NEURAL NETWORKS AND THEIR APPLICATION TO FINANCE

Martin P. Wallace (PhD)
Applied Technologies Centre
London, UK
Tel. +44 (0) 20 7732 2312
mw.sat@apcentre.edu

Abstract

Neural networks are one such process, that is, it maps some type of input stream of information to an output stream of data. It consists of ways to connect data/information to produce output that is consistent with the processes. It may seem simple, but as the analysis will highlight, this process is far from trivial. Today neural networks have been integrated into most fields and are a very important analytical tool. Neural networks are trained without the restriction of a model to derive parameters and discover relationships, driven and shaped solely by the nature of the data. This has profound implications and applicability to the finance field. These areas will be analyzed with specific examples in each area.

WHAT RE NEURAL NETWORKS?

The human brain is a very complex part of the human body, due mainly to the interactions and connectivity with other parts of our body, and the way it controls and defines every aspect of our being. The brain has continued to be a mystery to many scientists, but its role and capacity to process information is mimicked in many aspects of academia. Neural networks are one such process, that is, it maps some type of input stream of information to an output stream of data. It consists of ways to connect data/information to produce output that is consistent with the processes. It may seem simple, but as the analysis will highlight, this process is far from trivial.

A neural network works in a similar methodological way to connect processing elements to produce results from a complex analytical study or principle that depends on many interconnected explanatory variables. According to Smith initially neural networks were characterized as a computer science phenomenon with uses (Smith para 2):-

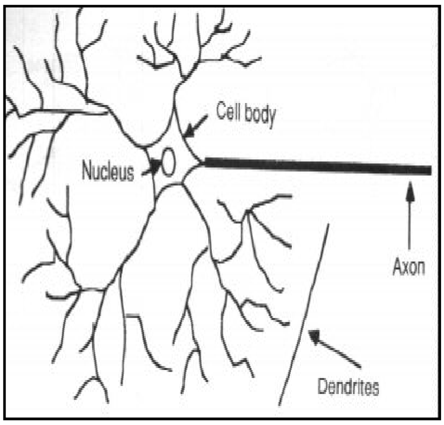
- processing elements
- a high degree of interconnectivity
- dependence of variables

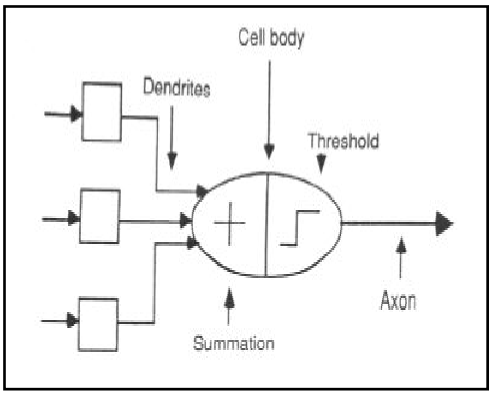
The basic idea behind a neural network is presented in Figure 1 below; where there are different inputs that combined create an output, however the ratio is not one to one, since there may be interactions between inputs and more so backward linkages between output and input, as presented in the diagram below. The figure was adapted form Stergiou and Siganos (para 2) to highlight the similarity between processes in the brain and neural networking.

THE HISTORY OF NEURAL NETWORKS

Neural networks were originally devised to understand the workings of the human brain (a formidable task). However, there developed a multidisciplinary trend with the constant interaction of researchers across disciplines who tried to apply the neurological activities of the brain with classifying computer programs and functions (Stergiou and Siganos para 5).

Figure 1: Neural Networking and Similarities with the Workings of the Human Brain





The first use and concept of neural networks began with linear classifications of the input-output relation represented generally equation 1 below:

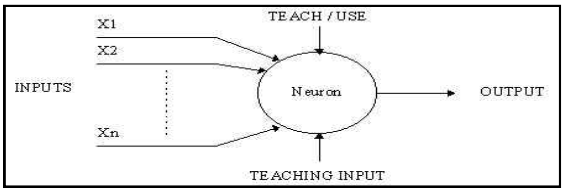
$$Y = a + bx, \text{ with } x \in R^n, a \in R^n, b \in R^n$$

Equation 1

Equation 1 was the typical development in neural networks and classified the general form of the Perceptron, which developed considerable interest and research in the 1950s (Stergiou and Siganos para 6). This model clearly has limitations, since it can only specify linear relationships in the input space; and will not classify complex data models that have a non-linear relationship.

Neural networks continued to advance and developed a multilayered algorithm that had the ability for bi-directional flow on inputs. Figure 2 below, highlights the general neural model that was adapted and transformed across disciplines. It highlights the development and historical progress of neural networks as its applicability across research arenas changed (Stasoft para 20).

<u>Figure 2: Multilayered Neural Network Model adapted from Stergiou and Siganos</u>



Neural network development was not without its period of criticism and general disrepute. During this period, the flaws of the single layered Perceptron model were highlighted (like that shown in figure 1). This caused a general decline in funding and research associated with neural networks. Its overall use and computational ability to solve complex problems was questioned and this lead to limited use.

Nevertheless, neural networks have regained popularity and are being used in a wide array of fields within the natural and social sciences. Models such as those in figure 2 generally increased in complexity, the development of the Cognitron in 1975 with training and learning algorithm, along with the ability to change weights and interactivity across input sets in R^n, were developed and re-popularized the field. Other popular models such as the back-propagation network is which utilized a stochastic function to generalize the relationship and determine optimal parameters of a complex model via a more robust methodology (Stergiou and Siganos para 8). Equation 2 below highlights the complexity and development within the historical timeline that shows the sequential development of neural networks (note the difference between equation 1 and equation 2).

$$Y = h\ (a + bx), \text{ with } x \in R^n, a \in R^n, b \in R^n$$

where h is a logistic function

Equation 2

Today neural networks have been integrated into most fields and are a very important analytical tool.

WHY USE NEURAL NETWORKS?

The recent increased interest and use of neural models stems primarily from its nonlinear models that can be trained to map past and future values of the input-output relationship. This adds analytical value, since it can extract relationships between governing the data that was not obvious using other analytical tools.

Neural networks are also used because of its capability to recognize pattern and the speed of its techniques to accurately solve complex processes in many applications. This is especially true of the backpropagation and Cognitron method introduced in the historical section of the paper. Neural networks help to characterize relationships via a nonlinear, non parametric inference technique, this is very rare and has many uses in a host of disciplines (Lendasse et al 9).

Since a neural network is basically a data processing technique that links input streams with output , its use can be distinguished by four types of applications:

1. Classification of input stream
2. Association of output given sectors of input groupings
3. Codification of input by producing output within a reduced dimensional subspace
4. Simulation of output from input relationships and interconnections.

Neural networks offer the best 'back-drop' in which to extend simply methodologies to gain unique and extended results from models. The networks offer the added advantage of being able to establish a 'training' phase, where example inputs are presented and the networks learns to extract the relevant information from these patterns. With this, the network can generalize results and lead to logical and other unforeseen conclusions through the model.

Clearly neural networks surpass traditional models that use linear techniques and parameter threshold testing, hence neural networks add flexibility to the model. In addition, with the non-linear modeling capabilities, there are a wide range of complex models that can be easily implemented and analyzed.

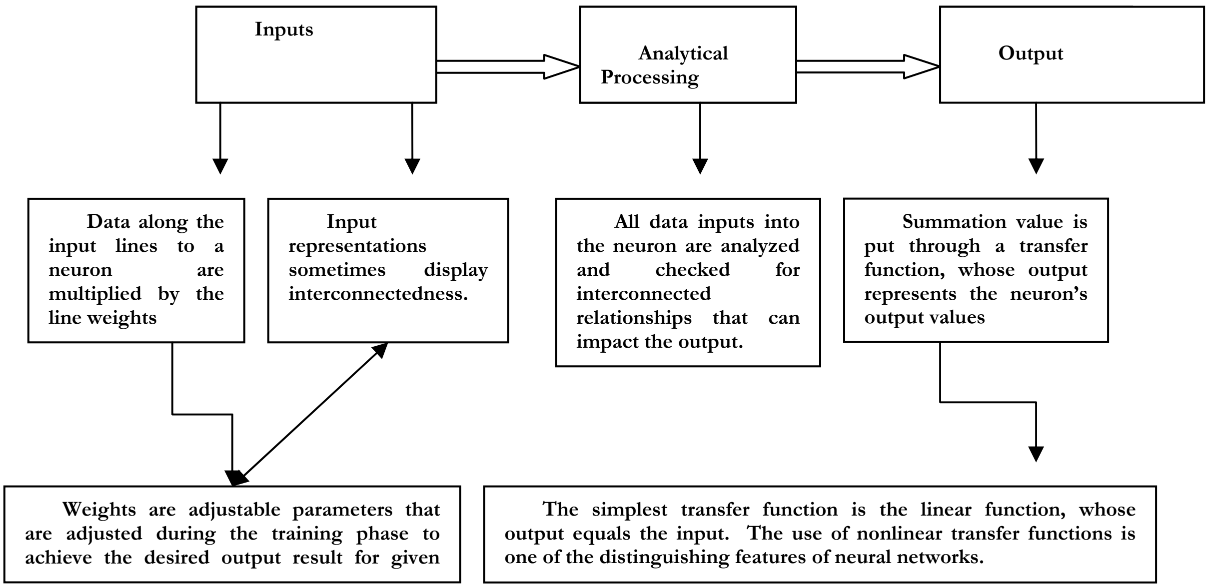
NEURAL NETWORKS VERSUS CONVENTIONAL COMPUTERS

Neural networks have the unique capability of learning. That is, unlike conventional computers, sequences do not need to be dictated in order for the algorithm to be executed and produce meaningful results. This problem solving tools, creates a unique likeness to the human brain, that is, neural networks, use the interconnectedness of the elements of the model to arrive at logical and robust decisions, rather than follow a set of sequential steps, that may or may not solve the problem like computers do.

Neural networks also allow modeling and forecasting to be more efficient, why?

The necessary analytical framework provides an expansive model to analyze relationships that were not embedded in the methodology or mechanism used to solve the model. This highlights the a different aspect of model building, where the unique relationships between the variables creates the model, rather than trying to force variables to conform to a theoretical abstract that may or may not exist. Nevertheless, it is clear that neural networks cannot replace traditional computers, but can and will complement each other in problem solving mechanisms. Figure 2a below shows the generalized view of the multilayer perceptron network with specific emphasis on the multiconnectivity of the variables.

Figure 2a: Multilayer Perceptron Neural Network



Neural networks try to find the solution to problems by analyzing the variables and may come to unpredictable results, since the relationship between inputs and outputs is not specified within a particular methodology, but is rather loosely based on the unspecified steps to solve the problem. Conventional computers need this model or sequence of steps to solve problems, and as such will produce results that are stipulated by the model or framework used to analyze data.

NEURAL NETWORKS IN FINANCE

Neural networks are trained without the restriction of a model to derive parameters and discover relationships, driven and shaped solely by the nature of the data. This has profound implications and applicability to the finance field. These areas will be analyzed with specific examples in each area.

TIME SERIES ANALYSIS

Time series is a special form of data where past values may influence future values. Many financial models rely on understanding time series to adequately predict the functionality of financial markets and uses statistical inferences for forecasting purposes. The relationship between time variant variables in finance can be characterized by trends, cycles, and non-stationary behavior between data points that have serve a predictive or informational purpose to the model. Linear models have been used in the past to extract these relationships, but non-linear relationships exists between many financial variable, as such neural networks have a specific place within the financial literature and can be trained to map and future values of time series, so as to extract hidden structures and relationships that may govern the data (Lendasse et al 5)

In discussing neural networks and time series analysis, it is beneficial to introduce the random walk Properties of pure random walk time series are of interest in providing a theoretical framework for financial time series and provides an applicable framework for neural networks in finance. Equation 3 below presents the random time series, which is used to model market prices.

$$p_t = p_{t-1} + u_t$$

Equation 3

Where p represents market prices, the ts subscripts are an index of time, and u is a stochastic variable, which is identically distributed. That is, u~(0, c).

Typically, the random walk theory is applied to stock market analysis and is a useful background to the question of the nature of financial time series ('Financial Time Series as Random Walk" 6). Direct test of randomness within financial time series is fraught with problems and even the most advanced nonlinear models, still have not devised efficient ways to model the behavior of financial time series.

Based on the analysis above, the neural network seems like an appropriate model to analyze financial time series, since it will provide insight into the nature of the relationship between time series data (which can be useful for forecasting and stock market analysis which is examined below).

Figure 3 below shows, since the hypothesis being tested and debated in finance is whether financial time series have information that can be useful for predictive purposes, or just happen to follow a random walk. Neural networks have been useful in testing this hypothesis.

Figure 3: Stock Market Data from the New York Stock Exchange for Newmont Mining: Random Walk?

STOCK MARKET ANALYSIS

More individuals own stock more than ever. Stock pricing is now expansive and is an important aspect of financial economics. Therefore, many theorist look for different analytical tools to arrive at logical conclusions. Neural networks are technical models that can lead to insightful results and have a significant impact on the market.

A stock is generally considered over-valued if the price-earning ratio is high relative to the rate at which a company's earnings are likely to grow. The converse holds true for an under-valued stock. Because of the complexity and importance of valuing common stock, various techniques for accomplishing this task have been devised over time. The techniques that will be used encompass: 1) discounted cash flow valuation techniques, where the value of the stock is estimated based upon the present value of some measure of cash flow, including dividends, operating cash flow, and free cash flow; and 2) the relative valuation techniques, where the value of a stock is estimated based upon its current price relative to variables considered significant to valuation; 3) cost of capital; 4) capital budgeting.

The dividend discount model (DDM) is very useful for the stock market analysis and has been applied to the neural network in order to verify if entities are relatively stable and if prices are efficient and fair for stocks. DDM assumes that the value of a share of common stock is the present value of all future dividends[1].

The inputs for the calculation include:

$$\textit{Value of stock} = \frac{D_1}{(1+k)} + \frac{D_2}{(1+k)^2} + \frac{D_3}{(1+k)^3} + \frac{T}{(1+k)^{\infty}}$$

Equation 4

The inputs for the calculation include:

D_t = Dividends during period t
k = The required rate of return on stock j
T= terminal stock value

The analysis above is just a brief overview of the applicability of neural networks in the stock market. The random walk theory and DDM seemed like the most applicable (and popular) methodologies to analyze.

CAPITAL BUDGETING AND RISK

Capital budgeting is one of the most important functions of financial management. It encompasses a process of planning expenditures on assets whose cash flows are expected to extend beyond one year. A company with growth rates and profit margins such as that are dictated by capital expenditure and investment cannot afford to ignore the importance of capital budgeting. Erroneous forecasts of asset requirements can have serious consequences, Therefore there is always a need for complex and accurate models to dictate the relationship between variables. How is capital budgeting associated with the neural networks? Capital budgeting typically involves a large amount of money, therefore when companies contemplate major capital expenditure programs, financing has to planned in advanced, hence the importance of stock value and forecasting mechanisms, as shown from the previous analysis, neural networks are important to this overall

[1] This model was adapted from Myron Gordon, *The Investment, Financing, and Valuation of the Corporation*. Irwin, 1962

process. What is clear is that there is a direct link between capital budgeting and stock values. The more effective the firm's capital budgeting procedures, the higher its stock price. These are hypotheses that are also tested via neural networks.

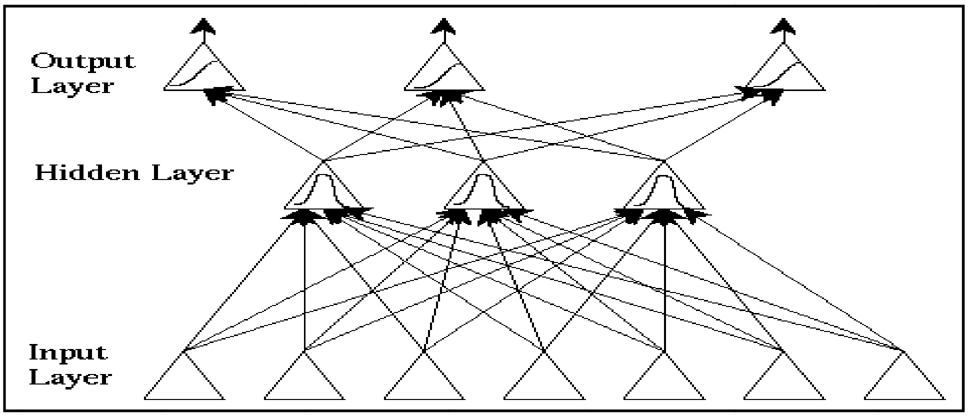
Once a potential capital budgeting project has been identified, its evaluation involves the same steps that are used in security analysis. Decision rules can be summarized by the fact that if the present value of the cash flows exceeds the cost the project is accepted. Otherwise, it should be rejected. (Alternatively, if the expected rate of return on the project exceeds its cost of capital, the project is accepted). With this similarity, it is also relatively easy to use neural networks for forecasting and arriving at relationships and estimates between the variables.

Risk analysis is best approximated with market risk, that is, the part of a project's risk that cannot be eliminated by diversification; it is measured by the beta coefficient.

With the cost of equity equation analyzed in previous sections, it is not surprising that as market risk increases, the cost of equity increases and stock value falls. Calculated risk coefficients and interactions with other variables in finance can also be approximated via neural networks.

Generally, these applications rely on the fact that neural network models can be used to devise a function from observations (that may or may not have existed before). This is usually within the finance field where data is too complex to analyze (Smith para 6). Specifically the use of artificial intelligence techniques, which is generalized in figure 4 below is used within the financial industry with the latest methodological approaches aimed at maintaining the competitive edge.

Figure 4: General Modeling of Neural Networks for Financial Capital Markets



(Inclusive of Capital Budgeting and Risk Analysis)
**Extracted from Leslie Smith, Centre for Cognitive and Computational Neuroscience*

FINANCIAL FORECASTING

Neural networks provide forecasts of market prices and actions. These can then form the basis for trading the market in an automated system. A pre-trained network is the natural choice for real-time trading. The implementation of forecasts requires a strategy for dealing with adverse market moves; the question of when to enter or exit the market is also largely determined by forecasts, hence neural networks always have a role in finance.

There are a number of considerations in using neural networks for financial forecasting, however the neural network has an advanced pattern recognition technique, which makes it particularly useful in time series forecasting.

Neural networks have also been used to analyze rather profound hypotheses. The efficient market hypothesis states that if a market is considered efficient, than prices fully reflect all the relevant information, and buying and selling stock for capital gain is purely a matter of luck, rather than sound investment skills. Neural networks have been used to chart the relationship between financial forecasting, especially for the stock market and to test the relevance of the efficient market theory(Smith para 19).

THE FUTURE OF NEURAL NETWORKS: A CRITICAL REVIEW

It is argued that neural networks cannot do anything that cannot be done using traditional techniques, but have simplified the process of completing otherwise complex and arduous tasks that researchers and analyst once had to do. Therefore, there exist many areas that can use neural networks to both increase efficiency and accuracy or as a way to improve the general analysis of the models. They include and are not limited to investment analysis, to predict stock currencies beyond the simple linear market, as a mechanism for comparing signatures with those stored, for process control, engineering applications, and in marketing for advertising and promotions. It is clear that neural networks have a rather expansive application base and will provide useful analytical results to users (Stasoft para 44).

Nevertheless, neural networks are highly technical and require a great deal of expertise to implement, although computers exist to run programs and generate results, these models are highly complex and require a great deal of technical expertise, as such there use is limited within the 'real world', although they have shown to be great theoretical models, outside of the natural science field (Smith para 34).

Some theorists have even argued that the use of neural networks undermines scientific knowledge, since it's applicable in other fields and highly technical nature may cause users to extract results without necessarily understanding the methodology used by the model.

Other areas of expansion within the neural network movement includes the production of a learning chip, sensory and sensing applications, new opportunities for forecasting stock and financial markets, as well as other financial and economic time series, the use in incomplete data to find relationships that exists, and extensions in neuroscience and biological neural networks (Stasoft para 55).

In conclusion recent developments in neural networks highlight the new opportunities that it provides as an analytical tool. The mathematical content of the methodology seems rather erudite and restrictive; however, this does not mean the neural networking is not a very analytical tool that can produce 'real' results, irrespective of the complexity of the methodology used.

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