Predicting loan status for risk management in P2P lending market

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Advanced Methods in Big Data

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Table of contents

P1. Introduction

Introduction

01 Context

- Lending Club is a peer-to-peer lending company
- Headquartered in San Francisco, California

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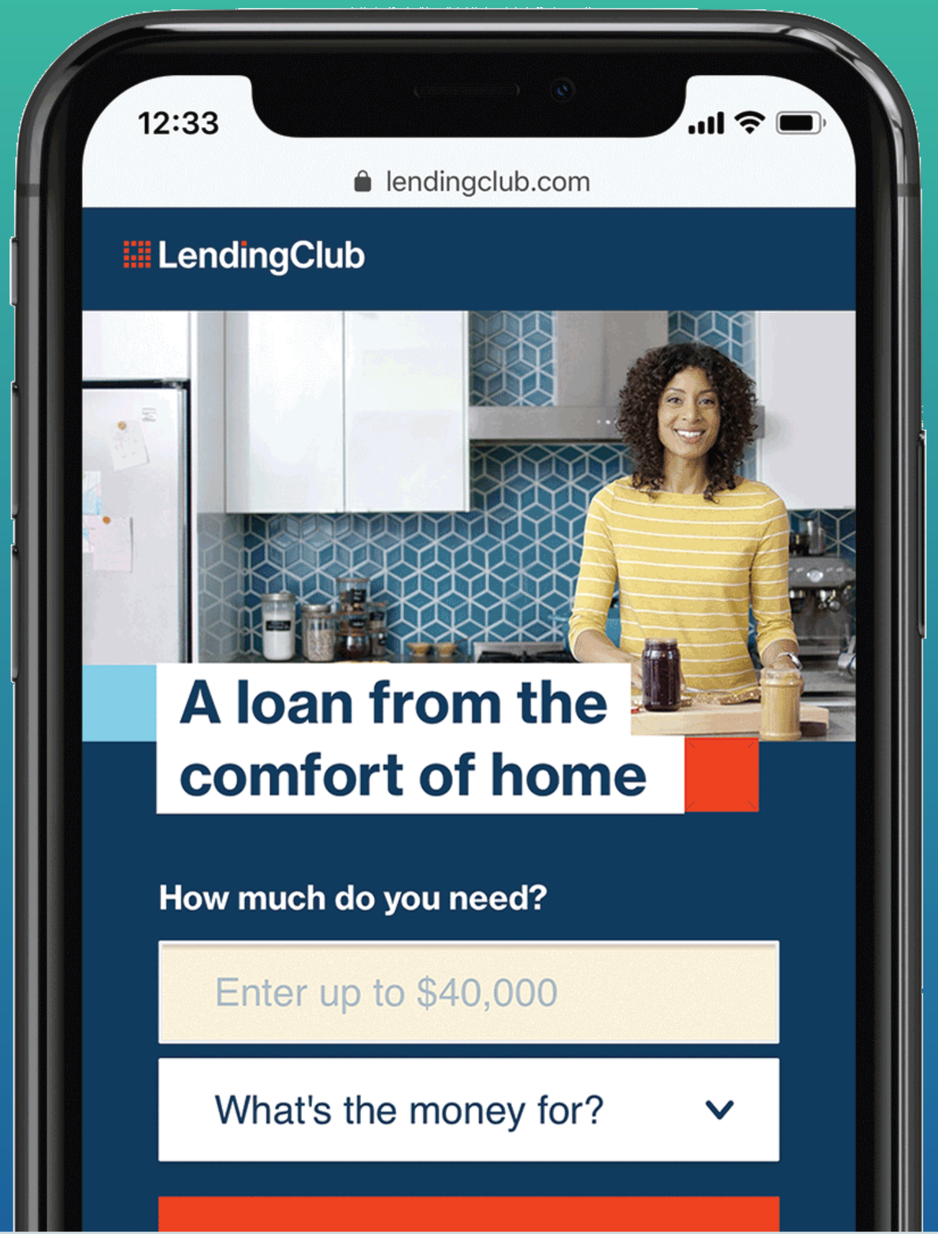
02 Objective

- Predict the loan status based on the applicants' profiles
- Understand the driving factors behind loan status



Peer-to-peer Lending

Economics Context

Peer-to-peer lending is pushing the sector of finance toward greater credit accessibility

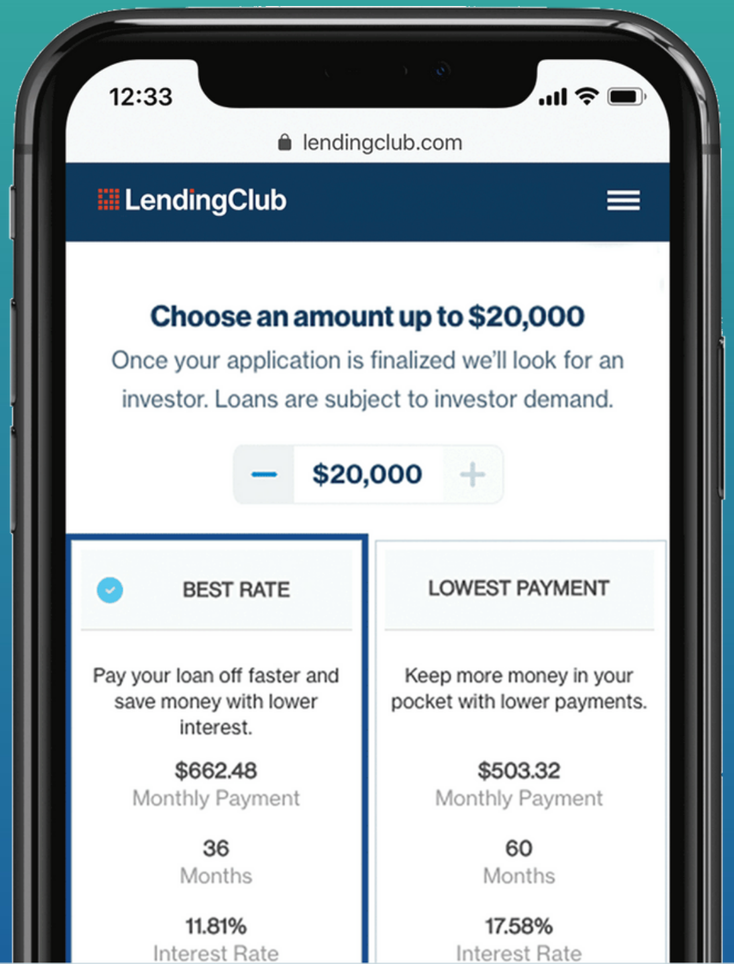
Making credit available for small businesses means economic growth, support for local entrepreneurs, and potentially more job opportunities

Peer-to-peer lending is quite risky for investors since there is credit risk, liquidity risk and even platform collapse risk

P2. Material & Methods

Material & Methods

Dataset and Feature Understanding



01 The dataset

- Official website of Lending Club
- Source of the dataset: Kaggle
- 396,030 observations and 27 features

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02 The loan status is the target variable

- Fully-paid
- Charged-off

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03 The variables can be divided into two segments

- Features related to the borrowers
- Features related to the loan characteristics

Material & Methods

Data Preprocessing

Detection and Treatment of duplicates and missing values

- No duplicate rows in our data
- Existence of missing values in 06 columns
  - Remove 'emp_title', 'emp_length', 'title'
  - Remove missing values in 'revol_util', 'pub_rec_bankruptcies'
  - Special treatment to 'mort_acc'

Feature Engineering

- Drop the 'grade' and 'issue_d' columns
- Extract the 'zip_code' column from the 'address' column
- Convert our categorical variables to numerical ones

Material & Methods

Data Preprocessing

Detection and treatment of outliers

- Only on the training set to avoid leaking information from the test set
- Inter Quartile Range (IQR) approach
- Trimming method since the outliers account for only 0.5 to 1 % of the training set

Dealing with imbalanced data

- Fully paid: 80%
- Charged-off: 20%
- Synthetic Minority Over-sampling Technique (SMOTE)

Material & Methods

Methodology

Information Reduction

Elastic Net

Autometrics

Prediction

Logistic Regression

Random Forest

Empirical Strategy

Model Selection

Cross Validation

GridSearch CV

SMOTE-NC

Performance Evaluation

Accuracy

Precision

Recall

F1 score

AUC

Specificity

P3. Results

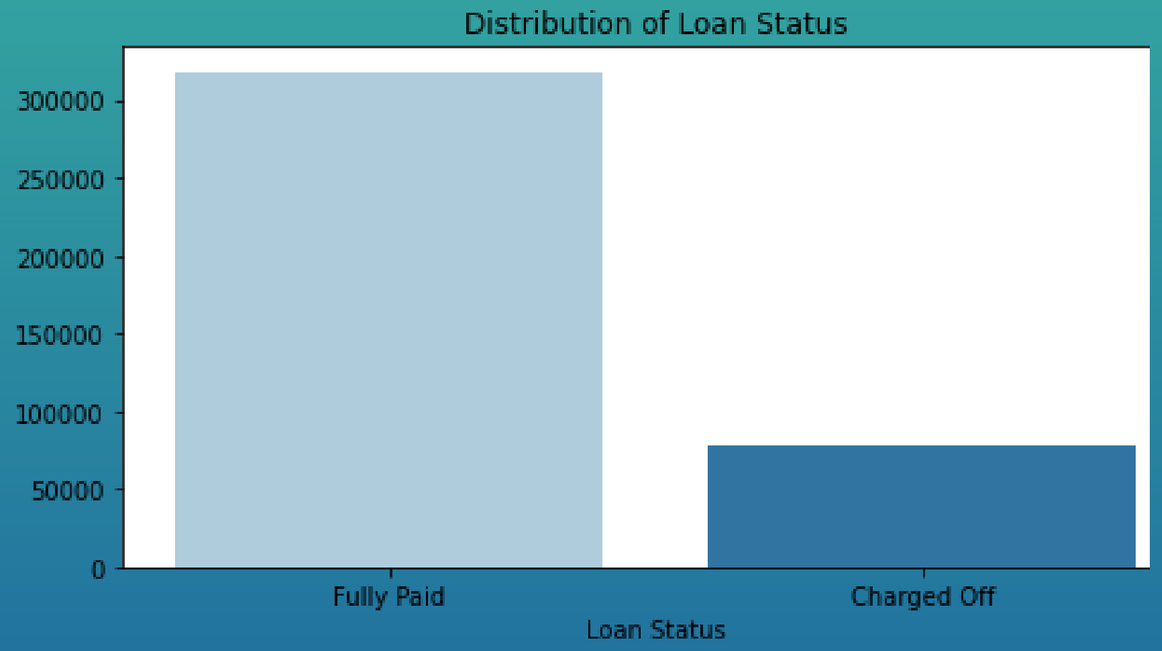
P3.1. Exploratory Data Analysis

Exploratory Data Analysis

Univariate analysis

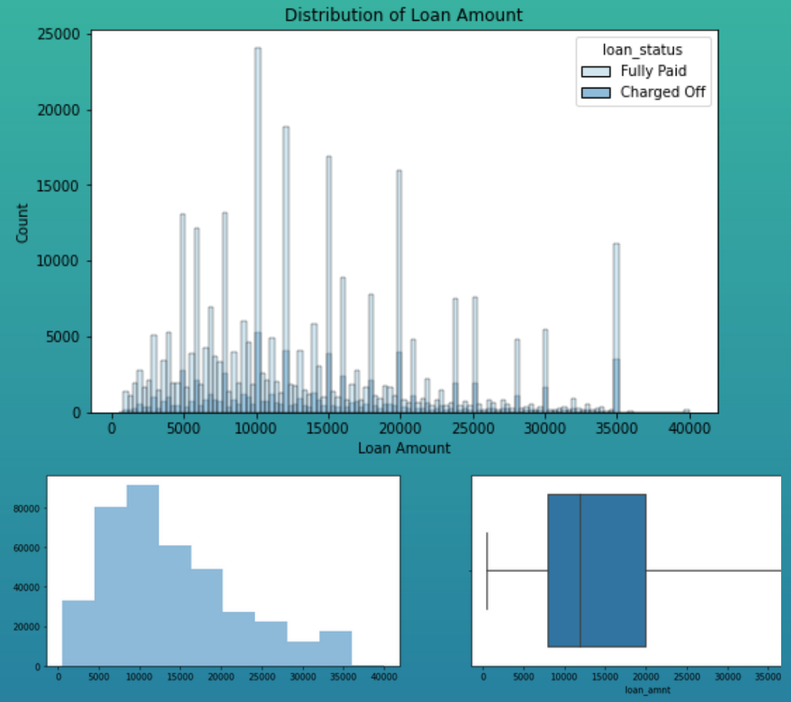
Loan status

- The dependent variable for our analysis is a categorical variable.
- Takes only two values : " Fully paid" or "Charged Off"
- Imbalanced data
  - Fully paid: 80% # observation
  - Charged off: 20% # observation



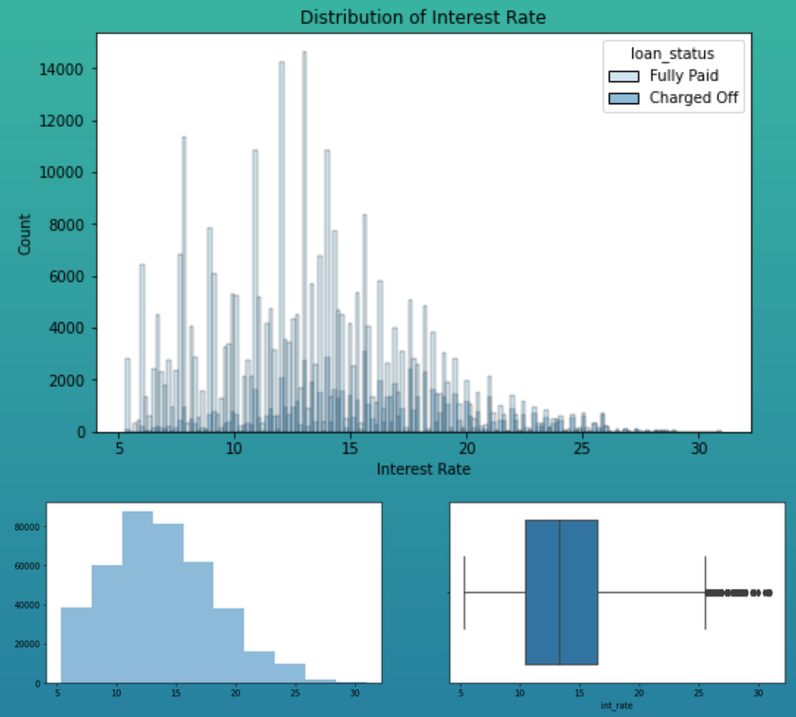
Exploratory Data Analysis

Multivariate analysis : Loan characteristics feature analysis



Loan amount

- Loan amounts is ranging from $5000 to $20000
- Normally distributed, slightly right skewed
- No outliers

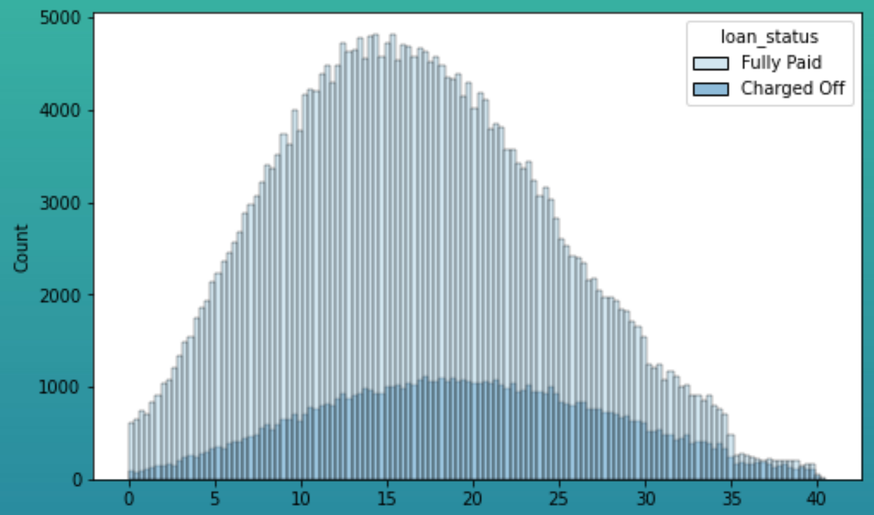


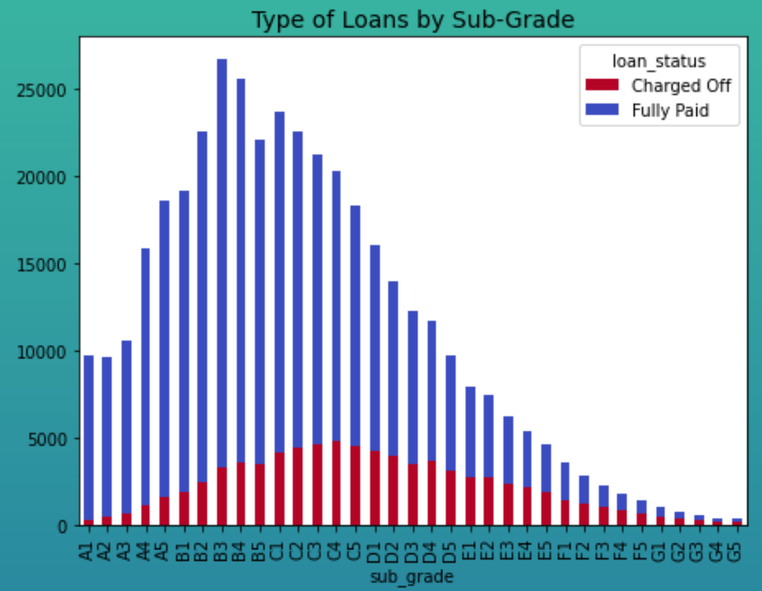
Interest Rate

- Interest rate is ranging from 10% to 15%
- Normally distributed, slightly skewed
- Few outliers => poor credit ratings

Exploratory Data Analysis

Multivariate analysis : Loan characteristics feature analysis





DTI - Debt to Income ratio

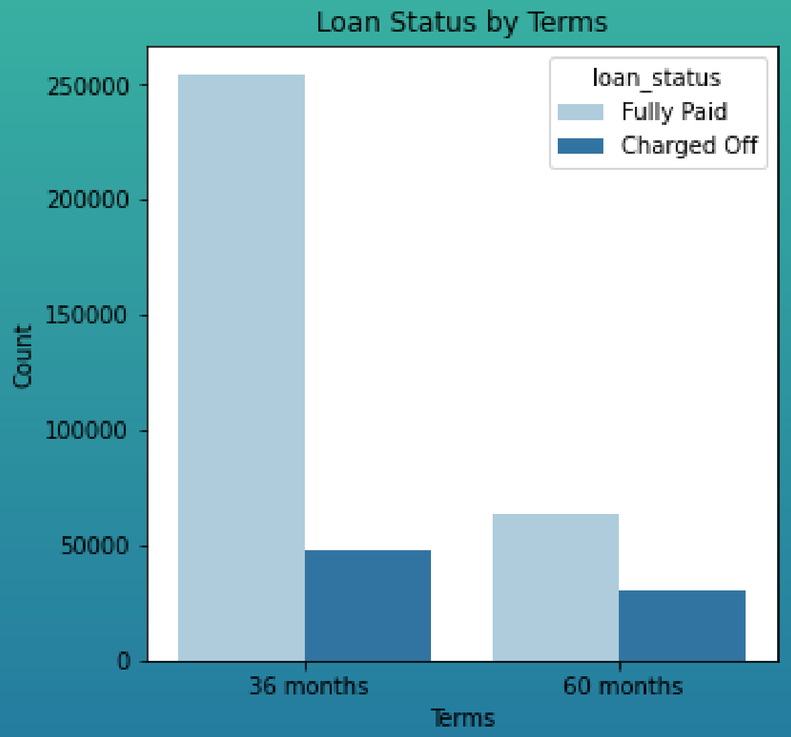
- Normally distributed
- Ranging from 0 to 40
- (bound is zero = no debt)

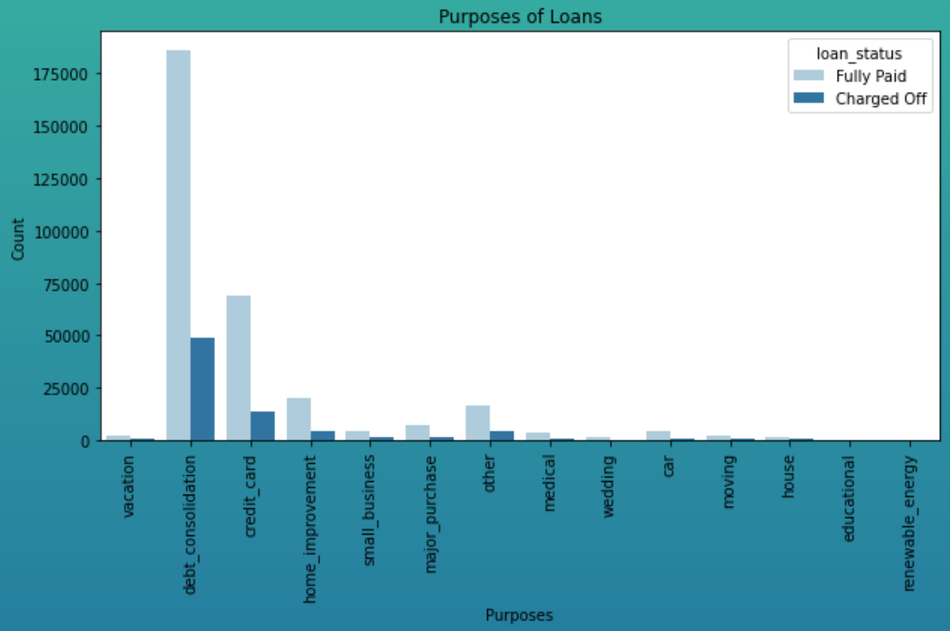
Sub-grade

- A is the highest grade => lowest interest rate
- Normally distributed with a heavy right tail
- The trend of higher fraction of loans charged-off

Exploratory Data Analysis

Multivariate analysis : Loan characteristics feature analysis





Loan status by terms

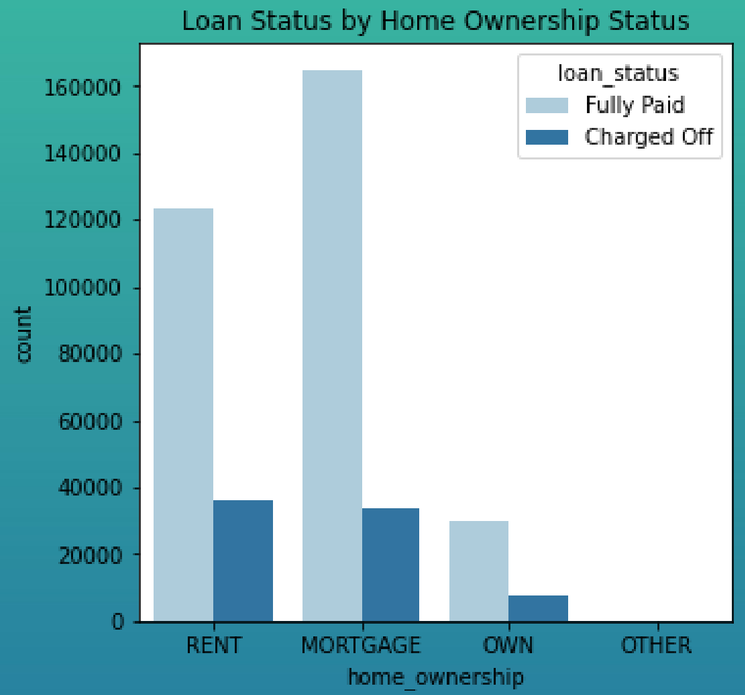
- 02 Categories: 36 months and 60 months
- The lower fraction of loans are fully paid within 60 months

Loans purposes

- The highest category: Debt consolidation
- Debt consolidation has less probability of being charged-off

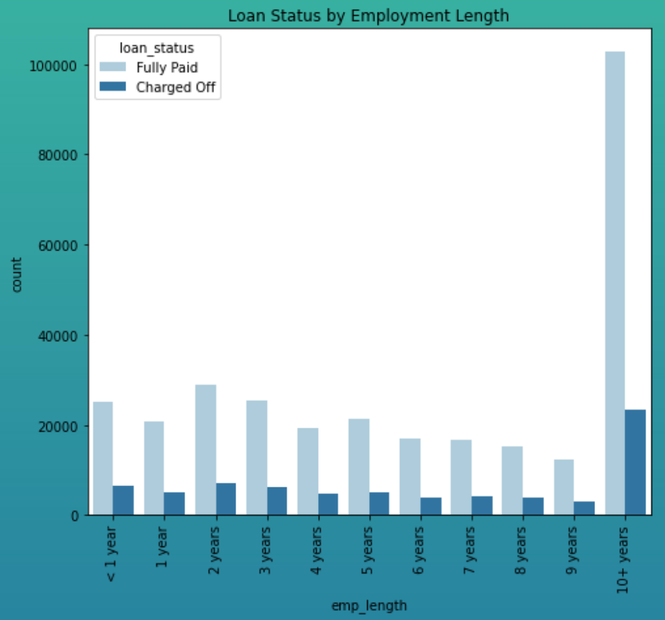
Exploratory Data Analysis

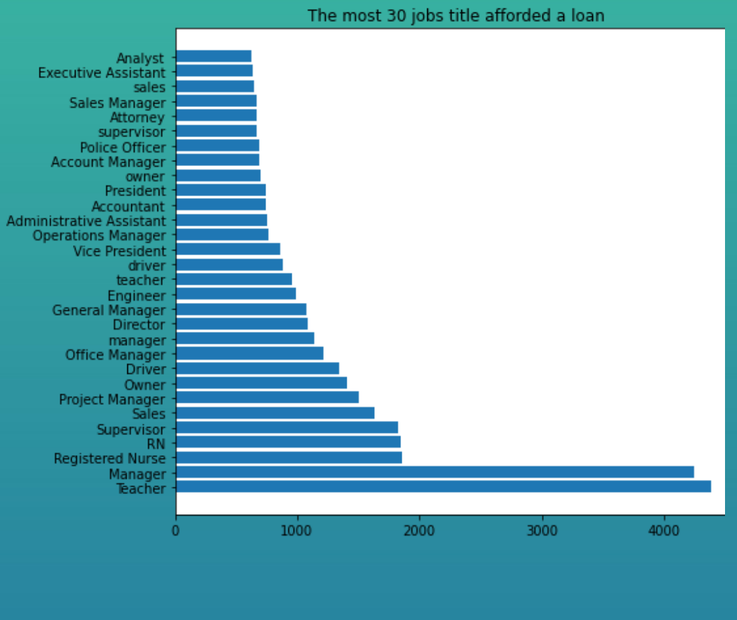
Multivariate analysis : Applicants' demographic feature analysis



Home ownership

- Small difference in charged-off rates
- Mortgage homes:
  - The most popular category
  - Less probability of being charged-off



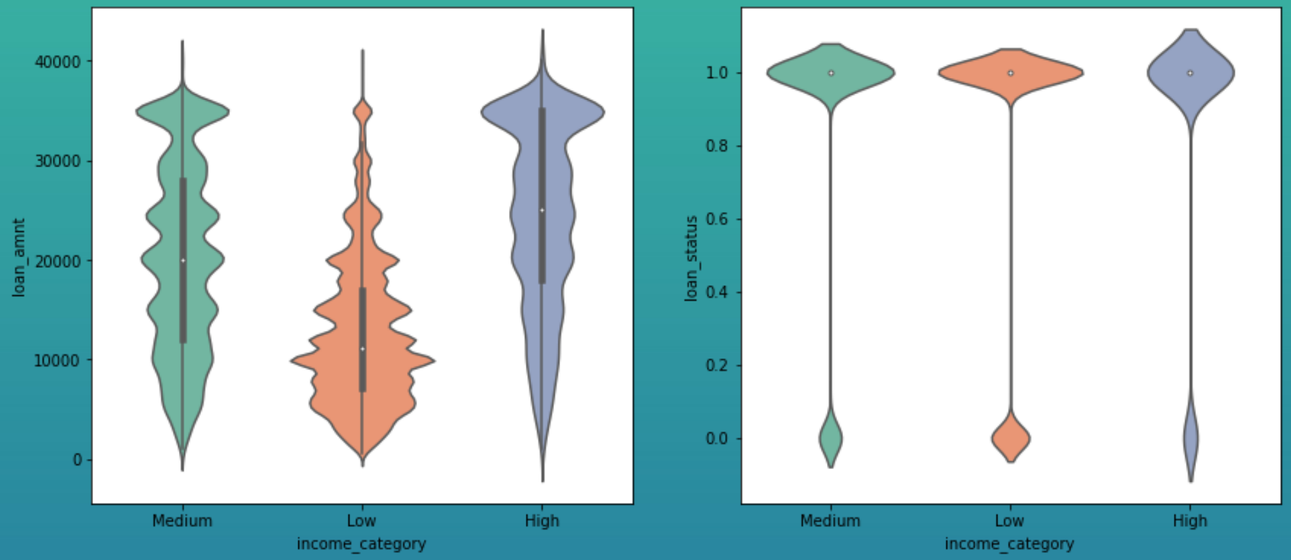


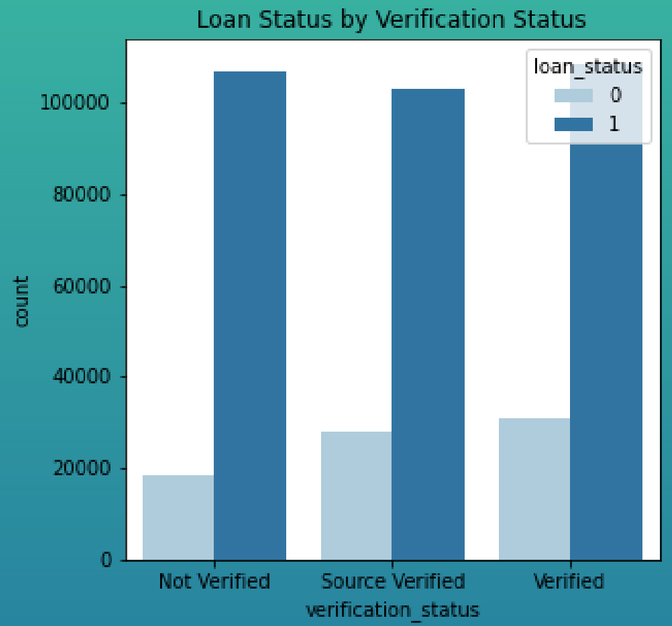
Employment title & Employment length

- More than 10 years of job experience:
  - Highest category
  - Higher probability of being fully-paid

Exploratory Data Analysis

Multivariate analysis: Applicants' demographic feature analysis





Income category

- Higher-income category => Higher loan amount
- Low-income category => Higher chance of being charged-off

Verification status

- 3 categories
- Verified loans => higher chance of charged-off (would guess the opposite)

Correlation analysis 1/2

Correlation between numerical features

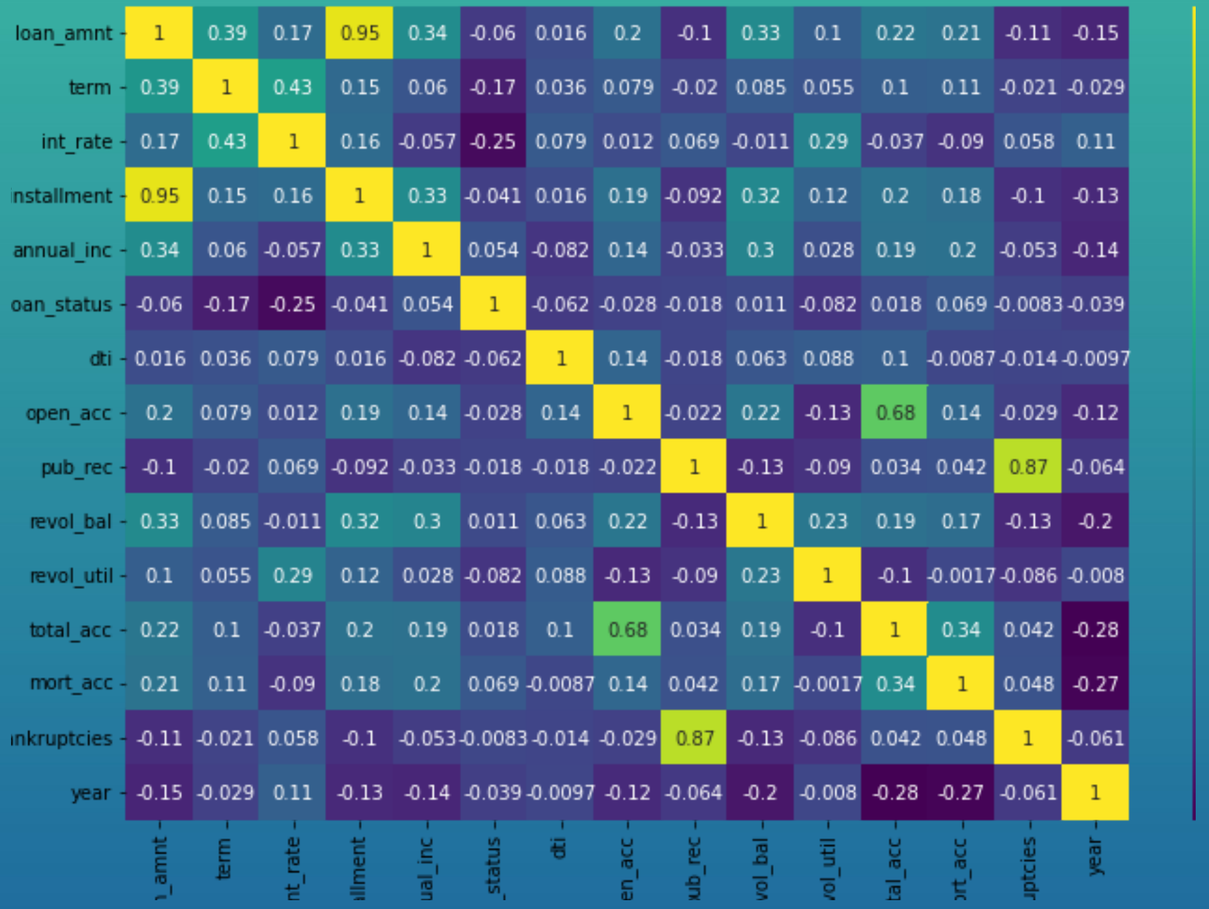
Heat map of Pearson correlation

A strong correlation between:

- loan amount and instalment with 95%
- pub_rec and pub_rec_bankruptcies with 87%
- total-acc and open-acc with 68%

Variance Inflation Factor

- High VIF for loan amount, installment, year
- Existence of multicollinearity

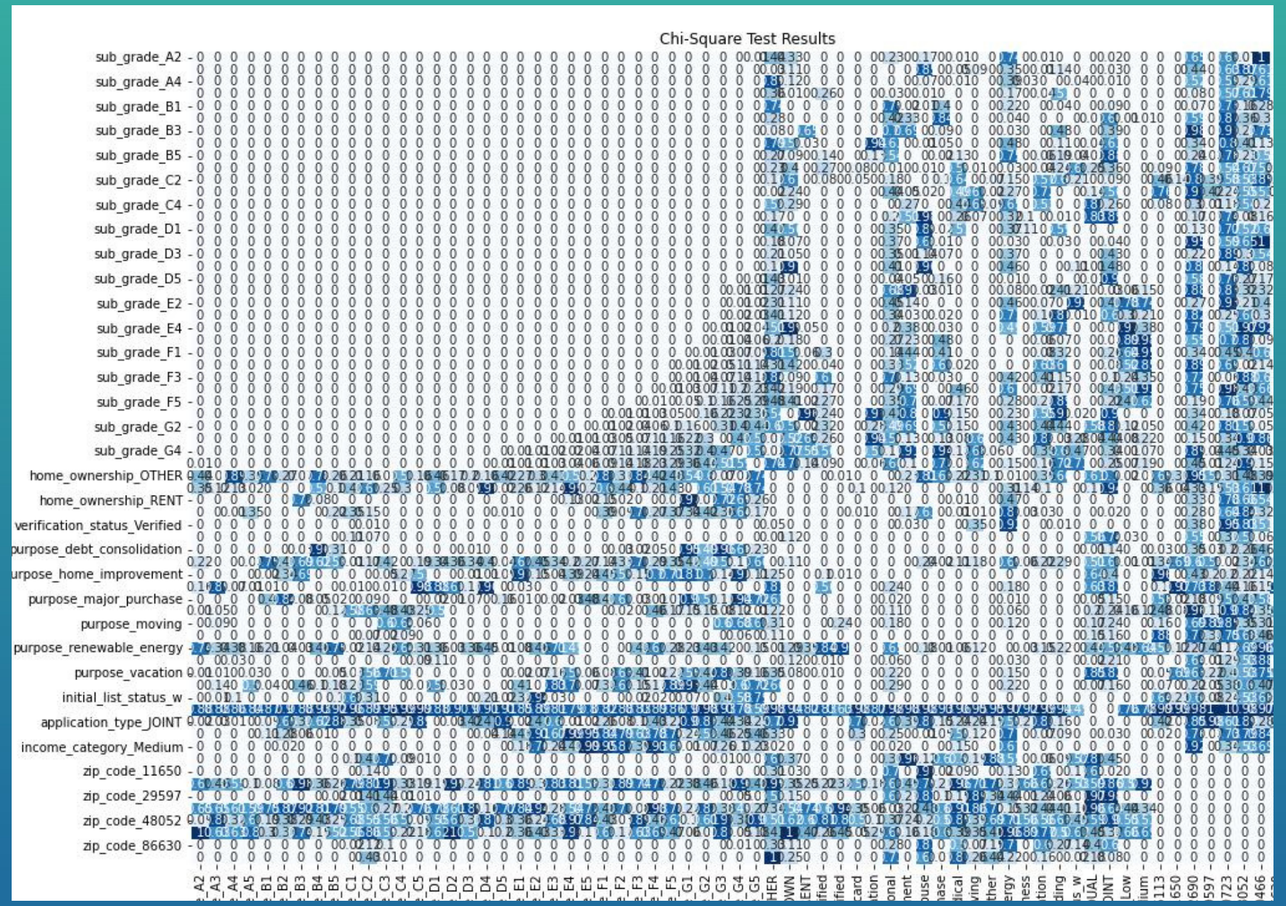


Correlation analysis 2/2

Correlation between categorical features

Heat map of the p-values for the Chi-Square test

- High correlation between most of the categorical features because most of the p-values < 0.05



P3.2. Information Reduction Models

Information Reduction Models 1/2

Before SMOTE-NC

Both ElasticNet and Autometrics models:

- Perform pretty well in classifying the positive classes (high Recall, F1 and Precision scores)
- But poorly in detecting actual negatives (low Specificity score)

=> Mainly due to the imbalanced dataset

Classifiers	Accuracy	Recall	F1	Precision	Specificity	AUC
Default ElasticNet Classification before SMOTE-NC	0.887771	0.989005	0.934104	0.884978	0.572985	0.730378
Tuned ElasticNet Classification before SMOTE-NC	0.887759	0.989036	0.934099	0.884943	0.572836	0.730297
Autometrics before SMOTE-NC	0.887506	0.988706	0.93394	0.884922	0.572823	0.730164

Information Reduction Models 2/2

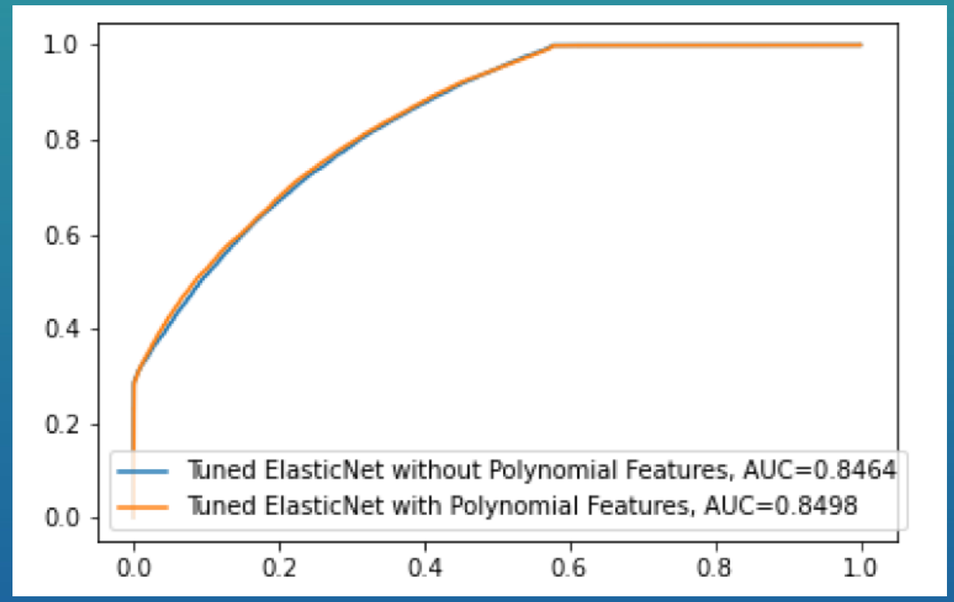
After SMOTE-NC

ElasticNet: Default & Tuned Hyperparameters

Classifiers	Accuracy	Recall	F1	Precision	Specificity
Tuned ElasticNet Classification before SMOTE-NC	0.887759	0.989036	0.934099	0.884943	0.572836
Default ElasticNet Classification after SMOTE-NC	0.783171	0.808428	0.85709	0.911987	0.704636
Tuned ElasticNet Classification after SMOTE-NC	0.783133	0.808381	0.857062	0.911982	0.704627

- The two models perform quite similarly
- But noticeably the Specificity scores for these 02 models are better than the before SMOTE-NC ones
- However, as a trade-off, the Recall and F1 scores decrease quite significantly

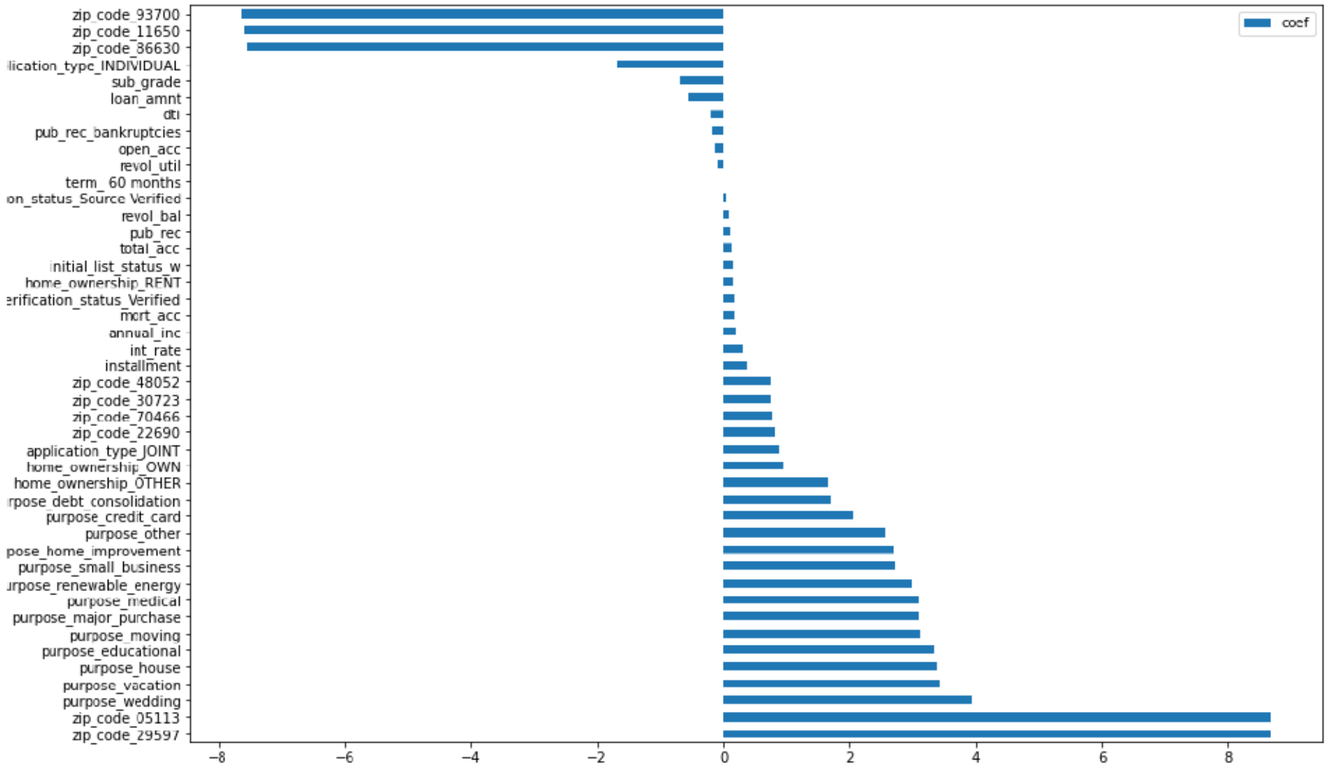
ElasticNet:
With Polynomial Features



Feature Importance

Interpretation of ElasticNet Classification model

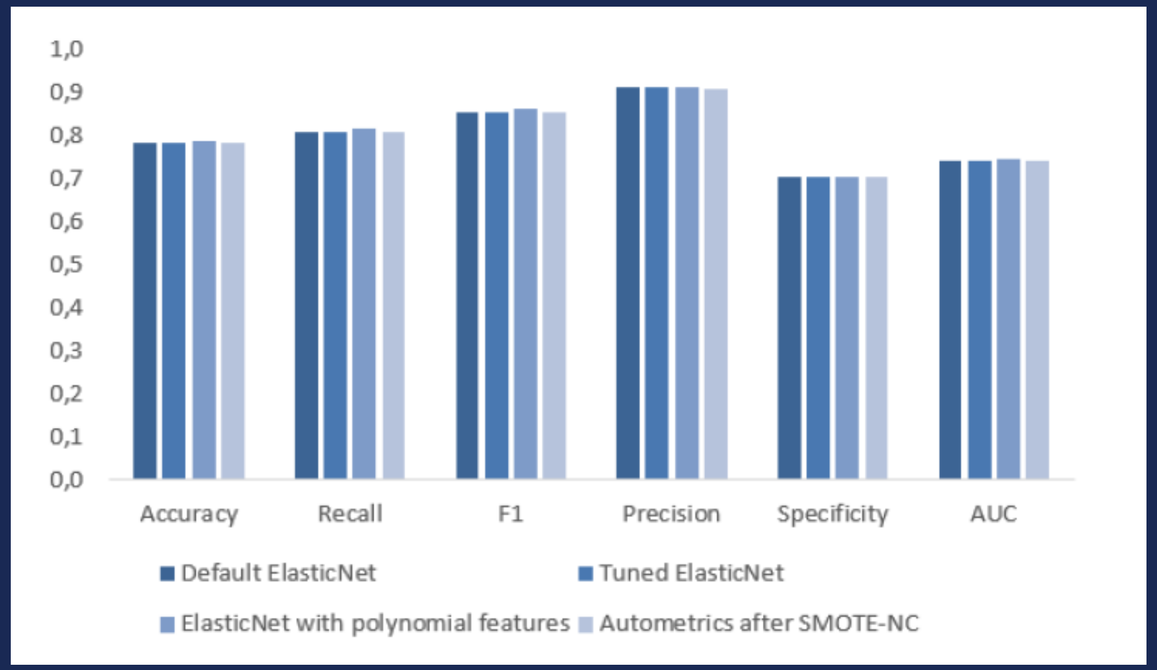
- The **zip_code** feature plays a vital role in our classifier's predictive power
- **Individual** loans: charge-off indicator >< **Joint** loans: fully-paid
- The higher the **sub-grade**, the lower the likelihood that the applicants will fully pay the loans
- **DTI** feature performs as expected



Information Reduction Models 2/2
After SMOTE-NC

Autometrics Models

- The regressor significance level is chosen as α=0.1
- Terminal model
  - Before SMOTE-NC contains 28 variables (not including the constant)
  - After SMOTE-NC contains 42 out of a total of 44 features
- Regarding the power of information reduction, there is no superior technique in the case of our study

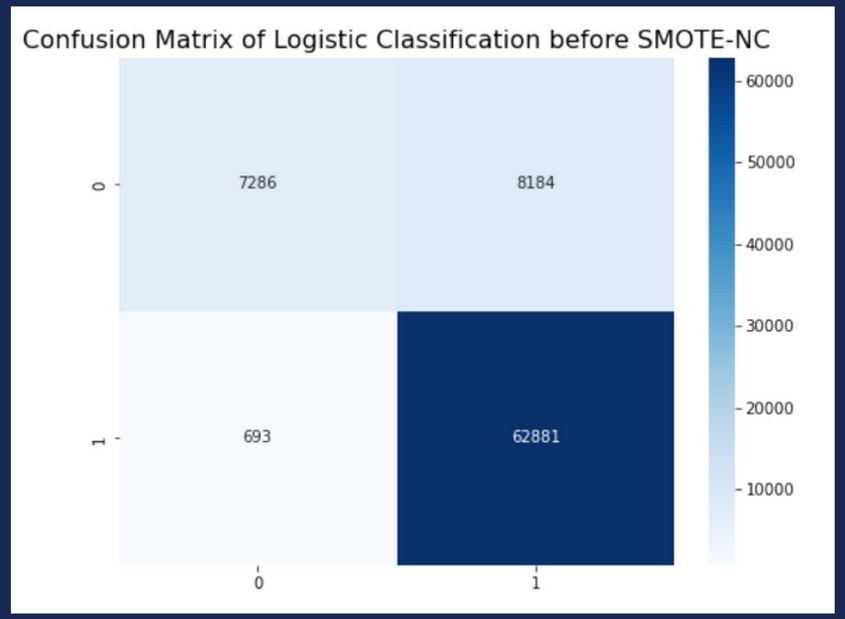


P3.3. Prediction Models

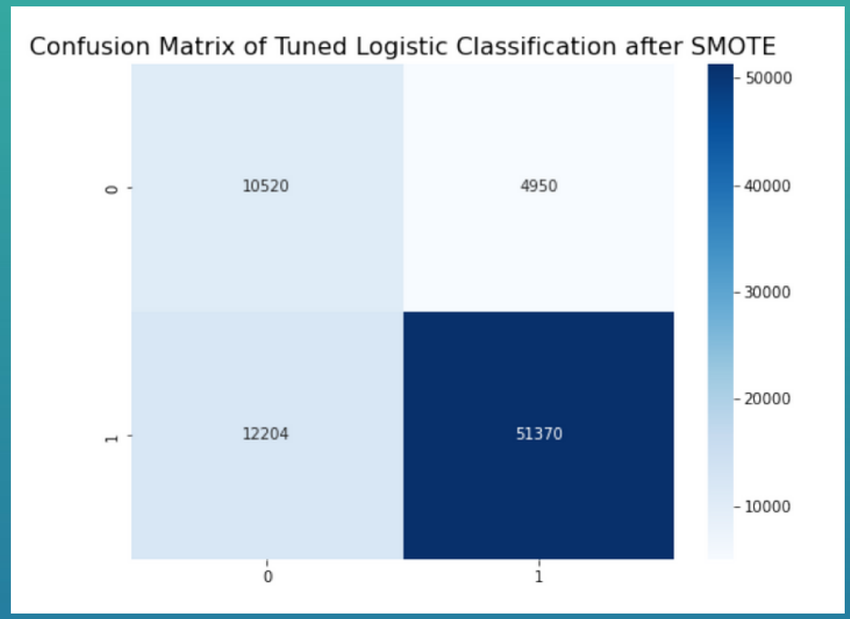
Prediction Models 1/2

Logistic Regression

Before SMOTE-NC



After SMOTE-NC



- The model after SMOTE can detect far more true negatives (i.e., actual charged-off loans) compared to the before SMOTE model
- This is what we expected when we synthetically increased the number of charged-off loans by using SMOTE-NC

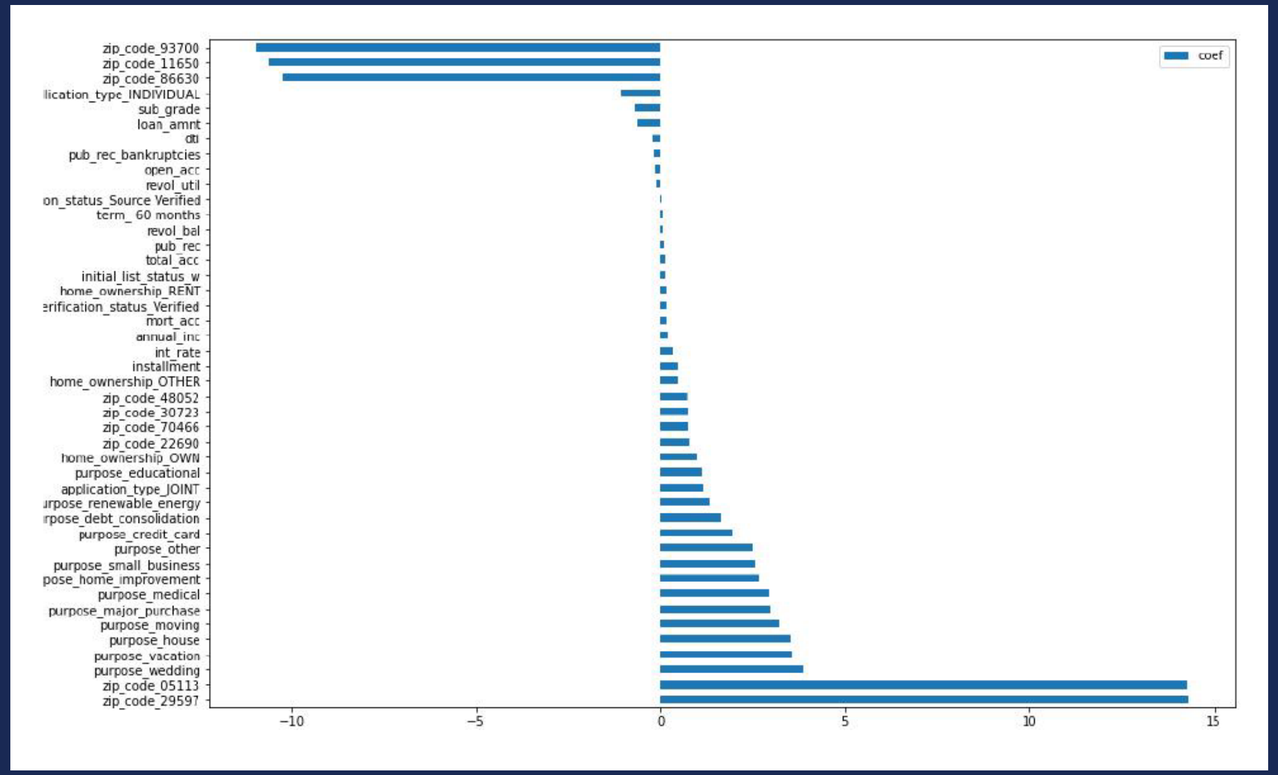
Feature Importance

Interpretation of Logistic Classification model

- Provides quite similar information to that of ElasticNet we interpreted before
- The coefficient magnitudes of Logistic Regression are higher than those of ElasticNet

=> Mainly due to multicollinearity

=> Implies that ElasticNet performs well in cases with highly-correlated data like ours



Prediction Models 1/2

Logistic Classification with Polynomial Features

- After adding polynomial features and interactions degree 02, Recall and F1 scores are improved while the Specificity and AUC scores decrease, both slightly
- Along with the mild results from ElasticNet with polynomial features analyzed in the section above, this result suggests that nonlinearity may not exist in our true Data Generation Process

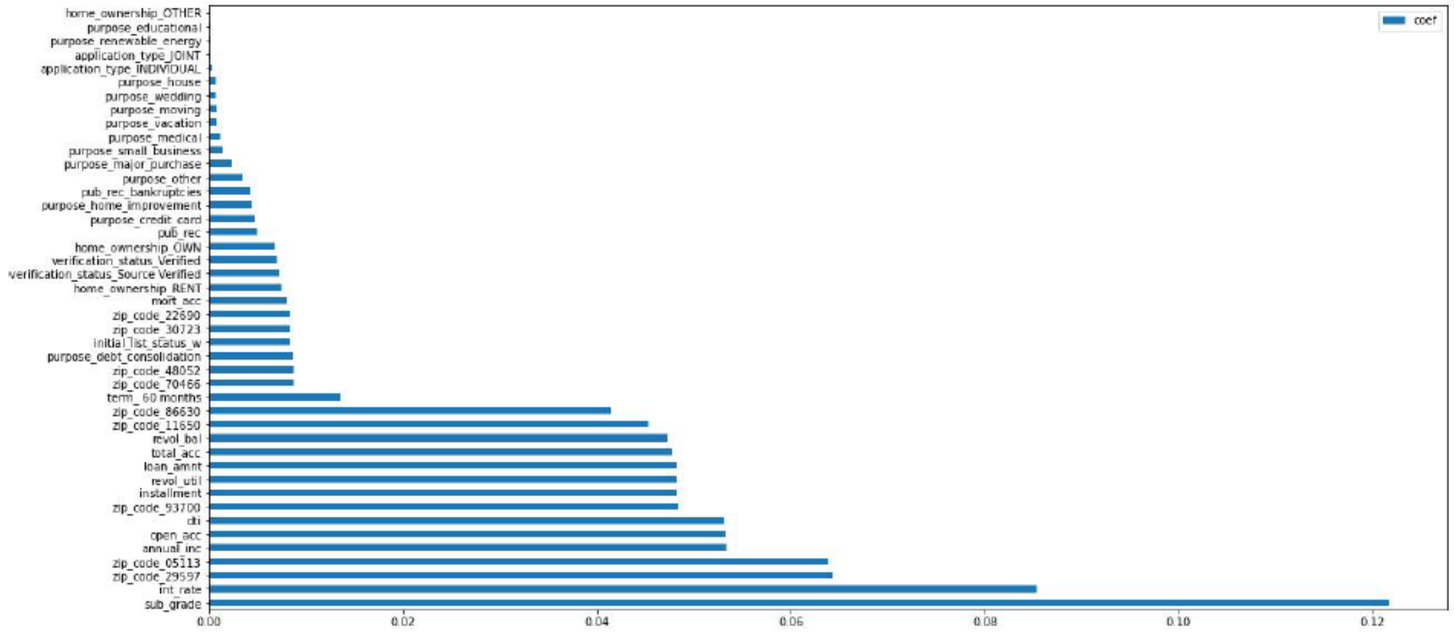
Classifiers	Accuracy	Recall	F1	Precision	Specificity	AUC
Tuned Logistic Classification after SMOTE-NC	0.782982	0.808035	0.856924	0.912109	0.705079	0.74403
Logistic Classification after SMOTE-NC with polynomial features	0.785309	0.812675	0.858936	0.910782	0.700216	0.742763

Prediction Models 2/2

Random Forest

- The evaluation metrics Recall and F1 show improvement compared to the other models
- However, the Specificity score of RF is lower than those of other models
- Sub-grade and interest rate are the two most vital variables
- Other variables which are not considered as important in other models appear in this plot of RF; for example: annual income, open account

Classifiers	Accuracy	Recall	F1	Precision	Specificity
Logistic Classification after SMOTE-NC	0.782918	0.807988	0.856881	0.912072	0.704966
Tuned Logistic Classification after SMOTE-NC	0.782982	0.808035	0.856924	0.912109	0.705079
Logistic Classification after SMOTE-NC with po...	0.785309	0.812675	0.858936	0.910782	0.700216
Random Forest after SMOTE-NC with polynomial f...	0.856181	0.924985	0.911861	0.899104	0.642236



Conclusion

01 Contribution

02 Limitation

03 Further research

Thank you for your attention!