LEAD SCORING CASE STUDY

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Introduction

In this case study, we will build a logistic regression model for X Education to assign a lead score between 0 and 100 to each lead. The lead score will help the company identify potential leads and prioritize them based on their likelihood of conversion. Our aim is to help X Education achieve their target conversion rate of 80%. Additionally, we will address the other problems presented by the company and provide recommendations on how to utilize the lead scoring model effectively to achieve their business goals. The model should also be able to adjust to any changes in the company's requirements in the future.

BUSINESS UNDERSTANDING

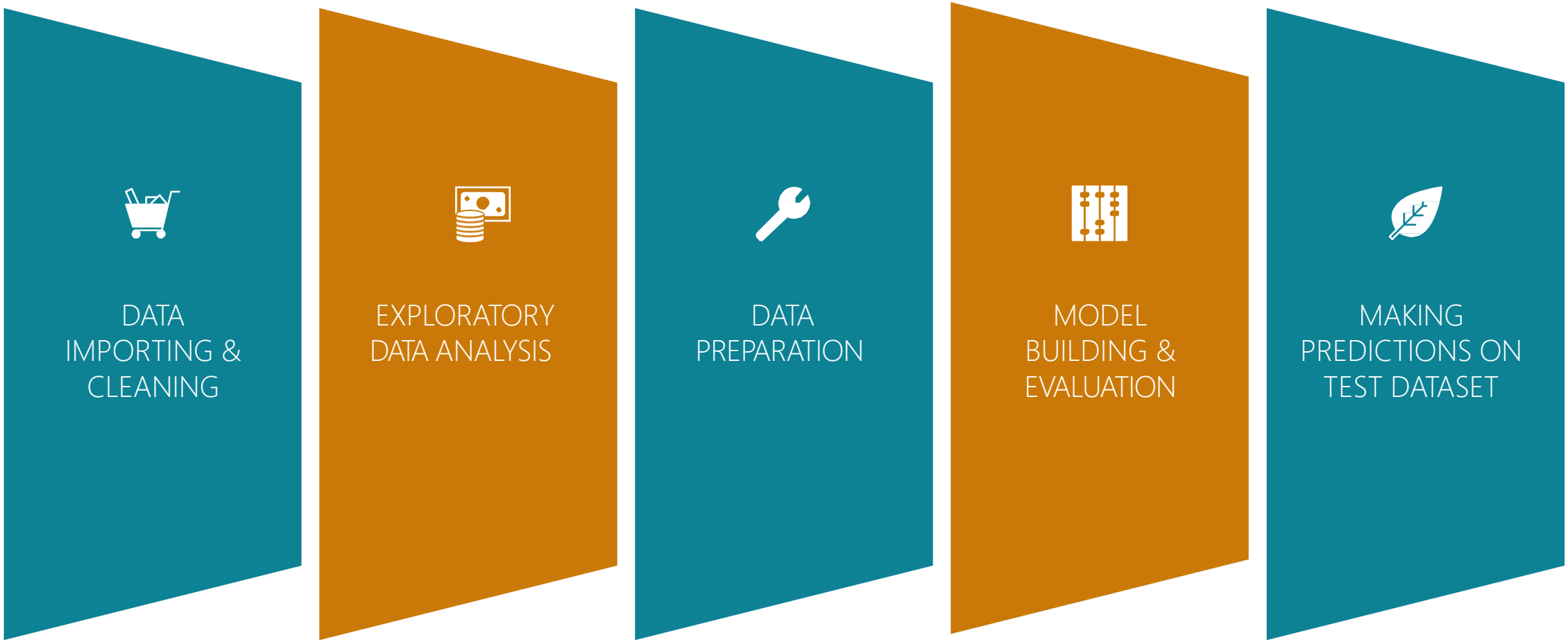
- X Education is an online education company that offers courses to industry professionals.
- The company promotes its courses through various online channels, including search engines like Google.
- Prospective customers who are interested in the courses visit the X Education website and browse through the available courses.
- Some of these visitors may fill out a form on the website with their email address or phone number to express interest in the courses. These visitors are classified as leads.
- X Education's sales team contacts the leads via phone or email to try and convert them into paying customers.
- While some leads do get converted into paying customers, the majority do not.
- X Education's typical lead conversion rate is approximately 30%.

Data Understanding

The dataset consists of two files: 'Leads.csv' and 'Leads Data Dictionary.xlsx'.

- The 'Leads.csv' file contains around 9000 data points. The target variable of the dataset is the column 'Converted', which indicates whether a past lead was converted or not. The values in the 'Converted' column are binary, where 1 means the lead was converted and 0 means it wasn't converted.
- The 'Leads Data Dictionary.xlsx' file provides a data dictionary that explains the meaning of the variables in the 'Leads.csv' file.

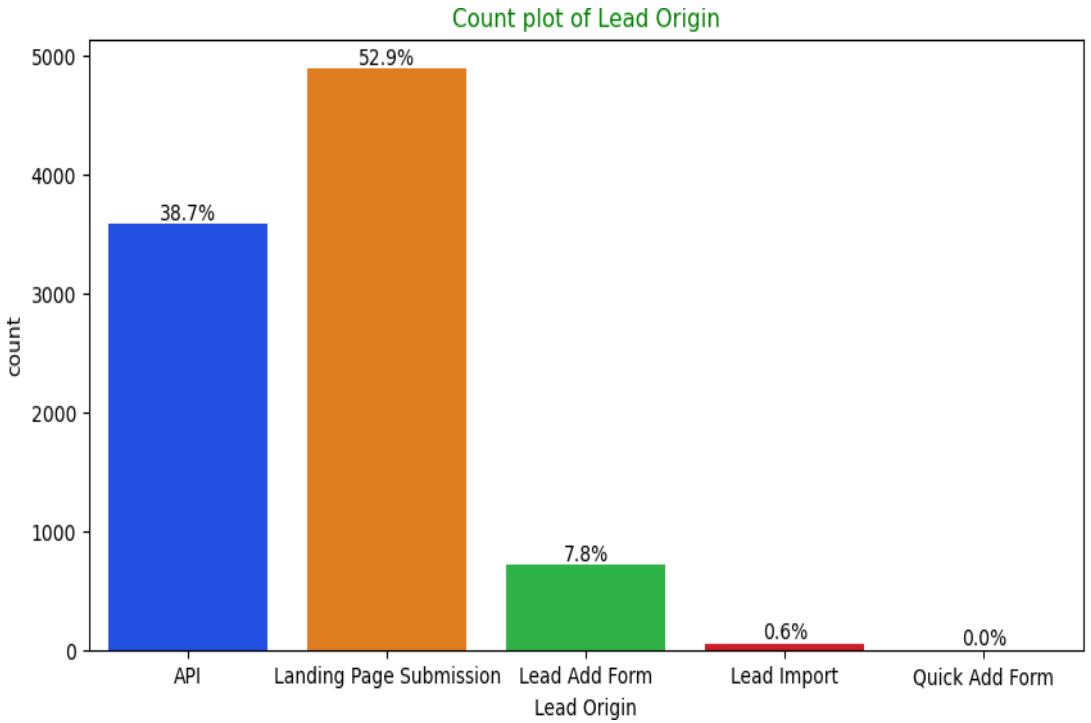
Steps of Analysis

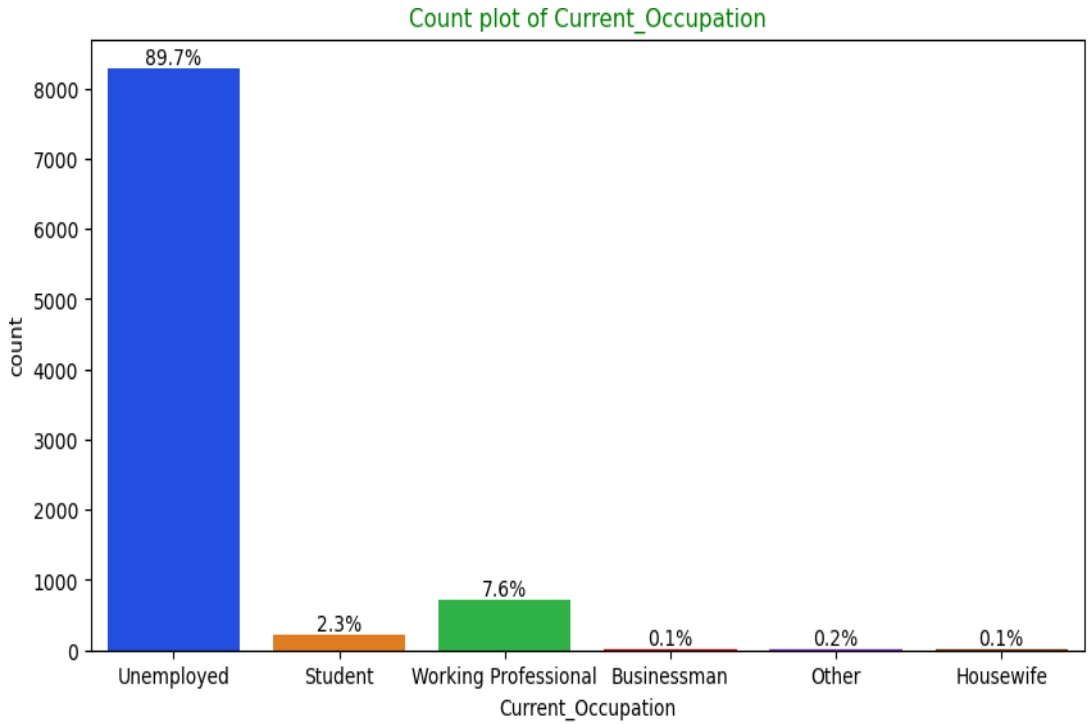


Data Cleaning

- "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 ('City', 'Tags', 'Country', 'What matters most to you in choosing a course')
- Imputation was used for some categorical variables.
- Columns with no use for modeling ('Prospect ID', 'Lead Number' and 'Last Notable Activity') were dropped.
- Numerical data was imputed with mode after checking distribution.
- Skewed category columns were checked and dropped to avoid bias in logistic regression models.
- Outliers in 'TotalVisits', 'Total Time Spent on Website' and 'Page Views Per Visit' were treated and capped.
- Low frequency values were grouped together to "Others".
- Standardizing Data in columns by checking casing styles, etc. ("Lead Source" has Google and google)

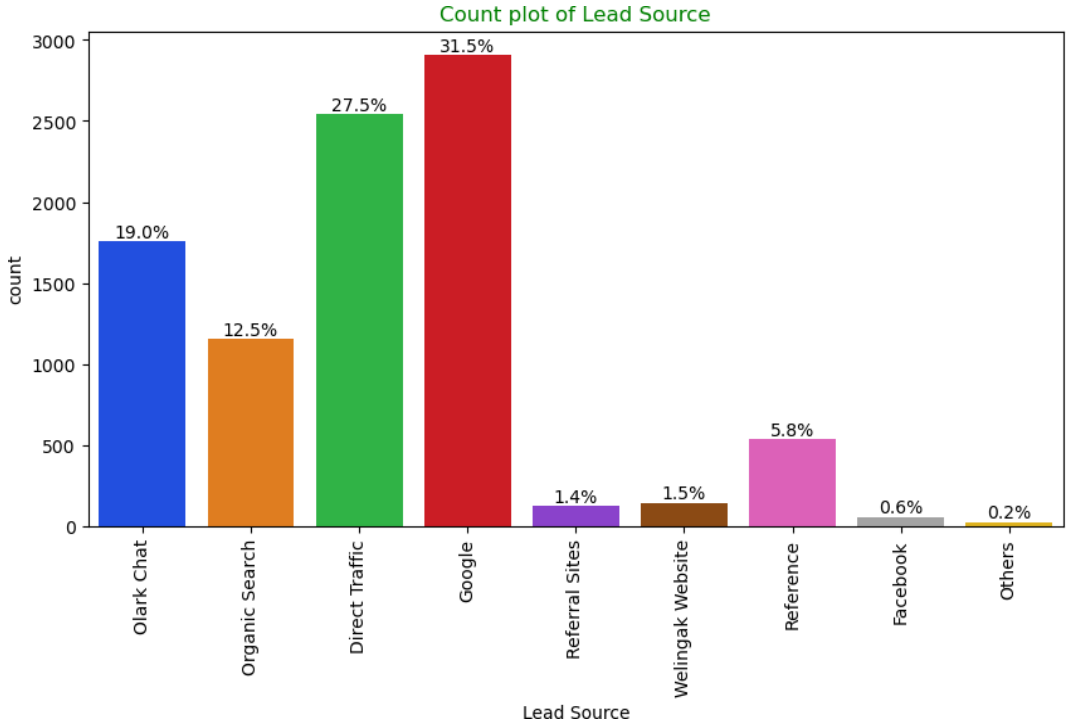
EDA & Univariate Analysis

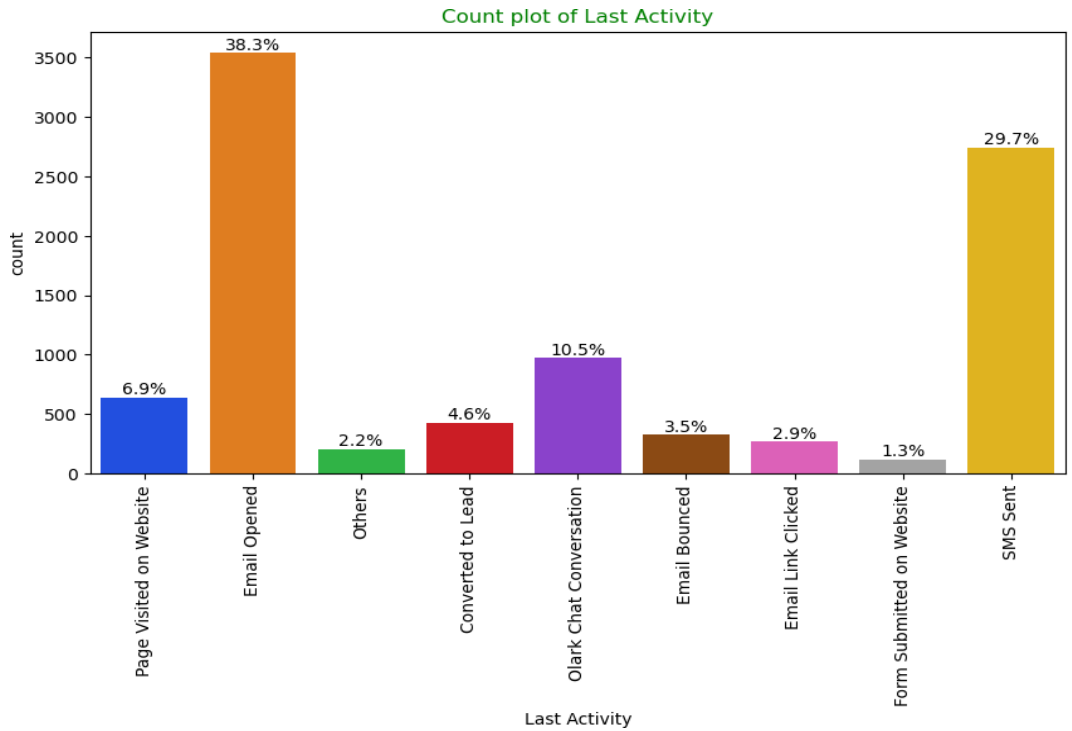




Inference:

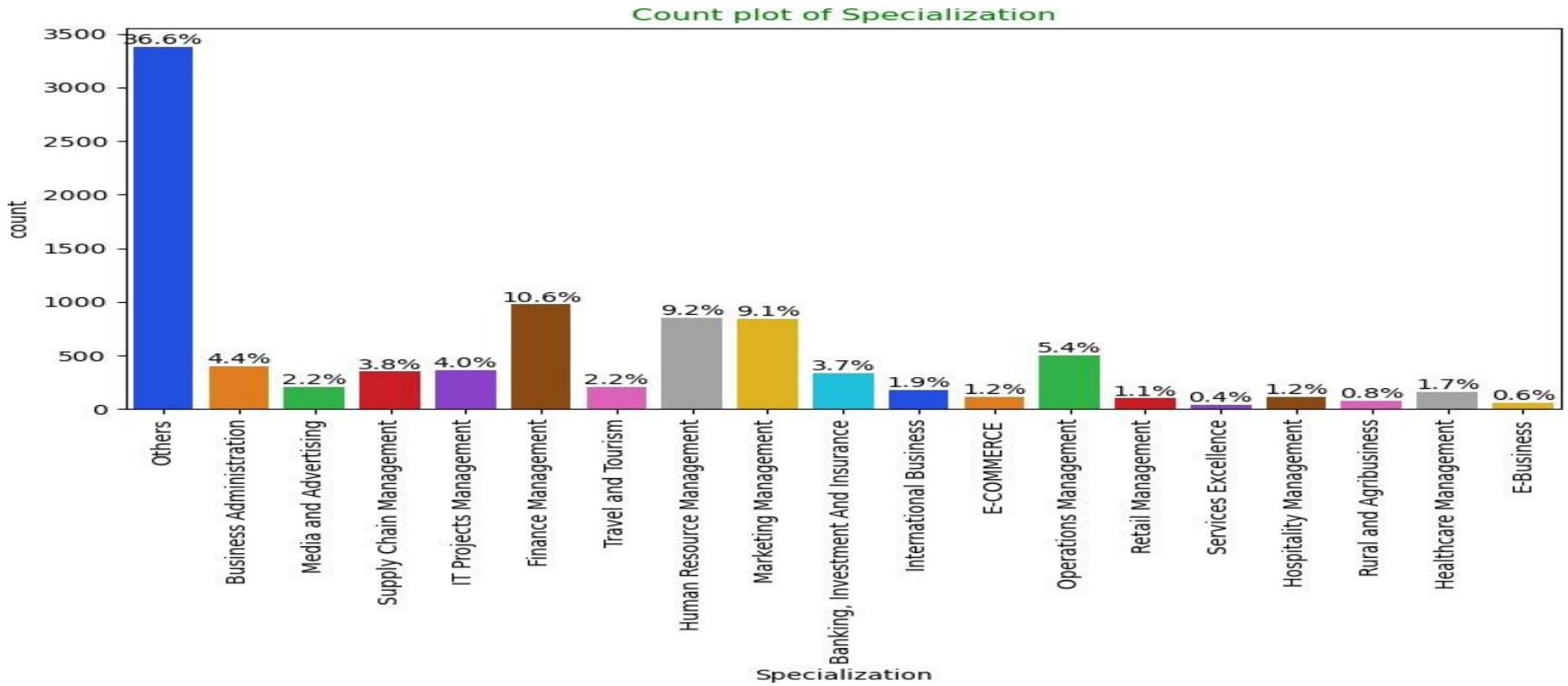
- Lead Origin: The majority of customers, 52.9%, were identified through 'Landing Page Submission' as the lead origin, followed by 'API' at 38.7%.
- Current_Occupation: A significant proportion of customers, 89.7%, are unemployed based on the current occupation information.





Inference:

- Lead Source: The primary lead source is Google at 31.5%, followed by Direct Traffic at 27.5%.
- Last Activity: Email is the most common last activity, with 38.3% of customers having opened an email, and 29.7% having sent an SMS.

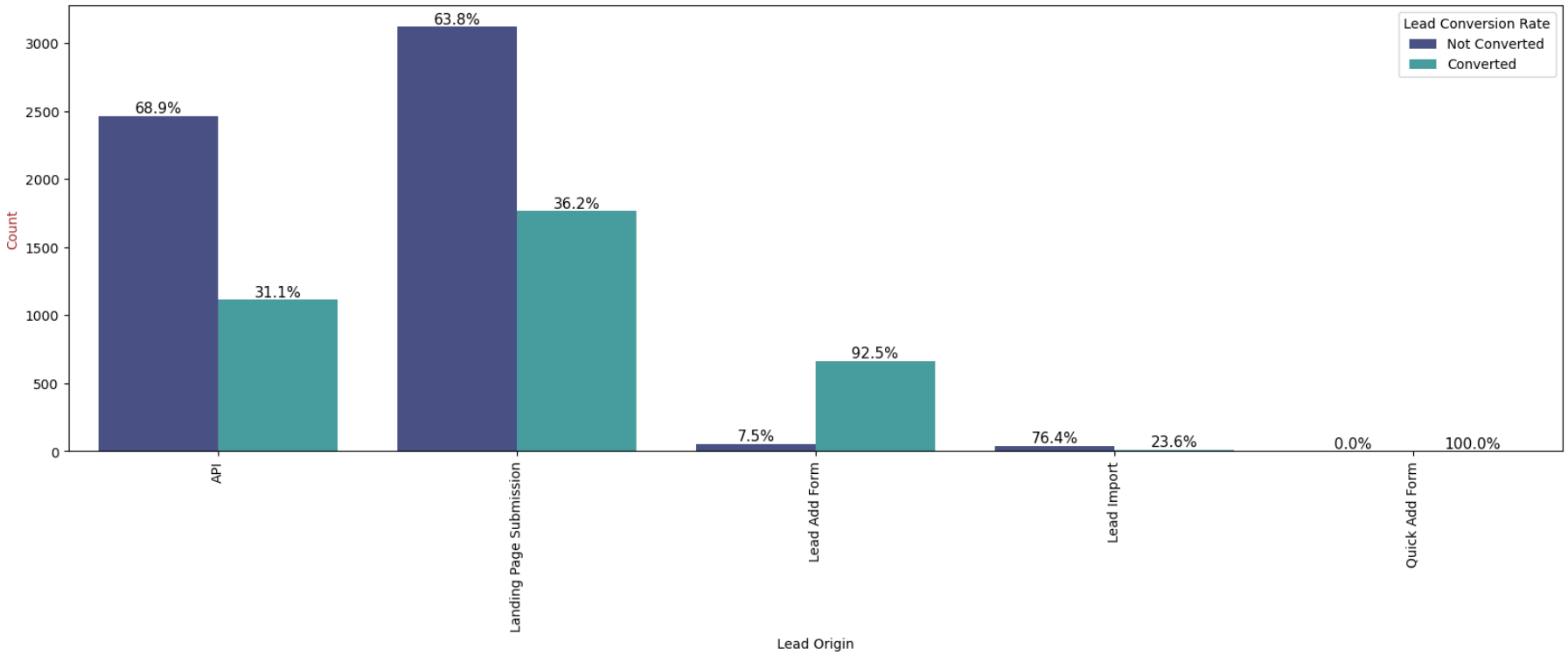


Inference:

- Specialization: The 'Others' specialization category is the most common among customers at 36.6%, followed by Finance Management at 10.6%, HR Management at 9.2%, Marketing Management at 9.1%, and Operations Management at 5.4%.

Bivariate Analysis

Lead Conversion Rate of Lead Origin

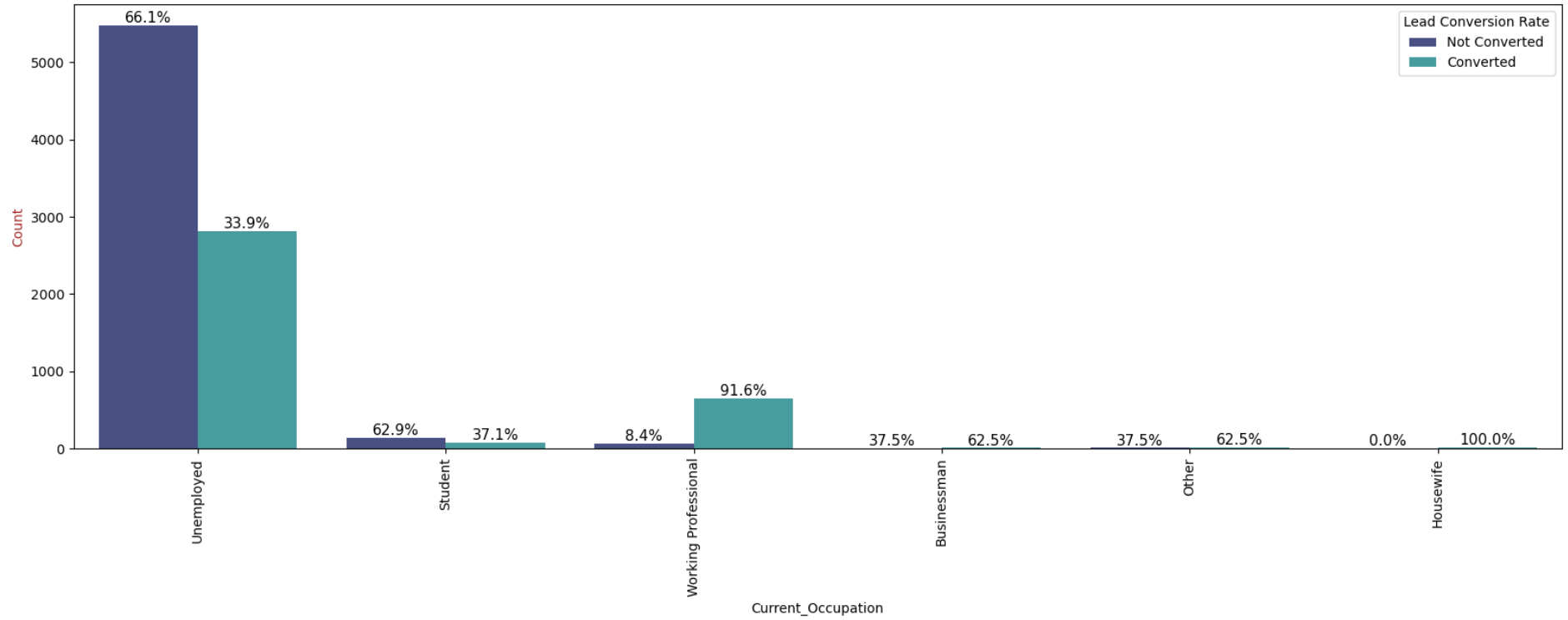


Inference:

- Lead Origin: 'Landing Page Submission' is the most effective Lead Origin with a Lead Conversion Rate (LCR) of 36.2%, followed by 'API' at 31.1%.

Bivariate Analysis

Lead Conversion Rate of Current_Occupation

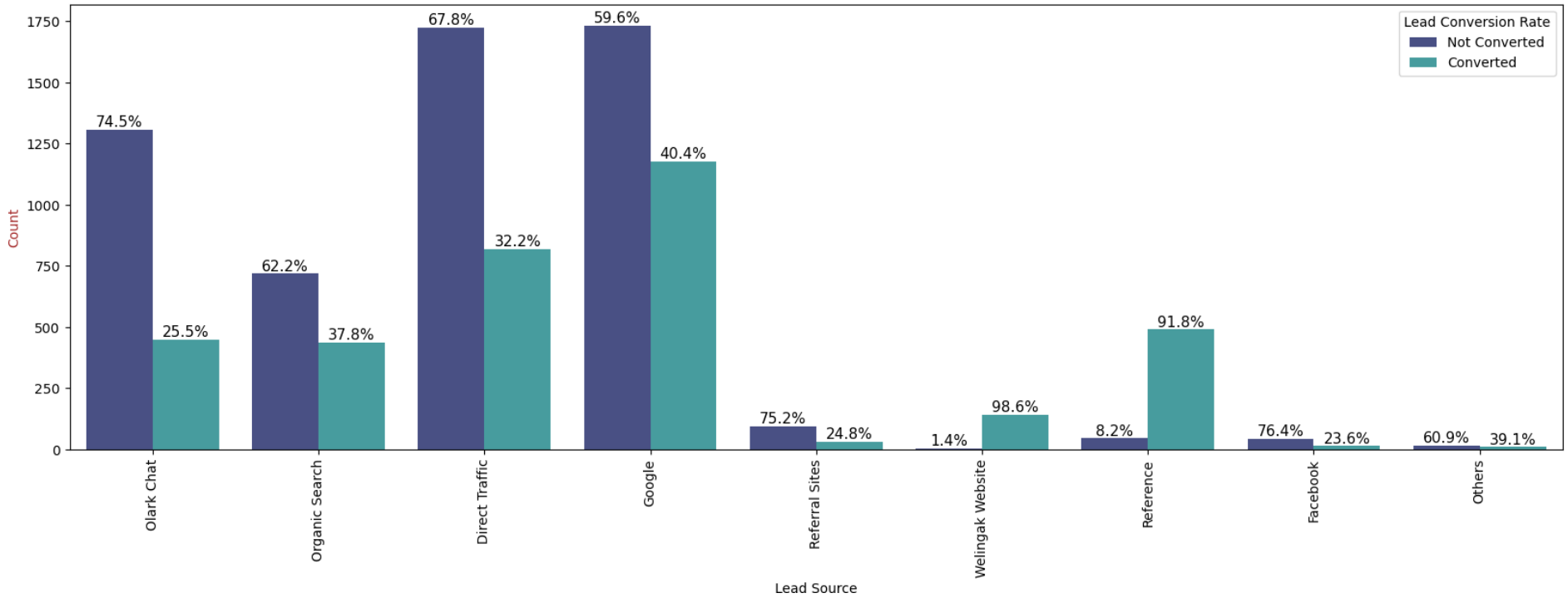


Inference:

- Current_Occupation: Working Professionals have a significantly higher LCR at 91.6% compared to Unemployed people at 33.9%.

Bivariate Analysis

Lead Conversion Rate of Lead Source

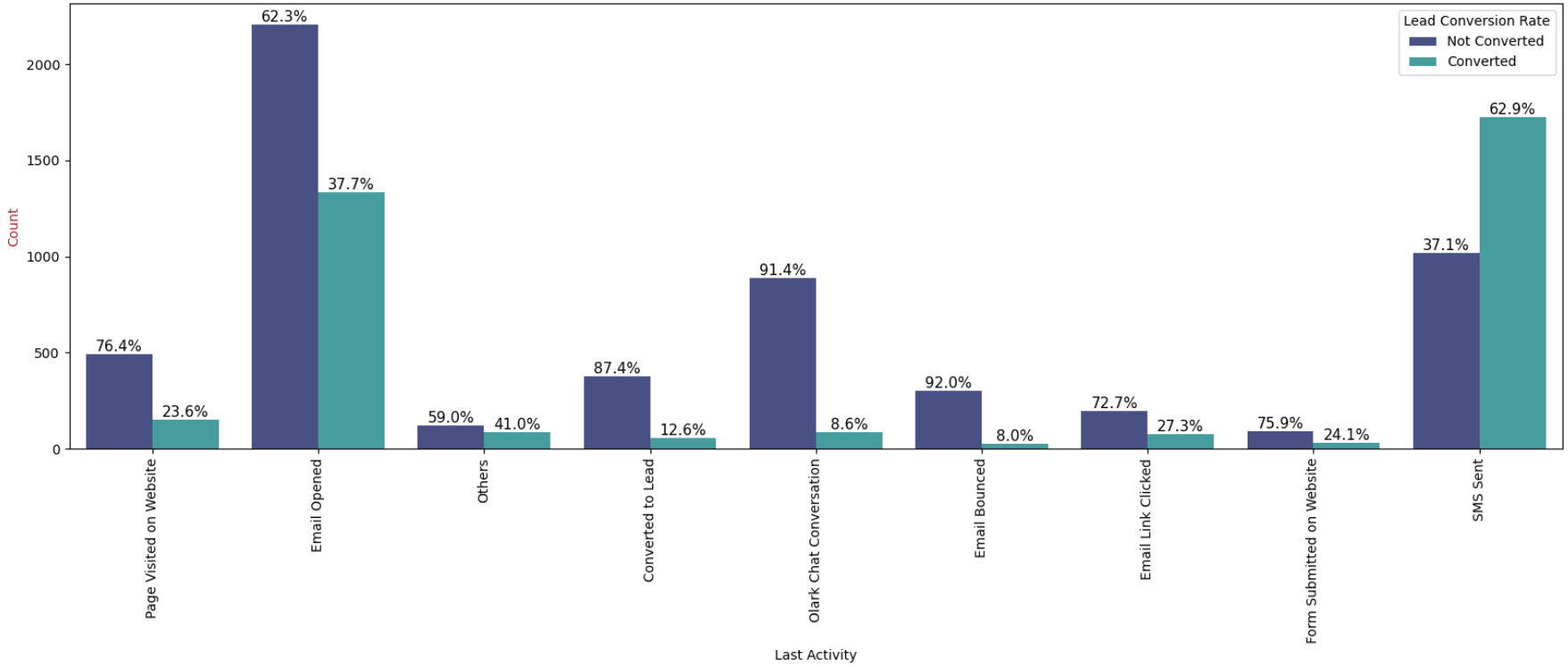


Inference:

- Lead Source: Google is the most effective Lead Source with an LCR of 40.4%, followed by Direct Traffic at 32.2% and Organic Search at 37.8% (contributing to only 12.5% of customers). Reference has the highest LCR at 91.8%, but there are only 5.8% of customers through this Lead Source.

Bivariate Analysis

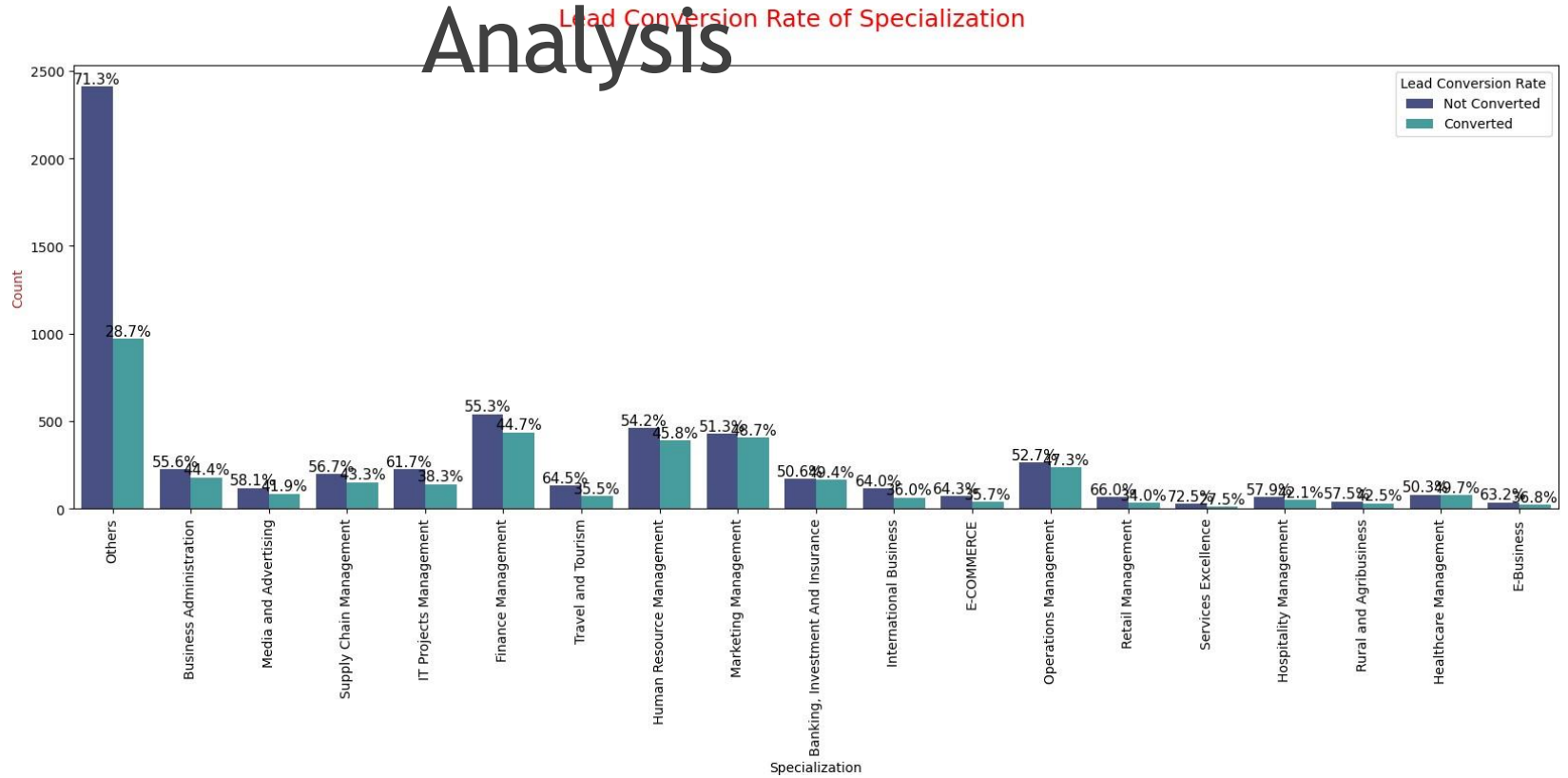
Lead Conversion Rate of Last Activity



Inference:

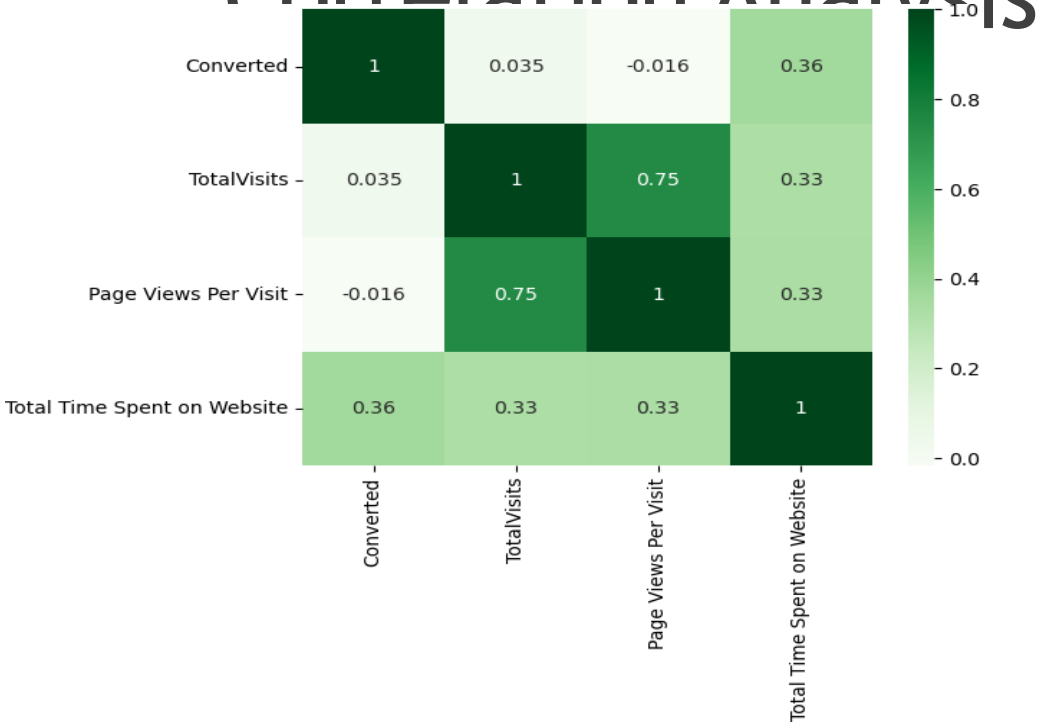
- Last Activity: SMS Sent and Email Opened are the most effective Last Activity types with LCRs of 62.9% and 37.7% respectively.

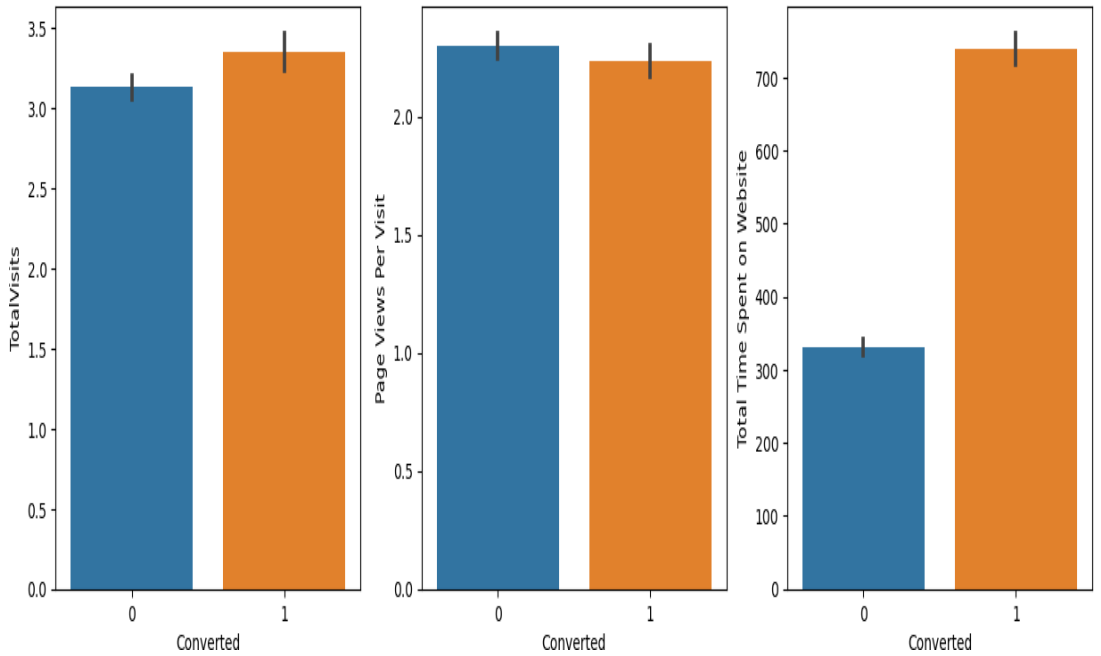
Bivariate Analysis



Inference:

- Specialization: Marketing Management, HR Management, Finance Management and Operations Management all show good LCRs, indicating a strong interest among customers in these specializations.





Inference:

- There is a strong positive correlation between 'Total Visits' and 'Page Views per Visit', indicating that customers who visit the website more frequently tend to view more pages per visit.
- Customers who spend more time on the website have a higher LCR, indicating that increasing the time spent on the website can lead to higher conversion rates.

Data Preparation

- Binary level categorical columns were mapped to 1/0 in previous steps to make them compatible with the logistic regression model.
- Dummy features were created for categorical variables such as Lead Origin, Lead Source, Last Activity, Specialization, and Current_Occupation, using one-hot encoding.
- The train and test sets were split in a 70:30 ratio to train the model and evaluate its performance on unseen data.
- Feature scaling was performed using the standardization method to ensure that all features were on the same scale and no feature dominated the others.
- Correlated predictor variables, such as Lead Origin_Lead Import and Lead Origin_Lead Add Form, were dropped to avoid multicollinearity issues.

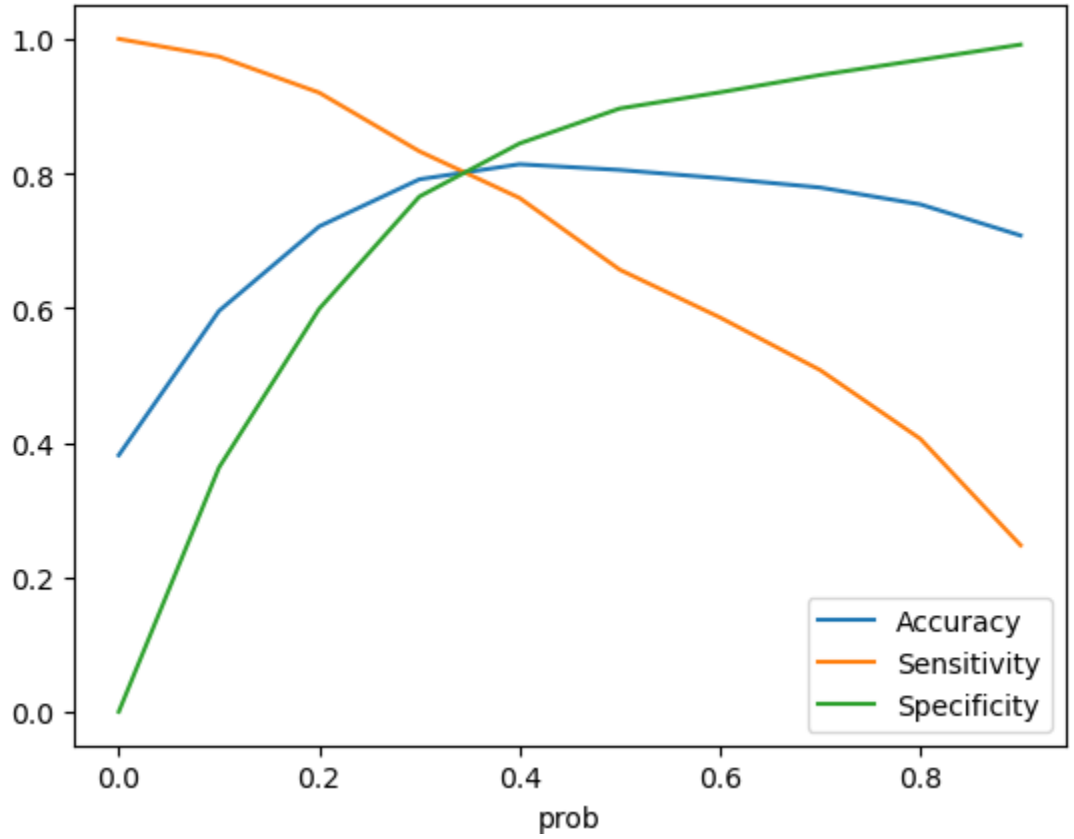
Model Building

- The data set has a large number of features and dimensions which can reduce model performance and increase computation time.
- Recursive Feature Elimination (RFE) is performed to select only the important columns.
- Pre RFE, the data set had 48 columns and post RFE it has 15 columns.
- Logistic Regression Model - 1 is a basic model.
- Manual feature reduction process was used in Logistic Regression Model - 2 and 3 to build models by dropping variables with p-value greater than 0.05.
- Logistic Regression Model - 4 is stable after four iterations with:
  - Significant p-values within the threshold (p-values < 0.05)
  - No sign of multicollinearity with VIFs less than 5
- **Logistic Regression Model - 4 (LRMod4)** is the final model used for model evaluation and making predictions.

Model Evaluation

CONFUSION MATRIX - 1		
Actual/Predicted	not_converted	converted
not_converted	**3588**	**414**
converted	**846**	**1620**

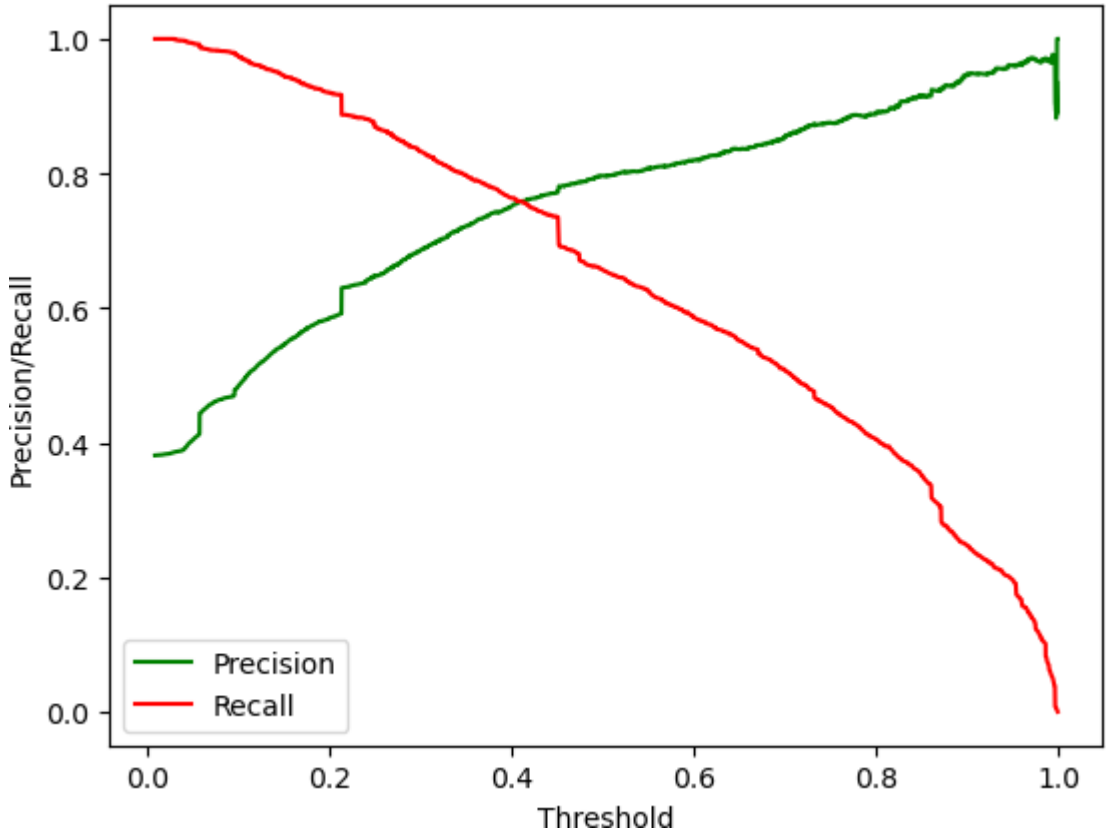
Accuracy	0.8052
Sensitivity	0.6569
Specificity	0.8966
False Positive Rate	0.1034
Precision	0.7965
Recall	0.6569
Negative Predictive Value	0.8092



Inference:

- Based on the curve analysis, a cutoff probability of 0.35(approx.) is suggested as the optimal point for classification.

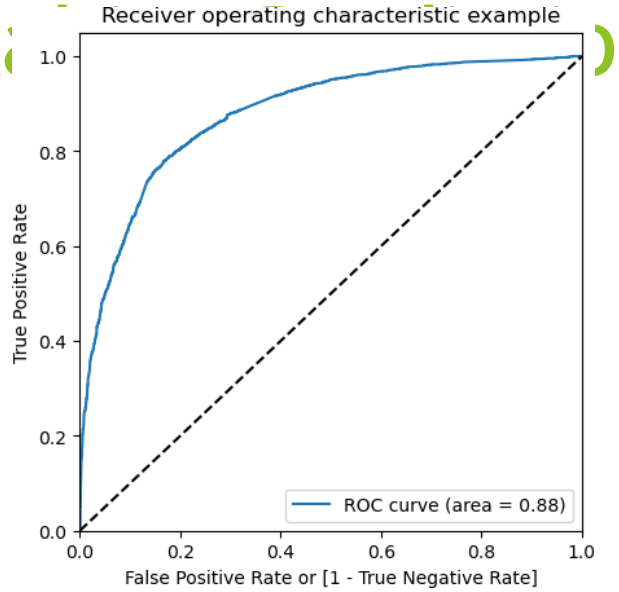
CONFUSION MATRIX - 2		
Actual/Predicted	not_converted	converted
not_converted	**3064**	**938**
converted	**412**	**2054**
Accuracy	0.8057	
Sensitivity	0.7972	
Specificity	0.8108	
False Positive Rate	0.1892	
Precision	0.722	
Recall	0.7972	
Negative Predictive Value	0.8665	



Inference:

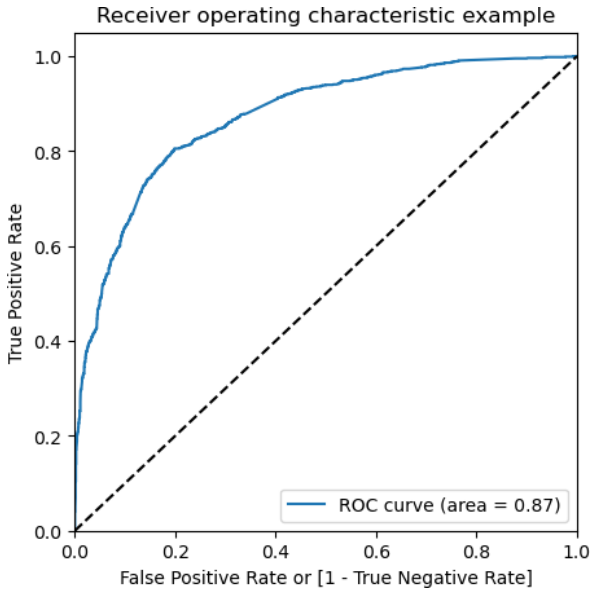
- Based on the precision-recall curve, a threshold of 0.4 provides a good balance between precision and recall.

Ma ons On Test Dataset



ROC Curve – Train Data Set

- The Area under ROC curve was found to be 0.88 out of 1, indicating that the model is a good predictor.
- The curve is plotted as close to the top left corner of the plot as possible, which indicates that the model has a high true positive rate and a low false positive rate at all threshold values.



ROC Curve – Test Data Set

- The Area under ROC curve was found to be 0.87 out of 1, indicating that the model is a good predictor.
- The curve is plotted as close to the top left corner of the plot as possible, which indicates that the model has a high true positive rate and a low false positive rate at all threshold values.

Making Predictions On Test Dataset

	Prospect ID	Converted	Converted_Prob	final_predicted	Lead_Score
0	4269	1	0.697934	1	70
1	2376	1	0.860665	1	86
2	7766	1	0.889241	1	89
3	9199	0	0.057065	0	6
4	4359	1	0.87151	1	87
5	9186	1	0.503859	1	50
6	1631	1	0.419681	1	42
7	8963	1	0.154531	0	15
8	8007	0	0.072344	0	7
9	5324	1	0.298849	0	30

Inference:

The customers with a high lead score have a higher chance of conversion and low lead score have a lower chance of conversion.

Conclusion

CONFUSION MATRIX - 3		
Actual/Predicted	not_converted	converted
not_converted	**1359**	**318**
converted	**227**	**868**

Accuracy	0.8034
Sensitivity	0.7927
Specificity	0.8104
False Positive Rate	0.1896
Precision	0.7319
Recall	0.7927
Negative Predictive Value	0.8569

Inference:

Train Data Set:

- Accuracy: 80.57%
- Sensitivity: 79.72%
- Specificity: 81.08%

Test Data Set:

- Accuracy: 80.34%
- Sensitivity: 79.27%
- Specificity: 81.04%

The evaluation metrics of the model are consistently close to each other, indicating that the model is performing consistently across different evaluation metrics in both the test and train datasets. This consistency suggests that the model is reliable and is not overfitting to the training data. It also implies that the model is generalizing well to new data, which is important for real-world applications. The similar performance across evaluation metrics also means that there are no significant biases in the model's predictions. This is a positive sign for the model's performance and provides confidence in its ability to make accurate predictions in the future.

Conclusion

We know that the relationship between ln(odds) of ‘y’ and feature variable “X” is much more intuitive and easier to understand. The equation is:

ln(odds) = - 1.0236 x const + 1.0498 x Total Time Spent on Website - 1.259 x Lead Origin_Landing Page Submission + 0.9072 x Lead Source_Olark Chat + 2.9253 x Lead Source_Reference + 5.3887 x Lead Source_Welingak Website + 0.9421 x Last Activity_Email Opened - 0.5556 x Last Activity_Olark Chat Conversation + 1.2531 x Last Activity_Others + 2.0519 x Last Activity_SMS Sent - 1.0944 x Specialization_Hospitality Management - 1.2033 x Specialization_Others + 2.6697 x Current_Occupation_Working Professional

- 'Lead Origin_Lead Add Form', 'Current_Occupation_Working Professional' and 'Total Time Spent are effective factors that contribute to a good conversion rate.
- Working professionals and Unemployed customers tend to have higher conversion rates.
- Referral leads generated by old customers have a significantly higher conversion rate
- Google and Direct Traffic are channels that are showing promising conversion rates.
- Leads whose 'Last Activity' is ‘SMS Sent’ or ‘Email Opened’ tend to have a higher conversion rate.
- The 'Others' specialization category is the most common among customers followed by Finance Management, HR Management and Marketing Management.

RECOMMENDATIONS

- Features such as 'Lead Origin_Lead Add Form', 'Current_Occupation_Working Professional', and 'Total Time Spent on Website' have a high conversion rate and should be utilized more in lead generation efforts.
- Working professionals should be aggressively targeted as they have a higher probability of converting and are likely to have better financial situations to pay for services.
- Referral leads generated by old customers have a significantly higher conversion rate and should be incentivized with discounts or other rewards to encourage more referrals.
- Increasing the frequency of media usage such as Google ads or email campaigns can save time and increase the conversion rate.
- Leads whose 'Last Activity' is ‘SMS Sent’ or ‘Email Opened’ tend to have a higher conversion rate and should be targeted more frequently.
- Analyzing the behavior of customers who spend more time on the website can help improve the user experience and increase conversion rates, and company should focus on creating engaging content and user-friendly navigation to encourage customers to spend more time on the website.
- Understanding the most popular specializations can help tailor course offerings and marketing campaigns to specific groups of customers. Providing targeted content and resources for popular specializations such as Marketing Management and HR Management can also help attract and retain customers in those fields.

THANK YOU