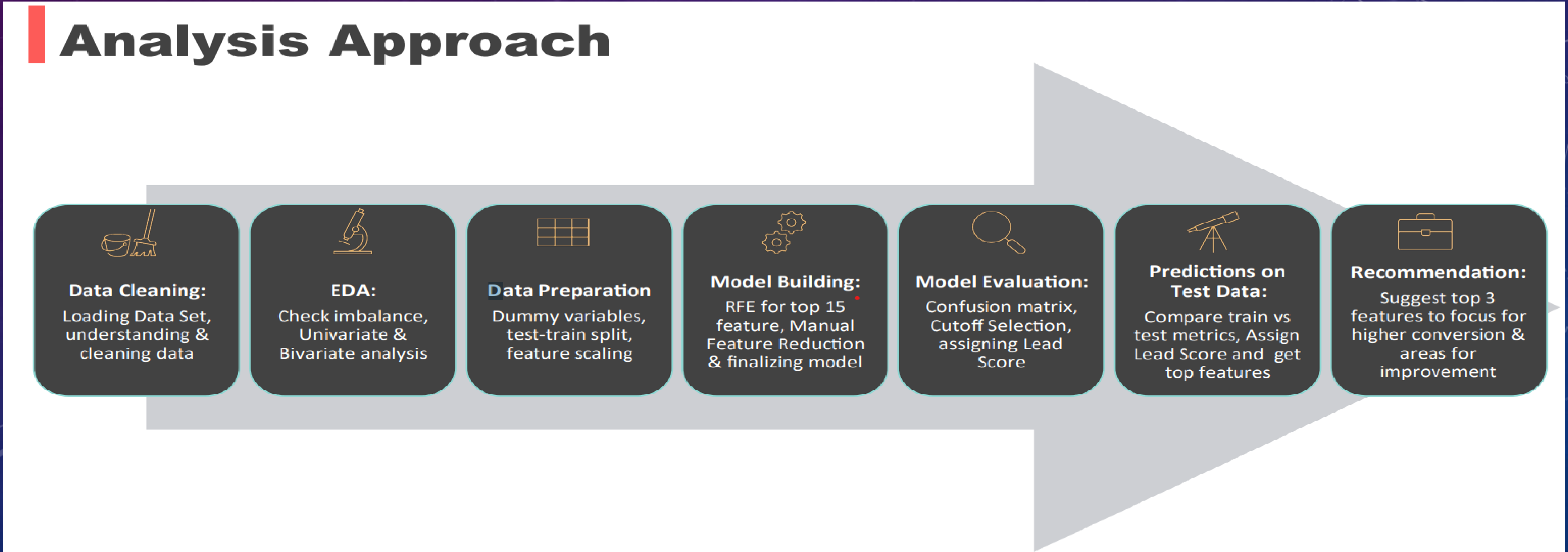
Nikhil khatri

LEAD SCORING CASE STUDY

PROBLEM STATEMENT

X Education, an online education company, seeks to enhance its lead conversion process. Despite generating many leads daily, the conversion rate remains low at 30%. The company aims to boost efficiency by identifying high-potential leads, termed 'Hot Leads'. To achieve this, a lead scoring model is needed, assigning scores to leads based on conversion likelihood. The objective is to prioritize communication with potential leads, ultimately raising the conversion rate to about 80%. This project aims to develop a model that sorts leads into high and low conversion probability categories, improving the overall lead conversion process for X Education.



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

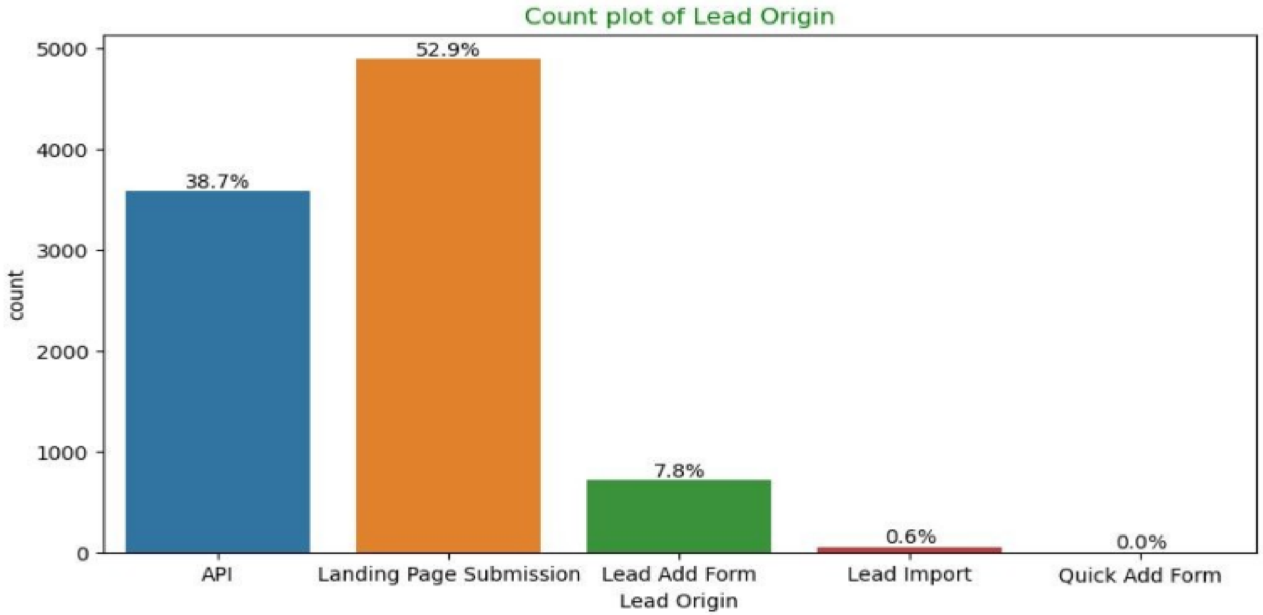
Background of X Education Company

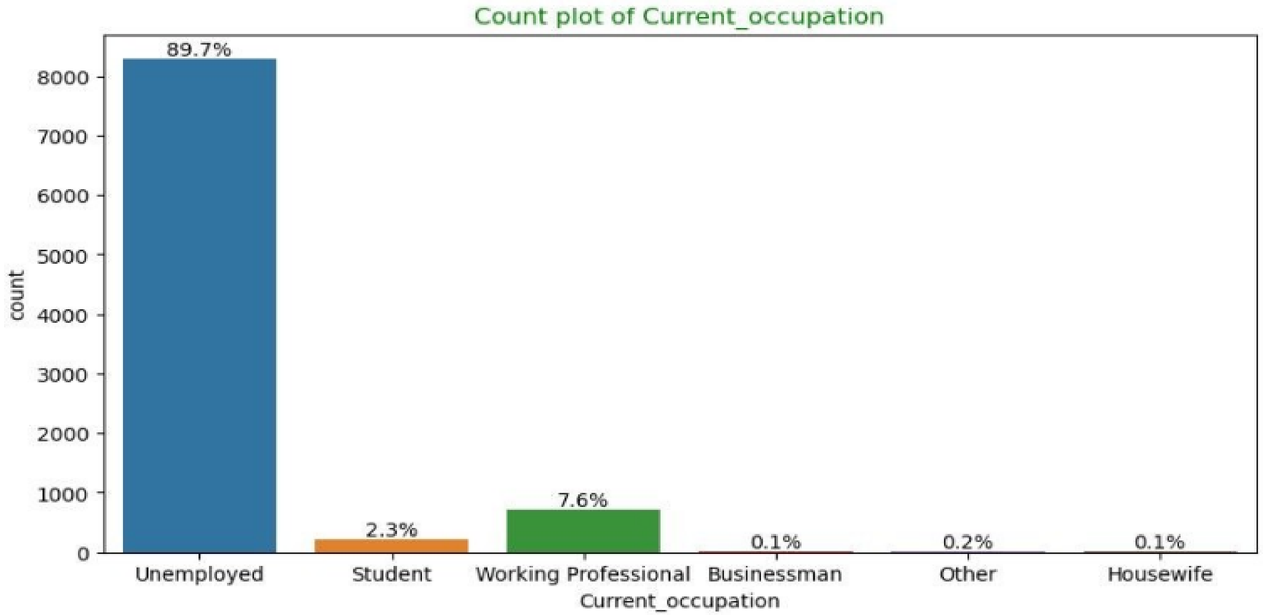
X Education is an online education company catering to industry professionals. Daily, many interested professionals visit their website, exploring courses. The company advertises on various platforms like Google. Visitors may view courses, complete forms, or watch videos. When forms are submitted with contact details, they become leads. The sales team contacts leads via calls or emails. While some leads convert to customers, most do not. X Education's average conversion rate is 30%.

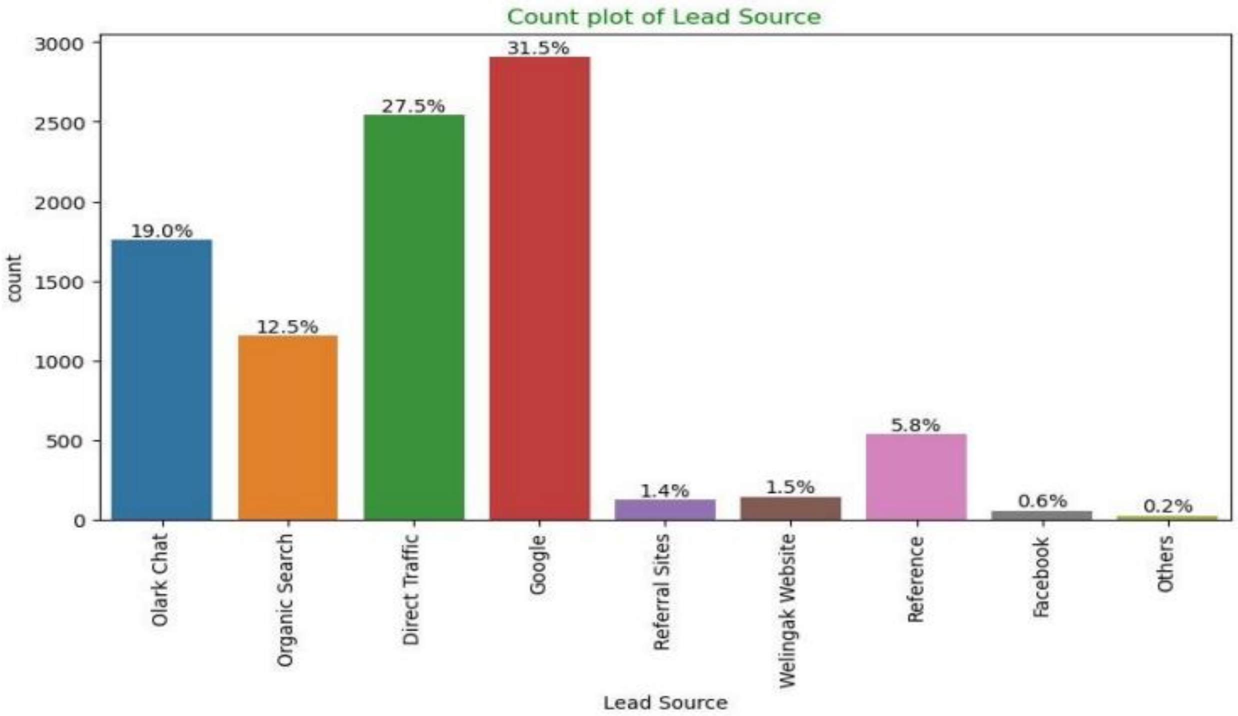
Data Cleaning Process Summary:

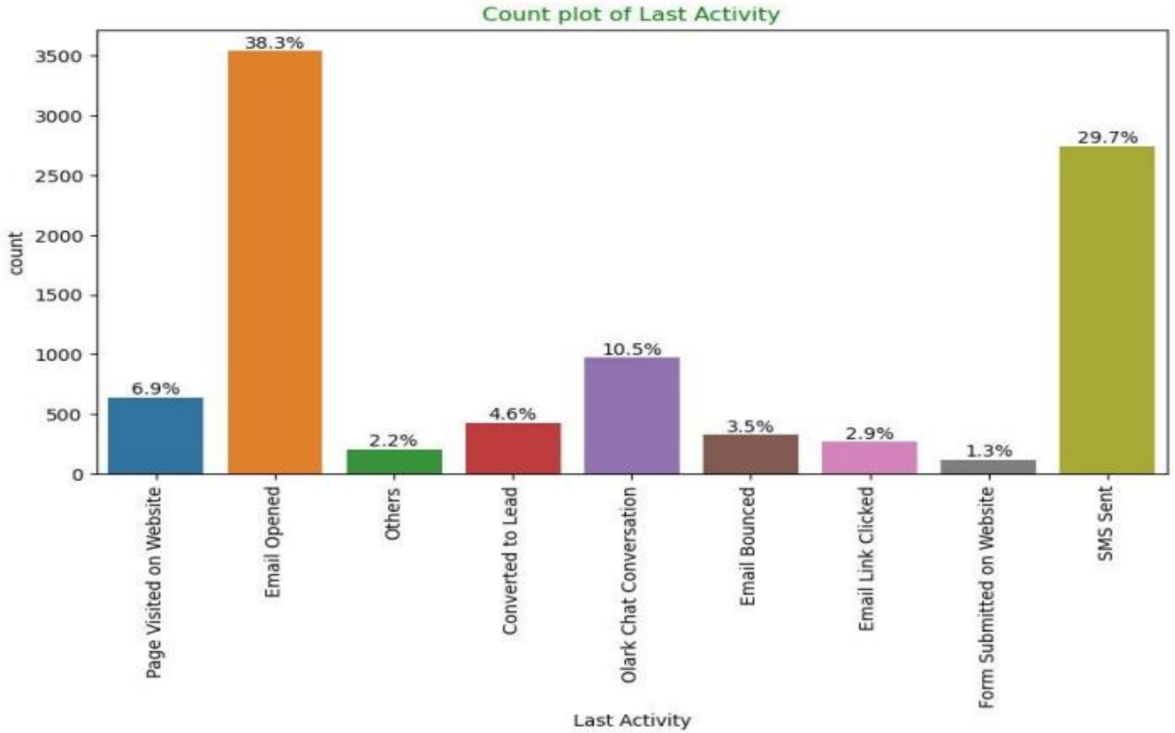
- ❑ Null values in categorical variables were represented as "Select" level, indicating non-selection.
- ❑ Columns with over 40% null values were dropped.
- ❑ Missing categorical values were managed based on value counts and considerations.
- ❑ Irrelevant columns (tags, country) were removed.
- ❑ Imputation was applied to certain categorical variables.
- ❑ New categories were created for specific variables.
- ❑ Columns with no modeling utility (Prospect ID, Lead Number) or just one response category were dropped.
- ❑ Numeric data was imputed with mode after assessing distribution.
- ❑ Skewed categorical columns were discarded to prevent logistic regression bias.
- ❑ Outliers in Total Visits and Page Views Per Visit were treated and capped.
- ❑ Invalid values were corrected, and data standardization performed (e.g., lead source).
- ❑ Infrequent values were grouped into an "Others" category.
- ❑ Binary categorical variables were mapped.
- ❑ Additional data quality checks and standardization steps were executed (e.g., fixing casing inconsistencies).

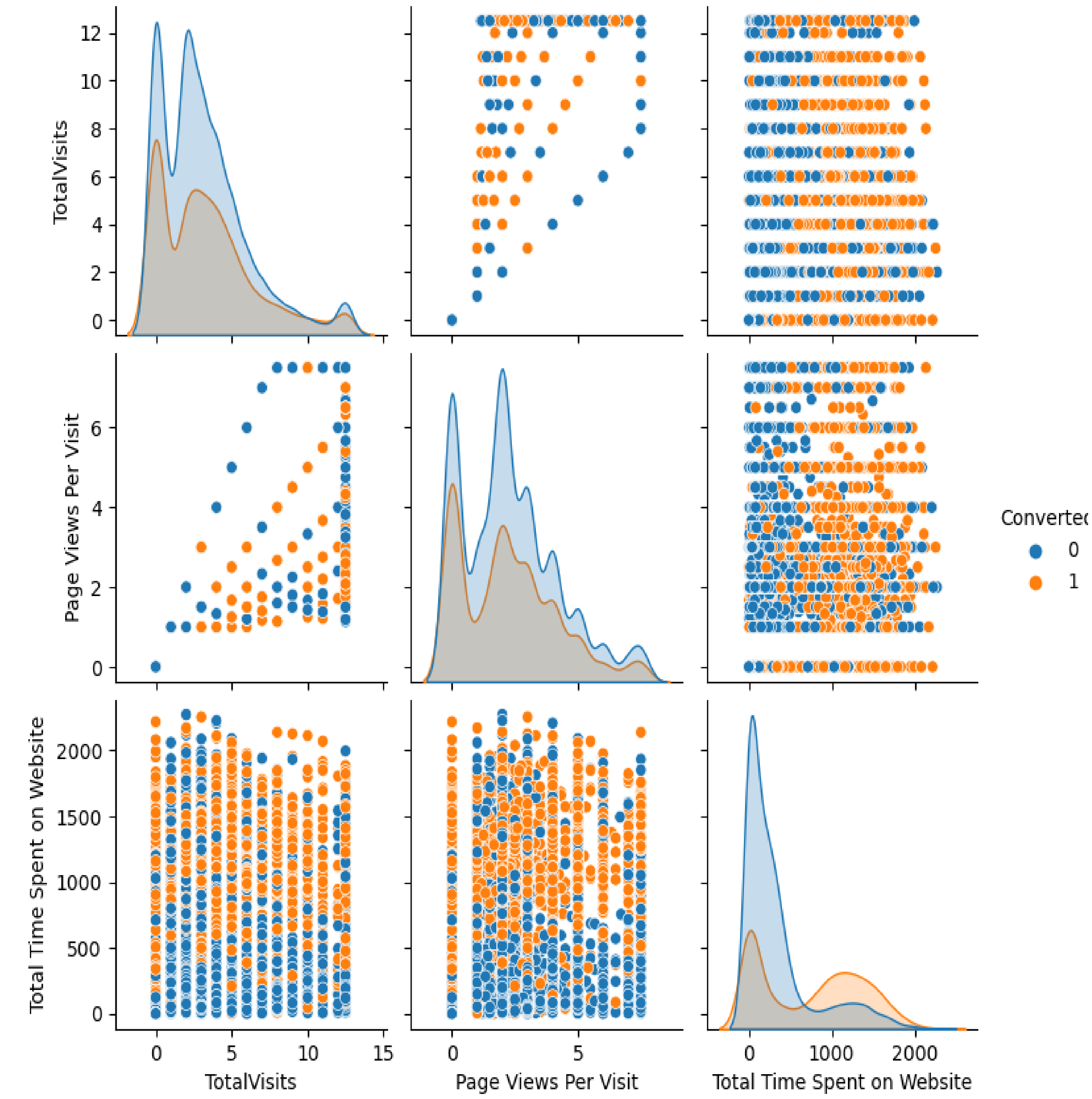
Univariate Analysis – Categorical Variables

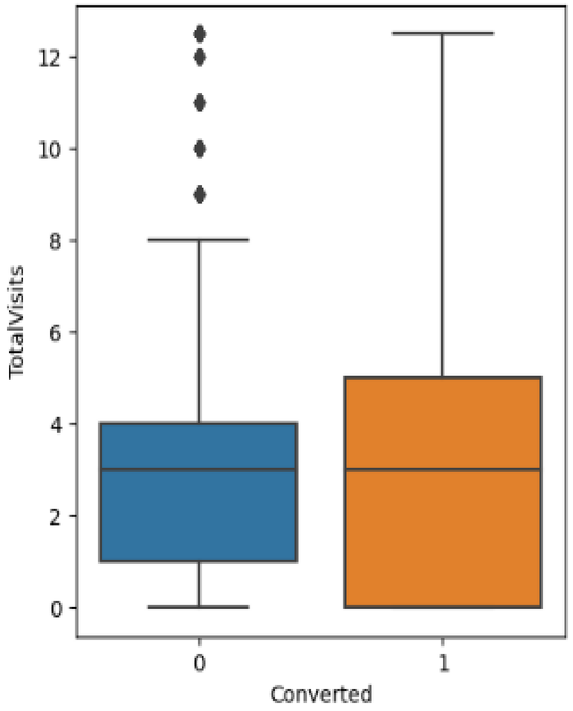

Count plot of Lead Origin

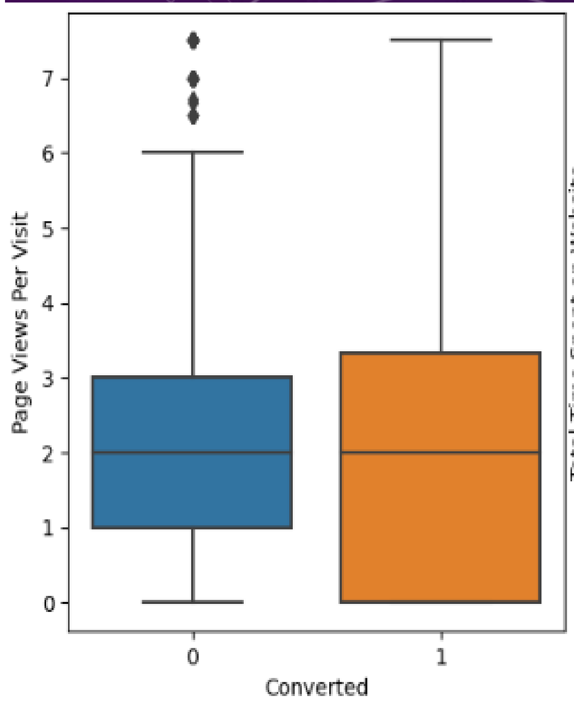

Count plot of Current_occupation

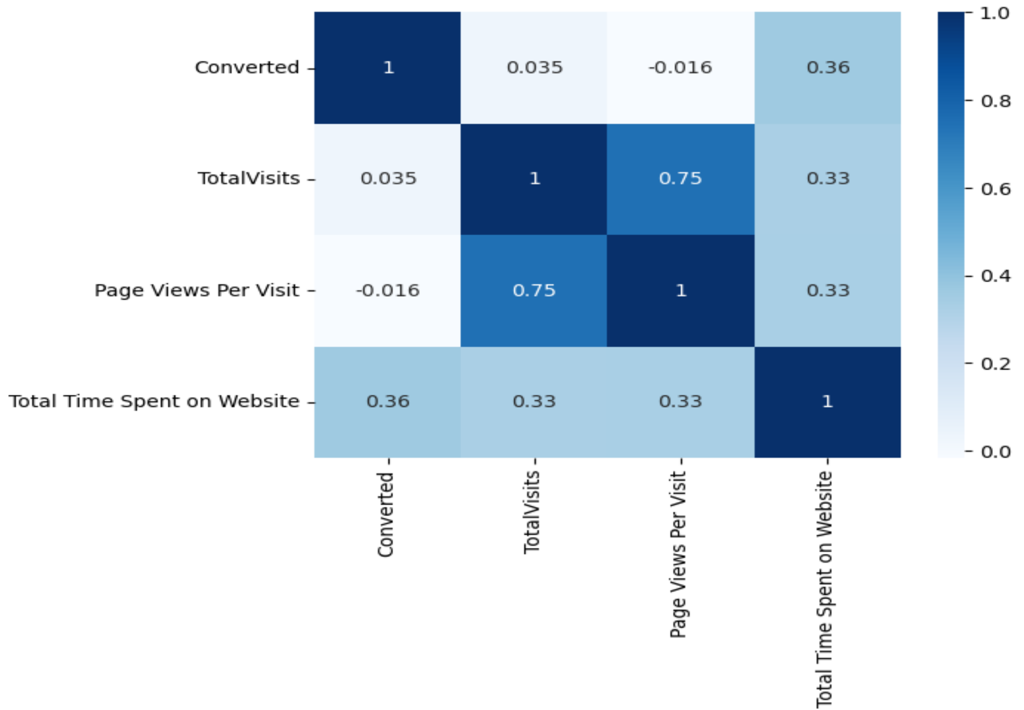

Count plot of Lead Source


Count plot of Last Activity


TotalVisits
Page Views Per Visit
Total Time Spent on Website
0
2
4
6
8
10
12
0
2
4
6
0
500
1000
1500
2000
0
5
10
15
0
5
0
1000
2000
TotalVisits
Page Views Per Visit
Total Time Spent on Website
Convertec
● 0
● 1


TotalVisits
0
2
4
6
8
10
12
0
1
Converted


Page Views Per Visit
0
1
2
3
4
5
6
7
0
1
Converted


Converted
TotalVisits
Page Views Per Visit
Total Time Spent on Website
1
0.035
-0.016
0.36
0.035
1
0.75
0.33
-0.016
0.75
1
0.33
0.36
0.33
0.33
1
Converted
TotalVisits
Page Views Per Visit
Total Time Spent on Website
1.0
0.8
0.6
0.4
0.2
0.0

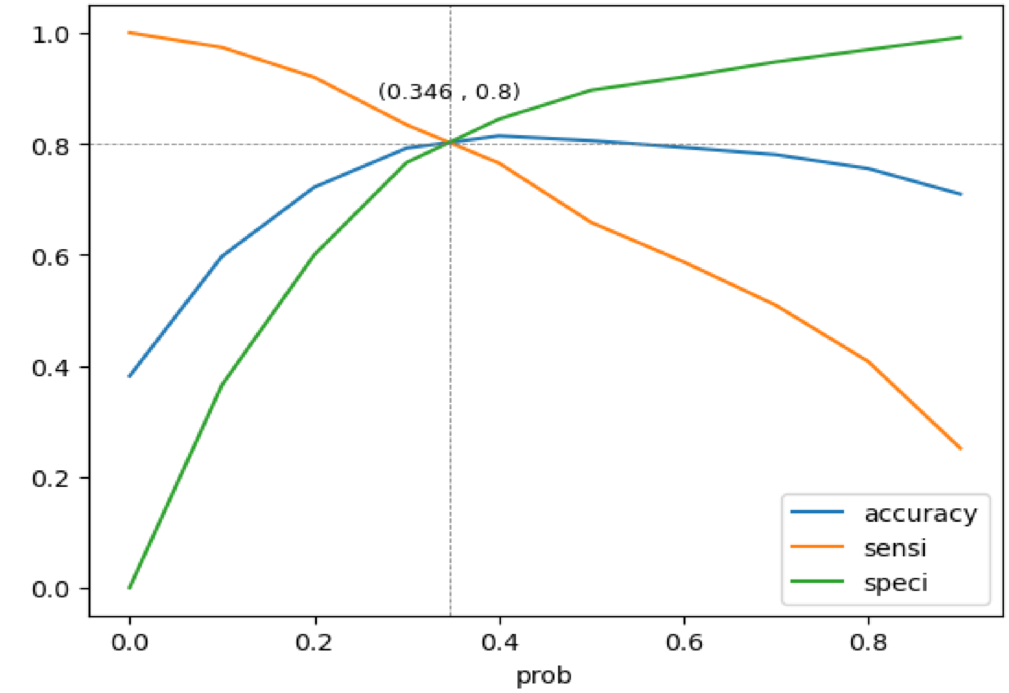
Data Preparation Summary Before Model Building:

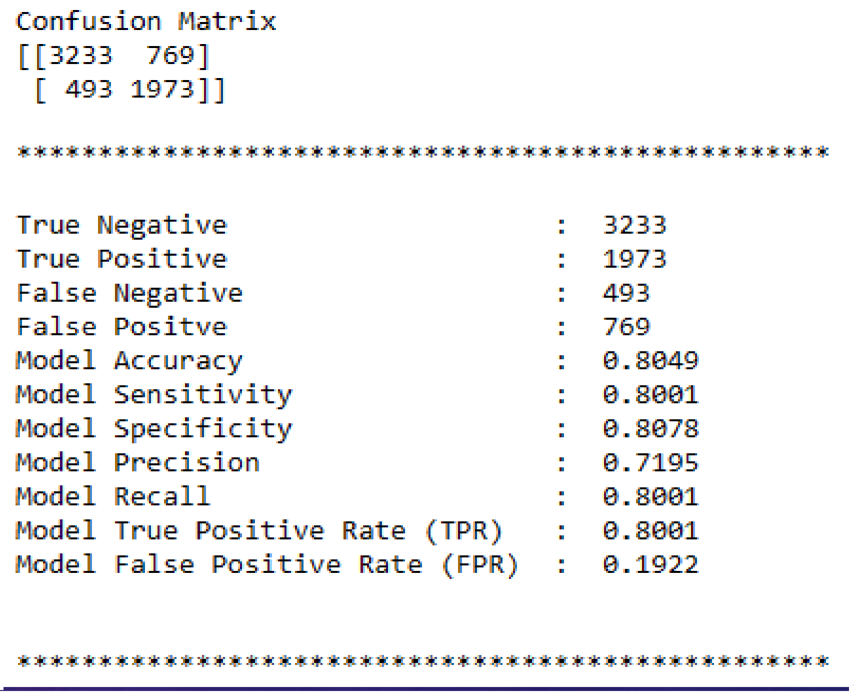
- Binary categorical columns were already transformed into 1/0 values.
- Dummy features (one-hot encoding) were created for categorical variables: Lead Origin, Lead Source, Last Activity, Specialization, and Current_occupation.
- The dataset was split into Train and Test sets using a 70:30 ratio.
- Feature scaling was performed using standardization to ensure consistent scales for model training.
- Correlations were checked, and highly correlated predictor variables were dropped (e.g., Lead Origin_Lead Import and Lead Origin_Lead Add Form).

Model Building Process:

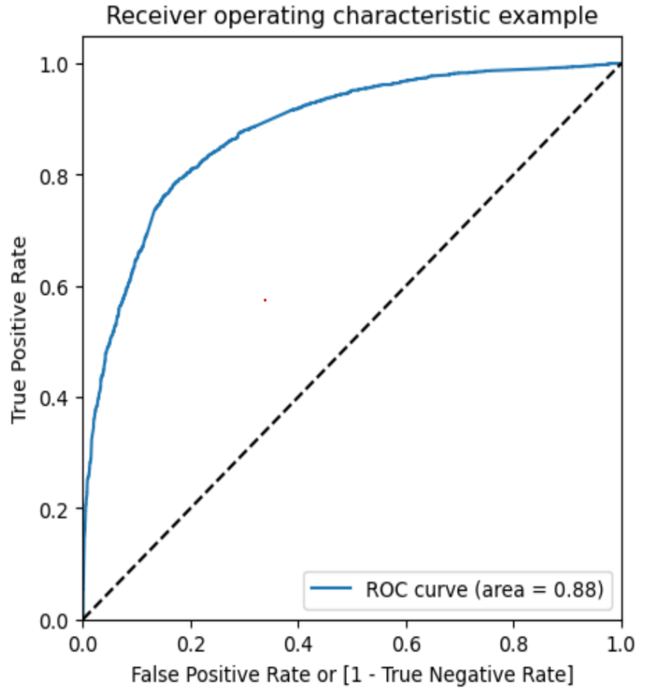
- Feature selection aimed to address the high dimensionality of the dataset.
- Recursive Feature Elimination (RFE) was employed to select important columns, reducing the number of features from 48 to 15.
- Manual Feature Reduction was conducted by iteratively dropping variables with p-values greater than 0.05.
- Model 4 emerged as stable after iterations, meeting criteria of significant p-values ($p < 0.05$) and absence of multicollinearity ($VIF < 5$).
- The final model, logm4, was selected for Model Evaluation and prediction.

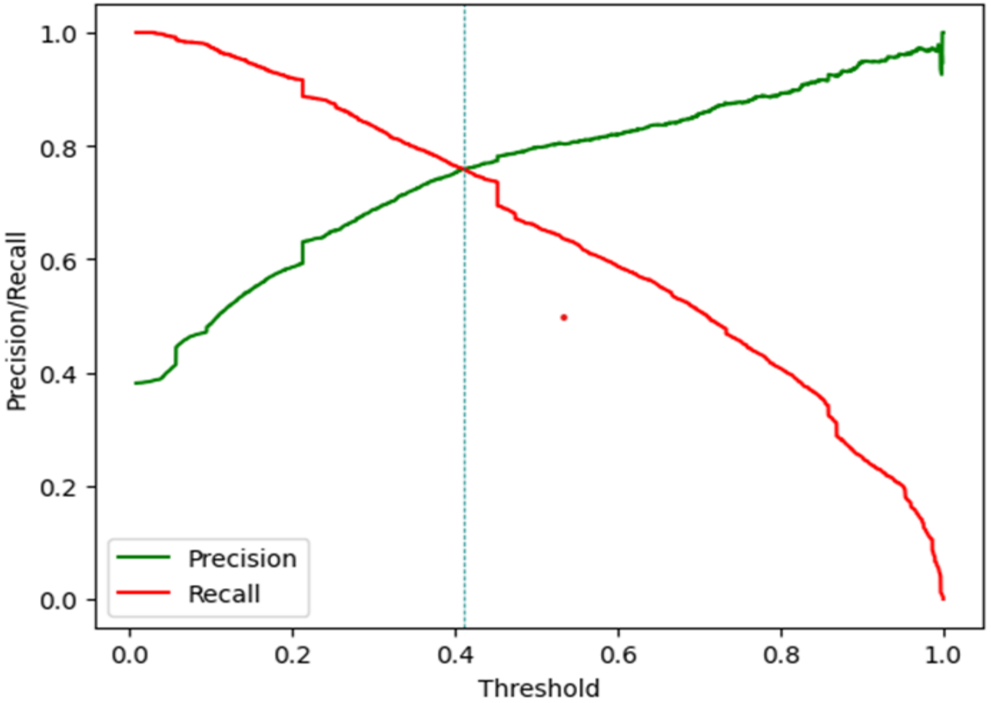
The data preparation and model building phases focused on optimizing feature selection and ensuring model stability, setting the stage for accurate evaluation and prediction in subsequent steps.

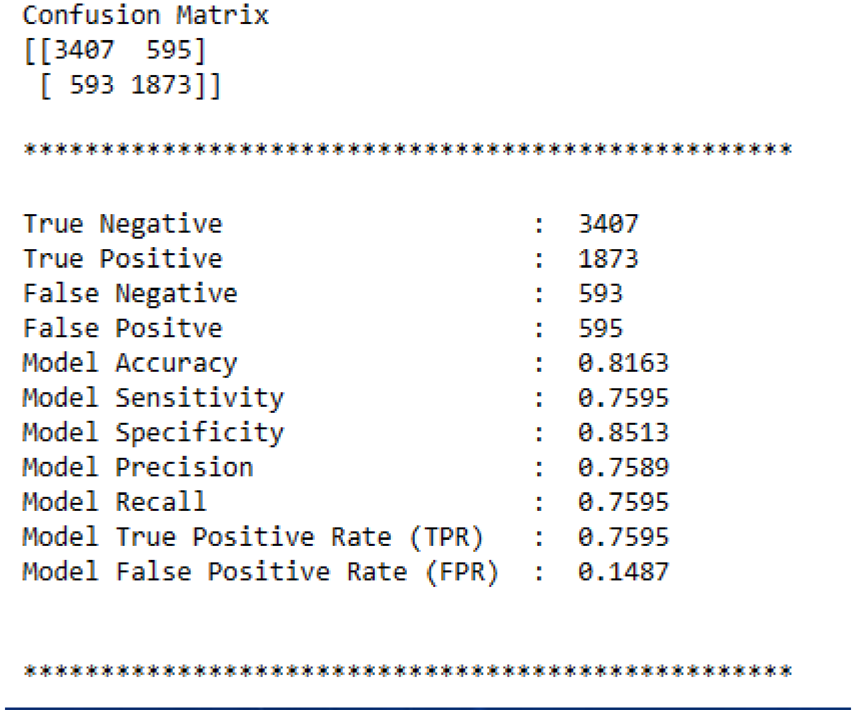




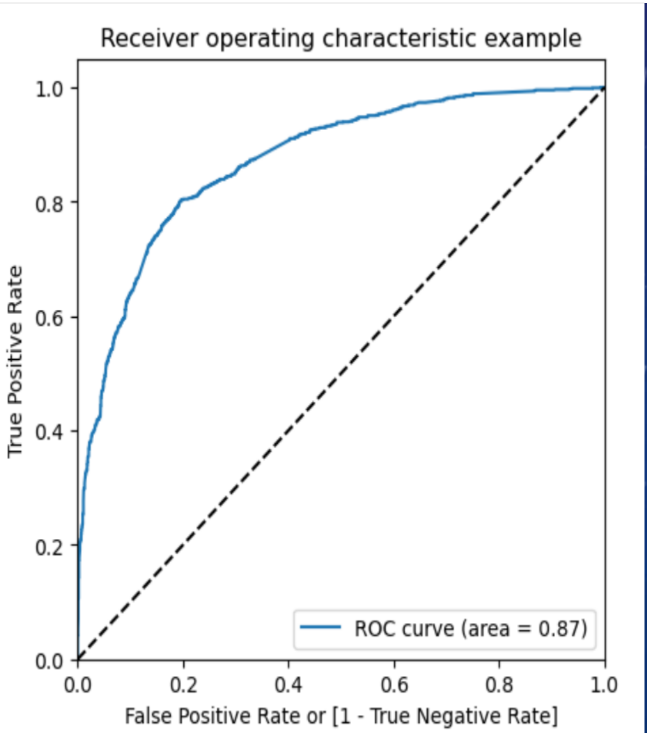
```
Confusion Matrix
[[3233  769]
 [ 493 1973]]

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

True Negative                        :  3233
True Positive                        :  1973
False Negative                       :  493
False Positve                        :  769
Model Accuracy                       :  0.8049
Model Sensitivity                    :  0.8001
Model Specificity                    :  0.8078
Model Precision                      :  0.7195
Model Recall                         :  0.8001
Model True Positive Rate (TPR)       :  0.8001
Model False Positive Rate (FPR)      :  0.1922


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







```
Confusion Matrix
[[3407  595]
 [ 593 1873]]

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

True Negative                        :  3407
True Positive                        :  1873
False Negative                       :  593
False Positve                        :  595
Model Accuracy                       :  0.8163
Model Sensitivity                    :  0.7595
Model Specificity                    :  0.8513
Model Precision                      :  0.7589
Model Recall                         :  0.7595
Model True Positive Rate (TPR)       :  0.7595
Model False Positive Rate (FPR)      :  0.1487


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



Recommendations Based on Final Model:

- To Improve Lead Conversion Rates:
- Prioritize marketing efforts towards features with positive coefficients, as they have the most impact on lead conversion.
- Develop targeted marketing strategies to attract leads from high-performing sources like Welingak Website and Reference.
- Optimize communication channels based on the engagement impact of leads. For example, focus more on channels like SMS Sent, Email Opened, and Olark Chat.
- Engage working professionals through personalized messaging, considering their higher conversion potential.
- Allocate a higher budget for Welingak Website advertising to increase lead acquisition from that source.
- Encourage customers to provide references by offering incentives or discounts, as these references have a positive effect on conversion.
- Aggressively target working professionals due to their higher conversion rate and better financial situation.

Areas for Improvement:

- Analyze specialization offerings with negative coefficients, such as Hospitality Management and Others, to identify opportunities for enhancement.
- Review the landing page submission process for potential improvements, as the Lead Origin of Landing Page Submission has a negative coefficient.

- In conclusion, the recommendations are geared towards leveraging the identified positive coefficients to optimize marketing strategies and increase lead conversion rates. Additionally, analyzing negative coefficients offers insights into areas that may need improvement for further enhancement of the lead conversion process.

thank
you