

# Stock Prediction Using Markov Chains

**Shashwat Singh Raghav**

School of Engineering (Computer Science)  
Bennett University, Greater Noida

This examination exhibits a Markov interaction model for financial exchange pattern expectation, which is an extremely gainful enhancement to set up specialized exploration, to counteract significant aspects of instability and unpredictability in stock market prediction and volatility. For investment considerations, it is critical to have a good comprehension of the stock market trend in aspects of anticipating price changes. The Markov chain model has been utilized to estimate stock indexes for a collection of stocks in various areas. The general objective of this examination is to utilize the Markov chain to foresee and expect stock patterns. A Markov chain is a set of alternative states and probabilities for a variable, where the variable's future situation or state is heavily influenced by its proximate prior state. Our model's main goal will be to forecast the future state, with the sole prerequisite being that we know the present state.

## Abstract

Markov chains are stochastic processes that contain absolutely all knowledge in the current state specification that may affect future development of the process. Markov chains can be utilized to imitate operation in a assortment of circumstances, involving traffic flow forecast, communication structures, genetic complications, financial exchange forecasting, and queuing. It would be incredibly difficult to come up with a physical model for these tumultuous purposes but using Markov chains makes it very straightforward. A Markov chain model is a forecast model that uses a change likelihood framework and an underlying state vector to decide the likelihood. Due to its Markov attributes (no eventual outcome properties), Markov forecast models assume a critical part in existing insights. Andrei Andreevich Markov (1856 - 1922) rushed to offer a Markov chain.

*Index Terms*—Markov Chains, Stocks, Stock Market.

## I. INTRODUCTION

The stock investors want to acquire a stock at a cheap cost and trade it for a greater value. However, when is the optimum moment to purchase or trade a stock, is a difficult query to answer. Due to the extreme volatility of stock values, stock acquisitions might provide a large profit or a substantial loss. Several models, including as the

"exponential moving average" (EMA) and the "head and shoulders" techniques, were employed to forecast stock transactions. Numerous forecast models, however, need the input time series to be static.

## II. INTRODUCTION TO STOCK MARKET

The stock exchange market is a dynamic environment. This dynamism arises from shifting company foundations, alterations in the macro-economy and shifts in market perception, which are difficult to articulate and have no rational foundation sometimes. Like any regular market, the stock exchange market contains purchasers and sellers, as well as commodities (company shares) that are traded for a cost. The commodities, on the other hand, are not desired for their own sake, but rather as a way of increasing fortune to promote future expenditure.

In terms of raising money and forming assets, the stock exchange market is one of the finest options for numerous company organizations and organizations looking to expand or start a new endeavor. Stocks are the possession interests in a company or association. A stock exchange is a legal mechanism that allows a person or a collection of individuals to purchase and trade stocks in a methodical manner. In other terms, a stock exchange is a venue where traders and sellers of stocks may meet. The term "stock market" refers to a broader range of stock exchanging operations.

## III. MOTIVATION

It is extremely challenging to decide when the right time is to purchase or trade a stock. The extreme elusiveness of the stock values can end up causing a huge loss or a substantial gain. Various models have been sent to handle this. The discovery of Markov chains came about as a consequence of demonstrating that even dependent outcomes maintain a pattern. Only independent outcomes were thought to follow a distribution in the past. Indeed, even Markov chains, as we've seen, eventually resolve to create a fixed appropriation. Understanding the state-space, starting



probability distribution  $q$ , and state transition probabilities  $P$  enables us to develop a model. To find exactly what will happen at time  $n$  in the future, we use simple matrix multiplication:  $q * P^n$ .

We operate numerous simulations to assemble a long series chain to ascertain the stationary distribution, which eventually informs us where the probabilities successfully lean to a specific condition greater than others. The frequency of connections in the state transition graph is proportional to the frequency of states in a series chain. The  $P$  matrix is also important in this case.

#### IV. MARKOV CHAINS

##### Markov Chains Definition

A stochastic procedure is defined as a variable whose magnitude varies in an unpredictable way over time. A Markov chain is a numerical method that relocates starting with one state then onto the next across a decent arrangement of states. It's a set of alternative states and probabilities for a variable, where the variable's prospective situation or state is heavily influenced by its proximate prior state. Time is categorized into two types: discrete and continuous. Persistent time can't be counted, yet discrete time can.

$P_{ij}$  denotes the probabilities, examining an arbitrary process,  $\{X_n\}$ ,  $n = 0, 1, 2, 3, 4, 5, \dots$  with discrete state space  $S$  and is passed on to be a Markov Chain in case it meets the accompanying condition to such an extent that:

$$P(X_{n+1} = j | X_n = i, X_{n-1} = i_{n-1}, \dots, X_1 = i, X_0 = i_0) = P(X_{n+1} = j | X_n = i)$$

for any  $i, j, i_1, i_2, \dots, i_{n-1} \in S$

The condition of the procedure can fluctuate in every time-step. The possibility that the procedure fluctuates from  $i^{\text{th}}$  state in the  $n^{\text{th}}$  trial to state  $j$  in the  $(n+1)^{\text{th}}$  trial is identified as transition probability and it is expressed as  $P_{ij}$ . Hence,

$$P_{ij} = P(X_{n+1} = j | X_n = i) \text{ for each } i, j \in S \text{ and } n \geq 0, 1 \leq i, j \leq n$$

with the state transition coefficients including the characteristics:

$$P_{ij} \geq 0$$

$$\text{and } \sum_{j=1}^n P_{ij} = 1$$

As the output of the procedure is the organization of states at each point of time, where each state correlates to a physical event, the recently referenced stochastic method can be named a recognizable Markov model. A square matrix of size  $n$  is formed by the transition probabilities for

every duo of states.

This showcase shows the mechanics of a discrete-time Markov chain with state space  $S$ .

All prospective Markov chain states are utilized as rows and columns, and the row total is invariably one. The change likelihood network is gotten thus,

$$P = [P_{ij}]_{m \times n}$$

The Markov Chain's fundamental conveyance at time 0 can be dictated by

$$p^{(0)} = P[X_0 = i] \text{ and } p^{(n)} = P[X_n = i], i \in S$$

are the row vectors of the probabilities presented at the time  $n$ .

$$p^{(n)} = p^{(n-1)}P = p^{(n-2)}P * P = p^{(n-2)}P^2$$

##### Irreducible Markov Chain

If the state space is not capable of being segmented into two or more disjoint closed sets, the Markov chain is shown to be irreducible. It only has one class.

##### Fixed Distribution of a Markov Chain

This Markov chain property says that irrespective of how the stochastic operation unfolds from its starting state, when the range of transition steps is high enough, the progress likelihood from state  $i$  to state  $j$  settles down to a static worth, hence

$$\lim_{n \rightarrow \infty} P_{ij}(n) = \pi_j$$

These quantities are known as steady state probabilities. In case the limits

$$\pi_j = \lim_{n \rightarrow \infty} P_j(n) = \lim_{n \rightarrow \infty} P_{ij}(n) \text{ subsists and is undependable on the initial state, then}$$

$$P_j(n) = \sum_k P_k(n-1) P_{kj} \text{ changes to } \pi_j = \sum_k \pi_k P_{kj},$$

because  $n \rightarrow \infty$  for  $j = 0, 1, 2, \dots$   
which will be equal to  $\pi = \pi * P$

The probability distribution  $\{\pi_i, i \in I\}$  is known as stationary or invariant for the following chain if

$$\pi_i = \sum_{i \in I} \pi_i P_{ij} \text{ such that } \pi_i \geq 0 \text{ and } \sum_i \pi_i = 1.$$



### Anticipated Number of Visits

$$\mu_{ij}(n) = E(N_{ij}(n))$$

Here,  $N_{ij}(n)$  expresses the count of visits to state  $j$  commencing from state  $i$  in  $n$ -steps.

Here,

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

And  $Y_{ij}(k) = 1$ , if  $X_k = j / X_0 = i$ ,  
0, otherwise

Then,

$$\mu_{ij}(n) = E[\sum_{k=1}^n Y_{ij}(k)] = \sum_{k=1}^n E(Y_{ij}(k))$$

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

$$\therefore \mu_{ij}(n) = \sum_{k=1}^n P_{ij}(k)$$

The anticipated count of visits to state  $j$  from state  $i$  after long - run would be:

$$\mu_{ij}(n) = \lim_{n \rightarrow \infty} E(N_{ij}(n))$$

### Anticipated Return Time

The anticipated return time to state  $j$ ,  $j \in I$  for a finite irreducible Markov chain may be determined by calculating the reciprocal of the limiting probability  $p_{ij}(n)$ .

## V. PREVIOUS RELATED WORK

The Markov chain model has been widely utilized by numerous specialists at several times to study and forecast stock market activity. The references given below highlight the importance of the Markov chain model in this situation. Markov analysis is a predictive method that is based on a probability forecasting approach and can be used to effectively model and predict stock price and closing stock price. It is an alternative method to more traditional forecasting techniques, and it is superior in some ways in the analysis of share price behavior.

Furthermore, several studies have been conducted to assess the share price behavioral patterns in the stock markets using the Markov Chain. Most of these studies tried to analyze financial time series from developed markets such as the United States, China, Sweden, and the Czech Republic. Zhang and Zhang (2009) researched forecasting stock market trends in the Chinese Stock Market (CSM) using the Markov Chain model from January 2007 to November 2007. The study used the Markov Chain model to analyze and determine the stock price index and market close. The Markov chain model is a technique for tracking a variable as it makes the transition from one state to another over time (Robertson, 2001). Ross (2014) describes the Markov chain as a form of stochastic method in which a system switches randomly between different states at

symmetric or asymmetric intervals. In order to predict the stock industry movement in China, Zhang and Zhang (2009) developed a Markov chain model. The examiner delivered a sensibly superb result by utilizing the Markov chain model in the financial exchange. They also proposed that this methodology ought to be applied to specific elective business sectors, for example, the futures market and security markets. To anticipate the stock business development in China, Zhang and Zhang (2009) fostered a Markov chain model. The examiner delivered a sensibly phenomenal result by utilizing the Markov chain model in the financial exchange. They also proposed that this methodology ought to be applied to specific elective business sectors, for example, the futures market and security markets. By showing the conduct of the main two banks, Assurance Trust Bank of Nigeria, and First Bank of Nigeria, Choji, Eduno, and Kassem (2013) utilized a Markov fasten model to estimate likely results. They determined the probability of a state change by joining the conduct of two banks. Using a three-state Markov model, this paper investigated the stock returns lead of First Bank of Nigeria from August 1, 2005, to August 1, 2012, zeroing in on the month-by-month progress probabilities across conditions of positive, zero, and negative returns in day by day exchanges, the chances of arriving at harmony in every one of these states, similarly as the time designations spent in all of these stages in different months.

The review, in principle, applies the finishes of the Markov fasten model to non-customary issues. Considering bank changes and the worldwide monetary emergency, an examination of the elements of First Bank plc's stock returns in Nigeria. The relating harmony and change probabilities of being in any stage in an exchanging day, given the earlier day's system, convey corresponding points of view on corporate security. These components have never under any circumstance been inspected before in the examination of Nigerian resource esteems.

Indeed, the examination adds to traditional time-subordinate unpredictability displaying and mean-fluctuation portfolio advancement by offering dealers and financial backers a wide assortment of information to help their speculation choices. Financial backers and Dealers, for instance, can utilize the Markov short-and since quite a while ago run change probabilities, alongside returning lengths in different systems, to work out the probabilities of various exchanging frameworks after some time, commonly estimated by momenta and procedures for exchanging on stocks in various months, be that as it may, this isn't explored further in the paper.

The potential for these plans to create conceivably beneficial exchanging methods will be upgraded later on. It is possible to make such strategies, for example, by going to analyze these Markovian elements across various banks and obliging relative return esteems close by return systems utilizing proper stochastic models, for example, stamped Markov and checked point processes, summed up or compound Poisson processes. To display the genuine positive and negative returns inside the parent, appropriate



probability distributions will be employed. In this paper, we used a Markovian model.

According to an instructive perspective, these portrayals of the conduct of bank stocks in countless banks in Nigeria give interesting contextual investigations for showing stochastic cycles to Nigerian understudies with genuine applications.

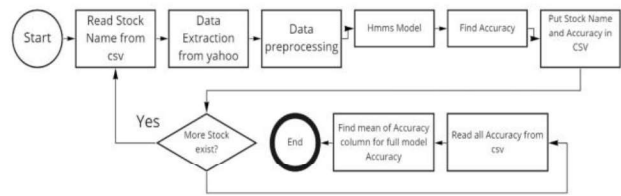
Mettle, Quaye, and Laryea (2014) analyzed the stock value movements for five distinct arbitrarily sampled stocks on the Ghana Stock Exchange using a Markov chain model with finite states. The adoption of the Markov chain model as a stochastic analytic approach in stock price research enhances investment judgments, according to this research. They propose that the Markov chain model be used as a technique to improve share investing choices. The implementation of this approach in stock research enhances consumer understanding as well as the likelihood of greater profits. The task of developing a stock exchange in Ghana was entrusted to a national committee set up by the government at the time to predict modalities in the direction of the establishment of an Exchange in February 1989.

Under the Companies Act of 1963, the market was created in July 1989 as a private limited-by-guarantee business, and it was recognized in October 1990. On November 12, the same day it was opened, transactions began on its floor.

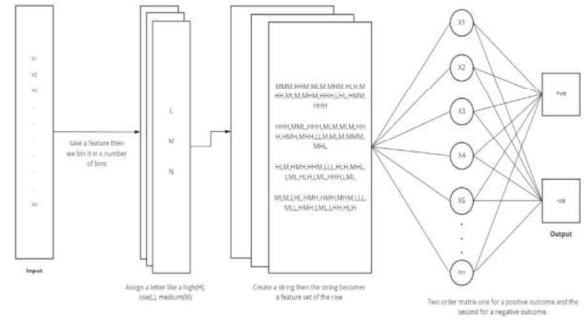
The Exchange's targets include making important information available to the public for the purchase and sale of shares, bonds, and other securities, restricting market quotations for securities by corporate bodies, including government agencies, tracking member and customer dealings, and trying to coordinate with stock markets and other stockbrokers in different countries.

The Ghana Stock Exchange currently has three markets: Fixed Income, Equity, and Ghana Alternative. The facilitation of long-term investment for expansion and growth, with approximately GH 2.1 billion raised since 1990, is one of its notable achievements since its inception. Its market valuation has also increased from GH 3.05 million in 1990 to GH 62,183.49 million as of October 31, 2015. Have also enhanced investor wealth and improved market efficiency by implementing an electronic trading system.

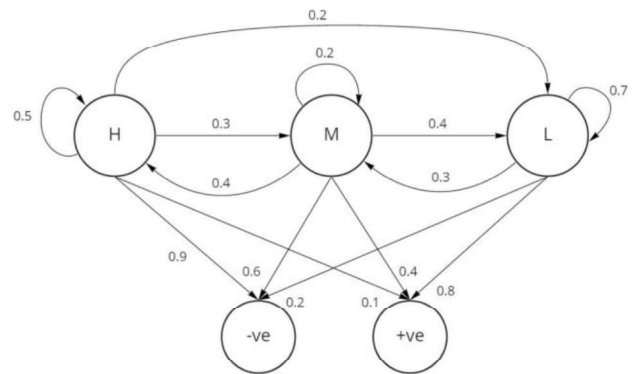
VI. FLOW CHART



VII. CNN MODEL



VIII. TRANSITION DIAGRAM



IX. PROPOSED APPROACH

Markov Chains

A. A stochastic procedure is defined as a variable whose magnitude varies in an unpredictable way over time. A Markov chain is a numerical technique that moves starting with one state then onto the next across a proper arrangement of states. It's a set of alternative states and probabilities for a variable, where the variable's prospective situation or state is heavily influenced by its proximate prior state. Time is categorized into

two types: discrete and continuous. Constant time can't be counted, yet discrete time can.

B.  $P_{ij}$  denotes the probabilities, examining an arbitrary process,  $\{X_n\}$ ,  $n = 0, 1, 2, 3, 4, \dots$  with discrete state space  $S$  and is passed on to be a Markov Chain assuming it meets the accompanying condition to such an extent that:

$$P(X_{n+1} = j | X_n = i, X_{n-1} = i_{n-1}, \dots, X_1 = i, X_0 = i_0) = P(X_{n+1} = j | X_n = i)$$

for any  $i, j, i_1, i_2, \dots, i_{n-1} \in S$

The condition of the procedure can fluctuate in every time-step. The possibility that the procedure fluctuates from  $i^{\text{th}}$  state in the  $n^{\text{th}}$  trial to state  $j$  in the  $(n+1)^{\text{th}}$  trial is identified as transition probability and it is expressed as  $P_{ij}$ . Hence,

$$P_{ij} = P(X_{n+1} = j | X_n = i) \text{ for each } i, j \in S \text{ and } n \geq 0, 1 \leq i, j \leq n$$

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All prospective Markov chain states are utilized as rows and columns, and the row total is invariably one. The progress likelihood framework is gotten subsequently,  $P = [P_{ij}]_{m \times n}$ .

### A. First-Order Transition Matrix

The ever-evolving network is a likelihood matrix from Markov chains. For the least difficult structure, choose the latest developments on the  $Y$  hub and look for and read the possibilities for the next opportunity for  $x$  pivot. In the figure below, you can see that  $C \#$  has the highest probability of the next note after  $A$ .

In our situation, we look at each occasion couple in the arrangement and index market behavior. At this point, count each of the movements you want to adjust and create two sets of information for volume activity. One is for up development and the other is for descending development.

$p^{(0)} = P[X_0 = i]$  and  $p^{(n)} = P[X_n = i]$ ,  $i \in S$   
are the row vectors of the probabilities presented at the time  $n$ .

$$p^{(n)} = p^{(n-1)}P = p^{(n-2)}P^2$$

Then the new opportunity on the stock exchange is split into a series of games, counting both positive and negative results to win the biggest move.

### 1st-order matrix

Note	A	C#	Eb
A	0.1	0.6	0.3
C#	0.25	0.05	0.7
Eb	0.7	0.3	0

### 1) Cataloging Patterns Using S&P 500 Market Data

Bring market information from Yahoo Finance recorded information for image ^GSPC

In its broad structure, the 10-year S & P 500 record information addresses only one group of multiple causes that led to the final cost estimate. In order to gain more consensus and improve our understanding of market behaviour even more critically, we need to divide the information into many examples of inheritance that lead to unique value design. By doing so, you can try to put together a very abundant inventory of market practices and align them with future examples to predict future outcomes. These include, for example, three ongoing S & P 500 Value Closing arrangements. They manage diverse time-frames and incorporate variable expense estimations. Think of each of these arrangements as an example that provides a final value clarification.

We should check out certain models:

**2012-10-18 to 2012-11-21**

1417.26 -> 1428.39 -> 1394.53 -> 1377.51 -> Next Day  
Volume Up

**2016-08-12 to 2016-08-22**

2184.05 -> 2190.15 -> 2178.15 -> 2182.22 -> 2187.02 -> Next Day  
Volume Up

**2014-04-04 to 2014-04-10**

1865.09 -> 1845.04 -> Next Day  
Volume Down

Consider the last model, in which recorded practices from days 1, 2, and 3 are matched beyond three days of the present market. You already have an example that corresponds to current economic conditions, and you may use the future value (day 4) as a pointer for the upcoming business sector course (for example market going down). This clearly isn't utilizing any of Markov's thoughts and is simply anticipating future conduct based on an up-down-up market design.

If you gather a great many these successions, you can fabricate a rich inventory of S&P 500 market conduct. We will not simply analyze the end costs, we'll likewise look at



the day's open versus the day's nearby, the separation between the earlier day's high and the current high,, the distinction between the earlier day's low and the current low, the contrast between the earlier day's volume and the current volume, etc (this will become clearer as we work through the code).

### ***B. Binning Values Into 3 Buckets***

The methodology is to address the isolated components within the arrangement at every opportunity. Divide the values into three groups: low, medium, and high. Extending an event to three containers allows coordination between other subsequent events to work, ideally to be very well used to capture the story and predict future behaviours.

For example, you can find the difference between the daily cost and the previous day's cost percentage to make the stock market information more likely. Each time you collect each, you can use the Info Theo package to place it in three collections with the same iteration. The smaller assembly is assigned an "L", the middle assembly is assigned an "M", and the larger assembly is assigned an "H".

The following are six value examinations between the end cost and the least cost-

**0.00061281019      -0.00285190466      0.00266118835**  
**0.00232492640 0.00530862595 0.00512213970**

Using the equivalent iterative class, the above numbers can be interpreted as follows:

**"M" "L" "M" "M" "H" "H"**

### ***C. Combining Event Features into a Single Event Feature***

At that point, glue each component to one item at a particular time. Looking at the price difference between closed, open, high and low, it is a four-letter element. Each addressing of the canister for that component:

**"MLHL"**

Then, at this point, line up the opportunities for all the components in the grouping and end with something like the following next to the determined result:

**"HMLL" "MHHL" "LLLH" "HMMM" "HHHL" "HHHH" -->**  
**Volume Up**

### ***D. Making Two Markov Chains – First will be for quite a long time with Volume Hops, and second will be intended for Volume Drops***

Another style of methodology is to separate the placement of opportunities into a separate collection of information that depends on the results. Because volume conversion is expected, one information index contains a sequence of volume increments, and another information index decrements. This

allows any information index to offer directional volume movement potential and maximum profit potential.

## **X. RESULT & ANALYSIS**

### ***A. Analysis:***

Hidden Markov Model was first made in talk affirmation but is extensively applied to check monetary trade data. Other real gadgets are furthermore open to making gauges on past time-series data. BoxJenkins used Time-series assessment for checking and control. White used Neural Organizations for monetary trade checking of IBM's step by step stock returns. Following this, various examinations gave a record of the practicality of elective learning estimations and assumption procedures using ANN. To guess the step-by-step close and morning open worth, Henry used the ARIMA model. Nonetheless, this large number of customary procedures had issues when non-linearity exists in time series. Chiang et al. have used ANN to gauge the completion of-year net asset worth of shared resources. Kim and Han found that the muddled dimensionality and covered \*Corresponding maker uproar of the protections trade data make it hard to reestimate the ANN limits. Romani and Shen in like manner saw that ANN intermittently encounters overfitting issues. They cultivated a creating standard-based expert structure and procured a procedure that is used to guess money related market direct. There were moreover hybridization models satisfactorily used to figure financial direct. The drawback was the need of expert data. To beat this huge number of issues Hassan and Nath used Well for predominant smoothing out. Hassan et al. proposed a mixed model of Well, ANN, and GA for financial exchange anticipating. In continuation of this, Hassan combined Well and cushioned reasoning standards to additionally foster the assumption precision on non-fixed stock educational records. Jyoti Identification used particular pointers as a data variable instead of loading costs for examination. Aditya Gupta and Bhuwan Dhingra contemplated the fragmented change in Stock worth and the intra-day high and low possible additions of the stock to set up the consistent Gee. In the past assessments, much investigation work had been finished using various systems and estimations for setting up the model for expecting or predicting the next day close worth of the protections trade, for which aimlessly conveyed Progress Likelihood Grid (TPM), Outflow Likelihood Lattice (EPM) and earlier likelihood structure has been thought of. In this paper, the example examination of the protections trade is found using Stowed away Markov Model by considering the one-day contrast in close motivating force for a particular period. For an offered point of view game plan, the mysterious progression of states and their relating probability regards are found. The probability potential gains of gives the example level of the stock expenses.

### ***Comparison:***

We present a Gee based Guide assessor for the stock estimate. The model uses inaction of days to anticipate the stock impetus for the (d + 1)st day. A Guide decision is made over all of the



possible potential gains of the stock using a once in the past pre-arranged constant  $G$ . We acknowledge four principal secret states which communicate the obvious insights (incomplete change, fragmentary high, fragmentary low). Transition probabilities changed on a given state are displayed as Gaussian Blend Models (GMMs). The model can be effortlessly stretched out to anticipate stock qualities for over one day later, but the exactness of such forecasts would diminish as we look further into what's to come. Execution of the proposed calculation was tried via preparing HMMs on four unique stocks throughout fluctuating timeframes. The model for one stock was thought to be free of different stocks. Our methodology was contrasted with the HMM-fluffy model, ARIMA, and ANN for stock gauging. Table III records the MAPE esteems for the four stocks utilizing the different methodologies. The MAP-HMM model beats others for Apple Inc. furthermore, IBM Corporation, and has tantamount execution for Dell Inc. Interesting to note is the straightforwardness of the philosophy conversely, with other existing methods. In the current methodology, we accept that the model for one specific stock is autonomous of different stocks on the lookout, but as a general rule, these stocks are vigorously related to one another and, somewhat, to stocks in different business sectors as well. As future work, it very well may be natural to attempt to assemble a model which thinks about these relationships. Likewise, as of now, the information is quantized to shape perception vectors for an entire day. An exhibition improvement may be accomplished by eliminating this quantization and on second thought requiring the full scope of moment-by-moment or hour-by-hour stock qualities.

[3] Neptune Blog “Predicting Stock Prices Using Machine Learning” <https://neptune.ai/blog/predicting-stock-prices-using-machine-learning>

## XI. CONCLUSION

On the Yahoo financial dataset, two approaches were used in this paper: Hidden Markov Model Simple and Regression. The two techniques have shown an improvement in expectation precision, bringing about great results. The use of recently released machine learning algorithms to stock prediction has generated encouraging results, paving the way for their implementation in profitable exchange systems. It has led to the conclusion that utilizing machine learning techniques, it is possible to predict the stock market with greater accuracy and efficiency. The stock market prediction system can be enhanced in the future by using a much larger dataset than the one now in use. This would support working on the accuracy of our expectation models. In fact, additional Machine Learning models could be investigated to see what accuracy rate they provide.

## XII. REFERENCES

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