ISSN2394-3777 (Print)
ISSN2394-3785 (Online)
Available online atwww.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 12, April 2018

Time Series Stock Prediction using Stochastic Signal Prediction Model

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Abstract— **Stock Market prediction is an ordinary issue which can be resolved by utilizing techniques and procedures of Machine Learning. A precise stock expectation may illuminate the time reliance issue to minimal.The Hidden Markov Model can ready to determine this issue by by forecast and predict the stock market.The Hidden Markov Model is a stochastic signal prediction model which has been used to predict the economic growth and stock price from multiple observation data and single observation data.The proposed approach uses the stock data of Tesla,Ford and GM.The performance measure of each dataset is calculated using MAPE.This approach tries to prove model for one stock is independent of other stocks.**

Key words: Stock Market,Stochastic,Machine Learning, Hidden Markov Model.

I. Introduction

The shareholders dependably purchase a stock at a low cost and offer it with a higher price.However,when to purchase or offer a stock can't be anticipated accurately.Stock venture can return enormous benefit and in addition huge misfortune to the stakeholder.There are numerous models accessible for stock value determining, for example, Exponential Moving Average(EMA) and Head and shoulder methods.Recently ,the Hidden Markov Model (HMM) approach was connected to securities exchange expectation. The explanation behind utilizing this approach is reasonable since have been fruitful in breaking down and anticipating time arrangement. They have been utilized as a part of numerous application, for example, discourse acknowledgment, ECG investigation and so on. Hidden Markov Models depend on an arrangement of states among-st which advances can happen and each state is related with an arrangement of conceivable perceptions. The stock exchange can likewise be found in a comparable way. The states decide the conduct of the stock esteem which is typically undetectable to the financial specialist. The changes between these states depend on organization approach, choices and monetary conditions and so forth. This will influence the estimation of the stock.

II. RELATED WORKS

Hassan and Nath [1] utilized HMM to predict stock cost for interrelated markets.Kritzman,Page and Turkington[4] connected HMM with two states to foresee plots in market turbulence and industrial population index..Guidolin, M. what's more, Timmermann[6] utilized HMM with four states and various perceptions to consider resource allocation in industry. Ang and Bekaert [7] connected HMM demonstrate named as regime shift model for worldwide asset allocation. Nguyen [2] utilized HMM with both single and different observations to figure financial schemes and stock costs. B. Nobakht, C.- E. Joseph and B. Loni [5] actualized HMM by utilizing various perception information of a stock to foresee its nearby costs. [8], utilized HMM for single perception information to foresee plans of some monetary pointers and make stock choices in view of the exhibitions of these stocks amid the anticipated plans.

SayaliMetkarandAkash[9]recommendedtheprescient power of online region movement with the respect to stock prices.A classifier is utilized to break the prescient energy of a standard classifier in light of cost time-arrangement, and to have related exhibitions as the classifier manufactured considering cost and activity includes by and large. The prescient exhibitions are accomplished when the data about stock capitalization is joined with long-terms, and midterm web activity levels.QASEM A.[10] expect that major data openly accessible in the past has some prescient connections to the future stock Returns. The decision taken will be founded on decision tree classifier and the CRISP-DM is used for system construction. This paper is sorted out as takes after: Section 3 gives a presentation about the HMM and its three primary issues and relating calculations. Segment 4 portrays the HMM demonstrate determinations and information accumulations for stock value expectation. Segment 5 shows the trial comes about and dissects their exhibitions, and Section 6 gives conclusions.

III. HIDDEN MARKOV MODEL

The HMM display was intended to change over a model for single observations to multiple observations.principal arrange of a Markov process. In this paper ,talk about HMM for multiple observationsanditsrelatingalgorithms.Themultiple observations information ought to be free and have the same length.The fundamental components of a HMM for various observations are:observation sequence

$$O = O_t^l \text{ , } t = 1,2,..,T, l = 1,2,..,L \qquad (1)$$

and hidden state sequence

$$Q = qt, \ t = 1,2,..,T \qquad (2)$$

The possible value of each state(S=1,2,..,N) and possible symbols per state(v=1,2,..,M). The parameters of HMM are the A and B matrices and the vector p.

$$\lambda = (A,B,P) \qquad (3)$$

A is the transition matrix and B is observation probability matrix.If observation probability assumes the Gaussian distribution then

$$B = N(vk,\mu i,\sigma i) \qquad (4)$$

where μi and σi are the mean and variance of the distribution corresponding to the state S and N is Gaussian density function.Then the parameter of HMM are

$$\lambda = (A,\mu,\sigma,p) \qquad (5)$$

When the observations are independent then the probability of observation denoted as follows:

$$P(O|\lambda) = \prod_{l=1} P(O(l)|\lambda) \qquad (6)$$

A. Forward and Backward algorithm

The forward-backward algorithm is an inference method for Hidden Markov models which computes the posterior marginals of all hidden state variables in a given sequence of observations or emissions Ot. The Forward and Backward calculation is an optimization on thelong total. The calculation makes utilization of the rule of dynamic programming to register proficiently the qualities that are required to get the the posterior marginal distributions in two passes. The first pass goes forward in time while the second goes backward in time.

B. Viterbi algorithm

The Viterbi algorithm is a dynamic programming calculation for findingtheprobablysuccessionofhiddenstatesknown as the Viterbi path that outcomes in a grouping of observed events.It keeps a store of two components, the best scores to reach a state at a give time, and the last step of the path to get there.

C. Baum-Welch algorithm

The BaumWelch algorithm is used to find the unknown parameters of a hidden Markov model (HMM). It makes use of the forward-backward algorithm A hidden Markov model describes the joint probability of a collection of ”hidden” and observed discrete random variables. It relies on the assumption that the i-th hidden variable given the (i+1)-th hidden variable is independent of previous hidden variables, and the current observation variables depend only on the current hidden state.The BaumWelch algorithm uses the well known EM algorithm to find the maximum likelihood estimate of the parameters of a hidden Markov model given a set of observed feature vectors.

IV. STOCK PRICE PREDICTION MODEL

This approach build up a HMM based model for time series forecasting.The different number of states can be utilized at the cost forecasting.The choice of various hidden states is a troublesome task.The appropriate strategy preparing calculation for HMM is Baum-Welch calculation in which the EM technique was utilized to augment the log probability of the model.The circulation relating with each hidden state is a Gaussian distribution.This approach utilize HMM to anticipate stock costs and contrast the expectations and genuine stock prices.This display gauge the stock cost of various associations utilizing HMM with various number of states and compute the mean absolute percentage error.According to crafted by Hassan and Nath[1] the forecast procedure can be partitioned by three steps:1.Define HMM parameters and figure the probability of model.2.Find a day that has comparative probability in the past contrast with current day.3.Using the distinction of day that like current day to determine the future stock cost. However this approach is diverse shape them since this utilization HMM with one perception information and HMM with various perception information to foresee future close cost. The info highlights for various perception information are opening price,closing price,highest cost and most minimal price.The following day's end cost is the focused on output.Thus the open,low,high and close is caliberate with the HMM parameters, and afterward compute the likelihood of observations,((O|λ).After that anticipate the stock cost at time T and contrast it and second expectation.

A. Model Implementation

1)HMM parameters: The given HMM parameter are set with the values.First need to assign value to each parameter in the HMM model.The parameters are number of hidden states,number of mixture component for each state and time period for determining latency.

2)Initialization: The prior probability and transition probabilities A are set to be uniform.Then initialize the mean,variance and weight of the Gaussian mixture components using a k-means algorithm.The mean and variance are assumed from the cluster found from k-means.The weights are the weights of clusters that is equally divided among the states to obtain the initial emission probability.

3)Prediction and Performance Evaluation:Compute the probability value over a range of possible values of the block (equation) and find the maximum value.Thus it predict the minimum and maximum fractional changes in stock price.The performance of Baum-Welch algorithm is evaluated by the mean absolute percentage error,MAPE.The MAPE is calculated as follows:

$$MAPE = 1/n \sum_{i=1}^{n} |p_i - a_i| / |a_i| * 100 \quad (7)$$

Where ai is the actual stock value,pi is the predicted stock value on day i and n is the number of days tested.

The real stock market data from S&P 500 has been used for the prediction models. The proposed techniques have been experimented with three data sets i.e., Stock data of Ford,Tesla and GM.Each data set is divided into two parts, one is used for training and other is used for testing.Then it find the stock return value of each day.The stock return shows the performance of this three stocks.

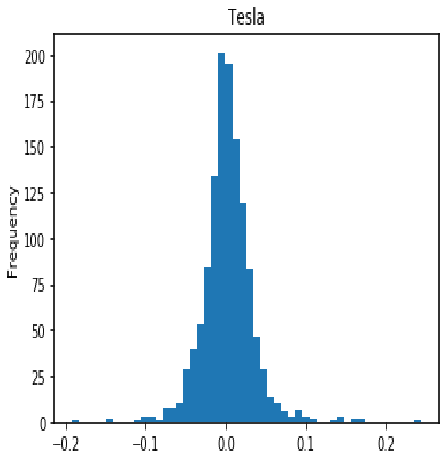

Fig. 1. Stock return value of Tesla from 3-01-2012 to30-12-2016.

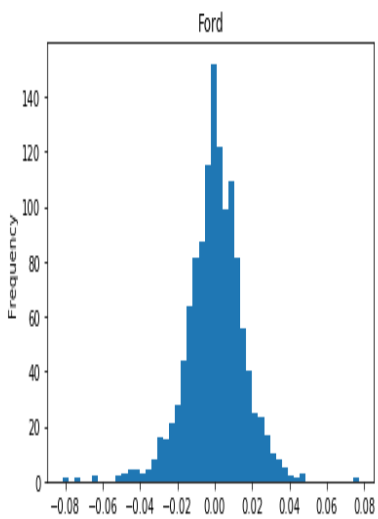

Fig. 2. Stock return value of Ford from 3-01-2012 to 30-12-2016.

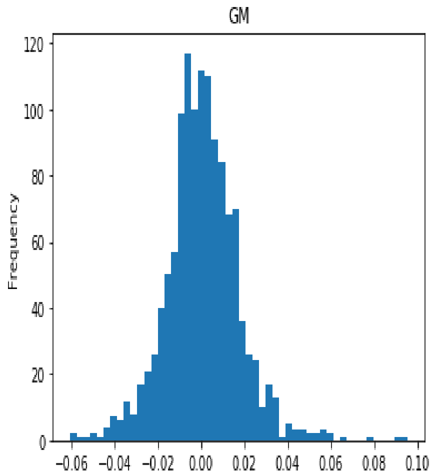

Fig. 3. Stock return value of GM from 3-01-2012 to

30-12-2016.

II. Conclusion

The proposed approach present a HMM based single observation and multiple observation data model for stock prediction.The model uses the latency of day to predict the stock price of next day.The number of states vary from 2 to 4 states and which emit the fractional changes in visible observations.The performance of the Baum-Welch algorithm is tested over trainning HMMs of different stocks in different time period.The proposed approach uses the stock data of Tesla,Ford and GM.The performance measure of each dataset is calculated using MAPE.The model for one stock is independent of other stocks.This approach can be compared with the HMM Fuzzy model,ARIMA and ANN for stock forecasting.In future the performance improvement can be achieved by Sequential Least Squares Programming(SLSP).

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