Predicting Corporate Bankruptcy using Inter-Connected Artificial Neural Networks

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ABSTRACT: The problem of forecasting corporate bankruptcy is well known to be difficult and previous statistical approaches have not been entirely successful. The approach reported here is to use domain knowledge to select the appropriate data and to determine the structure of a time dependent inter-connected artificial neural network. The paper discusses the methodology for handling the data and designing the network. Results are reported of a trained network that indicate this approach is successful in tackling problem of forecasting corporate failure.

KEYWORDS: Inter-connected neural networks, Domain Knowledge, Data.

1 INTRODUCTION

A number of researchers have investigated the development of the appropriate neural network architecture for predicting corporate bankruptcies (Alici and Valtchanov, 1994; Alici and Gifford, 1995). The current tendency in failure prediction emphasises the use of simple models derived from the financial data one year prior to failure. Much of the research on corporate failure prediction (Alici and Valtchanov, 1994), has concentrated on deriving models from one year prior to failure data of failed companies, for which conventional feedforward backpropagation networks are adequate. There exist alternative architectures for handling time-varying problems in financial modelling. This study proposes a new approach for implementing inter-connected neural networks for handling temporal tendencies in forecasting corporate failure.

An important contribution of this paper is to focus the attention of neural network researchers on the need to continue to search for the appropriate network architecture that will take into account the underlying properties of accounting statements and the changing environments in which most companies operate. The organisation of this paper is as follows; Section 2 provide an overview of previous work; Section 3 explains application development considerations; Section 4 presents our approach and results are presented in section 5.

2 BRIEF REVIEW OF RELEVANT RESEARCH

Corporate failure defies precise definition (Altman, 1968; 1993, Altman et. al., 1976). Financial failure occurs when the enterprise has chronic and serious losses or when the company becomes insolvent with liabilities disproportionate to the assets. The generally accepted reasons for corporate bankruptcy are poor management, autocratic leadership, failure to operate successfully in the market place, or inability to pay debts when due (Altman, 1993; Alici and Valtchanov, 1994, Beaver, 1977). There is no single reason for the collapse of corporate firms.

Beaver (1977) was among the first to use financial ratios to predict corporate bankruptcy using univariate analysis. Using a paired sample analysis, with size and industry type used as basis for pairing, he found overwhelming evidence of differences in the ratios of failed and healthy companies. To test the predictive power of ratios, he used a dichotomous classification technique, and found the cash flow to total debt ratio to be the best predictor of failure. His approach was criticised by a number of commentators (Altman, 1968; Aziz and Lawson, 1988; Casey and Bartczak, 1984) because a univariate technique of forecasting is only capable of picking out trends, and will have considerable difficulty in modelling cycles that are by no means repetitive in amplitude, period or shape.

Altman (1993), improved on Beaver's univariate method of analysis by introducing the multivariate approach, which allows for the simultaneous consideration of five variables in the prediction of corporate failure. The approach is that of the multivariate discriminant analysis (MDA). Discriminant analysis is a statistical technique used to construct classification schemes so as to assign previous unclassified observations to the appropriate group. Altman based his work on groups of appropriate financial reports extracted from company accounting statements. His work (known as Altman's Z-Scores) was expressed as follows:

$$Z = 0.012X_1 + 0.014X_2 + 0.0033X_3 + 0.006X_4 + 0.999X_5$$

In which Z = the overall solvency index and X_1 to X_5 are the independent variables.

X_1 = working capital to total assets
X_2 = retained earnings to total assets
X_3 = earnings before interest and taxes to total assets
X_4 = market value of equity to book value of total assets
X_5 = sales to total assets

Altman used MDA to calculate the numeric values as shown above. The Z values were used to classify companies as either bankrupt or non bankrupt. Where the Z-score was below 1.81, the company was considered to be failing; where it was above 2.99 it was considered to be healthy. The multivariate discriminant analysis had its difficulties, and its limited success can be attributed to one main reason. The standard discriminant analysis procedures assume that the variables used to describe members of the groups of companies being investigated are normally distributed (Alici and Valtchanov, 1994; Alici and Gifford, 1995). This assumption may not be valid especially when modelling the predictions of corporate failure where deviations from the normality assumption appear to be the rule rather than the exception. This implies, that violations of the normality assumptions may bias the test of significance and estimated error rates (Betts and Belhoul, 1987; Altman et.al., 1994; Argenti, 1976). There are other remaining problems that have either not been mentioned or only briefly touched upon.

An alternative approach is one based on artificial neural networks (ANN). This is the approach adopted here. The next section discusses how we collected the data and developed our methodology.

3 APPLICATION DEVELOPMENT CONSIDERATIONS

Developing a successful neural network application involves several stages. The initial stage is collection of data where domain knowledge can be used to select appropriate financial indicators of failure. The effectiveness of neural networks can be affected by spurious data; the solution lies in the research and criteria behind data sources and selection (David et.al., 1997; Duffy, 1997; Nasir et.al., 1996). The stages are narrated succinctly below:

3.1 Sample Determination

Data Sources:
a) The London Stock Exchange
b) Jordans Financial Database
c) The Bank of England
d) The Institute of Directors

Total Sample Size: 270,000 major public and private British companies

Reduction Process:

a) Exclude new firms
b) Exclude small firms
c) Exclude firms by Turnover
d) Exclude firms with small assets
e) Exclude overseas subsidiaries

Selection Criteria:
a) Define period of study
b) Define Bankrupt company
c) Define Non-Bankrupt company

d) Define “mates” category
e) Final selection: 2500 companies

Select Input Variables for:

Balance Sheet Network	(10)	1994	1995	1996
Profit & Loss Network	(8)	1994	1995	1996
Cash Flow Network	(10)	1994	1995	1996
Financial Summary	(6)	1994	1995	1996
Key Financial Ratios	(20)	1994	1995	1996

4 TRAINED NEURAL NETWORK MODEL

The software used for this work is NeuralWare Professional Development Plus/2 System (NeuralWare© NeuralWorks™ 2/Plus v5.30, 1996). The overall environment forms an efficient and easily expandable tool for methodological development. The tool allows selection from any of the major network types to create any of the 28 major paradigms and dozens of variations well supported by the product.

Our chosen model is made of a series of inter-connected networks each connected to its immediate neighbours. Thus the hidden layer in 1995 receive additional input from the 1994 network and the hidden of 1996 receive additional input from the 1995 network and provide an encoding of a three year period. There is a feedforward connection between the input units to the first hidden layer and full connection between the two hidden layers. High level topology captures temporal nature of data. Low level (i.e. connection between input units to the first hidden layer) topology of sub-networks uses domain knowledge. Figure 1 shows the chosen structure.

The network was trained with eighteen hidden units. Using standard error, we chose Hyperbolic Tangent (TanH) as the transfer function. The network learning was the learning Norm-Cum-Delta Rule. The global learning schedule is shown Table 1 below:

	1	2	3	4	5
Learning Count	50000	45000	60000	10000	10000
Momentum	0.20	0.10	0.20	0.30	0.40
Error Tolerance	0.10	0.10	0.10	0.10	0.10
Noise Decay	0.01	0.01	0.01	0.01	0.01
Learning Rate	0.10	0.20	0.10	0.10	0.20

Table: 1: Global Learning Schedule

The data was in three sets - 1400 companies in the training set, 400 companies in the test, and 700 companies in the validation set. The test set is then used to evaluate network performance. Validation set (unseen) is merely used to validate the network. Using the measurements of 58 input variables of 2500 companies, a backpropagation network (inter-connected) as shown in Figure 1 was successfully trained after 175,000 iterations.

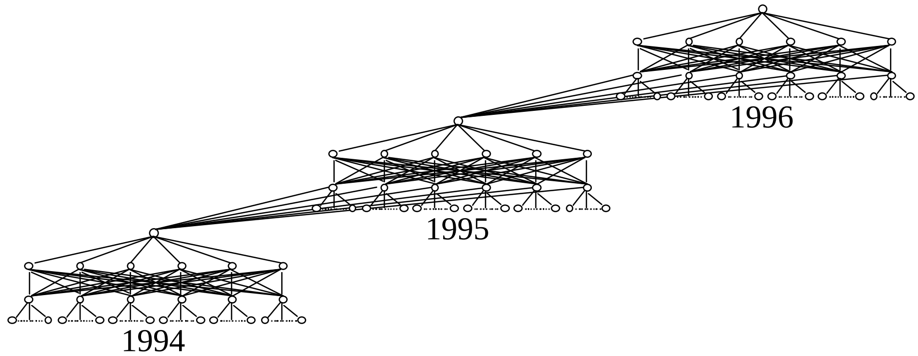

Figure: 1. Structure of the inter-connected neural sub-networks

6 RESULTS

The results generated represent training cases for 2500 companies. The input measurements used were 58, representing the Cash Flow network, Profit and Loss Statement network, Balance Sheet Network, Key Financial Ratios Network, Financial Summary Network, and Economic and Political factors Network. When evaluating the predictive capability of the neural network, a testing threshold, similar to the training tolerance, is specified. This testing threshold identifies how stringent the allowable variation in output neurons can be when predicting the status of the companies in the training set. In this study, two testing threshold were used; 0.1 and 0.9 and 0.05 and 0.95. This basis was used for correct and incorrect classifications for the neural network model. When checking the neuron output for both criteria, the network achieved the following results:

Classification Criteria	0.1 and 0.90				
No of Bankrupt	71				
No of Healthy	329				
% Bankrupt right	82	% bankrupt wrong	6	% bankrupt don't know	12
% Healthy right	92	% healthy wrong	1	% healthy don't know	7
Classification Criteria	0.05 and 0.95				
No of Bankrupt	71				
No of Healthy	329				
% Bankrupt right	66	% bankrupt wrong	6	% bankrupt don't know	28
% Healthy right	87	% healthy wrong	1	% healthy don't know	12

Table 2: Neural Network Results

As revealed in Table 2 above, there were 71 bankrupt companies and 329 healthy companies. Using the 0.1 and 0.90 criteria, the network correctly classified 82% of bankrupt companies and returning 12% as don't knows. The network misclassified 6% of bankrupt companies. Looking at the healthy companies, the network correctly classified 92% of healthy companies and returning 7% as don't knows. The network misclassified 1% of bankrupt companies. Using a more stringent criteria; 0.05 and 0.95, the network correctly classified 66% of bankrupt companies and returning 28% as don't knows. The network misclassified 6% of bankrupt companies. The network correctly classified 87% of healthy companies and returning 12% as don't knows. The network misclassified 1% of healthy companies. The level of accuracy shown above is encouraging. Having said that, it must be remembered that our chosen complex network was trained on a large amounts of data set. Backpropagation networks are notoriously difficult to train when large data sets are introduced (Denoeux and Lengelle, 1993). Improvement will be directed towards the numbers of don't knows and the small percentage of misclassifications.

7 CONCLUDING REMARKS

This paper has shown that neural networks can perform well in the domain of corporate failure prediction. Empirical results suggest that artificial neural networks can perform better than its classical counterparts where noisy and random environment exists. We have therefore shown that, a wide range of cases can be included in modelling corporate failure and yet obtain better results than has ever been published. Backpropagation networks are notoriously difficult to train where large data set is introduced. We have been able to overcome some of the known difficulties by introducing piecemeal iterations to the network and also, by appropriating training parameters.

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