Predicting Economic Crisis in Developing Economies

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Introduction

Many investors and entrepreneurs are discouraged from investing in unstable markets due to high risk of economic crises and unexpected financial downfalls. These can lead to heavy losses such as when local currencies over-inflate. For instance, in Zimbabwe, investors rushed to buy stocks to protect their money from the effects of a 766% inflation [1]. Despite their risks, emerging and frontier markets have the potential for above-average returns because of their relatively high economic growth rates [2]. Such progress is further fueled by injecting the right capital into the economy. Therefore, our motivation is to boost investor confidence by being able to predict the onset of an economic crisis in these markets and allow investors to take actions to de-risk their investments accordingly.

Concentrating on African markets, our goal is to model the onset of an economic crisis based on the state of other economic indicators. As there are different types of economic crises, our focus is on systemic, banking, inflation and currency crises. The indicators that will be inputs to the model are exchange rate, domestic and sovereign debt default, consumer price index (CPI), GDP growth, GNI per capita, foreign direct investment, foreign aid received, external debt stock, unemployment rate and population growth rate. Therefore, our final product will be a simple application that predicts if a country is at a high risk of an economic crisis, based on its current economic state.

Related Works

Predicting economic crises is of high interest to a wide range of people because of the high financial impact. There has been work done to develop models to predict crises using both traditional statistical methods like linear regression and discriminant analysis and modern computational machine learning methods like ANN, SVM models and random forests. Some studies have found that modem methods have up to 30% higher predictive accuracy when compared to traditional methods [3]. However, this is not in any way a conclusive result because in the financial setting, the biggest challenge is finding the appropriate parameters to use in a model. Non-economic indicators, like behavioral and panic response tracked through stock market price fluctuations can be used to predict financial instability as well [4]. In general, given the many types of economic crises, there is no one set of indicators that can be used to accurately predict multiple types of crises. Indicators that can be good predictors for a banking crisis might be poor predictors of a currency crisis [5]. Moreover, other factors like policies and the overall political landscape complicate the challenge of finding appropriate parameters [6].

Most of the prior studies focus on which model fairs better in comparison to other models or the effectiveness of a predefined set of economic indicators in predicting a crisis. Our approach tests different models and indicators to explore whether there is an indicator-model pair that results in better prediction, including socioeconomic indicators like population growth and unemployment.

Dataset and Features

Primary Set

Our primary dataset is a publicly available Kaggle set that contains economic data on 13 African countries — Algeria, Angola, Central African Republic, Côte d'Ivoire, Central African Republic, Egypt, Kenya, Mauritius, Morocco, Nigeria, Tunisia, South Africa Zambia and Zimbabwe [7]. It contains yearly data up to 2014 with no fixed start year. For most countries the data starts in the 1950s while for others, like Egypt, it dates back to 1860. Combined together, the data set contains 1059 rows (examples) of training examples to use for our model.

The dataset has 14 columns, 6 of which can be used as features and 4 as outputs. The columns of the dataset include:

- ***Features:*** *exchange_rate_usd, domestic_debt_in_default, sovereign_external_debt_default, gdp_weighted_default, inflation_annual_cpi, independence*
- ***Outputs:*** *systemic_crises, currency_crises, inflation_crises, banking_crisis.*
- ***Others:*** *case_number, country_code, country_name, year*

As seen on figure 1, the data is mostly evenly distributed between the countries with the exception of Egypt and South Africa. Taking all the examples with a crisis as positive examples, the balance of the dataset is at 799 negative and 260 positive examples.

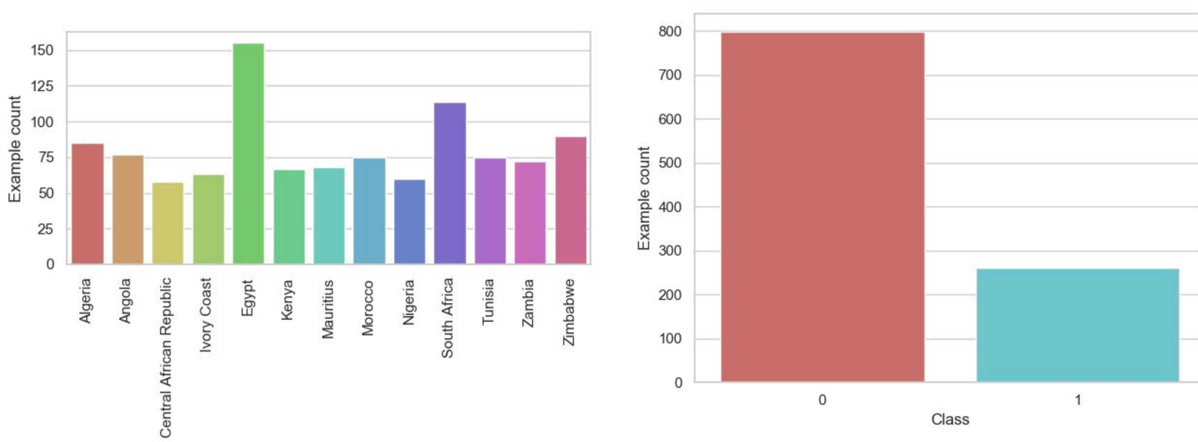

Figure 1 - Distribution of data examples by country (left) and the balance between positive and negative examples (right)

Secondary Set

To augment the data and add more features to our model, we combined the primary dataset with World Development Indicator (WDI) data from the World Bank [8]. This allowed us to explore 7 additional features — GDP growth, GNI per capita, foreign direct investment (FDI), foreign aid received, external debt stock, unemployment rate and population growth rate.

Similarly, the WDI data dates back to different years depending on the country. For every additional feature from the WDI set, we had to eliminate examples from the primary set that did not have a corresponding year and country on the secondary data set. For example, adding only GDP growth as an additional feature reduces the total number of examples from 1059 to 636 while FDI diminishes them to 526.

We defined our output as a single parameter “general_crisis”. The “general_crisis” column was created and populated by 1s and 0s by computing the ‘OR’ value across the 4 initial crisis columns (systemic, currency, inflation or banking). This represents an occurrence of any of the 4 types of crisis.

Ultimately, for any combination of features, we split the data into training and test at 80:20 ratio. This split was repeatable to allow comparing different models using a fixed set of features.

Methods

For our base prediction model, we started with a logistic regression classifier to determine its accuracy on the datasets as a benchmark. We then progressively tried more complicated neural network classifiers. We first implemented a single layer neural network and then increased the number of hidden layers and nodes while monitoring the performance. The ‘gdp_weighted_default’ feature was dropped by removing the corresponding column from the dataset. This is because its value was always ‘0’ hence had no effect on the model.

1. Logistic Regression

If we assume p to be the probability of a ‘positive’ binary outcome p = P(Y=1), the relationship between the variables can now be formalized as: $ln(\frac{p}{1-p}) = b_0 + b_1x_1 + b_2x_2 + ...n_nx_n$. (with x as our parameters).

Solving for p here gives us a sigmoid equation $S(x) = \frac{1}{1+e^{-(b_0+b_1x_1+..)}}$, and our loss function $L = \sum_{i=1}^{n}(y_i - \overline{y_i})^2$ is optimized by gradient descent.

2. Deep Neural Networks

Deep neural networks with multiple hidden layers have become a mainstream machine learning solution for modeling complex non-linear relationships from large datasets**.** In building an evaluating these models, we restricted our models to some hyperparameters; we used a sigmoid activation function, binary cross-entropy loss and a learning_rate of 0.001 (beta_1=0.9, beta_2=0.999, epsilon=1e-07). We again used a test/train split of 20/80 over 200 epochs.

We first built a simple single-layer neural network. This was equivalent to a perceptron model. In this model the input node in the next layer takes the sum of the weight input ($\sum_i w_iL_i$) .

For our final model for analysis, we built an ‘improved’ deep neural network model . It was expanded to include 3 hidden layers. For the ‘shape’ of the neural network (i.e. the number of layers, and the number of neurons in each layer) we decided to include 3 hidden layers (including the input and output layers) which include 32, 32 and 8 neurons respectively. We decided on 3 hidden layers since 3 layers are enough for the model to learn complex representations.[9]

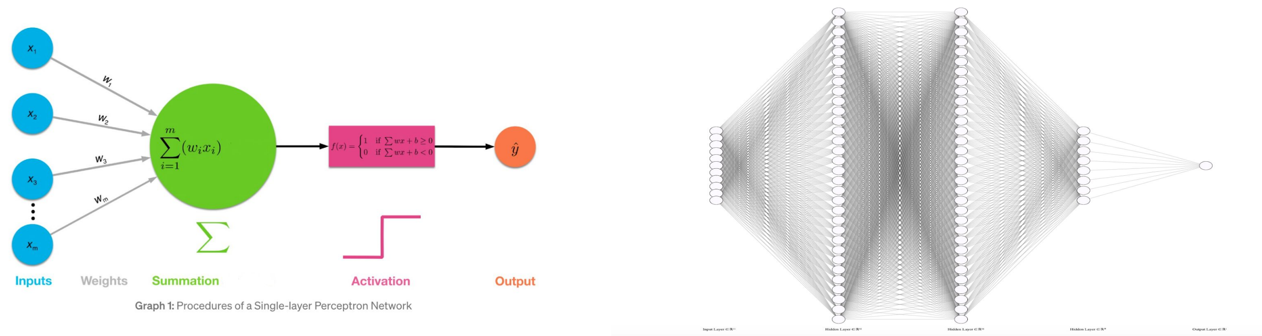

Figure 2 - A single layer neural network (left) and our final three hidden layer neural network (right)

Results and Discussion

We separated our results using the primary dataset features alone (Table 1) from those augmented with the secondary dataset features (Table 2). This is because, as mentioned before, each additional primary dataset feature limits the number of examples available to use and does not allow having a fixed test set across the board. We settled on using 4 of the 7 additional secondary features (GDP growth, GNI per capita, foreign aid received, and population growth rate) because they offered the best results, shrinking the number of examples to 587.

Table 1: Comparison of model metrics using primary dataset features alone ('0' represents the result of no crisis and '1' represents the incidence of an economic crisis)

Model	**Class**	**Precision**	**Recall**	**F1-score**	**Accuracy**	**AUROC**
Logistic Regression	**0**	0.88	0.98	0.92	0.87	0.74
	1	0.85	0.50	0.63		
Single Layer NN	**0**	0.90	1.0	0.95	0.90	0.50
	1	1.00	0.05	0.09		
Three Hidden Layers NN	**0**	0.90	0.99	0.95	0.90	0.54
	1	0.67	0.09	0.16		

Table 2: Comparison of model metrics using both primary and secondary dataset features ('0' represents the result of no crisis and '1' represents the incidence of an economic crisis)

Model	**Class**	**Precision**	**Recall**	**F1-score**	**Accuracy**	**AUROC**
Logistic Regression	**0**	0.76	0.99	0.86	0.77	0.60
	1	0.88	0.21	0.33		

The results show that a simple logistic regression model can perform as good or even better than the complicated neural network models given the AUROC, recall and F-1 scores across the board.

Our base model showed that adding extra features always reduced the prediction performance as seen on lower accuracy and AUROC values on table 1 vs table 2 and visualized on figure 4. This applied to the neural network models as well. The reason is adding the features resulted in a much lower number of examples (close to 50% less) available for training to the models.

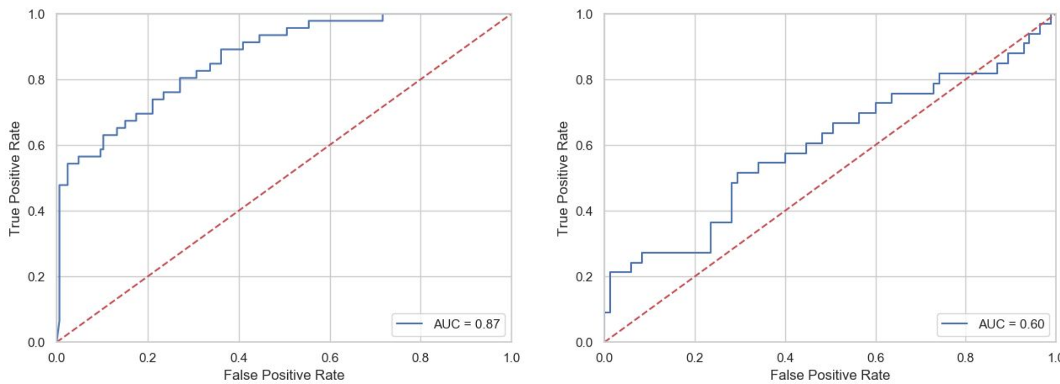

Figure 4 - ROC curves for the base model logistic regression using primary dataset features(left) and adding secondary dataset features(right)

Conclusion and Future Work

It is inconclusive which model performs better in predicting the onset of a financial crisis. Generally the logistic regression model has lower accuracy than the neural networks but a better ROC score. There is also no significant difference in performance between the single layer NN and three hidden layers NN. The additional parameters do not improve the model prediction of an economic crisis but rather deteriorate the performance because of limiting the number of examples available for training.

In the future, it would be interesting to extensively explore which combination of features perform better by a permutation of many more economic indicators as opposed to our 'primary vs combined' feature set comparison. Our models predict a crisis based on the economic state of a single year but economic crises are stirred by events that happen for a long period of time. Therefore, converting the data into an average of a defined number of previous years is an interesting avenue to explore.

Contributions

Every team member contributed to the project equally, including data sourcing, developing code and writing the report. Kirk sourced and preprocessed the primary dataset, and developed the training models. Moses sourced and preprocessed the secondary dataset and developed the metrics to analyze the model results.

Link to Github repository: https://github.com/mosesswai/cs229project

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