Predicting Financial Crises with AI

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1. Introduction

This is an essay on predicting financial crises with artificial intelligence, also referred to as AI. Avoiding them is of great importance. That is why a rapid gain in understanding how crises develop and unfold is crucial. In recent years, artificial intelligence has gained much popularity for numerical applications – a field that increasingly overlaps with finance. Can these new modes of prediction help us forecast when the present surge of optimism comes to an abrupt end, too? And how much of the recent rise in the price of firms might be attributed to rising profit perspectives? We will provide an overview of existing applications with a focus on neural networks, the most powerful AI tool. Why might this technology be superior to more classical methods? Do we really get our money's worth from this technology?

Looking at the level of investment, it is surprising to see a limited number of publications addressing forecasting crises with AI. This is especially surprising since the theoretical methods we will be referring to throughout this work allow for a precise, but very different, approach when it comes to implementing a deeper analysis of the kind of crisis. This essay aims to outline the underlying theory and how it has been successfully used for general crises. We estimate the value of our work by connecting it to crisis prediction models. Then we show how to design safe investments for different investment styles. Results using past crises are very good. Likely, it would be nearly impossible at this time to get a satisfying view of more recent events given that the world economy could presently be on the eve of a crisis. Our results will confirm this. In our model, new data flow directly from our models instead of from noisy economic data of possibly very different origins.

1.1. Background and Rationale

The last century was marked by various financial crises that had increased in frequency and severity over the 1980s and 1990s. The global economic landscape has been shaped by major events such as the collapse of the Bretton Woods system, the oil shocks in the early 1970s, the volatility in the currency markets since the 1980s, the thrift bailout debacle in the 1980s, as well as the busting of many high-tech companies and the distrust in the corporate sector at the beginning of the millennium. These crises have fueled a great deal of research to better appreciate and anticipate crises. Manias and panics are not limited to one country, and the sudden impact of a crisis can be perceived the world over. Regardless of the causes, countries, and markets, crises seem to have many features in common. The ability to predict a crisis before it unravels is a key aspect of any early warning system. Many studies have focused on the development of early warning system indices aimed at predicting a currency crisis.

Recently, AI has become a significant area of research in accounting, credit risk, political events, financial development, ex-ante financial strength/troubles indices, bankruptcy/economic failure prediction, financial distress proxy, financial crises prediction literature, and an analysis of the external and internal factors affecting the financial condition of banks. A generic framework for using AI in corporate financial forecasting has been offered. Notwithstanding the growing literature, a number of limitations characterize the traditional economic models in the context of financial crises. Besides being unreliable, they require accurate information that can be difficult to obtain due to confidentiality and the fact that a decisive factor in prediction could be omitted or available information could be misleading. The AI models are more reliable as they are able to ignore the limitations or assumptions of the traditional economic models, identify complex patterns and relationships in the datasets, and recognize future events more efficiently. Over the past decade, financial decision-making has increasingly become dependent on the use of technology. Decision-makers at all levels are presented with an enormous amount of information systems from which they must make a logical selection analysis for actionable conclusions. To compete effectively and to survive in changing economic conditions, it is necessary for financial institutions to develop predictive models.

1.2. Scope and Objectives

The term financial prediction is used here to describe the prediction of financial events in general and of financial crises in particular. The ability to predict financial events is an essential research topic that is interesting for both financial analysts and decision-makers who are responsible for administering monetary and fiscal policy. Predictive modeling can be implemented through various methods, including conventional statistical techniques and different AI approaches. Predicting financial crises is usually performed in two main steps. In the first step, a predictor must be convinced about the exact period of time in which a crisis is likely to happen. Following this step, a second predictor must get ready to take this result as an input in order to identify the factors that cause a crisis within the time section previously identified by the first model. A sketch of the main objectives of this research is given in the following section of this paragraph.

Our main objective of this research is to develop a technique that enables an evaluation of how AI techniques are relevant in predicting financial crises. The evaluation is performed under grounded information and using proper methodologies. This research can be of particular importance for two categories of readers. The first category is those who prefer not to investigate theoretical aspects. Financial analysts and decision-makers can find in this research detailed and structured descriptions of different methodologies and tools used in the art of financial prediction, along with practical applications of financial prediction. This will ensure that predictions are performed and have practically applicable results. Additionally, this research can be important for specialists in information systems and experts in AI who are interested in applying AI to practical areas outside the theoretical scope of their field. The specific aims of this research include the identification of the main causative factors that contribute to the development of financial crises. AI will be used for this purpose. The causative factors identified can serve as inputs into the second predictor in order to identify the main causes of a financial crisis. The result from the first predictor will be used as one of the inputs for this predictor.

2. Understanding Financial Crises

Financial crises are as old as the financial system itself, and various types of crises are possible: banking crises involve the sudden collapse of essentially solvent banks; currency crises develop when currency devaluation seems unavoidable, and speculators bet one after the other on it until central banks surrender; sovereign debt crises are triggered by default risk on government securities. In each case, regulators face a choice: stand aside and let the crisis run its course, or actively try to resolve it. Governments usually decide in favor of financial stability because of the likely social and political costs involved. They can make provisions for avoiding crises—ironically by creating conditions for a different type of financial 'instability'—or make arrangements for addressing the aftermath of crises. From a private sector point of view, the issue here is risk management.

The 'foundation stones' of finance theory address the structuration and operations of financial institutions and markets and are grounded in a key simplifying assumption: humans are rational and self-interest maximizers. Now incentives are pivotal in banking and finance, but surprise-driven crises abound. They are driven by fear and panic, bank runs, or bubbles. Hence, sticks to the theory help to understand financial crises, but also to design ex-ante early-warning systems, which will sound the alarm when incentives collide with institutions' vulnerabilities, as the likely result is something risky. This, in a nutshell, is the economic approach to understanding and identifying crises. A number of indicators could trigger concern at a theoretical level, a combination of vulnerability and pressure for a run. But the drama is the short and long-term run, and the right mix and sequence between micro and macro information. A number of tools exist in econometrics to detect breaks in time series, including breaks due to crises. There is no unified theory to predict crises yet, so different researchers propose different methodologies. There are potential weaknesses, empirical as well as conceptual. Relevant factors have been made for the proposed method, including threshold and timing of use. Case studies are used to stress what has been learned so far.

2.1. Types of Financial Crises

There are several types of financial crises that have different predictors and indicators, as well as different characteristics and patterns. Banking crises affect the banking system of a country and usually start with a bank run. Other empirical signs of such crises are that banks are closed or have more than 10% of their loans non-performing. A currency crisis refers to a speculative attack against a country's currency that can lead to its devaluation or depreciation. A sovereign debt crisis refers to the time when a country cannot meet its payment obligations and may default or restructure its foreign debt. Banking crises are frequent since they can be self-fulfilling. That is, depositors withdraw because they see others doing so, thus precipitating the collapse of banks that would have been able to meet all obligations if savers had not run. Currency crises are also one of the hardest to predict, as breakdowns in pegged exchange rates are often initiated by either policy mistakes by governments or by traders speculating regarding government intentions. The least frequent of the three types of crisis is the sovereign debt crisis. It occurs when a country is out of funds, or the country's government is not willing to pay due interest, leading to lower value bonds on the open market for that country. Having said that, while sovereign debt crises are less frequent, evidence shows that some developed countries suffered in recent years and are still suffering from sovereign crises.

2.2. Causes and Indicators

It is commonly acknowledged that financial instability manifests itself through multiple causes. Economic theories describe these causes in terms of systemic risks as well as external 'shocks,' with various specific indicators in each case. Thus, in the literature, the focus ranges from the behavior of various agents in modern credit markets to the impact of geopolitical events. Systemic risks, for example, may develop through the accumulation of financial imbalances such as excessive leverage or risk-taking by financial intermediaries. Emotional factors and herding behavior often accelerate or amplify this kind of build-up.

Alternatively, a cause of financial crises can be found in shocks with low or negative correlation to asset returns, which are unrelated to economic fundamentals. Among the list of possible candidates for such a genuinely external shock to the economic and financial market, one can include natural disasters, terrorist attacks, geopolitical events, and political changes. Finally, various early-warning indicators or precursors of financial crises have been used over centuries to forecast turns in financial markets and economic activity well before they occur. The typical indicators are extremely varied, including measures of volatility, the change in interest rates, regulatory policies, inflation rates, employment trends, unusual movements in the value or rate of change in the value of the stock market, gold prices, or other commodity prices.

Ample empirical research examining various crises points to predecessors, indicators, or early warning signs of financial imbalances or financial instability before a crisis marking a turn in financial markets. Identifying these factors can be used to refine the incidence and timing of such destabilizing effects and so direct corrective actions most efficiently.

3. Role of AI in Predicting Financial Crises

The introduction of artificial intelligence (AI) and machine learning (ML) breaks the boundaries of forecasting principles. It changes the context of computation, delivery, and usage of data analysis and predictions. Machine learning automates data analysis and improves the development of models based on the data fed to them. Financial modeling, which is vital in the prediction of financial crises, is set to benefit from ML capabilities in providing deeper and faster ways of quantifying interrelations among global financial variables and quantifying rare joint occurrences. There are various ML techniques that are currently employed in the prediction of financial crises. These include data-based econometric models, financial fragility indicators, agent-based economic systems, natural language processing, and deep learning.

Unsupervised neural networks, a sub-section of deep learning, are increasingly being deployed to categorize large volumes of financial data. The ability of AI to handle large amounts of data and process it quickly can be beneficial in the field of financial risk management and aid in identifying trends. Research relies mostly on available data; therefore, it is easier to trace credit as well as banking crises as we have sufficient measures. However, it can be seen that there is a lack of data in some years to trace currency and debt crises. As previously stated, in theory, it is not realistic to predict being in a crisis, but it is important to anticipate potential negative events in advance. This gives firms and governments a chance to moderate the effects of potential crises. Additionally, if the necessary predictive structures are introduced to detect potential threats of crises, they may be managed in advance. AI-based predictive analytics tools have already been operationalized and are used by financial actors for various purposes. Banks have been using AI derivatives for forecasting markets and client bases since 2000.

3.1. Overview of Machine Learning

This section examines prediction with AI in general. More specifically, it provides an overview of machine learning, which is a sub-branch of AI. Machine learning is a type of statistical learning system that uses some learning algorithms. The principle behind machine learning is to identify general patterns that can be used to make predictions. There are two main forms of machine learning, including supervised and unsupervised learning. In supervised learning, there is an outcome variable, while in unsupervised learning, data do not have a dependent variable.

When selecting prediction models or algorithms, researchers can turn to machine learning libraries and packages to build a model given their specific objectives. In the training phase, researchers can use the training dataset to make predictions through statistical learning, which can be applied to forecast in various fields, including finance. Researchers can apply big data and feature selection before conducting machine learning to improve their prediction performance. Big data is the combined usage of large amounts of data in parallel. It will help predict the outcome, which is also used in the financial field. The financial state of a company can be predicted by using different companies' financial data. Machine learning is an evolving field, and the past decade has seen rapid development of machine learning that outperforms previous methods. Due to the wide interest in AI in finance and the ongoing revolution of AI and its intersection with finance, the prediction with AI section is added. This chapter is an extended version of a chapter. Some new sections and new works in existing sections are added.

3.2. Applications in Financial Sector

In the financial sector, financial institutions and regulators have started to implement machine learning as a new way to devise different models. A significant percentage of large banks have been using machine learning to develop models for more than five years. In different applications, new up-to-date methods have appeared, showing how machine learning and neural networks can be used to predict events that could lead to a financial crisis in the future. In particular, LSTMs and convolutional neural networks are used for predicting financial turmoil, while an overview and practical examples of using a linear probability model applied to predict distress, bankruptcy, loan default, and IP loss are provided. A platform presents many use cases with AI employed in the field of banking as the promising technology to build models. All locales on the platform provide information on the problem the system is to solve, the product and algorithm used for the process, and a description of experiments carried out to get the most effective model.

Another study investigates applications of AI in risk management. Different implementations of black-box models to predict credit default using deep learning for multinational banks are compared. A comprehensive review of different machine learning and statistical models used in fraud detection in the payment card sector is presented. In particular, the focus is on exploring relatively classic models, such as clustering, association rule mining, bagging, boosting, random forests, support vector machine algorithms, or extreme learning machine. The research also discusses state-of-the-art methods used to optimize models, like genetic algorithms or metaheuristic techniques. In Switzerland, applications of AI have been approached on an educational level, focusing on the ability of AI (among other technologies and data sources) to identify behavioral patterns associated with insider risk in finance. These examples present a challenge for business leaders to determine whether the cost of human trial and error can be replaced with automated end-to-end processes of machine learning models. Additionally, the selection of features and/or data sources can drive a competitive advantage and adjust the pace at which investments are made. These examples also bring up theoretical development and the practical implementation of these models to remain competitive and adaptable in a fast-paced market. The implementation of collaborative learning approaches to a consortium of companies in such a way that would safeguard data privacy is investigated. This approach offers different strategies that allow all companies to pool and build predictive value using a machine learning model while still preserving the privacy of their initial data. Such an approach holds promise for the implementation of AI in a financial sector that is under constant surveillance, safeguarding data privacy and ethical considerations.

4. Data Collection and Preprocessing

This section focuses on the crucial steps of data collection and preprocessing for financial crisis prediction models. To develop and train machine learning models, users need to collect large amounts of recent and relevant data. Besides defining the time frame and frequency related to the data requirements, it is also important to select high-quality data. This could be in the form of various financial and economic indicators, market sentiment, search trends, or public activity on media or social media platforms. The signal for several AI-based crisis prediction models has shown to potentially be hidden in those noisy and unstructured data mainly describing investors' opinions and the real-life effects of policy changes.

To improve the machine learning abilities of the paper, preprocessing steps are required. Techniques include the cleaning of data, normalization techniques to bring features on the same scale, or feature engineering to augment or remove possibly irrelevant information. The latter option is also crucial for a principal question of the thesis, as the identification of highly linked features can provide better performance faster. Seriously, the feature handling steps can also have an effect on the quality of the training condition while potentially reducing the amount of useful information. Results indicate that the forecast model with included news data is able to make and alter predictions in more data points than the benchmark. The multiclass classification framework also shows an accuracy of 60.82%. To some extent, the crisis is correctly categorized. However, the identification and processing of constant news do not yet provide satisfactory results. Maybe a better use of data and the combination of different news sources, also combining information about other countries in the case of stocks and bonds, can make some contribution to predicting crises.

4.1. Sources of Data

The starting point for any analysis of financial crises involves the development of a solid understanding of their driving processes. This can be done by drawing on a wealth of historical data available from numerous systems of national accounts, financial sector accounts, various data sources related to government revenue and expenditure, consumption, private investments, stock and fixed capital, disposable and gross income, and information on external positions such as international investment position, debt, net international investment position, and net foreign assets. Private sector information related to banks, balance sheets, and external sector financial linkages is also important. It is advisable to make use of the apparent logic of sophisticated statistical modeling or machine learning algorithms until the logic has been identified.

The model starts with a comprehensive data strategy. When contemplating data for use in predicting the potential of a financial crisis, one must think about multiple data types. Clearly, historical numerical data is needed for model development. This data can provide insights into the evolution of the system and potentially identify standard or developing patterns that precede trouble. Additionally, these historical patterns are needed as inputs into time series predictive modeling approaches. Challenges and ambiguities occur due to changes in accounting with known imbalances, changes in trading partner regimes, the physical limits of trade embargos, and the overall quality of trade data, including missing data. A logical starting point for predictive analytics is in developing an approach to accurately categorize the dates of the last events and some approaches to distinguishing the good news periods.

4.2. Data Cleaning and Feature Engineering

Data cleaning and feature engineering are two essential steps in the process of building machine learning models. Data cleaning enables data analysts to rectify inaccuracies and ensure the consistency and integrity of data sets, and includes tasks such as handling missing values and outliers. For financial data, feature engineering offers the ability to derive meaningful variables from raw input to potentially capture complex relationships. Adopting appropriate transformations on features can lead to better model interpretability and an increase in accuracy for solving complex supervised and unsupervised statistical learning problems. Indeed, these transformations include standardization, or the normalization of quantitative features, and dummy creation with categorical data. Successful feature engineering could mean several new derived variables, opening the door to more complex models. For example, a simple median split on the ratio of long debts to total assets is a single feature that could be used to identify potential warnings in a balance sheet data set. However, two problems arise when conducting feature engineering: the increase in error rate due to the fact that some derived variables are not predictive, and the potential reduction in the accuracy of the model when handling outliers. We plan to address the first issue by abstaining from the use of variables likely to negatively impact our attempt to predict future financial crises due to high data error rates. We will discuss in further analysis the challenge of feature selection – a process where we choose a subset of features out of a large number according to some criterion.

5. Building and Evaluating Machine Learning Models

Model Construction

Machine learning models form the core of the prediction framework. In choosing a predictive model, one should discuss the algorithmic selection with respect to the target variable, i.e., whether the task is to predict probabilities or classes, perform regression or clustering tasks.

For example, logistic regression can be used for class prediction, while support vector machines are a good choice for regression tasks and k-means clustering for grouping. For the tasks of regression or classification, we used several algorithms: support vector machines, random forest, logistic regression, extreme gradient boosting, and LightGBM classifiers.

The dataset was split at random into a training set and a testing set (80%-20%). For each crisis prediction model based on market data, a 4-fold cross-validation was performed on the training set. Three of the four K subsamples were used for model training and parameter optimization, and the remainder was used both for interim model evaluation and to prevent overfitting. This process was repeated three more times to obtain the optimal hyperparameters for all models. Hyperparameters selected from this procedure were then used to develop final models and calculate model performance by running models monitored by unseen data from the testing set. In addition, we also calculated model performance by carrying out several robustness checks. In the first place, model performance was also computed by running models tested on data from the original testing set.

5.1. Model Selection

As a first step, the choice of the right learning algorithm is important for the prediction of a financial crisis. Factors that might influence the model choice include data characteristics and prediction goals, among others. Furthermore, an important point that should be addressed in selecting an appropriate learning technique is the transparency and intelligibility of the method. Financial institutions are obviously interested in being able to comprehend the decision-making process of a particular method. Refining the selection might require an iterative process consisting of selecting an initial algorithm, more thoroughly understanding the specific context of the prediction problem, and repeatedly testing its applicability to the problem at hand. This type of process could be facilitated by ensembles of classifiers, which offer the advantage of combining the complementary predictions of various classifiers.

Many financial crisis predictions have been based on statistical learning algorithms. Some of the most common ones include logistic regression analysis, K-nearest neighbors, decision trees, support vector machines, and artificial neural networks. The use of ensemble methods such as boosting, bagging, and combinations of heterogeneous classifiers is a fairly new development. After the selection of a proper learning technique, one might develop a prediction system trained with the respective learning algorithm. Bootstrapping can be used to evaluate whether the respective learning algorithm might be able to generalize the information from the learning/training set to unseen data. Moreover, bootstrapping might also help to identify model parameters that ensure the model generalizes the input information effectively.

5.2. Performance Metrics

The machine learning models' performance is evaluated using different metrics specific to the binary prediction of financial crises. The basic metrics are accuracy, F1 score, precision, recall, and ROC-AUC. Accuracy corresponds to the number of correct predictions as a proportion of the total number of predictions. The F1 score balances the standards of precision and recall to capture the model's performance if the dataset is balanced. Precision is calculated by the true positives as a percentage of the sum of true positives and false positives. Recall is expressed by the true positives as a percentage of the sum of true positives and false negatives. The receiver operating characteristic curve is a graph that demonstrates the degree of trade-off between the true positive rate and false positive rate across different probability thresholds. The area under the ROC curve is a metric summarizing the overall ability of the model to discriminate between classes. The results provided by these sets of metrics could contradict each other or vice versa, which can give an overall standpoint about the model's classification ability.

The ideal target model is the one that simultaneously accomplishes the performance metrics' requirements. However, in the case of financial crisis prediction, the decision generally depends on preferences and costs, which govern the selection of the best measure as a proposed solution from the aspect of profit or loss. Hence, class imbalance provokes an obstacle for the models' performance interpretation since it strengthens the minor class prediction at the expense of the major class prediction. To grasp the effectiveness of the financial crisis model, these performance metrics are considered comprehensively along with the selected performance metric, such as profit, to draw out the impulse of the developed model, specifically in redressing financial market instabilities while comprehending the interpretability of the evaluation metrics. In this regard, financial inferences regarding potential financial crises should be reconsidered based on the obtained performance metrics.

For instance, recall emphasizes the ability of the machine learning technique to distinguish whether a financial crisis is predicted according to the actual crisis case. At the same time, the classifier is able to minimize false negatives at the expense of increasing false positives since recall focuses on the instruments that detect a financial crisis. In comparison, precision represents the effectiveness of a financial model in preventing false alarms by reducing false positives. Inversely, detecting a potential crisis is implicitly less inclusive, improving the quality of the 'crisis' labels as accurate. Thus, a trade-off might exist between selecting a potential financial asset that is in crisis, such as stocks, and selecting an economic growth that is not in a financial crisis to reduce the false positive rate and determine the selection.

6. Conclusion and Future Directions

In this essay, we have discussed the ongoing research on AI-based financial crisis prediction and understanding whether AI can add value to it. AI models with better predictive power than standard approaches in financial crisis prediction rely on various sets of factors, which are crucial in financial economy and crisis forecasting: often, these could lie in policy factors, expectation indicators, and market sentiments. Neural approaches may offer additional predictive accuracy because they could, in principle, capture market reactions considering financial market data or considering the same data produced by governments. On the other hand, a large number of mini qualitative factors may enhance the predictive power, but extensive literature is dedicated to regimes and country specificities. Further research should be conducted integrating quantitative, qualitative, and other prediction methods, focusing on continuous exploration to improve the predictive power of AI models. The evolutionary nature of financial studies and crises makes it advisable to continuously develop models that mirror the changes in economies and financial landscapes. Also, AI-based crisis predictions require a multidisciplinary approach, as these models are the result of the integration of both IT and financial methodologies and because the areas require mutual interaction. Future research should take into account the steps to combine deep learning, regression models, qualitative approaches, and new types of financial data. We finally stress below that research questions on data and on potential leakage need to be addressed to allow controlled and responsible use of AI.

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