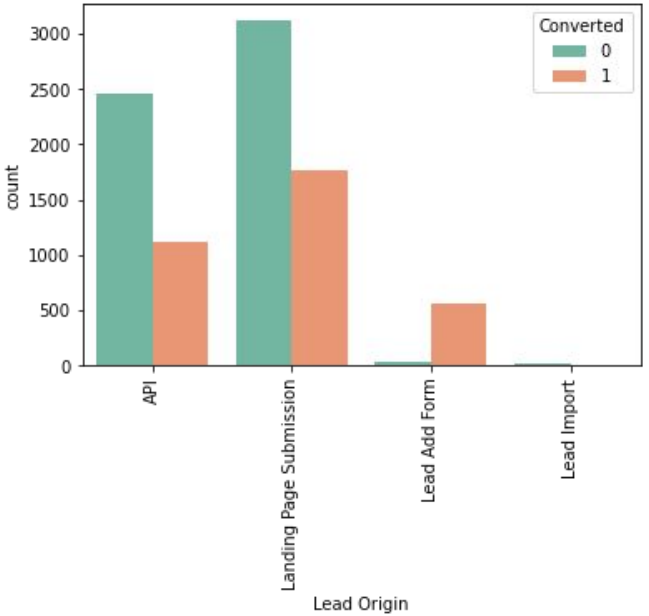
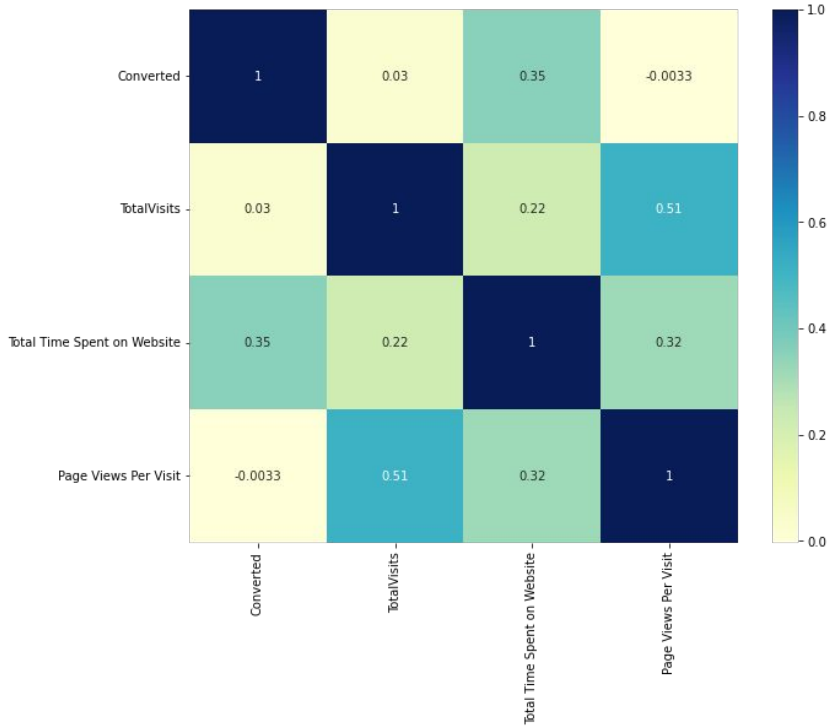




EDA – Bivariate Analysis for Categorical Variables



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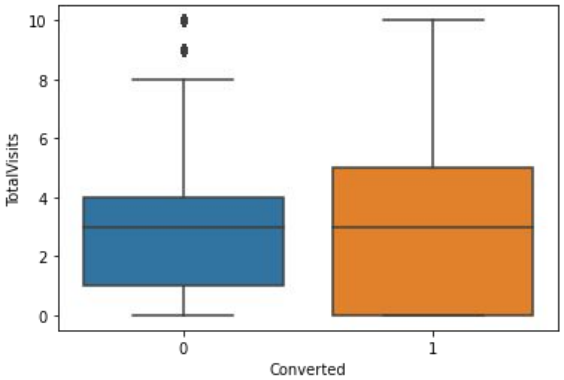
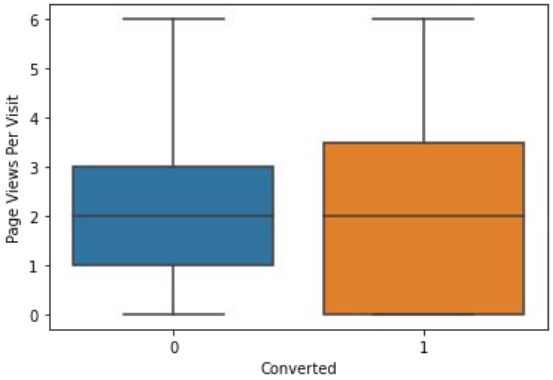
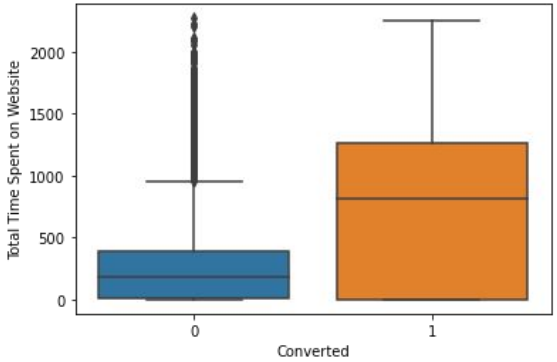






Past Leads who spends more time on the Website have a higher chance of getting successfully converted than those who spends less time as seen in the box-plot.

Data Preparation before Model building

- Binary level categorical columns were already mapped to 1 / 0 in previous steps
- Created dummy features (one-hot encoded) for categorical variables – Lead Origin, Lead Source, Last Activity, Specialization, Current_occupation.
- Splitting Train & Test Sets
  - 70:30 % ratio was chosen for the split
- Feature scaling
  - Standardization method was used to scale the features
- Checking the correlations
  - Predictor variables which were highly correlated with each other were dropped (Lead Origin_Lead Import and Lead Origin_Lead Add Form).

Model Building

Feature Selection

- The data set has lots of dimension and large number of features.
- This will reduce model performance and might take high computation time.
- Hence it is important to perform Recursive Feature Elimination (RFE) and to select only the important columns.
- Then we can manually fine tune the model.
- RFE outcome:
    - Pre RFE – 48 columns & Post RFE – 15 columns

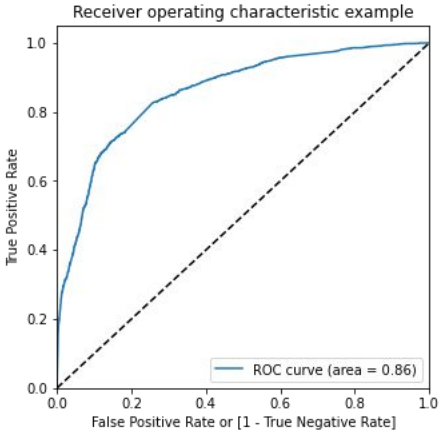
Model Building

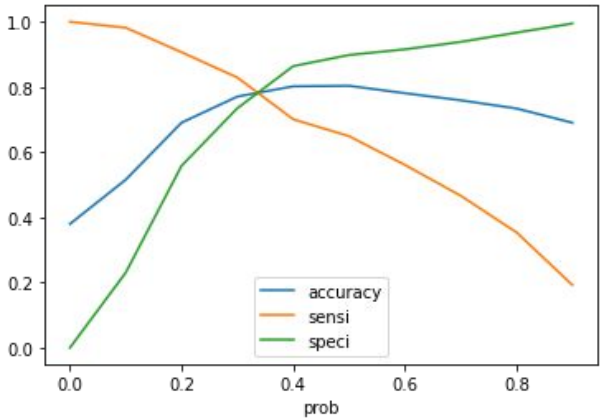
- Manual Feature Reduction process was used to build models by dropping variables with p – value .
- greater than 0.05.
- Model 4 looks stable after four iteration with:
  - Significant p-values within the threshold (p-values < 0.05) and
  - No sign of multicollinearity with VIFs less than 5 .
- Hence, logm4 will be our final model, and we will use it for Model Evaluation which further will be used to make predictions.

Model Evaluation

Train Data Set:

It was decided to go ahead with 0.345 as cutoff after checking evaluation metrics coming from both plots.





ROC Curve :

- Area under ROC curve is 0.88 out of 1 which indicates a good predictive model.
- The curve is as close to the top left corner of the plot, which represents a model that has a high true positive rate and a low false positive rate at all threshold values.

Recommendation based on Final Model

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.2020	0.094	-12.723	0.000	-1.387	-1.017
Do Not Email	-0.3600	0.043	-8.348	0.000	-0.445	-0.276
Total Time Spent on Website	1.1023	0.038	28.710	0.000	1.027	1.178
Lead Origin_Lead Add Form	4.6119	0.523	8.816	0.000	3.587	5.637
Lead Source_Direct Traffic	-1.0496	0.107	-9.783	0.000	-1.260	-0.839
Lead Source_Google	-0.7804	0.102	-7.615	0.000	-0.981	-0.580
Lead Source_Organic Search	-0.8639	0.124	-6.987	0.000	-1.106	-0.622
Lead Source_Reference	-1.7425	0.564	-3.089	0.002	-2.848	-0.637
Lead Source_Referral Sites	-1.3749	0.336	-4.094	0.000	-2.033	-0.717
What is your current occupation_Student	1.1342	0.224	5.057	0.000	0.695	1.574
What is your current occupation_Unemployed	1.2613	0.082	15.384	0.000	1.101	1.422
What is your current occupation_Working Professional	3.7575	0.189	19.919	0.000	3.388	4.127

- While we have checked both Sensitivity-Specificity as well as Precision and Recall Metrics, we have considered the optimal cut off based on Sensitivity and Specificity for calculating the final prediction.
- Accuracy, Sensitivity and Specificity values of test set are around 77%, 83% and 74% which are approximately closer to the respective values calculated using trained set.
- Also the lead score calculated in the trained set of data shows the conversion rate on the final predicted model is around 80%.
- Hence overall this model seems to be good.

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- **Top 3 important features responsible for good conversion rate or the ones' which contributes more towards the probability of a lead getting converted are :**
  - Lead Origin_Lead Add Form
  - What is your current occupation_Working Professional.
  - What is your current occupation_Student
  - What is your current occupation_Unemployed
  - Total Time Spent on Website