NEURAL NETWORKS IN AGRICULTURAL CREDIT MARKETS

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INTRODUCTION

Artificial neural networks are a new class of tools for analysis that have recently become available. Neural networks are based on biological computing—the activity of neurons. However, artificial neural networks are not intended to replicate neurons. Artificial neural networks are intended to mimic the abilities of a biological computer. Neural networks can substitute for statistical methods and nonlinear programming and have been shown to outperform these methods (Trippi and Turban). However, neural networks do not always provide as much information as statistical or programming methods and are not necessarily superior nor perfect substitutes. Neural networks may not supplant our current analysis tools, but may be a valuable addition to consider.

Neural networks have been applied commercially in financial markets. Trippi and Lee state, "Financial organizations are now the second-greatest sponsors of research in neural net applications (after the Department of Defense, which in 1989 embarked on a five-year, multimillion-dollar program for neural network research)." Bauer states that 80% of the Fortune 500 have investments in neural networks. Neural nets have been commercially implemented to make risk classification decisions in the mortgage insurance underwriting field, to score consumer and business credit, and to monitor credit card fraud (Trippi and Lee, Bauer, Trippi and Turban). Thus, the application of neural networks in agricultural credit markets is important to investigate.

The objectives of this paper are to:

- relate the history of neural computing and artificial neural networks,
- highlight potential applications in agricultural credit markets, and
- describe a typical neural network.

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HISTORY

The artificial neural networks used in financial analyses today are a by-product of research about the human brain. The jargon of neural networks is derived from biology and is maybe unfamiliar to a social scientist. Furthermore, the referenced researchers or algorithms named for researchers may be little known. Thus, this section chronicles milestones in the development of artificial neural networks to aid in the conceptualization of them.

The study of the human brain dates back to early civilization. Nelson and Illingworth indicate that the first attempts to understand the human brain in a physiological manner are attributed to Hippocrates and Edward Smith Papyrus. The Papyrus work on the location of sensory and motor control areas of the brain dates back to 3000 B.C., a few centuries before Hippocrates.

The discovery of the inner workings of the brain occurred at the end of the 19th century when William James initially hypothesized that a neuron-like structure existed. In the 1930s, Alan Turing, established the brain as a computer paradigm. Turing is one of the founding fathers of artificial intelligence. In the 1940s, a mechanical neuron was demonstrated by McCulloch and Pitts. Also in the 1940s, Hebb established the learning rule that states that a neural pathway is reinforced each time it is used or if a neuron receives an input that does not offset the existing output, the strength of the new output increases. Hebb's rule has a mathematical algorithm equivalent used in neural networks today.

The 1950s ushered in the age of computing and the idea that one could construct a computer with artificial intelligence. The Turing paradigm could now be tested with electronic computers. The essence of the "Turing test" for artificial intelligence is that if one cannot distinguish whether he or she has been communicating with a computer, then the computer possesses artificial intelligence. Usually, the computer fails the test.

The first artificial neural network was built in 1958 by Rosenblatt and was called the Perceptron. The purpose of the original Perceptron was to mimic the human brain. The ability of the Perceptron to mimic the brain was limited. However, Perceptrons are still used today in character recognition neural networks. The next significant neural networks developed were ADALINE and MADALINE. These neural networks were used to filter echoes on phone lines and, in modified form, are still used today. These neural networks represented the first application of artificial neural networks to problems other than the simulation of a brain. However, decades passed before neural networks were recognized for their ability to solve real world problems.

The decades of the 1960s and 1970s were void of much significant neural network developments. One reason research related to neural networks stopped was that they were only considered simulators of the brain and poor ones at that. It was not until the early 1980s that Hopfield changed the purpose of neural network research to develop neural networks more like ADALINE and MADALINE—ones that solved problems rather than simulate brain functions. The potential of neural networks that were first developed in the 1950s had been rediscovered.

POTENTIAL APPLICATIONS

Neural networks can be applied to many different types of problems in agricultural credit markets. First, neural networks are excellent classification tools. Neural networks have outperformed LOGIT and PROBIT classification models in predicting business failure, bond ratings, and mortgage insurance underwriting candidates (see Trippi and Turban for several instances). Thus, neural networks may be used instead of statistical methods for classification problems. Further, neural networks have been especially reliable at classifying the infrequent adverse outcomes, like loan defaults—the prediction most lenders are concerned about. With respect to agricultural credit, Baral, and Miller have found that neural networks outperformed statistical classification methods with agricultural loan data.

Another potential area where neural networks may of service is in the loan auditing field. Neural networks could be used by external auditors to identify loans for more complete examination. A loan review classification model could be used in addition to the subjective loan classifications already in existence. A neural network might be useful in identifying marginal loans which currently have acceptable ratings.

Neural networks could be used internally to monitor unusual behavior. Chase Manhattan Bank currently uses a neural network to monitor credit card usage to detect fraud or stolen card activity (Bauer). In a similar vein, neural networks could be used to monitor payment patterns to foretell financial stress before an actual payment is missed. Of course this would work better with monthly payment schedules than annual ones. On the other hand, unusual use of a credit line could signal the financial stress of a borrower with annual payments. The main idea is that monitoring could be potentially improved without a large increase in labor hours.

Using neural nets in marketing strategy is another natural application. Neural networks may be able to identify customers from demographic data bases that statistical methods are unable to find (Bauer). Furthermore, from farm records, neural nets may be able to identify which customers may be most likely to replace equipment and require financing. Thus, prospecting may have higher payoffs. Also, neural nets may be used to classify borrowers into psychographic categories, which may help loan officers close and price loans effectively.

Neural network applications are not limited to classification problems. They can be used in place of traditional optimization methods. Neural networks have been used to solve a quadratic programming problem (Zhao and Mendel). Further, Trippi and Lee discuss how portfolios can be constructed using neural nets. Thus, agricultural lenders could use neural nets for portfolio analysis. Neural nets have been used to solve the traveling salesman problem. A simple net may help loan officers meet with the most clients in the least amount of time or for the least cost. Hawley, Johnson, and Raina suggest that neural net works should be used for simulation of firms under changing economic conditions.

Neural networks can be used in place of statistical or mathematical programming tools to analyze a wide variety of problems. Neural networks can be used where the variable of interest is binary, multiple categories, or continuous. Neural networks can also handle any non-linear specification and are generally more flexible than parametric statistical methods.

BACKPROPAGATION NEURAL NETWORKS

A large number of experimental neural networks structures have been defined and incorporated into software packages.[2] However, the neural network structure that has been used

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[2]Both free and commercial software are available for constructing neural nets. A listing of software covering over 10 pages can be found in the neural net "frequently asked questions" (FAQ) document on the Internet. The FAQ is posted to comp.answers and is available by anonymous ftp at rtfm.mit.edu. The FAQ is in pub/usenet/news.answers. Although stand alone packages dominate the list, some well known software packages have neural net capabilities. For example, SAS and MATLAB can be used to construct neural networks.

the most by social scientists has been the backpropagation network. Thus, the structure described in the following section is the one that most social scientists would use.

The neural network described herein is termed a fully connected feedforward back-propagation network with supervised training (figure 1). To build a backpropagation network, a layer of neurons or processing elements is formed and all its inputs are connected to a preceding layer or the inputs the modeler supplies. The layer has its outputs connected to either a succeeding layer or the final output, but not to both. The layers are arrayed so that there is an input layer, potentially multiple middle or hidden layers, and an output layer.

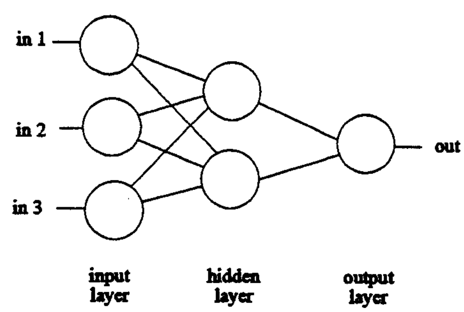

Figure 1 A Backpropagation Network

The first layer, as in all neural networks, is termed the input layer. If three ratios (explanatory variables) are expected to be predictors of loan quality, then the input layer would have 3 inputs. Any layers between the input layer and the output or final layer are termed hidden layers. Typically, at least one hidden layer is specified. A three layer neural net has been shown to be sufficient to analyze these types of classification problems (Salchenberger, Cinar, and Lash). Within the hidden layers are processing elements. The number of processing elements is somewhat arbitrary. In a three-layer neural net, usually more processing elements are included in the hidden layer than inputs to the first layer. The last layer, the output layer, contains one processing element if only one output was modeled. This is the case for a binary variable such as default/not default. If "n" multiple categories are modeled, then n-1 processing elements are required in the output layer. The neural network is termed fully connected because all inputs to a layer are included in the calculation of each processing element's output.

The output of a processing element in a given layer is represented in equations (1) and (2) and note that individual observation subscripts are omitted. First, the inputs, X_i, are weighted by

$$Z_j = \sum w_{ij} * X_i \tag{1}$$

parameters, w_{ij}, that minimize the classification error between the observed output, Y_j and the predicted Y^*_j. The weighted sum of the inputs and parameters, Z_j, is the intermediate output of the processing element. The Z_j are then added to a bias or threshold term, t_j, and transformed using a threshold (sometimes called a transformation or squashing) function. The output of a processing element, Z^*_j, is then sent to the next layer as an input.

$$Z^*_j = F(Z_j + t_j) \tag{2}$$

The threshold function typically used in a backprop neural net is a sigmoid function. Specifically, it is a familiar exponential function defined in equation (3). This function is typically used because the function and its derivatives are continuous and convergence is rapid compared to other threshold functions (Nelson and Illingworth).

$$Z^*_j = \frac{1}{1 + e^{-(Z_j + t_j)}} \tag{3}$$

This typical neural net is trained using the method of backpropagation. In this net, the original weights and thresholds are randomized and the network is solved. This is the feedforward step. Back propagation starts at the output layer and adjusts the parameters of the net work (the weights and thresholds) on the third layer using equations (4) and (5). In equation (4), the new weight, w_{ij}, is adjusted using the previous weight, w_{ij}', the momentum factor, M, the learning rate, LR, the backpropagation error, e_j, the input, X_i, and the weight from two iterations ago, w_{ij}''.

$$w_{ij} = w_{ij}' + [(1-M)*LR*e_j*X_i] + [M*(w_{ij}' - w_{ij}'')] \tag{4}$$

The momentum factor, M, allows a change to the weights to persist for a number of adjustment iterations. The momentum is a member of the set $MO=\{M \mid 0 \leq M < 1\}$. The closer the momentum is to 1, the longer the persistence. This can improve the convergence rate by smoothing out unusual conditions in the training set.

The learning rate also affects the rate of weight adjustment. The learning rate is a member of the set $L=\{LR \mid 0 < LR \leq 1\}$. The closer the learning rate is to 1, the greater the adjustment from the last iteration. A higher learning rate may increase the speed of convergence, but too high a learning rate may cause an unstable neural net.

The backpropagation error, e_j, at the output layer is defined in equation (5). The definition of the back propagation error is dependent on the threshold function. The delta, or the difference between the observed and predicted is multiplied by the first derivative of the threshold function (Nelson and Illingworth). The e_j in this neural net is equal to the product of the predicted value, its complement, and the difference between the observed and predicted values. Further, only one output and thus, one error term for each observation occurs.

$$e_j = Y_j^* * (1 - Y_j^*) * (Y_j - Y_j^*) \tag{5}$$

The adjustment of the weights in the hidden layer is similar to the previous discussion. Equation (4) is used to adjust the weights; however, equation (5), which defines the error, must be modified. Equation (6) indicates that the error is equal to the product of the predicted value, its complement, and the error in the succeeding layer's processing elements subscripted by k times the previous weights. This error equation properly attributes error to the processing elements in preceding layers based on error from the succeeding layer. For example, e_k is equal to $Y_j - Y_j^*$ for the correction of the weights in the hidden layer and w'_{jk} are the weights of the output layer.

$$e_j = Z_j^* * (1 - Z_j^*) * \sum (e_k * w'_{jk}) \qquad \textbf{(6)}$$

CONCLUSIONS

The field of neural networks is relatively new and still evolving. The commercial application of neural networks to real world problems suggest that they hold promise and are worth investigating. Neural networks can substitute for statistical methods and nonlinear programming and have been shown to outperform these methods. The limitations of the neural nets are that they sometimes do not provide as much information as our traditional methods and that they have a subjective construction.

Although several neural network structures exist, the typically employed net in financial and credit market research is a backpropagation net. The algorithm of a typical backpropagation network was presented to help understand the underpinnings of a neural net. Developments in the backpropagation network structure are to make the construction of a neural net less subjective and to provide more information about inputs. That is, to incorporate an objective method to select the inputs and to select the number of hidden layers and processing elements included in the neural net. Some of this work has statistical underpinnings and some of the work is based on other biologically based algorithms, genetic algorithms. If the objectiveness and information content of neural nets are improved, the general acceptance of neural networks in formal research may follow.

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