Lead Score - Case Study - Summary Report

Problem Statement:

X Education, an e-learning platform for professionals, is creating a logistic regression model to assign lead scores (0-100) for effective lead targeting. Higher scores signify better conversion chances (hot leads), while lower scores imply lower conversion likelihood.

The goal is to achieve an 80% conversion rate, aligning with the CEO's vision for sustainable business growth through valuable e-learning experiences.

Summary:

Step 1: Data Exploration:

Begin by delving into and thoroughly comprehending the dataset, followed by a detailed analysis.

Step 1.1: Data Cleaning:

- · Checked for duplicate values.
- · Replaced the 'Select' placeholder with NaN values.
- Dropped columns with over 40% null values.
- Imputed missing values for numerical columns.
- Transformed categorical variables by creating new classification variables.

Step 2: Exploratory Data Analysis:

- Utilized box plots to detect outliers in numerical columns.
- Applied capping techniques up to the **95th** percentile to manage outliers.
- Conducted an analysis of both categorical and numerical columns related to the target variable **'Converted,'** resulting in valuable insights and findings.

Step 3: Linear Regression :

Step 3.1: Creating dummy variables:

- We proceeded by generating synthetic data for the categorical variables.
- Dropped the columns for which we have created dummy variables

Step 3.2: Splitting data into 'Test' and 'Train' set:

• - Divided the dataset into training and testing subsets, following a 70-30% ratio.

Step 3.3: Rescaling using MinMax:

- Implemented Min-Max Scaling for numerical variables.
- Utilized the stats model to construct an initial model, providing a thorough statistical summary of model parameters.

Step 3.4: Feature Selection - RFE:

• Utilized Recursive Feature Elimination to select the top **20** important features, iteratively examining P-values to retain significant ones.

Step 4: Model Building:

Step 4.1: Constructing the models:

• Our initial model incorporated all **RFE**-identified columns. We improved it by excluding columns with high **P-values** and **VIF** values, resulting in a final model with **13** highly significant features and **VIF** values below **5**.

Step 5: Model Evaluation:

Step 5.1: Evaluating the final model :

- · Produced forecasts for the training dataset.
- Formed a DataFrame pairing actual conversion outcomes with predicted probabilities.
- Employed an initial threshold probability of **0.5** for predicted labels.
- Constructed a confusion matrix and generated a classification report.
- Computed supplementary metrics such as 'Accuracy,' 'Sensitivity,' 'Specificity,' 'False Positive Rate,' 'Positive Predictive Value (Precision),' and 'Negative Predictive Value' to evaluate model reliability.

Step 5.2: Plotting 'ROC' Curve:

• Plotted the ROC curve for the features, resulting in a strong 88% area under the curve, enhancing the model's reliability.

Step 5.3: Determining the Ideal Threshold:

Plotted 'Accuracy,' 'Sensitivity,' and 'Specificity' for different probabilities, identifying the optimal cutoff at 0.35 where these curves intersected. After this adjustment, about 81% of values were predicted accurately, resulting in updated metrics: 'Accuracy = 81%', 'Sensitivity = 80.8%', 'Specificity = 80.4%'.

Step 5.4: Determining the 'Precision' & 'Recall':

 We computed Precision and Recall metrics, yielding 79% and 70% on the training dataset. Balancing Precision and Recall, we determined an optimal cutoff value of around 0.42.

Step 6: Making Predictions on the 'Test' data set :

Next, we applied these insights to the test model, achieving an 80% Accuracy with approximately 80% for both Sensitivity and Specificity.

Step 7: Conclusion:

In the conclusion, we identified 'Prospect ID' records with lead scores exceeding 85, totaling **360** records. We also provided recommendations for the company/CEO.