X Education - Lead Scoring Case Study

Identifying leads to focus marketing efforts on them, thereby enhancing conversion rates for X Education

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Background

- An education company named X Education sells online courses to industry professionals.
- Daily, numerous interested individuals visit their website to check out the available courses.
- The company advertises its offerings on various platforms, including 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 visitors complete a form with their email or phone number, they are classified as leads.
- After generating these leads, the sales team reaches out via calls and emails.
- While some leads do convert into customers, many do not.
- X Education's typical lead conversion rate is approximately 30%.

PROBLEM STATEMENT AND OBJECTIVE

Problem Statement:

- X Education receives a substantial number of leads, but its lead conversion rate is quite low at around 30%.
- The company aims to enhance the lead conversion process by identifying the most promising leads, referred to as Hot Leads.
- The sales team is looking for a way to pinpoint these potential leads so they can focus their communication efforts on them rather than reaching out to every lead.

Objective of the Study:

- To assist X Education in selecting the most promising leads that are likely to convert into paying customers.
- The goal is to develop a model that assigns a lead score to each lead, indicating that leads with a higher score have a greater chance of conversion, while those with a lower score have a reduced likelihood.
- The CEO has set an ambitious target lead conversion rate of around 80%.

Ideas for Lead Conversion

- Given the target of an 80% conversion rate, we aim to achieve high sensitivity in identifying hot leads.

➢ Lead grouping

➢ Better communication

➢ Boost conversion

ANALYSIS APPROACH

- Data Cleaning: Loading Data Set, understanding & cleaning data
- EDA: Check imbalance, Univariate & Bivariate analysis
- Data Preparation: Dummy variables, test-train split, feature scaling
- Model Building: RFE for top 15 feature, Manual Feature Reduction & finalizing model
- Model Evaluation: Confusion matrix, Cutoff Selection, assigning Lead Score
- Predictions on Test Data: Compare train vs test metrics, Assign Lead Score and get top features
- Recommendation: Suggest top 3 features to focus for higher conversion & areas for improvement

Data Cleaning

- Select" level represents null values for some categorical variables, as customers did not choose any option from the list.
- Columns with over 40% 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 (tags, country)
- 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.

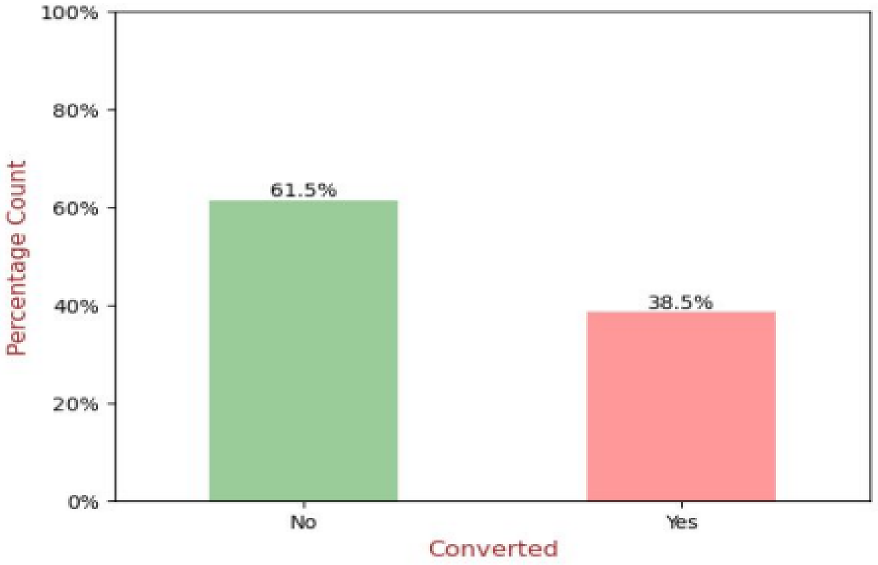
Data Cleaning

- 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.

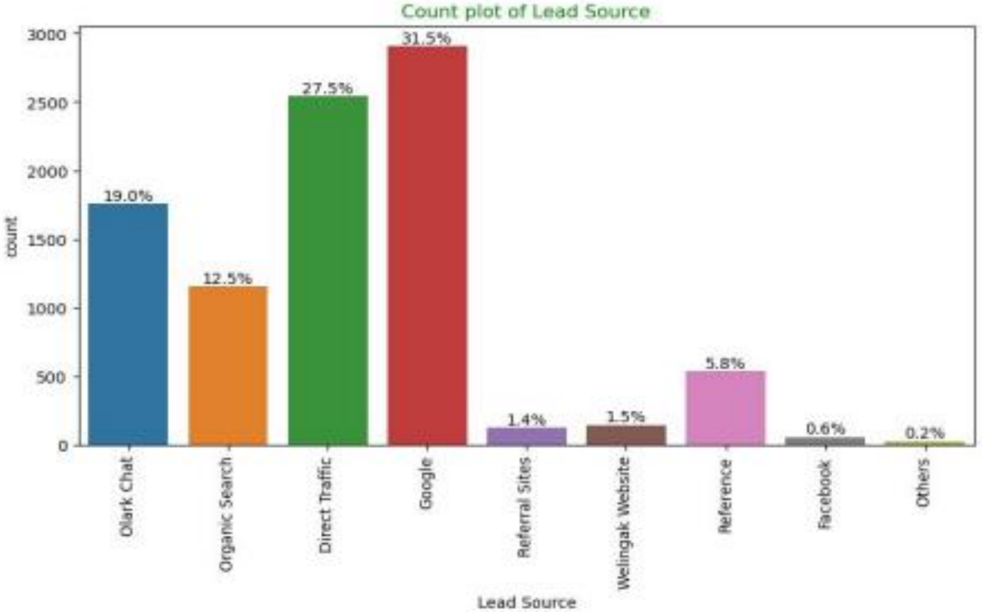
Leads converted

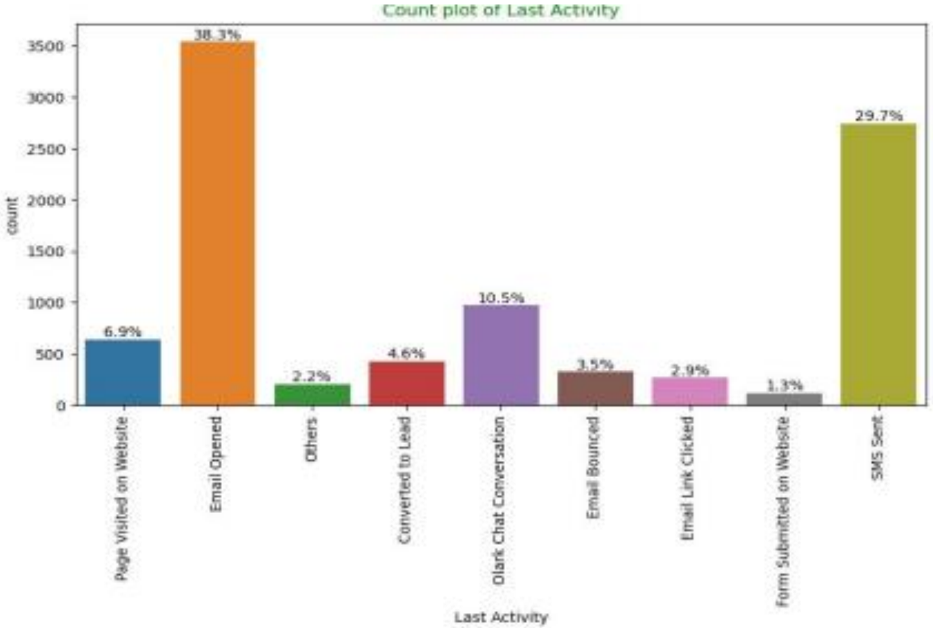


- 38.5% of the people have converted to leads.(Minority)
- 61.5% of the people didn't convert to leads. (Majority)

EDA

- Univariate Analysis – Categorical Variables

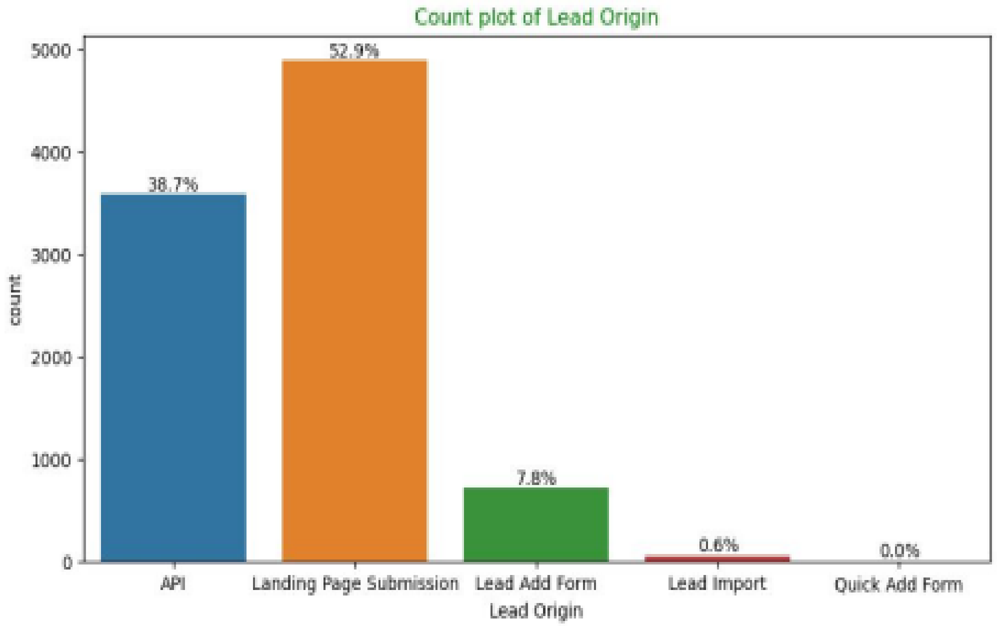


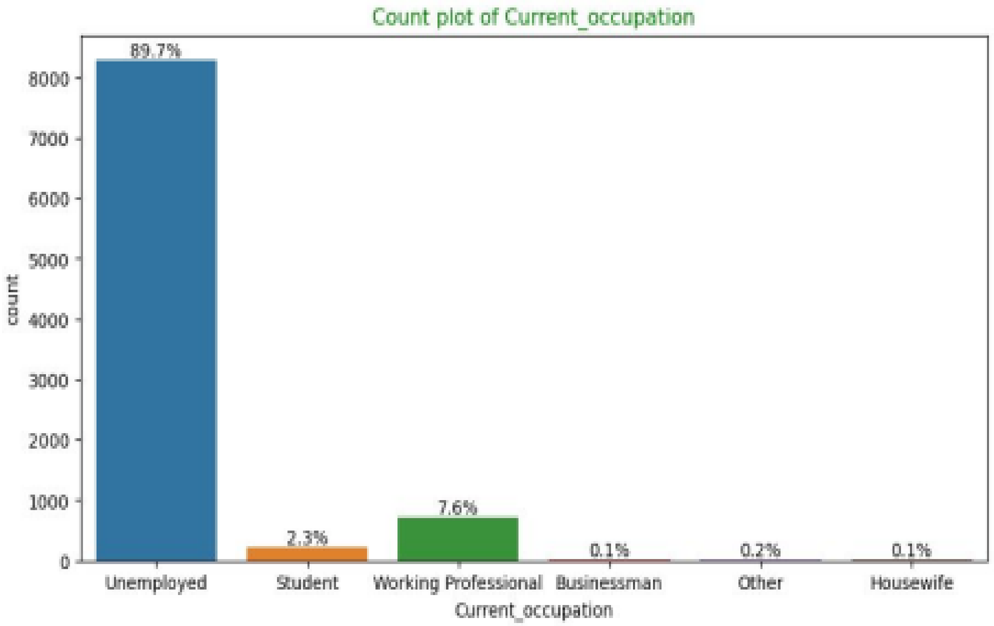


- 58% Lead source is from Google & Direct Traffic combined
- 68% of customers contribution in SMS Sent & Email Opened activities.

EDA

- Univariate Analysis – Categorical Variables

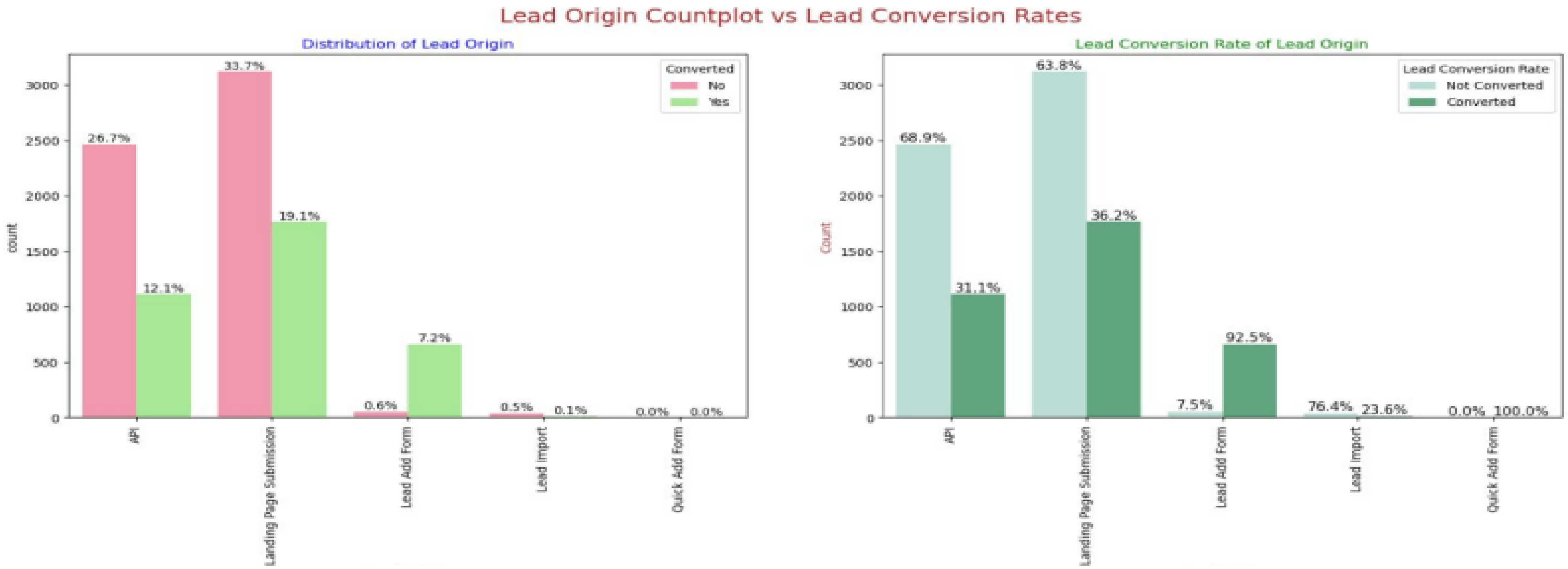




- “Landing Page Submission” identified 53% of customers, “API” identified 39%
- It has 90% of customers as unemployed

EDA

- Bivariate Analysis for Categorical Variables

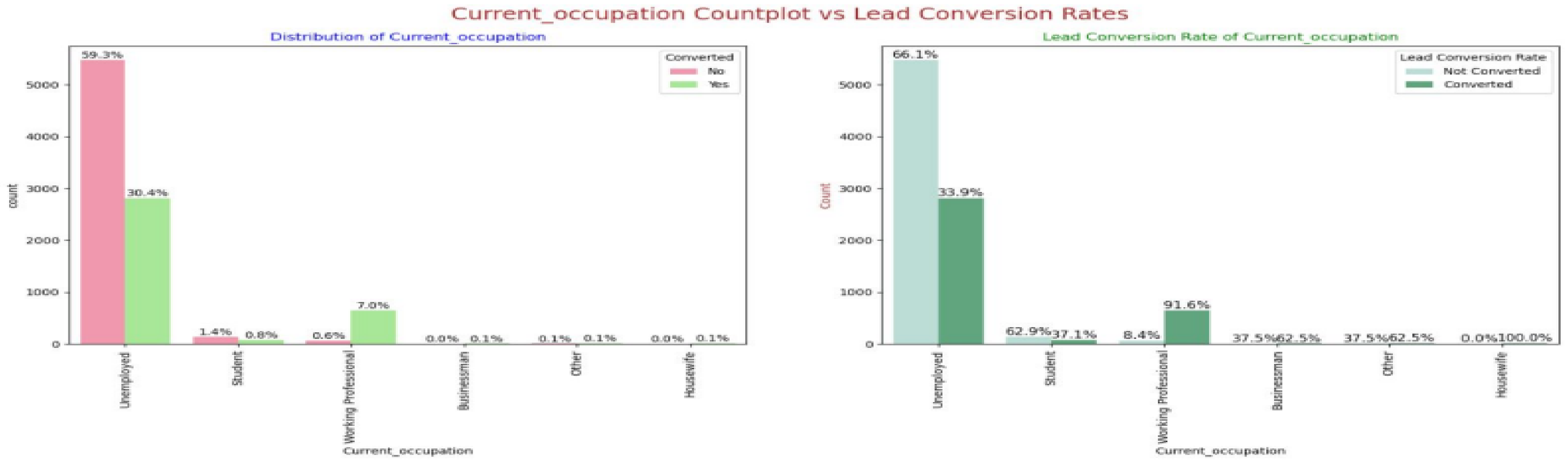


Around 52% of leads originated from “Landing Page Submission” with lead conversion rate of 36%

“API” identified approx. 39% of customers with lead conversion rate of 31%

EDA

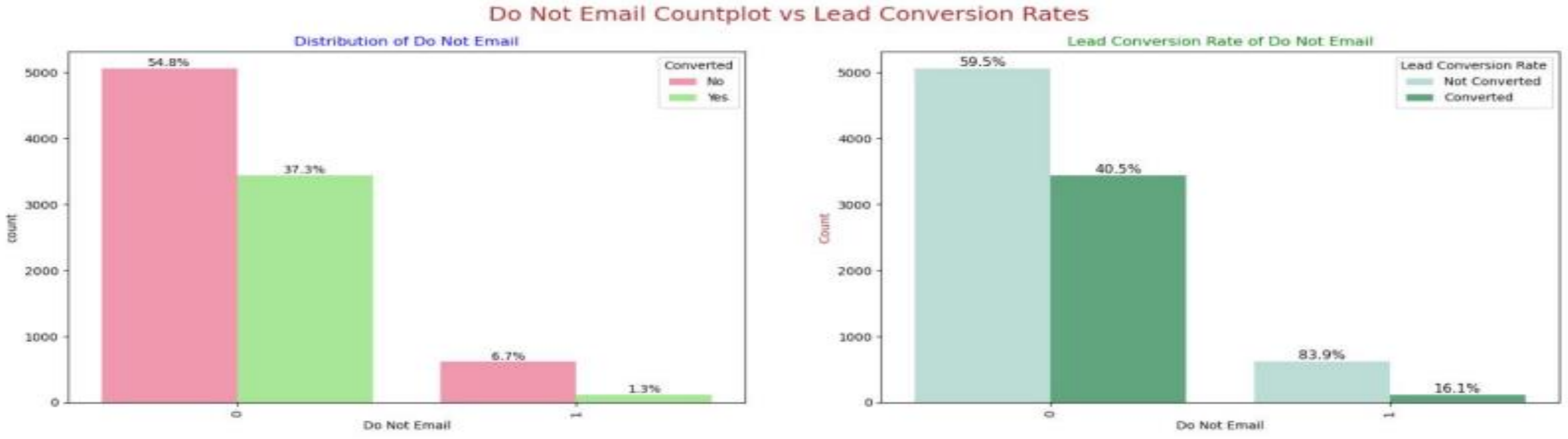
Bivariate Analysis for Categorical Variables



- Around 90% of the customers are Unemployed, with lead conversion rate (LCR) of 34%.
- While Working Professional contribute only 7.6% of total customers with almost 92% Lead conversion rate (LCR)

EDA

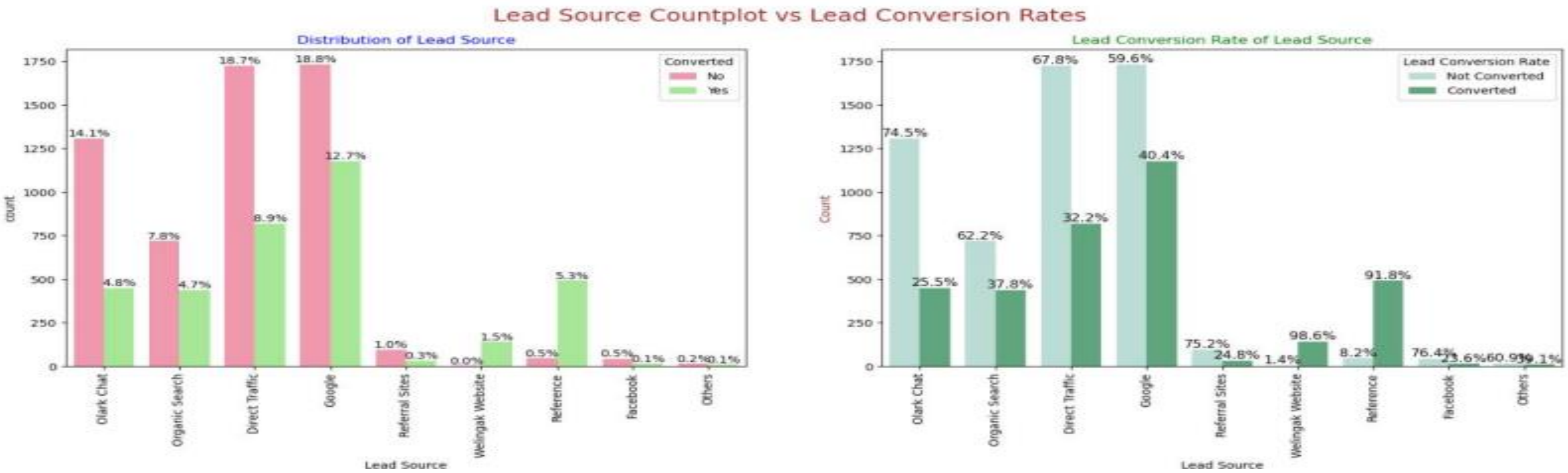
Bivariate Analysis for Categorical Variables



92% of the people has opted that they don't want to be mailed about the course & 40% of them are converted to leads

EDA

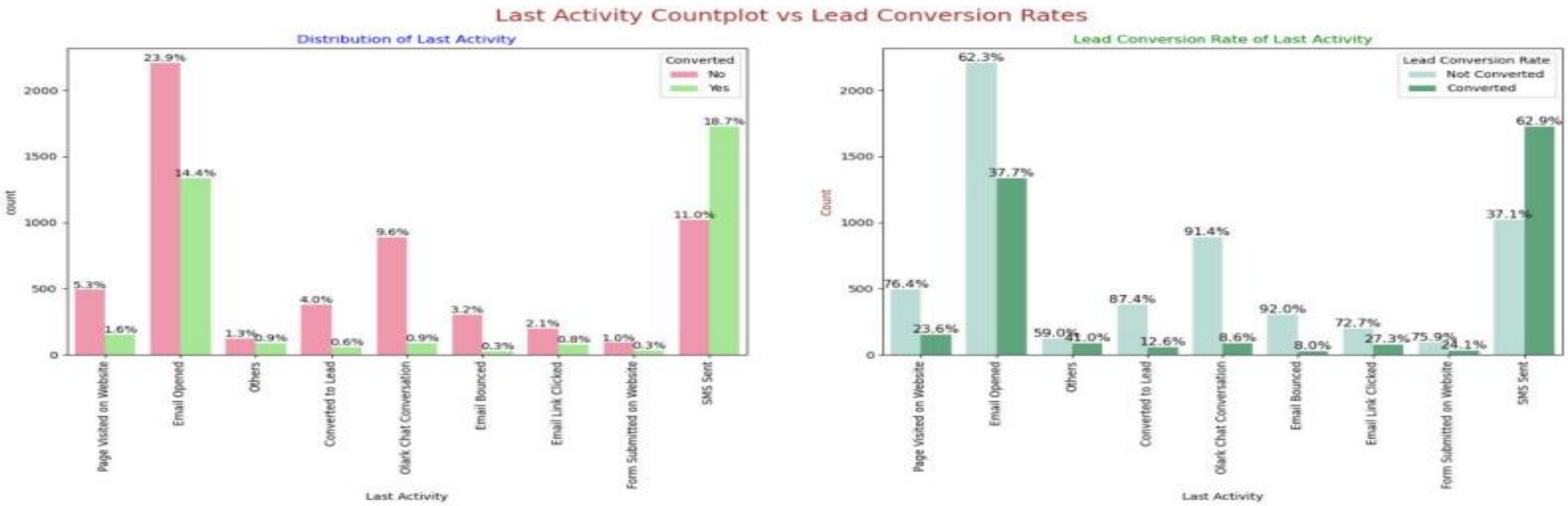
Bivariate Analysis for Categorical Variables



- Goggle has LCR of 40% out of 31% customers
- Direct Traffic has LCR of 32% with 27% customers
- Organic search LCR is 37.8% but contribution is 12.5% of customers
- Reference LCR is 91% but customer contribution is only 6%

EDA

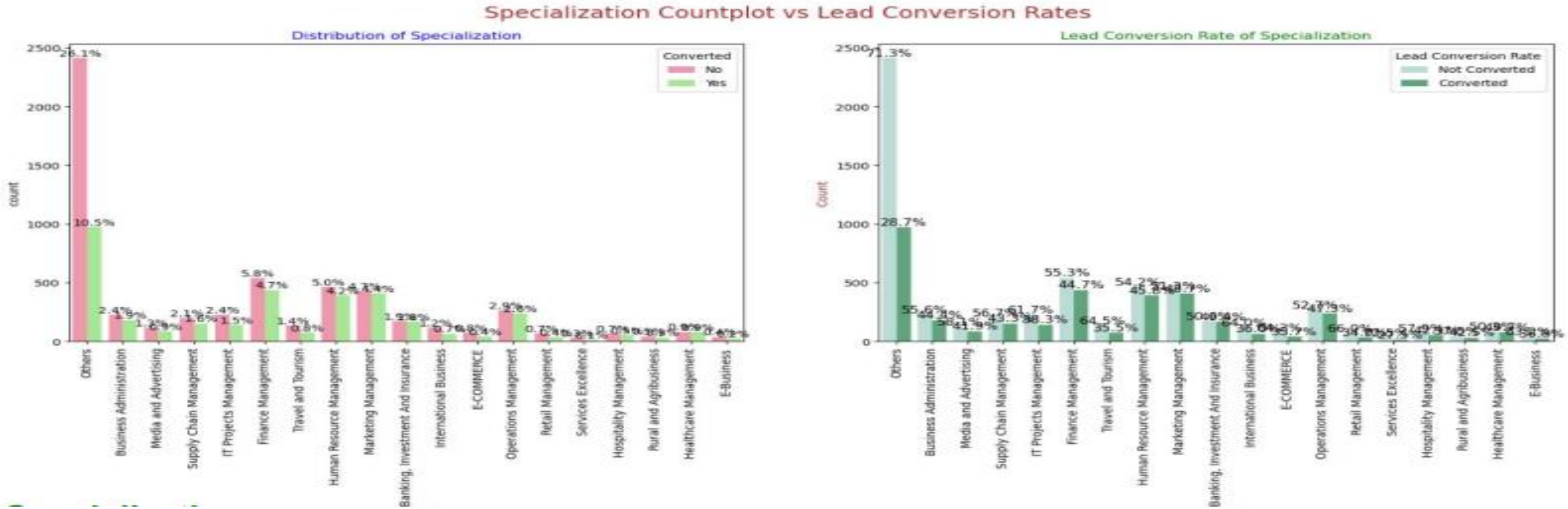
Bivariate Analysis for Categorical Variables



- 'SMS Sent' has high lead conversion rate of 63% with 30% contribution from last activities, ●
- 'Email Opened' activity contributed 38% of last activities performed by the customers, with 37% lead conversion rate

EDA

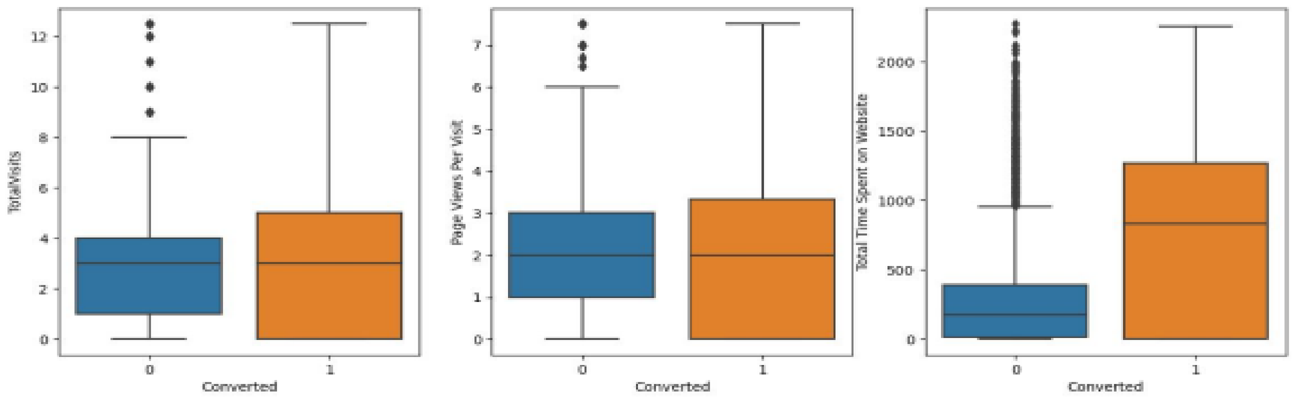
Bivariate Analysis for Categorical Variables

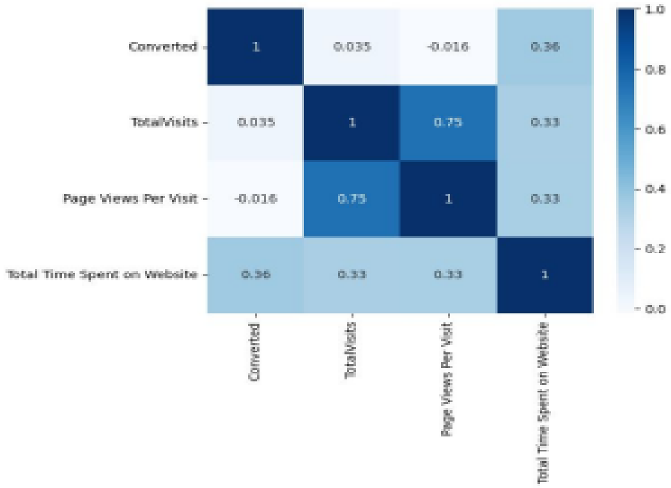


- Marketing Management, HR Management, Finance Management shows good contribution in Leads conversion than other specialization.

EDA

Bivariate Analysis for Categorical Variables





Past leads who spends more time on website have a higher chance of getting successful than those who spends less time as referred from 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

Confusion Matrix & Evaluation Metrics
with 0.345 as cutoff

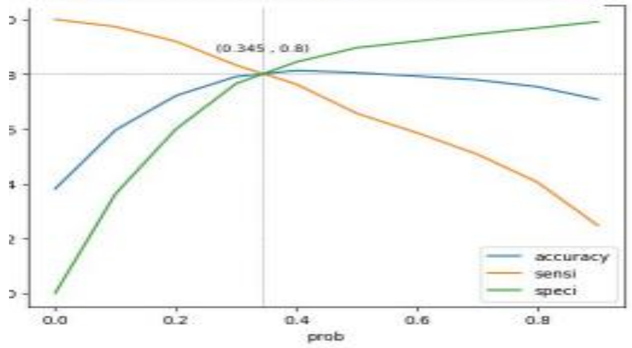
```
**************************************************

Confusion Matrix
[[3230  772]
 [ 492 1974]]

**************************************************

True Negative                       :  3230
True Positive                       :  1974
False Negative                      :  492
False Positve                       :  772
Model Accuracy                      :  0.8046
Model Sensitivity                   :  0.8005
Model Specificity                   :  0.8071
Model Precision                     :  0.7189
Model Recall                        :  0.8005
Model True Positive Rate (TPR)      :  0.8005
Model False Positive Rate (FPR)     :  0.1929

**************************************************
```



Confusion Matrix & Evaluation Metrics
with 0.41 as cutoff

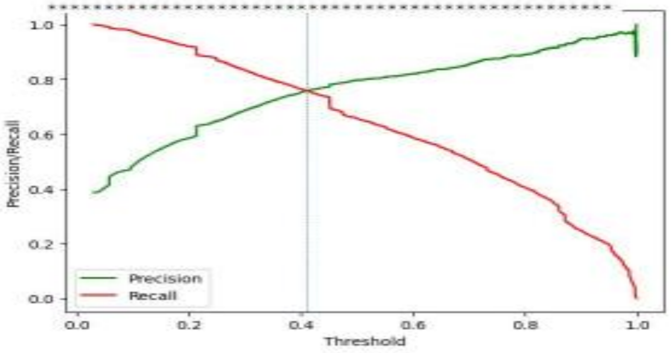
```
**************************************************

Confusion Matrix
[[3406  596]
 [ 596 1870]]

**************************************************

True Negative                       :  3406
True Positive                       :  1870
False Negative                      :  596
False Positve                       :  596
Model Accuracy                      :  0.8157
Model Sensitivity                   :  0.7583
Model Specificity                   :  0.8511
Model Precision                     :  0.7583
Model Recall                        :  0.7583
Model True Positive Rate (TPR)      :  0.7583
Model False Positive Rate (FPR)     :  0.1489

**************************************************
```



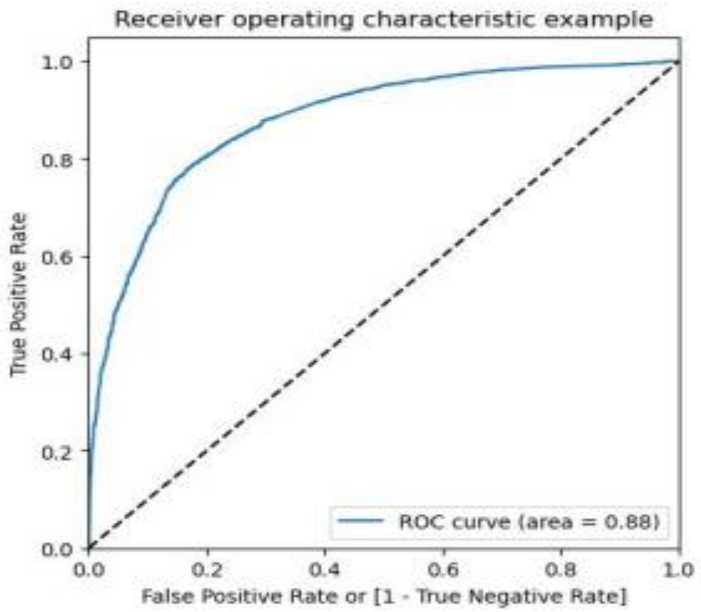
Train data set

After reviewing the evaluation metrics from both plots, it was decided to proceed with a cutoff of 0.345.

Model Evaluation

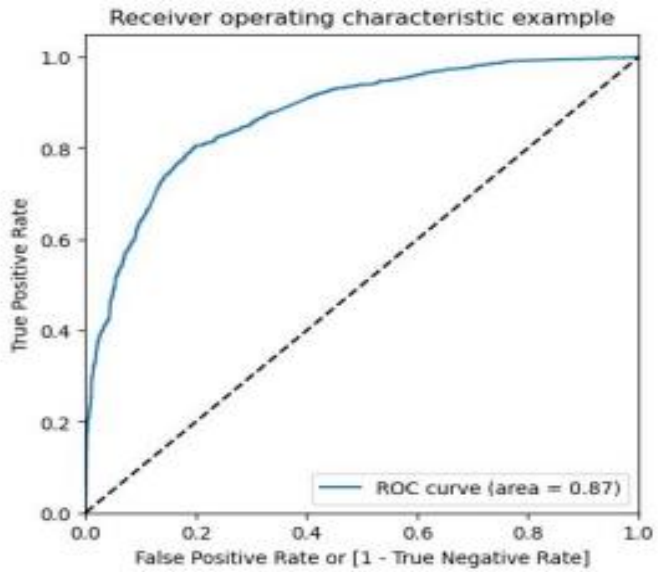
ROC Curve – Train Data Set

- 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.



ROC Curve – Test Data Set

- Area under ROC curve is 0.87 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.



Model Evaluation

Confusion Matrix & Metrics

Train Data Set

```
**************************************************

Confusion Matrix
[[3230  772]
 [ 492 1974]]

**************************************************

True Negative                   :  3230
True Positive                   :  1974
False Negative                  :  492
False Positve                   :  772
Model Accuracy                  :  0.8046
Model Sensitivity               :  0.8005
Model Specificity               :  0.8071
Model Precision                 :  0.7189
Model Recall                    :  0.8005
Model True Positive Rate (TPR)  :  0.8005
Model False Positive Rate (FPR) :  0.1929
```

Test Data Set

```
**************************************************

Confusion Matrix
[[1353  324]
 [ 221  874]]

**************************************************

True Negative                   :  1353
True Positive                   :  874
False Negative                  :  221
False Positve                   :  324
Model Accuracy                  :  0.8034
Model Sensitivity               :  0.7982
Model Specificity               :  0.8068
Model Precision                 :  0.7295
Model Recall                    :  0.7982
Model True Positive Rate (TPR)  :  0.7982
Model False Positive Rate (FPR) :  0.1932
```

- Using a cut-off value of 0.345, the model achieved a sensitivity of 80.05% in the train set and 79.82% in the test set
- Sensitivity in this case indicates how many leads the model identify correctly out of all potential leads which are converting
- The CEO of X Education had set a target sensitivity of around 80%.
- The model also achieved an accuracy of 80.46%, which is in line with the study's objectives

RECOMMENDATIONS

- As per the problem statement, increasing lead conversion is crucial for the growth and success of X Education. To achieve this, we have developed a regression model that can help us identify the most significant factors that impact lead conversion.
- We have determined the following features that have the highest positive coefficients, and these features should be given priority in our marketing and sales efforts to increase lead conversion.

➢ Lead Source_Welingak Website: 5.39

➢ Lead Source_Reference: 2.93

➢ Current_occupation_Working Professional: 2.67

➢ Last Activity_SMS Sent: 2.05

➢ Last Activity_Others: 1.25

➢ Total Time Spent on Website: 1.05

➢ Last Activity_Email Opened: 0.94

➢ Lead Source_Olark Chat: 0.91

We have also identified features with negative coefficients that may indicate potential areas for improvement. These include:

- Specialization in Hospitality Management: -1.09
- Specialization in Others: -1.20
- Lead Origin of Landing Page Submission: -1.26

RECOMMENDATIONS

To increase our Lead Conversion Rates

- Focus on features with positive coefficients for targeted marketing strategies.
- Develop strategies to attract high-quality leads from top-performing lead sources.
- Optimize communication channels based on lead engagement impact.
- Engage working professionals with tailored messaging.
- More budget/spend can be done on Welingak Website in terms of advertising, etc. Incentives/discounts for providing reference that convert to lead, encourage providing more references.
- Working professionals to be aggressively targeted as they have high conversion rate and will have better financial situation to pay higher fees too.

To identify areas of improvement

- Analyze negative coefficients in specialization offerings.
- Review landing page submission process for areas of improvement.

THANK YOU