X Education - Lead Scoring Case Study

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

Submitted by :- Jitendra Choure

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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 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

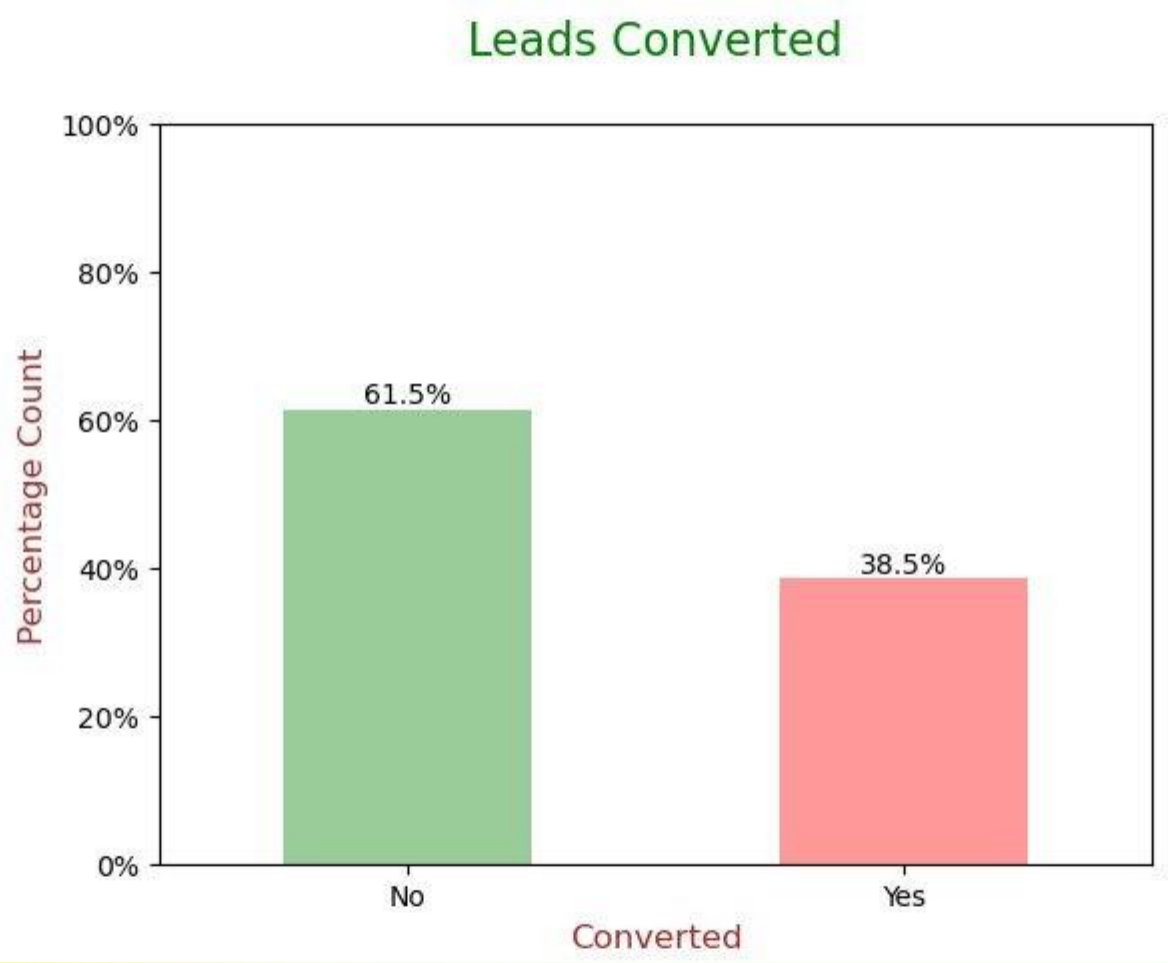
- **"Select"** level represents null values for some categorical variables, as customers did not choose any option from the list.
- Columns with over 40% null values were dropped.
- Missing values in categorical columns were handled based on value counts and certain considerations.
- Drop columns that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

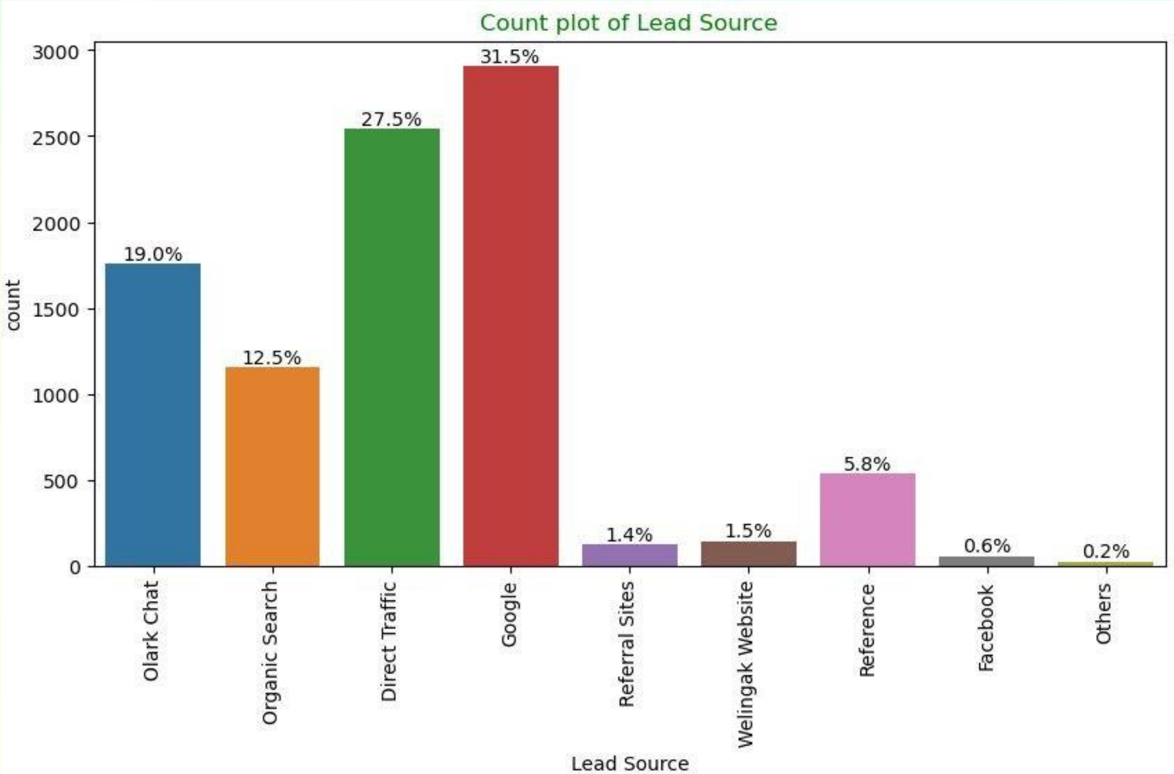
- Data is imbalanced while analyzing target variable.

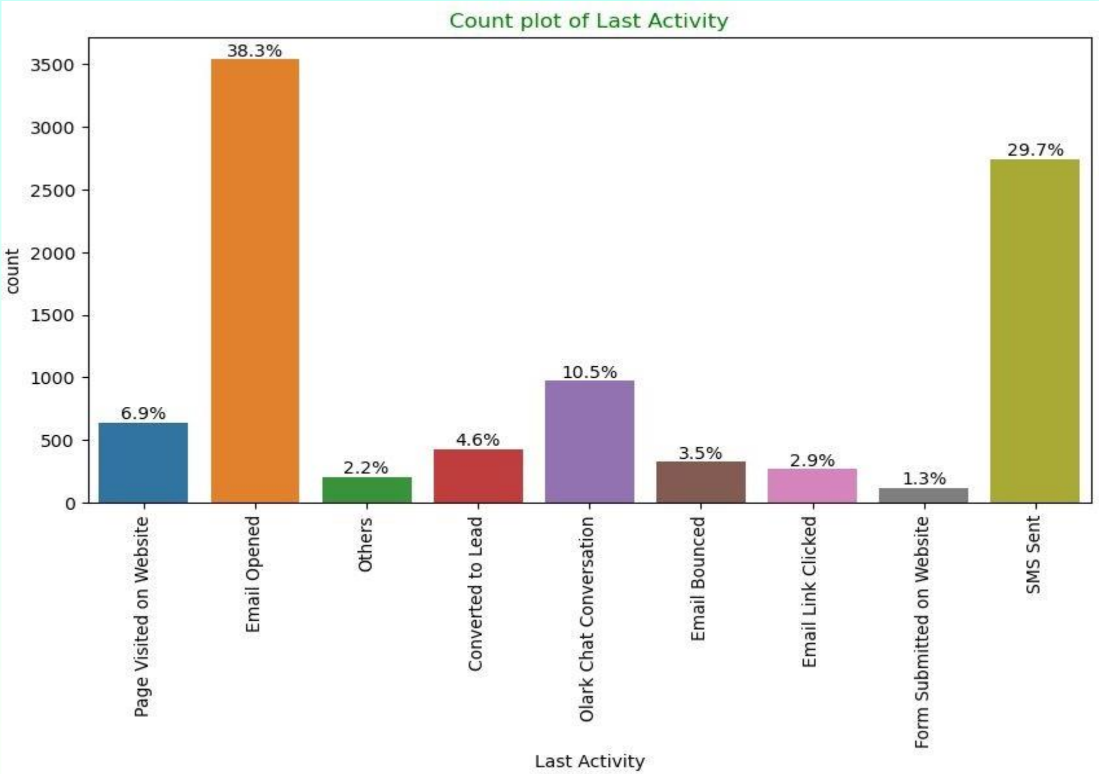


- Conversion rate is of 38.5%, meaning only 38.5% of the people have converted to leads.(Minority)
- While 61.5% of the people didn't convert to leads. (Majority)

EDA

➢ Univariate Analysis – Categorical Variables

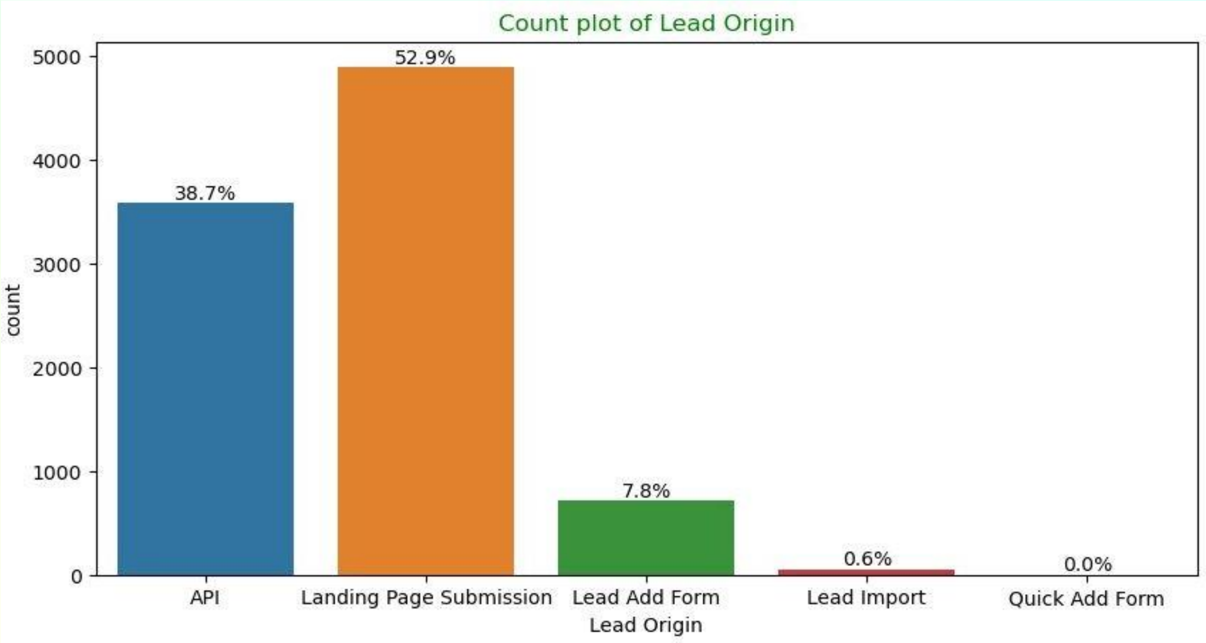


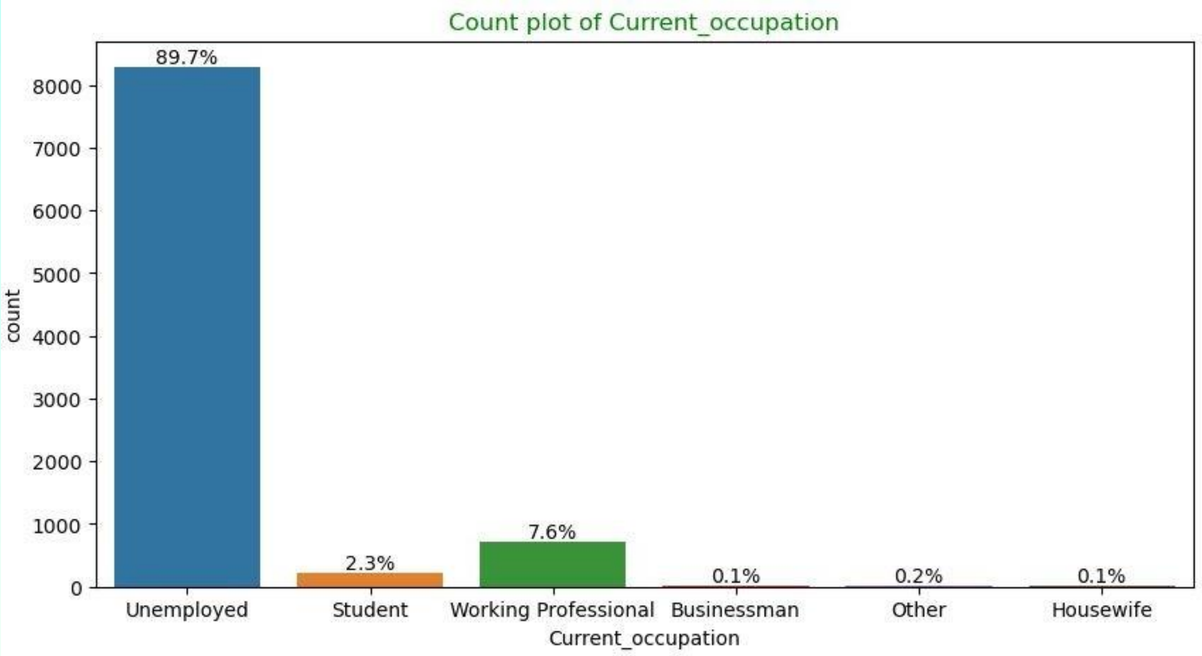


- **Lead Source:** 58% Lead source is from Google & Direct Traffic combined.
- **Last Activity:** 68% of customers contribution in SMS Sent & Email Opened activities.

EDA

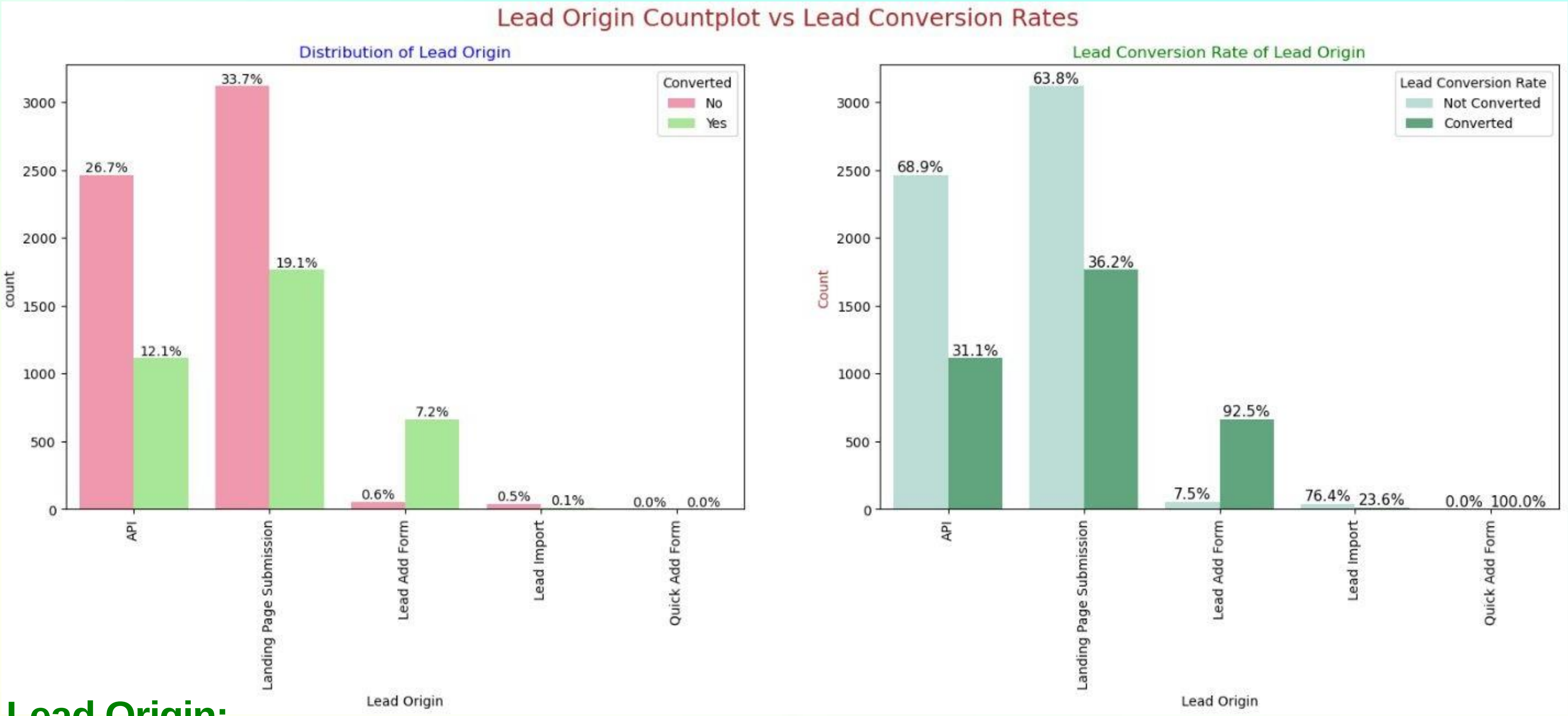
Univariate Analysis – Categorical Variables





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

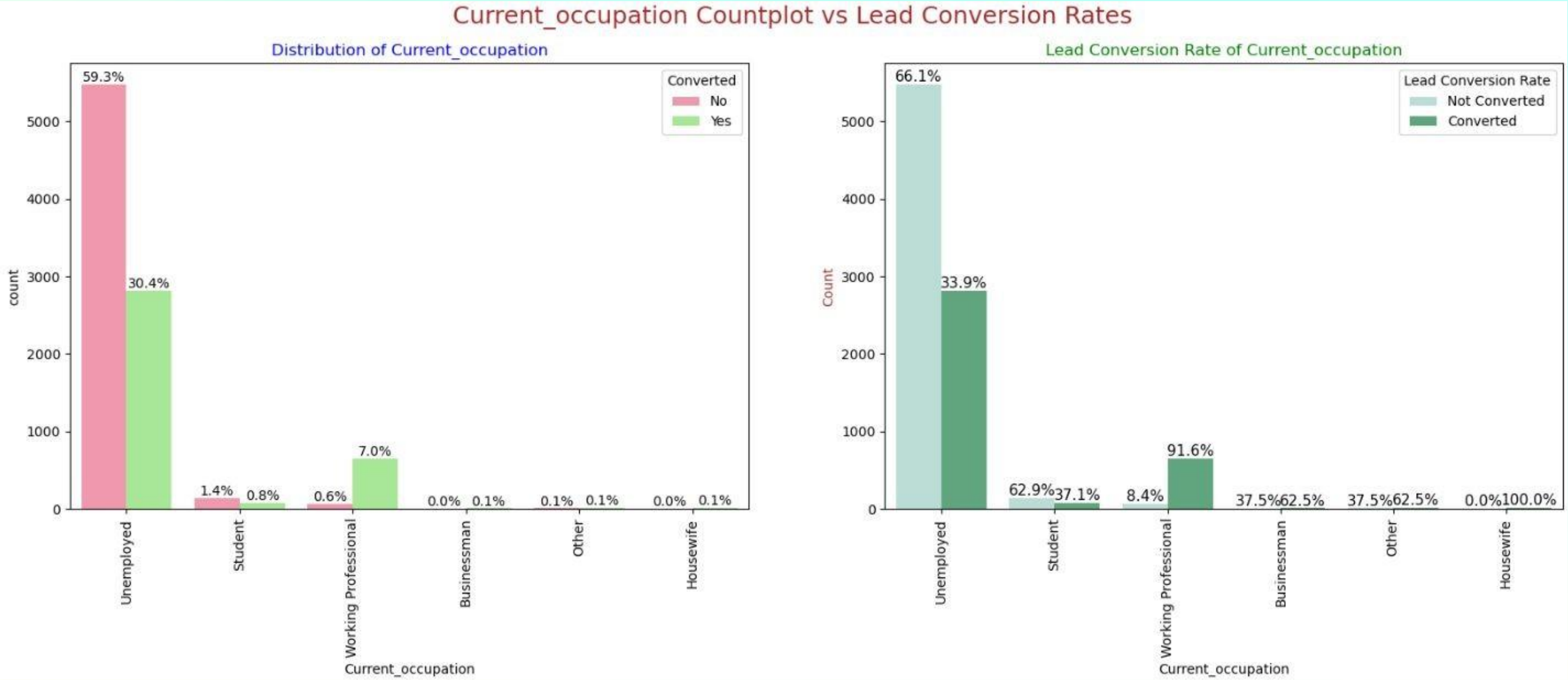
EDA – Bivariate Analysis for Categorical Variables



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%**.

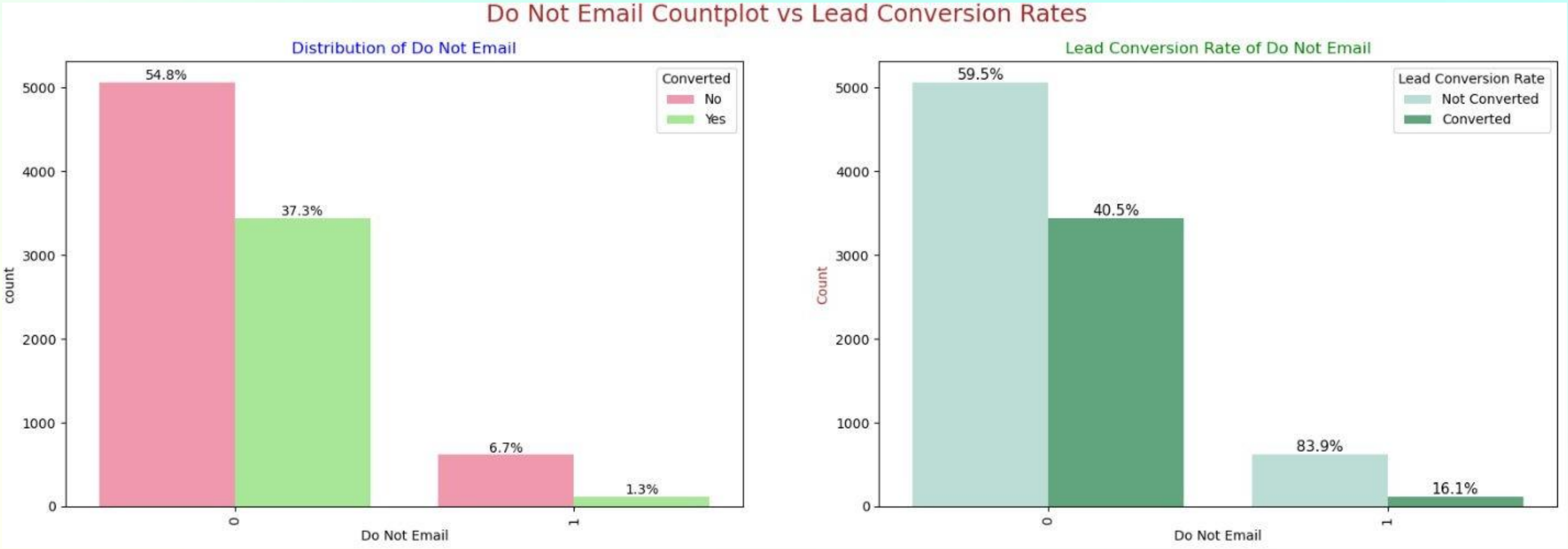
EDA – Bivariate Analysis for Categorical Variables



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)**.

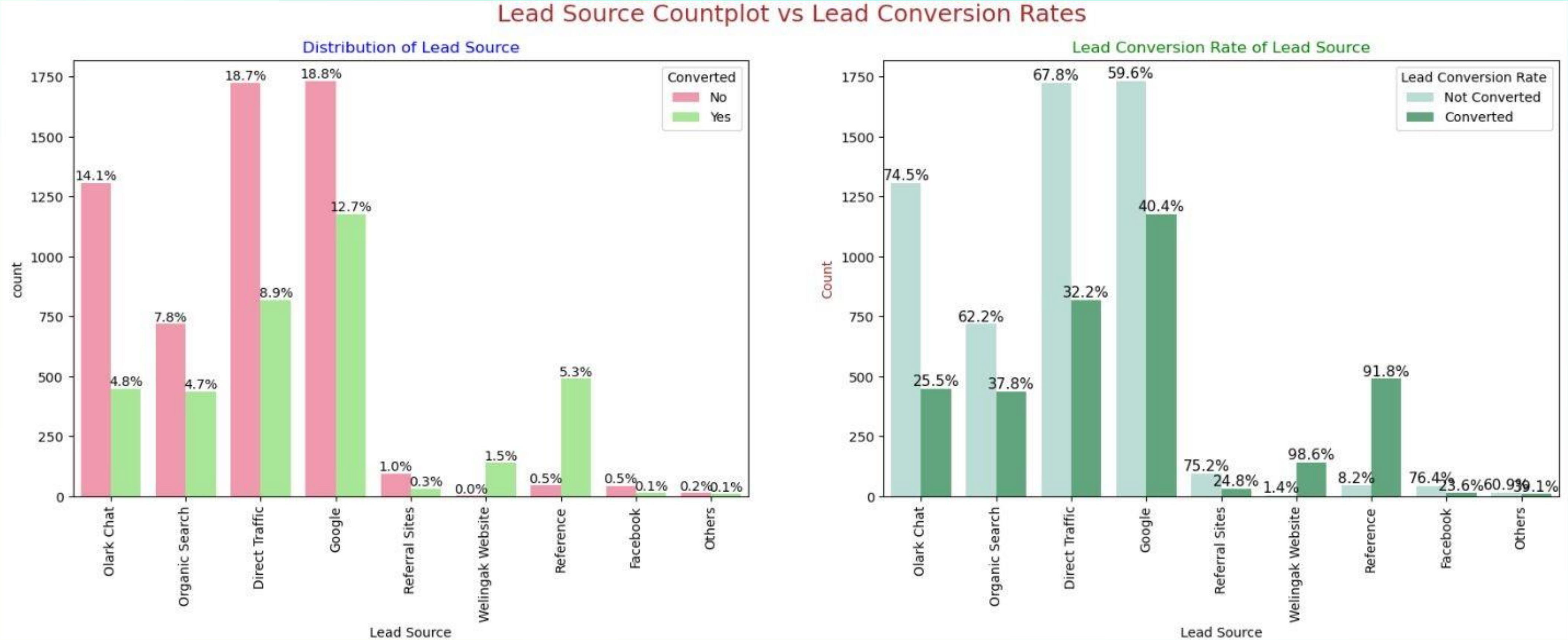
EDA – Bivariate Analysis for Categorical Variables



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.

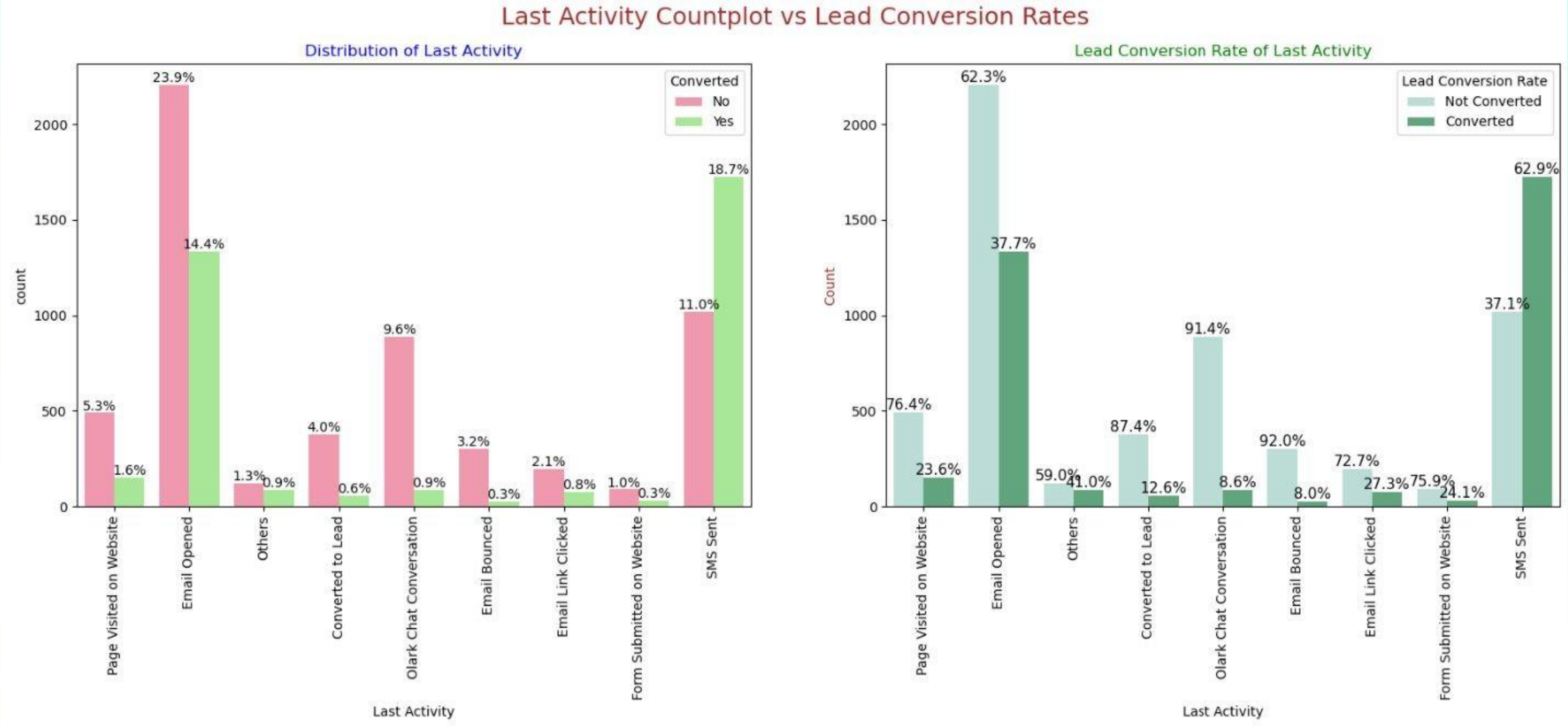
EDA – Bivariate Analysis for Categorical Variables



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.

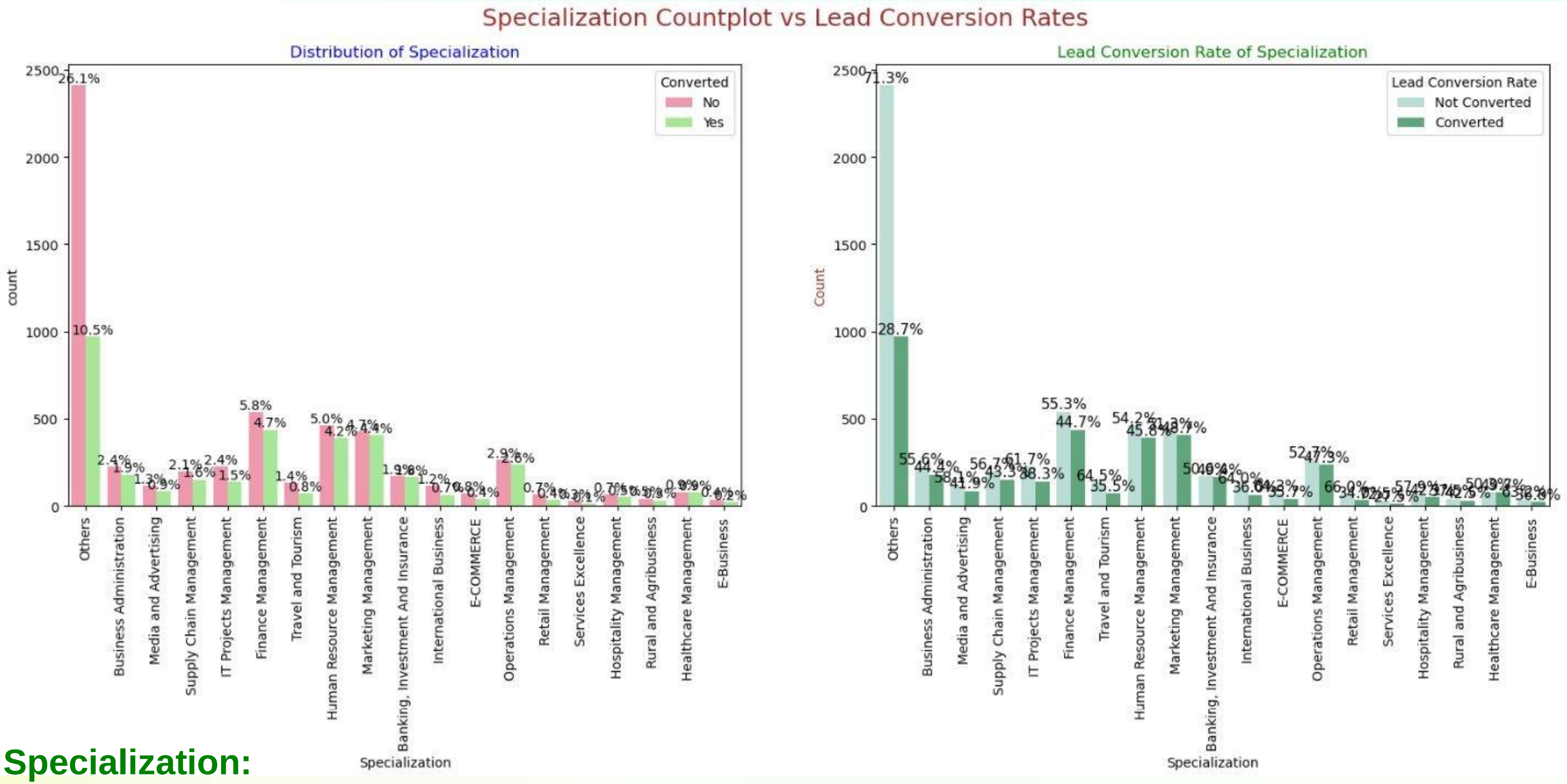
EDA – Bivariate Analysis for Categorical Variables



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.**

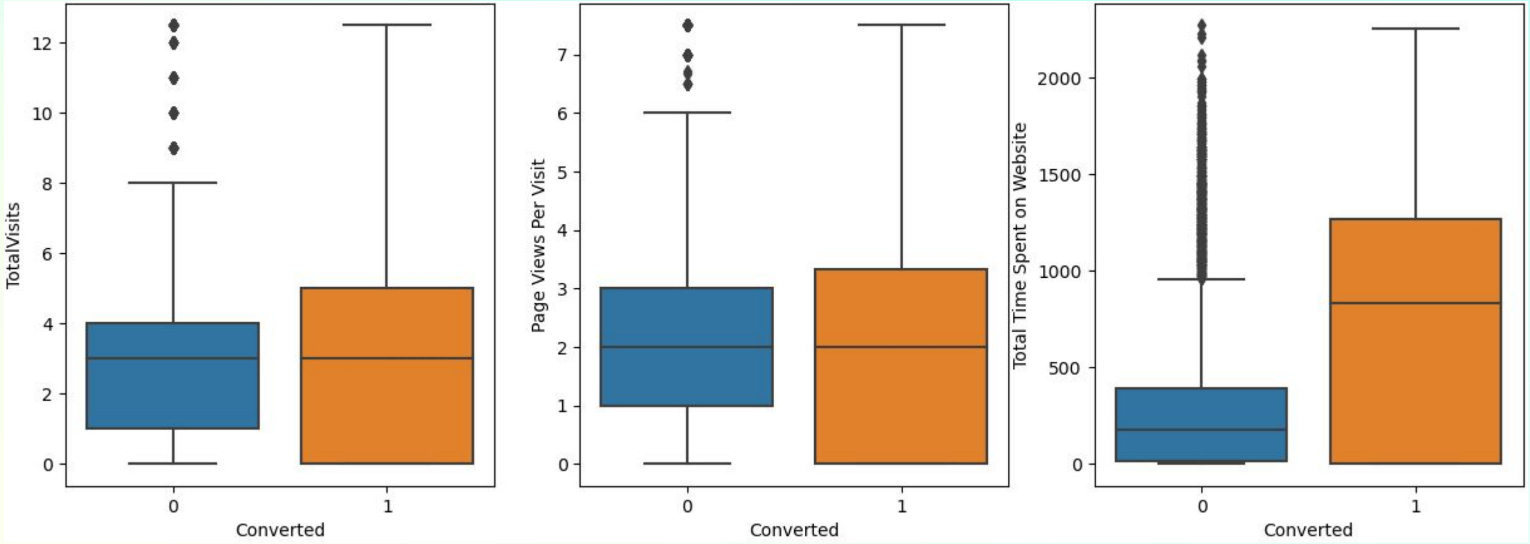
EDA – Bivariate Analysis for Categorical Variables

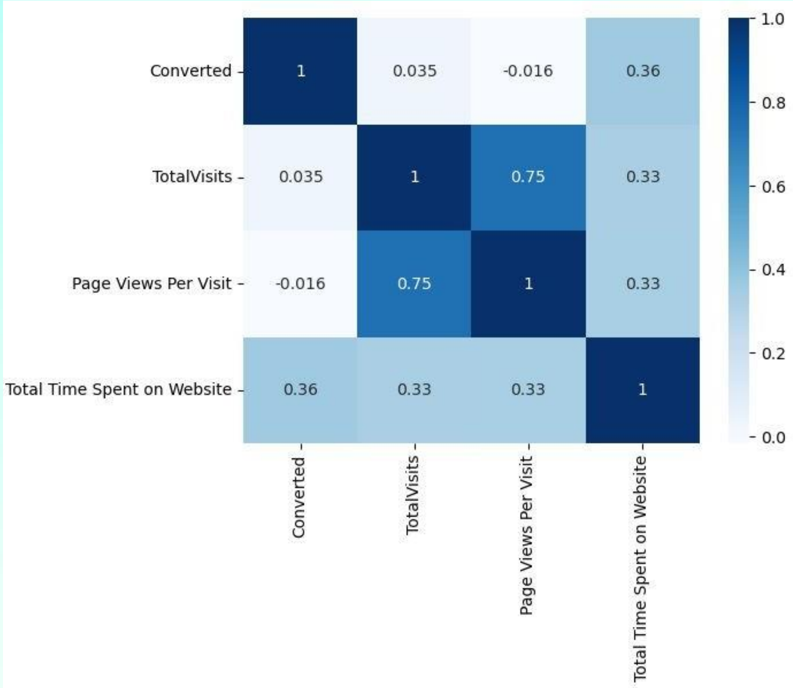


Specialization:

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

EDA – Bivariate Analysis for Numerical Variables





- Past Leads who **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.

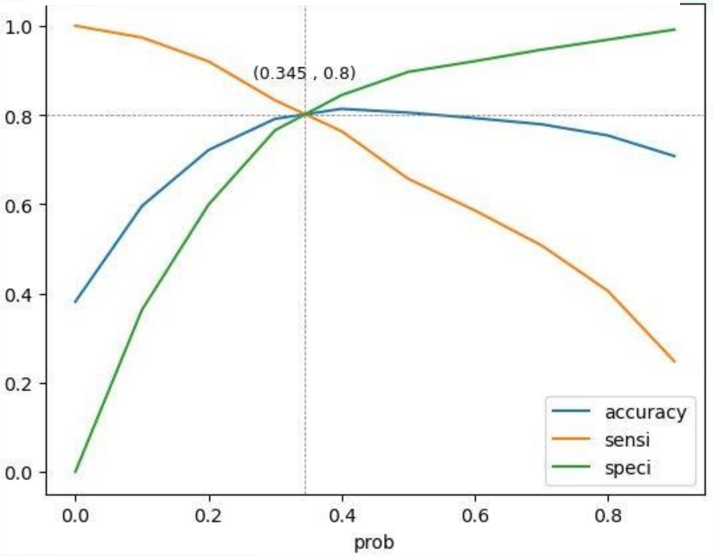
Model Evaluation

Train Data Set

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

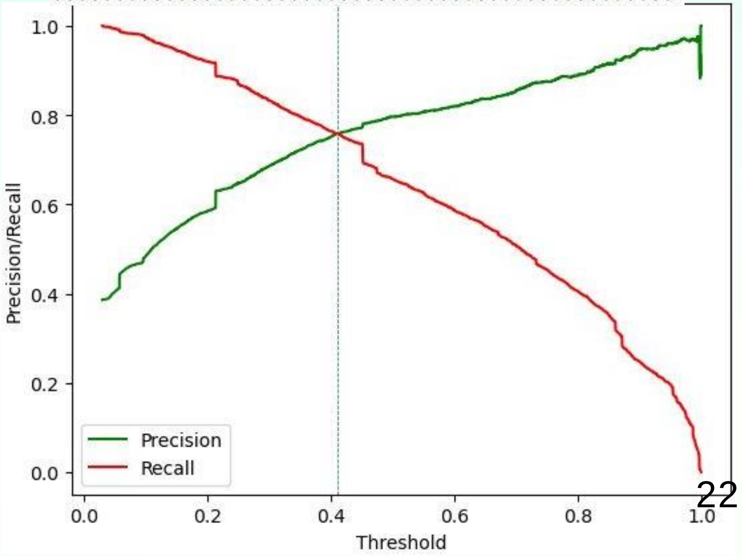
Confusion Matrix & Evaluation Metrics with 0.345 as cutoff

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

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

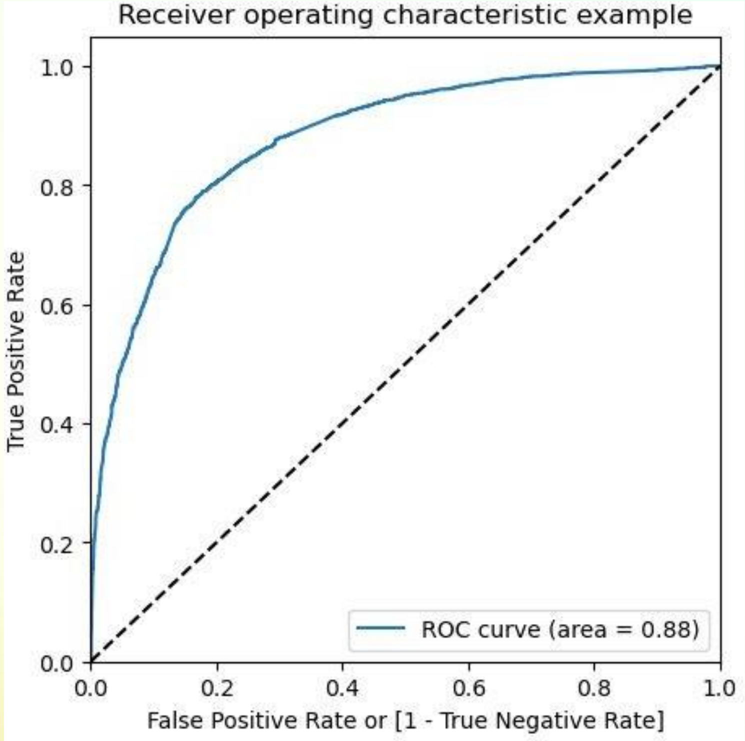
```
**************************************************

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

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



Model Evaluation

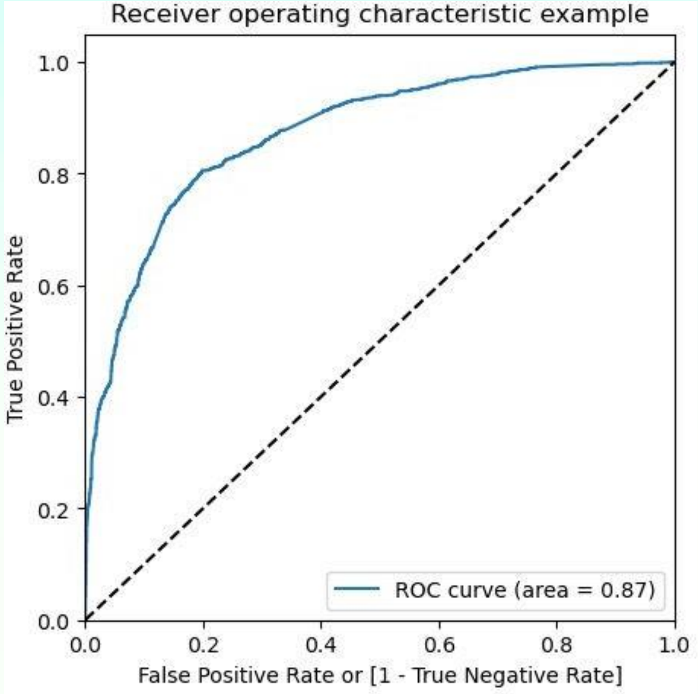
ROC Curve - Train Data Set

- 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.

Recommendation based on Final Model

- 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

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 **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!