Problem Chosen	2022 MCM/ICM Summary Sheet	Team Control Number
C		2217107

Golden Bitcoin: Quantitative Trading Model based on LSTM-GA

Summary

Market traders buy and sell volatile assets frequently, such as bitcoin and gold. This article mainly expounds the construction process of the currency quantitative trading strategy model based on the LSTM-GA model, and uses the model to conduct a 5-year simulated investment in Bitcoin and gold assets, and finally obtains considerable returns, and provides reasonable suggestions to investors.

For the first question, we build a quantitative trading strategy model(QTSM) based on the LSTM-GA model. First of all, we use ARIMA,GM model and LSTM to predict the price of bitcoin and gold. By comparison,LSTM model has the smallest MSE for prediction on the test set. Therefore, we choose to use LSTM to forecast the price of bitcoin and gold after the trading day.The second step is to build a single-day decision model. First, focusing on directional trend strategies including moving average strategies,we creatively put forward the idea of "gate", and expounded the trading ideas of the strategy. Secondly, using data to obtain quantitative trading signals , trading signal weights. Finally, through the intelligent control of the trading "gate" switch, the daily update of the trading strategy is realized. For the determination of the optimal weights, we take the different weights of the dummy variables as the decision variables, take the maximization of the funds owned on the 100th day as the optimization objective, and take the constraints such as the sum of the weights equal to 1 as the constraint condition to establish a single-objective optimization. The model is solved by genetic algorithm(GM) to obtain the optimal weights of trading signals. At the same time, we realize the construction of the investment trading platform through programming, only need to input the initial [C, G, B], and the bitcoin and gold prices 100 days before the trading day can realize intelligent investment and obtain ideal return. The final return was $170609.51697227947.

For the second question, we prove that the QTSM is the optimal model from two aspects. First of all, we consider directional trend strategies, and creatively propose an intelligent "gate" idea to quantify trading willingness through secondary weighting, so that the model learns the way people think to invest. This model combines micro-investment psychology analysis and macro-machine learning optimization algorithm to achieve truly intelligent investment. At the same time, from the perspective of economics, we use the Sharpe ratio to analyze our LSTM-GA model. The final Sharpe ratio of the model is 0.9909, which is higher than other basic models.

For the third question, Obviously, the higher the commission, the higher the loss incurred by the exchange, so fewer transactions are required. We creatively propose a commission-related gate to control whether to trade. Using this gate, the number of transactions can be adjusted intelligently. When the commission becomes higher, the number of transactions will naturally decrease, and when the commission becomes lower, the number of transactions will naturally increase, which achieves a dynamic balance and reduces the profit caused by the higher commission loss, which has strong robustness.

Keywords: LSTM,Single Objective Optimization Model,Genetic Algorithm,The "gate"

Contents

1 Introduction

1.1 Background

In recent years, with the update and iteration of Internet technology and the popularization of blockchain, virtual currencies led by Bitcoin have gradually become the investment products favored by a new generation of investors after gold. Bitcoin adopts a decentralization-based, peer-to-peer network and consensus initiative, with blockchain as the underlying technology. Due to its limited holdings and widespread circulation and recognition around the world, it has high investment value. Gold, which supports the Bretton Woods system in the 20th century and maintains its value for a long time, is also the best choice for investors to invest safely.

1.2 Restatement of the Problem

We are required to establish a model to determine the change of water temperature in space and time. Then we are expected to propose the best strategy for the person in the bathtub to keep the water temperature close to initial temperature and even throughout the tub. Reduction of waste of water is also needed. In addition, we have to consider the impact of different conditions on our model, such as different shapes and volumes of the bathtub, etc.

In order to solve those problems, we will proceed as figure1 shows:

1.3 Our Work

Firstly, we perform data preprocessing on the original datasets LBMA-GOLD.csv and BCHAIN-MKPRU.csv, including filling in missing data, data visualization, and mining new valuable information from the original data.

Task 1

For the first question, we proposed a currency quantitative trading strategy based on the LSTM-GA model. This question is completed in two steps. The first step is to build a Bitcoin and gold value prediction model. By comparing the prediction effect of traditional methods with long short-term memory model (LSTM), the model with the smallest mean square error MSE on the prediction set is finally obtained, and its prediction result is taken as Data input for a single-day decision model.

The second step is to build a single-day decision model. First define dummy variables to construct trading signals, quantify the timing of buying and selling Bitcoin and gold, and then assign different weights to different dummy variables, and finally determine whether to buy or sell Bitcoin or gold and the amount of buying and selling. Since investors did not fully understand the market at the beginning, in the first 100 days, no actual investment was made, but the optimal weights of dummy variables were determined as a training set. For the determination of the optimal weights, we take the different weights of the dummy variables as the decision variables, take the maximization of the funds owned on the 100th day as the optimization goal, and take the constraints such as the sum of the weights equal to 1 as the constraint condition to establish a single-objective optimization. The model is solved by using the genetic algorithm to obtain the optimal weight output of the trading signal. At the same time, drawing on the knowledge of investment psychology, when we use the intelligent optimization algorithm to solve the weights, we creatively set up a "gate" to simulate the way of thinking of people to open and close the "gate", that is, the amount of bitcoin bought and sold is divided into two Sub-weighting, and finally get the optimal daily trading strategy.

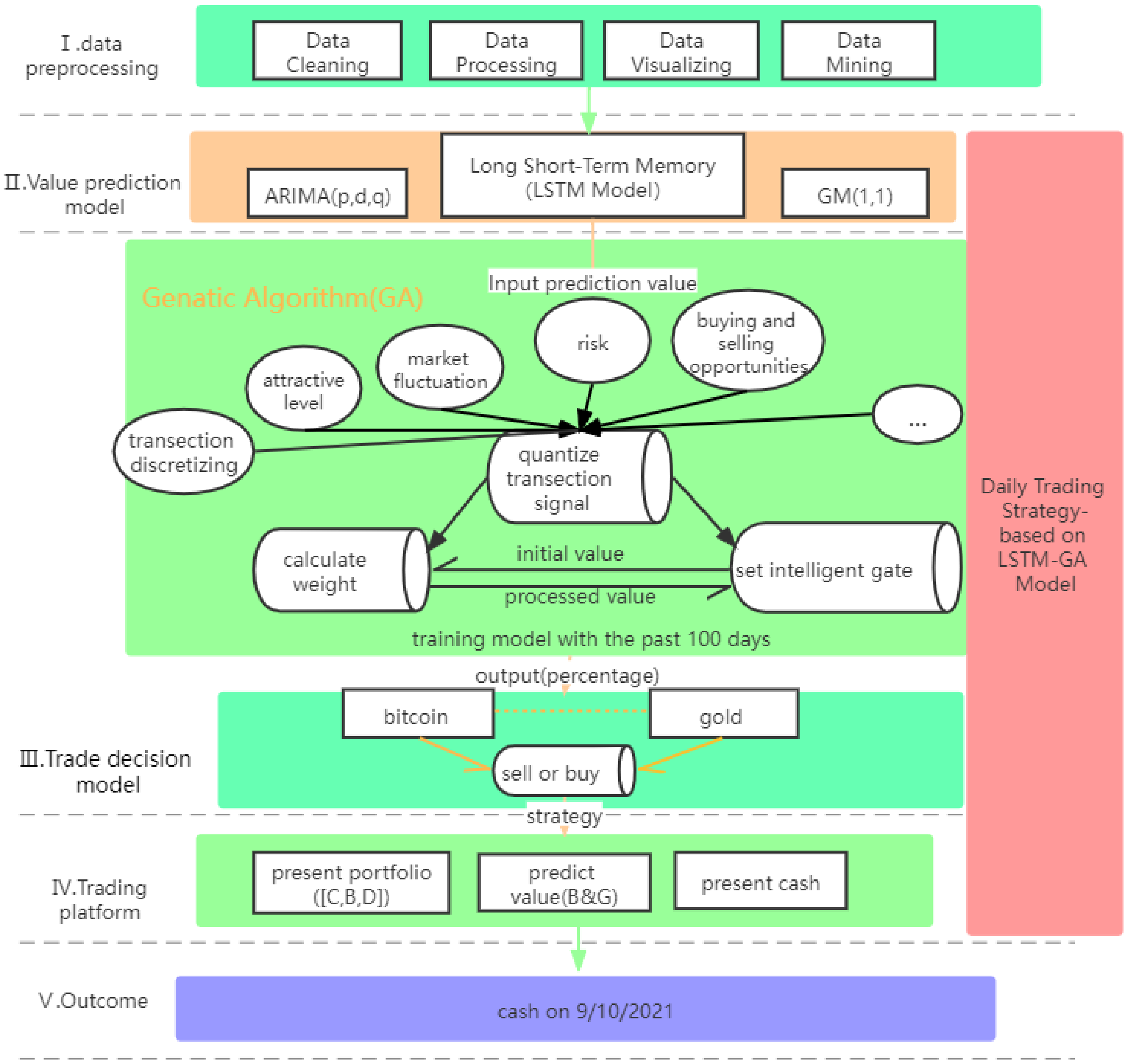

Figure 1: Our Workflow

At the same time, we realize the construction of the investment trading platform through programming, only need to input the initial [C, G, B], the price of Bitcoin and gold before the trading day and the price of the trading day can realize intelligent investment and obtain ideal income.

Task 2

For the second question, we prove that the currency quantitative trading strategy model based on the LSTM-GA model is the optimal model from two aspects of theoretical analysis and application verification. First of all, our model considers directional trend strategies including moving average strategies, quantifies its volatility characteristics by constructing trading signals, and creatively proposes an intelligent "gate" idea, that is, quantifying trading willingness through secondary weighting, so that the model learns the way people think to invest. This model combines micro-investment psychological analysis and macro-machine learning optimization algorithm to achieve truly intelligent investment. The existing portfolio strategies have not been considered in such detail, so we consider it to be the optimal strategy. At the same time, from the perspective of economics, we use the Sharpe ratio to analyze our LSTM-GA model, and after multiple calculations to calculate the average, the final Sharpe ratio of the model is 0.9909, which is compared with other basic models (the average Sharpe ratio of aggressive investment: 0.6358; mean Sharpe ratio for robust investments: 0.7327), our mean Sharpe ratio is high. This means that in the vast majority of cases, the risk-return per unit of risk is the highest, which is most beneficial to investors, illustrating the superiority of our model.

Task 3

We need to test the sensitivity of the model, that is, the impact of changing transaction costs on the model and the results.

Transaction costs generally refer to all the costs that are formed to facilitate transactions, and in this case, it mainly refers to changes in transaction commissions. Obviously, the higher the commission, the higher the loss incurred by the exchange, so fewer transactions are required. And our model took this problem into account at the beginning of its establishment. We creatively proposed a commission-related gate to control whether to conduct transactions. The formula is x = random.randint(1,(25-int(math.fabs(many))*10)*int(Commission * 100)), where many is the predicted transaction value, which is between -1 and 1 , and commission is the amount of commission.In order to test the sensitivity of the system, we designed a random number in the program to make the Commission fluctuate between 0.005 and 0.05. After trading, it is found that the impact of Commission on income is greatly reduced compared with the system without gate.

Obviously, the opening of the gate is related to the transaction value predicted by the commission model. When the commission is smaller and the predicted transaction value is larger, the range of x generated is smaller, that is, the probability of the gate opening is larger; conversely, when the commission is larger, The smaller the predicted transaction value, the larger the range of x generated, that is, the smaller the probability of the gate opening. Therefore, we can see that when the commission becomes higher, the number of transactions will naturally decrease, and when the commission becomes lower, the number of transactions will naturally increase, which achieves a dynamic balance and reduces the substantial loss of income caused by the higher commission. So it has strong robustness.

2 Assumptions and Justification

Due to lack of necessary data and limitation of our knowledge, we make the following assumptions to help us perform modeling. These assumptions are the premise for our subsequent analysis.

- Due to the limitation of data, the fluctuation of gold and bitcoin does not consider the impact of market policy.
- It is assumed that all investors are always rational and self-interest, pursue their subjective goals in the best way, and obtain their maximum economic benefits at the least economic cost.
- Assuming that the capital flow of investors is stable, they will not withdraw their investment funds due to other external risks
- Assuming that gold is only carried out on trading days, investors can not invest privately on non trading days

3 Notations

Symbols	Description	Unit
b_i	The daily price of bitcoin	\$ /bitcoin
g_i	The daily price of gold	\$ /ounce
eb_i	The parameter to determine the rising-day of bitcoin's price	
eg_i	The parameter to determine the rising-day of gold's price	
δ_{bi}	The first difference of bitcoin's price	\$ /bitcoin
δ_{gi}	The first difference of gold's price	\$ /ounce
bv_i	The changing rate of bitcoin	
gv_i	The changing rate of gold	
v_{bj}	The dummy variables to quantize trading signals of bitcoin	
w_{bj}	The weight of dummy variables	m^3, L
v_{gj}	The dummy variables to quantize trading signals of gold	
w_{hj}	The weight of dummy variables	
C	The capital sum	\$

where we define the main parameters while specific value of those parameters will be given later.

4 Model Preparation

4.1 Data description

BCHAIN-MKPRU.csv has a total of 1825 valid data. LBMA-GOLD.csv has a total of 1264 records, because gold is only traded on market open days, there are 10 missing values, and the method of adding the adjacent two days to take the average is used to fill in the missing values.

4.2 Data visualization

The daily trading price comparison chart of Bitcoin and gold is drawn based on the data given by the question as figure2 shows:

As can be seen from the figure, compared with Bitcoin, the price fluctuation range of gold is smaller, but at the same time, its rising space is small, which is due to the strong function of gold preservation; while the price range of Bitcoin is very large, and its highest The price can reach 100 times the initial price, and at the same time, it is accompanied by greater risk. The trade-off between bitcoin and gold prices is due to the tendency of consumers to convert bitcoin to gold when market confidence is low.

4.3 Data Mining

A.Annual fluctuation trend

Observing the trend stacking chart of the value of Bitcoin (left) and gold (right) from

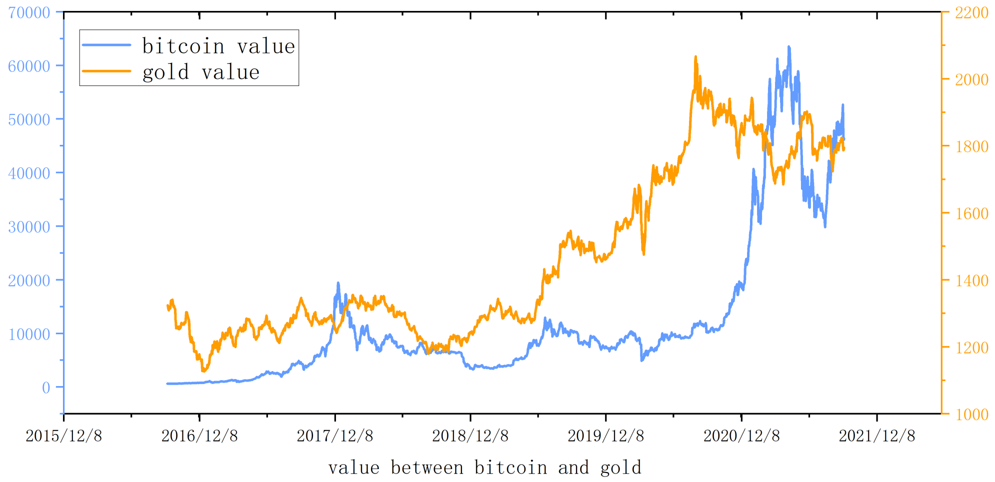

Figure 2: Wave line of bitcoin of gold

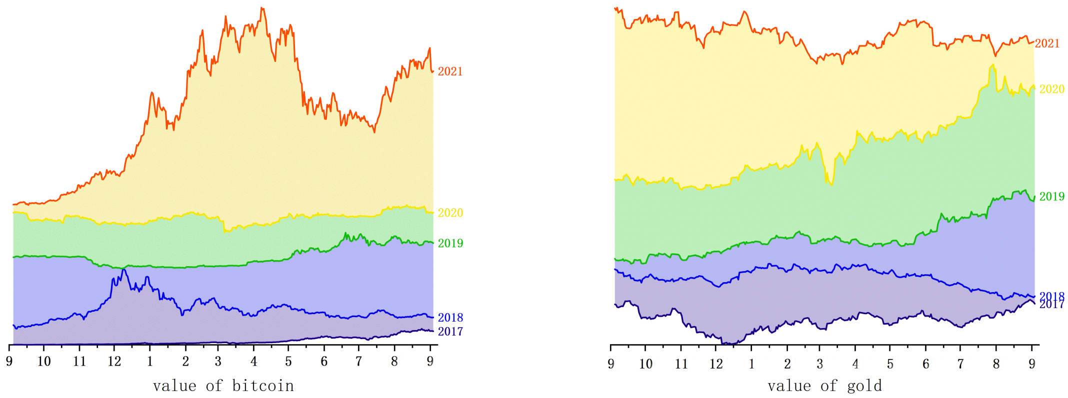

Figure 3: value of bitcoin and gold

2016 to 2021(figure3), it can be seen that although the two fluctuate greatly in the short term, the overall trend is increasing year by year. Since September 2019, the change of Bitcoin has increased sharply. The reason may be that on the one hand, Bitcoin has continued to fluctuate at a low level, and in the context of the strengthening of the US dollar and the continuous rise of global risk assets such as the stock market, Bitcoin still has no A new low is reached, which shows that the holders of the Bitcoin market have been inclined to reluctant to sell. As long as there is a little news or demand stimulation, the market will rapidly increase buying, leading to price increases; on the other hand, the US Congress has introduced two The cryptocurrency-related bill aims to address the markets persistent concerns about price manipulation and improve the U.S.s competitive advantage in the nascent cryptocurrency industry.

B.Data Processing

Since the volatility of the currency market is too large, it is not conducive to the making of investment decisions, so we define the daily change in the value of Bitcoin (δ_{bi}) as:

$$\delta_{bi} = b_{i+1} - b_i, \tag{1}$$

where b_i represents the bitcoin value on day i.

Draw a double y-axis graph as figure4 shows, where the left axis represents the bitcoin value ($/bitcoin), and the right axis represents the daily change in value ($/bitcoin)

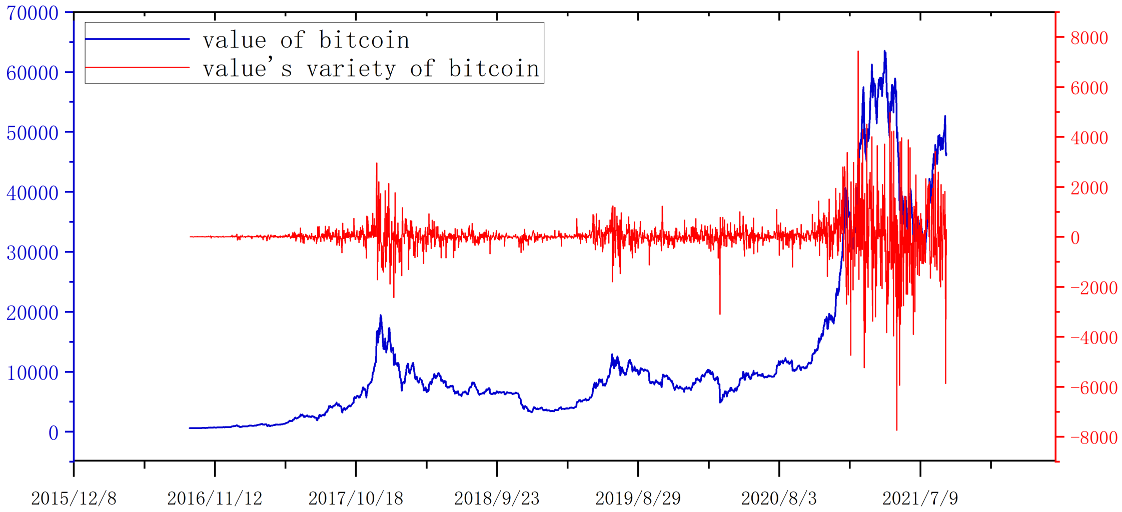

Figure 4: Difference between rise and fall of bitcoin in a single day

The daily change in the value of Gold (δ_{gi}) is defined as:

$$\delta_{gi} = g_{i+1} - g_i, \tag{2}$$

where g(i) represents the bitcoin value on day i Draw a double y-axis graph as figure5 shows, where the left axis represents the value of gold ($/ounce), and the right axis represents the daily change in value ($/ounce)

5 Bitcoin and Gold Value Prediction Model

After consulting the literature, it is found that the quantitative methods used for economic forecasting in the world can basically be classified into the following two types of models: one is the traditional forecasting model based on statistical mathematical modeling, including exponential smoothing method, ARIMA model and Grey forecasting model, etc.; another type is an innovative forecasting model based on the idea of simulation and based on neural network. Each forecasting model has its advantages and disadvantages, such as ARIMA is suitable for stationary time series, neural networks are slow to converge, etc. This paper attempts to use three models to predict the daily value of Bitcoin and gold, and obtains the optimal prediction model through comparison, and then provides support for the formulation of subsequent trading strategies.

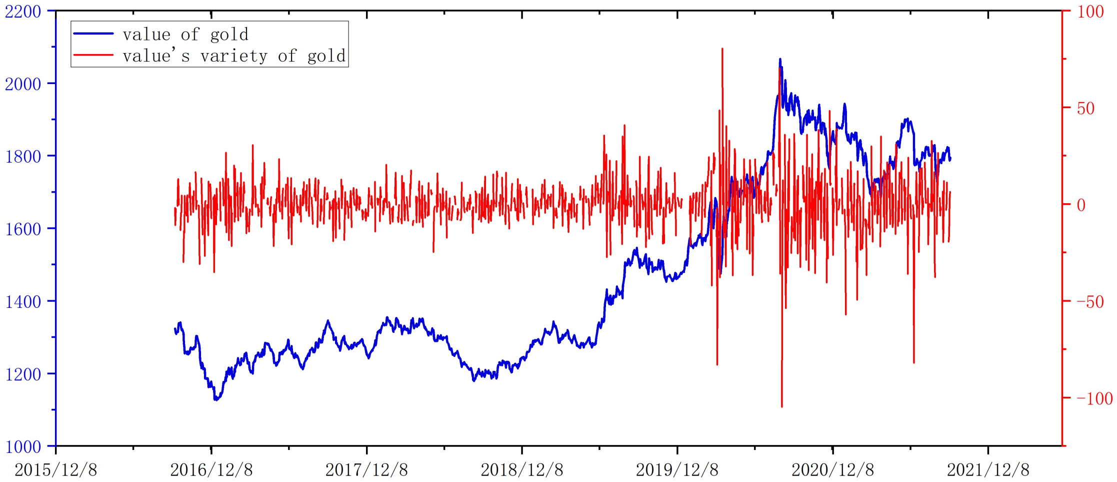

Figure 5: Difference between rise and fall of bitcoin in a single day

5.1 The Long Short-Term Memory (LSTM)

5.1.1 Model introduction

Due to the randomness and non-stationarity of financial time series data, it is difficult for traditional forecasting methods to analyze them accurately. Deep learning methods have more advantages than traditional econometric models in identifying the structure and patterns of data, and can effectively learn the nonlinear and non-stationary characteristics of time series, which is suitable for financial time series forecasting problems. As a deep learning model, the long-term and short-term memory model has long-term memory ability. Each layer of its network layer structure is connected to each other and consists of one or more units with forgettable and memory functions. Can handle time series data better than other neural network models. Conveyor belt transport mechanism, information travels along the entire chain with only some minor linear interactions.[1]

The LSTM has three gates (pictured below) that protect and control the cell state.

- Input gate: Determine how much of the input data of the network at the current moment needs to be saved to the unit state.
- Determine how much of the unit state at the previous moment needs to be retained to the current moment.
- Controls how much of the current cell state needs to be output to the current output value.[2]

With figure 6, information can be removed or added to the cell state, whereby structures called gates are carefully regulated. The specific implementation makes use of the sigmoid() function, the sigmoid layer outputs a number between 0 and 1, with a value of 0 meaning "don't let anything through" and a value of 1 meaning "let everything through."

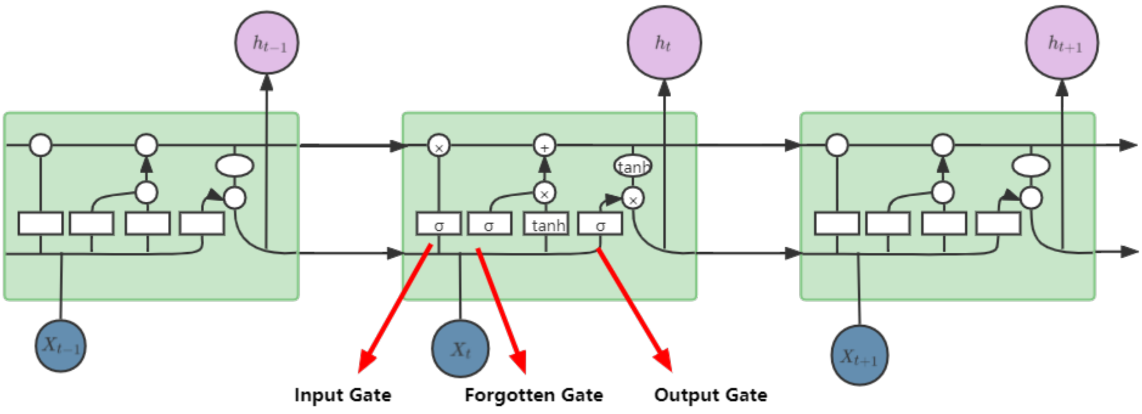

Figure 6: The component of LSTM

5.1.2 Model implementation

The specific implementation steps of the model (as shown in the figure7) are:

STEP1: Apply the output h_{t-1} of the previous moment and the current data input X_t, and obtain f_t through the forget gate.

STEP2: Apply the output h_{t-1} of the previous moment and the current data input X_t, obtain i_t through the input gate, and obtain the temporary state $\tilde{C}_t$ at the current moment through the unit state.

STEP3: Apply the cell state C_{t-1} of the previous cell structure, the forget gate output f_t, the input gate output i_t, and the cell state output $\tilde{C}_t$ to obtain the current cell state C_t.

STEP4 Apply the output h_{t-1} of the previous moment and the current data input X_t, obtain the process of o_t through the output gate, and combine the cell state C_t and o_t of the current cell to obtain the final output h_{t-1}.

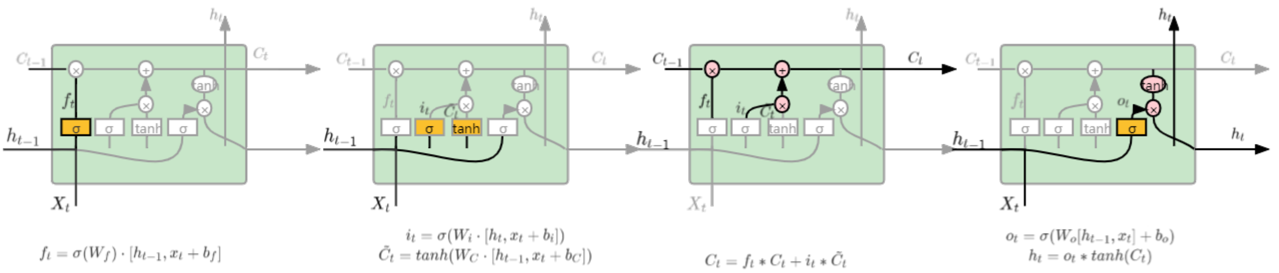

Figure 7: LSTM Steps

5.1.3 Results and Analysis

Since gold is only traded on working days, the discontinuity of the gold price will increase the difficulty of its price forecasting, so we make up for it to facilitate subsequent forecasting and strategy formulation. Since we can only use the past daily price stream to determine whether to trade, we use the previous day's gold price to fill in missing values.

The prediction results obtained by using the LSTM model to train Bitcoin and gold prices are shown in the figure 8.

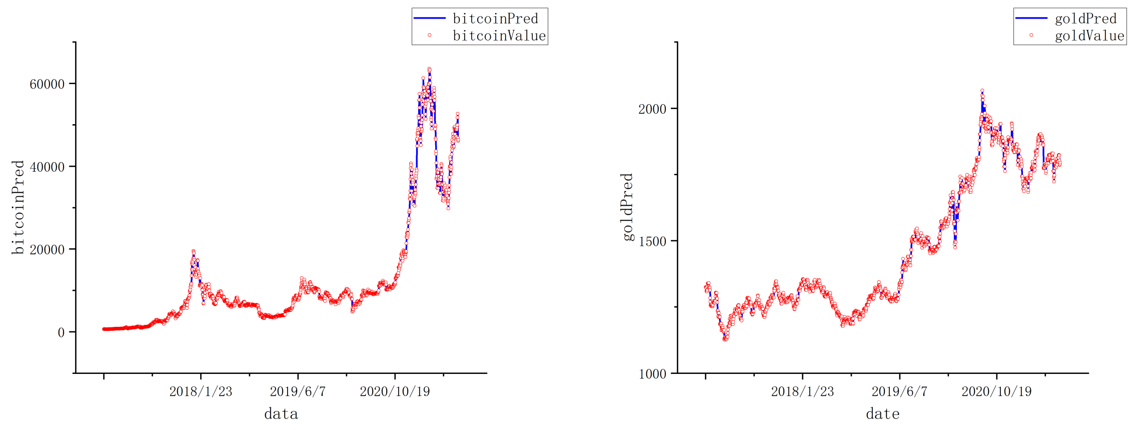

Figure 8: The prediction curve of bitcoin and gold

It can be seen from the figure that the predicted value overlaps the actual value with a high degree, and the prediction is more successful. The MSE of bitcoin and gold is [3.223,0.321].

5.2 ARIMA time series forecasting model

5.2.1 Model introduction

The full name is Autoregressive Integrated Moving Average Model, abbreviated as ARIMA, where ARIMA(p, d, q) is called differential autoregressive moving average model, AR is autoregressive, p is autoregressive term; MA is moving average, q is moving average The number of terms, d is the number of differences made when the time series becomes stationary. The so-called ARIMA model refers to a model established by converting a non-stationary time series into a stationary time series, and then regressing the dependent variable only on its lag value and the present value and lag value of the random error term.

5.2.2 Model implementation (taking gold price as an example)

Using the ARIMA model to predict time series data must be stable. If the data is unstable, it is impossible to capture the law. Use differential analysis to process the data stability.

We select a subset of the data series as training data, and our goal is to predict the last day of the series based on this input.Once the model has been fitted, we can check if does what we expect and if the assumptions we made are violated. To do this, we can use the plot-diagnostics method.The calculation results are shown in figure9.

5.2.3 Results and Analysis

ARIMA essentially only captures linear relationships, not nonlinear relationships. That is to say, to use the ARIMA model to predict time series data, it must be stable. If the data is not stable, it is impossible to capture the law. The price data of gold and bitcoin in this question are unstable and often fluctuate due to the influence of policies, so the effect is not good.

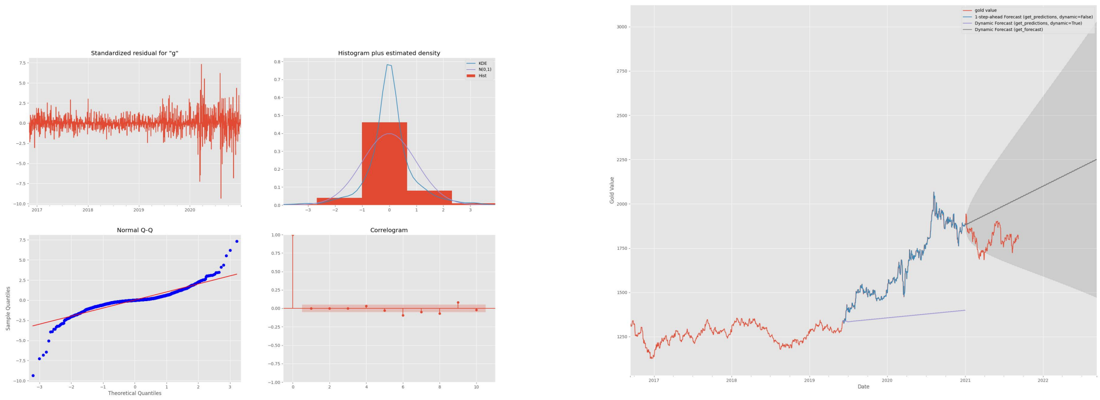

Figure 9: the prediction curve of ARIMA

5.3 Grey System Prediction Model

Grey forecasting is a method for forecasting a system with uncertain factors. The gray system is a system between the white system and the black system. It studies a system with few data and uncertainties with "partial information known and partial information unknown". In the currency market, due to factors such as interest rate policy, financial policy, international market, political environment and corporate reform, it is difficult for even the best analysts to accurately grasp it. Therefore, the grey system theory can generate information through the generation of known information. to study these gray uncertain systems.

The GM model has a better prediction effect for data with a clear trend, but for data with frequent oscillations, lack of consideration of the internal mechanism of the system, the prediction effect is significantly affected, and there may be large errors. This is due to GM It is determined by the mechanism of the model itself.

5.4 Conclusion

The following table lists the mean square error of the three models.

Table 1: The calculating results

Model	Bitcoin Mean Squared Error	golden mean squared error
LSTM	3.223	0.321
ARIMA	7.990	1.235
GM	9.652	2.235

Among the three models, the LSTM model has the smallest price prediction error MSE for gold and Bitcoin, indicating that the LSTM model has a stronger advantage in financial time series forecasting. At the same time, because the GM algorithm requires less modeling information and is easy to calculate, it can be used to process short-term predictions of small sample data, that is, predict the short-term prices of Bitcoin and gold, assist LSTM to search for hyperparameters, and then practice to a certain extent. Optimal LSTM model to improve prediction accuracy.[4]

6 Quantitative Trading Decision Model

6.1 Data feature extraction

first-level indicator

Define the daily price of Bitcoin as $b_i, i = 1, ..., 1826$; the daily price of Bitcoin predicted by the LSTM model is $vb_i, i = 41, ..., 1826$, then the difference between the predicted price of bitcoin on the second day and the current day is:

$$eb_i = vb_{i+1} - b_i \tag{3}$$

$eb_i > 0$, indicates that the price of Bitcoin will rise on the second day, $eb_i < 0$, indicates that the price of Bitcoin will fall on the second day.

Similarly, the daily price of gold is defined as g_i, and the daily price of gold predicted by the LSTM model is vg_i, then the difference between the predicted price of gold on the second day and the current day is:

$$eg_i = vg_{i+1} - g_i \tag{4}$$

Calculate the mean, maximum, and minimum $b_{mean}, b_{max}, b_{min}; g_{mean}, b_{max}, b_{min}$ of the bitcoin and gold prices for the 100 days before the trading day.

To characterize market volatility, we define the bitcoin changing rate:

$$bv_i = (b_i - b_{i-1}) / b_{i-1} \tag{5}$$

gold changing rate:

$$gv_i = (g_i - g_{i-1}) / g_{i-1} \tag{6}$$

Calculate the consecutive rising days BI and GI of Bitcoin and gold, and the consecutive falling days BD and GD before the trading day.

In order to study the periodic changes of Bitcoin and gold prices, we calculate the difference between Bitcoin every 10 days as follows:

$$\mathit{\Delta}_{bi} = b_{i-1} - b_{i-10} \tag{7}$$

At the same time, the difference between the maximum and minimum values of the ten days is calculated as follows:

$$\mathit{\Delta} t_{bi} = \underset{(i-10 \leqslant k \leqslant i-1)}{arg \max}\ b_k - \underset{(i-10 \leqslant k \leqslant i-1)}{arg \min}\ b_k \tag{8}$$

Similarly, the corresponding variables of gold are as follows:

$$\mathit{\Delta}_{gi} = g_{i-1} - g_{i-10} \tag{9}$$

$$\Delta t_{gi} = \underset{(i-10\leqslant k\leqslant i-1)}{arg\max}\ g_k - \underset{(i-10\leqslant k\leqslant i-1)}{arg\min}\ g_k \tag{10}$$

buy or sell bitcoin

After consulting the relevant information, define dummy variables to construct trading signals and describe the time of buying and selling bitcoins. 1 means buying bitcoins, -1 means selling bitcoins, and 0 means no operation.

a. If the daily price of bitcoin is greater than the average value of the previous 100 days, buy bitcoin, and sell if it is less than that, namely, If $b_i < b_{mean}$, output 1; if $b_i > b_{mean}$, output -1; if not satisfied, output 0

b. If $eb_i > 0$, output 1, if $eb_i < 0$, output -1; if not satisfied, output 0; if not satisfied, output 0

c. If $3 < BI < 6$, output 1; if $3 < BD < 6$, output -1; if not satisfied, output 0

d. If $BD > 6$, output 1; if $BI > 6$, output -1; if not satisfied, output 0

e. If $\Delta_{bi+1} < \Delta_{bi}$, and $\Delta t_{bi+1} > \Delta t_{bi}$, then output 1; if $\Delta_{bi+1} > \Delta_{bi}$, and $\Delta t_{bi+1} < \Delta t_{bi}$, output -1; if not satisfied, output 0

f. If $g_i > g_{mean}$, output 1; if $g_i < g_{mean}$, output -1; if not satisfied, output 0

g. If $eg_i < 0$, output 1, if $eg_i > 0$, output -1; if not satisfied, output 0

h. If $3 < GD < 6$, output 1; if $3 < GI < 6$, output -1; if neither is satisfied, output 0

i. If $GI > 6$, output 1; if $GD > 6$, output -1; if not satisfied, output 0

j. If$\Delta_{gi+1} < \Delta_{gi}$, and$\Delta t_{gi+1} > \Delta t_{gi}$, output 1; if $\Delta_{gi+1} > \Delta_{gi}$, and $\Delta t_{gi+1} < \Delta t_{gi}$, output -1; if not satisfied, output 0

k. If $bv_i > 0.08$, output 1; if $bv_i < -0.08$, output -1, if not satisfied, output 0

l. If $gv_i < -0.08$, output 1; if $gv_i > 0.08$, output -1; if not satisfied, output 0

In the same way, we can figure out a strategy for buying and selling gold

Algorithm introduction

We construct trading signals with dummy variables that characterize the timing of buying and selling Bitcoin and Gold and the number of trades. Since different dummy variables have different influences on decision-making, corresponding influence factors are added, that is, a fixed weight group is set to weight different dummy variables to determine the influence ability of dummy variables. And we compare the buying weights and selling weights through the weights of the dummy variables and their influencing factors, and finally get the corresponding strategy.

Step 1: Calculate the value of the dummy variable data, such as the difference in a single day, the highest value and the lowest value in the past 100 days, etc.

Step 2: Calculate and judge the dummy variable through the above method. If the corresponding judgment is true, the corresponding purchase or selling coefficient is added to the corresponding weight of the dummy variable.

Step 3: After executing the judgment of dummy variables and the weights of buying and selling, we can judge by the size of the buying weight and selling weight. When the buying weight is far greater than the selling weight When the weight is sold, that is, when the purchased weight minus the sold weight is greater than 0.5, we can determine the large purchase strategy. When the purchased weight is slightly larger than the sold weight, the purchased weight is reduced by When the weight of selling is greater than 0.2, we can determine the small purchase strategy. On the contrary, when the weight of selling is much larger than the weight of buying, we determine the strategy of large selling. When the weight of selling is slightly larger than the weight of buying When the weight of , we determine the small sell strategy.

Step 4: At the same time, we link the value of buying and selling with the value of buying and selling strategies.

Brilliant ideas

1.When it is judged to be a large amount of selling, we will activate the market downturn tag. When the next time it is worth buying, if our market downturn tag is activated, we will buy a large amount, that is, when we have a large amount of cash on hand, we will make a large amount of purchases. investment to increase the return on investment.

2.We adopt the method of fixed investment, and take out a stable small amount of funds every day for long-term investment. If the market is rising, we can obtain higher returns due to the long-term layout. If the market is falling, we will lose less. At the same time, our fixed investment is a floating strategy and adopts the moving average mode. When the value of yesterday is lower than the average value of the past 100 days, a higher fixed investment will be made. On the contrary, when the value of yesterday is higher than the average value of the past 100 days, Make a lower fixed bet. Therefore, it is ensured that the number of fixed investments at low positions is more frequent, and the stability of the investment and the return ratio are taken into account.

3.Due to the commission, we should reduce the number of transactions, so a gate is added. When the buy weight is not much different from the sell weight, that is, when it is impossible to judge whether to buy or not, we choose not to trade in most cases. At the same time, our trading probability is negatively correlated with the absolute value of the weight, that is, the greater the absolute value of the weight, the greater the possibility of our trading, the smaller the absolute value of the weight, the less likely we are to trade, and Reduce unnecessary losses caused by excessive trading and ensure the stability of investment

4.At the same time, the number of our transactions is also related to the size of the commission. Obviously, the higher the commission, the smaller the number of transactions. Therefore, we designed a function to link the possibility of transactions with the commission, which is negatively correlated. Therefore, we guarantee that the higher the commission is, the less the number of transactions, which guarantees the robust of transections.The specific formula is as follows:

$$x = \lfloor \frac{1}{rand\left(1, 25 - |many| \times 10\right) \times \left(commission \times 100\right)} \rfloor. \tag{11}$$

$$many \in [-1, 1]\,, commission \in (0, 1) \tag{12}$$

$$\begin{cases} x > 1\ close\ the\ gate \\ x \leqslant 1\ open\ the\ gate \end{cases} \tag{13}$$

where x is the probability of a transaction, that is, if x is less than a certain value, a transaction will occur, many is the mode and volume of the returned transaction, the probability of a transaction is positively correlated with many, commission is commission, and the probability of a transaction is negatively correlated with commission.

6.2 Establishment of trading decision-making model - solving the optimal weight based on genetic algorithm

6.2.1 Single-objective Optimization Model

STEP1:Decision variable

We set the above-mentioned bitcoin trading signal as v_{bj} and set corresponding weight value of it as $w_{bj}, j = 1, 2, ..., 12$. Similarly, we have v_{gj} and $w_{gj}, j = 1, 2, ..., 12$ for gold.

STEP2:Obejective function

$$\max_{w_b, w_g} f(x) \tag{14}$$

$$f(x) = b_i C \left(\sum_{j=1}^{12} w_{b_j} \cdot \tilde{v_{b_j}}^{+} \right) + g_j C \left(1 - \sum_{j=1}^{12} w_{b_j} \cdot \tilde{v_{b_j}}^{+} \right) \left(\sum_{j=1}^{12} w_{g_i} \cdot \tilde{v_{g_j}}^{+} \right) \tag{15}$$

$$+C \left[1 - \sum_{j=1}^{12} w_{b_j} \cdot \tilde{v_{b_j}}^{+} - \left(1 - \sum_{j=1}^{12} w_{b_j} \cdot \tilde{v_{b_j}}^{+} \right) \left(\sum_{j=1}^{12} w_{g_i} \cdot \tilde{v_{g_j}}^{+} \right) \right] \tag{16}$$

$$\tilde{v_{b_j}} = \begin{cases} v_{b_j}, v_{b_j} > 0 \\ -v_{b_j}, v_{b_j} < 0 \end{cases}, \tilde{v_{g_j}} = \begin{cases} v_{g_j}, v_{g_j} > 0 \\ -v_{g_j}, v_{g_j} < 0 \end{cases} \tag{17}$$

$$\tilde{v_{b_j}}^{+} = \begin{cases} \tilde{v_{b_j}}, v_{b_j} \geqslant 0 \\ 0, v_{b_j} < 0 \end{cases}, \tilde{v_{g_j}}^{+} = \begin{cases} \tilde{v_{g_j}}, v_{g_j} \geqslant 0 \\ 0, v_{g_j} < 0 \end{cases} \tag{18}$$

Thereinto,$w_b = (w_{b_1}, w_{b_2}, \cdots, w_{b_{12}})^T$,$w_g = (w_{g_1}, w_{g_2}, \cdots, w_{g_{12}})^T$

STEP3:constraint condition

$$\begin{cases} \sum_{j=1}^{12} w_{b_j} = 1 \\ \sum_{j=1}^{12} w_{g_j} = 1 \\ w_{b_j} \in [0, 1], 1 \leqslant j \leqslant 12 \\ w_{g_j} \in [0, 1], 1 \leqslant j \leqslant 12 \\ C \geqslant 0 \end{cases} \tag{19}$$

6.2.2 Model solving-Genetic Algorithms

A. Introduction to Genetic Algorithms

Genetic Algorithm (GA) originated from the computer simulation study of biological systems. It is a random global search and optimization method developed by imitating the biological evolution mechanism in nature, drawing on Darwin's theory of evolution and Mendel's theory of genetics.[6] Its essence is an efficient, parallel, global search method, which can automatically acquire and accumulate knowledge about the search space during the search process, and adaptively control the search process to obtain the best solution.[5]

B. Algorithm principle

The flow diagram of genetic algorithm is as figure10 shows:

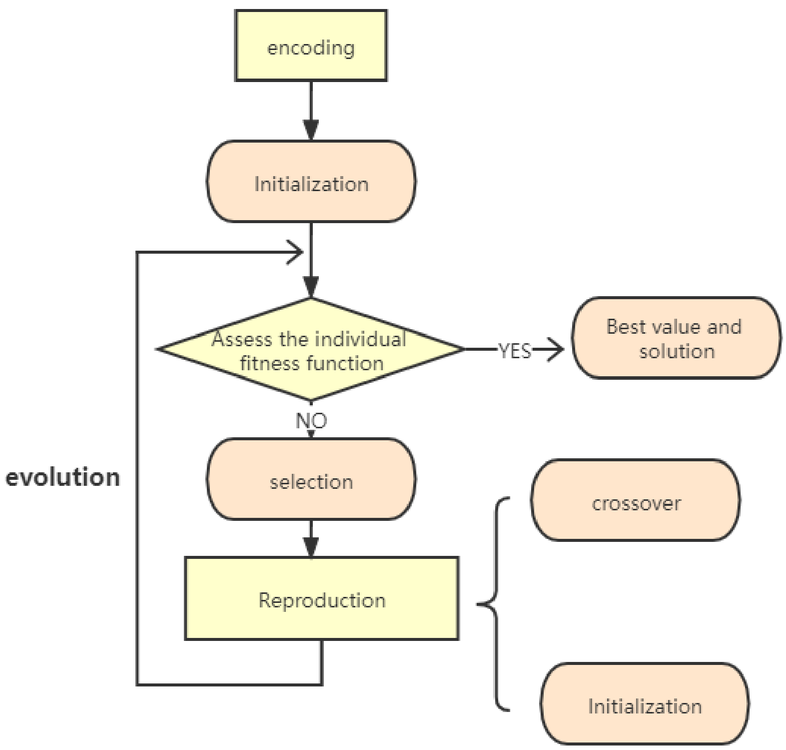

Figure 10: The flow chart of genetic algorithm

C. Solving steps

From the above, we can see that our trading signal needs to be weighted and summed with corresponding weights. If the sum reaches the threshold, we can choose to buy or sell and the corresponding amount. Therefore, we need to get a series of optimal weight ratios to reach the evaluation criteria of trading transactions. Therefore, we choose genetic algorithm to help us get the optimal weight.

Step 1: We randomly generate 10000 weight groups and normalize them to make the sum equal to 1, and perform the first operation.

Step 2: compare the calculation results, select 100 groups of weight groups at the 100th day, that is, the highest value of the final day, and average them in pairs to obtain a new 10000 hybrid weight groups.

Step 3: randomly modify the weight group, that is, there is a 20% probability of randomly modifying one of the parameter values, and there is a 1% probability of modifying two parameter values at the same time and recalculating.

Step 4: repeat steps 2 and 3 until the resulting parameter value group converges

Therefore, after 50 cycles, we select the best parameter value group of the final optimal return as the optimal parameter value group, and the parameter value group tends to converge. The parameter value group is the optimal parameter value group because it has passed multiple screening and combination.

D. Solution

The results of solving the corresponding weights of each trading signal are as follows:

Table 2: Variation of some parameters

	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_{10}	w_{11}	w_{12}
bitcoin	5.21	4.57	6.57	5.14	6.93	5.36	4	5.29	6	6	5.43	6.79
gold	2	3.29	7.57	4.57	7.71	2.5	4.5	5.64	6.71	2.07	4.79	7.07

We use it to implement daily updates of trading strategies, and each day gives whether to buy or sell Bitcoin or gold and how much to buy or sell based on its first 100-day Bitcoin and gold prices, holdings, and predicted prices thereafter.

6.3 Build a trading platform

We build the following investment trading platform through programming, just enter the initial [C, G, B], the bitcoin and gold prices before the trading day and the predicted price on the trading day, to achieve intelligent investment and obtain ideal returns.The flow chart for decision making is showing in figure 11 shows

We use the above platforms to arrive at the best investment strategy as figure12 shows:

The final return is $170609.51697227947.

7 Model Evaluation and Sensitivity Analysis

7.1 Model Evaluation

7.1.1 Model evaluation under different trading strategies

Aggressive trading strategy:

When the value of the asset increases, do not sell it easily, but wait for the value to continue to increase to obtain more benefits.

When the value of the asset decreases, do not buy it easily, but wait for the value to continue to decline and spend a smaller amount to buy.

Conservative trading strategy:

When the value of the asset increases, sell it in time to prevent future value decline;

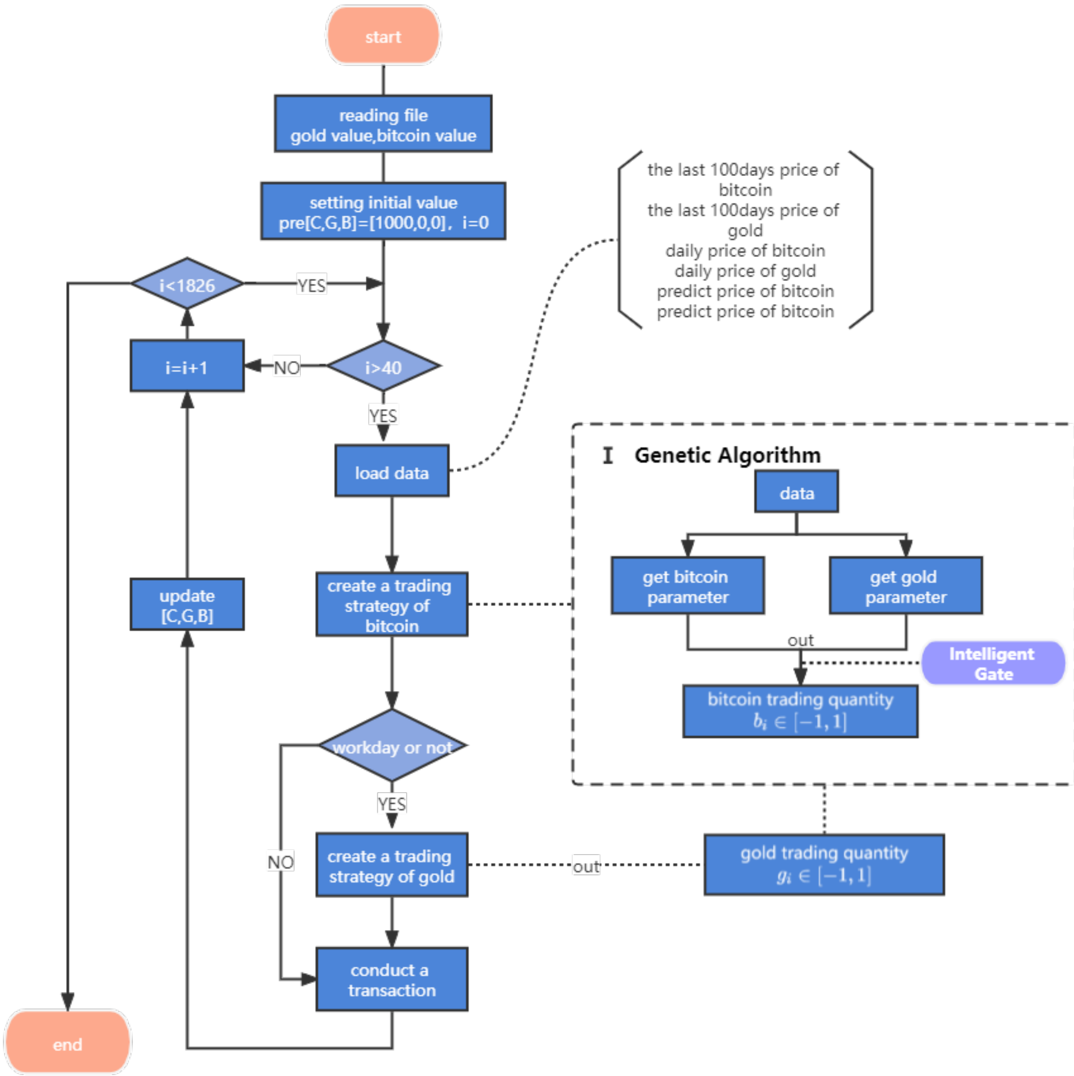

Figure 11: The flow chart for decision making

When the value of the asset decreases, buy it in time to prevent spending more money to buy the asset in the future;

After analyzing the above two trading strategies, and after modifying the model parameters, the three are compared as shown in the figure13, and there is a significant difference in the size of the final benefit, which shows the superiority of the model we built.

7.1.2 Model evaluation based on transaction frequency

Since there are commissions in the process of trading, frequent trading will lead to the loss of funds to a certain extent. We conduct random trading on the basis of artificially controlling the proportion of trading days to the total number of days, and observe the result graph. The results in figure14 verify our assumptions, It is consistent with the number of trading days after our model runs, which to a certain extent shows the superiority of our model.

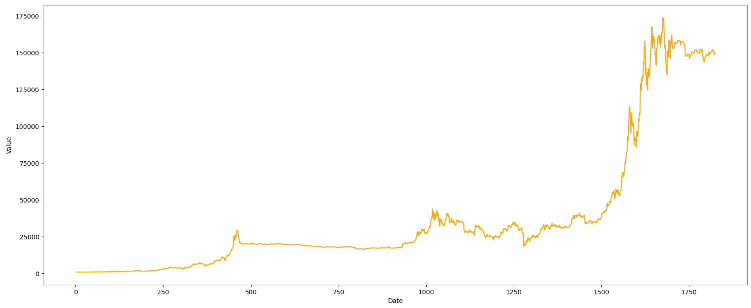

Figure 12: The result of return

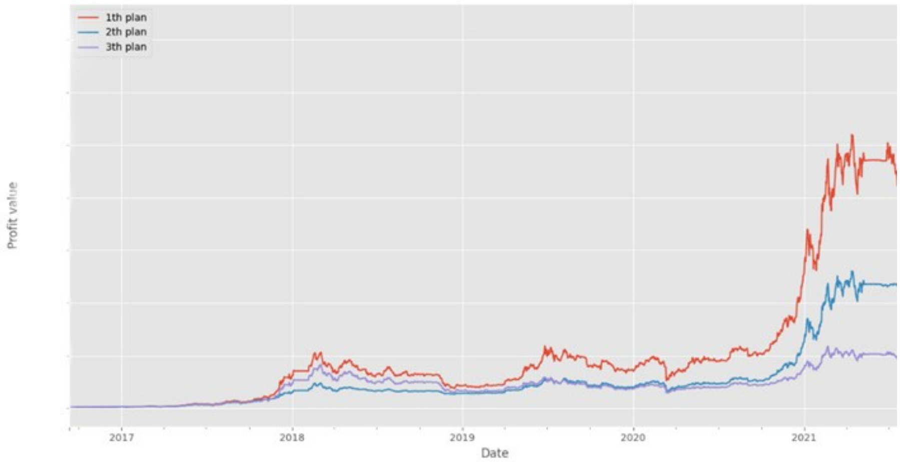

Figure 13: Reward of difference investment strategy

7.1.3 Sharpe Ratio from an Economic Perspective

a. Introduction to Sharpe Ratio

The Sharpe Ratio, also known as the Sharpe Index, is a standardized indicator of fund performance evaluation. The study of Sharpe ratio in modern investment theory shows that the size of risk plays a fundamental role in determining the performance of a portfolio. There is a conventional feature in investment, that is, the higher the expected return of the investment target, the higher the volatility risk that investors can tolerate; conversely, the lower the expected return, the lower the volatility risk.[6]

b.The Sharpe Ratio of different strategy

In 1966, scholar Sharpe proposed the Sharpe ratio:$S = (R - r)/$, where: R = expected return on investment (average return), r = return on risk-free investment, = standard deviation of return. The higher the Sharpe ratio, S, the higher the "quality" of the investment opportunity. The formula $S = fv/((0.5 * (2 - bwd - gwd)) * 200000)$that acts on the model to obtain the current Sharpe ratio, where fv(fanal value) = the final benefit obtained by the model, bwd = bits Coin's drawdown factor, gwd = Gold's drawdown factor. After multiple calculations to find the mean, we finally found that the Sharpe ratio of the model was 0.9909. Compared with

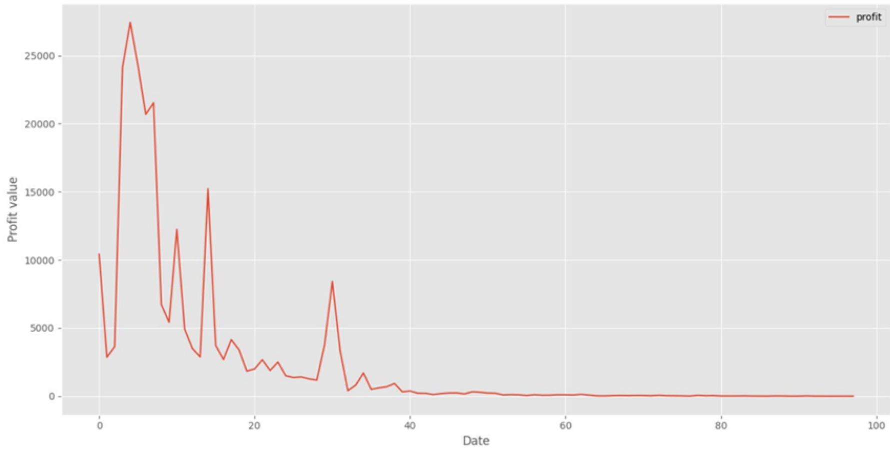

Figure 14: Relationship between trading times and returns

other basic models (the mean Sharpe ratio of a method 1: 0.6358 and the mean Sharpe ratio of a method 2: 0.7327), our mean Sharpe ratio was 0.9909. higher. This means that in the vast majority of cases, the higher the risk-reward obtained per unit of risk, the more favorable it is for investors, which shows the superiority of our model.

7.2 Sensitivity Analysis

We analyzed the sensitivity of some parameters in the model. We started to make investment decisions after 100 days of waiting on September 11, 2016, and ended on September 10, 2021. We can only choose two models of Bitcoin and gold for investment, and the initial capital is 1,000 US dollars. The results show that the model has strong robustness.

In our experiment, the default value of Bitcoin commission is 0.02, the default value of gold commission is 0.01, and the commission in real market conditions fluctuates with time, so we designed a random number in the program to make the commission fluctuate between 0.005 and 0.05. Obviously, the higher the commission, the higher the loss incurred by the exchange, so fewer transactions are required. In the model, we design a commission-related gate to control whether to trade or not, just as the formula(11).

Obviously, the opening of the gate is related to the transaction value predicted by the commission model. When the commission is smaller, the predicted transaction value is larger, the smaller the range of x is generated, that is, the higher the probability of the gate opening. On the contrary, when the commission is larger and the predicted transaction value is smaller, the range of x generation is larger, that is, the probability of the gate opening is smaller. Therefore, we can see that in figure15 when the commission becomes higher, the number of transactions will naturally decrease, and when the commission becomes lower, the number of transactions will naturally increase, which achieves a dynamic balance and reduces the substantial loss of revenue caused by the higher commission. So it has strong robustness.

8 Strength and Weakness

8.1 Strength

- Using a fixed investment strategy to quickly buy Bitcoin with most of the principal at the initial investment and after throwing most of the money has psychological and economic

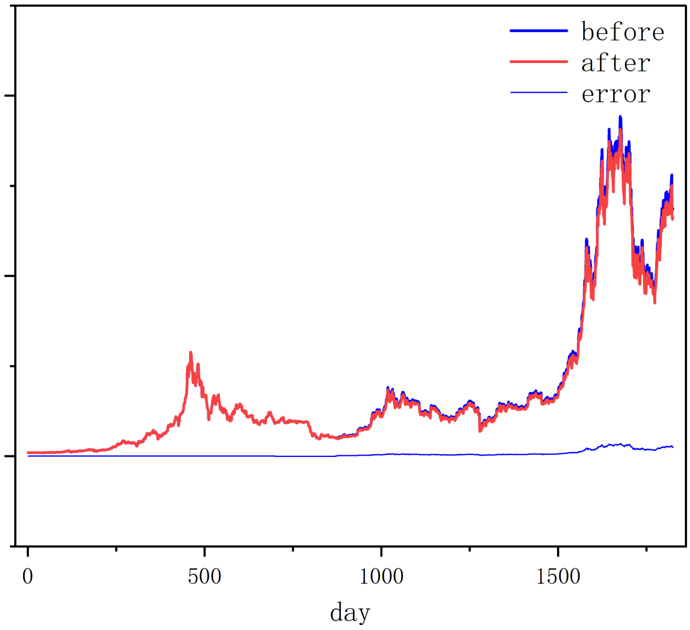

Figure 15: The difference of reward before and after the change of commission

significance. Both the moving average model and the low valuation model are adopted in the fixed investment strategy, which increases the stability of the investment. In the moving average mode, the current price of the reference index and the historical average value of the past 100 days are considered, and the investment interest rate is dynamically adjusted. When the price of the day is higher than the moving average, a short selling policy is adopted, and when the price of the day is lower than the moving average, a long position is adopted. Purchase Policy. In the low valuation model, the daily value and the forecast value of the next day are used to judge the growth and decline rate. When the rising rate is high, the principle of buying more is adopted and linked to the rising forecast. On the contrary, when the downward rate is high, Adopt the principle of short selling. Combining the two models at the same time can greatly increase the robustness of the investment and improve the return on investment.

- Grey forecasting, ARIMA time series forecasting and LSTM long short term memory model.
- Increase investment when entering the market and bottoming out, and gain greater benefits.

8.2 Weakness

- There are many factors to consider, and it may not be possible to obtain the best solution, but only a better solution.

9 Memorandum

"Investing without research is like playing stud poker and never looking at the cards.", As Peter Lynch said, building a good quantitative trading strategy is one of the important ways to invest in volatile assets for long-term returns. This paper mainly expounds the construction process of the quantitative trading strategy model based on the LSTM-GA model, and uses the model to conduct a 5-year simulated investment in Bitcoin and gold assets, and finally obtains a relatively considerable return, and puts forward reasonable suggestions to investors.

First of all, the basic principles of the model are described, and we build the model in two steps. The first step is to build a Bitcoin and gold value prediction model. By comparing the prediction effect of traditional methods such as GM and ARIMA algorithms with the prediction effect of the deep learning model represented by the long short-term memory model (LSTM), it is obtained that the prediction result of the LSTM model has the smallest mean square error on the prediction set and has the best fit. Some of the fitting results are shown in the following figure:

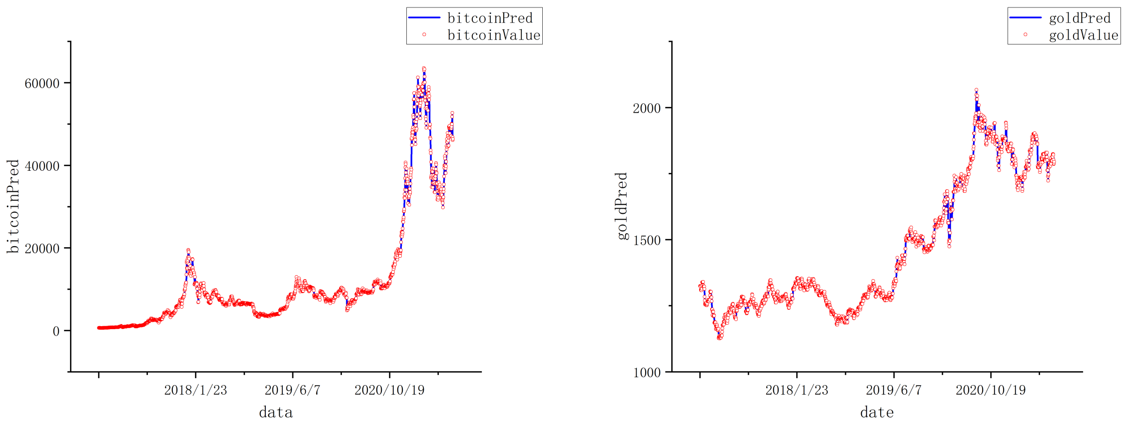

Figure 16: The prediction curve of bitcoin and gold

The second step is to build a single-day decision model. Firstly, focusing on directional trend strategies including moving average strategies, combined with the strategy ideas of volatility characteristics, creatively put forward the idea of "gate", and expounded the trading ideas of the strategy; secondly, from data acquisition and trading signal construction, trading signal weight solution, volatility indicator construction, etc. Finally, through the intelligent control of the transaction "gate" switch, the daily update of the trading strategy is realized.

For the construction of trading signals, factors such as the price of Bitcoin and gold on the day, the predicted price of the next day, the number of days of ups and downs, and market fluctuations are comprehensively considered, and dummy variables are defined for quantification. The genetic algorithm is used to solve the weights of each trading signal, and the trading willingness value is obtained comprehensively. At the same time, an intelligent "gate" is defined, whose function is to control the number of transactions and maximize revenue. If the willingness to trade is lower than a certain value, the round will not be traded; if the willingness to trade is extremely high and reaches the threshold, buy as much currency as possible. If the willingness to trade is between the two, the currency is purchased according to a certain ratio. At the same time, the higher the transaction commission, the lower the frequency of gate opening.

Finally, we built the following intelligent investment trading platform: From the above

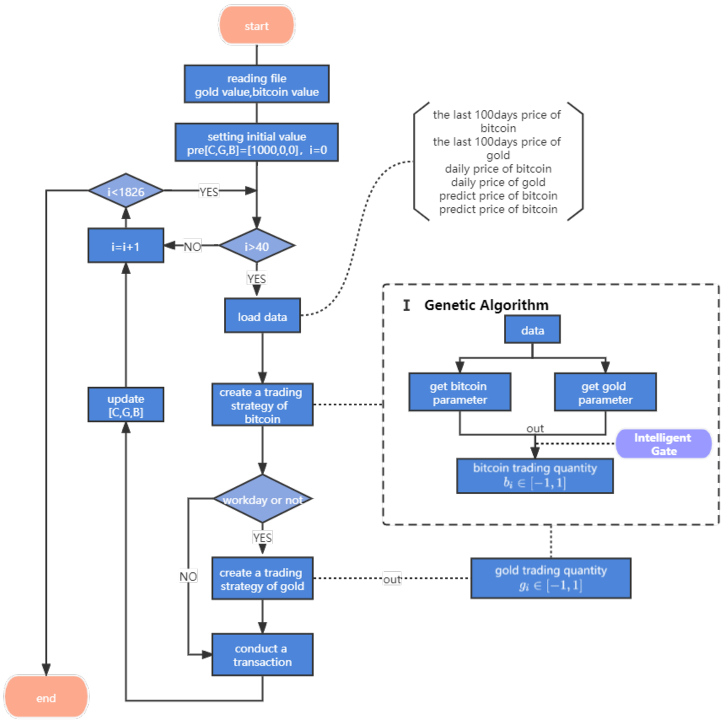

Figure 17: The flow chart for decision making

figure, the more the entrances are, the evener the temperature will be. Recalling on the before simulation outcome, when there is only one entrance for inflow, the temperature of corners is quietly lower than the middle area.

Users only need to enter the price of bitcoin and gold in the past period, the initial asset holdings, and the type of risk appetite, and the platform can automatically invest. Every day, the platform gives whether to buy or sell Bitcoin or gold and the amount of buying and selling according to the price of Bitcoin and gold in the first 100 days, the holding amount and the predicted price after that, and finally obtain a relatively ideal long-term income.

During the construction of the quantitative trading strategy model, we focus on micro-adjustments and have precise control over many details. For example, set a daily investment of 1% to maintain the stability of the investment; set the flag function to ensure that after investors enter the market and short-sell the currency, when a new buying time comes, a large amount of principal will be put into the market in time to earn more Profits; use genetic algorithm to solve the weight of trading signals, and then quantify the willingness to trade; innovatively propose the idea of "gate", intelligently control the opening timing, the gate will not be released when the willingness to trade is high, and the gate will be closed in time when the willingness to trade is low, At the same time, it uses it to control the number of transactions to reduce the cost loss caused by commissions. Combined with the gray prediction model, the deep learning model conducts macro-control to ensure optimal returns. Compared with ordinary aggressive or prudent investments, this strategy model can achieve a maximum annualized return of about 5 times that of the original investment portfolio.

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