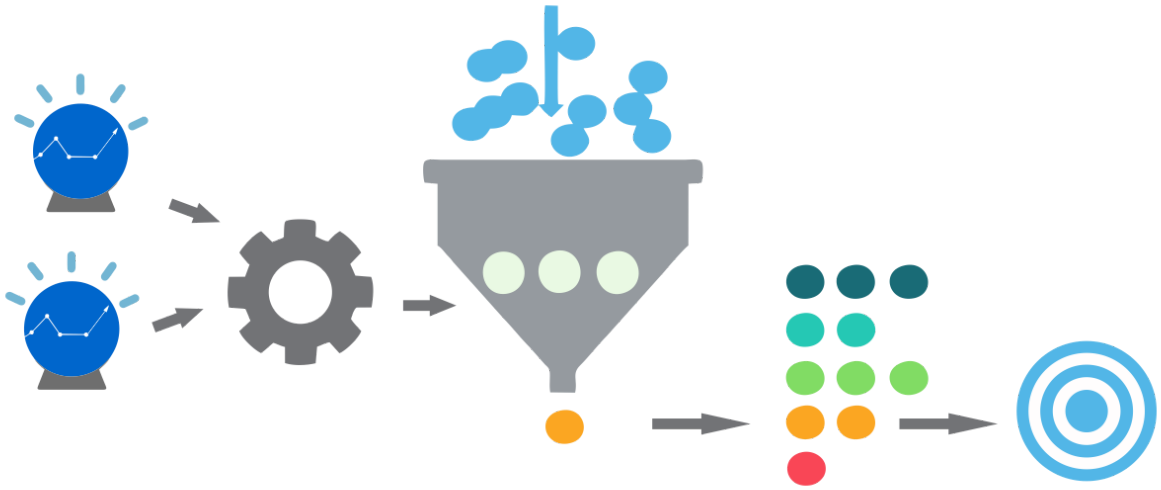
Executive summary

Lead Scoring Case Study



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3rd January, 2023

Introduction

This analysis is done for X Education which sells online courses to working professionals. The X EducationX gets a lot of leads, however its lead conversion rate is very poor. So, we have built a machine learning model based on logistic regression which helps to determine whether a lead is actually a hot lead or not based on top features variables and where the lead score is greater than 85.

This will actually improve the online sales of the X Education by converting the leads into the paying customers.

Data Provided

- Leads.csv
- Leads_Data_Dictionary.xlsx

Steps Involved

Data Cleaning

The dataset “Leads.csv” actually contains 9240 rows and 37 columns. Analyzing the dataset we came to know that there were a lot of missing values in the dataset. Also, we found a level called ‘Select’ in a few Categorical variables, which are as good as Null. So, we imputed the ‘Select’ level on a few variables with Null. Then we decided to drop the columns where there are missing values greater than 40% of the rows, as they don’t help in analysis. Similarly, we have also dropped multiple categorical columns where the data was highly imbalanced. We also imputed a few columns using mode.

So, after all the data clean-up we had 9074 rows i.e., we could retain ~98% of the actual data and that is good enough to build the model.

Exploratory Data Analysis

Performing a univariate and bi-variate analysis, we could infer the below from the existing data:

- ➔ The “Landing Page Submission” in the Lead Origin feature has high non-converted count followed by “API”
- ➔ The lead source from “Direct Traffic / Google” has high non-converted rate
- ➔ There is no big difference w.r.t Converted feature hued against “Do Not Email”
- ➔ There is a good converted count for the variable “SMS Sent” in the feature Last Activity
- ➔ The unemployment category has highest count of non-converted count

Dummification

We have taken all the categorical variables/feature/column and transformed it into several columns and performed a concat to the original dataframe

Train-Test Split

The split was done at 70% and 30% for train and test data respectively and the randomstate is set to 100

Scaling

There were a couple of numerical variables/features/columns excluding the target column “Converted” and we have normalized the values by using the MinMaxScaler which scales the data from 0 to 1.

Correlation Matrix

We tried to look at the correlations by plotting a correlation matrix however there were many features that have been created after the dummification. Hence, it turned out to be a little difficult to understand from the matrix.

Model Building

So, RFE was used to attain the top 15 relevant features. Later, we have analyzed the P-Values of each of the features and before dropping the features with P-Value > 0.05. We calculated the VIF for each of the above features and removed the feature which has both P-Value (> 0.05) and VIF (5) higher. We repeated the same process to build a better model by eliminating the features where it has higher P-Values and VIF score till we arrived at the final model.

Model Evaluation

The prediction of the Converted feature is made with the cut-off point as 0.5. We have created the confusion matrix from which we could calculate the accuracy, sensitivity and specificity of the model. The accuracy was close to 81% and specificity was close to 88%, but our sensitivity was only 70%. This was due to the fact that we have chosen an arbitrary cut-off as 0.5.

So, we proceeded further to find the optimal cut off value (using ROC curve) and it turned out to be ~0.35 and we have predicted the converted feature based on the updated cut-off value. We reevaluated the confusion matrix and the accuracy seems to be very close to the initial evaluation and sensitivity is close to 81%.

Test Data Prediction

Transformed the test data set and prediction was done on the test data frame and the accuracy of the dataset is close to the train set which actually tells that the model is good.

Precision and Recall

This method was also used to recheck and a cut off of 0.42 was found with Precision around 73% and recall around 81% on the train/test data frame

Observations

It was found that the variables that mattered the most in the potential buyers are (In descending order):

- When the Lead source was:
  - Welingak Websites
  - Reference
- Current occupation is Working Professionals.
- Last activity was:
  - Other Activity
  - SMS Sent
- Total time spent on website
- Lead source as Olark Chat