Lending Club Loan Prediction

Capstone Project #2

Outline

1. Introduction
2. Data
3. Exploratory Data Analysis
4. Model

Introduction

The project goal is to train a classification model to predict bad loans on a major lending platform, Lending Club.

The typical lending process:

1. Applicants submit their loan applications to Lending Club
2. Individual lenders can directly browse and select loan applications that they want to fund.

Eventually, borrowers pay interests and principals back to lenders.

Introduction

With this business model, Lending Club is considered P2P lending. There's still the risk of investors to run the risk of investing in a bad loan.

This issue is to be addressed in this project by **developing a predictive model to identify bad loans by using information available on loan applications**.

Then, investors can make more objective and data-driven assessment of loan applications to minimize risk.

Data

We can download dataset from Lending Club website: https://www.lendingclub.com/info/statistics.action.

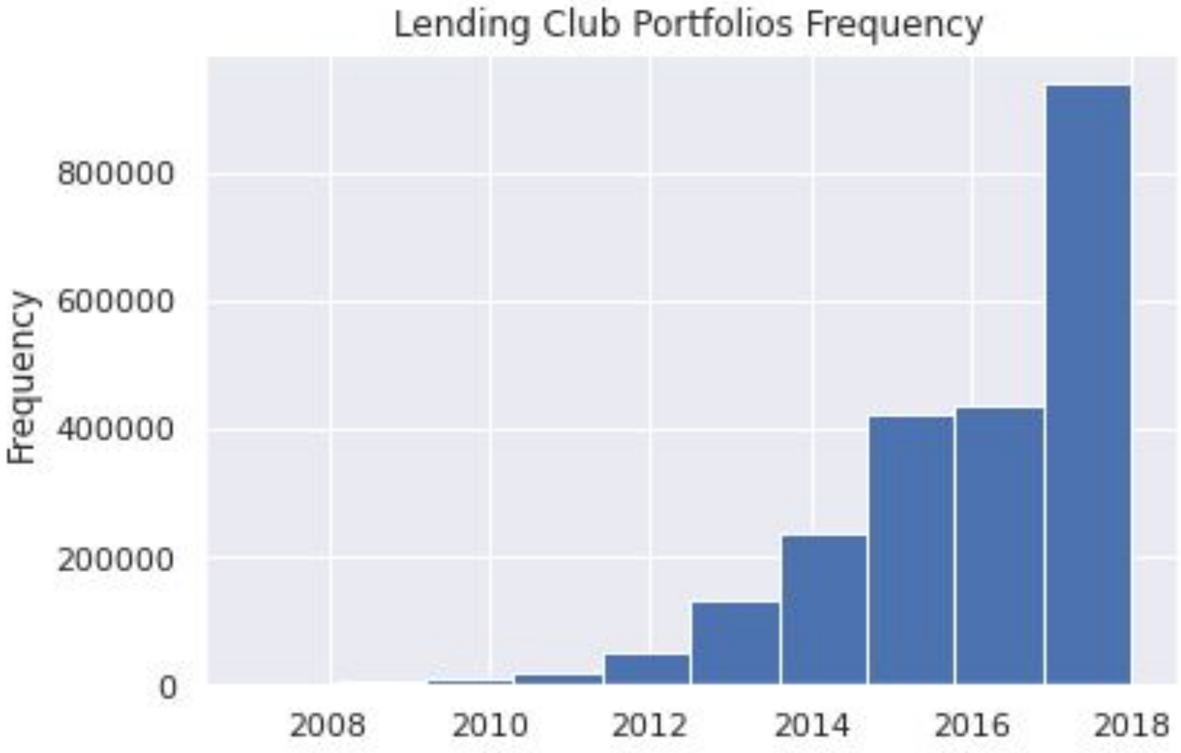
However, it requires signing up as member to download the dataset. Thus, in this project, we will use dataset available from Kaggle. The dataset was downloaded from : https://www.kaggle.com/wordsforthewise/lending-club?select=rejected_2007_to_2018Q4.csv.gz

Unfortunately, this was updated a year ago, so, it's not the most recent data.

Exploratory Data Analysis

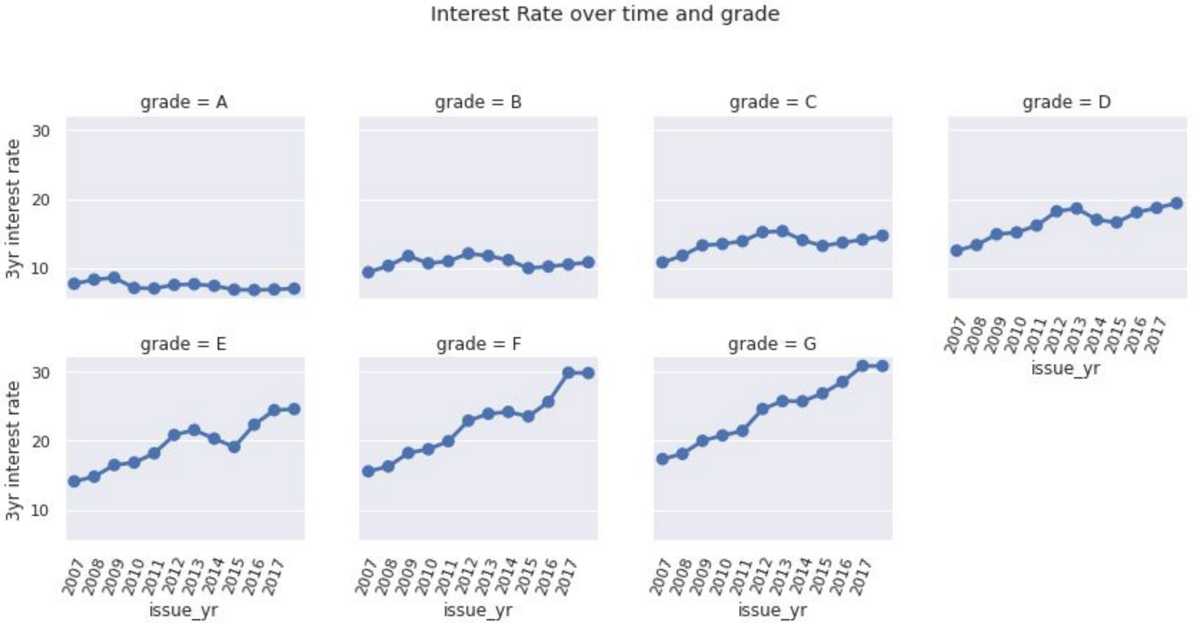
Loan Application Frequency

Lending Club was launched back in 2012. Since then, the platform has gotten more exposure and popularity. Thus, we expected significant increase in its loan portfolios over the years.



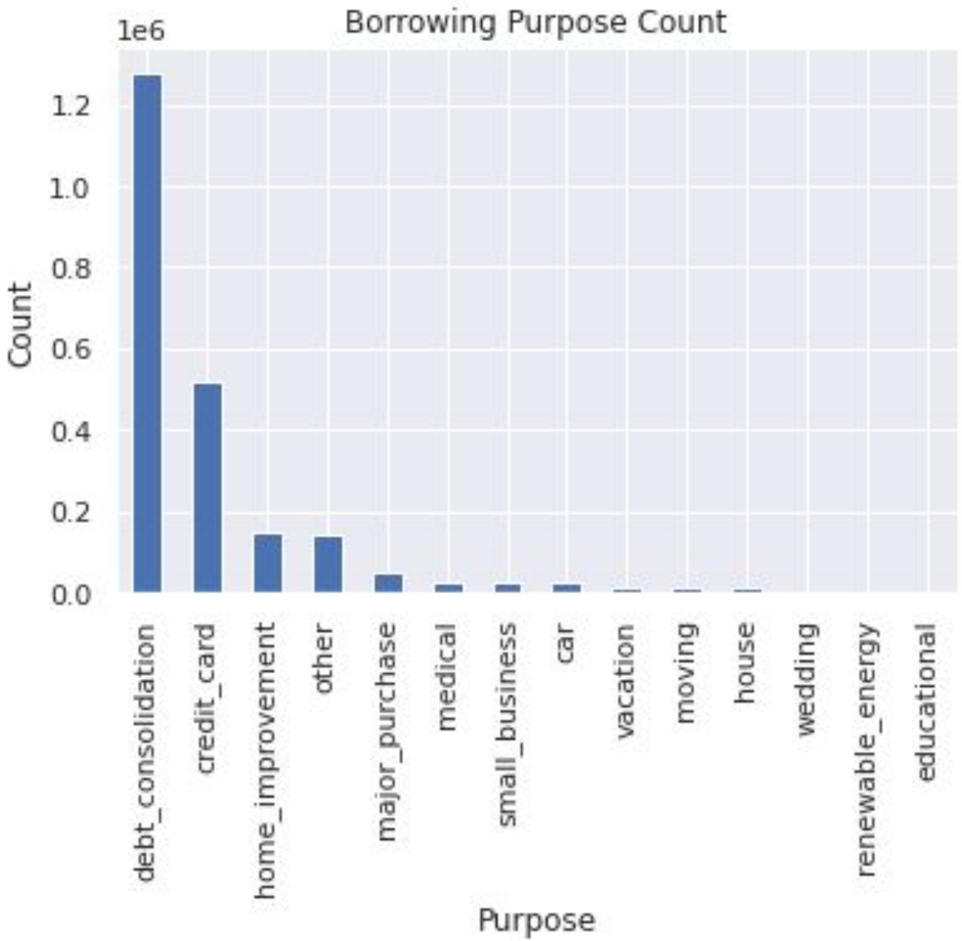
Interest Rate by Grade

We can see that interest rate for grade D, E, F, G increase quickly from 2014.



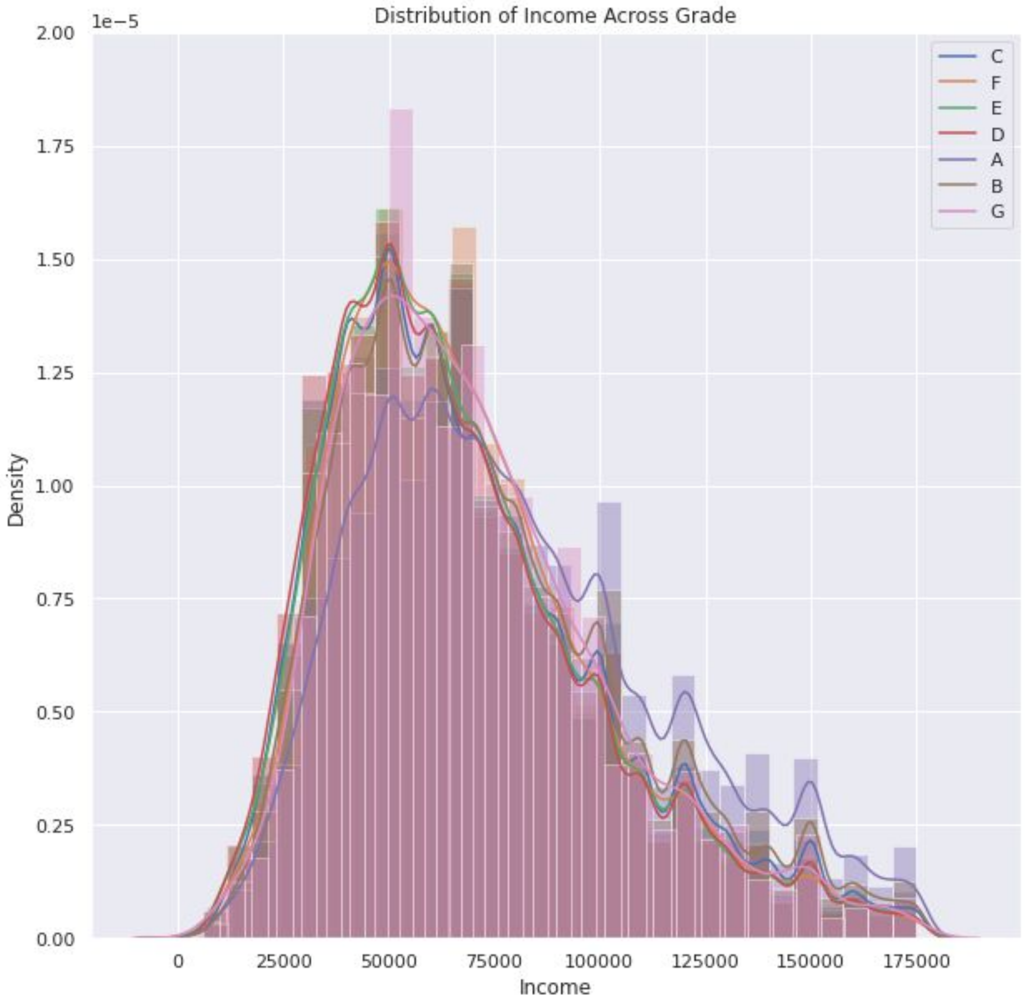
Borrowing Purpose

Debt consolidation, credit card, and home improvement seems to be the top 3 borrowing purpose through Lending Club.



Distribution of Income Across Grade

There seems to be a slight difference in income level across grade, with one grade has a high density of income above $100,000. Perhaps it may not be beneficial to dive too deep into it, except having a brief look at the median income across each grade. We do see that while other grades seem to have similar median incomes, grade A does stand out.



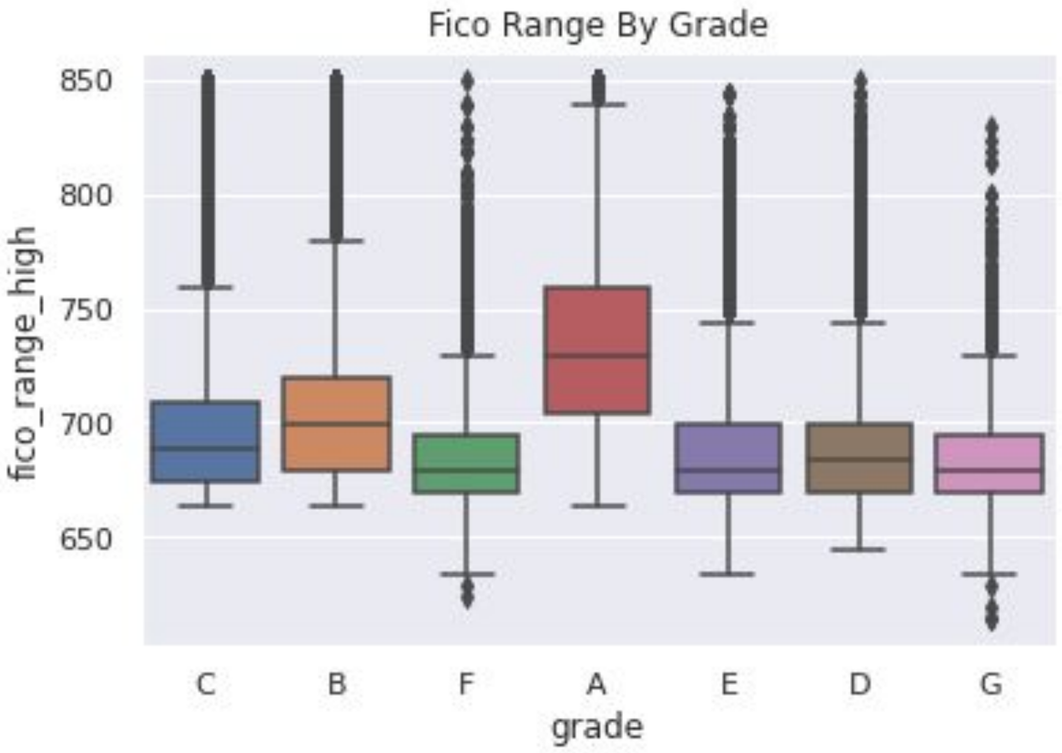
Income by Professions

Interesting Facts:

1. **Teacher and Nurse -** Their minimum salary is only around $12,000, which is lower than US' Poverty Level for individual.
2. Relatively higher income people (>$400,000 and even $1,000,000) still use Lending Club to borrow money.
3. Some jobs traditionally associated with high income have very min income, such as attorney, director, engineer. And these salaries have been verified by Lending Club. Might be just a typo and missing a ‘0.

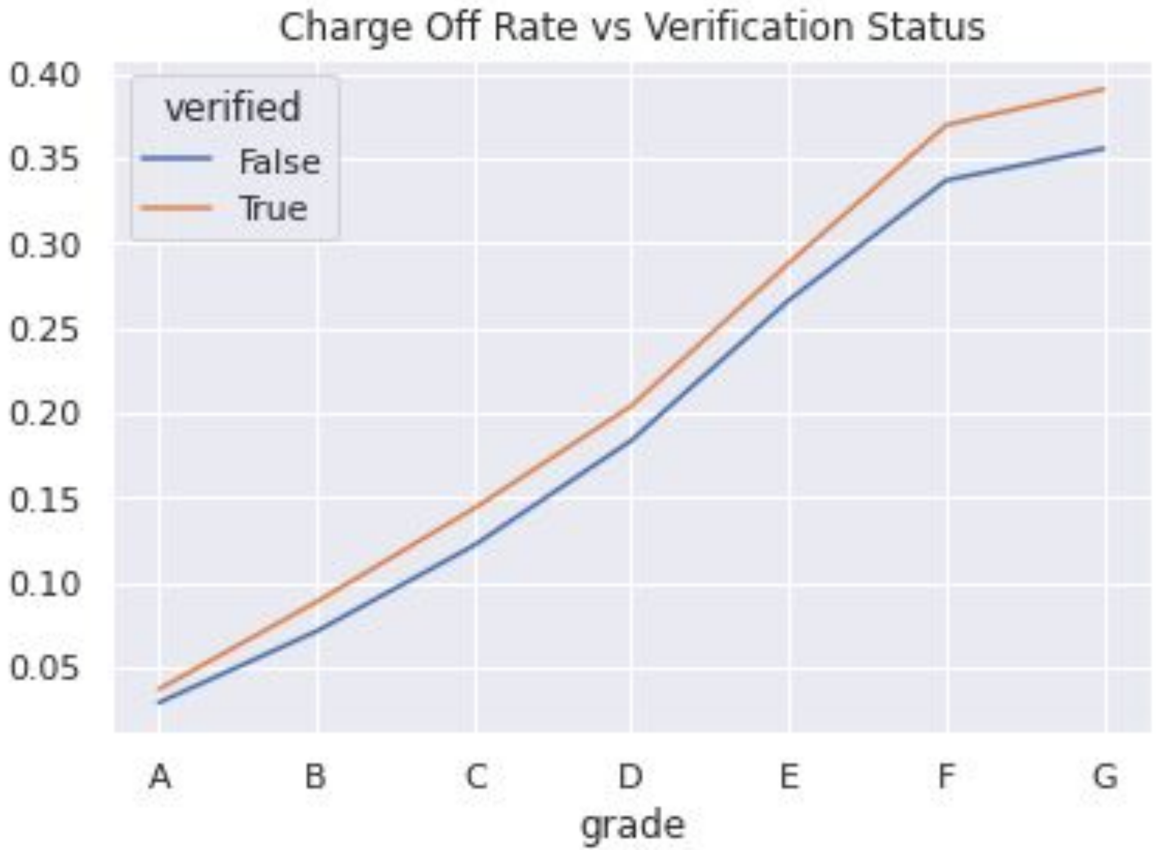
Fico Range and Grade

Obviously, Grade A has the highest overall fico score.

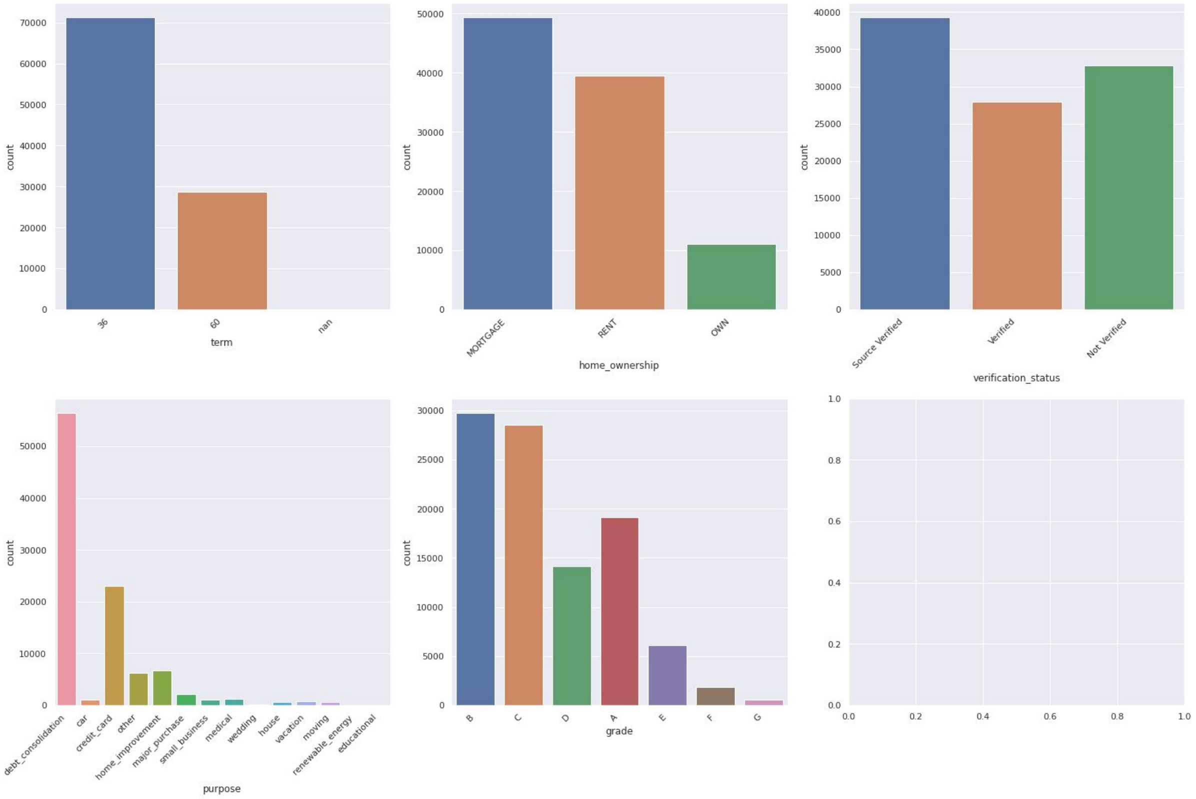


Charge off rate vs Verification status

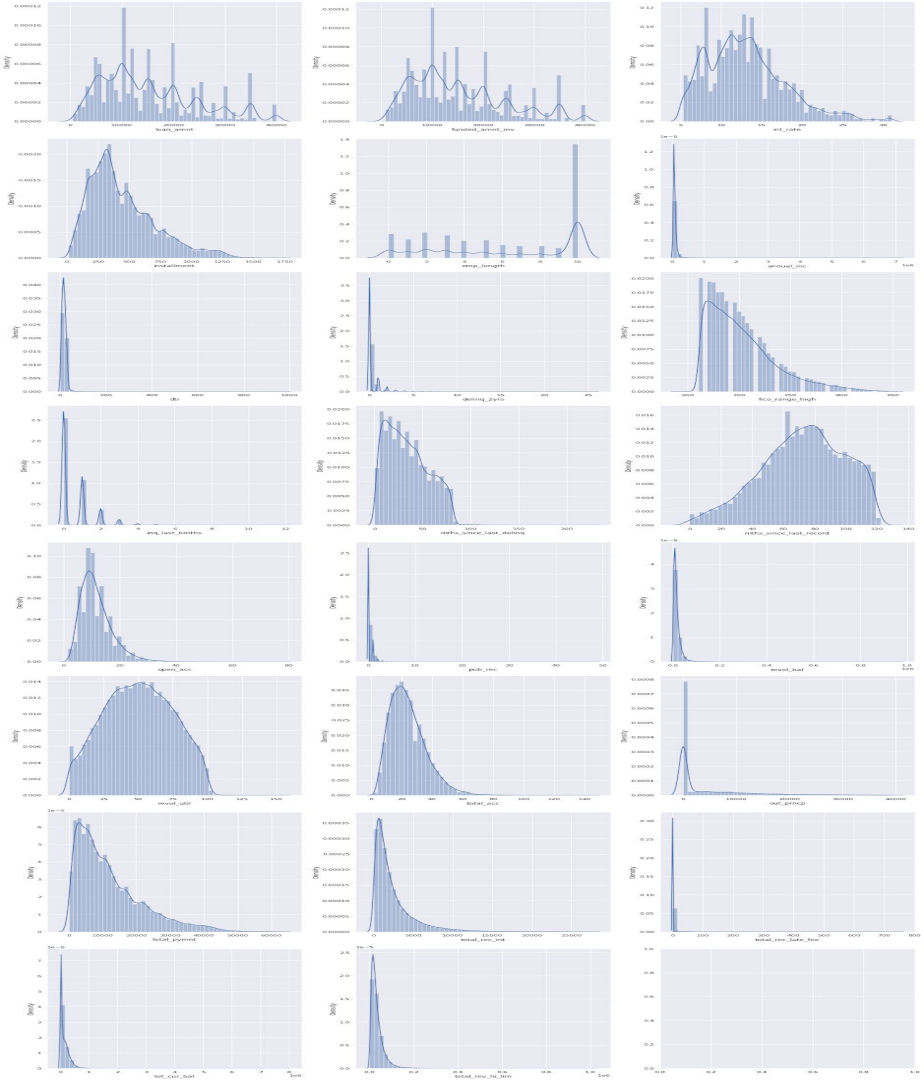
I define that a loan is considered charge-off when the value of loan_status is Charged Off or Default.



Categorical Features

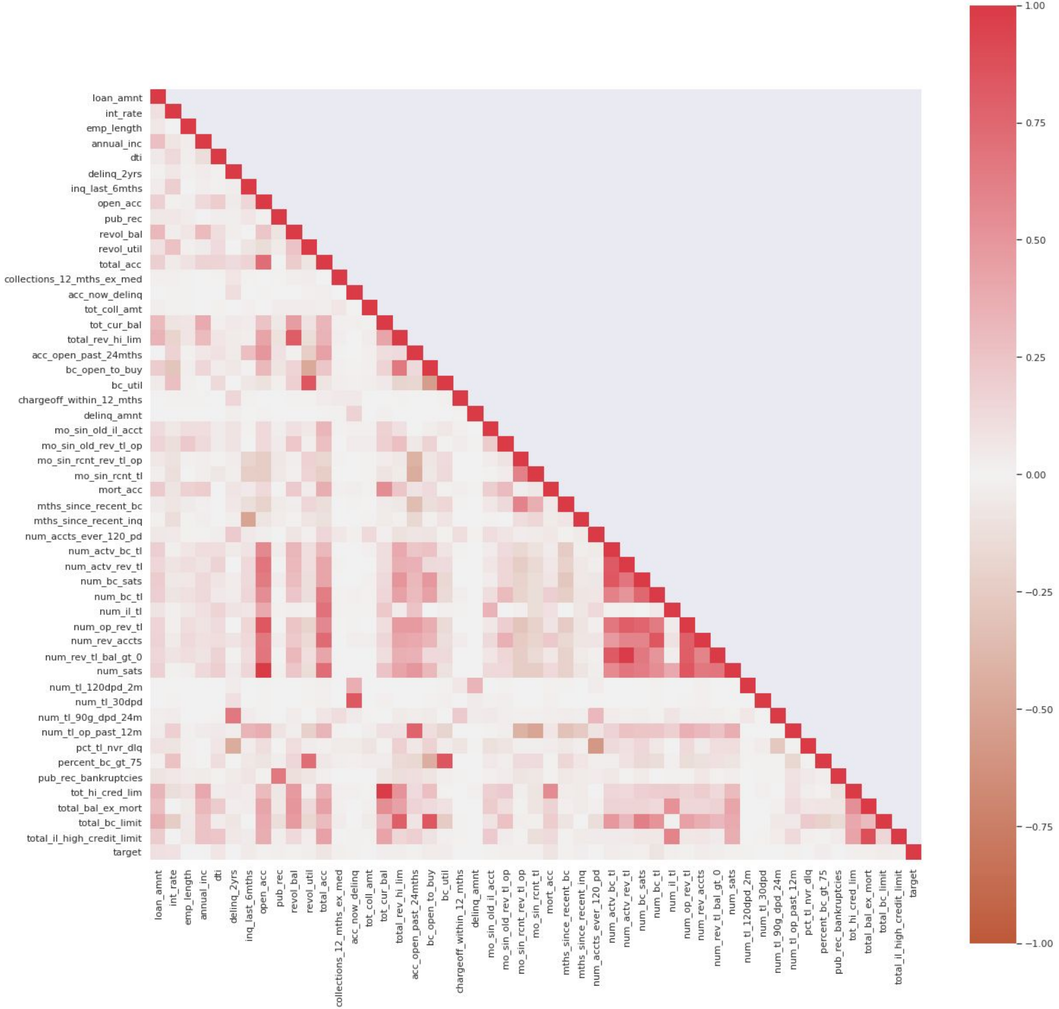


Numerical Features



Correlation Heatmap

We can see from the heatmap that there are several highly correlated features. Highly correlated features can affect the accuracy of regression model. We will find and drop highly correlated features.



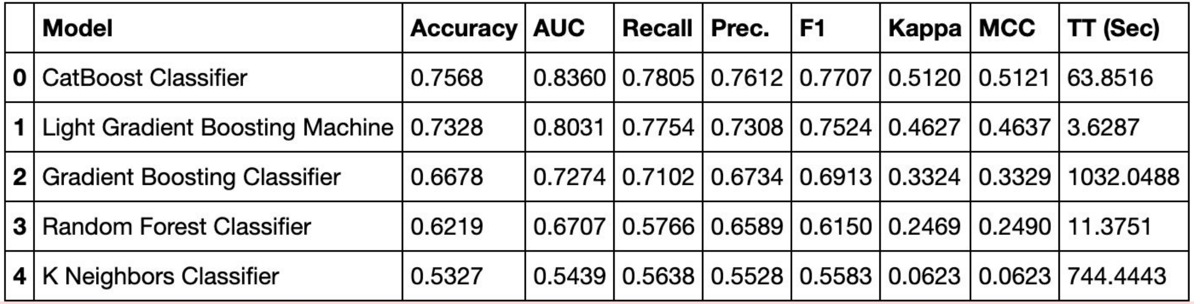
Classification Model

Classification Model – Comparison

In this projects, several widely used algorithms are compared using Pycaret module, including:

1. CatBoost Classifier
2. Light Gradient Boosting Machine
3. Random Forest Classifier
4. K Neighbors Classifier

CatBoost Classifier was found to be the best performing model for our purpose.

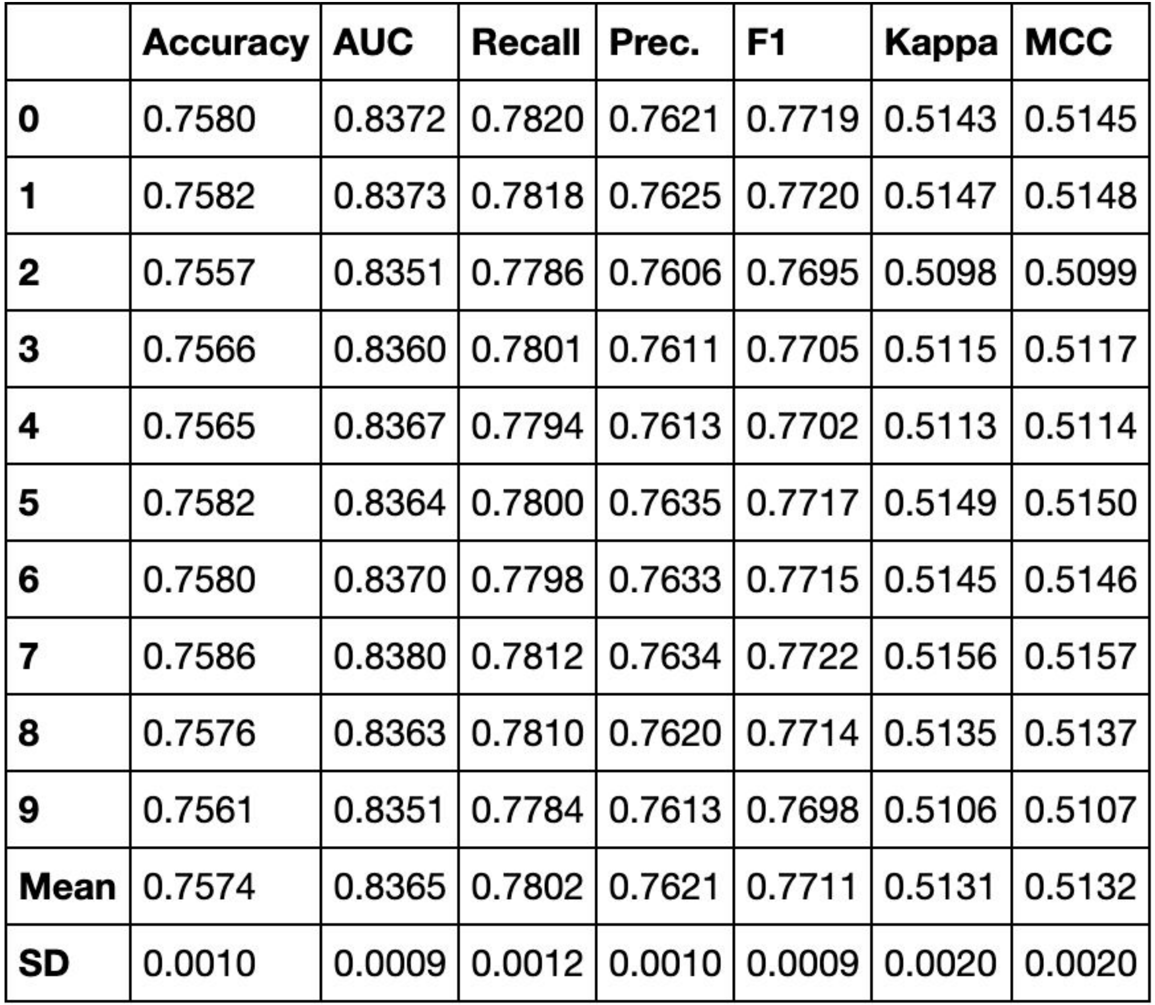


	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
0	CatBoost Classifier	0.7568	0.8360	0.7805	0.7612	0.7707	0.5120	0.5121	63.8516
1	Light Gradient Boosting Machine	0.7328	0.8031	0.7754	0.7308	0.7524	0.4627	0.4637	3.6287
2	Gradient Boosting Classifier	0.6678	0.7274	0.7102	0.6734	0.6913	0.3324	0.3329	1032.0488
3	Random Forest Classifier	0.6219	0.6707	0.5766	0.6589	0.6150	0.2469	0.2490	11.3751
4	K Neighbors Classifier	0.5327	0.5439	0.5638	0.5528	0.5583	0.0623	0.0623	744.4443

CatBoost Setup

Based on 10-fold CV CatBoost:

- Accuracy = 75%
- AUC = .84

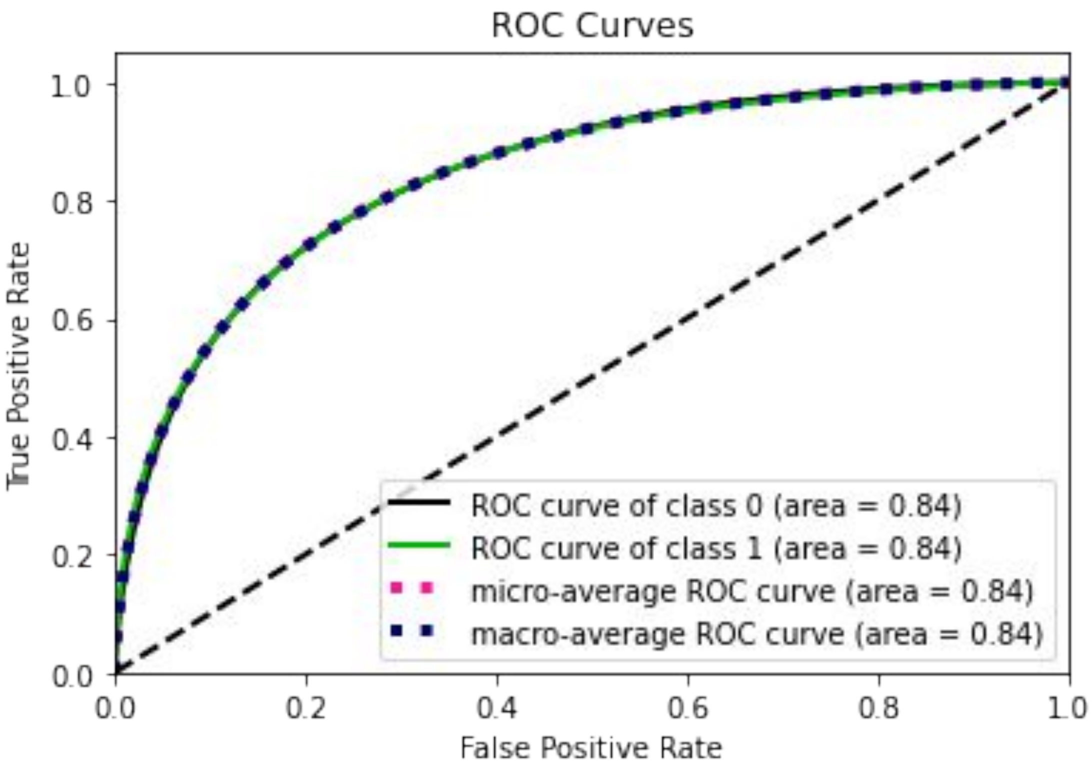


	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	0.7580	0.8372	0.7820	0.7621	0.7719	0.5143	0.5145
1	0.7582	0.8373	0.7818	0.7625	0.7720	0.5147	0.5148
2	0.7557	0.8351	0.7786	0.7606	0.7695	0.5098	0.5099
3	0.7566	0.8360	0.7801	0.7611	0.7705	0.5115	0.5117
4	0.7565	0.8367	0.7794	0.7613	0.7702	0.5113	0.5114
5	0.7582	0.8364	0.7800	0.7635	0.7717	0.5149	0.5150
6	0.7580	0.8370	0.7798	0.7633	0.7715	0.5145	0.5146
7	0.7586	0.8380	0.7812	0.7634	0.7722	0.5156	0.5157
8	0.7576	0.8363	0.7810	0.7620	0.7714	0.5135	0.5137
9	0.7561	0.8351	0.7784	0.7613	0.7698	0.5106	0.5107
Mean	0.7574	0.8365	0.7802	0.7621	0.7711	0.5131	0.5132
SD	0.0010	0.0009	0.0012	0.0010	0.0009	0.0020	0.0020

ROC

The performance of the model can also be seen in the ROC Curves.

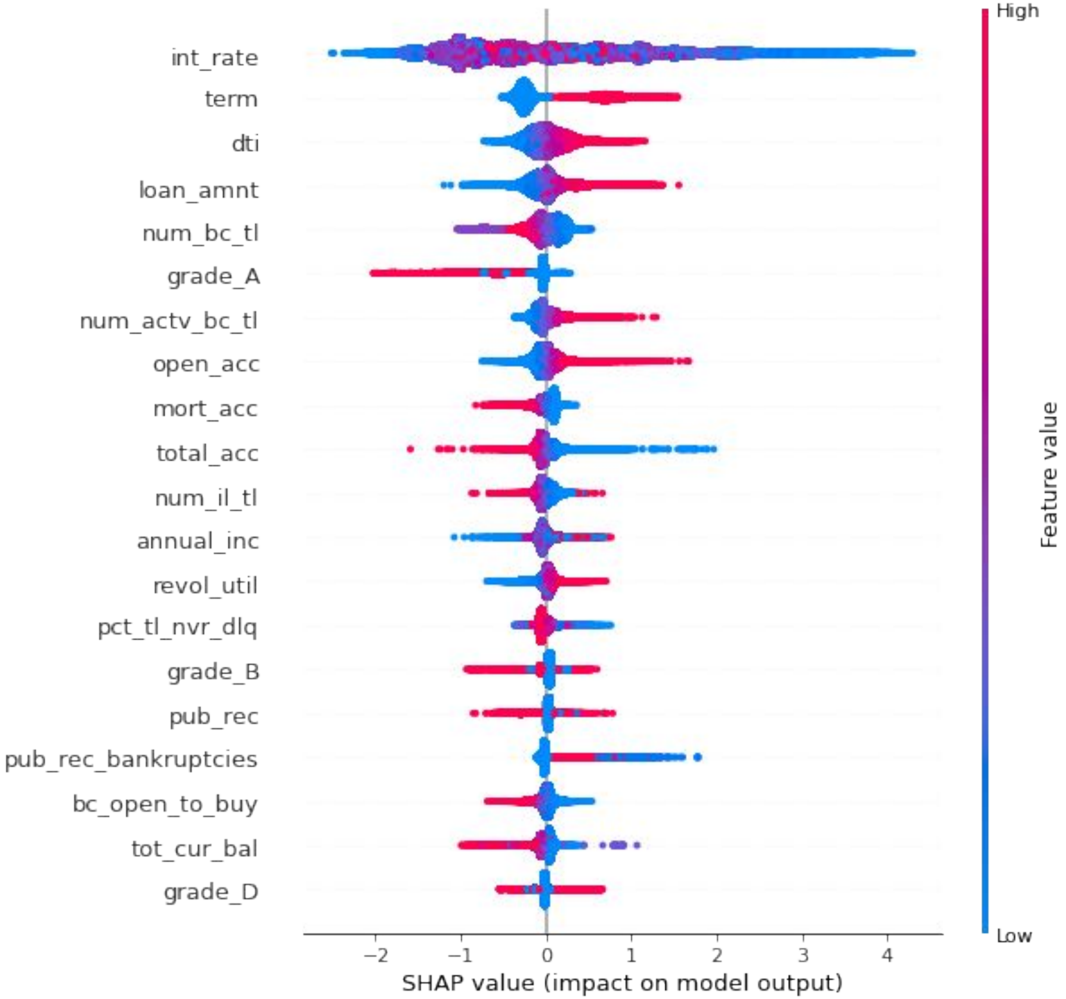
Using scikitplot package - ROC curves were plotted.



Feature Importance

SHAP value can be generated with Pycaret model. In this project, we used it to determine the feature importance.

Interest rate was found to have the highest feature value.

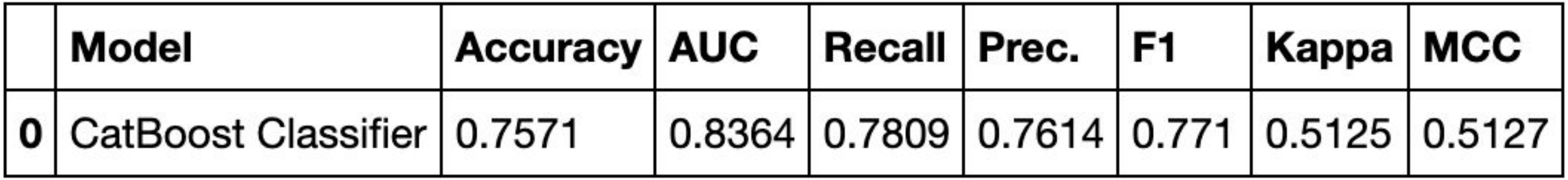


Prediction

Making prediction with our model resulting in similar performance of the training.

Accuracy = 75%

AUC = .84



	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	CatBoost Classifier	0.7571	0.8364	0.7809	0.7614	0.771	0.5125	0.5127

To be improved

There are things I would like to do in the future to improve accuracy:

1. Ensemble machine learning model
2. PCA