

Credit Card Lead
Prediction

Happy
Customer
Bank



INDUSTRY TREND

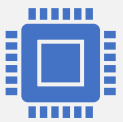
Credit Cards are usually allotted based on Age Profile

- Credit Profile of Customer
- Salary , Account Balance
- Age of Customer in Bank
- Transactional History

Approach



A brief on the approach, which you have used to solve the problem



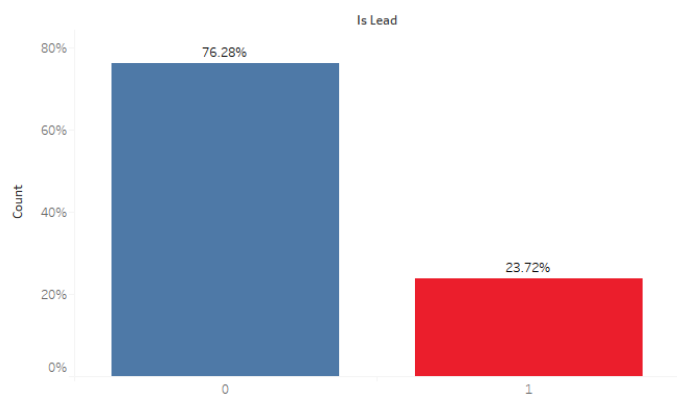
What data-preprocessing / feature engineering ideas really worked?
How did you discover them?



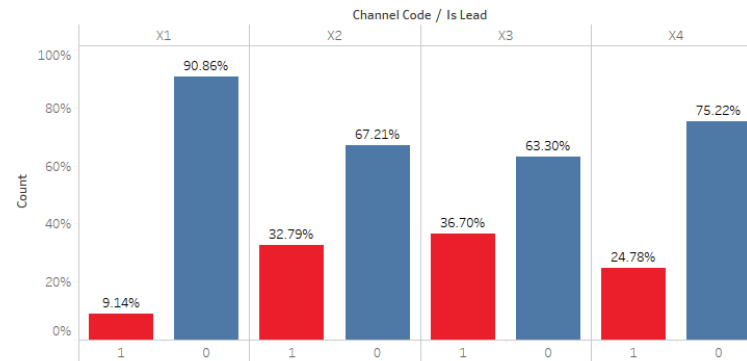
What does your final model look like? How did you reach it?

Exploratory Data Analysis

Distribution of Target Variable-Is_Lead



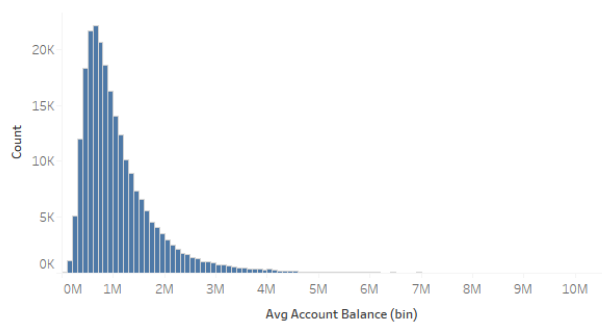
Distribution of Target vs Channel



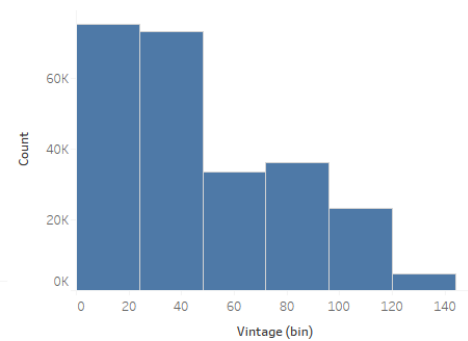
Is_Lead 23.72% conversions

Channel X2,X3

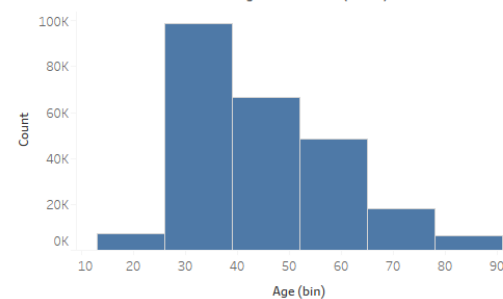
Distribution of Account Balance



Distribution of Vintage(Months)



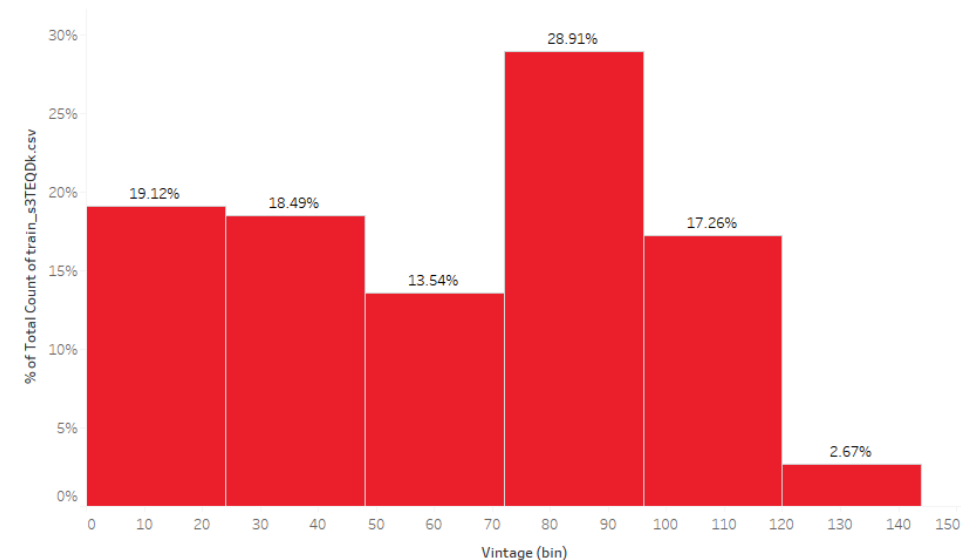
Distribution of Age of Customer(Years)



Continuous Variables Right skewed Account _Balance

Target 1 Distribution

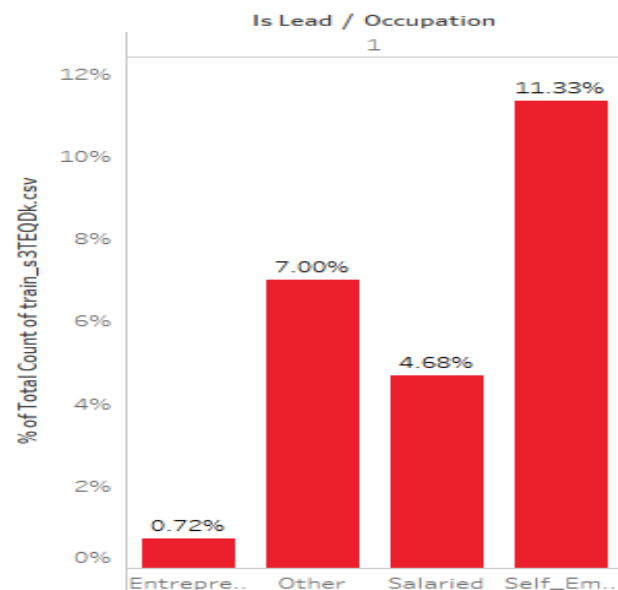
Distribution of Target -1 across Vintage Bins



The trend of % of Total Count of train_s3TEQDk.csv for Vintage (bin). Colour shows details about Is Lead. The view is filtered on Is Lead, which keeps 1. Percents are based on the whole table.

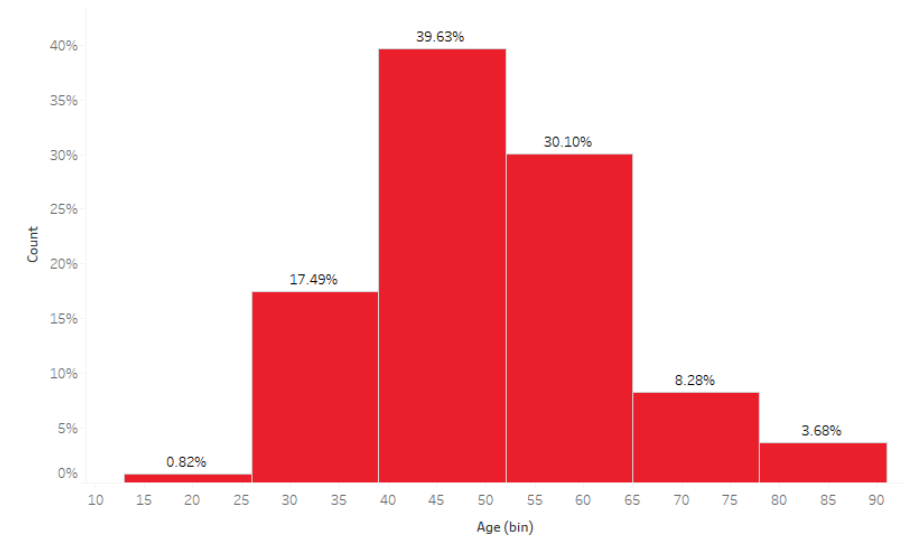
Is Lead
■ 1

Distribution of Target 1 vs Occupation



% of Total Count of train_s3TEQDk.csv for each Occupation broken down by Is Lead. Colour shows details about Is Lead. Percents are based on the whole table.

Distribution of Target Variable 1 Across Age Bins



The trend of % of Total Count of train_s3TEQDk.csv for Age (bin). Colour shows details about Is Lead. The view is filtered on Is Lead, which keeps 1. Percents are based on each row of the table.

Age Bins

Max conversions from Age-Bins 40-60

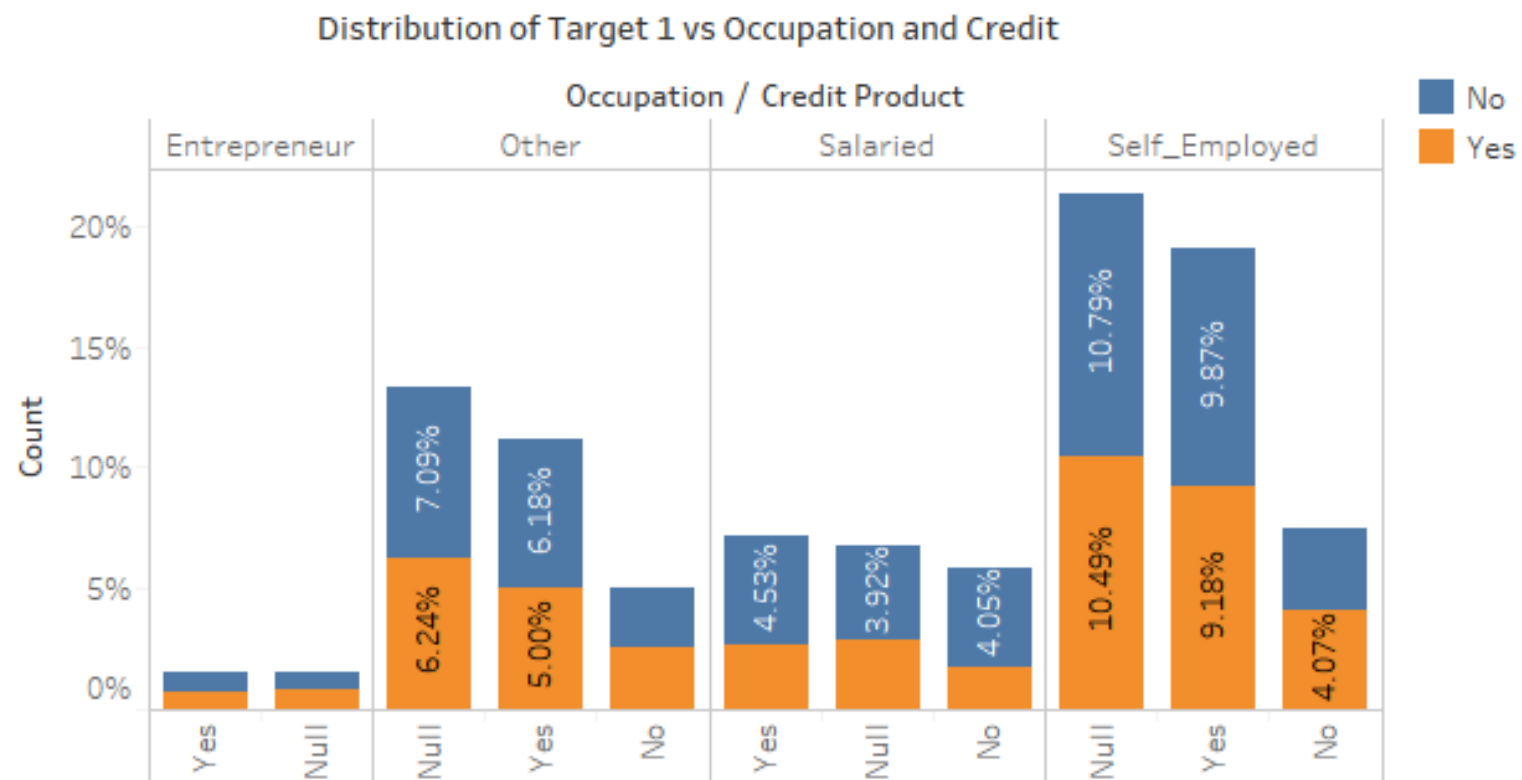
Vintage Bins

Max conversions from Vintage Bins 46% from 6-8 years, 32% from 0-4 years

Occupation

Max Conversions from Occupation Self Employed

Target 1 vs Occupation | Credit



Occupation and Credit have a higher impact

Building Interaction Features might help

% of Total Count of train_s3TEQDk.csv for each Credit Product broken down by Occupation. Colour shows details about Is Active. The data is filtered on Is Lead, which keeps 1. Percents are based on the whole table.

Pre-Processing

Min-Max Scaler of Age, Vintage , Account Balance

Label Encoding of Categorical variables

Frequency Encoding of interaction features since distribution of data across categorical features is captured

Reducing levels of Region – Top > 5000 were identified and grouped

Feature Engineering

Total of 138 features were built

Dropped ID

Aggregate Features of interaction features – min, max, mean, sum, standard deviation of all features

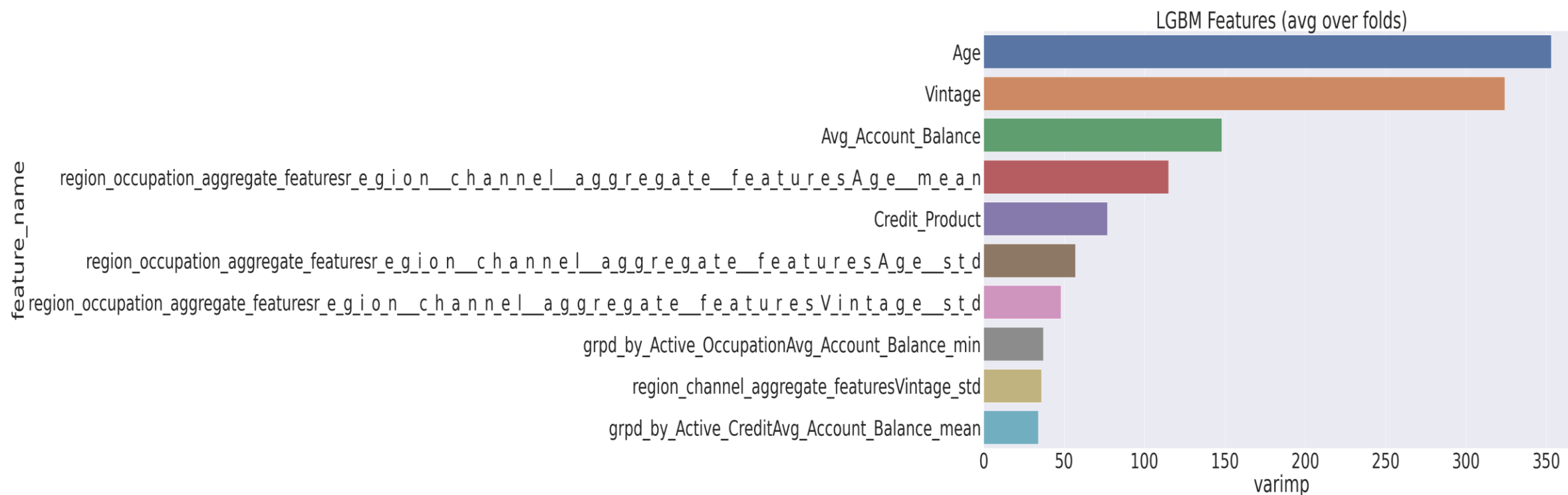
. Final shape

Train Predictors-(245725, 137)

Test Predictors-(105312, 137)

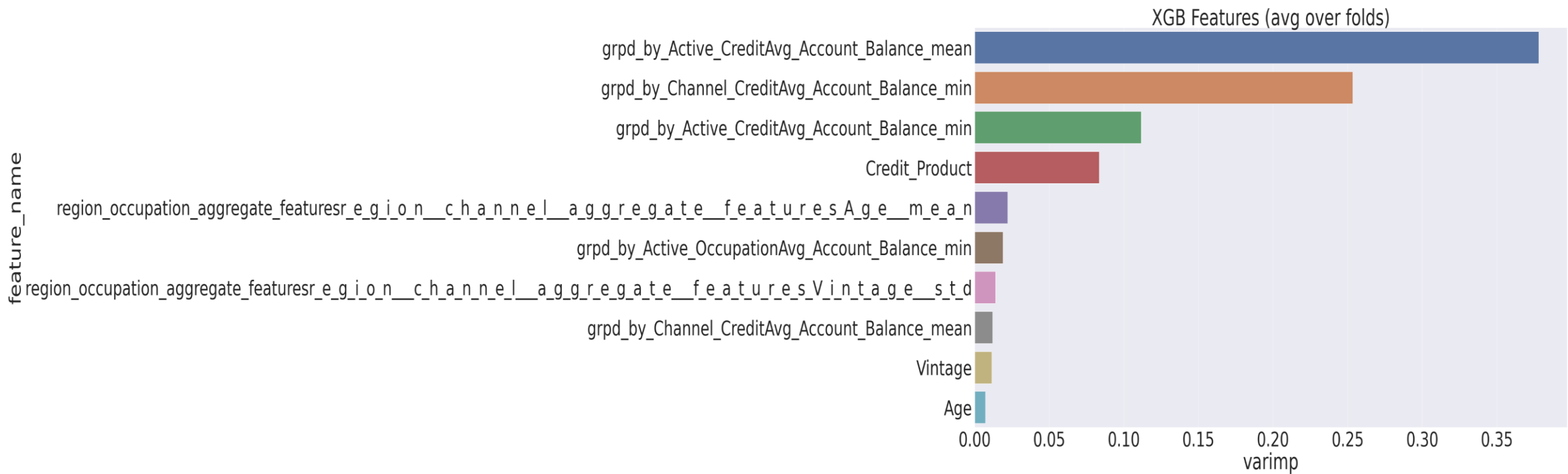
Models Used-LGBM

Average Stratified-KFold Score :
0.874109277726837



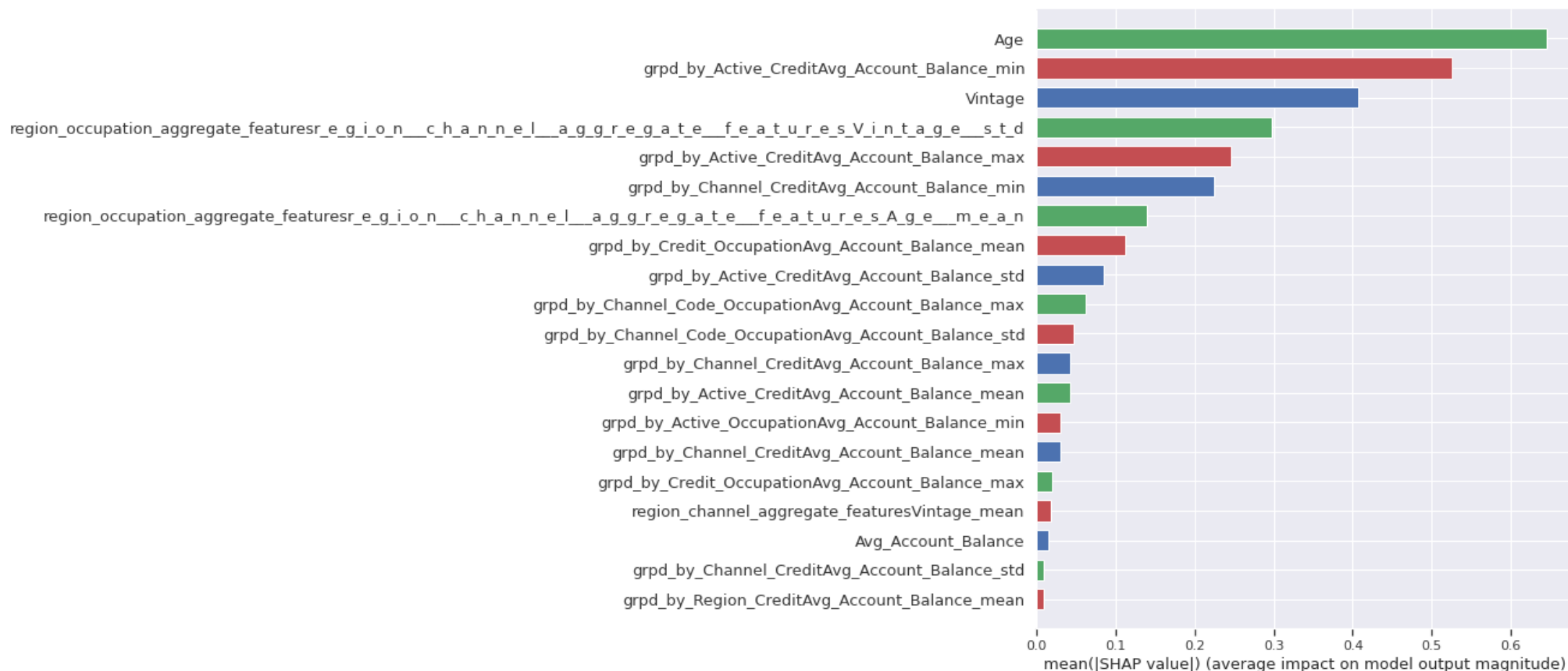
Models Used-XGBM

Average StratifiedKFold Score :
0.8731464590413118

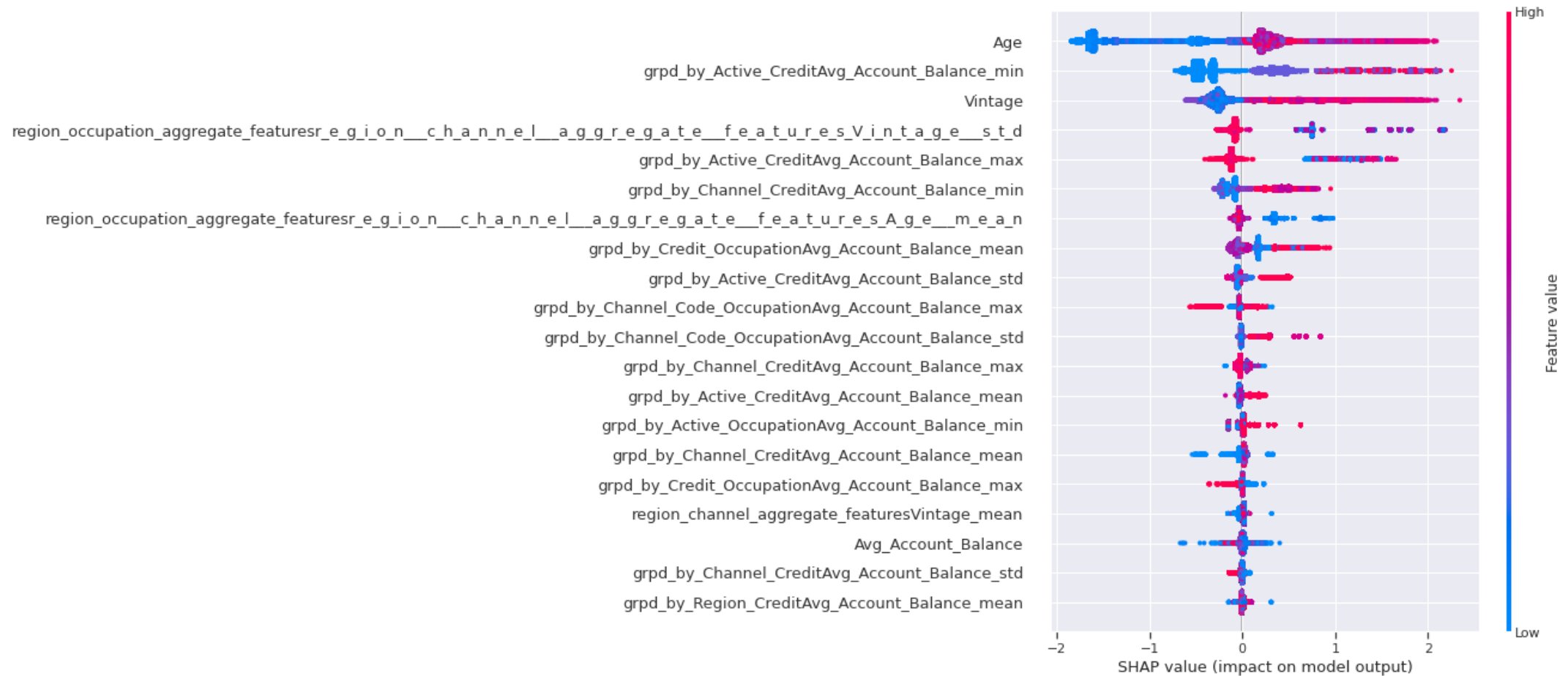


Models Used-CatBoost

Average Stratified-KFold Score :
0.8736018320655713



Models Used-CatBoost-SHAP values



Thank You

