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Gold Price Prediction based on LSTM Prediction Model

Liyan Pan, Yue Dong

Anhui University of Finance and Economics, Bengbu 233000, China

Abstract

As an important investment and trading asset, it is important to accurately predict the price of gold.This paper investigates gold price forecasting using LSTM models and BP neural network models, and compares their forecasting performance. First, we collected time series data of historical gold prices and performed pre-processing and feature engineering. Then, we built an LSTM model and a BP neural network model, and trained and optimized them respectively. By comparing the prediction results of the LSTM model and the BP neural network model, we found that the LSTM model exhibited better performance in gold price prediction. Specifically, the mean square error (MSE) and mean absolute error (MAE) of the LSTM model are smaller than those of the BP neural network model, indicating that the LSTM model is able to capture the time series patterns and trends of gold prices more accurately. After further analysis, it was shown that the LSTM model was able to better handle the long-term dependence in the time series data through its internal memory unit and gating mechanism, thus improving the accuracy of the forecasts. In contrast, the BP neural network model is susceptible to problems such as gradient disappearance or gradient explosion when dealing with time series data, resulting in larger errors in the prediction results. In summary, this study demonstrates the superiority of the LSTM model in gold price forecasting. the LSTM model is not only able to better capture the characteristics of time series data, but also provides more accurate forecasting results. This has important practical applications for financial market participants and can help them make more informed decisions.

Keywords

LSTM Model; BP Neural Network Model; Gold Price Forecasting; Time Series Analysis; Mean Square Error; Mean Absolute Error; Forecasting Accuracy.

1. Introduction

Gold has been regarded as a symbol of wealth since ancient times, nowadays gold still occupies a very important position in the international monetary and financial system, during the period of gold standard system, gold is the representative of a country's economic strength, the more gold indicates the stronger purchasing power and strength. After the "Jamaica Agreement" came into effect in 1978, gold was abolished as the world's currency, but it does not mean that the monetary function of gold in real life has disappeared. Today, the charm of gold is still reflected in its monetary functions, in the modern financial system still plays a huge role, especially in the protection of national economic security role can not be ignored.

However, the price of gold is a kind of time series data which is influenced by many factors, very unstable and difficult to predict retrospectively. How to use models to accurately predict the price of gold and determine the buying strategy has been a problem for people. On the one hand, the price of gold is difficult to predict accurately due to many uncertainties, and on the other hand, the purchase of gold is limited by the principal amount traded, making it difficult to obtain maximum returns. If classical time series models are used for forecasting, the non-linear factors in gold price information may not be extracted. However, with the continuous development of information technology, the theory and practice related to machine learning have been gradually improved, and many models using machine learning methods to forecast gold prices have emerged, such as BP neural network models, which make up for the drawback that the traditional time series models cannot fully extract the information of the nonlinear row part, but there are still limitations for dealing with the time series correlation between gold price data. The prediction model used in this paper is the long short-term memory neural network (LSTM), which can better solve the time series correlation of gold price data in BP neural network model and make the prediction results more accurate. In this paper, we use LSTM model to predict gold price and compare it with BP neural network to highlight the advantages of LSTM model when predicting price.

2. Model Building

2.1. BP Neural Network Model.

The BP neural network algorithm is an error back-propagation algorithm used to train multilayer feedforward neural networks. It continuously modifies the threshold value of each neuron and the weight of the connection by the error obtained from each training until the error is minimized, and then stops training.

Given the input variables $X=(x_1,x_2,\cdots,x_n)^T$, the results of the BP neural network algorithm can be obtained by the following equation:

$$net_{ij}=\sum_{k=1}^{N_i=1} O_{(i-1)k}\cdot W_{(i-1)kj}$$

$$O_{ij}=f_s(net_{ij})$$

In the above equation, net_{ij} is the input of the corresponding neuron, O_{ij} is the output of the corresponding neuron, and W_{ijk} is the weight of the corresponding connection.

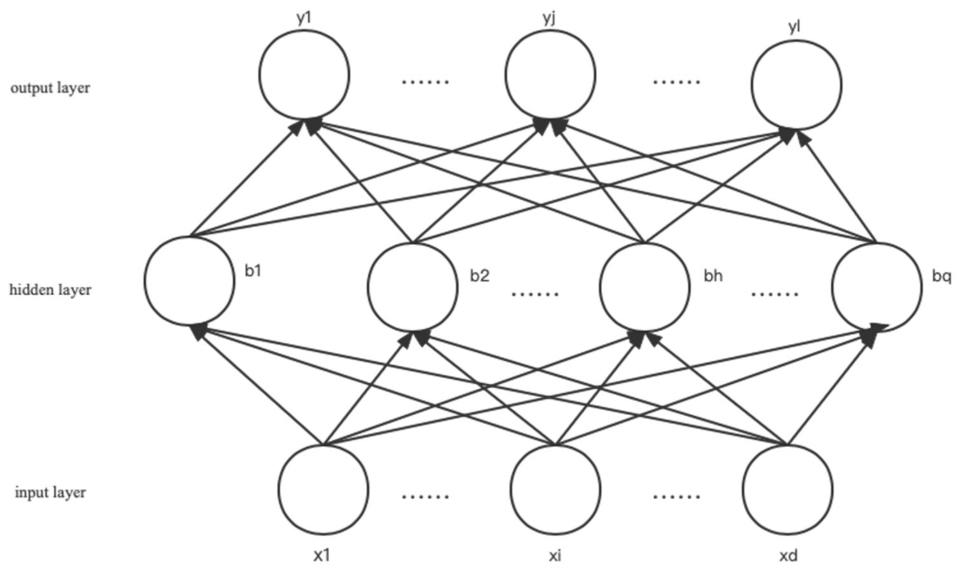

Figure 1. bp neural network model diagram

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2.2. Long Short-term Memory Neural Network Model

Long-Short Term Memory (LSTM) is a temporal recurrent temporal network model, which is proposed to solve the general recurrent temporal network model gradient dispersion. In general, LSTM model is a feedback neural network model, in which the feedback loop can feed the output signal of neurons to other neurons, and the LSTM model can predict the data in the future time by learning the relevant features of the data in the past period.

2.2.1. LSTM Model Building

The LSTM model has three internal gate structures, namely, forgetting gate f_t, input gate i_t and output gate o_t. The LSTM model selects or removes messages through these three gates, and the proportion of passed messages is controlled by the sigmoid function σ on each gate, which ranges from [0,1], and the function value of 0 means that all messages are not passed, where the expressions of the three gate structures are:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f$$
$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$
$$o_t = \sigma(W_0[h_{t-1}, x_t] + b_0)$$

Where W is the corresponding link weight and b is the corresponding bias. the LSTM model can calculate the cell state update value $\tilde{C}_t$, by combining the forgetting gate and the input gate to calculate the cell state C_t, based on the output in the previous period with the output at the current moment, calculated as:

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c)$$
$$C_t = fC_{t-1} + i_t\tilde{C}_t$$
$$\tanh(x) = (e^x - e^{-x}) / (e^x + e^{-x})$$

At this point, the calculated cell states are multiplied with the output gate results to obtain the stock price prediction, i.e:

$$h_t = o_t \cdot \tanh(C_t)$$

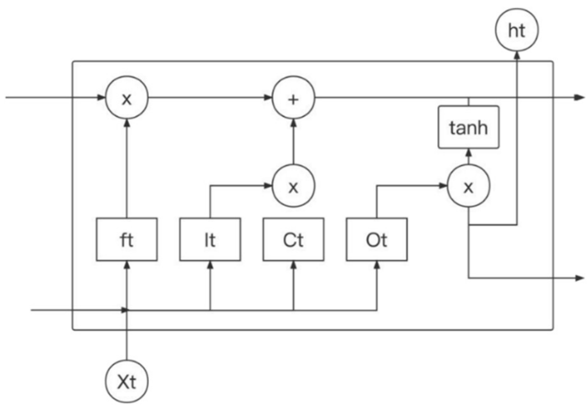

Figure 2. LSTM model diagram

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3. Empirical Analysis

3.1. Dataset Source and Pre-Processing

In this paper, we download the price data of gold from September 12, 2016 to September 10, 2021 with 1226 data from the gold trading platform.

Before conducting the experiment, the data are pre-processed. In this experiment, we divided the training set and test set according to the ratio of 7:3. After data input, we processed the data for missing values and outliers. Since there were no outliers and missing values in the dataset, there was no need for missing value and outlier processing. Next, we normalize the data set to eliminate the magnitude of the data and to make the model more accurate, and the normalization formula is as follows:

$$x_i' = \frac{x_i - \bar{x}}{\max(x) - \min(x)}$$

In the above equation, x_i denotes the price of gold in the ith period, $\bar{x}$ denotes the average price of gold in all periods, max(x) denotes the maximum price of gold, and min(x) denotes the minimum price of gold.

To evaluate the accuracy and error of the model, we use the mean square error (MSE) and MAE (absolute mean error) as metrics to evaluate the model.

where MSE is the sum of squares of the differences between the predicted and true values divided by the sample size n. Let the i-th true value be Y_i and the model predicted value be $\hat{Y}_i$, the MSE is calculated as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

where MAE is the absolute mean error, which is the average of the absolute errors and is the average of the absolute values of the deviations of all individual observations from the arithmetic mean. The mean absolute error avoids the problem of errors canceling each other out and thus accurately reflects the magnitude of the actual prediction error.MAE is calculated as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right|$$

3.2. Experimental Procedure

The main procedure of this experiment is as follows:

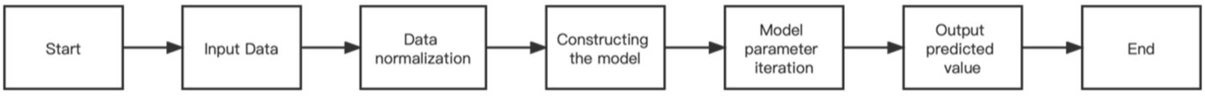

Figure 3. Experimental flow chart

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3.3. Experimental Results and Analysis

The data predicted by the BP neural network model and the LSTM neural network model were put together and compared to obtain the following figure:

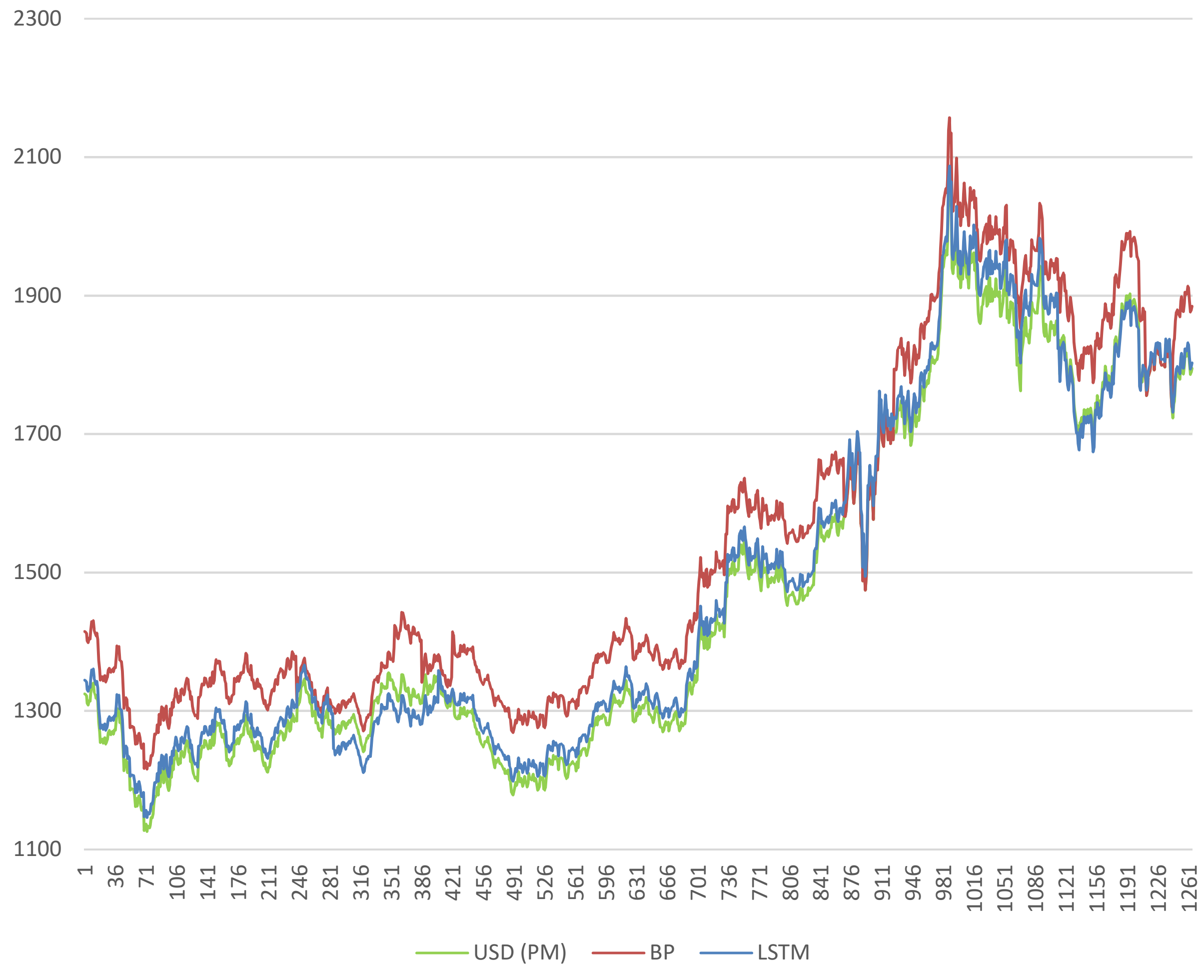

Figure 4. prediction results of bp neural network and lstm model

As can be seen from the figure, the trend of gold price predicted by the BP neural network model is generally correct but there are obvious deviations, as opposed to the LSTM model which not only has the same trend but also has higher accuracy compared to the BP neural network model. Therefore, it can be concluded that the LSTM model is better than the BP neural network model in predicting the gold price.

Table 1. Prediction error table

Models	MSE	MAE	Study time	Accuracy
BP Neural Network	23.7891	3.7946	11s	0.8917
LSTM neural network	3.1562	0.9485	76s	0.9532

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Again, the table shows that the MSE and MAE predicted by the LSTM neural network model are smaller than the BP neural network model, indicating that the LSTM neural network model predicts more accurately and better.

4. Conclusion

Based on the experimental results, it can be concluded that the LSTM model outperforms the BP neural network model in predicting gold prices. The BP neural network model showed a general alignment with the price trends but exhibited noticeable deviations. In contrast, the LSTM model not only captured the trend accurately but also achieved higher prediction accuracy.

The comparison of MSE and MAE metrics between the LSTM and BP neural network models further supported the superiority of the LSTM model. The LSTM model demonstrated smaller error values, indicating its higher precision and better performance in gold price prediction.

The findings suggest that the LSTM model provides a more effective approach for accurately forecasting gold prices compared to the BP neural network model. This has significant implications for investors and financial institutions, as it offers a valuable tool for predicting price trends and fluctuations in the financial market.

The success of the LSTM model can be attributed to its ability to capture long-term dependencies and temporal patterns through its recurrent structure. Unlike the BP neural network model, which lacks memory of past information, the LSTM model can retain relevant historical data and utilize it for improved predictions. This characteristic makes the LSTM model well-suited for time series forecasting tasks like gold price prediction.

However, it is important to acknowledge the limitations of the study. The results may be influenced by factors such as the specific dataset used, the chosen model architecture, and the parameter settings. Future research should consider exploring alternative data sources, incorporating additional features, and conducting further model optimization for more robust and generalizable results.

In conclusion, the experimental findings support the conclusion that the LSTM model is superior to the BP neural network model in predicting gold prices. This research contributes to the understanding of utilizing deep learning models in financial forecasting and provides valuable insights for both academia and industry. By incorporating LSTM models into decision-making processes, stakeholders can make more informed investment decisions and improve their risk management strategies in the gold market.

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