A Neural Network Based Clustering Procedure for Bankruptcy Prediction

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INTRODUCTION

In this paper we develop a multi-layered neural network model that uses unsupervised learning to predict business failures in the computer and computer peripheral manufacturing and merchandising industry, and software development and merchandising industry. The development of models to predict business failure has long been an important area of concern of professionals operating in the securities and banking industry [Bell et al. 1990]. Although many attempts have been made, a consistently successful model of bankruptcy prediction is not available. This area of research is particularly of interest in the environment of increased competition, downsizing, and recession. The past savings and loan debacle, weakening of real estate values during the period of economic slowdown, and declining industry margins make it even more important and urgent for economic market agents to possess a capability to predict the advent of business failure. In the early 1990s the number of business failures had increased more than 55 percent over the late 1980s, and business failures have been registered in all major industry sectors [Gardiner et al. 1996].

The area of bankruptcy prediction has been studied in detail in accounting and finance, and a great deal of data is available on the subject in the accounting and finance literature. The majority of the recent studies in this area involve the use of the discriminant analysis approach. One disadvantage of using a statistical approach like discriminant analysis is that the required assumptions are fairly restrictive, since the Gaussian distribution has to be assumed. Such an assumption may not be tractable to real world problems. By using a neural network approach, such an assumption can be avoided since the application of neural network models do not require Gaussian distribution assumptions. Further, neural systems are much faster than conventional statistical approaches, require less storage, more robust to noise or missing data, and have generalization ability.

Results yielded by the application of statistical methods to the bankruptcy prediction problem suggest that the financial ratios are a valid discriminator between bankrupt and nonbankrupt companies [Raghupathi et al. 1991]. Several researchers have used discriminant analysis to predict bankruptcies. The work performed by Altman [1968], Deakin [1972], Moyer [1977], Collins and Green [1982], and Karels and Prakash [1987] are noteworthy. Collins and Green [1982], Gentry et al. [1985], Harris [1989], and Theodossiou [1991] have compared performance of several statistical models for predicting bankruptcy. Odom and Sharda [1990] applied a backpropagation network for bankruptcy prediction. Their model performed better than the existing discriminant analysis methods that were being used to solve this class of problems. However, it should be noted that Odom and Sharda's model was developed simply to demonstrate the application of the neural network methodology to finance problems. Thus, they replicated Altman [1968], using a basic model with

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only five financial ratios.

Since Altman' [1968] study, a substantial accounting research has been performed and additional financial ratios have been found useful in bankruptcy prediction. Select examples of this research can be found in the works of Ball and Foster [1982], Helfert [1982], and McKinley et al. [1983]. In addition, some methodological and technical advancements have also been made in this area. For example, Gentry et al. [1985] used a probit and logit cash-flow-based model with minor improvement over basic works. Bell et al. [1990] compared the use of logistic regression and a neural network model to forecast commercial bank failures, and found similar performance between two methods, with minor improvements "on the margin".

The authors believe that there is a need to develop a more extensive and enhanced neural network model for predicting bankruptcy, which incorporates the advances noted in the accounting and finance literature. Some of the distinguishing features of the present research as compared to past studies are as follows. The data used for learning of the neural network model in the present research consists of financial ratios for a three-year period. This is different from most of the past neural network studies for bankruptcy prediction, as they used only one-year's financial ratios for training the network. In this study, the set of three-year period is used to take into consideration any trends associated with the financial strength or weakness of the firm. Further, it also seems inappropriate to evaluate the financial strength or solvency of a technology-based company using only one year's financial ratios as it may provide misleading indications. This is because a technology-based company may take two or more years to become profitable, and most investors may be willing to wait for that time period provided the company has promising technology. Computer hardware and software, and internet related companies are prime examples in which use of a single year's financial ratios for predicting bankruptcy may be misleading. Thus, authors believe that it is important to use multiple years of financial ratios for training the neural network model, especially, when predicting bankruptcy for a technology-based company. It also seems that use of two or more years of financial information for training neural networks may be useful for predicting bankruptcy in other industries like biotechnology. Most of the neural network models developed in the past research on bankruptcy prediction use backpropagation technique for training the network [Luther 1998]. While in this research unsupervised learning is used as it is most appropriate for clustering. None of the past studies have used the hybrid neural network model and the eight specific financial ratios used in this research effort.

METHODOLOGY

Neural networks, an area of machine learning, are mathematical models of brain activity. The original intent of neural networks was to explore and reproduce human information processing tasks. Recently, this methodology has been applied to classification, data compression, fraud prevention, function approximation, marketing, medical diagnosis, optimization, pattern matching, and system modeling [Simpson 1990; Burke and Ignizio 1992; Mangasarian 1993; Sharda 1994]. Neural networks have also been applied to different areas in finance and investing [Trippi and Turban 1993; Sharda 1994]. Forecasting has been an important area of neural network applications [Sharda 1994].

Neural networks have been applied to solve common business decision-making problems. Dutta and Shekhar [1988] applied backpropagation neural networks to predict corporate bond ratings. Collins et al. [1988] built a neural network to make mortgage underwriting judgments to replicate the decisions made by mortgage insurance underwriters. Using a variant of the nonlinear least squares method, neural networks have also been used to search and decode nonlinear regularities in asset price movements [White 1988]. Surkan and Singleton [1990] suggested that networks trained with two hidden layers outperformed a network with only one layer. Kimoto et al. [1990] applied modular neural networks to develop a trading and forecasting strategy for stocks on the Tokyo Stock Exchange. A hybrid neural network architecture was applied to decision-making problem encountered in construction management [Murtaza and Fisher 1990].

Neural networks have been applied to bankruptcy prediction problems in the past. Various architectures of neural networks have been used for solving this problem, for example, Raghupathi et al. [1991], Salchenberger [1992], Tam et al. [1992], and Raghupathi [1995]. Single hidden layer models are predominant network architecture for bankruptcy prediction [Suh et al. 1994]. Some of the recent studies in this area include those by Lee et al. [1996], Serrano-Cinca [1996], Brockett et al. [1997], Jain and Nag [1997], and Luther [1998]. Lee et al. [1996] compared the performance of three hybrid neural network models against those of multiple discriminant analysis and ID3 models using Korean bankruptcy data. Results of their study indicated that hybrid neural network models have superior performance compared to multiple discriminant analysis and ID3 models for bankruptcy prediction in terms of predictive accuracy and adaptability. Serrano-Cinca [1996] developed a neural network based decision support system for financial diagnosis of companies. The self-organizing neural network model was used in the decision support system. Brockett et al. [1997]

applied a feed-forward backpropagation neural network model for predicting insurer insolvency. Jain and Nag [1997] developed neural network models to predict the success or failure of new ventures. They also compared the performance of neural network models with that of similar logit models. Based on the results of their study, the authors concluded that neural network models provide a promising and more generalizable approach compared with statistical models to solve two-group classification problems like bankruptcy prediction. Luther [1998] used a neural network model consisting of one input layer, one hidden layer, and one output layer that was trained using genetic algorithm. Performance of this neural network model was compared with that of a logit model for predicting bankruptcy. Results of the study indicated that the neural network model has significantly higher prediction accuracy than the logit model. Based on the review of results of the past studies, it may be concluded that neural network based models outperform conventional statistical models like logistic regression, discriminant analysis, K nearest neighbor, and ID3 in predicting bankruptcy.

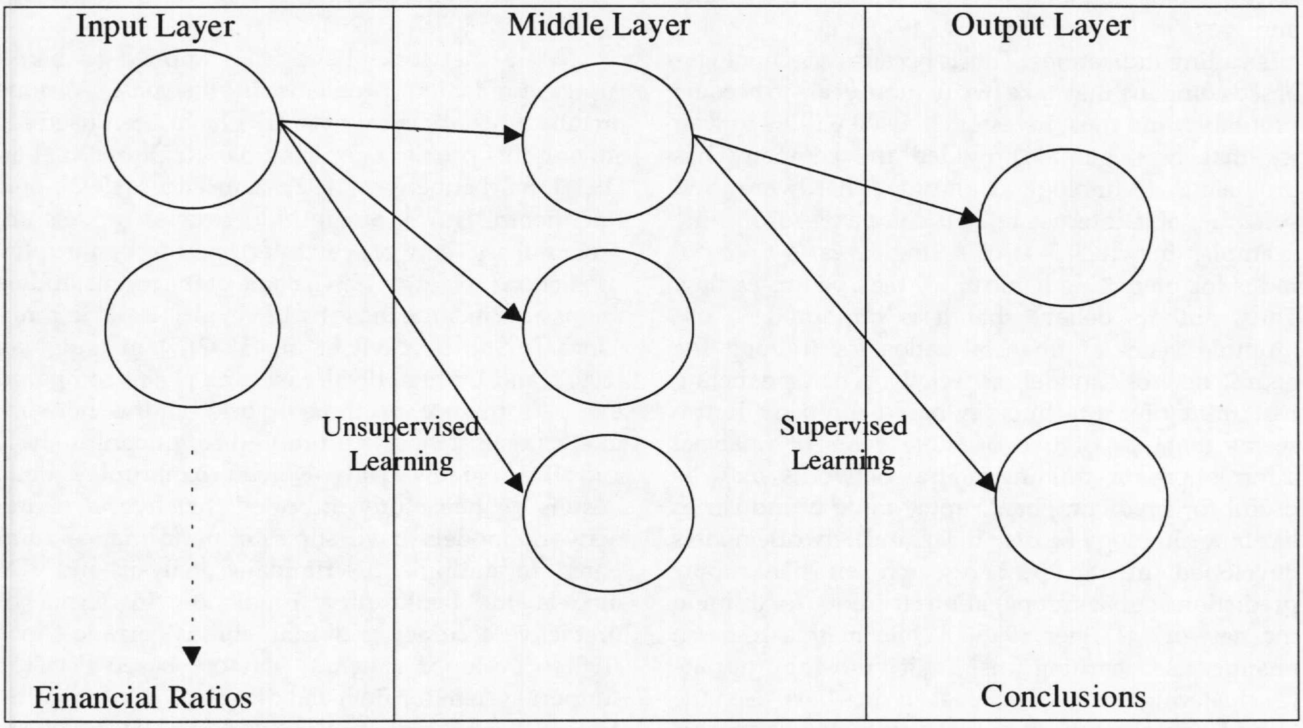
In this research effort, the authors have developed a hybrid neural network model for bankruptcy prediction in the computer-related industry. It is a competitive learning based hybrid unsupervised neural network model that is trained using three successive years of financial ratios. Brief description of this model is provided in the following section.

THE CLUSTERING MODEL

The authors in this research used a clustering procedure that utilizes a neural network. The learning in the neural network is essentially competitive and the network architecture involves three layers (Fig. 1). The connection weights link all the nodes (neurons) on the first layer to all the neurons in the second layer. The neurons of the first layer represent each of the relevant financial ratios listed in the following section and are considered important in predicting bankruptcy of corporations. The number of the second layer neurons are determined during the learning process. The learning data consists primarily of a time series of financial ratios of both types of sample firms: those that subsequently went into bankruptcy and those that did not. The third layer has only two neurons, one representing each type of firms, namely, bankrupt and non-bankrupt. There are connection weights from each second layer neuron to each third layer neuron. The learning is unsupervised for connection weights between first and second layers, and it is supervised for connection weights between second and third layers. This neural network architecture, in essence, resembles the counter-propagation network developed by Hecht-Nielsen [1991]. The neural network training procedure used in this research is presented in Appendix A.

FIGURE 1

Overall architecture of Neural Network based Model (for clarity connections from only one neuron are shown)



Most of the previous neural network applications to bankruptcy prediction use the most recent year's data for network learning. In the present research, previous three years data has been used for learning as this set of data highlights the trend of a firm's economic condition rather than presenting just a snapshot. Once the learning of the model is completed using the three consecutive years data the model is used to predict actual (or fourth year) outcomes for each of the sample firms. An analysis of the predictive power of the model is conducted by comparing the actual event of bankruptcy with that predicted by the model. As a part of this model's performance evaluation, a comparison is made against previous models contained in the literature.

SAMPLE FIRM SELECTION AND DETERMINATION OF FINANCIAL RATIOS FOR PREDICTION

Sixty firms were selected from the Standard Industrial Code (SIC) numbers 3571 to 3578, which include electronic computers, computer storage devices, and computer-related peripheral equipment. All firms were listed on the NYSE, AMEX or NASD stock exchanges. In this sample, 54 firms were financially stable in the fourth year of operations and six firms were known to have gone bankrupt. Bankrupt firms were identified using the Wall Street Journal Annual Index, The New York Times Index, and the Compact Disclosure for the years 1992, 1993, and 1994.

Historical financial ratios were gathered for each firm for a three-year period using data from the Compact Disclosure database. For bankrupt firms, this three-year period was the one prior to the year of bankruptcy, while for the non-bankrupt firms it was the three-year period immediately preceding the study. The following eight ratios were used for prediction of business failure:

1. Current Ratio = Current assets / Current liabilities,
2. Sale/Cash = Net sales / Cash and near cash assets,
3. Receivables Turnover = Net sales or (Net credit sales) / Average accounts receivable,
4. Times Interest Earned = Income before interest and taxes / Interest expense,
5. Total Debt to Equity = Total liabilities / Total assets,
6. Total Assets to Equity = Total assets / Total stockholders equity,
7. Net Income/Net Sales = Net income / Net sales, and
8. Net Income/Common Equity = Net income / Stockholders equity provided by common stockholders.

It should be noted that the above ratios were selected based on the discussion with accounting/finance experts, coupled with prior research results [McKinley et al. 1983; Houghton and Woodliff 1987; Raghupathi 1991; Luther 1998]. The emphasis was mainly placed on cash-related ratios, leverage, the ability to make debt payments when due, and profitability. Consideration was also given to including ratios that are sensitive to issues such as inflation, interest rate changes and credit availability, and economic business cycles. Once selected the above set of ratios were used without elimination or addition over the duration of the study.

RESULTS

The results of the clustering procedure using neural network model indicate that in a sample of 60 firms with six bankrupt and 54 non-bankrupt firms, the model was successful in the prediction of 73% of all firms correctly. Eighty three percent of the sample of bankrupt firms and 72% of non-bankrupt firms were predicted accurately into respective categories in the fourth year of operations. This result appears to perform favorably in comparison with the prediction accuracy of models noted in the literature [Bell et al. 1990; Coats and Franklin 1993; Suh et al. 1994; Raghupathi 1995]. For example, in the closely related work by Bell et al. [1990], it is found that the prediction rate was 99% for a sample of 131 bankrupt firms while only 50% for the 928 non-bankrupt firm sample. The overall prediction rate in their research was 56%.

CONCLUSIONS AND FUTURE RESEARCH

In this research, a neural network based clustering model was successfully applied to predict bankruptcy, which will represent an improvement over current methodologies. The model developed in this research will have an immediate and practical application in the fields of accounting information systems, the state and national regulatory agencies, the banking industry and the securities market.

The neural network based model performs as well as, if not better than extant studies cited in this paper. However, it must be acknowledged that the noted results are limited to the computer and software industry, and a particular set of financial ratios. There is a need for cross-validation of the model and the set of financial ratios used across various industries as significance of these ratios may differ across industry groups [Gibson and Frishkoff 1986]. Thus, a necessary extension of this research will be to apply these models and the set of financial ratios to firms in other industries and cross-validate the results. Some studies have used cash flow variables [Gombola et al. 1987] and nonfinancial factors [Cooper et al. 1991; Lussier 1995] to develop models for bankruptcy prediction. Thus, the performance of the proposed model for

bankruptcy prediction may be improved by including some cash flow variables and nonfinancial factors, in addition to the financial ratios used.

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APPENDIX A - NEURAL NETWORK TRAINING

The neural network training takes place in two steps. The middle layer uses self-organizing map (SOM) learning method [Kohonen 1989]. The input layer is fully connected to a middle layer. In the middle layer, none of the neurons or Processing Elements are connected to each other. The middle layer neurons each measure the Euclidean distance of its weights to the incoming input values. During recall, the middle neuron with the minimum distance is called the winner and has an output of 1.0, while the other middle layer neurons have an output of 0.0. A variation of this competitive output has more than one neuron with small Euclidean distance generate a positive output. Thus, the winning neuron is, in a measurable way, the closest to the input value and thus represents the input vector.

If the input data has M values and is denoted by

$$X = (x_1, x_2, \ldots, x_M), \tag{1}$$

then each middle layer neuron i will also have M weight values and can be denoted by

$$W_i = (w_{i1}, w_{i2}, \ldots, w_{iM}). \tag{2}$$

Now the Euclidean distance D_i is computed for each of the N middle neurons, according to

$$D_i = \|X - W_i\| \tag{3}$$

$$= \sqrt{(x_1 - wi_1)^2 + (x_2 - wi_2)^2 + \ldots + (x_M - wi_M)^2}.$$

The neuron with the lowest value of D_i will be the winner during recall. However, when training the network, the conscience mechanism is used to adjust the distances to encourage neurons that are not winning with an average frequency and, of course, to discourage neurons that are winning at an above average frequency. This conscience mechanism helps develop a uniform data representation in the middle layer.

Once the neuron with the smallest adjusted distance is determined, the weights of a neuron in the winner's neighborhood is adjusted by

$$W_{ij}new = W_{ij}old + \alpha(X_j - W_{ij}old), \tag{4}$$

where α is the learning parameter, usually kept to 0.25 or less.

The training procedure described above is an unsupervised procedure; that is, all we input to the network is the collection of input patterns. As a result, we have no control over exactly which middle layer neuron represents any particular class. In our case, however, having more control over the network result was considered desirable. Therefore, in the third layer (output layer) a supervised learning mechanism was used.

Basic network learning proceeds by computing the Euclidean distances, d_i, between a training vector, x, and each neuron's weight vector, w_i according to

$$d_i = \|w_i - x\| = \left\{ \sum_{j=1}^{N} (w_{ij} - x_j)^2 \right\}^{½} . \tag{5}$$

The winning neuron's weight vector is adjusted according to the following:

$$w' = \begin{cases} w + \alpha(x - w) \text{ if the winning neuron is in the correct class} \\ w - \alpha(x - w) \text{ if the winning neuron is not in correct class.} \end{cases} \tag{6}$$

For the third layer training, a neuron's weight vector is updated only if it correctly classifies an input vector.