ARTIFICIAL NEURAL SYSTEMS: A NECESSARY TOOL FOR FINANCIAL DECISION MAKING

BY

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Abstract

Artificial Neural Systems (ANS) is a computer program that simulates the processes by which human learning and intuition take place. Artificial Neural Systems are well suited to deal with output. In particular, artifial neural systems are most effectively applied to three areas - classification, associative memory and clustering. In the area of financial decision making, some poteential applications include assessment of bankruptcy risk, identification of arbitrage opportunities and technical fundamental analysis.

1.0 INTRODUCTION

Most of the attention of artificial intelligence application has largely been confined to Expert Systems (ES). While ES have been successfully applied to some financial decision task, there are many others that are beyond the scope of ES technology. The disadvantages of ES include difficulty of programming and maintaining the system, the enormous time and effort required to extract that knowledge base from human experts and translate it into the IF-THEN rules upon which the system is based, and the inability of an ES to use inductive learning and inference to adapt the rule base to changing situations. ES are cost effective only for frequently recurring problems of very narrow scope that can be solved by a knowledge base that is essentially static.

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Many of these problems could be solved by another product of artificial intelligence research the Artificial Neural Systems (ANS), also known as an artificial neural networks, electronic neural networks, electronic neural networks or neural nets.

A neural network attempts to model human intuition by simulating the physical process upon which intuition is based that is simulating the process of adaptive biological learning (although on a much less complex scale). A neural network is theoretically capable of producing a proper response to a given problem (or the best possible response, when more than one response is applicable) even when the information is noisy or incomplete or when there is no set procedure for solving the problem. Thus neural networks exhibits abilities such as learning, generalisation and abstraction. Neural networks are most effectively applied to three tasks (all based primarily on pattern recognition) - classification, associative memory and clustering.

Most decision faced by top level financial managers, are highly unstructured in nature and not easily adapted to conventional methods of computer aided analysis and decision support. The manager may have to rely upon incomplete, ambiguous, partially incorrect or irrelevant information tio make decisions. The manager may not be able to justify his decision process, or break it down in a step-by-step manner. Artificial neural networks are best applied to problem environments that are highly unstructured, require some form of pattern recognition and may involve incomplete or corrupted data.

In the following sections we outline some of the potential applications of ANS in solving problems faced by corporate financial managers, financial institutions and professional investors.

2.0 Corporate Finance

2.1 Financial Simulation

The financial structure of any business operation constitutes an immensely complex and dynamic environment. While financial management tasks can be broken down conceptually and functionally into a number of subtasks, the interrelations between these subtasks are still enormously complex. Artificial neural systems can be used to creat models of segments of the corporate financial environment. Such models can be:

(1) specific to a particular company,

(2) dynamic with respect to changes in the financial strúcture of the company over time and

(3) reflective of the relations between the segment modeled, other company and the external business environment.

A ANS might, for example, be created to simulate the behaviour of firm's credit customers as economic conditions change. The input vectors could consist of economic data and customer-specific data, and the output could be the expected purchase/payment behaviour of the customer given the input conditions. Training data would be based on actual behaviour of customer in the past. Such system would be useful for planning for bad-debt expenses and the cyclical expansion and contraction of accounts receivable and for evaluating the credit terms and limits assigned to individual customer.

Neural net simulations might also be designed for many other segments of the firm's financial environment, such as cash management, evaluation of capital investments, asset and personnel risk management (insurance), exchange rate, risk management, and prediction of credit costs and availability based on the firm's financial data. The potential for ANS application in corporate financial management may well lie in simulations of this sort.

2.2 Prediction

Some of tasks involving financial forecasting can be performed more efficiently using conventional computers and software rather than neural networks. This is particularly true of those tasks involving complex numerical calculations using well indentified models. However, the financial analyst is always concerned with the effects of certain actions on the behaviour of investors.

Investors do not reach to isolated bits of information about company; they are, rather influecned by the comprehensive body of information concerning all aspects of the company. It may be possible to train anADS to mimic the behaviour of investors in response to changes in the collective financial condition policies of the company. Using actual investors as training models, one might create an ANS that could simulate investors' reactions to, say, changes in dividend policy, accounting methods, reported earnings, capital structure, or any other items of interest. Past studies of this sort have relied primarily on changes in stock price to gauge decision investors may reach in many ways other than buying or selling stock. An ANS could improve the financial analyst's ability to predict investor reactions to changes in corporate financial policy.

2.3 Evaluation

It should be possible to train an ANS to estimate a value for eacquisition targets based on the target's financial information. The training procedure would involve both an input vector consisting of financial information concerning the target company and a target output consisting of the acquisition value estimate of a human expert. The objective of the ADS would be to simulate the evaluation process used by the human expert in order to derive for any target a value estimate that would be comparable to the estimates of a human expert.

The system could also be trained to select desirable acquisition targets on the basis of criteria other than simple valuation-criteria, for example, known only to the human expert and involving perhaps "hunches" or personal preferences. That is, the system would learn to mimic the idiosyncrasies and intuition of the human expert without depending on defiable rule or programmable logic in the process. The numerous benefits of such a system would include the following

1. The system could be used to screen a very large number of companies for undervaluation or desirability for acquisition. The decision-maker would save much time by looking only at companies that were closest to the "ideal" acquisition target.

2. Because the system would not depend on preprogrammed rules or a set knowledge base, it could easily adapt to mimic

the evaluation techniques of any decision-maker.

3. The system would automatically adapt to changes in a decision-maker's analytical procedures and selection criteria over time.

An expert system could conceivably perform a similar task, but it would be severely limited in comparison with an ANS. The ES would require knowledge base extracted from the human expert, and it is unlikely that such a knowledge base would incorporate all the subjective elements and idiosyncrasies of the expert's decision process. Even if it did, the resulting ES could not adaptto changes in personal preferences or selection criteria (or could not be adapted without substantial reprogramming costs and delays).

2.4 Credit Approval

While the tasks of approving customers for credit and assigning credit limits by staff, is still a labour-intensive and time-consuming process that has a significant impact on the profitability of most companies. Approval procedures based on credit scoring can be successfully implemented with conventional computer equipment and software, but such systems cannot incorporate the subjective and otherwise non quantifiable elements of a human's decision process. In addition, much of the information concerning customers does not come to the decision-maker in a standard format (e.g., Twiga Cement Company credit reports have a standardized form, but financial statements display a remarkable diversity).

An ANS could be trained using customer data as the input vector and the actual decisions of the credit analyst as the desired output vector. The objective of the system would be to mimic the human decision-maker in granting or revoking credit and setting limits. In addition, the system would be able to deal with the diversity of input information without requiring that the information be restated in a standard form.

3.0 Financial Institutions

3.1 Assessing Lending/Bankruptcy Risk

The credit approval system described above would be applicable in commercial and consumer lending as well. The diversity of loan applicants and lending arrangements encountered by most lending institution could be handled quite efficiently in an ANS environment. While the ANS may not be used to make the final decision on loans of major importance to the institution, its outputcould be viewed as one more expert opinion included in the decision process.

3.2 Security/Asset Portfolio Management

Financial institutions must manage a wide variety of investment portfolios involving many types of assets-stocks, bonds, mortgages, real estates, market timing, tax effects, maturity structure and many other variables must be made almost continuously. For trust departments in large banks, this can be an enormously tasks involving many people. The task is complicated even more by the constant
fluctuation of the financial and economic environment. Given the unstructured nature of the portfolio manager's decision processes, the uncertainty of the economic environment and the diversity of information

involved, this would be an appropriate arena for a neural network implementation.

4.0 Professional Investors

4.1 Identification of Arbitrage Opportunities

Consider an analyst who specializes in the identification of hostile take over targets in advance of tender offer announcements. This analyst's selection of likely targets, and therefore desirable investments, depends on many bits of information and a good amount of personal experience and judgement. An ANS could be trained to assist the analyst in the identification task by observing the actual decision he/she makes and the errors that those decisions have produced. After training, the ANS could improve upon the efficiency of the analyst by increasing the number of companies that can be examined in a given time span, thus allowing more thorough screening and more frequent updating of each company's evaluation. Even a small improvement in the performance of the decision-maker could result in substantial improvement in profitability.

4.2 Technical Analysis

Technical analysis, with the objective of predicting future short-term movements in stock prices based on patterns in ex post price and volume data, has been the subject of much research but has achieved almost no emperical support. Even so many professional and private investors use technical analysis as a primary investment-selection tool. This group has long voiced the opinion that emperical studies of technical analysis have failed to corroborate its usefulness because they applied it in an isolated, incomplete or erroneous manner and because the researchers lack the necessary level of experience, and the intuition it brings, to use technical analysis effectively. These investors believe that the intuition of the experienced analyst, not the blind application of a selection procedure or formular, is the key to success; someone has to interpret the data, recognize the important patterns and make the predictions. Market technicians may also argue that a successful technical analyst is unlikely to divulge the nature of his or her techniques to researchers, because any "edge" the techniques afford the analyst may be destroyed if other investors begin to use them. Consequently, researchers may have been studying a set of analysis tools that is missing the most important parts.

While the pattern-recognition capabilities of neural nets suggests possibilities for the application of ANS technology to research studies concerning technical analysis, it is likely that the most beneficial applications would be designed by and for the technicians themselves. If an ANS could be trained to simulate the experience-based intuition of a successful technician, it could result in a substantial increase in the number of stocks that could be analyzed in real time. While a similar result could probably be achieved with an expert system, the technician would have to divulge valuable information to a knowledge engineer and the resulting system could not be easily adapted to changes in the market environment or the prerogatives of the analyst. The special abilities of neural nets would be very well-adapted to this particular application.

4.3 Fundamental Analysis

Since fundamental analysis requires judgement and intuition based on experience (although possibly to lesser extent than technical analysis), this area offers great promise for successful ANS applications. Given the vast amount of information that can be involved for each company at each time point, the parallel processing capability or artificial neural systems offer a very important potential advantage in this area. Much more so than for technical analysis, the inputs for fundamental analysis are parallel in nature. An input data vector for one company could include all the raw data from many years of financial statement, current and historical market and economic data, industry average and more. The ANS could be trained to evaluate stocks using these inputs and the analyst's own evaluations as the target output vector. As with technical analysis, the goal of the system would be to improve upon the efficiency of the analyst by allowing analysis of a greater number of stocks and more frequent updates.

5.0 Relevance of the ANS technology to Third World Countries

It is worth noting that a lot of research has been going on Artificial Neural Networks in the last decade. Most of them being confined to the pattern recognition where substantial success has been achieved. Recognition of characters and handwriting has immediate use in banking, credit card processing, and other financial services where reading and recognizing handwriting on documents is crucial.

Some research has been going on in the application of the ANS technology to business sector and particulary to financial decision making. A number of software have been developed for use in financial decision making such as those which can assess the risk of mortgage loans and rate the quality of corporate bonds to mention a few. Once ANS are trained they do not need specialized training to be able to use them. They may not be as user friendly, but they are easy to learnand use. They do not need specialized hardware, most of todays Personal Computers can be used.

Looking at the changes in technology and the environment in the business sector, it is high time now for third world countries to start not only exploring the possibility of acquiring ANS but using them. It is a technology third world countries are going to need for the 21st century if at all they want to compete in world trade.

6.0 Conclusions

We hope that the preceding discussion will stimulate financial managers and researchers to recognize that artificial neural nets offer great potential for improvements in productivity and efficiency. The necessary technology exists, and significant improvements will certain continue in the years ahead. It is quite possible that the development of artificial neural networks will prove to be one of the most important, practical and fruitful endeavours in finance in the this decade. And according to optimistic predictions, by the year 2000, Neural Networks Technology will account for half the total revenues of the robotics and computer markets.

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