Financial Trading Systems Using Artificial Neural Networks

Bruce Vanstone
Bond University, Australia

Gavin Finnie
Bond University, Australia

INTRODUCTION

Soft computing represents that area of computing adapted from the physical sciences. Artificial intelligence techniques within this realm attempt to solve problems by applying physical laws and processes. This style of computing is particularly tolerant of imprecision and uncertainty, making the approach attractive to those researching within "noisy" realms, where the signal-to-noise ratio is quite low. Soft computing is normally accepted to include the three key areas of fuzzy logic, artificial neural networks, and probabilistic reasoning (which include genetic algorithms, chaos theory, etc.).

The arena of investment trading is one such field where there is an abundance of noisy data. It is in this area that traditional computing typically gives way to soft computing as the rigid conditions applied by traditional computing cannot be met. This is particularly evident where the same sets of input conditions may appear to invoke different outcomes, or there is an abundance of missing or poor quality data.

Artificial neural networks (henceforth ANNs) are a particularly promising branch on the tree of soft computing, as they possess the ability to determine non-linear relationships, and are particularly adept at dealing with noisy datasets.

From an investment point of view, ANNs are particularly attractive as they offer the possibility of achieving higher investment returns for two distinct reasons. Firstly, with the advent of cheaper computing power, many mathematical techniques have come to be in common use, effectively minimizing any advantage they had introduced (see Samuel & Malakkal, 1990). Secondly, in order to attempt to address the first issue, many techniques have become more complex. There is a real risk that the signal-to-noise ratio associated with such techniques may be becoming lower, particularly in the area of pattern recognition, as discussed by Blakey (2002).

Investment and financial trading is normally divided into two major disciplines: fundamental analysis and technical analysis. Articles concerned with applying ANNs to these two disciplines are reviewed.

BACKGROUND

There are a number of approaches within the literatures, which deal with applying ANN techniques to investment and trading. Although there appears to be no formal segmentation of these different approaches, this review classifies the literature into the topics proposed by Tan (2001), and augments these classifications with one more category, namely, hybrid. These categories of ANN, then, are:

- **Time series:** Forecasting future data points using historical data sets. Research reviewed in this area generally attempts to predict the future values of some time series. Possible time series include Base time series data (e.g., closing prices), or time series derived from base data, (e.g., indicators--frequently used in technical analysis).
- **Pattern recognition and classification:** Attempts to classify observations into categories, generally by learning patterns in the data. Research reviewed in this area involved the detection of patterns, and segregation of base data into "winner" and "loser" categories as well as in financial distress and bankruptcy prediction.
- **Optimization:** Involves solving problems where patterns in the data are not known, often non-polynomial (NP)-complete problems. Research reviewed in this area covered the optimal selection of parameters, and determining the optimal point at which to enter transactions.
- **Hybrid:** This category was used to distinguish research, which attempted to exploit the synergy effect by combining more than one of the previous styles.

There appears to be a wide acceptance of the benefit of the synergy effect, whereby the whole is seen as being greater than the sum of the individual parts.

Further, the bias in this style of research toward technical analysis techniques is also evident from the table, with one-third of the research pursuing the area of pattern recognition and classification. Technical analysis particularly lends itself to this style of research, as a large focus of technical analysis concerns the detection of patterns in data, and the examination of the behavior of market participants when these patterns are manifest.

USING NEURAL NETWORKS TO DEVELOP TRADING SYSTEMS

This section briefly considers the characteristics of each of the four main categories previously described. The selected articles were chosen as they are either representative of current research directions, represent an important change in direction for this style of research, or represent a novel approach.

Research into Time Series Prediction

The area of time series predictions is normally focused on attempting to predict the future values of a time series in one of two primary ways, either:

- Predicting future values of a series from the past values of that same series
- Predicting future values of a series using data from different series

Typically, current research in this area focuses on predicting returns, or some variable thought to correlate with returns (e.g., earnings). Some researchers focus on attempting to predict future direction of a series (e.g., increasing from last known value, decreasing from last known value, no change). Research of this nature is essentially a classification problem, and is discussed in that section.

The following articles were selected and reviewed as they are representative of the current research in Time Series Prediction (Austin et al., 1997; Chan & Foo, 1995; Falas et al., 1994; Hobbs & Bourbakis, 1995; Quah & Srinivasan, 2000, Wang et al., 2003; Yao & Poh, 1995). The articles reviewed consider both fundamental and technical data. For example, Falas et al. (1994) used ANNs to attempt to predict future earnings based on reported accounting variables. They found no significant benefit using ANNs compared to the logit model and concluded that the accounting variables chosen were not appropriate earnings predictors. This conclusion represents one of the major problems encountered when working with ANNs, namely, their non-existent explanatory capability. It is not unusual to find conclusions of this type when reviewing ANN research with non-correlation often being reported as wrongly chosen input variables. Quah et al. (2000) use mainly accounting variables to predict excess returns (with limited success). Chan et al. (1995) use ANNs to predict future time series values of stock prices, and use these "future" values to compute a variety of technical indicators. The ANN produced showed particularly promising results, the authors conclude that the networks ability to predict allows the trader to enter a trade a day or two before it is signalled by regular technical indicators, and that this accounts for the substantially increased profit potential of the network.

In many ways, these two primary prediction methodologies relate quite closely to technical analysis strategies. For example, the use (and projection) of a moving average over a series of stock prices could be regarded as predicting future values of a series (the moving average) from past values of the same series. Indicators in technical analysis are often composed of a number of constituent data items, like price, volume, open-interest, etc. These indicators are commonly used to give indications of future direction of price.

Research into Pattern Recognition and Classification

Pattern recognition techniques and classification techniques have been grouped together, as their goal is normally not to predict future values of a time series, but to predict future direction of a time series. For example, the primary goal of chartists (a style of technical analyst) is to attempt to predict trend turning points by studying chart price action, looking for certain patterns. Chartists have noticed that these patterns tend to re-occur, and are reasonably reliable indicators of the future direction of price trends. There are a great deal of these chart patterns, and different analysts attach different weightings to the predictive power of any given pattern. Also, these patterns normally need to be confirmed by values from another time series (such as volume) to be considered "reliable." For more detail on this area, the reader is encouraged to refer to Pring (1999). Non-pattern matching techniques, which also attempt to predict future direction of a time series are also classification problems. Quite often, in addition to predicting future direction of a time series, classification research attempts to classify stocks into two main groups, namely "winners" and "losers" as in bankruptcy and financial distress predictions.

The following articles were selected and reviewed as they are representative of the current research in pattern recognition and classification (Baba & Handa, 1995; Baba et al., 2004; Baba & Nomura, 2005; Baba et al., 2001; Baek & Cho, 2000; Enke & Thawornwong, 2005; Fu et al., 2001; Kamijo & Tanigawa, 1990; Michalak & Lipinski, 2005; Mizuno et al., 1998; Skabar & Cloete, 2001; Suh & LaBarre, 1995; Tan & Quek, 2005). As previously described, the research can generally be classified as "winner" and "loser" detection or pattern matching. The work of Tan et al. (2005), and later, Tan and Dihardjo uses the concept of "winner" and "loser" classification, as does Longo et al. (1995) and Skabar et al. (2001). Specifically, Skabar et al. (2001) do not predict "winners" and "losers," but predict two disparate categories, namely "up" and "down" (direction of returns). The work of Kamijo et al. (1990) provides an excellent example of pattern matching with the authors building ANNs to identify "triangle" patterns in stock market data (the "triangle" is a specific pattern used in technical analysis).

Classification involving pattern matching could also be validly discussed under the previous section on time series prediction, due to the fact that pattern constructs must occur in specific time order, and the majority of patterns are not time invariant. This leads to the desire of researchers to identify time invariant patterns, or attempt to determine a fixed period of time in which a pattern should occur. The work of Fu et al. (2001) provides examples of using genetic algorithms to "fix" the length of patterns, making them suitable for study using ANNs.

Research into Optimization

The focus of optimization is directed toward research that uses soft-computing specifically to attempt to optimize an otherwise accepted achievable result. Typical of this style of research article, an already accepted result is discussed, then considered for optimization. The optimization is characteristically proven by excess returns compared to the un-optimized case.

For an example of this style of optimization using ANNs, an index arbitrage timing has been proposed by Chen et al. (2001) and Zimmerman and Grothmann (2005). Their model attempts to optimise the correct entry point timing for index arbitrage positions. Current arbitrage models propose establishing an arbitrage position immediately an opportunity arises; the neural network approach is to attempt to locate the timing when there will be a maximum basis spread for the arbitrage, thereby increasing profit potential. Their research concludes that the neural model significantly outperforms the traditional approach.

Research into Ensemble Approaches

Research is classified as an ensemble approach if it combines work from more than one of the areas described next, effectively attempting to leverage the synergy effect by achieving an end result greater than that expected from each of the individual constituents. Among soft-computing research, there is a growing trend towards using the ensemble approach to analysis.

The following articles were selected and reviewed as they are representative of the current research in ensembles (Abdullah & Ganpathy, 2000; Baba et al., 2002; Chenoweth et al., 1995; Doeksen et al., 2005; Jang et al., 1991; Leigh et al., 2002; Liu & Lee, 1997; Wong & Lee, 1993). The majority of the ensembles draw their components from a variety of soft computing methods. The use of ANNs and genetic algorithms (GAs) together is quite popular, and is used by Leigh et al. (2002) to combine pattern recognition techniques with price forecasting. Another approach combining ANNs and GAs is provided by Baba et al. (2002) using ANNs for their predictive ability, and GAs to determine the best way to react to that information. Some ensembles combine multiple ANNs, for example, Jang et al. (1991) combine two ANNs, one that takes a short-term view of market movement, with one that takes a longer-term view. They then build a model, which reacts to a weighted output sum of the outputs of both models. Both Liu and Lee (1997) and Abdullah et al. (2000) also used ensembles of ANNs and concluded that the predictive ability of the ensemble approaches exceeded that of the individual ANNs. Other research reviewed combined ANNs with fuzzy logic and expert systems.

FUTURE TRENDS

Essentially, the field of financial trading is in a state of transition between traditional pricing models, the efficient market hypothesis, and ideas about behavioral finance. The challenge that presents itself is how best to unify financial trading pricing models. There is much debate about the validity of the efficient market hypothesis, which effectively contends that prices cannot be predicted using methods such as technical analysis. There is a large body of evidence that appears to contradict the efficient market hypothesis, and there seems little chance of academically moving forward en-masse unless an alternative valid pricing model exists. This offers substantial opportunity for soft computing research techniques, particularly neural models. These models are capable of acting as universal approximators, and determining complex non-linear relationships. The goal with these methods is to attempt to mine deep relationships, which can shed new light about the behaviour of markets and prices. These new relationships would inherently provide more scope for developing feasible and effective pricing models.

CONCLUSION

This article has surveyed recent and key literature in the domain of applying artificial neural networks to investment and financial trading. Within the context of investment discipline, this survey shows that the majority of this type of research is being conducted in the field of technical analysis. As discussed earlier, soft computing is particularly data intensive, and it is suggested that this observation goes someway to explaining this obvious bias in research.

Within the area of soft computing styles, the survey finds that the majority of research is within the area of both hybrid systems and pattern recognition and classification. It is suggested the reason for this is that the technical analysis approach lends itself towards the pattern recognition and classification areas. Also, many hybrid systems include pattern recognition and classification as one of their constituents.

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KEY TERMS

Continuation Pattern: A pattern in technical analysis, which suggests, on the balance of probabilities, that price trend will continue in its current direction.

Fundamental Analysis: The use of company reported financial data to determine an intrinsic (or fair value) for a security. Used to identify cases where companies are undervalued, with a view to profiting from the future price movements. This style of analysis is generally long-term.

Noisy Data: This term is generally used to describe data and datasets where there is a low signal-to-noise ratio. Any algorithm attempting to filter out the signal has to be capable of identifying and dealing appropriately with noise. In this sense, noise is that element of the data, which obscures the true signal.

Reversal Pattern: A pattern in technical analysis, which suggests, on the balance of probabilities, that price trend will change direction.

Technical Analysis: The study of the behavior of market participants, as reflected in the technical data. Used to identify early stages in trend developments, with a view to profiting from price movements. This style of analysis is generally short term.

Technical Data: Technical data is the term used to describe the components of price history for a security. These components are open price, low price, high price, close price, volume traded, and open interest.

Technical Indicators: Technical indicators are produced as results of various computations on technical data. They are primarily designed to confirm price action.

Triangle Pattern: A triangle is a particular pattern observed using technical analysis. There are a variety of circumstances under which a triangle can occur, and dependant on the circumstances, the triangle can be either a reversal or continuation pattern.