## **Credit Card Lead Prediction Problem**

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#### **Exploratory Data Analysis**

- 1. Shape and data types in train and test datasets
- 2. Checked given problem is balanced or imbalanced problem
- 3. Treated it as balanced problem given enough responders
- 4. Corelation and summary statistics for numeric features
- 5. Distinct categories across train and test datasets for object features
- 6. Found missing values in Credit\_Product feature
- 7. Did 80:20 startify split of train dataset for feature engineering

#### **Feature Enginnering**

- 1. Checked distribution of numerical features
- 2. Avg\_Account\_Balance was highly rightly (+ve) skewed so took the log transformation
- 3. Region\_code coulmn had multiple categories so replaced the value using frequency encoding
- 4. Scaled all the numerical features using Standard Scaler (Also tried out Min max scaler but it didn't add any incremental value so deleted this step)
- 5. Missing values in Credit\_Product feature were treated as a separate category for dummy encoding (Also tried out mode imputation which was deleted in later step)
- 6. Label encoding was performed on Gender, Is\_Active and, Credit\_Product features
- 7. Duumy encoding was performed on Occupation, Channel\_Code, Credit\_Product and Credit\_Product\_mode\_impute features
- 8. Co-relation across all the columns were checked, if any two columns had +/- 0.7 corelations coefficients then one of those features were deleted after checking the corelation with target variables
- 9. All the preprocessing steps were performed X\_test and test dataframes

### **Feature Selection**

- 1. Logistic model was built using all the features
- 2. On the basis of p values, features were selected

# **Model Building**

#### **Used 2 methods**

- Logistic Regression
   This was more of baseline model which gave 0.85504 score
- 2. XGBoost Model

  This was champion model which was trained using same set of features but with hyperparameter tuning and 3 fold cross validation technique which gave much better score
  (0.87096)

# THANKS