X Education - Lead Scoring Case Study

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

Team Members: - Rutuja Sunil Bhore

Table of Contents

- Background of X Education Company
- Problem Statement & Objective of the Study
- Suggested Ideas for Lead Conversion
- Analysis Approach
- Data Cleaning
- EDA
- Data Preparation
- Model Building (RFE & Manual fine tuning)
- Model Evaluation
- Recommendations

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 us 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

- Leads are grouped based on their propensity or likelihood to convert.
- This results in a focused group of hot leads.

Better Communication

- We could have a smaller pool of leads to communicate with, which would allow us to have a greater impact.

Boost Conversion

- 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:
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

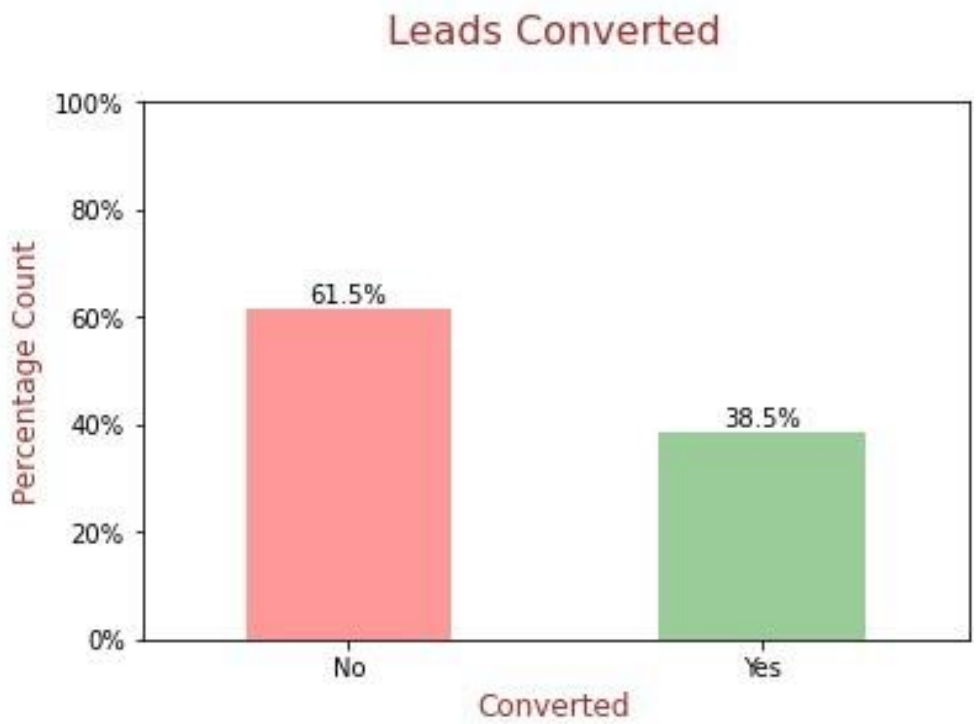
- **"Select"** level represents null values for some categorical variables, as customers did not choose any option from the list.
- Columns with over 40% null values were dropped.
- Missing values in categorical columns were handled based on value counts and certain considerations.
- Drop columns that 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 modelling (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

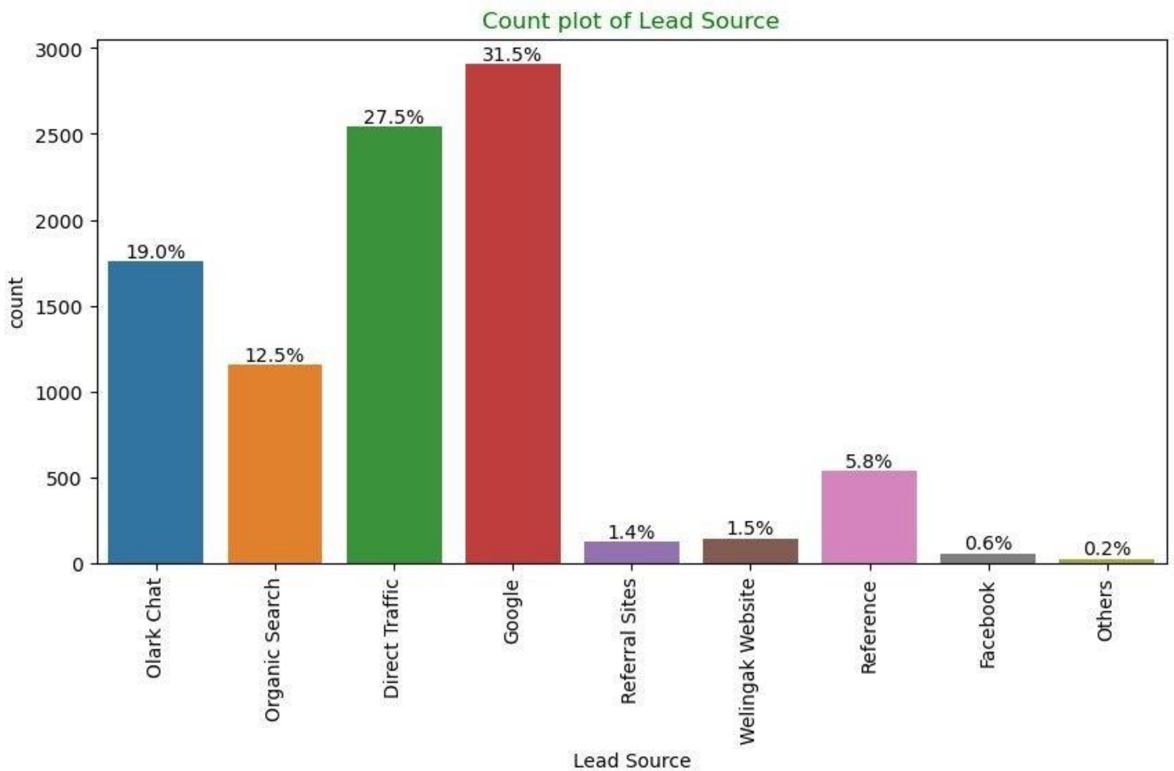
- Data is imbalanced while analyzing target variable.

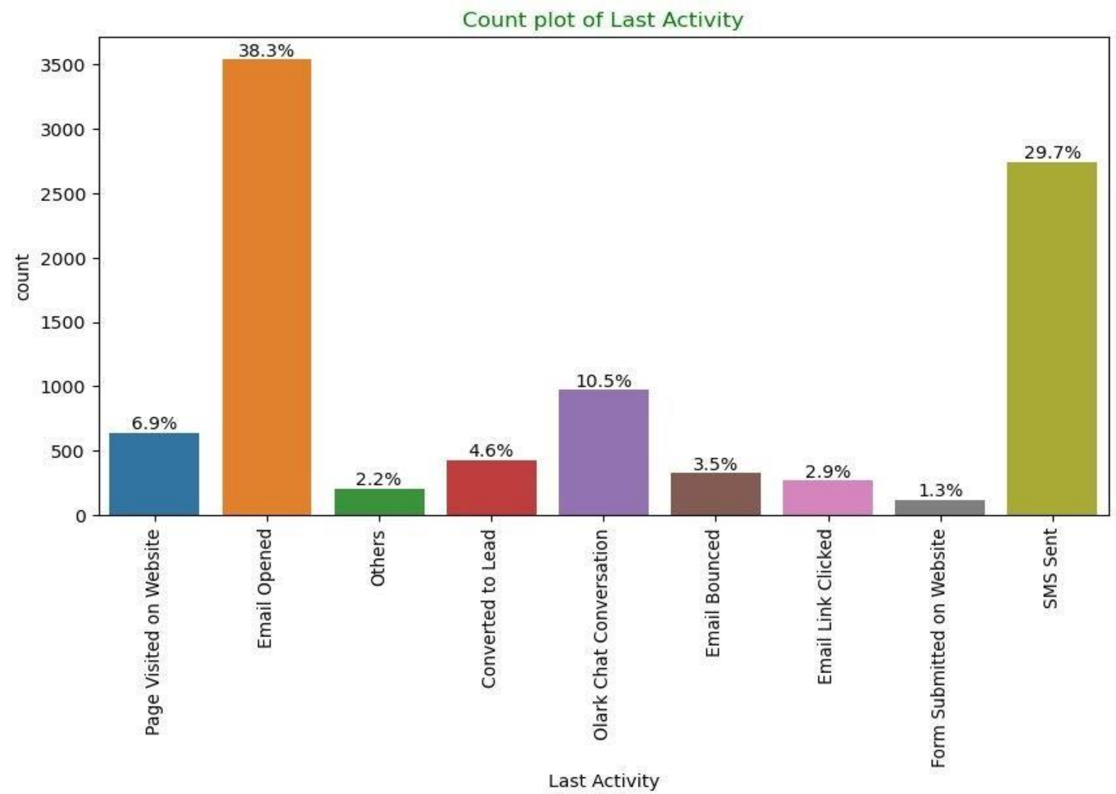


- Conversionrate is of 38.5%, meaning only 38.5% of the people have converted to leads.(Minority)
- While 61.5% of the people didn't convert to leads. (Majority)

EDA

- Univariate Analysis – Categorical Variables

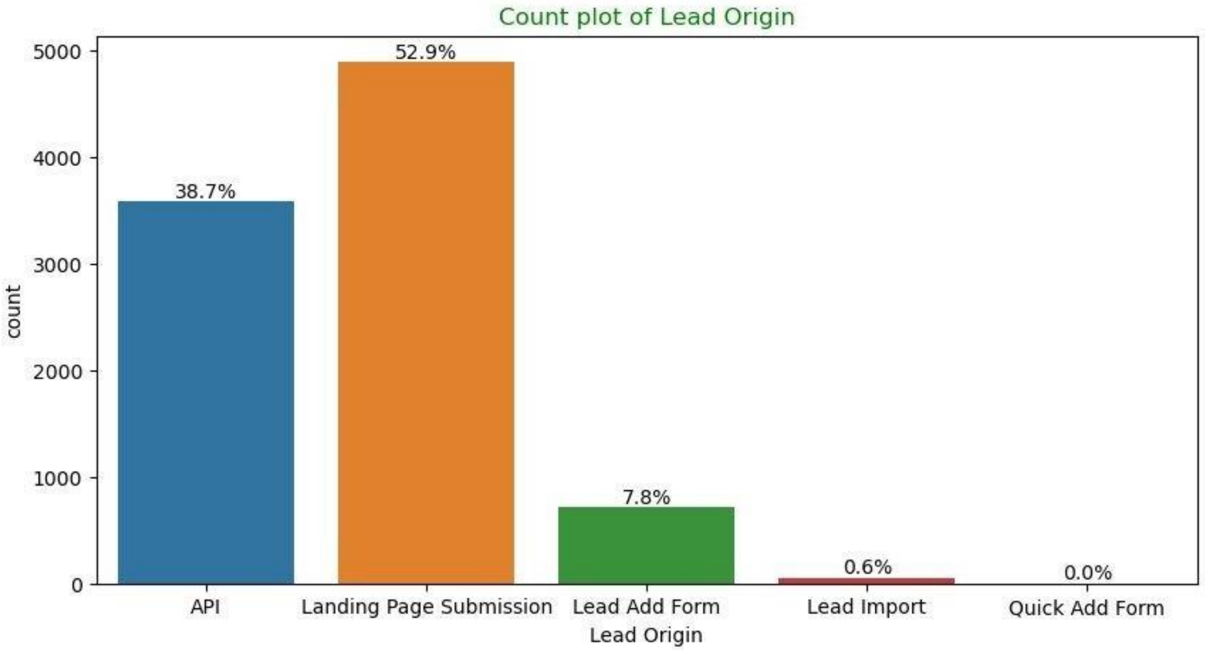


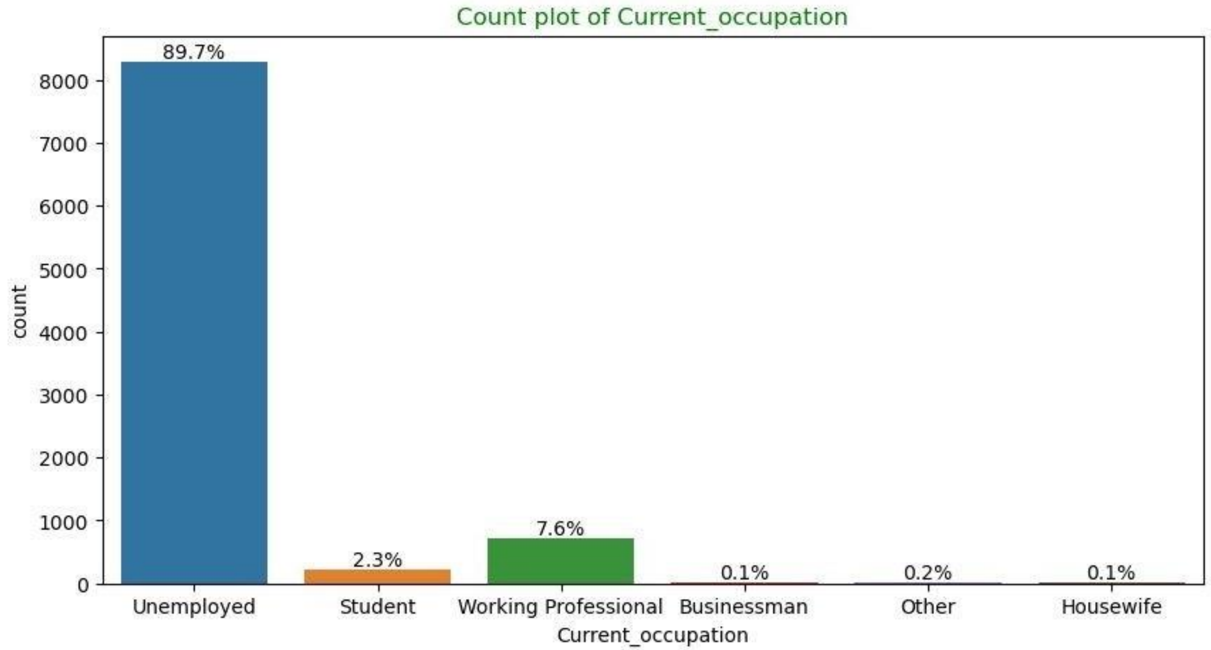


- **Lead Source:** 58% Lead source is from Google & Direct Traffic combined.
- **Last Activity:** 68% of customers contribution in SMS Sent & Email Opened activities.

EDA

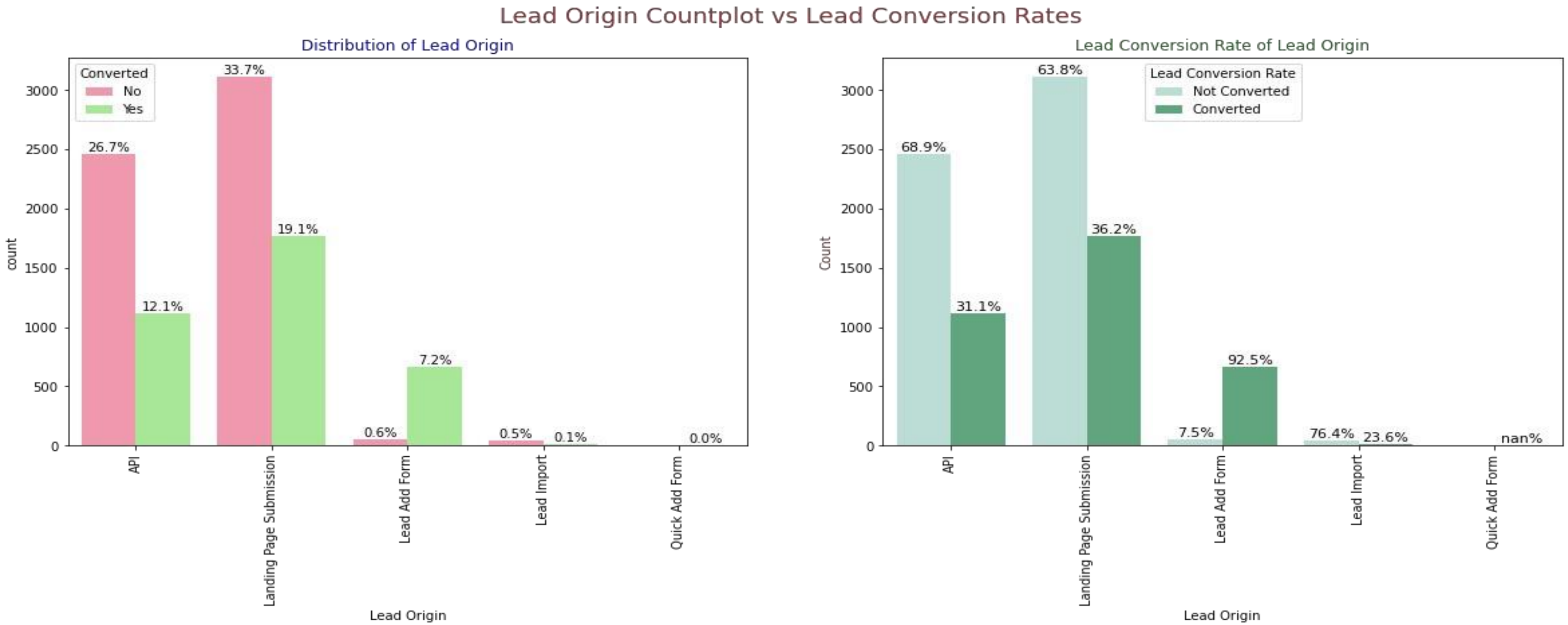
Univariate Analysis – Categorical Variables





- **Lead Origin:** "Landing Page Submission" identified 53% of customers, "API" identified 39%.
- **Current_occupation:** It has 90% of the customers a Unemployed.

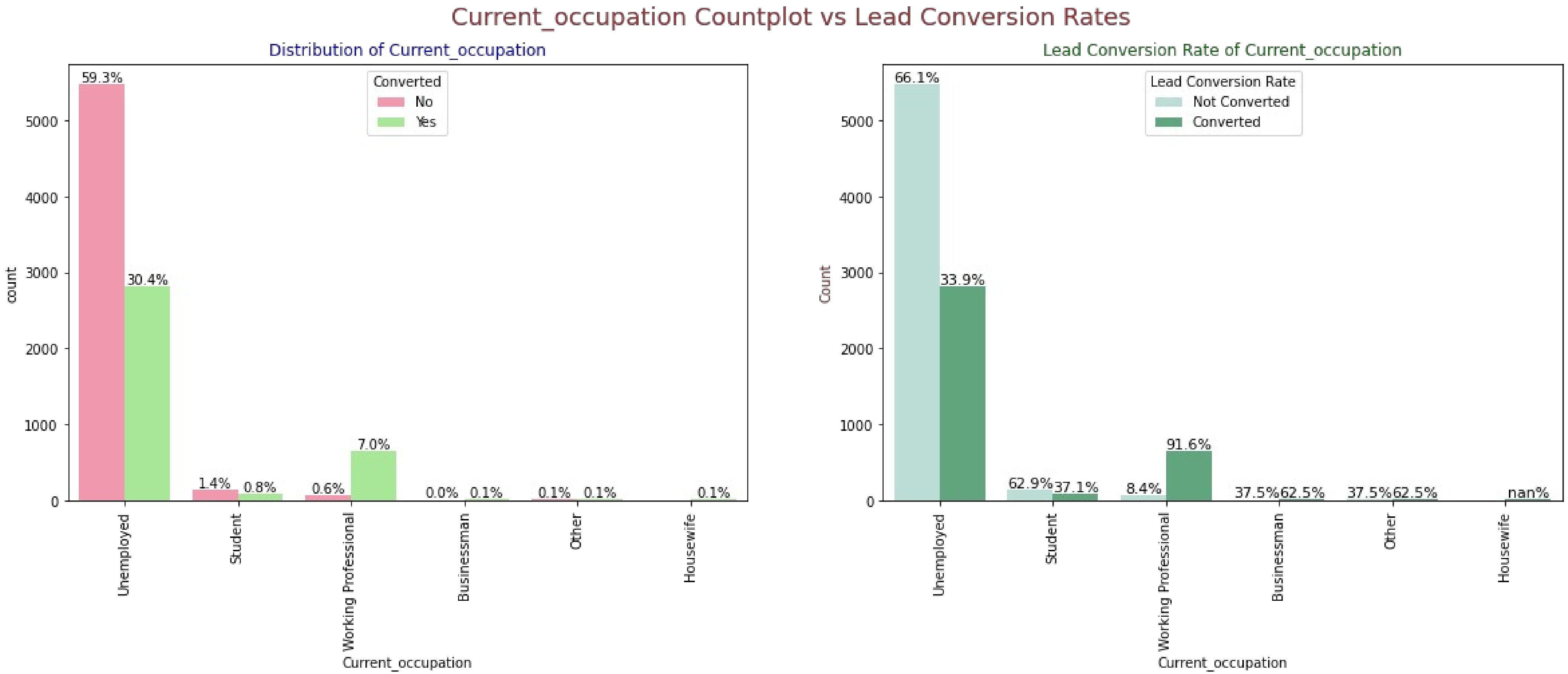
EDA – Bivariate Analysis for Categorical Variables



Lead Origin:

- Around 52% of all leads originated from *"Landing Page Submission"* with a **lead conversion rate (LCR) of 36%.**
- The *"API"* identified approximately 39% of customers with a **lead conversion rate (LCR) of 31%.**

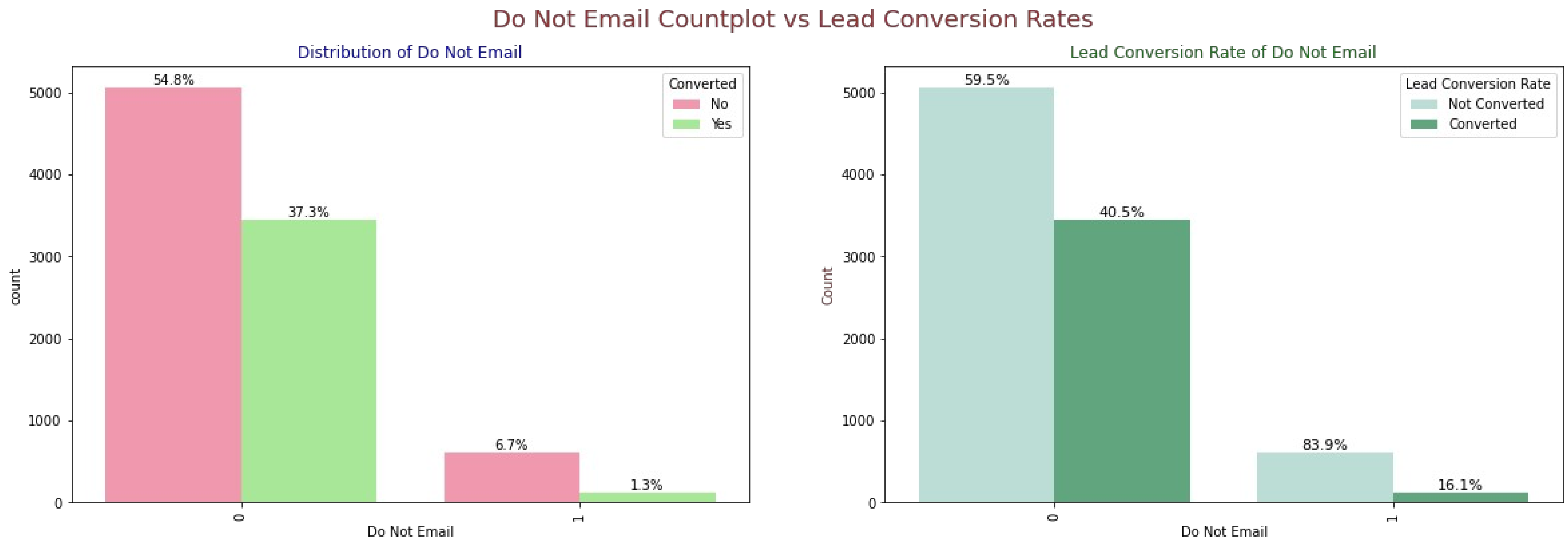
EDA – Bivariate Analysis for Categorical Variables



Current_occupation:

- 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)**.

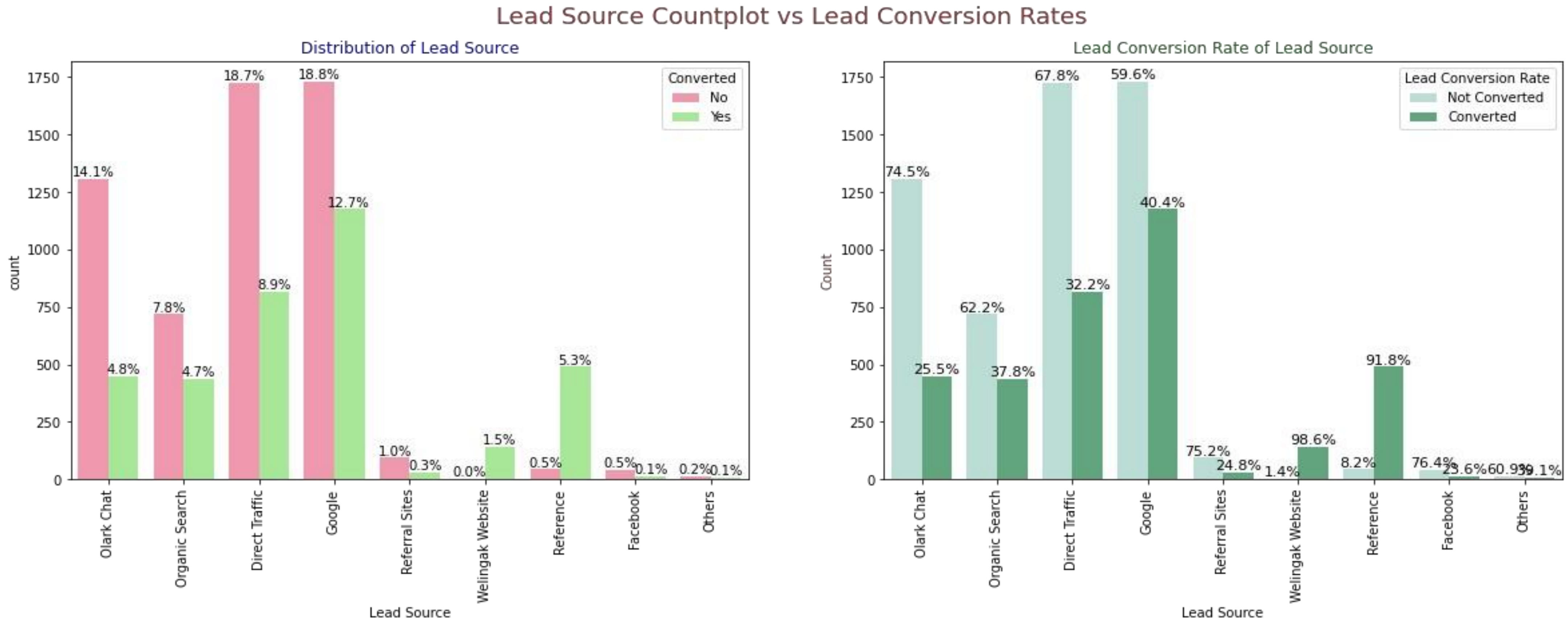
EDA – Bivariate Analysis for Categorical Variables



Do Not Email:

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

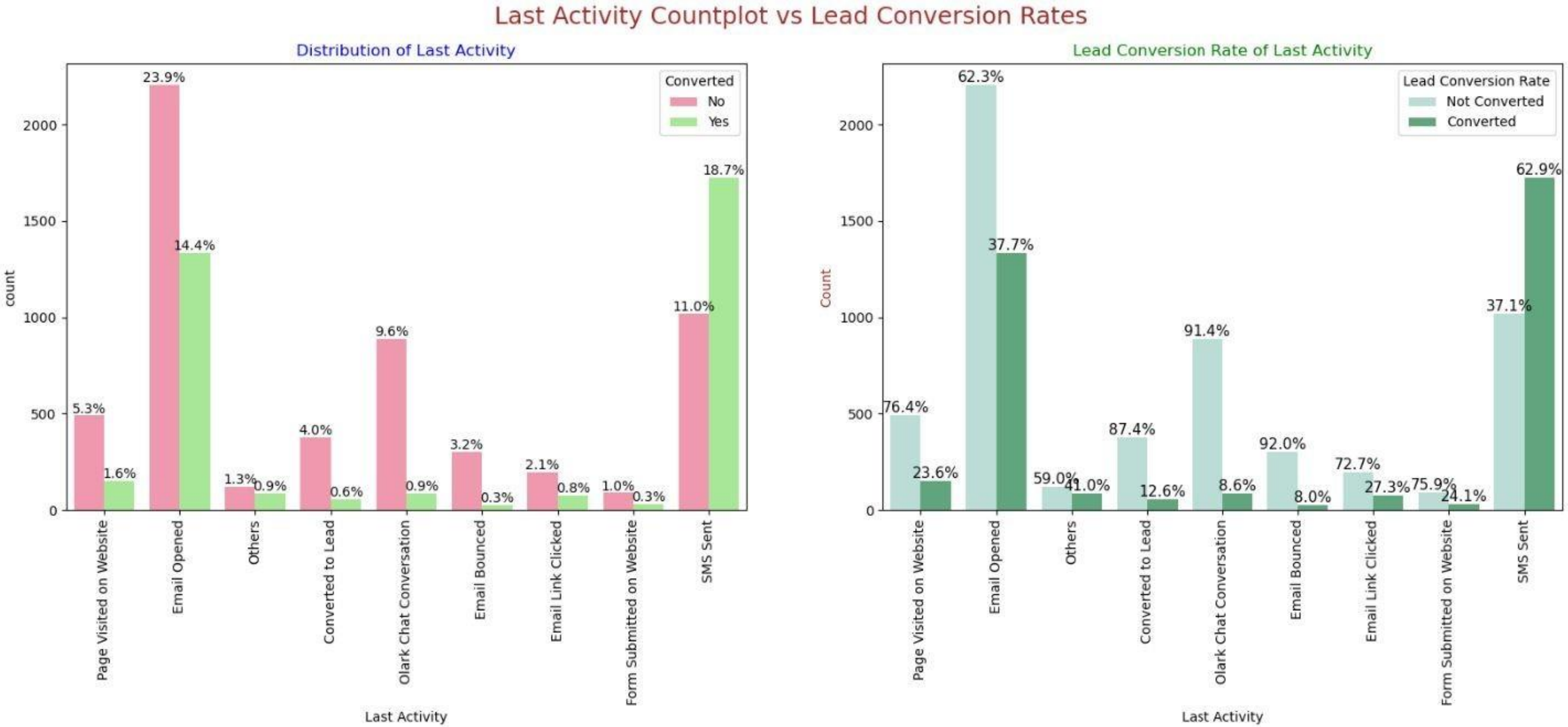
EDA – Bivariate Analysis for Categorical Variables



Lead Source:

- *Google* has **LCR of 40%** out of 31% customers,
- *Direct Traffic* contributes **32% LCR** with 27% customers, which is lower than Google,
- *Organic Search* also gives **37.8% of LCR**, but the contribution is by only 12.5% of customers,
- *Reference* has **LCR of 91%**, but there are only around 6% of customers through this Lead Source.

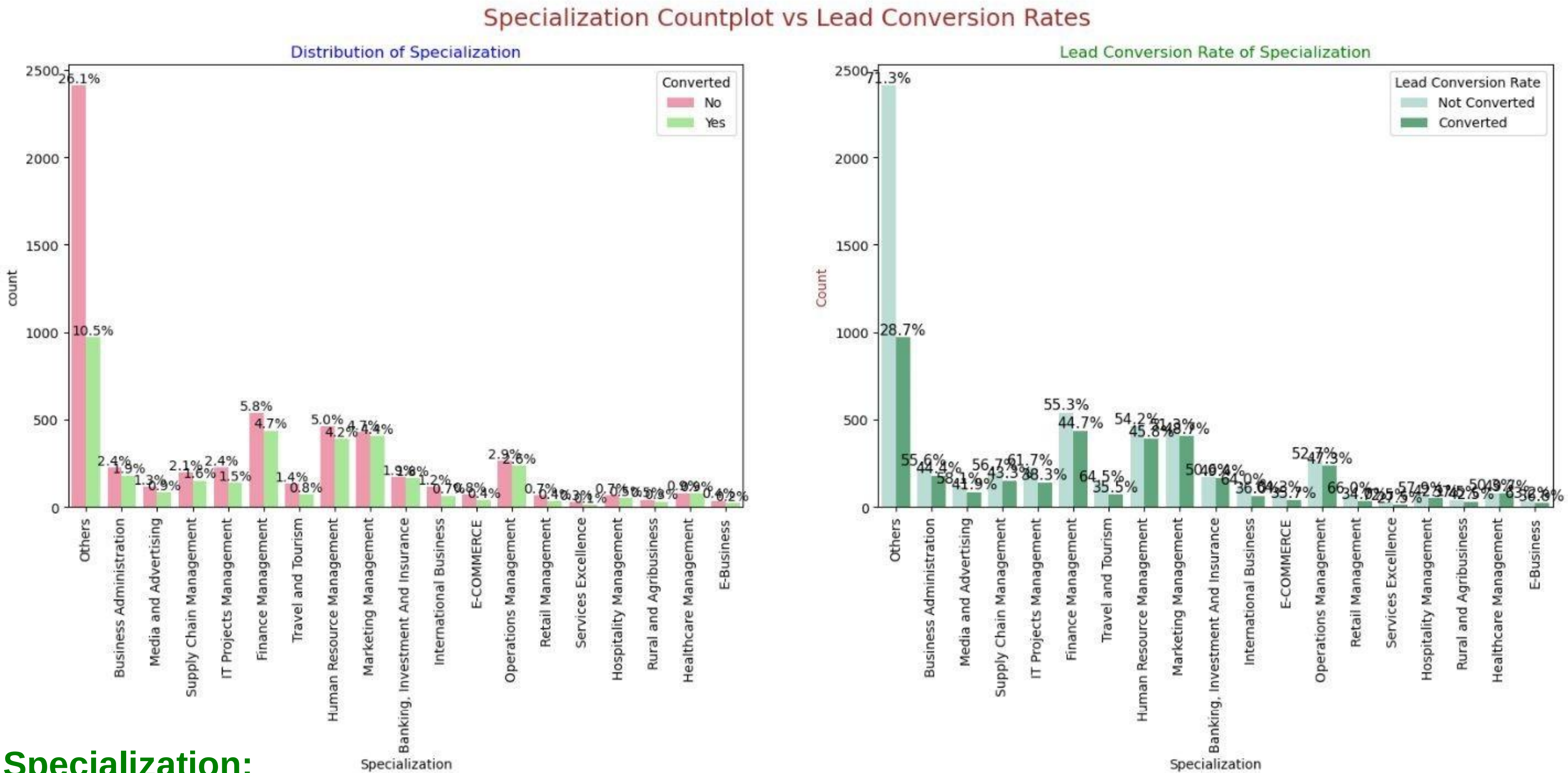
EDA – Bivariate Analysis for Categorical Variables



Last Activity:

- *'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.**

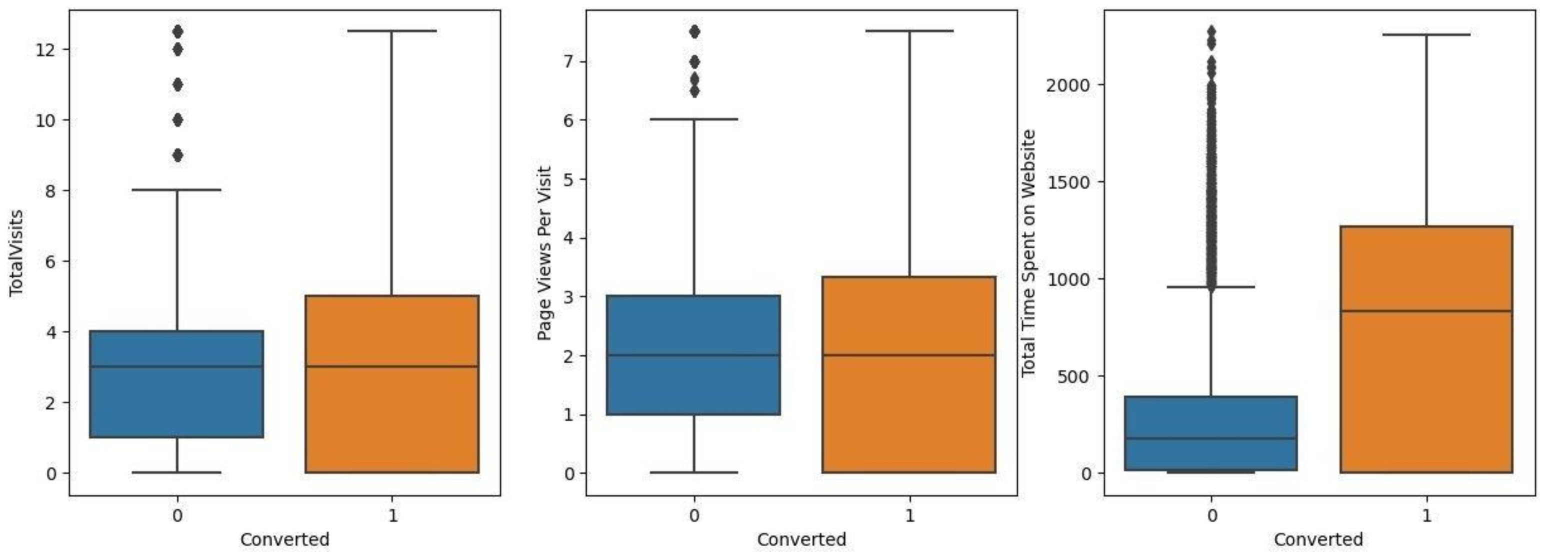
EDA – Bivariate Analysis for Categorical Variables

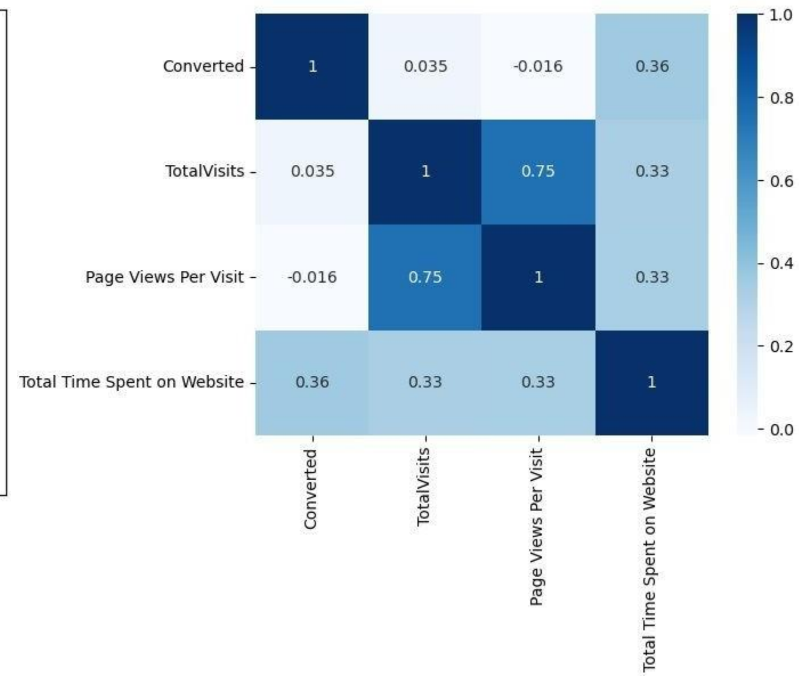


Specialization:

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

EDA – Bivariate Analysis for Numerical Variables





- Past Leads who **spend 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 – 47 columns & Post RFE – 15 columns

Model Building

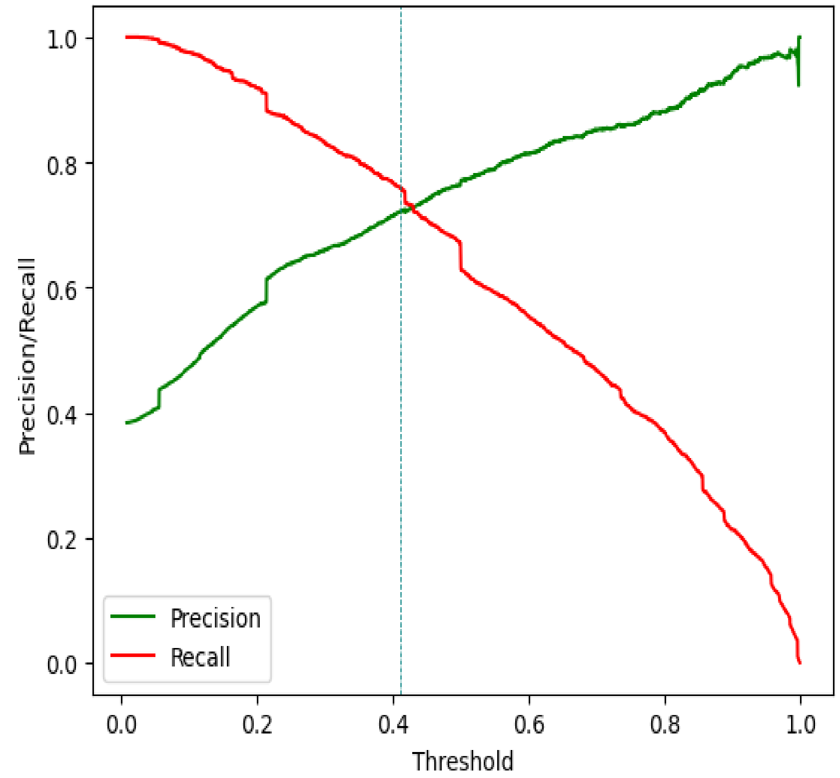
- Manual Feature Reduction process was used to build models by dropping variables with p – value greater than 0.05.
- Model 3 looks stable after four iterations with:
  - significant p-values within the threshold (p-values < 0.05) and
  - No sign of multicollinearity with VIFs less than 5
- Hence, **logm3** 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 0.37 as cutoff

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

Confusion Matrix
[[3132  852]
 [ 534 1950]]

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

True Negative                 :  3132
True Positive                 :  1950
False Negative                :  534
False Positve                 :  852
Model Accuracy                :  0.7857
Model Sensitivity             :  0.785
Model Specificity             :  0.7861
Model Precision               :  0.6959
Model Recall                  :  0.785
Model True Positive Rate (TPR)  :  0.785
Model False Positive Rate (FPR) :  0.2139


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

Confusion Matrix & Evaluation Metrics with 0.41 as cutoff



Train Data Set

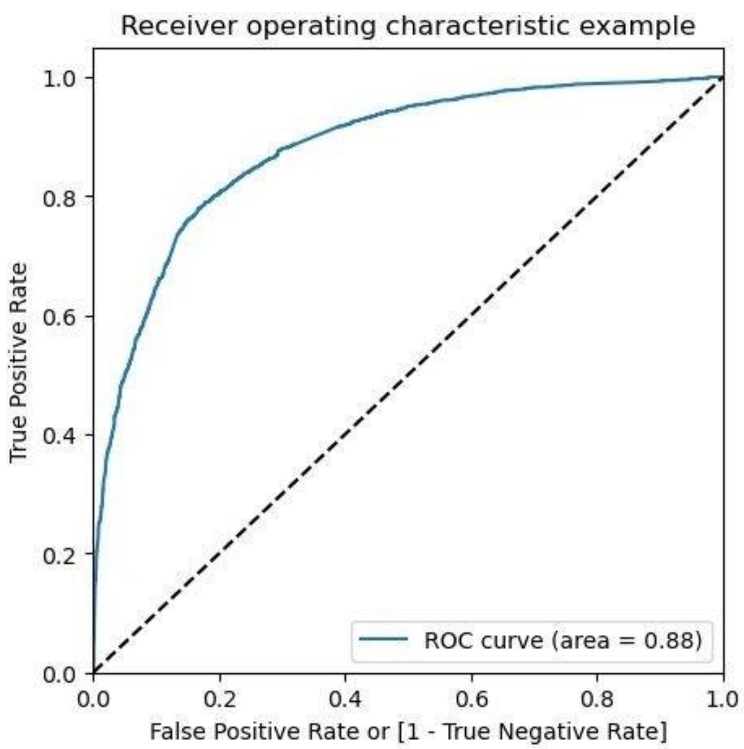
It was decided to go ahead with 0.345 as cutoff after checking evaluation metrics coming from both plots

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

Confusion Matrix
[[3255  729]
 [ 598 1886]]

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

True Negative                     :  3255
True Positive                     :  1886
False Negative                    :  598
False Positve                     :  729
Model Accuracy                    :  0.7948
Model Sensitivity                 :  0.7593
Model Specificity                 :  0.817
Model Precision                   :  0.7212
Model Recall                      :  0.7593
Model True Positive Rate (TPR)    :  0.7593
Model False Positive Rate (FPR)   :  0.183


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

Model Evaluation

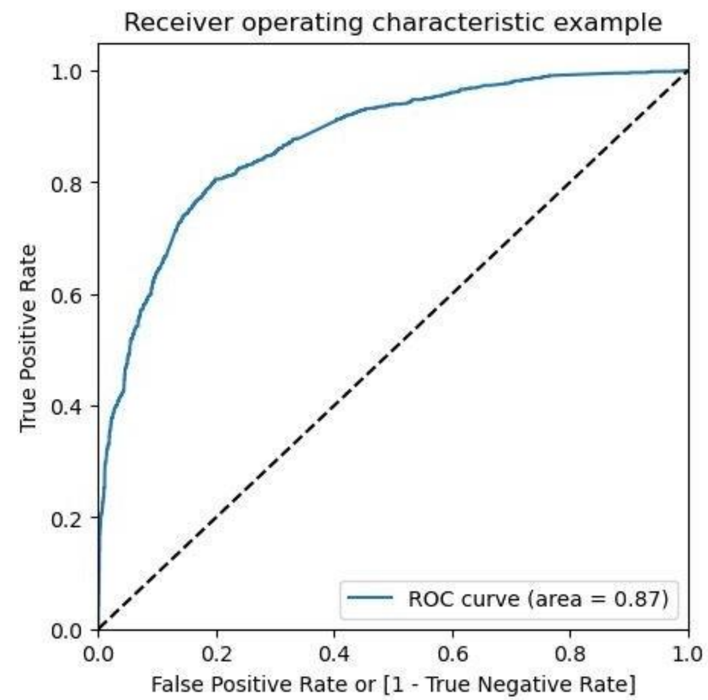
ROC Curve – Train Data Set

- 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

Test Data Set

- Using a cut-off value of 0.37, the model achieved a **sensitivity** of **78% in the train set** and **80% intest set**.
- Sensitivity in this case indicates how many leads the model identify correctly out of all potential leads which converting
- The CEO of X Education had set a target **sensitivity of around 80%**.
- The model also achieved an **accuracy of 80% approx.**, (78%) which is in line with the study's objectives.

Recommendation based on Final Model

- As per the problem statement, increasing lead conversion is crucial for the growth and success 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 thesefeatures should be given priority in our marketing and sales efforts to increase lead conversion.
- Total Time Spent on Website 0.963559
- Last Activity_SMS Sent 0.927586
- Current_occupation_Working Professional 0.630323
- Lead Source_Reference 0.553127
- Last Activity_Email Opened 0.355880
- TotalVisits 0.283450
- Last Activity_Others 0.202255
- Lead Source_Olark Chat 0.131033
- Last Activity_Olark Chat Conversation -0.251222
- Do Not Email -0.272475
- Page Views Per Visit -0.434605
- Specialization_Others -0.490786
- const -0.585619

Recommendation based on Final Model

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 **Total Time Spent on 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.