Usefulness of Artificial Neural Networks for Predicting Financial and Economic Crisis

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Abstract. The objective of the present study is to explore the issue of the forecasting of economic crisis using the neural network. The subject is of great importance in the economy, more so as that the most countries affected by crisis, declared on the end of 2010, the economic growth but the crisis paralyzed the financial world over the past three years. Neural network techniques have been frequently applied in order to predict problems like economic forecasting. The results show that creating a model using the neural networks might be a powerful tool and could be applied to prevent the economic crises.

Keywords: economic and financial crisis, forecasting models, neural networks

JEL Codes: C45, G01, C53

1. Introduction

The four major economic crises include the European Monetary System crisis (1992-1993), the Mexican crisis (1994-1950), the Asian crisis (1997-1998) and the Russian crisis (1998) all had negative impact on not only the countries where it happened but also on the international capital markets. The aim of this paper is to present the importance and the goals of forecasting that reduce uncertainty and provide benchmarks for monitoring actual and future performance in economic domain. Using statistical data, econometric and informatics techniques, these models are applied to predict the likelihood of economic and financial crises, using for this purpose a few number of indicators related to internal and external factors, as well as social and financial conditions. The financial crisis looks to be mostly behind us, and the economy seems to have stabilized and is beginning to grow again. Main causes of this situation are financial crisis become more frequent and more global before period. The global recovery has been stronger than expected, mainly because the level of confidence has picked up among consumers and businesses as well as in financial markets. Activity in emerging and developing economies makes the financial conditions to remain as difficult as was before the crisis. Macroeconomic forecasts predict the course of the aggregate economy concentrating on some variables such as interest rates, the rate of inflation, and the rate of unemployment. The recent economic crisis revived interest in developing different models able to signal their occurrence in timely manner. Neural Networks are flexible functional forms that allow approximating any continuous, hence also nonlinear function. Therefore, they can be expected to provide effective nonlinear models for financial time series and thus to allow for better prediction. The global economic crisis has affected all the investment and tends to impose more risks to all sectors on worldwide. Based on recent studies, this paper will try to emphasize the importance of creating models to predict the futures economic and financial crisis.

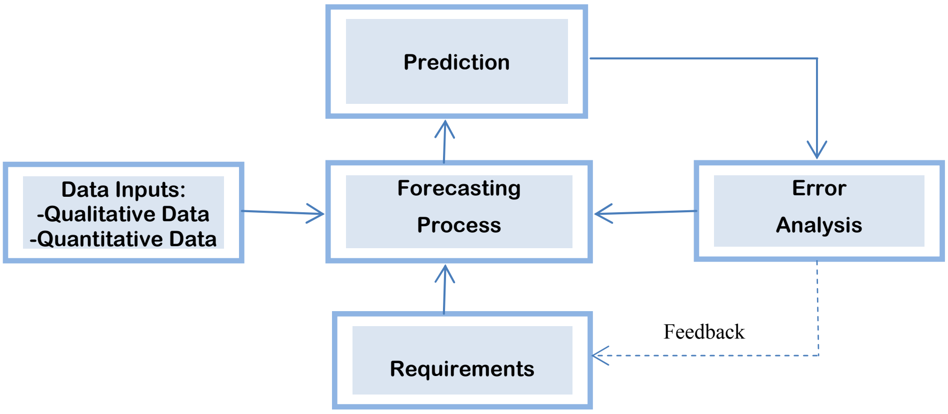
2. The importance of the neural network models

Neural networks are universal approximations and in theory can approximate any function arbitrarily closely. However, the mapping function represented by a network is not perfect due to the local minima problem, suboptimal network architecture and the finite sample data in neural network training. Therefore, it is clear that neural networks actually provide estimates of the posterior probabilities. [Cybenko, G., 1989] The indicators are useful in prediction, however they do not provide the underlying reasons for a financial crisis, and those reasons can be endless. Crises usually come with the convergence of multiple external and internal factors, which overwhelm the economy. Some causes tend to lead to crisis more than others, but most crises have several market failure causes in common. In preparing a financial response plan, an understanding of the various causes is crucial to that effort. [Allen & Gale, 1999]

One of the major causes to many crises for developed countries in the last several decades has been the lack of regulation or financial liberalization. That came as a result of lax government regulations of banking and financial institutions as well as other regulatory tools. Many countries had been following the "Washington Consensus", which promotes liberal financial regulation to create easy credit and money across all countries to develop their economies. Up until recently, this policy seemed to work, however recent events have shown that liberalization can go too far. The problem is that it takes years to see the effects of deregulation, so no warning or downside was visible to other countries including our own. In the case of the Nordic and Japanese crises, these governments cite several instances of liberalization leading to asset bubbles and financial crisis. [Aldean, C., 2009]

Which range from a few weeks to many years, the economic forecasts are widely used in business and government to help formulate policy and strategy. Can be said that the economic forecasting is the process of estimating future events, and it is fundamental to all aspects of financial and economic processes based on quantitative analysis, qualitative analysis or a combination of both.

Figure 1 Typical forecasting process



Source: adapted by [Cangiano M., 2010]

In Figure 1 can be observed the typical forecasting process scheme. The goals of forecasting are to reduce uncertainty and to provide benchmarks for monitoring actual and future performance; the resultant forecasts are evaluated by comparing predictions with actual results. This assessment is accomplished by examining the error terms. An error term is the difference between the prediction and the actual outcome. Based on an error assessment, the forecasting process is continually updated through the adjustment of model inputs. The artificial intelligence techniques and emerging information technologies are being used to improve the accuracy of forecasts and thus making a positive contribution to enhance the bottom line. Over the time predictive models to analyze economic crisis have raised two major problems: accuracy of prediction as a result of statistical data analysis and the explanatory power of economic models. The neural networks is the best option when there is a lot of data, information and empirical knowledge, and algorithms cannot be fast enough and correct for their processing. A terms of statistical methods, the simple functions can be used based on historical economic values (public data), available that can be used as a very good first approximation for the prediction very complex process in economics. The impacts of the financial crises that touch the entire world economy have been a massive burden to the public budgets in nearly all countries of the world. In addition to tax revenue shortfalls and higher costs for social benefits, governments have been massively burdened by bank rescue measures and economic stimulus packages. The governments try to bolster savings in periods of growth in order to mitigate the risk of boom and to generate savings for future economic downturns and redouble efforts to coordinate economic strategy internationally, to engage the developing world in this process and to ensure that recovery strategies are environmentally sustainable.

Some of the afflicted economies of euro zone countries have problems, in all this time from 2008 until now, with excessive wages and prices that far exceed the competitive level, the exports are held down by the high prices, and the high incomes generate a volume of imports that is not sustainable. All the anti-crisis politics assumed by some governs from wide world are launched to construct strategies for keeping workers gainfully employed, and also to ensure that they are trained for new jobs and maintained them above the poverty line so as not to permanently undermine their employment prospects. But, most important it is to analyze that the underlying conditions that caused the ongoing food crisis have not significantly changed and that policies are needed to ensure that food is available to the hundreds of millions living on the edge of starvation. [Cangiano M., 2010] In the last ten years, many empirical studies have sought to develop models able to emit timely signals of the occurrence of an economic and financial crisis. One of this was the result obtained by Manasse et al., who find that logit model predicts 74 percent of all crises entries while sending few (6 percent) false alarms, and the recursive tree 89 percent while sending more false alarms. [Manasse,P., 2003] In a survey of the literature, Hill et al._report mixed evidence as to forecasting results of Neural Networks, although they performed "as well as (and occasionally better than)" statistical method. [Hill, T., 1994]. Using statistical data and econometric techniques, these models are applied to predict the likelihood of economic and financial crises, using for this purpose a large number of indicators related to internal and external factors, as well as social and political conditions. According to the type of approach adopted, models can be classified between parametric and non-parametric. [Abiad, A., 2003; Berg, A., 2004; Ciarlone, A., 2004]

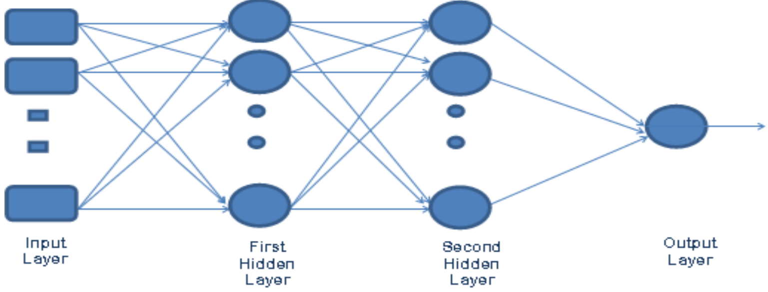
Economic theory has developed three generation of models explaining financial crises: the first and second generation models focus on currency crises and public imbalances, while third generation models include a wider variety of crises and are better suitable at explaining episodes occurred in the late '90s which were caused, principally, by private imbalances. Financial and economic crises that occurred in emerging countries in the 2008 have revived theoretical and empirical interest in understanding their causes and consequences, as well as in developing statistical and econometric models able to signal their occurrence in timely manner.

In the last decade, many empirical studies have concentrated their attention in developing models able to timely signal the occurrence of a financial crisis, the so-called early warning system. Using statistical and econometric techniques these models are applied to predict the likelihood of financial crises using a wide number of indicators related to internal and external factors, as well as social and political condition. A special feature of neural networks that distinguishes them from traditional methods is their ability to classify data which are not linearly separable. The most common neural network model is the multilayer perceptron (MLP). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown.

A multilayer perceptron is a backpropagation artificial neural network model that maps sets of input data onto a set of appropriate output. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training the network. MLP is a modification of the standard linear perceptron, which can distinguish data that is not linearly separable. The MLP model is schematically represented in Figure 2; the data are fed into the input layer and get multiplied by interconnection weights as they are passed from the input layer to the first hidden layer. Within the first hidden layer, they get summed then processed by a nonlinear function (usually the hyperbolic tangent). Figure 2 depicts a generic fully-connected multilayer feed-forward neural network (or a multilayer perceptron), trained by the back-propagation algorithm. The operation of an MLP is determined by the following four factors:

- the architecture or topology of the layers, neurodes and their interconnections;
- the learning law;
- the activation or transfer function and
- the training parameters.

Figure 2 Graphical representation of multi-layer perceptron (MLP)



Source: adapted by [Abolhassani, H., 2006]

As the processed data leaves the first hidden layer, again it gets multiplied by interconnection weights, then summed and processed by the second hidden layer. Finally the data is multiplied by interconnection weights then processed one last time within the output layer to produce the neural network output. The choice of output neurode depends on the nature of the research study. A single output neurode indicates a dichotomous and categorical output that can be expressed in binary terms: 1 and 0.

The architecture of an MLP specifies the number of layers, the number of neurodes each layer contains and how the neurodes are interconnected. The design of an MLP architecture is "more of an art than a science", in the sense that optimal design is based more on heuristics or experience rather than on proven methods. [Zhang, 1998; Haykin, 1999] The multi-layer perceptron and many other neural networks learn using an algorithm called backpropagation. With backpropagation, the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed.

This error is then fed back (backpropagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. Each problem is unique, and so are the solutions. Sometimes adding additional nodes or layers will stabilize a system. There are no hard rules, but there is one thing for certain; whether a neural network is computed by a computer, implemented in hardware, or propagated by hand, neural networks do not cogitate.

They are simply powerful computational tools and their sophisticated mathematical computation positions them to be used to solve a broad range of problems. The MLP depicted in Figure 1 is feed-forward, because none of the weights cycles back to an input unit or to an output unit of a previous layer. In addition, the MLP is fully connected, because each neurode provides input to every neurode in the next forward layer.

The neural network learning model is demonstrated by the exclusive-or data. The exclusive-or data is repeatedly presented to the neural network, and with each presentation, the error between the network output and the desired output is computed and fed back to the neural network. The neural network uses this error to adjust its weights such that the error will be decreased. In final this sequence of events is usually repeated until an acceptable error has been reached or until the network no longer appears to be learning. The neural networks are mathematical constructs that emulate the processes that people use to recognize patterns, learn tasks, and solve problems. Neural networks are usually characterized in terms of the number and types of connections between individual processing elements, called neurons, and the learning rules used when data is presented to the network. Every neuron has a transfer function, typically non-linear, that generates a single output value from all of the input values that are applied to the neuron. Every connection has a weight that is applied to the input value associated with the connection.

The power of neural networks comes from their ability to learn from experience (that is, from historical data collected in some problem domain). Neural networks are increasingly being used in real-world business and economic applications and, in some cases, such as fraud detection, they have already become the method of choice. Their use for risk assessment is also growing and they have been employed to visualize complex databases for marketing segmentation. This boom in applications covers a wide range of business interests-from finance management, through forecasting, to production.

Artificial neural network is a multivariate artificial intelligence technology that provides successful results in cases where sophisticated interference exists between the variants and there is not only one solution set. As a result of these properties, artificial neural nets seem to be a suitable method to be used in financial failure fields.

3. Conclusions

In conclusion the crisis should be used as an opportunity: structural reforms to enhance growth in general and fiscal frameworks in particular. In this context the neural networks' tolerance makes them an excellent choice for solving real economic world problems. But, as with any solution, there are costs which depend on the domain and obtaining sufficient and suitable training data, and this can be challenging. In the economic area, the neural network models exploit patterns found in historical and transactional data to identify risks and opportunities. Models capture relationships among many factors to allow assessment of risk or potential associated with a particular set of conditions, guiding decision making, which has importance for governs decisions. Predictive neural network model is used in science, financial services, insurance, telecommunications, retail, travel, business and other fields.

Everyone needs to know the forecast of the future: the bankers need to predict credit worthiness of customers, the marketing analyst want to predict future sales, and the economists want to predict economic cycles. Neural networks are very effective when lots of examples must be analyzed, or when a structure in these data must be analyzed but a single algorithmic solution is impossible to formulate. When these conditions are present, neural networks are used as computational tools for examining data and developing models that helps to identify interesting patterns or structures in data. The data used to develop these models is known as training data.

The present paper has conducted to some conclusions which show that the neural networks have been shown to be a promising tool for forecasting financial time series. Several design factors significantly impact the accuracy of neural network forecasts. These factors include selection of input variables, architecture of the network, and quantity of training data.

Another consequence of this study about predicting financial crisis with artificial neural network model is that creating a model using the neural networks could be applied to prevent the economic crises and could effectively capture the economic variables associated with the currency crises, and might be a powerful tool to provide macroeconomic time series data.

In the future work are many things worth to be tried. For example, to exam if the artificial neural networks forecasting is able to use the pre, during and post crises data to evaluate, investigate and predict new economic crises.

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References:

[1] Abiad, A., Early-Warning Systems: a survey and a regime-switching approach. IMF Working Paper No. 32, 2003.

[2] Abolhassani, H., Hariri, B. B., . Haeri, S. H., On Ontology Alignment Experiments,Webology, Volume 3, Number 3, September, 2006.

[3] Aldean, C., Recognizing A Financial Crisis, Brooks AFB, San Antonio, Texas, 2009

[4] Allen, F., Gale, D., Bubbles, Crises, and Policy, Oxford Review of Economic Policy 15.3, 16-17 p., 1999

[5] Berg, A., Borensztein, E., Pattillo, C., Assessing Early Warning Systems: how they have worked in practice, IMF Working Paper No. 52, 2004.

[6] Cangiano, M. Sovereign Balance Sheet and Accounting for the Fiscal Response to the Global Financial Crisis, http://www.oecd.org/dataoecd/20/3"/45033197.pdf, 2010.

[7] Ciarlone, A., Trebeschi, G., Currency and debt crises: a review of the Early Warning Systems, In: Wilkin, S. (Ed.), Country and Political Risk: Practical Insight for Global Finance (Risk Book), 2004.

[8] Cybenko, G., "Approximation by superpositions of a sigmoidal function", Mathematics of Control, Signals, and Systems, vol. 2, 303–314p., 1989.

[9] Haykin, S., Neural networks: A comprehensive foundation (2nd ed.). New Jersey, USA: Prentice-Hall,Inc., 1999.

[10] Hill, T., L. Marquez, M. O'Connor, W. Remus, Artificial Neural Network Models for Forecasting and Decision Making, International Journal of Forecasting 10, 5–15p., 1994.

[11] Kaminsky, G.L., Lizondo, S., Reinhart, C.M., Leading indicators of currency crises. IMF Staff Papers, vol. 45, No.1, 1998.

[12] Manasse, P., Rubini, N., Schimmelpfenning, A., Predicting sovereign debt crises. IMF Working Paper No. 221, 2003.

[13] Marco Fioramanti, Predicting Sovereign Debt Crises Using Artificial Neural Networks: A Comparative Approach, Istituto di Studi e Analisi Economica, Roma, Working paper no. 72, 2006.

[14] Oliver Selfridge, Oliver G. Selfridge, Neural Networks, In: AI's Greatest Trends and Controversies, http://aaai.org/AITopics/NeuralNetworks, 2005.

[15] Zhang, G., Patuwo, B., Hu, M., Forecasting with artificial neural networks: The state of the art. International Journal of Forecasting, volume 14, 35 – 62 p., 1998.