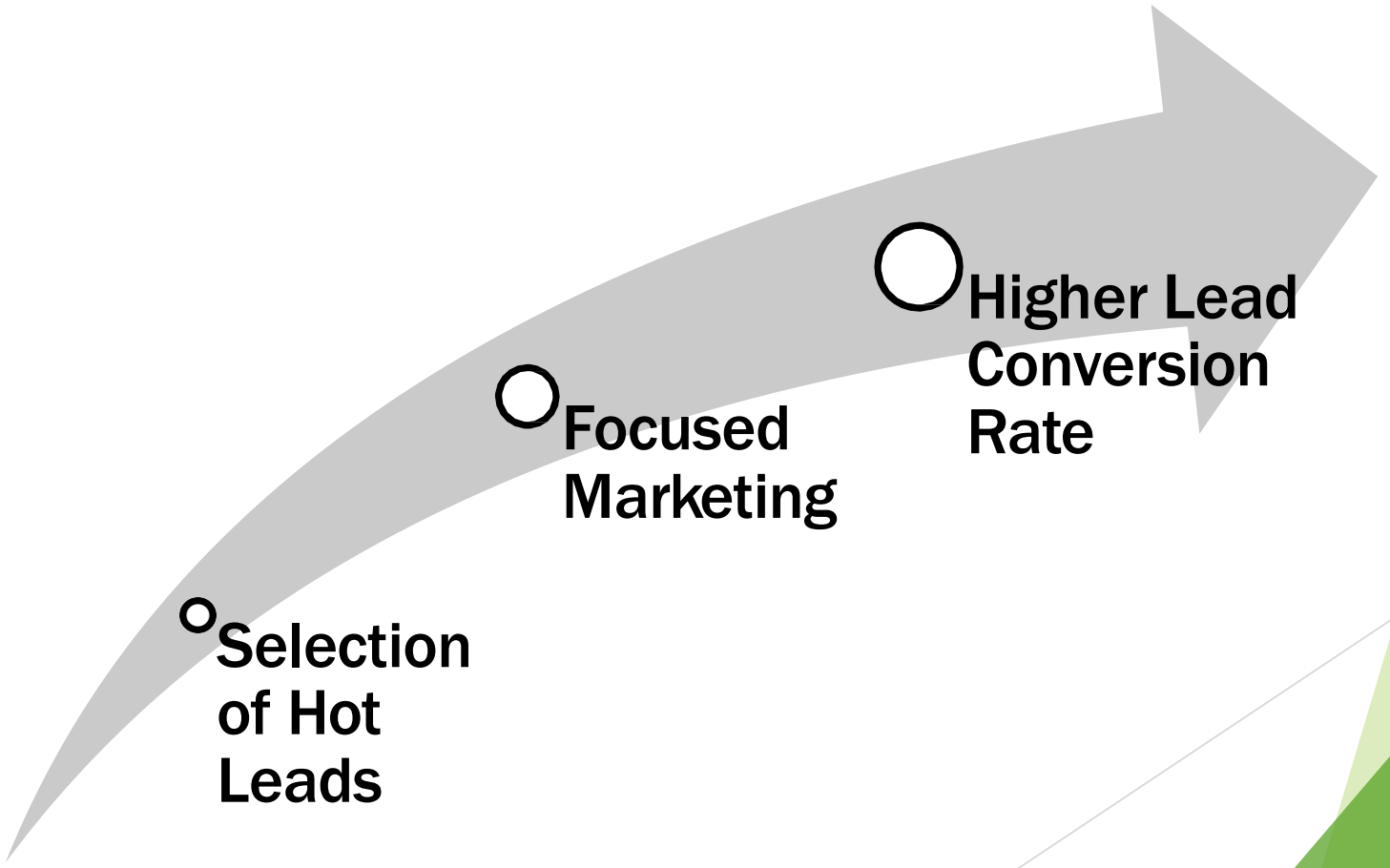
# LEAD SCORING CASE STUDY

**Focused business approach using logistic regression technique**

AYUSH GAUR

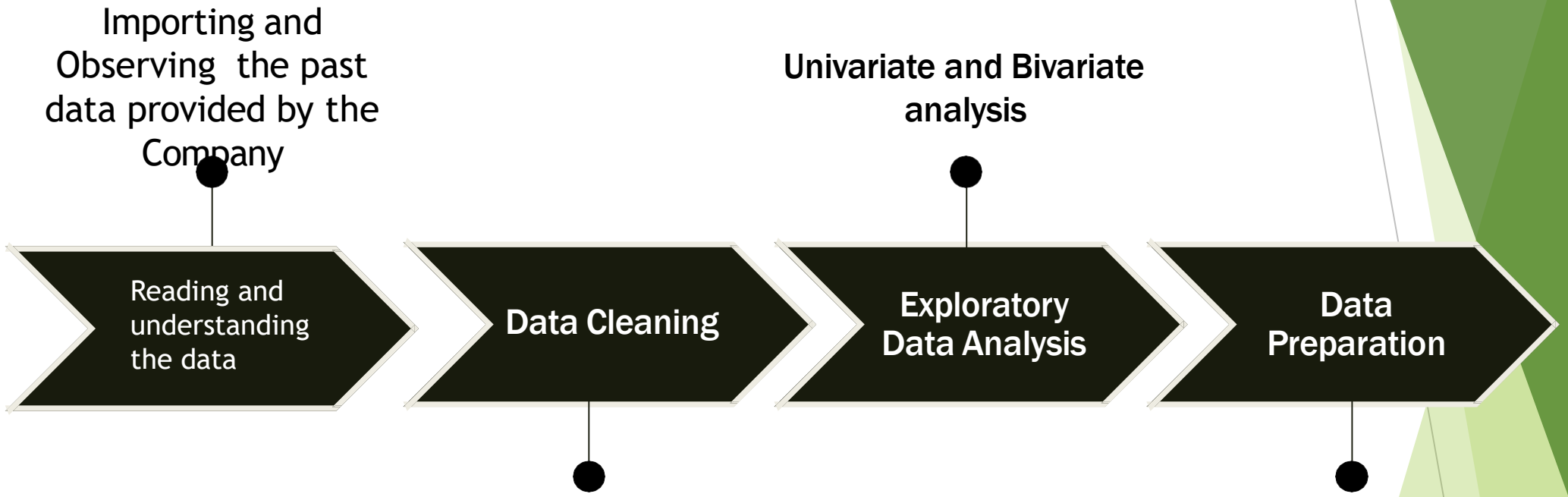
# Business Objective

To help X Education select most promising leads ***(Hot Leads)***, i.e. the leads that are most likely to convert into paying customers.



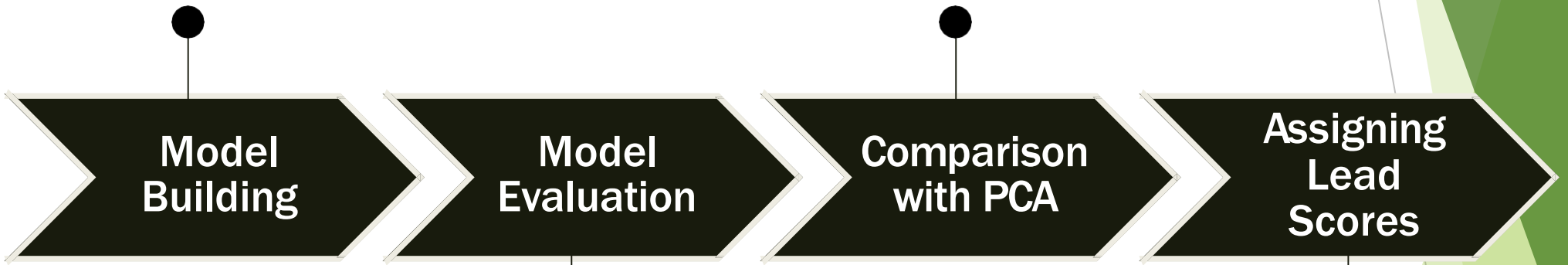
# METHODOLOGY

To build a Logistic Regression model that assigns lead scores to all leads such that the customers with higher lead score have a higher conversion chance and vice versa.
Target Lead Conversion Rate ≈ 80%


Importing and Observing the past data provided by the Company
Reading and understanding the data
Data Cleaning
Univariate and Bivariate analysis
Exploratory Data Analysis
Data Preparation
• Missing value imputation
• Removing duplicate data and other redundancies
• Outlier treatment
• Dropping unnecessary columns
• Dummy variable creation
• Feature standardization

- Feature selection using RFE
- Manual feature elimination based on p-values and VIFs

- Building another model using PCA
- Comparing the two models



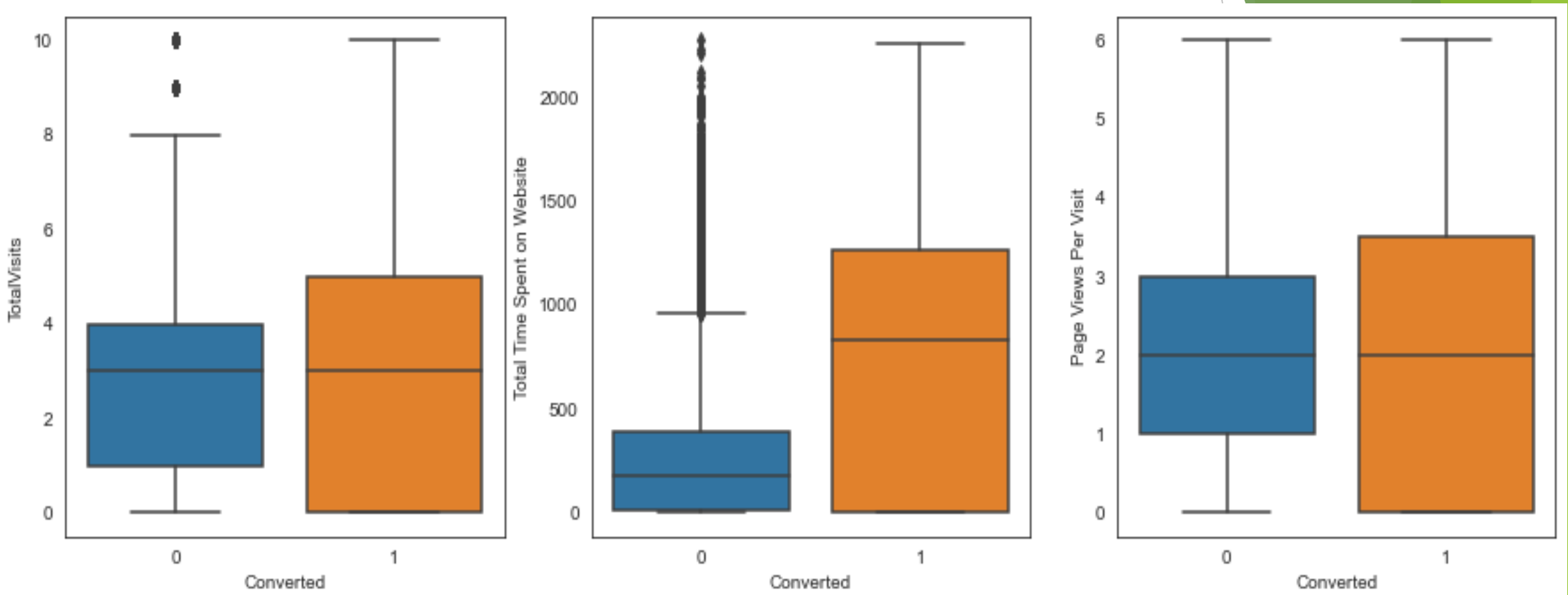

- Evaluating model based on various evaluation metrics
- Finding the optimal probability threshold

- Finalizing the first model
- Using predicted probabilities to calculate Lead Scores:
  **Lead Score = Probability* 100**

# DATA VISUALIZATION

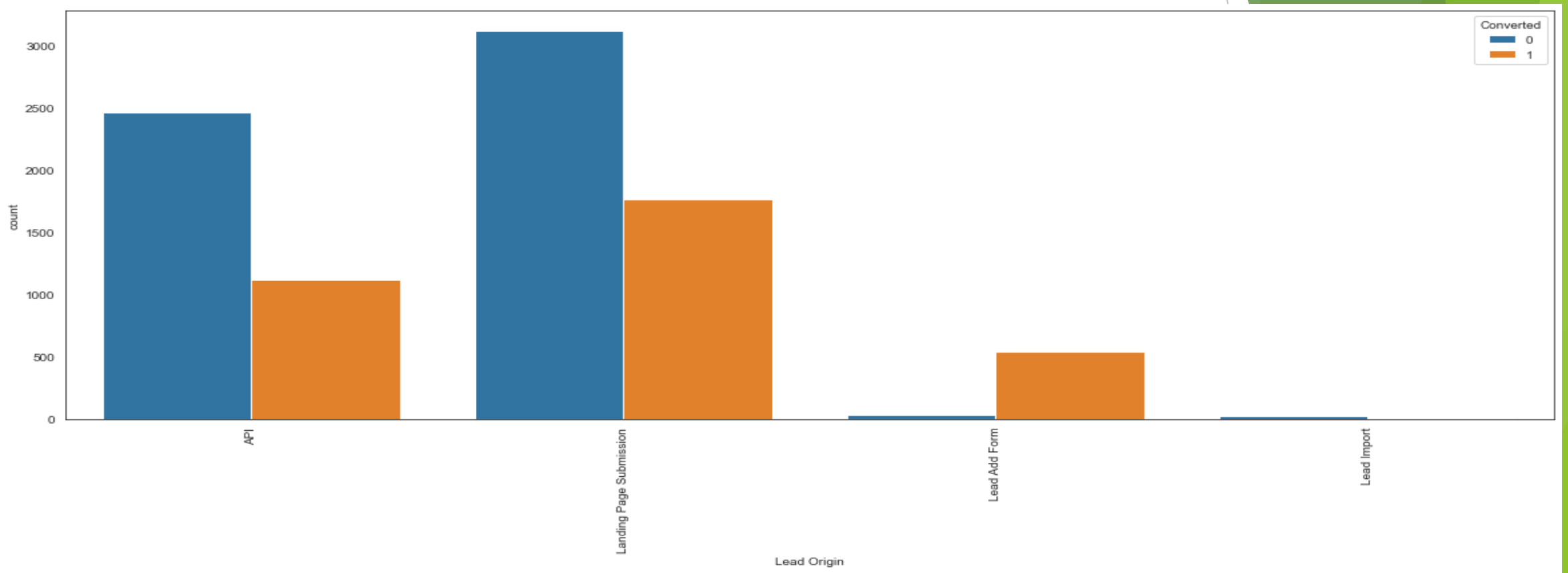
- To identify important features
- To get insights

# Numerical Variables



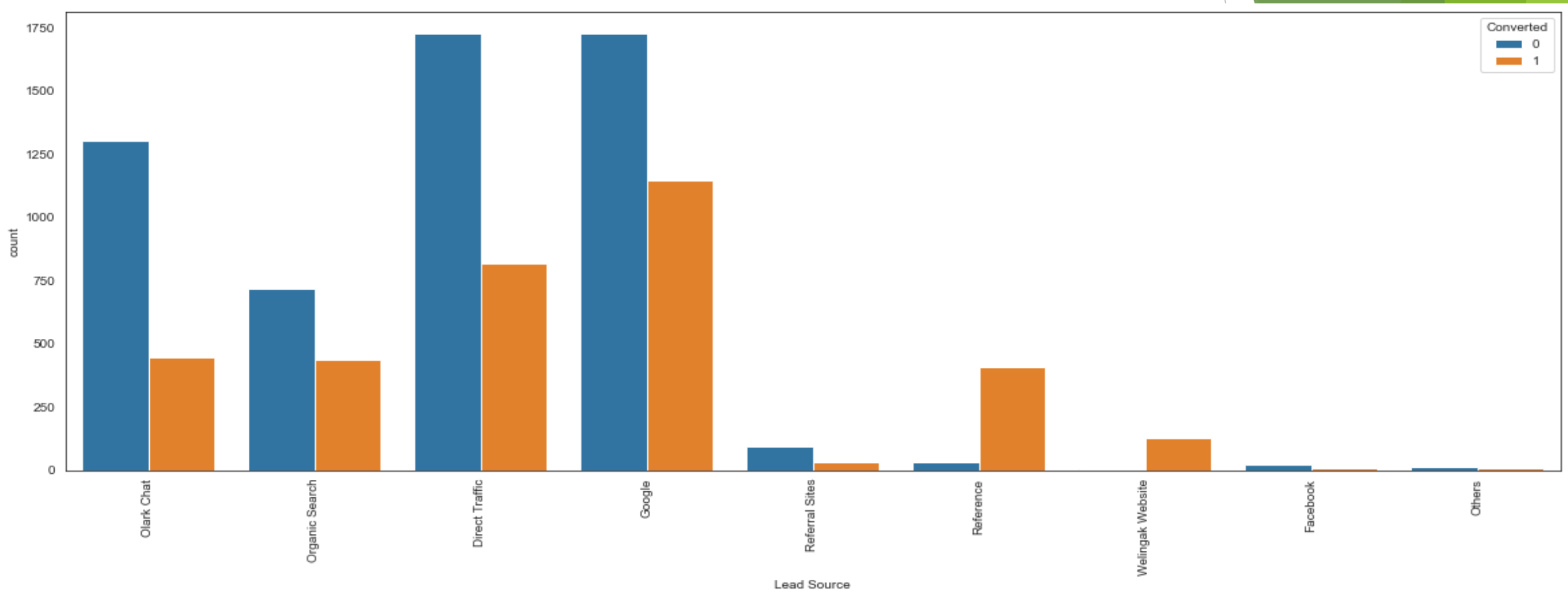

**People spending more time on website are more likely to get converted.**

# Lead Origin



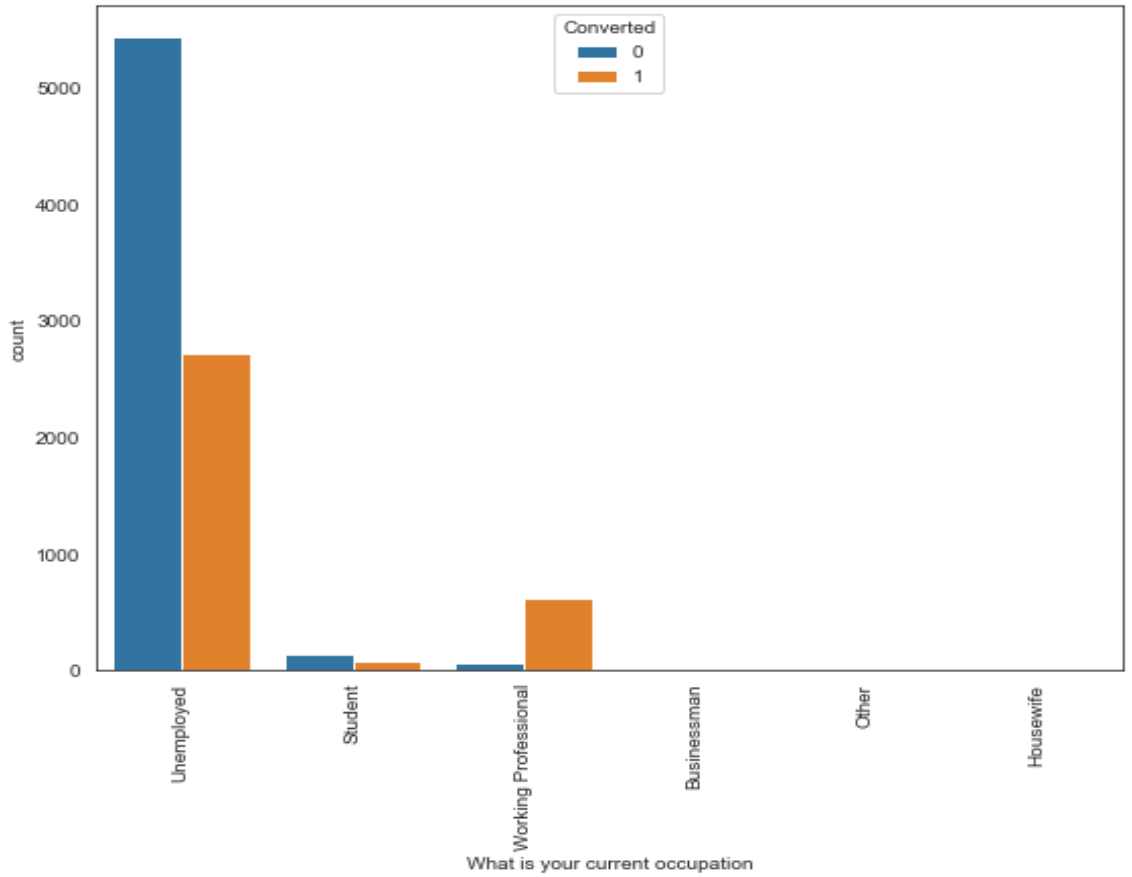

- ***'API'*** and '***Landing Page Submission***' generate the most leads but have less conversion rates, whereas '***Lead Add Form***' generates less leads but conversion rate is great.
- **Try to increase conversion rate for 'API' and 'Landing Page Submission', and increase leads generation using 'Lead Add Form'.**

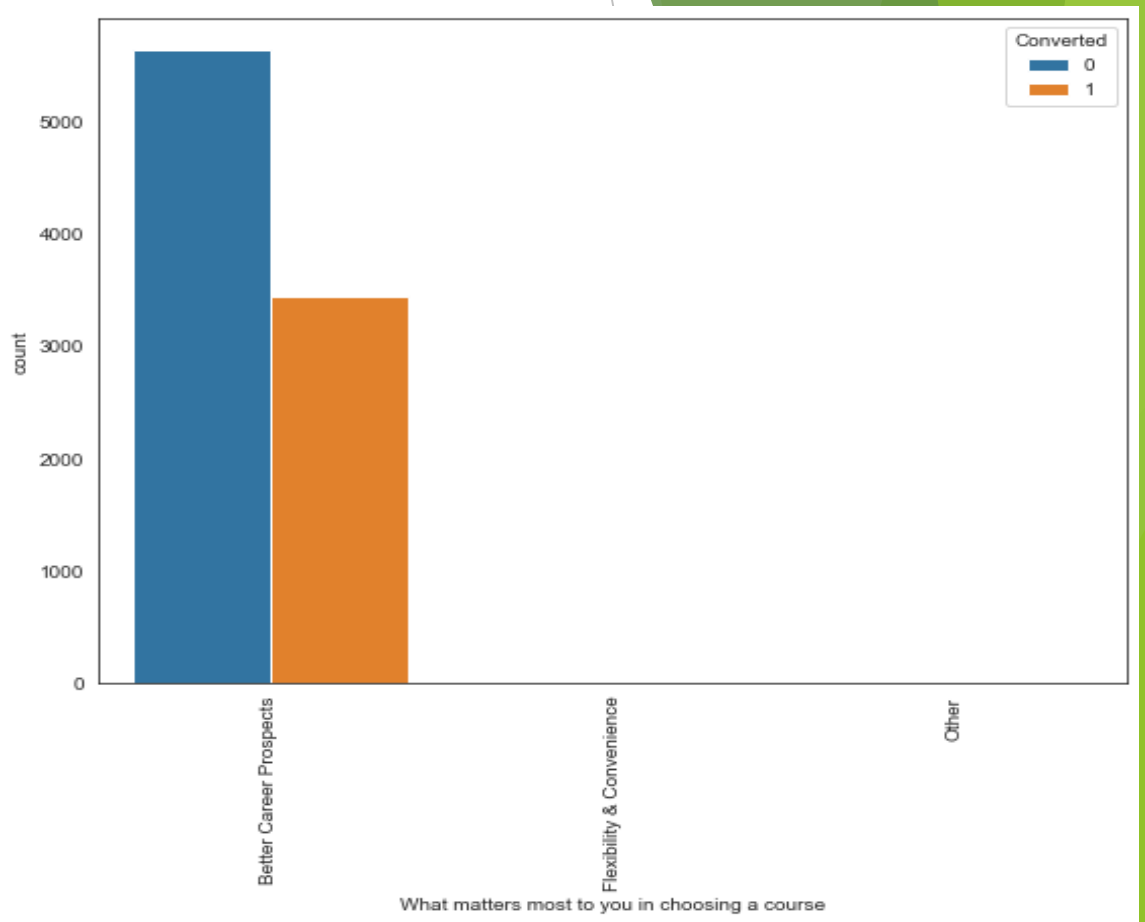
# Lead Source




- Very high conversion rates for lead sources '**Reference**' and '**Welingak Website**'.
- Most leads are generated through '**Direct Traffic**' and '**Google**'.

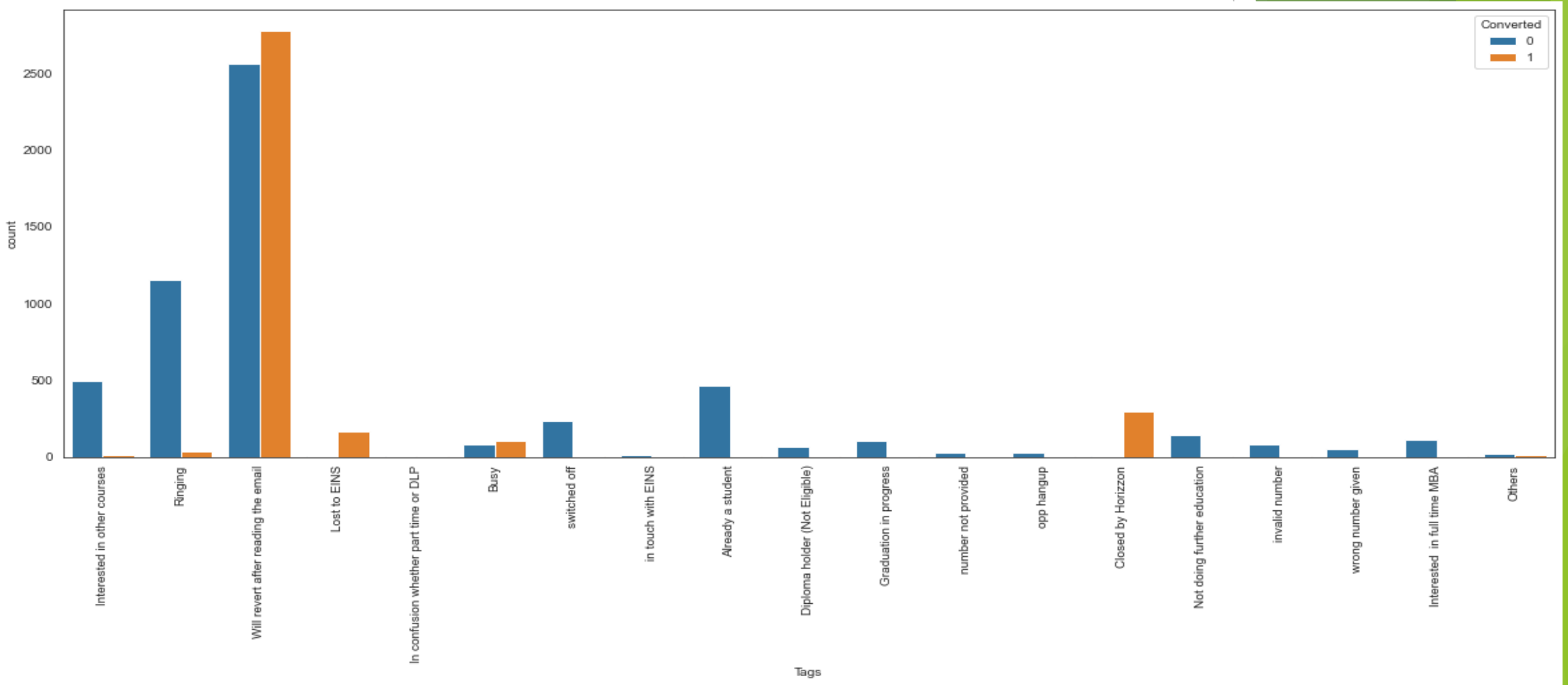
# Current Occupation



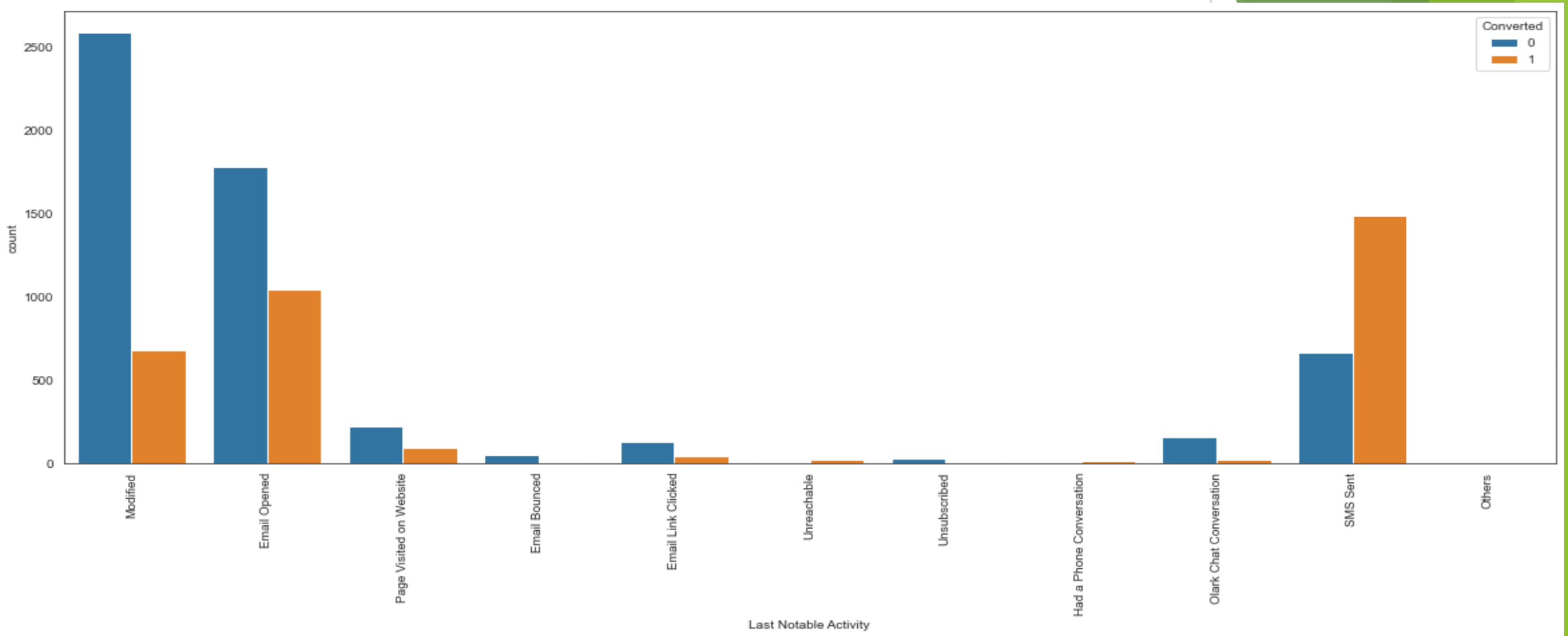

**Working Professionals** are most likely to get converted.

# Tags




**High conversion rates for tags 'Will revert after reading the email', 'Closed by Horizon', 'Lost to EINS', and 'Busy'.**

# Last Notable Activity




**Highest conversion rate is for the last notable activity '<u>SMS Sent</u>'.**

# MODEL EVALUATION

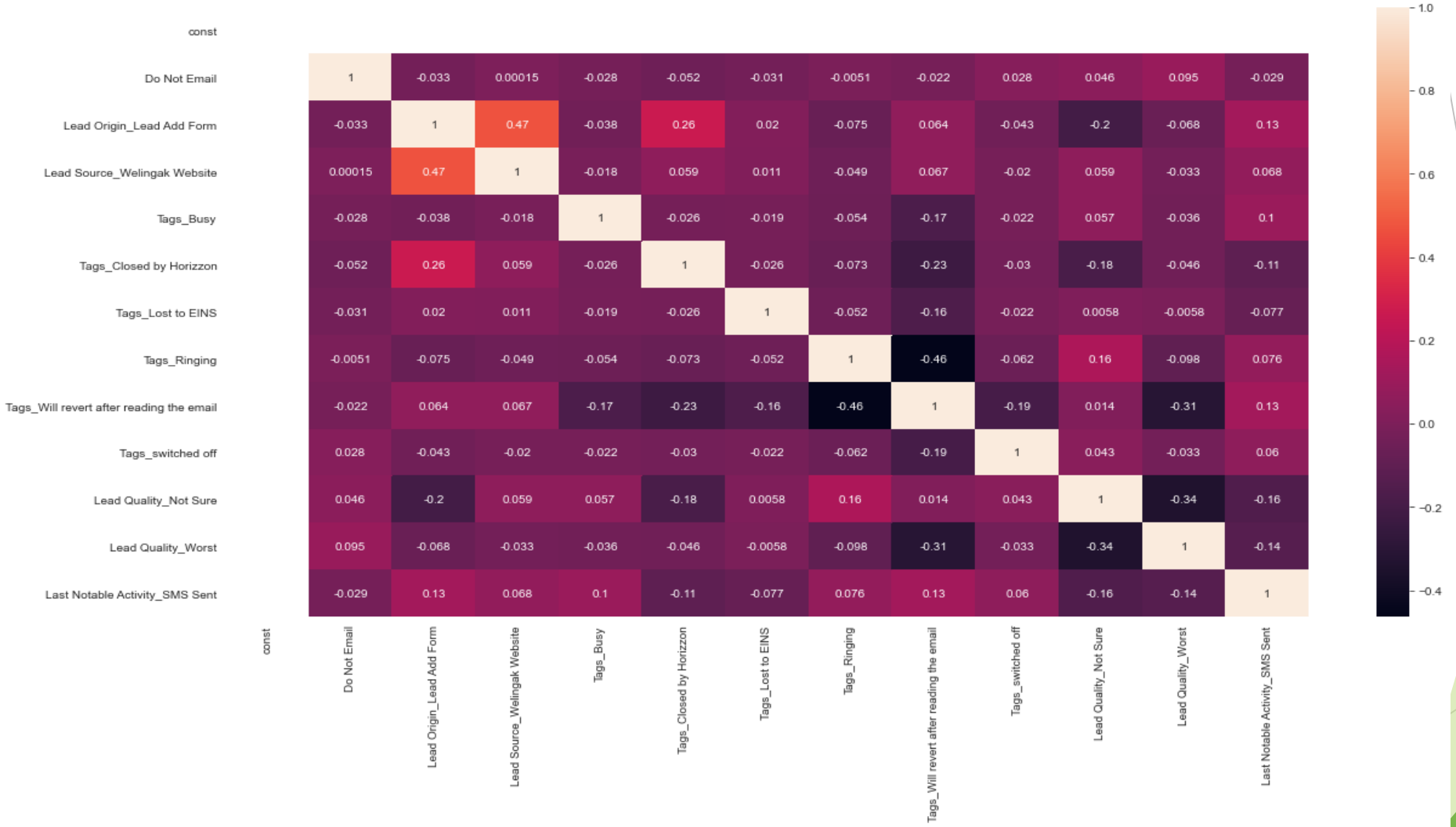
Generalized Linear Model Regression Results

| | | | |
|---|---|---|---|
| Dep. Variable: | Converted | No. Observations: | 6351 |
| Model: | GLM | Df Residuals: | 6338 |
| Model Family: | Binomial | Df Model: | 12 |
| Link Function: | logit | Scale: | 1.0000 |
| Method: | IRLS | Log-Likelihood: | -1601.0 |
| Date: | Mon, 18 May 2020 | Deviance: | 3202.0 |
| Time: | 02:23:54 | Pearson chi2: | 3.48e+04 |
| No. Iterations: | 8 | | |
| Covariance Type: | nonrobust | | |

| | coef | std err | z | P>\|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| const | -1.9192 | 0.211 | -9.080 | 0.000 | -2.333 | -1.505 |
| Do Not Email | -1.2835 | 0.212 | -6.062 | 0.000 | -1.698 | -0.868 |
| Lead Origin_Lead Add Form | 1.2035 | 0.368 | 3.267 | 0.001 | 0.482 | 1.925 |
| Lead Source_Welingak Website | 3.2825 | 0.820 | 4.002 | 0.000 | 1.675 | 4.890 |
| Tags_Busy | 3.8043 | 0.330 | 11.525 | 0.000 | 3.157 | 4.451 |
| Tags_Closed by Horizzon | 7.9789 | 0.762 | 10.467 | 0.000 | 6.485 | 9.473 |
| Tags_Lost to EINS | 9.1948 | 0.753 | 12.209 | 0.000 | 7.719 | 10.671 |
| Tags_Ringing | -1.8121 | 0.336 | -5.401 | 0.000 | -2.470 | -1.154 |
| Tags_Will revert after reading the email | 3.9906 | 0.228 | 17.508 | 0.000 | 3.544 | 4.437 |
| Tags_switched off | -2.4456 | 0.586 | -4.171 | 0.000 | -3.595 | -1.297 |
| Lead Quality_Not Sure | -3.5218 | 0.126 | -28.036 | 0.000 | -3.768 | -3.276 |
| Lead Quality_Worst | -3.9106 | 0.856 | -4.567 | 0.000 | -5.589 | -2.232 |
| Last Notable Activity_SMS Sent | 2.7395 | 0.120 | 22.907 | 0.000 | 2.505 | 2.974 |

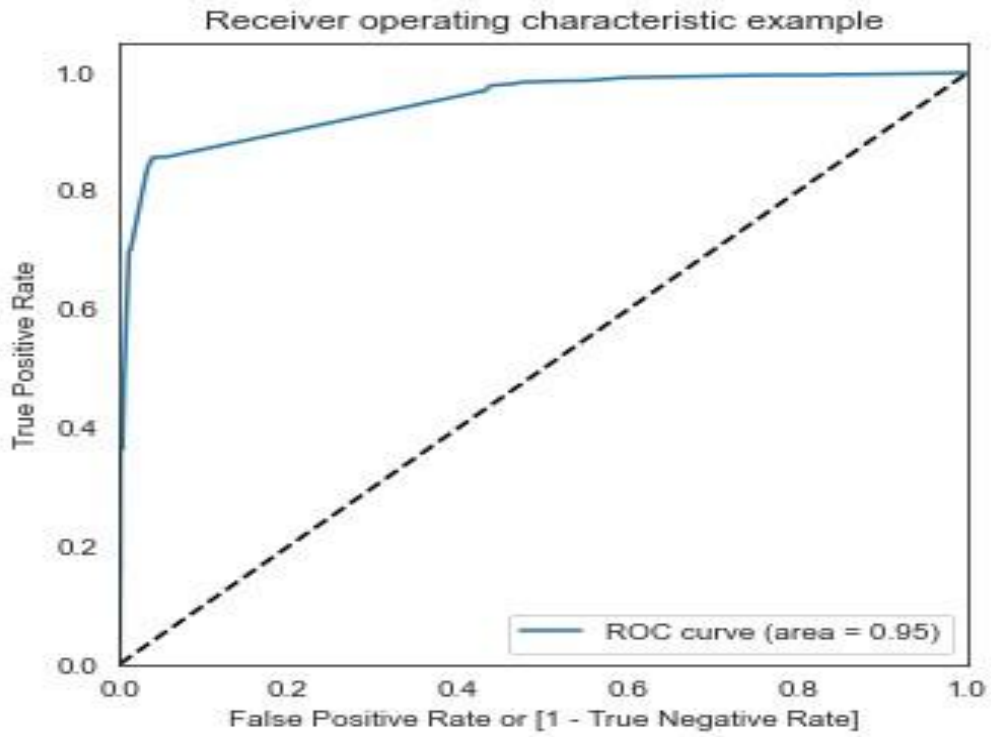
# Final Model Summary: All p values are zero.

# Heatmap



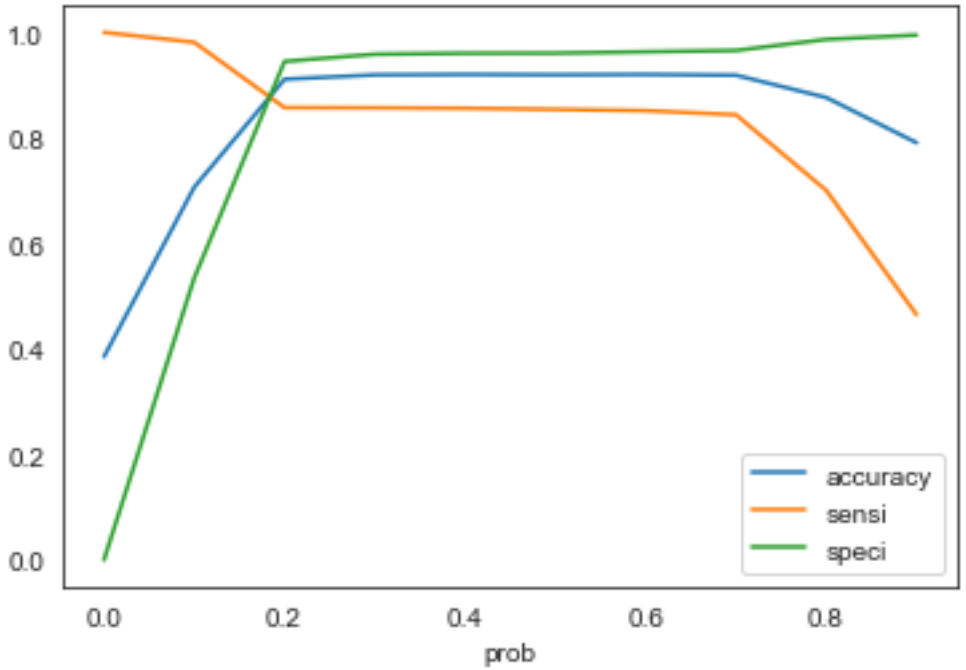

**Correlations** between features in the final model are **negligible.**

# ROC curve




**Area under curve = 0.95**

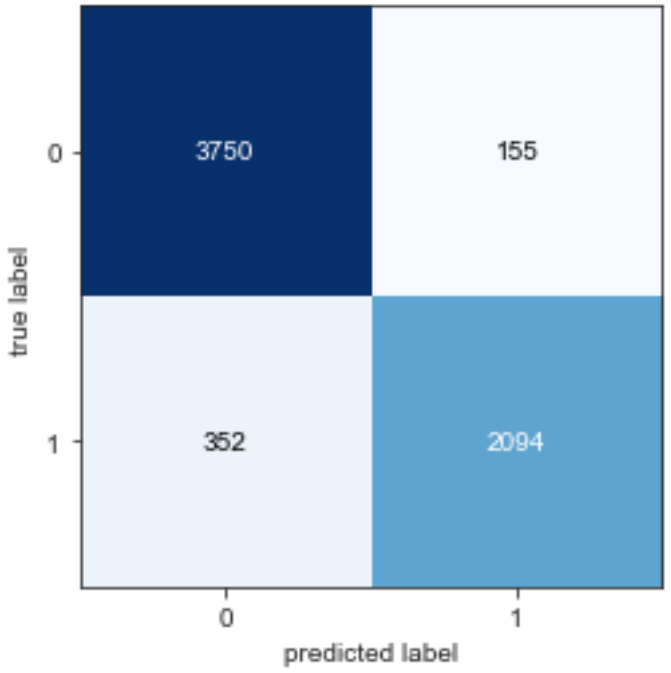
# Finding Optimal Threshold



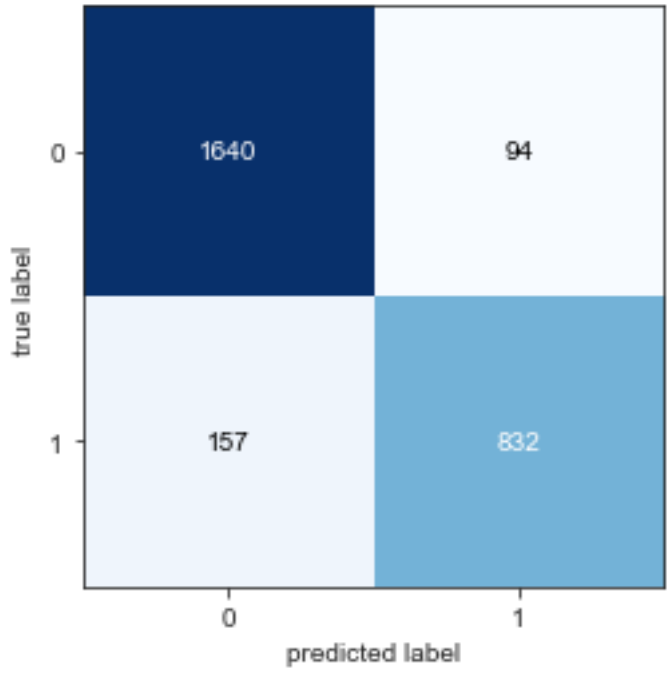

Graph showing changes in Sensitivity, Specificity and Accuracy with changes in the probability threshold values

**Optimal cutoff = 0.20**

# Confusion Matrix




For train set

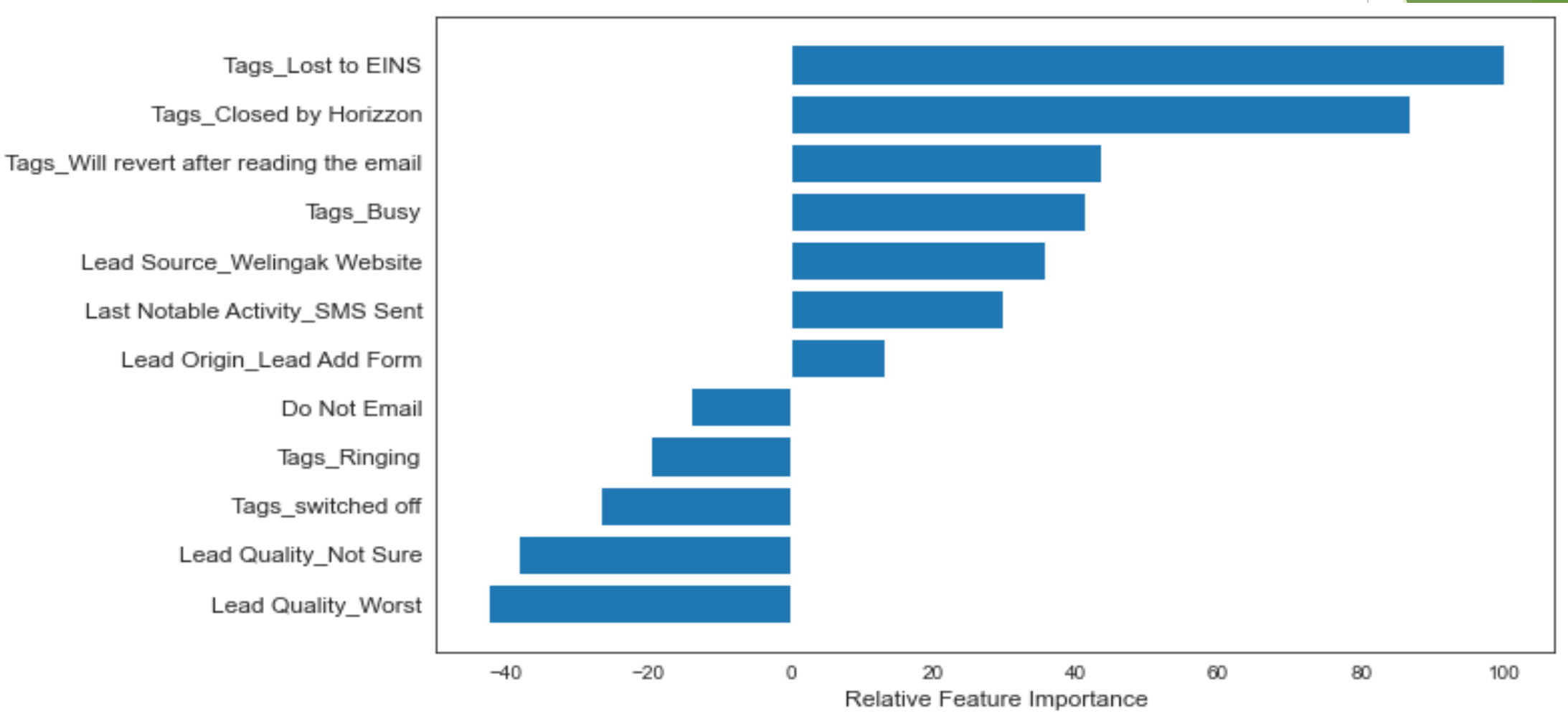



For test set

# Final Results

| Data | Train set | Test set |
|---|---|---|
| Accuracy | 0.9111 | 0.9078 |
| Sensitivity | 0.8573 | 0.8412 |
| Specificity | 0.9449 | 0.9457 |
| False Positive Rate | 0.0550 | 0.0542 |
| Positive Predictive Value | 0.9070 | 0.8984 |
| Negative Predictive Value | 0.9135 | 0.9126 |
| AUC | 0.9488 | 0.9388 |

# Relative Importance Of Features



# INFERENCES

# Feature Importance

- Three variables which contribute most towards the probability of a lead conversion in decreasing order of impact are:
  - * *Tags_Lost to EINS*
  - * Tags_Closed by Horizzon
  - * Tags_Will revert after reading the email
- These are dummy features created from the categorical variable Tags.
- All three **contribute positively** towards the probability of a lead conversion.
- These results indicate that the company should **focus more on the leads with these three tags.**

**Situation 1:** Company has interns for 2 months. They wish to make lead conversion more aggressive. They want almost all of the potential leads to be converted and hence, want to make phone calls to as much of such people as possible.

**Solution:**

- $Sensitivity = True\ Positives / (True\ Positives + False\ Negatives)$
- Sensitivity can be defined as the number of actual conversions predicted correctly out of total number of actual conversions. As we saw earlier, sensitivity decreases as the threshold increases.
- High sensitivity implies that our model will correctly predict almost all leads who are likely to convert. At the same time, it may overestimate and misclassify some of the non-conversions as conversions.
- As the company has extra man-power for two months and wants to make the lead conversion more aggressive, it is a good strategy to go for **high sensitivity**. To achieve high sensitivity, we need to **choose a low threshold value**.

**Situation 2:** At times, the company reaches its target for a quarter before the deadline. It wants the sales team to focus on some new work. So during this time, the company's aim is to not make phone calls unless it's extremely necessary.

**Solution:**

- $Specificity = True\ Negatives / (True\ Negatives + False\ Positives)$
- Specificity can be defined as the number of actual non-conversions predicted correctly out of total number of actual non-conversions. It increases as the threshold increases.
- High specificity implies that our model will correctly predict almost all leads who are not likely to convert. At the same time, it may misclassify some of the conversions as non-conversions.
- As the company has already reached its target for a quarter and doesn't want to make unnecessary phone calls, it is a good strategy to go for **high specificity.**
- It will ensure that the phone calls are only made to customers who have a very high probability of conversion. To achieve high specificity, we need to **choose a high threshold value.**

# Recommendations

- By referring to the data visualizations, focus on
  - *Increasing the conversion rates for the categories generating more leads and*
  - *Generating more leads for categories having high conversion rates.*
- Pay attention to the relative importance of the features in the model and their positive or negative impact on the probability of conversion.
- Based on varying business needs, modify the probability threshold value for identifying potential leads.

# THANK YOU