

# 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 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.

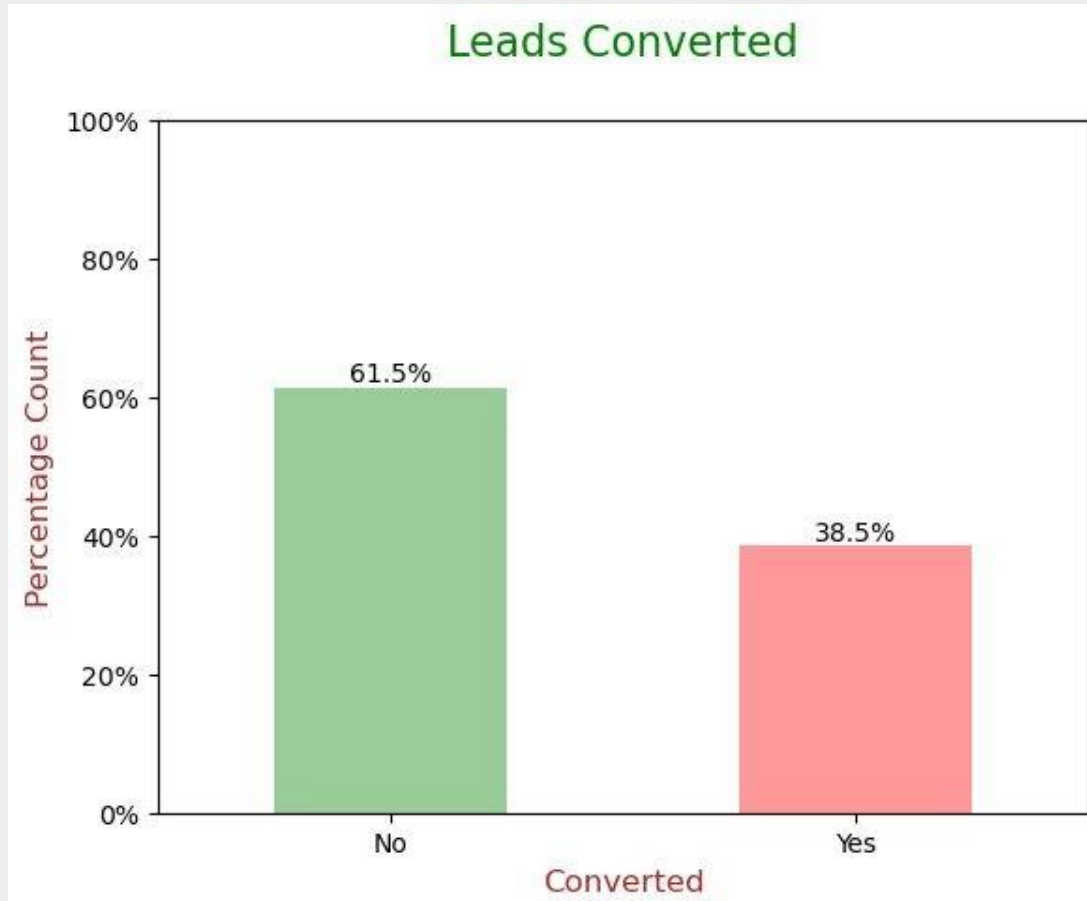
# Data Cleaning

- 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

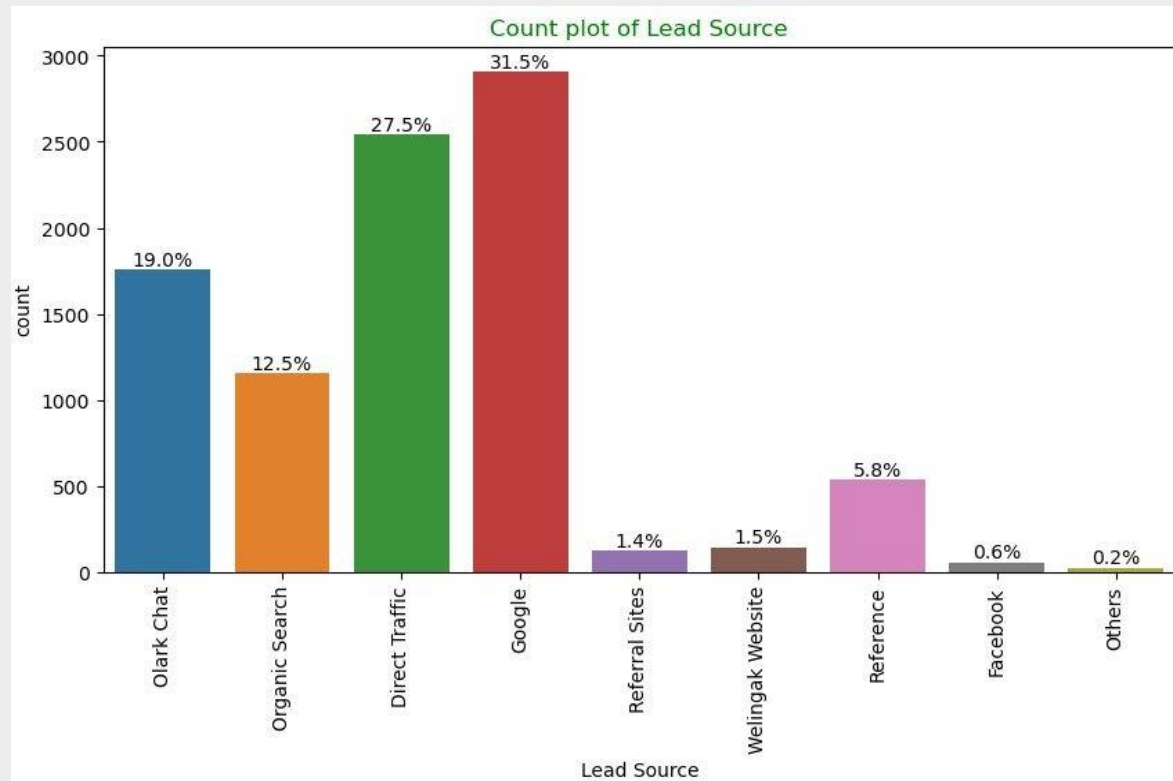
- Data is imbalanced while analyzing target variable.



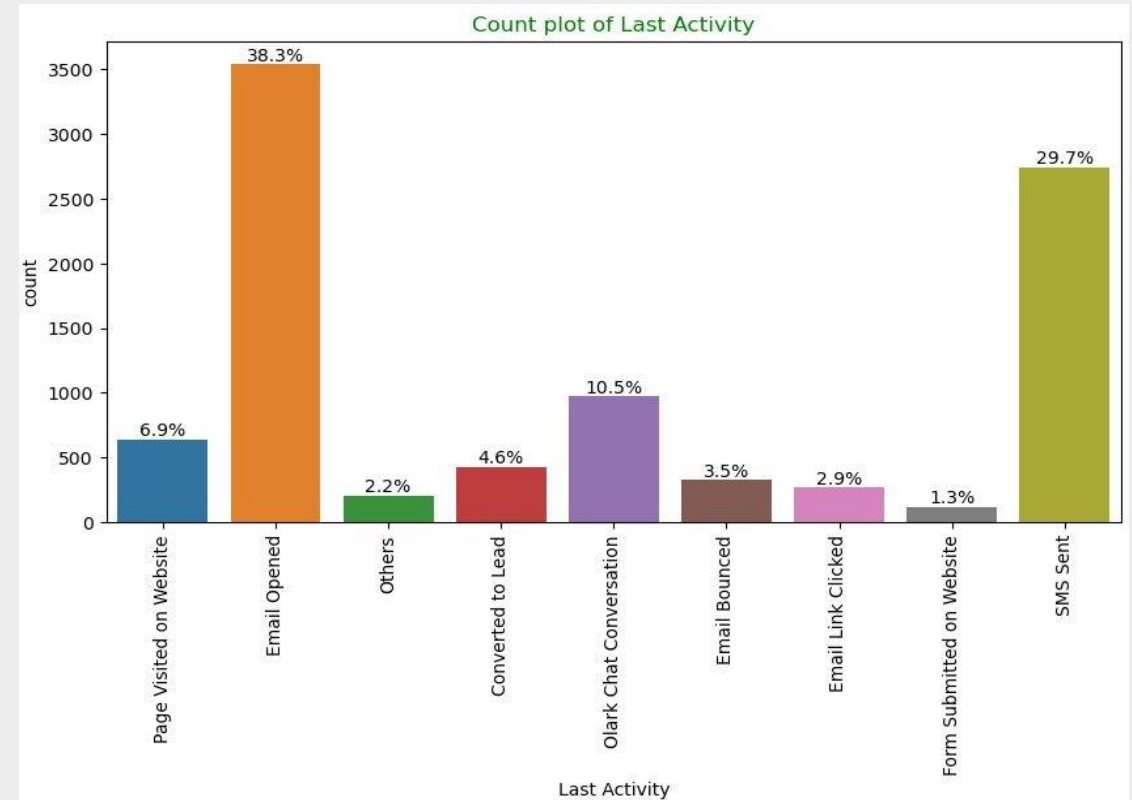
- Conversion rate is of 38.5%, meaning only 38.5% of the people have converted to leads.(Minority)
- While 61.5% of the people didn't convert to leads. (Majority)

# EDA

## ● Univariate Analysis - Categorical Variables



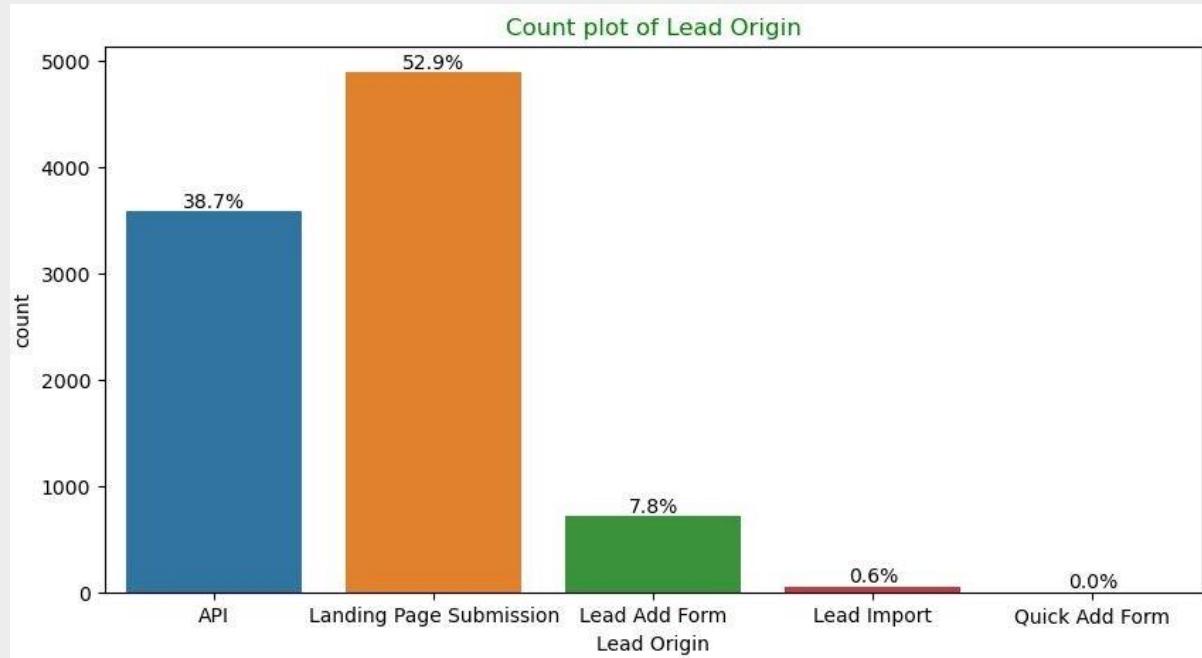
- **Lead Source:** 58% Lead source is from Google & Direct Traffic combined.



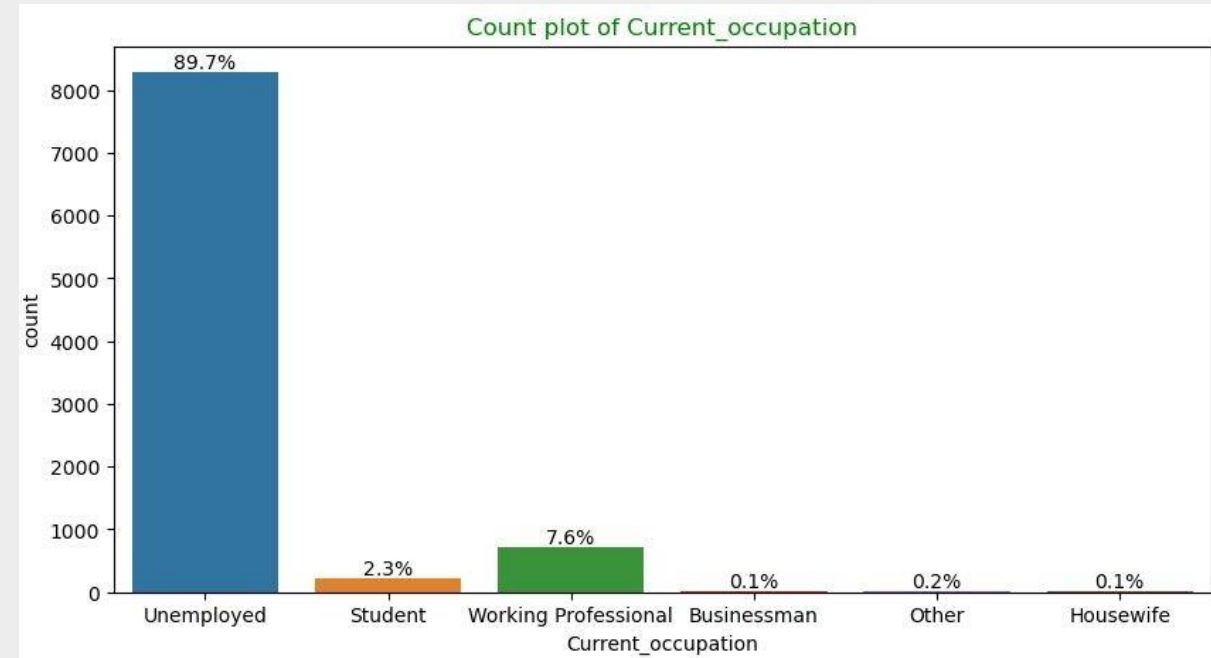
- **Last Activity:** 68% of customers contribution in SMS Sent & Email Opened activities.

# EDA

## ● Univariate Analysis – Categorical Variables

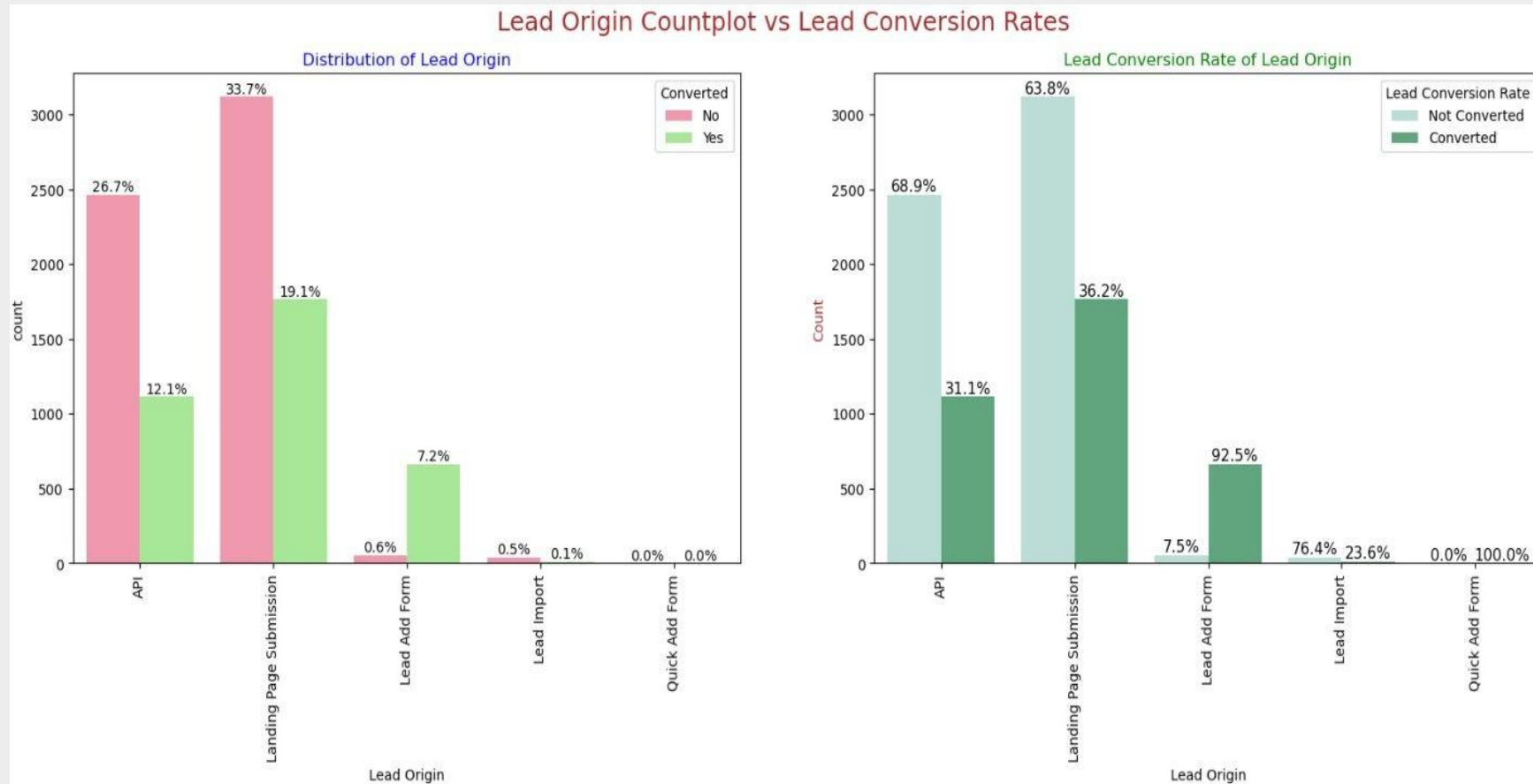


- **Lead Origin:** "Landing Page Submission" identified 53% of customers, "API" identified 39%.



- **Current\_occupation:** It has 90% of the customers as Unemployed.

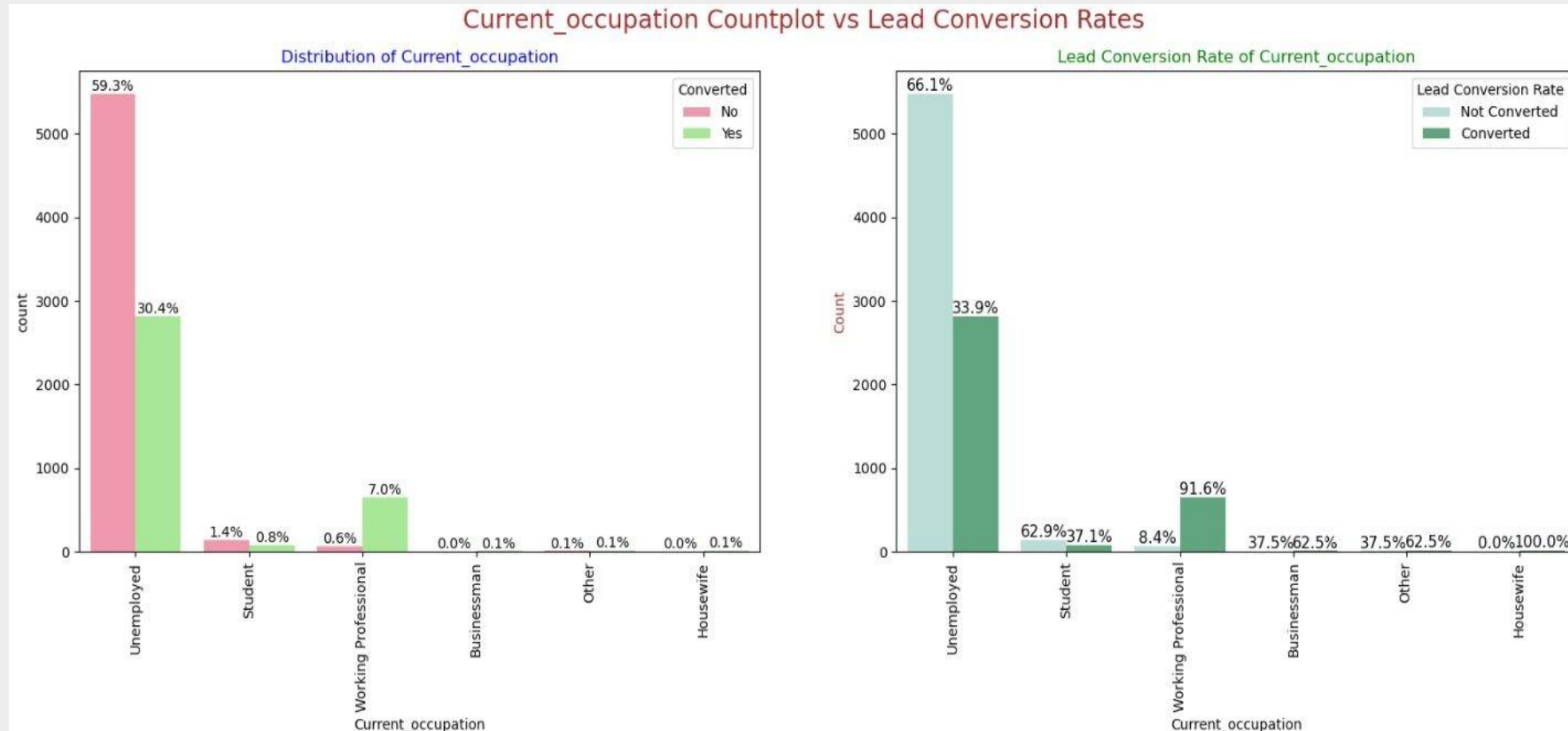
# EDA - Bivariate Analysis for Categorical Variables



## 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%**.

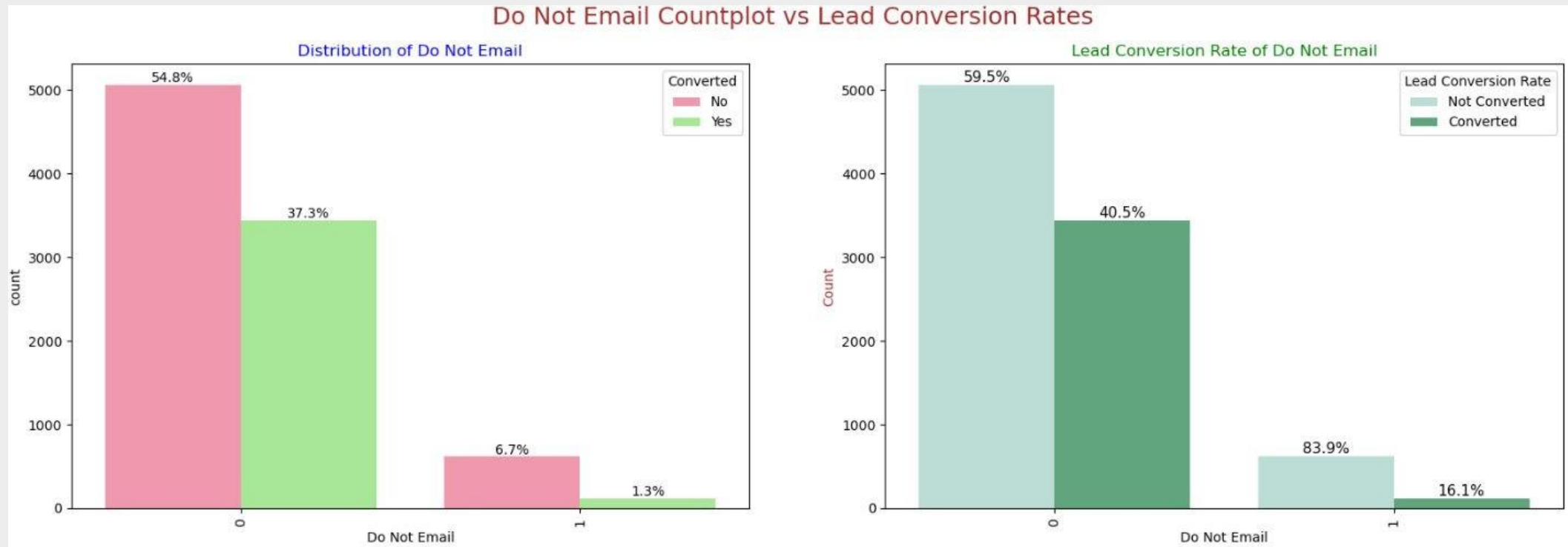
# EDA - Bivariate Analysis for Categorical Variables



## 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)**.

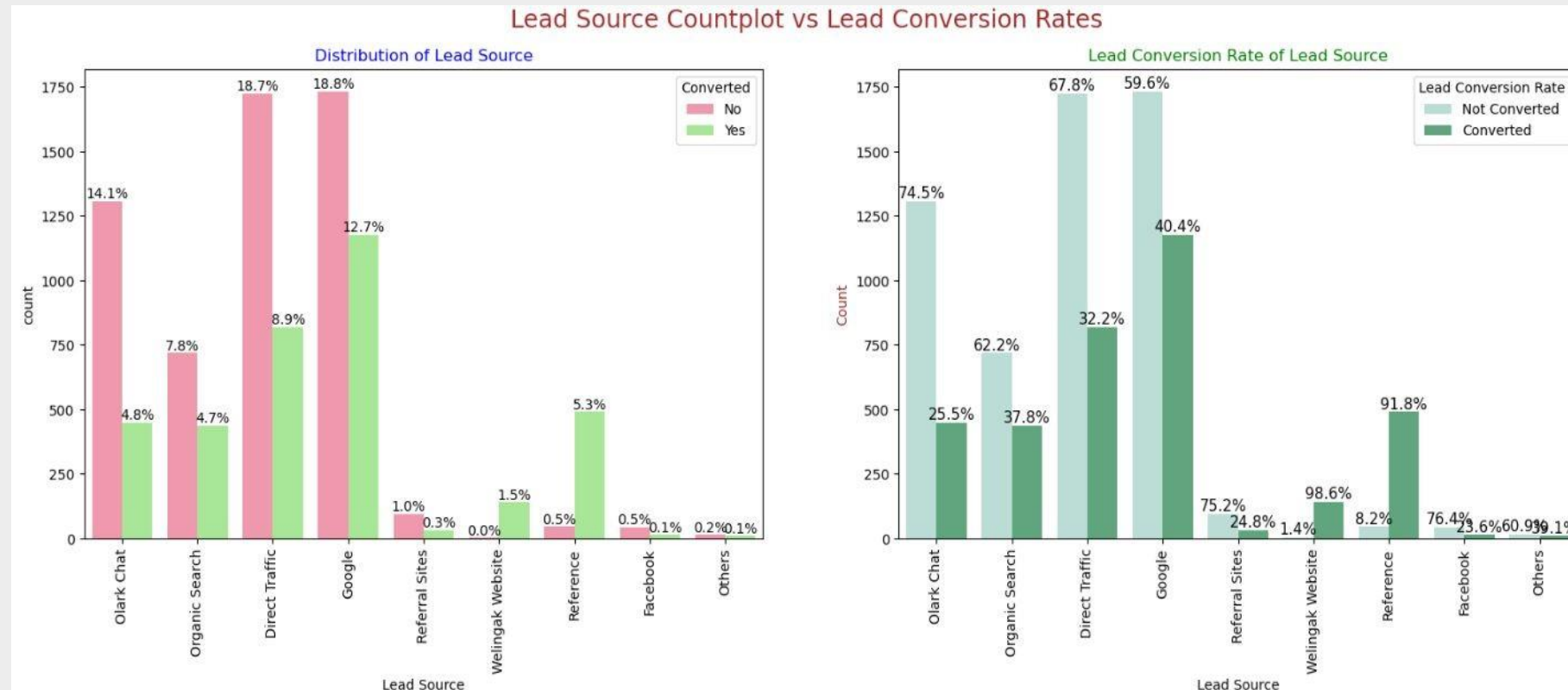
# EDA - Bivariate Analysis for Categorical Variables



## 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.

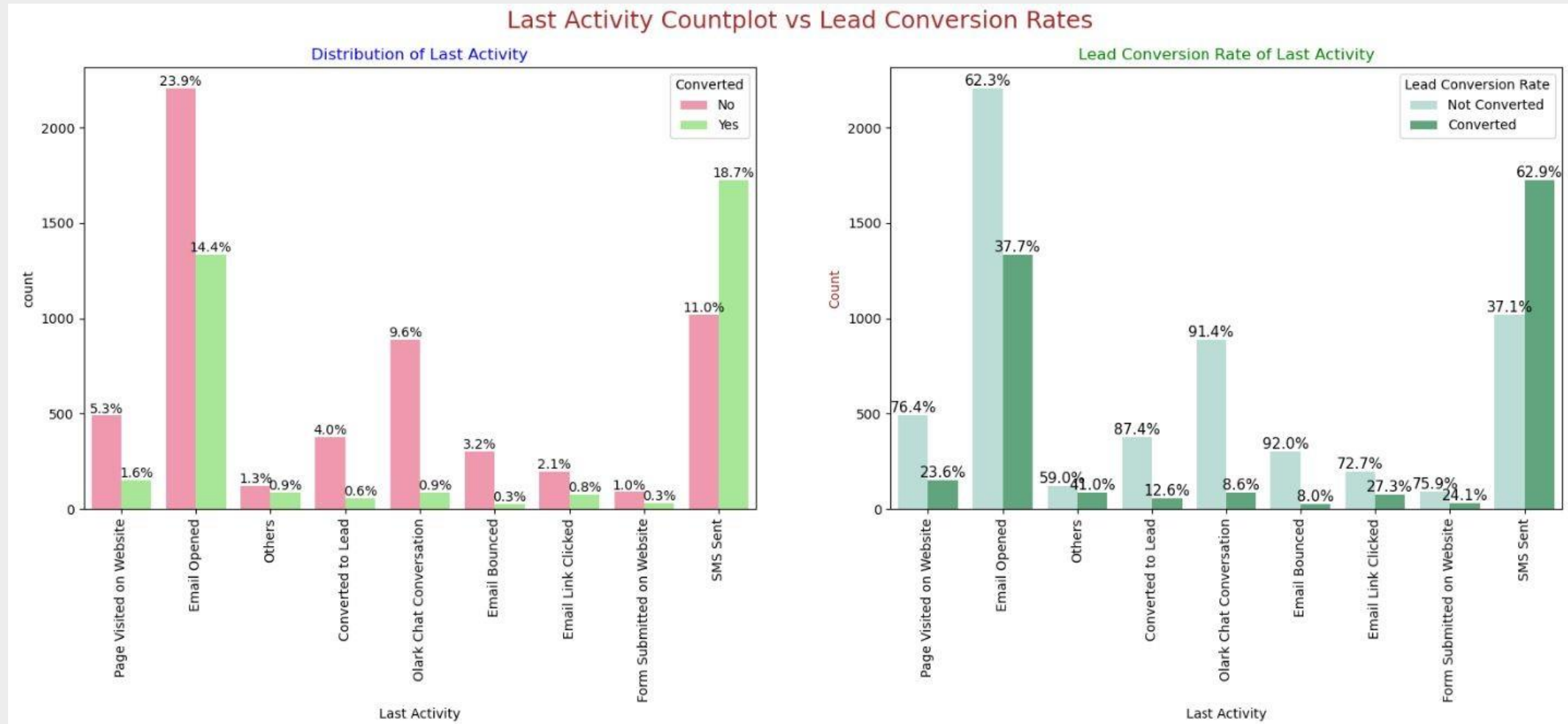
# EDA - Bivariate Analysis for Categorical Variables



## 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

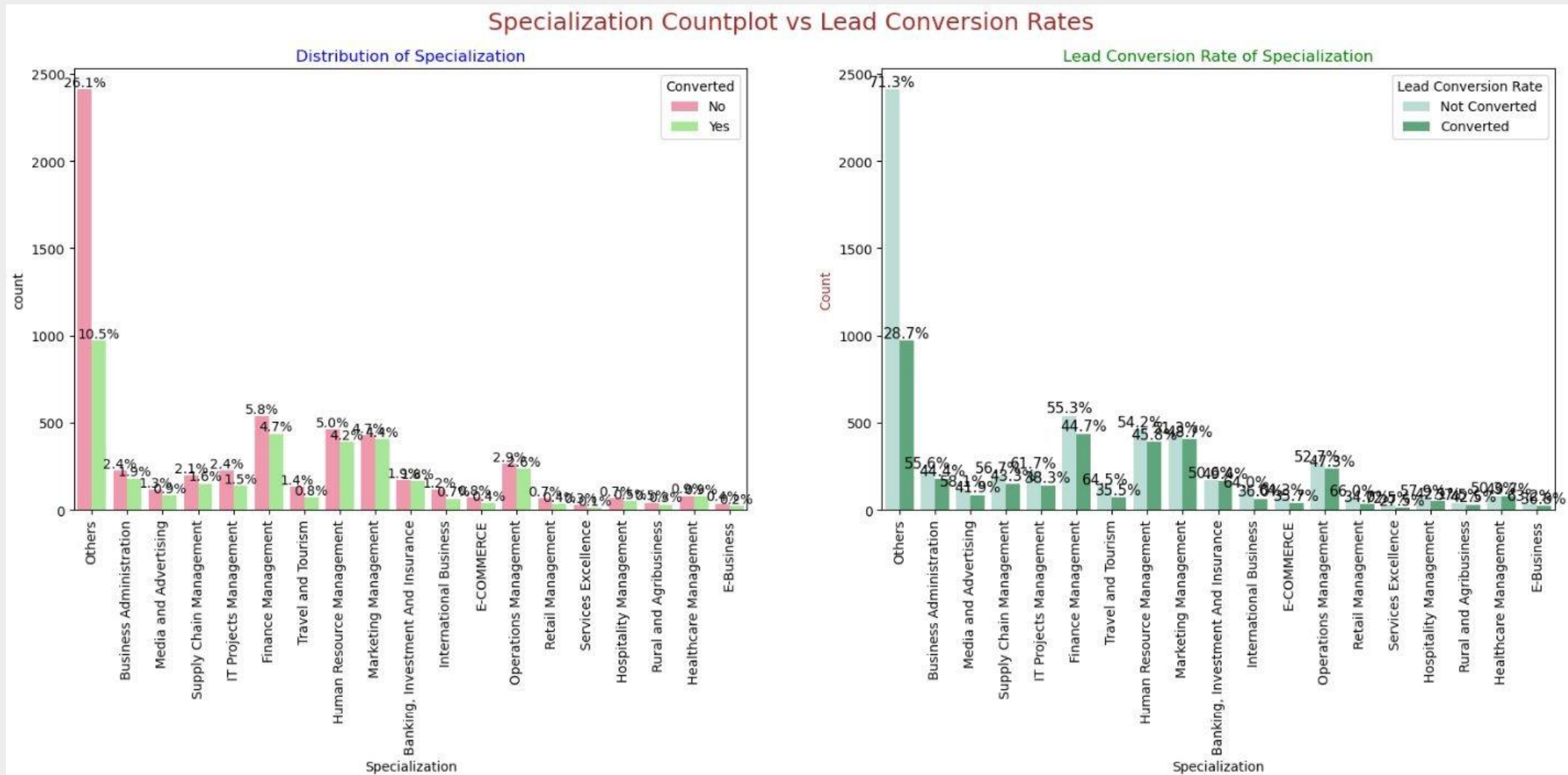


## Last Activity:

- **'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**.



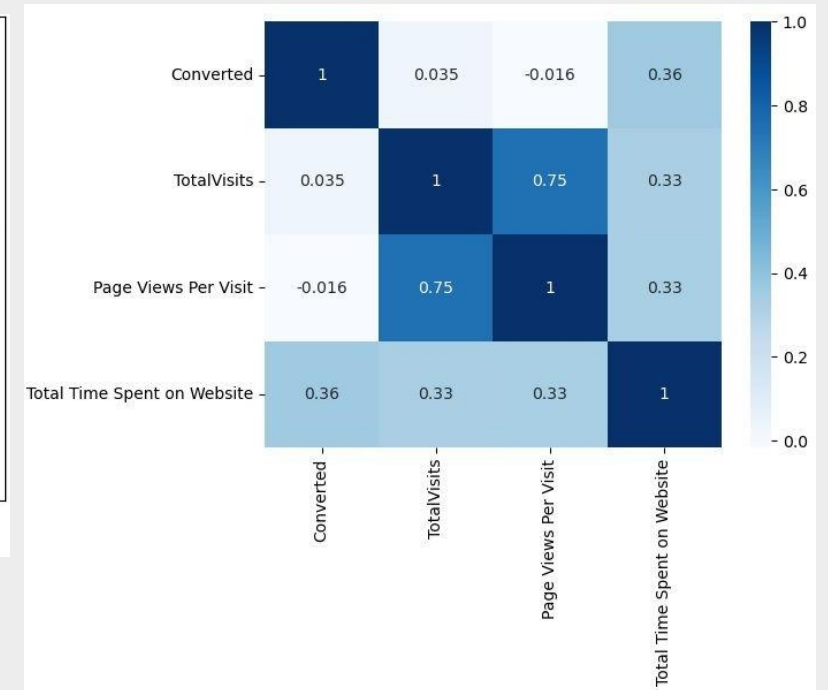
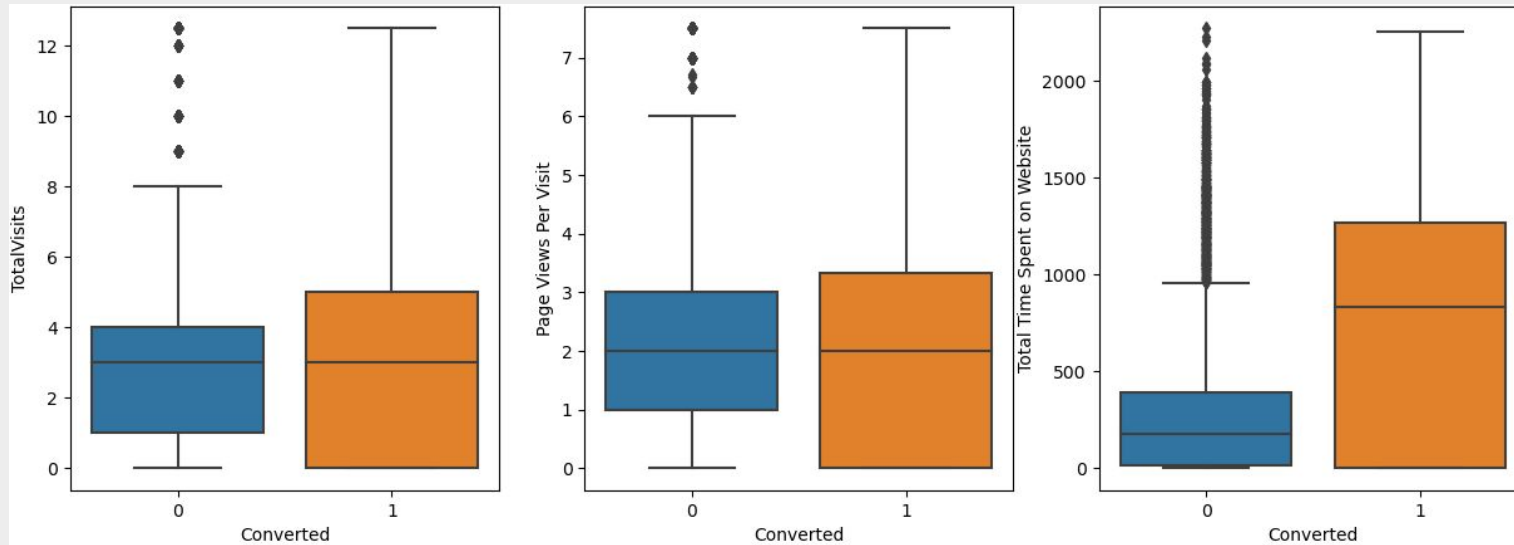
# EDA - Bivariate Analysis for Categorical Variables



## 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

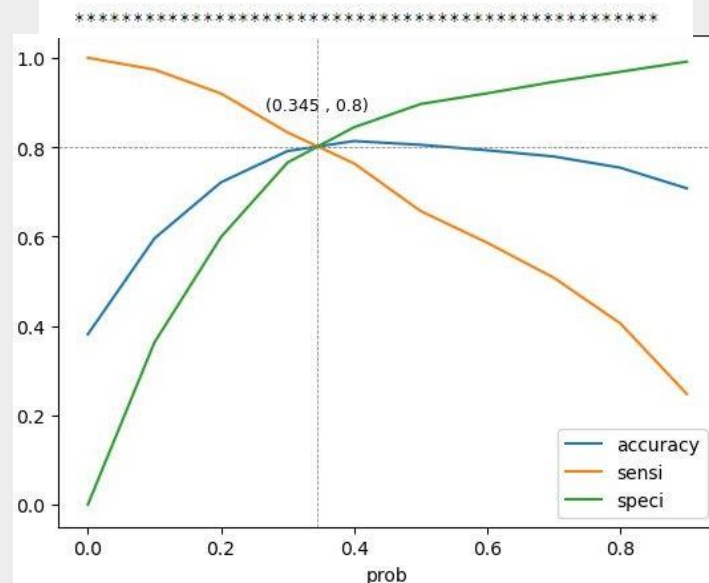
## Train Data Set

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]]  
*****
```

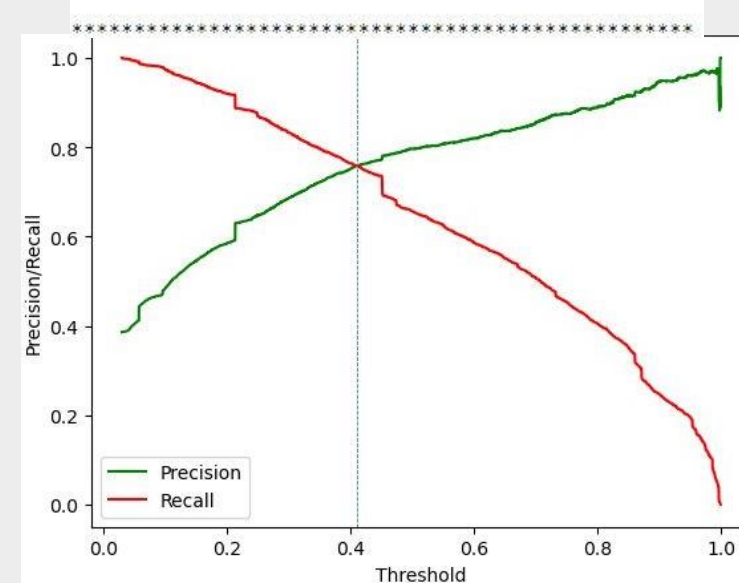
```
True Negative      : 3230  
True Positive     : 1974  
False Negative    : 492  
False Positive    : 772  
Model Accuracy    : 0.8046  
Model Sensitivity  : 0.8005  
Model Specificity  : 0.8071  
Model Precision    : 0.7189  
Model Recall       : 0.8005  
Model True Positive Rate (TPR) : 0.8005 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



Confusion Matrix & Evaluation Metrics with 0.41 as cutoff

```
*****  
Confusion Matrix  
[[3406  596]  
 [ 596 1870]]  
*****
```

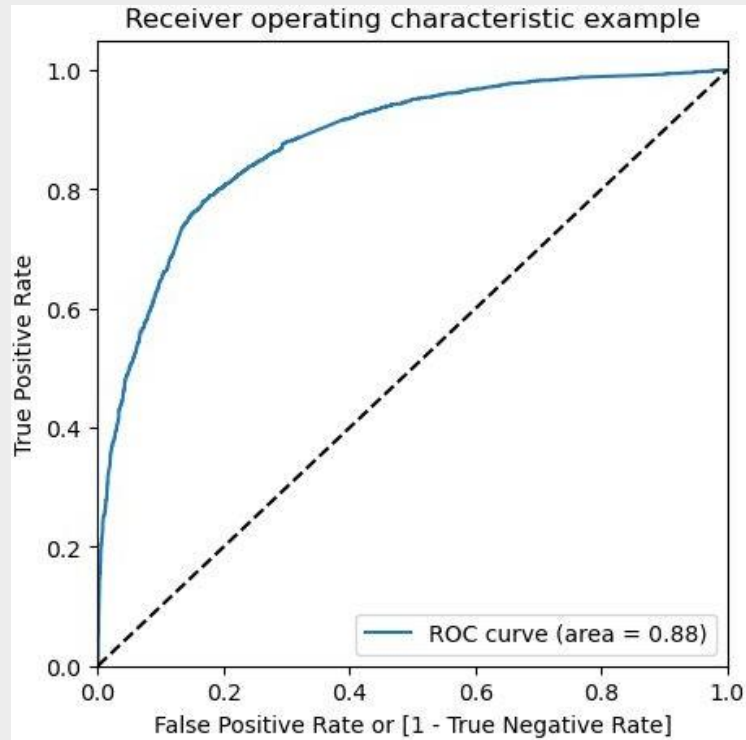
```
True Negative      : 3406  
True Positive     : 1870  
False Negative    : 596  
False Positive    : 596  
Model Accuracy    : 0.8157  
Model Sensitivity  : 0.7583  
Model Specificity  : 0.8511  
Model Precision    : 0.7583  
Model Recall       : 0.7583  
Model True Positive Rate (TPR) : 0.7583 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



# Model Evaluation

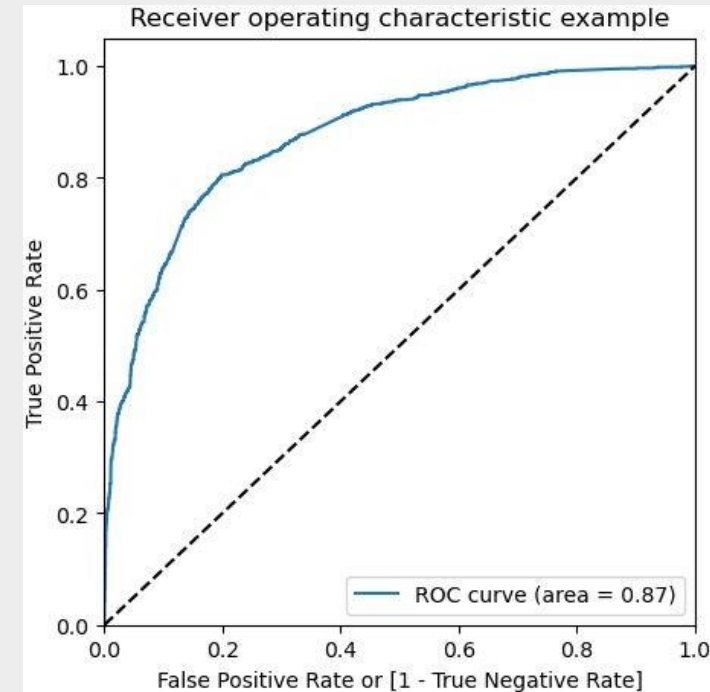
## ROC Curve - Train Data Set

- 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 Positive          : 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 Positive          : 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!**