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Using the artificial neural network to predict fraud litigation: Some empirical evidence from emerging markets

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Abstract

Detecting corporate fraud and assessing the relative risk factors have been significant issues confronting the auditing profession for decades. This study therefore aims to apply a neural network system to predict fraud litigation for assisting accountants on audit strategy making. The empirical results show that neural network provides not only a promising predicting accuracy, but also a better detecting power and a less misclassification cost comparing with that of a logit model and auditor judgments. This suggests that an artificial intelligence technique is quite well in identifying a fraud-lawsuit presence, and hence could be a supportive tool for practitioners. Further, a remarkable finding related to the greater effects of management's capability on fraud commitments acquires an attentive investigation of ethic issues in emerging markets where contribute the most important force in the global economy nowadays.

Keywords: Neural network; Internal controls; Fraud; Auditing

1. Introduction

Since Enron and WorldCom's collapse, a series of financial statement frauds have not only surprised local and international capital markets, but also awaked the authorities to have a prime interest in the problem. SAS No. 82 emphasizes auditor's responsibility and practically provides auditors with "how to" guidance on fraud detection whereas SAS No. 99 steps further into a brainstorming session that requires auditors to interact with audit team members to discuss fraud and to document the discussion. Also, researchers have largely addressed themselves to examine various aspects of the exploration of fraud models (Eining, Donald, & Loebbecke, 1997; Hansen, McDonald, Messier, & Bell, 1996); the magnitude of "red flags" or "red-flag cues" evaluated (Apostolou, Hassell, & Webber, 2001; Bell & Carcello, 2000); and audit decision support system implementation (Galderon & Cheh, 2002). Unfortunately, one thing holds true for the results is that financial scandal is still an everlasting hazard.

Noteworthy is that the professional literature makes it clear that failure in financial statement fraud detection rests with auditor's insufficient capability and decision aid system's inherent limits. Audit judgment consistency has been witnessed with being subject to auditor's work experience (Messier, 1983) as well as knowledge and ability of problem solving (Bonner & Walker, 1994), so that leads the audit decisions encountered in today's complex business environment to cover with a layer. Besides, models recently developed in fraud prediction have also been questioned about their intrinsic restrictions. The statistical assumptions such as linearity, normality and independence among variables of multi-variate discriminant analysis and regressions (Ohlson, 1980; Zmijewski, 1984) have constrained their applications whereas binary models such as logit and probit (Gessner, Kamakura, Malhortra, & Zmijewski, 1988) have been criticized for the subjective determination of cutoff points. Further, a recent trend to develop the artificial intelligence has brought a new alternative. The expert

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system can embed the past experience into the system; fuzzy logic can describe the problem in a way that is close to the human reasoning process and accommodate the inaccuracy and uncertainty associated with the data. However, their difficulty with the acquisition of the knowledge base has been challenged. Accordingly, a call for improvement of early warning system has inspired this research.

Neural network, an approach has been applied to several audit fields: the assessment of material misstatements, the evaluation of management fraud, the issue of audit opinion, the prediction of financial crises, the assessment of internal control systems and the decision of audit fee (Deshmukh & Talluru, 1998; Koskivaara et al., 2004). Its efficacy has been tested; it is limited, in most cases, in the USA. This study, therefore, is to adopt neural network to predict a fraudulent litigation crisis with data of Taiwan. Specifically, the proposed contributions of the study are two-fold: as a tool for eliciting knowledge of fraud risks and as a vehicle for supporting auditor's learning. The following section reviews the framework of neural network. Next, the research design and the results are discussed. The final section summarizes the findings.

2. An overview of neural network

Neural network has many different topologies for problem dissimilarities. Among them, back-propagation is the most well-known and commonly used, categorized as one of the supervised learning models. It draws the mapping function between the input and output from provided data set. Usually the mapping function is too complicated to explain the causal relationship between the variables with ease. The topology shown in Fig. 1 reflects three types of layers: input layer, hidden layer, and output later. Every node in the input layer represents an independent variable whereas the node in the output layer represents the dependent variable. The function of the nodes in the hidden layer is to complete the nonlinear transformation calculation.

When the obtained model is employed to make forecasting, each node in the input layer will send its value to the hidden layer. Each node in the hidden layer will calculate the weighted sum of the input values according to the after trained edge weight, and perform the nonlinear transformation of the sigmoid function to produce an output which is the input of the next hidden layer. Then each node in the second hidden layer and each node in the output layer will repeat the same procedure to produce an output. The final output of the node in the output layer will be the output of the model.

The purpose of the back-propagation training is to obtain the weight of each edge to minimize the squared error sum between the actual value and the predicted value. First and foremost, each edge is given a random value. Next, the squared error sum between the actual value and the predicted value can be calculated. Then the weight is updated according to the gradient search method until the squared error sum is less than or equal to the threshold value. The finally obtained model is called one that has been trained, which can then be used to forecast. Hornik (1989) has proven that neural network can approximate any function given enough number of hidden layers and number of nodes.

3. Methodology

3.1. Sample selection and study period

The sample of sued cases for the study was selected from the Securities and Futures Institute of Taiwan that ever experienced litigation during the period 1993–2002. The case was only chosen since it has the following features: (1) It was a public-trading company, (2) suspicion to fraud was primary element for suing, (3) litigation risk factors were associated with the deficiency of internal control, and (4) fraudulent action was conducted by the persons who worked for the sued firm. Further, this study followed the "matched-pair sampling" technique by Coats and Fant (1993), selecting non-sued firms from the same time period and industry as the sued firms. Our final sample size includes 74 sued cases and 148 non-sued cases, respectively.

To discover the ability of models on making accurate prediction, the sample set of 222 cases was subdivided into a training sample and a testing sample based on random numbers generated by the computer. The training sample is used to set up model for logit or to calculate network weights, and hence the testing sample is for measuring predictive accuracy of the models. The data of a training sample combined 49 sued and 98 non-sued cases while a testing sample consisted of 25 sued and 50 non-sued cases.

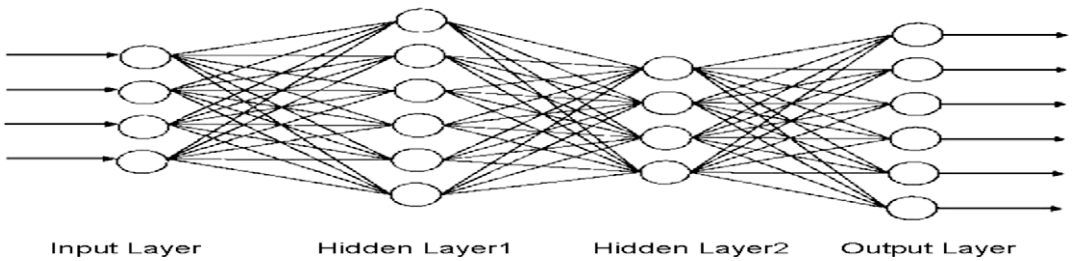

Fig. 1. Neural network topology.