

# Will Technical Analysis Price Patterns perform well?

## — Experiments based on Kaggle Stock Dataset from Group 8

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### Abstract

*The Technical Analysis Price Patterns, which uses price patterns to examine stock movements and forecast future movements, is a famous method in investing and has been widely used. In this method, patterns are identified and they can be as simple as trendlines or as complex as double head-and-shoulders formations. However, this method may use patterns happened many years ago. Therefore, we want to find out if this method will work well in real stock dataset. In this project, we aim at this problem and use a large stock dataset from Kaggle to run experiments. Our work consists of effective and comprehensive data cleaning and large scale distributed computing. Our results verify the fact that this method will work in real-world stock. Finally, we discuss our results and propose future work plans.*

### 1. Introduction

The Democratic candidate Joe Biden captured enough Electoral College votes to win the US Presidency (subject to recounts and court challenges), with the market now turning its attention to the implications of a divided government. Many investors are trying to gain more profit in this special time. Among many famous investing methods, there is one method called Technical Analysis Price Patterns that draws our group's attention.[1] It has been widely used to use price patterns to examine current movements and forecast future market movements. In this method, Patterns are the distinctive formations created by the movements of security prices on a chart and are the foundation of technical analysis. A pattern is identified by a line that connects common price points, such as closing prices or highs or lows, during a specific period of time. These patterns can be as simple as trendlines and as complex as double head-and-shoulders formations or even more. Technical analysts seek to identify patterns as a way to anticipate the future direction of a

security's price. The figure 1 shows a pattern consisting of triple bottoms on the daily McGraw Hill chart, leading to a trend reversal<sup>1</sup>.

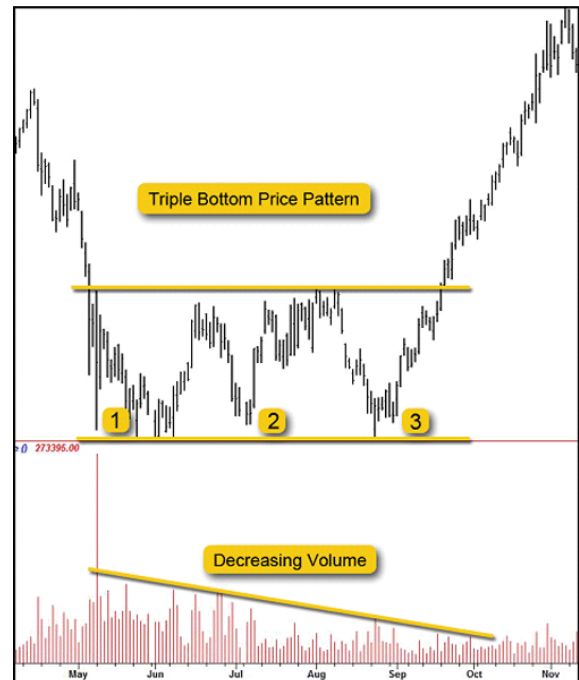


Figure 1. One pattern in the McGraw Hill chart

The problem is, this method will only see the patterns in the stock charts, which is drawn by using the stock price every day. It ignores all the other factors related to that

<sup>1</sup>Source: Investopedia. Chart created with TradeStation 9.0.

company. Also, some stock patterns happened many years ago, and some investors will try to identify that pattern in the stock chart nowadays. Is this method, which identifies a pattern many years ago and only considers stock price while ignoring all other factors, really reasonable? We select this question as our project topic and we run experiments to verify if this method will work.

In this project, we aim at this problem and use a large stock data set from Kaggle[2] to run experiment. Our work consists of effective and comprehensive data cleaning and large scale distributed computing. We first deal with missing values and wrong values in the stock dataset. Then we select one representative stock - Telsa and find the time period before it soars. We use its time series in that time period as our target pattern. Then we tried various methods to measure the similarity between time series. Several measurements are used in this project, including correlation, Euclidean distance, Mahalanobis distance and Pattern Model Representation (PMR). Since the dataset is more than 10GB, we use computing resources from the Center for High Throughput Computing at the University of Wisconsin - Madison and all our experiments were running in parallel on this platform.

In the following section, we briefly introduce several researchers' work that is related to this problem and provides us insights. In Section 3 we introduce our dataset and methods and concepts that we used in our projects. In section 4, the implementation of experiments is described. Final results, discussions and conclusions are involved in section 5 and 6.

## 2. Related Work

In this project, searching for similarities between time series plays an important role. In [3], the paper compares different methods of measuring similarity in long time series and presents their analysis in terms of accuracy and precision when various forced time series variations are imposed. In another paper [4], the authors proposed a new method that obtains relevant features from financial time-series based on the intrinsic information existing inside stock market time series based on their similarity and employing Metric Access Methods to speed up the process. These works may be a good reference for us to choose the proper measurement.

## 3. Statistical Methods

### 3.1. Framework Overview

In this project, our goal is to find out stocks with high similarities with our target stock. Our solution to this project contains four steps, including identifying the issue, data processing, calculating similarities and evaluation. The similarities measurements utilized are correlation, Eu-

clidean distance, Mahalanobis distance and pattern model representation (PMR).

### 3.2. Data Description

In this project, the dataset comes from Kaggle, which is a large platform for data science competition. You can access the data through this by *clicking me*. This dataset contains approximately 100k stocks and their price from 1st Jan 1996 to 7th Aug 2020. The size of this dataset is more than 10GB and therefore meets our requirement for this project.

Understanding the structure of the original data is key to processing data. This dataset contains two parts: One is Tickers.xlsx. This file consists of Tickers' names for more than 1,00,000 companies across the globe. This file contains six columns and Table 1 gives some brief information about the data.

Names	Definition
Ticker	Ticker name
Name	Name of company
Exchange	Short name of Exchange
Category	Category of business
Country	The registering country

Table 1. Details of Data Format

The other is the Data folder. This Directory Consist of more than 1,00,000 directory, in which company data is Stored. Each Company has a separate directory for its data file. The variables in the Data Folder are as follows:

Names	Definition
Date	The date of record
Open	The open price in a day
Close	The price at the end of a day
Low	The lowest price in one day
High	The highest price in one day

Table 2. Details of Data Format

We decide to choose Close in our project as the measurement of stock price. Figure 2 shows a stock chart that is drawn by using the close price.

### 3.3. Data Processing

#### 3.3.1 Deal with missing values

We count the number of samples that have missing time series in the whole dataset. It can be observed that the total number of stocks is 100k and the number of stocks that are missing is 134. We write scripts to get the right stock data from Yahoo Finance and replace all the missing data.

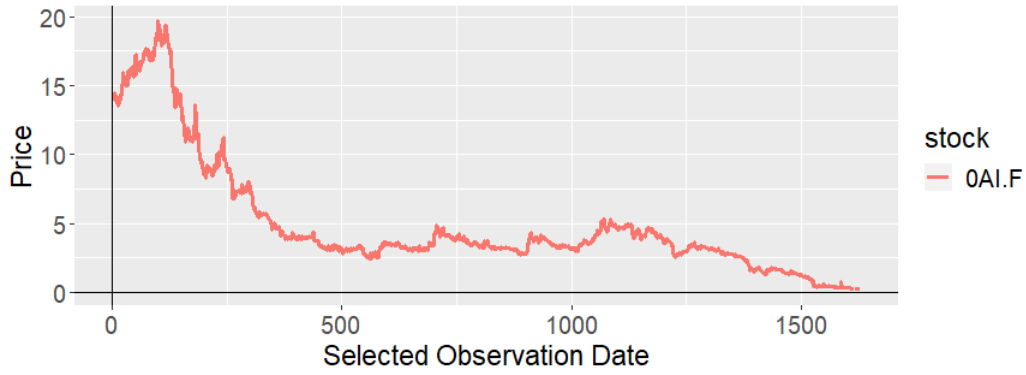


Figure 2. A sample stock chart

### 3.3.2 Deal with wrong values

Some stocks in the dataset have considerable large prices, e.g., 1 million Dollars per share yesterday and 1 Dollar today. That's impossible. Luckily, there are only a limited amount of files that contains the wrong value. We refer to Yahoo Finance and replace them with the right price.

### 3.3.3 Standardize the data

Since we only want to find stocks that look similar to our target stock, the absolute value of the price does not matter. Therefore, we standardize the time series before calculating their similarities.

### 3.3.4 Others

Another thing to note is that there are several folders like AAPL, AAPL34F.SA, AAPL34.SA, AAPL.BA, AAPL.MX, AAPL.SW. They are Apple Inc prices in different exchanges around the globe and are calculated in different currencies. Therefore, when we find stocks with high similarities, we need to remove duplicates like this.

## 3.4. Similarity Measurements

### 3.4.1 Pearson Correlation Coefficient

The Pearson Correlation Coefficient is the most famous similarity measure that is invariant to shifting and scaling being expressed by

$$r_{CC}(X(t), Y(t)) = \frac{\sum_{t=1}^N (X(t) - \mu_X)(Y(t) - \mu_Y)}{\sqrt{\sum_{t=1}^N (X(t) - \mu_X)^2} \sqrt{\sum_{t=1}^N (Y(t) - \mu_Y)^2}}.$$

In this expression,  $N$  is the length of the time series and  $\mu$  is the length of each time series. The Pearson Correlation Coefficient range is  $-1 \leq r \leq 1$  where 1 indicates a perfectly matched between two time-series and a value less than 0 indicates a negative association. 0 indicates that there is no association between the two variables.

### 3.4.2 Euclidean Distance

The Euclidean Distance is calculated as follows:

$$D_{\text{Euclidean}}(X(t), Y(t)) = \sqrt{\sum_{t=1}^N |x_t - y_t|^2}$$

The Euclidean distance has limitations. It does not allow different sequence lengths, different sampling rates, shifting in time axis even though these time series are similar to each other. These drawbacks make the Euclidean distance difficult for direct use.

### 3.4.3 Mahalanobis distance

The Mahalanobis distance defined a dissimilarity measure between two time-series with the same distribution and covariance matrix  $S$ .

$$D_{\text{Mahalanobis}}(X(t), Y(t)) = \sqrt{(X - Y)^T S^{-1} (X - Y)}$$

The advantage of using Mahalanobis distance is that it takes into consideration the correlations,  $S$ , between the time series by which different patterns can be identified and analysed with respect to a based or reference point. However, it does not work well in our project and its calculation takes too long.

### 3.4.4 Pattern Model Representation (PMR)

PMR is based on a piecewise linear representation (PLR) and is effective at describing the tendency of time series. Then, the pattern distance can be calculated to measure the similarity of tendency. This method overcomes the problem of time series mismatch based on point distance. According to the numbers of series' segmentations, pattern distance

has a multi-scale feature and can reflect different similarities with various bandwidths. Because normalization is unnecessary, the calculation consumption of pattern distance is low. Therefore, this might be a good measurement in our project.

## 4. Experiments

### 4.1. Software

- Coding: Bash, R
- Visualization: ggplot2, R
- Environment: CHTC

### 4.2. Implementation

First of all, we use Kaggle's official API to download the dataset into CHTC. Then we clean the dataset to deal with the missing values and wrong values. Then we do the data processing jobs to standardize the data. After this, we write Bash scripts to divide the whole dataset into about 1000 folders with each folder containing 100 csv files. Then we write an R file that can calculate the similarity between two time series.

Figure 3 below shows the overall record of Tesla stock from 6/29/2010 to 8/4/2020. And the target pattern we select is the stock performance between 1/1/2019 and 1/1/2020, which is the period from M to A as marked in the figure. We write CHTC scripts to run 100 in parallel and find time series in the stock that has the highest similarity with our target pattern. After finding those stocks, we will compare their performance with S&P500 in the next one month time period, i.e. A to B in the figure, and see if this method could find out good stocks.

### 4.3. CHTC Output

Our results show that the Pearson Correlation Coefficient method runs fast and behaves well in this project. There-

fore, we will only talk about it and its results in the following section. In this setting, we submitted 1000 jobs with each job containing 100 csv files. Every job takes about approximately 1 minute to complete. The resource usage is shown below in Table 3:

Resources	Usage	Request	Allocated
CPU	1	1	1
Disk(KB)	152775	1048576	1327910
Memory(MB)	436	1024	1024

Table 3. Details of Computing Resource Usage

## 5. Results and Discussion

The result shows the top 5 stocks that have the highest similarities, i.e. the lowest distance are ROLLT.BO, C1S.BE, C1S.F, EPMT.JK, CEATLTD.BO. The following figure 4 shows their distance with our target pattern.

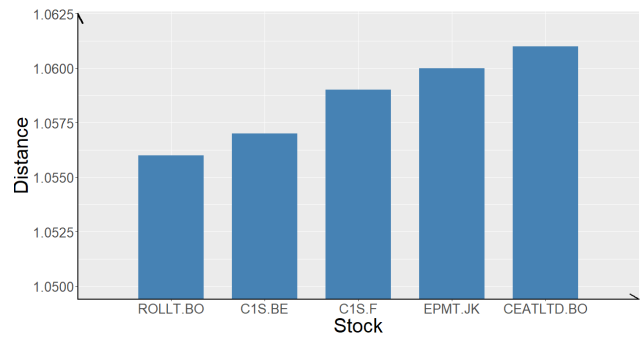


Figure 4. Top 5 stocks with their distances

By checking the stock chart of these stocks, we find these stocks having extremely high similarities with our target pattern. Example graphs are shown in figure 5 and figure 6, where dashed lines A and B stand for the same meaning as in figure 3. The time period from 0 to A has the highest

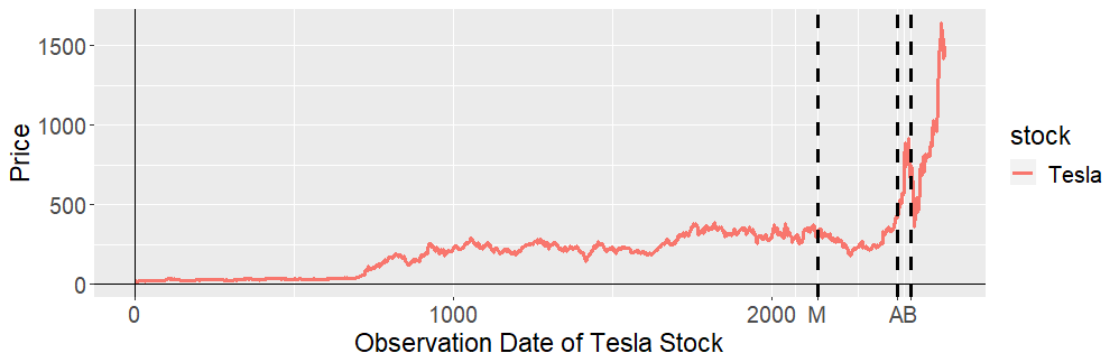


Figure 3. Tesla before 2019 as our pattern

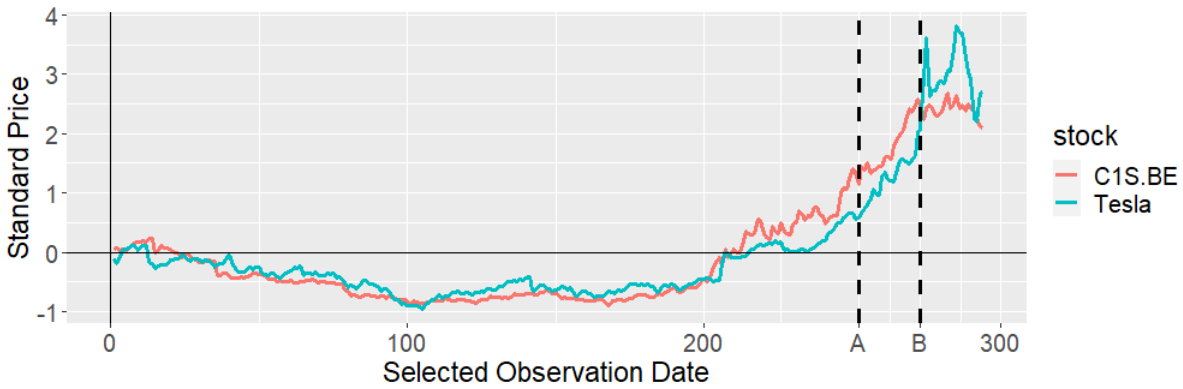


Figure 5. C1S.BE Stock Chart

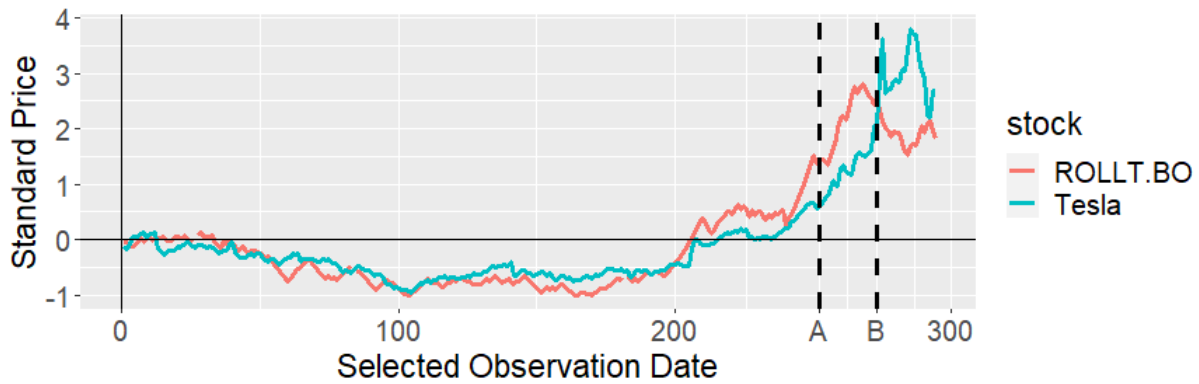


Figure 6. ROLLT.BO Stock Chart

similarity with the target Tesla stock price, which is the time period M to A in figure 3.

Now it's time for us to verify if these stocks behave well. By checking the figure 5 and 6 and the time period between A and B, we see that they all soar in the next month. But how about their performance compared with the whole market?

The figure 7 below shows the top 5 stock's performance compared with the S&P500 index in the same time period. It's obvious that their performances are much better than the S&P500 index at the same time period.

From the discussion above, we believe the Technical Analysis Price Pattern does really work. If you choose Tesla before 2019 as a pattern and buying stocks that look hugely like this pattern, the outcome is much better than buying the index like S&P500. In the future, if one stock chart has extremely high similarity with this pattern, it might have a better chance to become a good stock. However, the problem is, it's almost impossible to find a stock that has such a high similarity with Tesla if you start searching now. We verify the result in a large dataset with many years' data as

well as the help of CHTC, but it's just a verification that this method will work. It's not a get-rich-quick scheme.

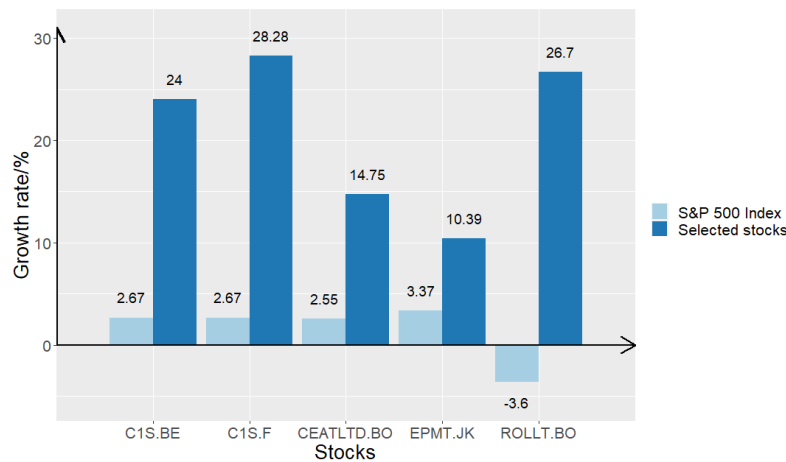


Figure 7. Top Stock's Performance

## 6. Conclusions and Future Work Plan

In this report, we presented our experiments to the Technical Analysis Price Pattern method. The method of simply looking at the stock that has some specific pattern may look strange, but our results based on the Kaggle dataset show that some stocks that have high similarities with another good stock pattern are more likely to become a good stock. As mentioned in the previous section, currently, our results show that the Pearson Correlation Coefficient works best for now. Meanwhile, there are many measurements for time series data out there. The measurement of similarities on the stock dataset may be an interesting direction to go in future investigations.

[https://link.springer.com/chapter/10.1007/978-3-642-40173-2\\_11](https://link.springer.com/chapter/10.1007/978-3-642-40173-2_11)

## 7. Acknowledgements

The dataset of this project were obtained from the Kaggle platform. We really appreciate that this online platform shares such great problems and real-industry datasets with public.

The computing resources in this project were provided by UW-Madison, Center for High Throughput Computing. We really appreciate the help from them.

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## 8. Appendix

For all the source codes, graphs and logs in our project, please check our GitHub repository at *Click me*.

## References

- [1] Adam Hayes (2020) *Introduction to Technical Analysis Price Patterns* <https://www.investopedia.com/articles/technical/112601.asp>.
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- [3] A. Kianimajd, M. G. Ruano, P. Carvalho, J. Henriques T. (2017) *Comparison of different methods of measuring similarity in physiologic time series.* <https://www.sciencedirect.com/science/article/pii/S2405896317333967/>
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