Provide Bitcoin's daily optimal trading strategy based on LSTM

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Abstract. The purpose of this report is to develop a model that gives the best daily trading strategy based only on the price data before the day. We want to provide traders with strategies that will enable them to maximize their returns.we first utilize the LSTM time series neural network model using the first 956 data sets are used for training , and the subsequent 300 test sets are used to evaluate the model accuracy, calculate the prediction error and word comparison plots, and assess the difference between the prediction performance of the model and the actual value,This method has a better credibility. Finally, based on this model, we construct the optimal trading strategy model with the maximum value of total assets held as the objective function, add constraints, and finally arrive at an investment value of $1000.

Keywords: optimal trading strategy model; LSTM; BP; investment risk model.

1. Introduction

With the increase of per capital disposable income, people's financial awareness is growing, and market traders often trade volatile assets to achieve the goal of maximizing total return, and how to achieve this goal has been a key concern for people from all walks of life. As the application of advanced mathematical theories and financial ideas has become more sophisticated, people have gradually diversified their single trading capital, until now, the two main assets are gold and bitcoin.

According to statistics, 90% of day traders lose 90% of their capital within the first 90 days of trading; 40% of traders will blow up their positions in less than 1 month, and only 13% will survive after 3 years. As you can see, maximizing profit is not simple to achieve. Therefore, it is essential for market traders, as the master of futures trading, to have a considerable strategy for analyzing price fluctuations, buying and selling assets, and trading on a daily basis in order to make it possible to maximize short-term profits. Therefore, it is particularly important to determine the trading strategy to buy, hold or sell the trader's assets.

Give the best daily trading strategy and model based on the price data of the day, combine the historical price float data and predict the future market trend. Considering the problems caused by two different properties of capital, gold and bitcoin, for example, bitcoin can be traded daily but gold can only be traded on days when the market is open, we have to make some adjustments to the trading strategy.

we constructed a time prediction model to forecast two price series and make decisions about trading based on future ups and downs by constructing a long and short term time series neural network LSTM and a BP neural network time prediction to compare the prediction effect of both and select the best strategy. We constructed and simulated a time prediction model of the stock closing price direction based on the RBF neural network and time prediction model, and made some adjustments using the BP neural network. With the adjusted model, we plotted the graphs of the weighted average price of the five-day, ten-day, and twenty-day closing prices of the stock with the help of the daily average manipulation method, which we used to predict the optimal way to trade gold and bitcoin. Then, we initially determine whether to trade based on the distance between the stock price and the five-day line, as there is a certain commission for each trade, and then substitute the trading commission based on the model to finally give the best daily trading strategy. In contrast, the long-short time series neural network LSTM forecasting model builds a nonlinear model that allows for large nonlinear complex forecasting. Comparing the two, it is easy to see that the LSTM possesses better prediction results, so we choose the LSTM model to determine the value of the initial $1,000 investment on September 10, 2021.

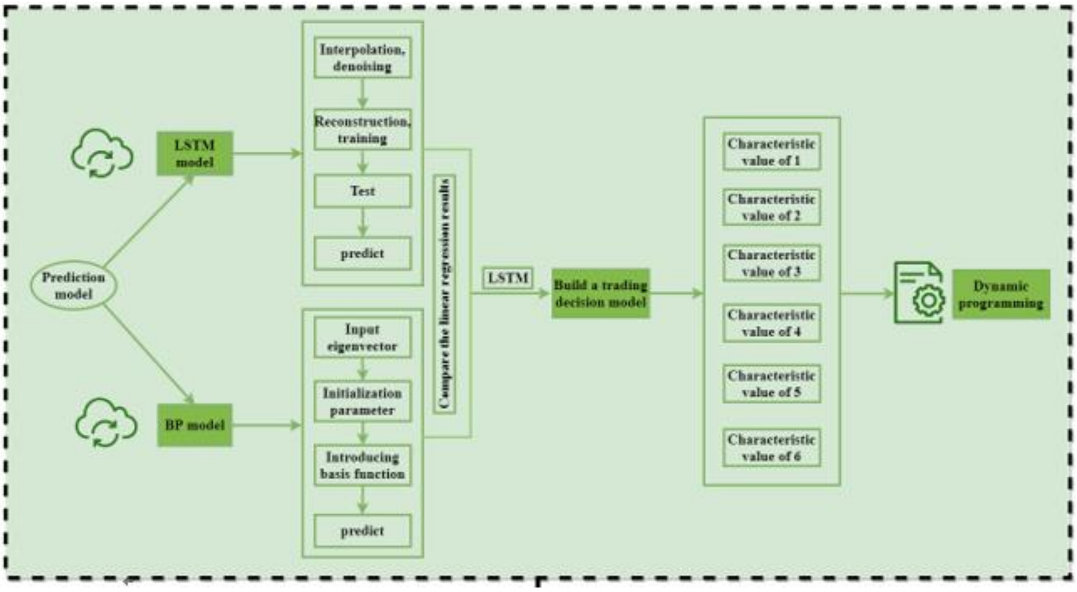

Fig 1 Work Overview

2. Data pre-processing

The original data is integrated and cleaned, the missing data is completed, the bitcoin and gold tables are combined, and the gold non-trading day data is completed, and the data is normalized.

As the data for Bitcoin and Gold are from the real world, there are inevitably a number of anomalies, and by looking at the graph? Therefore, before constructing the LSTM prediction model, we need to decompose the linear and nonlinear parts of the data, filter, smooth, and use the difference method to deal with missing values and other operations, which will help to eliminate or repair the outliers and improve the prediction accuracy of the model.

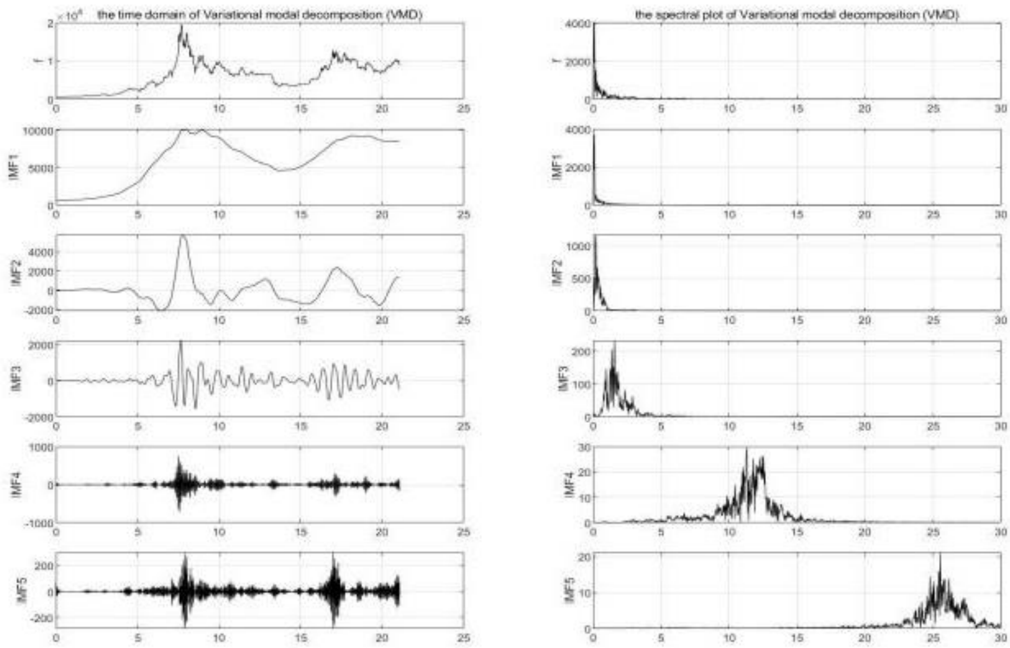

Fig 2 Data Cleaning for Bitcoin

For the processed data we normalize and use the first 956 sets of data to construct the LSTM time series neural network prediction model and participate in network training, and the second 300 test sets are used to evaluate the model accuracy.

3. LSTM model

3.1. Data description

The LSTM model is a special recurrent neural network model (RNN) with good support for long-term dependence, and the core of the model is the state of the cell and the gate structure in it. The cell state refers to the horizontal line running through the top with only a few linear interactions, and the information is easier to keep constant on top, which is also very beneficial for us to predict the closing price of this question, while the gate structure refers to the ability to remove or add information to the cell structure, containing the sigmoid layer and tanh layer, and this structure has an important role in our prediction of the closing price, see the figure 6 below for the specific model structure. The general flow of the model is that after the input is trained to obtain four states:

$$Z_f = \sigma(W_f[h_{t-1}, x_t] + b_f)$$
$$Z_i = \sigma(W_i[h_{t-1}, x_t] + b_i)$$
$$Z = tanh(W[h_{t-1}, x_t] + b)$$
$$Z_o = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

The output y_t is obtained after the gate structure is operated,

$$c_t = Z_f \odot C_{t-1} + Z_i \odot Z$$
$$h_t = Z_o \odot tanh \quad (c_t)$$
$$y_t = \sigma(W_y h_t)$$

The flow is shown in figure 3 .

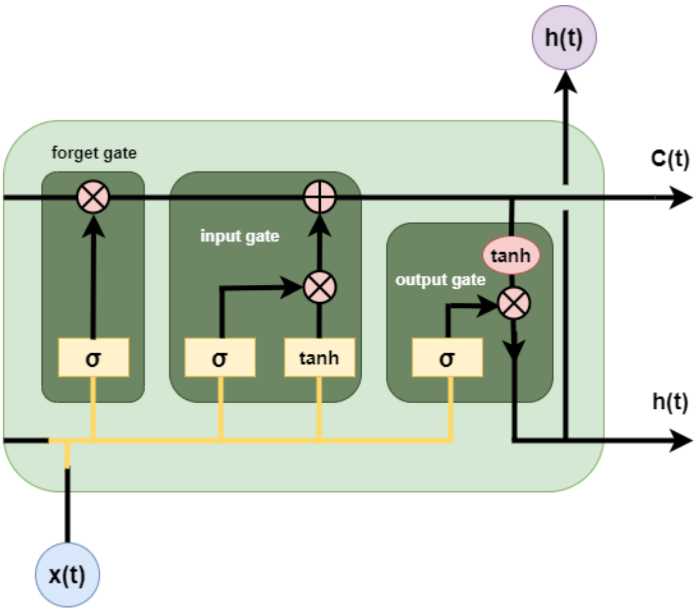

Fig 3 Structure Diagram

For this problem, we construct an LSTM model to predict the closing price for the next 1 unit of time based on the closing price for the previous N units of time.

First, the data set is transformed into a three-dimensional array for input into the LSTM model, tanh(x) is used as the activation function, linear is used as a fully connected artificial neural network, each layer of the network node A is set, the error is calculated by MSE, the weight parameters are iterated using the RMS prop algorithm, and finally the number of training iterations (epoch) and step size (batch size) are determined, and the training set is used to predict the future price after the training is completed.

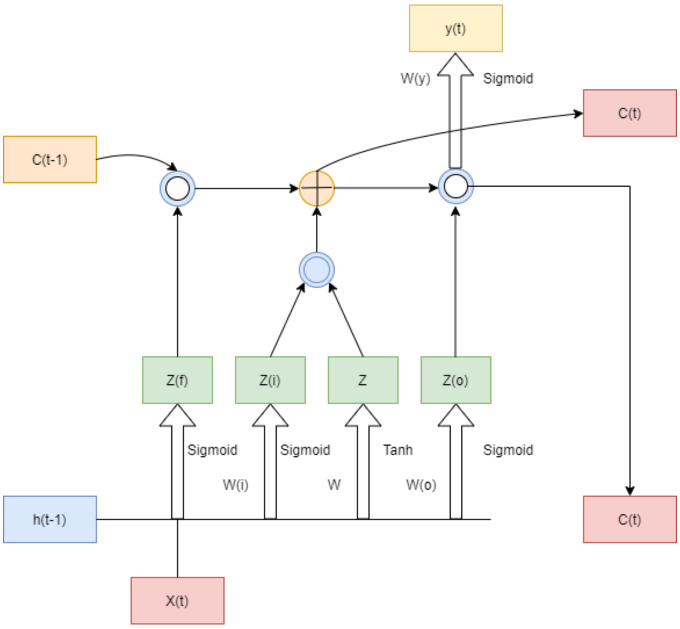

Fig 4 Process Diagram

3.2. Model construction

Theoretically, the future price trends of gold and bitcoin can be predicted, but there are many factors that affect their prices, and so far, their effects on prices cannot be clearly defined, because price prediction is highly nonlinear, which requires prediction models to be able to handle nonlinear problems, and, stocks have the characteristics of time series, so it is suitable to use recurrent neural networks, for stock forecasting. Although recurrent neural networks (RNN), allow the persistence of information, however, the general RNN models are weak in portraying time series data possessing long memory, and in case the time series are too long, because of the presence of gradient dissipation and gradient explosion phenomena RNN training becomes very difficult. Hochreiter and Schmidhuber proposed a long and short-term memory LSTM model based on the RNN structure, thus solving the problem that the RNN model cannot portray the long memory of time series.

By integrating and cleaning the existing data and normalizing them, we use the first 956 data sets for training and constructing the LSTM model, and the subsequent 300 test sets are used to evaluate the model accuracy, calculate the prediction error and the word comparison graph, and assess the difference between the prediction performance of the model and the actual value.

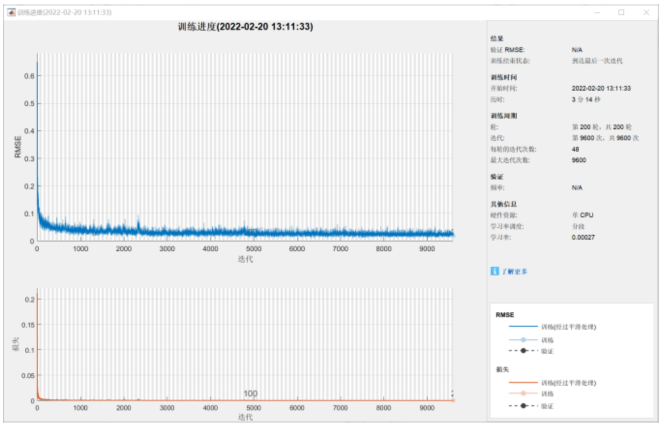

Fig 5 Training Progress Chart

After 9600 iterations, we can see that the RMSE tends to be close to 0, which shows the high accuracy of the LSTM training, while the loss is close to 0, which indicates that the training effect of the model performs well, and the model can be used to predict how Bitcoin and gold will move in the time dimension, providing a theoretical basis for the subsequent construction of the best strategy model.

Using the results shown above can be seen, black is the original data, Figure 1 red is the test data, Figure 2 red is the data after training and then prediction, we can see that our approximate trend is very consistent, there are some places where the peak prediction is not enough, but the overall effect is quite good, and can be used for gold and bitcoin future trend prediction.

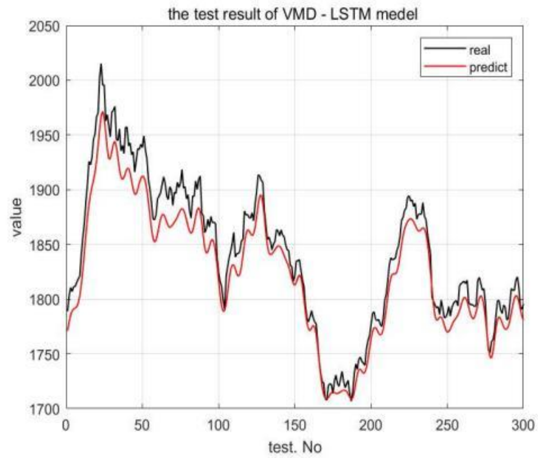

Figure 6 Training set

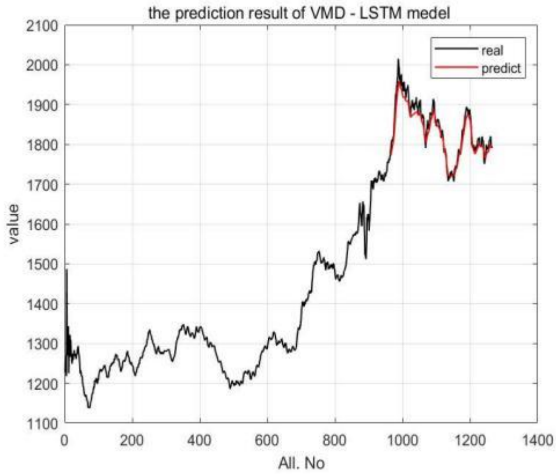

Figure 7 Testing set

4. Best Trading Strategy Model

In the process of asset trading, people often model the optimal trading strategy based on the daily closing price change curve in order to get a more reasonable trading strategy.

For the five-year trading market from September 11, 2016 to September 10, 2021, we find that building a decision model with a highly targeted objective function and multiple constraints based on the daily closing price change curve can be effective for risk-averse investment and optimal returns.

Building the optimal trading strategy model has the advantages of simplicity, ease of operation, tradability and risk aversion.

The model is designed to give the best daily trading strategy to obtain the maximum return, and to solve this problem, we use the maximum value of total assets held as the objective function. For a total trading period of five years from September 11, 2016 to September 10, 2021, bitcoin can be traded daily, but gold is only traded on days when the market is open, and the commission cost per trade for gold and bitcoin is 1% and 2%, respectively, so the following objective function is established:

$$maxY_i = W_i \times \eta_i + Q_i \times \gamma_i$$

The constraint is as follows:

The daily investment amount should not be greater than the amount of all available investments, the initial state is [1000,0,0], and the transaction cost per transaction (buy or sell) is a% of the transaction amount, where gold a=1 and bitcoin a=2. Then for $1000, buy or sell, the only amount of transactions we actually make is $940.

$$Z_i = \begin{cases} 940, & i = 1 \\ Y_i, & i = 2,3,4\ldots \end{cases}$$

The two asset weights should not be greater than 1.

$$W_i + Q_i < 1$$

The predicted tomorrow's gold price / today's gold price - 1 should be greater than 0.01 commission

$$(x_{i+1}/x_i) - 1 > 0.01 \times a\%$$

Predicted tomorrow's bitcoin price / today's bitcoin price -1 to be greater than 0.01 commission

$$(y_{i+1}/y_i) - 1 > 0.01 \times a\%$$

Gold is only traded on open market days

$$x_i = \begin{cases} x_i, & i = \text{Market Trading Day} \\ x_{i-1}, & i = \text{Non-market trading days} \end{cases}$$

In summary, the single-objective optimization model of the problem is obtained as follows:

$$\begin{cases} Z_i = \begin{cases} 940, & i = 1 \\ Y_i, & i = 2,3,4\ldots \end{cases} \\ W_i + Q_i < 1 \\ (x_{i+1}/x_i) - 1 > 0.01 \times a\% \\ (y_{i+1}/y_i) - 1 > 0.01 \times a\% \\ x_i = \begin{cases} x_i, & i = \text{Market Trading Day} \\ x_{i-1}, & i = \text{Non-market trading days} \end{cases} \end{cases}$$

$$maxY_i = W_i \times \eta_i + Q_i \times \gamma_i$$

Based on the above objective function, we use Lingo programming, combined with the LSTM prediction model, to find the maximum value of the assets held, (in USD) as shown in the following table.

Table 1: Results Show

	Bitcoin price	Gold price	Bitcoin increase	Gold increase	Bitcoin holdings	Gold Holdings	Total Assets
2016/9/12	609.67	1324.6	0.39%	0.29%	503.2	500.0	1237.71
2016/9/13	610.92	1323.65	0.10%	0.14%	519.5	499.37	1253.88
2016/9/14	608.82	1321.75	0.15%	0.56%	526.5	498.50	1266.23
2016/9/15	610.38	1310.8	-0.23%	0.09%	547.3	493.30	1279.33
2016/9/16	609.11	1308.35	0.81%	0.04%	551.4	491.81	1292.26
...	...	...	...	...	...	...	...
2019/5/28	8716.3	1899.95	-0.43%	0.48%	78422.7	0.000018	80827.34

Based on the results in the table above, the value of the initial $1,000 investment on September 10, 2021 is derived as $80827.34.

5. Sensitivity analysis

We conducted sensitivity analysis on the MSE values and the gradient of the predicted data, and from the figure, we can see that the training accuracy is very high during the 50,000 training sessions, and the mean square error value shows a decreasing trend as the number of training sessions increases.

For the gradient plot, we can see that the training gradient reaches a very considerable level during 50,000 training sessions, which positively reflects the stability of the deep learning prediction data.

We set the initial gold value as N and the initial allocation value of bitcoin as 1000-N,iterate N from 1 to 1000 with a step size of 10 to get the initial gold value in the third step, and use the line graph of the initial gold value versus the total asset value after five years to observe why N is smoother at times and analyze the transaction cost sensitivity of the trading best strategy model.

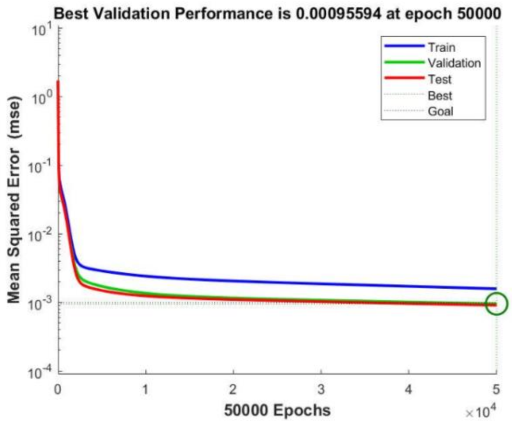

Fig 8 Sensitivity Analysis Chart

6. Model Evaluation and Further Discussion

Before building the model, we normalized the raw data to make the machine learning used in the problem solving have more powerful learning ability.

During the model building process, we considered the investment risk problem and built an investment risk multi-objective planning model with maximizing investment utility and minimizing risk value, and introduced several indicators, such as goods increase, investment share, investment risk, holding share, and asset change rate, to improve the prediction accuracy.

After building the model for prediction, we verified the reasonableness and feasibility of the prediction results by linear regression and gradient display.

But in the LSTM model, we found that the prediction trend is approximately the same, but there is an error in the peak value, and there is a lag in the real predicted data, which looks like the original data is shifted backward by one day.

As a good trader, we need to have a good grasp of market laws and financial knowledge to react to different situations of market trends.

We first used the LSTM model to predict the market closing price, and then adjusted the training results by RBF algorithm and BP algorithm to make the results very close to the real value.

We then used the five-day, ten-day and twenty-day averages to determine whether to trade or not, and simulated how to trade in the presence of commissions in order to maximize the profit. We verified the sensitivity of trading costs to trading results by varying the costs continuously through theoretical analysis and numerical simulation methods.

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