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Artificial Neural Networks: The New Age Technical Analyst

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Abstract
Predicting the stock price, though controversial, has been the center of attraction for the investors around the globe. The controversy is mainly due to the popularity of a theory on the working of stock markets called the Efficient Market Hypothesis (EMH), which ultimately concludes that price changes may never be predicted. However, the last century is all about innovative tools and techniques of predicting the stock prices. The stock movement prediction using traditional time series analysis and technical analysis has met with limited success giving rise to the increased focus on models that work in a noisy environment. The ANN is one such model that is believed to more suitable task, primarily because no assumption about a suitable mathematical model has to be made prior to forecasting. Furthermore, the ANN has the ability to extract useful information from large sets of data, which often is required for a satisfying description of a financial time series. If true, the ANN has potential to bring numerous rewards – both academic and financial – to researchers or analysts that find any patterns. With all this belief in mind, the author has tried to explore whether the ANN is the much needed supplement that technical analysts need to drive their point home.

I. INTRODUCTION

Much of economic and financial theory is based on the notion that individuals act rationally and consider all available information in the decision-making process. This idea had its foundation in the very old and accepted model of neo-classical man. The neo-classical economic perspective is the concept of rational self-interest. Individuals attempt this via what is often referred to as the rational, utility maximizing behaviour who settles only for the best. The widely accepted theory on the working of the stock market called Efficient Market Hypothesis (EMH) is based on this economic man model.

II. DEVELOPMENT OF RANDOM WALK AND EMH

The foundation of research into random walk or efficient markets is generally agreed to begin in 1900 when a doctoral dissertation published by Louis Bachelier (Reprinted in cootner, 1962) began to seriously explore the theory of speculation. His statement of the fundamental principle of equity pricing, "The mathematical expectation of the speculator is zero", laid the foundation for what we know today as the random walk theory. Put simply, the mean of past prices is the best estimation of future prices. Extensions of his work were not undertaken for more than fifty years, but seemed rather to restart as new streams of research.

An important parallel to the early work in financial fields was unfolding in science, mathematics and statistics. Holbrook Working wrote in 1934 what would become an important study of random differences in time series analysis. John Von Neumann (who later went on to make contributions to game theory, quantum mechanics and high-speed computer information system) did a study on mean squared successive differences. He wrote an application on the distribution of the ratio of mean squared successive differences to the variances. These studies could have been applied to financial theory quite accurately but did not partly because they were developed in different fields of study. Years later Working's early material and a later piece in 1960, became fuel for economists to better understand the dynamics of market pricing.

Kendall (1953) made a significant contribution to the growing foundation of applying probability to finance with his extensive work on economic time series and stock prices. Kendall's research found no logical or predictable pattern in stock prices. Based on these findings, he theorized that prices evolved randomly. This disturbed financial theorists and led them to conclude that these random price movements, in fact, indicated an efficient market and not an unpredictable one, as Kendall has postulated. This supposition, referred to as the

Random Walk Theory, was first seriously presented by Samuelson (1965), who proposed that randomness is realized through operative participation of many investors seeking wealth. Unable to control their appetite for profits, investors pounce on even the most negligible informational advantage at their disposal, and in doing so, they amalgamate their information into market prices and quickly eliminate the profit opportunities that led to their aggression. Financial theorists espoused the idea that the stock prices should follow a random walk made a case for the idea that markets are in fact efficient.

In 1965, Fama published a foundation piece of research that extended prior work on market randomness. This framework has received wide acceptance and subsequently textbook standard. The framework provides three categories of empirical tests: Tests of weak form, semi strong from and strong form efficiency. Fama defines efficient markets in terms of a fair game where prices fully reflect all available information. The expected value of excess returns in such a perfectly efficient market is zero. He defined three different degrees of market efficiency depending the information set.

2.1 Weak from EMH: In the weak from EMH the information subset of interest is restricted to historical prices. If the markets are efficient in weak form, investors should not be able to consistently earn abnormal gains by analyzing the historical prices. The reason behind such logic is that current prices of stocks already fully reflect all the information that is contained in the historical sequence of prices. This form of EMH is popularly known as the Random Walk Theory.

2.2 Semi strong form EMH:The semi strong form of EMH says that current prices of stocks not only reflect all informational content of historical prices, but also reflect all publicly available knowledge about the corporations being studied. Furthermore, the semi strong form says that efforts by analysts and investors to acquire and analyse public information will not yield consistently superior returns to the analyst. Examples of public information are corporate reports, corporate announcements, information relating to corporate dividend policy, forth coming stock splits etc.

2.3 Strong form EMH: The strong form EMH maintains that not only is publicly available information useless to the investor or analyst, but all information is useless. Specifically no information that is available, public or inside can be used to earn consistently superior investment return. Being an extreme hypothesis, it is not expected to hold good in any security market.

This theory focuses on three assumptions, all focusing on investor behaviour. These are:

- Investors are fully rational and respond rationally to all changes within the market. This may go so far as saying that investors subconsciously use tools like Bayesian probability to analyze probabilities and make decision.
- Irrational investors trade randomly, and as such, all random investments cancel themselves out, leaving no effect on the market.
- Even if investors' irrational decisions do not cancel out through probabilistic methods, other rational investors will take advantage of these irrational decisions to make a profit, which bring the market back to efficient state.

III. KEEPING EMH IN PERSPECTIVE

Over the past 35 years, there has been considerable investigating testing of the statistical validity of EMH. The EMH has been robustly examined from both theoretical and empirical positions. In 1990s Markowitz, Miller and Sharpe shared the Nobel prize for their work in equity valuation theory. Markowitz was recognized for developing modern portfolio theory, Miller for his theory of corporate finance and Sharpe for developing Capital Asset Pricing Model (CAPM).

However some authors have presented respectable and convincing evidence that are inconsistent with the determination of market rates according to the EMH and CAPM. The crux of their argument is as follows:

- From experience we know that investors may temporarily pull financial prices away from their long term trend level. Over-reactions may occur, so that excessive optimism (euphoria) may drive prices unduly high or excessive pessimism may drive prices unduly low.According to the efficient market hypothesis (EMH), only changes in fundamental factors, such as profits or dividends, ought to affect share prices. But the efficient-market hypothesis is sorely tested by such events as the stock market crash in 1987, when the Dow Jones index plummeted 22.6 per cent— the largest-ever one-day fall in the United States. This event demonstrated that share prices can fall dramatically even though, to this day, it is impossible to fix a definite cause.

- This largely theoretic academic viewpoint of efficiency also predicts that little or no trading should take place, since prices are already at or near equilibrium, *having priced in all public knowledge,* bringing the market to a halt. Disequilibrium or market inefficiency provides a constructive force that leads to a healthy trading environment. They argue that security markets in fact work because they are informationally inefficient and it is a necessary requirement along with costly information.
- On a simple behavoural lavel it is clear that people do not use Bayesian probability to learn from their mistakes (Shleifer, 2000) and are rarely fully rational.
- The theory also assumes that every investor has access to all the required information to value a stock. This problem of "perfect information" is its interpretation – while financial statements and economic statistics are widely available, one cannot assume that such information is interpreted correctly by all investors (Dyckman & Morse, 1986)
- In terms of large groups, one of the biggest problems with EMH is that the assumptions imply investors act independently of each other i.e. a naïve investor making mistakes will be taken advantage of by a rational investor. However it is often the case that investors act in unison said to follow *Herd mentality* (Shleifer, 2000), as can be seen during periods of irrationally increasing prices, like the late 1990's dot-com stock boom.
- The last and most convincing proof against market efficiency is the presence of well documented *market anomalies* (Dimson, 1988) like the January effect, the weekend effect, the low P / E effect etc.

IV. TECHNICAL ANALYSIS

The above mentioned discussion though, does not summarily discard the EMH as an explanation of stock prices, definitely encourages analysts to undertake the painful activity of stock price prediction. Stock price prediction may take any of the two routes of *Fundamental analysis and Technical analysis* though, not as substitutes of each other. The fundamental analysis posits that companies that do well in their line of work, be it having high profits, a good managerial structure, a successful focus on research and innovation, or any other similar factors, will do well in the stock market. So to predict whether a company will do well in future, the fundamental analyst looks at a host of factors starting from the economy to industry to company's operation and its profitability. Whereas the assumption inherent in technical analysis is that all such required information is available in a share's past prices. Bodie (1998) defines technical analysis as "an attempt to exploit recurring and predictable patterns in stock prices". Charles Dow the father of technical analysis is recognized for the establishment of the Dow theory, a technique that attempts to recognize trends in the market price of stocks. Dow is also credited with developing in 1897, the industrial average, a general index containing 12 blue chip stocks, and the rail average, a 20 stock rail industry index. Dow originally looked at these tow indicators, which we now call the Dow Jones Industrial Average (DJIA) and the Dow Jones Transportation Average (DJTA) in an attempt to determine the trend of the market.

The way technical analysis helps predict whether a stock will increase or decrease in value is by signaling trend reversals. According to technical analyst, many securities exhibit different types of growth over time, and the key to making a profit in the stock market is to predict when a stock's tendency to increase in value will rise, or a falling stock price will stop and begin to rise. By viewing a stock's past performance, one may begin to understand how people investing in that stock act and which prices they are comfortable with. Indeed, some researchers (Warneryd, 2001; Iihara, Kato & Tokunaga, 2001) have compared the theory behind technical analysis to herd behaviour in the stock market.

The use of technical analysis within investment decisions has been controversial. Technicians often referred to as chartists; remain oblivious to the fundamental reasons for a change in stock price, looking only to identify a trend which is completely divergent to the idea of an efficient market. Technicians are substantial computer users because of their indifference to fundamentals and exclusive interest in share price and volume (Cringley, 1994). However, the critics of EMH feel that technical analysis is an extremely useful tool to predict trend reversals and stock price fluctuation (Brock, Lakonishok & LeBaron, 1992).

However, the problem in technical analysis arises due to the large volume of data regarding past prices which are often available on a real time basis. The data is quite extensive as well, including daily high and low prices, adjusted closing prices to account for dividends and share splits, and numerous other variables. Indeed, the problem of technician is that there is so much of data and forms of analysis that he does not know what to do with it. For example, *Technical Analysis from A to Z* (Achelis, 2001,) a reference guide for technical analysts, lists 135 different tools for doing such analysis. But many of the details regarding these tools are subjective. It is upto the investors to choose values for the variables within each tool, and it is the investor's decision to follow a buy or sell signal from a technical indicator. With so many options, technical analysis sometimes looses its simplicity and predicting ability.

V. ARTIFICIAL INTELLIGENCE TO THE RESCUE

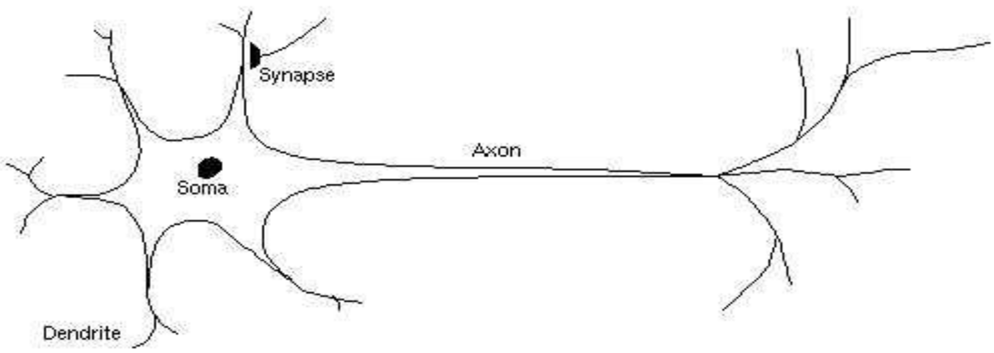
While computers have found widespread application in the financial industry, they are commonly used only for tabulation, accounting and various linear quantitative optimizations. Given the significant noise in financial time series data and the chaos of daily market fluctuation, it has been traditionally thought that the usefulness of computers to an investor was limited to simple book-keeping.

Many investors operate on haunches and feelings, and not on numerical calculations which could easily be automated. Clearly, designing a computer to emulate the elements of Byzantine human intuition is beyond our present level of understanding. It has been thought that without such intuitive cognition, a computer could never trade on a par with humans. Yet despite the inherent stumbling blocks, the few years have seen artificial Intelligence (AI) slowly creep into the financial sector. While industry skepticism of AI remains high, smatterings of innovative AI applications have emerged. There are two general classes of AI techniques that have found application in finance. The first class is comprised of expert system architectures that use knowledge-based or rule based reasoning to make decisions about a market. Typically, a sufficiently large knowledge-base of financial know-how is developed and is used to assist a real human trader in making decisions. The second major area is the application of connectionist networks and a surrounding body of non-linear techniques to predict new market data from historical databases. In some sense, these systems have no inherent knowledge of their own. Instead, they develop behaviours that predict the market based on a trial-and-error methodology. The Artificial Neural Networks belong to this second category.

VI. ARTIFICIAL NEURAL NETWORKS (ANN)

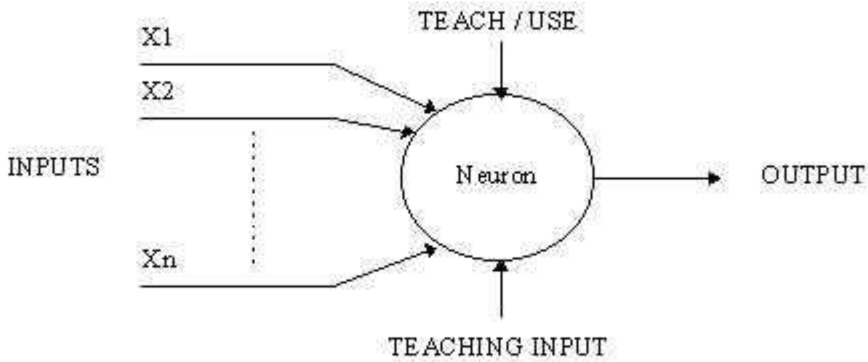
An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. These biologically inspired neural networks are systems loosely modeled after the human brain. They attempt to replicate the multiple layers of simple processing elements called neurons (fig.1).

Figure 1: A Biological Neuron



Each of the estimated 100 billion neurons in the human brain represents a primary working unit of the brain. Each neuron carries messages through an electromechanical process and is linked to some of its neighbours with varying co-efficients of connectivity that represents the power of these connections. Each neuron performs three basic functions: receiving input, processing and sending output signals (Fig.2).

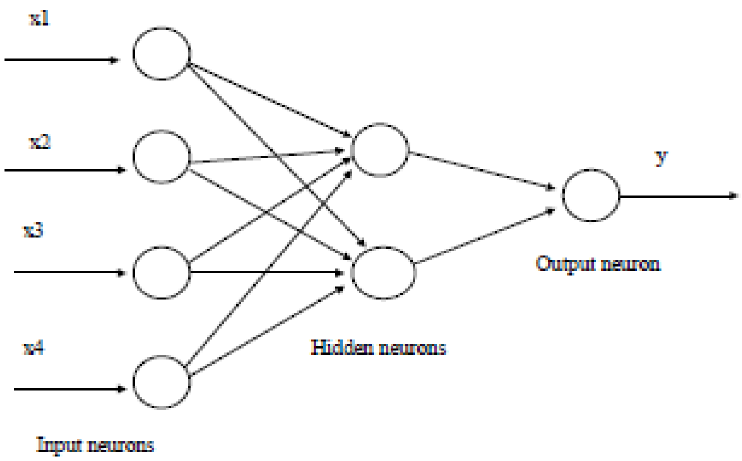
Figure 2: An Artificial Neuron



An artificial neuron is a device with many inputs and one output. The neuron has two modes of operation; the training mode and the using mode. In the training mode, the neuron can be trained to fire (or not), for particular input patterns. In the using mode, when a taught input pattern is detected at the input, its associated output becomes the current output. If the input pattern does not belong in the taught list of input patterns, the firing rule is used to determine whether to fire or not. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons.

Unlike traditional time series analysis where rules and instructions are central and some mathematical equation describes the dynamics; neural networks do not perform according to preset rules. When displayed to data the network gains experience, learns from regularities in the past and sets its own rules. The learning is accomplished by amending the strengths of neural connections to cause the universal network to yield suitable results. More simply, layers of these artificial neuron-like devices are adjusted until they synergize to look for patterns and to produce results based on the recognition of patterns. (Fig.3)

Figure 3: A simple Neural Network



ANNs are not programmed with descriptions or patterns to be recognized: they are trained to recognize these patterns as a result of the iterative process performed (Turban, McLean and Weatherbe, 1999). ANN discerns relationships among inputs by observation and progressive refining. It thus learns through adaptation. In addition, it is the nature of ANN to arrive at educated guesses or to infer from previous inputs and experience. ANN are a series of processing elements, with each one having only one output, but many inputs. The output of one processing element becomes an input to another processing element (Trippi, et al, 1992).

6.1 Advantages of ANN

Neural networks have several advantages. Most important is the ability to learn from data and thus potential to generalize i.e. produce an acceptable output for previously unseen input data. This even holds when input series contain low quality or missing data. Another valuable quality is non-linear nature of neural network. Potentially a vast amount of problems may be solved. Furthermore, no expert system (typically a programmer coding rules in a computer programme) is needed which makes the network extremely flexible to changes in the environment. One only has to retain the network.

Regarding downsides, the *black box property* first springs to mind. Relating one single outcome of a network to a specific internal decision (known as credit assignment problem) is very difficult. Noisy data also reinforce the negative implication of establishing incorrect causalities, *overtraining (overfitting),* which will harm generalizations. Finally, a certain degree of knowledge in current subject is required as it is not trivial to assess the relevance of chosen input series. A short summary of benefits and drawbacks are presented in the table below:

Table 1: Summary of Benefits and Drawbacks

Sl.No.	Benefits	Drawbacks
1	ANNs are able to learn any complex non-linear mapping, and approximate any continuous function	ANNs lack theoretical background concerning explanatory capabilities
2	Like non-parametric methods, ANNs do not make *a priori* assumptions about the distribution of the data or input-output relationship	ANN architecture topology and parameter selection lacks theoretical background. Still trial and error.

3	ANNs are very flexible with respect to incomplete, missing and noisy data (fault tolerant)	ANN learning process can be very time-concuming
4	ANN models can be easily updated and are therefore well suited for dynamic environments.	ANNs can over-fit the training data, and thus generalizability.
5	ANNs overcome limitations of other statistical methods while generalizing them	There are no explicit rules to select ANN paradigm / learning algorithm.

VII. WHY ANNS MAY BE BETTER TECHNICAL ANALYSTS

In 1990, most computer financial applications centered on expert systems. Hawley et al postulate that ANN are the only systems suitable for financial decision making and may well prove to be one of the most significant endeavours of finance in the next decade. They believe that there is no better suited area than financial decision making for the application of ANN. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyse. Other advantages include:

1. Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
2. Self-Organisation: An ANN can create its own organisation or representation of the information it receives during learning time.
3. Real Time Operation: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
4. Fault Tolerance via Redundant Information Coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

Turban et al (1999) refer to neutral computing as distinct approach to intelligent systems because it uses a structure that mimics certain of the processing capabilities of the brain. The results of the neural system are based on analogous processing, speedy recovery of vast amounts of information and the capability to recognize patterns in the data. The ability to recognize patterns in the data is what differentiates these systems from standard computing systems.

In addition, artificial neural networks are often able to detect subtle patterns and trends that may be too intricate for humans to identify. Individuals cannot digest and incorporate more that two or three variables simultaneously; ANN can simultaneously recognize correlations among hundreds of variables (Bylinsky, 1993). ANN are also gifted with the ability to "extract hidden trends and relationships from huge volumes of data" (Dineley, 2001).

Advantages of ANN include giving the investors a competitive advantage because of the ANN's agile nature. Individuals are often at a disadvantage while making decisions because of biases, which occur when emotions become a part of the decision making process. The human may see a pattern, but discount it because it is not what is desired. ANN do a more thorough and consistent job, with no emotional involvement in the decision making process. ANN learn by example and by their mistakes. They have no ego that prevents them from admitting their errors.

VIII. ANN in Financial Markets

ANNs have made big inroads into the financial world. Banking, credit card companies and lending institutions deal with decisions that are not clear cut. There are instances of firms using several neural architectures to deal with these decisions. Neural networks are also being used in all of the financial markets: stock, bonds, international, currency and commodities. Some users are crackling that these systems make them see green. For example, it is known that Fidelity Investments have many funds that use neural networks to manage over $ 3 billion (Ridley, 1993). Indeed, neural networks are reported to be highly successful in the Japanese financial market. Daiichi Kangyo Bank has reported that for Government bond transactions, neural networks have boosted their hit rate from 60 % to 75 %. Daiwa research institute has reported a neural net system which has scored 20 % better than the Nikkei average. Daiwa securities' stock prediction system has boosted the companies hit rate from 70 % to 80 %. Nikko Securities claims that a simulation of theirs rated corporate bonds correctly 24 out of 25 times. It reputedly ran over 40 times faster than traditional quantitative simulations.

Trippi et al (1992) reviewed the financial applications of ANN in a variety of investment management scenarios. They specifically focused on a simple ANN-based intraday trading system for S 7 P 500 futures contracts. They found ANN technology well suited for the pattern recognition, association and classification deemed necessary for this type of analysis.

Swales and Yoon (1992) studied the use of ANN as opposed to multiple discriminant analysis (MDA) in differentiating between stocks that perform well and stocks that perform poorly. They note that this superiority might well be attributed to the ability of ANN to accommodate fuzzy inputs; hence they are better able to compute qualitative rather than quantitative data.

Williams (2001) discusses some of the practical applications of ANN stock selection currently being used by a small group of mutual fund and pension fund managers. He postulates that the ANN are employed by this specialized group because of the ability of ANN to analyse more variables than a human possibly can and their ability to learn from their mistakes.

IX. CONCLUSION

All the above discussion may seem that the ANN is the magic box where historical data about stocks can be used to predict the future stock prices and may encourage investors to rush and buy an ANN package and start training. But the next question that comes to mind is that with so many bright analysts, money managers and scholars rigorously and continually researching, are only the inexpert and overconfident under the assumption that they are smarter than the market? The answer to that question is that because of these rational, well-informed traders who are continuously sharing knowledge among themselves, the markets are forced to be efficient in the long run, but in the short run this does not hold up. It is the behavior of investors that is the cause of the short lived inefficiencies. The period of inefficiency could be minutes, hours or days. Many cite the informational capacities of the internet to be a boon to the efficiency.

What does all these knowledge mean? It means that we should mean market efficiency because investing is a long-term activity. Further the time and risk incurred to attempt to beat the market may not pay off because the cost of capitalizing on the short tem market inefficiency may well be gobbled up by transaction costs and tax ramifications.

ANNs are by no means an empirical panacea and cannot foretell the future. The true lesson is that all the areas where ANN make sense share commonality, in that decisions are best made without bias and the nuances of human behaviour that appear to be the origin of these inefficiencies. With the plethora of noise about, the investing publis needs guidance more than ever. They need the discipline because the investors' greatest enemy is his own emotions. Hence the ANN have a scope of dealing with this scenarion in a subjective manner. So it said about the ANNs that they are unique and powerful techniques that can provide better forecasting capabilities than any other methods. However, the inherent limitations should be understood and used to prevent inappropriate applications.

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