Quantitative Trading Decision Model Based on Lstm Algorithm and Dynamic Programming

Yi Zhou*, **Longbiao Xie, Qianxi Zhang**

Qufu Nomal University, Rizhao, Shandong, 276800, China

cnzyyy99@163.com

*Corresponding Author

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Abstract: Quantitative trading is a way of trading that combines mathematical and financial knowledge and relies on computer programming. However, as we all know, the return and risk of investment is difficult to accurately estimate, this paper takes gold and Bitcoin as an example, uses machine learning methods to predict price trends, and builds a reasonable quantitative trading decision model based on this to seek a good trading strategy to assist traders in trading decisions. First, we preprocess the data to fill in the missing values in the gold data. Then, after analyzing the data for 5 years, we select the LSTM model in the constructed machine learning algorithm to predict the price of gold and Bitcoin in the next 1 day based on the data from the previous 10 days. Then, based on the predicted price, we set the goal of maximizing the value of the asset, take the trading conditions and return conditions as constraints, establish a quantitative trading decision model based on dynamic programming, and use Python deduction to derive the best trading strategy per day and calculate that when the initial capital is $1000, the final value of the asset at maturity is: $75,507. Then, for the verification of the best trade strategy, we carry out from the two aspects of price prediction model and trading strategy planning. The results show that the fit of the LSTM model selected in this paper is higher than that of the ARIMA model, and the final asset return obtained after adding perturbation terms to the original daily trading strategy is slightly lower than the asset return of the original model. Therefore, the trading strategy given in this article effectively passes the test. Finally, we perform a sensitivity analysis of the transaction cost of the model, so that the transaction cost ratio changes by 10%, and the sensitivity of gold and Bitcoin with the transaction cost change are 5.37 and -3.72. After the model analysis, it is found that: on the one hand, because the transaction cost increases, the number of transactions will be reduced, which will affect the trading strategy. On the other hand, an increase in transaction costs leads to an increase in total costs, which affects the final benefit.

1. Introduction

1.1 Background

In today's era, the development trend of economic globalization has been widely recognized, and the development of financial and monetary markets has gradually tended to globalization, which has greatly improved the development of trade practices. A large number of active traders have emerged in the market, and they have obtained the return on each purchase and sale through trading, thus maximizing the total return. However, as we all know, the returns and risks of investment are difficult to accurately predict. Investor blindness and macroeconomic stability make the operation mechanism of stock prices very complicated, the stock god Buffett once said: “I am afraid when others are greedy, and I am greedy when others are afraid.” “Excellent trade behavior requires super-human rationality, behind the rapid development of the financial market, in order to make objective and rational investment decisions, it is necessary to conduct quantitative analysis of investment data and trading behavior.” Therefore, this paper will use mathematical models and computer algorithms to predict the price trend of gold and Bitcoin, and construct a quantitative trading decision model to seek a better trading strategy[1].

1.2 Restatement of the Problem

You have been asked by a trader to develop a model that uses only the past stream of daily prices to date to determine each day if the trader should buy, hold, or sell their assets in their portfolio[2].

You will start with \$1000 on 9/11/2016. You will use the five-year trading period, from 9/11/2016 to 9/10/2021. On each trading day, the trader will have a portfolio consisting of cash, gold, and bitcoin [C, G, B] in U.S. dollars, troy ounces, and bitcoins, respectively. The initial state is [1000, 0, 0]. The commission for each transaction (purchase or sale) costs α% of the amount traded. Assume $\alpha_{gold} = 1\%, \alpha_{bitcoin} = 2\%$. There is no cost to hold an asset[3].

Build a mathematical model based on past data to solve the best strategy for daily trade. The value of the final assets as of October 9, 2021 is calculated using the model when the initial fund is \$1,000.

Prove that the above model can provide the best strategy.

Conduct sensitivity analysis to determine the sensitivity of the trade strategy regarding transaction costs, as well as the associated changes.

Communicate team strategies, models, and results with traders on no more than two pages.

1.3 Problem Analysis

(a) According to the requirements of the topic, taking gold and Bitcoin as examples, building a mathematical model to find out the best trading strategy for traders is essentially a problem of building a quantitative transaction decision model. Therefore, our model can be divided into two parts:

Predicting the price movement of gold and Bitcoin. First, the data information given by the question is analyzed, the appropriate algorithm is selected according to the data characteristics of gold and Bitcoin, and the data is processed so that the future price of the two can be predicted later.

Using the predicted prices of gold and Bitcoin to build mathematical models to derive the best strategy for trading every day. Trading behavior can lead to gains and losses, therefore, we hope to maximize the returns, minimize losses, that is, the final asset value maximization as the goal to establish a dynamic planning equation, with gold trading volume and Bitcoin trading volume as the independent variable, to the predicted value of the asset after the end of the transaction as the dependent variable, to the income, trading conditions as constraints, the use of Python to solve the best trading strategy for daily gold and bitcoin under the condition of maximizing the value of the predicted asset after the end of the daily transaction. After that, the hypothetical initial funds substitute model will be repeated in computer language until October 9, 2021, to obtain the final remaining asset value.

(b)To prove that the mathematical model we have established can provide the best trading strategy, then based on the process of establishing a quantitative trading decision model, we will also divide the proof into two aspects, one is to verify whether the prediction methods of gold and Bitcoin are highly accurate, and the other is to verify whether the return effect of the quantitative trading strategy is good.

(c) Setting the transaction costs of gold and Bitcoin to fluctuate by 10% and 20% respectively, comparing the change in the value of the final asset with the change in transaction costs, the sensitivity of the trade strategy to the transaction cost, and the change in the impact between them.

(d) Summarizing and refining the mathematical modeling methods, models, and final decisions.

2. Assumption

Due to the incompleteness of the data and the limitations of our knowledge, we make the following assumptions to help us perform modeling. These assumptions are the premise of our subsequent analysis.

When trading on day i, know the price of gold and bitcoin up to day i, and buy at this price, calculating the income from the day.

The transaction fee for gold and Bitcoin is settled on the same day and generates a gain from the next day.Both buying and selling are traded at the price of the day on which the signal is sent.

If the buy and sell signals are not issued, it indicates that the position is open.

Every trade can be traded in the up-down board.

Only the closing price is considered, the opening price and the intraday price are not considered.

3. Nomenclature

Table 1 Symbol Description

Notation	Meaning
α_t	Correlation coefficients between variables in armature models
β_{gold}	Sensitivity of asset value to gold transaction costs
$\beta_{bitcoin}$	Sensitivity of asset value regarding bitcoin transaction costs
M_t	Sample sequence
X_t	Bitcoin price on day t
Y_t	The price of gold on the t day
$\tilde{c}_t$	Memory unit values in LSTM models
i_t	The value of the gate in the LSTM model
f_t	The value of the forgotten gate in the LSTM model
α_{gold}	The transaction cost of gold as a percentage of the transaction amount
$\alpha_{bitcoin}$	Bitcoin's transaction costs as a percentage of the transaction amount
Z_i	Cash held after day i transaction
V_i	Predict the value of the initial asset on day i
x_i	Day i Gold Trading Volume
y_i	The volume of Bitcoin on day i
$P_i(G)$	The trading price of gold on day i
$P_i(B)$	The trading price of Bitcoin on day i

4. Data Analysis and Processing

4.1 Data Analysis

First of all, according to the title requirements, Bitcoin can be traded every day, and gold can only be traded when the market is open, so the quantitative trading strategy model needs to take into account the trading time limits of the two.

Secondly, the inspection and analysis of the data shows that some of the data are missing and need to be filled. In addition, the analysis of data to obtain Bitcoin price, gold price and US dollar cash has different dimensions and dimensional units, in order to eliminate the dimensional impact between prices, the data needs to be standardized to solve the comparability between the data, so that subsequent analysis and modeling.

Finally,it is known that there are generally two kinds of financial time series forecasting methods for stock prices, one is a financial time series forecasting model based on statistical methods, and the other is a financial time series forecasting model based on machine learning algorithms.

In the category of statistical methods, ARIMA models are widely used, but the primary premise of this type of method is to make linear assumptions about the variables of financial time series, but financial time series is very complex in nature, and naturally there will be perturbation terms in the data, which makes the financial time series not meet the assumptions of linearity and stationarity, so the use of ARIMA model needs to process the data to make it a stationary time series and then predict. At the same time, the machine learning algorithm has no requirements for the smoothness of time series, in addition, it can solve the problem of long dependence of RNNs in the application process, and has good performance in image recognition, speech recognition and time series problems, as show in fig 1.

In fig.2, as can be seen from the figure, the price series of gold and Bitcoin is a non-stationary series, so we use the LSTM model to predict the price of gold and Bitcoin.

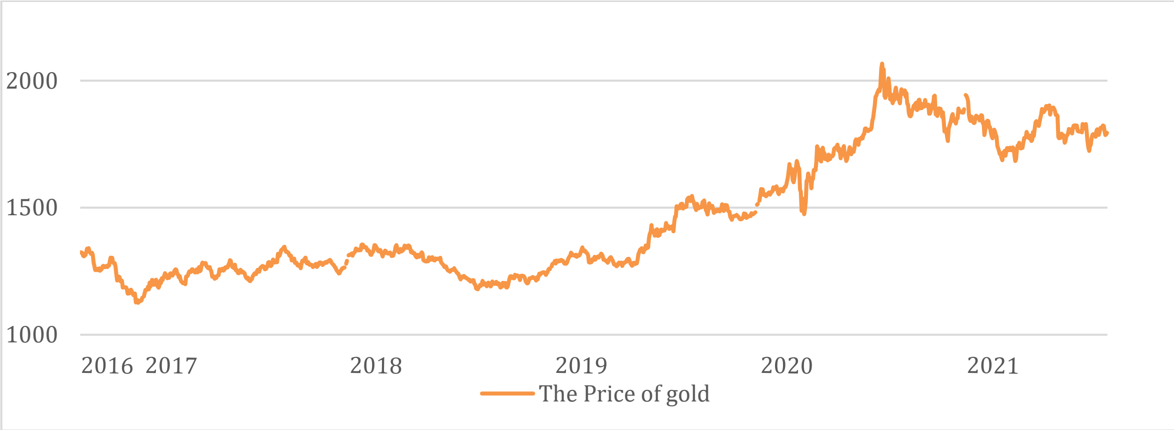

Fig.1 Gold Price Trend

Fig.2 Bitcoin Price Trend

4.2 Data Processing

Set bitcoin price data series to $\{X_t\}$ and gold price series is $\{Y_t\}$.

First, fill in the missing values of the data to make the data more complete and feasible.

Second, standardize the data using the most normalized method to solve the problem of comparability between data and prepare for prediction and modeling.

Compare the difference between the sample data and the minimum value to the extreme difference of the sample data, the formula is as follows:

$$X_{scale} = \frac{X - X_{min}}{Xmin_{max}} \tag{1}$$

X_{scale} is the standard data after normalization processing.

5. Analysis and Modelling

5.1 Financial Time Series: Price Trend Forecasting for Bitcoin and Gold

A time series is a sequence of numbers in which the values of the same statistical indicator are arranged in the order in which they occur. As it is often said, the order in which life appears is important, and there are some hidden relationships between the past and the future in the time series. Time series analysis attempts to predict the future by studying the past. Time series analysis has a wide range of applications in many fields such as engineering, finance, and technology. In the era of big data, time series analysis has become a branch of AI technology, which is better applied to data detection, prediction and other scenarios by combining time series analysis with classification models.

Based on the data analysis and processing results above, we then use the LSTM model to predict the prices of gold and Bitcoin.

Model 1:LSTM(Long-Short Term Memory)

Recurrent neural network RNNs exert their short-term memory advantages by constructing connections between neurons in the same implicit layer and obtaining the contextual correlation information of the data. However, when the parameters of RNNs are optimized and applied to long-term span sequence processing, gradient disappearance and gradient explosions often lead to small memory values, so RNNs are often ineffective in dealing with long-term timing problems.

The data used in the LSTM neural network should be the time series characteristics of the time series data to be extracted. In layman's terms, set the window length to 10 days, the rolling window period to 1 day, the forecast period to 1 day, we will be able to predict the price of gold and Bitcoin 1 day later by looking at the data of the previous 10 days.

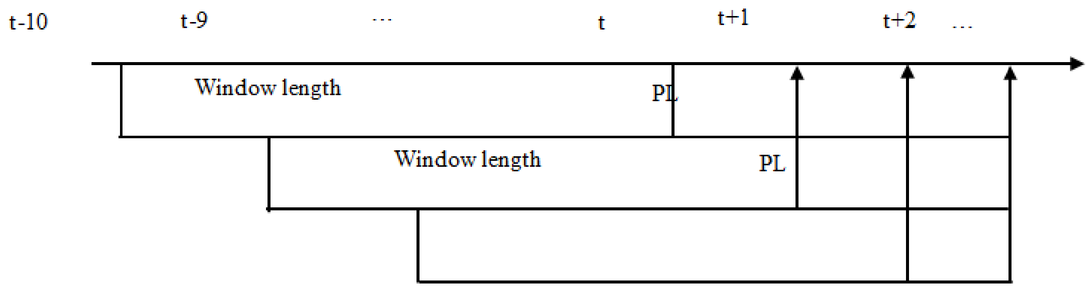

Fig.3 Simplified Diagram of Lstm Prediction Principle

PL represents the length of the prediction interval.

The idea of LSTM is that the original RNN hidden layer has only one state h, which is sensitive to short-term inputs, and LSTM adds a unit state c to let it preserve the long-term state, which is schematically shown in the figure 4:

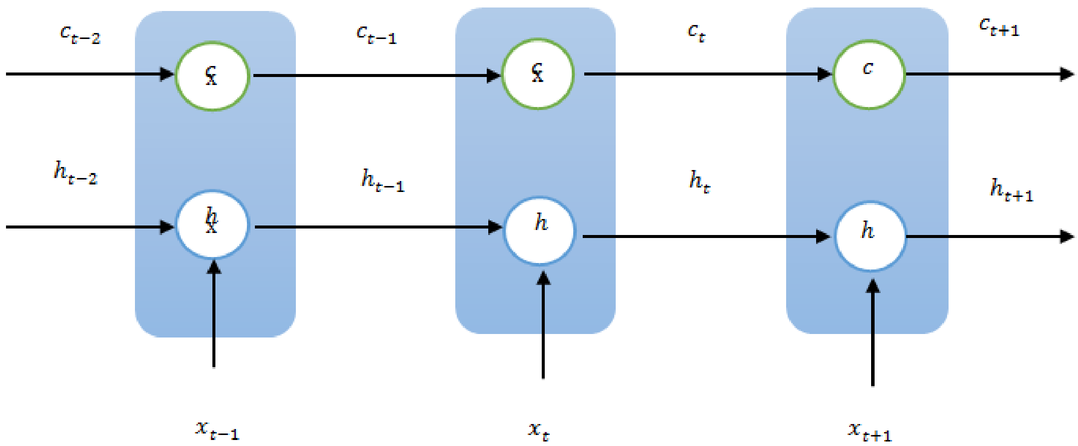

Fig.4 Schematic Diagram of Unit Status

As can be seen from the figure, at the t-moment, the LSTM has 3 inputs,

The input value x_t for the current moment,the input value h_{t-1} for the previous moment and unit state c_{t-1} at the previous moment. Its output is the output value h_t of the current moment and unit state c_t at the current moment. The key to the LSTM is how to control long-term state c,The control of long-term state c has three switches, the role of the first switch is to control the continued preservation of the long-term state c, the second switch controls the input of the instant state to the long-term state c, and the third switch is responsible for the long-term state c as the output of the current LSTM.

The implementation of the switch uses the concept of a gate, which is actually a fully connected layer whose input is a vector and whose output is a real vector from 0 to 1. The weight vector of the gate is W, the bias term is b, and the gate can be expressed as:

$$g(x) = \sigma(Wx + b) \tag{2}$$

We multiply the output of the gate by the vector we need to control, because the output of the gate is a real vector from 0 to 1, and when the output of the gate is 0, nothing can pass, and when the output of the gate is 1, it means that everything can pass, because the domain of the sigmoid function is (0, 1), so the state of the gate is half open and half closed.

The specific structure of LSTM is as in Fig.5:

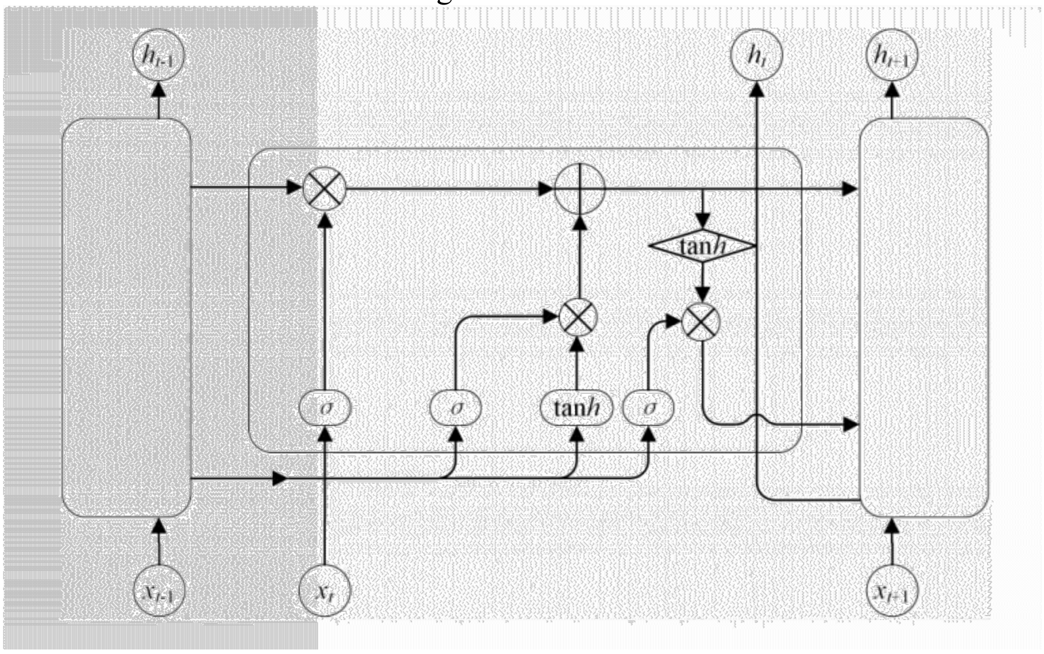

Fig.5 Lstm Specific Structure Diagram

The calculation process of the LSTM unit is divided into the following steps.

(a)The candidate memory cell value $\tilde{c}_t$, the input gate i_t and the forgetting gate value f_t of the t-time are calculated separately, and the calculation formula is as follows:

$$c_t = tanh(\omega_c[h_{t-1}, x_t] + b_c) \tag{3}$$

$$i_t = \sigma(\omega_i[h_{t-1}, x_t] + b_i) \tag{4}$$

$$f_t = \sigma(\omega_f[h_{t-1}, x_t] + b_f)\, \sigma \tag{5}$$

$\omega_c, \omega_i, \omega_f$ are the corresponding weight matrices;b_c, b_i, b_f are the corresponding biases;h_{t-1} is the LSTM unit output at the moment before the t-moment;x_t is the value of the t-moment memory unit;σ is a sigmoid function.

(b)Multiplying the old state with the forgotten gate information and discarding some of the information, plus the input gate and candidate memory cell values, the value c_t formula of the memory unit at the current moment is:

$$c_t = f_t c_{t-1} + i_t \tilde{c}_t \tag{6}$$

(c)Finally, the value of the output gate o_t is confirmed by the output gate, and the output part h_t is determined:

$$o_t = \sigma(\omega_o[h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t\, tanh(c_t) \tag{8}$$

ω_o *and* b_o are their corresponding weight matrices and biases.

By establishing the above control gate and memory unit structure, a longer period of data preservation and processing can be realized, and problems such as gradient explosion can also be solved by establishing a long delay in input feedback.

The LSTM algorithm is used to obtain the degree of fit of the bitcoin predicted price line to the actual price line as follows, Fig. 6:

Fig.6 Fitted Plot of Predicted and Actual Bitcoin Price

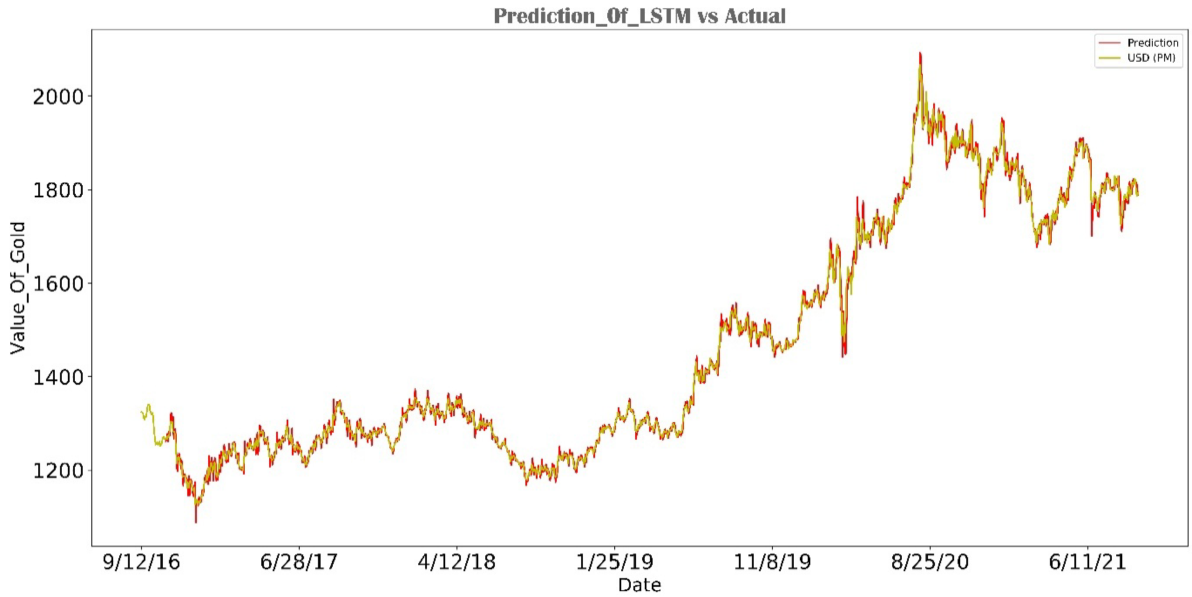

Fig.7 Fitted Plot of Predicted and Actual Gold Price

Using MAE as the evaluation criterion for prediction results, the smaller the average absolute error value and the greater the correlation coefficient between the prediction data and the real data, the smaller the error of the prediction result.

For sample sequence $\{M_t\}$, its MAE formula is:

$$e_{MAE} = \frac{1}{n}\sum_{t=1}^{n}|m_t - m_t| \tag{9}$$

$$Bitcoin_{MAE} = 482.3759$$

$$Gold_{MAE} = 11.5361$$

The prediction and actual value of the gold price fit 96.3%, and the prediction and actual value of the Bitcoin price fit 95.8%, which works well.

5.2 Quantitative Trading Decision Model

Model 2:Dynamic programming equtions

Set the initial portfolio of assets on day i to $[C_i, G_i, B_i]$,the price of gold and Bitcoin on day i is

$P_i(G), P_i(B)$,the trading volume of gold and Bitcoin on day I are x_i and y_i. $x_i, y_i > 0$ means “sell”;$x_i, y_i > 0$ means “buy”;$x_i, y_i = 0$ means no transaction.The price of gold and bitcoin on day i+1 is $P_{i+1}(G), P_{i+1}(B)$.The known transaction cost rate is: $\alpha_{gold} = 1\%, \alpha_{bitcoin} = 2\%$.

We use the sum of the initial values of cash, gold and Bitcoin held by the trader of the day to express the total asset value of the day, and with this goal, we build a model to predict the total asset value that will be available for the next day after the transaction.

The remaining cash value after the transaction on day i is as follows:

$$Z_i = C_i + P_i(G)x_i + P_i(B)y_i - P_i(G)|x_i|\alpha_{gold} - P_i(B)|y_i|\alpha_{bitcoin} \tag{10}$$

Set the price of gold and Bitcoin on the i+1 day of the forecast to $P'_{i+1}(G), P'_{i+1}(B)$.

The portfolio on day i+1 becomes $[Z_i, G_i - x_i, B_i - y_i]$ after day i trading. At this point, the total predicted value of the portfolio of assets traded by the trader on day i+1 is:

$$V^*_{i+1} = Z_i + P'_{i+1}(G)(G_i - x_i) + P'_{i+1}(B)(B_i - y_i) \tag{11}$$

The actual total value of the portfolio on i+1 days is:

$$V_{i+1} = Z_i + P'_{i+1}(G)(G_i - x_i) + P'_{i+1}(B)(B_i - y_i) \tag{12}$$

The value of the asset repeatedly extrapolated to the last trading day using computer language is counted as V.

Therefore, the dynamic programming model for maximizing the value of assets on i+1 days after day i trading is established as follows:

$$\begin{cases} max\, V^*_{i+1} \\ Z_i > 0 \\ x_i \le B_i \\ y_i \le C_i \end{cases} \tag{13}$$

Start with the trading day and find out today's best trading strategy by today's initial assets and forecasting tomorrow's share price. Using the above methods, the Python language and linear programming model are used to gradually find the best trading strategy for each day, and the total value of the asset after 5 years is obtained.

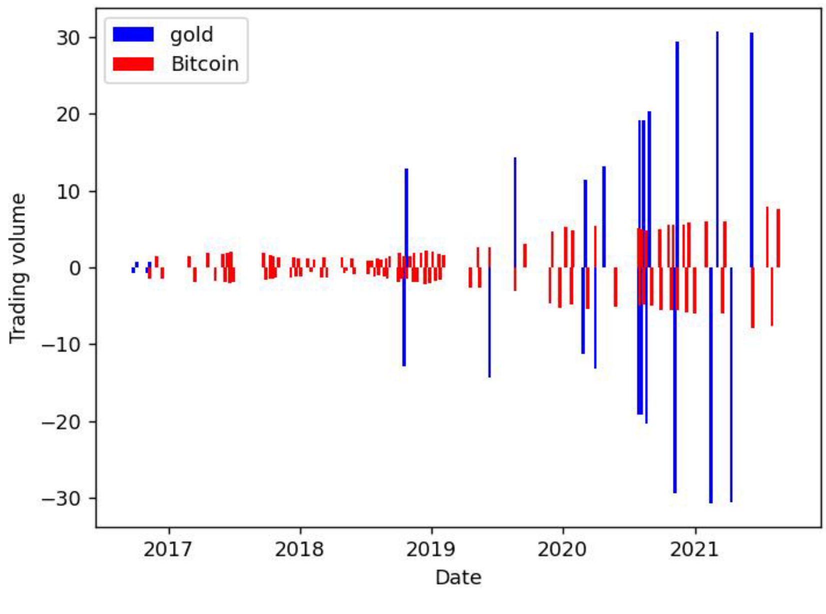

Fig.8 Daily Trading Strategy

Supposing s_i be the daily rate of return.

The rate of return is calculated as:

$$s_{i+1} = \frac{V_{i+1}}{V_i} - 1 \tag{14}$$

The daily yield is as follows:

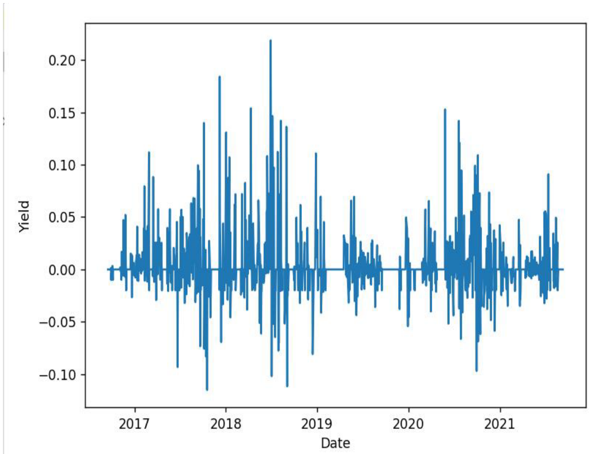

Fig.9 Yield on Daily Trades

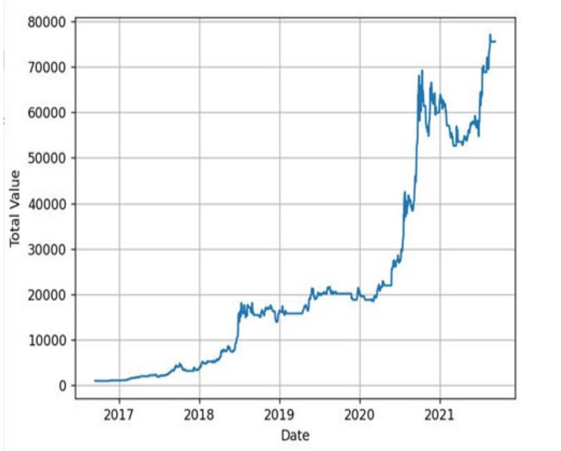

Fig.10 Daily Asset Value

The initial capital of $1,000 is substituted for the above dynamic programming model on value maximization, and the computer language is used to repeat the operation from November 9, 2016 to October 9, 2021, and the value as of October 9, 2021 is: $ 75,507.

6. Model Testing

Since people cannot accurately predict the future price trend of financial time series in real life, the best trade strategy in theory is often not available in practice. We can only prove that the optimal trading strategy derived from the quantitative trading decision model established in this paper is superior to the trading strategy provided by the general mathematical model

Based on this line of thinking, we have decided to prove that the strategy we offer is the best trading strategy from two aspects, as follows:

On the one hand, the prediction results of gold and Bitcoin prices are compared with those of the LSTM model and the AEIMA model, which proves that the forecast model is excellent. On the other hand, adding a perturbation item to the daily trading strategy verifies that the original trading strategy is superior by comparing the results after the disturbance and the final return.

6.1 Testing of the Prediction Method

Our test idea for the fit of the prediction method is to compare the prediction results of gold and Bitcoin prices using the machine learning LSTM algorithm with the prediction results predicted using the ARIMA model in the statistical method.

The steps to establish the ARIMA model are as follows:

First, plot the Bitcoin price series and perform an ADF test to see if the sequence is stable; for non-stationary time series, the d-order difference is performed to convert it into a stationary time series

Second,to obtain the autocorrelation coefficient (ACF) and partial autocorrelation coefficient (PACF) for the stationary time series, respectively, through the analysis of the autocorrelation graph and the partial autocorrelation graph, the best order p and q are obtained, and the ARMA model is established.

Third,substitute the differential formula into the ARMA model, which results in the ARIMA model.

Model 3: Series Forecasting-ARIMA

The ARIMA model is one of the methods of time series forecast analysis. The ARIMA model is a combination of the ARMA model and the difference method, and the ARIMA prediction model is established below:

1). AR model

Autoregressive models describe the relationship between current and historical values, using the variables' own historical time data to predict themselves.

For gold price series $\{X_t\}$, the general P-order autoregressive model AR is as follows:

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \ldots + \alpha_p X_{t-p} + \mu_t \tag{15}$$

If the random perturbation term is a white noise ($\mu_t = \varepsilon_t$), it is called a pure AR (p) process, denoted as:

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \ldots + \alpha_p X_{t-p} + \varepsilon_t \tag{16}$$

2).MR model

In the AR model, if (μ_t) is not a white noise, it is generally considered a moving average of order q. namely:

$$\mu_t = \varepsilon_t + \beta_1 \varepsilon_{t-1} + \ldots + \beta_q \varepsilon_{t-q} \tag{17}$$

ε_t represents a sequence of white noise.

In particular, when $X_t = \mu_t$, the current value of the time series has no relationship with the historical value, but only relies on the linear combination of historical white noise, the MA model is obtained:

$$X_t = \varepsilon_t + \beta_1 \varepsilon_{t-1} + \ldots + \beta_q \varepsilon_{t-q} \tag{18}$$

It should be noted that the effect of historical white noise in the AR model indirectly affects the current predicted value (by influencing the historical time series value).

3). ARMA model

Combine AR (p) with MA (q) to get a general autoregressive moving average model ARMA (p, q):

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \ldots + \alpha_p X_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \ldots + \beta_q \varepsilon_{t-q} \tag{19}$$

4).ARIMA model

By combining AR model, MA model and the difference method, we get ARIMA (p, d, q), where d is the order of the data that needs to be differential.

Denote ∇ as a difference operator, when $W_t = \nabla^d X_t$, has the following equation:

$$W_t = \alpha_1 W_{t-1} + \alpha_2 W_{t-2} + \ldots + \alpha_p W_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \ldots + \beta_q \varepsilon_{t-q} \tag{20}$$

Then the above formula is called $ARIMA(p, d, q)$ model, $\{X_t\}$ is called $ARIMA(p, d, q)$ procedure.

When $d = 0, ARIMA(p, 0, q)$ model actually is $ARMA(p, q)$ model.

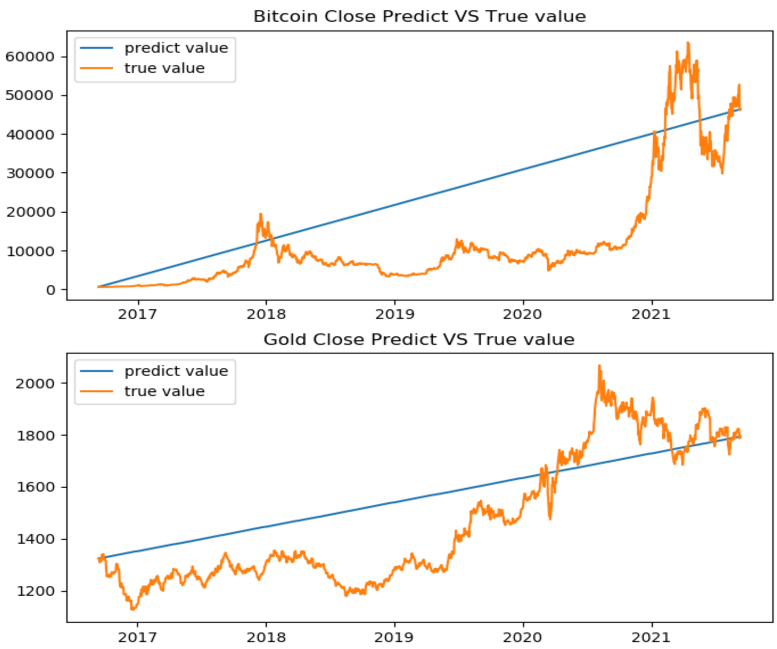

Fig.10 the Predicted Value of the Price of Gold and Bitcoin Fits the Chart with the Actual Value

After comparing the yield, mean yield and yield variance of the two models, it is found that the prediction effect of the LSTM model is better than that of the ARMA model in all aspects.

6.2 Testing of Trading Strategies

The main idea of the test of the trading strategy is to add a perturbation term on the basis of the original model. Make the daily trading strategy fluctuate up and down a certain range on the basis of the original. By comparing the original trade strategy with the change in yield of the perturbed trade strategy, we measure the effectiveness of the quantitative trading decision model we have established.

The trading volume in the original trading strategy is reduced by 15% and 30% respectively, and the yield after the disturbance is calculated compared with the original yield to measure the effect of the trading model.

Model 4 : Perturbation trading model

Setting gold and bitcoin new trading volume $x_i^{'}$, $y_i^{'}$ respectively,the volume change ratio is η,letting $x_i^{'} = x_i\eta, y_i^{'} = y_i\eta$.

Then, the cash value after the transaction on day i is:

$$Z'_i = C_i + P_i(G)x'_i + P_i(B)y'_i - P_i(G)|x'_i|\alpha_{gold} - P_i(B)|y'_i|\alpha_{bitcoin} \quad (21)$$

Predict the price of gold and bitcoin on day $i+1$ is $P_{i+1}^{'}(G), P_{i+1}^{'}(B)$.

The portfolio on day i+1 becomes $[Z_i, G_i - x'_i, B_i - y'_i]$ after day i trading, the total predicted value of the portfolio of assets traded by the trader on day i+1 is:

$$V_{i+1}^{'} = Z'_i + P_{i+1}^{'}(G)(G_i - x'_i) + P_{i+1}^{'}(B)(B_i - y'_i) \quad (22)$$

The value of the asset that is repeatedly extrapolated to the last trading day using computer language is counted as V_2.

Therefore, the dynamic programming model for maximizing the value of assets on i+1 days after day i trading is established as follows:

$$\begin{cases} max\, V'_{i+1} \\ Z'_{\ i} > 0 \\ x'_{\ i} \le B_i \\ y'_{\ i} \le C_i \end{cases} \tag{23}$$

From this, the daily asset value after the disturbance is obtained, and the value curve of the disturbance and the original value curve are plotted, which are compared as follows:

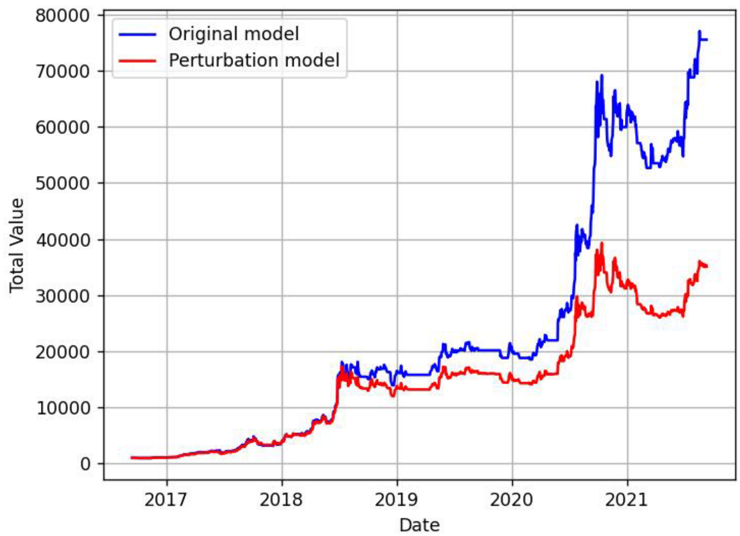

Fig.11 a Comparison of the Disturbed Value Curve and the Original Value Curve

Through comparison, it is found that the final asset value after the disturbance is slightly lower than the asset value of the original model. Therefore, the trading strategy of the original model effectively passes the test.

7. Sensitivity Analysis

To determine the sensitivity of trade strategies to changes in transaction costs, and the changing relationship between the two. To make the transaction cost of gold as a proportion of the trade amount, α_{gold} up and down 10%, the remaining cash value of the day after the end of the transaction is:

$$Z_o = C_i + P_i(G)x_i + P_i(B)y_i - P_i(G)|x_i|\alpha_{gold}(1 \pm 10\%) - P_i(B)|y_i|\alpha_{bitcoin} \tag{24}$$

Substitute the formula for predicting the value of the total assets held by the trader, get

$$V'_{\ i+1} = Z_o + P_{i+1}(G)(G_i - x_i) + P_{i+1}\,(B)(B_i - y_i) \tag{25}$$

Remember that the total value of the assets held by the trader on the last trading day is V' .

The amount of change in asset value caused by changes in the transaction costs of gold is:

$$\Delta V = V' - V \tag{26}$$

The percentage change in asset value is expressed as:

$$\gamma = \frac{\Delta V}{V} \tag{27}$$

The sensitivity of the final asset value regarding the transaction costs of gold is:

$$\beta_{gold} = \frac{\gamma}{10\%} \tag{28}$$

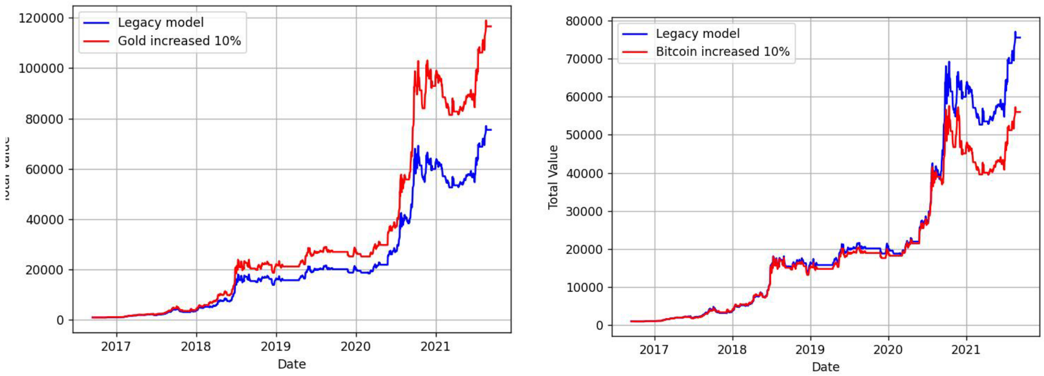

Fig.12 Changes in Asset Value with Respect to Transaction Costs

β_{gold} =5.37. Similarly, the sensitivity of the final asset value regarding the transaction cost of Bitcoin is $\beta_{bitcoin} = -3.72$.

From the calculation results, it can be seen that a 10% increase in the transaction cost of gold will cause a 50.37% increase in the value of the trader's final asset, and a 10% change in the transaction cost of Bitcoin will cause a 30.72% reduction in the value of the trader's final asset.

8. Model Evaluation

8.1 Strengths

Make full use of the information: The team conducted in-depth analysis and processing of the data, found that the financial time series was a non-stationary series, and selected the appropriate LSTM model to predict future price movements.

Accuracy: This article aims to quantify the trading strategy, represent the intuitive pictures and trend lines with specific numbers, and more accurately describe and evaluate the prediction results, mathematical models, and final strategies.

Practicality: Quantitative trading models can assist traders in making investment and trade decisions, and traders can also adjust their dependence on the model according to the gap between the forecast value and the actual value in the early forecast period, so as to make more favorable decisions in the future.

8.2 Weaknesses

Limited data: Based on the requirements of this topic, only the two kinds of price data provided can be used for analysis and modeling, but in real life, there are policy factors, economic factors, social factors, human factors and other factors that have an impact on the transaction, so the quantitative trading model is only a reference recommendation, and the actual transaction trader also needs specific analysis.

Subjective error: “Investment is risky, and you need to be cautious when entering the market.” Different people have different judgments and preferences about investment and trade behavior, and we need to combine the actual situation with qualitative and quantitative analysis, so it is biased to rely only on mathematical models to make trade decisions. It is recommended that everyone think rationally and make careful decisions.

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