How to Become Rich Using Quantitative Trading?

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Abstract. Bitcoin has become a very common investment product, also known as 'digital gold' because of its global discussion and rising prices. This paper develops a model that can only rely on these data to predict future price fluctuations and plan trading decisions. The trading decision planning model consists of three sub-models that are mutually undertaken. For model 1, in order to judge the price trend reliably, this paper uses the Long Short-Term Memory (LSTM) neural network, which is sensitive to the time series, to learn all the time series price data up to the trading day, and to predict the future price data of them respectively, which is provided to another sub-models for subsequent work. For Model 2, after obtaining the follow-up price data, all the technical indicators needed are calculated in this model, and then the moving average convergence divergence (MACD) rule is used to determine whether the transaction is carried out for the first time, and then the predicted price trend is used for the second judgment. For model 3, the model begins to make decision- making planning. This model mainly solves the bi-objective programming problem with the goal of maximizing returns and minimizing risks. In the range of controllable risks, the model will give the optimal solution of maximizing returns. Finally, using the model, the sensitivity of the model to transaction cost is studied by changing the transaction commission, and it is found that the final investment income is more sensitive to the transaction commission of bitcoin.

Keywords: LSTM, MACD Theory, bi-objective programming, mean-variance theory.

1. Introduction

1.1. Background

As one of the most important investment products in the global financial market, gold is of great significance to the stability of the international financial market. At the same time, due to the stability of its own value, investors are more willing to use it as a means of financing. Within ten years after Bitcoin was legally issued and circulated, Bitcoin has become an investment product similar to gold in the financial market. Computer technology has enabled it to maintain value and diversify risks similar to gold, which is why Chamath Palihapitiya said “Bitcoin Has Effectively Replaced Gold” [1].

However, even investment products such as gold and bitcoin will have price fluctuations in the financial market. In order to maximize returns in the process of buying and selling such volatile assets through quantitative trading, it is necessary to be familiar with and effectively use the existing price data. At the same time, predicting the future price trend with high accuracy is also of great importance. Only thus, investors can make the best trading decisions based on these conditions. In summary, in the process of volatility asset trading, a model with price data prediction and trading behavior planning function is very necessary.

1.2. Restatement of the Problem

In order to maximize the returns on transactions, it is necessary to establish a transaction model that can only use the price data before the trading day to complete the price trend prediction and the quantitative trading behavior planning. This model will be used to determine the transaction behavior that should be taken for the portfolio assets held in each trading day.

- What we know:

➢ On each trading day, traders will have a portfolio consisting of cash, gold and bitcoin [C, G, B].

➢ The trading period is 5 years and the initial state of portfolio is [1000,0,0].

➢ Each transaction has a commission costing α% (αgold=1% and αbitcoin=2%) of the amount traded.

➢ Bitcoin can be traded daily, but gold is only traded on the opening day.

● What we have:

➢ Price volatility data. Two data files respectively containing gold and bitcoin prices for the five-year trading period from 11/9/2016 to 10/9/ 2021.

➢ Initial trading cash. Only$1,000 in cash in the portfolio at the beginning of the trading period.

● What we should Do:

➢ Develop the transaction model. Transaction behavior planning based only on price data up to target date and existing portfolios

➢ Problem scenario reappearance. Run the model is run in the given scenario to obtain the final investment value after the end of the trading period.

➢ Verify the optimality of the model. The transaction behavior given by the model is proved to be the best under the current price conditions by data evidence.

➢ Perform sensitivity analysis. Determining the sensitivity of trading strategies to costs and how changes in initial transaction costs affect trading behavior planning and ultimate investment value.

1.3. Literature Review

This question is mainly about finding the best investment strategy. In recent years, research on quantitative investment in financial products is very hot. Generally, according to Figure 1, it can be divided into 2 parts: Investment Strategy Selection Model and Investment Planning Model of Financial Products.

For Investment Strategy Selection Model:

➢ Almost all authors use models to predict the future trend of financial products, such as rough cognitive networks and so on [2]. Particularly, LSTM performs well in time series prediction and can deal with data sets with less features [3].

➢ In the process of investment decision-making, some papers propose to use classical financial data indicators to assist decision-making and form a complete method [3], such as MACD, RSI, KD, etc. Other papers use deep reinforcement learning for decision simulation [4].

For Investment Planning Model:

➢ Some papers proposed investment planning methods based on data mining and machine learning, but the disadvantage is the need for large and accurate data sets [4]. There are also studies using investment planning methods based on genetic programming algorithm and good results are obtained [5].

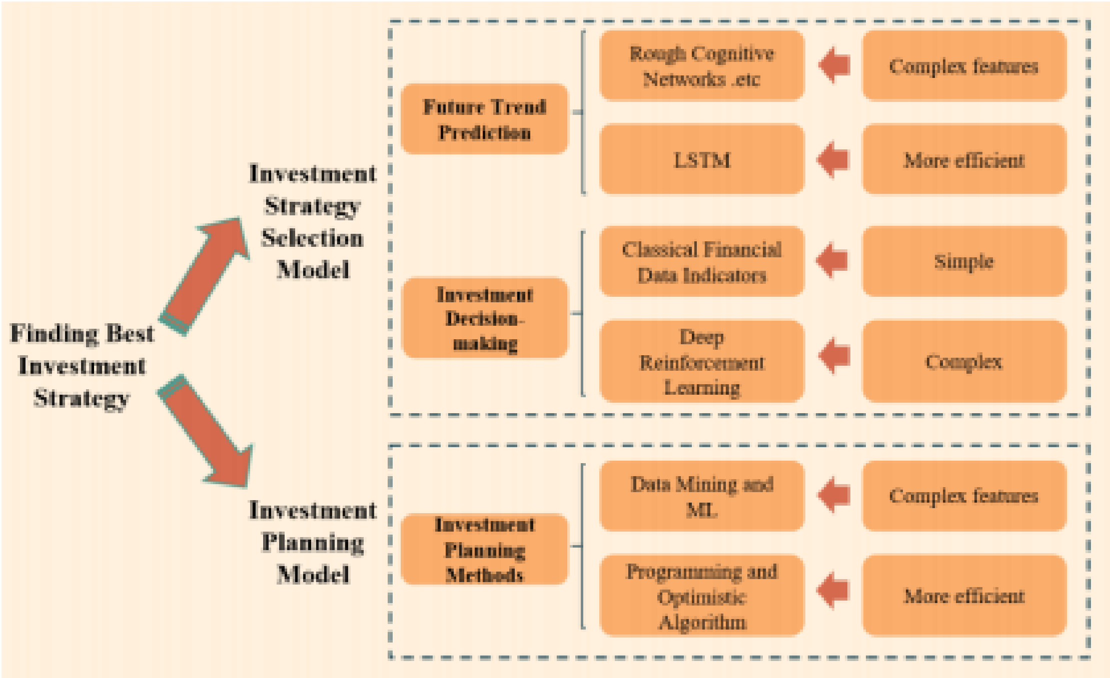


Figure 1. Literature review framework.

1.4. Our Work

In this paper, we establish three models to solve the problem, shown in Figure 2. Firstly, because quantitative investment requires a better understanding of future price trends, we developed a future price forecasting model based on LSTM to predict gold and bitcoin prices for subsequent use. Secondly, we set up an investment strategy selection model to judge the trading behavior of gold and bitcoin (buying, selling, holding) every trading day. Next, we establish a bi-objective optimization model for balancing income and risks using results from LSTM and investment strategy selection model. Then, we prove that our models give the best investment strategy and do some sensitive analysis. Finally, we communicate our strategy, models, and results to the trader in a memorandum.

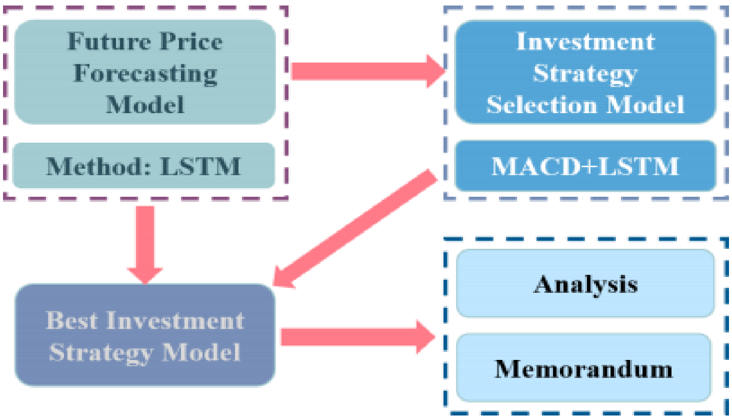


Figure 2. Flow chart of our work.

2. Assumptions and Justifications

Assumption 1: Gold and bitcoin are similar in financial markets to stocks.

Justification: The fluctuation characteristics of gold and bitcoin are similar to stocks and both have closing prices, which is reasonable. The MACD theory is based on the stock trading theory, and we extend it to gold and bitcoin.

Assumption 2: Prices on the market reflect all information on the market in a timely and impartial manner.

Justification: Our model only plans investment strategies from current prices, so we agree that price information can reflect market information.

Assumption 3: All investments are completely separable.

Justification: This model does not consider the possible minimum trading units of gold and bitcoin in actual transactions.

3. Notations

We will mainly introduce some important notations, other notations will be explained in the model derivation (see Table 1):

Table 1. Notations.

Notations	Meaning
$EMA(i)$	Exponential moving average price of gold or bitcoin on day *i*
$DIF(i)$	Deviation value of gold or bitcoin on day *i*
$DEA(i)$	Average value of DIF on day *i*
$MACD(i)$	Moving average convergence and divergence on day *i*
$X_{bitcoin}(i), X_{gold}(i)$	Trading strategy variables of gold and bitcoin on day *i*
$signal_1(i), signal_2(i)$	Decision variables of trading strategy on day *i*
$p_n \quad i$	Income of trading day *i* ' s investment after *n* days
$P_{bitcoin}(i), P_{gold}(i)$	Price of gold and bitcoin on day *i*
$m_{gold}(i), m_{bitcoin}(i), m_{dollar}(i)$	Amount of gold, bitcoin and cash on day *i*
x^{n+i}	Predicting deviation ratio of the price after *n* days from day *i*
w^{i+n}	Income weight ratio of trading day *i* ' s investment after *n* days
$V_{bitcoin}(i), V_{dollar}(i), V_{gold}(i)$	Proportion of the value of gold, bitcoin and cash on day*i*

4. Data Pre-processing

4.1. Data Description

The data files given in the text are the price fluctuations of bitcoin and gold in all trading days in five years. Bitcoin can be traded every day and gold is not allowed to be traded in weekends. Firstly, the data in the two data files are visualized in the form of a broken line graph according to the line graph given in the text. It should be noted that in the process of drawing the broken line graph, all the places where there is a null value are set to zero so that the existence of the null value can be judged by the decline of the broken line, and all the missing values can be found. The broken line graphs are drawn as shown in Figure 3 and Figure 4.

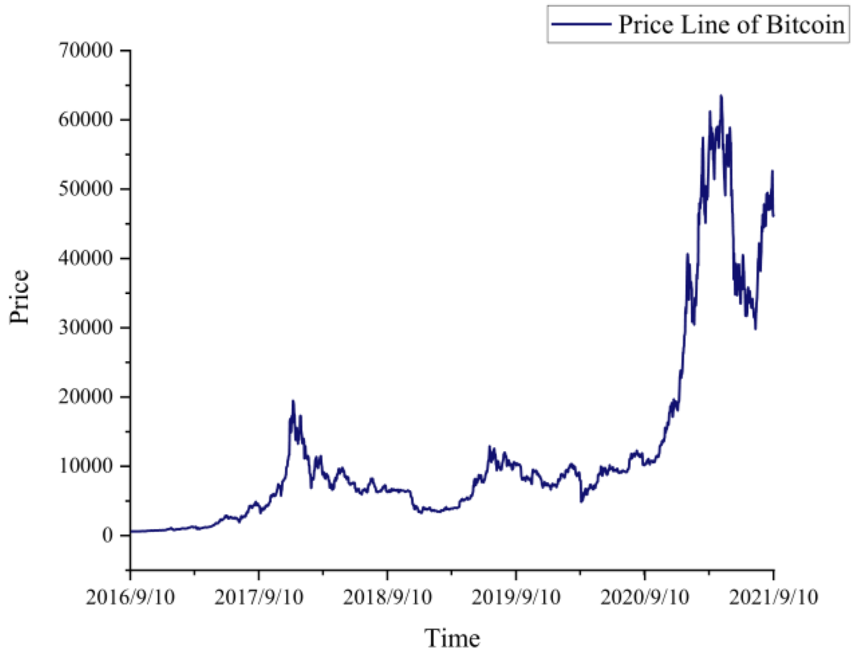


Figure 3. Price line of bitcoin.

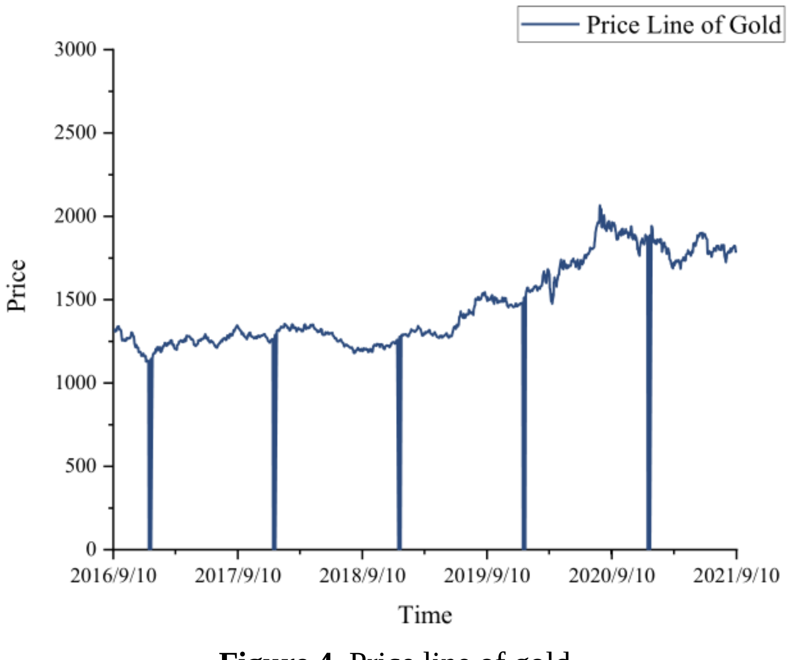


Figure 4. Price line of gold.

It is obvious from the figure 4 that there are many numerical missing values in the gold price data file. Amplifying the sharp fall of the broken line in the broken line graph can clearly see that there are two missing values in each place, so there are 10 missing values in the gold price data file. According to the calculation principle of MACD, it can be known that the missing value has a great influence on whether to trade and buy and sell decisions, which will lead to the interruption of the calculation and cannot get the final results. Therefore, the missing value needs to be filled in the data pre-processing part. This paper uses the linear interpolation filling method.

4.2. Principle of Linear Interpolation

Linear interpolation is an interpolation method for one-dimensional data, which estimates the values according to the left and right adjacent two data points of the points to be interpolated in one-dimensional data sequence. However, this method is not to calculate the average value of the data size of the two points, but to allocate their proportion according to the distance to the two points, so as to obtain the numerical results to be calculated. The advantage of this method is that it can quickly calculate the missing value and reduce the phenomenon of block graphics. According to the assumption in Figure 4, the size of interpolation y at x is required by known points (x_0, y_0) and (x_1, y_1). The function graph between two points can be approximately represented by the line between two points. According to the following formula, the size of y can be calculated, which is the basic principle of linear interpolation method.

$$y = y_0 + \frac{y_1 - y_0}{x_1 - x_0}(x - x_0) \quad (1)$$

Table 2. Linear interpolation results.

date of missing data	interpolation result
2016-12-23	1132.975
2016-12-30	1148.45
2017-12-22	1271.975
2017-12-29	1301.525
2018-12-24	1263.075
2018-12-31	1280.95
2019-12-24	1496.8
2019-12-31	1520.925
2020-12-24	1874.65
2020-12-31	1915.4

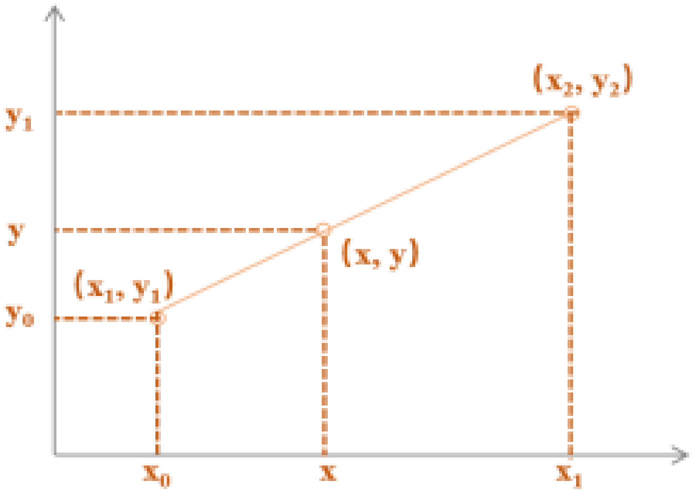


Figure 5. Principle of linear interpolation.

Through the linear interpolation method to process the data, the final data results can be obtained and the gold price data is supplemented completely, which is fully prepared for the subsequent model calculation. The interpolation results are shown in Table 2 and Figure 5.

5. Model Derivation

5.1. Future Price Forecasting Model Based on LSTM

Long Short Term Memory Network (LSTM) is a special neural network that can be used to solve the long-term dependence problem. Compared with other neural networks, LSTM is more suitable for the learning of time series sensitive data. The price fluctuation data that can be used in this paper are very typical time-sensitive data. The price of fluctuating assets is constantly changing with time, so LSTM is very suitable. LSTM is formed on the basis of Recurrent Neural Networks (RNNs), usually considered as a type of RNN. Therefore, this paper first briefly introduces the basic principle of RNN as the groundwork.

5.1.1. RNN Principle [6]

In the traditional neural network, the model does not pay attention to what information can be used for the next moment in the processing of the previous moment. Each time, it only pays attention to the processing of the current moment, that is to say, the traditional neural network does not have the memory function. In order to make the information of the continuous moment interact and transmit, RNN arises at the historic moment. The biggest difference between RNN and the traditional neural network is that it has a closed loop pointing to itself, which is used to transmit the information processed at the current moment to the next moment for use. The specific structure is shown in Figure 6.

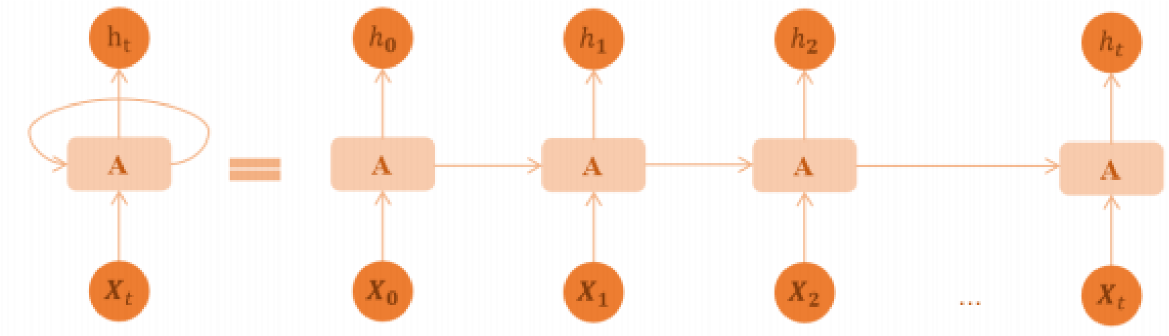


Figure 6. RNN schematic diagram.

In the figure, X_t is the input, A is the model processing part, and h_t is the output. The equation shown in the figure is the interaction mechanism of the RNN obtained after the closed-loop is expanded over time. Such a chain network shows a recurrent neural network, which can be considered as a multiple replication of the same neural network. The neural network at each moment will transmit information to the next moment. The detailed structure of the chain network is shown in Figure 7.

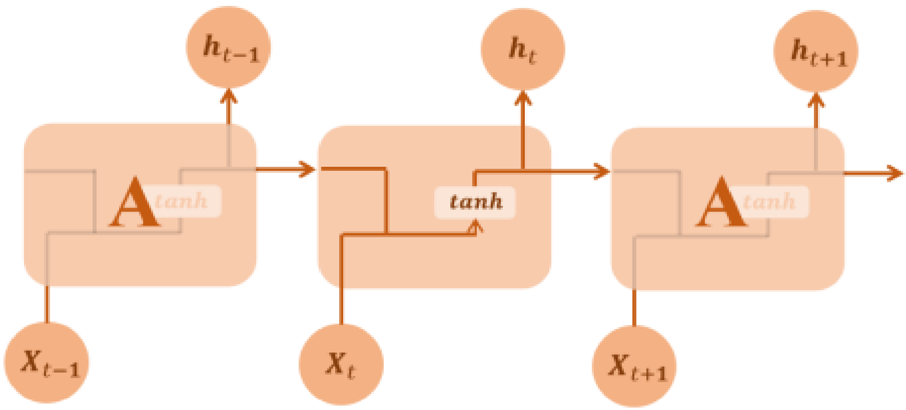


Figure 7. Specific structure of RNN.

All recurrent neural networks are a chain composed of repetitive neural network modules. It can be seen that the processing layer of each module is very simple, generally a single tanh layer, and the current output is obtained through the current input and the output of the previous moment. Compared with the traditional neural network, it has been able to use the information learned at the previous moment to learn at the current moment. This makes the recurrent neural network have a certain memory function and can be used to solve many problems, such as speech recognition, language model, machine translation, etc. But it cannot handle long-term dependency problem well.

5.1.2. The Meaning of Long-Term Dependence Problem [6]

Long-term dependence is such a problem: it is difficult to learn the relevant information when the prediction point is far away from the relevant information of dependence. Simply speaking, some information at the initial time may have a significant impact on the model processing after a long time. In the practical application process, RNN cannot keep these information after a long time. Based on this, LSTM algorithm which overcomes the long-term dependence problem is developed.

5.1.3. LSTM Principle Explanation [6]

It can be known from the above introduction that LSTM is modified on the basis of RNN, so that it has special ability to solve long-term dependence problems. Its chain structure is similar to RNN but more complex. In the model processing part, it is divided into four layers. The specific situation is shown in Figure 8.

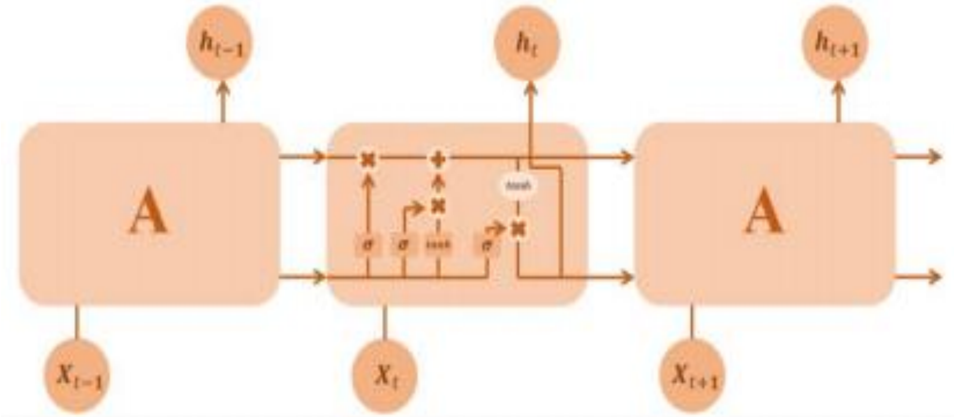


Figure 8. LSTM chain structure.

It can be seen that each block structure of LSTM contains three gates (forget gate, input gate, output gate) and one memory cell. The horizontal line above is called cell state, which can control the information to be transmitted to the next moment. The specific composition is shown in Figure 9.

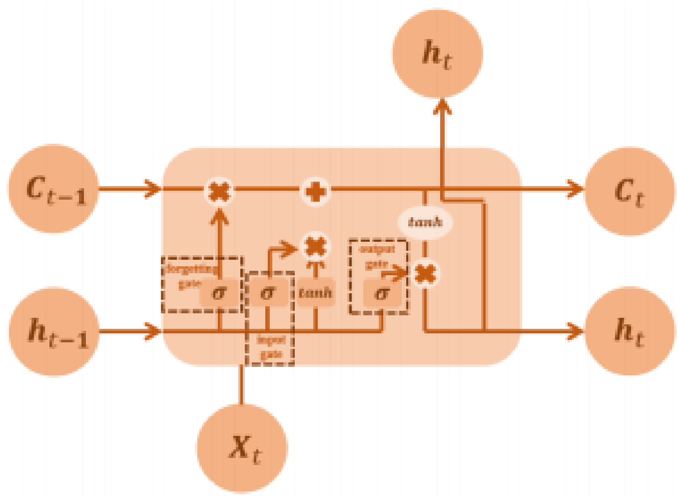


Figure 9. Composition structure of LSTM single module.

In the figure, f_t represents the forgetting gate, i_t represents the input gate, o_t represents the output gate, C_t represents the neural unit state at time t, h_t represents the hidden layer state at time t, and Γ and tan h are the activation function. LSTM has short-term memory channel h and long-term memory channel C, which are used to maintain the training memory of nonlinear operation and linear operation respectively. Because the linear operation is relatively stable, the long-term memory of useful information can be realized by training. The following is the specific training process of LSTM.

(a) Decide what information to discard from the cell state. The input at the current moment and the output at the previous moment are controlled by the forget gate layer passing through sigmoid. It will generate a f_t value of 0 to 1 according to the output h_{t-1} at the previous moment and the current input x_t, to determine whether to let the information C_{t-1} learned at the previous moment pass through or partially pass through.

$$f_t = \Gamma(W_f.[h_{t-1}, x_t] + b_f) \tag{2}$$

(b) Determine which new information is stored in the unit state. x_t and h_{t-1} output through the input gate i_t, combined with x_t and h_{t-1} through tan h function to create a new candidate value vector. This step consists of two parts, the first is an input gate layer through sigmoid to determine which values are used to update, the second is a tan h layer to generate a new candidate value C_t, which as the candidate value generated by the current layer may be added to the cell state.

$$i_t = \Gamma(W_f.[h_{t-1}, x_t] + b_i) \tag{3}$$

$$C_t = 0(W_c.[h_{t-1}, x_t] + b_c) \tag{4}$$

(c) Update the old unit state C_{t-1} to the new unit stateC_t.

$$C_t = f_t.C_{t-1} + i_t.C_t \tag{5}$$

(d) Determine the output information. The new cell state is filtered through the output gate O to get the output h_t at this time.

$$O_t = \Gamma(W_o.[h_{t-1}, x_t] + b_o) \tag{6}$$

$$h_t = O_t.0(C_t) \tag{7}$$

In this way, a typical LSTM link completes the operation, so that the transmission of information between links can well solve the long-term dependence problem that RNN cannot handle, and better learning results can be obtained.

5.2. Investment Strategy Selection Model

MACD (Moving Average Convergence and Divergence) was proposed by Geral Appel in 1979. It uses the aggregation and separation between the short-term (commonly used for 12 days) exponential moving average of closing price and the long-term (commonly used for 26 days) exponential moving average to study and judge the technical indicators of buying and selling timing [7]. Based on MACD technical indicators and judgment theory, we study and judge the trading choices of gold and bitcoin in each trading day.

5.2.1. MACD Technical Indicators

Since our data only contain daily price information of gold and bitcoin, it is very important to use appropriate and computable indicators. Through the calculation of indicators, we can get more data information on the basis of price. Before using the indicators, it needs to be clear that since Bitcoin can be traded every day, we convert the trading date of bitcoin into i= 1, 2, 3... 1826 (from 11/9/2016 to 10/9/ 2021). As gold is not allowed to be traded in weekends, we convert trading date of it into j = 1, 2,3... 1265 to ensure that it can be continuously calculated. The indicators we use are as follows:

● EMA

EMA means Exponential Moving Average. It carries on the weighted arithmetic average to the day price, uses to judge future trend tendency of the price. It focuses on the weight of the day's price and determines it can overcome the lag defect of price trend as a kind of trend analysis index. We use EMA in 12 days and 26 days.

Take bitcoin for example:

$$EMA_{12}(i) = EMA_{12}(i-1) \times \frac{11}{13} + P_{bitcoin}(i) \times \frac{2}{13} \tag{8}$$

$$EMA_{26}(i) = EMA_{26}(i-1) \times \frac{25}{27} + P_{bitcoin}(i) \times \frac{2}{27} \tag{9}$$

Gold's calculations are the same, just replace i with j. Note that EMA on the first trading day is the first trading day's price.

● DIF

DIF means deviation value. According to MCAD Theory, in the continuous fluctuation, the positive deviation value (+DIF) will become larger and larger. On the contrary, the possible negative deviation (-DIF) becomes larger and larger in the decline.

Take bitcoin for example:

$$DIF(i) = EMA_{12}(i) - EMA_{26}(i) \tag{10}$$

Gold's calculations are the same, just replace i with j. DIF (1) = 0

● DEA

DEA is the average of DIF over a period of time, a slow line indicator. Take Bitcoin for example:

$$DEA(i) = DEA(i-1) \times \frac{4}{5} + DIF(i) \times \frac{1}{5} \tag{11}$$

Gold's calculations are the same, just replace i with j. DEA (1) = 0

● MACD

MACD means Moving Average Convergence and Divergence. It's closely related to DIF and DEA. Take Bitcoin for example:

$$MACD(i) = \left(DIF(i) - DEA(i)\right) \times 2 \tag{12}$$

Gold's calculations are the same, just replace i with j.

Generally, the MACD indicator system includes DIF, DEA and MACD indicators. We will make transaction decisions based on the calculation of these indicators and MACD theory.

5.2.2. Investment Strategy Selection Model

According to the MACD theory, we can use the indicators in the MACD system to select the trading strategy. Since the modeling process of bitcoin and gold is similar, we take bitcoin as an example to illustrate.

● Define Strategies

First, we need to define the strategy in this model, we define the bitcoin strategy as $X_{bitcoin}$ (i) which means our operations on bitcoin on trading day i.

$$X_{bitcoin}(i) = \begin{cases} 1\ (buy) \\ 0\ (hold) \\ -1\ (sell) \end{cases} \tag{13}$$

● Selection Rule I: MACD

Second, we need to make the first strategic judgment. We define the outcome variable of this strategy on trading day i as $signal_1$ (i). With MACD theory [7], when both DIF and DEA have an upward trend and the same sign, the bitcoin price may rise, we can choose to buy or hold. Bitcoin prices may fall when DIF and DEA both have a downward trend and the same sign, we can choose to sell or hold. Define $signal_1$ as follows:

$$signal_1(i) = \begin{cases} 1\ (buy\ /\ hold) \\ 0\ (hold) \\ -1\ (sell\ /\ hold) \end{cases} \tag{14}$$

Then the following equation ofjudgment can be written:

$$DIF(i) > 0 \cap DEA(i) > 0 \cap DIF(i) - DIF(i-1) > 0 \cap DEA(i) - DEA(i-1) > 0 \Rightarrow signal_1(i) = 1$$
$$DIF(i) < 0 \cap DEA(i) < 0 \cap DIF(i) - DIF(i-1) > 0 \cap DEA(i) - DEA(i-1) > 0 \Rightarrow signal_1(i) = 1$$
$$DIF(i) > 0 \cap DEA(i) > 0 \cap DIF(i) - DIF(i-1) < 0 \cap DEA(i) - DEA(i-1) < 0 \Rightarrow signal_1(i) = -1$$
$$DIF(i) < 0 \cap DEA(i) < 0 \cap DIF(i) - DIF(i-1) < 0 \cap DEA(i) - DEA(i-1) < 0 \Rightarrow signal_1(i) = -1$$
$$others \Rightarrow signal_1(i) = 0$$

We define ‘buy or hold’ and ‘sell or hold’ because MACD is only a selection model based on current and historical information. In order to make our decision more accurate, we will further establish the selection model.

● Selection Rule II: LSTM

Third, 5-day mean line theory is the most common technical analysis method in financial markets, which has a magic guiding role in market operations. On the basis of MACD, we decide to use LSTM to predict the average price of the next 5 days P_{next-5} (i) compared with the average price of the past 5 days P_{last-5} (i) to form the second selection model. We define the outcome variable of this strategy on trading day i as $signal_2$ (i).

$$signal_2\,(i) = \begin{cases} 1\; P_{next-5}\,(i) > P_{last-5}\,(i) \\ -1\; P_{next-5}\,(i) < P_{last-5}\,(i) \end{cases} \tag{15}$$

Next, we will consider how to form the final model.

● Final Model

For the final model, our idea is to use selection rule II to verify selection rule I, that is, if the future prediction is the same as the conclusion of MACD, we choose to trade. For example, we choose “buy” in “buy or hold”, and if the future prediction is different from the conclusion of MACD, we choose not to trade. For example, we choose “hold” in “buy or hold”. The final model are as follows:

Therefore, we not only use the past information (MACD indicators), but also use the predicted information. This will make our model more reasonable and robust. This idea comes from California Congestion Judgment Algorithm in Transportation [8].

Through this model, we can calculate the trading strategy (buy, hold, sell) of each trading day. The calculation method of gold is similar to that of bitcoin, but it should be noted that although gold is closed at weekends, it can still be regarded as a continuous process.

5.3. Best Investment Strategy Model

In 5.2, we use the investment strategy selection model to determine whether the gold and bitcoin trading strategies of each trading day are bought, sold or not. Next, we will establish the best investment strategy model to calculate the best trading amount of each trading day.

5.3.1. Determination of Optimization Objective

● Investment Portfolio Theory

Markowitz proposed an operable ‘Mean-Variance methodology’ (Mean-Variance methodology) that was strictly stated under uncertain conditions in 1952 [9]. The mean ideas: 1. Risk is measurable in a sense. 2. Various risks may inhibit each other, so investment should be decentralized. 3. In the sense of some optimal investment, high income means greater risk.

● Model Preparation

The assets invested in this topic have an income on each day, and an income vector can be obtained by recording the income of trading day i’s investment after *n* days as d_n ! .

$$\text{income\_vector} = (p_{1+i}, p_{2+i} \dots p_{n+i})i \tag{16}$$

Since only historical information is available for investment (already used in 5.2), the calculation of income needs to use LSTM predictions. Take d_n ! as an example: The price predicted by LSTM is d_{q} ! !?o ! *n* (! *n*) and $d_{6o/p}$ (! *n*) , amount of Bitcoin and Gold is m_{q} ! !?o ! *n* (!) and $m_{6o/p}$ (!). So we can see:

$$p_{n+i} = \left[P_{\text{bitcoin}}\,(i+n) - P_{\text{bitcoin}}\,(i)\right] \cdot m_{\text{bitcoin}}\,(i) + \left[P_{\text{gold}}\,(i+n) - P_{\text{gold}}\,(i)\right] \cdot m_{\text{gold}}\,(i) \tag{17}$$

$$S(i) = P_{\text{bitcoin}}\,(i) \cdot m_{\text{bitcoin}}\,(i) + P_{\text{gold}}\,(i) \cdot m_{\text{gold}}\,(i) + m_{\text{dollar}}\,(i) \tag{18}$$

P_n 1 is the income in day $n+i$ (from day i). S is our total assets on the end of day i. We can calculate P_1 i, P_2 i... P_n i in the same way.

According to Markowitz's theory, we use expectation to measure income and variance to measure risk. We only need to calculate the weight of the income vector to calculate expectation and variance.

We need to know the possible future benefits. Since the prediction of the LSTM model cannot be completely accurate, and with the increase of the estimated span, the accuracy of the prediction will decline significantly. For example, the price after 20 days of prediction will have a greater deviation than the price tomorrow. We may assume that the deviation ratio x_n of the price after predicting n days conforms to the normal distribution. Therefore, after obtaining a certain observation value, the confidence interval can be calculated. The intermediate value of confidence interval is its expectation.

$$\mu \in \left[x - t_{1-\frac{c}{2}}(n-1)\frac{S}{\sqrt{n}}, \bar{x} + t_{1-\frac{c}{2}}(n-1)\frac{S}{\sqrt{n}}\right] \quad (19)$$

So we can get a one-dimensional vector about deviation ratio, and then the softmax function is used to normalize it to obtain the weight w_i n .

$$\text{deviation\_ratio} = (x_{1+i}, x_{2+i} \dots x_{n+i}) \quad (20)$$

$$w_{i+j} = \text{softmax}(x_{i+j}) = \frac{\exp(x_{i+j})}{\sum_1^n \exp(x_{i+j})}\left(w_{i+1} + \underline{w}_{i+2} + \dots + w_{i+n} = 1\right) \quad (21)$$

● Optimization Objective I: Maximum Income Principle

For a specific investment product, we can calculate the income after several days by LSTM, and we have calculated the weight of the income in the previous step, so we can calculate the expected return. And since w_n gradually approaches zero as n becomes larger, it is not necessary to incorporate all the gains and weights into the expected calculation. After fitting, we select n = 20 to achieve higher accuracy. On each trading day $!$, our goal is:

$$maxE(p)_i = \sum_{i+1}^{i+20} (p_{i+j} \cdot w_{i+j}) \quad (22)$$

● Optimization Objective II: Minimum Risk Principle

We want to choose a less risky strategy, that is, the smaller the variance of the income, the higher the stability of the income we get, which can be considered to be less risky.

$$(minD(p)_i = \sum_{i+1}^{i+20} \left((p_{i+j} - E(p)_i)^2 \cdot w_{i+j}\right) \quad (23)$$

5.3.2. Constraints

● Investment proportion constraint

Here we regard cash, gold and bitcoin as investment products, and all of them are substituted into the above two methods for calculation. However, the special point of cash is that it does not exist fluctuation. We calculate the proportion of investment products in total assets:

$$V_{\text{dollar}}(i) = \frac{m_{\text{dollar}}}{P_{\text{bitcoin}}(i) \cdot m_{\text{bitcoin}} + P_{\text{gold}}(i) \cdot m_{\text{gold}} + m_{\text{dollar}}}, V_{\text{bitcoon}}(i) = \frac{P_{\text{bitcoin}}(i) \cdot m_{\text{bitcoin}}}{P_{\text{bitcoin}}(i) \cdot m_{\text{bitcoin}} + P_{\text{gold}}(i) \cdot m_{\text{gold}} + m_{\text{dollar}}}, V_{\text{gold}}(i) = \frac{P_{\text{gold}}(i) \cdot m_{\text{gold}}}{P_{\text{bitcoin}}(i) \cdot m_{\text{bitcoin}} + P_{\text{gold}}(i) \cdot m_{\text{gold}} + m_{\text{dollar}}} \quad (24)$$

We calculate the covariance matrices of these three proportions.

$$O = \begin{pmatrix} V_{dollar} & Cov(V_{dollar}, V_{bitcoin}) & Cov(V_{dollar}, V_{gold}) \\ Cov(V_{bitcoin}, V_{dollar}) & V_{bitcoin} & Cov(V_{bitcoin}, V_{gold}) \\ Cov(V_{gold}, V_{dollar}) & Cov(V_{gold}, V_{bitcoin}) & V_{gold} \end{pmatrix} \tag{25}$$

According to the effective frontier theory [10], the standard deviation of the internal elements of the covariance matrix is calculated. The proportion of three investment products whose standard deviation is less than a certain threshold is a set. As a result, we can determine the constraints of the proportion change of three kinds of investment products per trading day.

● Cash Constraint & MACD Constraint

Cash constraint refers to the relationship between the amount used to invest in gold and bitcoin on day ! and the cash on day ! −1. We also use the investment strategy (buy, sell, hold) in 5.2 to establish the following constraints:

$$|m_{dollar}(i-1) - m_{dollar}(i)| \geq X_{dollar}(i) \cdot \left(\alpha_{bitcoin} + P_{bitcoin}(i)\right)[m_{bitcoin}(i) - m_{bitcoin}(i-1)] + X_{gold}(i) \cdot \left(\alpha_{gold} + P_{gold}(i)\right)\left[m_{gold}(i) - m_{gold}(i-1)\right] \tag{26}$$

$$X_{bitcoin}(i)\,[m_{bitcoin}(i) - m_{bitcoin}(i-1)] > 0 \tag{27}$$

$$X_{gold}(i)\,[m_{gold}(i) - m_{gold}(i-1)] > 0 \tag{28}$$

5.3.3. Final Model

Finally, with the goal of maximizing the expected income and minimizing the risk, we establish the best investment strategy model through investment proportion constraint and cash constraint in adjacent trading days. We use the program to memorize the previous information and solve the day plan, and the results will be shown later.

6. Model Results

6.1. Future Price Forecasting Model

6.1.1. Computational Process

The text requires that the decision of each transaction can only be made based on the price data up to the current trading day. That is to say, the data that can be used in each price prediction are only the two sets of price data up to the current. These data are used as training sets to train the LSTM neural network, and then predict the price corresponding to each moment of the subsequent time series. From the first trading day to the last trading day, each additional day of the trading day will use the supplementary price data to retrain the LSTM and predict the future price trend.

At the end of each forecast, the results are calculated as follows: (1) Percentage deviation between the predicted prices for the next 15 days and the actual prices for the next 15 trading days is calculated. (2) The predicted prices of the next 5 trading days are averaged. The results of the above two calculations are to serve the subsequent transaction behavior planning, which is convenient for the subsequent calculation to determine whether the transaction is carried out within the trading day and the total amount of the transaction products. The specific calculation process is shown in Figure 10 below.

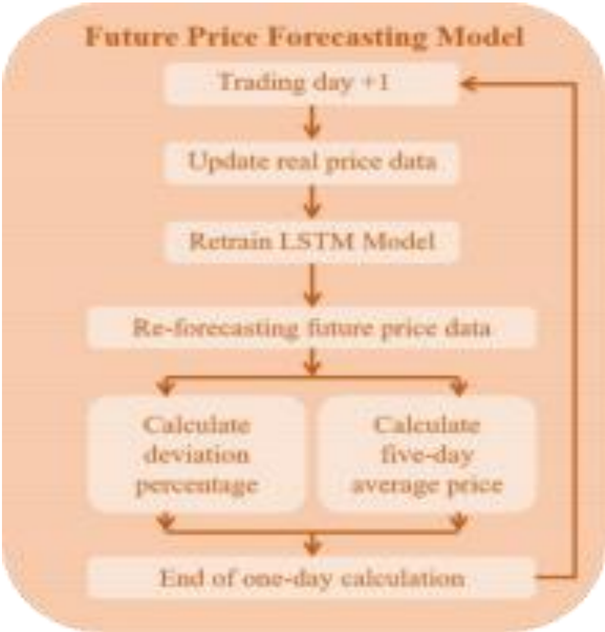


Figure 10. Flow chart of prediction calculation.

6.1.2. Computation and Conclusion

By observing and summarizing all the calculated deviation percentage data, the following conclusions can be drawn: (1) The average deviation between the predicted price of bitcoin and the real price is much larger than the price deviation of gold, indicating that the model is more accurate in predicting the gold price. (2) In general, for a certain trading day, the closer the predicted price in the next few days is to the current trading day, the higher the prediction accuracy is, the smaller the deviation is, the farther the time is, the smaller the accuracy is, and the more inaccurate the prediction result is, which is more obvious in the price prediction of bitcoin. The above two conclusions can be directly reflected in Figures 11 and 12 below.

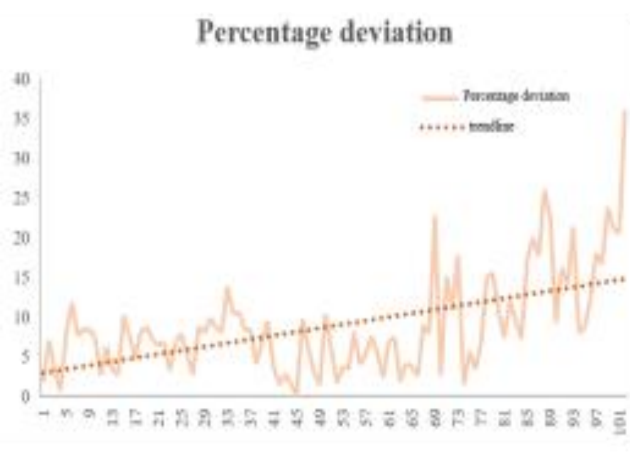


Figure 11. Percentage deviation of bitcoin.

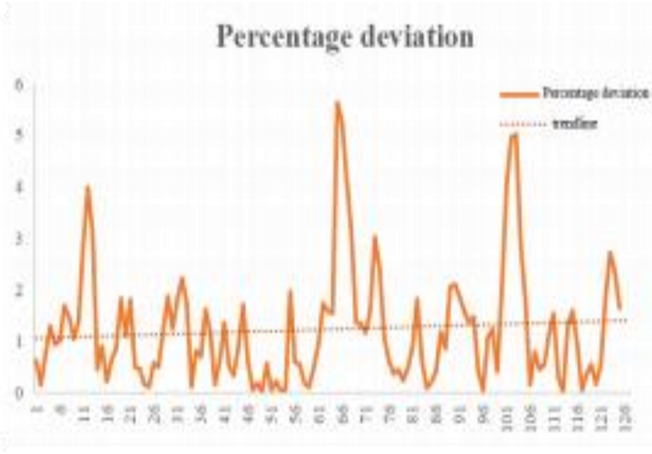
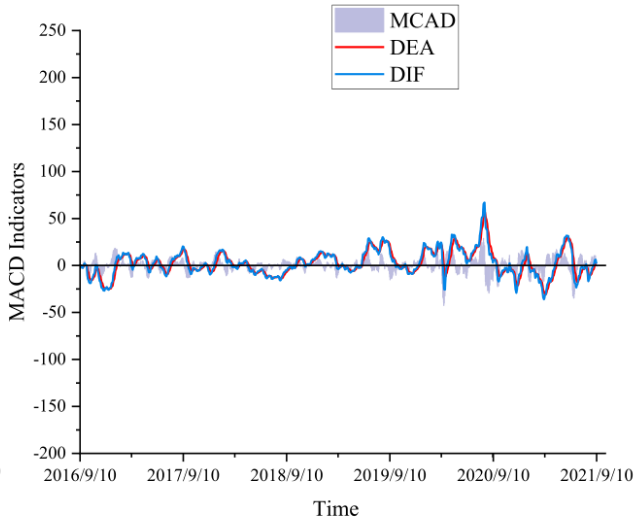


Figure 12. Percentage deviation of gold.

The above chart shows the deviation changes of bitcoin and gold in a certain period of time. It can be clearly seen that the deviation percentage of bitcoin fluctuates greatly between 0~40%, and the deviation percentage of gold is distributed between 0~6%. It can be seen that LSTM is more suitable for predicting the price fluctuation of gold from the perspective of prediction accuracy. The above-mentioned second conclusion can be easily drawn from the direction of the trend line and is no longer redundant.

6.2. Investment Strategy Selection Model

We use python to calculate MACD system indicators, the results are drawn as follows:



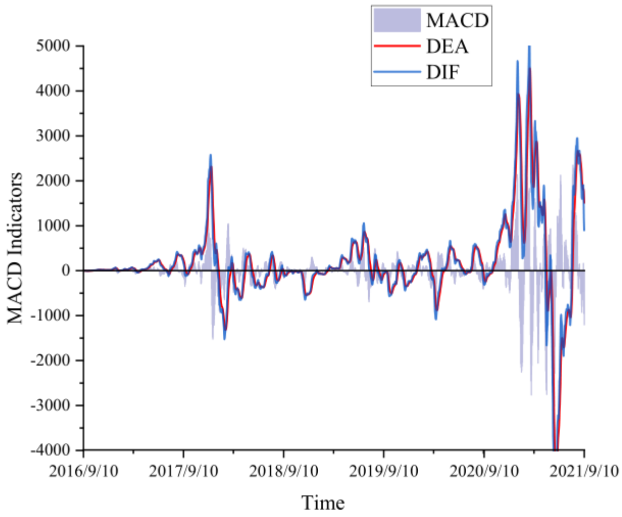


Figure 13. MACD indicators lines of bitcoin. **Figure 14.** MACD indicators lines of gold.

Compared with Figure 13 and Figure 14, we can find that bitcoin's DEA, DIF, MACD have stronger changes than gold (even bitcoin has a larger drawing scale). This proves that Bitcoin has the characteristics of fast price changing rate and poor price stability, which is suitable for short- term investment. On the contrary, the price of gold changes more stable, suitable for long-term investment. Our subsequent models will also use this feature.

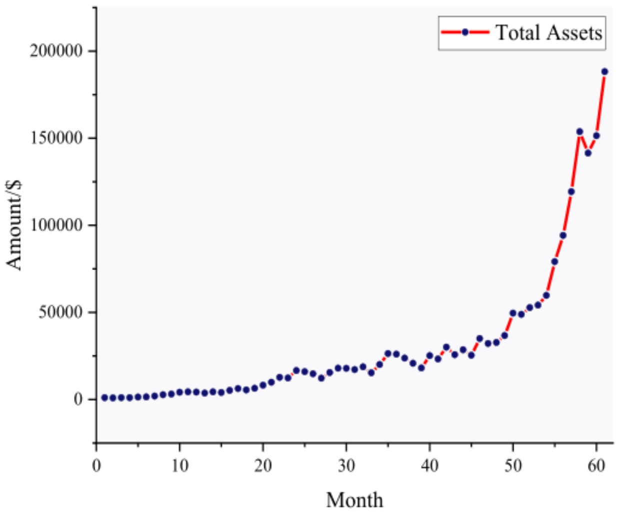
After that, we use python to solve our model. We use the model to select trading strategy of gold and bitcoin (buy, hold, sell). After the solution is completed, we unify the results of gold and bitcoin: we assign gold 's weekend strategy directly to 0 which means no trading, so there are gold and bitcoin investment strategies every day from 11/9/2016 to 10/9/ 2021.

Here are some results:

Table 3. Some results of investment strategy selection model.

DATE	GOLD	BITCOIN	DATE	GOLD	BITCOIN
27/10/2017	- 1	0	3/11/2017	0	1
28/10/2017	0	- 1	4/11/2017	0	1
29/10/2017	0	0	5/11/2017	0	1
30/10/2017	0	- 1	6/11/2017	0	0
31/10/2017	0	0	7/11/2017	1	0
1/11/2017	0	1	8/11/2017	1	0
2/11/2017	1	0	9/11/2017	1	0

6.3. Best investment strategy model



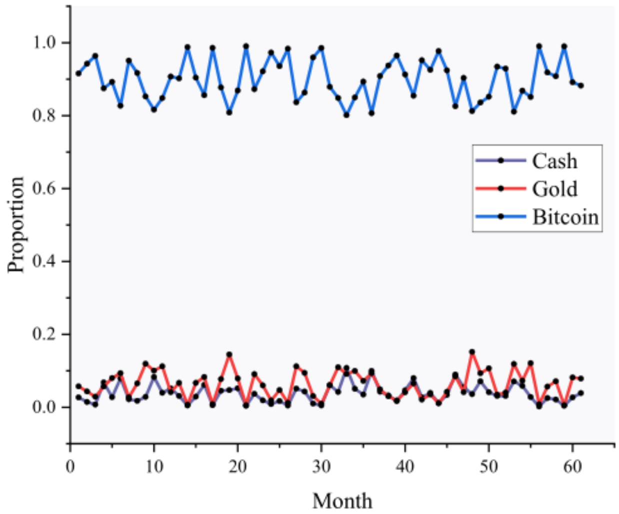


Figure 15. Investment result lines. **Figure 16.** Proportion lines of cash, gold, bitcoin.

In the analysis of the results, we mainly analyze the weight ratio of cash, gold and bitcoin and the income obtained.

In Figure 15 and Figure 16, according to the proportion of cash, gold and bitcoin (the proportion here refers to the proportion of total value), the proportion of bitcoin has been at a high level for a long time, while the proportion of cash has been at a low level for a long time. The proportion of gold is in the middle position, and the amount of cash held is very small. Thus, our model is inclined to believe bitcoin 's rise, which is consistent with the fact that bitcoin 's rise is far greater than the other two (cash's rise is seen as 0), more than 100 times. Although gold has also achieved a certain increase in the end, but from the perspective of the opportunity cost theory [11], investment in gold needs to bear the opportunity cost that cannot be invested in bitcoin. In our prediction model, the increase of bitcoin is far greater than that of gold, so the opportunity cost that needs to be borne is much higher than the income. Therefore, our model chooses to hold a large number of bitcoins, and from the perspective of the final income, our model has also achieved good results.

Although there is a slight loss in some cases, overall, our total assets have always been on the rise, and the final average monthly income is about 8%. This is mainly due to the excellent market performance of bitcoin and the relatively accurate prediction of our model and the better investment decision scheme made according to the prediction. In the process of several small declines in bitcoin, our model has also made some reactions, turning funds into some gold, and effectively avoiding some risks.

Finally, the investment value obtained after the end of the five-year trading period is $188182.59. The total number of transactions is 183. The total transaction commission is $5399.25.

7. Model Analysis

7.1. Evidence for Proving Our Model Provides the Best Strategy

7.1.1. Superiority of LSTM Future Price Forecasting Model

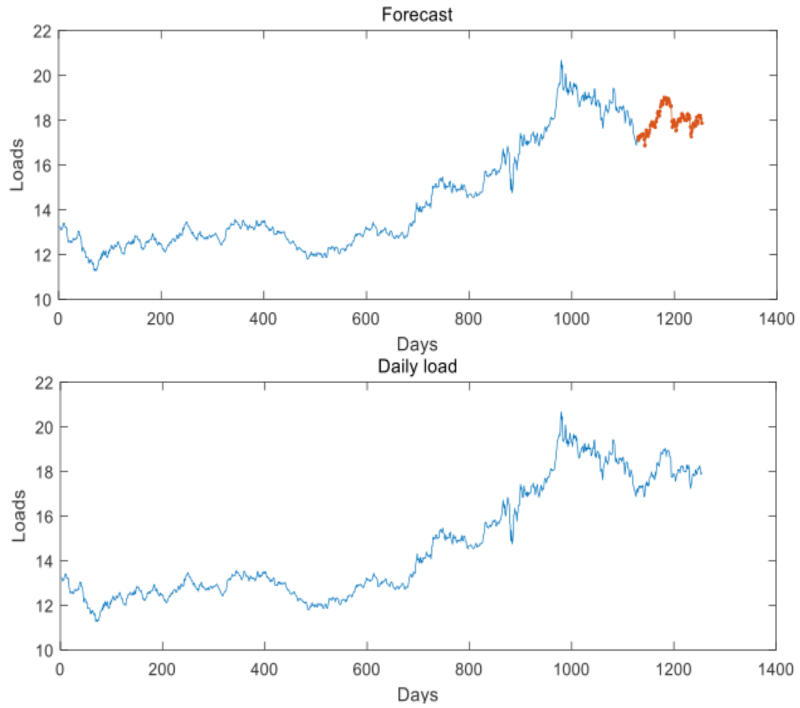


Figure 17. Prediction results of LSTM.

In this paper, 96*3 hidden units are set in the training process of LSTM neural network, and the initial learning rate is specified as 0.005. After 125 rounds of training, the learning rate is reduced by multiplying factor 0.2. Through such parameter setting, LSTM has very excellent time series data prediction ability and high prediction accuracy.

The prediction effect of using the price in the first 90% trading period of gold as a training set to predict future gold price fluctuations is shown in the above Figure 17. It can be seen that the root mean square error (RMSE) of the prediction results is 0.16303*100, which shows that the average difference between the prediction results and the real value is $16.303. The error is very small and the effect is very good. The effect is the best in all the prediction methods that have been tried to use. The root means square error of the results obtained by other methods for the same data prediction is shown in the Figure 18 below. The best trading strategy can be produced only by judging trading strategy on the basis of high accuracy prediction results. Therefore, from the perspective of data prediction, the method used in this paper is the best.

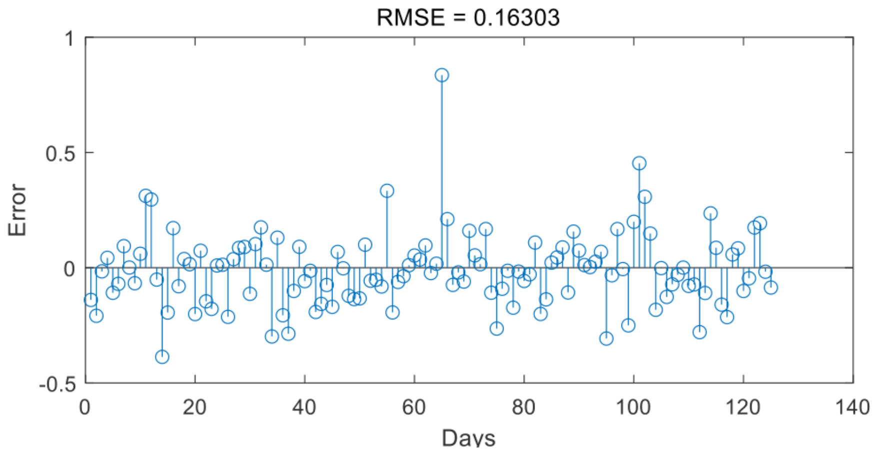


Figure 18. Error chart during days.

Table 4. Different RMSE among models.

Model Types	RMSE
LSTM	16.303
grey prediction model	184.236
time series analysis model	53.091
BP neural network model	38.908

7.1.2. Superiority of Investment Strategy Selection Model

Mentioned in 5.2, We used the dual judgment method of MACD + LSTM to judge whether to trade. To demonstrate the superiority of this method, we take bitcoin as an example and combine Figure 18 with Figure 19 as follows:

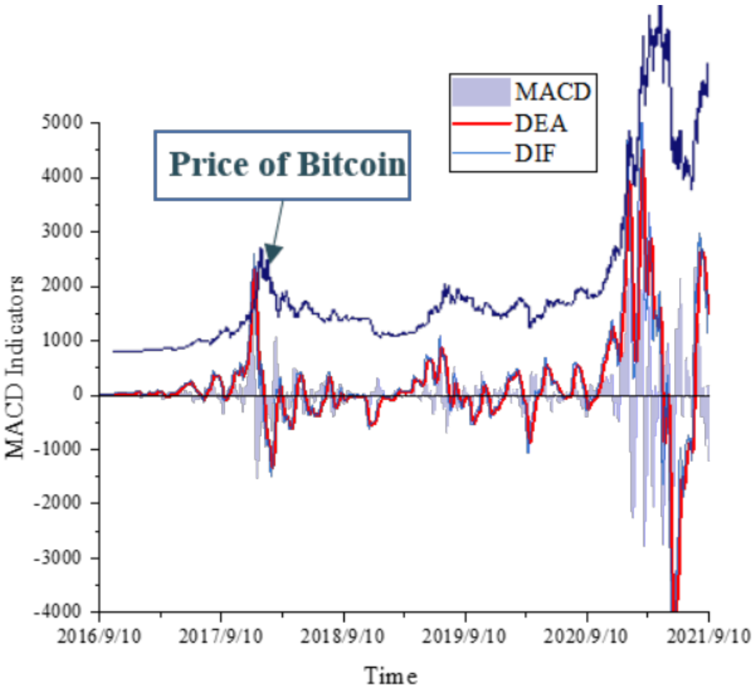


Figure 19. Combination of Figure 8 and Figure 9.

We can find that:

(1) DEA and DIF lines are very sensitive to price changes. It can be seen from the Figure 19 that near the time points with large price changes such as 10/2017, 5/2021 and 7/2021, the DEA and DIF lines also change greatly.

(2) DEA and DIF lines have certain predictability on price changes. It can be found from the Figure 19 that the great changes of DEA and DIF lines are always before the price, which proves that MACD theory is conducive to the proposal of the best strategy.

In general, model 5.2 is very suitable for finding the best strategy of this problem and make our model 5.3 the best strategy finding model.

7.2. Sensitive Analysis

In order to find out the influence of transaction cost on transaction strategy, we need to adjust the value of transaction cost in the established best investment strategy model to observe its influence on transaction strategy and transaction results. Therefore, we need to adjust the commission ratio in the model, and then let the model plan to obtain the final results and carry out the sensitivity analysis of the best investment strategy model.

In the process of sensitivity analysis, (1) $\alpha_{gold} = 1\%$ is maintained, and $\alpha_{bitcoin}$ is accumulated from 0.25% to 8% with 0.25% step length. (2) Keeping $\alpha_{bitcoin} = 2\%$ unchanged, α_{gold} is accumulated from 0.25% to 8% with 0.25% step length, and the planning model is run many times to analyze the final results.

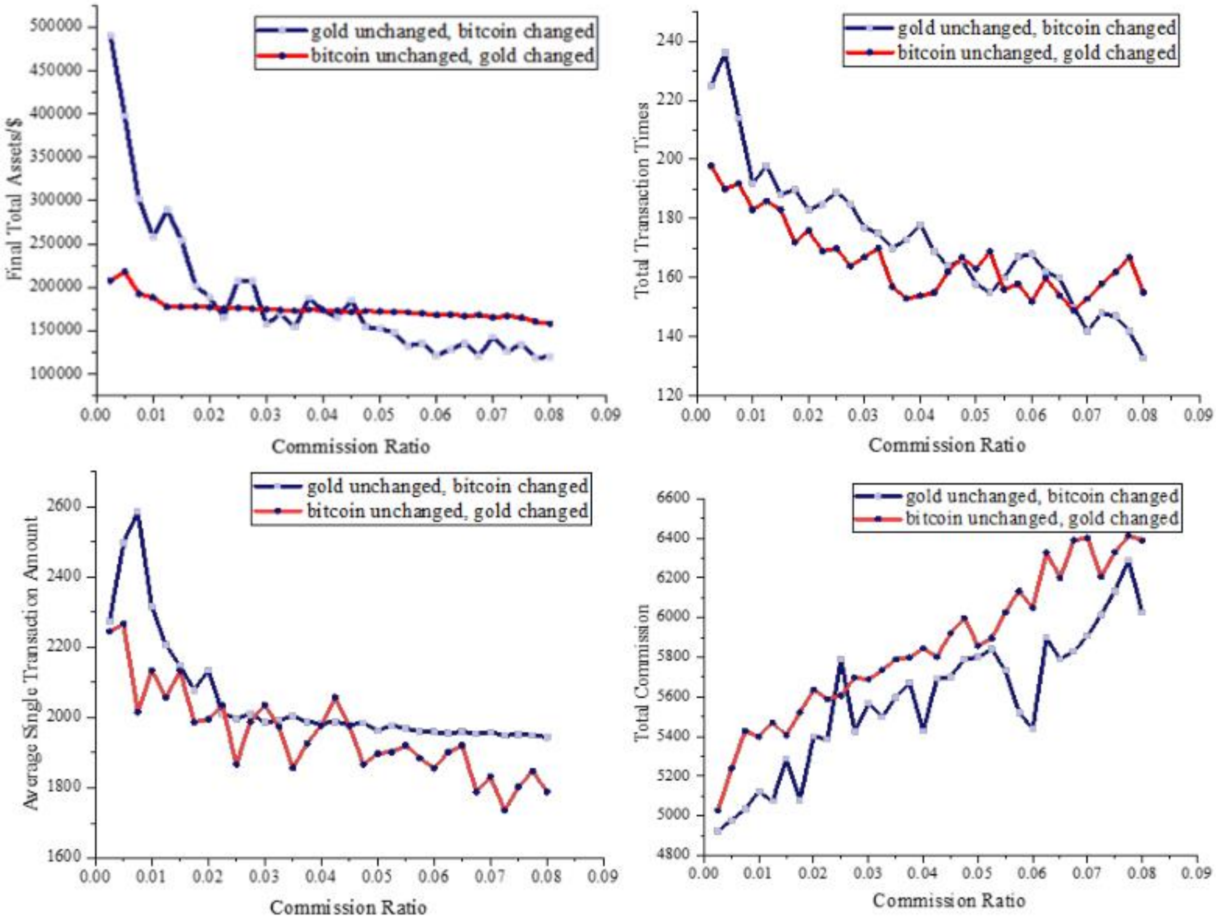


Figure 20. Sensitivity analysis chart.

It can be seen from the above Figure 20 that when the commission ratio of one product is fixed and the commission ratio of another product is accumulated with a certain step length, the increase of commission ratio will make the final investment value continue to decline, and the decline rate shows the characteristics of fast first and then slow. When the commission ratio increases to a certain size, the final investment value declines very slowly. In addition, it can also be clearly seen that the change in the proportion of bitcoin commission has the greatest impact on the final investment value, which will make the final investment value drop from nearly $500,000 to $100,000. When the proportion of gold commission changes, the final investment value remains around $200,000, with only a slight decline.

The three indicators of total transaction times, total commission and average single transaction amount reflect the sensitivity of transaction cost to transaction strategy from three perspectives. As can be seen from the above figures, the sensitivity of transaction strategy to the commission ratio of two products is very close, and there is no obvious difference in trend direction and change speed. Overall, the higher the commission ratio, the greater the transaction costs, resulting in a decline in the total number of transactions, a rise in total commissions and a decline in the total average single transaction, but the change is not large and basically stable.

In general, we can draw two conclusions: (1) transaction costs are less sensitive to trading strategies and more sensitive to the final value of the transaction. (2) In areas with lower commission ratios, the decline in final investment value caused by changes in the same commission ratio is significantly higher than in areas with higher commission ratios, that is to say transaction costs are more sensitive to investment outcomes in areas with lower commission ratios.

8. Conclusion

8.1. Strength

From qualitative analysis to quantitative analysis, there is double insurance in investment strategy model design.

Although the price prediction deviation of LSTM will gradually increase with the increase of prediction span, we design the mean-variance model to estimate the prediction deviation of different spans, so that the prediction results of different spans have different weights for investment decisions, which to some extent makes up for the deficiency of LSTM as the prediction result.

Investment strategy selection model considers both current and historical information and makes use of future information to make decisions more accurate.

9. Weakness

Without considering the game between investors in the market, there will certainly be a considerable number of investors in the market. If everyone invests according to similar strategies, it is bound to make it difficult for everyone to achieve profitability.

Markowitz model is based on the premise of market effectiveness, only when the market price can timely and impartially reflect all information on the market, the market is effective. Because the market itself may exist failure phenomenon, so the market effectiveness must be an ideal concept.

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