

LEAD SCORING CASE STUDY

Using logistic regression technique

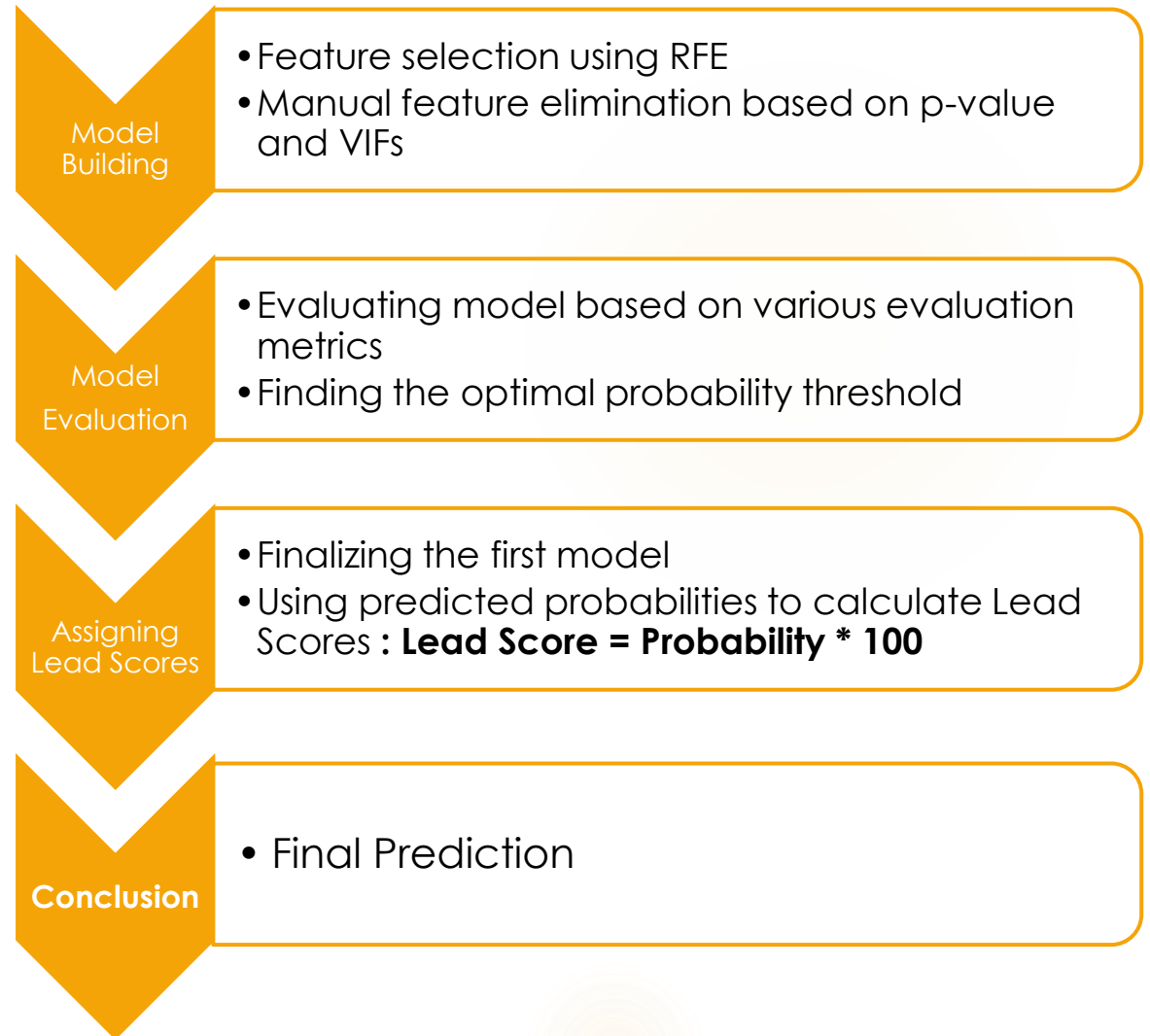
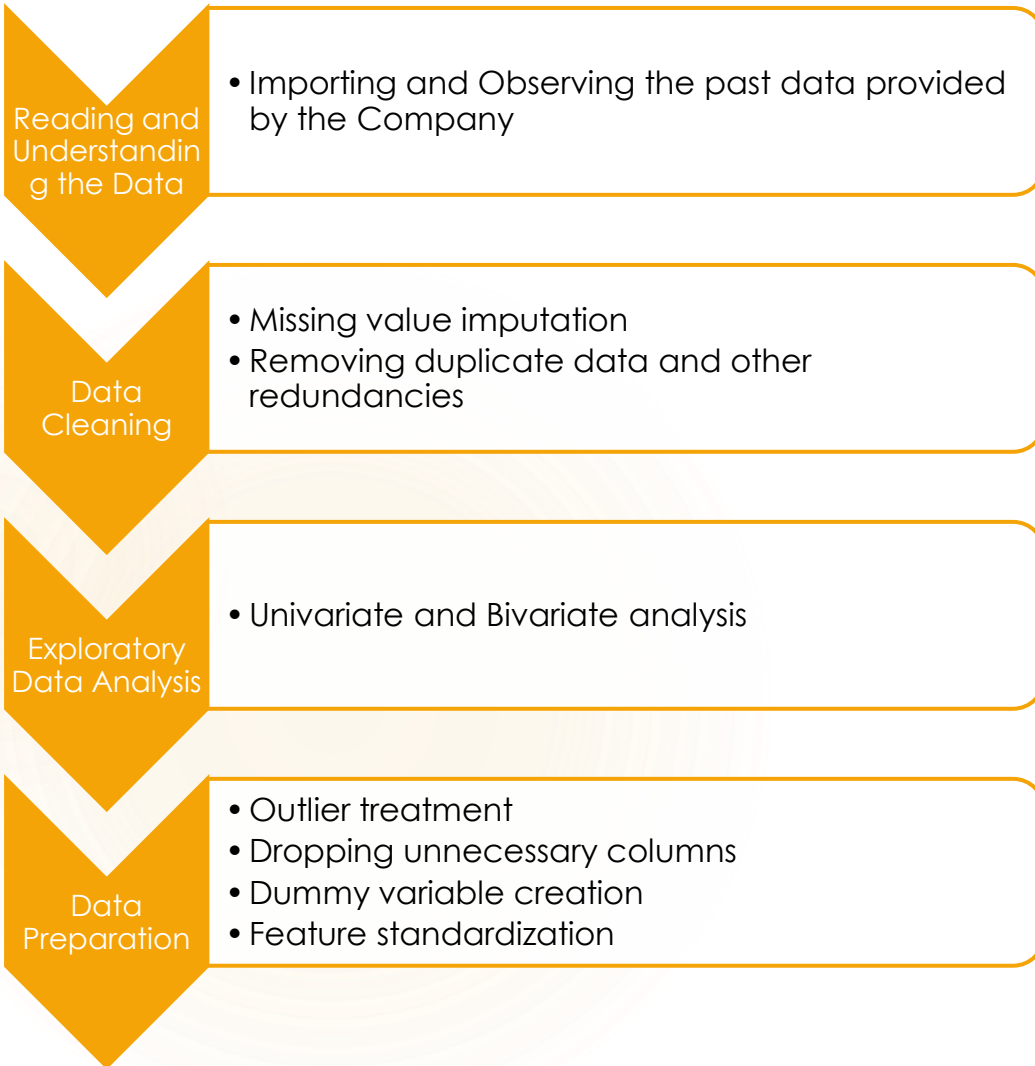
Problem Statement

- ▶ 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. There are a lot of leads generated in the initial stage but only a few of them come out as paying customers. The company needs to nurture the potential leads well (i.e. educating the leads about the product, constantly communicating etc.) in order to get a higher lead conversion.
- ▶ The problem is to help the company select the most promising leads, i.e. the leads that are most likely to convert into paying customers. The CEO, in particular, has given a ballpark of the target lead conversion rate to be around 80%.

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%

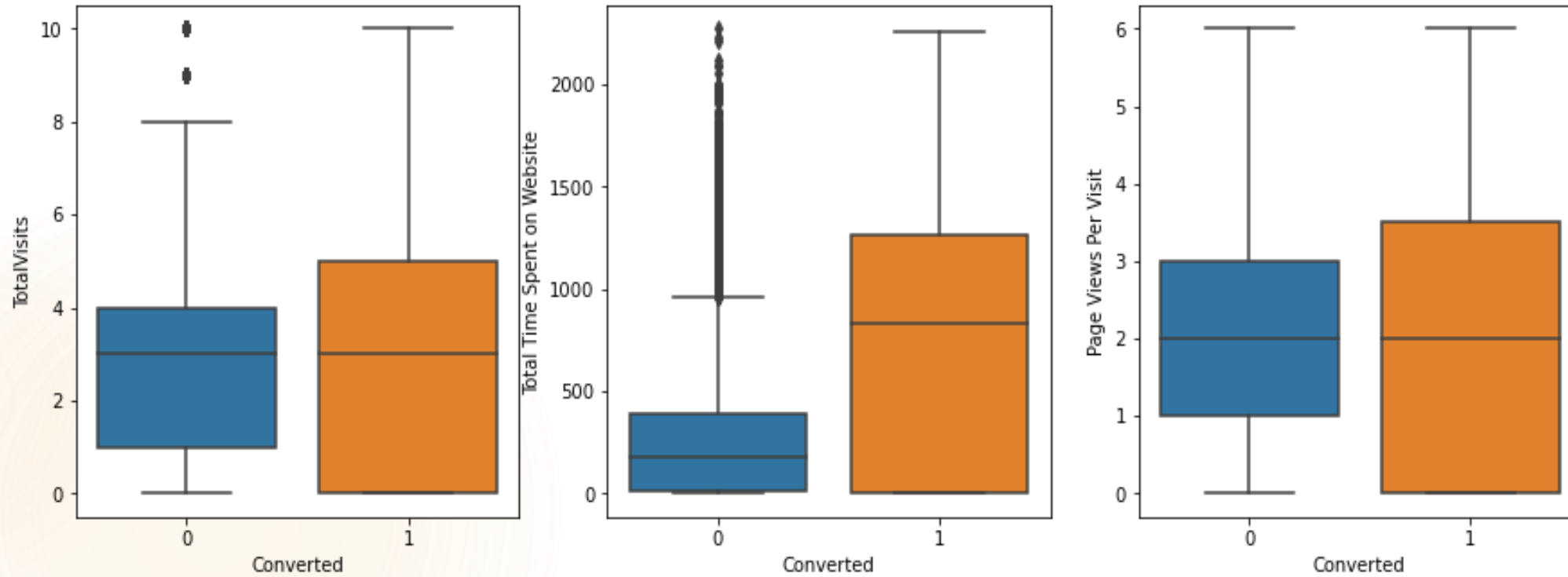
Approach



DATA VISUALIZATION

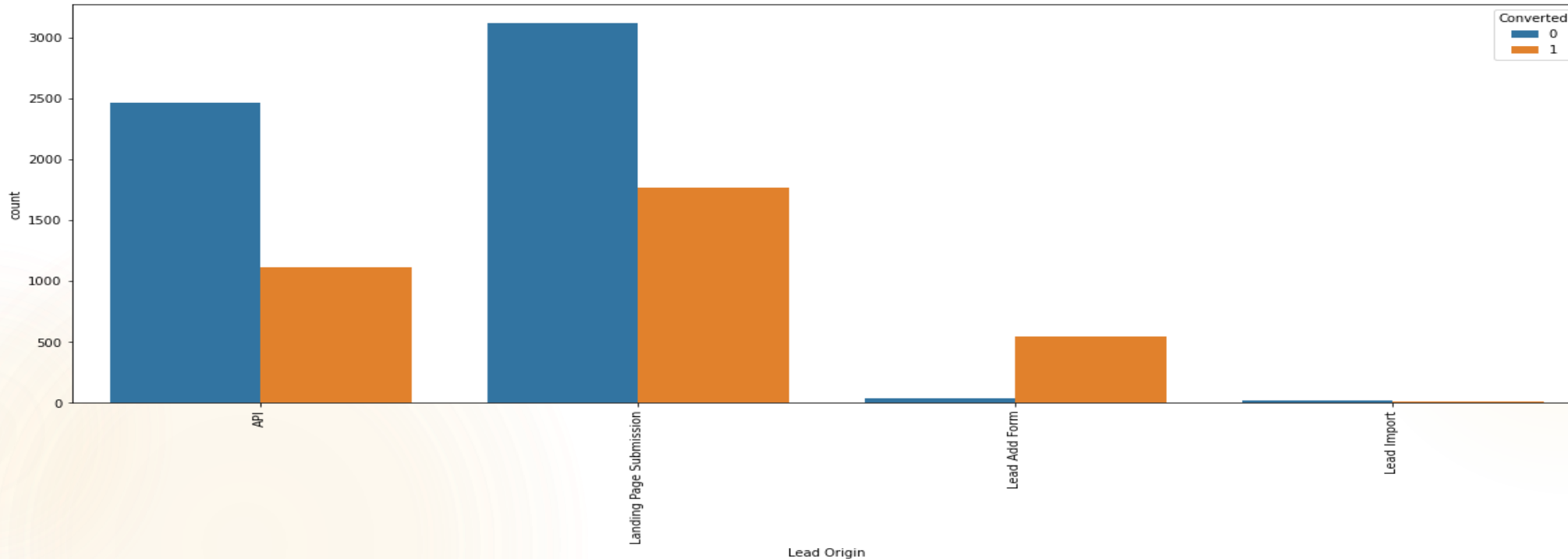
- ▶ To identify important features
- ▶ To get insights

Numerical Variables



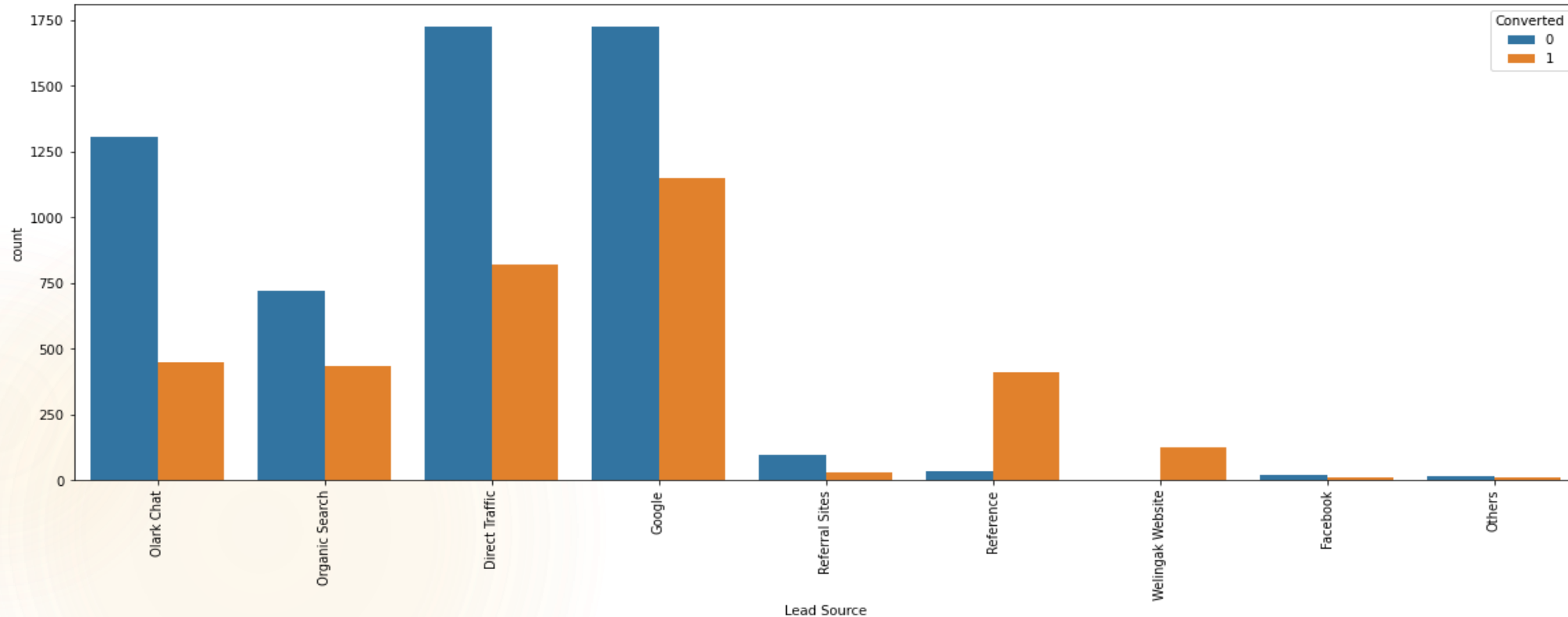
- ▶ People spending more time on website are more likely to get converted.

Lead Origin



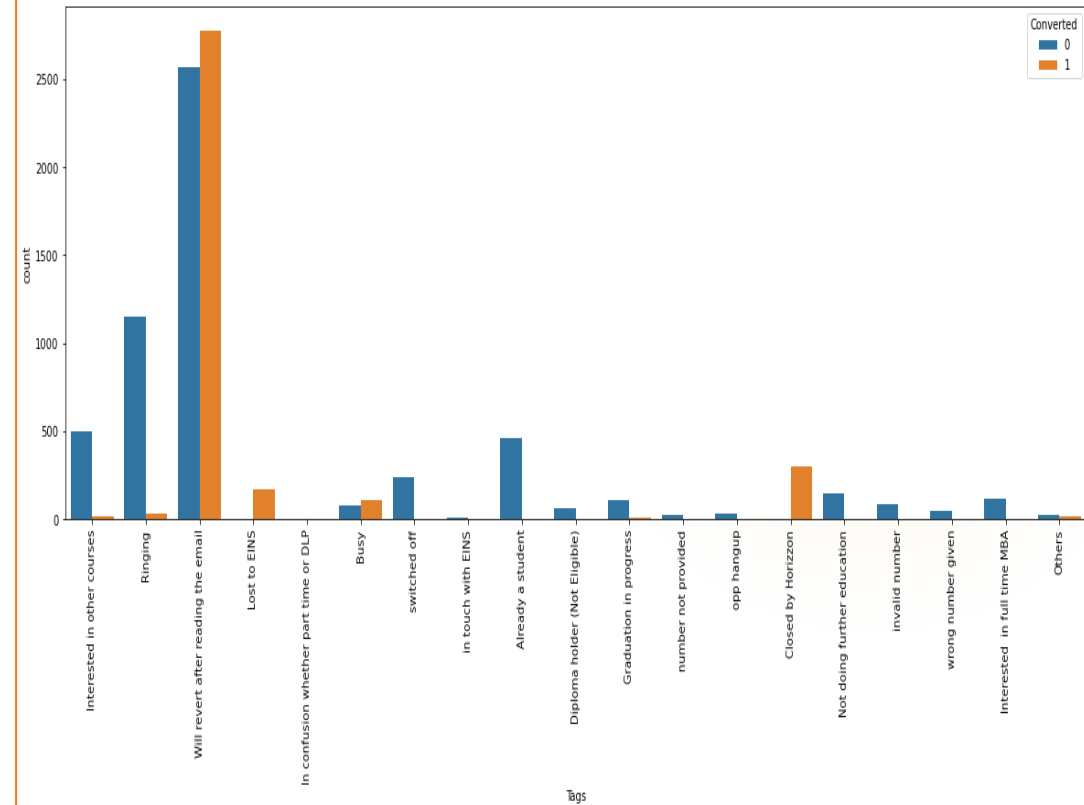
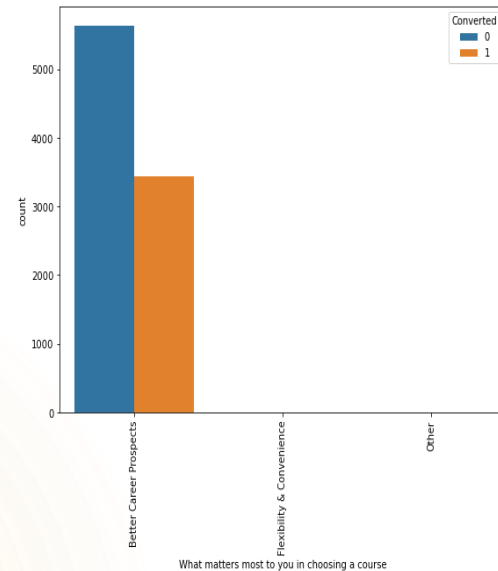
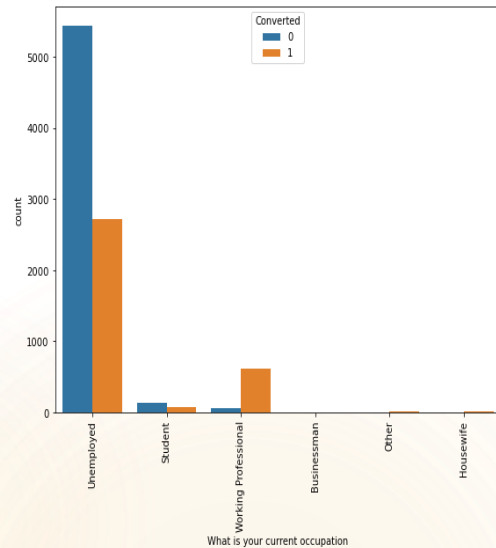
- 'API' and 'Landing Page Submission' generate the most leads but have less conversion rates, whereas 'Lead Add Form' generates less leads but conversion rate is great.
- Try to Increase conversion rate for 'API' and 'Landing Page Submission', and increase leads generation using 'Lead Add Form'

Lead Source



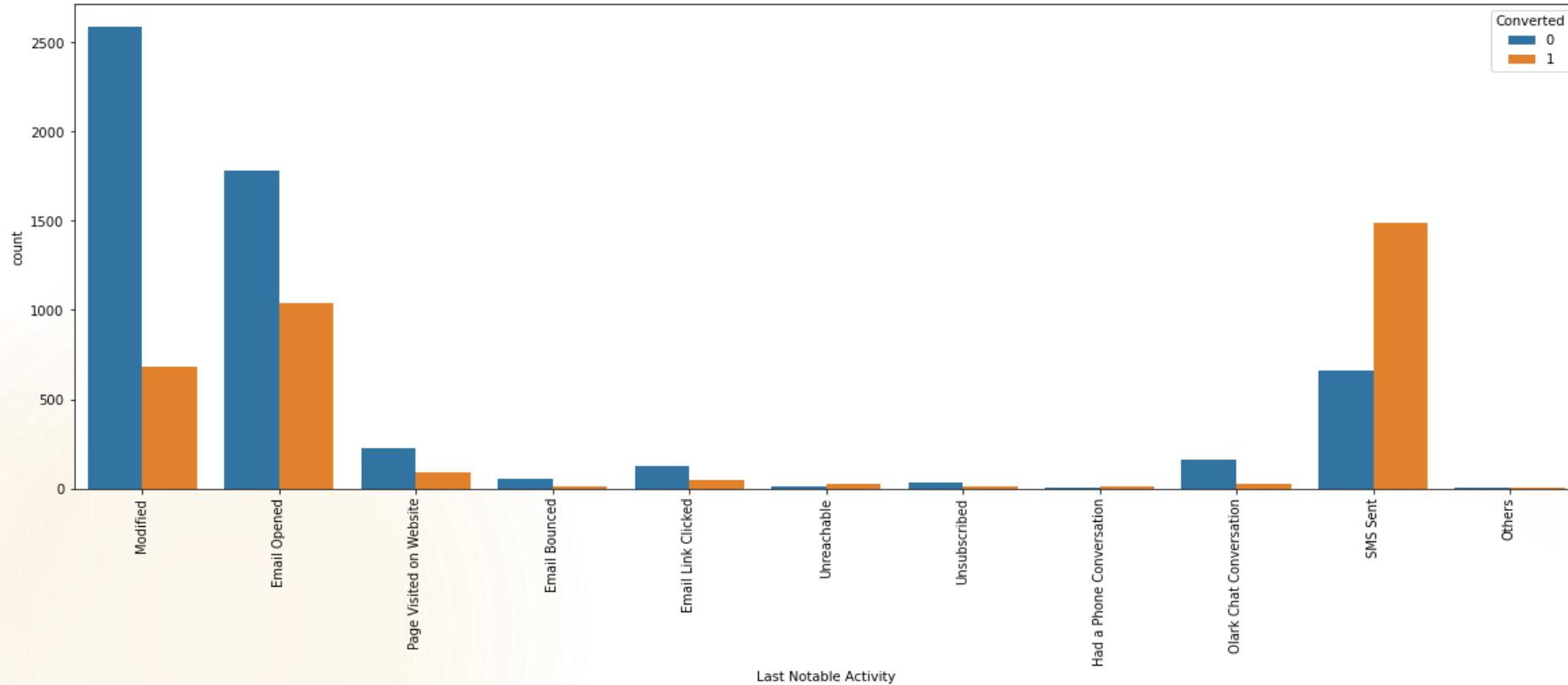
- Very high conversion rates for lead sources 'Reference' and 'Wellngak website'.
- Most leads are generated through 'Direct Traffic' and 'Google'

Current Occupation & Tags



- Working Professionals are most likely to get converted.
- 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 'SMS Sent'.

MODEL EVALUATION

Generalized Linear Model Regression Results

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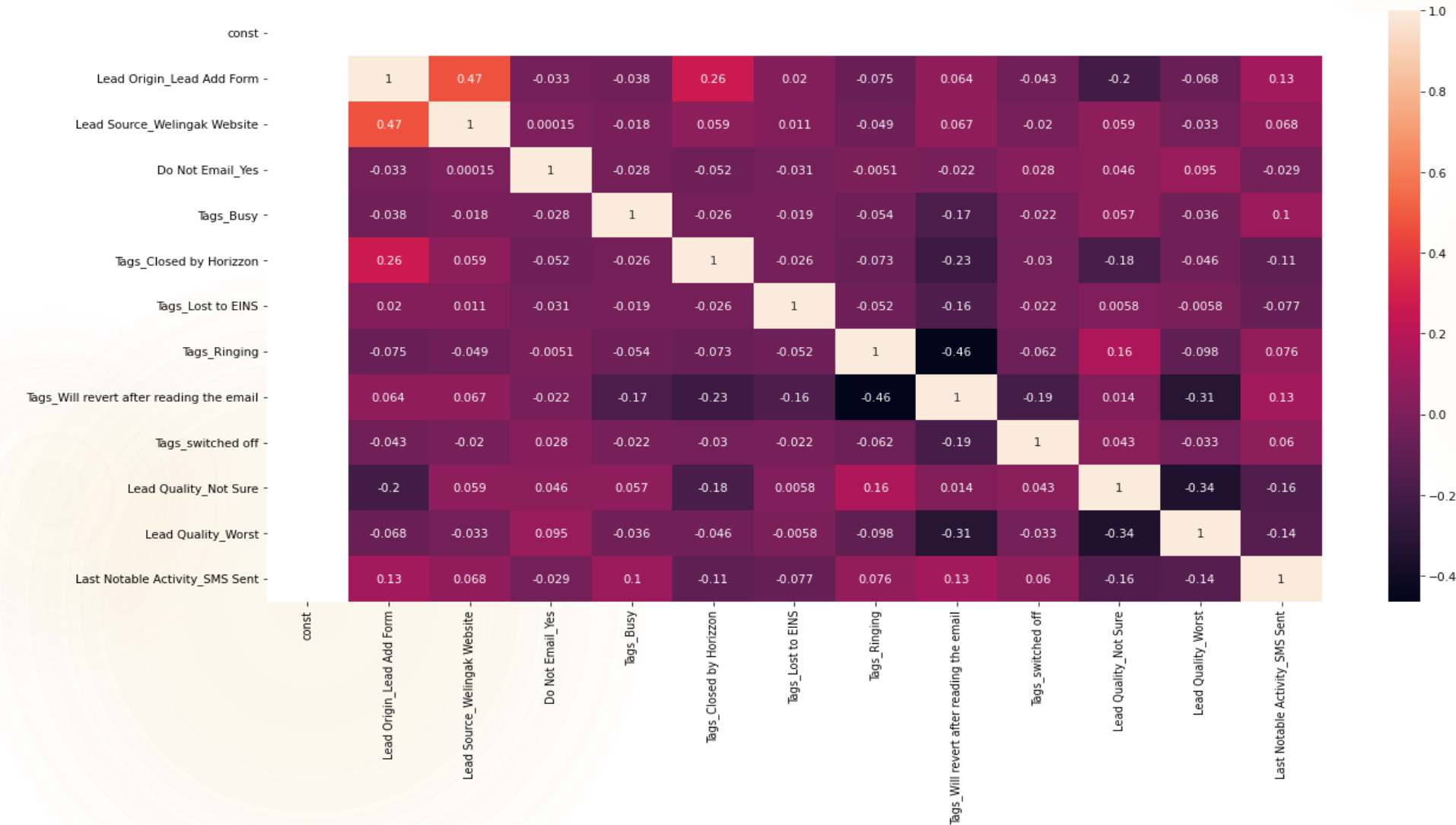
=====
Dep. Variable:          Converted    No. Observations:          6351
Model:                  GLM         Df Residuals:              6338
Model Family:          Binomial    Df Model:                  12
Link Function:          logit       Scale:                    1.0000
Method:                 IRLS        Log-Likelihood:           -1601.0
Date:                   Mon, 17 Oct 2022    Deviance:                3202.0
Time:                   12:09:05    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
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
Do Not Email_Yes	-1.2835	0.212	-6.062	0.000	-1.698	-0.868
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

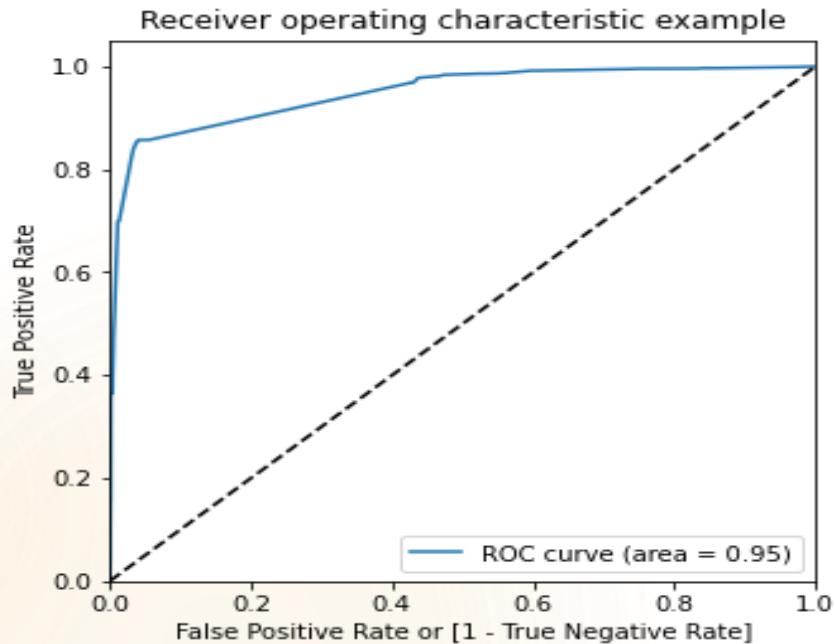
Final Model Summary : All p-values are zero

Heatmap



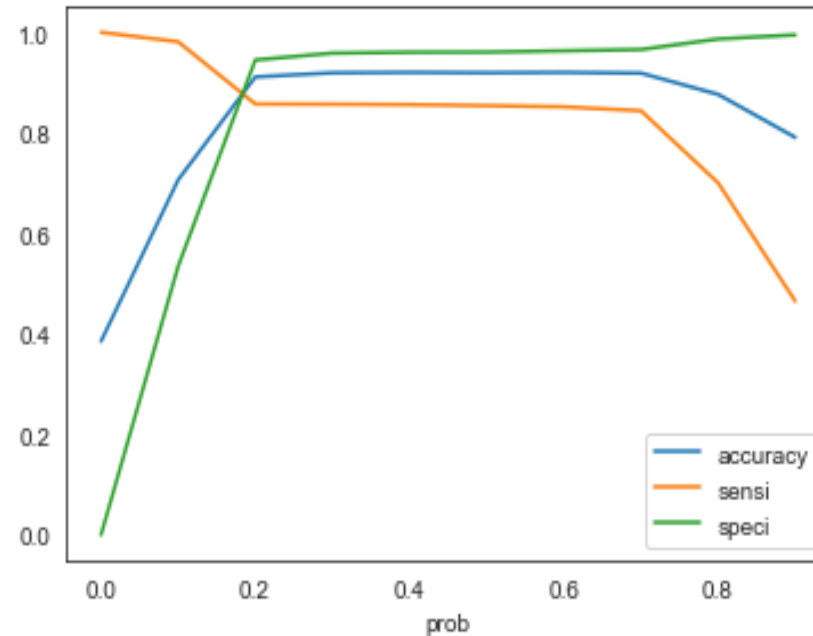
- Correlations between features in the final model are negligible.

ROC Curve



- Area Under curve are aprox 95%

Finding Optimal threshold

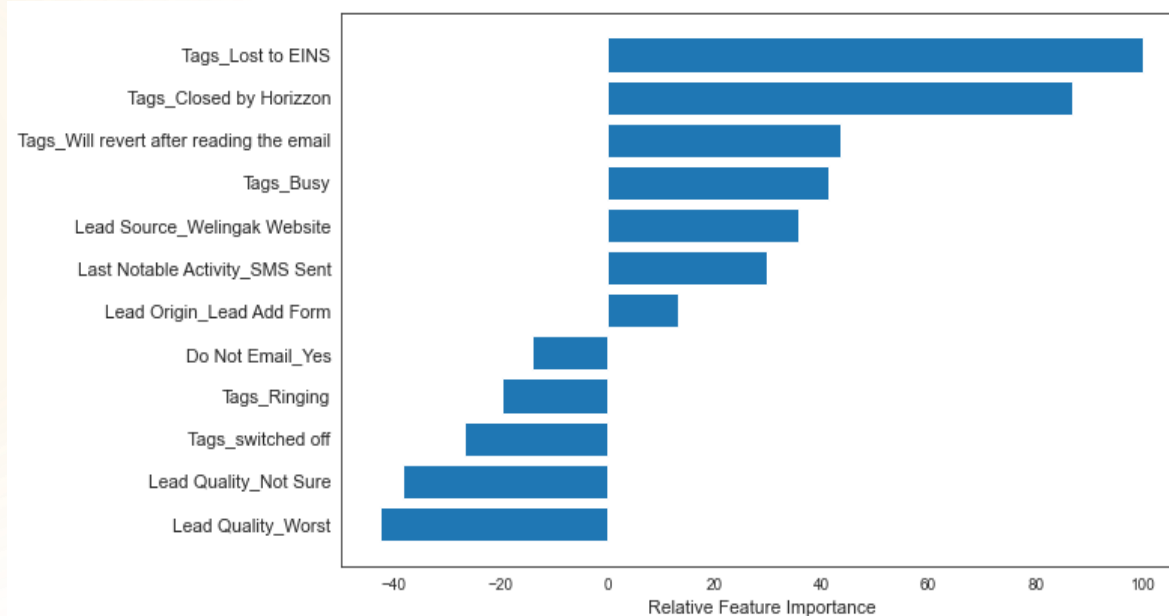


- Graph showing changes in Sensitivity, Specificity and Accuracy with changes in the probability threshold values.
- Optimal cutoff = 0.20

Final Results

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

Relative Importance Of Features



The background features several concentric circles in shades of light orange and yellow, creating a subtle pattern. In the top right corner, there is a solid orange rectangle.

INFERENCES

Feature Importance

- ❑ Three variables which contribute most towards the probability of a lead conversion in decreasing order of impact are:
 1. Tags_Lost to EINS
 2. Tags_Closed by Horizzon
 3. 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.

Twelve features were selected as the most significant in predicting the conversion:

- Features having **positive impact** on conversion probability in **decreasing order** of impact:

Features with Positive Coefficient Values

Tags_Lost to EINS
Tags_Closed by Horizon
Tags_Will revert after reading the email
Tags_Busy
Lead Source_Welingak Website
Last Notable Activity_SMS Sent
Lead Origin_Lead Add Form

- Features having **negative impact** on conversion probability in **decreasing order** of impact:

Features with Negative Coefficient Values

Lead Quality_Worst
Lead Quality_Not Sure
Tags_switched off
Tags_Ringing
Do Not Email

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.