Neural Networks: Tools For Financial Prophesy ?

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NEURAL NETWORKS: TOOLS FOR FINANCIAL PROPHECY?

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In the quest for forecasting performance, numerous devices have been developed, each with its own promises and prophets. Indeed, new claimants for improvement seem as common as unsolicited credit card applications. However, sorting through all this hype is a daunting challenge, especially given the highly mathematical and statistical nature of the arguments that are used to support the results. More is involved than comparing cheap teaser rates.

This article provides a non-technical overview of a recently developed advantageous technique—neural networks (NNs)—for those who might justifiably be skeptical of replacements for the tried and tested, though far from perfect, statistical techniques. We begin by outlining the basics of NNs, touch on the burgeoning popularity of this family of models—particularly with practitioners—and then compare them with more conventional statistical approaches equally applicable to finance problems.

We direct our discussion to those in finance who are curious, but not yet initiated, in NNs. While we do not provide a tutorial, we do offer a brief, non-technical description of the procedure's underlying mechanics, as well as a short description of several specific applications and limitations of the technique. Our investigation asks whether this often-heralded technique can be relied upon to provide superior, almost prophetic, results often enough to justify the sizable investment of time required to master a complex methodology and the material investments in required software, hardware and employee training.

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EXECUTIVE SUMMARY

- *Neural networks (NNs) are non-linear tools from the artificial intelligence branch of computer science that can be utilized in financial analysis and forecasting, especially for short-term predictions. They offer a useful alternative to traditional methods such as discriminant analysis and regression, especially when exploring non-linear or unknown patterns in massive, sometimes incomplete, data sets.*

- *Powerful, NNs do have major limitations. Results are sometimes not robust, but are training-specific and not replicable. Sorting adjacent categories in applications such as bond ratings is often subject to high error rates.*

- *Software used to process NNs is available, but applications may become time-consuming and costly, depending on the size of the data set and the complexity of the NN.*

POPULARITY OF NNs

Modern computers, coupled with available large data sets, encourage the use of NNs. The lure of huge profits from their application has, predictably, made NN applications immensely popular in corporate finance and in security markets. Improving decision-making capability by even a small factor could result in additional profits totaling in the billions, since trillions of dollars of transactions take place every day around the world.

Not surprisingly, some fascinating breakthroughs have attracted considerable attention from both academics and practitioners. During the mid-1980s small high-tech firms were involved in the development of NN applications on an experimental basis, encouraged by banks and other financial institutions. The initial success of these experiments has encouraged well-known banks, like Wells Fargo Bank, Citibank, Chase, the World Bank and other financial institutions in New York, London, and Tokyo, to develop this technology in a sustained manner, since the early 1990s. Similarly, large firms like IBM and Microsoft, among others, started developing NNs for financial applications. For example, IBM's Neural Network Utility Brochure states that its products have banking and finance applications in forecasting and automatic loan processing.

Whether the recent embrace of NNs is yet another in a long line of passing financial management fads or an enduring, worthwhile approach remains an open question. It is entirely possible that the alluring technological tail is again wagging the substantive dog. Glamour aside, the real question concerns whether mastering this complex methodology is profitable, given the demonstrated alternatives.

The lure of huge profits from NN applications has predictably made them immensely popular.

WHAT NEURAL NETWORKS DO

A NN is an information processing program or model that attempts to mimic the information processing of the human brain. Neural networks can be thought of as universal simulators since they can simulate any function to any desired level of accuracy.[1] NNs consist of multiple, extensively interconnected processing elements, called "neurons," which are organized in layers, like those of a decision tree, and which work in unison to solve specific problems. Combining this procedure with a wide-ranging, richly detailed database creates a potent tool for forecasting and analysis.

What makes NNs especially noteworthy is their learning ability. Like human brains, NNs are able to learn from past experience. In NN language, this learning is called "training." Learning in the human brain involves adjustments to the synaptic connections that exist between the neurons. NNs attempt to replicate this process.

Zurada[2] provides a detailed explanation of this system of training. NNs can aid researchers in unraveling the non-linear forces behind the directional change in time series problems, and these results can be further applied to short-term forecasting, with potentially improved results. For example, Bansal, Kauffman and Weitz[3] show that neural network forecasts were more robust than those they obtained through traditional statistical methods like regression analysis.

The revolutionary structure of NN information processing units consists of three distinct types of neuron or node layers, namely:

- The input layer
- The output layer
- What are labeled "hidden layers"

The actual design of input, output and hidden layers is called "neural network architecture."

Hidden layers permit non-obvious, intuitive outcomes to be generated. As with the human brain, the NN's stored information is a function of the type and strength of different neuron layer interconnections. The technique thus advances several steps beyond straightforward data crunching. Input values are weighted, then usually summed and acted upon by a non-linear function referred to as an activation function, with sigmoid functions being the most commonly used. (Sigmoids are S-shaped functions. They differ from step functions, which act like a regular light switch and represent off-on once some condition is reached. Sigmoids resemble dimmer switches in that they "turn on" gradually.) These values are mapped to the next layer of neurons and so on until reaching the output layer. The weights can be "improved" (network training) using a variety of approaches, and the process can be repeated until the outcome is judged appropriate.

The success of NNs depends on several factors, notably the neural network architecture used, the choice of training method, the training data set quality, the selection of the activation function, and the preprocessing of the data. Kingdon[4] notes that simple models are preferred over more complex versions.

Having enough representative data is a necessary, but not a sufficient condition for NN success. The training data set should contain all possible patterns. This means the data set will likely contain hundreds of observations. For example, a stock market data set should cover an entire business cycle.

Kryzanowski and Galler[5] apply NNs to financial statement analysis of small firms and demonstrate that NN performance improves when the training data set is expanded. In an actual bankruptcy prediction application developed for Peat Marwick by the NeuralWare's Application Development Services and Support (ADSS) group, statistics from 1,000 banks (900 viable, 100 bankrupt) were used to train the NN. The resulting model predicted both viable and bankrupt banks with an accuracy of 90 percent.[6]

WHAT NEURAL NETWORKS LEARN

NNs may be either supervised or unsupervised, which refers to the type of training method employed. Supervised NNs employ learning algorithms that compare the pattern output by the net to a target output; errors are calculated, the weights that connect the neurons are revised, and the net is run again. An example is the Multilayer Perceptron, which is considered an especially powerful NN.

Unsupervised NNs lack a target pattern, and are considered "self-organizing" (hence the label "Self-Organizing Feature Map" or SOFM). Unsupervised NNs attempt to assort similar units together, rather like cluster analysis or factor analysis. Supervised NNs endeavor to separate units with a

Generally, NNs are simulated using standard computers with the appropriate software.

known output value into the right categories, a process that is comparable to discriminant analysis.

Supervised and unsupervised nets are utilized for specific purposes. In supervised training, the objective is to determine a succinct output so the trained net can be used for forecasting membership in predetermined output classes. For example, a bank's borrower data can be fed into an NN, and the NN can be trained until 90 percent of the control or hold-out data are accurately predicted.

Under unsupervised learning, the data are presented to the NN to elucidate important data set properties. Here identifying the interrelationships of multiple factors is the goal, and the output is generally a compressed data representation. Consider, again, a data set of all a bank's borrowers. With the application of unsupervised learning, NNs can process these data to summarize characteristics distinguishing borrowers from one another without resulting in a conformance to a particular predetermined borrower classification.

HOW NEURAL NETWORKS WORK

The data used to create a neural network are divided into two sets. One set trains the NN, while the second set, variously called the test, control or validation set, evaluates the NN's accuracy. Clean, complete training sets increase NNs usefulness. The training data set is processed through the NN until the connection weights between the neurons have adjusted enough to reflect data patterns, that is, until the NN has "learned" the patterns. The test data set then is employed to evaluate NN performance. The test set used for a model's external validation should be similar to the information encountered in the model's deployment environment.

The thoroughness of training is critical. A balance must be struck between utilizing too many cycles versus too few iterations. A natural trade-off occurs between speed and accuracy. The necessary training runs typically depend on the complexity of the patterns being processed. Zirilli[7] mentions a minimum of one thousand runs. Insufficiently training an NN—i.e., with too few training runs—often results in missing patterns in the data. Excessive training of NN could consume inordinate amounts of time without the benefit of improved pattern recognition, even diminishing network performance while over-amplifying trivial cases. This is called overfitting.

Generally, if the data set is large, NNs can perform properly even when the data set is incomplete, noisy, or not "clean." Since standard statistical techniques are far more sensitive to incomplete or faulty data, this is an important advantage of using NNs.[8]

The last step in model building is model validation using the "validation set." The NN is used to process this data to verify the model's robustness. If the model's attainment falls short of expectations, rebuilding and retraining is required.

EXHIBIT 1
Some Internet Sources of NN Software

http://www.neuralfusion.com/nnmodel/index.html
http://www.mikuni.com/neurolab/NeuroLabDownload.html
http://198.137.221.245/NetProphet/license.html
http://www.e-nalytics.com/gc1.htm
http://www.neuralware.com/prod01.htm
http://www.mathworks.com/products/neuralnet/
http://www.neuroshell.com/welcome.htm
http://www.lmt-expo.com/neural.htm
all URLs 9/1/98

*Sarle also provides a list of NN freeware and shareware available for use.[8]

NEURAL NETWORK TOOLS

Generally, NNs are simulated using standard computers with the appropriate software. Additionally, the hardware itself can be designed to better run NN programs. For example, Intel developed the 80170 chip, which is designated as an electrically trainable artificial neural network (ETANN).[9]

As already noted, the Internet abounds with downloadable shareware and some freeware. Stock price prediction models are especially numerous. Exhibit 1 provides a list of Internet sites through which software is available. Neural network program packages are similar to the user-friendly standard statistical packages available in the market.

NNs are to be tailored for a specific application, and therefore must be customized for each application. Generally, NN programs provide several user-friendly design choices. Nonetheless, given the learning curves involved, considerable time and effort must be expended to secure profitable outcomes. Overall, the educational investment in new theory and technique can be substantial.

NN costs are moderately high, but not so expensive as to make them inaccessible. Prices are coming down quickly. Software carries the largest expense, especially for academics whose interests are purely scholarly. Depending on the input numbers, software costs can quickly escalate. BioComp System, for example, charges between $4,000 to $6,000 for 512 inputs, probably the barest minimum necessary. However, on the plus side, these programs are accessible on technically up-to-date personal computers.

The NeuralWare product line is relatively extensive, offering software packages for several platforms, on disk and tape media, and provides powerful, state-of-the-art techniques. Prices range from about $100 to about $10,000, with annual maintenance fees of $300 to $3,000 (including updates and technical assistance). University discounts are offered.

Common NNs use standard platforms like MS-DOS and Windows and are occasionally integrated with standard spreadsheets like Excel or Lotus. Braincel, produced by The Palisade Corporation, is a simple-to-use Excel add-on, and is quite affordable at about $250. A notable Braincel feature is its version of back-propagation, called back-percolation, which is up to 100 times faster for some problems. Neuralyst, another Palisades product, is also Excel-based. It has somewhat more general purpose NN capabilities, though it still focuses on back-propagation. The cost is about $225. Excel's limited fields and memory availability will, naturally, restrict network size.

NEURAL NETWORK APPLICATIONS IN FINANCE

In the financial arena NNs have been used mainly but not exclusively, for forecasting. Applications in this field include:

- Stock price prediction
- Security trading systems
- Estimations of the option pricing model, to price and hedge derivatives
- Foreign exchange rate forecasts
- Predictions of bond ratings and changes
- Forecasting financial success and demise of firms
- Credit scoring
- Estimating T-bill rates and inflation rates
- Predicting merger targets
- Detection of fraud, used especially by credit companies
- Comparison of signatures, speech patterns and other general pattern recognition

Scientific papers have been written to show the usefulness of NN applications for all but the last two items. Exhibit 2 provides a brief summary of many of these studies. For individuals who wish to do further research, we recommend scouring the Internet to obtain breaking news of the mushrooming collection of new NN applications.

EXHIBIT 2
Empirical Studies

Topic	Authors	NN-Applications	Comments
Stock price prediction Used by Daiwa and NEC for Tokyo Stock Exchange listed stocks.	Kryzanowski, Galler and Wright,[15] Zirilli [7] Refenes, et al.,[11] Bansal and Viswanathan[16] Donaldson & Kamstra[17]	Prediction of market-outperforming stock based on historical performance (technical analysis) with 72% success rate. Use of NNs in connection with dynamic APT to rank stocks and to identify those which outperform the market. Exploration of 1929 "price bubble"	NNs are superior in dealing with structurally unstable relationships, stock market returns. Superior predictions may or may not result in superior trading profits.
Security trading systems. Used by Brad Lewis of Fidelity investments, Deere & Co.	Loofbourrow and Loofbourrow,[18] Schwartz,[19] Fortune (December 27, 1993)	Lewis has registered a 99.8 percent gain since December 28, 1988. Since 12/92 Deere applies NNs to its pension fund, and outperformed the S&P 500 by 3 percent. Similar reports come from Midland Global Markets using Neural Analytics	Greatest impact is achieved with trading of smaller company stocks
Pricing and hedging of derivatives	Hutchinson, Lo, and Poggio[20]	Estimation of the option pricing model [OPM] via a neural network. This allows for adapting to structural changes, applying it to a variety of derivatives and avoiding restrictive parametric assumptions.	Radial Basis, MLPs, and the Projection Pursuit Regression price delta hedge options out of sample better than the B-S OPM
Foreign exchange rate forecasts. Offered by Olsen & Assoc of Switzerland[i]	Mehta,[21] Refenes and Zaidi,[14] Neely, Weller and Dittmar[22]	NNs and genetic programming are currently the best problem-solving tool available for nonlinear time series. They outperform moving averages and mean value-based forecasts	A lot of understanding, experience and experimentation are needed to achieve a stable set of networks
Predictions of bond ratings and changes	Dutta and Shekhar[23] Moody and Utans,[24] Singleton and Surkan[25,26]	The authors found that NNs outperform their linear regression model. NNs and more accurately predict bond rating changes than did multiple discriminate analysis.	Difficulty distinguishing between adjacent subgroups such as A and AA, or AA and AAA ratings. Better predictions were obtained with fewer rating classifications.
Estimating T-bill rates and inflation rates. Used by Falcon Asset	Schwartz[27]	NNs to predict 90-day T-bill, 30-day T-bill, and inflation rates for its bond trading activities. Similarly interest rates can be predicted to guarantee mortgage rate.	60 to 65 percent and 95 percent accuracy for T-bill and inflation rate predictions respectively over a 15-month period
Future spot rates forecasts	Swanson and White[12]	Applying forward rates with the help of NNs.	
Analysis of small businesses	Kryzanowski and Galler[5]	Evaluation of financial statements ratios by way of NNs	
Forecasting financial success and demise of firms	Coats and Fant[28] Martin-del-Brio et al.[29] Altman et al.[30] Poddig [31]	NNs (SOFMs) ability to employ ratio level data improves accuracy over the more conventional MDA which relies on cruder nominal level data. Increased validity since MDA's utilizations of ratio data violates statistical assumptions. SOFM was judged easier to grasp and less time consuming than MDA.	Altman warns that the marginally higher success rates require longer training phases and the risk of "overfitting." He suggests using MDA and NNs simultaneously.
Analysis of small businesses	Kryzanowski and Galler[5]	Evaluation of financial statements ratios by way of NNs	
Credit scoring Used and offered by ADS, Chase and IBM[ii]	Jensen[32]	NNs are trained with past loan applications, environmental factors and previous payment habits of consumers and corp. customers. Sorting as to approve, reject, or further investigate.	Aiding or even automating loan underwriting
Predicting merger targets	Sen, Oliver, and Sen[33]	NNs capture the non-linear relationships between predictor and predicted variables. Significance of inputs is interpreted through sensitivity analysis and graphical plots.	Slight improvement over logistic regression without sampling bias though still less than optimal (49 percent over 45 percent)
Detection of fraud credit card companies Visa, MasterCard	Classe[34]	Employing NNs with fuzzy logic and genetic algorithms.[iii]	

[i] More information on Olsen & Associates can be obtained from Olsen & Associates (http://www.olsen.ch/index.html) (8/97)
[ii] http://www.research.ibm.com/people/a/almasi/nnu/brochure.html (8/10/97)
[iii] http://www.mastercard.com/press/html (11/24/96)

COMPARING NEURAL NETWORKS TO TRADITIONAL STATISTICAL METHODS

Until about a decade ago, analytical predictions in finance had been based almost solely on statistical analysis of data, using one or more of the following techniques:

1. *Linear regression models.* These models are used to predict the dependent variable or response variable using a linear combination of independent variables.
2. *Time series analysis.* A class of procedures used for analyzing and forecasting time series data.
3. *Non-linear regression.* This procedure is used to predict the dependent variable using a non-linear combination of independent variables.
4. *Nonparametric regression.* A class of procedures used for modeling variables that are distribution-free, or whose distribution is unknown (for example, relative preferences) or that have small samples.
5. *Cluster analysis.* A large number of methods which attempt to determine whether or not a data set contains distinct groups or clusters of observations.
6. *Multiple discriminant analysis.* A method that can distinguish between two groups or classes in some optimal manner using a particular set of variables.
7. *Principal component analysis and factor analysis.* Methods that are used to describe the variation in a set of multivariate data in terms of a set of variables (which are uncorrelated in the case of principal components analysis), each of which is a particular linear combination of the original data.

The great advantage of these traditional statistical methods is that they produce extensive diagnostics with known distributions that are used in assessing the quality of data and results. They also provide confidence and prediction intervals, including graphical displays, which are helpful in financial analysis.

NNs cannot supersede human decision-making.

Though helpful in hypothesis testing and forecasting, these methods have fallen short in analyzing the ever more complicated models in finance that are being developed to explain financial data or to replicate financial decision-making for practitioners. For example, it is difficult to integrate statistical models into computerized trading systems. NNs, on the other hand, can be incorporated without having any knowledge of or making assumptions about underlying variable distributions.

As mentioned earlier, one of the most frequently used, extremely powerful neural networks is the multi-layer perception (MLP). Its multi-layered, flexible architecture can simulate any function to any desired level of accuracy. Thus, literally any statistical method, like regression analysis, cluster analysis, time series analysis and so forth, can be replicated using properly designed MLPs. The complexity of the MLPs can easily be varied by changing the number of hidden layers and by the number of neurons per hidden layer.

The NN literature discusses different types of neural networks that have been shown to be superior in performance to statistical methods. NN procedures can be used more appropriately to optimize financial variables or financial criteria. Their flexibility also does not demand that the input data be as clean as is required for statistical analysis. A recent article by Refenes, Zapranis and Utans[10] explains how neural networks can even be designed for hypothesis testing in the areas of model adequacy and variable significance. Other advantages to the neural network approach are:

- NNs can be used even when there are no theoretical models, whereas statistical procedures usually require well developed hypotheses.
- NNs can easily handle non-linear relationships.
- NNs can develop decision rules from historical data even if the input variables are highly correlated.
- NNs have a high degree of fault tolerance and flexibility with respect to the data type.
- NNs can easily be modified by retraining.

Since neural network methods are being developed largely by computer scientists while traditional statistical methods have been developed by statisticians and econometricians, there is some overlap between the two techniques. Sarle discusses different types of MLPs that perform the same functions as do some of the traditional statistical procedures.

However, NNs are not without disadvantages. NNs are known to exhibit a degree of predictive unreliability with outcomes sometimes exhibiting over-sensitivity to specific training samples. Even with identical input data, results cannot always be replicated. Excessive learning times may contribute to this; iterations may number 50,000 and more. Such extreme numbers of iterations are obviously costly and time-consuming.

Since there are no "proven" procedures for any specific application, it may be necessary to try different architectures, which contributes to the effort and cost required. Problems may also derive from unusual initial conditions when using back-propagation for instance, commencing analysis with an uncommon interest rate level.[11] To counter "totally wild one-step forecasting," Swanson and White designed an "insanity filter."[12]

NN computing requires a large amount of data and extended training time, and, even then, one cannot guarantee an optimal solution. A danger exists of either underfitting or overfitting the data, a dilemma compounded by the absence of strict guidelines regarding where one ends and the other begins. Overfitting is particularly problematic for financial applications where the data are noisy or contaminated. Swanson and White[12] report an instance of overfitting when examining whether forward interest rates predict future spot rates.

Another problem, data snooping,[13] involves obtaining what appears to be a well-fitting, powerful model through extensive specification searches. Nevertheless, through the NN fits the training data well, it rests on atypical information derived from this relentless quest. The upshot is a model that inadvertently misleads.

Yet another pitfall is the "malicious vector" problem. NNs, when used as a replacement for discriminant analysis, are often unable to sort adjacent cases correctly. That weakness especially impacts bond rating applications and bankruptcy predictions. Only by reducing the number of classes and consequently reducing the procedure's usefulness can one mitigate this drawback.

And finally, interpreting results may occasionally be perplexing. NNs involve a high degree of "black box" processing since the models comprising the hidden layers are invisible and their form must be assumed. Thus, Refenes and Zaidi [14] suggest applying sensitivity analysis—i.e., by eliminating input variables one by one, and then repeating the whole process—thereby attempting to discern the underlying structure. Another problematic aspect to the interpretation of NNs is the lack of available techniques of statistical inference, such as significance testing, brought about by nesting of layers.[13]

SUMMARY

Financial researchers should realize that NNs are hardly a cure-all for their problem-solving despite their enticing promise. NNs cannot supersede human decision-making, although the claims of artificial intelligence might indicate otherwise. Instead, NNs help recognize certain patterns heretofore hard to quantify precisely.

Comparisons with the human brain may also be overdrawn. Artificial neural networks consist, at most, of a few thousand neurons, while the human brain functions with about one hundred billion neurons. Also, the similarities between NNs and statistical methods, particularly those used in econometrics, are sometimes overlooked since many NN researchers lack a strong statistical background and are unfamiliar with statistical terminology.

On the plus side, NNs are heuristic procedures best applied where:

- One can specify particular influences on a phenomenon whose outcome is known with certainty.
- The relationship cannot be described.
- The relationship is not necessarily linear.

There are no known models.

NN financial applications research has undergone rapid expansion during this decade. Increasingly, both supervised and unsupervised NNs are being applied inter aler in stock market predictions, foreign exchange forecasting, credit risk assessment, and fraud detection. The class of training procedures, including back-propagation, has proven powerful and robust. Nevertheless, NNs are hardly a Quicken-like device for amateurs. Successful application requires substantial technical expertise, and prophetic results are not always obtained. ■

Notes

1. Sarle, Warren S. (1994). "Neural Networks and Statistical Models," Proceedings of the Nineteenth Annual SAS Users Group International Conference. Cary NC: SAS Institute, pp. 1538-1550. Or ftp://ftp.sas.com/pub/sugi19/neural/neural 1.ps.
2. Zurada, Jacek M. (1992). *Introduction to Artificial Neural Systems*. St. Paul: West Publishing Company.
3. Bansal, Arun, Kauffman, Robert J. and Weitz, Rob R. (Summer, 1993). Comparing the Modeling Performance of Regression and Neural Networks as Data Quality Varies: A Business Valuation Approach. *Journal of Management Information Systems*. Vol: 10 #1, 11-32.
4. Kingdon, Jason (1997). *Intelligent Systems and Financial Forecasting*. London: Springer Verlag.

5. Kryzanowski, Lawrence and Galler, Michael (Winter 1995). Analysis of Small-Business Financial Statements Using Neural Nets: Professional Adaptation. *Journal of Accounting, Auditing and Finance*, Vol.: 10 #1, 147-172.
6. Zahedi, Fatemeh (1993). *Intelligent Systems for Business: Expert Systems with Neural Networks*, Belmont, CA: Wadsworth Publishing Co.
7. Zirilli, Joseph S. (1997). *Financial Prediction Using Neural Nbtworks*, London: International Thompson Computer Press.
8. Sarle, Warren S. (1997). Neural Network FAQ. ftp://ftp.sas.com/pub/neural/FAQ4.html. (25 Jun. 1997).
9. Chester, Michael (1993). *Neural Networks: A Tutorial.* Prentice Hall, Englewood, NJ.
10. Refenes, Apostolos-Paul, Achileas Zapranis, and J. Utens, "Neural Model Identification, Variable Selection and Model Adequacy," in *Decision Technologies for Financial Engineering*, eds., A.S. Weigend, Y.S. Abu-Mustafa and A.-P.N. Refenes. 1997.
11. Refenes, Apostolos-Paul, Achileas Zapranis, and Gavin Francis, (1995). Modeling Stock Returns in the Framework of APT. In Refenes, A. P. (ed.) *Neural Networks in the Capital Markets*, Chichester: John Wiley & Sons, 101-125.
12. Swanson, Norman R. and Halbert White (1995). A Model-Selection Approach to Assessing the Information in the Term Structure Using Linear Models and Artificial Neural Networks. *Journal of Business & Economic Statistics*, Vol. 13, No. 3, 265-275.
13. Campbell, John Y., Andrew W. Lo and A. Craig MacKinlay (1997). *The Econometrics of Financial Markets*, Princeton University Press, Princeton, NJ.
14. Refenes, Apostolos-Paul and Ado Zaidi (1995). Managing Exchange Rate Prediction. Strategies with Neural Networks. In Refenes, A. P. (ed.) *Neural Networks in the Capital Markets*, Chichester: John Wiley & Sons, 213-219.
15. Kryzanowski, Lawrence, Galler, Michael, & Wright, David W. (July-August 1993). Using Artificial Neural Networks to Pick Stocks. *Financial Analysts Journal*, 49, 21-27.
16. Bansal, Ravi and Viswanathan, S. (September 1993). No Arbitrage and Arbitrage Pricing: A New Approach. *Journal of Finance*, Vol.: 18 #1, 1231-1262.
17. Donaldson, R. Glen and Mark Kamstra (1996). A New Dividend Forecasting Procedure Rejects Bubbles in Asset Prices: The Case of 1929's Stock Crash. *The Review of Financial Studies*, Vol. 9, No. 2, 333-383.
18. Loofbourrow, John & Loofbourrow, Tod (1993, Special Report). Neural Networks for Trading. *The Magazine of Artificial Intelligence in Finance*, 42-51.
19. Schwartz, Tom (January 1995). Rounding out Intelligent Systems. *Wall Street & Technology*, 58-62.
20. Hutchinson, James M., Andrew W. Lo, and Tomaso Poggio (1994). "A Nonparametric Approach to Pricing and Hedging Derivative Securities Via Learning Networks." *The Journal of Finance*, Vol. XLIX, 3, July, pg.851-899.
21. Mehta, Mahendra (1995). Foreign Exchange Markets. In Refenes, Apostolos-Paul (ed.) *Neural Networks in the Capital Markets*, Chichester: John Wiley & Sons, 177-198.
22. Neely, Christopher, Paul Weller, and Rob Dittmar (1997). Is Technical Analysis in the Foreign Exchange Market Profitable? A Genetic Programming Approach. *Journal of Financial and Quantitative Analysis*, Vol. 32, No.4, 405-426.
23. Dutta, Soumitra & Shekhar, Shashi (1988). Bond Rating: A Non-Conservative Application of Neural Networks. In *Proceedings of the IEEE International Conference on Neural Networks*, 2, 443-450.
24. Moody, John & Utans, Joachim (1995). Architecture Selection Strategies for Neural Networks. In Refenes, A. P. (ed.) *Neural Networks in the Capital Markets*, Chichester: John Wiley & Sons, 277-300.
25. Singleton, J. Clay & Surkan, Alvin J. (1991). Modeling the Judgment of Bond Agencies. *Journal of the Midwest Finance Association*, 20, 72-80.
26. Singleton, J. Clay & Surkan, Alvin J. (1995). Bond Rating with Neural Networks. In Refenes, A. P. (ed.) *Neural Networks in the Capital Markets*, Chichester: John Wiley & Sons, 301-307.
27. Schwartz, Evan I. (November 2, 1992). Where Neural Networks are Already at Work. *Business Week*, 136-137.
28. Coats, Pamela K. & Fant, L. Franklin (1993). Recognizing Financial Distress Patterns Using a Neural Network Tool. *Financial Management*, 22, 142-153.
29. Martin-del-Brio, Bonifacio & Serrano-Cinca, Carlos (1993). Self-Organizing Neural Networks for the Analysis and Representation of Data: Some Financial Cases. In *Neural Computing & Applications*, 1, 193-206.
30. Altman, Edward, Marco, Giancarlo, & Varetto, Franco. (1994). Corporate Distress Diagnosis: Comparisons Using Linear Discriminant Analysis and Neural Networks (the Italian Experience). *Journal of Banking and Finance*, 18, 505-529.
31. Poddig, Thorsen (1995). Bankruptcy Prediction: A Comparison with Discriminant Analysis. In Refenes, A. P. (ed.) *Neural Networks in the Capital Markets*, Chichester: John Wiley & Sons, 311-323.
32. Jensen, Herbert L. (1992). Using Neural Networks for Credit Scoring. *Managerial Finance*, Vol.: 18 #6, 15-26.
33. Sen, Tarun, Oliver, Robert, & Sen, Nilanjan (1995). Predicting Corporate Merger. In Refenes, A. P. (ed.) *Neural Networks in the Capital Markets*, Chichester: John Wiley & Sons, 325-340.
34. Classe, Alison (1995). Caught in the Neural Net. *Accountancy*. February, 58-59.

Baestens, Dirk E. & van den Bergh, Willem M. (1995). Tracking the Amsterdam Stock Index Using Neural Networks. In Refenes, A. P. (ed.) Neural Networks in the Capital Markets, Chichester: John Wiley & Sons, 149-161.

Brown, David L. (1997). (2nd ed.) Cyber Investing: Cracking Wall Street with your Personal Computer, New York: John Wiley.

Freedman, Ray S., Klein, Robert A. and Lederman, Jess (eds.) (1995). Artificial Intelligence in the Capital Markets, Chicago: Probus Publishing Company.

Hopfield, John. (1982). Neural Networks and Physical Systems With Emergent Collective Computational Properties. Proceedings of the National Academy of Sciences of the USA. Vol. 79, 2554-2588.

Kohonen, Teuvo (1984). Self-Organization and Associative Memory.
Springer Verlag.

Kuan, Chung-Ming and Halbert White (1994). Artificial Neural Networks: An Econometric Perspective. Econometric Reviews, Vol. 13, No 1, 1-92.

Sarle, Warren S. (1996). Neural Network and Statistical Jargon.
ftp://ftp.sas.com/pub/neural/jargon. (23 Oct. 1996).

Skapura, David M. (1995). Building Neural Networks, New York:
Addison-Wesley Publishing Company. 129-154.

Staff. (December 27, 1993). A New Age for Stock Pickers. Fortune, 58.

Trippi, Robert R. and Turban, Efraim (eds.) (1993). Neural Networks in Finance and Investing: Using Artificial Intelligence to Improve Real-World Performance, Chicago: Probus Publishing Company.

White, Halbert (1989a). Learning in Artificial Neural Networks: A Statistical Perspective. Neural Computation, Vol.1, 425-464.

White, Halbert (1989b). Neural-Network Learning and Statistics. AI Expert, 48-52.