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

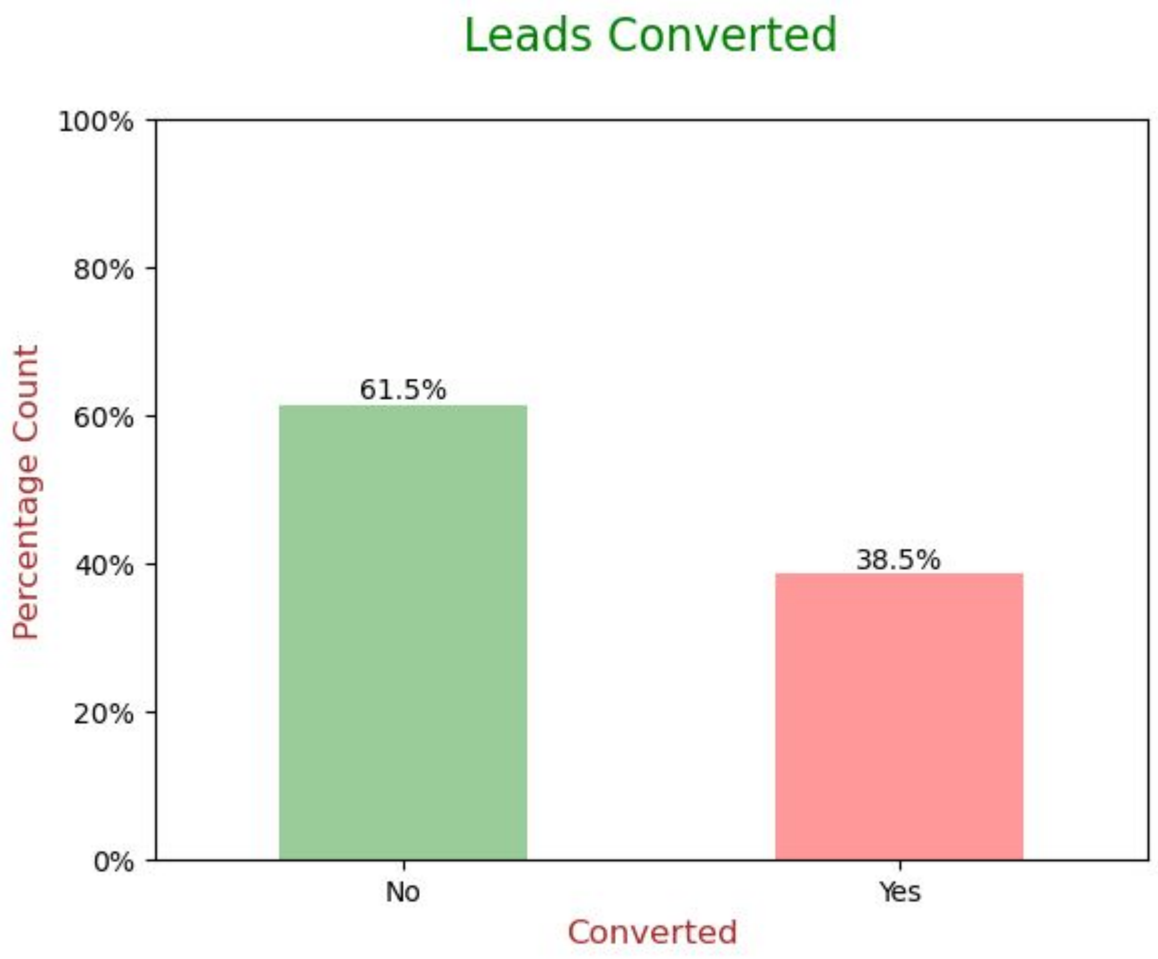
- **"Select"** level represents null values for some categorical variables, as customers did not choose any option from the list.
- Columns with over 40% null values were dropped.
- Missing values in categorical columns were handled based on value counts and certain considerations.
- Drop columns that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

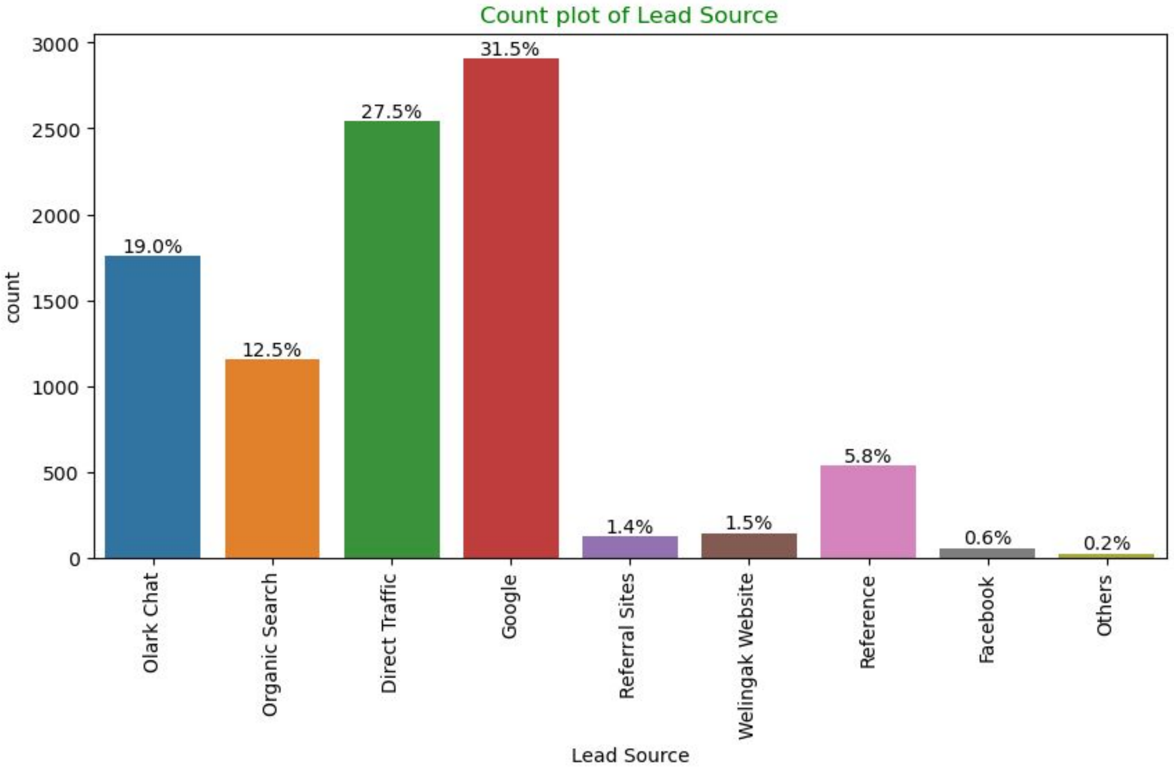


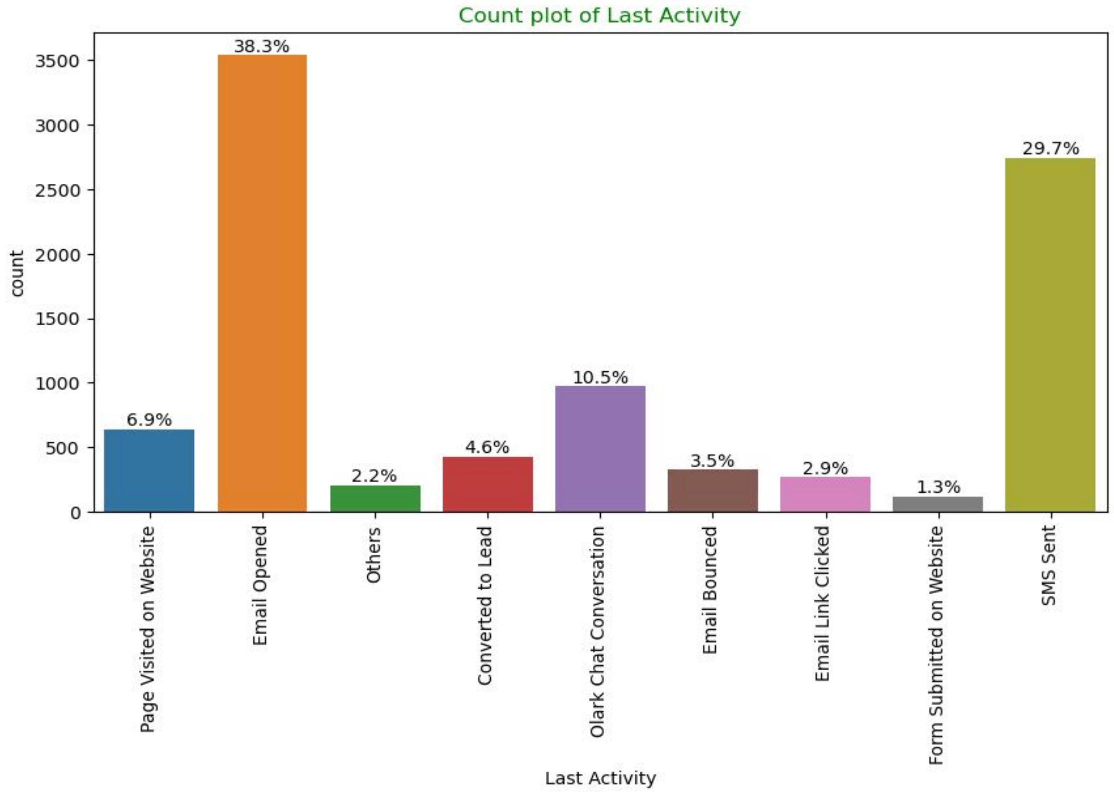
- Conversion rate is of 38.5%, meaning only 38.5% of the people have converted to leads.(Minority)

- While 61.5% of the people didn't convert to leads. (Majority)

EDA

- Univariate Analysis – Categorical Variables

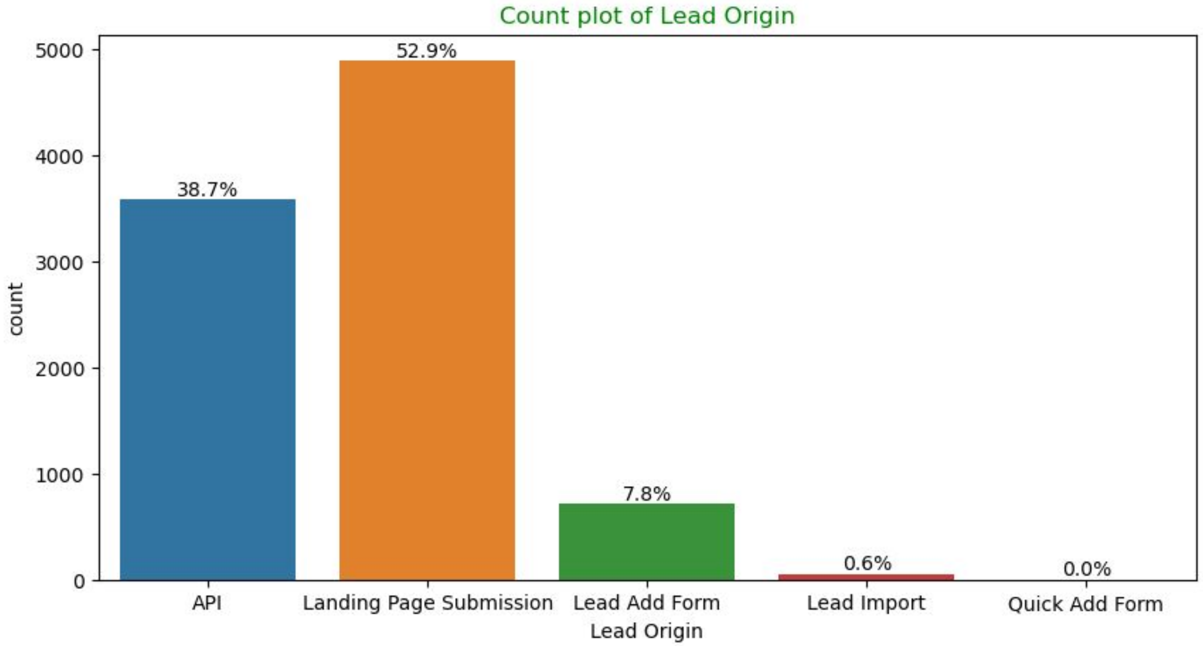


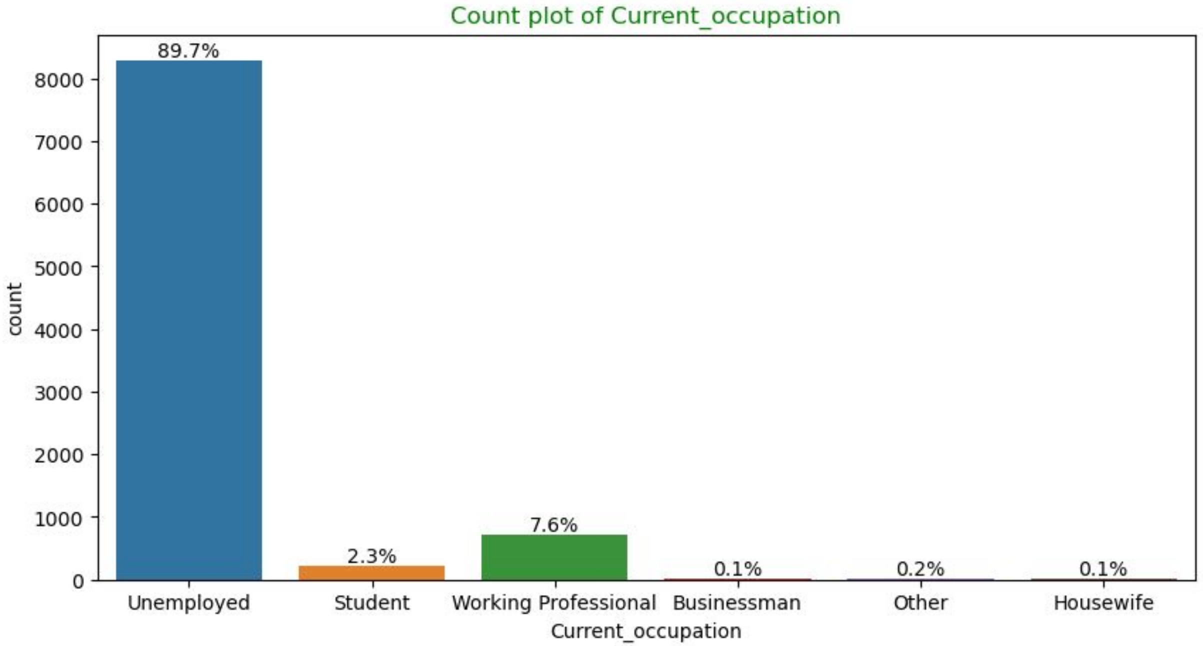


- **Lead Source:** 58% Lead source is from Google & Direct Traffic combined.
- **Last Activity:** 68% of customers contribution in SMS Sent & Email Opened activities.

EDA

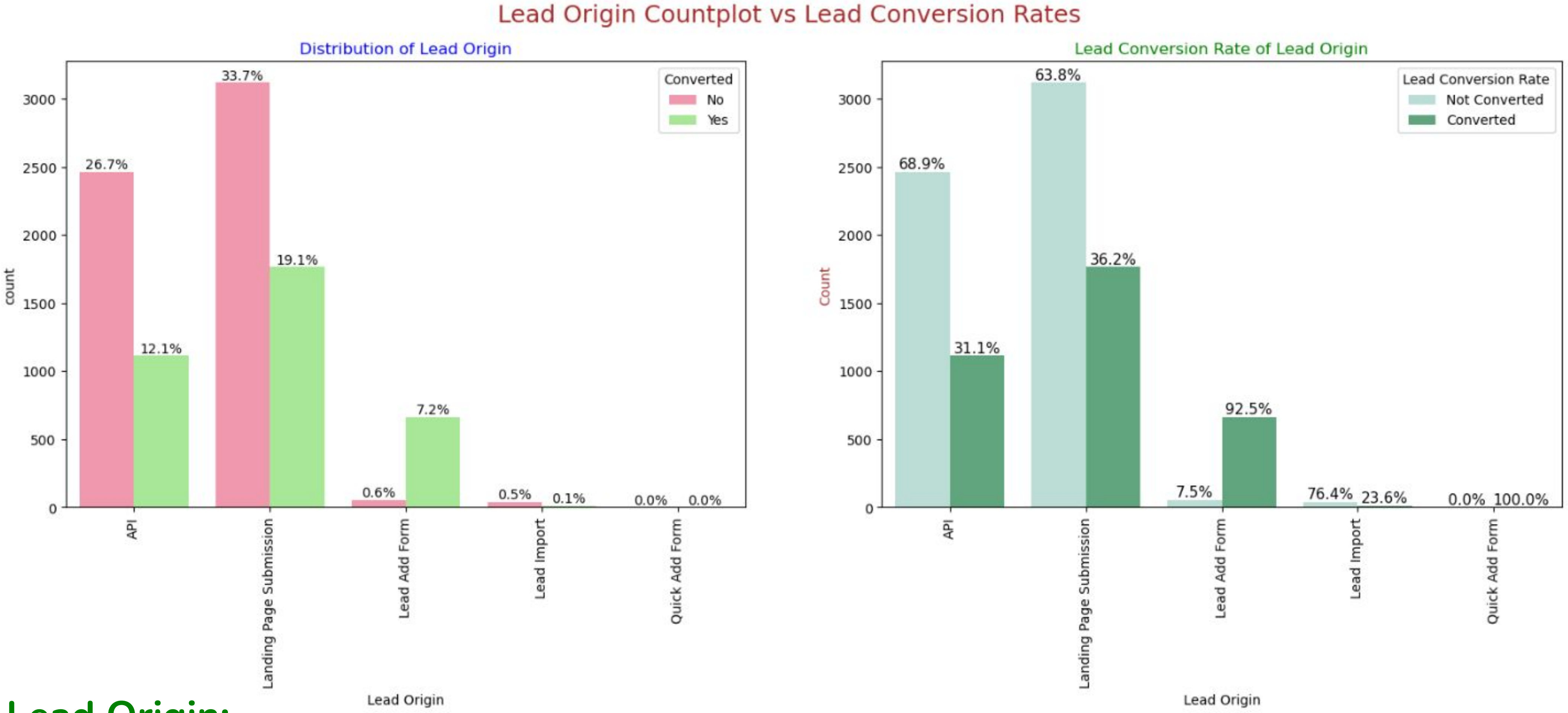
- Univariate Analysis – Categorical Variables





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

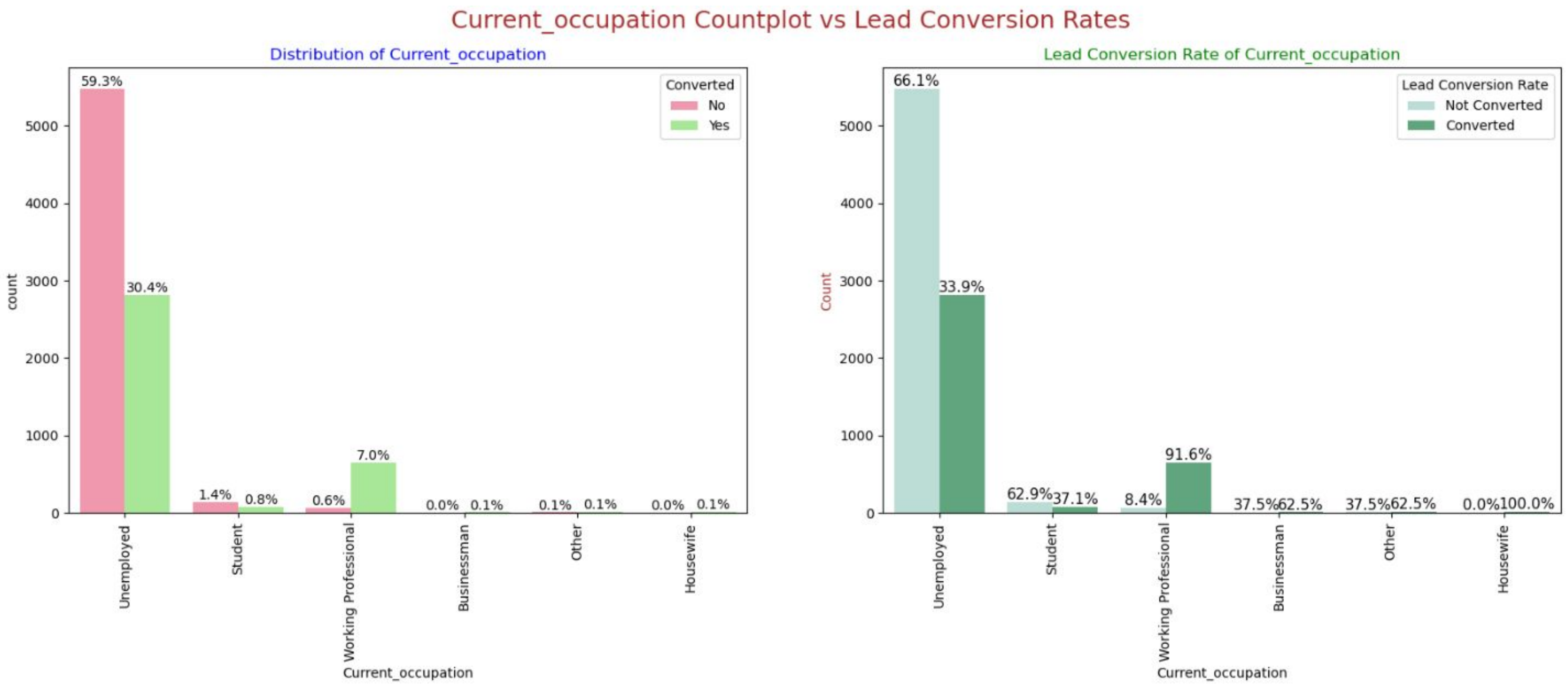
EDA – Bivariate Analysis for Categorical Variables



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%**.

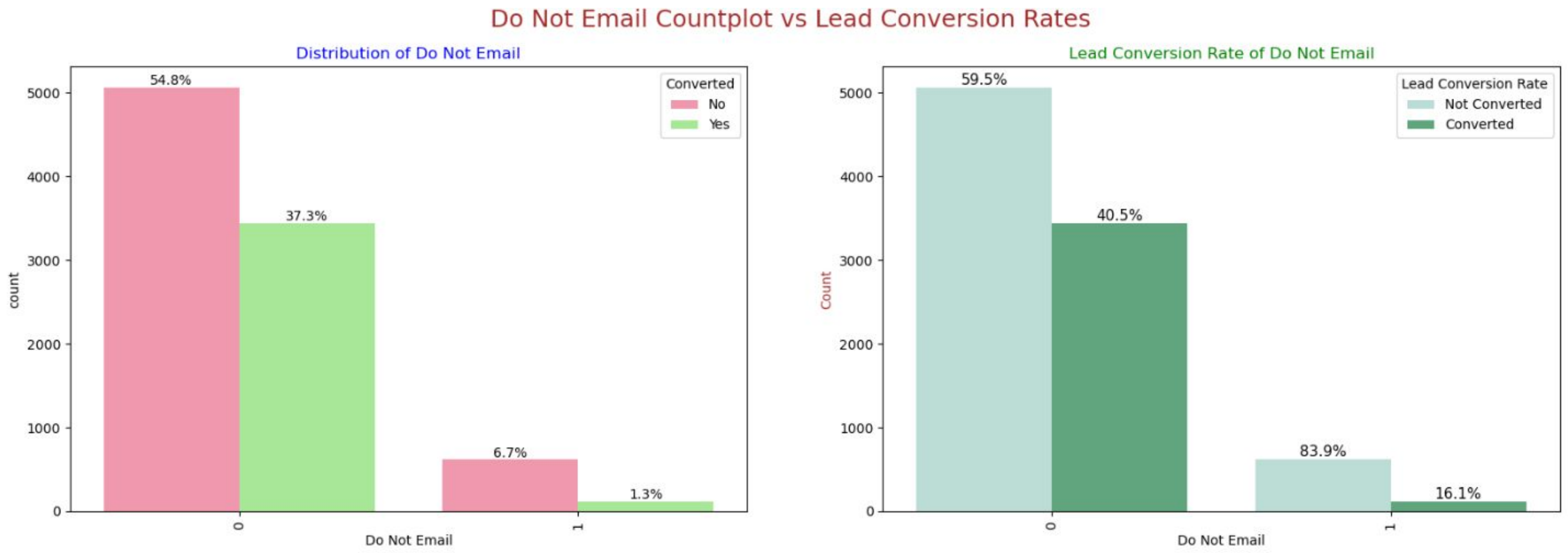
EDA – Bivariate Analysis for Categorical Variables



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)**.

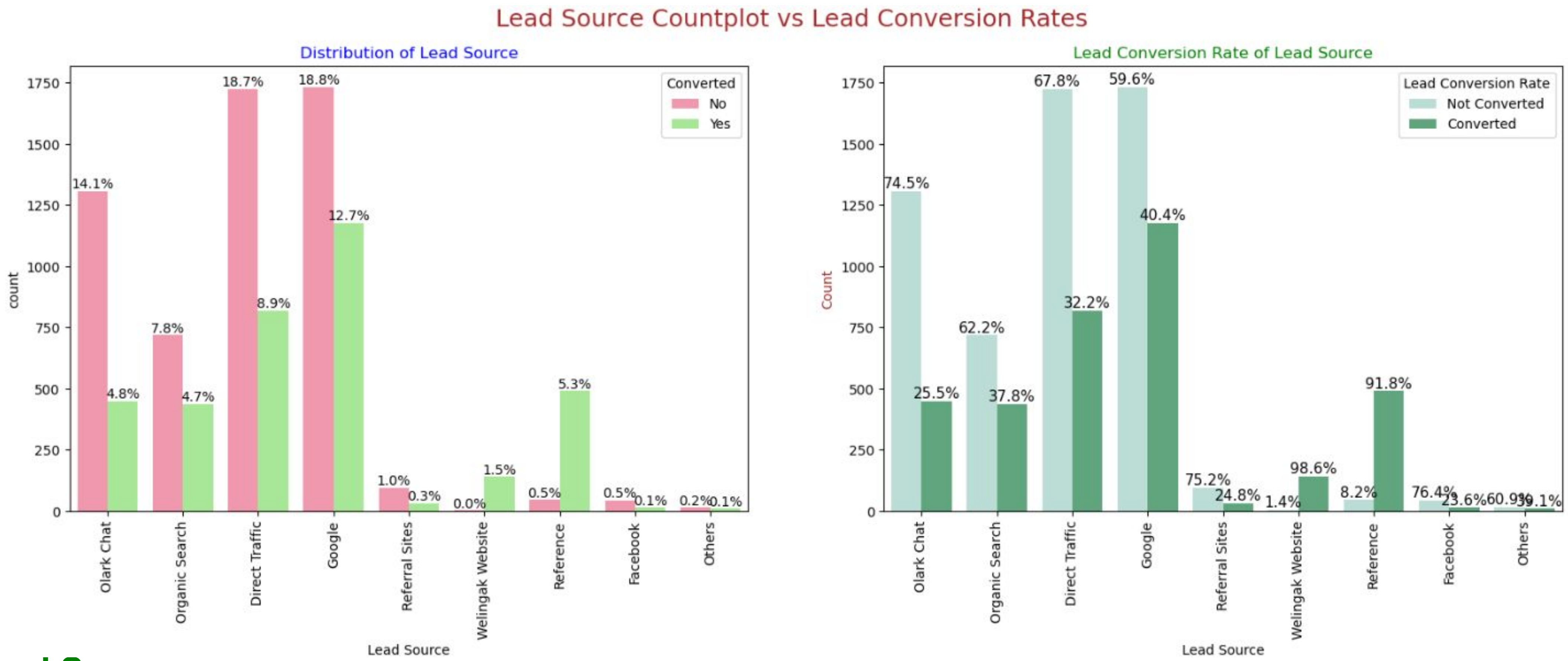
EDA – Bivariate Analysis for Categorical Variables



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.

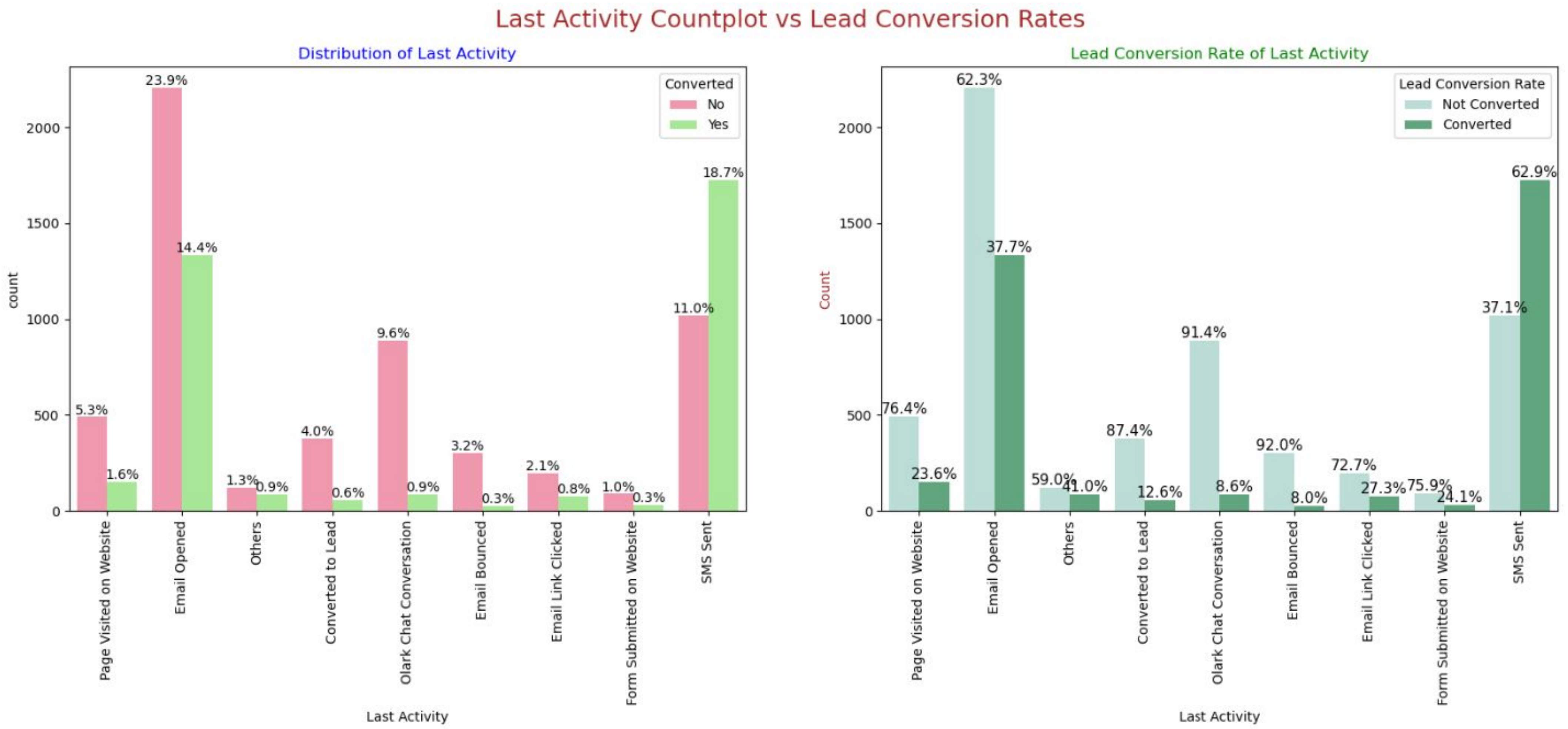
EDA – Bivariate Analysis for Categorical Variables



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.

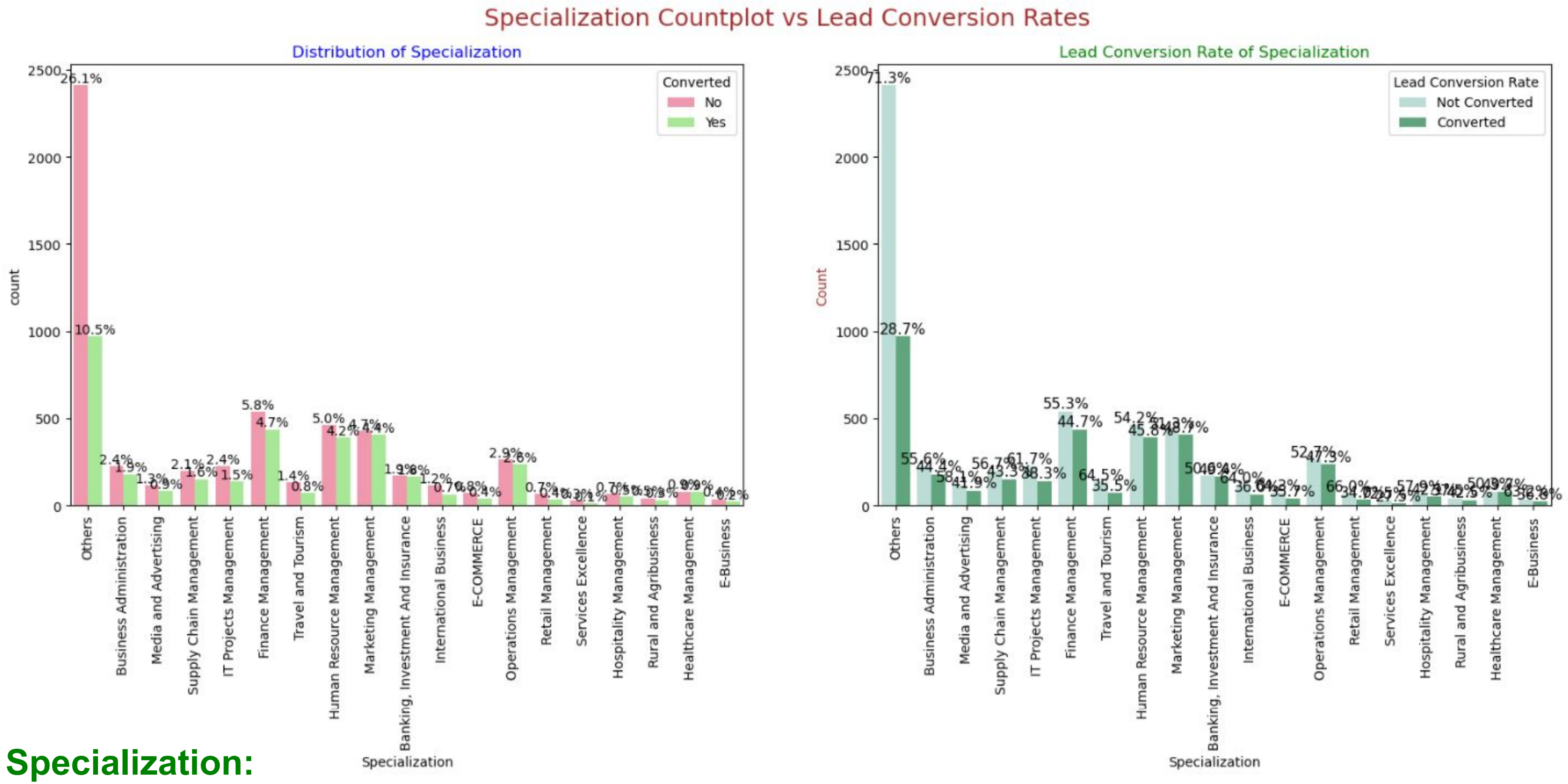
EDA – Bivariate Analysis for Categorical Variables



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.**

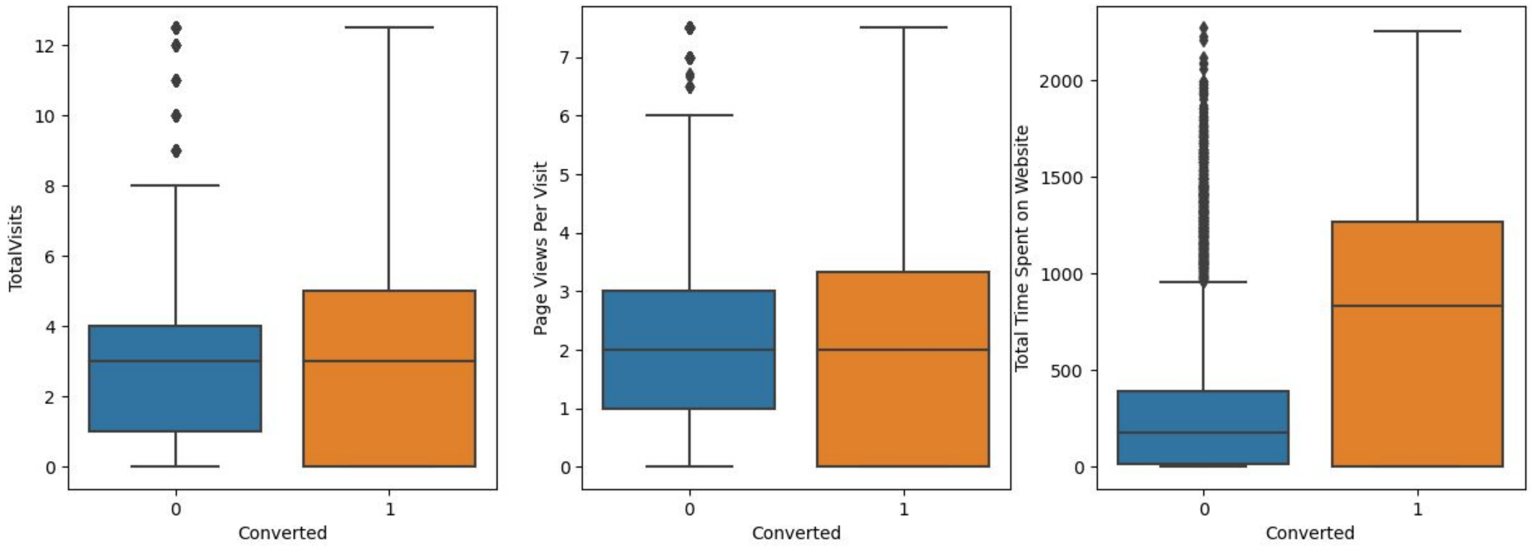
EDA – Bivariate Analysis for Categorical Variables

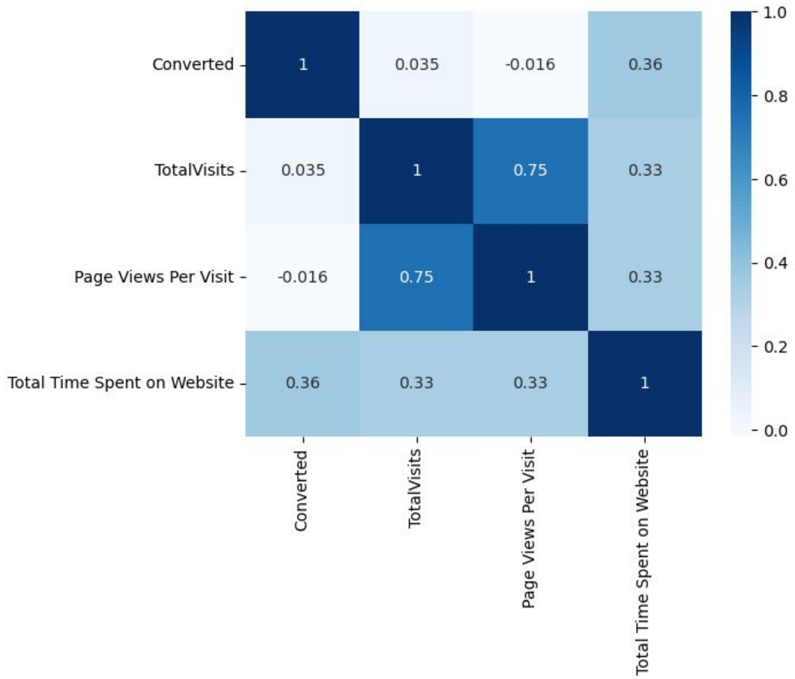


Specialization:

- 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 – 20 columns

Model Building

- Manual Feature Reduction process was used to build models by dropping variables with p – value greater than 0.05.
- Model 7 looks stable after seven iteration with:
  - significant p-values within the threshold (p-values < 0.05) and
  - No sign of multicollinearity with VIFs less than 5
- Henc **logm7** will be our final model, and we will use it for Model Evaluation which further will be used to make predictions.

Model Evaluation

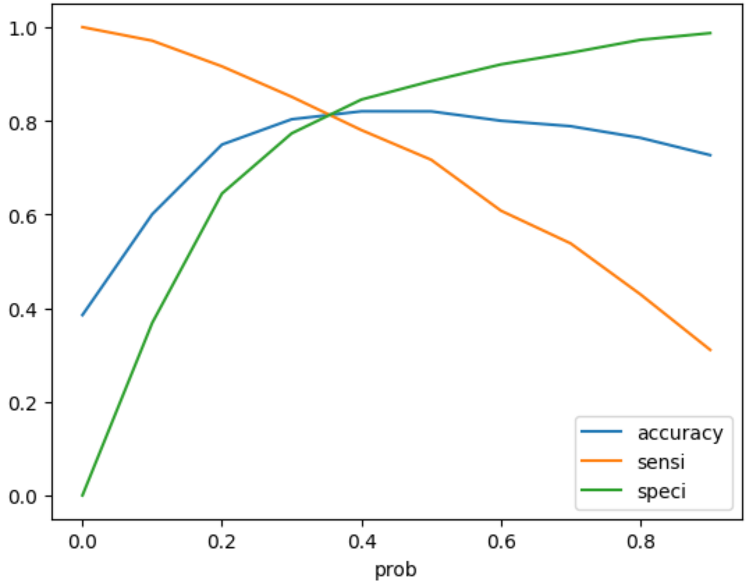
Train Data Set

Confusion Matrix & Evaluation Metrics
with 0.35 as cutoff

It was decided to go ahead with 0.35 as cutoff after checking evaluation metrics coming from both plots

Dep. Variable:	Converted	No. Observations:	6351
Model:	GLM	Df Residuals:	6335
Model Family:	Binomial	Df Model:	15
Link Function:	Logit	Scale:	1.0000
Method:	IRLS	Log-Likelihood:	-2580.7
Date:	Tue, 23 May 2023	Deviance:	5161.3
Time:	19:06:36	Pearson chi2:	6.36e+03
No. Iterations:	7	Pseudo R-squ. (CS):	0.4057
Covariance Type:	nonrobust		

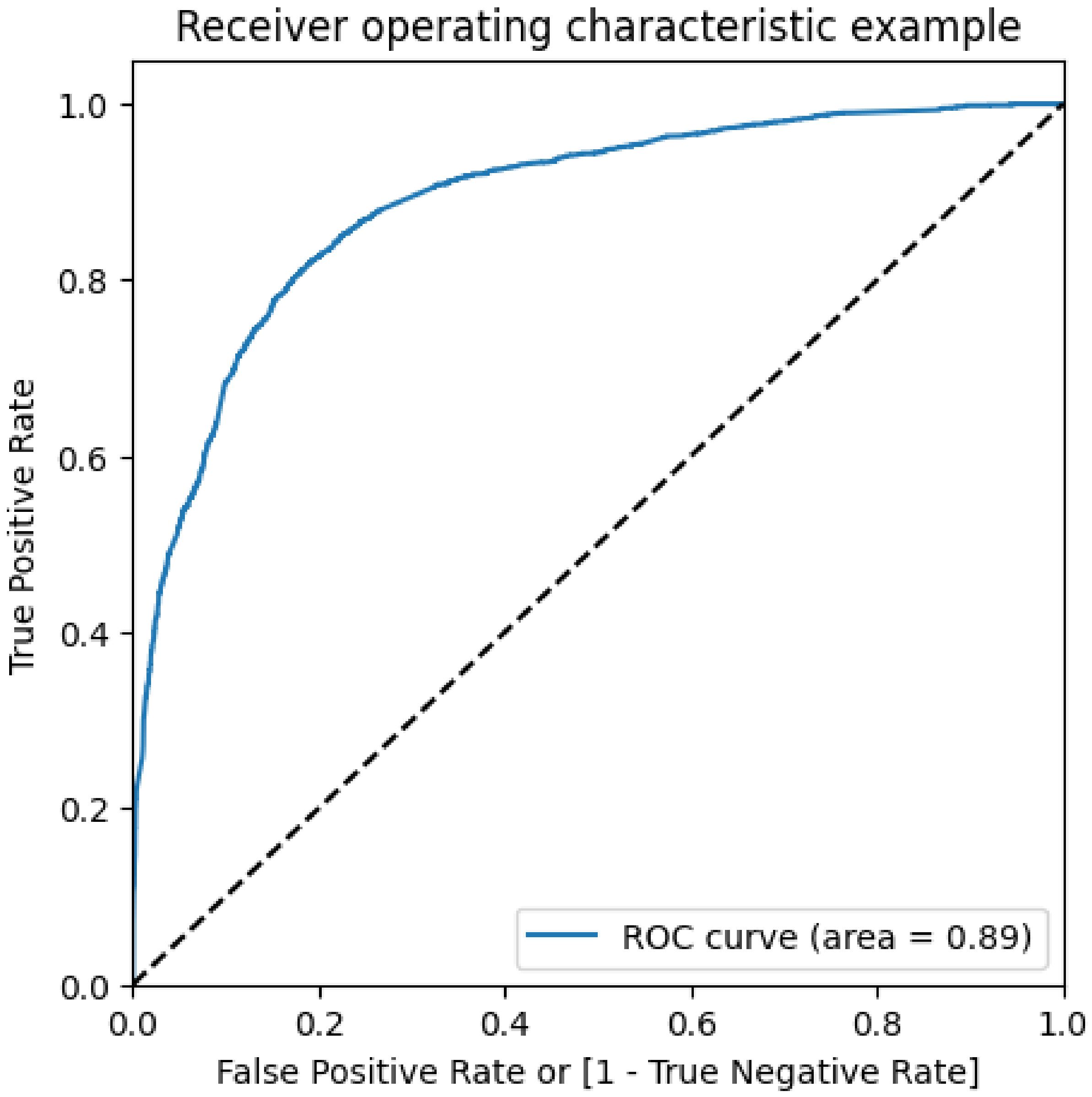
	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.1406	0.127	-1.108	0.268	-0.389	0.108
Do Not Email	-1.6984	0.191	-8.887	0.000	-2.073	-1.324
Total Time Spent on Website	1.1171	0.040	27.686	0.000	1.038	1.196
Lead Origin_Landing Page Submission	-1.1961	0.128	-9.339	0.000	-1.447	-0.945
Lead Source_Olark Chat	1.1430	0.124	9.242	0.000	0.901	1.385
Lead Source_Reference	3.4019	0.243	14.026	0.000	2.927	3.877
Lead Source_Welingak Website	5.9684	0.732	8.158	0.000	4.535	7.402
Last Activity_Olark Chat Conversation	-1.0216	0.173	-5.914	0.000	-1.360	-0.683
Last Activity_Other_Activity	2.1646	0.461	4.691	0.000	1.260	3.069
Last Activity_SMS Sent	0.7940	0.157	5.047	0.000	0.486	1.102
Last Activity_Unreachable	0.7494	0.310	2.415	0.016	0.141	1.358
Last Activity_Unsubscribed	1.4180	0.480	2.952	0.003	0.476	2.360
Specialization_Others	-1.1989	0.126	-9.514	0.000	-1.446	-0.952
What is your current occupation_Working Professional	2.6042	0.195	13.337	0.000	2.221	2.987
Last Notable Activity_Modified	-0.6922	0.097	-7.138	0.000	-0.882	-0.502
Last Notable Activity_SMS Sent	0.6910	0.177	3.894	0.000	0.343	1.039



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.



Model Evaluation

Confusion Matrix & Metrics

Train Data Set

```
[[3455  450]
 [ 693 1753]]
```

```
Accuracy : 0.8200283419933869
Sensitivity :  0.7166802943581357
Specificity :  0.8847631241997439
False Positivity Rate : 0.11523687580025609
Positive Predictive Value : 0.7957330912392192
Negative Predictive Value : 0.8329315332690453
```

```
Precision :  0.7347391786903441
Recall :  0.8119378577269011
```

Test Data Set

```
array([[1521,  213],
       [ 294,  695]], dtype=int64)
```

After running the model on the test data, we obtained the following observations:

- The accuracy of the model was 81%.
- The sensitivity of the model was 70%.
- The specificity of the model was 87%.

- Using a cut-off value of 0.35, the model achieved a **sensitivity** **71% in the train set** and **70% 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 tar **sensitivity of around 70%** .
- The model also achiev **accuracy of 81%** , 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	5.914695
Lead Source_Reference	3.392774
What is your current occupation_Working Professional	2.618774
Last Activity_Other_Activity	2.226927
Last Activity_Unsubscribed	1.380067
Last Activity_SMS Sent	1.328999
Lead Source_Olark Chat	1.141863
Total Time Spent on Website	1.118245
Last Activity_Unreachable	0.811978

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

Last Activity_Olark Chat Conversation	-0.922916
Lead Origin_Landing Page Submission	-1.190922
Specialization_Others	-1.197650
Do Not Email	-1.676398

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!