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STOCK MARKET TREND ANALYSIS AND PREDICTION USINGMARKOV CHAIN ON NATIONAL STOCK EXCHANGE

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Abstract: In developing economies, the stock market plays a vital role in capital formation and economic development. Forecasting stock price movements remains a challenging yet crucial task for investors and researchers due to the inherent stochastic nature and volatility of stock prices. This study employs a Markov Chain (MC) model to analyze and predict the price trend of ITC Ltd. shares traded on the National Stock Exchange (NSE) of India. A two-state Markov model was constructed using 700 days of historical daily closing prices, with states defined as “Increase” and “Decrease” based on day-to-day price changes. Initial and transition probabilities were computed, and the long-term behavior of the stock was evaluated through steady-state probabilities and n-step transition matrices. The analysis reveals that the stock has approximately a 50% probability of increasing and a 49% probability of decreasing in the long run. The study further calculates the expected number of visits and return times for each state. The results demonstrate that the Markov Chain model can serve as a reliable probabilistic framework for stock trend forecasting and can assist investors in making informed decisions. This approach offers significant utility for portfolio management and market risk analysis in the Indian equity context.

Keywords:*Markov Chain, Stock Market Forecasting, NSE, ITC Ltd., Transition Probability Matrix, Stationary Distribution*

I.INTRODUCTION:

In developing economies, the stock market plays a crucial role in shaping the structure and growth of various business sectors. It facilitates capital formation by enabling corporations to raise funds through equity offerings. Shares are sold by companies to individuals and institutional investors to meet their capital requirements, thereby providing a platform for investment and economic participation at both domestic and international levels.

A growing stock market is widely regarded as a strong indicator of a nation’s economic health. The legal and institutional platforms for trading such equities are the stock exchanges. In India, the two major stock exchanges—Bombay Stock Exchange (BSE) and National Stock Exchange (NSE)—are among the top five in developing economies in terms of market capitalization.

The desire for profit motivates investors to shift their capital between companies based on performance expectations. As a result, stock price movement becomes a critical signal for potential investments. Predicting the behavior of stock prices is an increasingly important research area due to its significance for companies, investors, and shareholders seeking to make informed and confident investment decisions.Toanalyze and forecast stock movements, various statistical and probabilistic models have been proposed. However, the inherent volatility and nonlinearity of stock prices, often described as following a "random walk," pose challenges to traditional time series models that assume constant variance. Therefore, stochastic models—particularly those capable of capturing dynamic and probabilistic transitions—have emerged as effective tools for stock market prediction.

India, as one of the most active electronic stock market hubs in the developing world, presents a rich landscape for such analysis. Among stochastic methods, the Markov Chain (MC) model has shown considerable promise due to its reliance on current state conditions rather than historical dependencies, making it suitable for capturing short-term volatility and long-run behavior.

This study focuses on constructing and analyzing a stochastic model using the Markov Chain approach to forecast stock price movements. Historical daily closing prices from the NSE are used, with a specific focus on ITC Ltd. (and SBI for broader reference). Daily price changes are categorized into two states: "Increase" and "Decrease" based on whether the next day's price is higher or lower than the previous day's. The analysis centers on ITC stock over the last three years to extract trends and transition patterns.

The primary objectives of this study are:

- To forecast the long-term behavior of ITC share prices using the Markov Chain model;
- To determine the average number of visits to each state;
- To compute the expected return time to each state.

These insights aim to support both short- and long-term investors in optimizing their portfolio management strategies through probabilistic forecasting.

II LITERATURE REVIEW

Stock markets are inherently stochastic, and the challenge of predicting their behaviour has driven researchers to adopt probabilistic and mathematical models such as the Markov Chain. The foundational premise of the Markov Chain, defined by its memoryless property, has shown potential in capturing short-term market fluctuations and in estimating the long-run behaviour of financial instruments.

Zhang and Zhang (2009) investigated the predictive power of stochastic models for stock markets and illustrated that discrete-time Markov Chains are particularly effective in modelling short-term trends. Their study confirmed that such models can identify frequent patterns in price movements and support data-driven trading strategies.

In the Indian context, Vasanthi et al. (2011) demonstrated the application of first-order Markov Chains on stock indices such as the BSE Sensex. They formulated transition probability matrices to forecast the directional movement of stock prices. Their findings suggest that by modelling daily price transitions, it is possible to estimate the likelihood of future trends and reduce investment risk.

Singh et al. (2017) extended the application of Markov Chain analysis to major Indian stocks and indices, emphasizing the usability of steady-state probabilities in long-term investment planning. Their work also showed that despite the simplicity of the model, it aligns well with the probabilistic nature of price fluctuations in equity markets.

In a more focused study, Bhardwaj and Gaur (2020) examined the volatility of mid-cap stocks using transition matrices and concluded that the Markov process is suitable for predicting the probable movement and momentum of stock categories over short horizons. They proposed that incorporating transition analysis enhances investors' decision-making efficiency in high-volatility environments.

However, most existing literature concentrates either on index-level analysis or single-stock evaluation. Limited studies have compared stocks from different sectors using a unified Markov framework. Moreover, few researchers have explored the implications of steady-state probabilities from a practical investor's standpoint.

The current study fills these gaps by examining the transition dynamics and long-run probabilities of two prominent companies—ITC Ltd. and State Bank of India (SBI)—using the Markov Chain model. By comparing daily price transitions and modelling the convergence behaviour of their transition matrices, the study aims to provide insights into sector-specific volatility and return stability.

III.METHODLGY

MARKOVCHAINMODEL

Markov Chain is a series of random variables having discrete state space and following the memory less property (Short Term Memory). The probability of a particle reaching to state j starting from state I is . MC can be defined as a series of transitions going from one state to another, with the associated probabilities such that the probability of reaching the future state is based solely on its current state and not on its past history.

The MC model can mathematically be defined as the sequence $\{X_t, t \geq 0\}$ such that,

$$P[X_{t+1}=j|X_t=i_{t-1},\dots X_1=i_1,X_0=i_0]=P[X_{t+1}=j|X_t=i].$$

That is, the system's state at time t+1 is solely determined by the system's state at time tthis is called memoryless or Markovproperty. The basic difference between the MC does not need any jointly as between factors from complex predictors, instead, it only needs initial state probabilities to estimate the transition probabilities for various possible states at different times in the future. Therefore, after knowing the IPV and TPM, it is simple to forecast the potential state value for some particular period of time using the help of the MC model. The MC model has widely been used to forecast stock indexes for both a group of stocks and a single stock. If the states pace of an MC cannot be portioned into two or more disjoint closed sets, it is said to be irreducible MC.

DESCRIPTIN OF THE STATES OF MARKOV CHAIN

In this paper, it is assumed that the stock price variations represent Markov's dependence and time-homogeneity, and we specify a two-state Markov chain process, i.e., price increase (I) and price decrease(D). These two states are obtained on the basis of the difference between the next day closing share price. Symbolically, we write the Increasing Decreasing state as follows.

When (- $_{-1}$)≥0,the process is in an increasing state(I).

When (- $_{-1}$<0, the process is in decreasing state (D).

Where,

is the current and $_{-1}$ is the previous closing price.

INTIAL PROBABILITY AND TRANSITIION PROBABILITY MATRIX

The state space of the Markov chain E(D,I). Therefore, the IPC is the Probabilities of the states

Iand D. These initial probabilities are denoted as P($_1$= $_1$=, ∀ i=1,2,3… such that $\sum_{i=1}^{2} \pi_i=1$ .That is the sum of all these probabilities must be 1. Hence the IPV is represented as =[$_1$ $_2$], Where, $_1$ $_2$ are the probabilities of Decreasing and Increasing closing price.

TRANSITION POBABILITY AND TRANSITION PROBABILITY MATRIX

Since the share price movement has been separated into two states (D, I), the TPM will also include these two states. The TPM gives a detailed description of how an MC behaves. The probability of going from one state to another state is represented by each element in the TPM.

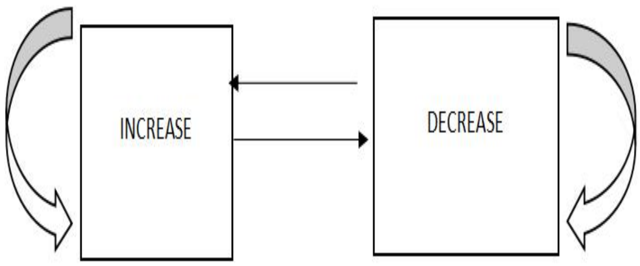
A process is called a MC if ,it follows the following property

$$P[X_{t+1}=j|X_t=i_{t-1},\dots\dots X_1=i_1, X_0=i_0]=P[X_{t+1}=j|X_t=i].$$

The probabilitiesP$[X_{t+1}=j|X_t=I]$ are called transition probabilities and are denoted by such That $\sum_{i=1}^{2} a_{ij}=1\ \forall$ i,j=1,2,3…….In the matrix form the two state TPM is expressed as

$$\begin{array}{c c} & \begin{array}{cc} I & D \end{array} \\ \begin{array}{c} I \\ D \end{array} & \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \end{array}$$

The elements of TPM are represented through the diagram known as transition diagram or the schematic diagram



Where,

a_{11}=p(I/I)= probability of price will increase tomorrow if it is in increasing statetoday.
a_{12}=P(D/I)= probability of price will decrease tomorrow if it is in increasing state today.
a_{21}=P(I/D)= probability of price will increase tomorrow if it is in decreasing state today.
a_{22}=P(D/D)= probability of price will decrease tomorrow if it is in decreasing state today.

THE n-STEP TRANSITION MATRIX AND THE STATIONARY DISTRIBUTION:

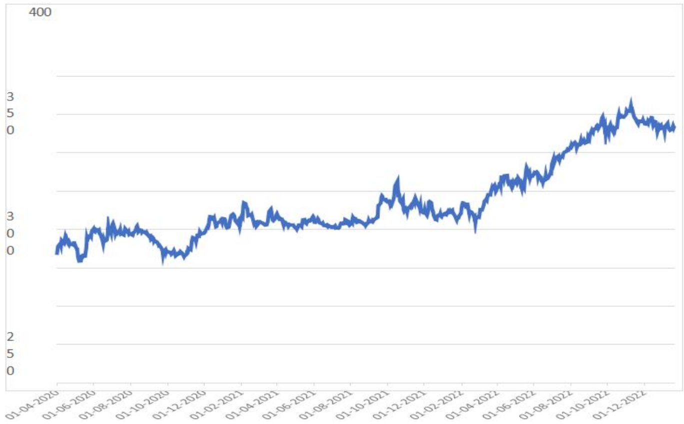
Then-step TPM isused to calculate the likehood of states at any stage n such that n>1. These are called the higher-order transition probability (n). The behaviour of share prices n days later is depicted in then-step TPM. These repeated transition steps are obtained to evaluate if the TPM converge to the identical columns over repeated iterations which is called stationary probability matrix of the MC. According to this property of the MC, the probabilities of transitioning from the state it state settles down to a certain constant value regardless of how the system is initially set or how the stochastic process develops over time.Thus, symbolically we write the stationary property of Markov chain is

$$\lim_{n\to\infty} P_{ij}(n)=\pi_i$$

Such quantities are also referred to as steady-state probabilities. The steady state probabilities are applied in order to forecast the behaviour of states of the MC in the long run.

NUMERICAL ANALYSIS :

The daily data of ITC closing prices were taken from online for the period from April 01 2020 to January 20 2023. It was the secondary data that consist of 700 trading days of ITC during the period. The trend movement of the daily data of ITC closing prices are presented in this figure 4.1



The ananalysis starts with finding the change in the daily closing price for all 700 days using the formula,

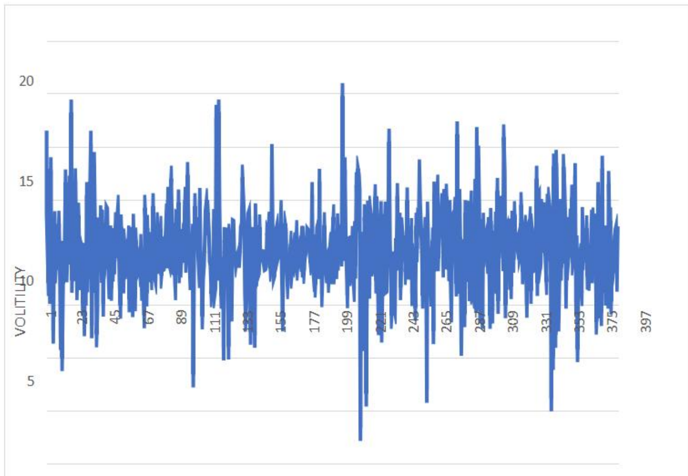
The Increasing Decreasing state as follows.

When (C_t-C_{t-1})≥0, the process is in an increasing state(I).

When (C_t-C_{t-1})<0, the process is in decreasing state (D).

Where,C_t is the current and C_{t-1} is the previous closing price.

The below graph shows that the Volatility of change in the share prices of ITC from April 01, 2020 to January 20,2023.



INTIAL PROBABILITY VECTOR :Initial state probability vector consists the probability of all the states of Markov Chain. We denote this vector by л and it is be defines as =[$_1$ $_2$] where $_1$ and $_2$ are the initial probabilities that the stock prices would increase and decrease respectively. The frequency table for both the states I and D is given by

States	I	D	Total
Probability	353	346	699

FREQUENCYOFSTATES

Therefore, there quired probability vector (IPV) is obtained as follows

$$л = \begin{array}{cc} I & D \\ [0.50501 & 0.49499] \end{array}$$

P(I)=0.505and P(D)=0.494

TRANSITION PROBABILITY MATRIX :A through observation of the closing price of ITC across the research period reveals that they pass through two distinct states of transition. The values of the ITC could increase or decrease at the end of each trading say. As a result, these two separate movements are considered two different states in the MC for the sake of building a TPM. In the table show that the frequency transition table from one to another state of the ITC.

FREQUENCY TABLE OF TRANSITION STATES

	I	D	TOTAL
I	177	176	353
D	175	170	346

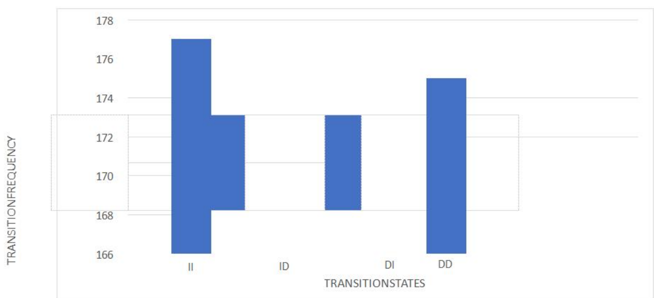
Transition-frequency table shows the number of times the specific state makes the transition to another state. From the given table, the share prices increase when it was in the increasing state 234 times. The process makes 1,888 transitions from the decreasing state to the decreasing state. In the same way, the process goes 185 times from increasing state to decreasing state and 185 times from decreasing state to increasing state. The frequency diagram of the transition matrix is presented in a figure.

FREQUENCYDIAGRAMOFTRANSITIONSTATE

	I	D	TOTAL
I	177	176	353
D	175	170	346

Transition frequency table shows the number of times the specific state makes the transition to another state. From the given table, the share prices increase when it was in the increasing state is 234 times." The process makes 1888 times transition from decreasing state to decreasing state. In the same way the process goes 185 times from increasing state to decreasing state and 185 times from decreasing state to increasing state. The frequency diagram of the transition matrix is presented in a figure .

FREQUENCYDIAGRAMOFTRANSITIONSTATE



Therefore,

From the above transition frequency table, it derived the TPM as in matrix A

$$A = \begin{array}{c|cc} & I & D \\ \hline I & 0.501420 & 0.49858 \\ D & 0.505780 & 0.49133 \end{array}$$

LONG TERM BEHAVIOUR OF CLOING SHARE PRICE

The forecasting of long run behaviour of ITC is very meaningful for investors. The long run behavior of ITC is observed by determining the higher order TPM of ITC. The TPM obtained in above section since the closing price of ITC from an Ergodic MC and this condition will be helpful for the prediction of long-term behaviour of the share prices since there exist a unique stationary distribution for an Ergodic MC. The chain will converge to its stationary distribution regardless of its initial state distribution as n→∞ that is,

lim (n)=

Therefore, the stationary

matrix for there altime data set is obtained as

$$A=\begin{bmatrix} 0.50142 & 0.49858 \\ 0.5078 & 0.494967 \end{bmatrix}$$

$$A^2=\begin{bmatrix} 0.503592 & 0.494967 \\ 0.50211 & 0.493578 \end{bmatrix}$$

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$$A^7=\begin{bmatrix} 0.49998 & 0.49145 \\ 0.49854 & 0.49004 \end{bmatrix}$$

This stationary matrix ^{7} represents that after the 7th trading day ssince 700 days, the TPM will converge to the state of equilibrium or the stable state and then the TPM remains same for the onwards consecutive trading days. This steady state TPM of ITC reveals the following information.

There are 50% chances that the ITC share price will increase after 7th day irrespective of its initial day's state whether increase or decrease and the probability of decreasing the closing price of ITC on 7th day onwards is 49% irrespective of its initial state

STATE PROBABILITIES FOR FORECASTING THE SHARE PRICE:

The main purpose in this paper is to forecast the stock prices movement of ITC at the end of 700th day and study its long-term behaviours. It computes the probability of forecasting the stock prices at the end of 700th day for ITC. According to the MC model, the state probabilities are found out by multiplying the IPV with the TPM. Symbolically it can be written as

$$\prod{}_{+1}=\prod 0 \quad *A=\prod 0 \quad ^{+1}$$

Where for this study,

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$\prod_0$=л, the probability vector

Therefore, the state probability reveals that ITC limited closing price for 701thday

$\prod_1$=[0.50358 0.49499]

The above state probability reveals that ITC closing prices have 49% chance to decrease and 50%likely to increase from their previous closing price on 699th day. Now, it computes the state probabilities for the ITC at 701th day. =1

$\prod_2$=[0.50286 0.49428]

These results further reveal that on 702th day the probability that the price of ITC will increases with 50%likely to increase and y that the price will decrease with probability 49%.

$\prod_3$=[0.50214 0.49357]

These results further reveal that on 703th day the probability that the price of ITC will increases with 50% likely to increase and y that the price will decrease with probability 49%.

$\prod_4$=[0.50142 0.49286]

These results further reveal that on 704th day the probability that the price of ITC will increases with 50%likely to increase and y that the price will decrease with probability 49%.

$\prod_5$=[0.5007 0.49216]

These results further reveal that on 705th day the probability that the price of ITC will increases with 50%likely to increase and y that the price will decrease with probability 49%.

$\prod_6$=[0.49998 0.49145]

These results further reveal that on 706th day the probability that the price of ITC will increases with 50%likely to increase and y that the price will decrease with probability 49%.

$\prod_7$=[0.49927 0.49075]

These results further reveal that on 707th day the probability that the price of ITC will increases with 50%likely to increase and y that the price will decrease with probability 49%.

"These findings provide information that investing in this stock is a good long-term venture since the probability of price increase grows with time. Similarly, it continues for *n* times. The condition for the steady state probability vector is

$\prod A=\prod$,

That is when the input vector and the output vector reach same.

EXPECTED NUMBER OF VISITS (ENV): The average number of visits or ENV to a certain state j from some state I in various steps can be calculated to determine how long the moving particle will spend in each state. The formula for obtaining the expected number of visits in the chain to a specific state j from state I is denoted by

μ(n)is expressed as

$$\mu(n)=E[N_{ij}(n)]$$

Where,

$N(n)$ is the number of times the system is reaching to state j from state I infinite-steps

=1 $\mu(n)=\sum^{n}$ $P_{ij}(k)=\sum^{n}$ A^{k}

Also, after along run the ENV to state j from the state I is

$$\mu(n)=E[N_{ij}(n)]$$

Here, for ITC products, frequency of visits to a state j in six trading days is shown in the following matrix

V.RESULT:

The average closing price of ITC for after 7days from the 699th trading days may 50% increase and 49% decrease And also, the expected return days 2 days increase and decrease approximately.

VI.CONCLUSION:

Stock price forecasting is complex due to factors like economic conditions, politics, and investor sentiment. This study uses the Markov Chain (MC) model to predict ITC's stock price, assuming that price changes depend only on the previous day's value. The model uses initial and transition probabilities to estimate future price directions. Results show about a 50% chance of price increase and a similar chance of decrease, with an average return time of two days for each state. The MC model, being probabilistic, proves effective for capturing stock price behavior and helps investors make confident, informed decisions.

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