Predicting Financial Crises Using Machine Learning

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Abstract

A financial crisis is an important event in a country's financial health and has a significant potential impact on the lives of its people. Prediction for financial crises has typically been done through manual analysis of financial indicators such as inflation, debt, or exchange rate. We use the same data but attempt to leverage machine learning tools to see if we can determine these crises more reliably. The models we trained performed poorly at identifying financial crises, indicating possible weaknesses in our data or methods.

Introduction

Financial crises have a significant and enduring detrimental impact on the economy. A substantial amount of research has demonstrated notable growth and welfare consequences. Financial crises are fortunately not wholly unforeseeable events. Fast credit growth and inflation of sovereign foreign debt are indicators of impending crises; this is a well-known theory that has been put out in various forms for a long time. A stock market crash, a sovereign default, the bust of a speculative financial bubble, or a currency crisis are examples of events that might be classified as financial crises. A financial crisis might affect just banks or it can affect every economy in a country, a region, or the planet.

We approached the problem as multiple binary classifications for various types of crisis (currency, inflation, banking, systemic) so we can train a number of models for each crisis type and combine them into an ensemble. The models we chose are naive-bayes, decision tree and logistic regression and we use an ensemble to combine the predictions. Then we compare all the models with the performance of the ensemble based on the accuracy, precision and recall.

Previous Work

In their paper, T. Hennig, et al. attempt to predict financial crises by examining changes in financial crises, credit-based and asset prices. Their database covers 108 countries over the period 1995 to 2017, focusing on 53 financial crisis episodes and emphasizes emerging and developing economies' data coverage. The composite indicator, called Mispricing Risk, combines various macrofinancial variables to assess slack in financial conditions and potential mispricing of risk in asset markets. It exhibits pro-cyclical behavior, preceding systemic banking crises by two to three years and demonstrating suitability as an early warning indicator. They also make a comparative analysis against traditional credit metrics using Receiver Operating Characteristics (ROC) Curve analysis reveals Mispricing Risk's superior predictive ability. In summary, this research establishes Mispricing Risk as a potent early warning indicator for financial crises, demonstrating superior predictive power compared to traditional credit metrics across various horizons and thresholds. The study offers valuable insights for policymakers in assessing the probability of financial crises based on Mispricing Risk levels. Their approach of using financial signifiers to predict financial crises inspired us to attempt to leverage machine learning tools to solve the same problem.

Data

The dataset employed in this project is from Carmen Reinhart et al. It spans a broad variety of features, incorporating dates of banking crises for 70 countries, extending from 1800 to the current period. It also includes data on exchange rate crises, stock market crises, and inflation crises.

Method

Pre-processing

In the data preprocessing our first step was to remove all the null and empty values from the dataset. Doing this cleaned most of the unwanted data and made it more suitable for a machine learning model. We also had to remove columns from the data that contained only comments or redundant information. Two thirds of the dataset selected at random is used for training data and the remaining one third is used for validation data. The data is zero-meaned before training the models. Before training data is split by country as a means of categorizing data.

Models

For the prediction of those crises (currency, inflation, banking, system), we used three different models: Logistic Regression, Decision Tree and Naive Bayes.

Logistic Regression:

Logistic regression estimates the probability of an event occurring by using a logistic function of independent variables. Our implementation used a gradient descent approach, minimizing mean log loss. This model aims to find the optimal weights and bias that would minimize the logloss. The log loss is a measure of the discrepancy between actual class labels and projected probability.

$$J(\theta) =- ((y \, log \, h_\theta(x) + (1 - y) \, log(1 - h_\theta(\mathrm{x})))$$

where y is the class label and h_θ is the predicted probability. The sigmoid function ensures the outputs are between 0 and 1 by converting a linear combination of data into probabilities:

$$\sigma = \frac{1}{1+e^{-z}}$$

where z is the linear combination of input features and coefficients. The hypothesis function in logistic regression utilizes the sigmoid function and weights to combine the input features, estimating the likelihood of falling into a particular class.Additionally, a probability threshold with a value of 0.5 has been set to calculate the class labels using the anticipated probabilities. The model was trained using a gradient descent approach for over a set of 10000 epochs to update the weights and bias iteratively. The process will stop if the change in the log loss falls over a specific tolerance of 1×10^{-6}.

Decision Tree:

Decision tree uses a number of binary decisions based on a vector of features to classify instances of data. To ensure a relatively compact tree, the feature being evaluated is calculated based on the entropy of that feature. Entropy for a feature is calculated as:

$$H(p) = -\sum_{i=1}^{k} p_i log(p_i)$$

where p is a probability distribution for a feature.

Naive Bayes:

The Naïve Bayes method predicts class based on Bayes' Theorem with an independence assumption among predictors. Bayes theorem provides a way of computing posterior probability P(c|x) from P(c), P(x) and P(x|c) via the following equation:

$$P(c|x) = \frac{P(x|c)P(c)}{P(x)}$$

Where P(c|x) is the posterior probability of class (c, target) given predictor (x, attributes), P(c) is the prior probability of class, P(x|c) is the probability of the predictor given class, and P(x) is the prior probability of the predictor.

The naive Bayes approach makes the assumption that the feature priors are independent and can be calculated as:

$$P(\bar{x}|c) = \Pi_{i \to D} P(x_i|c)$$

Where $\bar{x}$ is a vector containing the values of the features and D is the length of the vector.

Ensembles:

An Ensemble method creates multiple models and combines them to solve it. Combining multiple methods can help to improve the robustness/generalizability of the model. The ensemble we built checks if our models predict a crisis and returns a positive if any of them do.

We predicted that this would be a method that produces meaningful results because financial crises are relatively infrequent and any indicator of one is valuable; on average financial crises do not occur, so averaging multiple models may result in an extremely high false negative rate.

Results

The tables below show the accuracy, precision, and recall for all the implemented models and for each type of crisis averaged over each country for which he had data

Currency Crisis:

	Accuracy	Precision	Recall
Decision Tree	0.91448413	0.72514172	0.18013374
Naive Bayes	0.91150794	0.69864199	0.16142778
Logistic Regression	0.92361111	0.86223248	0.18981808
Ensemble	0.89781746	0.7146902	0.2483704

Inflation Crisis:

	Accuracy	Precision	Recall
Decision Tree	0.91031746	0.6410369	0.36477324
Naive Bayes	0.91884921	0.68873976	0.31473639
Logistic Regression	0.95496032	0.88859606	0.57059807
Ensemble	0.91329365	0.69430448	0.59063209

Banking Crisis:

	Accuracy	Precision	Recall
Decision Tree	0.94484127	0.74501134	0.32405896
Naive Bayes	0.93154762	0.70497639	0.33344517
Logistic Regression	0.94464286	0.76846939	0.26990569
Ensemble	0.91011905	0.65988472	0.39520717

Systemic Crisis:

	Accuracy	Precision	Recall
Decision Tree	0.96230159	0.788344	0.38025356
Naive Bayes	0.95357143	0.80106419	0.38384045
Logistic Regression	0.96269841	0.84547619	0.32394558
Ensemble	0.93948413	0.74393117	0.42603587

Discussion

Examining the above tables, we find that accuracy is consistently rather high across all models, with logistic regression usually being the highest. Precision is always above sixty percent with logistic regression usually being the highest. Recall is frequently quite poor, never going above sixty percent and sometimes going as low as sixteen percent.

Going model by model, we find that logistic regression frequently performs the best. Interestingly, the ensemble performs worse in most measures with the notable exception of recall in which it is consistently the highest performing. This means that our intended behavior of minimizing false negatives occurred as planned.

Looking at the various crisis types, inflation crises were the easiest to consistently positively identify, as shown by the relatively high recall in that table. Conversely, currency crises were hard to positively identify with the lowest recall among all crisis types.

Future Work

This problem is far from solved. Future similar approaches could include more models, different ensemble methods, or different data sets. We could also use similar data to predict other significant events such as wars or the outcomes of elections.

Conclusion

In this paper we attempted to use machine learning models to predict and identify financial crises. Ultimately, our classifiers performed poorly at detecting financial crises. While accuracy is high, we can conclude from our low recall values that this is mostly due to true negatives dominating the dataset. Overall, there is much room for improvement in this problem and our approach is only one of many.

References

Hennig, T., Varghese, R., & Iossifov, P. (2023). Predicting financial crises: The role of asset prices. *IMF Working Papers*, *2023*(157), 1. https://doi.org/10.5089/9798400248498.001

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