

Research on Trading Strategy Based on Machine Learning

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Abstract. In this paper, we choose the best trading strategy by building a suitable forecasting model. Specifically, we choose XGBoost, ELM, and long short-term memory network (LSTM) as our baseline models in constructing forecasting models. Furthermore, based on further predictions given by our model, we construct a set of ground rules. On this basis, two correction methods, disturbance correction and multi-step correction are proposed for the dilemma. Then we studied the investment period of this strategy and found that the optimal investment period is 1 day. Finally, a sensitivity analysis of the commission rates for bitcoin and gold is performed.

Keywords: Financial time series, long short-term memory network (LSTM), XGBoost

1. Introduction

Because the market is influenced by society, economy, politics, and other aspects, time series of financial products are often characterized by chaos, high noise, nonlinearity, and non-stationarity [1]. Therefore, it is very challenging to predict financial time series with high confidence, let alone apply it to asset allocation and transactions. The time series of two volatile assets, gold and bitcoin, is given. It is hoped that traders engaged in related product transactions can get some help in decision-making by analyzing and modeling these two-time series.

In this paper, we make the following assumptions to help us with our modeling. The price of Gold and Bitcoin in the data set is regarded as the average transaction price of that day, which represents the transaction price of that day. Moreover, we assume all the price data is accurate. Both Gold and Bitcoin are traded 24 hours a day, and their prices fluctuate all the time during trading days. However, the price data in the data set takes a single day as the unit, which cannot reflect the daily price fluctuation. Therefore, in order to estimate the income, it is necessary to explain the meaning of price.

On each trading day, the trader can carry out a buying or selling operation only once for every kind of volatile asset. The given data is based on the minimum unit of the day. If there are many transactions involved, the price of each transaction cannot be known. Furthermore, if the average price is used instead of the transaction price, multiple transactions are equivalent to one transaction. For simplicity, we assume that only one trading operation can be conducted on one volatile asset per trading day.

Among all trading strategies and regulations, the long strategy is only considered. The actual trading process involves trading strategies such as long, short, and hedging. In addition, there are trading rules such as leverage. We assume that traders only adopt a long strategy to simplify the consideration. The minimum unit of gold trading is ounces. The trading volume of gold must be an integral multiple of ounces. We can trade 0.1 bitcoins, 0.01 bitcoins, and 0.0001 bitcoins in actual transactions. It can be considered that the minimum unit does not limit the transaction of bitcoins. However, for gold, the lowest trading unit of an international trading platform is always one ounce. This assumption aims to make our model more in line with the actual trading situation.

2. Price Forecasting Model Based on Machine Learning Strategy

The deep learning model has also been proved to have a considerable empirical effect on time series prediction [2]. Through reading related literature [3], it is found that an extended short-term memory network (LSTM). As a common method to deal with time series problems, it can effectively

solve the difficult prediction problem caused by the non-stationarity of financial time series. However, according to the literature [4], the success of deep neural networks often relies on the availability of a large amount of labeled data that is expensive or hard to collect. More than that, the training process of the deep network model is often computationally expensive, which means it is quite hard to apply it to our prediction model that is updated day by day.

Considering the advantages and disadvantages of machine learning and deep learning strategies, we plan to update the daily model only by using machine learning strategies in the early stage. After accumulating a certain amount of data, we train an LSTM model and integrate its decision results with the actual machine learning decision results to further improve the prediction ability of the model for daily time series. The basic idea of building the prediction model is shown in Fig.1.

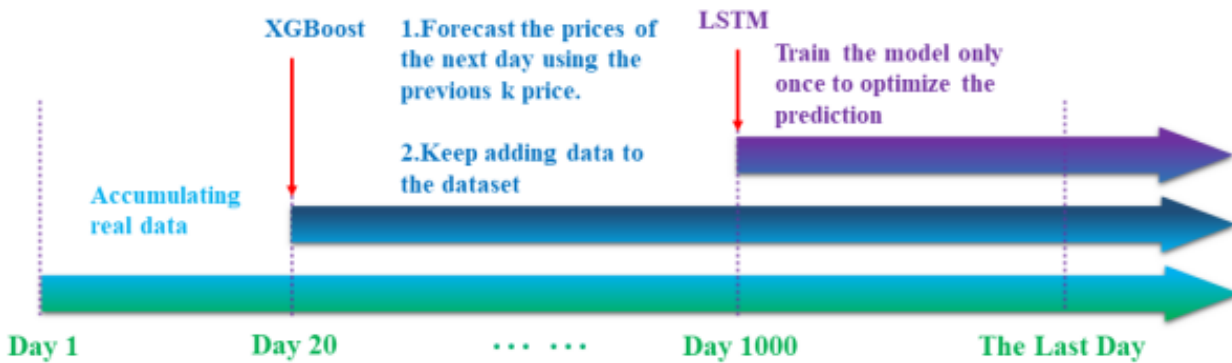


Figure 1. Construction strategy of the prediction model.

2.1. Xgboost

XGBoost is an improvement of the GBDT algorithm, widely used in Kaggle competitions and many other machine learning competitions [5]. Xgboost provides new ideas in futures price prediction and shows good prediction ability and application value. The prominent strength of this algorithm is its efficiency and convenience, so we think it is very suitable for our learning task. The specific principle of XGBoost is quite complex. In the prediction task, we should pay more attention to the actual prediction effect of each model, so we do not introduce the related principles here.

2.2. Elm

As a fast learning method, a limit learning machine is widely used in time series prediction [6]. Different from the feed-forward neural network, the weights and bias of the input layer and hidden layer of the extreme learning machine (ELM) are randomly generated rather than be iteratively by the BP algorithm, which can be expressed as:

$$\sum_{i=1}^L \beta_i g(W_i \cdot X_j + b_i) = t_j, j = 1, \dots, N \tag{1}$$

Where the weights W and bias b of the input layer and hidden layer of E ELM are randomly generated, L refers to the number of hidden layer nodes, and N represents the number of time series samples we get. As for the weight of the output layer β , it can be solved by:

$$\beta = H^+ T \tag{2}$$

Where H^+ is the MP generalized inverse of the hidden layer's output H , and T is our label sets consisting of assets' prices at the next moment.

After solving β , then we can put ELM into the prediction task. Since there is no iterative process in the training process of ELM, its learning rate can be greatly improved. Therefore, we think it is also suitable for the current forecasting task.

2.3. Lstm

The LSTM structure we use is shown in Fig. 2.

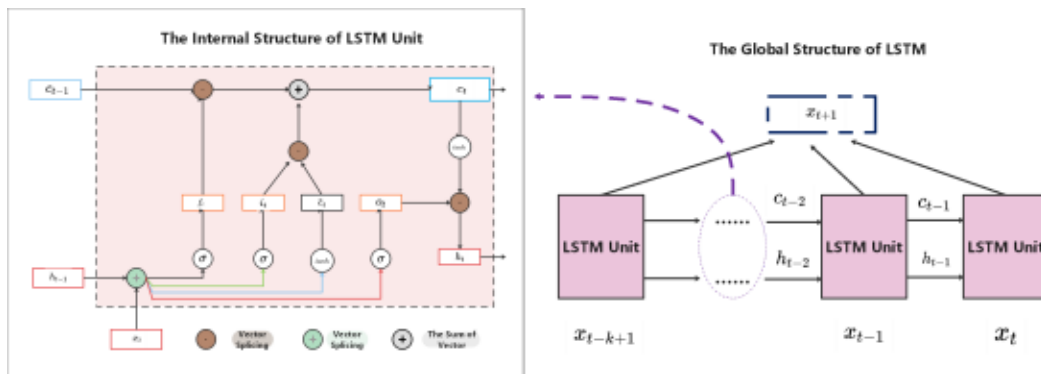


Figure 2. The structure of LSTM.

The selection of gating activation function mainly includes sigmoid and tanh. The curves of the two functions are shown in Fig. 3. The sigmoid function is in the range of [0, 1]. It means it can only control whether the current information affects the situation. If the function value is 0, there is no influential information, and if the function value is 1, there is influential information.

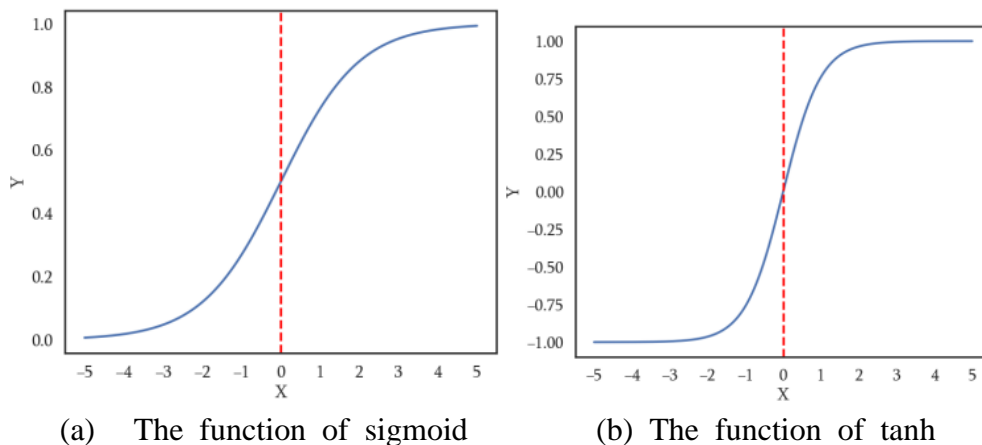


Figure 3. The function of tanh and sigmoid.

However, the range of tanh function is [-1, 1]. It can describe whether there is any influence and describe the influence direction of the current input. In the economic environment, information is changing rapidly, so it is of great significance to judge whether its impact is positive or negative. Therefore, we choose tanh as our activation function to capture the change information during the transaction.

Besides the predicted price value, the prediction of price direction is also essential. If the price we predict is a rising process, but in fact, it is a declining trend, at this time, although the prediction result of the model is very close to the actual value, the prediction direction of the model is wrong, which will make us miss some important investment opportunities. Inspired by the literature [7], and build a loss function to measure the direction of price change, which can be expressed as:

$$l_{add} = e^{-(x_{t+1}-x_t)(\hat{x}_{t+1}-x_{t+1})} \tag{3}$$

Where x_t represents the price on tth day. $x_{t+1} - x_t$ represents the actual change direction of the price, $\hat{x}_{t+1} - x_{t+1}$ represents the predicted change direction of the price. When they are in the same direction, their product is negative. They are exponential so that the whole loss will be small. When the two are reversed, their product is positive, and the loss will increase exponentially. Obviously, as long as the function term is minimized, the direction of forecast price change and the direction of real price change can be kept as consistent as possible. The final loss function we use in the model is as follows:

$$L = w_1(x_{t+1} - x_t)^2 + w_2e^{-(x_{t+1}-x_t)(\hat{p}_{t+1}-p_{t+1})} \quad (4)$$

2.4. Construction of baseline model

In order to compare the performance of ELM, XGBoost, and LSTM models, we take the time-series of gold as an example and selected mean-squared-error (MSE) as the metric. Then we train the data of the previous 1000 days, and XGBoost adopts the daily iteration update strategy, with a total of 980 iterations, while LSTM is trained only once with the dataset consisting of 1000 samples. The trading price fitting curves of gold and bitcoin of the first 1000 days corresponding to XGBoost ELM and LSTM are shown in Fig.4.

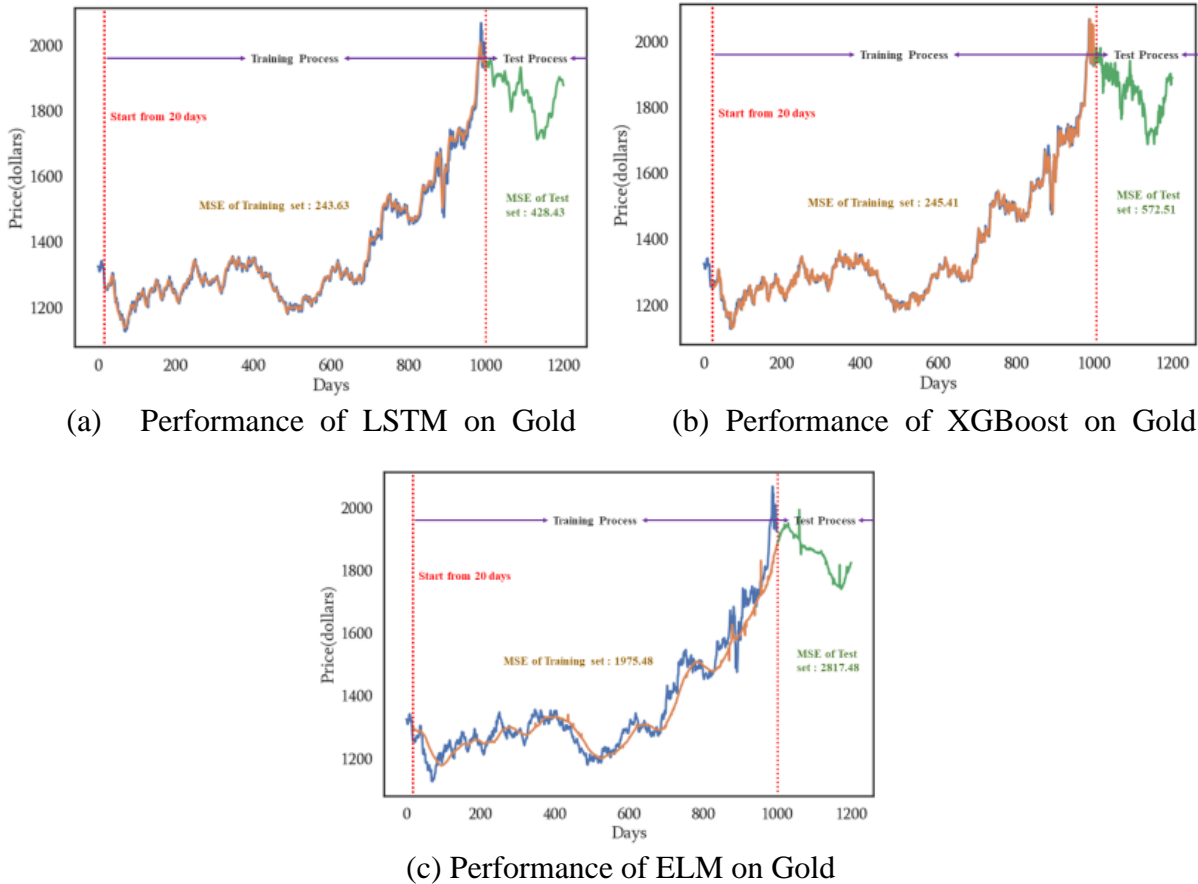


Figure 4. Performance comparison among three models.

In Fig.4, we mark three periods with different colors. The first 20 days of the "wait-and-see" period, the period where we train our model, and the period we test our model from June 8th, 2019, to December 24th, 2019.

In order to further compare the performance of the models, we marked two MSEs in Fig. 5. From Fig. 5, we can see that the MSE of LSTM during the test period is 428.43, which is the smallest among them. Following by XGBoost with an MSE of 572.51. As for ELM, its fitting curve is relatively smooth, which cannot predict the price very well. LSTM is the best baseline model for forecasting, but considering its huge demand for data and high computational cost, it is not suitable for daily iterative updating. XGBoost, as a compromise scheme. It reaches a relatively satisfying balance between training time and prediction effect, so we choose it as the baseline model for our daily iteration.

2.5. Combination and optimization of the baseline model

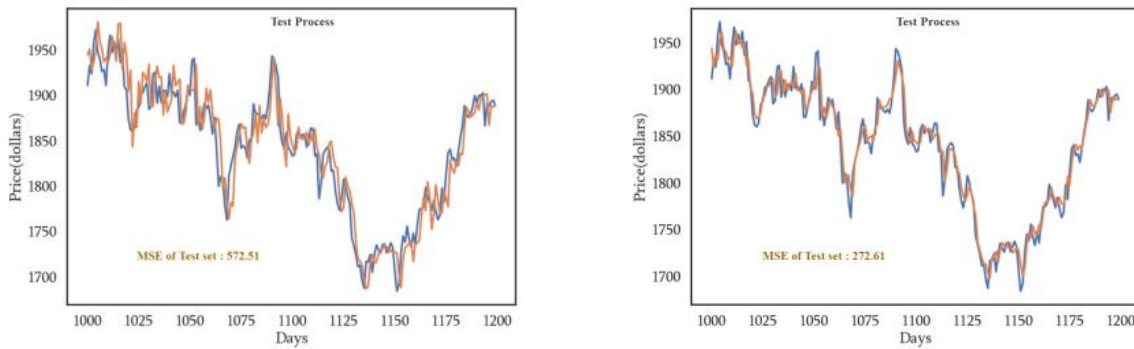
Although we cannot use LSTM for daily iterative training, we can still train an LSTM after accumulating enough data with the evolution of the trading process. By combing its prediction results

with XGBoost's prediction results, we may further improve the prediction accuracy of XGBoost, which can be expressed as:

$$x_{t+1} = w_1 \hat{x}_{t+1}^{Xgb} + w_2 \hat{x}_{t+1}^{LSTM} \tag{5}$$

where \hat{x}_{t+1}^{Xgb} represents the prediction of XGBoost, \hat{x}_{t+1}^{LSTM} represents the prediction of LSTM.

We continue to use XGBoost and LSTM that have been trained by the data of the first 1000 days. Then we compare the performance of XGBoost and XGBoost+LSTM over the next 200 days. We still take the time series of gold as an example, and the results are shown in Fig. 5. From Fig.5. It can be seen that the MSE on test data declines from 572.51 to 272.61 after combining two models, which means the combination of two models does improve our model significantly.



(a) Performance of XGBoost on test data (b) Performance of XGBoost+LSTM on test data
Figure 5. Performance comparison between XGBoost and XGBoost+LSTM.

3. Optimal Trading Strategy Model Based on Trend Inference

Fig. 6 shows the optimization process of our investment strategy. We first propose a series of basic rules. After getting the prediction information from our prediction model, we can apply these rules to help us make the trading strategy for the next trading day. However, these rules will lead to a dilemma. To solve this problem, we introduce the multi-step prediction made by ELM. Then we study the best investment cycle T and the influence of investment proportion K in this problem. Finally, we comprehensively considered risks and benefits and introduced a dynamic risk monitoring mechanism. We provide adjustable risk control factors for the trader. Traders can adjust this parameter based on their own investment experience and investment preferences, which provides an interactive way between traders and our models.

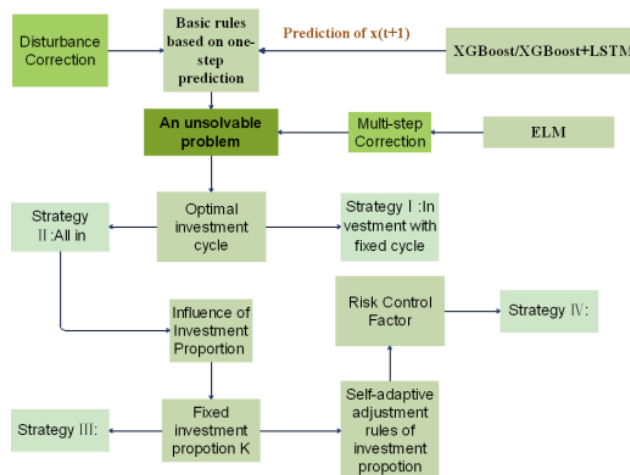


Figure 6. Optimization process of our strategy.

Based on the prediction model we built, we can predict the price changes of Gold and Bitcoin on the next day. We expect to make the investment decisions that can maximize the profits of the tth day

based on the forecast information of the t+1 th day. Naturally, we can get that our optimization goal should be like this:

$$\max x_t^{gold} y_t^{gold} + x_t^{bitcoin} y_t^{bitcoin} + z_t, y_t^{bitcoin} \in N \tag{6}$$

Where y_t^{gold} and $y_t^{bitcoin}$ represents the volume of gold we hold respectively. As long as we make the best investment decision every trading day, we can get the best investment strategy from the overall point of view. It is a process of getting global optimum through the iteration of local optimum.

The machine learning strategy based on XGBoost cannot make a multi-step prediction. Because of the time cost and the amount of data, LSTM can not be used for daily forecasts. Then we find that although ELM cannot predict the price very well, it can be used to predict the rough trend of the price by adding output units. We can roughly predict the price through ELM in the next five days. Based on the previous rules, consider calculating the average value of the predicted prices \bar{x}_t of the two assets in the next five days and comparing it with the current day. So we can calculate a growth rate, which can be expressed as:

$$g = \frac{\bar{x}_t - x_t}{x_t} \tag{7}$$

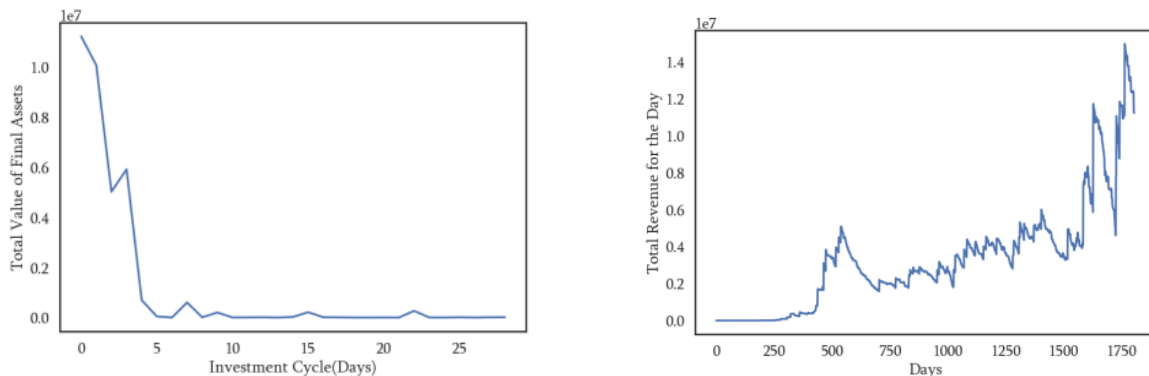
If g is higher than the commission rate, then we should buy. Otherwise, we should sell.

Considering that making decisions according to the predicted values will produce great contingency, to improve the robustness of the model, we add a disturbance ϵ to the daily forecast rise and fall. The ϵ obeys the uniform distribution in the form of:

$$\epsilon \sim U(-0.002, 0.002) \tag{8}$$

In practice, we run our model 20 times and select the medium of the final total value as our result.

Investment Cycle T is an essential parameter in our model. In order to study the relationship between the investment cycle T and the final asset value V, we set the cycle as a continuous integer from 1 to 30 and calculate the final asset value corresponding to each investment cycle in this range by adopting the previous basic strategies and amendments. As shown in Fig. 7 (a), we finally get the results.



(a) The change of the final asset value with the investment cycle (b) The change of total assets every day in the "All-in" strategy

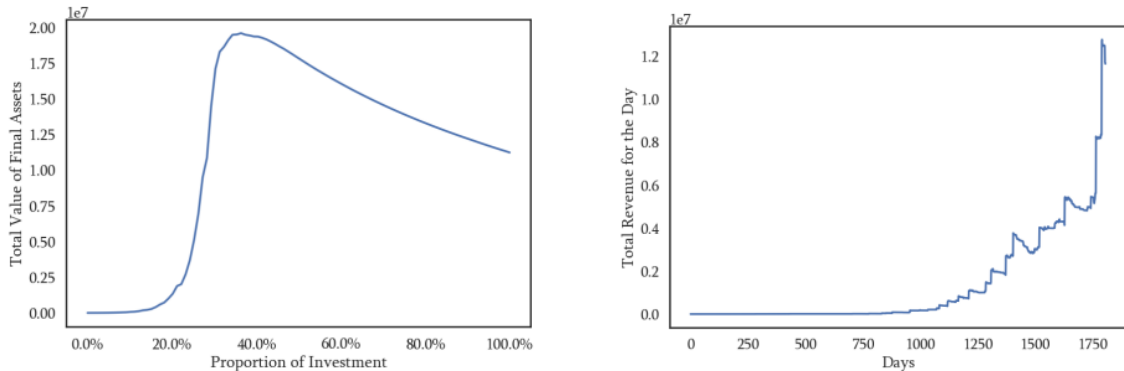
Figure 7. The change of final asset value.

From Fig.7 (a), we find that the final total asset value is the largest when the investment cycle is set to be 1. Since then, with the increase of the investment cycle, the final asset value shows a trend of rapid decline and then tends to be flat. Therefore, we think that the optimal investment period should be one day.

After getting one day as the optimal investment cycle, a natural strategy based on the basic rules is to put all the available cash into the portfolio. We call it the "All-in" strategy. Fig. 7 (b) reflects the

change of total assets value with time when this strategy is adopted. We find that the fluctuation of total assets is evident during the trading period, which depicts a potential trading risk.

Generally, not all cash will be used for investment in the actual investment situation. Moreover, the investment based on the prediction results has the risk of loss, which leads to the deterioration of the investment effect. We limit the proportion K of the maximum investment amount to the total assets to control the risk of investment activities. All investment activities shall meet the requirement that the maximum investment amount shall not exceed the proportion of total assets K . We take K from 0 to 100% and fix the value of K in each simulation. Different final assets value results are shown in Fig. 8 (a).



(a) Influence of K on the final total assets (b) Daily change of total assets when taking Dynamic risks

Figure 8. Influence of various factors on total assets.

We can see from Fig. 8 that the final asset value is not monotonically rising, but there is the highest point. When K is higher than a threshold, the final asset value will decrease instead. It also proves that risks influence our investment decisions. Casual investment can easily lead to a loss of income.

Although for the current asset price curve, a certain k value can make the total income reach the highest. However, this conclusion is based on the global perspective and has no practical value. In practice, we often do not know how to set an appropriate investment proportion. Therefore, we further propose an adaptive investment proportion control scheme, which can dynamically control the next K based on the current risks, which can be expressed as:

$$K = e^{-\alpha\beta} \tag{9}$$

Where α is a risk control factor that can be set by hand. As for β , it stands for the volatility of the current asset.

Fig. 8 (b) shows the daily change of total assets when α is set to be 3000. Compared with Fig.7 (b), it is clear that the daily fluctuation range of assets is reduced after adding a dynamic risk adjustment strategy. However, there is no significant difference in the total value of assets. The revenue is reduced by about 14.3. It proves that the indicators we built are indeed effective.

Finally, we need to give the maximum profit based on our strategy, so we need to optimize the value of α . In Fig.9, we find that with the growth of α , the final total asset value is a bowl-shaped curve that first rises and then falls. When α reaches 1030, the final asset value reaches the maximum value, which is also the optimal result based on our strategy, which is 22974459.23 U.S. dollars. This extreme point is evidence that our strategy has reached the optimum.

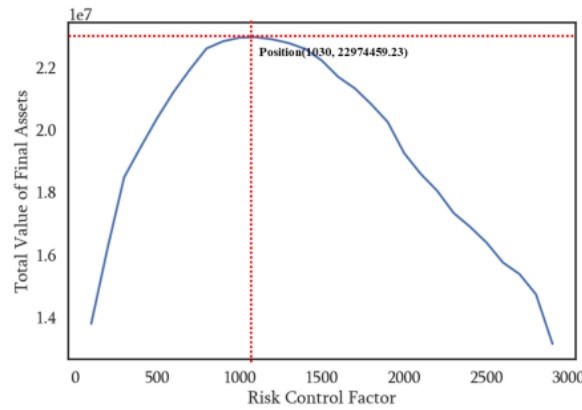
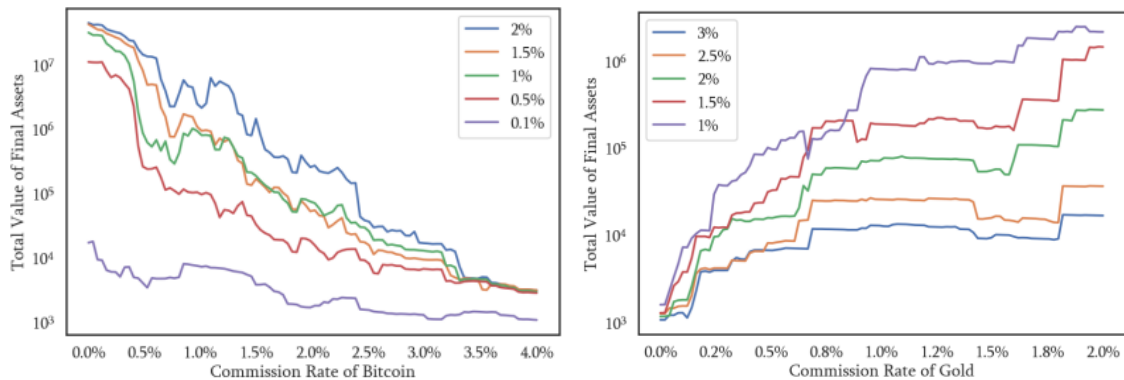


Figure 9. Daily change of total assets when α is changing.

It can be seen from Fig. 10 that when the fixed gold commission rate changes the bitcoin commission rate, the total value of the final assets will generally decrease with the increase of the bitcoin commission rate. It is mainly because the price of bitcoin fluctuates greatly, and its holdings will greatly affect the asset value. When bitcoin's transaction rate is higher, to avoid losses, the early trading strategy will become more conservative and tend to hold less bitcoin. In addition, due to the high unit price per ounce of gold in the previous period. It is impossible to conduct any transactions at many times. It greatly reduces the final profit.



(a) Sensitivity of total asset value to the bitcoin commission rate

(b) Sensitivity of total asset value to the gold commission rate

Figure 10. Sensitivity of total asset value to both assets.

When the fixed bitcoin commission rate changes the gold commission rate, the total value of the final assets will generally increase with increasing the gold commission rate. Because the purchase conditions of gold itself are more stringent, coupled with higher transaction rates, our strategy will not tend to buy gold but will turn to buying bitcoin. With the increase in trading times, the yield curve will be more stable due to the slow change in the gold price. To sum up, our strategy is sensitive to transaction costs.

4. Conclusion

This paper describes a model optimization process from local to overall step-by-step. Starting from the formulation of the daily trading strategy, we simulated the overall decision-making of trading in multiple different cycles. We concluded that based on the trading strategy formulated in this paper, the daily decision-making would be able to obtain the maximum benefit. Then, based on the decision-making of taking one step in the trading cycle, we consider the impact of the proportion of disposable investment on the profit. When the proportion of fixed investment reaches 37%, the profit is maximized. Due to the limitations of fixed investment proportion, we have constructed a dynamic risk assessment model to adapt to the risk trend that will change with time and use controllable

coefficients to control the impact of the model on the investment proportion. The larger the coefficient is, the more sensitive it is to risk and the more stable the return curve is, but the growth range is small, which is suitable for conservative people.

On the contrary, the return curve fluctuates greatly. The growth rate is large, which is suitable for active people. Finally, by observing the curve between parameters and returns, it can be seen that there are extreme values in the curve. When the parameter is 1030, the profit is the largest, which is the US \$22974459.23. Of course, the best strategy varies from person to person and does not necessarily depend on the income. Controllable parameters can be further adjusted to obtain a strategy suitable for their conditions.

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