# Review of Bankruptcy Prediction Using Machine Learning

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## Introduction

From financial institutions to iconic department stores, the coronavirus has seemingly spared no one in its devastation of the world's economy. The fall of consumer demand, stay-at-home orders, a reduction in consumer spending, and a mandate for certain businesses to stay closed continue to take their toll on the financial stability of said businesses. Bankruptcy prediction is an important technique of forecasting a company's future as well as projecting a company's financial distress. The reason for predicting bankruptcy is basic in evaluating the monetary state of an organization and its prospects in its operations. Corporate bankruptcy is an exceptionally critical phenomenon in financial institutions. The monetary security of an organization plays a critical role in determining its future.

Additionally, bankruptcy prediction is fundamental for financial backers just as providers or retailers to the business. Credit loan specialists and financial backers need to assess the monetary risk of an organization before settling on an investment or credit-giving decision to avoid a significant loss by banks and other credit lenders. An organization's providers or retailers consistently manage credit exchanges for the organization, and they likewise need to completely comprehend the organization's monetary status and settle on choices on the credit exchange. To accurately anticipate an organization's monetary distress is of incredible worry to the different partners of an organization.

The purpose of this paper aims to see which variables are most important in predicting whether a company will fall into bankruptcy. Machine learning methods that will be used for this paper are Logistic Regression, Random Forest, Xgboost, and Gradient Boosting Machines. To evaluate the performance of each of my models, I will primarily be using 4 criteria to assess my models which are precision, recall, f1 score, and area under the curve (AUC). Precision quantifies the number of positive class predictions that actually belong to the positive class. Recall quantifies the number of positive class predictions made out of all positive examples in the dataset.[2] The differences between accuracy, recall, and precision can be seen in Figure 1. One might notice I neglected one of the most common metrics in evaluating a model, which would be the accuracy score. I neglected to use the accuracy metric for two reasons. First, my response variable is imbalanced with over 6000 instances of non-bankruptcy, and only 220 instances of bankruptcy. Secondly, in the case of bankruptcy prediction, we are more interested in sensitivity rather than specificity. Most financial models are like this, where predicting the true positive rate is of much greater importance. Such as a credit card company predicting if an individual is being accused of fraud. Therefore, rather than correctly predicting all the cases where no fraud is involved, financial institutions are much more interested in finding those few transactions of fraud that could greatly benefit both the client and the company itself. By comparing the precision, recall, AUC, and f1 scores of each of the models to one another, I will be able to obtain the best model in predicting company bankruptcy.

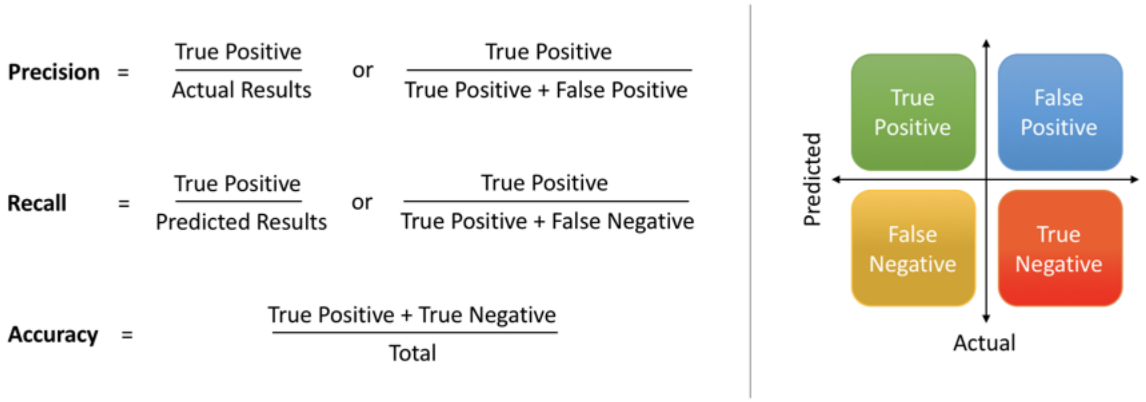
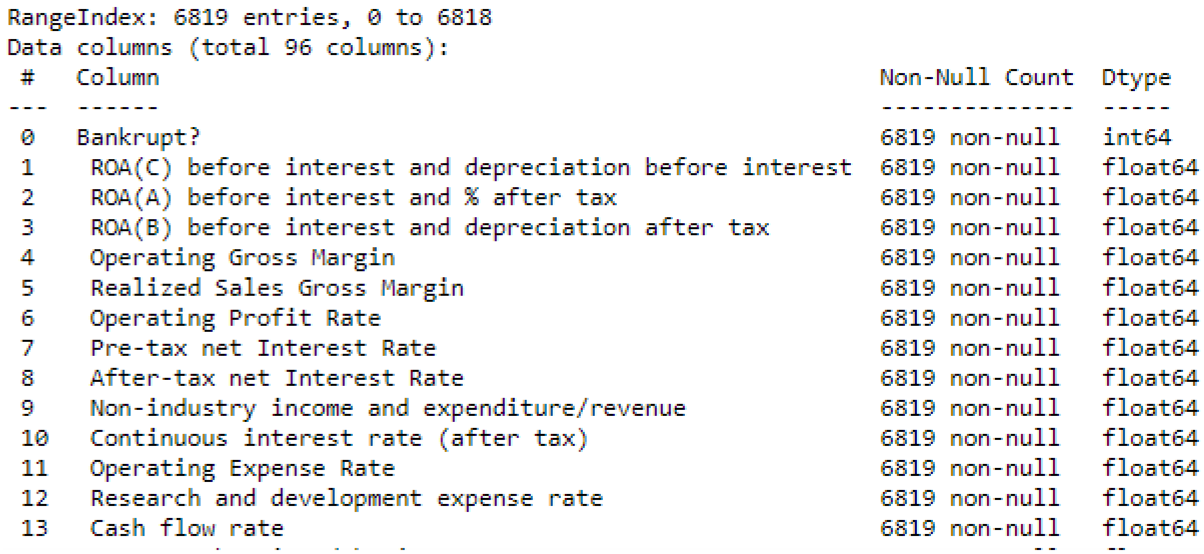

Precision = True Positive / Actual Results or True Positive / True Positive + False Positive
Recall = True Positive / Predicted Results or True Positive / True Positive + False Negative
Accuracy = True Positive + True Negative / Total
Predicted
True Positive
False Positive
False Negative
True Negative
Actual

**Figure 1: Precision-Recall And Accuracy**

## Data Description

The data was collected from the Taiwan Economic Journal from the years of 1999 to 2009. Company bankruptcy was defined based on the business regulations of the Taiwan Stock Exchange. For the purpose of my project, the second version of the dataset can be found on Kaggle (www.kaggle.com/fedesoriano/company-bankruptcy-prediction). Version 2 of the data has updated column names and data descriptions to make the data easier to understand (Y = Output feature, X = Input features). The data contains 6819 instances, 1 response variable, and 95 explanatory variables, there are no NA values, and all the columns from the data set are numeric values. From Figure 2 you can see the output feature and many of the possible input features. Evidently, there are many more variables I will just not mention until they are relevant.



```
RangeIndex: 6819 entries, 0 to 6818
Data columns (total 96 columns):
 #   Column                                                    Non-Null Count  Dtype
---  ------                                                    --------------  -----
 0   Bankrupt?                                                 6819 non-null   int64
 1    ROA(C) before interest and depreciation before interest  6819 non-null   float64
 2    ROA(A) before interest and % after tax                   6819 non-null   float64
 3    ROA(B) before interest and depreciation after tax        6819 non-null   float64
 4    Operating Gross Margin                                   6819 non-null   float64
 5    Realized Sales Gross Margin                              6819 non-null   float64
 6    Operating Profit Rate                                    6819 non-null   float64
 7    Pre-tax net Interest Rate                                6819 non-null   float64
 8    After-tax net Interest Rate                              6819 non-null   float64
 9    Non-industry income and expenditure/revenue              6819 non-null   float64
 10   Continuous interest rate (after tax)                     6819 non-null   float64
 11   Operating Expense Rate                                   6819 non-null   float64
 12   Research and development expense rate                    6819 non-null   float64
 13   Cash flow rate                                           6819 non-null   float64
```

**Figure 2: Data Set Attributes**

## Data Cleaning And Transformations

Unlike most real-world data this data set does not contain any NA values, however, there are still changes that need to be made to the data set in order to achieve higher scores for precision and recall. First, there is the problem with outliers and normalizing the data set. The goal of normalization is to scale the values of numeric columns in the dataset to a range of [0,1], while also no distortion in the differences in the ranges of values. The formula used to scale this data is Xnormalized = (X - XMinimum)/(Xmaximum - Xminimum), or better known as the MinMaxScaler function in Python.[15]

For machine learning purposes, we should only normalize the data if the ranges between predictors are vastly different. In the case of this data set, we have features that range from 0 to 1 and we have other features that range in the millions. In this instance, the variable that ranges in the millions is about a million times larger than the range from 0 to 1. When we do further analysis, and we begin to model the data using machine learning, the attributes in the range of the millions will intrinsically influence the result more due to its larger value. Even though machine learning methods will place more value into variables with larger ranges, it does not necessarily mean that it is more important as a predictor. Thus, I will be normalizing the data before running the data through my machine learning models to bring all the values into the same range.[15]

Before we normalize the data we have to examine the outliers in the data set. As you can see from the boxplots before and after outlier removal from Figure 3 we have better-looking box plots. The original formula I used to eliminate outliers was if observations are (Q1-1.5*IQR) or *(Q3+1.5*IQR). However, using this standard method I eliminated over 2000 out of the 6819 observations. Typically outliers will fall into one of 3 categories: **Outliers**: Data points that are far away from the mean or median. e.g., a heart rate of 140 beats/min for a subject during resting condition, **Anomaly**: A data point that is not legitimate due to error in data collection or device issue. e.g. a heart rate of 10 beats/min, **Outliers-anomaly**: a data point that is far away from the mean or median, but you cannot decide the source of it. It would be fine to remove outliers if it were the anomaly case, however, we have no information about the data collection and data entry of this data set so eliminating outliers will not do here.[7]

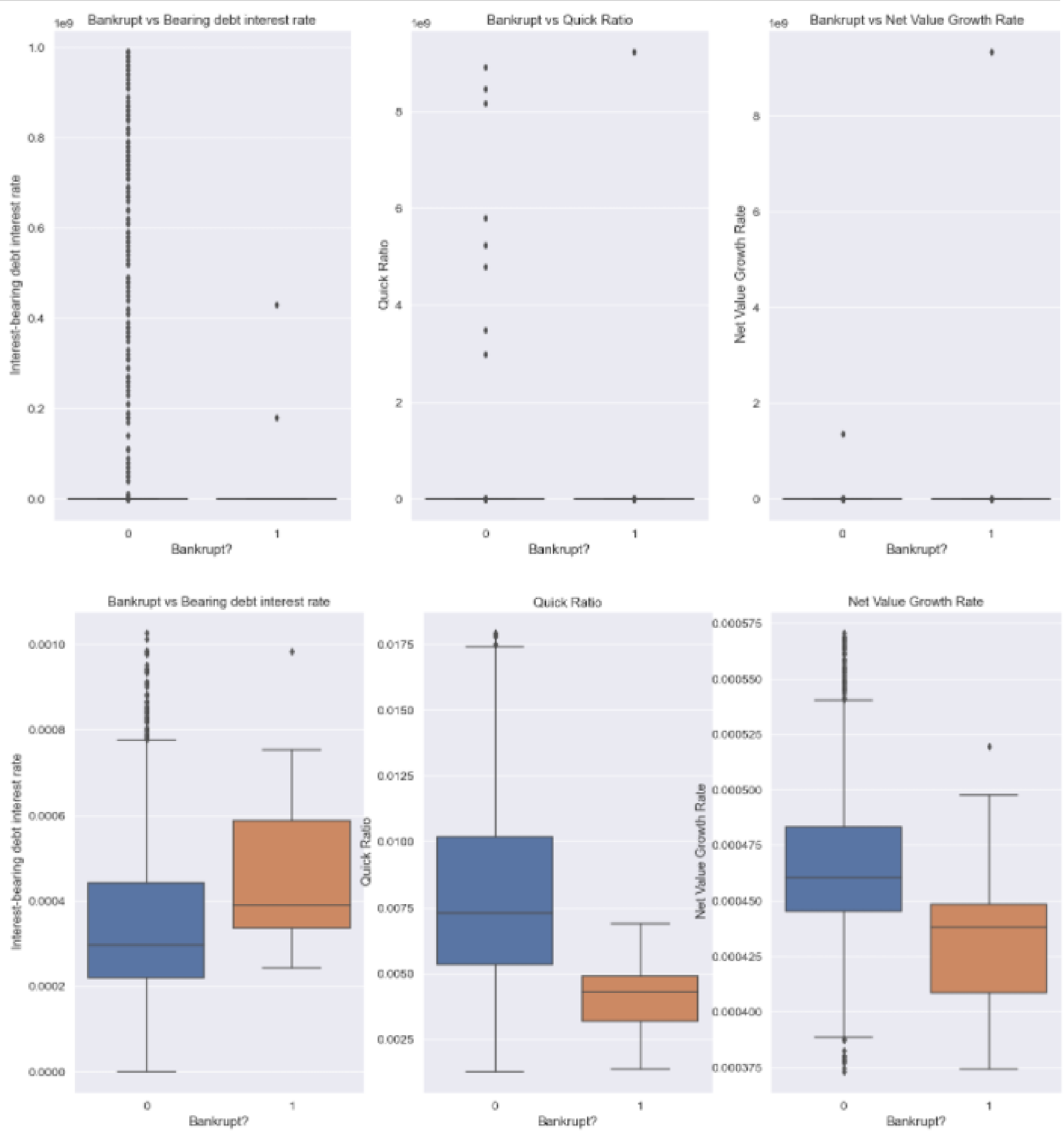


**Figure 3: Before And After Boxplots After Outlier Removal**

Instead, I will use a new method to deal with outliers by transforming the data with a log(x+1) transformation. My new criteria to transform a column is if observations in the 100th percentile are at least 100 times greater than 99th percentile values, or there are 68 or fewer records for the 100th percentile. For any variables satisfying my outlier condition, I will transform from x to log(x+1).[1] Before applying my transformations, it splits the data into 24 non-fractional only columns and 72 fractional columns for a total of 95 features. A 'fractional only column' is defined by a column whose values are strictly in between 0 to 1, thus making it a column consisting of only fractions. Only data from the non-fractional columns are considered for a log transformation. As you can see in Figure 4, we have transformed 19 out of the 24 non-fractional columns in boxplot format. After the log transformation, 5 of the columns are corrected in regards to outliers, while the other 14 columns remain practically unchanged. However, I found this method to be preferable since it handles the outlier problem without removing 2000 observations.

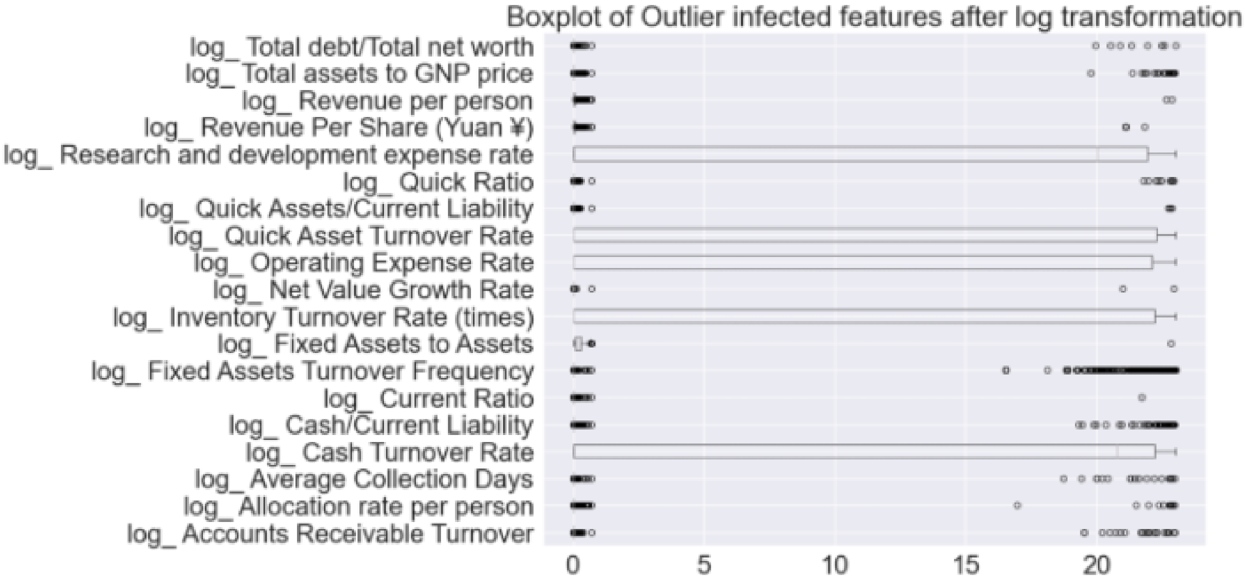


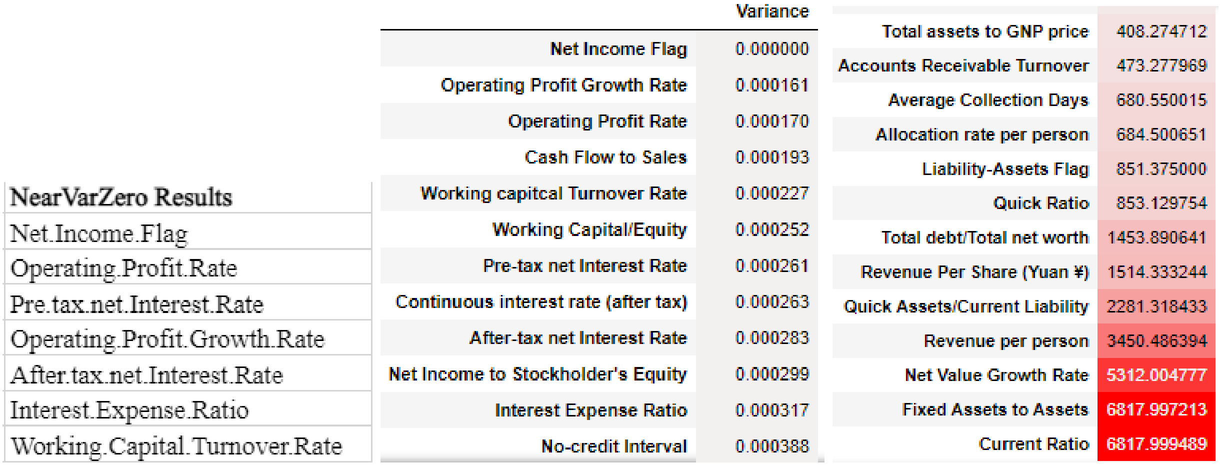
**Figure 4: Boxplot of Outlier Features After Log Transformation**

## Variable Selection

Why would one go through variable selection when the machine learning methods can handle all 95 attributes and make an accurate model with that information? If unnecessary variables are placed into the machine learning models then you will get unnecessary noise for the output of your models. Feature/variable selection is especially important in a situation where the number of features at your disposal is very large, much like the data set I am currently using.[5] Furthermore, the main reasons to use feature selection boils down to it enables the machine learning algorithm to train faster, reduces overfitting, it can improve metrics such as accuracy and AUC if the right subset of features is chosen, lastly, it will reduce dimensionality and complexity in the model, making it easier to interpret.

There are 4 different ways I did variable selection, which was: variance threshold, recursive feature selection, logistic stepwise, and through economic factors. Based on these 4 methods I wanted to see how they would compare to one another when selecting from the 95 features, what they had in common, what was different, why are there differences?

From the sklearn library, I imported the VarianceThreshold function.[12] I used this as a foundation, however, I made alterations to the function to account for unscaled data. If the features have different medians, quartiles, and distributions, then we can not compare these features using a variance threshold. One solution to this problem is by dividing all the features by their mean.[13] The idea behind using a variance threshold was to only consider variables with high variability in the columns$_7$. If variables had low variance, it would be difficult for the machine learning algorithm to distinguish between bankrupt and non-bankrupt companies with values so close to one another. There are many ways to decide what threshold to use. For instance, one could pick a value that seems ok for you and your dataset through intuition then eliminate the variables below your chosen threshold. Another way to do this is by creating a function, which when given a threshold, tells you how many variables would be removed if you used that threshold. Then you could plot out the number of variables removed/kept with different thresholds.[7] I used a mix of both methods, and with this, I can eliminate 74 columns off the bat, which can be seen in Figure 5. In order to check my work I also utilized the caret package in R and the function nearZeroVar() to see whether or not this function would eliminate the same columns as 'VarianceThreshold,' and sure enough, the results were the same.[11]



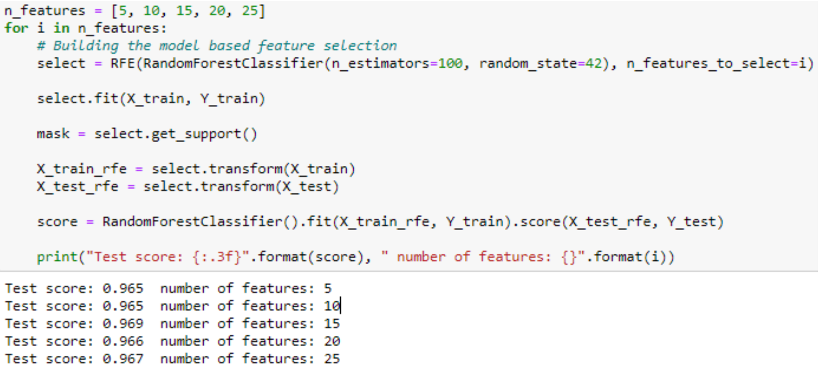
| NearVarZero Results |
|---|
| Net.Income.Flag |
| Operating.Profit.Rate |
| Pre.tax.net.Interest.Rate |
| Operating.Profit.Growth.Rate |
| After.tax.net.Interest.Rate |
| Interest.Expense.Ratio |
| Working.Capital.Turnover.Rate |

| | Variance |
|---|---|
| Net Income Flag | 0.000000 |
| Operating Profit Growth Rate | 0.000161 |
| Operating Profit Rate | 0.000170 |
| Cash Flow to Sales | 0.000193 |
| Working capitcal Turnover Rate | 0.000227 |
| Working Capital/Equity | 0.000252 |
| Pre-tax net Interest Rate | 0.000261 |
| Continuous interest rate (after tax) | 0.000263 |
| After-tax net Interest Rate | 0.000283 |
| Net Income to Stockholder's Equity | 0.000299 |
| Interest Expense Ratio | 0.000317 |
| No-credit Interval | 0.000388 |

| | |
|---|---|
| Total assets to GNP price | 408.274712 |
| Accounts Receivable Turnover | 473.277969 |
| Average Collection Days | 680.550015 |
| Allocation rate per person | 684.500651 |
| Liability-Assets Flag | 851.375000 |
| Quick Ratio | 853.129754 |
| Total debt/Total net worth | 1453.890641 |
| Revenue Per Share (Yuan ¥) | 1514.333244 |
| Quick Assets/Current Liability | 2281.318433 |
| Revenue per person | 3450.486394 |
| Net Value Growth Rate | 5312.004777 |
| Fixed Assets to Assets | 6817.997213 |
| Current Ratio | 6817.999489 |

**Figure 5: Highest Variances Amongst The Predictor Variables**

In Figure 6 we see the scores from Random Forest recursive feature elimination by using the function RFE().[13] I decided to use the Random Forest algorithm and run a for loop to fit a model with 5, 10, 15, 20, and 25 features while reporting back their corresponding score. When looking at the code one can see that as we added more variables the scores showed minuscule improvement. By the time the model had 5 features the test score was already at 0.965. When adding an additional 10 more variables the score only increased by 0.004. However, the model with 15 variables was still taken into account for the final model since it still received the highest score amongst the 5 models.

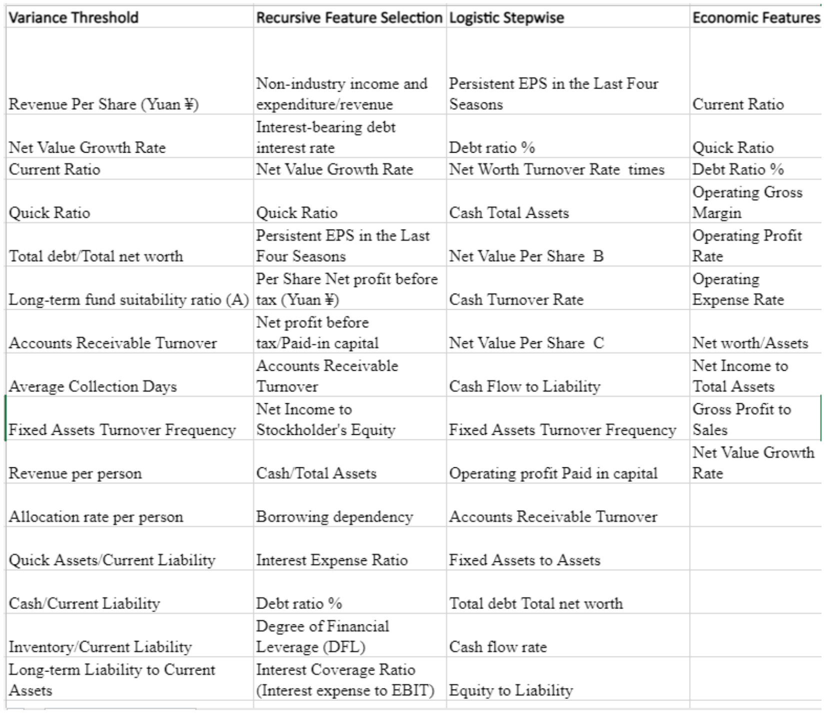


```
n_features = [5, 10, 15, 20, 25]
for i in n_features:
    # Building the model based feature selection
    select = RFE(RandomForestClassifier(n_estimators=100, random_state=42), n_features_to_select=i)

    select.fit(X_train, Y_train)

    mask = select.get_support()

    X_train_rfe = select.transform(X_train)
    X_test_rfe = select.transform(X_test)

    score = RandomForestClassifier().fit(X_train_rfe, Y_train).score(X_test_rfe, Y_test)

    print("Test score: {:.3f}".format(score), " number of features: {}".format(i))
```

```
Test score: 0.965  number of features: 5
Test score: 0.965  number of features: 10
Test score: 0.969  number of features: 15
Test score: 0.966  number of features: 20
Test score: 0.967  number of features: 25
```

**Figure 6: Recursive Feature Elimination And Test Scores**

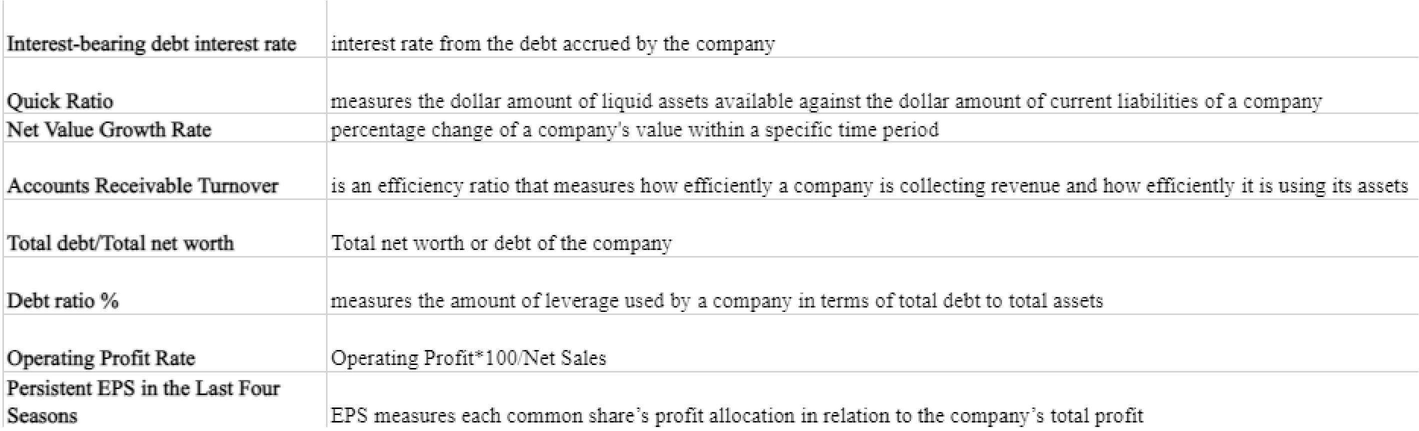
Logistic stepwise was utilized next, by using the caret and MASS packages and the function step().[6] This method can be used backward, forward, or with a combination of the two. In all three cases, logistic stepwise returns the same 18 variables by comparing the AIC between all possible models and returns the model with the lowest AIC. As a reminder of estimating the amount of information lost by a model, AIC deals with the trade-off between the goodness of fit of the model and the simplicity of the model. In other words, AIC deals with both the risk of overfitting and the risk of underfitting. Lastly, I looked at the economic side of things. For instance, if I were running a company, what would be the most important metrics one would keep track of in order to evaluate the financial performance of the company? The most important indicators for a company's financial performance were liquidity, solvency, profitability, the bottom line, and operating efficiency. In Figure 7, we have a table of the variables selected from each of the feature selection methods.



| Variance Threshold | Recursive Feature Selection | Logistic Stepwise | Economic Features |
|---|---|---|---|
| Revenue Per Share (Yuan ¥) | Non-industry income and expenditure/revenue | Persistent EPS in the Last Four Seasons | Current Ratio |
| Net Value Growth Rate | Interest-bearing debt interest rate | Debt ratio % | Quick Ratio |
| Current Ratio | Net Value Growth Rate | Net Worth Turnover Rate  times | Debt Ratio % |
| Quick Ratio | Quick Ratio | Cash Total Assets | Operating Gross Margin |
| Total debt/Total net worth | Persistent EPS in the Last Four Seasons | Net Value Per Share  B | Operating Profit Rate |
| Long-term fund suitability ratio (A) | Per Share Net profit before tax (Yuan ¥) | Cash Turnover Rate | Operating Expense Rate |
| Accounts Receivable Turnover | Net profit before tax/Paid-in capital | Net Value Per Share  C | Net worth/Assets |
| Average Collection Days | Accounts Receivable Turnover | Cash Flow to Liability | Net Income to Total Assets |
| Fixed Assets Turnover Frequency | Net Income to Stockholder's Equity | Fixed Assets Turnover Frequency | Gross Profit to Sales |
| Revenue per person | Cash/Total Assets | Operating profit Paid in capital | Net Value Growth Rate |
| Allocation rate per person | Borrowing dependency | Accounts Receivable Turnover | |
| Quick Assets/Current Liability | Interest Expense Ratio | Fixed Assets to Assets | |
| Cash/Current Liability | Debt ratio % | Total debt Total net worth | |
| Inventory/Current Liability | Degree of Financial Leverage (DFL) | Cash flow rate | |
| Long-term Liability to Current Assets | Interest Coverage Ratio (Interest expense to EBIT) | Equity to Liability | |

**Figure 7: Variables Selected From Each of The Feature Selection Methods**

Final feature selection is the culmination of all these methods. My criteria for the final features that would go into my machine learning models is that a variable must show up on at least 2 of the 4 columns. For example ‘Quick Ratio’ was found in 3 of the 4 columns so it was considered in my final model. After I had a list of these variables I made sure there was at least one variable in my final feature selection that incorporated the following economic features: liquidity, solvency, profitability, the bottom line, and operating efficiency. The final list of 8 variables with their description can be seen in figure 8.



| | |
|---|---|
| Interest-bearing debt interest rate | interest rate from the debt accrued by the company |
| Quick Ratio | measures the dollar amount of liquid assets available against the dollar amount of current liabilities of a company |
| Net Value Growth Rate | percentage change of a company's value within a specific time period |
| Accounts Receivable Turnover | is an efficiency ratio that measures how efficiently a company is collecting revenue and how efficiently it is using its assets |
| Total debt/Total net worth | Total net worth or debt of the company |
| Debt ratio % | measures the amount of leverage used by a company in terms of total debt to total assets |
| Operating Profit Rate | Operating Profit*100/Net Sales |
| Persistent EPS in the Last Four Seasons | EPS measures each common share’s profit allocation in relation to the company’s total profit |

**Figure 8: Final list of 8 variables with their descriptions**

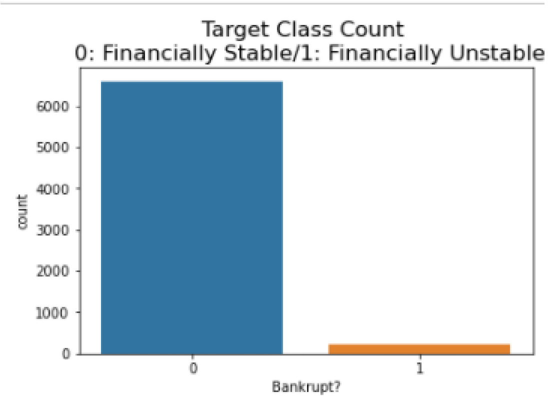
## Model Specification

The machine learning models I will be compared with one another will be Logistic Regression, Random Forest, Gradient Boosting, and Xgboost. Logistic regression typically never does the best in comparison to the other methods, but it is the one most commonly used for classification projects and it sets a foundation for our performance metrics. “The random forest algorithm is an expansion of a decision tree, in that, you first construct some-axis real-world decision trees with training data, then fit your new data within one of the trees as a random forest.”[5] This method averages the data and connects it to the nearest tree within the data scale. The main advantage of random forest over the decision tree is that it does not force data points into categories.

Both Xgboost and gradient boost machines follow the principle of gradient boosting. Gradient boosting consists of 3 components: a loss function, a weak learner, and an additive model.[1] The loss function estimates how well a model is at making predictions with the given data. In the case of bankruptcy prediction, we need a loss function that helps us understand how accurate our model is when it comes to classifying companies into bankrupt or not bankrupt. Weak learners are used as building blocks in order to make a more complicated model.[1] Finally, our additive model component sequentially adds one weak learner at a time, then the model gets evaluated, and with each iteration, we should be reducing the value of our loss function. The main difference between Xgboost and gradient boost machines is in the modeling details. Specifically, Xgboost used a more regularized model formalization to control over-fitting, which typically allows it to perform better.[2]

## Sampling Techniques

With the data set, we have an imbalance class problem. Over 96% of the observations are under ‘Financially Stable’ while a little over 3% of the observations are under ‘Financially Unstable,’ which can be seen in Figure 9.



```
Financially stable:  6599
Financially unstable:  220
```

**Figure 9: Bar Graph of Companies That Are Financially Stable And Not Financially Stable**

The solution to this problem stems from resampling the data, and there are many ways to resample it. I decided to use 3 sampling techniques, run each of the new datasets into their own machine learning models to compare which of the 3 were best for my situation. The 3 techniques are random undersampling, random oversampling, and oversampling using SMOTE.[4] Random undersampling involves randomly selecting examples from the majority class and deleting them from the training dataset. In this case, it would delete instances of companies that are ‘Financially Stable.’’ Random oversampling increases the size of the training data minority class through the repetition of the original examples. It does not cause any increase in the variety of training examples. Figure 10 shows how the original data set will be transformed into the final data set after using oversampling and undersampling respectively.

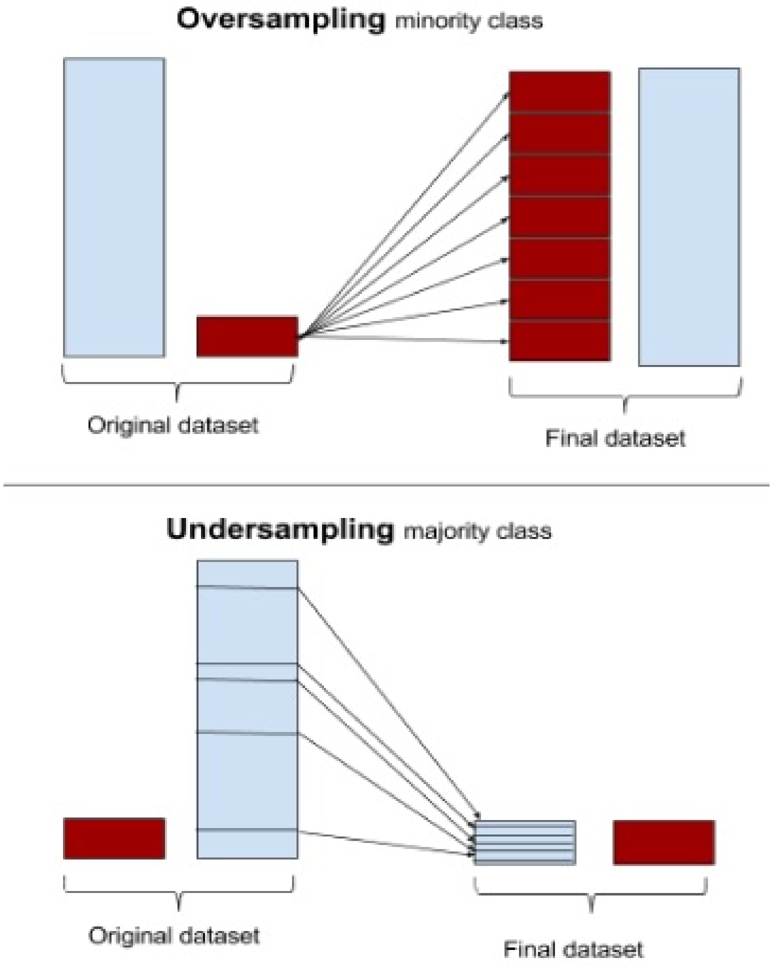
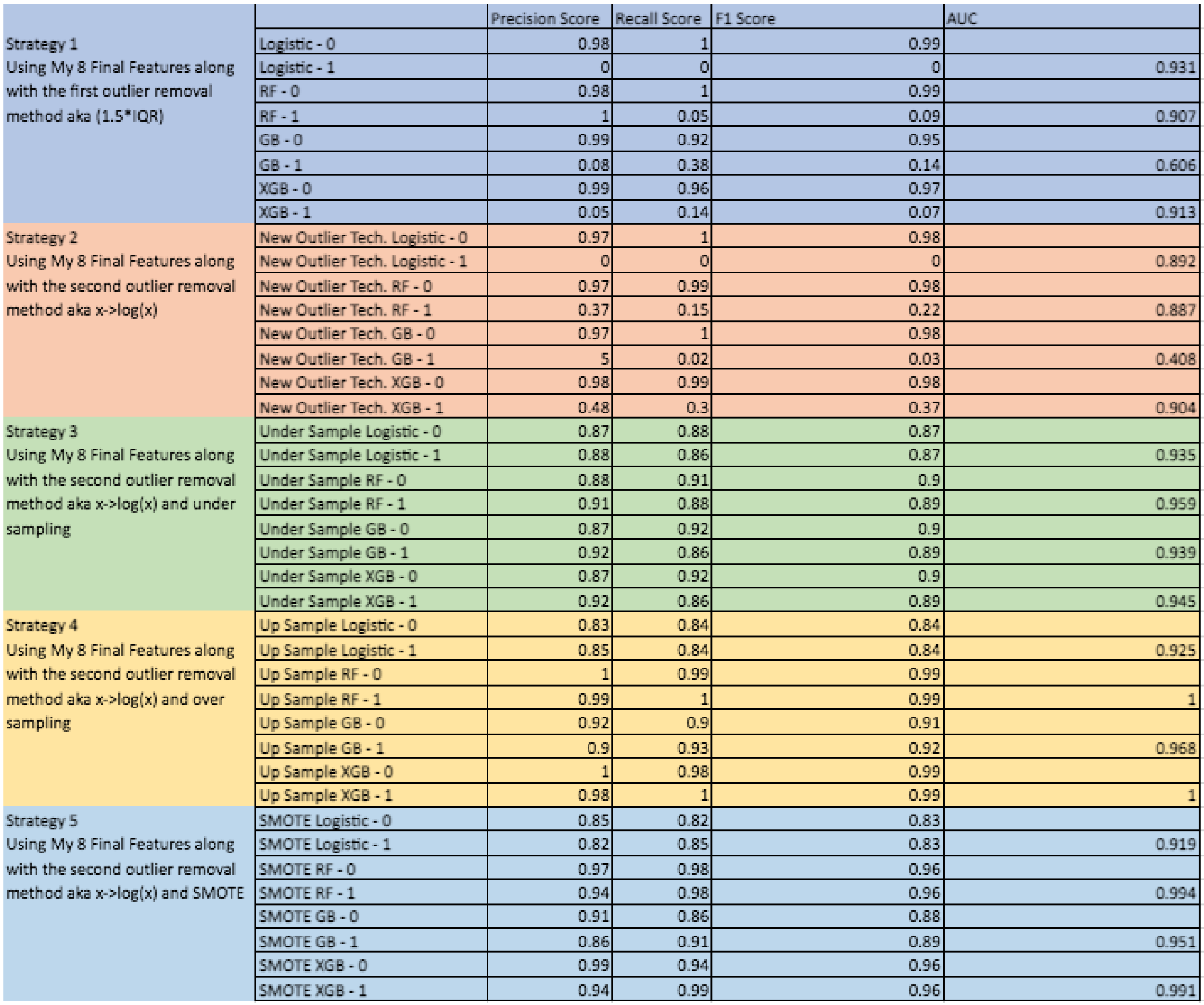


**Figure 10: Changes To Data After Oversampling Or Undersampling**

However, the most commonly used technique is sampling using SMOTE. This technique not only increases the size of the minority class, it also does not rely on simply replicating the data to increase its size, thus, increasing the variety of the data set. “SMOTE first selects a minority class instance at random and finds its k nearest minority class neighbors. The synthetic instance is then created by choosing one of the k nearest neighbors b at random and connecting a and b to form a line segment in the feature space. The synthetic instances are generated as a convex combination of the two chosen instances a and b.” (Page 47, Imbalanced Learning: Foundations, Algorithms, and Applications, 2013.) When done correctly SMOTE is the preferable method compared to random oversampling. Moreover, an instance where it would not be proper to use SMOTE would be on an input variable with categorical values such as “table” and “chair.” In this instance, there is no ‘legal’ value in between the 2 values. However, in my data set SMOTE would be fine to use since all of the variables are numeric.

## Model Diagnostics



| | | Precision Score | Recall Score | F1 Score | AUC |
|---|---|---|---|---|---|
| Strategy 1 Using My 8 Final Features along with the first outlier removal method aka (1.5*IQR) | Logistic - 0 | 0.98 | 1 | 0.99 | |
| | Logistic - 1 | 0 | 0 | 0 | 0.931 |
| | RF - 0 | 0.98 | 1 | 0.99 | |
| | RF - 1 | 1 | 0.05 | 0.09 | 0.907 |
| | GB - 0 | 0.99 | 0.92 | 0.95 | |
| | GB - 1 | 0.08 | 0.38 | 0.14 | 0.606 |
| | XGB - 0 | 0.99 | 0.96 | 0.97 | |
| | XGB - 1 | 0.05 | 0.14 | 0.07 | 0.913 |
| Strategy 2 Using My 8 Final Features along with the second outlier removal method aka x->log(x) | New Outlier Tech. Logistic - 0 | 0.97 | 1 | 0.98 | |
| | New Outlier Tech. Logistic - 1 | 0 | 0 | 0 | 0.892 |
| | New Outlier Tech. RF - 0 | 0.97 | 0.99 | 0.98 | |
| | New Outlier Tech. RF - 1 | 0.37 | 0.15 | 0.22 | 0.887 |
| | New Outlier Tech. GB - 0 | 0.97 | 1 | 0.98 | |
| | New Outlier Tech. GB - 1 | 5 | 0.02 | 0.03 | 0.408 |
| | New Outlier Tech. XGB - 0 | 0.98 | 0.99 | 0.98 | |
| | New Outlier Tech. XGB - 1 | 0.48 | 0.3 | 0.37 | 0.904 |
| Strategy 3 Using My 8 Final Features along with the second outlier removal method aka x->log(x) and under sampling | Under Sample Logistic - 0 | 0.87 | 0.88 | 0.87 | |
| | Under Sample Logistic - 1 | 0.88 | 0.86 | 0.87 | 0.935 |
| | Under Sample RF - 0 | 0.88 | 0.91 | 0.9 | |
| | Under Sample RF - 1 | 0.91 | 0.88 | 0.89 | 0.959 |
| | Under Sample GB - 0 | 0.87 | 0.92 | 0.9 | |
| | Under Sample GB - 1 | 0.92 | 0.86 | 0.89 | 0.939 |
| | Under Sample XGB - 0 | 0.87 | 0.92 | 0.9 | |
| | Under Sample XGB - 1 | 0.92 | 0.86 | 0.89 | 0.945 |
| Strategy 4 Using My 8 Final Features along with the second outlier removal method aka x->log(x) and over sampling | Up Sample Logistic - 0 | 0.83 | 0.84 | 0.84 | |
| | Up Sample Logistic - 1 | 0.85 | 0.84 | 0.84 | 0.925 |
| | Up Sample RF - 0 | 1 | 0.99 | 0.99 | |
| | Up Sample RF - 1 | 0.99 | 1 | 0.99 | 1 |
| | Up Sample GB - 0 | 0.92 | 0.9 | 0.91 | |
| | Up Sample GB - 1 | 0.9 | 0.93 | 0.92 | 0.968 |
| | Up Sample XGB - 0 | 1 | 0.98 | 0.99 | |
| | Up Sample XGB - 1 | 0.98 | 1 | 0.99 | 1 |
| Strategy 5 Using My 8 Final Features along with the second outlier removal method aka x->log(x) and SMOTE | SMOTE Logistic - 0 | 0.85 | 0.82 | 0.83 | |
| | SMOTE Logistic - 1 | 0.82 | 0.85 | 0.83 | 0.919 |
| | SMOTE RF - 0 | 0.97 | 0.98 | 0.96 | |
| | SMOTE RF - 1 | 0.94 | 0.98 | 0.96 | 0.994 |
| | SMOTE GB - 0 | 0.91 | 0.86 | 0.88 | |
| | SMOTE GB - 1 | 0.86 | 0.91 | 0.89 | 0.951 |
| | SMOTE XGB - 0 | 0.99 | 0.94 | 0.96 | |
| | SMOTE XGB - 1 | 0.94 | 0.99 | 0.96 | 0.991 |

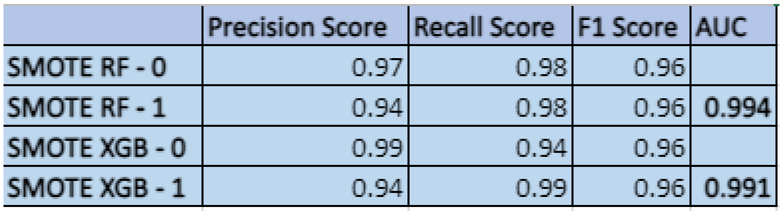
**Figure 11: All Strategies With Performance Metrics**

Above in Figure 11 is my table with all the different models along with each strategy that was used. I would like to note that all 5 strategies use normalization. As you can see the first two strategies did not utilize the sampling techniques I discussed previously, therefore, the precision, recall, and F1 scores are all below 0.5. Once we get to strategies 3 and beyond all of our scores exceed 0.85. If we strictly used AUC as the metric to evaluate our performance then over-sampling with random selection would be the best choice. However, the main problem with over-sampling with random selection is that it just duplicates the minority class observations with no variation. That would inherently make all the models overfit and perform better since it already had the same observations to classify with.

Now the question comes down to whether our final table will be from the undersampling strategy versus oversampling using SMOTE. The initial problem I had with SMOTE was that logically it seemed unrealistic to create over 6000 companies that do not exist and label them as 'Financially Unstable.' However, even regarding this issue, I have decided to use the SMOTE strategy for my final model. The main disadvantage of using undersampling is that it can discard potentially useful information. SMOTE is optimal to solve our imbalance class problem if one is looking to build a predictive model, however, it should not be used when building a representative model.[4] For the purposes of this project I am indeed looking to build a predictive model. Therefore, SMOTE along with the log transformation will be the only portion of the chart that will be taken into account when looking for the optimal machine learning model.

## Conclusion

Ultimately, there are 2 models from strategy 5 that performed extremely well. They were Random Forest and Xgboost. When taking into consideration recall, precision, f1, and AUC I decided that the Xgboost model will be the one that represents my final predictive model. From Figure 12, we can directly compare the metrics between Random Forest and Xgboost. Although Random Forest had an AUC of 0.003 greater while also having a higher recall score when predicting the 0's. The Xgboost model had a recall score of 0.01 greater when predicting the 1's, which is more important for the purposes of predicting bankruptcy.



| | Precision Score | Recall Score | F1 Score | AUC |
|---|---|---|---|---|
| SMOTE RF - 0 | 0.97 | 0.98 | 0.96 | |
| SMOTE RF - 1 | 0.94 | 0.98 | 0.96 | **0.994** |
| SMOTE XGB - 0 | 0.99 | 0.94 | 0.96 | |
| SMOTE XGB - 1 | 0.94 | 0.99 | 0.96 | **0.991** |

**Figure 12: Random Forest And Xgboost Performance Metrics**

Even though this project achieved great accuracy with a small subset of predictors there are limitations regarding this project. The primary issue stems from not knowing which industry the companies are gathered from. For instance, I do not know whether all the companies are all software, finance, healthcare, retail, or a mix of all of them. I predict that if my models were trained with the 'software industry companies' then applying models from other industries will result in a reduction in performance. Additionally, my project strictly predicts bankruptcy, it does not take into account other company's financial states. For example, a company does not always need to result in bankruptcy, they could fall under debt settlement, debt consolidation, restructure, etc[6]. In order to avoid future errors when applying models such as mine, it is mandatory for researchers to understand the purposes of models like mine as well as their limitations.

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