

Analysis of gold and bitcoin price prediction based on LSTM model

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Abstract: As a new investment method, quantitative investment is expanding its market scale and share due to its stable investment performance. In this paper we propose a prediction model based on LSTM. It is helpful for the traders to predict the future price to formulate the best trading strategy. Using this model, we can precisely forecast each price separately to determine when the asset should be traded based on future price fluctuations. Simulation results show that our model can successfully predict the future price trend of the two assets within the acceptable range of error, which helps us to better optimize our portfolio. In addition, the RMSE (root mean square error) is selected as the loss function to describe the accuracy of our prediction model.

Keywords: Trading Strategy; Long Short Term Memory(LSTM); Deep Learning

1. Introduction

Traders in the investment market allocate assets with the goal of maximizing total return. At present, traders can invest in two assets, Gold and Bitcoin. Gold, as a general equivalent, is a regular customer in asset allocation. The rise of virtual currency provides traders with new investment channels. Bitcoin is a cryptocurrency based on decentralization, adopting point-to-point network and consensus initiative, opening the source code and taking blockchain as the underlying technology. From the initial unpopularity to world recognition, Bitcoin not only brings high returns, but also high risks[1].

Quantitative trading strategies can contribute to investors by reducing the risk more effectively and maximizing their own interests.[2]Quantitative investment refers to replacing artificial subjective judgment with advanced mathematical models, and using computer technology to select a variety of "high probability" events that can bring excess returns from huge historical data to formulate strategies, which greatly reduces the impact of investor sentiment fluctuations and avoids making irrational investment decisions in the case of extreme fanaticism or pessimism in the market. As a new investment method, quantitative investment is expanding its market scale and share due to its stable investment performance. The model of quantitative investment is shown in Table 1. Trading strategy is the core issue in quantitative investment. There are many kinds of quantitative models used in formulating trading strategies. Whether an investment is successful or not and its effect are largely determined by the trading strategy. A key issue when formulating a trading strategy is the asset price prediction

Table 1 : The Model of Quantitative Investment

Model	Release time	Feature
Aberration trading	1993	Long term Large amount of transaction fund
Andromeda trading	2002	Long term Completely objective trading
R-breaker trading	1993	Intraday No more than two transaction per day

There are three conventional approaches for assets price prediction: technical analysis traditional time series forecasting, and machine learning method[3].Recently, the deep learning (DL) technique has been applied for Financial Market, because of its nonlinear mapping ability, good self-learning and adaptive performance, which can predict the future assets price from learning the rule at the training stage. Thus no determinant price evaluation rule is required to be known.In [4] use an artificial neural network (ANN) to find the best time of the investment. ANN has strong nonlinear approximation ability .Due to the temporal nature of the more advanced algorithms, the LSTM are favored over the traditional

multilayer perceptron (MLP) [5] Therefore, in this paper we construct a LSTM network to predict the bitcoin and the gold price to further assist in the formulation of trading strategies.

Briefly, In this paper, we propose a prediction model based on LSTM, which is helpful for the traders to predict the future price to formulate the best trading strategy. The main contributions of this paper include:

Firstly, we calculate the median price before and after missing price to supply the missing price information. Secondly, we construct a LSTM network that predicts future price trend of the assets gold and bitcoin. Then, we use metrics RMSE (root mean square error) as the loss function to describe the accuracy of the predictive model. Finally, we utilize the US daily gold and bitcoin price in recent years as the dataset for the LSTM model to predict the price.

2. Model Construction

2.1 Data Preprocessing

According to the recent price information of bitcoin and gold, we preprocess the data and carry out the corresponding visualization processing.

For the missing gold price date, we use python's pandas library to complete the missing Date. And for the missing price information, we calculate the median price before and after missing price to supply the missing price information. The data processed is shown in figure 1.

For the given gold and Bitcoin data, we divide the training set and test set in a 3:1 ratio, using the US daily gold settlement price for a total of 1370 days from September 16, 2016 to June 20, 2020. Carry out training, and finally use the data given in the question from June 21, 2020 to September 10, 2021 as the testing data set for verification.

Prices have different dimensions and dimensional units, which will affect the results of data analysis. In order to eliminate the dimensional influence between prices, data standardization processing is required to solve the comparability between data. Then, for the prices of gold and Bitcoin, subtract their mean and divide by the variance to make it follow a distribution with a mean of 0 and a variance of 1.

$$\text{Price} = \frac{X - \mu}{\sigma} \tag{1}$$

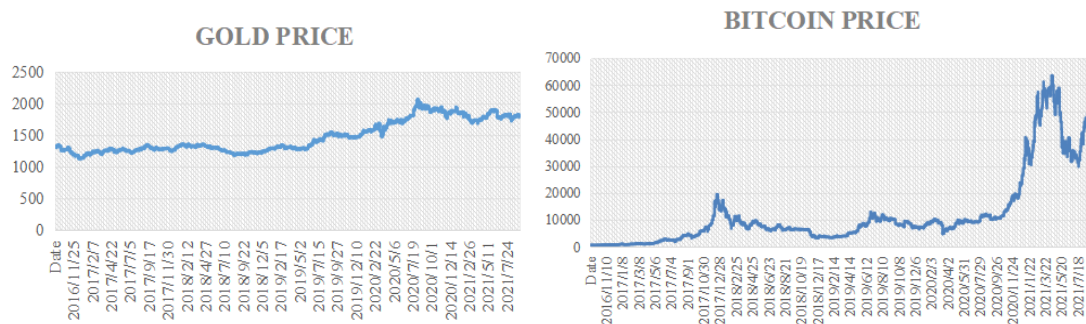


Figure 1: Gold and Bitcoin price

2.2 The construction of the LSTM network

RNN and LSTM

A recurrent neural network (RNN) model is a deep learning model with memory.

Figure 1 shows the time series expansion model of RNN. Therefore, the RNN model has a chained form of repeating neural network modules, so that the output is affected by the previous data at any time, and the historical information can be remembered and the current output can be calculated.

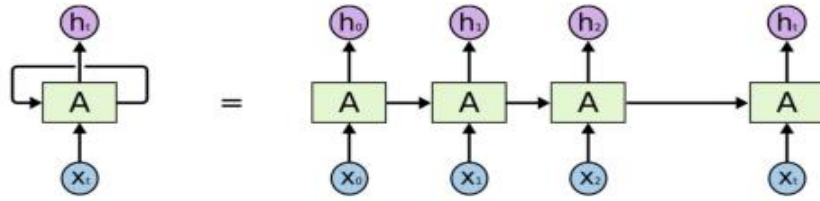


Figure 1: Process of RNN

Long-Short Term Memory (LSTM) is an extension of RNN that can learn long-term dependencies in the sequence. The basic unit is composed of the input gate, forget gate, and output gate, and specific process is shown as Figure 2.

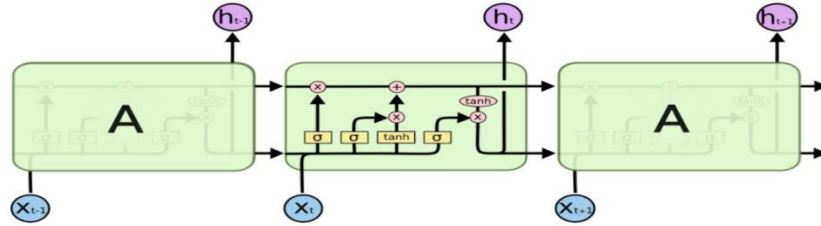


Figure 2: Process of LSTM

Loss function and optimizer

The loss function is used to estimate the network model function of the degree of inconsistency between the predicted value \tilde{Y} , of the type and the true value Y . It is a non-negative real-valued function, usually denoted by $L(\tilde{Y}, Y)$. The smaller the loss function is, the better the robustness of the model. The mark is to predict the future closing price of non-ferrous metal futures. The mean square error (MSE) of back propagation is the loss function, which is essentially RMSprop with a momentum term, which dynamically adjust each moment using the first and second moment estimates of the gradient learning rate of the parameters.

$$MSE = \frac{\sum_{i=1}^N (\tilde{Y} - Y)^2}{N} \quad (2)$$

In terms of selecting the optimizer, this paper selects the Adam optimizer adaptive moment estimation (Adaptive moment estimation) for optimization training. The main advantage of Adam is that after bias correction, the learning rate of each iteration has a certain range, which makes the parameters relatively stable. Take Bitcoin and Gold as examples, set the learning rate to 0.001, it can be seen that if the number of iterations is 150. As is shown below Figure 3, the network is relatively stable.

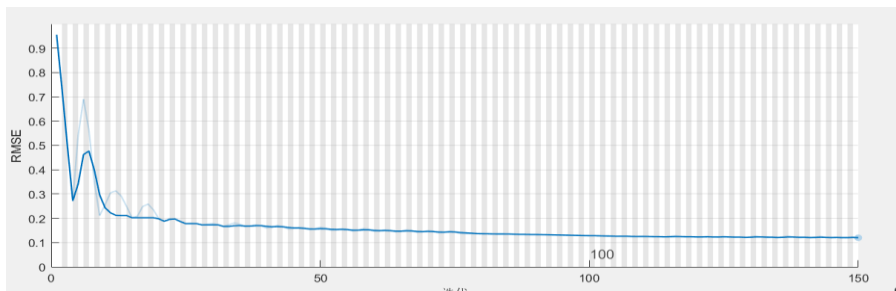


Figure 3: RMSE

Sliding Window

The data used in the LSTM neural network should be the time series features of the time series data to be extracted. Setting the window length to 30 days and the rolling window length to 1 day. The forecast period is set to 3 days which means that we will predict the price 3 days later by looking at the data of the previous 30 days based on the current time point of each day. The figure 5 of the sliding window is shown below which is from “Hands-on TensorFlow Multivariate Time Series Sequence to Sequence Predictions with LSTM”

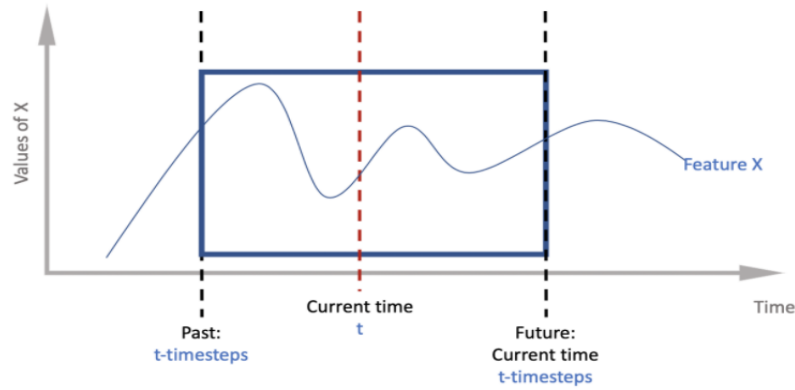


Figure 4: Sliding Windows

Network Structure

For LSTM model, the main experimental parameters of forecast models are shown in Table 2. The model uses historical data for the first 1370 days to predict sales for the remaining days. The daily forecast uses historical data from the pass three days to forecast sales in the next day.

Table 2: Experimental Parameters

Parameters	Description	Unit
epochs	The number of iteration which is optimized for training	150
Gradient Threshold	The maximum number if the Gradient	0.05
Input Nodes	The dimension of the input vector	1
Output Nodes	The dimension of the input vector	1
Layers	The description of the network depths	3
Neurons	The basic component of the networks	288

3. Simulation analysis

We apply the LSTM model to predict the price of the gold and the Bitcoin in our testing data set, the results are shown as follows:

3.1 For the Bitcoin

The Forecast Bitcoin Price is shown in Figure 5 and the difference between the actual price and the predicted price is shown in Figure 6. Obviously, our predicted bitcoin price is not very different from the actual bitcoin price.

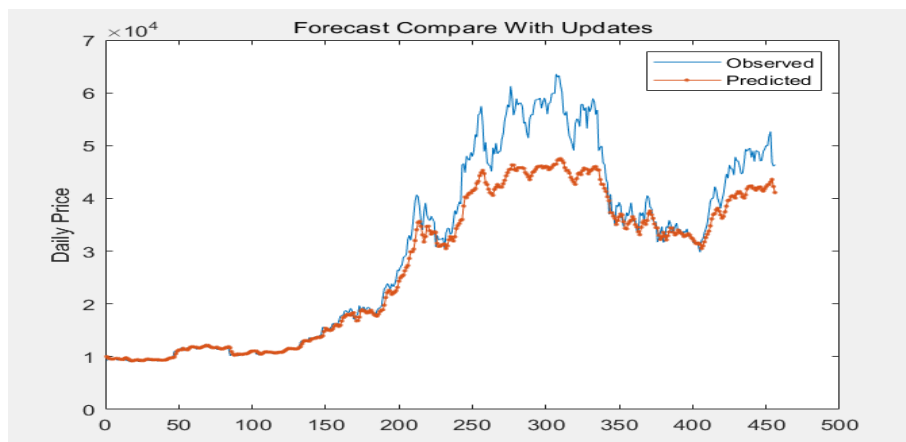


Figure 5: Forecast Bitcoin Price

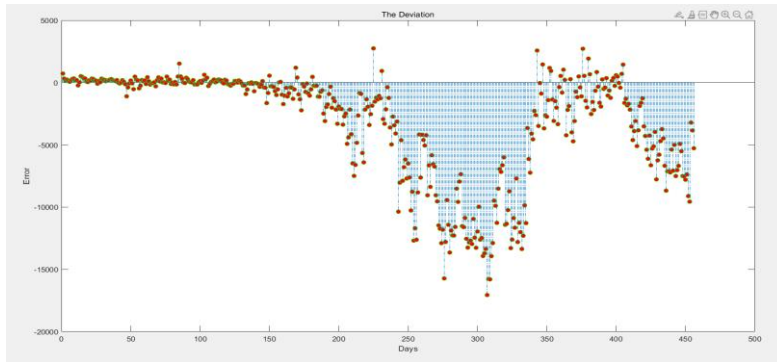


Figure 6: The difference between the actual price and the predicted price

3.2 For the Gold

Forecast gold price and the difference between the actual price and the predicted price are shown as Figure 7 and Figure 8. Obviously, our predicted gold price is not very different from the actual gold price. What's more, better predictions for gold than Bitcoin. That's because gold price is more stable.

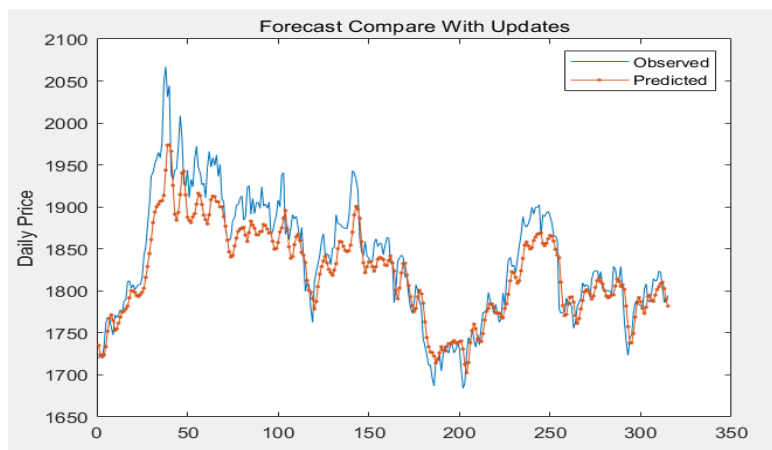


Figure 7: Forecast Gold Price

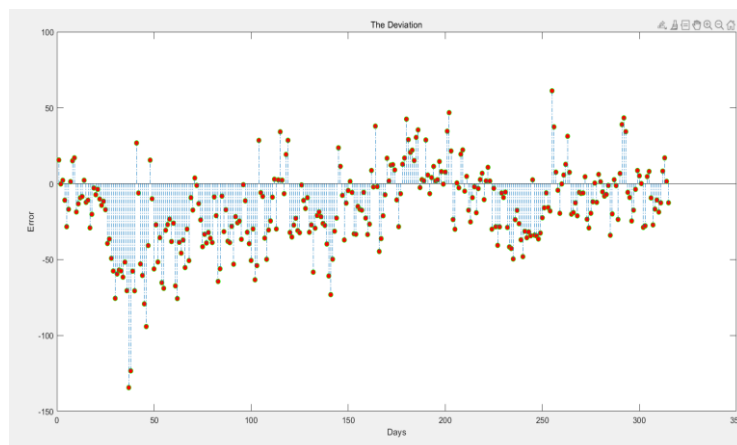


Figure 8: The difference between the actual price and the predicted price

4. Conclusion

In this paper, we establish a prediction model based on LSTM. We supply missing values through data processing, and divide the data into training set and testing set. In the process of constructing the prediction model, we train LSTM through training set, and apply the testing set to the model to obtain the prediction results. Through this model, we can predict the asset price movements over a period of

time. It has obvious advantages in sequence modeling. LSTM has the function of long and short memory, using software and toolkit can greatly reduce the difficulty of implementation. The problems of gradient disappearance and gradient explosion in long sequence training are solved. LSTM can handle sequences of up to hundreds of orders of magnitude, but still has little advantage in handling sequences of higher orders. Large amount of information processing and time-consuming calculation. There are multiple full connection layers (MLPS) in each LSTM cell.

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