Stat 652 Semester Project: Lending Club Challenge Report

Michael Najarro

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Abstract

The goal of this project is to predict whether a borrower will be at risk to default on his or her loan. Here I classify lending club members based on the response variable loan status. After refining the initial data performing and tuning a random forest classification model, I was able classify the likelihood of a banking client defaulting as being a risk or safe lend with Accuracy of 97.71% (95% CI: (0.9746, 0.9795)), Sensitivity 0f 89.21% and Specificity of 99.46%. The variables with greatest contribution to classification was the value of colelction recovery fees and last payment amount

Introduction

Lending Club is a peer-to-peer lending company where Lending club facilitates the borrowing and leasing of capital amongst its clients, with minimal fees. This financial system allows for local economies to grow by allowing its members to fund its members privately and also gain from such investments.

The Lending club data used was posted on 2018 as part of a Kaggle competition to evalaute the likelihood of whether a borrower would be at risk or not at risk for defaulting on a micro loan. Originally the data set contained infromation on borrowers from 2007 up to 2018 (roughly 2 million rows). The goal of this project was to classify whether borrower defaulted or did not default on his or her loan, for a small subset of the years offered, from 2012 to 2014, and for the variable Loan Stauts

Methods

Importing the lending club data to the R environment

Due to the limitations in computing power of my local machine, I was able to obtain a 10% portion of the of the 2012-2014 Lending club data; I applied a stratified random sample to the 3 years of the issue_d column and extracted those rows from the main data set.

The response variable,Loan Status, was a factor variable contain 6 levels on the condition of the loan: "Fully paid", "Does not meet the credit policy. Status:Fully Paid", "In Grace Period", "Late (16-30 days)", "Late (31-120 days)", "Charged Off", "Default", "Does not meet the credit policy. Status:Charged Off."

For the sake of classification I combined "Fully paid" and "Does not meet the credit policy. Status:Fully Paid" Into one classifier called "safe," and all other levels into another classifier called "risk."

From there, I then applied a random stratified sample to each year of 2012 through 2014 such that the total sample collected represented 20% of the 2012-2014 years. The procedures for collecting this data can be found in a seperate Rmarkdown file titled "LC_data_cleaning.Rmd."

Munging the data

I used several approaches to clean the data:

1. I removed any personal identifying variables (two existed)
2. I removed all rows whose response variable had a value of NA.
3. I removed all predictor variables that contained 50% more of its measures as NA.
4. I then took a detailed look at factor and numeric variables:

a. for factor variables, any variables that were cateogircal measures of another numeric variable column, had many levels, and ahd an uneven spread of data amongst its levels I removed.

b. for numeric variables, Any variables that contained low variance, highly skewed distributions, and/or had high correlations, I removed

5. For remaining Nas, I imputed the median value for numeric variables, and then removed Nas for factor variables.

The remaining predictor variables are presented below, as well the remaining data used to perform the classification. Note that the variable "chance default" is the response variable and that there were no remaining NAs within the data.

Table 1: Variables names of the refined lending club data

variables
loan_amnt
term
int_rate
home_ownership
annual_inc
Issue_Year
dti
delinq_2yrs
revol_bal
revol_util
total_acc
initial_list_status
total_rec_int
total_rec_late_fee
collection_recovery_fee
last_pymnt_amnt
last_fico_range_high
last_fico_range_low
tot_cur_bal
total_rev_hi_lim
acc_open_past_24mths
avg_cur_bal
bc_open_to_buy
bc_util
mo_sin_old_il_acct
mo_sin_old_rev_tl_op

variables
mo_sin_rcnt_rev_tl_op
mo_sin_rcnt_tl
mort_acc
mths_since_recent_bc
mths_since_recent_inq
num_actv_bc_tl
num_actv_rev_tl
num_bc_sats
num_bc_tl
num_il_tl
num_op_rev_tl
num_rev_accts
num_rev_tl_bal_gt_0
num_sats
num_tl_op_past_12m
pct_tl_nvr_dlq
tot_hi_cred_lim
total_bal_ex_mort
total_bc_limit
total_il_high_credit_limit
chance_default

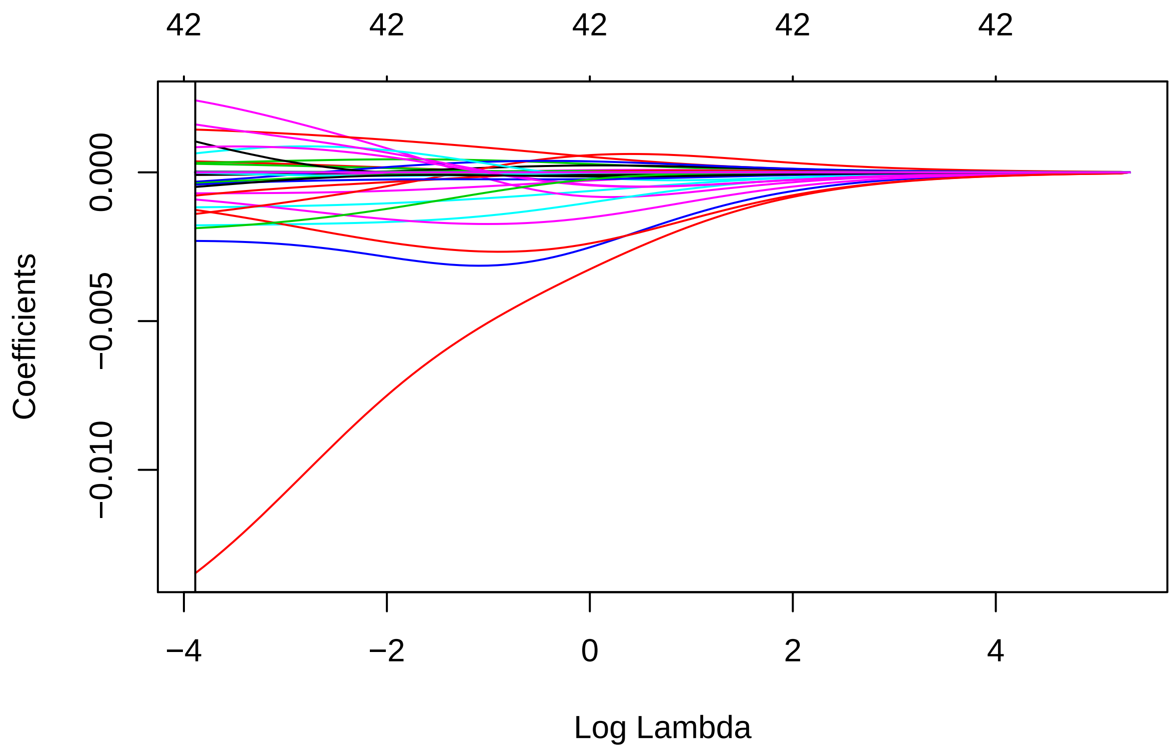
Table 2: Dimensions of refined lending club data

rows	columns
59267	47

Analysis and results

To evaluate whether I could remove more variables I applied LASSO regression analysis for further variable selection. Surprisiingly the analysis indicated not to exlude all variables despite their near zero value

```
## [1] 0.0204821
```




```
## 44 x 1 sparse Matrix of class "dgCMatrix"
##                                      1
## (Intercept)               4.696079e+00
## (Intercept)               .
## loan_amnt                -1.160878e-05
## int_rate                 -1.347627e-02
## annual_inc                1.225477e-07
## Issue_Year               -2.305606e-03
## dti                      -1.174941e-03
## delinq_2yrs               2.419661e-03
## revol_bal                 2.029442e-07
## revol_util                3.677105e-04
## total_acc                 2.265215e-05
## total_rec_int             2.197494e-05
## total_rec_late_fee       -1.781446e-03
## collection_recovery_fee  -7.050846e-04
## last_pymnt_amnt           1.615489e-05
## last_fico_range_high      1.437923e-03
## last_fico_range_low       3.186185e-04
## tot_cur_bal               7.591140e-09
## total_rev_hi_lim         -1.916439e-07
## acc_open_past_24mths     -9.130129e-04
## avg_cur_bal              -2.549100e-07
## bc_open_to_buy           -4.576650e-07
## bc_util                   2.863547e-04
## mo_sin_old_il_acct       -5.352402e-05
```

```
## mo_sin_old_rev_tl_op       -3.298199e-05
## mo_sin_rcnt_rev_tl_op      -4.844483e-05
## mo_sin_rcnt_tl             -8.848765e-05
## mort_acc                   -1.399094e-03
## mths_since_recent_bc        1.465552e-05
## mths_since_recent_inq      -3.159224e-04
## num_actv_bc_tl              6.358996e-04
## num_actv_rev_tl             1.610527e-03
## num_bc_sats                 1.039005e-03
## num_bc_tl                  -7.807824e-04
## num_il_tl                  -3.663472e-04
## num_op_rev_tl              -4.113586e-04
## num_rev_accts              -1.276247e-05
## num_rev_tl_bal_gt_0         8.446981e-04
## num_sats                   -4.913342e-04
## num_tl_op_past_12m         -1.263125e-03
## pct_tl_nvr_dlq             -1.877767e-03
## tot_hi_cred_lim             2.502261e-08
## total_bal_ex_mort           1.905688e-08
## total_il_high_credit_limit  1.626692e-07
```

```
## [1] 43
```

I performed a random forest classification algorithm on the remaining data, which I split into test and training data. I used all predictors and then used the model to predict loan status outcomes on the test data.

Using Caret to tune my model, I modified the model to have 325 trees and set mtry equal to 46. Results below indicate the ouput of the Random forest confusion matrix:

Confusion Matrix and Statistics

Reference Prediction risk safe risk 2249 67 safe 272 12229

Accuracy : 0.9771
95% CI : (0.9746, 0.9795) No Information Rate : 0.8299
P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.9163

Mcnemar's Test P-Value : < 2.2e-16

Sensitivity : 0.8921
Specificity : 0.9946
Pos Pred Value : 0.9711
Neg Pred Value : 0.9782
Prevalence : 0.1701
Detection Rate : 0.1518
Detection Prevalence : 0.1563

Conclusion

The reduction in data greatly increased the predictive power of the model. Specificity was quite accurate at 99%, while sensitivity was at 89%; accuracy was quite high at 98%. the False negative rate was at .45%.

Part of the specificty's low value was due to an uneven balance in the number of risky to safe outcomes on defaulting loans even after combining levels of loan status. Further, a majority of the variables kept in the model were all equally poor in contributing to the classification of loan status based on the Lasso regresison analysis and the contribution of each predictor variable in purity at each node split (gini-index, see figure below).

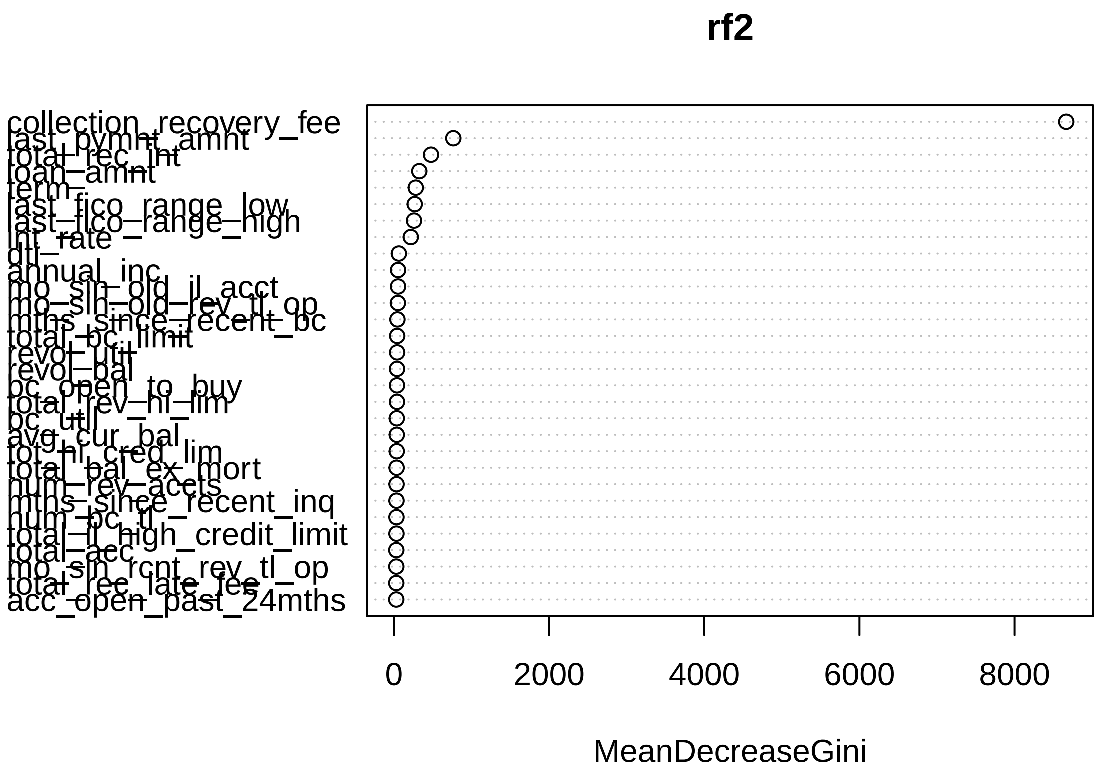
```
## randomForest 4.6-14

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:dplyr':
##
##     combine

## The following object is masked from 'package:ggplot2':
##
##     margin
```



We see that collection recovery fee, last payment amount and total recieved interest (to lender) contributed greatly to average Gini index per tree if the variable was excluded, indicating high importance to classification to defaulting.

Overall, I find that the great majority of observational data is not of importance to classification, and only a few variables were ableto help create an ensemble consensus for predicting loan default status.