Lead Scoring Case Study

Jibin
Shreya
Prashanth

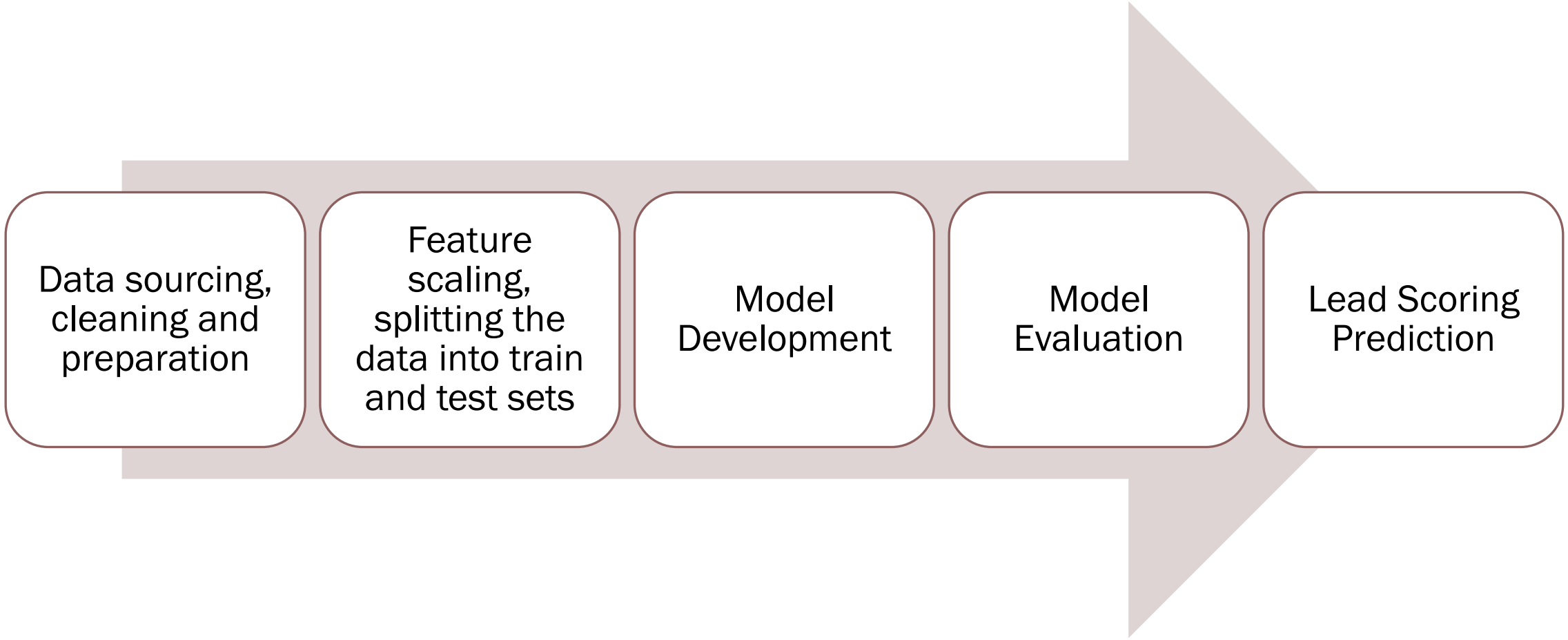
Problem Statement

X Education, an online education company, has a significant challenge with low lead conversion rates. Despite acquiring a large number of leads (via marketing efforts, website visits, and referrals), only 30% of leads are converted into paying customers. The company aims to improve this conversion rate by identifying the "Hot Leads" — those that are most likely to convert — and prioritizing them for follow-up by the sales team. This approach will help optimize resources, increase efficiency, and ultimately raise the lead conversion rate to approximately 80%.

Objective

The goal is to build a predictive model that scores leads based on their likelihood of conversion, using historical data on lead activities, behavior on the website, and other relevant factors. The leads with higher scores should have a higher probability of conversion, allowing the sales team to focus on the most promising leads.

Analysis Methodology



EDA

- Handled Null values.

  Dropped columns with more than 40% null values.

  For cases where the value was captured as Select, the same was replaced with UNKNOWN.

  Remaining rows with null values were deleted.

- Handled Categorical Values by using get dummies method.

Variables impacting the Conversion Rate

- TotalVisits
- Total Time Spent on Website
- Lead Source_Welingak Website
- Last Activity_SMS Sent
- Country_Germany
- Tags_Closed by Horizzon
- Tags_Lost to EINS
- Tags_Ringing
- Tags_Will revert after reading the email
- Tags_switched off

Model Evaluation – Train Set

Confusion Matrix :

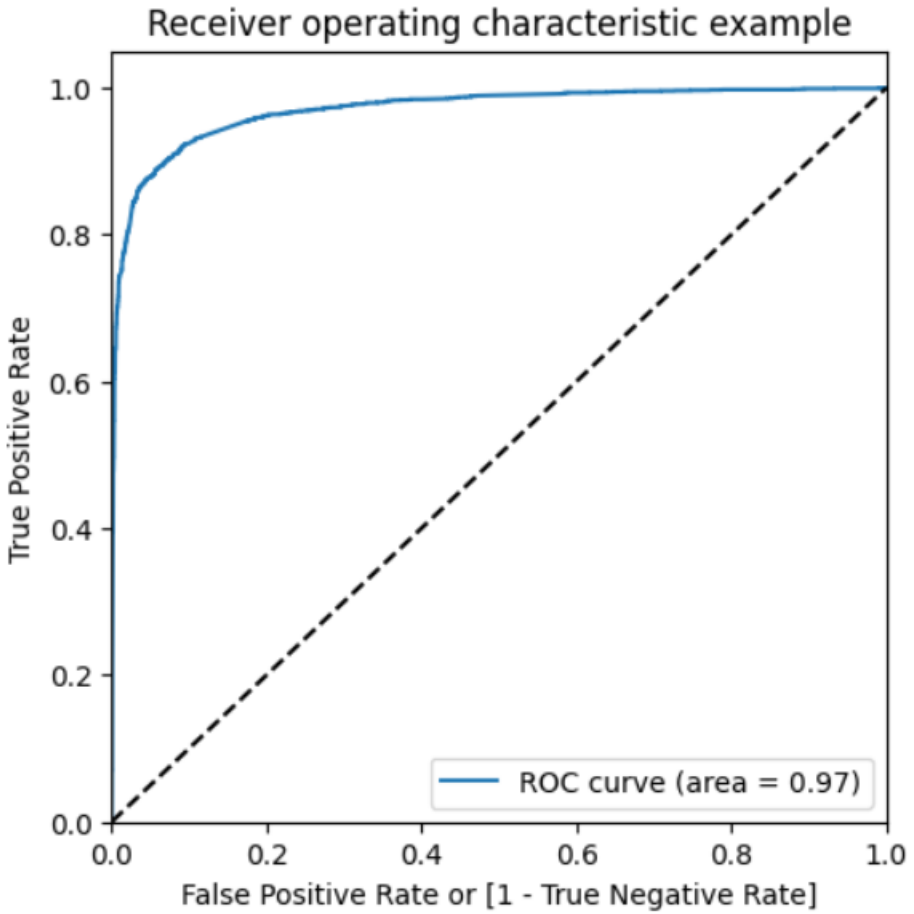
Actual/Predicted	Negative	Positive
Negative	True Negative 3763	False Positive 152
Positive	False Negative 323	True Positive 2113

Model Performance:

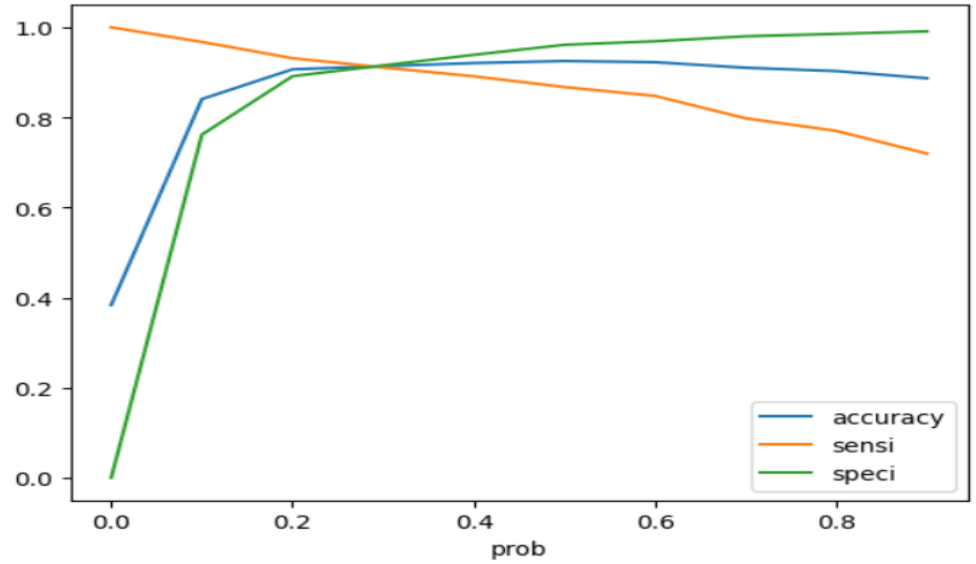
Accuracy	91.3 %
Sensitivity	91.0%
Specificity	91.5%
False Positive	8.45%
Positive predictive value	87%
Negative predictive value	94.2%

Model Evaluation – Train Set

ROC Curve



Model Performance:



From the curve above, 0.3 is the optimum point to take it as a cutoff probability.

Precision	93.2 %
Recall	86.7%

Model Evaluation – Test Set

Confusion Matrix :

Actual/Predicted	Negative	Positive
Negative	True Negative 1569	False Positive 155
Positive	False Negative 93	True Positive 906

Model Performance:

Accuracy	92.5 %
Sensitivity	85.4%
Specificity	91%
False Positive	8.9%
Positive predictive value	90.6%
Negative predictive value	94.4%

Train and Test Data Comparison :

	Train Data	Test Data
Accuracy	91.3 %	92.5 %
Sensitivity	91.0%	85.4%
Specificity	91.5%	91%
False Positive	8.45%	8.9%
Positive predictive value	87%	90.6%
Negative predictive value	94.2%	94.4%

The model metrics for test and train data are very similar and higher than 85%

=> Model performance is predictable

Business Implications

- **Accuracy** gives an overall sense of how well the model is performing. An accuracy of more than **90%** means the model is making mostly correct predictions
- **Sensitivity** of **85-91%** signifies that a high percent of leads will convert into paying customers
- **Specificity** is important to ensure the model is not identifying non-converting leads as potential converts – Sensitivity of **91%** means the sales team avoids wasting time on leads that are unlikely to convert
- **Positive Predictive Value** is important because it shows how reliable the model's predictions of "hot leads" are. A high value of **87-90%** means that the sales team is spending time on leads that are more likely to convert, which leads to higher efficiency and better return on investment
- **Negative Predictive Value** tells you how reliable the model is when predicting that a lead will not convert. Value of **94%** means the model is effective at filtering out leads that are unlikely to convert

Business Implications

In the sample data considered for the model building:

- Out of 999 converting leads, 906 leads are identified correctly
- Only 11% of predicted leads are non-converting
- 91% of non-converting leads are correctly identified