Neural Networks and the financial forecasting: a review

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***Abstract*— An overview of the artificial neural network basics and operation, architectures, and the major algorithms used for training the neural network models are presented in this paper. Till date, neural networks have made many useful contributions to solve theoretical and practical problems in finance related areas. We see that while the main strength of Neural Networks is embedded in its non-linearity and data-driven aspects, its main shortcoming relates to the lack of explanation power in the trained networks due to the complex structure of the networks. Further, a brief review of artificial neural network applications in finance concerned areas has been discussed. It has been observed that in finance domain significant applications are in trading and forecasting such as future price estimation, foreign exchange rate forecasting, corporate bankruptcy prediction, fraud detection etc. A wide range of software based on ANNs is available today offering solutions to a number of financial problems. However, focus remains on improvement of accuracy of prediction by these networks.**

Keywords—feed forward neural networks; bankruptcy prediction; stock market analysis; foreign currency exchange rates; investment portfolio.

I. INTRODUCTION

Artificial Neural networks, ANNs, have attracted increasing attentions in recent years for solving many real-world problems and have been successfully applied in solving many complex problems where traditional problem-solving methods have failed or proved insufficient. With significant advances in processing power, neural networks research has been able to address problems that were often tackled by using simplified assumptions in the past. This has given way to new approaches based on neural networks in many areas, particularly in finance and manufacturing. This is evidenced by the exponential growth of scientific literature covering applications of neural networks in these areas. They have become well established as viable, multipurpose, robust computational methodologies with solid theoretic support and with strong potential to be effective in any discipline. Although developed as a model for mimicking human intelligence into machine, neural networks have excellent capability of learning the relationship between input-output mapping from a given dataset without any knowledge or assumptions about the statistical distribution of data. This capability of learning from data without any a prior knowledge makes neural networks particularly suitable for classification and regression tasks in practical situations.

II. WHAT ARE ARTIFICIAL NEURAL NETWORKS?

Artificial neural networks, originally developed to mimic basic biological neural network that is the human brain in particular are composed of a number of interconnected simple processing elements called *neurons* or *nodes*. Each node receives an input signal which is the total information from other nodes or external stimuli, processes it locally through an activation or transfer function and produces a transformed output signal to other nodes or external outputs. Although each individual neuron implements its function rather slowly and imperfectly, collectively a network can perform a surprising number of tasks quite efficiently. Like the linear and polynomial approximation methods, a neural network relates a set of input variables $\{X_i\}$; i= 1,2,…m, to a set of one or more output variables, $\{Y_j\}$; j= 1,2, . . . ,n. The difference between a neural network and the other approximation methods is that the neural network makes use of one or more hidden layers, in which the input variables are squashed or *transformed* by a special activation function, such as a *Log sigmoid* or *Linear* or *Hyperbolic tangent* or *Gaussian transformation* and even *exponential function*. While this hidden layer approach may seem obscure, it represents a very efficient way to model nonlinear statistical processes.

III. ARCHITECTURE OF NEURAL NETWORKS

The architecture of the network defines how the nodes in a network are highly interconnected. Two broad categories are Feed-forward and Feedback architectures. The feed-forward architecture can be of three basic types;

- A Single layer feed forward network
- A Multilayer feed forward network
- A Recurrent network

A. Single Layer feed forward network

The Single Layer Feed-forward Network consists of a single layer of weights, where the inputs are directly connected to the outputs, via a series of weights. The synaptic links carrying weights connect every input to every output, but not other way. This way it is considered a network of feed-forward type. The sum of the products of the weights and the inputs is calculated in each neuron node, and if the value is above some threshold (typically 0) the neuron fires and takes the activated value (typically 1); otherwise it takes the deactivated value (typically -1).

B. Multilayer feed forward network

Multilayer feed forward network architecture is depicted in Figure 1. The nodes are organized into a series of layers with an input layer, one hidden layer (more hidden layers are possible) and an output layer. Data flows through this network in one direction only, from the input layer to the output layer displaying parallel processing technique. Figure 1 illustrates the architecture on a neural network with one hidden layer containing four neurons, three input variables $\{X_i\}$; i = 1, 2, 3, and one output {Y}.

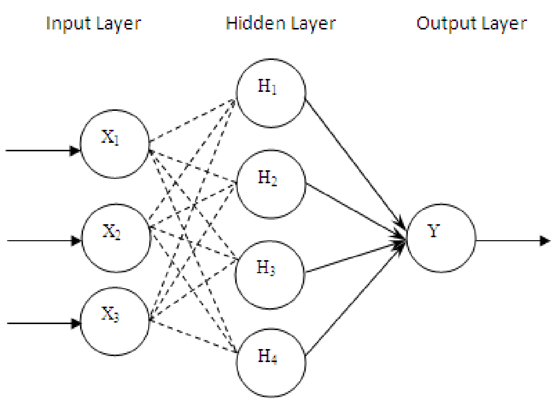

Fig 1. Multilayer Neural Network

C. Recurrent network

The Recurrent type differs from the other two in the manner that it has at least one feedback loop as shown in Figure 2.

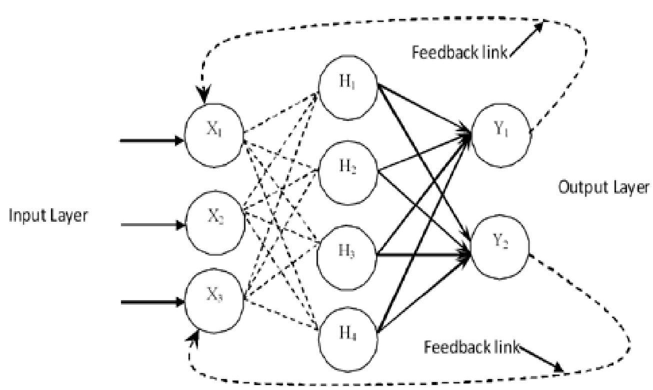

Fig 2. Recurrent Neural Network

In addition to the sequential processing of typical linear systems, in which only observed inputs are used to predict an observed output by weighting the input neurons, the four neurons in the hidden layer process the inputs in a parallel fashion to improve the predictions. The connectors between the input variables, often called input neurons, and the neurons in the hidden layer, as well as the connectors between the hidden-layer neurons and the output variable, or output neuron, are called *synapses*.

This single-layer feed-forward or multi perceptron network with one hidden layer is the most basic and commonly used neural network in economic and financial applications. More generally, the network represents the way the human brain processes input sensory data, received as input neurons, into recognition as an output neuron. As the brain develops, more and more neurons are interconnected by more synapses, and the signals of the different neurons, working in parallel fashion, in more and more hidden layers, are combined by the synapses to produce reaction. However, very simple input sensory data, such as the experience of heat or cold, need not lead to processing by very many neurons in multiple hidden layers to produce the recognition that it is time to turn up or down the heat. But as experiences of input sensory data become more complex or diverse, more hidden neurons are activated, and insight as well as decision is a result of proper weighting or combining signals from many neurons, perhaps in many hidden layers.

IV. TRAINING OF THE ARTIFICIAL NEURAL NETWORK

Before an ANN can be used to perform any desired task, it must be trained to do so. Training is the process of determining the arc weights, which are the key elements of an ANN. The knowledge learned by a network is stored in the arcs and nodes in the form of arc weights and node biases. It is through the linking arcs that an ANN can carry out complex nonlinear mappings from its input nodes to its output nodes. A multilayer network's training is a supervised one in that the desired response of the network (target value) for each input pattern is always available.

The learning methods in neural networks are classified into three basic types:

1. Supervised Learning (error based)
2. Unsupervised Learning (output based)
3. Reinforced Learning

These classifications are based on the presence or absence of teacher and the information provided for the system to learn.

1. Supervised learning:

A teacher is present during learning process and presents expected output. Every input pattern is used to train the network. Learning process is based on comparison, between network's computed output and the correct expected output, generating "error". The "error" generated is used to change network parameters that result improved performance.

2. Unsupervised learning:

No teacher is present. The expected or desired output is not presented to the network. The system learns of its own by discovering and adapting to the structural features in the input patterns.

3. Reinforced learning:

A teacher is present but does not present the expected or desired output but only indicated if the computed output is correct or incorrect. The information provided helps the network in its learning process. A reward is given for correct answer computed and a penalty for a wrong answer.

However the Supervised and Unsupervised learning methods are most popular forms of learning compared to Reinforced learning.

V. Neural Networks Application

Applications of neural networks includes a wide range of real world problems, for example, future price estimation, derivative securities pricing and hedging, exchange rate forecasting, bankruptcy prediction, stock performance and selection, portfolio assignment and optimization, financial volatility assessment and so on.

a) Bankruptcy prediction

Bankruptcy prediction has been an important and widely studied topic. The prediction of the likelihood of failure of a company given a number of financial measures, how soon an "ill" business can be identified, possibility of identifying the factors that put a business at risk these are of main interest in bank lending. Supervised neural network models have been tested against a number of techniques, like discriminant analysis (Kiviluoto, 1998; Olmeda & Fernandez, 1997); regression (Fletcher & Goss, 1993; Leshno & Spector; 1996); decision trees (Tam & Kiang, 1992); *k*-nearest neighbor (Kiviluoto); multiple adaptive regression splines (MARS) (Olmeda & Fernandez); case-based reasoning (Jo, Han, & Lee, 1997), and so on. In most cases, neural network models attained significantly better accuracy compared to other methods.

b) Stock market analysis

Stock analysis has long been one of the most important applications of neural networks in finance. Most international investment bankers and brokerage firms have major stakes in overseas markets. Hence, this topic has attracted considerable attentions from the research community. In most cases, neural networks outperformed other statistical methods.

c) Foreign currency exchange rates

Modeling foreign currency exchange rates is an important issue for the business community. The investment companies are dependent on the prediction of accurate exchange rates so that they may make investment decisions. This is quite a challenging job as the rates are inherently noisy, non stationary, and deterministically chaotic. Yao & Tan (2000) developed a neural network model using six simple indicators to predict the exchange rate of six different currencies against the U.S. dollar.

d) Investment portfolio

For every investment, there is a tradeoff between risk and return. So, it is necessary to ensure a balance between these two factors. Optimizing one's portfolio investment by analyzing those factors, maximizing the expected returns for a given risk, and rebalancing when needed is crucial for secure investment. Steiner and Wittkemper (1997) developed a portfolio structure optimization model on a day-to-day trading basis. While the stock decisions are derived from a nonlinear dynamic capital market model, the underlying estimation and forecast modules are based on the neural network model. Using German stock prices from 1990 to 1994, this model leads to a portfolio that outperforms the market portfolio by about 60%. Hung, Liang, and Liu (1996) proposed an integration of arbitrage pricing theory (APT) and an ANN to support portfolio management and report that the integrated model beats the benchmark and outperforms the traditional ARIMA model. Yeo, Smith, Willis, and Brooks (2002) also used k-means clustering and neural networks for optimal portfolio selection. Classification of policy holders into risk groups and predicting the claim cost of each group were done using k-means clustering while price sensitivity of each group was estimated by neural networks.

Other applications include detecting financial fraud; creating wealth; and modeling the relationship among corporate strategy, its financial status, and performance (Smith & Gupta, 2000). Holder (1995) reports that Visa International deployed a neural network based fraud detection system that saved it an estimated $40 million within the first 6 months of its operation. Apart from theoretical research, Coakely and Brown (2000) describe a number of ANN based systems that are widely used in commercial applications. These are:

- "FALCON", used by six of the ten largest credit card companies to screen transactions for potential fraud.
- "Inspector", used by Chemical Bank to screen foreign currency transactions.
- "AREAS", used for residential property valuation.

Several ANNs used to assist in managing investments by making predictions about debt and equity securities, as well as derivative instruments. Fadlalla and Lin (2001) cited examples from companies like Falcon Asset management, John Deere and Co., Hyman Beck and Company, Multiverse Systems, Advanced Investment Technology, and Ward System who used neural network-based systems. It has been reported that a significant number of Fortune-1000 companies use neural networks for financial modeling. Several ANNs used for credit granting, including GMAC's Credit Adviser that grants instant credit for automobile loans.

VI. CONCLUSION

Artificial neural networks possess many desirable features that have made them suitable for practical financial and forecasting applications. We learnt brief description of ANN architectures and different training algorithms that are most commonly used in these applications. Specific areas in finance that have experienced remarkable results by modeling with neural networks are described and some of the important and relevant works are reported. ANNs offer a promising alternative approach to traditional linear methods. Unlike expert systems which have hard-coded rules for the analysis of events, neural networks adapt their analysis of data in response to the training which is conducted on the network. The connection weights and transfer functions of the various network nodes are usually frozen after the network has achieved an acceptable level of success in the identification of events. While the network analysis is achieving a sufficient probability of success, the basis for this level of accuracy is not often known. Hence, while ANNs provide a great deal of promises, they also embody a large degree of uncertainty.

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