Predicting Stock Price Performance: A Neural Network Approach

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Abstract

The prediction of stock price performance is a difficult and complex problem. Multivariate analytical techniques using both quantitative and qualitative variables have repeatedly been used to help form the basis of investor stock price expectations and, hence, influence investment decision making. However, the performance of multivariate analytical techniques is often less than conclusive and needs to be improved to more accurately forecast stock price performance. A neural network method has demonstrated its capability of addressing complex problems. A neural network method may be able to enhance an investor's forecasting ability. The purpose of this paper is to examine the capability of a neural network method and compares its predictive power with that of multiple discriminant analysis methods.

1. Introduction

The prediction of stock price performance involves the interaction of many variables, making prediction very difficult and complex. Many analysts and investors use financial statement data to assist in projecting future stock price trends. Qualitative information, while not as easily interpreted, may also have an effect on investment value. Both quantitative and qualitative variables help form the basis of investor stock price expectations and, hence, influence investment decision making.

The multivariate analytical techniques using both quantitative and qualitative variables have repeatedly been used in finance and investments. However, the performance of multivariate analytical techniques is often less than conclusive and needs to be improved for more accurately forecasting stock price performance.

The Neural Network (NN) method has demonstrated its capability of addressing problems with a great deal of complexity. The neural network method may be able to enhance an investor's forecasting ability. However, comparatively few applications [8] [12] [13], using the neural network, have been attempted in finance.

The purpose of this paper is to apply the Neural Network (NN) approach to a dynamic and complex problem in a business environment and to investigate its ability to predict stock price performance. It also illustrates the methodology of applying this approach and compares its predictive power with that of multiple discriminant analysis (MDA) methods.

2. Literative Review

Discriminant analysis techniques are used to classify a set of independent variables into two or more mutually exclusive categories. It involves finding a linear combination of independent variables that reflect large differences in group means. The technique can be used for description as well as prediction.

Multivariate analytical techniques have repeatedly been used in finance. Applications are found in corporate finance, banking, and investments. Crediting scoring of loan applications to estimate the probability of consumer or corporate default and bond rating analysis are examples of discriminant analysis applications in the finance discipline.

Perhaps the best known, seminal work in the field of multiple discriminant analysis (MDA) methodology applied to finance was conducted by Edward I. Altman [1]. Altman's use of multiple discriminant analytical techniques focused on predicting corporate bankruptcy. After several early attempts, he settled on a discriminant model that contained five financial ratios that were used

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as independent variables. The model could reasonably predict corporate bankruptcy for up to two years in the future. Subsequent development and refinement of the model increased the two-year accuracy level and obtained a 70 percent accuracy rate for up to five years in the future [2]. A drawback of this linear approach is that it classifies some firms as likely to go bankrupt when in actuality, they do not.

Since Altman's original work, there have been numerous attempts by researchers to modify and enhance his MDA model. Some of the results have been successful, while others have not. Gentry, Newbold, and Whitford [10] found that adding cash-based funds flow components to Altman's model provided superior results in predicting financial failure. They also concluded that cash outflow components were more closely related than cash inflow components to corporate failure.

Meyer and Pifer's method of predicting corporate bankruptcy utilized the same financial ratios as were found in Altman's model, but added financial data from more than one period prior to failure to determine a time trend. Collins [7] tested both models, using credit union financial data and concluded that this approach adds little, if anything, to Altman's model.

Altman and Spivack compared the Value Line relative financial strength system and the zeta bankruptcy classification methods of predicting corporate bankruptcy [3]. Their findings reveal that although significant methodological differences do exist, a high correlation between the methods is evident and that bond systems' scores correlate well with published bond ratings.

Pinches and Mingo [15] and others utilized the MDA concept to classify industrial bonds into multiple categories, using multiple independent variables. Most of these attempts have utilized quantitative financial variables to construct the model with reasonably good predictive results.

Direct applications of the use of the MDA technique to enhance corporate performance are found in the literature. An example is given by La Fleur Corporation, who finding financial ruin at their doorstep, worked Altman's model backwards to turn the company around [4].

While most of the development of MDA techniques involves the use of quantitative financial data, other approaches using qualitative assessments have been used in finance. Forecasting how a firm's stock will perform in equity markets, using qualitative variables found in the firm's annual report to the stockholders, has recently been attempted. McConnell, Haslem, and Gibson [14] and Swales [17] have found that qualitative data can provide additional information to forecast stock price performance.

As indicated above, using qualitative information to supplement an investor's forecasting ability in equity markets is beneficial. This type of information is often overlooked by investors, perhaps due to its subjective, not readily interpreted, form. While these techniques are valuable, other methods using non-linear approaches may further enhance forecasting ability.

3. Research Question

The studies mentioned above have generally indicated that multiple discriminant analysis, as used in the finance discipline, can be a valuable tool to the decision maker. It has also been recognized that qualitative information can enhance an investor's stock price forecasting ability.

Given the above factors, can non-linear methods significantly enhance an MDA model's stock price predictive power? Specifically, how does multiple discriminant analysis compare with the neural network approach in forecasting stock price performance? Additionally, can the use of neural network methods enhance the results of a recently published study which used multiple discriminant analysis to assess the investor's ability to forecast stock price performance. These questions are addressed in the paragraphs that follow.

4. Description of the Data

As mentioned earlier, qualitative variables can provide an often neglected source of valuable information to the investor. Two independent research groups presented the results of the multiple discriminant analysis method which used qualitative information found in the firm's annual report to the stockholder [14] [17]. The study conducted by Swales serves as the basis for the application of the neural network approach, which this paper addresses.

The data used in this study was gathered from two information sources frequently used by investors: The <u>Fortune 500</u> and <u>Business Week</u>'s "Top 1000" [18] [19]. These sources provide total return (dividends and stock price appreciation) and market valuation data, respectively, for widely-followed companies. A stock's total return and market valuation are used by investors and financial analysts as performance measures.

For this experiment, two separate sets of data were gathered. From the <u>Fortune 500</u> forms, five industries that offered investors the highest total returns in each year were selected; the sample consisted of 58 companies. The 10 industries that were reported by Business Week to have the highest market valuations provided the data for the second set; 40 firms were included in this sample. It was felt that, if differences across firms could be found among the top industries, then more pronounced differences were likely to exist in industries further down the line.

We classified the Fortune set of companies into two groups according to their total return. Group 1 provided investors with the highest total returns in their respective industries; Group 2 provided the lowest returns in their industries. We classified the Business Week set of 40 companies in each of 10 industries into two groups. Again, Group 1 consisted of those firms with the highest market valuations for their industries; Group 2 consisted of those firms with the lowest market valuations for their industries.

For each company in the study, the president's letter to stockholders from the annual report for the period immediately prior to the group selection year was studied. A qualitative content analysis technique was used to classify and tally recurring themes that were identified by similar word or phrases. An examination of president's letters to stockholders identified nine recurring themes commonly addressed in discussion of the future. These themes included reference to confidence, economic factors outside the firm's control, growth, strategic plans, new products, anticipated losses, anticipated gains, long-term optimism and short-term optimism.

Each letter was read for content and references to the themes noted above. The frequency and percentage of each letter devoted to these themes was then recorded. When the letter did not contain a specific, direct reference to one of the themes, a subjective judgment was made by the researcher as to which, if any, theme should be credited with the phrase or statement. In those instances when reference was not made to a theme(s) in the letter, the data set reflected this finding. The frequency data set was then used for both MDA techniques and NN methods to predict stock price performance.

Content analysis techniques have been widely used in the social sciences [5]. Financial researchers have also applied these techniques to analyze narrative components of financial reports [6] [9] [14] [17]. Refer to [14] [17] for further details of the content analysis technique used to analyze the president's letter to stockholders.

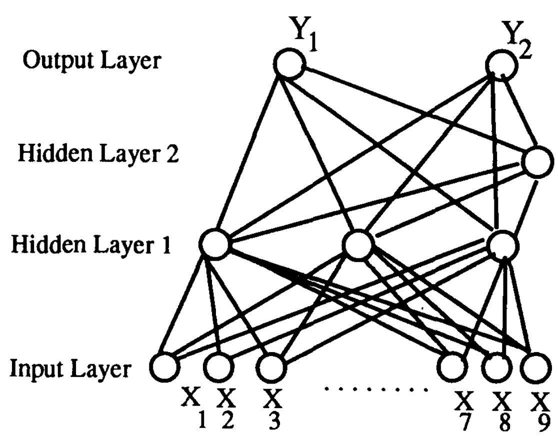
5. Neural Network Model

5.1 Design of the Network

The neural network (NN) model is structured in a four-layered network, as shown in Figure 1: an input layer, two hidden layers, and an output layer. An input unit has excitatory (positive) or inhibitory (negative) connections to a hidden unit in the hidden layer, and a hidden unit has connections to an output unit in the output layer. Therefore, an input unit in this network structure has indirect connections to an output unit.

Input for the network was a list of nine variables: confidence, economic factors outside the firm's control, growth, strategic gains, new products, anticipated loss, anticipated gain, long-term optimism and short-term optimism. Output was a classification of two patterns: a firm whose stock price performed well and a firm whose stock price performed poorly. In a network, each input parameter is represented in an input unit. Therefore, the network has the nine input units in the input layer and the two output units in the output layer. The number of hidden units necessary to accurately predict the stock price performance was determined empirically.

Figure 1:
Four-Layered Network



The network for the prediction of stock price performance uses the following nine input (X_1 - X_9) and two output (Y_1 - Y_2) parameters.

Input Parameters:	Output Parameters:
X_1: Confidence	Y_1: well-performing firms
X_2: Economic factors	Y_2: poorly-performing firms
X_3: Growth	
X_4: Strategic plans	
X_5: New products	
X_6: Anticipated loss	
X_7: Anticipated gains	
X_8: Long-term optimism	
X_9: Short-term optimism	

5.2 Learning Process

Once a network structure was developed, a set of initial weights was assigned at random. Then, the Back Propagation Learning Algorithm (BPLA) [16] was used with the Fortune set to estimate the weights of the feed forward network. In this algorithm, the input vector with nine input values was assigned as the activation vector of the input layer. The activation vector of an input layer propagates forward to the upper layer as the product of weights on the interconnections and the activation values. A sigmoid function in equation 1 was used to compute the activation value of a unit, A_j, on the upper layer.

$$A_j^{(L)} = \frac{1}{1 + Exp\left(\sum_{i=0}^{n} W_{ji}\ A_i^{(L-1)} - \theta_j^{(L)}\right)} \qquad [1]$$

If the upper layer is not an output layer, its activation vector propagates forward to the higher layer in a network in the same manner. The superscript L and L-1 represents an upper and lower layer, respectively. If the upper layer is an output layer, an activation value of each output unit is compared to the desired one and the error is measured according to

$$E = \frac{1}{2} \sum_{j=0}^{n} (D_j - A_j)^2 \qquad [2]$$

The learning algorithm iteratively modifies the set of weights in order to reduce this error. Thus, BPLA is a gradient descent algorithm in which weights in the network are iteratively modified to minimize the overall mean square error between desired and actual output values for all output units over all input patterns. The amount the weights are to be adjusted for each input pattern is determined by the derivative of the error function in equation 2 with respect to the weight as follows.

$$\Delta W_{ji} \propto -\frac{\partial E}{\partial W_{ji}} \qquad [3]$$

This derivative yields the error signal,

$$\delta_j = (D_j - A_j)\ A_j\ (1 - A_j) \qquad [4]$$

for an output unit, and

$$\delta_j = A_j\ (1 - A_j) \sum_{k=0}^{n} \delta_k\ W_{kj} \qquad [5]$$

for hidden units.

Finally, the connection weight between the jth unit in the Lth layer and the ith unit in the L-1st layer is modified according to

$$\Delta W_{ji} = \alpha\ \delta_j^{(L)}\ A_i^{(L-1)} \qquad [6]$$

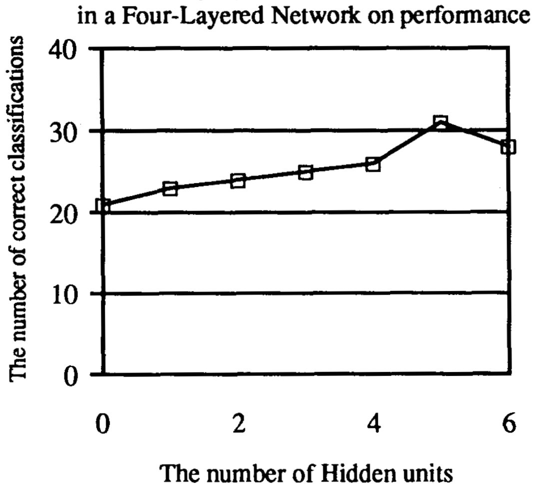
where δ_j is defined above, A_i is the activation values of the ith unit, and α is the learning rate, which is used to control the speed of the training process. For further details and discussions of BPLA, see Rumelhart [16]. In this experiment, the initial training data consisted of 58 cases in the Fortune set. A small learning rate of $\alpha = 0.1$ was used. The experiment was conducted on a VAX 11/750 using the C programming language.

6. Results

The performance of the trained network was tested with the Business Week set which contains 40 cases. In the first experiment, the effect of varying the number of hidden units in a four-layered network was tested. The result of this experiment is represented in Figure 2. In a four-layered network, performance improved as the number of hidden units increased up to a certain point. This supports previous findings on the importance of the hidden layer for the different applications [11] [20]. The best performance was achieved by a network with four hidden units on the first hidden layer and one hidden unit on the second hidden layer. Increasing the number of hidden units beyond this point produced no further improvement, but impaired the network's performance.

Figure 2

Effect of varying the number of Hidden units in a Four-Layered Network on performance



The performance of the NN model was also compared with that of MDA. Table 1 summarizes the result of this experiment. The report includes the performance of MDA and four-layered network on a training data set, as well as a testing data set, to demonstrate the important aspects of this study. The value indicates that MDA resulted in a 74 percent mean posterior membership probability for the training set: 21 of the 29 companies were correctly classified into Group 1, while 22 of the 29 companies were correctly classified into Group 2. However, during the testing phase, the model yielded only an overall 65 percent success rate for the testing data set: 14 and 12 of the 20 companies were correctly classified into Group 1 and 2, respectively.

The four-layered network correctly classified 91 percent of the mean training data and appropriately predicted 77.5 percent of the mean testing data: 18 of 20 companies were correctly classified into Group 1, whereas 13 of 20 companies were correctly classified into Group 2. During the training phase, the MDA model provided better predictive capability for firms in the lower performance category than for firms in the higher performance category. However, during the testing phase, all models demonstrated better predictive capability for firms in the higher performance category.

Table 1:
Performance of the MDA and Four-Layered Network on the training and testing data.

Models	Training Data			Testing Data		
	Group 1	Group 2	Mean	Group 1	Group 2	Mean
MDA	72%	76%	74%	70%	60%	65%
Four-Layer	86%	96%	91%	90%	65%	77.5%

This study shows that the mean success rate during the testing phase for the four-layered network was 77.5 percent as compared with 65 percent for the MDA technique. This result shows that a NN method significantly enhanced the MDA model's stock price predictive power. Dutta and Shekhar [8] also reported the better performance in rating bonds by the NN approach than by the regression method. The higher performance of the four-layered NN model indicates that this non-linear technique with hidden units in the network was a more appropriate method to use to forecast stock price performance than the multiple discriminant analysis method.

However, the NN approach demonstrates a limitation. In general, MDA is useful for both descriptions, as well as predictions, since it can explain the characteristics of each group and the significance of each input parameter. In the NN model, it is a difficult task to analyze the characteristics of each group and the importance of input parameters in a NN model due to the hidden units employed in the network. The hidden unit is useful to extract the high-order mapping function between output and input; however, it makes separating the contribution of each input parameter to the output value very difficult.

7. Concluding Remarks

The study demonstrated that the neural network approach is capable of learning a function that maps input to output and encoding it in the magnitudes of the weights in the network's connection. The number of hidden units employed in the network contributed to its viability. The increase in the number of hidden units resulted in higher performance up to a certain point. However, additional hidden units beyond the point impaired the model's performance. Comparison of the NN technique with the MDA approach, indicated that the NN approach can significantly improve the predictability of stock price performance.

While some limitations of this approach were noted, it is evident that its use can improve an investor's decision making capability. Further research into the application of neural network techniques, using both quantitative and qualitative data, is suggested and encouraged.

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