A Neural Network Model for Bankruptcy Prediction

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A NEURAL NETWORK MODEL FOR BANKRUPTCY PREDICTION

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ABSTRACT

One interesting area for the use of neural networks is in event prediction. This study develops a neural network model for prediction of bankruptcy and tests it using financial data from various companies. The same set of data is analyzed using a more traditional method of bankruptcy prediction, multivariate discriminant analysis. A comparison of the predictive abilities of both the neural network and the discriminant analysis method is presented. The results show that neural networks might be applicable to this problem.

I. INTRODUCTION

Neural networks have proven to be good at solving many tasks. They may have the most practical effect in the following three areas: modeling and forecasting, signal processing, and expert systems [Lippmann, 1987]. The predictive ability of neural networks falls into the forecasting area. Predictive type problems relate to the auto associative memory of certain neural networks. The method used for neural network prediction is called generalization [Dutta and Shekhar, 1989]. Generalization is different from auto associative memory, in that once the network has been trained, new data is input for the network to predict the output. Previous business applications of neural networks include predicting the ratings of corporate bonds [Dutta and Shekhar, 1989], and emulating mortgage underwriting judgments [Collins, et. al., 1989].

The purpose of this study is to compare the predictive ability of a neural network and multivariate discriminant analysis models in bankruptcy risk prediction. This area has been studied extensively in accounting literature. The first studies were performed to determine whether financial ratios provide useful information [Beaver, 1966; Altman, 1968]. Many different studies have used financial ratios for bankruptcy prediction since that first study by Beaver [1966]. The majority of these later studies use a discriminant analysis approach instead of the univariate approach used by Beaver. Studies which applied discriminant analysis include Altman [1968], Deakin [1972], Blum [1974], Moyer [1977], Altman, et. al. [1977], and Karels and Prakash [1987]. Discriminant analysis is valid only under certain restrictive assumptions, including the requirement for the discriminating variables to be jointly multivariate normal. This multivariate normality of the variables is critical to the discriminant analysis procedure, otherwise, the results obtained may be erroneous [Karel and Prakash, 1987]. Neural networks are not subject to the restriction of normality. A comparison of a neural network model and a discriminant analysis model, in bankruptcy prediction, is worthwhile in that we will be able to compare a new, more robust approach against an established method that makes a priori assumptions about the discriminatory variables.

The importance of failure analysis provides another motivation for this study. Failure analysis using financial ratios is very important for several reasons. First, management can use it to identify potential problems that need attention [Siegel, 1981]. Second, investors use ratios to evaluate a firm. Last, auditors use it as a tool in going-concern evaluation [Altman, 1982]. The American Accounting Association, in A Statement of Basic Accounting Theory, defines accounting as "the process of identifying, measuring, and communicating economic information to permit informed judgments and decisions by users of the information." [1966, p. 1] Ratio analysis is just one means of using accounting data for this purpose. This study will see if neural networks are better predictors of business performance when these same ratios are presented to them.

The approach taken in this study is discussed in the next section. Section 3 is divided into two parts a discussion of the discriminant analysis model and a description of training the neural network model. Section 4 compares the results of the multivariate discriminant analysis model with the results of the neural network model. This is followed by the conclusions of the study and some comments on future studies that may be conducted using neural network models.

II. METHODOLOGY

The purpose of this study is to perform analysis on ratios using both discriminant analysis and a neural network. The Altman [1968] study is used as the standard for comparison for subsequent bankruptcy classification studies using discriminant analysis. For this reason, we have chosen to use the same financial ratios that Altman used in his 1968 study. These ratios are:

X1 Working Capital/Total Assets
X2 Retained Earnings/Total Assets
X3 Earnings before Interest and Taxes/Total Assets
X4 Market Value of Equity/Total Debt
X5 Sales/Total Assets

The sample of firms from which the ratios were obtained consisted of firms that went bankrupt between 1975 and 1982. The sample, obtained from Moody's Industrial Manuals, consisted of a total of 129 firms, 65 of which went bankrupt during the period and 64 nonbankrupt firms matched on industry and year. Two subsamples were developed from this sample of 129 firms. The first (training) subsample of 74 firms data (38 bankrupt firms and 36 nonbankrupt firms) was used as the training set for both methods. The second subsample consisted of 55 firms (27 bankrupt firms and 28 nonbankrupt firms) and was used as the holdout sample. Data used for the bankrupt firms is from the last financial statements issued before the firms declared bankruptcy.

Ratios computed from the data for each original subsample were entered into both a conventional discriminant analysis program and a neural network. The models derived from this original subsample were used to predict the classification for both the training subsample and the holdout subsample.

III. MODELS FOR BANKRUPTCY PREDICTION

Discriminant Analysis

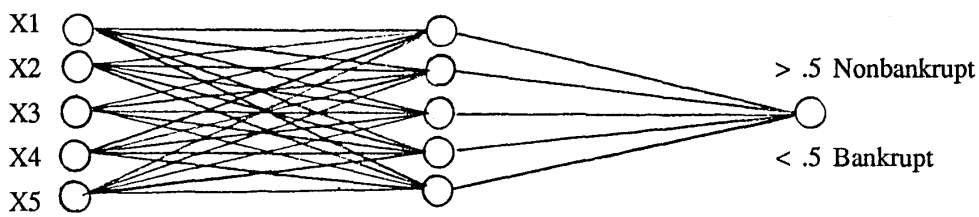
The multivariate statistical technique known as discriminant analysis is by far the most widely used method for bankruptcy risk analysis. The program used in this study was SAS DISCRIM available on the university mainframe computer.

The discriminant analysis method correctly classified 33 of the 38 bankrupt firms for a correct classification rate of 86.84% when using the training subsample. The model correctly classified all of the nonbankrupt firms in the training subsample. While this looks promising, the classification results are based on the same data that was used in model formulation. Therefore, caution should be exercised in assessing the validity of the model at this point.

Neural Network

The neural network used for training was a three perceptron network consisting of an input layer, a hidden layer, and the output layer. The input layer consisted of the five nodes, one for each of the ratios. The hidden layer consisted of 5 nodes. The output layer consisted of only one neuron with a response of 0, representing bankrupt, and 1, representing nonbankrupt. The network was presented with the ratios for the firms. The network classified the data on a scale between 0 and 1. Firms with output below .5 were classified as bankrupt. Firms with output greater than .5 were classified as nonbankrupt.

Figure 1



The neural network was trained by presenting the five ratios for each of the firms in the first subsample and the correct output for each to the network. The learning threshold for the network was .075. The initial learning rate and momentum were .6 and .9, respectively. The learning rate and momentum were adjusted downward as suggested by Lippmann [1987, p. 18] to improve performance during training. The learning rate and momentum at the time of convergence were .1 and .8 respectively.

One problem with the backpropagation rule, as explained in Caudill [1988, p. 58], is the number of iterations needed to learn the data. This criticism held true in this project. Convergence was reached after 191,400 iterations. All of the training was performed on PC-XT. The average time for training was approximately 24 hours. The software used was Neuroshell, release 1.1, a commercial neural network simulator package available for the micro computer from Ward System Group, Inc. This program uses a backpropagation rule neural network. For more in depth description of the backpropagation rule refer to Lippmann [1987, pp. 13-18] and Rummelhart, et. al. [1986, pp. 318-362].

The neural network correctly predicted all 36 of the nonbankrupt firms in the training subsample as nonbankrupt. The trained network also correctly predicted all 38 of the bankrupt firms as bankrupt. This was very promising when compared to the discriminant analysis prediction rates for the training subsample.

IV. COMPARISON OF RESULTS

The results of the multivariate discriminant analysis method and the neural network are presented in Table 1 for the holdout sample only. An analysis of the incorrect classifications that were made by the neural network is presented after explaining Table 1. In order to test the robustness of the discriminant analysis model and the neural network, the training sets were randomly adjusted to be more realistic of the real world ratio of nonbankrupt firms to bankrupt firms. Three separate groups were formed. The original sample with the 50/50 proportion. The second consisted of 36, (80%), nonbankrupt firms and 9, (20%), bankrupt firms. The third group had 36, (90%), nonbankrupt firms and 4, (10%), bankrupt firms. These will be referred to as the 80/20 and 90/10 training sets.

A comparison of the results from the models' predictions for the holdout subsample with the 50/50 training set shows that the discriminant analysis has a correct prediction rate of 59.26% for the bankrupt firms which is well below the correct prediction rate of 81.48% for the neural network. When the training sample was changed to the 80/20 proportion of non-bankrupt to bankrupt firms, the discriminant analysis had a correct prediction rate of 70.37% for the bankrupt firms as compared to the neural network's correct prediction of 77.78%. When the training sample was reduced to the 90/10 proportion, the discriminant analysis had a correct prediction rate of 59.26% and the neural network had a correct prediction rate of 77.78% for the holdout subsample. The neural network appears to be more robust, performing better than the discriminant analysis method in each of the three situations. The neural network also appears to be more consistent than the discriminant analysis method.

The discriminant analysis method correctly predicted 89.29% of the nonbankrupt firms while the neural network predicted 82.14% correctly when trained with the 50/50 sample. Using the 80/20 sample, the discriminant analysis method correctly predicted 85.71% as compared to the neural networks correct prediction rate of 78.57%. However, when the 90/10 sample was used for training, the neural network did better correctly predicting 85.71% of the holdout subsample, while the discriminant analysis method predicted only 78.57%.

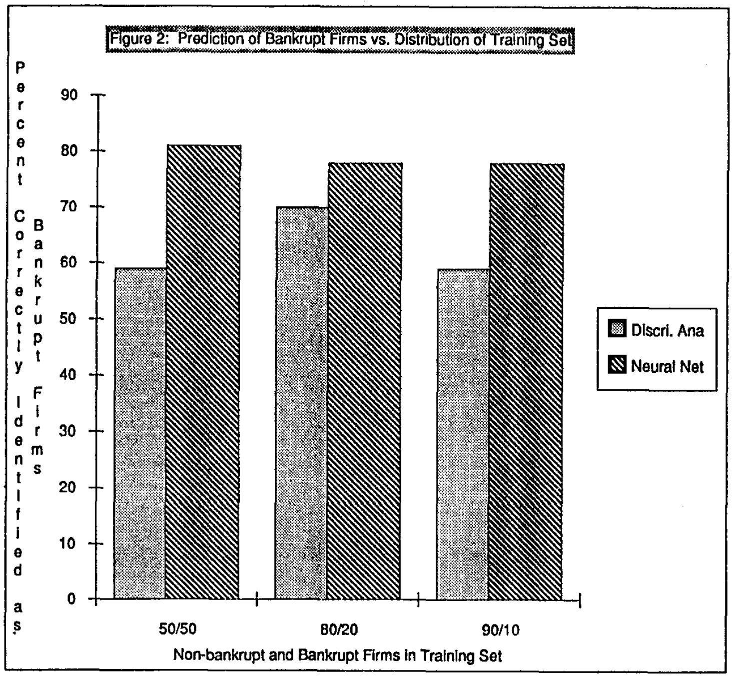
Table 1
Comparison of Discriminant Analysis and Neural Networks on Holdout Sample

Training Sample Proportion		50/50		80/20		90/10	
Model	Actual / Predicted	BR (27)	NBR (28)	BR (27)	NBR (28)	BR (27)	NBR (28)
Neural Network	BR	22 (81.48)	5 (18.51)	21 (77.78)	6 (22.22)	21 (77.78)	6 (22.22)
	NBR	5 (17.86)	23 (82.14)	6 (21.43)	22 (78.57)	4 (14.29)	24 (85.71)
Discrim Analysis	BR	16 (59.26)	11 (40.74)	19 (70.37)	8 (29.63)	16 (59.26)	11 (40.74)
	NBR	3 (10.71)	25 (89.29)	4 (14.29)	24 (85.71)	6 (21.43)	22 (78.57)

BR = Bankrupt, NB = Nonbankrupt, % in parentheses

Further analysis of the incorrect predictions of the neural network revealed that the five bankrupt firms that were incorrectly classified as nonbankrupt were also misclassified by the discriminant analysis model. Of the five nonbankrupt firms that were incorrectly classified by the neural network, as bankrupt, three were also misclassified by the discriminant analysis model and one more was nearly misclassified by this model because it received only a 51.31% probability of membership in the nonbankrupt group. These results show that the firms misclassified by the neural network were also a problem for the discriminant analysis method.

It is more costly to classify a failed firm as nonfailed than to classify a nonfailed firm as failed [Watts and Zimmerman, 1986]. The accountant will be more interested in getting an early indication of a firm heading towards bankruptcy. Figure 2 exhibits the performance of the two models in predicting bankruptcy of a firm as the training set proportions are varied. It clearly states that regardless of the training sample proportions, the neural network model predicted the likelihood of a firm getting into bankruptcy better.



V. CONCLUSIONS

The results obtained from this project show promise in using neural networks for prediction purposes. This research compared neural networks against a method that has become the "rule" in bankruptcy prediction, and the neural network performed better on both the original set of data and on predicting the bankrupt firms in the holdout sample. The neural network proved to be more robust than the discriminant analysis method on reduced sample sizes.

Further research should be done in this area using different ratios to see if the prediction accuracy can be increased. The ratios in this study were based on a study completed in 1968, different ratios may perform better today [Altman, et. al., 1977]. Another area for future research may be in applying different neural network architectures to this problem. Comparison of these other architectures may help to identify the best architecture for this type of problem.

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