Credit Default Prediction

Part of recruitment process at Billie.io
by Hoang Luong

Purpose

- Introduction
- Data
  a. Some visualisation
  b. data manipulation
  c. dealing with missing values
- Introduction to Model Used
- Model Tuning
- Performance comparison
- Summary

Introduction

In this project, my goal is to predict credit default, while using results from [Suspiciously Datalicious](#) as a benchmark.

Main Outcome:

- Performance improved mainly by choosing right features

Difference from the benchmark:

- Default definition
- Using more powerful algorithms

Data

- Loan data available from Lending Loan Club
- 144 features
- Loan Status as the outcome variable
- 2,260,066.8 observations

Manipulation, Data Wrangling

- Removed about 30 variables that are found to be less useful, hard to deal with missing data, or computationally heavy to process
- Took a logarithm of some variables to make them look "normal"
- Imputed missing values, mainly with 0 (not ideal)
- Created the outcome variable
  - Dropped Current Loans. Interested default or non default. Current Loans should be a third category.
  - Defined Churn: { **'Default'**: ['Late (31-120 days)','Late (16-30 days)' ,'In Grace Period', 'Does not meet the credit policy. Status:Charged Off', 'Charged Off', 'Default'], **'Not Default'** : ['Fully Paid']}
  - 1,340,968 observations left. Still a very big amount of data
  - Other option might be just too consider Fully Paid and Default

Manipulation, Data Wrangling

- Transformed some date value to numerical
  - For example hardship_length by using the amount of days between hardshi_start, hardship_end, or experience by calculating day between today and earliest_credit_line
- Created dummies for categorical variables

Due to the time constraint and fact that the project is an extension of other results, most visualisations and description of data can be already found on Suspiciously Datalicious. Here only some "interesting" variables are provided.

Loan Status Histogram
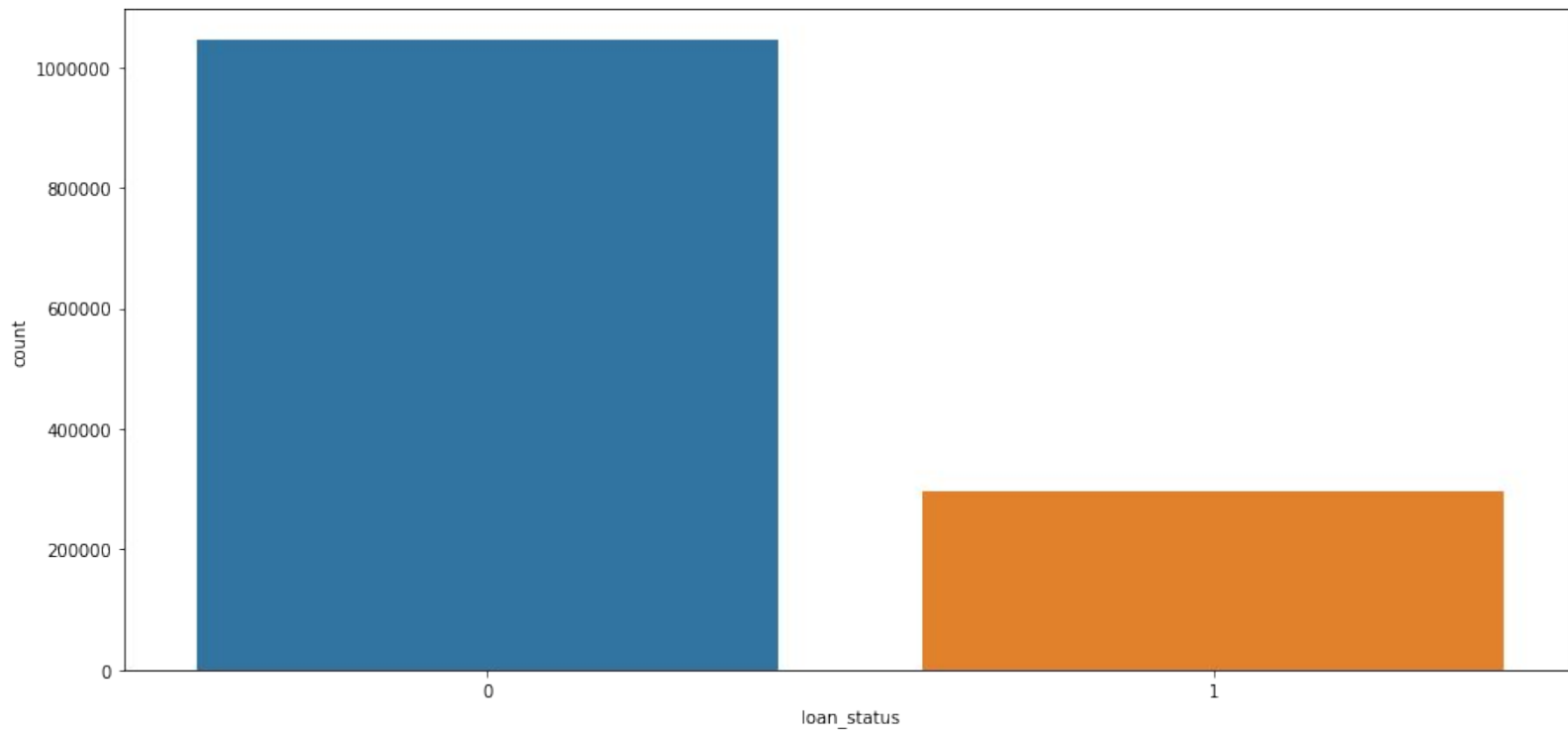
Outcome Variable Discussion

The rate of default is much smaller than the rate of non-default. Accuracy of the model is important but it is just a small part of the story. The emphasize should be put on "Recall," namely the number of true positives divided by the number of true positives plus the number of false negatives.

Features Picking

- Using Mutual Information (MI) criteria is used to pick get the "best" 40 features
- With the left 40 features, Forward Search Algorithm to pick up 10 features
  - Reason: MI doesn't consider that some variables might be highly correlated
  - Algorithm:
- 10 variables should be enough to build a good prediction model that does not overfit

Mutual Information (MI)

Intuitively, if x_i is a feature and y is an outcome variable, MI is a measures of how the distribution of $p(x_i, y)$ is different from the $p(x_i)p(y)$. If x_i and y are independent, then we would have $p(x_i, y) = p(x_i)p(y)$, and the MI between the two distributions would be zero.
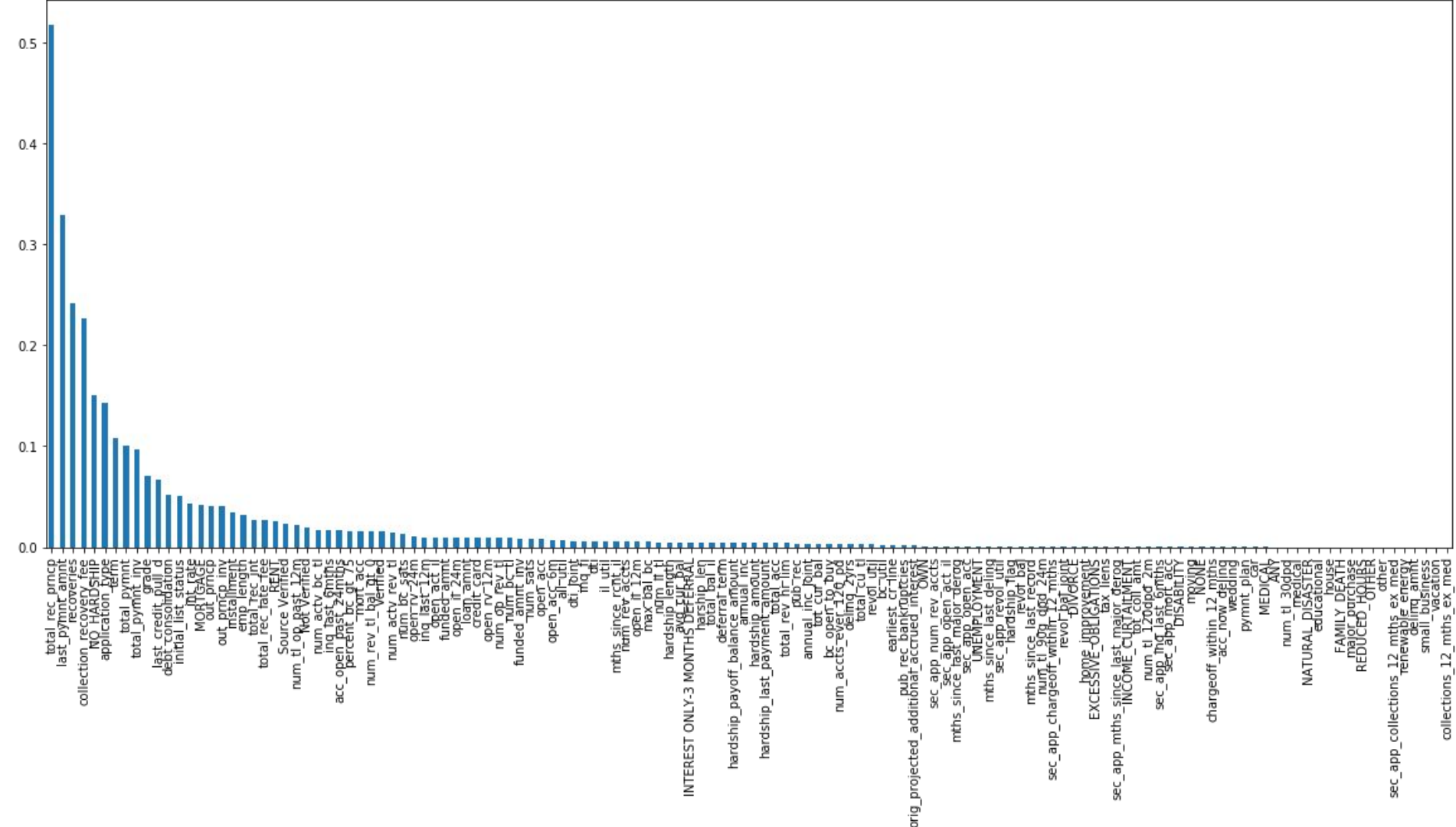
Forward Search Algorithm

1. Initialize an empty set F and a desired amount of features k.
2. Repeat {
(a) For each Feature, if Feature is not in F, add Feature to F and evaluate the model with Features in F via cross validation.
(b) Set F to be the best feature subset

}

3. Stop the algorithm when the amount of elements in F == k

Forward Search Algorithm

After **hours** of computation, I got these variables:

- 'int_rate'
- 'installment'
- 'grade'
- 'out_prncp'
- 'total_pymnt_inv'
- 'total_rec_late_fee'
- 'recoveries'
- 'collection_recovery_fee'
- 'Source Verified'
- 'NO_HARDSHIP'

Modelling

- Since we have a big imbalance between two outcomes (10% default vs. 90 % non-default), just looking at accuracy is a bad flawed
- Intuition: we don't want to label/ predict default (True Positive) as non-default (False Negative).
- Recall and Precision
- Extreme case: 90% accuracy and 0% recall would mean that a lender might have used this information and have given loans to all people that would default
- Solution? ROC and F1

ROC and F1

- ROC: compares Specificity vs (1 - Specificity)
- F1: 2*Precision*Recall/(Precision + Recall)
- ROC assumes a balance in the outcome variable, which in our data set is not the case
- F1 might be a better measurement for imbalanced data

Steps

1. Normalize Data
2. Split Data into training and test set (it can also be split into training, test, and validation)
3. Train models on training set
4. Use models on test set
5. Tune parameters if needed
6. Evaluate with metrics

Logistic Regression

We started with a simple Logistic Regression that already gave us a quite nice performance

- F1: 0.94
- Accuracy: 0.97
- Precision: 0.99
- Recall: 0.90
- ROC: 0.94

"Best" Parameters for Random Forest

After running Random Grid Search, I got some improvement of the model.

- F1: 0.92
- Accuracy: 0.96
- Precision: 0.99
- Recall: 0.86
- ROC: 0.93

There is still a room for improvement. Due to a low computational power, I could only test on small grid sizes.

Multilayer Perceptron

Using Neural Network can be useful to find nonlinear relationships, instead of me trying to find manually. After testing different layers, a model with 2 layers with 5 nodes each gave a good performance. Optimizing on recall and precision.

- F1: 0.91
- Accuracy: 0.96
- Precision: 0.99
- Recall: 0.84
- ROC: 0.92

Multilayer Perceptron

Model was run with an optimization algorithm Adam, with default parameters. Loss function used was Binary Cross-entropy. Activation function were ReLu and Sigmoid. There is a big room for improvement. Due to computation constraint, like in Random Forest I couldn't experiment too much with the parameters.

Summary

- The performance was mainly improved by using algorithms to find "right" features.
- Best Performing algorithm was a surprisingly Logistic Regression, followed by Random Forest, and Neural Network (Note that little tuning was done)

Thank you!

Regardless of the outcome I would love to hear your feedback in order to improve for the future. I was actually very surprised that the results were much better than from the website.