MORTGAGE LOAN VALUE PREDICTION WITH MACHINE LEARNING

by

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ABSTRACT

This project aims to use contemporary machine learning algorithms such as Random Forest (RF) and Random Generalized Linear Models (RGLM) to better predict loan values on a single loan level.

1 Introduction

Our research primarily focuses on using contemporary machine learning techniques to predict mortgage values more accurately than traditional linear methods. Previous research has focused on classifying loans at time of origination as prepaid, paid as planned, or default. However, since banks are ultimately interested in making money as opposed to making sure everyone carries out their loan, there is still a large difference amongst the financial impact of loans within each of these categories. To remedy this, we compute the Net Present Value (NPV) of each loan which adjusts all payments to the time the loan was issued. This is a fairer way to compare the financial impact of loans compared to previous classification methods. Additionally, once we calculate NPVs we predict them using data collected before a loan is issued.

2 Literature Review

By the time most people would save up to buy a home outright, they likely would not have much of their remaining life to occupy it. Mortgages allow younger people to occupy homes by borrowing a large sum from a bank and paying it back with interest, typically in monthly payments across 30 years. However, by lending mortgages, banks expose themselves to considerable risk. Banks can lose large sums of money if borrowers can no longer make payments and their home value has depreciated. Due to this high risk, there has been considerable research conducted in an effort to better select quality mortgage borrower candidates. In recent years, the development of new statistical regression and classification techniques have proven to be more effective than traditional linear models [5]. Additionally, due to the availability of large public datasets of loan level data, it has become an attractive dataset to look for significant relationships.

When a bank writes a home loan, they take on considerable risk. If the borrower makes all their payments, the bank can recoup their original investment with interest. However, if the borrower reneges on their end of the agreement there can be considerable financial consequences for the bank. Because of the high-risk, high-reward nature of loans there has been much research conducted attempting to model the behavior of these mortgages. These are a few of the papers that have done similar research to our project. One project uses contemporary machine learning techniques to model whether loans will carry out as planned, end in default, or end prepaid [4]. Of all the techniques used, the most accurate model was random forest (RF) classification. This model could classify loans with 93% accuracy. However, a loan that loses the banks tens of thousands of dollars due to a default, and a loan where the bank can fully recover its outstanding liabilities are considered the same. To remedy this, we analyze the financial impact on banks by opting for an NPV approach. Additionally, due to the accuracy of RF classification, we decided to use an RF model in our analysis. Another project involved an unprecedented dataset of 120 million prime and subprime mortgages from 1995 to 2014[5]. After adding local economic metrics to the data, neural networks were used to predict how many loans would be end as either prepaid or default within random portfolios of thousands of loans. This research showed that neural networks considerably outperformed similar analysis using traditional logit techniques. This is particularly impactful for agencies that package and sell mortgage-backed securities as it improves their methods of choosing loans for their products. This is also a good indicator that machine learning algorithms will yield better predictions of NPV as compared to linear regression.

3 Our Dataset

Our dataset was obtained from the Federal Home Loan Mortgage Corporation, better known as Freddie Mac, which is a public government-sponsored enterprise. We used their Single Family Loan Level Dataset, which lists origination and performance data for loans based on financial quarter of origination [1]. The dataset is composed of two files where the first file lays out the details of each loan's origination. It contains 391,419 observations of 26 variables, which are:

Credit Score	A number summarizing the borrower's creditworthiness prepared by third parties
First Payment Date	Date of the first scheduled payment
First Time Homebuyer Flag	Indicates if an individual is 1) Purchasing the mortgaged property, 2) will reside in the property as primary residence, 3) does not have ownership interests in other residential properties
Maturity Date	Date of the final scheduled payment
Metropolitan Statistical Area	Similar to Zip Codes for large metropolitan areas containing 2.5 million people or more
Mortgage Insurance Percentage	Percentage of loss coverage on the loan, to be paid in the event of a default
Number of Units	Number of properties covered by this mortgage
Occupancy Status	Denotes whether the home is owner occupied, a second home, or investment property
Original Combined-Loan-to-Value	Original mortgage loan amount plus possible second mortgage amount divided by initial property value

[1]The dataset can be found at http://www.freddiemac.com/research/datasets/sf_loanlevel_dataset.html, and you must register to download it

Original Debt-to-Income Ratio	Borrower monthly income divided by monthly mortgage payment
Original Unpaid Balance (UPB)	Initial amount loaned in the mortgage
Original Loan-to-Value	Initial mortgage loan amount divided by initial property value
Original Interest Rate	Original rate indicated on mortgage note
Channel	What type of organization sold Freddie Mac this loan (Retail, Broker, etc.)
Prepayment Penalty Flag	Indicates if the borrower is penalized for prepayment
Product Type	All entries are Fixed Rate Mortgages
Property State	The U.S. State the property is located in
Property Type	Indicates property type (Single-Family Home, Condo, Co-op, etc)
Postal Code	First three numbers of the property's Zip Code
Loan Sequence Number	Unique identifier assigned to each loan
Loan Purpose	Indicates if the loan is to purchase the house, or refinance the property
Original Loan Term	Number of payments based on First Payment Date and Maturity Date
Number of Borrowers	Number of Borrowers obligated to repay the mortgage (1 or ¿1)
Seller Name	Entity who sold the loan to Freddie Mac

Servicer Name	Entity who is currently servicing the loan on Freddie Mac's behalf
Super Conforming Flag	Loans that exceed conforming loan limits
Pre-HARP Loan Sequence Number	Links a HARP loan to its pre-HARP origination data

This is the data we will be using to predict NPV, as it is all collected during the loan selection process.

The second file of the dataset contains monthly performance data for each loan where each loan has an entry for every month regarding the status of the loan.This file has 2,311,802 observations of 23 variables such as:

Loan Sequence Number	Same number found in origination file and used to link the two
Monthly Reporting Period	Current Month of entry
Current Actual UPB	Mortgage ending balance for the monthly reporting period. It includes scheduled and unscheduled principal reductions
Current Loan Delinquency Status	Continuous number of months since Due Date of Last Paid Installment (DDLPI)
Loan Age	Number of months since the origination of the loan
Remaining Months to Legal Maturity	The remaining number of months to the mortgage Maturity Date

Repurchase Flag	This indicates loans that have been repurchased or made whole
Modification Flag	Indicates that the loan has been modified
Zero Balance Code	A code indicating why the loan's balance was reduced to zero (1 = Prepaid/Matured Voluntarily, 3 = Foreclosure, etc.)
Zero Balance Effective Date	Month which the event triggering the Zero Balance Code took place
Current Interest Rate	The current interest rate on the mortgage after any modifications
Current Deferred UPB	Current amount of non-interest bearing UPB (Only occurs in the event of some loan modifications)
Due Date of Last Paid Installment (DDLPI)	The date that the loan's scheduled interest and principal payments were paid through, regardless of when last payment was actually made
MI Recoveries	Proceeds received from mortgage insurance in the event of default
Net Sales Proceeds (NSP)	Amount received from sale of property less selling expenses
Non-MI Recoveries	Other proceeds such as tax, insurance, etc. paid to Freddie Mac

Expenses	Expenses Freddie Mac bears in the event of foreclosure. This is an aggregation of Legal Costs, Maintenance and Preservation Costs, Taxes and Insurance, and Miscellaneous Expenses
Legal Costs	Legal costs associated with sale of property (not included in NSP) in the event of foreclosure
Maintenance and Preservation Costs	Costs associated with maintaining property during foreclosure
Taxes and Insurance	Amount of taxes and insurance owed associated with sale of property
Miscellaneous Expenses	Other expenses associated with sale of property
Actual Loss	Default UPB - NSP + Delinquent Accrued Interest - Expenses - Recoveries where Delinquent Accrued Interest is the interest owed on payments missed since DDLPI
Modification Cost	Costs associated with a rate modification event

The Actual Loss column is particularly relevant to our research, as it gives us a comprehensive overview of losses suffered by the bank holding the loan in the event of default. Between the loan origination and performance data, we can accurately asses how valuable each loan was for the bank at the time it was written and associate that with data collected at origination. It is also important to note that given the time restrictions of our research we only used the first quarter of 1999 as our dataset. We chose first quarter of 1999 because it was the oldest set. This gives it a larger proportion of loans that are already settled as compared to other sets which will have more loans which are still being paid off.

3.1 Matching Origination and Performance

Due to the fact that this data is comprised of two files, it was imperative to find a way to match the performance data for each loan to its respective origination data. This was challenging because the number of performance entries for each origination entry is variable. Additionally, due to the size of our data set we had to solve this problem in an efficient manner. Our first solution that worked utilized a for loop and took roughly 30 minutes to match performance data to 1000 origination entries. Once we switched to an sapply() method, the time was cut to around 10 minutes. Finally, by using matrix algebra we could match 1000 origination entries to their performance counterparts in around 6 seconds. We determined that this was fast enough to precess the full dataset in a reasonable amount of time. The R code for this can be found in my Github Repository, but an outline of the process is as follows:

Step 1: Read in the datasets	Read both with read.delim()
Step 2: Look for when the Sequence Number Changes	Subtract each sequence number from the previous entry
Step 3: Determine which have differences	Isolate nonzero entries
Step 4: Partition performance data into sets by origination file	Use lapply() with our list of sequence number changes

Once we had all the performance data for each origination entry, we can calculate the NPV and attach it to the origination entry for our data set that is ready for analysis.

4 The Net Present Value

The ability to spend money has value. A dollar received today is worth less than a dollar will not receive for a year. The dollar received today has the option to to be spent any time during the next year, which the delayed dollar does not. This implies that part of money's value is tied to the ability to spend it through time. This is the concept called the time value of money and the driving force behind a Net Present Value(NPV). This is a tool to compare assets that have cash inflows and outflows at different points in time. In general, to compute a NPV, take the sum of all the financial inflows and outflows associated with an asset and adjust them to the present time. We let R_t represent a cash flow at time t. If money is received, R_t is a positive number and if it is an amount paid R_t will be negative. $(1+i)$ represents amount an investment should appreciate to compensate you for the time value of your money for one unit of time t. All these principals yield the following formula.

$$NPV_{total} = \sum_{j=1}^{n} \frac{R_t}{(1+i)^t}$$

Because you include all the cash flows associated with an asset, and bring them all to time 0, the NPV_{total} represents what an asset is worth at time 0. It is also worth noting that we assume that if the bank did not invest in this loan, they would invest in a 30 year bond instead, as the most comparable financial asset. Because of this, we set i to be the monthly LIBOR rate from Q1 of 1999. Since the LIBOR rate was 2.93% yearly, our monthly rate came out to around .0241%.

4.1 Our Dataset

To calculate the NPVs of these loans, we first need to determine whether or not they ended paid off or with a foreclosure. We used the programming language R for all the analysis of this project, and all code can be found at the link at the bottom of the page. [2] We began by associating each loan with its corresponding performance data. The code checks the final value of the Zero Balance Code for each loan. If it is not present or NA, it is assumed that the loan is still current to this day and assigns the value "Current". If the Zero Balance Code is 1, that means that the loan is prepaid, and it is marked "Prepaid".Finally, if the Zero Balance Code is 3 or 9, the loan ended in foreclosure and it is marked "Default". These value codes and their meanings can be found in the data set user guide[3]. Once the loan has been classified, it gets put into one of two NPV calculation formulas.

4.2 Prepaid and Current Loans

If a loan is either current or prepaid the NPV is calculated with the same function. Due to the fact that many people do not make level payments on their loans, we use the performance data to compute each payment made individually. This theory behind this is that each payment has two parts. One part of the payment compensates the bank for the time value of holding their outstanding balance, and the other part pays down their outstanding balance. This can be represented as the interest and principal of the payment, respectively. Additionally, since this is the only cash flow for the bank at this time, it is represented by R_t in our NPV calculations. So:

$$R_t = Payment_t = Interest_t + Principal_t$$

[2] GitHub Repository: https://github.com/tbillman/Wang499

[3] Data set guide: http://www.freddiemac.com/research/pdf/user_guide.pdf

We define the amount outstanding, or Current Unpaid Balance, at time t as $CUPB_t$. Additionally, since the interest rate r is quoted as a yearly percent in our data set (3 for 3% instead of .03) we have to divide by 1200 to determine the monthly interest rate charged by the bank. It follows that the interest owed in a given payment is the previous CUPB multiplied by the monthly interest rate. Additionally, by checking the difference in CUPB we find the amount the principal was paid down. Mathematically:

$$Interest_t = CUPB_{t-1} * (r/1200)$$

$$Principal_t = CUPB_t - CUPB_{t-1}$$

Therefore:

$$R_t = CUPB_{t-1} * (r/1200) + CUPB_t - CUPB_{t-1}$$

$$NPV_{payments} = \sum_{t=1}^{n} \frac{R_t}{(1+i)^t}$$

To get the total NPV of the loan however, we need to subtract the original amount lent or Original Unpaid Balance (OUPB). This does not need to be adjusted for time as it was lent at time of origination, yielding us a final:

$$NPVtotal = NPV_{payments} - OUPB$$

Our R code reflects this formula for NPV calculation.

4.3 Default

In the event that a loan ended in foreclosure, we needed a different NPV formula. To find the NPV here, we take a similar approach as in the previous case with one major difference. A defaulted loan has a remaining outstanding balance that was not paid off at the end of their loan. This balance has to be adjusted using all the expenses associated with foreclosing on a home and the net proceeds received by selling the home.

$$NPV_{total} = \sum_{t=1}^{n} \frac{R_t}{(1+i)^t} - OUPB + \frac{CUPB + AL}{(1+i)^T}$$

In this formula OUPB represents the original unpaid balance, or original loan amount. CUPB is the current unpaid balance at time of account closure, and AL is a figure called Actual Loss given in the data. AL represents any amount of the unpaid balance they could not recuperate from foreclosure. Since it is listed as a negative number, the cash flow the bank receives at time of account closure would by CUPB + AL. Since this occurs many years into the mortgage, it is important to adjust it back to time of origination. In this case we assume account closure happens T months after origination. In our code we find this by taking the date of the last payment and adding the number of months it took until account closure. This is a simple task, as both of those terms are given in the performance file. This gives us the total number of months between origination and foreclosure, or T.

4.4 Miscellaneous

Finally, once we had our loans classified and developed a formula to compute the NPV in either case, we computed them all. It is also worth noting that we did not compute NPVs of loans that only have one performance file or were marked as repurchased prior to property disposition. These were all minor cases, and not useful for prediction. We took these values and added them as another column to the origination file, and used this for all our analysis.

5 Geographic Mapping

Given that our data had the first three numbers of each loan's zip code, we decided to look at how these NPVs look across the country. To do this, we used R packages such as ggplot2, evaluate, mapproj, fiftystater, zipcode, ggmap, and tidyverse. Our code followed this process:

Step 1: Load libraries	library("ggplot2"), etc.
Step 2: Read data	read_csv("File Location")
Step 3: Find representative Zip Code for all leading 3 digits of Zip Codes in our dataset	00200 -¿ 00210, 00500 -¿ 00501 ... 99800 -¿ 99801,99900 -¿ 99901
Step 4: Find representative states for all leading 3 digits of Zip Codes in our dataset	00200 -¿ NH, 00500 -¿ NY ... 99800 -¿ AK, 99900 -¿ AK
Step 5: Match each entry's Zip Code to it's respective state with our data frame	Entry 1 has Zip Code 19300, is in PA, and has NPV $-12,008.92
Step 6: Compute the mean NPV for each state	AK -¿ $19,284.79, AL -¿ $18,721.94 ...
Step 7: Compute the standard deviation of NPV for each state	AK -¿ $13,673.22, AL -¿ $15,694.98 ...
Step 8: Compute the ratio of mean of NPV and standard deviation of NPV for each state	AK -¿ 1.4104, AL -¿ 1.1927 ...
Step 9: Graph data with ggplot2()	Figures 1, 2 and 3

The three graphs we plotted were the average NPV (Figure 1), standard deviation

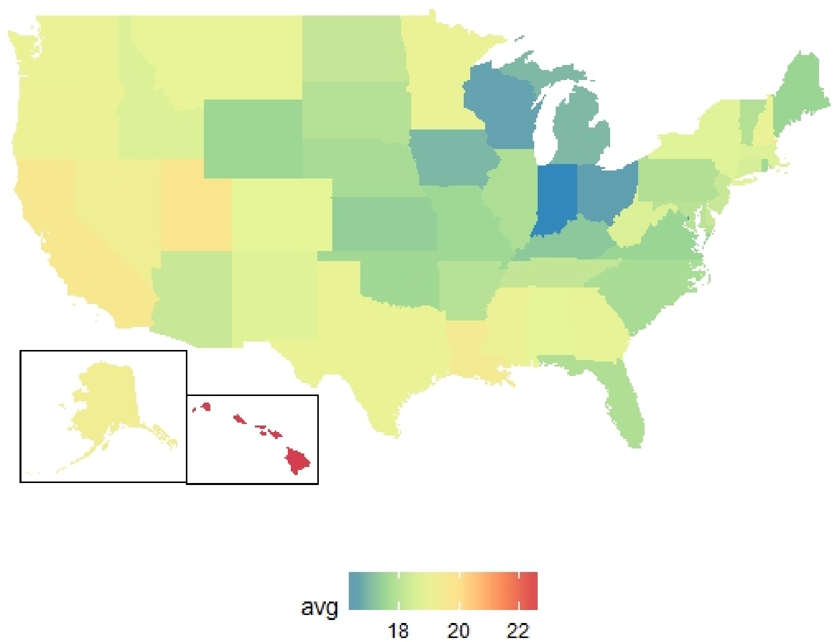


Figure 1: Average NPV by state

of NPVs (Figure 2), and the ratio between the two (Figure 3). Figure 3 is useful for banks looking for the best risk adjusted loan opportunities.

6 High Performance Computing

Due to the large size of this data set and the computational requirements of the regression methods we are implementing, access to the Stampede2 supercomputer greatly sped up our ability to run this analysis. From the Stampede2 User Guide:

> Stampede2, generously funded by the National Science Foundation (NSF) through award ACI-1134872, is the flagship supercomputer at the Texas Advanced Computing Center (TACC), University of Texas at Austin. It entered full production in the Fall 2017 as an 18-petaflop national resource that builds on the successes of the original Stampede system it replaces. The first phase of the Stampede2 rollout featured the second generation of processors based on Intel's Many Integrated Core

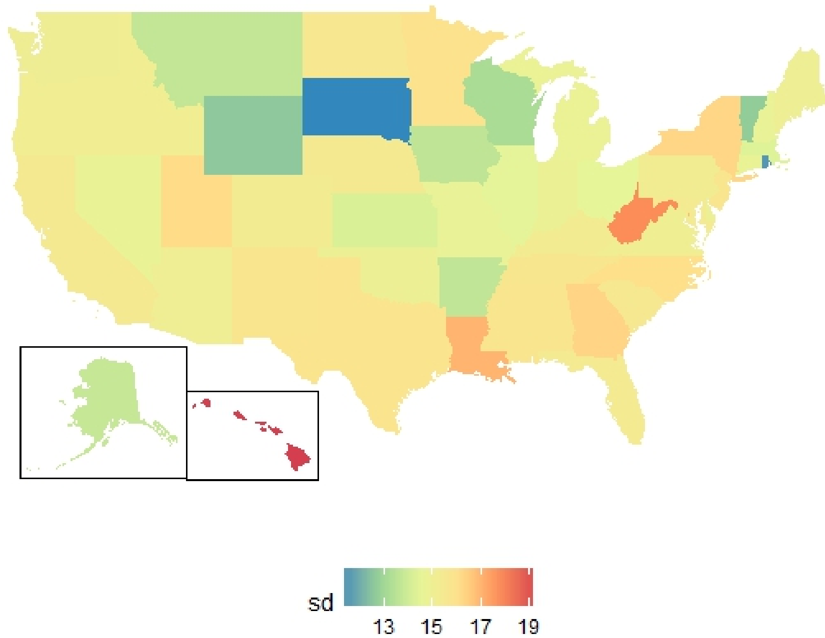


Figure 2: NPV standard deviation by state

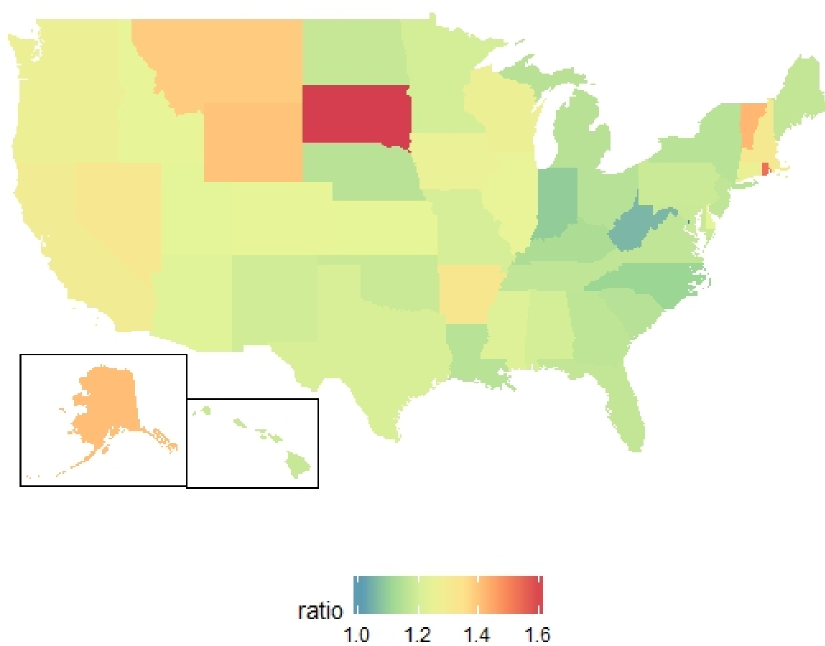


Figure 3: $\frac{AverageNPV}{NPV standarddeviation}$ by state

(MIC) architecture. Stampede2's 4,200 Knights Landing (KNL) nodes represent a radical break with the first-generation Knights Corner (KNC) MIC coprocessor. Unlike the legacy KNC, a Stampede2 KNL is not a coprocessor: each 68-core KNL is a stand-alone, self-booting processor that is the sole processor in its node. Phase 2 added to Stampede2 a total of 1,736 Intel Xeon Skylake (SKX) nodes.[7]

Due to the high computing power and memory of the KNL nodes, we could run RF and RGLM analysis on our full data set in only 3 hours.

7 Linear Regression

7.1 Initial Data Cleaning

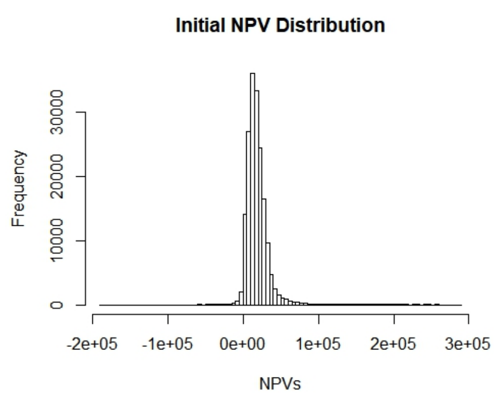


Figure 4: NPVs of complete cases

Once we had our NPVs calculated, we began with simple linear regression to see if there was much correlation between the origination data and NPVs. After removing trivial columns with only one unique value and only keeping rows that had information in all columns, we were left with a 178,058 x 25 matrix. Figure 4 shows the initial distribution of the NPVs. After running an initial Linear Regression on this data, we obtained an R_a^2 value of .008039, which is very low. Given the strong clustering in the middle, we believed that there were some outliers on both ends of the curve and that systematically removing these would help the predictive power of our regression.

7.2 Cook's Distance

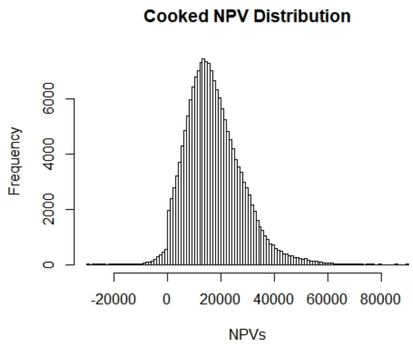


Figure 5: Entries without outlying covariates

In order to remedy our outlier problem, we calculated the Cook's Distance of each point. "Cook's distance, denoted by D_i is an aggregate influence measure, showing the effect off the ith case on all n fitted values":

$$D_i = \frac{\sum_{j=1}^{n}(\hat{Y_j} - \hat{Y_{j(i)}})^2}{pMSE}$$

Where $\hat{Y_j}$ denotes the predicted value of the jth observation and $\hat{Y_j}(i)$ is the predicted value of the jth observation when the ith observation is removed. Additionally, p represents the number of covariate predictors in our linear regression model, and MSE is the mean squared error of our model([2, p. 402]). This is useful because our regression is aimed at predicting mortgage values for typical loans, and outlying loans can be considered on a case by case basis. A general rule of thumb is to discard points with distance greater than $\frac{4}{n}$, where n is the number of data points([3]). After points with outlying values were removed our distribution can be seen in Figure 5. It is also worth noting that in this distribution there is a large spike right around where NPV = 0. This is because there is a large number of defaulted mortgages with Actual Loss = 0. I believe this is because due to regulations, if the bank can recover more than their CUPB and foreclosure costs the remaining proceeds go to the borrower. This leaves many defaults that would have a positive NPV just above 0. After rerunning another linear regression, our R_a^2 value jumped to .01711. However, this is still very low, so we looked to other tactics to improve predictive power.

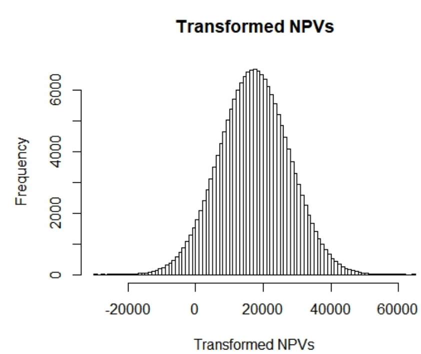
7.3 Multi-collinearity

We also checked for multi-collinearity between our different predictors. "A formal method of detecting the presence of multicollinearity that is widely accepted is the use of variance inflation factors [VIFs]. These factors measure how much the variances of the estimated regression coefficients are inflated as compared to when the predictor variables are not linearly related"[2]. This can be expressed quantitatively as follows:

$$(VIF)_k = (1 - R_k^2)^{-1}$$

Where R_k^2 is the R^2 value predicting the covariate k using the remaining covariates. Common tolerance limits for VIF are 10,100, and 1,000 ([2, p. 408-410]). A low VIF indicates low multicollinearity, whereas a high value indicates that certain variables are not important in our linear regression. When computing the VIF for all of our variables, all values were below 3 with the exception of Combined Loan to Value Ratio (CLTV) and Loan to Value Ratio (LTV). These variables had VIFs of over 2000. This is because CLTV is only different than LTV if someone refinances their mortgage, which is rare. Since LTV is more useful for loan origination, we kept that variable and removed CLTV from the regression. After removing CLTV, the VIF of LTV dropped below 3, but our R_a^2 value remained similar. This indicates that multicollinearity was not having a large effect on suppressing our R_a^2 value.

7.4 Data Transformation



The final tactic we tried was transforming the data into a normally distributed set. This was mostly to test if the non-normality of our dataset was having an effect on suppressing our pre-

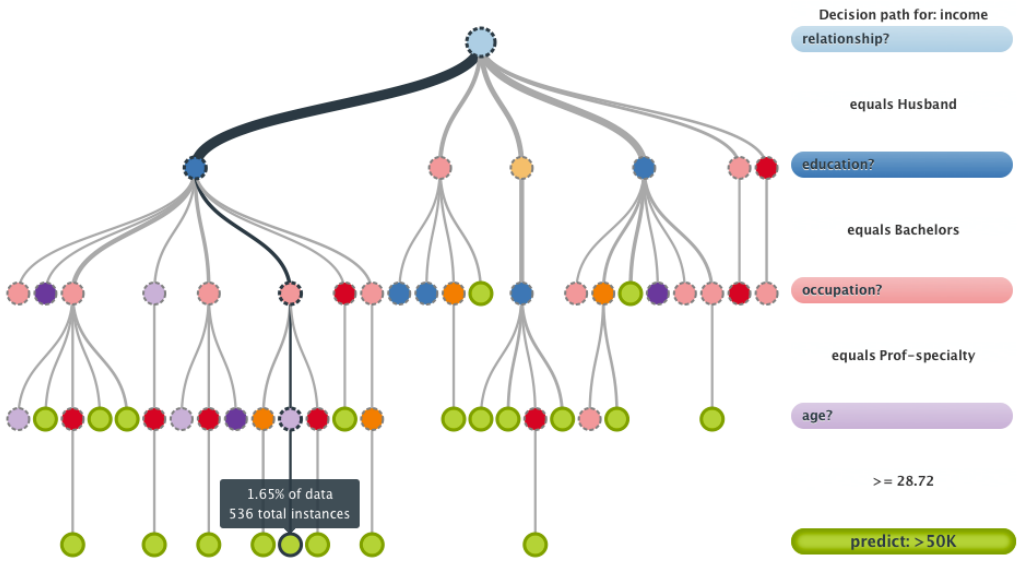


Figure 6: An example decision tree for income prediction

dictive power. To do this, we found the

percentile of each NPV value, and mapped it to a normal distribution with the same mean and standard deviation as our dataset. To do this we used the ecdf() function in R. However, even after this our R_a^2 value only rose to .01812. After this we concluded that simple linear regression would not have strong enough predictive power on this dataset to be useful.

8 Random Forest

Random forest is a contemporary machine learning technique developed by Dr. Leo Breiman at University of California at Berkeley in 2001. Fundamentally, RF takes random subsets of the data and uses them to train decision trees. An example of a decision tree can be found in Figure 6. By training many of these trees on subsets of the data and taking an average of their predictions, we develop a more robust prediction model. This method can be used to predict either continuous or categorical variables. When going about how to analyze this dataset with RF, we had a few options. Our first attempt was using the dataset to predict net present values via regression model. Another option was partitioning the NPV data into categories (Negative, Low, Medium, High) and predicting which NPV category a particular loan would fall into.

8.1 Regression

When running regression we recognized the importance of cross validation. This is a strategy of partitioning the data into a training set and testing set multiple times. For each partition you build a model using 80% of the data, then test it on the remaining 20% and check its accuracy. This is useful to prevent over-fitting in our model. We randomly assigned a group from 1 to 5 to each entry. Each entry consisted of the origination data of a loan as well as its NPV. We built five models, each with one index as our test data and the remaining four as our training data. This is a technique we used for all our machine learning analysis. Our R_a^2 values were all between .064 and .0661 with an average of .065. While this is significantly better than the linear regression, this still very poor predictive power.

8.2 Classification

Due to the low predictive power of regression, we also used RF to predict the NPV of a loan in a more general sense. To do this, we split the data into the following four categories:

- $\$-\infty - \$0$
- $\$0 - \$10,000$
- $\$10,000 - \$30,000$
- $\$30,000 - \$\infty$

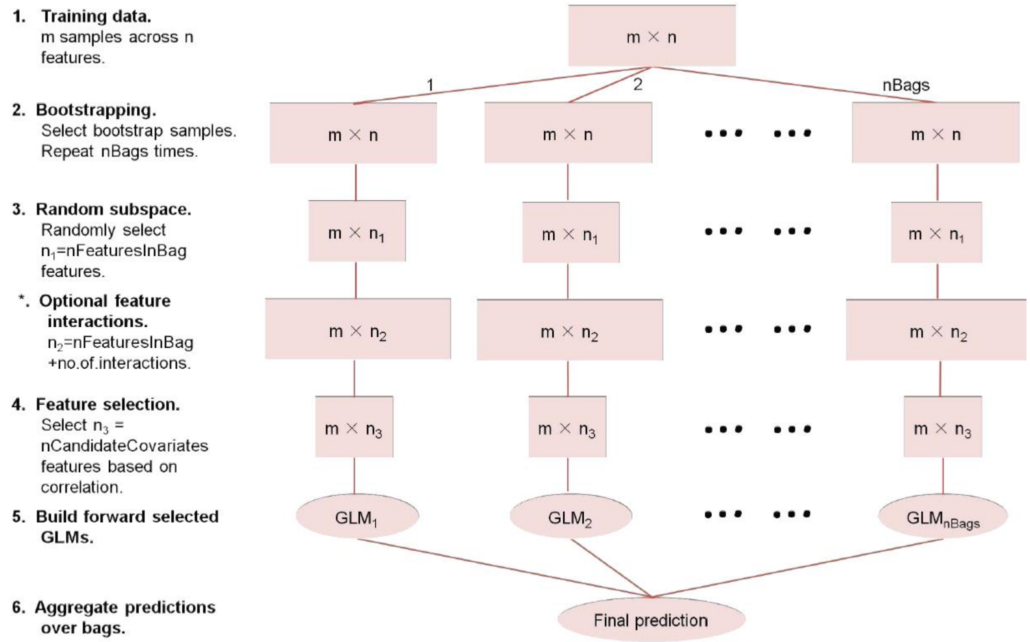


Figure 7: An overview of how RGLM works [6]

Once we did this, we used RF to use the origination data to predict which NPV category a given loan would fall into. If the model had no predictive power, we would still expect a correct guess 25% of the time by chance. After running our classification, our results had a minimum of .614, maximum of .625, and average of .620. ADD IN AN INTERPRETATION

9 Random Generalized Linear Model

Another technique we thought would be useful was using Random Generalized Linear Models. The way RGLM works is very similar to RF, however instead of training decision trees, RGLM trains generalized linear models. This is very nice because it takes the ensembling aspect of RF with a model that is easier to interpret.

9.1 Regression

One issue we encountered with RGLM is that our code could not use factor variables for regression prediction. As such, the R_a^2 value for our RGLM regression suffered. After running our analysis our five values ranged from .0174 to .0194 with an average of .0187. This is around the same as our initial linear regressions, and does not have strong predictive power.

9.2 Classification

Due to the binary nature of GLM classification, to classify NPV with RGLM, we decided to opt for classification into positive and negative NPV. After running our analysis in a similar way to RF, our cross validated results had a minimum accuracy of , maximum accuracy of, and average of .

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