

# **Case Study: Lead Scoring Model Building**

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# Case Study - Leading Scoring Model

## Introduction

X Education has appointed you to help them select the most promising leads, i.e. the leads that are most likely to convert into paying customers. The company requires you to build a model wherein you 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, in particular, has given a ballpark of the target lead conversion rate to be around 80%.

## Objective of the Study

In this study, we built a logistic regression model using a leads dataset from the past with around 9000 data points and create a model that assigns a lead score between 0 and 100 to each of the leads which can be used by the company to target potential leads. A higher score would mean that the lead is hot, i.e. is most likely to convert whereas a lower score would mean that the lead is cold and will mostly not get converted.

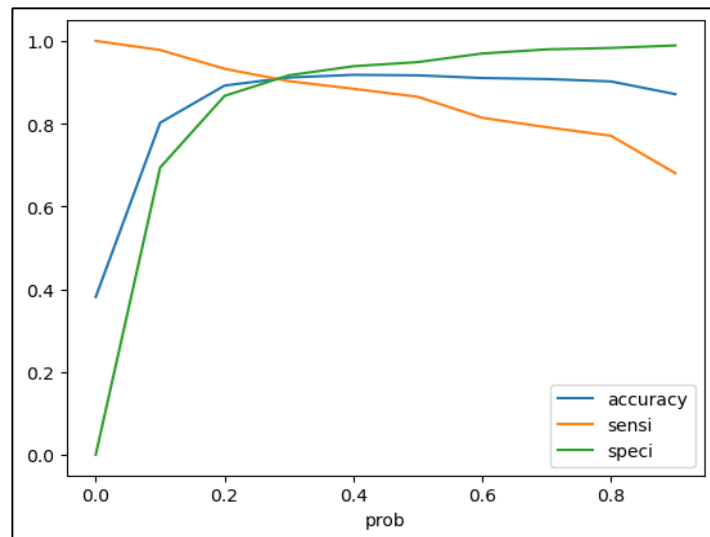
## Approach –

We performed the following to build the Logistic Regression (LR) model for lead scoring –

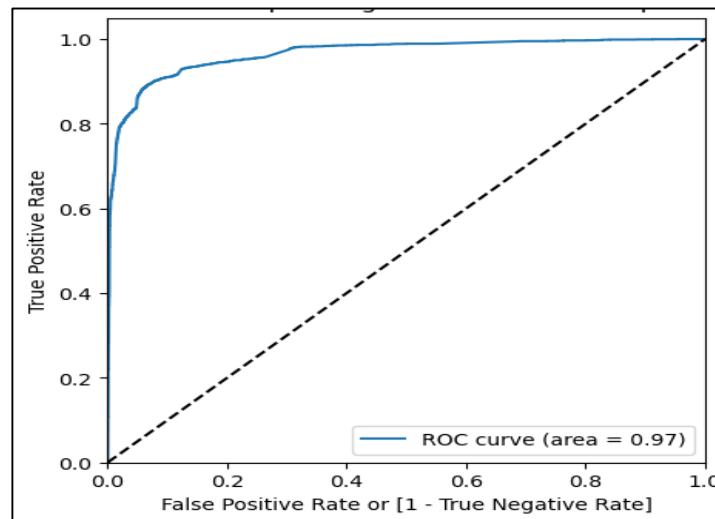
- i. **Data Cleaning Steps** – Fixing Rows & Columns, Missing Value Handling, Variable Transformations, etc
- ii. **EDA - Categorical & Numerical Variables:** Findings Variables with Good Predictive Power
- iii. **Preprocessing** – Applied Normalization Scaling for Numerical & One-Hot Encoding for Categorical Variables, Divided data into test and train sets, & selected best variables using RFE
- iv. **Model Building & Evaluation** – Created the LR Model using StatsModel.api Library following an iterative approach. Generated confusion matrix to find the accuracy% of the predictions made for both train & test sets.

# Findings & Results of the Study

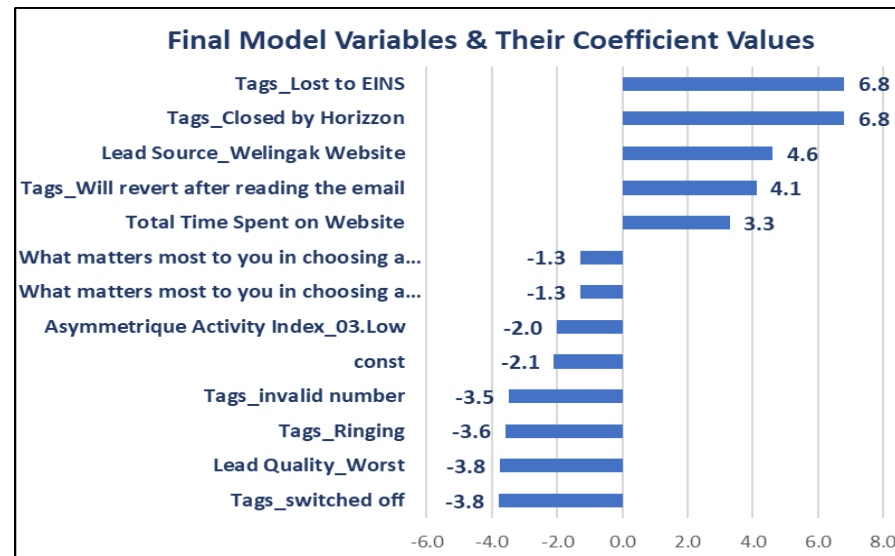
## Accuracy vs Sensitivity vs Specificity of Model



## ROC Curve



## Final Model Variables



## Confusion Matrix: Train & Test Set

| Dev Set     |           |           | Test Set    |           |           |
|-------------|-----------|-----------|-------------|-----------|-----------|
| Actual      | Predicted |           | Actual      | Predicted |           |
|             | Dropout   | Converted |             | Dropout   | Converted |
| Dropout     | 3670      | 332       | Dropout     | 1571      | 106       |
| Converted   | 240       | 2226      | Converted   | 121       | 974       |
| Accuracy    |           |           | Accuracy%   |           |           |
| %           | 91.2%     |           | %           | 91.8%     |           |
| Specificity |           |           | Specificity |           |           |
|             | 91.7%     |           |             | 93.7%     |           |
| Sensitivity |           |           | Sensitivity |           |           |
|             | 90.3%     |           |             | 88.9%     |           |

## Findings -

- **Area under Curve (AUC) or Receiver operating characteristic (ROC) curve** was used to evaluate and compare the performance of Logistic Regression model
- **Higher the AUC score, better the model** – ROC with area of 0.97 suggests that model is able to distinguish (separates) events and non-events well
- The point at where the **Accuracy, Sensitivity, and Specificity Curves** cross is considered the best probability cut-off value. Based on this technique, the model's **optimal probability cut-off is 0.3**.
- Using the 0.3 cut-offs, the **Accuracy Score for both the Train and Test Sets is in the 91%-92% range**, indicating good model performance.

## Recommendations -

- X Education can transform the model's likelihood to lead scores and should target possible leads with scores more than 30 or probabilities greater than 0.3.
- A few variables improve the likelihood of lead conversion based on the Model Outcome. As a result, the business should prioritise consumers with favourable variables, i.e. variables with positive coefficient values in the model.