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A Modular Approach for Forecasting Stock Market Using Neural Networks

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Abstract

Neural networks have been applied to a variety of challenging pattern detection problems, including stock market prediction, as an intelligent data mining tool. The optimum neural network for making predictions cannot, however, be selected in a formal manner according to the literature. This study uses an Elman recurrent network and a feed forward multilayer perception to calculate a company's stock value based on the performance of its stock shares in the past. The experimental results indicate that when anticipating changes in stock value, neural network application has more potential than Elman recurrent network and linear regression technique. However, we demonstrate that the Elman recurrent network and linear regression are superior to the based model for predicting the direction of changes in stock value.

There are presently no practical solutions to make it easier to create neural networks for specific applications; hence major progress in neural network theory is still needed.

Keywords: *Neural networks, stock market prediction, linear regression, mining tool, anticipating changes in stock value.*

Introduction

Making life easy for himself has been a shared human endeavour from the dawn of humanity. It is not unexpected that there has been so much research done on methods to anticipate the markets given that the dominant belief in society is that riches provides comfort and pleasure. With varied degrees of success, a number of technical, basic, and statistical indicators have been presented. However, no one tactic or set of tactics has proven effective enough to regularly "beat the market." Researchers and investors are hopeful that the market riddles may be solved with the development of neural networks. This study analyses existing market forecasting methods with a focus on their shortcomings and how neural networks have been utilized to enhance them.

For many years, conventional statistical forecasting techniques have provided the foundation for predictions in the field of financial engineering. Such conventional statistical forecasting has always been based on linear models. However, because of the noise and non-linearity in the time series, conventional approaches have seldom been successful. The successful use of non-linear approaches in other fields of study has raised expectations for those working in finance. A fresh perspective on financial asset values is put forth by nonlinear dynamics, along with new methods for experimentally determining their characteristics. This emerging field suggests that previous prices influence present prices, but not in a clear manner. The relationship between previous prices and future prices will initially be nonlinear rather than linear.

Because of this non-linearity, prior price changes may have a significant impact on future prices. The precise process by which past prices are connected to future prices will determine whether previous prices cause calm or agitated changes in future prices. With the use of nonlinear dynamics, one may determine if a certain condition of nature is more likely to exist than another (which is unexpected). Nonlinear dynamics can kind of determine when a forecast starts to become suspect. From such a prognosis, the greatest advise one can hope to receive is that it is preferable to stay out of a certain market entirely. Consequently, this study makes an effort to comprehend how neural networks are used in the banking industry.

Because of their intriguing learning capabilities, neural networks have attracted a lot of attention in financial engineering recently. They have the ability to handle issues with structural instability. When the mapping from the input to the output incorporates both regularities and exceptions, it is regarded as a successful modeling technique. As long as the network has a significant amount of free parameters (i.e., hidden units and/or connections), they may theoretically solve any non-linear classification problems. The study of neural networks has grown quickly and gained a lot of attention from both academic and industrial research organizations. Similar to nonparametric, non-linear regression models are neural networks.

Their uniqueness comes in their capacity to simulate non-linear processes with little (or no) prior knowledge of the make-up of the generating process.

Prediction Method Analysis:

The majority of stock and commodity trading relied on intuition. People looked for strategies and systems that could reliably forecast share prices as trading became more popular in order to maximise profits and reduce risk. Share price forecasts have been made using a variety of techniques, including fundamental analysis, technical analysis, and machine learning, but none of these techniques has been consistently effective.

Fundamental Analysis :

In order to comprehend a company's position in the market and, consequently, its profitability as an investment, fundamental analysis entails physically studying it in terms of its product sales, workforce, quality, infrastructure, etc. [7]. According to the fundamental analysts, logical variables account for 90% of market definitions and physiological factors account for 10%. However, this technique is not appropriate for our study since the data it utilises to calculate an asset's intrinsic worth doesn't change every day and is therefore unsuitable for short-term usage. However, only long-term predictions of the share market can be made using this methodology..

Technical Analysis:

Technical analysis makes predictions about when it is best to purchase or sell a stock. Technical analysts forecast future share movements using charts that include technical information including price, volume, and the highest and lowest prices per trade. Trends can be identified using price charts. These trends can be explained by supply and demand problems, which frequently have cyclical or other observable patterns. Some criteria can direct an investor toward making a thoughtful choice by helping them comprehend a firm and its profitability through the share prices it trades on the market. Indicators and oscillators are the names given to these characteristics [7]. This kind of market forecasting is fairly common. However, the issue with this analysis is that drawing trading conclusions from the examination of charts is somewhat subjective, thus various analysts draw different conclusions from the same charts. This study may be used to forecast market prices on a daily basis, but we won't do so due to the subjective nature of the method.

Machine Learning Methods:

Since it is founded on the idea that learning comes through experience and training, the machine learning technique is appealing for artificial intelligence. A network's performance may be enhanced by adjusting the connection weights in connectionist models [8] like ANNs, which are particularly suited for machine learning.

Challenge In Prediction Of Share Market Price

The fact that the stock market is a chaotic system makes prediction difficult. There are several factors that might have a direct or indirect impact on the stock market. The factors and the price have no meaningful relationships. There is no mathematical connection that can be made between the variables. The share price cannot be predicted using these factors according to any rules.

Our System Architecture

The neural network technique is appropriate for this type of chaotic system since we do not need to grasp the answer. This is a significant benefit of neural network methods [9]. The inputs, methods, and outputs for traditional procedures, on the other hand, require a deep understanding. We only need to display the right output using the neural network given the inputs. The network will simulate the function with enough training [9, 10]. The network will learn to disregard any inputs that don't contribute to the output during the tanning process, which is another benefit of neural networks [9, 10].

The training phase of our system involves the discovery of some parameters called weights from this section using the Backpropagation Algorithm. The same equations that were employed in the training phase are applied to these weights in the prediction phase. This is our system's fundamental architecture, and this method is referred to as a feedforward network. There are several elements that affect share price in the stock market. However, not all inputs are incorporated in our system since their effects on share market price are insignificant. The system has 5 inputs total. General Index (GI), P/E ratio, Net Asset Value (NAV), Earnings per Share (EPS), and volume are the inputs. The data set was then adjusted for the network and sent back into the network.

Section I

Neural Network Architecture

A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. Artificial neural networks are computers whose architecture is modeled after the brain. It resembles the brain in two respects: knowledge is acquired by the network through a learning process and inter-neuron connection strengths known as synaptic weights are used to store the knowledge. They typically consist of many hundreds of simple processing units, which are wired, together in a complex communication network. Each unit or node is a simplified model of a real neuron, which fires (sends off a new signal) if it receives a sufficiently strong. Input signal from the other nodes to which it is connected. The network may execute various tasks according to various patterns of node firing activity by varying the strength of these connections.

Neural networks may be applied to financial decision-making in one of three ways, seen from a very wide perspective:

1. It can be given inputs that allow it to discover rules connecting the state of the system being forecasted now to states in the future.
2. It can link a window of inputs that describe a predetermined collection of recent past states to future states.
3. It may be created with an internal state that allows it to use recurrent connections to learn the correlation between an infinitely large set of past inputs and future states.

Section II:

Neural Networks in financial forecasting

Jason E. Kusturelis examines the use of neural networks to predict the future trend of stock market indices. The accuracy of forecasting is compared with traditional multiple linear regression analysis. Besides, the probability of the correctness of the model forecasted is calculated using conditional probabilities. The back propagation algorithm is used in order to minimize the error term between the output of the neural network and the actual desired output value. The error term is calculated by comparing the network is output to the desired output and is then fed back through the network causing the weights to be changed in an effort to minimize error. This process is repeated till the error reaches a minimum value. The study concludes by registering a 93.3% probability in predicting a market rise and 88.07% probability in predicting a market drop in the S&P 500. The author also affirms that linearity assumption in multiple regression analysis may not be true in all cases while neural network can model both linear and curvilinear systems. Besides, neural network models are significantly more accurate than multiple linear regression analysis. The author also cautions not to blindly follow the networkís advice but recommends to double check the network using multiple networks incorporating different inputs to predict the same output.

A.N. Refenes et.al (1997) have developed a model to predict the 30-day stock returns of the Paris Stock Exchange. The stock returns are estimated as a function of long and short-term interest rates, earnings per share, price earning ratio and exchange rate of Franc against the U.S. dollar. The network chosen is the feed-forward, multi-layered and fully connected networks and is trained using the standard backpropagation algorithm. The work concludes by reinforcing the fact that the back propagation networks are more efficient for non-linear data. Peter C. McCluskey, Peter C. (1993) has used neural network training algorithms to predict the Standard & Pooris 500 Index and then has compared the results with the Genetic programming and hand coding approaches. Feed forward networks are used to predict the Index returns and the network is trained using the back propagation algorithm. The networks are trained to predict the change in S&P 500 closing prices for the next 1, 2 and 4 weeks. The data used is divided into two parts: prior to November 16, 1979 and November 19, 1979 to April 2, 1993. Though the model has worked well based on the historical data set taken as input, the author mentions that the future performance of the model is not warranted as the results are not likely to match the ideal of the historical closing prices.

Tan Sen Suan, Koh Hian Chye (1997) have developed a neural network model to predict bankruptcies. The network consisted of an input layer of six neurons for six financial ratios: quick assets to current liabilities, market value of equity to total assets, total liabilities to total assets, interest payments to earnings before interest and tax, net income to total assets, retained earnings to total earnings. The hidden layer consisted of 13 nodes and the output layer had one node. It was noted that the network ís accuracy rate was 100% for bankrupt firms, non-bankrupt firms and overall. A.N. Burgess describes a study of Eurodollar futures. The data consists of daily, high, low, open and close prices for Eurodollar futures over the time period August 1987 to July 1994, giving 1760 daily observations in all. The futures contract ranged from less than three months at the short end to three years at the long end. The standard multi-layer perception network was used with two hidden layers. The out of the sample test showed that the neural network could generate consistent profits resulting in an average return of 47% per year which is sufficient enough to conclude that the Eurodollar yield appears to be predictable by non-linear techniques. M. Thenmozhi 64 James M.Hutchinson et.al (1994) have proposed a non-parametric method for estimating the pricing formula of a derivative using learning networks. The inputs to the network are the primary economic variables that influence the derivativeís price namely, current fundamental asset price, strike price, time to maturity, etc. The derivative price is defined to be the output into which the learning network maps the inputs. Once the network is trained, the network becomes the derivative pricing formula. The data used here is the daily closing prices of S&P 500 futures and options for the 5-year period from January 1987 to December 1991. On comparing the results with the parametric derivative pricing formula, the authors have been cautiously optimistic about their general approach with a number of promising directions for future research. The stock price movements have been basically analysed on the assumption of linearity of the time series in the Indian scenario. The trends in stock prices are estimated using moving averages, regression and other linear methods when the time series seldom moves in a linear fashion.

Thenmozhi (2001) has examined the nonlinear nature of the Bombay Stock Exchange time series using chaos theory. The study examines the Sensex returns time series from 16/01/1980 to 26/09/1997 and shows that the daily returns and weekly returns series of BSE sensex is characterised by nonlinearity and the time series is weakly chaotic. The study recommends the use of nonlinear methods to predict the time series rather than using linear methods for prediction. Subrata Kumar Mitra has used Artificial Neural Networks (ANN) to generate trading signals using five year daily sensex values of Bombay Stock Exchange (BSE) between 1st January 1994 to 31st December 1998. The input parameters included the underlying close to close return, the underlying intra-day return and the intra-day range and the output is the trading signal. Typical non-linear energy transfer function f(x) = 1/(1+e-x) is used to determine the output. The weights are adjusted such that the error is minimized using ìsolverî computer program. Positive valued output signals up-trend while the negative values signaled downtrend. The strategy adopted for up-trend was to ìbuyî while downtrend confirms, ìsellî. The network performance is evaluated based on total cumulative return, profit over loss ratio, correlation coefficient of signal, actual price change following signal and t-statistic of daily returns. The results are found to be quite encouraging. The work concludes with suggestions to incorporate other parameters such as interest rate, foreign institutional investments, etc., which influences the sensex values to be incorporated into the structure for better evaluations.

The literature survey shows that: (i) Neural network models are significantly more accurate than multiple regression models in financial forecasting. (ii) Neural networks have been used to predict the stock market index, predict bankruptcy, predict the eurodollar futures, estimate derivative price and so on. (iii) The input used for neural network modeling ranges from 3 to 12 nodes depending on the time series. The output is only one node and the hidden layer varies upto 12 nodes. (iv) It is observed that the most commonly used neural network model is the multi-layer perceptron. The prediction is done using feed forward network while, the training is predominantly done using error back propagation algorithm. (v) In the Indian scenario, attempt has been made to examine the nonlinear nature of the BSE Sensex time series and the complexity of the time series recommend the use of nonlinear models for prediction. An effort has been made to generate trading signals for the sensex time series considering only five year data

Section III:

Data and Methodology The data consists of daily index values of the BSE Sensex. The period under consideration is 16/01/1980 to 26/09/1997. The time period chosen for analysis is similar to the time series used by Thenmozhi (2001).The data set consists of 3667 data points. The data has been obtained from Capitaline 2000 database that provides daily stock market data. The entire analysis has been done basically on the daily returns rather than the raw index value as such. The approach adopted to train the neural network using daily returns is explained in terms of the following: a) Inputs and Outputs: The historical price is used as inputs to the network. The inputs to the neural network are basically the delayed coordinates of the time series. The number of inputs to the network is 4 and they are the 4 consecutive daily returns. The output is the prediction of the return on the fifth day. b) Network Structure: The simplest of the neural network architecture ñ Multi Layer Perceptron (MLP - Fig. 2) neural network is chosen for the purpose of prediction. It essentially consists of three layers of nodes namely, input, hidden and output layers. The first layer consists of the input data. The last layer is the output layer, which consists of the target values. All layers between the input and the output layers are called as the hidden layers

Conclusion

The goal of this research is to investigate the potential of neural networks in predicting the daily returns of the BSE sensex. The daily returns model is constructed using a multi-layer perceptron network, and the network is trained using the error backpropagation technique. The findings demonstrate that the inputs from the first three days have less predictive ability than the return from the previous day. The hidden layer is saturated and the network employs every hidden node, showing that four hidden nodes are the most helpful for the network. The model's prediction accuracy is excellent for both the training and test sets of data, and it matches the test set of data better than the training set.It is possible to anticipate stock market behaviour using neural networks of various forms, and the prediction abilities of the various designs may be compared. The development of stock market trading methods utilising neural networks should be considered by participants in the global financial markets, institutional investors, and developers of general software. Most likely, more testing for weekly or monthly returns as well as the inclusion of other micro and macroeconomic data as inputs will be necessary to provide a better stock price forecast. To create a better network structure, it is also necessary to take into account the impact of macroeconomic factors like interest rates, political stability, GDP, global stock market trends, etc.. In addition to core data, the network may also be constructed using technological indicators. By changing the settings of the training algorithm, a better network structure could be achieved, and various trading strategies could be created for various market participants. If taught properly, neural networks have the potential to foresee the financial markets, which might be useful for both individual and institutional investors.

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