Application of Hidden Markov Models in Stock Trading

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***Abstract*— The stock market index forecasting is quite a popular topic in the present economy. There are many micro and macro-economic factors which influence the stock prices. With the emergence of machine learning techniques, algorithmic trading became most popular in forecasting the stock prices. There are many traditional machine learning techniques like ARMA, ARIMA which are used to forecast the stock market index. However these techniques consider trends and patterns involved in the data. Since the stock market data is a time series and irregular in nature there will be some noise involved. The present research paper studies the forecasting of stock market index by applying Hidden Markov models which considers the hidden states within the stock market index and traditional ARIMA model. HMM considers the posterior probabilities on different hidden states using Expectation Maximization algorithm. The data considered for the study includes 5 different stock market index Dow Jones, NIFTY 50, S & P 500, New York Stock Index (NYSE) and KOSPI. The data includes daily prices of Low, High, Close, Open, Volume for a period of 5 years that is 2014-2019 which accounts to approximately 1380 data points. In HMM model the closing price of the index is considered for determining the transition states and posterior probabilities at 2, 3, 4 and 5 hidden states. Akaike Information Criteria (AIC) and Bayesian information Criterion (BIC) are used to determine the states from HMM. The research paper studies the direction of the market the closing price of the stock index considering HMM. The paper is divided into 5 parts which include Part 1: Introduction, Part 2: Past study, Part 3: Machine Learning Algorithms, Part4: Data Analysis using HMM and Part 5: Results and Conclusion.**

Keywords— Stock Market Index, Hidden Markov Models, Posterior probabilities, Expectation Maximization algorithm, Akaike Information Criterion, Bayesian Information Criterion.

I. INTRODUCTION

Hidden Markov Models are the type of statistical techniques which includes calculation of probabilities with the observed and unobserved states. Hidden Markov models have many forms and different types of algorithms involved.Baum and Petrie, (Baum and Petrie, 1966) introduced Hidden Markov models (HMM) for signal detection. HMM considers the observed events and hidden events which cause a reason for the change in the forecasting. HMM involves five components:

1. Number of States represented by Q

2. Transition probability matrix: This determines the probabilities of moving from one state (i) to another state (j).

3. Observation: a sequence of T observations each drawn from an observation.

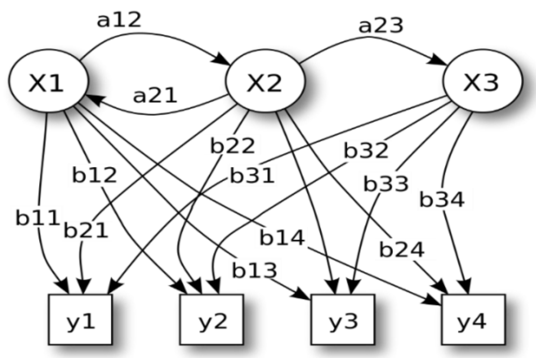
4. Observation Likelihood: It is also termed as emission probabilities, which expresses the probability of an observation being generated from a state (i).

5. Initial Probability Distribution: this is calculated over states, π_i represents the probability that the Markov chain will start at state 'i. For some states 'j' may have $\pi_j = 0$, which means that there exists no initial state.

Assumptions of HMM:

1. The probability of the particular state depends on the previous state.

2. The probability of the output observation depends only on the state that produced the observations and not on any other states or any other observations.



Source: https://en.wikipedia.org/wiki/Hidden_Markov_model

Figure 1. Probabilistic parameters of a hidden Markov model (example)

X — states

y — possible observations

a — state transition probabilities

b — output probabilities

The hidden states are calculated by using gaussian distribution. The major applications of HMM is into speech recognition, hand writing, parts of speech tagging and temporal pattern recognition. HMMs are also capable of carrying time series analysis.

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II. Application of different Hidden Markov Models:

Aditya Gupta and BhuwanDingra, applied HMM to forecast and predict the stock market prices for one day by providing the past data. Maximum posterior HMM is used for the prediction. Later Artificial Neural network is also used for the stock market prediction. Then the obtained results of both the models are evaluated using Mean Absolute Percent Error (MAPE).

Nguyet Nguyen (2018) article titled "Hidden Markov Models for stock Trading", used statistical signal prediction model to predict economic regimes and statistical prices. Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan Quinn Information Criterion (HQIC) and Bozdogen Consistent Akaike Information (BCAI) are used to determine an optimal number of states for HMM. The analysis clearly proves that HMM outperforms from traditional method in predicting and trading stocks.

Nd. Raifull Hassan and Baikunth Nath (2005) titled " Stock Market Forecasting using Hidden Markov Models: A New Approach", applied HMM to forecast some of the airline stocks. HMMs have been extensively used for pattern recognition and classification problems using past data.

Nguyet Nguyen (2017), "An Analysis and Implementation of the Hidden Markov Model to Technology stock prediction used HMM to predict the close prices of three stocks using the performance parameters as AIC and BIC to decide the number of states worked the best among two, three and four states for the three stocks. The results proved that two states worked the best.

Marcinn Jaruizewicz and Jack Mandiziuk [2016], paper titled "One Day Prediction of NIKKEI Index considering information from other stock markets, tried predicting the next day opening values of the Japanese stock exchange NIKKEI with consideration of German and USA stock indices. The average prediction error is found to be 0.27% with 0.96% volatility in stock.

Kashyap Kitchu, Shubham Kumar Singh, Dr.Vimuktha Evangeleen Salis in their research paper titled "Gold Stock Market using HMM Approach considered commodity market to predict the commodity price and to know the behaviour and direction of the market using the past data. HMM is applied for prediction and the model is evaluated based on the performance metric of Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

G. Kavitha, A Udhayakumar, D Nagarajan [2013], " Stock Market Trend Analysis using Hidden Markov Models" implemented HMM to study the market behaviour. The close value of the stock for a certain period is found and the corresponding state probabilities are evaluated to identify the trend pattern involved. Six optimal hidden state sequence are generated and compared for the best optimum state sequence.

Kei Wakabayashi, Takao Miura [2009], "Data Stream prediction using Incremental Hidden Markov Models proposes new technique for time series prediction using Baum-Welch algorithm of HMM. New parameter estimates are evaluated to find the new patterns in the time series data.

III. Machine Learning Algorithms Hidden Markov Models

A. *Expectation Maximization Algorithm:*

Expectation Maximization algorithm is a general algorithm for optimization of the likelihood function where observed probabilities and unobserved probability components are specified. Hidden Markov Models take the same form because they have both observed components which are called the emission probabilities and the unobserved probabilities called as hidden states.

If the model consists of two components (X,Y) which take finite values and if the probabilistic model specifications consist the joint probabilities Pθ (x,y) where θ is parameterized, then the loglikelihood when observing only X=x is

$$Lx(\theta) = \sum P\theta\ (x,y)$$

This loglikelihood function gives the overall possible transitions between the hidden states.

Hidden Markov Model - Expectation Maximization is iterative with two steps:

1. Conditional Expectation: when the observed state 'x' is given under the current estimate of θ.

2. Maximization

Hence is an iterative method of performing statistical analysis and the inference on a variety of generative statistical models.

The statistical models used in the Expectation Maximization includes:

1. Gaussian Network Model

2. Bayesian Network Model

Apart from the above network models there are other model algorithms like Viterbi which computes the most probable sequence of hidden states.

The Assumptions of Hidden Markov Models include:

1. Discrete state space assumption: The values of qtare discrete that is

$$qt \in \{S1, S2, \ldots SM\}$$

2. Markov Assumption:

a. Given the state at the time t, the state at time t+1 is independent to all previous states, that qt+1qi|qt, for all i< t.

b. Given the state at the time t, the corresponding observations yt is independent to all other states, yt, qi|qt, for all i≠t

Then the behaviour of HMM is fully determined by the three probability states:

1. The transition probability P(qt+1/qt), is the probability of qt+1when its previous state qt is given. Since the states are discrete, the transition probabilities are described as M x M matrix called as transition matrix.

2. The ijth element of the matrix denotes the probability of the state transiting from ith state to jth state.

3. The emission probability P(yt/qt) is the observed qt and gives its hidden states qt.

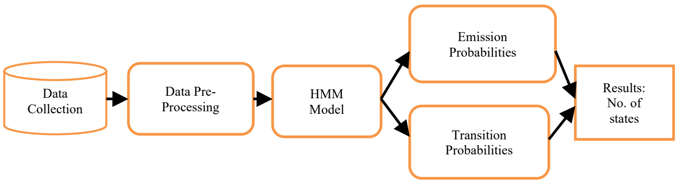
4. The initial state distributions.

B. Data Description:

The data considered for the study includes the 5 selected stock indices: S&P 500, Dow Jones, NIFTY 50, KOSPI and New York Stock Exchange (NYSE). The data is been collected through the stock Exchanges for about 5 years 2014-2019. The data collected for the study approximates to 1387 data points. Around 6 attributes are been captured. The daily stock indices data includes High Price, Low Price, Close Price, Open Close, Volume and Adjusted Volume. The percent returns of the stock index is calculated using

Returns = (Next day Close Price – Previous day Close Price)/Previous Day Close Price.

C. Analytical Framework:



D. Analysis of the Study:

The data analysis for the selected stock indices includes the close price of the every stock index to see the market behaviour based on the number of states that the observation has transmitted. The closing price of the stock indices is given as the input and the market behaviour is estimated based on the emission and transition probabilities.

The parameter estimated under the study includes loglikelihood function, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to estimate the number of states that the stock indices transmits.

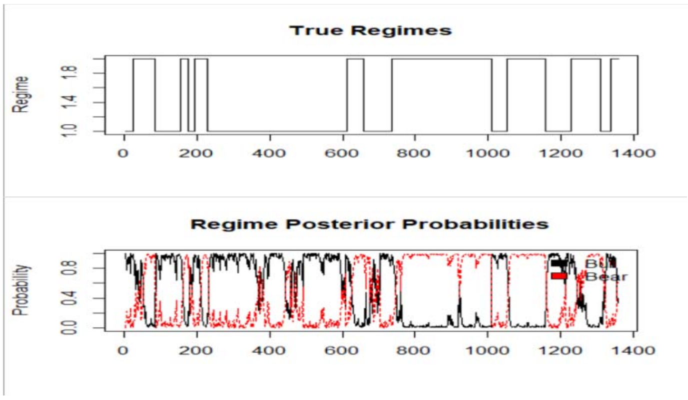
Nifty 50:

The transition and emission probabilities of the stock index with respect to two hidden states, three hidden states, four hidden states and five hidden states are found to be:

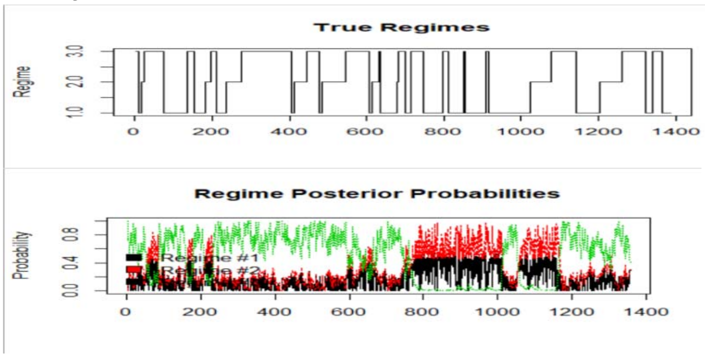
No. of States	Loglikelihood	AIC	BIC
N = 2	4619.385	9224.771	9188.274
N = 3	4628.529	9229.057	9156.065
N = 4	4655.537	9265.074	9145.157
N = 5	4662.917	9257.834	9080.566

From the above it is clear that even the number of states are increased the AIC and BIC values did not decrease after 3rd state the values increase drastically.

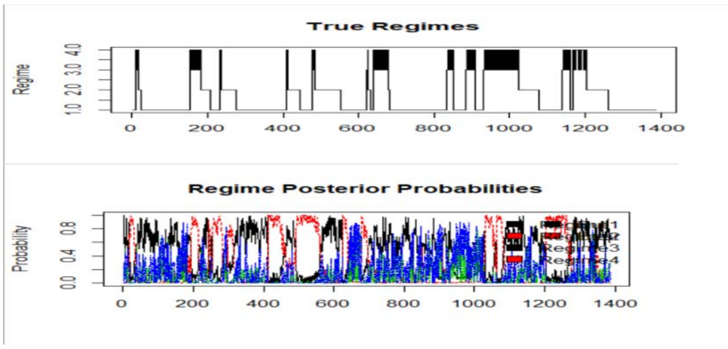
Graph Showing regime probabilities and the hidden states when number of states is 2:



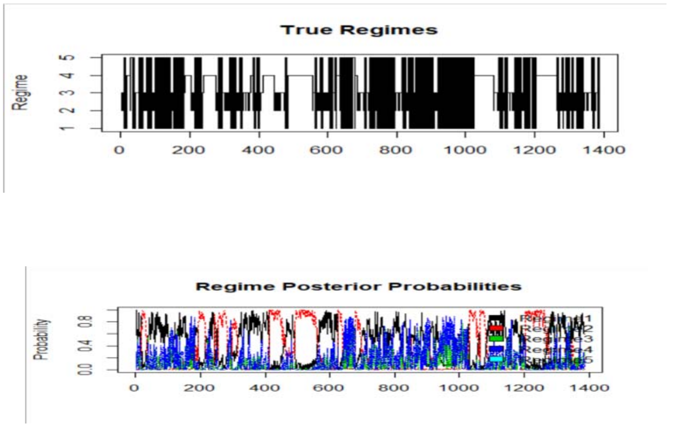
Graph Showing regime probabilities and the hidden states when number of states is 3:



Graph Showing regime probabilities and the hidden states when number of states is 4:



Graph Showing regime probabilities and the hidden states when number of states is 5:



New York Index:

No. of States	Loglikelihood	AIC	BIC
N = 2	4924.312	9834.624	9797.985
N = 3	4945.138	9862.277	9788.998
N = 4	4960.131	9874.262	9753.876
N = 5	4963.903	9859.807	9681.845

From the above table it is clear that the AIC value and BIC value is found to be least at 2 hidden states which means that the market shows clearly two states that is bullish or bearish.

S & P 500:

No. of States	Loglikelihood	AIC	BIC
N = 2	4893.017	9772.035	9735.396
N = 3	4922.045	9816.091	9742.812
N = 4	4938.403	9830.806	9710.420
N = 5	4956.775	9845.551	9667.589

DOW JONES

No. of States	Loglikelihood	AIC	BIC
N = 2	4882.605	9751.121	9714.570
N = 3	4912.842	9801.683	9728.405
N = 4	4933.683	9821.367	9700.981
N = 5	4945.885	9823.771	9645.809

From the above table it is clear that the AIC is found to be the least at two states and the corresponding BIC values is also least at the two states.

KOSPI INDEX

No. of States	Loglikelihood	AIC	BIC
N = 2	4692.185	9370.371	9333.869
N = 3	4707.517	9387.035	9314.032
N = 4	4717.069	9388.139	9268.205
N = 5	4721.85	9375.700	9198.407

From the above table it is clear that the AIC is found to be the least at two states and the corresponding BIC values is also least at the two states.

IV. Conclusion

The stock indices are the very important indicators of the financial status of the economy. The above analysis of Hidden Markov Models are done using R language. The performance of the algorithm is evaluated by using the performance parameters AIC and BIC. This helps the investors in knowing the market behaviour and helps them to plan their investments. From all the above tables it is clear that the all the markets show two hidden states and continue to be in that state for some time. Hence for the investors to decide on their investment plan one has to look whether the market is moving in uptrend or downtrend specifying bullish and bearish market.

V. Future Work

The above work can be further taken ahead in predicting the closing price of the stock index by applying further machine learning techniques and by building a hybrid model combining HMM and ANN. The study can also be conducted taking wavelet transformation functions.

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