US FINANCIAL CRISIS PREDICTION WITH MACHINE LEARNING

Xinhao Zhu
New York University

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Abstract:

Financial Crisis are important economic events, but it is difficult to predict. In this paper, the researcher picked meaningful predictors and employed machine learning algorithms to predict US recession or financial crisis. It turns out that term spread (10-year treasury yield minus 2-year treasury yield), stock index change, total credit to GDP growth, and CPI change are the most four significant economic indicators for US recessions.

1. Statement of the Problem

Financial Crises are known to be unpredictable and destructive. Therefore, it will be meaningful if people could predict a crisis, especially the turning point. In this paper, the researcher attempted to utilize some proven useful leading indicators and up-to-date machine learning algorithms to predict US recession.

2. Methodology

The researcher first employed 8 economic indicators in this paper, including total credit to GDP, term spread, M1 money supply, M2 money supply, Nasdaq index, debt to GDP, CPI, and employment rate. All eight indicators are used as percentage change. In terms of crisis label, a specific quarter is listed as a crisis if it was the crisis starting point in history. For example, Q2 2007 is listed as the starting point for 2008 crisis, even though the full-blown international banking crisis did start in 2008 Q3. Besides, the following 2 years (8 quarters) of starting point are labeled as non-crisis to avoid repetition. For instance, 2007-2009 is labeled as non-crisis. This way of labelling is consistent with our goal of predicting the starting point instead of the duration of a crisis. From the aspect of machine learning algorithms, three models, including SGD-Classifier, SVM and Random Forest, are implemented. On top of these, Neural Networks, the state-of-the-art model, is excluded in this paper for the reason that this dataset is only for the US and therefore too small to fit a Neural Networks model.

3 Review of Related Literature

Our work is closely related to the literature on Financial Crisis Prediction with Machine Learning (Bluwstein, et al., 2019) and other research papers of applying machine learning into crisis prediction.

Bluwstein, et al. (2019) included more features, such as current account imbalances, global credit, real consumption per capita and investment because their work incorporated all crises happened in all countries from 1870s to present and therefore it is of great importance for them to take in some features which represents interconnections between global economies. Then, they used a variety of machine learning models, including decision trees, random forests, extremely randomized trees, support vector machines, and artificial neural networks. Among these models, extremely randomized trees performed best in the accuracy of over 90%. The top 4 most predictive indicators, in the decreasing order of importance, are global credit, term structure slope, domestic credit and CPI.

Beutel et al. (2018) conducted an analysis of out-of-sample predictive performance between logit regression and all kinds of state-of-the-art machine learning techniques used to predict banking crisis. The paper included 7 developed countries, like the US, European countries and Japan. Besides, the predictors they used are similar to the above-mentioned literature on Financial Crisis Prediction with Machine Learning (Bluwstein, et al., 2019). The result showed that logit regression outperformed all machine learning models in out-of-sample prediction.

4. Data and Variable Selection

Given that this prediction is limited to the US only, all data were directly extracted from FRED using Python FRED API, and used FRED data codes include T10Y2Y, QUSNAM770A, MANMM101USQ657S, MABMM201USQ189S, NASDAQCOM, GFDEGDQ188S, CPIAUCSL, and EMRATIO, respectively representing 10 year to 2 year treasury yield difference, credit to GDP ratio, M1 growth, M2 growth, Nasdaq index, debt to GDP ratio, CPI, and employment rate. The indicator selection follows above-mentioned papers but is not identical; furthermore, our data sources are difference.

In this paper, the researcher selected eight predictors which roughly covers credit boom, money supply, macroeconomics environment, and asset price. Obviously, both dataset and predictor selection are simplified, far from being comprehensive and exhaustive; briefly, the researcher just aimed to explore the practicality of crisis early warning via machine learning instead of setting up a cutting-edge tool.

5. Results

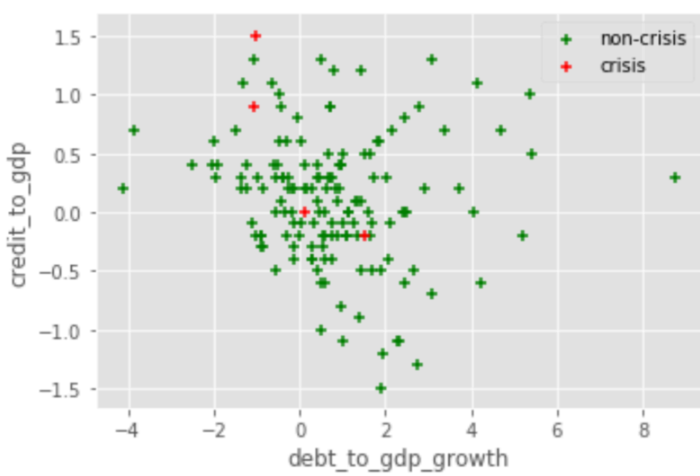
5.1 Introduction of Machine Learning Techniques Used

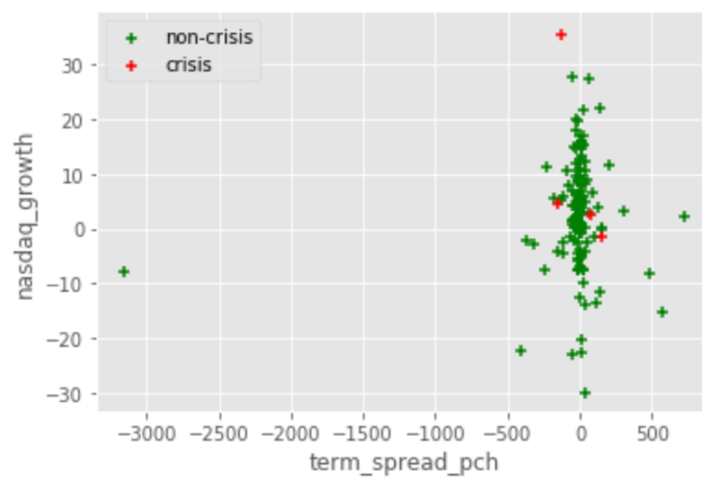
In this paper, three models were implemented, including SGD-Classifier (linear model), Support Vector Machine, and Random Forest Classifier. Three models are all used to classify whether a crisis is coming or not at a specific quarter. Considering that an earlier prediction than the label in target variable is desirable, the researcher decided to adopt a slightly different evaluation method, which is plotting both predicted training set and predicted testing set on a graph to see how the model performs. For example, let's say that the labeled quarter for 2008 crisis in our dataset is Q2 2007; then, suppose that predicted starting point for 2008 crisis is Q3 2007, in this way, most evaluation metrics in sklearn will categorize it into failure; however, such an exceptionally successful prediction is it! For this reason, the researcher decided to discard what most people used to, including precision score, recall score, confusion matrix, ROC and etc.

5.2 Pre-fitting Processing

Feature Engineering is known to be critical for many models, and this research is not an exception. All the inputs were taken as percentage change, and then standardization was performed to all inputs since SVM is known to be sensitive to feature standardization and normalization.

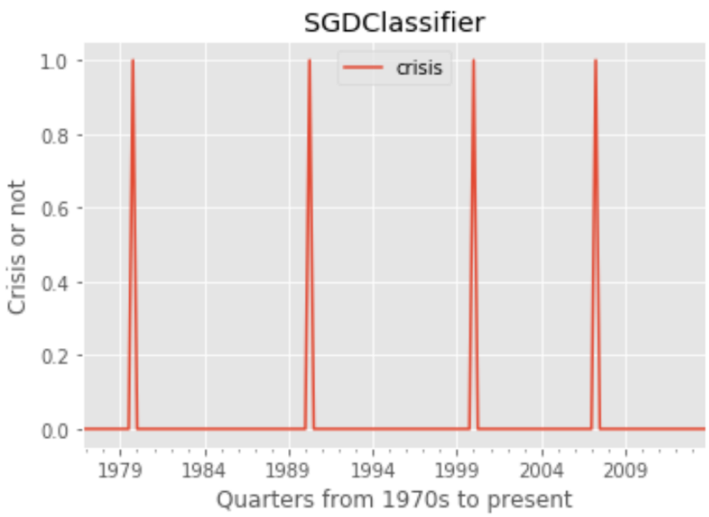
Next, simple 2D scatterplots commands were ran to visualize simple relationship between indicators and crisis. The following plots showed no clear hyperplane to separate crisis and non-crisis in 2D space whichever pair of indicators were used.

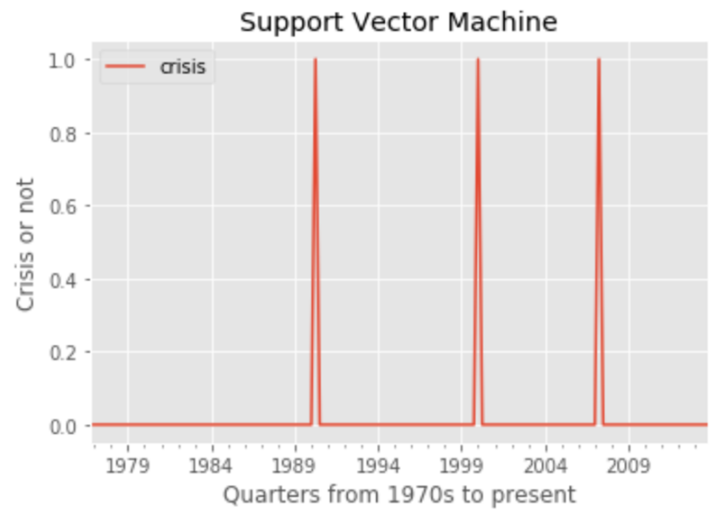


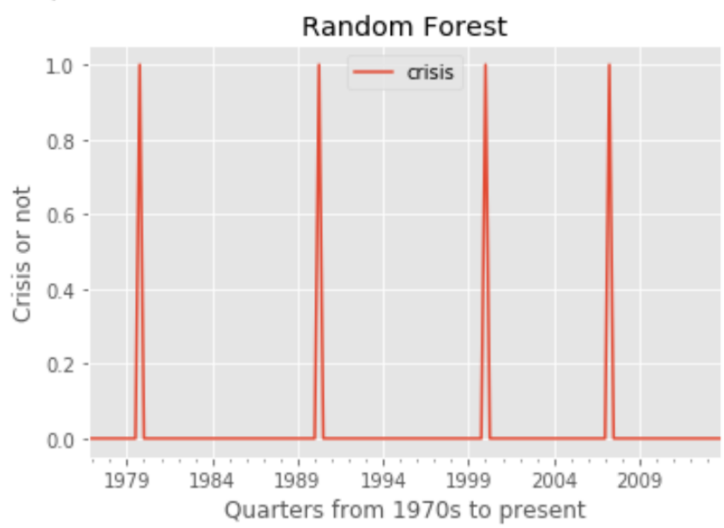


5.3 In-sample and Out-of-sample Predictive Performance across Methods.

For better illustration, 1976-2007 is predicted training set, and 2007-present is predicted testing set. As 3 graphs below show, both SGC-Classifier and Random Forest completely catches all 4 crisis ever since 1976, including 1980s ‘double-dip’ recession, early 1990s recession, 2000 dotcom bubble bust, 2008 great recession; meanwhile, the models did give no false alarm after 2008, which indicates a potential good out-of-sample performance. It did indicate the prospect of robust out-of-sample performance, but it needs larger dataset to test. The bottom line is that no false alarm in the test set motivates us to explore this project with more comprehensive dataset.







Reference

Beutel, Johannes, Sophia List, and Gregor von Schweinitz (2018) "An evaluation of early warning models for systemic banking crises: Does machine learning improve predictions?".

Bluwstein, K., Buckmann, M., Joseph, A., Kang, M., Kapadia, S., & Simsek, O. (2019, January 25). Financial Crisis Prediction with Machine Learning. Retrieved from https://editorialexpress.com/cgi-bin/conference/download.cgi?db_name=EEAESEM2019&paper_id=1163.