ECONOMIC FORECASTING USING ARTIFICIAL NEURAL NETWORKS

Trippi, Robert R. and DeSieno, Duane. "Trading Equity Index Futures with a Neural Network." *Journal of Portfolio Management*, Vol. 19 (1), Fall 1992, pp. 27-33

In trying to decide upon a topic for this paper, I initially chose an article concerning the relationship between a person's income and the amount of money spent on his education. However, when I was doing some unrelated research on artificial neural networks, I stumbled across a fascinating article on the internet entitled "Rule Inference for Financial Prediction Using Recurrent Neural Networks."[1] Although the article itself was not suitable for this assignment, I was intrigued by the broader idea of using artificial neural networks as a functional economic prediction tool. For that reason I ran a keyword search on *Econlit* to see if there were any relevant articles in economic journals. To my surprise, the search keywords "neural network" came up with ninety-four hits. Of these ninety-four, only seventy-five were journal articles, and roughly thirty of these seventy-five seemed appropriate for the class. From the six such articles that Olin had, I chose the Trippi and DeSieno article because it was the most straightforward and clear. In addition, the results from the Trippi and DeSieno article were citied in many of the other articles on the subject.

Trippi and DeSieno's goal was to predict the behavior of Standard & Poor's 500 index using "a machine learning-enhanced trading strategy." The article briefly describes their methodology and presents the results, which indicate that their best model outperformed a trading strategy based on random trades ninety-nine percent of the time.

To predict the market behavior, Trippi and Desieno used an artificial-neural-network-based computer model. This type of model is incredibly useful because it can adapt and "learn." In other words the artificial network will, even in the absence of a human operator, constantly improve upon its results. As Bass describes them, "[artificial neural networks] are capable of performing complex computations, recognizing patterns, and displaying other forms of artificial intelligence."[2] In the case of Trippi and DeSieno the network was to find a set of rules that roughly described the behavior of the S&P 500 index. The 'rules' are not rules in the sense that they can be deciphered by any person, but instead they are retained within the computer for further computations (i.e. a *black box* model). Once the system has derived these rules, it will use these patterns to predict future positions of the market.

The actual mechanism through which the network processes the data was omitted from the Trippi and DeSieno article, but Ntungo and Boyd gave a fairly clear description of a generic artificial neural network in their comparison of the artificial neural network with linear ARIMA models, which I will try to

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[1] See http://www.neci.nj.nec.com/homepages/lawrence/papers/finance-cifer97/latex.html
[2] Bass, p.105

summarize: In a standard artificial neural network there are two sets of visible data: the input data and the output data. In the Trippi and DeSieno model the input, or *training* data was the daily Open, High, Low, and Close prices of the S&P 500 over a four-year period. Between these two visible layers of data are multiple layers of *hidden* data. In each layer of hidden data, each single data point is determined by taking the *weighted* sum of every point on the previous layer. It is the 'weighted' sum because each point (a.k.a. *neuron*) is given a different weight before it is summed with the rest of the data from the same layer. The weight that each neuron is assigned by the system is determined by the amount it correlates to the total accuracy of the system,[3] each neuron will have a different weight for each point on the next layer it is leading to. Through exhaustive trial and error, the network will continue adjusting the weights on all of the data points until the predicted data match the actual data. The network, which is modeled after the human brain, continuously updates itself over time as it is fed more data on which to train.[4]

After building six such artificial neural networks, each of which gave a Boolean prediction of either "buy" or "sell" for a given trading day, Trippi and DeSieno created an ingenious "composite" system by combining the outputs of each of the six independent systems. This synthesized system prescribed the desired course of action on days where the different individual networks gave different advice. In the words of Trippi and DeSieno, "the composite rule generation procedure examines the results of all possible combinations of networks on trading days where no rule yet applies."[5] An example of a composite rule was "If Net2 and Net3 agree and others disagree, then do the opposite of Net6," where Net2, Net3 and Net6 represent three different neural networks.

The composite system that they designed was incredibly successful. Of the individual systems, the lowest percentage gain over an 106-day test period was 45.3%. With the best composite system, they realized a $14,247 gain (on an initial $5,000 investment, a 285% gain!) over a period of only eight weeks. Given these results, they concluded: "We expect production versions of such systems to be commonplace within the next few years."[6, 7]

While these results were astonishing, I felt the article itself left much to be desired. It functioned as a quick-and-dirty overview of their general approach to the problem of economic prediction, but left out much of the critical information –both qualitative and quantitative -- that is essential to really understand the fundamental principles.

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[3] In practice, the weight is determined by its effect on the inaccuracy (*error*) of the system.
[4] Taken from Ntungo and Boyd, pp.979-982, Trippi and DeSieno, pp. 28-30, and Bass, pp.173-174
[5] Trippi and DeSieno, pp. 30-31
[6] Trippi and DeSieno, p. 32
[7] Although Abhyankar et. al. make a good point in noting that "this type of process [i.e. nonlinear forecasting] *could* be consistent with market efficiency if it is only forecastable at horizons too short to allow for profitable exploitations by speculators." (Abhyankar, Copeland, and Wong, p.1)

An example of Trippi and DeSieno's neglect of these fundamental principles is illustrated in the fact that they never addressed the incredibly controversial issue of whether or not the market is deterministic in the first place. The artificial-neural-network approach to predicting financial markets *relies* on the weighted assumption that the markets, although not necessarily linear, are deterministic in nature. Only given this assumption can the model be said to have found legitimate patterns in the data. Although one might argue that the success of their model is proof in itself that there is deterministic structure to the market, I feel that they should have acknowledged their assumptions.

The real significance of this omission is highlighted by the fact that countless studies, namely the 19-study meta-analysis by Abhyankar et. al., have suggested that "it seems improbable a priori that the pattern of returns could be explained to any substantial degree by a deterministic process, given that the major cause of market movements is normally assumed to be the random flow of news."[8] As Granger writes:

> Discussion of nonlinearity in economics is made more complicated by the usual problems with economic data – which are usually in discrete time and discrete space, probably contain a substantial measurement error with unknown properties, are affected by both cross-sectional and temporal aggregation and may have been filtered to remove a seasonal component.[9]

If the markets truly are nonlinearly deterministic, as the success of Trippi and DeSieno's model seems to suggest, that fact in itself is much more noteworthy (especially in the field of Economics) than 285% returns. This suggestion of nonlinear structure in the economic realm implies the possibility of nonlinear foundations in many other social sciences, from political science to sociology. Although Trippi and DeSieno's article was never meant to address these issues, I believe that this is where the real substance of the topic lies. Even on a purely economic level their findings appear to discount the fundamentalist efficient market hypothesis, because in an efficient market one should not be able to predict the point to which the markets will randomly adjust.

In short, Trippi and DeSieno's article is best used as an anecdotal account of the possible success of using an artificial neural network for economic forecasting. Within a very limited scope, it provides a concise and informative description of a new method of analyzing economic data. However, the article barely scratches the surface of the true foundations of the principles being applied, and fails to acknowledge the mind-boggling implications of the success of such a system.

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[8] Abhyankar, Copeland, and Wong, p.1
[9] Granger, pp.264-265

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