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Predict the Price Change over Time with LSTM Neural Network

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Abstract: *Time series analysis can be used to analyze the price. The LSTM Neural Network model is used to predict the price. Moreover, the correlation analysis between variables and price is conducted. By improving and optimizing the mathematical model, the RMSE values of LSTM (Long Short Term Memory) with a single function of weight price are 8.719 and 13.759, and the RESM values of prediction results are larger than those of other models, so the accuracy of prediction results is higher.*

Keywords: *LSTM; Neural Network; Time series*

1. Introduction

Market transactions frequently buy and sell volatile assets to maximize profits. According to the characteristics of the prices, time series analysis can be considered to predict the future of each day, and then establish a decision model after prediction, and by establishing a suitable objective function, the optimal solution is obtained under constraint conditions, and different model methods are compared horizontally.

2. LSTM Neural Network

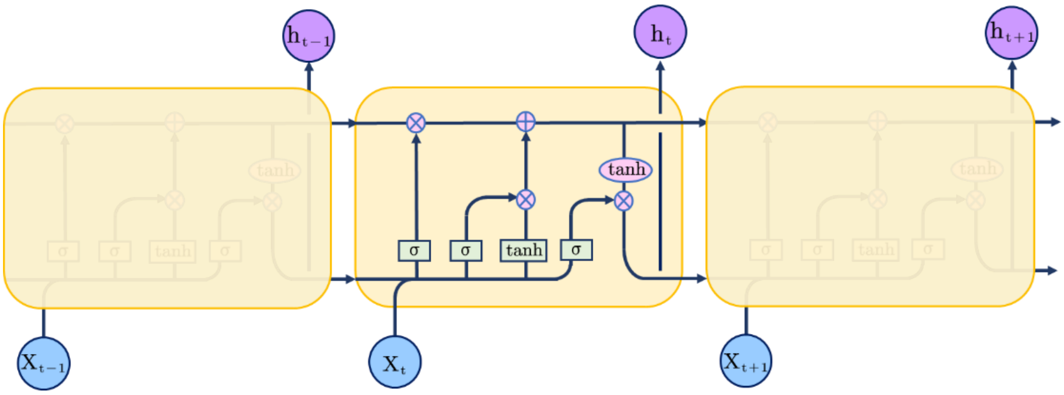

Figure 1: Schematic of the LSTM

LSTM (Long Short Term Memory) is essentially a specific form of recurrent neural network that improves the problem of the RNN-related vanishing gradient by increasing the threshold based on the RNN model. This enables recurrent neural networks to truly make effective use of long-distance timing information. In addition to the RNN infrastructure, LSTM adds three logic control units, Input Gate, Output Gate, and Forget Gate, and each is connected to a multiplicative element (see Figure 1), Control the inputs, outputs, and state of the Memory cell by setting the weights at the edges of the neural network's memory unit connected to other parts.

LSTM neural network systems not only maintain a spontaneous way adjacent to time information to control long term information, that is, but LSTMs can also retain previous information, which can greatly improve its ability to learn signal sequences and inherent nonlinear patterns, and its main innovation is the introduction of the concept of "Gate".

- Input Gate: Controls whether the flow of information flows into the Memory cell, noted as i_t.

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$$i_t = sigmoid\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{1}$$

- Output Gate: Controls whether the information in the Memory cell flows into the current hidden state, denoted as o_t.

$$o_t = sigmoid\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{2}$$

- Forget Gate: Controls whether the information in the Previous Moment Memory cell accumulates in the Memory cell at the current moment, and is recorded as f_t.

$$f_t = sigmoid\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{3}$$

- Cell: A memory unit that represents the state of a neuron in memory, such that the LSTM cell can save, read, reset, and update long-distance historical information, as C_t.

Two types of memory:

Long memory:

$$C_t = f_t \times C_{t-1} + i_t \times \widetilde{C}_t,\ \widetilde{C}_t = tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \tag{4}$$

Short Memory:

$$h_t = o_t \times tanh\left(C_t\right) \tag{5}$$

In addition to the i_t, f_t, o_t recursive connection C_t weights mentioned above, w^*, which represent their corresponding thresholds, sigmoid and tanh are two activation functions. With this brought in the data, the historical sequence is processed as the output of LSTM used to extract hidden information, while the predicted values are considered the target output.

This data analysis will use the transaction data, using a simple LSTM model to make predictions, and each prediction will only use the data of the day and before for training while looking for variables that may be highly correlated. The forecast was repeated continuously, focusing on the true value of the transaction data in the five years and the forecast value, and the method of the previous day was adopted to compare the data of the real feedback and the predicted feedback, and the LSTM was explored.

Since the number of sample observations that can be used is limited, finally by using the RMSE metric, RMSE is given by the following formula:

$$RMSE = \sqrt{N^{-1} \sum_{t=1}^{N} \left(X_t - \bar{X}_t\right)^2} \tag{6}$$

Where N is the number of observations used for testing, X_t is the truth value, $\bar{X}_t$ is the predicted value, and t is the time script. Several rounds were obtained by experimental regression, and the RMSEs of LSTM with a single function of weighted price were 8.719 and 13.759.

Table 1: Prediction results

Type	Gold			Bitcoin		
Data	Average	Min	Max	Average	Min	Max
SR-Square	0.091	0.091	0.091	0.025	0.025	0.025
R-Square	0.905	0.905	0.905	0.997	0.997	0.997
RMSE	8.719	8.719	8.719	13.759	13.759	13.759
MAP	0.505	0.505	0.505	0.609	0.609	0.609
Max APE	2.113	2.113	2.113	5.174	5.174	5.174
MAE	6.516	6.516	6.516	9.22	9.22	9.22
Max AE	27.112	27.112	27.112	97.947	97.947	97.947
BIC	4.42	4.42	4.42	5.266	5.266	5.266

Plot heat maps and observes the correlation of variables with the average price of gold in Bitcoin. It can be seen from Table 2 that the volume is related to the average price of Bitcoin. Open, High, Low, Close are directly related to the Bitcoin average price (Weighted Price).

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Table 2: The variables that affect the price of bitcoin and gold

	Open	High	Low	Close	BTC	Volume	Weighted Price
Open	1	1	1	1	0.72	0.86	1
High	1	1	1	1	0.74	0.87	1
Low	1	1	1	1	0.71	0.85	1
Close	1	1	1	1	0.73	0.86	1
BTC	0.72	0.74	0.71	0.73	1	0.9	0.72
Volume	0.86	0.87	0.85	0.86	0.9	1	0.86
Weighted Price	1	1	1	1	0.72	0.86	1

The data is pre-processed first, splitting the dataset into 70% of the data for training, and another 30% of the data for testing, as shown in Figure 2 and Figure 3.

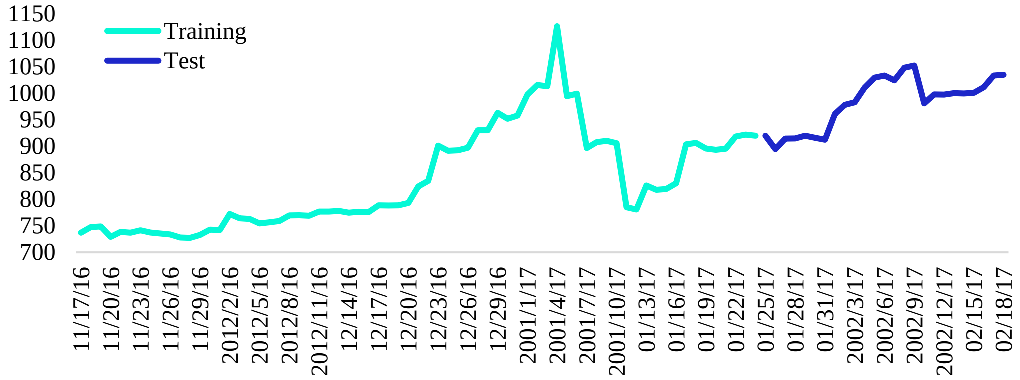

Figure 2: Gold train and test

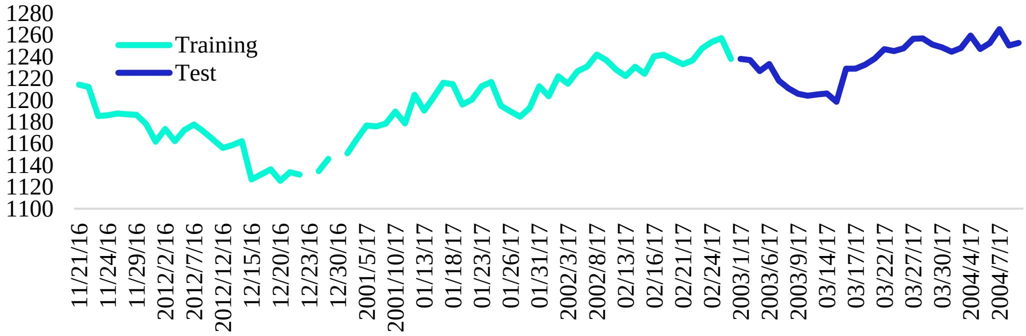

Figure 3: Bitcoin train and test

3. Conclusion

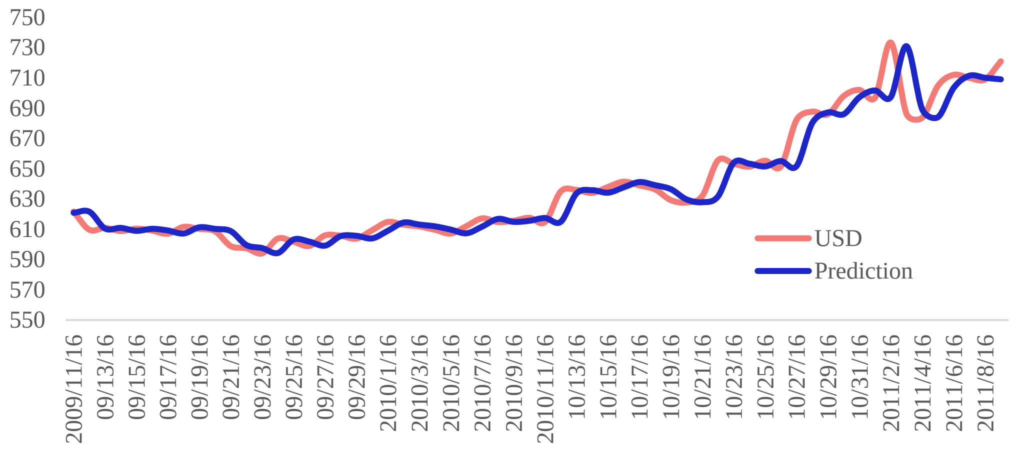

Figure 4: Gold Forecast

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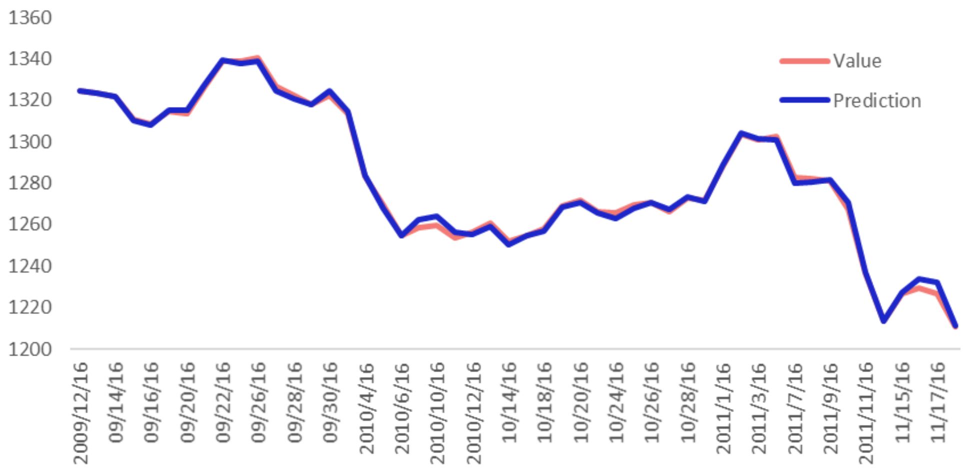

Figure 5: Bitcoin Forecast

Regard the data as a window, and each window normalizes the data, using a simple neural network. With each day as the X-axis and USD as the Y-axis, the predicted value correlation is shown in Figure 4 and Figure 5. The experiment obtained MAE are 6.516 and 9.22, preliminarily observed the line chart of the predicted value and true value of the LSTM model, and found that the degree of similarity was very high.

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