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# Spiking Back Propagation Multilayer Neural Network Design for Predicting Unpredictable Stock Market Prices with Time Series Analysis

Amit Ganatr and Y. P. Kosta

***Abstract*—Stock prediction is, so far, one of the popular topics not only for research purposes but also for commercial applications. Owing to its importance, a well-established school of concepts and techniques, including fundamental and technical analysis, has developed in recent decades. However, because these techniques or tools are based on totally different analytical approaches, they often yield contradictory results. More importantly, these analytical tools are heavily dependent on human expertise and justification in areas such as the location of reversal (or continuation) patterns, market patterns, and trend prediction. Predicting stock data with traditional time series analysis has proven to be difficult. An artificial neural network may be more suitable for the task primarily because no assumption about a suitable mathematical model has to be made prior to forecasting. With their ability to discover patterns in nonlinear and chaotic systems, neural networks offer the ability to predict market directions more accurately than current techniques. Furthermore, a neural network 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. Our focus of study is to build neural network for stock market prediction. We propose to study feed forward back propagation network and their predictive accuracy. We propose to study architecture model of neural network and its different network parameters. The study attempts to understand network parameter like momentum, learning rate, number of neurons etc. We will compare architecture and result of above models. Our aim is to build best model by studying various parameters of the neural network. And also study other related model to compare accuracy of the model. In this study we have used R tool to implement the neural network [1]. We have taken closing price, turnover, global indices, interest rate, and inflation as a neural network input. We proposed to include other indicator like news, currency rate, and crude price as input to the neural network. We compared stock prediction accuracy by setting different network parameters. Subsequently, an attempt is made to build and evaluate a neural network with different network parameters. Technical as well as fundamental data are used as input to the network. In benchmark comparisons, the price prediction proves to be successful. Input to the System is Time Series Stock data and the output is Predictions of stock prices**

***Index Terms*—Classification, Neural Network, Feature Selection, Prediction, Stock Market**

amitganatra.ce@ecchanga.ac.in ; ypkostaresearch@yahoo.com
U & P U. Patel Department of Computer Engineering, Charotar University of Science & Technology-CHARUSAT, Gujarat, India

## I. Introduction

*Stock market analysis*: People invest in the stock market based on some analysis. Before the age of computers, people traded stocks and commodities primarily on intuition. As the level of investing and trading grew, people searched for tools and methods that would increase their gains while minimizing their risk. Statistics, technical analysis, fundamental analysis, and linear regression are all used to attempt to predict and benefit from the market's direction. None of these techniques has proven to be the consistently correct prediction tool. However, these methods are presented as they are commonly used in practice and represent a base-level standard for which neural networks should outperform. Also, many of these techniques are used to pre-process raw data inputs, and their results are fed into neural networks as input [1].

*Technical Analysis*: The idea behind technical analysis is that share prices move in trends dictated by the constantly changing attitudes of investors in response to different forces. Using price, volume, and open interest statistics, the technical analyst uses charts to predict future stock movements. Technical analysis rests on the assumption that history repeats itself and that future market direction can be determined by examining past prices. However, it is used by approximately 90% of the major stock traders. Despite its widespread use, technical analysis is criticized because it is highly subjective. Different individuals can interpret charts in different manners.

*Fundamental Analysis:* Fundamental analysis involves the in-depth analysis of a company's performance and profitability to determine its share price. By studying the overall economic conditions, the company's competition, and other factors, it is possible to determine expected returns and the intrinsic value of shares. This type of analysis assumes that a share's current (and future) price depends on its intrinsic value and anticipated return on investment. As new information is released pertaining to the company's status, the expected return on the company's shares will change, which affects the stock price [2].

The advantages of fundamental analysis are its systematic approach and its ability to predict changes before they show up on the charts. Companies are compared with one another, and their growth prospects are related to the current economic environment. This allows the investor to become more familiar with the company. Unfortunately, it becomes harder to formalize all this knowledge for purposes of

automation (with a neural network for example), and interpretation of this knowledge may be subjective. Also, it is hard to time the market using fundamental analysis. However, fundamental analysis is a superior method for long-term stability and growth. Basically, fundamental analysis assumes investors are 90% logical, examining their investments in detail, whereas technical analysis assumes investors are 90% psychological, reacting to changes in the market environment in predictable ways.

Neural networks are less easily communicated to humans than learned rules.

## II. Neural Network

The structure of a neural network of most commonly used type is schematically shown in figure 1. It consists of several layers of processing units (also termed neurons, nodes).

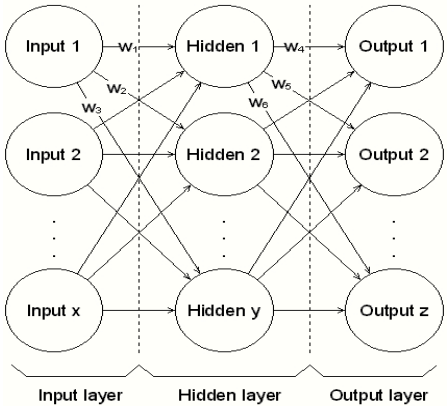


Figure 1: Basic structure of a multi-layer perceptron

The input values (input data) are fed to the neurons in the so called input layer in the left part of figure 1. The input values are processed (the data processing in the neurons is discussed later in this chapter) within the individual neurons of the input layer and then the output values of these neurons are forwarded to the neurons in the hidden layer. The arrows indicate connections from the input nodes to hidden nodes, along which the output values of the input nodes are passed on to the hidden nodes. These values obtained as inputs by the hidden nodes are again processed within them and passed on to either the output layer or to the next hidden layer (there can be more than one hidden layer).

Each connection has an associated parameter indicating the strength of this connection, the so-called weight. By changing the weights in a specific manner, the network can "learn" to map patterns presented at the input layer to target values on the output layer. The description of the procedure, by means of which this weight adaptation is performed, is called learning or training algorithm. Sometimes, so-called bias units (also called bias parameters, thresholds) are also present in the neural network. These are neurons with the property that they always produce a +1 at the output [12].

**Input:** Time Series Stock market Data

**Output:** Prediction of stock prices based on various criteria.

- **Properties of neural networks**

ANN learning is well-suited to problems in which the training data corresponds to noisy, complex sensor data, such as inputs from cameras and microphones. It is also applicable to problems for which more symbolic representations are often used, such as the decision tree learning tasks. In these cases ANN and decision tree learning often produce results of comparable accuracy.

The back propagation algorithm is the most commonly used ANN learning technique. It is appropriate for problems with the following characteristics: [4]

- Instances are represented by many attribute value pairs. The target function to be learned is defined over instances that can be described by a vector of predefined features, such as the pixel values. These input attributes may be highly correlated or independent of one another. Input values can be any real values.
- The target function output may be discrete-valued, real-valued, or a vector of several real- or discrete-valued attributes.
- The training examples may contain errors. ANN learning methods are quite robust to noise in the training data
- Long training times are acceptable. Network training algorithms typically require longer training times than, other learning algorithms. Training times can range from a few seconds to many hours, depending on factors such as the number of weights in the network, the number of training examples considered, and the settings of various learning algorithm parameters.
- Fast evaluation of the learned target function may be required. Although ANN learning times are relatively long, evaluating the learned network, in order to apply it to a subsequent instance, is typically very fast.
- The ability of humans to understand the learned target function is not important. The weights learned by neuralnetworks are often difficult for humans to interpret. Learned neural networks are less easily communicated to humans than learned rules.
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## III. Predicting Stock Market

Stock market trading is an application domain with a big potential for data mining. In effect, the existence of an enormous amount of historical data suggests that data mining can provide a competitive advantage over human inspection of this data. On the other hand there are authors claiming that the markets adapt so rapidly in terms of price adjustments that there is no space to obtain profits in a consistent way. This is usually known as the efficient markets hypothesis.

How to use ANN in stock prediction the individual steps of this process are listed below:

1) Variable selection
2) Data collection
3) Data pre-processing
4) Data partitioning
5) Neural network design
6) Evaluation of the system
7) Training the ANN
8) Implementation

## IV. Data Collection

Data collection plays an important role in the time series

modelling. In this study, the experiment data is obtained from NSE (National Stock Exchange), data dated from 1994 until 2008 is downloaded. The data downloaded in spreadsheet like csv (comma separated values) format. It includes date, trading volumes, opening price, closing price, high price, low price and average price. The long duration of collected data will help the model to have an enough learning process. The example of data can be viewed in Table I.

All these companies are listed on NSE (National Stock Exchange) and BSE (Bombay Stock Exchange). We have taken inflation and interest rate data from RBI (Reserve Bank of India) website. We downloaded global market (FTSE, NASDAQ and NIKKEI) data from finance.yahoo.com website. Table VII. We have also done experiment to see the effect of news on stock price.

## V. Data Pre-Processing

Before applying appropriate data modelling on time series data, a process called data cleaning need to be conducted because most of the time original data may contain noise and these noise will affected the prediction results [6].

Besides, the other important task in preparing data sets is data normalization. Importance of data scaling such as to avoid attributes in greater numerical ranges dominate values in smaller numerical ranges and also to avoid numerical difficulties during the calculation. The recommended the range of data for neural network is to be scaled in between [-1, +1] or [1, 0]. We have normalized all data in the range 0 to 1.

TABLE I Normalization of Value

| Counter | period | low | high |
|---|---|---|---|
| RIL | 1994-2008 | 101 | 3220 |
| ITC | 1994-2008 | 115 | 1940 |
| SBI | 1994-2008 | 141 | 2464 |
| Infosys | 1994-2008 | 362 | 16855 |
| NASDAQ | 1994-2008 | 720 | 7161 |
| FTSE | 1994-2008 | 2943 | 6930 |
| Interest rate | 1998-2008 | 10.25 | 13.75 |
| Inflation | 1998-2008 | 1.1 | 12.6 |

## VI. Parameter Selection

- Determine the size of training and testing data.
- Determine the learning algorithm (back propagation algorithm).
- Determine the structure of input, hidden and output nodes of the network.
- Determine the activation function (sigmoid function).
- Determine the learning rate. The learning rate eta is set to 0.1.
- Determine the number of iterations. It is depends on the error generated from BPNN.
- Determine the size of training and testing data.[11]

Common practice is to divide the time series into two distinct sets called the training and testing sets. The training set is the largest set and is used by the neural network to learn the patterns present in the data. The testing set, ranging in size from 10 % to 30 % of the training set, is used to evaluate the generalization ability of a supposedly trained network. We have used 3200 records set for training and 200 records set for testing.

- Determine the learning algorithm (back propagation algorithm).
- Determine the structure of input, hidden and output nodes of the network.

Deciding on the number of output neurons is somewhat more straightforward since there are compelling reasons to always use only one output neuron. Neural networks with multiple outputs, especially if these outputs are widely spaced, will produce inferior results.

## VII. Experiment Plan

We plan to do following experiments:

- Experiment 1: input data is closing price of stock with different no. of hidden nodes.

TABLE II Different Parameter and its values

| Parameter name | value |
|---|---|
| Input | Closing price |
| Data | Data from year 1994-2008<br>3300 record for training<br>200 record for testing |
| Decay(Learning rate) | 0.01 |
| Input nodes | 15 |
| Hidden nodes | 10,15,20,25 |
| Output nodes | 1 |
| Activation function | Sigmoid function |
| Learning algorithm | Backpropagation |
| Iteration(size of training) | Max 5000 |

- Experiment 2: input data is closing price and turnover of stock with different no. of hidden nodes.
-

TABLE III Different Parameters and its Value

| Parameter name | value |
|---|---|
| Input | Closing price, turnover |
| Data | Data from year 1994-2008<br>3300 record for training<br>200 record for testing |
| Decay | 0.01 |
| Input nodes | 30 |
| Hidden nodes | 20,25,30,35,40 |
| Output nodes | 1 |
| Activation function | Sigmoid function |
| Learning algorithm | Backpropagation |
| Iteration(size of training) | Max 5000 |

- Experiment 3: input data is closing price of stock and global market data with different no. of hidden nodes.
-

TABLE IV Different Parameter and Its Values

| Parameter name | value |
|---|---|
| Input | Closing price, NASDAQ, FTSE, Nikkei |

| | |
|---|---|
| Data | Data from year 1998-2008<br>3300 record for training<br>200 record for testing |
| Decay | 0.01 |
| Input nodes | 45 |
| Hidden nodes | 25,35,45 |
| Output nodes | 1 |
| Activation function | Sigmoid function |
| Learning algorithm | Back propagation |
| Iteration(size o f training) | Max 5000 |

- Experiment 4: input data is closing price of stock and interest and inflation with different no. of hidden nodes.
-

TABLE V DIFFERENT PARAMETER AND ITS VALUES

| **Parameter name** | **value** |
|---|---|
| Input | Closing price, Interest rate, Inflation, Effect of News on stock data |
| Data | Data from year 1998-2008<br>3300 record for training<br>200 record for testing |
| Decay | 0.01 |
| Input nodes | 45 |
| Hidden nodes | 25,35,45 |
| Output nodes | 1 |
| Activation function | Sigmoid function |
| Learning algorithm | Backpropagation |
| Iteration(size of training) | Max 5000 |

- Experiment 5: we have done experiment to check the effect of news on stock price.

### *A. Reliance Industries*

The Reliance Group, founded by Dhirubhai H. Ambani (1932-2002), is India's largest private sector enterprise, with businesses in the energy and materials value chain. Group's annual revenues are in excess of US$ 34 billion. The flagship company, Reliance Industries Limited, is a Fortune Global 500 company and is the largest private sector company in India.

### *B. ITC Limited*

ITC is one of India's foremost private sector companies with a market capitalisation of nearly US $ 19 billion* and a turnover of over US $ 5.1 Billion. ITC ranks among India's `10 Most Valuable (Company) Brands', in a study conducted by Brand Finance and published by the Economic Times.

### *C. State Bank of India*

State Bank of India is premier Nationalized Indian Bank. State Bank of India is actively involved since 1973 in non-profit activity called Community Services Banking.

**4**. Infosys Technologies Ltd Infosys Technologies Ltd. was started in 1981 by seven people with 15000Rs. Today, it is a global leader in the "next generation" of IT and consulting with revenues of over US$ 4 billion.

### *D. NASDAQ*

The NASDAQ (acronym of National Association of Securities Dealers Automated Quotations) is an American stock exchange. It is the largest electronic screen-based equity securities trading market in the United States. With approximately 3,200 companies, it has more trading volume per hour than any other stock exchange in the world.

### *E. FTSE*

The FTSE informally, the "footsie" is a share index of the 100 most highly capitalized UK companies listed on the London Stock Exchange. The index began on 3 January 1984 with a base level of 1000; the highest value reached to date is 6950.6, on 30 December 1999.

### *F. NIKKEI*

Nikkei 225 , is a stock market index for the Tokyo Stock Exchange (TSE). It has been calculated daily by the Nihon Keizai Shimbun (Nikkei) newspaper since 1950. It is a price-weighted average (the unit is Yen), and the components are reviewed once a year. Currently, the Nikkei is the most widely quoted average of Japanese equities, similar to the Dow Jones Industrial Average. In fact, it was known as the "Nikkei Dow Jones Stock Average" from 1975 to 1985.

### *G. INFLATION and INTEREST RATE*

In economics, inflation is a rise in the general level of prices of goods and services in an economy over a period of time. The term "inflation" once referred to increases in the money supply (monetary inflation); however, economic debates about the relationship between money supply and price levels have led to its primary use today in describing price inflation. Inflation can also be described as a decline in the real value of money—a loss of purchasing power in the medium of exchange which is also the monetary unit of account. Interest rates targets are also a vital tool of monetary policy and are used to control variables like investment, inflation, and unemployment.

## VIII. EXPERIMENT AND RESULT

In this phase, several experiments will be conducted according to the sample data collected. Experiment on the structure of the model. This is to determine which parameters are best for our model. Coming down to the second method used, the hit rate is very useful when a trading decision is based solely on whether the predicted future price goes up or down as compared to the current price(Saadetal.1998).

**Hit rate:**

We are usually interested in looking at the accuracy in predicting the direction of the market, i.e. whether the next day returns are positive or negative. The hit rate of a predictor indicates how often the sign of the return, i.e. the daily change is correctly predicted.

**We have done following experiments:**

Experiment 1: input data is closing price of stock with different no. of hidden nodes.

Experiment 2: input data is closing price and turnover of stock with different no. of hidden nodes.

Experiment 3: input data is closing price of stock and global market data with different no. of hidden nodes.

Experiment 4: input data is closing price of stock and interest and inflation with different no. of hidden nodes.

Experiment 5: we have done experiment to check the

effect of news (economical, political, industry or other) on stock price.

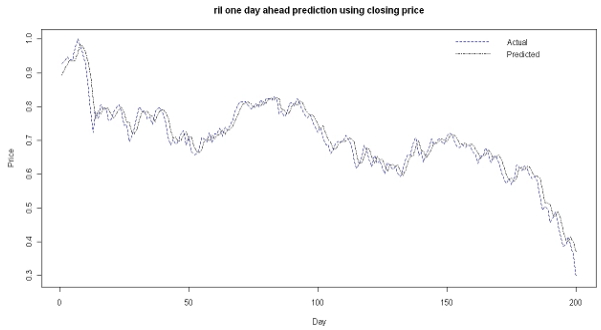


Fig. 2 RIL One Day Ahead Prediction using Closing Price

The above figure shows the One day ahead prediction using closing price of RIL data.

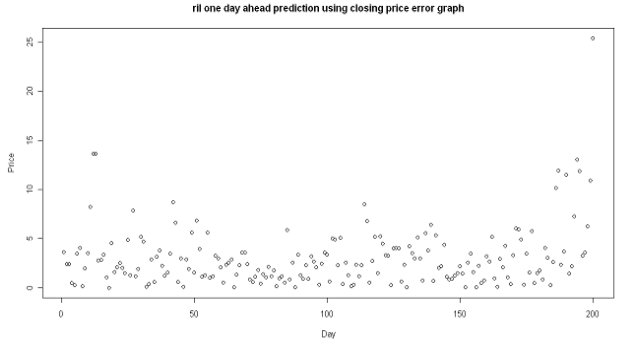


Fig. 3 RIL One Day Ahead Prediction using Closing Price error Graph

The above figure shows the One day ahead prediction using closing price and error graph of RIL data.

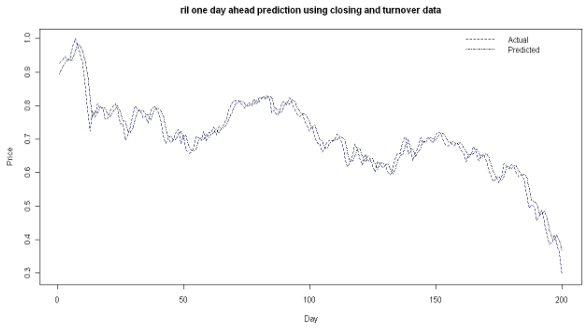


Fig. 4 RIL One Day Ahead Prediction using Closing & Turnover data

The above figure shows the One day ahead prediction using closing and Turnover data.

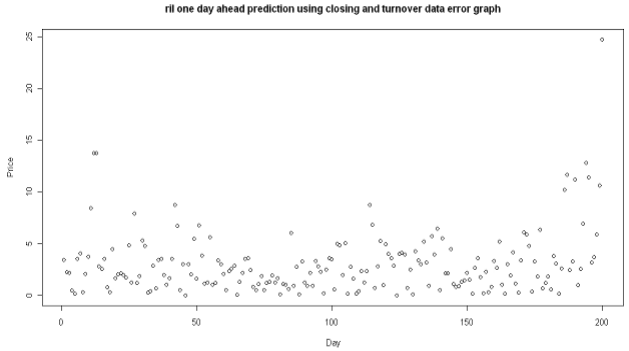


Fig. 5 RIL One Day Ahead Prediction using Closing & Turnover data error Graph

The above figure shows the One day ahead prediction using closing and turnover data error of RIL data.

In this phase, several experiments have been conducted according to the sample data collected. This is to determine which parameters are best for our model.

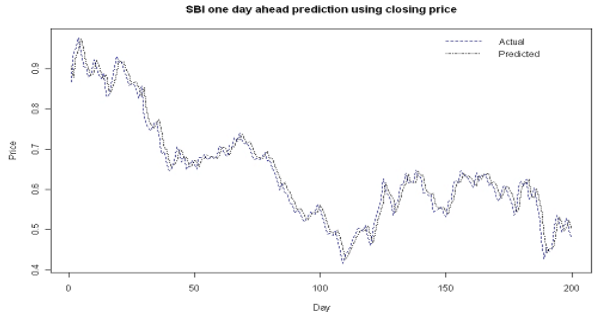


Fig. 6 SBI One Day Ahead Prediction using Closing Price

In this phase, several experiments have been conducted according to the sample data collected. This is to determine which parameters are best for our model.

Experiments are conducted with these data sets in order to see whether segmenting the data according to different companies and in different sectors with different dataset will affect prediction performance and aims to evaluate prediction accuracy between them. In addition to that, back-propagation neural network architecture is also evaluated.

We have done first experiment-I on each (RIL, ITC, SBI, Infosys) data, in which we have used 15 input nodes and closing price as input. The decay can be from 0.01 to 0.1. If we keep high value then it oscillates around the pattern line, so we keep it minimum to 0.01. We have 3300 records for training and 200 records for testing. We have used different number of hidden nodes like 10, 15, 20, and 25.

Second experiment on each data, in which we have used 30 input nodes and closing price and turnover data, is given as input. The decay is 0.01. We have 3300 records for training and 200 records for testing. We have used different number of hidden nodes like 20, 25, 30, 35, and 40

Third experiment on each data, in which we have used 45 input nodes and closing price, interest rate and inflation data, is given as input. The decay is 0.01. We have 3300 records for training and 200 records for testing. We have used different number of hidden nodes like 25, 35, and 45. Fourth experiment on each data, in which we have used 45 input nodes and closing price and global market data, is given as input. The decay is 0.01. We have 3300 records for training and 200 records for testing. We have used different number of hidden nodes like 25, 35, and 45. We have done above experiment for one day and one week ahead prediction of stock price. In above study we have included only news about RIL, if we include news about political, economical and industry news than we get better results.

From above example we can see that stock price has very much effect of news.

## IX. Conclusion

**Reliance:**

Above result shows that experiment-IV gives better results than other for one day prediction. We observed that high

initial weight will require more iteration to converge. And more input and hidden node also requires more iteration to converge. Final total weight of the network in each experiment for different number of hidden nodes remains same.

In experiment-I for closing price network architecture 15-20-1 gives good result. In experiment-II for closing price and turnover network architecture 30-30-1 gives good result. In experiment-III for interest and inflation data network architecture 45-45-1 gives good result. In experiment-IV for global indices network architecture 45-25-1 gives good result. For weekly prediction above experiment gives average performance.

**SBI:**

Above result shows that experiment-I gives better results than other for one day prediction. We observed that high initial weight will require more iteration to converge. And more input and hidden node also requires more iteration to converge. Final total weight of the network in each experiment for different number of hidden nodes remains same.

In experiment-I for closing price network architecture 15-25-1 gives good result. In experiment-II for closing price and turnover network architecture 30-30-1 gives good result. In experiment-III for interest and inflation data network architecture 45-35-1 gives good result. In experiment-IV for global indices network architecture 45-35-1 gives good result. For weekly prediction above experiment gives poor performance.

**ITC:**

Above result shows that experiment-I gives better results than other for one day prediction. We observed that high initial weight will require more iteration to converge. And more input and hidden node also requires more iteration to converge. Final total weight of the network in each experiment for different number of hidden nodes remains same.

In experiment-I for closing price network architecture 15-15-1 gives good result. In experiment-II for closing price and turnover network architecture 30-20-1 gives average result. In experiment-III for interest and inflation data network architecture 45-45-1 gives good result. In experiment-IV for global indices network architecture 45-35-1 gives good result.

For weekly prediction above experiment gives mixed performance. For example experiment-I and II gives good performance, experiment-IV gives average and experiment-III gives very poor performance.

**Infosys:**

Above result shows that all experiment gives poor results than earlier experiment. The experiment-IV for global indices gives average result all other gives poor result. For weekly prediction above experiment gives mixed performance. For example experiment-I, II and IV gives average performance, experiment-III gives very poor performance.

In above study we have included only news about RIL, if we include news about political, economical and industry news than we get better results. From above example we can see that stock price has very much effect of news.

## X. Future Work

Performance analysis in terms of accuracy with the Support Vector Machine and Back Propagation Neural Network with Genetic Algorithms can be checked. In this paper, it is assumed that all the input data set has no noise and missing values because artificial neural networks have high tolerance to noisy data. So missing value handling along with continues & categorical values handling should be done as future enhancement.

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## References

[1] Goldberg, D.E. "Genetic algorithms in search, optimization, and machine learning", Pearson Education, 2001.
[2] R. K. Gupta, A. K. Bhunia, "An Application of real-coded Genetic Algorithm for integer linear programming", AMO-Advanced Modeling and Optimization, Volume 8, Number 1, 2006.
[3] V.srinivas,G.L.Thompson. "Benefit-cost Analysis of coding techniques for the Primal Transportation Algorithm.", Journal of the association for computing machinery, Vol.20, April 1973, pp194-213
[4] Man Mohan, Gupta P.K .Operations research, Methods and Solutions.Reading, Sultan Chand and Sons, 1992
[5] BL Mak, H Sockel – Info. & Mgmt, A confirmatory factor analysis of IS employee motivation and retention, 2001
[6] K. Hornik, M. Stnchcombe and H White, Multilayer Feedforward Networks are Universal Approximates, Neural Network, 2:pg359- 366, 1989
[7] Poonam Garg, Advanced in Computer Science & Engineering, MacMillan Publication, 2009.
[8] Vijyalakshmi Pai G.A. & Rajasekaran S. Neural networks, fuzzy logic and genetic algorithms, Synthesis and applications. Reading, Prentice-Hall of India, 2004
[9] S. Kullback and R. A. Leibler, 'On Information and Sufficiency', The Annals of Mathematical Statistics, Vol. 22, No. 1, pp. 79–86, 1951
[10] H. Akaike, 'A new look at the statistical model identification', IEEE Transactions on Automatic Control, Vol. 19, No. 6, pp. 716–723, 1974
[11] H. Linhart and W. Zucchini, Model Selection, John Wiley and Sons, 1986
[12] C. M. Hurvich and C. Tsai, 'Regression and Time Series Model Selection in Small Samples', Biometrika, Vol. 76, pp. 297–307, 1989
[13] J. E. Cavanaugh, 'Unifying the Derivations for the Akaike and Corrected Akaike Information Criteria', Statistics & Probability Letters, Vol. 33, pp. 201–208, 1997
[14] Mengjie Zhang, "Artificial Neural Networks" Victoria University of Wellington
[15] V.P. Plagianakos, G.D. Magoulas, M.N. Vrahatis, "Learning rate adaptation in stochastic gradient descent", Department of Mathematics, University of Patras

TABLE IIII Sample Input Data

| Symbol | Date | Prev. Close | Close Price | Turnover(Lk) |
|---|---|---|---|---|
| SBIN | 4-Aug-98 | 202.55 | 203.2 | 4586.84 |
| SBIN | 5-Aug-98 | 203.2 | 204.25 | 7062.541 |

| | | | | |
|---|---|---|---|---|
| SBIN | 6-Aug-98 | 204.25 | 202.25 | 6704.061 |
| SBIN | 7-Aug-98 | 202.25 | 201.45 | 6640.555 |
| SBIN | 10-Aug-98 | 201.45 | 197.75 | 4933.432 |
| SBIN | 11-Aug-98 | 197.75 | 195.3 | 4747.839 |
| SBIN | 12-Aug-98 | 195.3 | 190.2 | 7294.994 |
| SBIN | 13-Aug-98 | 190.2 | 194.8 | 7527.036 |
| SBIN | 14-Aug-98 | 194.8 | 191.95 | 4830.411 |
| SBIN | 17-Aug-98 | 191.95 | 189.75 | 4438.461 |
| SBIN | 18-Aug-98 | 189.75 | 183.05 | 8626.86 |
| SBIN | 19-Aug-98 | 183.05 | 182.55 | 9335.36 |
| SBIN | 20-Aug-98 | 182.55 | 191.8 | 10565.11 |
| SBIN | 31-Aug-98 | 181 | 182.7 | 4752.003 |
| …… | …… | …… | …… | …… |

TABLE IVI SAMPLE INPUT DATA

| Date | FTSE | NASDAQ | Nikkei | inflation | Int.rate |
|---|---|---|---|---|---|
| 8/4/1998 | 5736.1 | 1785.64 | 16023.58 | 8.8 | 12.75 |
| 8/5/1998 | 5632.5 | 1788.2 | 15992.16 | 8.8 | 12.75 |
| 8/6/1998 | 5594.1 | 1829.51 | 15876.22 | 8.8 | 12.75 |
| 8/7/1998 | 5680.4 | 1846.77 | 15829.17 | 8.8 | 12.75 |
| 8/10/1998 | 5587.6 | 1839.21 | 15626.42 | 8.8 | 12.75 |
| 8/11/1998 | 5432.8 | 1792.7 | 15406.99 | 8.1 | 12.75 |
| 8/12/1998 | 5462.2 | 1825.53 | 15378.97 | 8.1 | 12.75 |
| 8/13/1998 | 5399.5 | 1802.54 | 15382.02 | 8.1 | 12.75 |
| 8/14/1998 | 5455 | 1790.19 | 15123.93 | 8.1 | 12.75 |
| 8/17/1998 | 5467.2 | 1818.04 | 14794.66 | 8.1 | 12.75 |
| 8/18/1998 | 5648.2 | 1855.12 | 15063.79 | 8.1 | 12.75 |
| 8/19/1998 | 5694.3 | 1842.69 | 15406.34 | 8.1 | 12.75 |
| 8/20/1998 | 5667.4 | 1832.45 | 15391.41 | 8.1 | 12.75 |
| 8/21/1998 | 5477 | 1797.61 | 15298.2 | 8.1 | 12.75 |
| 8/24/1998 | 5553.7 | 1790.82 | 14988.36 | 8.1 | 12.75 |
| 8/25/1998 | 5654.4 | 1798.17 | 15072.93 | 8.6 | 12.75 |
| 8/26/1998 | 5545.4 | 1768.13 | 14866.03 | 8.6 | 12.75 |
| 8/27/1998 | 5368.5 | 1686.41 | 14413.79 | 8.6 | 12.75 |
| 8/28/1998 | 5249.4 | 1639.68 | 13915.63 | 8.6 | 12.75 |

An experiment is done to see the effect of news on stock price. Given below is one example about Reliance Industries that shows news effect on that stock price.

TABLE VII SAMPLE DATA

| Date | Change in RIL % | Change in Nifty % | news |
|---|---|---|---|
| 7-Jan-08 | 0.91 | -0.08 | RIL, ONGC sharing rigs |
| 9-Jan-08 | -0.69 | 0.25 | RIL bids. asia oil block |
| 10-Jan-08 | -0.19 | 1.83 | |
| 11-Jan-08 | 3.30 | -0.70 | RNRL gas case hearing |
| 15-Jan-08 | -1.72 | 2.14 | |
| 18-Jan-08 | -6.57 | 3.52 | result profit grows |
| 21-Jan-08 | -9.24 | 8.70 | gas find orissa |
| 22-Jan-08 | -7.22 | 5.94 | SEZ proposal cleared |
| 5-Feb-08 | 1.00 | -0.37 | lignite gasification venture |
| 6-Feb-08 | -2.47 | 2.94 | |
| 7-Feb-08 | -4.98 | 3.56 | reality plan |
| 20-Feb-08 | -2.76 | 2.39 | hikes petrol price |
| 27-Feb-08 | 0.46 | 0.03 | Strikes gas in mahanadi block |
| 1-Jul-08 | -2.43 | 4.09 | ethanol plant run |
| 2-Jul-08 | 4.88 | -2.30 | biodiesel policy |
| 3-Jul-08 | -3.45 | -0.35 | |
| 7-Jul-08 | -3.32 | -4.23 | custom sieze aircraft |
| 18-Jul-08 | 4.69 | -1.94 | |

| | | | |
|---|---|---|---|
| 21-Jul-08 | 1.88 | -5.58 | mtn-rcom issue |
| 23-Jul-08 | 5.35 | 2.74 | rnrl hearing |
| 24-Jul-08 | 1.80 | -0.47 | |
| 25-Jul-08 | -6.97 | 3.28 | results profit rise 13% |
| 28-Jul-08 | 1.53 | -2.95 | sets autozone goregaon |
| 31-Jul-08 | 1.94 | 0.41 | rnrl hearing |

TABLE IX SAMPLE DATA

| **Result of RIL with different parameters** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | one day | | | | | | |
| | | input data | | nn | | accuracy | | weight | |
| | network | training | test | decay | iterations | hit rate | error < 5% | initial | final |
| closing | 15-10-1 | 3300 | 200 | 0.01 | 780 | 50.5 | 83 | 968.7897 | 0.156378 |
| | 15-15-1 | 3300 | 200 | 0.01 | 1010 | 52 | 82.5 | 1007.003 | 0.15576 |
| | 15-20-1 | 3300 | 200 | 0.01 | 1080 | 53 | 83 | 1215.26 | 0.154293 |
| | 15-25-1 | 3300 | 200 | 0.01 | 1520 | 53 | 81.5 | 2096.512 | 0.154429 |
| closing & turnover | 30-20-1 | 3300 | 200 | 0.01 | 1280 | 51.5 | 81.5 | 3020.961 | 0.153947 |
| | 30-25-1 | 3300 | 200 | 0.01 | 1900 | 53 | 84 | 6555.508 | 0.152296 |
| | 30-30-1 | 3300 | 200 | 0.01 | 1920 | 53 | 84 | 406.1769 | 0.151913 |
| | 30-35-1 | 3300 | 200 | 0.01 | 1900 | 52.5 | 83.5 | 2215.547 | 0.151512 |
| | 30-40-1 | 3300 | 200 | 0.01 | 2720 | 51.5 | 83.5 | 11368.39 | 0.151325 |
| irate | 45-25-1 | 2400 | 200 | 0.01 | 2290 | 53 | 75 | 1516.339 | 0.190457 |
| | 45-35-1 | 2400 | 200 | 0.01 | 2420 | 53.5 | 76 | 305.4761 | 0.190189 |
| | 45-45-1 | 2400 | 200 | 0.01 | 2020 | 53.5 | 77.5 | 929.7969 | 0.190124 |
| global mkt | 45-25-1 | 3300 | 200 | 0.01 | 2900 | 55 | 76.5 | 224.213 | 0.195962 |
| | 45-35-1 | 3300 | 200 | 0.01 | 2790 | 54.5 | 76.5 | 377.8882 | 0.195515 |
| | 45-45-1 | 3300 | 200 | 0.01 | 1640 | 55 | 76 | 279.2605 | 0.195306 |
| | | | | | | | | | |
| | week | | | | | | | | |
| closing | 15-10-1 | 3300 | 200 | 0.01 | 350 | 47 | 48 | 511.341 | 0.447117 |
| | 15-15-1 | 3300 | 200 | 0.01 | 520 | 46.5 | 49 | 60.12299 | 0.446846 |
| | 15-20-1 | 3300 | 200 | 0.01 | 680 | 45.5 | 50 | 533.3283 | 0.445675 |
| closing & turnover | 30-25-1 | 3300 | 200 | 0.01 | 1260 | 47 | 48.5 | 2507.43 | 0.439915 |
| | 30-30-1 | 3300 | 200 | 0.01 | 2100 | 47 | 48.5 | 14311.54 | 0.439633 |
| | 30-35-1 | 3300 | 200 | 0.01 | 960 | 47 | 48.5 | 1382.993 | 0.439632 |
| | 30-40-1 | 3300 | 200 | 0.01 | 1620 | 47 | 48.5 | 11356.88 | 0.439486 |
| irate | 45-25-1 | 2400 | 200 | 0.01 | 2230 | 13.5 | 13.5 | 2812.693 | 0.582419 |
| | 45-35-1 | 2400 | 200 | 0.01 | 2280 | 13 | 13 | 5023.283 | 0.582375 |
| | 45-45-1 | 2400 | 200 | 0.01 | 1620 | 13 | 13 | 16094.95 | 0.582302 |
| global mkt | 45-25-1 | 3300 | 200 | 0.01 | 2350 | 43.5 | 43.5 | 15282.36 | 0.585259 |
| | 45-35-1 | 3300 | 200 | 0.01 | 1650 | 44 | 44 | 9832.758 | 0.584776 |
| | 45-45-1 | 3300 | 200 | 0.01 | 2420 | 44 | 44 | 327.5688 | 0.584352 |
| | 45-50-1 | 3300 | 200 | 0.01 | 2730 | 44.5 | 44.5 | 24402.37 | 0.584403 |

TABLE X SAMPLE DATA

| **Result of SBI with different parameters** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | one day | | | | | | | |
| | | input data | | nn | | accuracy | | weight | |
| | network | training | test | decay | iterations | hit rate | error < 5% | initial | final |
| closing | 15-10-1 | 3300 | 200 | 0.01 | 750 | 51 | 81.5 | 2245.77 | 0.202207 |
| | 15-15-1 | 3300 | 200 | 0.01 | 660 | 52.5 | 81 | 83.6034 | 0.200333 |
| | 15-20-1 | 3300 | 200 | 0.01 | 1100 | 53.5 | 81.5 | 12799.6 | 0.199339 |
| | 15-25-1 | 3300 | 200 | 0.01 | 1200 | 54 | 81.5 | 1813.22 | 0.198761 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| closing & turnover | 30-20-1 | 3300 | 200 | 0.01 | 1280 | 51.5 | 79.5 | 9010.26 | 0.200764 |
| | 30-25-1 | 3300 | 200 | 0.01 | 1780 | 52.5 | 81 | 1119.27 | 0.197692 |
| | 30-30-1 | 3300 | 200 | 0.01 | 1920 | 53.5 | 81.5 | 198.469 | 0.197223 |
| | 30-35-1 | 3300 | 200 | 0.01 | 2130 | 53 | 81.5 | 141.788 | 0.196186 |
| | 30-40-1 | 3300 | 200 | 0.01 | 2670 | 53 | 81.5 | 988.406 | 0.195839 |
| irate | 45-25-1 | 2400 | 200 | 0.01 | 2600 | 51.5 | 81.5 | 13565.6 | 0.211788 |
| | 45-35-1 | 2400 | 200 | 0.01 | 2660 | 52 | 81.5 | 7313.62 | 0.211543 |
| | 45-45-1 | 2400 | 200 | 0.01 | 3300 | 51.5 | 81.5 | 2632.36 | 0.211231 |
| global mkt | 45-25-1 | 3300 | 200 | 0.01 | 1810 | 51.5 | 80.5 | 2393.66 | 0.196587 |
| | 45-35-1 | 3300 | 200 | 0.01 | 1850 | 52.5 | 100 | 7338.82 | 0.196189 |
| | 45-45-1 | 3300 | 200 | 0.01 | 2720 | 52 | 100 | 13775.3 | 0.196032 |
| | 45-50-1 | 3300 | 200 | 0.01 | 3950 | 52.5 | 100 | 1554.9 | 0.195964 |
| | | week | | | | | | | |
| closing | 15-10-1 | 3300 | 200 | 0.01 | 340 | 40.5 | 40.5 | 1884.95 | 0.69271 |
| | 15-15-1 | 3300 | 200 | 0.01 | 940 | 40.5 | 40.5 | 3118.68 | 0.692477 |
| | 15-20-1 | 3300 | 200 | 0.01 | 510 | 40.5 | 40.5 | 697.339 | 0.69256 |
| closing & turnover | 30-25-1 | 3300 | 200 | 0.01 | 1600 | 39.5 | 39.5 | 112.195 | 0.673321 |
| | 30-30-1 | 3300 | 200 | 0.01 | 1560 | 39.5 | 39.5 | 1421.46 | 0.673065 |
| | 30-35-1 | 3300 | 200 | 0.01 | 780 | 39.5 | 39.5 | 3786.6 | 0.673417 |
| | 30-40-1 | 3300 | 200 | 0.01 | 1220 | 39.5 | 39.5 | 4769.37 | 0.673299 |
| irate | 45-25-1 | 2400 | 200 | 0.01 | 1020 | 32 | 32 | 1494.98 | 0.650208 |
| | 45-35-1 | 2400 | 200 | 0.01 | 2950 | 33.5 | 33.5 | 1806.21 | 0.649813 |
| | 45-45-1 | 2400 | 200 | 0.01 | 2090 | 33.5 | 33.5 | 167.383 | 0.649706 |
| global mkt | 45-25-1 | 3300 | 200 | 0.01 | 1730 | 39.5 | 39.5 | 2389.63 | 0.680756 |
| | 45-35-1 | 3300 | 200 | 0.01 | 1370 | 39.5 | 39.5 | 3663.06 | 0.680491 |
| | 45-45-1 | 3300 | 200 | 0.01 | 2080 | 39.5 | 39.5 | 3951.06 | 0.680425 |
| | 45-50-1 | 3300 | 200 | 0.01 | 1710 | 39.5 | 39.5 | 3543.06 | 0.680117 |