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STOCK PRICE PREDICTION USING NEURAL NETWORK

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Abstract

In recent years researchers have developed a lot of concern in stock market prediction because of its dynamic & unpredictable temperament. Predicting anything is very tough especially if the relationship between the inputs and outputs are non-linear in nature and stock price prediction is one of such item. Predicting stock data with customary time series analysis has proven to be intricate. An artificial neural network may be more pertinent for the task .Primarily because no postulation about a suitable mathematical model has to be made prior to forecasting. Furthermore, a neural network has the knack to extract useful information from hefty sets of data, which frequently is required for a satisfying description of a financial time series.

There have been vast studies using **artificial neural networks (ANNs)** in the stock market prediction. A large number of triumphant applications have shown that ANN can be a very handy tool for time-series modeling and forecasting. Much research on the applications of NNs for solving industry problems has established their advantages over statistical and other methods that do not embrace AI, although there is no optimal methodology for a certain problem. In order to recognize the main benefits and limitations of previous methods in NN applications and to find associations between methodology and problem domains, data models, and outcome obtained, a proportional analysis of selected applications is conducted. It can be concluded from inspection that NNs are most implemented in forecasting stock prices, takings, and stock modeling.

1. Introduction

Prediction in stock market has been a hot research subject for many years. Generally, there are four schools of thought in terms of the ability to profit from the stock market.

The **first school** believes that no patron can achieve above average trading advantages based on the historical and present information.

The key theories incorporate the ***Random Walk Hypothesis*** and the ***Efficient Market Hypothesis –***

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- According to "The **Random Walk Hypothesis** "prices on the stock arise without any influence by precedent prices.
- According to "The **Efficient Market Hypothesis** "price on the stock arise without any influence by precedent prices. The Efficient Market Hypothesis states that the market entirely reflects all of the freely available information and prices are adjusted fully and immediately once new information becomes accessible. If this is true then there should not be any benefit for prediction, because the market will respond and reimburse for any action made from these available information.

According to **second school's** view, in the actual market, some people do react to information immediately after they have received the information while other people wait for the confirmation of information. The waiting people do not retort until a trend is clearly established because of a specific company and the underlying behavior of its common stock. The importance of a stock is established by analyzing the fundamental information coupled with the company such as accounting, competition, and management.

The **third school's** view is technical study, which assumes the stock market moves in trends and these trends can be captured and used for forecasting. It attempts to exploit past stock price and volume information to forecast future price movements. The technical forecaster believes that there are recurring patterns in the market behavior that are conventional. They use such tools as charting patterns, technological indicators, and specialized techniques like Elliot Waves and Fibonacci series. Indicators result from price and trading volume time series. Unfortunately, most of the techniques used by technical analysts have not been publicized to be statistically compelling and many lack a rational explanation for their use.

The **fourth school's** view is dynamic systems and chaotic behavior of stock price. From this perspective, stock price movements have a very complex and nonlinear relations to some variables which advanced mathematical modeling of its can be done. One of the challenges of modern capital market analysis is to develop theories that are capable of explaining the movements in asset prices and returns. The learning of stock market has led pecuniary economists to apply statistical techniques from chaos theory for analyzing stock market data. Based on these new techniques, current empirical studies document nonlinearities in stock market data.

Our **core result** is that stock price structure is much complex and neural network model is apposite for capturing all the nonlinear vibrant relationships.

Why neural network is best for prediction?

The prototype extraction in time-series prediction is referred as the process of identifying past relationships and trends in historical data for predicting future values. The pattern modeling technique performs frequently used statistical methods such as Exponential Smoothing on different error measures and predicting the direction of change in time-series (Zhang, 2004). Green and Pearson (1994) and others argue that a better method for measuring the performance of neural networks is to analyze the direction of change (Walczak, 2001). Therefore, the reported accuracy of the neural network forecasting models developed for the research presented in this paper is the percentage of correct market direction forecasts made by the neural network.

The direction of alteration is calculated by subtracting today's price from the forecast price and determining the sign (positive or negative) of the result. The percentage of correct direction of change forecasts is equivalent to the percentage of profitable trades enabled by the ANN system. Depending on the trading strategies adopted intensity-based forecasting models, forecasting methods based on latent smoothing, Bayesian vector auto regression minimizing forecast error may not be adequate regression, multivariate transfer function, and to meet their objectives (Leung et al., 2000). In other terms, trading (multilayered feed forward neural network) which driven by a certain forecast with a small fore-will be tested against their classification error may not be as profitable as trading counterparts. The design of the guided by an exact prediction of the direction experiment (movement or sign of return) is discussed, predicting the direction of change of the stock and how to apply the directional forecasts and market index and its return is also significant in the posterior probabilities supplied by the classification development of effective market trading models.

Instead of predicting the authentic value of the stock return, the direction of future change of the financial market is what really needed. Predicting the direction of change is easier for the neural network when compared to actual value because of the noisy and non-stationary behavior of the financial time series. The predicted direction can then be used to make a trading conclusion. This can be accomplished by changing the time series prediction problem into a classification assignment. Recently, Leung et al. (2000) find that the forecasting models based on the direction of stock return outperform the models based on the level of stock return in terms of predicting the direction of stock market return and maximizing profits from investment trading.

Machine learning approach is alluring for artificial intelligence since it is based on the principle of learning from training and practice. Connectionist models, such as ANNs, are well suitable for machine learning where connection weights are adjusted to improve the performance of a network. An ANN is a association of nodes connected with directed arcs each with a numerical weight *i* , *j* ,w specifying the strength of the connection (Figure1). These weights indicate the influence of previous node, *j u* , on the next node, *i u* ,where positive weights represent reinforcement; negative weights represent inhibition.

Normally the initial connection weights are randomly selected.

Figure 1: Connection weight involving nodes

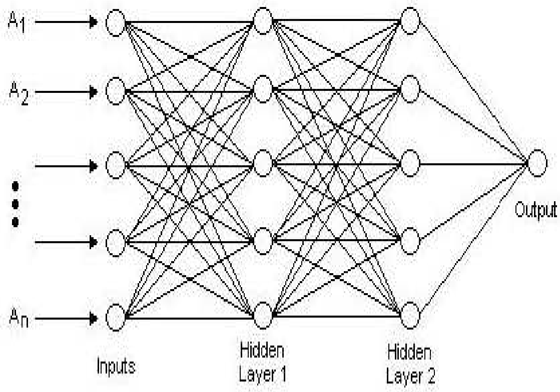

Figure 2: 2-hidden layers arrangement with n inputs and 1 output

Neural Networks-

There are several distinguished features that propound the use of neural network as a preferred tool over other traditional models of calculation. Artificial neural networks are nonlinear in nature and where most of the natural real world systems are non linear in nature, artificial neural networks are favored over the traditional linear models. This is because the linear models usually fail to understand the data pattern and analyze when the underlying system is a non linear one. Nevertheless, some parametric nonlinear model such as Autoregressive Conditional Heteroskedasticity (Engle, 1982) and General Autoregressive Conditional Heteroskedasticity have been in use for stock prediction. But a good number of the non linear statistical techniques require that the non linear model must be specified before the estimation of the parameters is done and generally it happens that prespecified nonlinear models may not succeed to observe the critical features of the complex system under study.

Artificial neural networks are data driven models. The originality of the neural network lies in their ability to discover nonlinear relationship in the input data set without a priori assumption of the knowledge of relation between the input and the output (Hagen et al., 1996) the contributing variables are mapped to the output variables by hush-up or transforming by a special function known as activation function. They autonomously learn the relationship inherent in the variables from a set of labeled training example and therefore involves in modification of the network parameters. Artificial neural networks have a built in potential to adapt the network parameters to the changes in the studied scheme. A neural network trained to a particular input data set subsequent to a particular environment; can be easily retrained to a new environment to predict at the same level of environment. Besides, when the system under study is non stationary and dynamic in nature, the neural network can change its network parameters (synaptic weights) in real time. So, neural network suits superior than other models in predicting the stock market returns.

Stock Market Prediction through Neural Network-

There are many real life tribulations in which future events must be predicted on the basis of past history. An instance of that task is that of predicting the behavior of stock market indices. Weigend and huberman in 1990 observe that prediction hinges on two types of knowledge underlying laws, a very compelling and accurate means of prediction and the discovery of strong empirical regularities in observations of a given system.

Though perfect prediction is hardly ever feasible, artificial neural networks can be used to obtain reasonably good prediction in a number of cases. In prediction problems, it is significant to consider both short-term ("one leg") and long term ("multi lag") predictions.

- In one leg prediction, we anticipate the next value based only on actual past values.
- In multi lag prediction, on the other hand, a few predicted values are also used to predict futures values.

From a very broad outlook, artificial neural networks can be used for financial prediction in one of the three ways-

- It can be provided by means of inputs, which enable it to find rules relating the current state of the system being predicted to future states.
- It can have a window of inputs unfolding a fixed set of recent past states and relate those to future states.
- It can be considered with an internal state to enable it to learn the relationship of an indefinitely large set of past inputs to future states, which can be accomplished via recurrent connections.

Prediction on stock outlay by neural network consists of two steps training or fitting of neural network and prediction. In the training step, network generates a cluster of connecting weights, receiving an output result through positive spread, and then compares this with probable value. If the error has not reached estimated minimum, it turns into negative spreading process, modifies linking weights of network to reduce errors. Output computation of positive spread and connecting weight calibration of negative spread are doing in turn. This process lasts till the error between realistic output and expected value meets the requirements, so that the satisfactory connecting weights and threshold can be achieved. Network prediction practice is to input testing sample to predict, through stable trained network (including training parameters), connecting weights and threshold.

It is nowadays a common notion that vast amounts of capital are traded through the stock markets all around the globe. National economies are robustly linked and heavily influenced by the performance of their stock markets. Furthermore, recently the markets have become a more available investment tool, not only for strategic investors nevertheless for common people as well. Accordingly they are not only related to macroeconomic parameters, but they persuade everyday life in a more direct way. Therefore they comprise a mechanism which has important and direct social impacts. The attribute that all stock markets have in regular is the ambiguity, which is related to their short and long term future state. This feature is objectionable for the investor but it is also unavoidable whenever the stock market is selected as the investment tool. The finest that one can do is to try to reduce this uncertainty. Stock market forecast is one of the instruments in this procedure.

The main **benefit** of artificial neural networks is that they can estimate any nonlinear function to an arbitrary degree of accuracy with a suitable number of hidden units .

"Halbert White" reported some results of an on-going project using neural network modeling and learning techniques to search for and decode nonlinear regularities in asset price movements. Author, focus on case of IBM common stock daily returns. Having to deal with the significant features of economic data highlights the role to be played by statistical inference and requires modifications to standard learning techniques which may prove useful in other contexts.

"Dase R.K. and Pawar D.D" predicated stock rate because it is a challenging and intimidating task to find out which is more effective and accurate method so that a buy or sell signal can be generated for specified stocks. Predicting stock index with customary time series analysis has proven to be difficult an artificial neural network may be suitable for the task. Neural network has the knack to extract useful information from large set of data. In this paper author also presented an appraisal on application of artificial neural network in stock market prediction.

"Phaisarn sutheebanjard et al." predicted the stock exchange of Thailand index movement. presently, there are two stock markets in Thailand; the stock exchange of Thailand (SET) and the market for alternative investment (MAI). This paper focuses on the association of the stock exchange of Thailand index (SET Index). The back propagation neural network (BPNN) technology was employed in prediction the SET index. An research was conducted by using data of 124 trading days from 2 July 2004 to 30 December 2004. The data were alienated into two groups: 53 days for BPNN training and 71 days for testing. The experimental outcome shows that the BPNN successfully predicts the SET Index with less than 2% error. The BPNN also achieves a lower prediction error when compared with the adaptive evolution approach, but a higher prediction error when compared with the (1+1) evolution strategy.

"Tong-Seng Quah" presented methodologies to select equities based on soft-computing models which focus on applying fundamental analysis for equities screening. This paper compares the act of three soft-computing models, namely multilayer perceptrons (MLP), adaptive neuro-fuzzy inference systems (ANFIS) and general growing and pruning radial basis function (GGAP-RBF). It studies their computational time complexity; applies several benchmark matrices to compare their performance, such as generalize rate, recall rate, perplexity matrices, and correspondence to appreciation. Author moreover suggests how equities can be picked systematically by using relative operating characteristics (ROC) curve.

"Manna majumder and MD anwar hussian" presented a computational approach for predicting the S&P CNX Nifty 50 Index. A neural network based representation has been used in predicting the direction of the movement of the closing value of the index. The model presented in the article also confirms that it can be used to predict price index value of the stock market. After studying the different features of the network model, an finest model is proposed for the purpose of forecasting. The representation has used the pre-processed data set of closing value of S&P CNX Nifty 50 Index. The data set comprises the trading days from 1st January, 2000 to 31st December, 2009. In the article, the model has been validated across 4 years of the trading days. Accuracy of the performance of the neural network is compared using various out of sample performance measures. The highest performance of the network in terms of accuracy in predicting the direction of the closing value of the index is reported at 89.65% and with an average accuracy of 69.72% over a period of 4 years.

"Yumlu et al" have studied 12 years of financial data (a set of ISE index close value, USD value and two interest rates) using a modular ANN model and have concluded that the model outperforms the conventional autoregressive model used for evaluation. The authors state that the model introduces a powerful way to predict the volatility of financial point in time series records, contradicting EMH.

Modeling of Stock Market Index Value-

Forecasting of stock exchange market index values is an important issue in financial sector. The objective of this paper is to illustrate that the ANNs can effectively be used to predict the Stock Exchange (ISE) index values using previous day's index value, previous day's TL/USD trade rate, preceding day's overnight interest rate and 5 dummy variables each representing the working days of the week. Supervised learning models have been utilized in which certain output nodes were trained to respond to certain input patterns and the changes in connection weights due to learning caused those same nodes to respond to more general classes of patterns.

Feed-forward networks were first studied by Rosenblatt (1961). Input layer is composed of a set of inputs that feed input patterns to the network. Following the input level there will be at least one or more intermediary layers, often called hidden layers. Hidden layers will then be followed by an output layer, where the results can be achieved . In feed-forward networks all connections are unidirectional.

Multi Layer Perceptron (MLP) networks are layered feed-forward networks typically trained with static back propagation. These networks, moreover known as back propagation networks, are mainly used for applications requiring static pattern classification (Egeli et al., 2003). The back propagation algorithm selects a training exemplar, makes a forward and a backward pass, and subsequently repeats until algorithm converges satisfying a prespecified mean squared error value. The key advantage of MLP networks is their ease of use and approximation of any input/output map. The main shortcoming is that they train slowly and require lots of training data.

Generalized feed forward (GFF) networks are a generalization of the MLP networks where connections can jump over one or more layers, but these networks often solve problems much more efficiently (Arulampalam and Bouzerdoum, 2003; Enke and Thawornwong, 2005).

1. System Model

In this study the subsequent input variables were considered to ultimately affect the stock exchange market index value.

Previous day's ISE National 100 index value (according to closing price) (ISE_PREV)

Previous day's TL/USD exchange rate (average of buying and selling values) (TL_USD_PREV)

Earlier day's Simple Interest Rate Weighted Average Overnight (ON_PREV)

Dummy variable 1 representing Monday (will be 1 when the day is Monday, else would be 0) (M) Dummy variable 2 representing Tuesday (TU) Dummy variable 3 representing Wednesday (W) Dummy variable 4 representing Thursday (TH) Dummy variable 5 representing Friday (F)

Considering the input variables, the following structure model was considered for the prediction stock exchange market index value:

ISE f = *f* (ISE_PREV, TL_USD_PREV, ON_PREV, M, TU, W, TH, F)

2. Network Parameters

For the system model described before, two different ANN models (MLP* and GFF* were applied with different number of hidden layers (HL = 1, 2, 4) for minimum mean squared fault value of 0.003, for the data set. Thus, 6 dissimilar ANN models have been used.

3. Training Results

In this study, 6 ANN models were applied to the system model, via an ANN software package. ANN models' performances can be considered by the coefficient of determination (R2) or the mean relative percentage error. This coefficient of determination is a evaluation of the accuracy of prediction of the trained network models. Elevated R2 values indicate better calculation. The mean relative percentage error may also be used to measure the accuracy of prediction through representing the degree of scatter. For each prediction model, the relative error for each case in the testing set is calculated. Then, the calculated values were averaged and factored by 100 to express in percentages.

Table-1 depicts the ANN models with the R2 values of the 3 MLP* and 3 GFF* network models applied to system model.

Number of Hidden Layers	ANN Model	
	MLP*	GFF*
1	0.81	0.82
2	0.79	0.81
4	0.78	0.81

Table-1 Coefficient of determinations (R2) intended for ANN models

4. Comparison with Moving Averages

The ANN performances can be compared with Moving Averages (MA) approach. The moving average is the average of lagged index values over a specified past period (5 and 10 days in this study). The mean comparative percentage errors were calculated as 0.022 for 5 days and 0.03 for 10 days. Table-2 shows the entire models with mean relative percentage errors.

Model	Mean Relative Percentage Error (%)
MLP* - 1	Hidden Layer 1.62
MLP *– 2	Hidden Layers 1.65
MLP *- 4	Hidden Layers 1.70
GFF *- 1	Hidden Layer 1.59
GFF *– 2	Hidden Layers 1.65
GFF *- 4	Hidden Layers 1.71
MA - 5 days	2.17
MA - 10 days	3.03

Table-2 Mean relative percentage errors intended for all models

5. Evaluation

The accuracy of the prediction for each ANN model has been compared by the coefficient of determination. The competence of ANN models assorted with the number of hidden layers. For both MLP* and GFF* network models, the maximum accuracies are obtained with 1 hidden layer.

The mean relative percentage errors intended for all models verified that the ANN models were superior to the MA model.

6. Conclusion-

This study was aimed at finding the best model for the prediction of Stock Exchange market index values. On the whole of 8 sets of predictions, result from the application of 6 ANN models and two MA were performed. Results were compared using the coefficients of determination for ANN models and using mean relative percentage errors for all of the models.

Based on the outcome of this study it can be concluded that:

1. The prediction models based on ANNs were more accurate than the ones based on MAs.
2. Among the ANN models, GFF* network model was found to be more appropriate for the prediction.

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