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AI, Deep Machine Learning via Neuro-Fuzzy Models: Complexities of International Financial Economics of Crises

Research Article

Haider A. Khan*

JKSIS, University of Denver, USA.

Abstract

This paper addresses one of the five major areas of AI research identified by Domingos in computer science. I demonstrate that certain Artificial Intelligence (AI) and Machine Learning (ML) type of modeling has great relevance for difficult areas of financial economics and complex financial systems analysis. In a neural network and fuzzy set theoretic formal setting, the ML model predicts the currency crises by combining the learning ability of neural networks and the inference mechanism of fuzzy logic. The empirical results show that the proposed neuro fuzzy model can not only provide better prediction (for both in-sample and out-of-sample data) but also model causally more detailed relationships among the variables through the obtained knowledge base. Additionally, causal structural path analysis can have significant implications for policy making. The (partially identified) causal path scan also be the bases for further theoretical modifications. One interesting feature of this approach is that it points towards the salient causal role of deep inductive learning in the study of financial crises.

Keywords: Learning Algorithms; Artificial Intelligence(AI); Deep Machine Learning (ML); Currency Crises; Neuro Fuzzy Model; Signal Aproach; Logit; Econometrics.

Introduction

A General Background of AI ResearchLeading to Specific Neuro-Fuzzy Type of Machine Learning for Better Understanding and Prediction of Financial Crises:

Since the pioneering work by some economists during the early years of the 21st century, other economists have increasingly recognized that they have good reasons to be interested in AI and machine learning. For example, a paper by [20] makes an interesting and highly relevant comparison between the language of econometrics and the language of Artificial Intelligence(AI) and Machine Learning.[20] "…discuss a list of tools that … should be part of the empirical economists' toolkit and that …should be covered in the core econometrics graduate courses."(p.3) They cover a wide-ranging list of topics and point out usefully that the nature of the economic problem should dictate the ML algorithmic modeling that can be the most relevant. In particular, the causal structure[2] of the relevant economic model derived from an appropriate theory should dictate what kind of ML model one should use. I agree with this logic and try to follow it by presenting a particular model of inductive learning that can be embedded in a neuro-fuzzy learning model for predicting, among other things, financial crises. Of course, financial crises are among the most intractable areas of (financial) economics. The claim on behalf of the neuro-fuzzymodel (NFM) ML algorithmic approach(from now on NFM-ML approach) is not that it is absolutely the best predictor with all causal pathways clearly identified once and for all. Rather it is a relative and comparative claim. In keeping with scientific realism, the claim here is that relative to and in comparison with commonly used econometric models, this AI-derived ML approach performs better, given the available data and the cognitive model of inductive learning[3].

As Domingos (2015) points out, the hope for researchers on what he calls "master algorithm" is to find an algorithm that can per-

***Corresponding Author**:
Haider A. Khan,
JKSIS, University of Denver, USA.
Tel: 303-871-4461/720-748-2555
E-mail: hkhan@du.edu

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[2] For a discussion of causal depth from the scientific realist perspective, see Khan(2003, 2019b)
[3] A number of recent papers dealing with both econometric and ML methods are highly relevant to our themes. We mention only a few here: (1, 2, 3, 4, 5, 6, 7, 8, 9,10, 11,12, 13, 14, 15, 16,17,18,19, 20,21, 22,50

form all the given tasks of AI, with sufficient and relevant data on which ML is to be trained . But he is careful to note the limits of the so-called "Big Data" because 'sufficient' data means, in some cases, that the data required for the model can be infinite. Learning from finite data means making specific assumptions, which may not be of use in all the cases. This is true of the class of all P and NP-complete problems[4]. If we think of a Turing machine for computational problems as a deductive procedure, the search for AI algorithms can be conceived as the ever more intelligent inductive search for algorithms that can use data efficiently. One solution for such a problem is that the necessary assumptions (with a few restrictions) can also be fed to the algorithm as an explicit input along with the original input, thus granting the user the flexibility of plugging the necessary attributes or even create new ones.

The hypothesis of the Master Algorithm is:

'*All knowledge – past, present and future- can be derived from data by a single, universal learning algorithm.*'[5]

If such an algorithm is possible, inventing it would be one of the greatest scientific achievements of all time. In fact, the Master Algorithm (MA) is the last thing we will ever have to invent because, once we let it loose, it will go on to invent everything else that can be invented. All we need to do is provide it with enough of the right kind of data, and it will discover the corresponding knowledge. However, since the MA is not yet within reach, Domingos suggests five main families that are collectively close to being an MA. These five are:symbolists, connectionists, evolutionaries, Bayesians and Analogizers, Each has its strengths and limitations. In this paper I elucidate a more modest claim than being the top claimant to MA. I show the relevance and efficacy of NFM-ML for analyzing one subset of challenging problems in International Financial Economics.

Of the five families, I would argue, NFM-ML has a great potential for computational economics of complex financial systems. I demonstrate this through a concrete NFM machine learning exercise and carry out predictions that can be compared with econometric models derived from statistical theory. This is the procedure of causal comparison from the perspective of scientific realism defended by Miller(1987) and Khan(2008; 2019).

The insight from neuroscience that has been used by researchers in NFM-ML is that, even the human brain functions on the basis of a variety of algorithms that seem to all belong to a parent algorithm uncovered by recent research. For example, we can cite the results of an experiment where the process of rewiring the brain by swapping the respective nerves did not result as how the researchers expected it to be as a severely dysfunctional animal. Instead, the respective nerves learnt to do the other nerve's functions, i.e. when the visual input is redirected to the somatosensory cortex, which is responsible for touch perception, it also learns to see. This is the primary principle of the 'echolocation' procedure for the blind people by clicking their tongue and listening to its echoes without bumping into obstacles. With the help of such algorithms, the blind can even play some sports. All of this is evidence that the brain uses the same learning algorithm throughout, with the areas dedicated to the different senses distinguished only by the different inputs they are connected to the different organs of the body. Perhaps in the formation of the cortex, the same wiring pattern with local variations is repeated everywhere. The learning mechanism is also the same: memories are formed by strengthening the connections between neurons that fire together, using a biochemical process known as long-term potentiation similar to the neurobiological concept called *clustering*. The most important argument for the brain being the "Master" Algorithm, however, is that it is responsible for everything we can perceive and imagine. Most importantly, the brain learns through layers of neural networks. This is essentially what thetheorists who proposed ---for example---the backward propagation mechanism with hidden layers in complex neural network learning procedure used to model Hebbian learning in a detailed way [85, 86].

In international finance, since the breakout of the 2008 advanced countries'financial crisis, there have been much attention devoted to the construction of the early warning systems. In fact, this started with the Asian Currency and Financial Crises [62]. In fact, the motivation came from the European currency crisis in 1992 and the Mexican currency crisis in 1994 preceded the Asian crisis in 1997 which was followed by the Russian currency crisis in 1998. But especially since 2008, the search for an effective early warning system has become a particularly important issue.

There have been a lot of related research in macro and financial economics since Krugman's 1979 contribution. Using a broad classification approach, these contributions can be divided into four main categories. The first set of papers all emphasize the qualitative dimensions, exploring the change of important indicators before the crisis. However, these papers did not conduct rigorous empirical testing using these indicators [36, 46, 70, 74]. A second group of papers have emphasized the difference between the variables during the crisis period and non crisis period [39, 43, 77]. Yet a third set of paper have stried to predict the probability of the crisis according to some theoretical model for example [25]. This set can also be subdivided into two further categories, single country models [31, 56, 82] and multiple countries' models [29, 43, 68, 75], including some papers using macro economic variables to explain the contagion-related phenomena as well [87]. Finally in our fourth category, some researchers like Kaminsky and Reinhart (1996) propose the signal approach to construct the early warning system. However, according to Chowdhry and Goyal (2000), the forecasting results of the out-of-sample periods for Asian crisis are disappointing for most of the theoretical models that use the signal approach. The inference to draw from such critiques is that this problem of building early warning system for financial crisis still needs further investigation. The possibility of non-linear causal relationship among the variables ordered

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Jushan Bai and Serena Ng. Principal components and regularized estimation of factor models. arXiv preprint arXiv:1708.08137, 2017.
O. Barkan. Bayesian neural word embedding. arXiv preprint arXiv:1603.
(51, 52,. 53)

[4] As we know: a problem is in class P if we can solve it efficiently, and a problem is in NP if we can check the solution efficiently.

[5] Domingoes (2015), p. 25

according to a complex causal structure motivates this paper to explore the problem via a particular AI-based machine learning approach.

As far as the nonlinear learning problem is concerned, the progress in artificial intelligence approach to learning in the 1980s and afterwards---- starting with Hinton's path breaking contribution in 1986--- has provided an alternative methodology to make steady advances towards a global solution to the signaling problem[6]. As is already clear from practical experience, expert systems, fuzzy logic, and neural network approach all have been of use to the managers who have to make decisions. However, although the standard expert system algorithm can embed the experience into the system, it is often too rigid to learn effectively with flexibility. The neural network---particularly after Hinton's contributions--- can learn more flexibly from relevant historical data. Furthermore, in neural networks with fuzzy logic an algorithm can describe the problem in the way close to the human being's reasoning process and accommodate the inaccuracy and uncertainty associated with the data from the real world or from experiments with human subjects. It stands to reason that a method which can combine the advantages of neural networks and fuzzy logic can be a more flexible algorithmic approach to learning problems. Therefore, following this line of thinking, I present a model that I have constructed with some colleagues for learning in the uncertain environment of the financial markets. It is a hybrid of neural network and fuzzy logic with inductive machine learning capacity. Here I present the specific example of an application in order to construct a currency crisis early warning system. In addition to providing better out-of-sample forecasting results, the proposed model also aims to providing a knowledge base to describe the complicated relationship among the variables. Such aknowledge base can provide a more concrete way to predict in a boundedly rational way or with some luck, even help prevent--- or at least mitigate the effects of---an impending crisis. This paper is structured as follows. Section 2 is the relevant literature review of the early warning model construction efforts. The construction of neuro fuzzy model and its benchmarks are described in section 3. Section 4 presents the broader research methodology. The empirical results are shown and discussed in section 5.s Conclusionsand a discussion offurther research problems follow in section 6.

Literature Review for early warning model construction

In terms of the early warning model construction, usually a multivariate logit model or a multi-variate probit model is constructed to predict the probability of the occurrence of the crisis for the next period or the next k periods. Although the explanatory variables are not exactly the same for most of the papers, the estimation technique is quite consistent. On the other hand, an alternative is to check the difference of the selected variables between before the crisis and during the crisisto see which variables can be helpful in predicting the crisis. Kaminsky and Reinhart (1996) proposed the signal approach to construct a warning system by modifying this method.

The advantage of logit or probit model is to represent all the information contained in the variables by giving the probability of the crisis. The disadvantage is that it cannot tell the forecasting ability of each variable though it can give the significance level of each variable. In other words, the ability of the correct signal and false alarm for each variable cannot be seen from the model. Therefore, it cannot provide the clues where the problem is and how to improve it, which is not beneficial for the authority to monitor and to prevent.

On the other hand, the signal approach proposed by Kaminsky and Reinhart (1996) can show the contribution (the percentage of correct signal and the percentage of false alarm) of each variable for the crisis prediction. Besides, it can also construct a summary indicator by calculating the conditional probability given the number of indicators signalizing. Later on, there are some researchers studying on the difference between this method (signal approach) and log it. Berg and Pattillo(1999) tries to predict the currency crisis in 1997 by using the signal approach based on the work of Kaminsky Lizondo and Reinhart(1998), the probit model based on the work of Frankel and Rose(1996), and the regression model based on the work of Sachs Tornell and Velasco(1996). The empirical results show that the performance of all these three methods are not significant.

As for the explanatory variables, Kaminsky Lizondo and Reinhart(1998) divide the variables into seven categories, external, financial, real sector, fiscal, institutional/structural, political, and contagion by summarizing from 105 indicators in 17 papers. Finally 15 variables are selected to construct the warning system by using signal approach. This paper has done an excellent job to explore the related leading indicators for the currency crisis.

From the empirical results of the above literature it can be seen that the conclusions may be inconsistent due to the different explanatory variables, different data frequency (monthly data or quarterly data), and different models employed. Besides, some variables are significant for single variable model but insignificant for multi-variate model due to the possible multicollinearity. Most of all, a theoretical model which can provide an effective out-of-sample prediction is still unavailable. Therefore, this paper is trying to construct a warning model through a different approach in the hope to not only provide a better out-of-sample prediction, but also can provide a more detailed relationship among the variables, which can be the basis for further modification of the existing theory and can provide the financial authorities more effective ways to prevent or mitigate a financial crisis.

This paper is different from the earlier literature in the following manner:

First, it is a data driven method to extract the relationship among the variables from the historical data. The obtained relationship can be the reference for theoretical modification of the existing theory. Second, it is an inter-disciplinary effort to use cognitive science and artificial intelligence tools to understand the international financial economics domain problem of the currency crisis. This crisis had not been explored using such an approach until we constructed the first such interdisciplinary model. Needless to say, one advantage of the nero-fuzzy modeling approach is that it puts in sharp relief the question of the forecasting accuracy for both in-sample and out-of -sample data.

[6] See also Khan (2004, 2006,2011,2013a, b;2019a,b) for related approaches and results.

The Construction Of The Competitive Warning Models For Causal Comparison[7]

Signal Approach

The basic philosophy of this approach is that the economy behaves differently on the eve of financial crises and that this aberrant behavior has a recurrent systemic pattern. For example, currency crises are usually preceded by an overvaluation of the currency; banking crises tend to follow sharp declines in asset prices. Let A and B represent the number of times signaling when there is really a crisis to happen and no crisis to happen in 24 months respectively. C and D represent the number of times without signaling when there is really a crisis to happen and no crisis to happen 24 months respectively. These numbers are shown in Table 1. A and D are the correct predictions, but B and C are the wrong predictions. We call B the false alarm. Let =[B/(B+D)]/[A/(A+C)], where B/(B+D) represents the wrong prediction rate when there is no crisis, and A/(A+C) represents the correct prediction rate when there is a crisis. is called noise-to-signal ratio. The signal approach is given diagnostic and predictive content by specifying what is meant by an "early warning, by defining an "optimal threshold" for each indicator, and is decided by minimizing the ratio . Usually the threshold value can be searched between the tenth percentile and the twenty-th percentile [56] or between the first percentile and the twenty-th percentile [47]. This paper adopts the former method. Different countries can have different threshold values.

However each indicator has different contribution in predicting crisis. In order to consider all the information and the different contribution among the variables at the same time, [55] proposed four methods to assemble the information. Since there is no big difference among these four methods, two methods are introduced here as the benchmarks. First method records the number of indicators signalizing. The more the number of indicators signalizing the more likely the crisis is to occur. Let I_t^1 represent the index of method one at time t. $S_t^j = 1$ represents indicator j is signalizing at time t, and $S_t^j = 0$ otherwise I_t^1. is calculated as follows.

$$I_t^1 = \sum_{j=1}^{n} S_t^j, \ j = 1, 2, \ldots, n \text{ ----- (1)}$$

where j represents the number of indicators. After this, is viewed as another indicator. The threshold value for this indicator is found in the same way as the other indicators do.

Since method one does not consider the different contribution of each indicator, method two is trying to modify method one by multiplying each S_t^j with the reciprocal of ω. The index of method two, I_t^2, is calculated as follows.

$$I_t^2 = \sum_{j=1}^{n} \frac{S_t^j}{\omega^j}, \text{ ---- (2)}$$

where ω^j is the value of of indicator j. Similarly the threshold value of this index is found in the same way as the other indicators do.

Logistic Regression Model

Since the dependent variable, currency crisis, is a binary variable, the logistic regression model is therefore adopted (Baltagi,1995). Let $Y_i = 1$ represent country i has a crisis at time t, and $Y_i = 0$ otherwise. Let P_i indicate the probability of country i to have a crisis at time t, then,

$$E(Y_{it}) = 1 \times P_{it} + 0 \times (1 - P_{it}) = P_{it}, \text{ ---- (3)}$$

which can be expanded by including n explanatory variables and can be written as the following equation.

$$P_{it} = \mathrm{P_r}(Y_{it} = 1) = E(Y_{it} \mid X) = F'(\beta' X_{it}) \text{ ---- (4)}$$

$$Y_{it}^* = \beta' X_{it} + \varepsilon_{it}, \text{ ----- (5)}$$

where y_i^* are the actual dependent variable which cannot be observed, is the vector consisting of n explanatory variables, is the vector consisting of n unknown coefficients, is the error term. Then the log-likelihood function can be written as follows.

$$\text{Lon L} = \sum_{t=1}^{T} \sum_{i=1}^{N} \{P_{it} ln[F(\beta' X_{it})] + (1 - P_{it}) \ln[1 - F(\beta' X_{it})]\},$$

where is the number of periods, N is the number of countries. The parameters can be obtained through the maximum likelihood method. However, since the data set contains the cross sectional and longitudinal data, it is worthwhile to consider the panel logit to consider both the cross sectional and time series effects simultaneously.

The panel logit with fixed effect model is also named least squares dummy variable model (LSDV), allowing the difference existing in the cross sectional part but no difference for the time series part. In other words, the intercept of the regression model for each country is different and is fixed, showing the difference coming from the different characteristics of each country. The equation can be written as follows.

$$Y_{it} = \alpha_0 + \sum_{i=1}^{I} \alpha_i D_i + \sum_{j=1}^{J} \beta_j X_{ijt} + \mu_{it},$$

Table 1. Contingency table of the crisis.

	Crisis	No crisis
Signaling	A	B
No signal	C	D

[7] This section and the next draw heavily upon my joint work with coauthors in our 2008 paper in the Journal of International Money and Finance.

i=1,2,....I, j=1,2,...J, t=1,2.... T ---- (7)

where i represents the i-th country, j represents the j-th variable, t represents the number of periods, D_i is the dummy variable, $\alpha_i D_i$ represent the specific characteristics of country I, X_{ijt} is the value of the j-th variable of country I at time t, and is the error term of country i at time t.

Panel logit with random effect is also named as error components model, (ECM). This model assumes that the difference among the countries are random, which effects can be described in the error term. The equation can be written as follows.

$$Y_{it} = \beta_{0i} + \sum_{j=1}^{J} \beta_j X_{ijt} + \mu_{it} \text{ -----(8)}$$

where $\beta_{0i} = \beta_0 + \varepsilon_i, i = 1,2,\ldots,I$, ε_i is a random variable, and E(ε_i) = 0, var (ε_i) = σ_ε^2 . Replace $\beta_{0i} = \beta_0 + \varepsilon_i$ into equation (7), we could obtain the following result:

$$Y_{it} = \beta_0 + \sum_{j=1}^{J} \beta_j X_{ijt} + \varepsilon_i + \mu_{it} \text{ ----- (9)}$$

in other words, the error term now contains two parts, ε_i and μ_{it} . ε_i represents the error term of cross sectional part, μ_{it} and represents the error term of the time series part. The general assumptions for the ECM model are as follows (Gujarati, 2003).

$$\varepsilon_i \sim N(0, \sigma_\varepsilon^2) \quad (10)$$
$$\mu_{it} \sim N(0, \sigma_\mu^2) \quad (11)$$
$$E(\varepsilon_i \mu_{it}) = 0 \quad (12)$$
$$E(\varepsilon_i \varepsilon_j) = 0 (i \neq j) \quad (13)$$
$$E(\mu_{it}\mu_{is}) = E(\mu_{it}\mu_{jt}) = E(\mu_{it}\mu_{js}) = 0 (i \neq j; t \neq s) \quad (14)$$

Neuro Fuzzy Logic

Basically fuzzy logic is dealing with the extent an object belongs to a fuzzy set. Usually $\mu_A(X)$ is used to describe the extent object x belongs to fuzzy set A. The difference between fuzzy logic and the traditional expert system is that the rules in fuzzy logic are described through the use of linguistic variables instead of the numerical variables. And the linguistic variables are described by several terms. For example, a simple fuzzy logic rule can be stated as follows.

IF export is low and reserve is medium, then currency crisis is high...... [15] where export, reserve, and currency crisis are called linguistic variables; low, medium, and high are the so called terms. Each term has a corresponding membership function. A fuzzy logic model is constructed by a set of "IF-THEN" rules as equation [15] to describe the relationship among the input and output variables. The process to construct a fuzzy logic model generally consists of three main steps, fuzzification, inference, and defuzzification, which are described briefly as follows.

Fuzzification Procedure: The first step in constructing a fuzzy logic is to clearly define the linguistic variables which stated in the "if-then" rules. A linguistic variable can be described by several terms. For example, we can use three terms, high, medium, and low to describe export and reserve. Each term has a corresponding membership function as shown in Figure 1a and 1b. There are four commonly used membership functions, Z, Λ, Π, and S type (91)° Since there is no rule available to decide which type to choose, and the preliminary experiment shows that there is no significant difference for these four different membership functions, we choose the most commonly used one, Λ type membership function.

Assume there is a country with export and reserve equal to 0.872 and 0.578, respectively. The values for each term can be obtained from figure 1a and 1b as follow.

Export: $\mu_{low}(0.872) = 0$, μ_{medium} (0.872) = 0.5, $\mu_{high}(0.872) = 0.5$ Reserve: $\mu_{low}(0.578) = 0.13$, μ_{medium} (0.578) = 0.87, μ_{high} (0.578)=0.00

The above process is what we call fuzzification. Since a linguistic variable can be described by several terms, this method has broken the binary logic constraint.

Inferential Steps: The knowledge base of fuzzy logic is constructed by a series of "If–Then" rules. Each rule consists of two parts, the "if" part and the "then" part. The "If" part measures the extent how the condition is satisfied and the "then" part describes how the model responds the input. Therefore, each inference consists of two calculations. The extent of the validity for the then part depends on the extent how the "if" part is satisfied. According to Thole (1979), the extent how the "if" part is satisfied is determined as the minimum value of the membership functions in the "if" part. In other words, $\mu_{A \cap B} = \min\{\mu_A, \mu_B\}$. Take the above rule for example. Since $\mu_{high}(0.872) = 0.5$, and $\mu_{medium}(0.578) = 0.87$, the validity of the "if" part is min{0.8720, 0.5780}=0.5780. Therefore, the output for this rule is currency crisis is low with validity equal to 0.578.

Defuzzification Procedure: After the fuzzification and the in-

Figure 1a. Membership function of export.

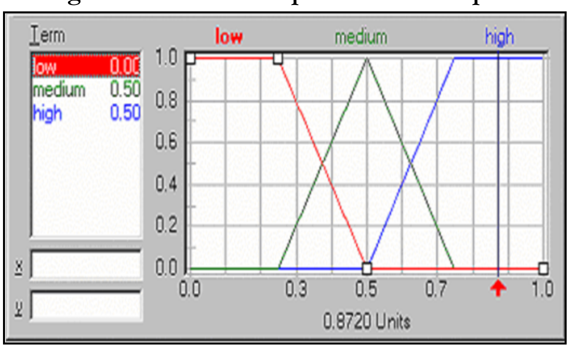
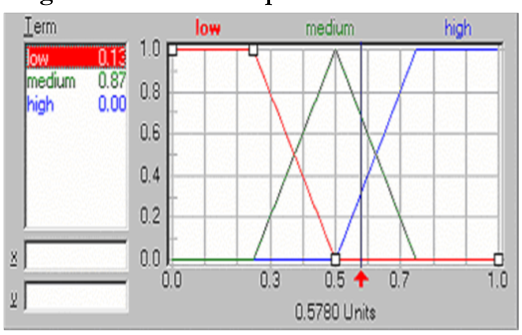


Figure 1b. Membership function for reserve.



ference steps, a result as equation [15], the currency crisis is low with validity equal to 0.578, will be obtained from each rule. Assume that the similar results from the other rules are currency crisis is medium with validity equal to 0.23 and currency crisis is high with validity equal to 0.97. The process to transform these linguistic results into a numerical value is called defuzzification. Usually it entails two steps. First, find out the proxy value for each term. Second, combine these proxy values. Usually the proxy value is determined as the value with the maximum membership function value. Then calculate the weighted value of the proxy value of each term with its membership function value as its weight. For example, if the proxy value for each term is {0.2,0.5,0.7}, then the weighted average is 0.5780* 0.2 + 0.2300*0.5 + 0.9700*0.7 = 0.8236°In other words the probability for currency crisis is 0.8236. This commonly used method is called gravity method (91)°.

The process is what we called the inference mechanism of fuzzy expert system. The problem is that the influence of each rule should be different. The way to improve this is to assign the weight (DOS, degree of support) to each rule, representing the relative importance of each rule compared to the other rules. Then the calculation for the "then" part should be modified as the validity of the "if" part multiplied by the corresponding weight. However, how can the correct knowledge base be obtained? How to decide the weight for each rule? Among all the possible alternatives, the learning ability of neural network can be used to solve this problem. Therefore, the hybrid of neural network and fuzzy logic can be a good possibility for this problem, which is what we called neuro fuzzy.

Algorithmically, the neuro fuzzy model uses the learning ability of neural network to find the parameters in the fuzzy logic system. In this paper, we adopt the fuzzy associate memory model proposed by Kosko (1992) to implementing the learning process. Each rule is seen as the neuron in the neural networkand the weight of each rule is updated by using back propagation. The knowledge base is obtained when the training stopping criteria is satisfied. Due to its simplicity and learning ability, this method has been applied a lot to many fields (Stoeva, 1992).

The neuro fuzzy model building process is described as follows.

Step 1.Divide the data set into in-sample and out-of-sample.
Step 2.Construct the complete knowledge base and set all the weights (DOS)associated with each rule equal to 0 as the initial solution.
Step 3. Use the learning ability of neural network to update the weights. If the relationship described in a rule really exists in the data set, the weight of this rule will be strengthened, otherwise the weight will remain 0. The training process stops when the stopping criterion is satisfied. All the rules with weight value less than a predetermined threshold value will be eliminated, the remaining rules are what we obtain to describe the relationship among the variables existing in the data set.
Step 4. Use the out-of-sample data set to validate the obtained model. If the out-of-sample can be predicted accurately, the model building process stops. Otherwise, repeat step 3 and step 4.

Methodology

Data Set

The data set mainly comes from the work of Kaminsky and Reinhart(1999), including 20 countries ranging from 1970 June to 1998 June. Some missing values are filled in by referencing to other data base. It is divided into two parts, in-sample and out-of-sample data sets. In-sample data set goes from 1970 through 1995, used for model building. Out-of-sample data goes from 1996 through 1998, used for model validation.

Definition of Crisis

According to Eichengreen, Rose, and Wyplosz(1996), currency crisis can be measured through the EMP, which is calculated as follow.

$$EMP_{i,t} = \left[(\alpha\%\Delta e_{i,t}) + (\beta\%\Delta(i_{i,t} - i_{USA,t})) - (\gamma\%\Delta r_{i,t})\right] \text{ ----(11)}$$

where $(\%\Delta e_{i,t})$ is the deflation rate of nominal exchange rate of country i at time t,% $\Delta(i_{i,t} - i_{USA,t})$ is the difference of interest rate between country i and America, is the change rate of reserve, $\alpha, \beta, \text{and } \gamma$ are the weights to adjust the variance to be equal among these three parts. A currency crisis can be defined as follows.

$$Crisis_{i,t} = \begin{cases} 1 \;\; if \;\; EMP_{i,t} > 1.0\sigma_{EMP,i} + \mu_{EMP,i} \\ 0 \;\; otherewise, \end{cases} \text{ ---- (12)}$$

where $\mu_{EMP_{i,t}}$ and $\sigma_{EMP_{i,t}}$ represents the mean and variance of EMP respectively. This definition is proposed by Sachs, Tornell, and Velasco (1996) first, and used latter by many researches. Goldstein, Kaminsky, and Reinhart(2000) modified this formula as follows.

$$EMP = (\Delta e / e) - (\sigma_e / \sigma_R) * (\Delta R / R) \text{ ----- (13)}$$

where $\Delta e / e$ is the change rate of exchange rate, $\Delta R / R$ is the change rate of σ_e, is the standard deviation of $\Delta e / e$, σ_R is the standard deviation of $\Delta R / R$. The reason to remove the interest rate change is that some countries adopt the interest rate control which makes this variable have no significant explanation for the currency crisis. The function of σ_e / σ_R is similar to that of $\alpha, \beta,$ and γ to adjust the variance of each part equal. This research will follow the definition of [47] to define a currency crisis occurs when the EMP is greater than the average at least 3 standard deviations, otherwise no currency crisis occurs.

The Selection of Indicators

Among the 15 indicators obtained in Kaminsky and Reinhart(1996), we choose 13 indicators due to the availability of the data set. They are M2 multiplier, Domestic Credit/GDP、 real interest rate、Lending-deposit rate ratio、M2/reserves、Bank Deposits、export、Terms-of-Trade、real exchange rate、Impo rts、Reserves、output、and Stock Prices. The sources of these data are listed in Appendix 1.

Performance Criteria

To compare the performance among the models, we use the accuracy rate and noise to signal ratio as the criteria. The accuracy rate is defined as the ratio of the number of the correct prediction divided by the total number of predictions. The higher the accuracy rate the better the model. Similarly the smaller the noise to signal ratio the better the model is.

Empirical Results and Discussion

Results of the signal approach

The results of the signal approach for the variable sare shown in table 1. The second column is the threshold value for each variable. The third column is the accuracy rate. The fourth column is the noise to signal ratio. The fifth column is the rank of the variables sorted according to the noise to signal ratio, from small to large. Besides, we put the empirical results from KLR(1996) at the right hand side for comparison. Basically the order of the rank is similar except for some variables. The difference may come from the data modification every two year, the ways data are transformed, and the ways to deal with missing values [38].

Comparison between the logit and panel logit

The panel logit results are shown in table 2. All the coefficients are statistically not significant for both random effect and fixed effect models except for the constant term of random effect model. In addition to the panel logits, we construct the logit for each one of the four Asian countries. The empirical results are shown in Table 3. It can be seen that the significant coefficients are different for each countries, implying the inappropriateness of the panel logits.

Table 1. Comparisons between this research and KLR.

	This research				KLR(1996)			
Variables	Threshold Value	Accuracy Rate	N/S	Rank	Threshold Value	Accuracy Rate	N/S	Rank
Real exchange rate	0.1	0.28	0.22	1	0.1	0.28	0.19	1
M2/reserve	0.86	0.3	0.49	2	0.87	0.29	0.48	4
Export	0.1	0.31	0.51	3	0.11	0.29	0.42	2
Real interest rate	0.9	0.3	0.53	4	0.89	0.28	0.77	9
Reserve	0.11	0.33	0.54	5	0.15	0.28	0.55	6
Stock price	0.1	0.32	0.59	6	0.11	0.31	0.47	3
Domestic credit/ GDP	0.8	0.29	0.7	7	0.9	0.28	0.62	8
M2 multiplier	0.87	0.3	0.73	8	0.86	0.29	0.61	7
Terms of trade	0.1	0.29	0.77	9	0.16	0.3	0.77	9
Import	0.9	0.29	0.86	10	0.9	0.29	1.16	10
Bank deposits	0.14	0.3	1.08	11	0.1	0.29	1.2	11
Output	0.19	0.31	1.18	12	0.11	0.33	0.52	5
Lending/deposit rate	0.8	0.31	1.6	13	0.8	0.27	1.69	12

Table 2. Results of the Panel Logit with random and fixed effect Models.

Fixed effect		Random effect
Variables	Coefficients	Coefficients
Constant	0.299	0.295
Domestic credit/ GDP	0.000	0.000
Export	0.001	0.001
Import	-0.001	-0.001
Real exchange rate	2.68E-5	2.43E-5
Argentina	0.312	0.036
Bolivia	0.387	0.101
Greece	0.416	0.128
Denmark	0.264	-0.006
Finland	0.284	0.012
Indonesia	0.268	-0.003
Israel	0.315	0.040
Malaysia	0.104	-0.146
Mexico	0.284	0.012
Norway	0.296	0.023
Peru	0.107	-0.142
The Philippines	0.124	-0.128
Spain	0.334	0.056
Sweden	0.294	0.021
Thailand	0.299	0.025
Turkey	0.298	0.024
Uruguay	0.131	-0.122
Venezuela	0.398	0.112
R-squared	0.045	0.039
Adjusted R-squared	0.040	0.038
Log likelihood	-2657.982	
P Value	0	

The comparisons among these three models are shown in Table 4. Although the accuracy rate of the logit is worse than that of the panel logits for the in-sample data set, it is the opposite result for the out-of-sample data set.

Since the logit model seems more consistent in terms of both noise to signal ratio and accuracy rate than the panel logits, we use it as the benchmark for the further comparison.

Neuro Fuzzy model

To make the comparison fair, we include the same four variables shown in the logit model into the neuro fuzzy model as input variables. BOP is the output variable representing the probability for a currency crisis to occur. If the probability is greater than a threshold value, it is considered as signalling a warning that a currency crisis is about to happen. Otherwise, there is no currency crisis.

This research describes these four independent variables by using three terms, low, medium, and high, and describes the dependent variable BOP by using five terms, very low, low, medium, high, and very high. Overall this model consists of four input variables, one output variables, and one knowledge base.

As alluded to before, the neuro fuzzy modeling approach(from here on called simply neuro fuzzy) is a fuzzy logic system with the learning ability of neural network to modify its parameters, including the parameters of the membership function and the relative importance of each rule. There are different ways to combine these two techniques (Buckley and Hayashi, 1994; Nauck and Kruse, 1997; Lin and Lee, 1996). These methods turn out to be not so different from one another in practice. This paper adopts the FAM (fuzzy associative memory; FAM) proposed by Kosko (1992). Each rule is viewed as a neuron, the weight of each rule is represented as the weight of each edge in the neural network. For each data point there is a predicted value generated by the system associated with a realized value. The training process will stop until the error between the predicted value and realized value is less than a certain threshold value.

The general neural network model gives the output as a nonlinear function of the data inputs with the specification of the transfer functions in accordance with lowering the errors. Thus the transfer functions connect the hidden node and output node, respectively. The most popular choice for the transfer function specification is the sigmoid function.

In practice matrices of linking weights from input to hidden layer and from hidden to output layer, respectively are found experimentally.

The comparisons among the models

Let SA1 represent the signal approach method one, SA2 the signal approach method two, NF the neuro fuzzy model, and LG the logit model. Due to the availability of the data set, we use the out-of-sample data of Indonesia, Malaysia, Philippine, and Thailand

Table 3. Logit model for each country.

Country	Indonesia		Malaysia		Philippine		Thailand	
Constant	0.032		3.272	***	1.416	***	0.714	***
Domestic credit/ GDP	0.770		10.716		-0.368		8.212	
Export	3.091	***	0.024		2.039	*	4.259	***
Import	1.022	**	-4.219	***	1.269		-3.495	***
Real exchange rate	-0.012	**	-0.001		0.093	***	-0.007	**
Likelihood ratio	64.183		25.305		16.883		27.374	
p-value	<0.0001		<0.0001		0.002		<0.0001	

***, **, * represents the significance level for 1%, 5%, 10% respectively.

Table 4. Comparisons Among The Three Models.

		In-sample			Out-of-sample		
Countries	Ratios	logit	fix	random	logit	fix	random
Indonesia	N/S	1.03	0	0.18	1.00	1000.00	0.00
	Accuracy	0.26	0.74	0.74	0.63	0.38	0.40
Malaysia	N/S	1.00	1000.00	1000.00	1.00	1000.00	1000.00
	Accuracy	0.10	0.29	0.90	0.63	0.38	0.38
Philippine	N/S	1.00	1000.00	1000.00	1.04	1000.00	1000.00
	Accuracy	0.12	0.88	0.88	0.6	0.38	0.38
Thailand	N/S	1.01	0.00	0.00	0.93	1000.00	0
	Accuracy	0.30	0.70	0.71	0.65	0.38	0.4
Average	N/S	1.01	500.00	500.04	0.99	1000.00	500.00
	Accuracy	0.19	0.65	0.81	0.63	0.38	0.39

for testing. The empirical results are shown in the following two parts, in-sample data set and out-of-sample data set.

Forecasting performance for in-sample data: Table 5 shows the forecasting performance of these four models based on the in-sample data set. It can be seen that NF has the lowest noise to signal (n/s) ratio among these models for each country in addition to the lowest average ratio.

Table 6 shows the accuracy rate of each model for each country. It can also be seen that NF has the highest accuracy rate among the models for each country in addition to the highest average accuracy rate.

In addition to the noise to signal ratio and the accuracy rate of each model, we also show the signal given by each model during the crisis period and during the tranquil period. The grey area in Figure 3 represents the crisis periods when the model must give a signal to indicate the crisis. We use 1 to represent a signal and 0 to represent non-signal. In other words, during the grey area, if there is a signal, it is a correct signal. If the signal happens outside the grey area, it is a false alarm. Figure 2, 3, 4, and 5 shows the signals given by each model for Indonesia, Malaysia, Philippine, and Thailand respectively.

Figure 3 shows that almost each model gives a signal during the crisis periods for Indonesia. In other words, each model can effectively signal the crisis. However, they also have many false alarms during the normal periods except NF. LG almost gives a signal all the time. Therefore, NF has the lowest noise to signal ratio and the largest accuracy rate among these models. The similar results are shown in figure 3, 4, and 5 for Malaysia, Philippine, and Thailand.

Forecasting performance for out-of-sample data: Table 7 shows the noise to signal ratio of each model for each country. It can be seen that NF has the lowest average ratio among these four methods in addition to the lowest ratio for each country. Table 8 shows the accuracy rate of each model for each country. It can also be seen that NF has the highest average accuracy rate in addition to the highest accuracy rate for each country.

Figure 5 to figure 8 shows the signals given by each model for each country. The results are similar to the training data set.

Conclusion

It will not be an overstatement to say that in the 21st century the related fields of Artificial Intelligence(AI) and Machine Learning(ML) have made rapid progress. So much so that their algorithmic approaches have become common outside of economics. We have tried to show in this paper through formal AI and ML modeling in an important area of international financial economics that it is possible to demonstrate that certain AI and ML type of modeling has great relevance for difficult areas of international financial economics and complex financial systems analysis. We follow scholars such as A they who have pointed out that AI and ML have great relevance for causal analysis of economic problems along with standard econometrics causality exploration techniques. We have shown through our formal and empirical demonstrations how we can illustrate at least one strand of this general argument for complementarity of econometrics

Table 5. Forecasting results for in-sample n/s.

	SA1	SA2	NF	LG
Indonesia	0.4649	0.5909	0.0360	1.0389
Malaysia	0.3055	0.2647	0.0772	1.0000
Philippine	0.7948	0.8352	0.0917	1.0000
Thailand	0.3937	0.4026	0.0409	1.0125
Average	0.4071	0.5230	0.0625	1.0183

Table 6. Forecasting results for out-sample -- accuracy.

	SA1	SA2	NF	LG
Indonesia	0.6600	0.5666	0.9700	0.2575
Malaysia	0.7600	0.8027	0.9307	0.1041
Philippine	0.7103	0.4444	0.9166	0.1244
Thailand	0.7142	0.7106	0.9670	0.2952
Average	0.7111	0.6355	0.9470	0.1969

Figure 2. The signals given by each model for Indonesia.

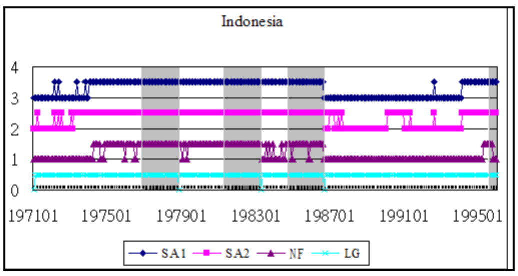


Figure 3. The signals given by each model for Malaysia.

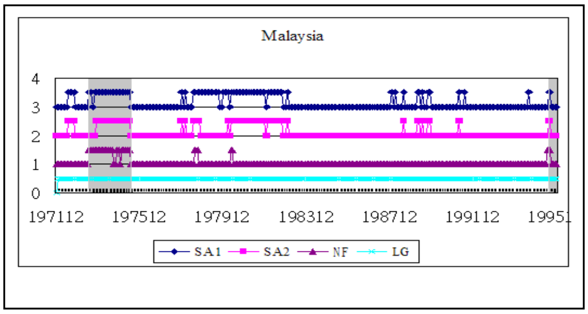


Figure 4. The signals given by each model for Philippine.

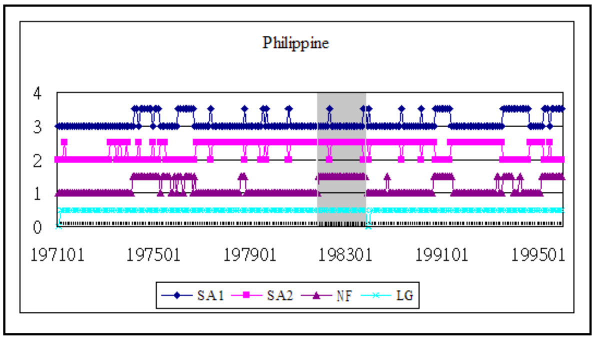


Figure 5. The signals given by each model for Thailand.

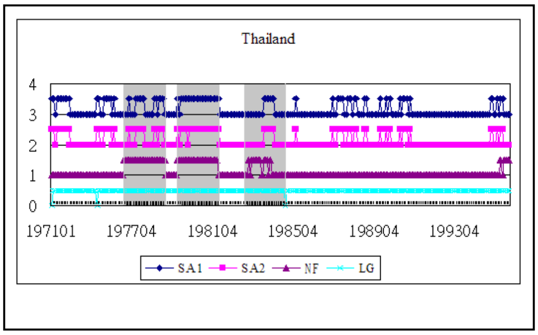


Table 7. Forecasting results for out-sample. n/s.

	SA1	SA2	NF	LG
Indonesia	0.590	0.744	0	1
Malaysia	0.5	0.476	0.25	1
Philippine	0.974	1.488	0	1.042
Thailand	0.665	0.744	0.076	0.933
Average	0.792	0.828	0.091	0.993

Table 8. Forecasting results for out-sample - Accuracy.

	SA1	SA2	NF	LG
Indonesia	0.590	0.718	0.875	0.625
Malaysia	0.575	0.5	0.8	0.625
Philippine	0.5	0.385	0.65	0.6
Thailand	0.590	0.538	0.9	0.65
Average	0.563	0.449	0.806	0.625

and AI-based ML by considering machine learning type of AI in a neural network and fuzzy set theoretic formal setting. Our hybrid model appears to predict comparatively better the currency crises by using neuro fuzzy approach to ML, which combines the learning ability of neural network and the inference mechanism of fuzzy logic.

Since currency crises have been important and puzzling areas of international finance from at least the last decade of the 20th century throughout the 21st century so far. In order to avoid the devastating damage caused by such crises often leading to broader financial and economic crises, we need an effective early warning

Figure 6. The signals given by each model for Indonesia.

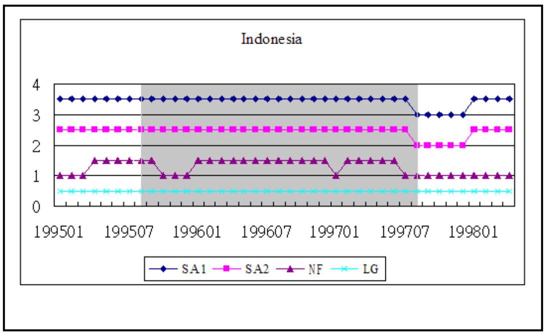


Figure 7. The signals given by each model for Malaysia.

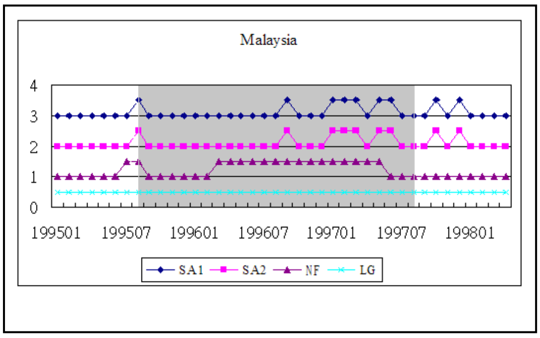
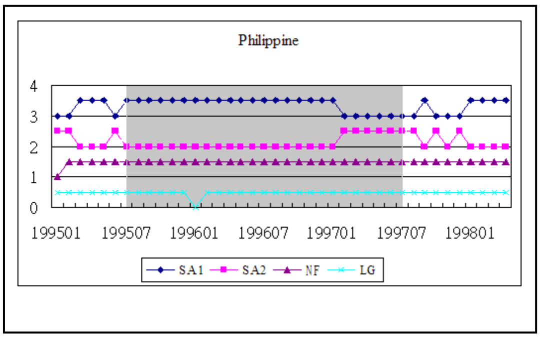


Figure 8. The signals given by each model for Philippine.



system. This paper shows how to make a start on this by trying to construct an early warning system through the AI-based ML using the neuro fuzzy nonlinear modeling technique. We compare its forecasting performance with those of signal approach and logit models. The empirical results show that our ML-based neuro fuzzy model can providerealtively a high accuracy rate of 80.62% for the out of sample data set. Besides, the knowledge base provides a more detailed relationship among the variables, showing how to make further progress towards averting or at least mitigating the worst effects of the crisis through the construction of a relatively more effective early warning system. The 3-dimensional graphics can also show a more clear relationship depicting the interaction effects between the key variables. These relationships can also be the basis for theoretical modification for further research for modeling inductive learning.

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