X Education - Lead Scoring Case Study

Detection of Hot Leads to concentrate more of marketing efforts on them, improving conversion rates for X Education

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Background of X Education Company

- 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.
- The company markets its courses on several websites and search engines like Google.
- Once these people land on the website, they might browse the courses or fill up a form for the course or watch some videos.
- When these people fill up a form providing their email address or phone number, they are classified to be a lead.
- Once these leads are acquired, employees from the sales team start making calls, writing emails, etc.
- Through this process, some of the leads get converted while most do not.
- The typical lead conversion rate at X education is around 30%.

Problem Statement & Objective of the Study

Problem Statement:

- X Education gets a lot of leads, its lead conversion rate is very poor at around 30%
- X Education wants to make lead conversion process more efficient by identifying the most potential leads, also known as Hot Leads
- Their sales team want to know these potential set of leads, which they will be focusing more on communicating rather than making calls to everyone.

Objective of the Study:

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

Suggested Ideas for Lead Conversion

Leads Grouping

- Leads are grouped based on their propensity or likelihood to convert.
- This results in a focused group of hot leads.

Better Communication

- We could have a smaller pool of leads to communicate with, which would allow us to have a greater impact.

Boost Conversion

- We would have a greater conversion rate and be able to hit the 80% objective since we concentrated on hot leads that were more likely to convert.

Since we have a target of 80% conversion rate, we would want to obtain a high **sensitivity** in obtaining hot leads.

Analysis Approach

Data Cleaning:

Loading Data Set, understanding & cleaning data

EDA:

Check imbalance, Univariate & Bivariate analysis

Data Preparation

Dummy variables, test-train split, feature scaling

Model Building:

RFE for top 15 feature, Manual Feature Reduction & finalizing model

Model Evaluation:

Confusion matrix, Cutoff Selection, assigning Lead Score

Predictions on Test Data:

Compare train vs test metrics, Assign Lead Score and get top features

Recommendation:

Suggest top 3 features to focus for higher conversion & areas for improvement

Data Cleaning

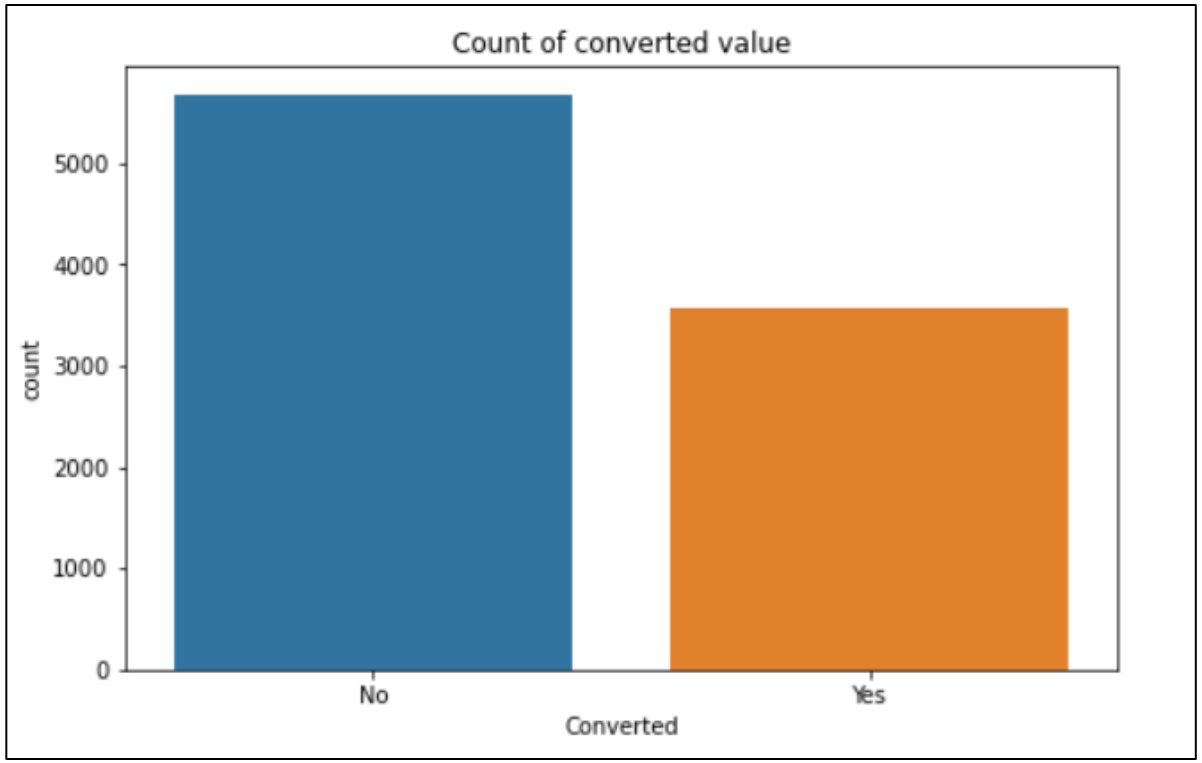
- **"Select"** level represents null values for some categorical variables, as customers did not choose any option from the list.
- Columns with over 45% null values were dropped.
- Missing values in categorical columns were handled based on value counts and certain considerations.
- Drop columns that don't add any insight or value to the study objective (tags, country)
- Imputation was used for some categorical variables.
- Additional categories were created for some variables.
- Columns with no use for modeling (Prospect ID, Lead Number) or only one category of response were dropped.
- Numerical data was imputed with mode after checking distribution.

Data Cleaning

- Skewed category columns were checked and dropped to avoid bias in logistic regression models.
- Outliers in **TotalVisits** and **Page Views Per Visit** were treated and capped.
- Invalid values were fixed and data was standardized in some columns, such as lead source.
- Low frequency values were grouped together to “Others”.
- Binary categorical variables were mapped.
- Other cleaning activities were performed to ensure data quality and accuracy.
    - Fixed Invalid values & Standardizing Data in columns by checking casing styles, etc. (lead source has Google, google)

EDA

- Data is imbalanced while analyzing target variable.



- Conversion rate is of 38.5%, meaning only 38.5% of the people have converted to leads.(Minority)
- While 61.5% of the people didn't convert to leads. (Majority)

Data Preparation before Model building

- Binary level categorical columns were already mapped to 1 / 0 in previous steps
- Created dummy features (one-hot encoded) for categorical variables – Lead Origin, Lead Source, Last Activity, Specialization, Current_occupation
- Splitting Train & Test Sets
  - 70:30 % ratio was chosen for the split
- Feature scaling
  - Standardization method was used to scale the features
- Checking the correlations
  - Predictor variables which were highly correlated with each other were dropped (Lead Origin_Lead Import and Lead Origin_Lead Add Form).

Model Building

Feature Selection

- The data set has lots of dimension and large number of features.
- This will reduce model performance and might take high computation time.
- Hence it is important to perform **Recursive Feature Elimination** (RFE) and to select only the important columns.
- Then we can manually fine tune the model.
- RFE outcome
  - Pre RFE - 48 columns & Post RFE - 15 columns

Model Building

- Manual Feature Reduction process was used to build models by dropping variables with p – value greater than 0.05.
- Model looks stable after two iteration with:
  - significant p-values within the threshold (p-values < 0.05) and
  - No sign of multicollinearity with VIFs less than 5
- Hence, **m2** will be our final model, and we will use it for Model Evaluation which further will be used to make predictions.

Recommendation based on Final Model

- As per the problem statement, increasing lead conversion is crucial for the growth and success of X Education. To achieve this, we have developed a regression model that can help us identify the most significant factors that impact lead conversion.
- We have determined the following features that have the highest positive coefficients, and these features should be given priority in our marketing and sales efforts to increase lead conversion.
  - Tags_Closed by Horizzon 5.8044
  - Tags_Lost to EINS 5.3792
  - Lead Source_Welingak Website 3.3398
  - Tags_Will revert after reading the email 2.8839
  - Last Activity_SMS Sent 2.1058

- We have also identified features with negative coefficients that may indicate potential areas for improvement. These include:
  - What is your current occupation_not provided -2.5065
  - Tags_Interested in other courses -3.5818
  - Tags_Other_Tags -4.1538
  - Tags_Ringing -5.0951

Recommendation based on Final Model

To increase our Lead Conversion Rates

- Focus on features with positive coefficients for targeted marketing strategies.
- Develop strategies to attract high-quality leads from top-performing lead sources.
- Optimize communication channels based on lead engagement impact.
- Engage **working professionals** with tailored messaging.

- More budget/spend can be done on **Welingak Website** in terms of advertising, etc.
- Incentives/discounts for providing reference that convert to lead, encourage providing more references.
- Working professionals to be aggressively targeted as they have high conversion rate and will have better financial situation to pay higher fees too.

To identify areas of improvement

- Analyze negative coefficients in specialization offerings.
- Review landing page submission process for areas of improvement.

Thank You!