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Abstract

A neural fuzzy system was developed to estimate sovereign debt service capacity. This system performed at the comparable level as Probit, a common statistical method. Its performance compared favorably with a system developed using neural networks alone.

Introduction

Fuzzy logic is a logical system that is used to operate on fuzzy sets. First proposed by Zadeh in the 1960s (Zadeh 1965), fuzzy logic has gained tremendous popularity in recent years as its applications are found in areas ranging from consumer products to industrial process control and portfolio management (Cox 1992; Trippi and Turban, 1995). Along with neural networks and genetic algorithms, fuzzy logic constitutes three corner stones of "soft computing" (Zadeh 1994). Unlike the traditional or hard computing, soft computing strives to model the pervasive imprecision of the real world. Solutions derived from soft computing are generally more robust, flexible, and economic. In addition, constituent technologies of soft computing are generally complementary rather than competitive. As a result, many hybrid systems have been proposed to integrate these complementary technologies (Lin and Lee, 1996). In this paper, a system integrating fuzzy logic with neural networks was developed to predict debt service capacity of sovereigns.

Assessing Sovereign Debt Service Capacity

Sovereign debt service capacity is usually estimated by some kind of prediction model. A number of financial variables are collected to construct models that can predict whether a country will default on its loans. This is a important and timely topic given the recent financial crisis in Asia. We collected data from 43 countries over the period between 1983-1990 from the "World Debt Table" published by the World Bank. Two hundred and ninety cases were available of which 94 had incidents purporting debt rescheduling.

Ten explanatory variables were selected in this study: Total Debt to Export Ratio, Total Debt to GNP Ratio, Debt Service Ratio, Interest Payment to Export Ratio, Interest Payment to GNP Ratio, International Reserves to Total Debt Ratio, International Reserves to Imports Ratio, Short-term Debt to Total Debt Ratio, Concessional to Total Debt Ratio, and Multilateral to Total Debt Ratio. Until now no economic theory has suggested a unique set of indicators with which to build an optimal prediction model. The above specification can only be taken as a plausible choice among many alternatives (Parhizgari and Liu 1997).

Developing the Neural Fuzzy System

Our system was created in two steps. During the first step, training data were utilized to develop a fuzzy model, which was then refined during the second step using neural network techniques. We randomly selected 180 cases (about 62% of the total sample) as training data. The developed neural fuzzy system was evaluated using the checking data--the remaining 110 cases (about 38% of the total sample).

A Fuzzy Model Based on Fuzzy Clustering

A fuzzy system can be built if human expertise or experience is available for the definition of membership functions. If such knowledge is unavailable, sample data can be used to derive membership functions using techniques known collectively as fuzzy clustering.

The purpose of fuzzy clustering is to identify the number of clusters that exist in a given data set. Similar to traditional clustering procedures, a user can specify the expected number of clusters or let the system to "find" the likely number of clusters from input data. In this research, the GENFIS2 function of the Fuzzy Logic Toolbox (Gulley and Jang, 1996) was used to cluster the training data and generate an initial fuzzy model. The general format of the GENFIS2 function is:

$$\text{Fismat} = \text{genfis2}(\text{Xin, Xout, weight}) \tag{1}$$

where fismat is the fuzzy model estimated, Xin is the input data set, Xout is the output data set, and weight specifies the relative influence of each variable. A large weight results in a few rules and clusters, whereas a small weight results in many rules and clusters.

Since, ideally, the data should form two clusters (default vs. Non-default countries) different weights were tried and eventually a large weight (1.5) was used for the final specification of the GENFIS2 function. The resulting fuzzy model includes two membership functions for each input variable. The fuzzy model also includes two fuzzy rules that take the following form:

$$\text{If } x \text{ is } A \text{ and } y \text{ is } B \text{ then } z = p*x + q*y + r \tag{2}$$

where A and B are fuzzy sets (of input variables), p, q, and r are constants estimated by the model, and z is the output variable, i.e., the default risk. The consequent of the rules is a linear function rather than a fuzzy set. A fuzzy model that has this type of fuzzy rules is known as a Sugeno fuzzy model (Sugeno, 1985). A Sugeno fuzzy model is easier to work with than the other type, the Mamdani fuzzy model (Mamdani, 1975), because the defuzzification process is simplified.

Improving the Fuzzy Model with Adaptive Learning

Even though many alternative ways of integrating fuzzy logic and neural networks have been proposed, few have actually been implemented (von Altrock, 1997). The fuzzy model developed from the first step was improved through an iterative adaptive learning process implemented in Fuzzy Logic Toolbox (Gulley and Jang, 1996). The training algorithm was developed by Jang (1993) and termed Adaptive Neuro-Fuzzy Inference System, or ANFIS. Basically, ANFIS takes a fuzzy model and tunes it with a backpropagation algorithm. During each epoch, an error measure, usually defined as the sum of the squared difference between actual and desired output, is reduced. Training stops when the predefined epoch number or error rate is obtained.

The ANFIS technique is implemented in Fuzzy Logic Toolbox as a function with the following format:

$$\text{Fismat1, TrnErr, StepSize, Fismat2, ChkErr} = \text{Anfis (TrnData, Fismat, ChkData)} \tag{3}$$

where Fismat is the fuzzy model to be trained, TrnData is the training data set and ChkData is the checking data set. Fismat1 is the resulting fuzzy model that records the minimum training error and Fismat2 is the resulting fuzzy model that records the minimum checking error.

The fuzzy system was trained with 50 epochs. The initial training error was 0.3152, which was reduced through each epoch and the minimum of 0.3045 was reached at epoch 50. The system's performance using the training data could be improved further; however, it would be at the expense of higher checking errors. The initial checking error was 0.5452 and the minimum checking error of 0.5117 was reached at epoch 36, suggesting that the optimal performance of the neural fuzzy system using the checking data had been achieved. Because we were interested in developing a model that would minimize checking errors, Fismat2 was used to calculate the predicted output of the system.

System Performance Evaluation

The performance of the improved neural fuzzy models was evaluated using the checking data. "Default errors" were committed when the system predicted that a borrowing country would not default on the debt obligation but in actuality default took place. On the other hand, when the system predicted that a country would default on the debt obligation but actually the country did not, "non-default errors" were committed.

Table 1 reports the performance of the neural fuzzy system along with that of the Probit model and a neural network system developed previously (Parhizgari and Liu, 1997). As shown in Table 1, the neural fuzzy system achieved comparable performance as the Probit model and both in turn performed better than the neural network system.

The integration of the constituent technologies of soft computing is a new and exciting area. This research has provided empirical evidence that the integration of fuzzy logic and neural networks is an effective solution to the sovereign debt service capacity problem. The application of the same approach to other classification problems should be equally promising.

Table 1. Error Rates of Neural Fuzzy, Probit, and Neural Network Systems

	Neural Fuzzy	Probit Model	Neural Network
Default Error Rate	7.27%	7.27%	8.56%
Non-default Error Rate	10.91%	9.09%	14.51%
Total Error Rate	18.18%	16.36%	23.07%

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