Trading strategy model based on LSTM neural network and Extreme Value-Dynamic programming

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Abstract. The advantage of a trading strategy is that it can help us identify potential trading opportunities. Traders need to use the best investment strategy to take into account factors such as market volatility and transaction costs, so as to get the maximum benefit on the target date. this paper uses LSTM neural network to make predictions. The predicted value is the price of gold and bitcoin five days after the investment date, the model fits well. By analyzing the problem, the goal is to find the optimal value, which can be regarded as a multi-stage decision-making process optimization problem. Therefore, this paper selects the Extreme value-DP model for planning and decision-making, and uses the maximum (minimum) value to evaluate the strategy.

Keywords: Trading strategy, LSTM neural network, dynamic programming, risk-taking, sensitivity analysis.

1. Introduction

1.1 Background

The advantage of a trading strategy is that it can help us identify potential trading opportunities and enter the market early in the trend to maximize returns. Since the collapse of the Bretton Woods System in 1971, gold lost its role in circulation, then it has been widely valued as an important investment method. Although bitcoin was invented 11 years ago, according to 11 quantitative indicators that can be researched, bitcoin is gaining momentum, creating economic opportunities. It has changed the world's view of money and has extremely high investment value. In the trading market, traders can apply trading strategies to maximize the return on their volatile assets. Traders need to use the best investment strategy taking into account market volatility, transaction costs and other factors, so as to get the maximum return on the target date.

1.2 Literature review

In the process of studying the historical closing price data of stocks in the financial market, Liu Song and Zhang Shuai used Python as an implementation tool to establish an ARIMA model for testing and prediction [1]. This shows that the short-term prediction of price changes with ARIMA model has a good effect, and can provide reliable prediction data for our decision-making model.

In order to realize the prediction model, Liu Chong and Du Junping used a deep LSTM network to model financial data, which proved that the model can solve the problem of long-term dependence between data. And it can learn more complex market dynamic characteristics [2].

Chen Xiaoxin etc. analyzed the performance of dynamic asset allocation in China's securities market, repeatedly applied the decision-making model to make asset allocation decisions and continuously calculated the current asset value to obtain an investment model with the greatest final return [3]. Finally, the research on dynamic asset allocation based on stochastic programming shows that dynamic asset allocation can generally produce better returns in medium and long-term investment.

Gerd Infanger from Stanford university used stochastic programming and stochastic dynamic programming techniques when studying dynamic asset allocation problems. The final conclusion was: For general serially dependent asset returns and/or consideration of transaction costs, a multi-stage stochastic programming approach may be needed [4].

1.3 Restatement of the problem

We need to develop a model to determine whether a trader should buy, hold or sell an asset in a portfolio on a daily basis. Available data are daily prices prior to the current day, and transaction costs also need to be considered. We decompose the problem into two steps: prediction and decision. Predicting the price for the next day, we can apply the model to determine the best scenario for today.

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

• Provide the best daily trading strategy. We want to provide the best daily strategy based on the market data of the day, which requires the forecasting model just mentioned. At the same time, we have to ensure that the gains brought by the price fluctuations the next day are greater than the transaction costs, otherwise there will be losses. Regarding the models of the forecasting class, we consider that there are gray forecasting models, time series models and LSTM neural network models are forecasting models with a high degree of fit. Then we complete a planning model based on the forecast for the next day and try to maximize the value of the investment on the target date.

• Prove the strategy is optimal. When the prediction reaches a certain accuracy, we can determine the investment strategy based on the obtained data. Investment often has more uncontrollable disturbance factors, we also need to consider the influence of other factors, and in a comprehensive and more realistic situation, to find the local optimal solution is our best strategy. At the same time, the more accurate the result of predicting the next day, the more beneficial it is to expand the income, so a prediction model with higher accuracy is needed.

• Determine the sensitivity of the strategy to transaction costs. The commission cost of each transaction is α% of the transaction amount. The larger the α, the greater the loss of a transaction, and the number of transactions should be reduced. When α is smaller, we can appropriately increase the number of transactions by comparing the relationship between the rate of return of a single transaction and α%, and we need to analyze the relationship between and the result.

2. Assumptions and justification

To simplify the problem and make it convenient for us to simulate real-life conditions, we make the following basic assumptions, each of which is properly justified.

• Gold and bitcoin have fixed prices on a daily basis. We can guarantee that gold and bitcoin only need to be operated once a day, while also reducing transaction costs.

• Both buy and sell transactions can be completed quickly without fail. If there are trade failures that clearly no longer fit the optimal strategy provided by the model, the decisions provided are meaningless.

• The gold and bitcoin on the last day will not be traded in US dollars. And the total value of the assets is directly converted into US dollars by the prices of gold and bitcoin on that day and then added to the existing US dollars on hand.

• The missing data is filled by using the exchange rate of the previous day. The consideration is to reduce operations and reduce transaction fees.

• Gold and bitcoin can only be traded in US dollars. There will be a handling fee for each transaction. If you trade directly with gold and bitcoin, the transaction cost cannot be directly calculated. Moreover, in today's market, gold and bitcoin represent two asset classes that cannot be directly traded.

3. Notations

Table 1. Symbol Description

Symbols	Description	Unit
i	Day i	–
j	Operation j	–
Gi	The prices of gold on day i	$/oz
Bi	The prices of bitcoin on day i	$/b
Xij	Operation j on day i	–
Cij	U.S. dollar holdings in operation j on day i	$
Bij	Bitcoin holdings in operation j on day i	$
Gij	Gold holdings in operation j on day i	$
Zij	The total value of assets in operation j on day i	$

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

4. Model overview

Our model is an equation constructed with the data of $1,000 as the investment principal considering the daily price changes of bitcoin and gold. We want to achieve three goals:

1. Predict the unit price of bitcoin and gold in the next five days.
2. Provide the best daily trading strategy based on the price of the day.
3. Give the model the potential for long-term investment.

We start by building a price prediction model for bitcoin and gold. According to the given two files, LBMA-GOLD.csv and BCHAIN-MKPRU.csv, use the LSTM neural network for training, validation and prediction. The predicted value is the market price of bitcoin and gold in the next five days.

Then build a planning model to get the best strategy of the day. According to the dynamic programming model, we initially established the state transition equation, and deduced the indicator function: the total value of assets owned on that day. At the same time, we define an optimal indicator function. We find that when there is only one asset (exists handling fee, no holding cost), if there is a time series with a monotonic price nearby, the optimal strategy is trade at the point and large trades at the extreme point.

For example, when there is a maximum value point, all buy at this point, then all sell at the maximum value point, and vice versa. Based on this, the optimal indicator function in the case of multiple assets is established, and our decision-making model is completed after solving a series of problems such as adding a small fluctuation.

Finally, we analyze the relationship between the strategy and the final result and the transaction cost, so that the model has a more practical conditional basis. Our entire modeling process is shown in Figure 1:

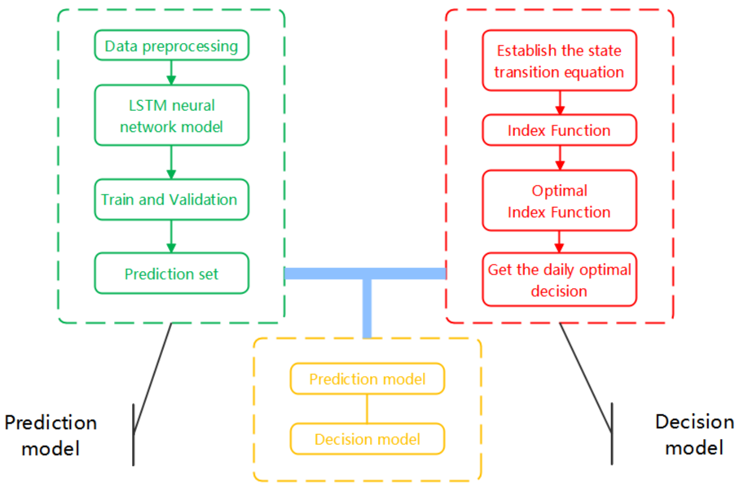

Figure 1. Modeling process

5. Predictive models

5.1 Data preprocessing

In order to ensure the uniformity of the data volume, we not only filled in the missing values on the gold market opening day, but also filled in the price of the gold market closing day according to the daily date of bitcoin through the program. The price is the same as the price of the previous gold closing day. The closing day uses the price of the day before the closing day. Therefore, the gold price data predicted by the gold prediction model and the bitcoin price data predicted by the bitcoin prediction model are the same amount. In this way, the solution process required by the problem should be considered and reflected in the vacancy of the golden rest day.

5.2 ARIMA

(Taking gold as an example)

The ARIMA (Autoregressive Moving Average) model was proposed in the 1970s by American statistician Jenkins and British statistician Box. This model is mainly used in the short-term prediction of time series variables, because the single time series value is unpredictable, but the overall time series value has a certain law, and the ARIMA model is used to express this law in mathematical form [1].

And through the study of the mathematical form, the short-term prediction of the series value is realized. ARIMA is a more comprehensive model developed on the basis of ARMA, and its characteristics include: trend, serial correlation and randomness. The ARIMA model is closer to the reality in our life and work, so the application is more common.

5.2.1 ADF test

The ARIMA model requires the sequence to satisfy stationarity. If the test result is not stationary, it is necessary to pass the difference change or other changes to make the sequence meet the stationarity condition. Therefore, after performing a unit root test on the data in Figure 2, we found that the t statistic of ADF is -0.446, which is smaller than the corresponding critical value at the significant level of 1%, 5%, and 10% [1].

ADF Test							
Variable	Order Difference	t	p	AIC	Critical Value		
					1%	5%	10%
USD (PM)	0	-0.446	0.902	10031.17	-3.436	-2.864	-2.568
	1	-8.093	0.000***	10021.892	-3.436	-2.864	-2.568
	2	-12.875	0.000***	10068.193	-3.436	-2.864	-2.568
Note: ***, ** and * represent the significant levels of 1%, 5% and 10% respectively							

Figure 2. ADF Test

Prove that the original data are time-stationary. Therefore, we performed the first-order difference and second-order difference on the original data in Figure 2, and performed the ADF test to obtain that the statistical values of t were -8.093 and -12.875, both of which were greater than the three critical values, and $p < 0.01$, rejecting the original sequence that is not stationary. Suppose: That is to say, after one difference processing, the result is stable.

5.2.2 The establishment of ARIMA model

Based on the AIC information criterion the system automatically seeks the most parameters, the model result is the ARIMA model (0, 1, 0) test table and is based on the first-order difference data, based on the field: USD (PM). From the analysis of the Q statistic results, it can be concluded that Q6 is not significant at the level, and the hypothesis that the model is a white noise sequence cannot be rejected.

5.2.3 Predictive model results and applications

The goodness of fit R2 of the model is 0.997, and the model has excellent performance and basically meets the requirements. Comparing the predicted results with the actual value, it can be seen from the table that the predicted value is very close to the actual value, which means that the error between the predicted price and the actual value is small, and the use of the ARIMA model can provide a reliable predicted price for the decision-making model.

Similarly, when we establish the ARIMA model for bitcoin, we can get the model result as the ARIMA model (0, 1, 2) test table and based on the first-order difference data, based on the field: Value. The goodness of fit R2 of the model also reached 0.997, and the model performed well.

ARIMA Model (0, 1, 0) Test		
Term	Symbol	Value
	Df Residuals	1263
Sample size	N	1265
Q statistic	Q6 (p Value)	0.393 (0.351)
	Q12 (p Value)	34.687 (0.000***)
	Q18 (p Value)	48.235 (0.000***)
	Q24 (p Value)	57.625 (0.000***)
	Q30 (p Value)	68.45 (0.000***)
Information criterion	AIC	10234.998
	BIC	10245.282
R-squared	R^2	0.997

Figure 3. ARIMA Model Test

5.3 LSTM prediction model

5.3.1 Model introduction

Our team adopts LSTM (Long Short Term Memory) neural network, which is an improved recurrent neural network [5], which solves the problem that RNN cannot handle long-distance dependencies. The cell unit of the LSTM neural network has the ability to store data for sequential learning, and has great advantages in time series feature extraction, showing more excellent results, and many studies regard it as a benchmark model [6].

The structure of LSTM is shown in the Figure 4 below. LSTM consists of three gates: Input Gate it, Forget Gate ft, and Output Gate Ot. Ct is the state of the current cell unit, ht is the state of the hidden layer, and xt is the input data.

LSTM uses two gates to control Ct the content of the unit state, one is the Forget Gate, which determines how much of the unit state at the previous moment is Ct−1 retained to the current moment Ct; the other is the Input Gate, which determines how much of the cell state at the previous moment is retained. How much of the network's input xt is saved to the cell state at the current moment Ct. The LSTM uses an Output Gate to control Ct how much of the cell state is output to the current output value of the ht.

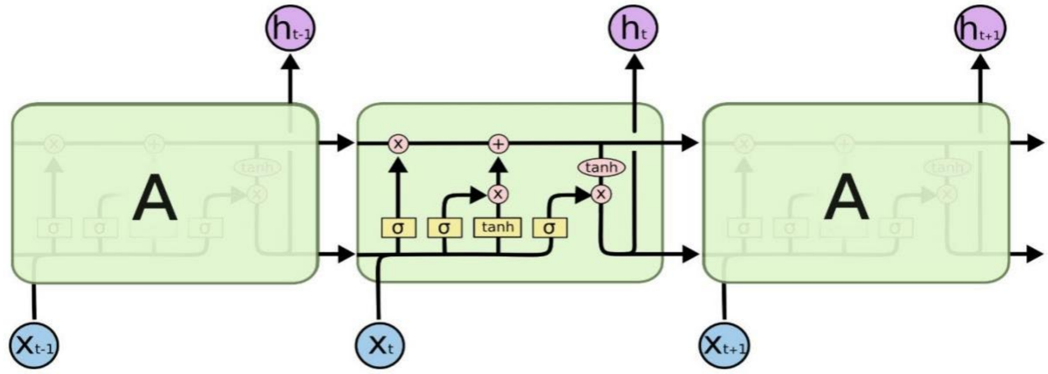

Figure 4. LSTM basic model

5.3.2 Model training

The training set is trained using the LSTM neural network model, and the parameters are set as follows:

1) Time Step: This is a parameter that distinguishes the LSTM neural network model from other models. LSTM requires the input data to be the price when inputting training data, and the input sequence step size is initially set to 5.

2) LSTM Units: Similar to other neural network models, the LSTM neural network also needs to define the number of neurons in each neural layer. In the definition, the shape of the input data should be considered, and the number of neurons in the LSTM layer should be slightly larger than the shape of the input data to ensure that the model can run normally, but it should not be set too large, otherwise it will affect the performance of the model. Considering the above problems and after training, the number of neurons in the LSTM layer initially adopted is 16 (Bitcoin) and 32 (Gold).

3) Optimizer: The purpose of the optimizer is to minimize the loss function. Among all neural network optimizer, adam is the most commonly used optimizer, so the initial setting of the optimizer is adam.

4) Input Shape: As specified by the title, only gold price/bitcoin price can be used for investment prediction, so the input data dimension is 1 dimension.

5.3.3 Model evaluation

Mean Absolute Error (MAE) was chosen to evaluate the model, and the equation is as follows:

$$MAE = \frac{1}{n}\sum_{n}^{i=1}\left|\hat{y}_i - y_i\right|$$

where $\hat{y}_i$ is the predicted value and yi is the true value.

5.3.4 Forecast result

In order to accurately predict the model, we have carried out a long period of training. In order to better fit the US dollar investment in bitcoin and gold, and in line with the reality, we used the method of memory for 5 days to train the LSTM. After the screening of the training model, the models with the smallest mean absolute error (MAE) were selected, which were bitcoin (8.68%) and gold (1.44%). The bitcoin price (Value) and the gold price (USD (PM)) for each day of the five-year period were predicted, and the results are as follows:

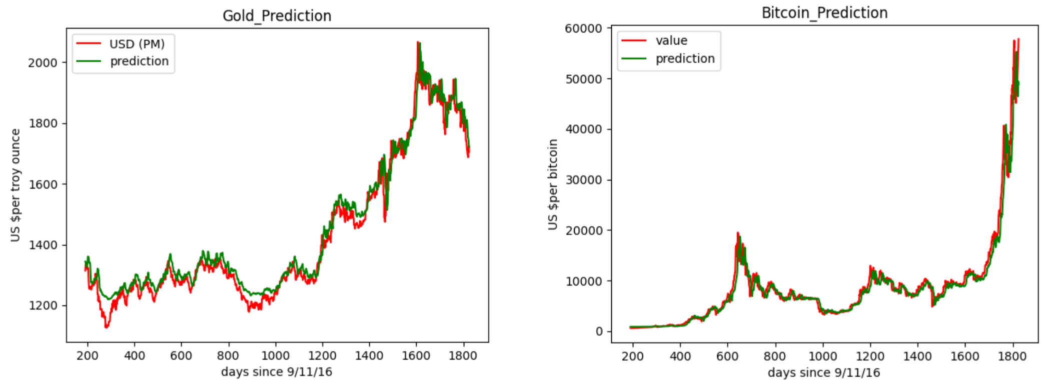

Figure 5. Forecast Results

Figure 5(a) is plotted by gold price and Figure 5(b) is plotted by bitcoin price. Among them, the red line is the original data, and the green line is the predicted data, and a better fitting effect is obtained.

6. Decision model

6.1 Problem analysis

Through preliminary analysis of the problem, it can be intuitively recognized that this is a problem of solving the optimal value, that is, the optimization problem. This problem generally belongs to the category of operations research.

The main research objects of the optimization method are the management problems of various organized systems and their production and operation activities. The purpose of the optimization method is to obtain an optimal solution for the rational use of human, material and financial resources for the system under study, to exert and improve the efficiency and benefit of the system, and finally achieve the optimal goal of the system [7].

The optimization method is widely used in various fields such as public management, economic management, engineering construction, national defense, etc. This problem can also be regarded as a problem in the financial field to a certain extent, including portfolio theory [8, 9], arbitrage theory and so on.

The problem can be regarded as a problem of resource allocation, that is, under a certain resource constraint (USD), by allocating resources to obtain the maximum return. In the problem, you can trade gold and bitcoin in US dollars, and according to their price fluctuations [10, 11, 12], you can gain profits in the future by "buying at a low level and selling at a high level" You can realize that with your decision, your resources will change, and your dollar holdings will also change, that is, it can be said that each decision-making process can be regarded as a "period", which is the problem of optimization of the classic multi-stage decision-making process. At the same time, because the state has no effect, dynamic programming is a more suitable solution

6.2 Basic concepts of dynamic programming

Dynamic programming requires the use of the following concepts:

1) Stage: The process of the given problem is decomposed into several interrelated stages according to time or space characteristics, and the solutions of each stage are solved in sequence.

2) Condition: The objective conditions at the beginning of each stage are called states. The set of values that describe the state of each stage is called a state variable, and the set of values of a state variable is called a state set.

3) Decision and strategy: When the state of each segment is determined, different decisions (or choices) can be made to determine the state of the next stage, which is called decision-making.

Variables that represent decisions are called decision variables. In practical problems, the value of decision variables is often limited to a certain range, which we call the allowable decision set.

4) State transition equation: The state of this stage in dynamic programming is often the state of the previous stage and the decision result of the previous stage. The law of this state transition is called the state transition equation.

5) Indicator function: The quantitative indicators used to measure the pros and cons of the selected strategy are called indicator functions. It is divided into stage index function and process index function.

6.3 Model building

According to the general steps of dynamic programming model establishment, the stage, condition, decision and strategy, state transition equation and index function are respectively found.

6.3.1 Division of stages

According to the problem, simply divide each day into a big stage according to the most obvious stage division-time. Because of the characteristics of the problem, every day can be operated many times, so as to further divide the daily operation into small stages. We use i to represent time (days) and use j to represent operations, so there are at most i · j stages.

According to the actual trading situation and the model hypothesis, in the process of finding the optimal value, the best or extreme trading method must be to buy and sell only once a day, and it must be to sell the asset first and then buy another asset. Therefore, we divide the daily trading into five stages, namely, selling gold, selling bitcoin, buying gold, buying bitcoin and ending the trading stage.

6.3.2 Looking for the status

We can ignore the big stage first and start with the small stage. Since the U.S. dollar can be traded for gold and bitcoin, and gold and bitcoin can also be traded for the U.S. dollar, there should be at least three states, the holdings of dollars, the holdings of gold, and the holdings of bitcoins, which we record separately for:

$C(i, j)$is the holdings of USD in the operation j on day i(unit: USD);

$G(i, j)$is the holdings of gold in the operation j phase of day i (unit: ounces);

$B(i, j)$is the holding amount of bitcoins in the operation j stage on day i(unit: pieces).

According to the requirements of the question, we set the transaction cost of gold and bitcoin as α gold = 1% respectively and α bitcoin = 2% , we set

$$\alpha = \left(\alpha_{gold}, \alpha_{bitcoin}, -\alpha_{gold}, -\alpha_{bitcoin}\right)$$

to meet the requirements of the stage.

At the same time, according to the assumption, we can know the prices of gold and bitcoin so far. We record the prices of gold and bitcoin as Gi , respectively Bi .At the same time, in order to correspond to the small stage, we might as well set a price state $V_{\mathrm{i}} = \left(-G_i, -B_i, G_i, B_i\right)$.

On day i, it is a fixed value, then Gi, is Bi unchanged, and does not belong to the state variable of the small stage. Therefore, the states of the small stage are Ci,j, Gi,j, Bi,j.

The state of the large stage is based on the small stage, and an additional state is added Vi.

6.3.3 Selection of decision variables

According to the division of the stage, the search of the state and the goal of the problem, we set the decision variable as Xi,j , which represents the transaction volume of operation j on day i. We regard the selling asset as a negative number and the buying asset as a positive number, shown as follows:

$Xi,1$ It is the first stage of day i, that is, the amount of gold sold

$Xi,2$ It is the second stage of day i, that is, the amount of bitcoin sold

$Xi,3$ It is the third stage of day i, that is, the amount of gold bought

$Xi,4$ It is the fourth stage of day i, that is, the amount of bitcoin bough

6.3.4 State transition equation

Same as above mentioned, lets start at a small stage. According to simple reasoning, the state transition equation of the small stage is:

$$\begin{cases} C_{\mathrm{i},j+1} = C_{\mathrm{i},j} + X_{i,j+1} \cdot V_{i,j+1} \cdot (1 - \alpha_{\mathrm{j}}) \\ G_{\mathrm{i},j+1} = G_{\mathrm{i},j} + X_{i,j+1} \cdot \mathrm{n}_{1,j} \\ B_{\mathrm{i},j+1} = B_{\mathrm{i},j} + X_{i,j+1} \cdot \mathrm{n}_{2,j} \end{cases}$$

In order to satisfy the state transition, we set the decision according to "the asset sold cannot exceed the holding amount", "the value of the purchased asset cannot exceed the holding amount of USD", and "sell is negative and buy is positive". The variable constraints are as follows:

$$-G_{i,1} \le X_{\mathrm{i},1} \le 0$$

$$-B_{i,1} \le X_{\mathrm{i},2} \le 0$$

$$0 \le X_{\mathrm{i},3} \le \frac{C_{i,3}}{X_{i,3} \cdot V_{i,3} \cdot (1 - \alpha_3)}$$

$$0 \le X_{\mathrm{i},4} \le \frac{C_{i,4}}{X_{i,4} \cdot V_{i,4} \cdot (1 - \alpha_4)}$$

We can deduce the state transition equation of the large stage according to the small stage:

$$\begin{cases} C_{\mathrm{i+1},1} = C_{\mathrm{i},5} \\ G_{\mathrm{i+1},1} = G_{\mathrm{i},5} \\ B_{\mathrm{i+1},1} = B_{\mathrm{i},5} \end{cases}$$

6.3.5 Establishment of indicator function

According to the requirements of the problem, our goal is to find the maximum total value of assets, so we can use the indicator function to measure the total value of assets, and the indicator function is set to *fi,*j, as follows:

$$f_{i,j}(C_{i,j}, G_{i,j}, B_{i,j}, V_{i,j}) = C_{i,j+1} + G_{i,j+1} \cdot V_{i+1,j} + B_{i,j+1} \cdot V_{\mathrm{i+1},j}$$

Since all operations are completed in the next stage of the current stage, the indicator function takes the state of j+1, and in order to make a decision, that is, whether to choose to trade gold or bitcoin, we choose to use the price of the next day to measure.

6.4 Model optimization

6.4.1 Modification of the indicator function

During the establishment of the indicator function in the model, we chose to use the value of the next day to measure. As shown in the Figure 6 below, due to the existence of transaction costs, if the price fluctuation is monotonous in a period of time, there is a big difference between trading every day and the income obtained only at the extreme point [13].

Based on this, we optimized the model and modified the indicator function as follows:

$$f_{i,j}(C_{i,j}, G_{i,j}, B_{i,j}, V_{i,j}) = C_{i,j+1} + G_{i,j+1} \cdot V_{\mathrm{te},j} + B_{i,j+1} \cdot V_{te,j}$$

Suppose *t* (*t* ≤ 5, because the prediction model predicts 5 days) is an interval with monotonous price fluctuations, and *te* is the extreme point in *t*, that is, the asset price reaches the extreme value on day *t*. When *t* > 5, make a decision according to *t* = 5. In order to distinguish, we set the extreme points of gold and bitcoin as *g-te* and *b-te* (Figure 6) respectively, and then consider the price of gold and bitcoin on day *t* when there are two assets of gold and bitcoin at the same time.

There are three possible situations:

1) Gold has extreme value, Bitcoin does not have extreme value;

2) Gold does not have extreme value, Bitcoin has extreme value;

3) Gold and Bitcoin both have extreme values;

Figure 6. The nearest extreme point

To this end, in the selection of *te*, we first find out the nearest extreme point of gold and Bitcoin on day *i*, and by comparing *g-te* and *b-te*, choose the closest *i* as *te*, so as to satisfy the most excellent.

6.4.2 Measure of risk

Since the known data is only price data, it is difficult to use a more complex risk model, and the risk measurement may have large errors. We have selected a variety of comparative classic models to calculate risk, including Sharpe ratio, maximum drawdown rate and portfolio theory to measure risk.

According to behavioral finance, we classify traders into three categoriesrisk-loving, risk moderate, and risk-averse. Through the above theory, we set the safety asset coefficient for the three types of people to distinguish the decisions made by different traders.

1) Sharpe ratio Sharpe (Sharpe, 1966) put forward the Sharpe ratio on the basis of modern portfolio theory. The Sharpe ratio not only pays attention to the return of the asset, but also pays attention to the risk of the asset.

It measures the return of the asset after adjusting the risk, and is the price display of the unit risk. It describes how much unit return can be obtained for each unit of risk taken.

Since the Sharpe ratio comprehensively reflects the risk-return characteristics of the capital market, it has been widely used in evaluating the performance of asset portfolios, judging the operating efficiency of the capital market, constructing effective asset portfolios, and guiding investment decisions. Its mathematical expression is:

$$SharpRatio = \frac{E(\mathrm{r}_p) - \mathrm{r}_f}{\sigma_p}$$

Where E(rp) is the average rate of return, rf is the risk-free interest rate (the US dollar interest rate is taken as the risk-free rate, which is 0), and σp is the standard deviation.

2) Maximum drawdown rate Maximum drawdown is a common measure of risk in the stock market. In order to obtain the maximum profit, traders need to conduct frequent transactions, so the decision can be regarded as a short-term transaction. According to research data, we choose a period of 5 days. Its formula is as follows:

$$\mathrm{Max}D = Max - Min$$

$$Drawdown = \max\left(\frac{V_{i,j} - V_{t,j}}{V_{t,j}}\right)$$

It is generally considered that the maximum drawdown rate is 0.2 is suitable.

3) Portfolio theory

Portfolio is the allocation of wealth held to different assets in order to achieve the purpose of risk diversification. Markowitz (1952) first constructed a mean-variance model of investment portfolios, using the mean to represent the return and the variance to represent the risk, and assumed that investors always pursue the configuration portfolio that maximizes the return under a certain risk.

The formula for calculating the return on a portfolio is:

$$E(\mathrm{r_p}) = \sum_{\mathrm{k=1}}^{2} w_k \cdot E(r_k)$$

The formula for calculating variance is:

$$Var(r_p) = w_1^{\ 2} \cdot Var(r_1) + w_2^{\ 2} \cdot Var(r_2) + 2w_1 \cdot w_2 \cdot COV(r_1,\ r_2)$$

$$COV(r_1, r_2) = \frac{1}{n-1} \sum_{\mathrm{k=1}}^{n} [r_{1,k} - E(r_1)][r_{2,k} - E(r_2)]$$

7. Decision model algorithm optimization

7.1 Proof of the optimal solution

Since the time complexity is too high when the algorithm performs simple iterative operations during the actual operation, it is necessary to optimize the decision model algorithmically.

Because the decision model is a multi-stage decision process optimization problem, we consider particle swarm optimization in the heuristic algorithm type [14].

7.2 Introduction to algorithm model

Particle swarm algorithm is an optimization algorithm established by simulating swarm intelligence. Particle swarm algorithm can take birds randomly foraging in a space as an example. All birds do not know where the food is, but they know the approximate distance. The easiest and most effective way is to search the area around the bird that is currently closest to the food.

Therefore, the particle swarm algorithm is to regard birds as particles, and they have the two attributes of position and speed, and then according to the solution that has been found closest to the food and the closest solution shared by the entire cluster to change the direction of their flight, and finally we will find that the entire cluster gathers roughly in the same place. And this place is the area closest to the food, and if the conditions are good, food will be found. In summary, this is the particle swarm algorithm.

7.3 Algorithm description

Table 2. Algorithm description

Symbols	Description
PBest	Record the optimal solution searched by the individual
GBest	Record the optimal solution searched by the group in one iteration
Speed[*i*]	The velocity of the particle i
W	Inertia weight
*C*1, *C*2	Learning parameters
random()	A random number between 0-1
PBest[*i*]	The optimal value searched by the particle i
Present[*i*]	Position of particle i

The update formulas for velocity and particle position are as follows:

$$S\mathrm{peed}[i] = W \cdot S\mathrm{peed}[i] + C_1 \cdot \mathrm{random}() \cdot (P_{Best} - \mathrm{Present}[i]) + C_2 \cdot \mathrm{random}() \cdot (G_{Best} - \mathrm{Present}[i])$$

Algorithm steps:

Step1: Initialize a group of particles (the size of the group is m), including random positions and speeds;

Step2: Evaluate the fitness of each particle;

Step3: For each particle, compare its fitness value with the best position *PBest* it has passed through, and if it is better, take it as the current best position *PBest*;

Step4: For each particle, compare its fitness value with the best position *GBest* it has passed through, and if it is better, take it as the current best position *GBest*;

Step5: Adjust the particle speed and position according to Step 2 and Step 3;

Step6: If the maximum number of iterations is not reached and the convergence criterion is not met, go to Step 2, if it is reached, exit the loop, and the algorithm ends.

7.4 Optimization results

The optimization strategy of multi-stage decision-making process is found in parallel by particle swarm algorithm, and the daily optimal strategy is obtained at a relatively high speed.

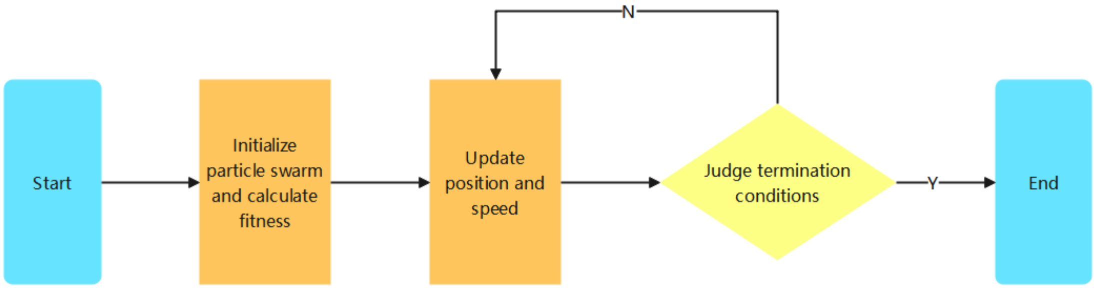

Figure 7. Algorithm steps

8. Sensitivity analysis of transaction cost α

Sensitivity analysis is a method of studying and analyzing the sensitivity of a system (or model) state or output changes to changes in system parameters or ambient conditions. Sensitivity analysis is often used in optimization methods to study the stability of the optimal solution when the original data are inaccurate or changed. Sensitivity analysis can also determine which parameters have a greater impact on the system or model.

8.1 Proof of the optimal solution

We introduce the concept of safe assets. In this article, we try to use the US dollar as a safe asset, that is, traders will always hold a certain percentage of US dollars to combat risks. If the existence of safe assets is considered, the USD that can be traded in the hands of traders will be reduced. According to the model, the income at this time will be reduced, and the total asset value will no longer be the maximum value. Specifically, we limit the status of the US dollar, add fluctuations in the range of 5% to the US dollar holdings, and re-plan the buying and selling plan. The results of multiple experiments are as Table 3:

Table 3. Sharpe rate with disturbance

	1(Disturbance)	2	3	4	5	6	7
Funal asset value	4253.988905	4014.177026	4328.009861	4099.514187	4303.11705	4248.60071	4102.960161
Standard deviation	1112.46286	1123.784967	1182.513399	1146.449023	1175.422056	1164.830035	1137.044301
SharpRatio	3.823924474	3.571992462	3.660009234	3.575838553	3.660813139	3.647172333	3.608445506

Final asset value represents the final asset value, Standard deviation represents the global standard deviation, and Sharp Ratio represents the Sharpe ratio. It can be seen that in the final result, the value is not as large as when there is no disturbance. Therefore, the investment strategy we have chosen can be considered as the best strategy.

8.2 Determine the sensitivity of the strategy to transaction costs

In order to observe the impact on the strategy and results we have asked before when the transaction cost changes, we float the parameters α gold and α bitcoin. In order to be more in line with the actual situation of traders, we use the objective function of risk rational person to invest, and the results are as Table 4:

Among them, α gold and α bitcoin represent the commission cost ratio of gold and bitcoin, respectively, Final asset value represents the final asset value , Standard deviation represents the

Table 4. The impact of fluctuations in transaction costs on trading strategies and results

αGold	*1.0*	*1.5*	*0.5*	*1.0*	*1.0*	*0.5*	*2.0*
αbitcoin	*2.0*	*2.0*	*2.0*	*1.5*	*2.5*	*1.0*	*4.0*
final asset value	4240.895302	4250.740561	3992.134651	5655.804277	2787.148872	5918.263777	4091.145156
standard deviation	1171.802148	1089.67985	1059.26177	1306.455953	825.942312	1440.17735	928.6759052
number of gold transactions	*118*	*65*	*238*	*122*	*122*	*285*	*50*
number of bitcoin transactions	*633*	*620*	*641*	*712*	*533*	*850*	*386*

Global standard deviation, Number of gold transactions (>= 1) represents the number of large gold transactions, and Number of bitcoin transactions (>= 1) represents the number of large Bitcoin transactions. We can see that as the handling fee becomes higher, the number of large-value transactions of gold and bitcoin decreases significantly, the speed of arbitrage is slower, and the final asset value declines. As the handling fee becomes lower, the speed of arbitrage faster, the number of large-value transactions in gold and bitcoin increased significantly, and eventually the value of the asset rose.

9. Summary

Based on question and through analysis, we have built a comprehensive model consisting of a predictive model and a planning model. This model can help you predict the price movement of bitcoin and gold in the next 5 days and help you with your daily trading strategy. Depending on risk appetite, it will help you make the best return on September 10, 2021 from the $1,000 you held on September 11, 2016.

We are convinced that our comprehensive model is effective in predicting the next 5 days and planning the best daily trading strategy, our proposed comprehensive model of the joint LSTM neural network model and Extreme value-DP model is mainly composed of the following aspects:

1) In order to improve the prediction accuracy on the price trend of gold and bitcoin, and help you plan the best daily trading strategy more reasonably, we used the LSTM neural network to make predictions, and the predicted value is the price of bitcoin and gold in next 5 days, which is tested and works well, so you can see exactly what the price of gold and bitcoin will do for the next five days.

2) To help you plan the best daily trading strategy more rationally, we abstracted and naturalized the problem, and transformed the problem into a multi-stage decision-making process optimization. Therefore, the DP model was selected, and used the maximum (minimum) value to evaluate the strategy. When your holdings are fixed, allocate and trade your assets to help you maximize returns.

3) In order to help you get the price forecast value of bitcoin and gold in the next 5 days and the best daily trading strategy faster, we used particle swarm algorithm to optimize the model algorithm, which accelerates the convergence of the model.

4) You can change the parameters in the model according to risk appetite, and the model will adjust your daily best trading strategy based on Sharpe ratio, maximum drawdown and portfolio theory to make you more satisfied.

In the future, we will continue to optimize the existing model to obtain a comprehensive model of trading strategies with faster planning speed and more accurate prediction data.

Should you need more information, I'll be glad to provide you with more details about this model.

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