Trend Analysis and Prediction of Indian Stock Market using Markov Chain Model

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Abstract

The purpose of the study is to analyze and predict the National Stock Exchange (NSE) Index. For Investors, who are seekers of Capital Appreciation, trend analysis and predictionare very essential. Therefore, investors, whether retail or institutional, must predict the trend of the stock market where the investments have been made to create wealth. The study uses the Markov Chain Model over a period from 3rd February 2020 to 29th January forming, 247 days of trading data from the official website of the NSE. The NSE Index shows three different states - Increase, Unchanged and, Decrease. The Markov Chain model is a probability model based on the transition probability matrix and initial state vector. The transition probability metric has been obtained by observing the number of transitions from one state to another. The study explores that in the long run, regardless of the current state of the NSE index, the probability of index increase, unchanged, and decrease are 42.29%, 32.87%, and 24.84 %, respectively. If the closing value of the NSE index is in the state Increase on day one, then it can be expected to return to the state increase for the first time in two days or on the third day.

Keywords: *markov chain; trend analysis; prediction; transition probability matrix; indian stock market.*

Introduction

The Stock Market is a barometer of any economy. The Stock market plays a significant role in the life of Investors with the sole objective of making a profit by investing in different shares of listed companies. The Stock market is the legal platform where such shares are traded. And according to the performance of the company, the price of the shares grows up or down in the stock market. Apart from the performance of the company, worldwide trend of business, natural calamities, the sociopolitical policy, global market conditions also affect the stock market. Therefore, there lies the significance of stock market prediction, which may benefit an investor. Various scientific methods are implemented for stock market prediction through the analysis of past information. Investors in the stock market are interested to know the future occurrence of the market as they are motivated by the desire for capital appreciation. However, the fluctuating nature of the stock market makes the analysis and prediction a complicated phenomenon and making accurate prediction of the stock market by any single method a very difficult task. Different methods such as Machine Learning, Neural Network, Moving Average, Regression Analysis, ARIMA, Data Mining, MarkovChain analysis, Hidden Markov model are used by different researchers to forecast the stock market.

Review of Related Work

Prediction is the method where we find the future value on a specific field with the help of the past data records and conclude the specific result. There are several fields where prediction is used, and various prediction methods have been proposed and implemented. These methods range from Machine Learning (Jigar Patel, Sahil Shah, Priyank Thakkar, and K Kotecha; David Enke and Suraphan Thawornwong),Neural Network (Manna Majumder and MD Anwar Hussian; Akintola K.G., Alese B.K. and Thompson A.F.; Sneha Soni; Tiffany Hui-Kuang and Kun-Huang Huang; R.K. and Pawar D.D.; Halbert white; Jing Tao Yao and chew Lim tan; Riki Herliansyah and Jamilatuzzahro), Moving Average [MA] method (Abdulsalam Sulaiman Olaniyi, Adewole, kayoed s, Jimoh R.G),Data mining techniques (M. Suresh Babu, N. Geethanjali and B. Sathyanarayana; Y.L. Hsieh, Don-Lin Yang, and Jungpin Wu; K. Senthamarai Kannan, P. Sailapathi Sekar, M.Mohamed Sathik and P. Arumugam),Hidden Markov Models (HMM) (Md. Rafiul Hassan and Baikunthu Nath, Kavitha G, Udhayakumar A, and Nagarajan D),Moving Average Autoregressive Exogenous (ARX) prediction model (Kuang Yu Huang, Chuen-Jiuan Jane),ARIMA model and vector ARMA model with fuzzy time series method (Hsien-Lun Wong,Yi-Hsien Tu and Chichen Wang; Swapnil Jadhav, Saurabh Kakade, Kaivalya Utpat, Harshal Deshpande) to Markov Chain Approach.

The Markov Chain Model has been used by many researchers to predict and analyze the trend of the stock market at different times.

Styan, George P. H. and Smith, Harry Jr. (1962) used market behavioral analysis data provided by the transitional or switching, habits of the consumer. They had taken types of laundry powder purchased by a housewife to define the state space of a Markov chainand predicted the future purchase behavior and statistical inferences on the switching habits. Zhang, Deju and Zhang, Xiaomin (2009) applied the Markov process model for the Chinese stock market trend forecasting and concluded that the operational status of the stock market is subject to the impact of various factors from the market; hence, no single method can accurately predict changes in the stock market every day. Doubleday, Kevin J., and Esunge, Julius N. (2011) determined the relationship between a diverse portfolio of stocks and the market. The DJIA and portfolio of five stocks wereanalyzed using a Markov Chain. They concluded that when treated as a Markov process, the entire market was useful in gauging how a diverse portfolio of stocks might behave. Vasanthi S*et al.* (2011) tried to predict the stock index trend of various global stock indices using Markov Chain Analysis and found that majority of the time, the Markov model outperformed the traditional trend prediction methods.Badge, Jyoti (2012) used selected technical indicators of macro-economic factors of the Indian stock market as an input variable. Future prices have been found through Hidden Markov Model (HMM). It has been observed that HMM with PCA performed well and provided a Mean Absolute Percentage Error (MAPE) of 1.77%.Choji, Davou Nyap*et al.*(2013) used the Markov chain model to analyze and to make predictions of the two top banks in the three states. They found that regardless of a bank's current share price, in the long run, its share price will depreciate with a probability of 0.4229, remain unchanged with a probability of 0.2072, and appreciate with a probability of 0.3699. Otieno, Simeyo *et al.* (2015) used secondary quantitative data on the daily closing share prices of Safaricom from the NSE website. It has been observed that irrespective of the current state of share price, the model predicted that the Safaricom share prices would depreciate, maintain value, or appreciate with a probability of 0.3, 0.1, and 0.5, respectively. Bairagi, Aparna and Kakaty, Sarat C. (2016) used the Markov Chain model to analyze and predict the stock behavior considering three different states, 'up', 'down', and 'remain same'. The study revealed that regardless of the bank's current share price, steady-state probabilities of share 'up', 'down' and 'remain same' for SBI were 46.99%, 49.81%, and 3.19%, respectively. If the closing value of SBI share was on the state 'up' on day one, then it can be expected to return to the state 'up' for the first time on the third day.Singh, Waikhom Rojen *et al.* (2017) presented a paper with objectives to predict the prompt future change in opening stock price and to find a steady-state transition probability matrix. The opening stock price of National Stock Exchange NIFTY 50 of India has been studied and the opening price of Stock was examined as following Markov chain. Bhusal, Madhav Kumar (2017) attempted to apply a Markov Chain model to forecast the behaviors of the Nepal Stock Exchange (NEPSE) index. The study explored that regardless of the present status of the NEPSE index, in the long run, the index will increase with a probability of 0.3855, remains in the same state with probability 0.1707, and decrease with a probability of 0.4436.

The study is an attempt to analyze the trend and prediction of the National Stock Exchange (NSE) Index, India, using the Markov Chain Model in line with the above-mentioned work of the authors.

Objectives of the Study

1. To study the long-run behavior of the NSE Index

2. To find out the expected number of visits to a particular state and
3. To find out the expected first reaching time of various states.

Markov Chains and their respective diagrams can be used for predicting the likelihood of future market conditions. These conditions, also known as trends, are:

Increase (Bull Markets): periods where prices generally are rising due to the investors having optimistic hopes of the future, i.e., the closing value is greater than the closing value of the previous day.

Unchanged (Stagnant Markets): periods, where the market is characterized by neither a decline nor rise in general price,i.e., closing value, is equal to the closing value of the previous day.

Decrease (Bear Markets) periods where prices generally are declining due to the investors having pessimistic views of the future, i.e., Closing value is less than the closing value of the previous day.

Data and Methodology

For the study, secondary quantitative data on the daily closing prices of the NSE Index was obtained over a period from 3rd February 2020 to 29th January, forming 247 days of trading data from the official website of the NSEwww.nseindia.com. Here, the number of observations for Index value Increase, Unchanged, and Decrease has been found as 105, 81, and 61, respectively. Since the last trading day is recorded as a decrease and there is no information regarding the next day's transition, the total number of decreases should be recorded as (61-1) = 60.

The basic theory of the Markov chain model

In 1907, A. A. Markov began the study of an important new type of chance process. In this process, the outcome of a given experiment can affect the outcome of the next experiment. This type of process is called a Markov chain.

Markov process is a special type of stochastic process for which the future occurrence of any event depends only on the present state. The set of values that the Markov process takes is known as its state-space. Depending on the values of state-space, the process may be discrete or continuous. The process with discrete state space is known as the Markov chain. Markov chain is one of the mostwell-developed theories of a stochastic processwith wider applications.

Definition of Markov chain

The sequence $\{X_n, n \geq 0\}$ is said to be a Markov chain if for all state values $i_0, i_1, i_2, \ldots\ldots, i_n \in I$, then

$P\{X_{n+1} = j / X_0 = i_0, X_1 = i_1, \ldots\ldots\ldots\ldots, X_n = i\} = P\{X_{n+1} = j / X_n = i\}$

Where, $i_0, i_1, i_2, \ldots\ldots, in$ are the states in the state space I.

This kind of probability is called Markov chain probability. This implies that regardless of its history before time n, the probability that it will make a transition to another state j depends only on state i.

Transition probability and transition probability matrix

The transition probability, as defined by the Markov chain, is called transition, or jump probability from state i to state j. Then,

$P\{X_{n+1} = j / X_n = i\} = p_{ij}$

This is also termed as one-step transition probability. If the transition probabilities defined above are independent of time (n), then such an assumption is called a homogenous or stationary Markov chain. Thus,

$P\{X_{n+1} = j / X_n = i\} = P\{X_1 = j / X_0 = i\} = p_{ij}$

The transition probabilities p_{ij}'scan be written or arranged in a matrix form as,

$P = [p_{ij}],\ i, j \in I$

Here, the matrix P is called the transition probability matrix (TPM) or stochastic matrix. The matrix P insists on non-negative elements with row sum unity. Hence

$0 \leq p_{ij} \leq 1$ and $\sum_{j=1}^{n} P_{ij} = 1,\ \surd\ i \in I$

The k-step transition probability from state i to state j in k stepsis,

$P_{ij}(k) = P\{X_{n+k} = j / X_n = i\},\ \surd\ k > 0,\ n \geq 0,\ I, j \in I$

The Transition matrix P has the following property.

$P(n) = P^{n-1} * P = P^n$

State Probability Matrix

The average transition process of the Markov chain depends on the system's initial state and the transition probability matrix. The initial state is a line matrix called initial probability vector defined as;

P (X_0 = i) = P (0) = [p_0 (0) p_1 (0) ……… p_n (0)], 0 ≤ p_i (0) ≤ 1 and $\sum_{i=0}^{n} Pi(0)$ =1 for all states.

Similarly, the probability vector at time n may be defined as

P (X_n = i) = P (n) = [p_0 (n) p_1 (n) ……… p_n (n)], 0 ≤ p_i (n) ≤ 1 and $\sum_{i=0}^{n} Pi(n)$ =1 for all state.

By knowing the initial state of the system and transition matrix after the n^{th} step,

P (k+1) = P (k) * P

Which gives;

P(1) = P (0) * P

P(2) = P (1) * P = P (0) * P^2

P(k) = P (k-1) * P = P (k-2) * P^2 = ………… = P(0) * P^k

Hence,

P(k+1) = P (0) * P^{k+1} , for k ≥ 0

This indicates that the transition probability matrix after the (k+1) step is the product of the initial probability vector and $(k+1)^{th}$ power of the one-step transition probability matrix.

Irreducible Markov Chain

If it is not possible to partition the state space into two or more disjoint closed sets, a Markov chain is said to be irreducible. Which means it consists of only of a single class.

Absolute Probability

The state probability distribution {P_j (n), j ϵ *I*} shows the probability of finding the particle at state j at the n^{th} trial. If P_i (0) be the probability of finding such particle at state I at initial trial then,

P (X_n = j) = P_j (n) = $\sum_i P$ (X_n = j, X_0 = i) = $\sum_i P\ (Xn\ =\ j|X0\ =\ i)$ P (X_0 = i)

= $\sum_i P_i$ (0) . P_{ij} (n) , n >0

Here, {P_j (n), j ∊ I} is the initial probability distribution.

Stationary Distribution of a Markov Chain

This property of the Markov Chain states that regardless of the initial state of the system, how does the stochastic process evolve, when the number of transition steps is sufficiently large, then the transition probability from state i to state j becomes settle down to some constant value. Thus,

$$\lim_{n \to \infty} pij\ (n) = \pi\ j$$

Such quantities are referred to as steady-state probabilities.

If the limits π_j =$\lim_{n \to \infty} pj\ (n)$ =$\lim_{n \to \infty} pij\ (n)$ exists and does not depend on the initial state, then

P_j (n) = $\sum_k P_k$ (n-1) P_{kj} becomesπ_j =$\sum_k \pi_k$ P_{kj} , as n →∞for j = 0,1,2,……….

This is equivalent to π = π * P

The probability distribution {π_j , i ∊ I} is called stationary or invariant for the given chain if

π_i = $\sum_{i\epsilon\ \mathrm{I}} \pi i\ Pij$ such that π_i ≥ 0 and $\sum_i \pi_{\mathrm{I}}$ =1

This property of the Markov Chain helps to determine the long-run behavior of the chain.

Expected number of Visits

The expected number of visits made by the chain to state j starting from state i is given by

μ_{ij} (n) = E (N_{ij} (n))

Where N_{ij} (n) denotes the number of visits to state j starting from state i in n-steps.

Were,

N_{ij} (n) = $\sum_{k=1}^{n} Yij\ (k)$ with Y_{ij} (0) = ∂_{ij} , the Kronecker delta.

And Yij (k) = $\begin{cases} 1, if\ Xk\ =\ j/X0 = \mathrm{i} \\ 0, \qquad otherwise \end{cases}$

Then, μ_{ij} (n) = E [$\sum_{k=1}^{n} Yij(k)$]

= $\sum_{k=1}^{n} E(Yij(k))$

= $\sum_{k=1}^{n} P[Yij(k) = 1]$

∴ $\mu\mathrm{ij\ (n)}\ =\ \sum_{k=1}^{n} Pij(k)$

Also, the expected number of visits to state j from state i after long-run is;

$$\mu\mathrm{ij\ (n)}\ =\ \lim_{n \to \infty} E\ (Nij\ (n))$$

Expected Return Time

For a finite irreducible Markov chain, the expected return time to state j, j ∊ I can be obtained by taking the reciprocal of limiting probability p_{ij}(n).

Determination of Initial State Vector

The closing price shows three different states Increase, Unchanged, and Decrease, as each closing price index is taken as a discrete-time unit. The Initial state vector gives the probabilities of the three different states.

The state vector is denoted by $\pi^{(0)} = (\pi_1, \pi_2, \pi_3)$ then π_1, π_2 and π_3 gives the probability of the NSE index increase, unchanged and decrease as

π_1 = 105/246 = 0.4268

π_2 = 81/246 = 0.3293

π_3 = 60/246 = 0.2439

So, the initial state vector for the NSE index is -

$\pi^{(0)} = [0.4268 \quad 0.3293 \quad 0.2439]$

Determination of Three state transition probability metrics

The states are the chances that the NSE index increases, that is unchanged, and that it decreases. That transitions from one state to another observed from the data panel and were compiled in Table 1 as follows:

Table 1: The Transition Matrix of NSE Index

	Increase	Unchanged	Decrease
Increase	50	38	105
Unchanged	25	29	81
Decrease	29	14	51

The transition probability matrix of the NSE index using the above information can be constructed as;

$$P^{(1)}_{NSE} = \begin{bmatrix} 0.4762 & 0.3619 & 0.1619 \\ 0.3086 & 0.3580 & 0.3333 \\ 0.3922 & 0.2745 & 0.3333 \end{bmatrix}$$

The transition digraph for the explicit presentation of transition probability of the NSE index is shown below -

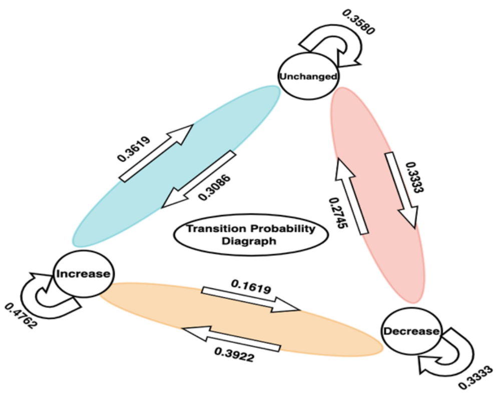

Figure 1 Transition Probability Digraph of the NSE Index

Calculating state probability for forecasting the next day NSE index price

By applying initial state vector and transition probability metrics, it is possible to find out the state probability of various closing days in the future. The state probability of closing price of the NSE index for the 248th day will be -

$$\pi^{(1)} = \pi^{(0)} * P_{NSE} = [0.4268 \quad 0.3293 \quad 0.2439] * \begin{bmatrix} 0.4762 & 0.3619 & 0.1619 \\ 0.3086 & 0.3580 & 0.3333 \\ 0.3922 & 0.2745 & 0.3333 \end{bmatrix}$$

248th Day = $\pi^{(1)} = [0.4228 \quad 0.3293 \quad 0.2480]$

This indicates that on the 248th day the state Increases have maximum probability, and it can be predicted that the NSE index will increase on this day with a probability of 0.4228. Similarly, the state probabilities of closing index price for 249th day will be

$$\pi^{(2)} = \pi^{(1)} * P_{NSE} = [0.4228 \quad 0.3293 \quad 0.2480] * \begin{bmatrix} 0.4762 & 0.3619 & 0.1619 \\ 0.3086 & 0.3580 & 0.3333 \\ 0.3922 & 0.2745 & 0.3333 \end{bmatrix}$$

249th Day = $\pi^{(2)} = [0.4228 \quad 0.3287 \quad 0.2485]$

Thus, it can be said that there is a possibility of the NSE index price increases with a probability of 0.4228, unchanged with a probability of 0.3287, and decreases with a probability of 0.2485. These predictions are the same as the actual data.

The n-step Transition Metrics

The prediction of the long-run behavior of the NSE index is very meaningful and important for investors. The long-run behavior of the NSE index can be determined by using the n-step transition probability matrix. The n-step metrics $P^{(n)}_{NSE}$ shows the behavior of stock index n-step later. If the number of steps increases then the $P^{(n)}_{NSE}$ converges to limiting transition metrics $P^{(\infty)}_{NSE}$, where each row of the matrix is identical, and it is said that the chain has attained a steady-state or state of equilibrium. The steady-state metrics provide the probability of the NSE index increase, unchanged, and decrease in the future. In other words, the nth power transition probability metrics will provide the probability that the NSE index price will be in a particular state in n days, given that it is currently in some specified state. To examine the long-term behavior of the NSE index, the higher-order transition probability metrics are calculated with the help of Microsoft Excel.

$$P^{(1)}_{NSE} = \begin{bmatrix} 0.4762 & 0.3619 & 0.1619 \\ 0.3086 & 0.3580 & 0.3333 \\ 0.3922 & 0.2745 & 0.3333 \end{bmatrix}$$

$$P^{(2)}_{NSE} = \begin{bmatrix} 0.4167 & 0.3397 & 0.2436 \\ 0.4186 & 0.3177 & 0.2638 \\ 0.4391 & 0.3246 & 0.2363 \end{bmatrix}$$

$$P^{(3)}_{NSE} = \begin{bmatrix} 0.4210 & 0.3293 & 0.2497 \\ 0.4249 & 0.3268 & 0.2484 \\ 0.4235 & 0.3303 & 0.2462 \end{bmatrix}$$

$$P^{(4)}_{NSE} = \begin{bmatrix} 0.4228 & 0.3285 & 0.2487 \\ 0.4232 & 0.3287 & 0.2481 \\ 0.4226 & 0.3290 & 0.2484 \end{bmatrix}$$

$$P^{(5)}_{NSE} = \begin{bmatrix} 0.4229 & 0.3287 & 0.2484 \\ 0.4229 & 0.3287 & 0.2482 \\ 0.4228 & 0.3287 & 0.2485 \end{bmatrix}$$

$$P^{(6)}_{NSE} = \begin{bmatrix} 0.4229 & 0.3287 & 0.2484 \\ 0.4229 & 0.3287 & 0.2484 \\ 0.4229 & 0.3287 & 0.2484 \end{bmatrix} = P^{(7)}_{NSE} =$$

$P^{(8)}_{NSE} = P^{(9)}_{NSE} = P^{(10)}_{NSE} = \ldots\ldots..$

The higher-order transition probability matrix of the NSE index computed above shows that after the 5th trading day since 247 trading days, the transition probability metrics tend to the steady-state or the state of equilibrium. After then the transition probability matrix remains unchanged for the onward consecutive trading days. These steady-state transition probability metrics of the NSE index reveals the following information.

The probability that the NSE index increases shortly irrespective of its initial state increase, unchanged or decrease is 0.4229. There is a 0.2484 chance that the NSE index will decrease shortly irrespective of its initial state increase, unchanged or decrease. The chance of the NSE index unchanged in the same state shortly irrespective of its initial state increase, unchanged or decrease is 0.3287.

If the NSE index starts in a given state with initial state vector $\pi^{(0)} = [0.4268 \quad 0.3293 \quad 0.2439]$, then the probability of the NSE index will increase, unchanged, or decrease at a particular trading day in steady-state condition can be determined by multiplying the initial state vector by the higher-order transition probability metrics obtained at the state of equilibrium. Then,

$$\pi(0) * P^{(6)}_{NSE} = [0.4268 \quad 0.3293 \quad 0.2439] * \begin{bmatrix} 0.4229 & 0.3287 & 0.2484 \\ 0.4229 & 0.3287 & 0.2484 \\ 0.4229 & 0.3287 & 0.2484 \end{bmatrix}$$

$$= [0.4229 \quad 0.3287 \quad 0.2484]$$

This result indicates the long-run probability of the NSE index being in increasing, unchanged, or decreasing states. The probability that the NSE index increases at the state of equilibrium are 0.4229, unchanged is 0.3287, and the probability that the NSE index decreases are 0.2484.

Expected number of visits

Here an attempt has been made to find out the expected number of visits, the NSE index makes to a particular state from another state in different steps.

For the NSE index, the number of visits the chain makes in five trading days is given by the following metrics.

$$\mu_{ij}(5) = \begin{bmatrix} 2.1596 & 1.6880 & 1.1523 \\ 1.9982 & 1.6599 & 1.3419 \\ 2.1914 & 1.5458 & 1.2628 \end{bmatrix}$$

From the matrix obtained above, it may be revealed that if the NSE index starts from the increasing state, the expected number of visits the chain for the NSE index makes to the increasing state out of five trading days is 2.1596, to the state unchanged is 1.6880 and to the state, the decrease is 1.1523.

Likewise, if the NSE index starts from an unchanged state, the expected number of visits the chain makes to the state increase is 1.9982, to the state unchanged is 1.6599 and to the state, a decrease is 1.3419.

Similarly, if the NSE index starts from decreasing state, the expected number of visits the chain makes to the state increase is 2.1914, to the state unchanged is 1.5458 and to the state, a decrease is 1.2628.

Expected return time

It will be meaningful to understand the expected duration the NSE index will stay in the increase, decrease, or unchanged state. The steady-state transition probability is used to determine the expected return time to a state starting from the same state. For a finite irreducible MarkovChain, the expected return time to the same state is a reciprocal of the steady-state probabilities. Here for the NSE index the expected return time to the increasing state, starting from the same increasing state is 1/0.4229 = 2.3646. This result shows that the chain for the NSE index should visit the increasing state on an average in two days. Similarly, the expected return time to remain unchanged, starting from the unchanged state is 1/0.3287 = 3.0423.

This means the chain for the NSE index should visit the state unchanged on an average of three days. The expected return time to the decreasing state, starting from the decreasing state is 1/0.2484 = 4.0258. This result helps to conclude that the chain should visit the decreasing state on an average of four days.

Conclusion

To predict the stock market behavior, the Markov Chain model assumes that the performance of the stock market is completely affected by stochastic factors. The movement of a stock index to various states in a particular trading day is independent of the index of initial trading days but depends only on the index of the most recent day. The prediction of the behavior of the stock market is very complexbecause the operational status of the stock market is subject to the influence of various factors from the market; therefore, there is no single method available that can accurately predict changes in the stock market every day. Hence, investors can combine the results of forecasts from using the Markov chain to predict with other factors and achieve relatively good results.

In this paper, the Markov Chain Model is applied to predict the behavior of the NSE Index. The predicted results are stated in terms of the probability of a certain state of the NSE Index in the future. The model does not provide the prediction results in an absolute state.The initial state vector and the transition probability matrices are used to estimate the probability of the NSE Index being in different states in the future days. The steady-state probabilities are obtained from the n-step transition probability matrices. The result of the steady-state probability matrix shows that the chance of the NSE Index will increase in the future is 0.4229, will be unchanged soon is 0.3287, and will decrease soon is 0.2484. The expected number of visits to a particular state from other states is also computed. The result shows that out of five trading days, the expected number of visits the chain for the NSE Index made to the increasing state starting from the increasing state is 2.1596. The expected number of visits to the decreasing state starting from the decreasing state is out of five trading days for the chain is 1.1523.The result of the expected return time shows that the chain for the NSE index should visit the increasing state on an average in two days and the expected return time to the decreasing state, starting from the decreasing state is four days.

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