

PAPER

Icyanalysis: An R Package for Technical Analysis in Stock Markets*

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SUMMARY With advances in information technology and the development of big data, manual operation is unlikely to be a smart choice for stock market investing. Instead, the computer-based investment model is expected to bring investors more accurate strategic analysis and more effective investment decisions than human beings. This paper aims to improve investor profits by mining for critical information in the stock data, therefore helping big data analysis. We used the R language to find the technical indicators in the stock market, and then applied the technical indicators to the prediction. The proposed R package includes several analysis toolkits, such as trend line indicators, W type reversal patterns, V type reversal patterns, and the bull or bear market. The simulation results suggest that the developed R package can accurately present the tendency of the price and enhance the return on investment.

key words: technical indicators, R package, big data analysis, stock market, investment

1. Introduction

Changes in commodities prices in every sector of the securities market are complex, and stock indices and averages only provide a tool for measuring stock price movements. However, people are more concerned with how to predict future stock price trends and determine appropriate timing for trades. As such, when investors invest, they must be equipped with methods to determine or select effective investment strategies. Furthermore, technical analysis is an extremely widely applied type of analytical method in the securities investment market. Every type of analytical method is established on a certain theoretical basis, and the strategies, timing, and results of each type vary accordingly. Put simply, this involves a study of past market information and prices and an analysis of the different equations and strategies adopted by each analytical method to predict future price trends and market orientation. However, the perspective on the overall securities market of investors who use a certain analytical method determines the investment strategy they adopt.

The stock market follows certain patterns, meaning researchers can analyze prices based on fundamental, technological, policy, and psychological aspects. They can even identify patterns in the changes in stock price using underlying stock transaction behaviors, while obtaining key stock

price information from historical data through comprehensive data analysis to yield more accurate trade signals, and thereby, effectively increase profits from investment. Although technical analysis indicators play an important role in stock data analysis, some investors argue that fundamental analysis serves as the only important condition for effective stock selection. Hsu [1] utilized macroeconomics to analyze the influence of stock returns in Taiwan's semiconductor industry, finding that these variables had a significant effect on annual stock returns with an explanatory power of 79.3%. Fundamental analysis influences the selection of investment stocks, after comparing fundamental analysis to technical analysis. However, Wafia et al. [2] argued that in contrast to stock price predictions from fundamental analysis, technical analysis stock price predictions have a higher degree of reliability because when stock information is not immediately available, inaccurate, or has low reliability, fundamental analysis results in serious errors of judgment, causing large discrepancies between predicted stock prices and real stock prices. Sharma et al. [3] analyzed 15 firms recommended by a *Business Standard* report and used mean values and *t*-testing for verification, finding that technical analysis can be effectively utilized to determine appropriate timings for entering and exiting the stock market.

The abovementioned literature confirms that technical analysis is capable of effectively predicting stock prices. Furthermore, the literature related to the present study on the topics of reversal patterns and market analysis by bull power and bear power, such as Pan [4], defines W type reversal patterns using candlestick analysis. The absolute point values and percentages were used to determine the decline in Taiwan's futures market in an empirical study of historical data from January 1, 2007 to June 30, 2010, examining when investors buy long by entering the market at the second bottom of the W-pattern. According to the original strategy of [4], it is possible to obtain positive returns and deliver superior performance compared to buy and hold strategies. Baek and Cho [5] used auto-associative neural networks (AANN) as a tool to detect left shoulder peaks in their analysis of trend patterns. They collected historical data from the Korea Composite Stock Price Index from April 1, 1977 to July 24, 2000, with data from left shoulder mode and non-left shoulder mode patterns to train their neural network and provide buy and sell signals. The results showed that when using the left shoulder test investment strategy, it was possible to achieve 124% returns on investment (ROI), while the use of the non-left shoulder test and hold strategy delivered 39%

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ROI. In order to find the input features of the learning system, Lee et al. [6] calculated the body, upper shadow, lower shadow, and rate of change by observing Japanese candlesticks. From September 2000 to January 2002, their system increased assets by 108.84%. Adrian [7] tested whether the relative strength index (RSI) module trading strategy could be used to analyze market trends and achieve relatively high profits using historical data from the S&P 500 from May 1, 2004 to April 30, 2010. The results show that RSI modules could effectively analyze market orientations and produce higher profits. Sahin and Ozbayoglu [8] utilized RSI to analyze the strength of stock price trends as a strategy for selling and buying, finding that under bull and bear market conditions, RSI could be effective.

The abovementioned literature indicated that analyzing the strength of share price trends could be effective with regards to reversal patterns and bull and bear market conditions. In terms of the efficacy of RSIs, Nithya and Thamizhchelvan [9] used technical analysis to understand stock price movement trends. They utilized moving average convergence and divergence (MACD) and RSI to analyze the share price trends of 15 stocks with historical data from 2013 to 2014. They adopted a random sampling method to analyze the capabilities of MACD and RSI with regard to forecasting stock prices, and to speculate on stock price trends. According to this study, RSI can be used in stock price analysis to accurately judge price trends and preemptively propose buying and selling signal orders. However, in the strategy proposed in [9], MACD delivered a weaker profitability with regard to investment return rates. Singla [10] utilized RSI and the exponential moving average (EMA) to judge the efficiency of indices in the Indian market and verify whether index analysis is appropriate for stock market forecasts. In [10], historical data from the National Stock Exchange of India's benchmark index (NIFTY) from January 2010 to December 2014 were used for analysis with the Brock statistical method to test the efficacy of RSI and EMA. According to this study, RSI and EMA had predictive power for the Indian stock market in long-term strategy conditions and were capable of achieving effective return rates.

In this study, we used R to develop a technical analysis indicator package and technical indicators written therein. We then analyzed historical stock price data in order to find upward and downward movements in stock price bands, in addition to overbuying and overselling information. This method can provide investors with reference information when investing, thereby improving their investment success rates. The objectives of our study are as follows:

1. Plot trend line: this pattern analyzes periodic upward and downward bands.
2. Find V-bottoms and V-tops: this pattern is appropriate for use with sudden strong market fluctuations.
3. Find W-bottoms and M-tops: this pattern can analyze stock price surge and plunge patterns.
4. Detect bull power and bear power: this pattern analyzes

overbuying and overselling waves and conducts investment strategy backtesting.

2. Proposed Definitions of Chart Patterns

There exists a lack of consensus regarding a clear and precise definition of each chart pattern. Here, we suggest definitions and meanings with input from researchers from the various pieces of contributing literature.

2.1 Trend Lines

In investment trading, stock price trends can provide profit opportunities. Trends can be defined as the direction in which the market is moving. In upward-moving situations, the bottom parts of a price trend can often be connected with a single straight line; during downward-moving situations, the peaks of price trends can also be connected with another single straight line. These straight lines are referred to as trend lines. Trend lines are an important tool and the most basic technique in graphical analysis; in graphs, they connect the highest points at the peak of each wave, or they connect lowest points at the troughs of each wave. Here, we can distinguish between “up,” “down,” or “sideways” trends, in addition to long-term trend periods (from six to 12 months), medium-term trends (from one to three months), or short-term trends (a week). For example, if a trend line covers several months, it can be called a major trend line or a long-term trend line; where a trend line covers a longer period of time, it exerts greater support and pressure.

There are several types including up trend, down trend, and sideways trend.

Up Trends. They are straight lines connecting a series of troughs, and move upwards and to the right, as shown in Fig. 1. They represent support in the market. The supportive force of up trends in the market shows that the force of current market demand is greater than that of supply, and that when a price band falls below an up-trend line, a trading strategy must shift to a short strategy.

Down Trends. They are straight lines that connect a series of peaks and move downwards and to the right, as shown in Fig. 2. Down trends play a type of pressure role in the market and indicate that the force of current supply is greater than that of demand. That is, they act as resistance, and indicate that net-supply is increasing even as the price

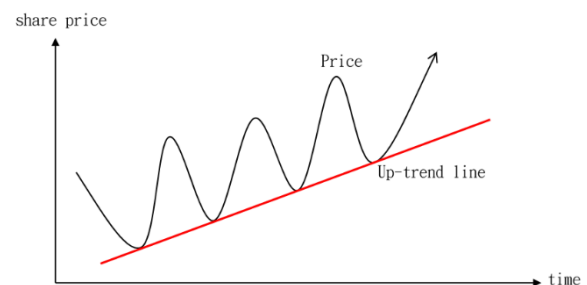


Fig. 1 The red line is an up-trend line.

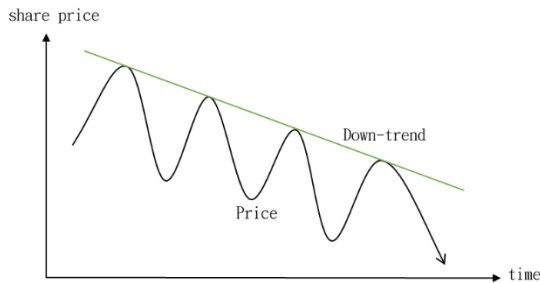


Fig. 2 The green line is a down-trend line.

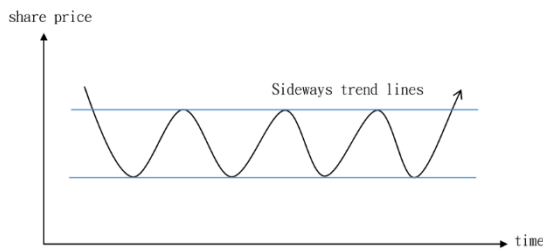


Fig. 3 The blue lines are sideways trend lines.

declines. When a price band exceeds a down-trend line, a trading strategy may shift towards a long strategy.

Sideways Trends. They are also known as neutral trend and are straight lines that connect a series of peaks and troughs, forming two horizontal lines as shown in Fig. 3. Sideways trends indicate that current market pressures and market support are level; when a price band falls below an uptrend line, a trading strategy must shift to a short strategy, or when a price band exceeds a down trend line, a trading strategy may shift to a long strategy.

2.2 V-Bottoms and V-Tops

V-type reversal patterns are very strong in the stock market. They occur frequently during market fluctuations, where one-off reversal peaks or troughs occur at the bottom or top of price ranges. Subsequently, band trends exhibit very large changes, causing stock prices to move in the opposite direction.

V-type reversal patterns can be generally divided into the following types:

V-Bottoms. A continuous fall in stock prices and a drastic increase in the trend is represented in a “V” shape, which is a type of strong upside signal. The V-bottom typically occurs if the stock market experiences a long period of large decline. After reaching a given low point, the appearance of relatively bullish information will reduce the force of the short-term downwards movement, and the share price trend will immediately move upwards. This trend will continue for a significant period, as shown in Fig. 4.

Typically, this type of reversal happens in two situations. The first situation is at the end of a downward trend. The index decreases sharply and then rises rapidly, without any prior indication. The second situation is caused by in-

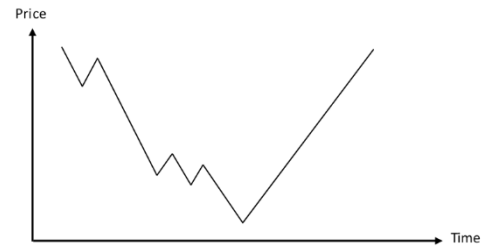


Fig. 4 V-bottom reversal pattern.

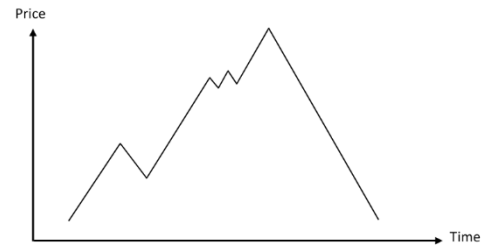


Fig. 5 V-top reversal pattern.

vestors' inability to react to rapid market changes driven by a market reaction to rumors or emotion-driven market operations.

V-bottoms can be separated into three stages:

1. Downward stage: generally, the left falling part of a V-bottom declines very rapidly and continues to do so for some time.
2. Reversal point: the trough of a positive V-bottom is extremely sharp, indicating the bottom of the shoulder. The turning point forms over only two to three trading days, and furthermore, long trading volumes increase significantly at such points. Sometimes, these occur on panicked trading days.
3. Upward stage: next, share prices increase from their low point, at which point trade volumes will increase, showing the emergence of bullish information against the short-term price decline.

V-Tops. After stock prices rise to a relatively high level, and the trend suddenly falls sharply, the chart forms an inverted “V” shape, which is a type of strong downside signal. V-tops typically appear after the stock market experiences a long period of significant increase, and reaching a certain peak point, the appearance of relatively bearish information reduces the force of the short-term upward movement, at which point the share price trend will decline rapidly. This trend will remain continuously for some time, as shown in Fig. 5.

Typically, this type of reversal occurs under the following two circumstances. The first circumstance is at the end of an upward trend in the market. The index increases rapidly and declines sharply, without any prior indication. The second circumstance is because of a reaction to market rumors or emotion-driven market operations. This results in investors' inability to react to rapid market changes.

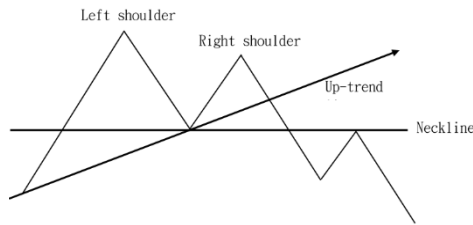


Fig. 6 M-top reversal pattern.

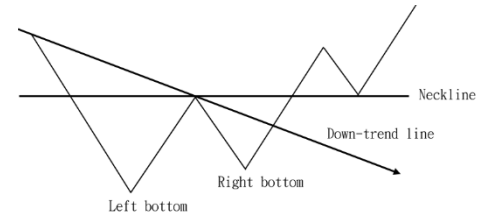


Fig. 7 W-bottom reversal pattern.

The V-tops reversal can be divided into three stages:

1. Upward stage: the left side of the inverted V-shape is typically very steep and persists for some time.
2. Reversal point: the peak of a V-top is extremely sharp, indicating the peak of the shoulder. A turning point forms over only two to three trading days. Furthermore, the short trading volumes increase significantly at such points. Sometimes, these occur on panicked trading days.
3. Downward stage: next, the emergence of bearish information weakens the short-term price increase and share prices decline from their high point, at which point trading volumes will increase.

2.3 M-Tops and W-Bottoms

In terms of the internal and external variables that affect prices, each type of commodity encounters some bottlenecks or stagnancy. When this happens, investors are more likely to change their view of these commodities' prices, and this reversal in attitude is reflected in the prices, thereby forming a variety of patterns, referred to as a more complicated reversal pattern than V-tops and V-bottoms. M-tops and W-bottoms are the graphs formed by reversals in stock price trends, namely, signals of shifts in stock price trends from increasing to decreasing, or from decreasing to increasing. Trend patterns are used to predict future price trends. M-tops and W-bottoms are illustrated as follows:

M-Tops. Such reversal patterns easily occur when stock price bands are high. After the first stage of rising fluctuations, stock prices suddenly lose their rising price support and decline rapidly, forming two peaks, or the "double top" M shape due to the influence of sudden information. This pattern is composed of two peaks and one trough. Regardless of whether the left or right shoulder is higher, or if each is equally high, such patterns all constitute a double top M-type reversal pattern. When such a pattern occurs, trading strategies must shift towards a short trade. A standard double top M-type reversal pattern can be formed in three steps, as shown in Fig. 6:

1. At the first peak, the corrective movement does not persist. The upward trend weakens and sells off.
2. At the second peak, the initial decline dips below the upward trend line, and the subsequent decline falls below the neckline.
3. Trading volume significantly declines after the share

price reaches its first record high.

W-Bottoms. Such reversal patterns easily occur when stock price bands are low; after the first stage of declining fluctuation, stock prices suddenly gain price support, and rise rapidly, forming two troughs, or the "double bottom" W shape due to the influence of sudden information. This pattern is composed of two troughs and one peak. The pattern is formed after a sustained trend when a price tests the support level twice without a breakthrough. Regardless of whether the left or right trough is lower, or if each is equally low, such patterns all constitute a double bottom W-type reversal pattern. When such a pattern occurs, trading strategies must shift towards a long trade. A standard double bottom W-type reversal pattern can be formed in three steps, as shown in Fig. 7:

1. Where the first trough appears, there are low level fluctuations.
2. At the second trough, the initial increase moves above the downward trend line, and then passes above the neckline.
3. Trading volume significantly declines after the share price reaches its first record low and increases significantly after the second trough.

2.4 Bull Power and Bear Power

In the ever-changing stock market, the orientation of daily stock market movements changes along with the fluctuations in financial markets, capital flows, political factors, or economic cycles. According to Elliot Wave Theory [11], when a stock market is situated in a long-term upward trend due to long-term economic growth, this is called "bull power," or a "bull market." On the contrary, when the economy exhibits a long-term declining state, and the stock market is situated in a long-term falling trend, this is called "bear power," or a "bear market." The bull and bear market indicators are determined by the RSI and show the strength or weakness of stock prices and price band points.

Wilder [12] proposed the RSI, which is a commonly used short- to medium-term indicator for stock market technical analysis. It is an index used to represent a counterweight for the strength of buyers and sellers in a market. It can indicate increases or decreases in aggressive buying and also be used to determine whether a share price or index ought to be approached with a long or short strategy, thus serving as a reference when buying or selling. The RSI is

defined as:

$$RSI = 100 - \left(\frac{100}{1 + RS} \right) \quad (1)$$

where $RS = (u/d)$ and u represents an absolute increase within a period, while d represents an absolute decrease within a period.

By using the RSI to set buying and selling prices, we can conduct data screening and analysis. For example, when the RSI value exceeds 50, the stock's movement has entered a strong state; while when the RSI falls below 50, the stock's movement has entered a weak state. Data analysis periods can be divided into short-term period (less than five days) and long-term period (more than 14 days).

3. Proposed Methods

3.1 Trend Line

First, we obtain the pivot point as calculated in Eq. (2) of historical stock prices:

$$Pivot\ Point = \frac{H + L + C}{3} \quad (2)$$

where H stands for the highest price, L the lowest price, and C the closing price. According to the pivot point, the resistance levels and support levels can be calculated by:

$$R_1 = (Pivot\ Point \times 2) - L \quad (3)$$

$$S_1 = (Pivot\ Point \times 2) - H \quad (4)$$

$$R_2 = Pivot\ Point + (R_1 - S_1) \quad (5)$$

$$S_2 = Pivot\ Point - (R_1 - S_1) \quad (6)$$

where S_1 and S_2 represent the support levels, and R_1 and R_2 the resistance levels. We then separate the support point and resistance point data according to a set number of days x_1 .

For example, if the number of days x_1 is set at 10, then we arrange each unit of data in groups of 10, and we derive the maximum of the first three data sets and the maximum of the last three data sets to draw a down-trend line. We also derive the minimum of the first three data sets and the minimum of the last three data sets to draw an up-trend line. These points serve as the new starting and ending values for each data set. We use a conditional formatting formula to test each data set. The factors comprising upward trend lines include the ending value, which must be larger than the starting value, and the difference between the values must be greater than one. If established, we use interpolation to fill in the values between the starting and ending values. In contrast, downward trend lines are comprised of a final value, which must be lower than the starting value, and the difference between the two must be less than -1 . If established, we conduct interpolation to fill in the values between the starting and ending values.

3.2 V-Bottom and V-Top Reversal Patterns

We use RSI to analyze the historical data and determine the

horizontal spread. According to the horizontal spread, the two tops of a positive V shape and the two bottoms of an inverted V shape can be detected. Finally, we find the lowest price between two tops and the highest price between two bottoms. The details of V type formations are explained as follows:

1. **V-bottoms:** the left top must be lower than the right top, and there should be a low price band between the tops. Then, the V-bottom can be formed. That is, the price of the right shoulder should be higher than that of the left shoulder. In addition, the RSI between those prices has to be less than a certain value V_b that users can define for themselves in our system.
2. **V-tops:** the left bottom must be higher than the right bottom, and there should be a high price band between the bottoms. Then, the V-top can be formed. The definition of the high price band can be determined by users' adjustment in the RSI value V_t .

3.3 M-Top and W-Bottom Reversal Patterns

We use the RSI to analyze historical data, and after setting buy and sell levels according to RSI values, the levels are applied to judge the screening conditions for M-top and low price bands, and W-bottom and high-price bands. For example, for a buy level M_b set at 60 and a sell level M_s set at 40, if the RSI is greater than 60, then this is considered a high price band, and is suitable for M-top and W-bottom maximum value search conditions. In contrast, where RSI is less than 40, it is considered a low price band, and is suitable for M-top or W-bottom minimum value search conditions. The details of M type formations are explained as follows:

1. **M-tops:** the conditions for forming this pattern require that the left peak be higher than the right peak, and that the distance between peaks be less than a certain period P_m that users can adjust in our system. Furthermore, one minimum value in the space between the two peaks must satisfy the low price band conditions. Backtesting for the right trough must fall below the neckline as shown in Fig. 6; if the above conditions are satisfied, the M-top reversal pattern is formed.
2. **W-bottoms:** the conditions for forming this pattern require that the left trough be lower than the right trough and that the distance between troughs be less than a certain period P_w that users can adjust in our system. Furthermore, one maximum value in the space between the two troughs must satisfy the high price band conditions. Backtesting for the right peak must pass above the neckline as shown in Fig. 7; if the above conditions are satisfied, the W-bottom reversal pattern is formed.

3.4 Bull Power and Bear Power

When using the RSI to analyze historical data, the RSI values determine buy levels. We screen the high and low price band data according to the user-defined buy level B_b . When

the RSI value is greater than the buy level, the dataset is compatible with the high band price, and these data values are retained. When establishing a bull market trend line, the RSI values must be greater than the set buy level, and the trend line period must exceed several days' B_d that users can define. If the RSI value is lower than the established sell level B_s , this dataset is compatible with the low band price, and these data values are retained. Furthermore, when establishing a bear market trend line, the RSI value must be below the set sell level, and the trend line period must exceed several days.

3.5 Data Pre-Processing for Neural Networks

We designed several scenarios to show the advantages of using the proposed package for technical analysis. All scenarios have the same neural network architecture. The input layer contains three neurons to collect the previous prices, the hidden layer contains 21 neurons, and the output layer contains one neuron to produce the future price. The sigmoid transfer function was used in all hidden layers. Therefore, the input features are the stock prices three days prior, and then the neural network predicts the future price. The structure of the neural network is a controlled variable. The way of conducting data pre-processing is an independent variable.

There are four kinds of situations. In the first model, the input data of the neural network are the untreated data. In the second model, the raw data were smoothed by a third-order low-pass Butterworth filter with a cut-off frequency of 1.885 rad/s. In the third model, the raw data were analyzed by our proposed toolkit and were replaced by the data points on the chart patterns. The fourth model combines the concepts of data smoothing and technical analysis. The treated data from the third model were then passed through the low-pass filter in the second model. We therefore can check if the proposed toolkit can actually improve predictions.

We downloaded the stock prices from January 4, 2007 to April 6, 2016. The data for January 4, 2007 to February 23, 2016 serve as the training data. After conducting one of the pre-processing models, we fed the processed data into the neural network for training. The test data are from February 24, 2016 to April 6, 2016. Figure 8 shows the predicted prices of Texas Instruments (TXN) by different mod-



Fig. 8 Actual and predicted prices of Texas Instruments (TXN).

els. The comparisons between data pre-processing models are investigated in the next section.

4. Results

In this section, we show several examples of using our proposed toolbox. The example data were from the Yahoo Finance public database. The instance of using the toolkit to plot trend lines is shown in Fig. 9. The historical data were from Apple Inc. (AAPL) for August 17, 2007 to June 5, 2008 in Fig. 9 (a) and November 11, 2015 to August 4, 2016 in Fig. 9 (b). The number of days x_1 was set at 20. In Fig. 9 (a), the toolkit automatically found several up-trend lines, and the trends after those lines enhanced the chance of being upward. On the other hand, in Fig. 9 (b), several down-trend lines were automatically plotted, and the trends after those lines were less likely to be at a high price level.

An example of using the V type reversal pattern function is shown in Fig. 10. The candlestick charts were from AAPL for September 21, 2015 to March 5, 2018 in Fig. 10 (a), and the others were from GOOGL for January 31, 2011 to August 29, 2011 in Fig. 10 (b). The RSI value V_t was set at 60, and the RSI value V_b at 40. That is, in this setting, the price below V_b is called the low price band, and the price higher than V_t is called the high price band. In Fig. 10 (a), the toolkit automatically found a V-bottom, and the share prices following the V type pattern were more likely to soar. On the other hand, in Fig. 10 (b), an inverted V type pattern was automatically plotted, and the trend after the V-top immediately went down.



Fig. 9 Trend line function. Examples of using (a) up-trend lines and (b) down-trend lines



Fig. 10 V type reversal pattern function. Examples of using (a) V-bottom and (b) V-top.



Fig. 11 M type reversal pattern function. Examples of using (a) M-top and (b) W-bottom.

Figure 11 shows the example of using the W type reversal pattern function. The historical data were from Google Inc. (GOOGL) for September 14, 2009 to October 11, 2010

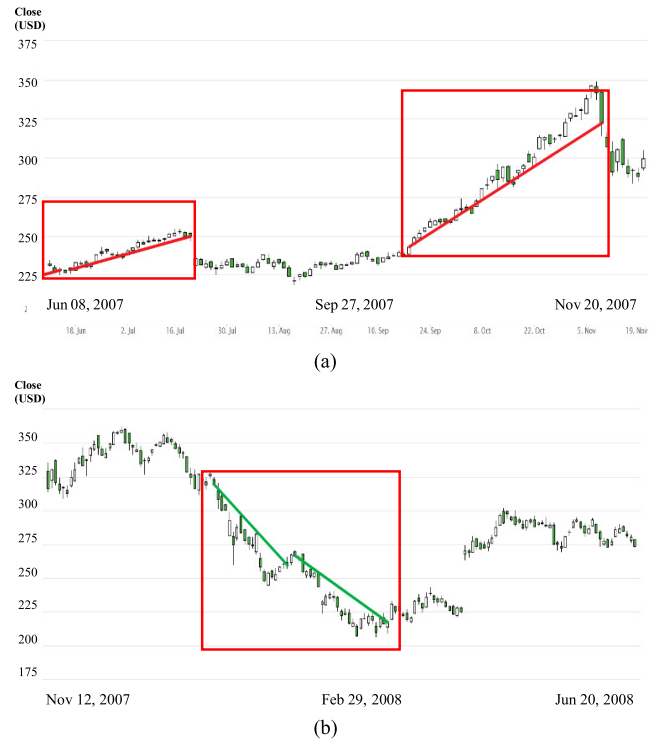


Fig. 12 Bull and bear power function. Examples of detecting (a) bull market and (b) bear market.



Fig. 13 Backtesting of trading strategy determined by our proposed function

in Fig. 11 (a) and December 30, 2008 to October 23, 2009 in Fig. 11 (b). The number of months P_m was set at 5, and RSIs M_b and M_s at 60 and 40, respectively. Therefore, in a M-top, the time period from the left top to the right top must be shorter than 5 months, and there should be a closed price with $RSI < 40$ between the tops. Figure 11 (a) shows the proposed system detected an M-top, and the share prices immediately fell after suffering this pattern. In a W-bottom, the time period from the left bottom to the right bottom must also be shorter than $P_w = 5$ months, and there should be a closed price with $RSI > 60$ between the bottoms. The proposed system detected a W-bottom in Fig. 11 (b), and the share prices immediately rose after the detection.

We used GOOGL's share prices to illustrate the use of

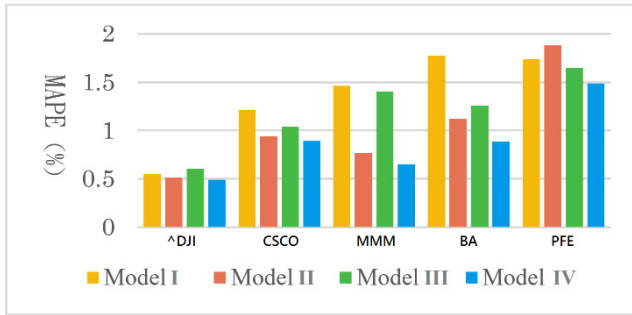


Fig. 14 Mean absolute percentage errors (MAPEs) of the Dow Jones Industrial Average (^DJI) including: Cisco Systems (CSCO), 3M (MMM), Boeing (BA), and Pfizer (PFE)

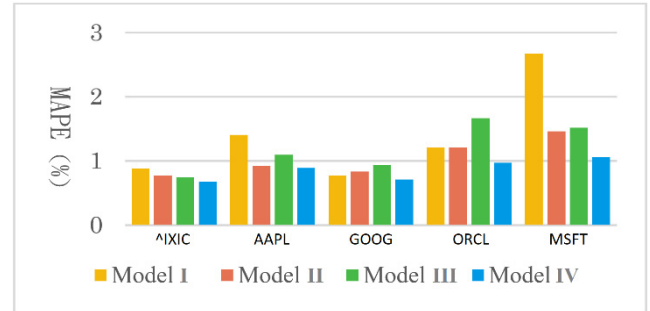


Fig. 16 Mean absolute percentage errors (MAPEs) of the NASDAQ Composite (^IXIC) including: Apple (AAPL), Alphabet (GOOG), Oracle (ORCL), and Microsoft (MSFT)

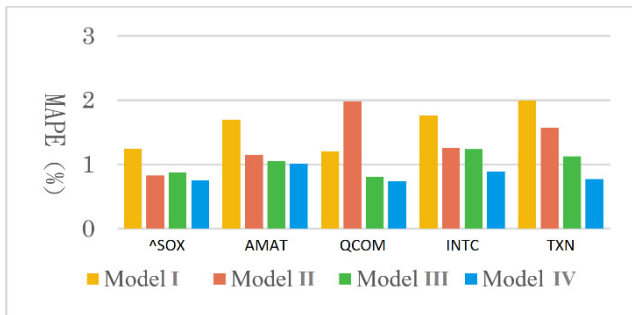


Fig. 15 Mean absolute percentage errors (MAPEs) of the PHLX Semiconductor (^SOX) including: Applied Materials (AMAT), Qualcomm (QCOM), Intel (INTC), and Texas Instruments (TXN)

the bull and bear power function. Figure 12 (a) shows the share prices of GOOGL for June 8, 2007 to October 20, 2007 and Fig. 12 (b) November 12, 2007 to June 20, 2008. The buy level B_b was set at 60, and the sell level B_s was set at 40. The minimum period B_d was three days. If the period contains at least three consecutive ROIs > 60 , a bull power is formed as shown in Fig. 12 (a). By contrast, in Fig. 12 (b), there are several bear markets, each of which contains more than three consecutive ROIs < 40 . Our strategy was backtested from January 3, 2012 to December 30, 2016, and Fig. 13 shows that the ROI of backtesting is about 350% by using the bull and bear power function.

Finally, we integrated the proposed technical analysis into a neural network. The four pre-processing models are evaluated by the mean absolute percentage error (MAPE) defined as:

$$\text{MAPE} = \frac{100\%}{N} \sum_{n=1}^N \left| \frac{A(n) - P(n)}{A(n)} \right| \quad (7)$$

where N is the total number of days, $A(n)$ is the actual stock price on the n^{th} day, and $P(n)$ is the predicted stock price. We examined several major markets in the United States: the Dow Jones Industrial Average (^DJI) as shown in Fig. 14, PHLX Semiconductor (^SOX) as shown in Fig. 15, and NASDAQ Composite (^IXIC) as shown in Fig. 16. Several important companies that contribute to those markets were also examined separately. The fourth model reliably obtained the smallest errors, whilst the performances of the

other three models were not stable.

5. Discussion

The experiment shows that the toolkits can automatically find the corresponding chart patterns in financial data. The proposed technical analysis also supports artificial intelligence in forecasting stock prices. Through analyzing a significant amount of financial data, we concluded several points that would help us develop recommender systems in future works.

First, up- and down-trend line indices are set by periods, and they can be used to accurately analyze upward and downward trend price bands in periodic prices. When upward and downward trend lines together form a downward-oriented pennant-shaped trend, future trade volumes may increase, and stock prices may rise.

Second, V-bottom patterns typically form late in a market downtrend, or after a stock has already suffered a big decline in buying. V-top patterns, on the other hand, form at the end of an uptrend, or after a market has already enjoyed a long run. V-top and V-bottom patterns are the fundamental elements of several chart patterns, such as the Elliott Wave Principle [11] and head and shoulders patterns [5].

Third, double top M-type and double bottom W-type reversal patterns can accurately analyze trend patterns for large increases and decreases in share prices and provide valid information for buying and selling. If it is necessary to determine relatively short-term trend patterns, we suggest expanding the range of buy and sell levels and increasing the data range for conditional analysis in order to find short-term reversal pattern indices.

Fourth, for short-term traders, buy and sell levels in bull and bear market trend lines can be decreased, and the range and period for data analysis can be expanded to provide buy and sell information for short-term trading.

Finally, we integrated the proposed algorithm into data pre-processing for neural networks. The results indicate that the proposed package, together with a low-pass filter, was more likely to obtain the best performance. If we feed only raw stock prices into the neural network without any pre-processing, the prediction is less likely to be accurate. The

results also indicate that using a low-pass filter in the second model can somewhat reduce the noise. Although the third model performed well, the quality was not stable in some cases. The system could only achieve optimum performance levels when low-pass filtering and technical analysis worked together.

6. Conclusion

We provide general toolkits for technical analysis in the stock market. In the past, there were no fixed formulas or conditions for plotting chart patterns, and it was thus necessary to rely on personal experience to conduct technical analysis of indicators. This paper developed an R package to improve the effectiveness of stock market data analysis. Several software packages can be utilized to collect financial data on the Internet, and there have also been many toolkits developed for artificial intelligence. However, there should be a connection between data collection and machine learning to avoid “garbage in, garbage out.” The proposed technical analysis serves as a powerful pre-processing toolbox to enhance the accuracy.

Although technical indicators are capable of providing effective share price analysis information, as modern information technology continues to develop, modern investors are more interested in understanding the use of analyzed data to transmit direct messages regarding proper buying and selling, and even forecast continuing stock price trends. Investors care about these relatively direct and effective messages that allow them to make judgments as analytical functions. As such, follow-up research can address topics such as buy and sell signals, index forecasting analysis, and automated trading. The developed toolkit can help artificial neural networks [13] to find the input features of substantial data in finance.

One of the important issues in artificial intelligence is the adjustment of variables to obtain the optimum solution. In current commercial software, the source codes are normally not available to the public, so users have trouble with modifying the parameters inside the functions. Our package passed a comprehensive R archive network (CRAN) check and each function has been well verified in this paper. The developed package has been put on CRAN and can be downloaded from [14].

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