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Predicting Nifty 50 Trends Using A Markov Chain Approach

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Abstract:

This paper explores the application of the Markov Chain model to forecast stock behaviour, focusing on stocks indexed within the NIFTY 50. The NIFTY 50, an Indian stock market index, represents the float-weighted average of the 50 largest companies listed on the National Stock Exchange (NSE). Alongside NSE, the Bombay Stock Exchange (BSE) serves as a prominent trading platform in India.

The stock market is an attractive avenue for investment, enticing both domestic and foreign investors. Understanding and predicting stock market trends are crucial for making informed investment decisions. While the Markov Chain model has been widely utilized to predict stock market trends, most applications focus on indices or groups of stocks rather than individual stocks.

The overall objective of this study therefore, was to apply Markov Chain to model and forecast trend. The study was conducted through 2 years historical data of Nifty 50 daily closing price. Secondary quantitative data on the daily closing share prices was obtained from Yahoo Finance website over a period covering 12th December 2022 to 12th December 2024 forming a 493 days trading data panel. A Markov chain model was determined based on probability transition matrix and initial state vector. MATLAB software used to determine initial state vector, transition matrix and trend values using moving average. In the long run, irrespective of the current state of share price, the model predicted that the Nifty 50 would increase, decrease and remains constant with a probability of 0.5639, 0.4341 & 0.0020 respectively.

Index Terms – Markov Chain, Transition Matrix, Initial State Vector, MATLAB

I. Introduction

The stock market is a well-established network of markets and exchanges facilitating the regular buying, selling, and trading of company shares. It serves as a critical platform for gauging a country's economic strength and growth. Fluctuations in share indices are directly influenced by investor activities, making it essential for investors worldwide to monitor the performance of various stock market indices closely.

The NIFTY 50, launched on April 22, 1996, is India's premier stock market index, representing the float-weighted average of 50 major companies across 13 sectors listed on the National Stock Exchange (NSE). Managed by NSE Indices, a subsidiary of NSE, it provides comprehensive market exposure through index funds, ETFs, and futures and options trading. Recognized as the world's most actively traded options contract post-2021, it remains a key benchmark for investment managers. As of July 2024, the index allocates 32.76% to financial services, 13.76% to IT, 12.12% to oil and gas, 8.46% to consumer goods, and 8.22% to automotive.

Svoboda and Lukas [8] applied Markov Chain Analysis (MCA) to predict stock index trends for the Prague Stock Exchange (PX) similarly Zhang et al. [2] introduced a Markov process model to forecast stock market trends, addressing the inherent disorder and randomness of stock market fluctuations in China. Ganesan et al. [6] demonstrated the efficacy of an integrated New Threshold Fuzzy Cognitive Maps (NTFCMs) and Markov Chain model in analyzing stock trading trends. Vasanthi et al. [12] employed a first-order Markov Chain model to study stock indices from various global exchanges. Furthermore Otieno, Otumba, and Nyabwanga (2015) [11] applied a Markov chain model to forecast stock market trends for Safaricom shares on the Nairobi Securities Exchange. Using probability transition matrices and an initial state vector, they analysed data from April 1, 2008, to April 30, 2012, to predict the probabilities of future stock price states rather than absolute values. Their findings highlighted the model's suitability, leveraging its memory-less property and random walk analysis to accurately predict trends and achieve favourable results. Mettle et al. (2019)[14] highlighted that modeling share prices as Markov chains offers valuable insights for investors, aiding in return maximization. Among the equities analyzed, 3M Comp and Apple emerged as top investment choices, with 3M Comp slightly outperforming. This second-of-its-kind model aims to refine equity portfolio decisions. A Markov chain model with finite states was utilized to study share price fluctuations in five randomly selected equities from the Ghana Stock Exchange. Mettle, Quaye, and Laryea (2014) [13] concluded that this stochastic analytical approach significantly improves equity price analysis and enhances portfolio decision-making. They also advocated for the Markov chain model as a powerful tool to refine stock trading decisions, offering valuable insights to investors and boosting the potential for higher returns in stock market analysis.

II. MARKOV CHAIN

The stochastic process $\{X_n,\ n = 0,\ 1,\ 2,\ \dots\}$ is called a *Markov chain*. If, for $j,\ k,\ j_1,\ \dots,\ j_{n-1} \in N$

$$\Pr\{X_n = k | X_{n-1} = j,\ X_{n-2} = j_1,\ \dots,\ X_0 = j_{n-1}\} = Pr\{X_n = k | X_{n-1} = j\} = p_{jk}.$$

Thus, A Markov chain is a stochastic process where the outcomes, known as states, depend only on the present state, not on past states. At each trial (or step), the process is in a specific state, and the probability of transitioning from one state to another is called the transition probability. This probability is conditional on the current state and represents the likelihood of moving from state *j* at the nth trial to state *k* at the (n+1)th trial.

The transition probability can either be independent or dependent on the trial number *n*. If the probability is independent of *n*, the Markov chain is homogeneous, meaning the transition probabilities remain constant over time. If the transition probabilities depend on *n*, the chain is non-homogeneous.

A time-homogeneous Markov chain has stationary transition probabilities, where the probability of moving from state *i* to state *j* remains the same for all steps *n*. The transition probability for one step from state *j* to state *k* is denoted as *P(j, k).*

$Pr\{X_{n+1} = k | X_n = j\} = Pr\{X_n = k | X_{n-1} = j\} = p_{jk}$ for all $n \geq 1$,

where $p_{jk} \geq 0$ for all j, k and $\sum_{j=0}^{\infty} p_{jk} = 1$. Here p_{jk} is called one – step transition probability from state *j* to state *k*.

Additionally, when considering transitions between states at non-consecutive trials, the probability of transitioning from state *j* at the nth trial to state *k* at the mth trial is called the *m-step transition probability*, denoted by $p_{jk}^{(m)}$, i.e.,

$$p_{jk}^{(m)} = Pr\{X_{n+m} = k | X_n = j\}.$$

III. TRANSITION MATRIX

The transition probabilities p_{jk} satisfy $p_{jk} \geq 0$ for all *j*, *k* and $\sum_{j=0}^{\infty} p_{jk} = 1$.

These probabilities can be written in matrix form as

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & \cdots \\ p_{21} & p_{22} & p_{23} & \cdots \\ p_{31} & p_{32} & p_{33} & \cdots \\ \cdots & \cdots & \cdots & \cdots \end{bmatrix}.$$

This is called the transition probability matrix or matrix of transition probabilities of the Markov chain. *P* is a stochastic matrix i.e., a square matrix with non - negative elements and unit row sums.

IV. Methodology

In this study we have taken daily closing Data of Nifty 50 indexed at National Stock Exchange (NSE) from 12th December 2022 to 12th December 2024. Using MATLAB software, computation of Initial state transition matrix and 5 Days Moving average has been done. Daily closing share prices of Nifty 50 has been taken from website of Yahoo Finance.

V. Model Development

Using the Markov process, we developed a transition probability matrix based on the historical behavior of the system. This matrix serves as a comprehensive representation of the likelihood of transitions between various states. By combining the transition probabilities from this matrix with the current state probabilities of the system, we can accurately estimate the probabilities associated with the system's next state. This approach provides a systematic framework for predicting future behavior based on past patterns and current conditions.

VI. Initial State Matrix

Each trading day during the observed period is considered a distinct time unit. The closing prices of the Nifty 50 index are categorized into three states based on their movement:

1. Increases (Inc): Days when the closing price increased compared to the previous day.
2. Decreases (Dec): Days when the closing price decreased compared to the previous day.
3. Unchanged (Unc): Days when the closing price remained the same as the previous day.

Let x_1, x_2 and x_3 represent the number of trading days corresponding to each state: Increase, Decrease, and Unchanged, respectively. Specifically, x_2 corresponds to "Dec" and x_3 corresponds to "Unc." The observations for these states are derived from data collected over the period from 12th December 2022 to 12th December 2024, which comprises 493 trading days in total.

The total number of observations across all three states adds up to 493, as every trading day is classified into one of the three states. The probabilities for each state are calculated by dividing the number of observations for that state by the total number of trading days. These probabilities reflect the relative frequency of occurrence for Increase, Decrease, and Unchanged states during the given period.

$$P_1 = x_1/493 \quad P_2 = x_2/493 \quad P_3 = x_3/493.$$

Therefore, Initial State Vector is $\left[\frac{x_1}{493} \quad \frac{x_2}{493} \quad \frac{x_3}{493}\right]$.

From 494 trading days, Number of share price increases 278, Number of share price decreases 213 and unchanged share price 1.

Initial State Vector is $\left[\frac{278}{493} \quad \frac{213}{493} \quad \frac{1}{493}\right] = [0.5639 \quad 0.4341 \quad 0.0020]$.

VII. Three state Transition Matrix

The transition matrix used in this research encompasses three distinct states, representing the likelihood of the closing share value either increasing, decreasing, or remaining unchanged. This analysis is grounded in historical data spanning from 12th December 2022 to 12th December 2024, focusing on the Nifty 50 index listed on the National Stock Exchange. By examining the share price movement patterns over this period, a detailed study of transitions between states was conducted. These patterns include scenarios such as an increase in price followed by another increase, an increase followed by a decrease, or a decrease followed by an increase, as well as instances where prices remained unchanged. The study utilized data collected from 493 trading days to observe and analyze these state transitions, providing insights into the behavior of share price movements.

	Increase in share Price (Inc)	Decrease in Share Price (Dec)	Unchanged in Share Price (Unc)
Increase in share Price (Inc)	ii	id	iu
Decrease in Share Price (Dec)	di	dd	du
Unchanged in Share Price (Unc)	ui	ud	uu

VIII. Transition Matrix

As per trading days of shares under Nifty 50 the transition value from increase to increase is 163, increase to decrease is 115, increase to unchanged 0, decrease to increase is 114, decrease to decrease is 98 and decrease to unchanged is 1, unchanged to increase 0, unchanged to decrease 1 and unchanged to unchanged is 0. As per the values the share price movement is given as below,

	Increase in share Price (Inc)	Decrease in Share Price (Dec)	Unchanged in Share Price (Unc)
Increase in share Price (Inc)	163	115	00
Decrease in Share Price (Dec)	114	98	01
Unchanged in Share Price (Unc)	00	01	00

1 denotes increase (Inc)
2 denotes decrease (Dec)
0 denotes unchanged (Unc)

Thus, the transition probability as per share price movement be

$$P = \begin{bmatrix} 0.5863 & 0.4137 & 0 \\ 0.5352 & 0.4601 & 0.0028 \\ 0 & 1.0000 & 0 \end{bmatrix}.$$

Here the values for each vector transition of Tata share are as follows: -

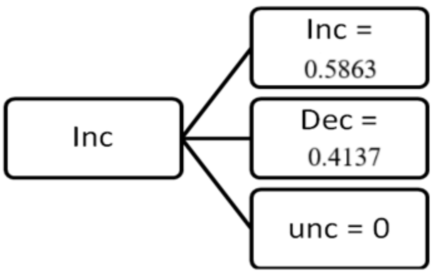

Figure 1

Figure 1 implies that 0.5863 NIFTY 50 value that increase will still increase; 0.4137 values that increase will decrease and 0 will remain unchanged.

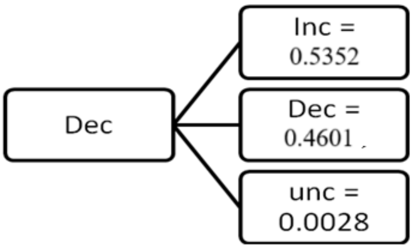

Figure 2

Figure 2 implies that 0.5352 Nifty 50 values that decrease will increase; 0.4601 probability that decrease will decrease and 0.0028 will remain unchanged.

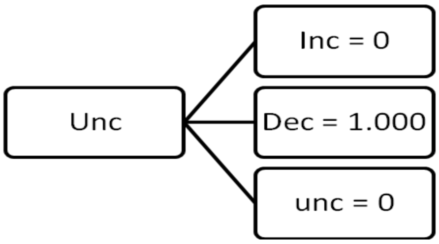

Figure 3

Figure 3 implies that 0 shares unchanged will increase; 1 share unchanged will decrease and 0 unchanged will unchanged.

The absolute probability can be calculated by the use of n – step transition probabilities. Higher order transition probability of P_{ij} is $P_{ij}^{(n)}$. n – step transition matrix shows the behavior in the next n – steps. This results in the steady state probabilities shows that the probabilities of the share price decreasing, increasing and unchanged according to share recent changes in daily closing price. The higher order Transition probability matrix of the transition matrix P_{ij} was calculated to observe the behaviour of the share price using MATLAB Software

$$P^2 = \begin{bmatrix} 0.5652 & 0.4329 & 0.0019 \\ 0.5601 & 0.4378 & 0.0022 \\ 0.5352 & 0.4601 & 0.0047 \end{bmatrix},$$

$$P^4 = \begin{bmatrix} 0.5629 & 0.4351 & 0.0013 \\ 0.5629 & 0.4351 & 0.0020 \\ 0.5627 & 0.4353 & 0.0021 \end{bmatrix},$$

$$P^5 = \begin{bmatrix} 0.5629 & 0.4351 & 0.0013 \\ 0.5629 & 0.4351 & 0.0020 \\ 0.5627 & 0.4353 & 0.0021 \end{bmatrix},$$

$$P^{16} = \begin{bmatrix} 0.5629 & 0.4351 & 0.0020 \\ 0.5629 & 0.4351 & 0.0020 \\ 0.5629 & 0.4351 & 0.0020 \end{bmatrix}.$$

From the above n – step transition matrix, it can be observed that after 5th trading days, the transition matrix approaches to stationary probabilities. After calculating till 16th trading day we conclude that all the probabilities converges to attain equilibrium.

IX. Determination of Moving Average

At first to determine the trend of NIFTY 50 value listed in National Stock Exchange we have taken 493 days trading data panel for daily closing prices of Nifty 50.

Five days weekly moving average of daily closing prices of Nifty 50 was taken from 12th December 2022 to 12th December 2024 then computed and the trend graph presented below:

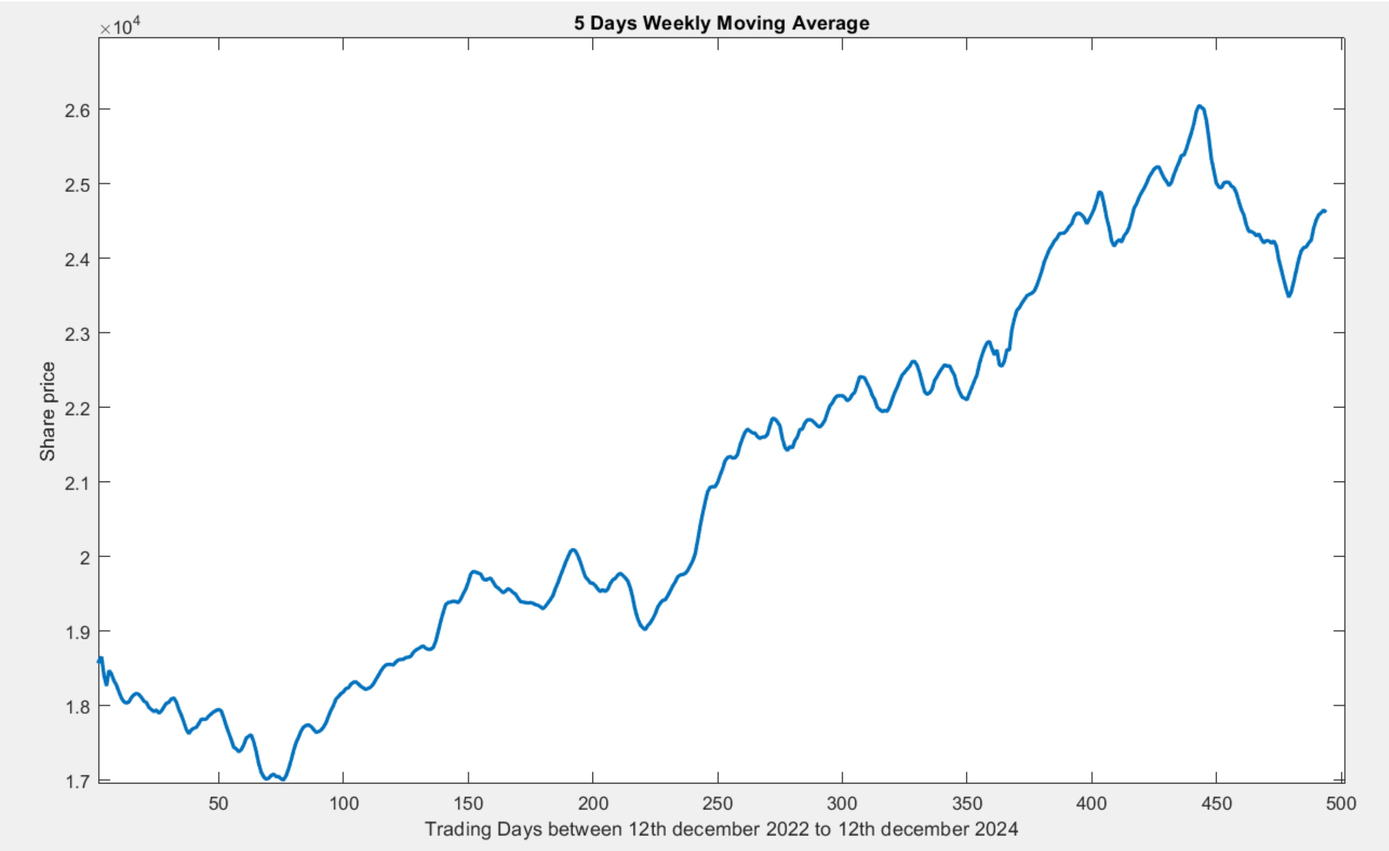

Figure A

The Moving Average (MA) is a powerful tool widely used by market analysts to identify trend lines and chart patterns in stocks, enabling a clearer understanding of their price behaviour. Stock prices often experience significant fluctuations due to changing market sentiment, sector dynamics, and profit-taking activities. These rapid changes can obscure the underlying price movement, making it challenging to interpret trends effectively.

To address this, the Moving Average smoothens these fluctuations by averaging stock prices over a specific period. This creates a more stable and visually comprehensible line that helps reveal the stock's prevailing trend.

As illustrated in **Figure A**, the Moving Average analysis of Nifty 50 values highlights the **dominant market trends**, which fall into three categories:

1. **Uptrend**: Indicates bullish sentiment among market participants, where prices generally move upward.
2. **Downtrend**: Reflects bearish sentiment, characterized by a consistent downward movement in prices.
3. **Sideways Trend**: Suggests market indecision, where prices fluctuate within a narrow range without a clear direction.

Understanding these trends is crucial for traders, as it enables them to identify key turning points—such as market tops and bottoms—offering valuable opportunities for strategic buying or shorting decisions. By using Moving Averages, traders gain a comprehensive view of price movements, improving their ability to navigate the complexities of the stock market effectively.

The analysis of the 5-day weekly moving average reveals distinct patterns in the price trends. The trend begins with a sideways movement at a share price of 18,497.15, reflecting market indecision. This is followed by a bearish trend, where the price declines to a low of 17,809. Subsequently, the trend shifts to a bullish phase, reaching a peak of 18,118.00.

The pattern continues with another bearish movement, dropping to a low of 17,915, before transitioning to a bullish trend that climbs to a high of 18,598. Following this, the Nifty 50 experiences a significant bullish surge, reaching a peak share price of 25,014.60, but then reverses into a bearish trend, falling to a low of 23,349.00.

The Moving Average serves as a critical tool for interpreting price dynamics by comparing the moving average line to the price action. A buy signal is triggered when the price rises above the moving average, while a sell signal occurs when the price falls below it. However, this system is not designed to capture the exact market bottom for entry or the exact peak for exit.

Instead, the moving average trading system allows traders to act in alignment with the prevailing trend—buying shortly after prices have bottomed out and selling soon after prices have peaked. By following these trend values, traders can make more informed decisions, leveraging the moving average to navigate market fluctuations effectively.

X. Result and Conclusion

The primary goal of this study was to construct a Markov model for predicting trends in the Nifty 50 index on the National Stock Exchange. The analysis involved utilizing historical data from 493 trading days to derive the **initial state vector** and the **transition matrix**, which served as the foundation for forecasting the state of share prices. The model demonstrated high accuracy in predicting the dynamic behaviour of the Nifty 50 index, highlighting its practical applicability in financial forecasting.

One of the significant findings of the study was the model's **ergodicity**, a fundamental property of Markov chains that ensures convergence to a steady state over time. This characteristic is particularly relevant in stock market analysis, as it indicates that long-term trends become independent of the initial state of the system. The steady-state probabilities derived from the transition matrix revealed that, in the long run, the Nifty 50 index is expected to exhibit specific trends with probabilities of approximately **0.5639** for an **increase**, **0.4341** for a **decrease**, and **0.0020** for the price to remain **unchanged**.

Additionally, a detailed examination of Nifty 50 daily closing prices through a 5-day moving average graph provided further insights into market behaviour. The graph highlighted alternating **bearish** and **bullish** trends, reflecting the inherent volatility and dynamic nature of the stock market. Despite these fluctuations, the overall pattern indicated a positive growth trajectory, suggesting that Nifty 50 is experiencing a significant upward trend over time.

Such a trend is particularly encouraging for investors, as it signifies potential long-term gains. The findings underscore the utility of combining Markov models with moving average analyses to provide a comprehensive understanding of market behaviour, making it a valuable tool for both financial analysts and investors aiming to make informed decisions.

References

[1] Davou Nyap Choji, Samuel Ngbede Eduno and Gokum Titus Kassem, Markov chain model application on share price movement in stock market, Computer Engineering and Intelligent Systems 4(10) (2013), 84-95.

[2] Deju Zhang, L. China and Z. Xiaomin, Study on forecasting the stock market trend based on stochastic analysis method, International Journal of Business Management 4(6), 163 – 170, (2009)

[3] J. K. Sharma, (5th Edition) Operations Research Theory and Application Macmillan Publisher India Limited, New Delhi, India

[4] J. Medhi, Fourth Edition, Stochastic processes, 2019.

[5] Kanti Swarup, P. K. Gupta and Man Mohan, Operations Research, 2003.

[6] Kavitha Ganesan, Udhayakumar Annamalai and Nagarajan Deivanayagampillai, An integrated new threshold FCMs Markov chain based forecasting model for analyzing the power of stock trading trend, Financial Innovation 5(1) (2019), 1-19.

[7] Madhav Kumar Bhusal, Application of Markov chain model in the stock market trend analysis of Nepal, International Journal of Scientific and Engineering Research 8(10) (2017), 1733-1745.

[8] Milan Svoboda and Ladislav Lukas, Application of Markov chain Analysis to trend prediction of stock indices, Proceedings of 30th International Conference Mathematical Methods in Economics, Karvina: Silesian University, School of Business Administration, 2012, pp. 848-853.

[9] Neo Ease, Indicator forex : how to interpret Moving Average indicator; World Press, 2009.

[10] Ng Ee Hwa and Chart Nexus, Different uses of Moving Average 2007.
downloaded at http://www.chartnexus.com/learning/static/pulses_apr2007.

[11] Simeyo Otieno, Dr. Edgar Ouko Otumba and Robert Nyamao Nyabwanga, Application of Markov chain Model and Forecast stock Market trend : A study of Safaricom shares in Nairobi securities exchange, Kenya, International Journal of Current Research 7(04) (2015), 14712-14721.

[12] S. Vasanthi, V. Subha and T. Nambi, An empirical analysis on stock index trend prediction using Markov chain analysis, Sri Krisha International Research and Education Consortium 1(1) (2011), 2231-4288.

[13] Mettle, Quaye, and Laryea, *A methodology for stochastic analysis of share prices as Markov chains with finite states*, SpringerPlus, 3:657, (2014).

[14] Mettle, Quaye, Laryea, Asiedu, *Analysis of share prices as Markov chains with countably infinite states*, Advances and Application in Statistics, Volume 54, Number 1, Pages 1 – 20, ISSN: 0972 – 3617, (2019).