Stock Market Prediction Using Hidden Markov Model

Poonam Somani
Department of Computer Engineering
and Information Technology
College of Engineering Pune
Maharashtra, India
Email: somanipoonam7393@gmail.com

Shreyas Talele
Department of Computer Engineering
and Information Technology
College of Engineering Pune
Maharashtra, India
Email: shreyastalele@gmail.com

Suraj Sawant
Department of Computer Engineering
and Information Technology
College of Engineering Pune
Maharashtra, India
Email: sts.comp@coep.ac.in

***Abstract*—Stock market is the most popular investment scheme promising high returns albeit some risks. An intelligent stock prediction model would thus be desirable. So, this paper aims at surveying recent literature in the area of Neural Network, Hidden Markov Model and Support Vector Machine used to predict the stock market fluctuation. Neural networks and SVM are identified to be the leading machine learning techniques in stock market prediction area. Also, a model for predicting stock market using HMM is presented. Traditional techniques lack in covering stock price fluctuations and so new approaches have been developed for analysis of stock price variations. Markov Model is one such recent approach promising better results. In this paper a predicting method using Hidden Markov Model is proposed to provide better accuracy and a comparison of the existing techniques is also done.**

Keywords—Neural networks, Hidden Markov Model, Support Vector Machine, Stock market prediction, Mean Squared Error, Mean Absolute Percentage Error.

I. Introduction

The stock markets in the recent past have become an integral part of the global economy. Any fluctuation in this market influences our personal and corporate financial lives, and the economic health of a country. The stock market has always been one of the most popular investments due to its high returns. However, there is always some risk to investment in the stock market due to its unpredictable behaviour. Stock market prediction is a classic problem which has been analysed extensively using tools and techniques of Machine Learning. The successful prediction of a stock's future price could yield significant profit. So, an intelligent prediction model for stock market forecasting would be highly desirable and would be of wider interest.

Recent techniques such as Neural networks, Support Vector Machine, ARIMA and Hidden Markov Model provide tools to efficiently predict stock market trends. This paper highlights some of the key techniques used to predict stock market.

II. Literature Survey

Aditya Gupta and Bhuwan Dhingra in [1] used a method to predict the next days Close using Hidden Markov Model. Stocks of four different companies viz. TATA Steel, Apple Inc., IBM Corporation and Dell Inc. Were taken into consideration. The input parameters were Open, Close, High and Low. The model for one stock was assumed to be independent of other stocks. The model was first trained for a period of 7 months. The model was tested using MAPE values.

Abhishek, Khairwa, Pratap and Prakash in [2] predicted the stock rate using feed forward architecture. The stocks of Microsoft Corporation of the year 2011 were used. The parameters such as Open, High, Low, Adjacent Close and Volume were considered. Next days Close value was predicted using back propagation with multilayer feed forward network. Mean Squared Error (MSE) was used to check for the accuracy of the proposed system. The author also presented a literature review on application of neural network to predict stock markets.

Luo, Wu, Yan in [3] presented a novel method for the study of Shanghai Stock Exchange (SSE) index time series based on SVM regression combination model (SVR-CM) linear regression with non linear regression. Linear regression was used to extract linear features while NN algorithms were used to extract non linear features. Finally, SVM regression was used to combine all output results. Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Trend Accuracy were used to indicate the effectiveness of the proposed system. SVM-CM was found to have good learning ability and forecasting capability.

Wang and Leu in [4] developed a prediction system useful in forecasting mid-term price trend in Taiwan stock exchange weighted stock index (TSEWSI). The system was based on a recurrent neural network trained by using features extracted from Auto Regressive Integrated Moving Average(ARIMA). The input is same as the standard input given to ARIMA while the output approximates conditional mean predictor. Features were operated using difference operator. The accuracy was found good for six weeks when the training data was taken for 3 years and the testing data for 3 months.

Akinwale adio T, Arogundade O.T and Adekoya Adebayo F in [5] examined the use of error back propagation and regression analysis to predict the untranslated and translated Nigeria Stock Market Price (NSMP). The author used 5-j-1 network topology to adopt the five input variables. The j variables in network determined the number of hidden

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neurons needed. The translated and untranslated statements were analysed and compared. The accuracy of translated NSMP was better than untranslated NSMP.

Wang, Liu and Dou in [6] presented the first work which shows a service oriented approach to facilitate the incorporation of multiple factors in stock market volatility prediction. Multi kernel learning approach was used. The system was a two tier architecture. The top tier was dedicated to prepare the datasets from multiple information while the second tier was dedicated to the market volatility analysis and prediction. The accuracy of the prediction was obtained by checking whether the direction of the predicted volatility and actual trend are the same. The output is either up or down.

Naeini, Taremian and Hashemi in [7] used two methods to predict feed forward multi layer perceptron and Elman recurrent network. Model based on MLP NN for Tehran Stock Exchange (TSE) was developed to predict next days stock based on history without the knowledge of current market. Error percentage was around 1.5%. Main factors in the model were number of layers, neurons and connections, activation function in each neuron and training algorithm. The input parameters were Lowest, Highest, Average value in d days. Mean Absolute Deviation, Mean Absolute Percentage Error, Mean Squared Error, Root Mean Squared Error were used as the criteria for evaluation. Elman was found to be better than MLP but it suffered greater errors.

Li and Liu in [8] determined network structure and prediction precision. The sample data was divided into training and testing data. The network was trained in order to fix study sample time order as much as possible. Testing sample data was used to test the trained network. The network giving satisfactory result was used for prediction. Weekly closing price from Shanghai Stock Exchange Centre was used as the dataset. The data was treated by sampling standard, sampling normalisation, number of nodes in hidden layer and LM algorithm to modify weight value and threshold.

Schierholt and Dagli in [9] focused mainly on maximising the performance of portfolios rather than maximising the percentage of correct decisions. The dataset used was 400 patterns of Standard and Poors (SNP) 500 index. Only the Closing values were considered. One of three outputs namely buy, sell or keep the current status was given. The two models used were MLP with back propagation and probabilistic NN. MLP worked in static environment with separate training and testing phases whereas probabilistic NN performed better in all the cases.

Hassan and Nath in [10] used Hidden Markov Model to locate patterns from past data sets that matched the current days stock price behaviour. These two data sets were then interpolated with appropriate neighbouring price elements. $\lambda = (A, B, \pi)$ was the overall HMM model, where A is the transition matrix consisting of transition probabilities from state i to state j. B is the observation emission matrix and π is the prior probability matrix. Forward backward algorithm was used to compute the probability of occurrence of observation sequence. Viterbi algorithm was used to choose state sequence best explaining the observations. Baum Welch algorithm was used to train HMM. Input features were Open, Close, High, Low. The next days closing value of the respective stock was given as the output.

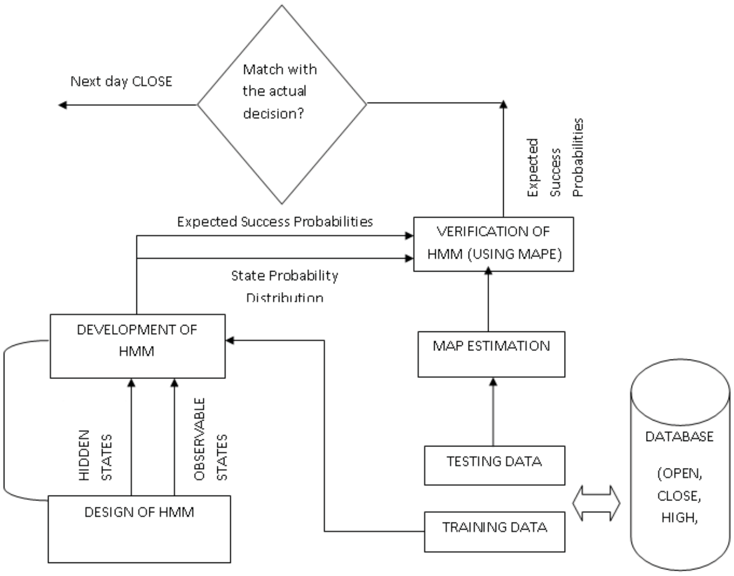

Fig. 1: System Architecture

Xiang and Fu in [11] predicted the stock market using multiple models. In this study the SP 500 return rates are predicted instead of the index as the return rates are more stationery over time. The novel and significant part of this work is in the use of each NN to model a particular trend which are Bear, Choppy and Bull market trends. A second significance of the work is that an attempt is made at evaluating the trading performance considering commission costs which are important when predictions on higher frequency data are made. The model outputs next days closing value. The metrics used for performance evaluation are Directional Accuracy and Annual Return rate. The 3 NN system is more consistent in getting better performance than other systems.

III. Implemented System

A. System Architecture

Fig explains the complete system architecture including the names of major modules.Training of data is used for developing model of HMM which is done using Baum Welch algorithm. This developed model is used for testing of data using Maximum a posteriori(MAP) approach. The model then selects one best probablity value using Viterbi algorithm. The next day's closing value is given as output.

observation	training data	training data	testing data	testing data
SBI	18-3-2002	22-12-2004	23-12-2004	28-7-2005
ICICI	1-12-2003	21-11-2005	22-11-2005	02-02-2007
IDBI	18-11-2011	09-01-2013	10-01-2013	29-05-2013

TABLE I: Dataset table

B. Datasets

The implemented algorithm was tested on three different stock indices ICICI, SBI, IDBI. Details of the training and testing periods are given in Table I.

C. Implementation

Open source HMM toolbox by Kevin Murphy [12] was used to implement the various HMM functions.

1) Parameters: The parameters were considered by varying over suitable range and choosing the value with minimum error.

1) Hidden states, n = 4
2) Number of coefficients in a vector, O = 3
3) Number of vectors in a sequence, T = 5
4) Number of sequences, nex = 700
5) Number of mixtures, M = 5
6) Number of states, Q = 4

2) Initialization: For initializing HMM parameters, prior probability π and transmission probability A were made uniform across all the states. K- means algorithm initializes mean, variance and weights of Gaussian Mixture Components.

Using the stock market database, this algorithm predicts next days closing price. Procedure is as:

- Open, High, Low, Close values of the daily shares are input.
- Require: trained HMM $\lambda = (A, B, \pi)$
- The emission probabilities for a continuous HMM are modelled as Gaussian Mixture Models (GMMs).
- The above model is trained using Baum-Welch algorithm which uses Expectation Maximisation.
- $Date \longleftarrow start\_date$
- $O(Open, High, Low, Close) \longleftarrow load(date)$
- Observations are the daily stock in the form: $O_t = (fracChange, fracHigh, fracLow)$
  Where: $fracChange = \frac{close-open}{open}$ $fracHigh = \frac{high-open}{open}$ $fracLow = \frac{open-low}{open}$
- Testing is done using an approximate Maximum a Posteriori (MAP) approach.
- Given stock values for d days, close value of $(d+1)^{st} day \equiv \frac{close-open}{open}$ for the $(d+1)^{st}$ day.
- $O_{d+1} = argmaxP(O|\lambda)$ using forward backward algorithm.

3) Training Of Data: For training of above HMM from given sequences of observations is done using the Baum-Welch algorithm which uses Expectation-Maximization (EM) to arrive at the optimal parameters for the HMM. We have taken stocks of three Banks. Training for some period is done using EM algorithm. This data is converted into Observation vector which is further used for processing of stock prediction.

In our model the observations are the daily stock data in the form of the 3-d vector,

$$O_t = (\frac{close-open}{open}, \frac{high-open}{open}, \frac{open-low}{open}) \quad (1)$$

where: open is the day opening value, close is the day closing value, high is the day's highest value of stock, low is the lowest value of stock.We use fractional changes along to model the variation in stock data which remains constant over the years. Above equation is represented as: $O_t = (fracchange, frachigh, fraclow)$

4) Testing of Data: Once the model is trained, testing is done using an approximate Maximum a Posteriori (MAP) approach. We assume a latency of d days while forecasting future stock values. Hence, the problem becomes as follows - given the HMM model and the stock values for days $(O_1, O_2, O_3, ..., O_d)$ along with the stock open value for the $(d+1)^st$ day, we need to compute the close value for the $(d+1)^st$ day. This is equivalent to estimating the fractional change $\frac{close-open}{open}$ for the $(d+1)^st$ day. For this, we compute the MAP estimate of the observation vector O_{d+1}.

D. Result Analysis

We use Mean Absolute Percentage Error as a metric to evaluate the performance of the algorithm. MAPE is the average absolute error between the actual stock values and the predicted stock values in percentage. The formula is:

$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{(p_i-a_i)}{a_i} \times 100$

Where a_i is the actual stock value, p_i is the predicted stock on day i and n is the number of days for which the data is tested. Table II compares the corresponding MAPE values using the HMM-Fuzzy logic model, ARIMA and ANN.

Author	Model used	Input parameters	Accuracy
Hassan *et al*	HMM	Open, Close, High, Low	2.01 (in MAPE)
Xiang *et al*	Multiple models	Return rates	50%
Fangqiong *et al*	SVM	Prices, Moving Average, Moving Variance, Moving Variance Ratio, Exponential Moving Average, Disparity	60%
Feng *et al*	Multi-kernel model	Trading Volume, News Articles and Historical Price Movements	64.23%
Aditya Gupta *et al*	HMM	Open, Close, High, Low	TATA steel - 1.560 Apple Inc - 1.510 IBM - 0.611 Dell - 0.824 (in MAPE)

TABLE II: Performance table

The graph of the actual stock values and the values predicted by our algorithm is shown in following figures:

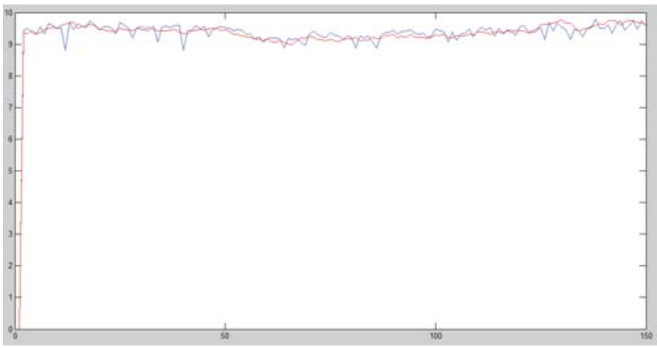

Fig. 2: Stock of SBI

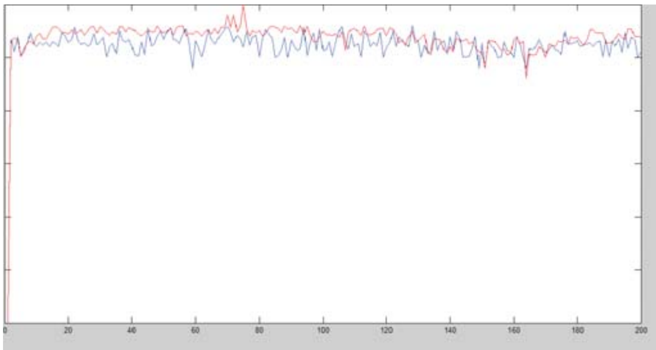

Fig. 3: Stock of ICICI

Actual stocks are represented in red while the predicted stocks are shown in blue.

IV. Conclusion

This paper surveyed the application of Neural Network, Support Vector Machine, Hidden Markov Model in the area of stock market prediction. Markov Model is more efficient in extracting information from the dataset. Also, it has a strong foundation so it is easier to explain the reason of the outcome. These techniques play significant role in monitoring the entire stock market price behaviour and fluctuation. In this paper we propose a predicting method to provide better accuracy than the traditional techniques. The MAPE value for our stocks were as follows ICICI - 2.1, SBI - 1.7, IDBI - 2.3. Fig.3 shows the performance graph of MAPE vs. dataset. The performance decreases with increase in training data as shown.

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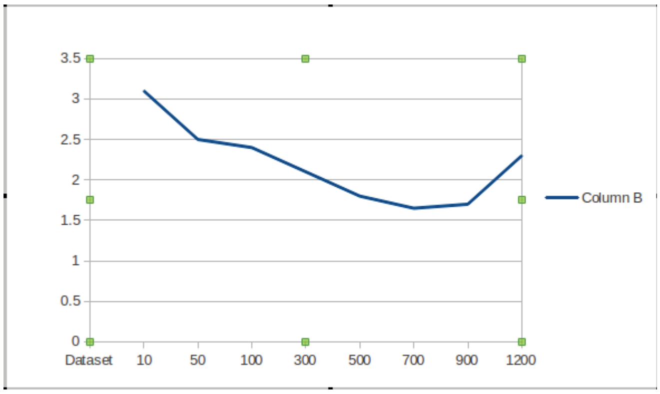

Fig. 4: Performance table

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