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A hybrid financial analysis model for business failure prediction

Shi-Ming Huang [a], Chih-Fong Tsai [a], David C. Yen [b,*], Yin-Lin Cheng [a]

[a] Department of Accounting and Information Technology, National Chung Cheng University, Taiwan
[b] Department of Decision Sciences and Management Information Systems, Miami University, USA

Abstract

Accounting frauds have continuously happened all over the world. This leads to the need of predicting business failures. Statistical methods and machine learning techniques have been widely used to deal with this issue. In general, financial ratios are one of the main inputs to develop the prediction models. This paper presents a hybrid financial analysis model including static and trend analysis models to construct and train a back-propagation neural network (BPN) model. Further, the experiments employ four datasets of Taiwan enterprises which support that the proposed model not only provides a high predication rate but also outperforms other models including discriminant analysis, decision trees, and the back-propagation neural network alone.

Keywords: Artificial neural networks; Business failure prediction; Financial analysis

1. Introduction

The prediction of business failures is one of the major activities to audit enterprise risks and/or uncertainties. Business failure can be defined as a situation that a firm cannot pay lenders, preferred stock shareholders, and suppliers, a bill is overdraw, or the law makes the firm go bankruptcy (Dimitras, Zanakis, & Zopounidis, 1996).

The development of financial analysis models to predict business failures can be thought of as 'early warning systems', which proves to be very helpful for managers, and relevant authorities who can prevent the occurrence of failures. In addition, these models are able to assist the decision-makers of financial institutions to evaluate, assess. and select the firms to collaborate with or invest in (Ahn, Cho, & Kim, 2000; Balcaen & Ooghe, 2006).

Earlier studies related to financial forecasting mainly utilized various statistical methods such as multiple discriminant analysis, regression analysis, and linear discriminant analysis (Altman, 1968; Collins & Green, 1972). It was not until recently that much related work focuses on the development and application of artificial intelligence and machine learning techniques (Ahn et al., 2000; Min & Lee, 2005; Shin, Lee, & Kim, 2005; West, Dellana, & Qian, 2005). In addition, these studies have shown that machine learning models outperform traditional statistical models. Kumar and Ravi (2007) provide a detailed review of these models in the domain of bankruptcy prediction.

Financial ratios are important tools to predict business failures and it is commonly used to develop the models or classifiers. Financial analysis includes fiscal indicators and statistical forecasting which allow people to measure the current fiscal condition of the operating units and consequently predict trends for their future fiscal condition. Fiscal indicators can be used to provide quantitative information to evaluate the fiscal conditions and compare current financial statements with that of previous years and also that of other similar units. Fiscal indicators focus on proportional distributions within the reports, which is usually called as 'static analysis' and on factors and trends over a relatively long period of time, which is referred as 'dynamic analysis' or 'time serials analysis'. The process of developing fiscal indicators provides a framework for assembling and analyzing information about enterprises

* Corresponding author. Tel.: +1 513 529 4827(o); fax: +1 513 529 9689.
E-mail address: yendc@muohio.edu (D.C. Yen).

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on a regular basis (Damodaran, 2002; Mulford & Comiskey, 2002; Penman, 2003).

In general, there are two types of financial analysis models, which are static and trend analysis models (Damodaran, 2002; Mulford & Comiskey, 2002; Penman, 2003). For the static financial analysis model, its main characteristic is aimed at some significant financial ratios and compares the relationship between these significant financial ratios and the outcomes they expected. On the other hand, the main characteristic of the trend financial analysis model is focused on tracking to the one or the few characteristic marks, maybe the value or the ratios or any others. Each of these two analysis models has its own distinctive capabilities and certainly some inherited limitations. It is believed that if the strengths and weaknesses of these two aforementioned models could be combined, more flawless analyses are likely to be acquired (Anandarajana & Anandarajanb, 1999; Andr, Landajo, & Lorca, 2005; Calderon & Cheh, 2002).

There are a number of arguments which promote the consideration of the hybrid analysis model for business failure prediction using some machine learning technique. First, the underlying problem to use of a large number of parameters as the inputs is that each parameter has its mutual influence. One specific parameter may not be significant in statistics, but it would present the significant result when several pieces of parameters 'interact' at the same time, which is called covariation (Gujarati, 2002).

Second, if we only consider the minority important financial ratios which lead people to place focus on these pieces of values, enterprises would be able to play tricks most frequently and cover up these conspicuous ratios. On the other hand, if we could put a lot of effort into the analysis with carefulness, enterprises which cover up the financial ratios would show their slip in some places (Mulford & Comiskey, 2002).

Third, from the view point of pathology, let us personify an enterprise and auditor to be a person and a doctor, respectively. An effective and accurate method to diagnose a person is to make a detailed inspection to the whole body and then, track it regularly for a long time. In addition, if the symptoms could match the condition database with abundant case information, it will bring out the best outcome in each other. It is, thus, believed that such the diagnosis concept that most people can accept.

Using the same scenario, the following issues can be thought of as our diagnose model. "Check in detail all over to find out the condition" as "Use various relevant financial rates as input parameters to find out the enterprise's risk". "Follow the trail of the condition regularly" as "Use the time serials method to analyze enterprise's risks", and "Abundant pathology database" as "Perfect disciplined risk database".

This paper is organized as follows. Section 2 briefly describes artificial neural networks as the learning model or classifier used in this paper. Section 3 presents the research methodology including the proposed hybrid financial analysis model. Section 4 reports the experimental results as system evaluation. Finally, the conclusion is given in Section 5.

2. Artificial neural networks

Neural networks (or artificial neural networks) learn by experience, generalise from previous experiences to new ones, and can make decisions, and they are motivated by information-processing units as neurons in the human brain that a neural network is made up of artificial neurons (Haykin, 1999). A neural network can be thought of as a *black box* non-parametric classifier (Bishop, 1995). That is, different from naïve Bayes, we do not need to make assumptions about the distribution densities. Neural networks are therefore more flexible.

A multilayer perceptron (MLP) network consists of an input layer including a set of sensory nodes as input nodes, one or more hidden layers of computation nodes, and an output layer of computation nodes. The input nodes/neurons are the feature values of an instance, and the output nodes/neurons (usually lying in the range $[0, 1]$) represents a discriminator between its class and all of the other classes. That is, each output value is a measure of the network's confidence that the class corresponding to the highest output value is returned as the prediction for an instance. Each interconnection has associated with it a scalar weight which is adjusted during the training phase. Fig. 1 shows an example of a three-layer feed-forward network having input, output, and one hidden layers.

The neurons receive inputs from the initial inputs or the interconnections and produce outputs by using an adequate non-linear transfer function. The common transfer function is shown below.

$$Y_j = f\left(\sum W_{ij}X_i - \theta_j\right) = f(\text{net}_j) \quad (1)$$

where Y_j means the output signal of the neuron, f for the transfer function of the neuron, i.e. transferring the input

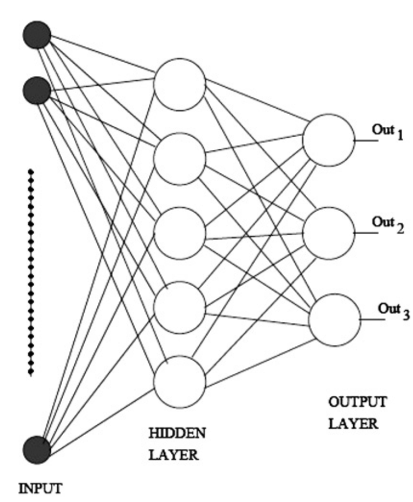

Fig. 1. The three-layer neural network.