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Short-term Prediction of Stock Price Fluctuation based on Back Propagation Neural Network

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Abstract

Using study samples from Guizhou Maotai and Wuliangye stock prices from January 1, 2017, to December 31, 2019, the back propagation (BP) neural network forecast model is utilized to make Short-term predictions of stock price fluctuations in this study. The study results determine the accuracy of the forecast results and applicability of the forecast model in the financial field. Moreover, they provide a new model and algorithm for dealing with complex, multi-factor influence, high uncertainty, and nonlinear financial price prediction. The study results also found that the accuracy of the model was more than 60% and reached up to 72%, whereas the model recall rate was more than 60% and reached up to 82% when using the BP neural network parameter training and model prediction, as well as the classification model evaluation algorithm, to analyze the prediction results of the test set. Lastly, the study results also show that the models have good fitting effect and prediction accuracy and effectively address the shortcomings of traditional financial models and forecasting algorithms. Therefore, these results can provide a basis to guide investors in comprehensive decision-making.

Keywords

BP Neural Network; Stock Price Fluctuation; Index Analysis Method; Short-term Forecast.

1. Introduction

Machine learning, as an emerging algorithm, has become popular in various research areas over the past few years. Scholars have focused on machine learning algorithms because of their special characteristics and future potential, compared with traditional algorithm models. Neural network algorithm--the most representative machine learning algorithm--shows its spectacular advantages in image processing, speech recognition, optimization solution, huge data mining, artificial intelligence, and other subdivisions. Derivative neural network models--starting from early artificial neural networks (ANN) to the emerging convolutional neural networks (CNN), circulatory neural networks (RNNs), and so on--are created and applied to various research fields.

ANN simulates how the network of neurons in the human brain processes information, thus creating a synthetic network-like model. Since the end of the last century, this model has been continuously developed and optimized and has gradually become the focus of artificial intelligence. Currently, dozens of ANN types are classified according to the characteristics of neurons, topology between neurons, and the way networks are trained. Neural network models are established based on individual neurons connected to each other according to certain weights. The ANN model has demonstrated excellent intelligent characteristics and unpredictable development potential. Moreover, the ANN model has been applied in various

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research topics, such as user portrait, intelligent robot, medicine, finance, high-tech research and development, and automatic control.

As a representative algorithm in the ANN model, BP neural network is selected for stock market price prediction in this study. BP neural network is a multi-layered feed-forward neural network model that updates the weights of the neural network by using an error reverse transfer algorithm and precisely depicts complex nonlinear relationships through forward transmission, error feedback, and modification of various parameters.

To address the volatile financial market environment and unpredictable economic situations, as well as to improve the efficiency and accuracy of investment decisions, traditional stock price prediction models have been gradually replaced by emerging machine learning methods. Due to their various characteristics, such as high computational speed, good data relationship fitting effect, and efficiently mining hidden information in massive data, researchers can use BP models to address massive information and complex relationships faced by investors, solve the limited rationality of investors, and help investors make accurate and favorable investment decisions. Stock price analysis refers to identifying the market value of stocks, predicting potential future fluctuations, determining optimal trading operations at the most favorable time, as well as avoiding risks. Through a series of empirical studies, researchers developed many methods of stock prediction in the following categories: (1) traditional investment analysis, comprising fundamental and technical analysis; (2) time series analysis, including moving average, exponential smoothing, and trend extrapolation; (3) non-linear system analysis, including BP neural network, which is suitable for complex, multi-factor, highly uncertain, and non-linear financial price prediction, such as stock price prediction.

The stock market is a nonlinear trading system with numerous influencing factors and complex mechanisms, including the sophisticated influences of politics, economy, social culture, technology, investor behavior, and psychological expectations of investors, wherein fluctuations of individual factors may cause strong volatility in stock prices. Numerous influencing factors can be examined using the BP neural network because of its high self-learning, self-adjustment, self-organization, and adaptive ability. The unique nonlinear structure can indicate the quantitative relationship of research subjects by simulating human image thinking mode to process data. Like the organic combination of human conventional thinking and logic, the BP neural network associates and learns similar situations through training samples. This model effectively addresses the shortcomings of traditional financial models and prediction algorithms, with better fitting effect and predictive accuracy.

Tong Hanfei applied the neural network model to stock market index prediction and stock trading signal research and showed that the neural network has a good prediction effect on real stock price index [1]. Wang Sha examined stock from Hunan Sany Heavy Industries and used the trained BP neural network stock market prediction model to predict stock data, finally observing a good fitting effect [2]. Jia Jia applied BP neural network to predict stock price index [3]. Zhou Dan conducted a comparative analysis of three neural networks--feed-forward neural network, recurrent neural network, and long Short-term memory (LSTM). Zhou Dan proposed an effective model optimization method by adjusting the learning rate and depth of the LSTM model structure [4]. Xiongwen Pang et al. developed an innovative neural network approach with multi-stock high-dimensional historical data to achieve better stock market predictions, and found the deep LSTM with embedded layer model has better predictive power [5]. In foreign studies, Jasic and Wood used a single-variable neural network-based approach to predict yields, such as the Eastern and FTSE, and the empirical results provide strong evidence of the predictability of stock returns, thereby suggesting that neural networks can efficiently predict stock returns [6]. Niaki and Hoseinzade showed that the ANN was able to forecast the daily direction of Standard & Poor’s 500 index significantly better than the traditional logit model, and improved the trading profit as compared with the buy-and-hold strategy [7]. Dixon,

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Klabjan and Bang used deep neural networks (DNNs) to predict price fluctuations in commodity and foreign exchange futures [8].

In the current study, two representative domestic stocks, Guizhou Maotai and Wuliangye, are selected as research objects. A BP neural network model is constructed to predict Short-term fluctuation in stock price, explore the accuracy of prediction results and practicality of the model in the financial field, as well as provide new models and algorithms for dealing with complex mechanisms, multi-factor influence, high uncertainty, and nonlinear financial price prediction.

2. Data Processing

Based on the BP algorithm, the BP neural network model is constructed and used to derive Short-term predictions about the rise and fall of stock prices (the opening price of the T+1 versus the closing price of the T-day).

2.1. Sample Selection

The stock price-related indicators, including daily opening price, closing price, high price, low price, volume, and adjusted closing price, of Guizhou Maotai and Wuliangye from 2017 to 2019 are selected. Based on daily data, the relative strength index (RSI), Bollinger Line indicator (BB_Middle_Band, BB_Upper_Band, BB_Lower_Band), price trend indicator (PVT), and parabolic SAR (PSAR) are calculated. The function missing_value_table () is designed to count the sum of the missing values of each column of the two stocks obtained. Based on the stock data obtained, the stock price prediction index of the two stocks can be calculated, stock data can be visualized, Short-term trends can be predicted, and trading advice can be provided.

2.2. BP Model Data Pre-processing

1) Divide the dataset into two sets—the training and test sets—in a 7:3 scale. Training set data is used to train the model and complete the adjustment and optimization of the internal parameters of the model, whereas the test set is used to test predict the Short-term stock variation trend.

2) The input X of the model is set to High (Daily high), Low (Daily low), Open (Open), Close (Close), Volume (Volume), Adj_Close (closed price adjusted for legal entity behavior), RSI, BB_Middle_Band, PVT, and PSAR.

3) The forecast indicator Y of the model is the stock price up-down index, which is a series of 0 and 1. The opening price is selected on the day of each stock, and the closing price is selected on T-day, with a difference being derived between the opening price on the T+1 day of the stock and the closing price on T-day. If the difference is higher than 0, the value of T+1 will increase and the value of Y will be recorded as 1. If the difference is less than or equal to 0, the value of Y will fall on the day of T+1 and will, thus, be recorded as 0.

4) Process the original data with "Max-Min Normalization," that is, data is scaled to a target range of [0, 1].

5) The training set and test set comprise stock data in different periods for each of the two stocks, respectively. The training set is stock-related data of the first two years, on which the BP neural network model is based. The training set debugs the model through repeated calculation, error feed-forward, and parameter adjustments. The last year of the test set of stock data X is transferred to the well-trained model to predict the corresponding Y.

2.3. Study Model

Research using ANN often combines the BP algorithm with the gradient descent method to train the model. The basic principle is to calculate the minimum value of the error function by using the gradient descent method and using the error value reverse propagation to adjust

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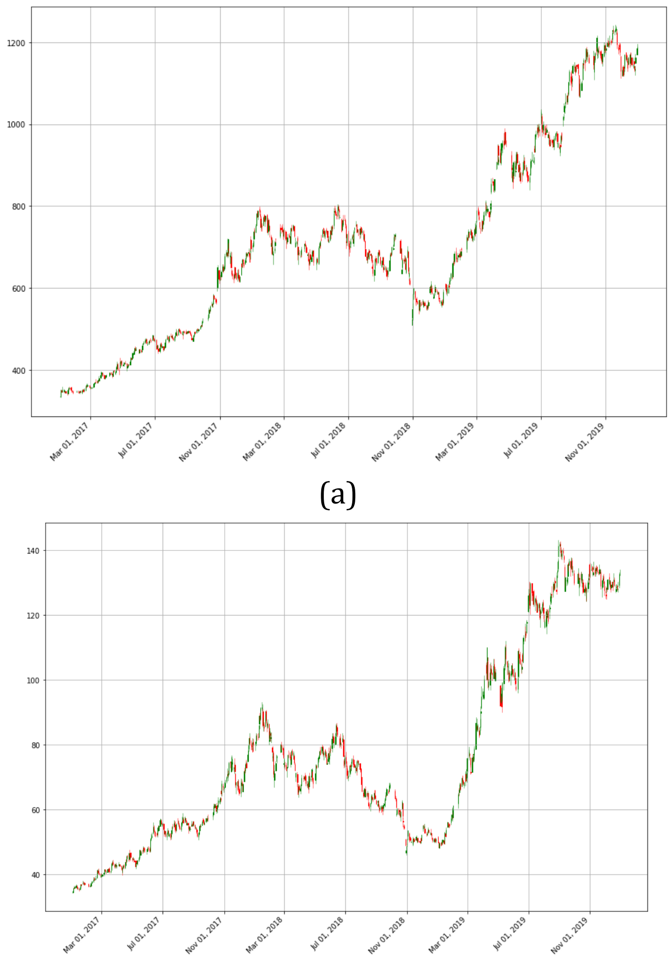
parameters and bias values. Based on the mathematical principle of BP neural network, a feed-forward neural network model is developed. Following this, the model training process occurs, wherein it is necessary to allow the model to learn the law in the data by continuously adjusting the weights and bias value of each node of the network.

After importing the training set data into the model, train the model, and adjust the internal parameters. The test set data is imported into the model with well-adjusted internal parameters and weights; thus, the model predicts the rise and fall of the stock price, and then it compares the model prediction results with the real data. The classification model is used to statistically calculate classification metrics displaying information, such as the accuracy, recall rate, and F1 value, for each class, and finally, to determine how well the model fits.

3. Visual Analysis

3.1. Stock Candle Chart

The "positive line," as marked in red, depicts the closing price of the day if it is higher than the opening price. On the contrary, the green "negative line" demonstrates the closing price when it becomes lower than the opening price. The minimum unit of the graph is one day; thus, the rise and fall of a stock are recorded on a daily basis. Through the continuous arrangement and consolidation of the stock price according to the time series, investors can derive the basic situation of the stock price in a certain period, and the movement pattern and color of the curve show different market conditions.



(b)

Figure 1. Candle charts of (a) Guizhou Maotai and (b) Wuliangye

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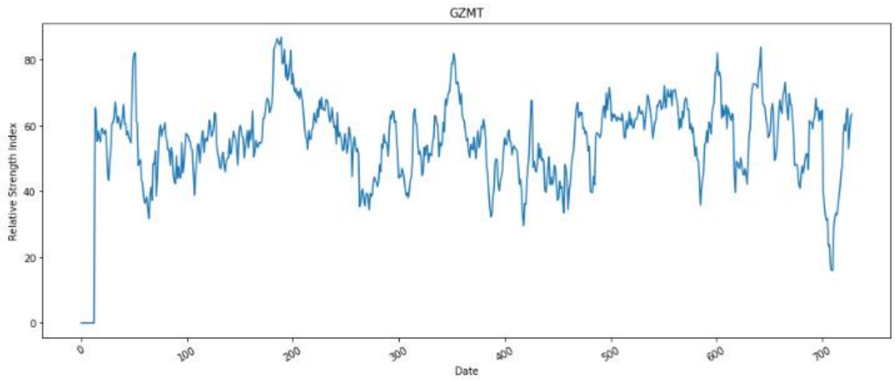
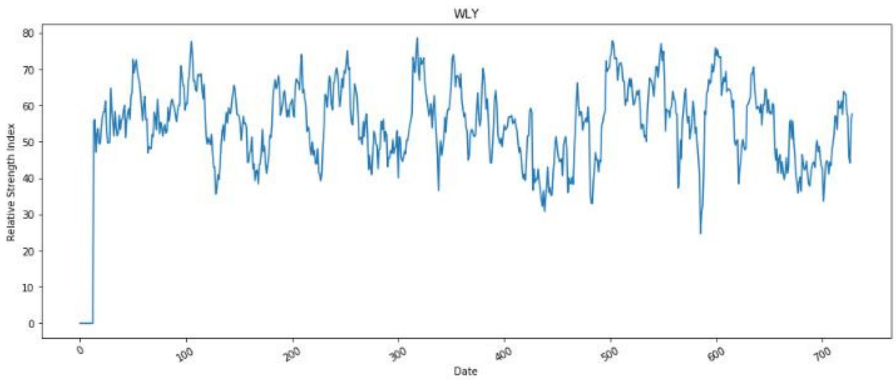
3.2. RSI Relative Strength Indicator

RSI calculation measures the magnitude of the stock price movement to infer the strength of the moving trend of the stock market (direction and timing) and derives a reading from 0 to 100. Based on mathematical statistical analysis, RSI is considered to vary between 30 and 70. When RSI values reach above 70, the market overbuys, and future market prices may fall. Moreover, if RSI values reach below 30, the market is determined to be oversold, and future market prices may rise.

The RSI of Guizhou Maotai and Wuliangye stocks are distributed within a reasonable range, and only a few points reach the condition of overbought or oversold. When investors find these breakout values, they can detect the buying and selling signals.



(a)



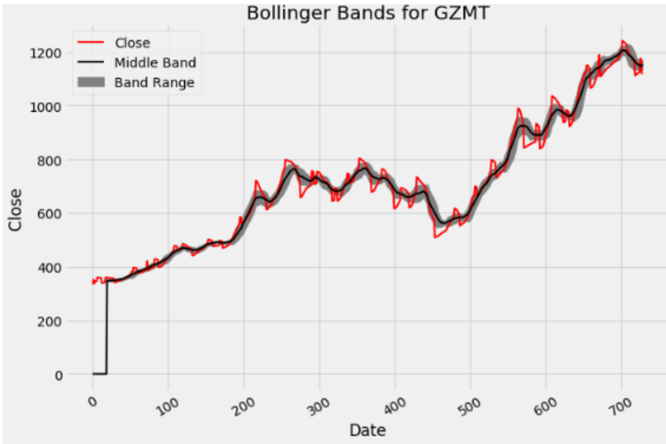
(b)

Figure 2. RSI visualization of (a) Guizhou Maotai and (b) Wuliangye

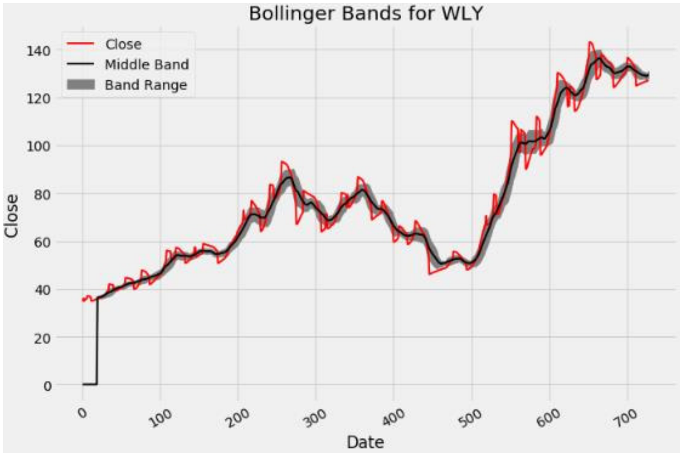
3.3. Bollinger Line Indicator

The share price channel is closely related to market volatility. When the stock price is stable, the stock price channel becomes narrow, and vice versa.

When the stock price volatility exceeds the channel upper track, it indicates that future stock price may fluctuate violently upward, and if the stock price fluctuation exceeds the channel lower track, it indicates that future stock price may move violently downwards. When all tracks go upward simultaneously, thereby indicating that stock prices will rise in the short term, investors should hold stocks or buy at lower prices. When the tracks decline simultaneously, thereby indicating a potential fall in the short term, investors should determine a good time to sell the stock.



(a)



(b)

Figure 3. Bollinger line of (a) Guizhou Maotai and (b) Wuliangye

When Guizhou Maotai stock time index is in the range of 500–600, the upper, middle, and lower lines rise simultaneously, the corresponding stock price is in the rising stage, and the Wuliangye Bollinger line is also identical during most of the period. Investors can observe the broad and narrow stock channels to determine the current stock market volatility and can predict the trend of stock prices as an investment reference by observing the movement of the track.

The visual analysis results of the above indicators show that these technical analysis indicators have certain credibility in trend and volatility prediction. However, the prediction accuracy of the above indicators is generally low and limited to qualitative analysis; thus, investors require a more accurate and reliable model as the core support of trading decisions.

4. Predictive Model Results

4.1. Stock Price Movement Forecast

The training set data of the two stocks are transferred into the model, which is trained according to the established algorithm. The internal parameters are adjusted, and the number of hidden neurons m is set by the press, as in:

$$m = \sqrt{n + l} + a \tag{1}$$

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where n is the number of input layer nodes, l is the number of output layer nodes, and a is a constant within [0, 10].

[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1,
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Figure 4. Stock movement prediction of Guizhou Maotai

[1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1,
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1, 1, 0, 1, 1, 1, 0, 0]

Figure 5. Stock movement prediction of Wuliangye

After many trials and debugs, the accuracy of the model is improved, with m eventually set to 7. The test set is input into the trained model, and the stock moving direction is forecasted. Moreover, the prediction error is calculated through comparisons with the real data.

4.2. Model Accuracy Analysis

The model accuracy analysis is conducted by using the classification valuation model. The fitting effect of the model is determined based on accuracy, recall rate, and F1 value.

Table 1. Prediction results of Guizhou Maotai

	Precision	*Recall*	*f1-score*	*Support*
0	0.64	0.68	0.66	142
1	0.69	0.81	0.75	284
avg / total	0.65	0.71	0.68	426

Table 2. Prediction results of Wuliangye

	Precision	*Recall*	*f1-score*	*Support*
0	0.66	0.71	0.68	175
1	0.72	0.82	0.77	251
avg / total	0.67	0.72	0.69	426

The results show that the prediction accuracy of BP neural network for both stocks is higher than 60% and the recall rate is higher than 65%. When predicting the moving direction of Wuliangye, the model's prediction accuracy for 1 (up) reaches 72%, and the recall rate for 1 (up) reaches 82%. When using BP neural network to predict the moving direction of Guizhou Maotai, the model's prediction accuracy for 1 (up) reaches 69%, and the recall rate for 1 (up) reaches 81%. The model's prediction accuracy for 1 (up) is higher than the accuracy of 0 (down) prediction. This can be explained using the richer data of 1 (up) in the original data set, which offers better fitting in the model prediction. Therefore, when using the model to predict the Short-term moving direction of the stock price, the forecast of an upward trend is increasingly valuable.

5. Conclusion

The stock price indicators of Guizhou Maotai and Wuliangye stocks from 2017 to 2019 are selected in this study. Moreover, the RSI, BB line indicator, PVT, and PSAR indicators of each stock are calculated, the BP neural network model is trained, and the Short-term price moving directions are forecasted. The study results are as follows:

1) Investors can draw the corresponding graphs based on the stock price forecast index and derive simple Short-term predictions of stock price trends by visualizing the index.

2) Based on BP neural networks to predict the rise and fall of Guizhou Mao and Tai Wuliang's share price, the accuracy of the model prediction is higher than 60%, and reaches up to 72%, and the recall rate of the model is higher than 65%, and reaches up to 82%. Overall, the BP neural network has improved predictive accuracy. Moreover, the model provides improved predictions with index 1, and the results are more valuable as reference.

In future studies, algorithms and data can be further processed and adjusted: (1) Adjust and optimize the model with gradient cropping and use activation functions, such as ReLU and LeakReLU, and short- and long-term memory networks. (2) To address overfitting problems, regularize the parameters, add the batch normalization layer, and apply random hidden neurons and other methods to adjust and optimize the model.

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