Markov Chain Model: A Markov chain is a set of trials with a finite number of states and probabilities that are known. P, where P represents the probability of advancing from state I to state j, or simply expressed, a stochastic process that is based on the immediate outcome rather than on the past. It can be thought of as a series of transitions between different states, with the probabilities associated with each transition based solely on the current state and not on how the process got there, and the probabilities associated with the transitions between the states remaining constant over time. When the current outcome is known, knowledge from previous trials has little bearing on the likelihood of future events. The Markov chain model can then be said to be a sequence of consecutive trials such that,

P{Xn = j/Xn-1 = in-1,…, X0 = i0} = P{Xn= j/ X n-1 = in-1}

P{xn= j} = Pj (n) is the absolute probability of outcome Pj, , j = 1,2,3,… is a system of events (actually set of outcomes at any trial) that are mutually exclusive (Voskoglou, 1994; Hoppensteadt, 1992).An important class of Markov chain model is that of which the transition probabilities are independent of n, we have P{xn = j/xn-1= i}= Pij which is a homogenous Markov chain where the order of the subscripts in Pij corresponds to the direction of the transition i.e i j. Hence we have ∑ Pij = 1 and Pij ≥ 0, Since for any fixed i, the transition probability Pij will form a probability distribution. If the limiting distribution of xn as n ∞ exist, the transition probabilities are most conveniently handled in matrix form as P = Pij i.e

P11 P12 . . . P1n

P21 P22 .

. . . P2n

P =

. . . . .

. . . . .

. . . . .

Pn1 Pn2 . . . Pnn

And this is referred to as the transition matrix, which depends on the number of states involved and may be finite or infinite (Hamilton, 1989; Michael, 2005).

The absolute probabilities at any stage where n is greater than unity is determined by the used of n-step transition probabilities i.e. In matrix terms, let p be the transition matrix of the Markov chain, then

P 1= PP(0) (for n=1)

Also P2= PP1= P(PP(0) ) = P2P (0) (for n =2)

And in general P (n) = PnP (0)

**Share Price Movement:**

This study focused on the top three corporations in the US stock market. Data on the share prices of the mentioned three companies was gathered from Yahoo Finance's daily list from 2002 to 2022 (except for the random walk equilibrium matrix). The transition from one state to another (that is, the share price movement pattern, which could be that a decrease in price is followed by another decrease, a decrease is followed by unchanged, a decrease is followed by an increase, and so on) was observed from the data collected, and the results for each company under study were compiled using Python (Jupyter Notebook) as follows (below represents only Apple Inc.;; Google Inc. and Comcast Corp. will be found in the Appendix.).

| Date | **High** | **Low** | **Open** | **Close** | **Volume** | **Adj Close** | **state** | **Prior state** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **2022-04-25** | 163.169998 | 158.460007 | 161.119995 | 162.880005 | 96046400.0 | 162.880005 | Upside | Downside |
| **2022-04-26** | 162.339996 | 156.720001 | 162.250000 | 156.800003 | 95623200.0 | 156.800003 | Downside | Upside |
| **2022-04-27** | 159.789993 | 155.380005 | 155.910004 | 156.570007 | 88063200.0 | 156.570007 | Downside | Downside |
| **2022-04-28** | 164.520004 | 158.929993 | 159.250000 | 163.639999 | 130216800.0 | 163.639999 | Upside | Downside |
| **2022-04-29** | 166.199997 | 157.250000 | 161.839996 | 157.649994 | 124911916.0 | 157.649994 | Downside | Upside |

Table: **The Share Price Movement of Apple Inc.**

## Construction of the Markov Chain Using Python

## Apple Inc., Google Inc., and Comcast Corp Inc. can all have three states using the Markov Chain:

## Upside: Today's pricing is higher than yesterday's price.

• Downside:  today's pricing is lower than yesterday's price.

• Consolidation: The price is the same as the day before.

The first step in obtaining the states in our data frame is to calculate the daily return. Then, based on the return, we'll utilize a function to identify the possible states. Now, defining Consolidation as a condition in which there is literally no movement on a given day is realistically untenable. As a result, we've kept the legroom to a bare minimum. Even if the movement is limited to a short range, it is still referred to be a consolidation condition.

|  |  |  |
| --- | --- | --- |
| State  Prior State | Downside | Upside |
| Consolidation | 0.000000 | 1.000000 |
| Downside | 0.495127 | 0.504873 |
| Upside | 0.508036 | 0.491964 |

However, in a volatility market like stock market, there is no current state of Consolidation. As a result, instead of a 3x3 matrix, it produces a 3x2 matrix. When all of the values in a column in a matrix calculation are 0, the column can be omitted. Thus, moving forward I will use only two states which are downside and upside.

Like, we know that, Transition Matrix shows the probability of the occurrence instead of the number of occurrences. That’s why it is also called **“Initial Probability Matrix”**. Let’s consider time as t. Basically, “Transition Matrix” is the probability matrix at t=0. Thus, if I build the Markov Chain by multiplying this transition matrix by itself to obtain the probability matrix in t=1 which would allow me to make one-day forecasts.

With the formula of  **π\_0 = t\_0 = A**, I am going to calculate the Markov Chain similarly. Below represents the Markov chain of three different companies at t = 0

Transition Matrix for Google Inc:

|  |  |  |
| --- | --- | --- |
| State  Prior State | Downside | Upside |
| Downside | 0.470894 | 0.529106 |
| Upside | 0.477147 | 0.522853 |

Transition Matrix for Apple Inc.:

|  |  |  |
| --- | --- | --- |
| State  Prior State | Downside | Upside |
| Downside | 0.469959 | 0.530041 |
| Upside | 0.479345 | 0.520655 |

Transition Matrix for Comcast Inc..:

|  |  |  |
| --- | --- | --- |
| State  Prior State | Downside | Upside |
| Downside | 0.479636 | 0.520364 |
| Upside | 0.508501 | 0.491499 |

This is the Initial Probability Matrix. With, t =1 I will be able to get the one day forecasts, and with the same process I will be able to see the foreseeable future point from which the state will not change and will remain equilibrium. In the next part, I will cover to find the equilibrium point with random walk for these three companies.

**Finding Equilibrium Matrix using Python**

To find out the equilibrium matrix we can iterate the process up to the probabilities don’t change more.

Equilibrium Matrix Number: 9

state Downside Upside

priorstate

Downside 0.474888 0.525112

Upside 0.474888 0.525112

The equilibrium Matrix is a stationary state. So, As per the theory of the Markov Chain, **This figure will stay the same for foreseeable data points (hence, future)**

**The Random Walk**

Let’s do a random walk using out Yahoo Finance Library and use 10000 days. As We theoretically can not have ∞ days of data, I have taken 10,000 days from the start date to the end date. Now, As We are supposedly “walking” randomly from one day to another, We need to consider our 10,000 days of walking as ∞ steps.

Equillibrium point with random walk:

To find the equilliibrium point, I have taken the previous 10000 days in order to find the equilibrium point of three companies.

|  |  |  |  |
| --- | --- | --- | --- |
| Specification | Google Inc. | Apple Inc. | Comcast Inc. |
| Equilibrium Matrix Number: | 11 | 9 | 12 |

From the table, the result represents that after 11 days, we will get our equilibrium point for Google Inc and after 9 and 12 days, we will get our equilibrium point for Apple Inc and Comcast Inc respectively. However, the value of the matrix matters much which we will be found next.

Equilibrium Matrix of Google:

|  |  |  |
| --- | --- | --- |
| State  Prior State | Downside | Upside |
| Downside | 0.461052 | 0.538948 |
| Upside | 0.461052 | 0.538948 |

The result meant that, for Google Inc., if we had a Downside day today, tomorrow there is 46.1052% of probability of having downside day and again if we had a downside day today, tomorrow there is a chance of having upside day is of 53.8948%.

Equilibrium Matrix of Apple:

|  |  |  |
| --- | --- | --- |
| State  Prior State | Downside | Upside |
| Downside | 0.487522 | 0.512478 |
| Upside | 0.487522 | 0.512478 |

Similarly, for Apple Inc., if we had a Downside day today, tomorrow there is 48.7522% of probability of having downside day and again if we had a downside day today, tomorrow there is a chance of having upside day is of 51.2478%.

Equilibrium Matrix of Comcast Inc.:

|  |  |  |
| --- | --- | --- |
| State  Prior State | Downside | Upside |
| Downside | 0.501523 | 0.498477 |
| Upside | 0.498477 | 0.498477 |

The result meant that, for Comcast Inc., if we had a Downside day today, tomorrow there is 50.152% of probability of having downside day and again if we had a downside day today, tomorrow there is a chance of having upside day is of 49.8477%.