# Research on the Three-Stage Trading Strategy of Gold and Bitcoin Using Technical Indicators and A LSTM Model

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**Abstract.** In recent years, in pursuit of higher returns, people began to try the combination of bitcoin and gold. This study explored how to use the current and past prices of gold and bitcoin to get the best investment strategies for the next day to get the maximum return. The obtained historical price data of gold and bitcoin from 2016 to 2021 are divided into three stages according to the time axis, namely, stage Ⅰ (1st day-300th day), stage Ⅱ (300th day-400th day) and stage III (400th day-1825th day). Different methods are used for each stage to determine the trading strategy. In stage I, a comprehensive index is constructed by using four technical indexes closely related to the formulation of daily strategies in the financial market, such as moving average convergence and divergence, deviation rate, stochastic index and detrended price oscillator, and the trading strategy is determined by using this comprehensive index. In stage II, the four technical indicators and product prices in stage I are used as training sets, and the daily trading strategy is given by using the decision tree classification model. In the third stage, the long-term and short-term memory neural network is used to develop the future price prediction model of gold and bitcoin, and the trading strategies of gold, bitcoin and cash asset portfolios are formulated according to the dynamic optimization results of different types of traders' risk tolerance. The results show that during the five years from September 11, 2016 to September 10, 2021, the whole strategy created a net profit of $170,381 for aggressive traders and $7,694 for rational traders. After verification, our strategy is effective and robust, and its volatility is relatively small. The research provides theoretical guidance for investors on how to choose portfolios and trade to get the maximum return.

**Keywords:** Trading strategies, Decision tree classification, Long-term and short-term memory (LSTM) networks, Dynamic optimization.

## 1. Introduction

In the financial industry, the most fundamental data is the price of different assets. And all rational market traders buy and sell volatile assets frequently, intending to maximize their total return within a reasonable risk tolerance level [1]. During the transaction, a commission for each purchase and sale always has a huge impact on the trader's return [2-3].

At present, there are mainly two methods to choose the best asset in China's investment market, one is Barra multi-factor model, and the other is a multi-factor model using machine learning. Several approaches based on machine learning have come into the spotlight in recent years such as cluster analysis, neural network, and random forest. But most of them are used to construct more effective factors or act as data analysis tools for factors. After reading a few reports, we find that LSTM [4] is especially suitable for processing series data and it is possible to combine LSTM neural network and dynamic optimization to find the best trading strategy.

The goal of this study is to develop an optimal decision-making model to formulate the best daily trading strategies and prove that this model provides the best strategy. On this basis, the sensitivity of transaction strategy to transaction cost is deeply analyzed, to explore the potential law that transaction cost affects process strategy and result, and provide theoretical support and help for investors to make more reasonable investments.

# 2. Formulation of trading strategy

## 2.1 Analysis of making daily trading strategy

### 2.1.1. Classification of trader types

In real life, different traders have different risk tolerance levels. The best daily trading strategy should be able to meet the needs of different traders. At present, there are two main types of traders in the investment market: aggressive traders and rational traders. The former can take any risks to maximize profits, accounting for a relatively small proportion; The latter considers both benefits and risks, accounting for a relatively large proportion. To make the established model reflect the real situation better, it is necessary to set different trading strategies for rational traders. It is believed that rational traders form a portfolio of 50% risky assets and 50% risk-free assets. Moreover, when rational traders are optimized, an additional constraint will be set to quantify the upper limit of risk tolerance.

### 2.1.2. Timeline division

To optimize profits, LSTM is used for price forecasting before determining the best trading strategy. However, all the data should not be input into the LSTM network to predict the daily price, because using all the data for training and then using the data for prediction will lead to the incredibly high prediction accuracy of the model established by the network. In addition, this is not in line with the practice of forecasting the price of financial products in practice, because the historical data on financial products are often unavailable or even insufficient. Based on this consideration, the research divides the acquired gold and bitcoin price data in five years (1825 days in total) from 2016 to 2021 into three stages according to the time axis:

(1) Stage Ⅰ (1st day 1-300th day)

The trading strategy is formulated by using a comprehensive index composed of four technical indexes closely related to the formulation of the trading strategy.

(2) Stage Ⅱ (300th day-400th day)

The decision tree model outputs trading decisions by processing the four technical indicators in the first stage.

(3) Stage Ⅲ (400th day-1825th day)

The LSTM network can be used to establish a price forecasting model. Then, combined with the optimization model, a better trading strategy at this stage is further determined.

## 2.2 Data preprocessing

Before establishing the model, the data of financial products should be preprocessed: bitcoin can be traded every day while the gold is only traded on days the market is open, namely the gold is not traded on weekends and holidays. For the continuous regression analysis for the prediction of gold, we fill the missing value on a non-traded day by propagating the last valid observations.

For the fact that we are optimizing the value of our portfolio, we focus on the volatility of daily returns. We observe that the fluctuation of bitcoin daily return is bigger than that of gold. For this consideration, we need to employ different strategies for investing in gold and investing bitcoin. At the same time, considering the high risk and high reward of the two assets, we manage to implement different investment schemes for different people in two aspects, namely conservative and radical.

## 2.3 Stage I: Determination of trading strategy

### 2.3.1. Composition of technical indicators

(1). Moving average convergence divergence

Moving average convergence divergence (MACD) is a trend-following momentum indicator that shows the relationship between two moving averages of an asset's price [5]. It is calculated by subtracting the 26-period exponential moving average (EMA) from the 12-period EMA. A sharp change in MACD, means long period line and short period line moving rapidly against each other which represents a huge trend of change in the asset price. Thus, MACD triggers technical signals when it crosses above (to buy) or below (to sell) its signal line (0). It is calculated as:

$$DIFF = EMA(CLOSE, Short) - EMA(CLOSE, Long) \tag{1}$$

$$EDA = EMA(DIFF, Medium) \tag{2}$$

$$MACD = 2*(DIFF - EDA) \tag{3}$$

(2). Deviation rate

Deviation rate (BIAS) is an indicator that reflects the degree of deviation between the asset's price and its moving average in a certain period. The moving average price can be viewed as an acceptable price by both the buy-side and the sell-side in the past short period. When the stock price moves drastically to deviate from this accepted price, the possibilities for a pullback or rebound largely increase. When the stock price movement does not deviate from the trend, the trend will likely continue. In our model, we chose the rolling period to be 24 days and the bar to be 11%. When the BIAS is above the positive bar, a sell signal triggers because the stock has been overbought. When the BIAS is below the negative bar, a buy signal triggers because the stock has been oversold. The indicator is calculated as:

$$BIAS = \frac{(price\, of\ the\, day)}{N\ day\ average\ price} \tag{4}$$

(3). KDJ

KDJ indicator which is also known as the random index used to analyze and predict changes in stock trends and price patterns in a traded asset. According to the statistical principle, the immature random value RSV of the last calculation cycle is calculated through the highest price, lowest price and the closing price of the last calculation cycle (usually 9 days, 9 weeks, etc.) and the proportional relationship between the three. Then it calculates the K value, D value and J value according to the method of smoothing the moving average, and draws a curve to study and judge the stock trend. This indicator is often used to analyze short-term stock. The indicator is calculated as:

$$RSV = \frac{CLOSE - LLV(LOW, N)}{HHV(HIGH, N) - LLV(LOW, N)} \tag{5}$$

$$K_i = \frac{2}{3}K_{i-1} + \frac{1}{3}RSV_i \tag{6}$$

$$D_i = \frac{2}{3}K_{i-1} + \frac{1}{3}K_i \tag{7}$$

$$J_i = 3K_{i-1} + 2D_i \tag{8}$$

(4). Detrended price oscillator

The detrended price oscillator (DPO) is an indicator in technical analysis that attempts to eliminate the long-term trends in prices by using a displaced moving average so it does not react to the most current price action. This allows the indicator to show intermediate overbought and oversold levels effectively. The DPO is not a momentum indicator. It instead highlights peaks and troughs in price, which are used to estimate buy and sell points in line with the historical cycle. Also, DPO triggers technical signals when it crosses above (to buy) or below (to sell) its signal line (0). The indicator is calculated as:

$$DPO = Close - moving\ average \times \left[ (n/2+1) days\ ago \right] \tag{9}$$

### 2.3.2. Methods and results to determine a trading strategy

On day 1-day 300, the effectiveness and the stability of a single indicator are affected by its periodic failure. To grasp the valid period of each indicator, we composed them into a composite indicator. The synthetic method of indicators adopts the scoring method, that is, the synthetic signal of each day is obtained by adding the signal of all four technical indicators with equal weight. Each indicator will contribute 1 if it triggers a buying signal, contribute -1 if it triggers a selling signal, and contribute 0 if it doesn't trigger at all. To denoise, we set a bar (=2) for composite indicator, namely, we consider receiving a buying or selling signal only when the value of the synthetic indicator is out of range [-1,1].

In Stage I, aggressive traders made a profit of 78.3% and rational traders made a profit of 39.1%.

## 2.4 Stage II: Determination of trading strategy

### 2.4.1. Analysis to determine the trading strategy in stage II

In stage I, four technical indicators are selected according to experience, and the trading strategy is determined by constructing them into a comprehensive indicator. However, the constructed comprehensive index is subjective and can't determine the objective trading strategy. When enough data points are accumulated in the first stage, this stage can improve the previous decision-making process by using a machine learning model, to determine a more reasonable and better trading strategy. Considering that the decision tree model has the characteristics of less sample size and higher classification accuracy compared with other classification models, the decision tree model is used to determine the trading strategy at this stage.

### 2.4.2. Data processing

To train a decision tree model, a training set of $\{(x_{i,1}, x_{i,2}, x_{i,3}, x_{i,4}, y_i), i=1, 2, ..., 270\}$ is required. To set $y_i$ on each data point, we calculate the *return* of $day_i$ to $day_{i+1}$, Then $y_i$ is set as -1, 0, 1 if $return_i < -0.02$, $-0.02 \le return_i \le 0.02$, $return_i > 0.02$ respectively. We set -0.02 and 0.02 as thresholds since it is more profitable to adjust our portfolio only if the absolute value of the return exceeds the transaction rate.

### 2.4.3. Methods and results to determine trading strategy in stage II

From the 300th day, the four technical indexes in the first stage are input into the trained decision tree model, and a classification result is obtained. Based on the classification results of -1, 0, 1, aggressive traders are respectively engaged in transactions such as selling all bitcoins, not trading and buying bitcoins with all cash; For rational traders, since they initially hold $500, they only use the other $500 to carry out the same trading strategy as aggressive traders.

Then, we adopt the same trading strategy as that of the aggressive traders but with an initial trading amount of 500 dollars. In Stage II, aggressive traders made a profit of 15.6% and rational traders made a profit of 10.0%.

## 2.5 Stage III: Determination of trading strategy

### 2.5.1. Analysis to determine the trading strategy in stage Ⅲ

A long-term memory network (LSTM) has been proved to be a good predictor of the future prices of financial products. Therefore, LSTM is adopted to predict the future prices of bitcoin and gold on that day.

However, if all the data are put into the training set and the same data as the test set is used, this will lead to an incredibly small error between the real value and the predicted value. The research data are divided into a training set and test/verification set to ensure the correctness of model prediction. Based on the characteristics of the acquired data set, the first 400 days of data of Bitcoin and Gold are used as the training set of the network, and the data after the 400th day of Bitcoin and Gold are used as the testing set of the network.

### 2.5.2. A price prediction model based on LSTM

(1) 3-layer LSTM design

To predict the reputation score, we use Long and Short-Term Memory (LSTM) to model the variation pattern of the review sequence. LSTM model is a variant of the recurrent neural network (RNN) [6]. It is well-suited to classifying, processing and making predictions based on time series data. A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell [7-8].

Instead of using a single-layer structure, we implement a 3-layer LSTM model based on the characteristic of the dataset (different adaptations of gold and bitcoin). This LSTM network computes a mapping from an input sequence $X = (X_1, \ldots, X_T)$ to an output sequence $y = (y_1, \ldots, y_T)$ by calculating the network unit activations using the following equations iteratively:

$$\begin{aligned}
i_t &= \sigma(W_i x_t + U_i h_{t-1} + b_i) \\
z_t &= \tanh(W_z x_t + U_z h_{t-1} + b_z) \\
f_t &= \sigma(W_f x_t + U_f h_{t-1} + b_f) \\
c_t &= i_t z_t + f_t c_{t-1} \\
o_t &= \sigma(W_o x_t + U_o h_{t-1} + V_o c_t + b_o) \\
h_t &= c_t o_t \tanh
\end{aligned} \tag{10}$$

Where σ is the sigmoid function, W is the Weight matrix, x is the concatenated input vector, h is a hidden state, b is the bias, tanh is the hyperbolic tangent function, it is input gate, ft is forgot gate, ct is cell state, and ot is output gate.

Research Frameworks for the prediction model can be described using the following diagram in Figure 1. The proposed model is a stacked LSTM (3 layers) with 50 nodes of each hidden layer [9-10]. The last part of the model is a fully connected neural network with 1 output node. The function activation is relu function and the model was set for 100 epochs.

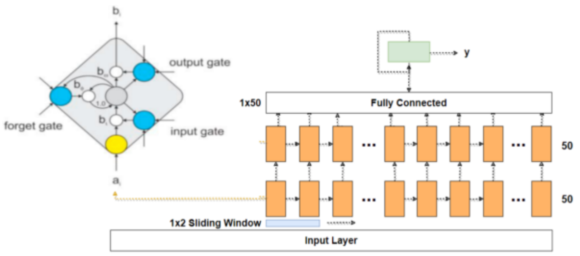


**Figure. 1** Three-layer LSTM Model for Price Prediction

(2) Instructions for LSTM network training

Before we show the training and testing results, there are several training details to be stated:

(1) Loss Function

We use mean square error (MSE) as the loss function:

$$MSE(y, \hat{y}) = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{11}$$

Where y is the true target vector and $\hat{y}$ is the predicted feature vector and N is the number of dimensions.

(2) Normalization

Due to the different domains of each dimension in the input vector normalization technique is needed. Before we feed the input vector into the LSTM module, we apply the following per-featured normalization operation:

$$x_i = \frac{x_i - \mu_i}{\delta_i} \tag{12}$$

Where $\mu_i$ and $\delta_i$ are the mean and standard deviation of the $i^{th}$ feature.

(3) Training Configuration To make our model robust, we generate training data by sampling from the original price sequence with different lengths (i.e., width of the slicing time window) and different starting points (i.e., length of the training set). Our model is trained on these generated price sequences for 50 epochs (10 batches each epoch) with an ADAM optimizer.

(3) Solution and analysis of the price prediction model

After finishing the training period, we feed the whole price sequence for the test set into the well-trained LSTM model to predict and do comparisons. With the actual value information, we can compute the prediction score for the price sequence. For a regression-like prediction problem, a prediction trend with a higher R2 can be identified as a potentially successful product. Otherwise, it can be a potentially failing product. As shown in Figures 2 and 3, the predicting results for gold daily price and bitcoin daily price are both potentially successful with the high R2 (both surplus 95%).

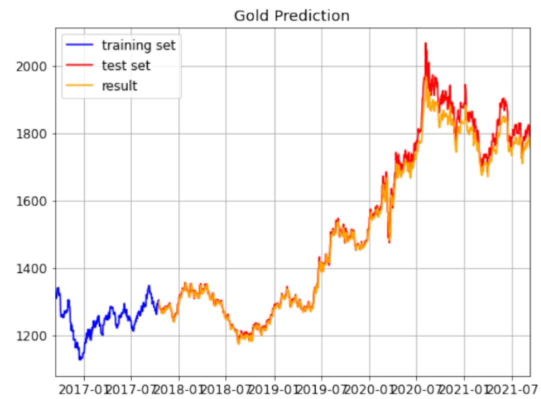


**Figure. 2** Prediction results of gold daily price

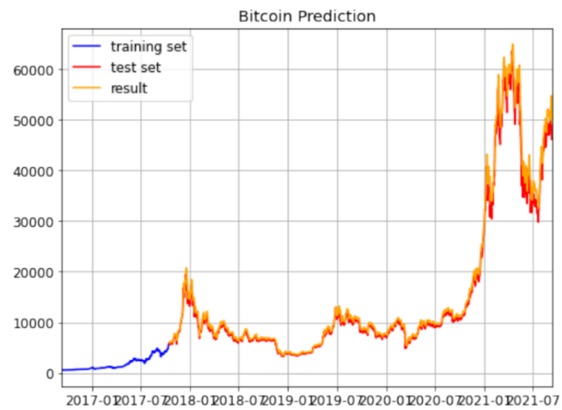


**Figure. 3** Prediction results of bitcoin daily price

### 2.5.3. Dynamic programming for best trade strategies after 400 days

$$\sigma_{j,i} = \sqrt{\sum_{k=1}^{2} \omega_{k,i}^2 \sigma_{k,i}^2 + 2\sigma_{1,i}\sigma_{2,i}\rho_i\omega_{1,i}\omega_{2,1}} \le 0.2 \tag{13}$$

Where $\sigma_{j,i}$ is the standard deviation in the past 30 days, $\omega_{j,i} = \frac{\sum_{j=1}^{2} h_{j,i}P_{j,i} + c_i}{h_{j,i}P_{j,i}}$ and $\rho_i$ is the correlation between gold and bitcoin in the past 30 days, $h_{j,i}$ is the number of gold holdings or bitcoin holdings on $i$ day, $P_{j,i}$ is a gold daily price or bitcoin daily price on $i$ day, and $c_i$ is the amount of cash on $i$ day.

We adopt the above formula to measure the portfolio risk. After conducting a test on the first 400 days, we have found that the risk of a portfolio consisting of 50% bitcoin and 50% gold ranges from 0.15 to 0.25. We then assume that the upper limit of risk that a rational trader can bear is 0.2. According to the rules for the transaction of gold (trade only on workdays), we divide the optimization problem into two situations: transaction on workdays and transaction on weekends or holidays. The optimization formula and constraints for the workdays are shown below:

$$\text{Min} \quad \begin{array}{l} v_i = \sum_{j=1}^{2}(h_{ji} + t_{ji}) f_{j,i+1} - \\ \sum_{j=1}^{2} |t_{ji}| f_{j,i+1}\alpha_1 + c_i - \sum_{j=1}^{2} t_{ji}P_{ji} \end{array} \tag{14a}$$

$$\text{subject to} \qquad t_{1i} \ge -h_{1i} \tag{14b}$$

$$\sum_{j=1}^{2} t_{ji}P_{ji} - \alpha_2 t_{2i}P_{2i} \le c_i, \quad \forall t_1 > 0,\ t_2 < 0 \tag{14c}$$

$$\sum_{j=1}^{2} t_{ji}P_{ji} - \alpha_1 t_{1i}P_{1i} \le c_i, \quad \forall t_1 < 0,\ t_2 > 0 \tag{14d}$$

$$\sum_{j=1}^{2} t_{ji}P_{ji}, \quad \forall t_1 > 0,\ t_2 > 0 \tag{14e}$$

$$v_i \ge \sum_{j=1}^{2} h_{j,i-1}P_{j,i-1} \tag{14f}$$

$$\textit{Complex Constraints} \tag{14g}$$

Where *Complex Constraints* is given by Equation (13) and is only for rational traders.

The optimization formula and constraints for the weekends are shown below:

$$\text{min} \qquad v_i = (h_{2,i} + t_{2,i}) f_{2,i} - |t_{2,i}| f_{2,i}\alpha_2 \tag{15a}$$

$$\text{subject to} \qquad t_{2i} \ge -h_{2i} \tag{15b}$$

$$t_{2i}P_{2i} \le c_i, \quad \forall t_2 > 0 \tag{15c}$$

$$v_i \geq \sum_{j=1}^{2} h_{j,i-1} P_{j,i-1} \tag{15d}$$

$$\textit{Complex Constraints} \tag{15e}$$

Where (15e) is the same as (14g) and is only for rational traders, $f_{ji}$ is predicted gold price or predicted bitcoin price on $i$ day, $\alpha_j$ is a commission of gold or bitcoin for each transaction, and $v_i$ is optimal assets value on $i$ day.

## 3. Model Assessment

During the first three hundred days, we test the validity of every single indicator and the composite indicator. As it turns out, all of the indicators attain positive returns. The best single indicator is MACD which generates a return of 77.6% in the test period. The composite indicator outperforms all single indicators with a return of 77.82%, more than that, it also attains much smaller volatility. The overview of the return of all technical indicators is shown in Figure 4.

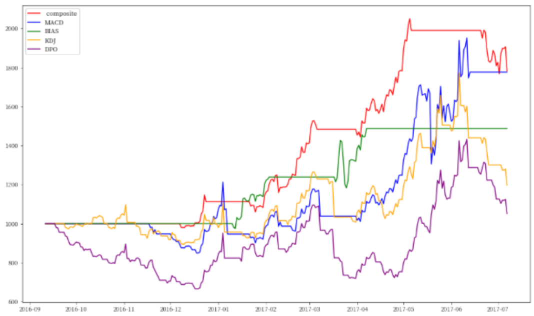

**Figure 4** Return of all technical indicators

Before training the decision tree model, we divide the first 300 data into a training set (90%) and a testing set (10%). Our decision tree model attains 71.2% of accuracy on the testing set, which is within our acceptability.

For aggressive traders, our trading strategy achieves a profit of 171,385 dollars, which attains a return of 17138.5% in these five years. For rational traders, our trading strategy achieves a profit of 8,271 dollars, which attains a return of 827.1% in these five years. Figures of the value of the assets are shown in Figure 5 and Figure 6. The overlapped shaded areas of gold and bitcoin represent a high trading frequency on those days.

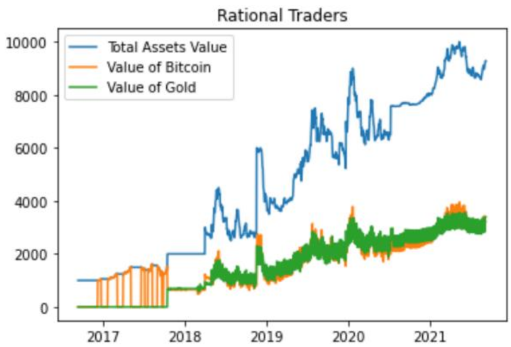


**Figure. 5** Return of rational trader

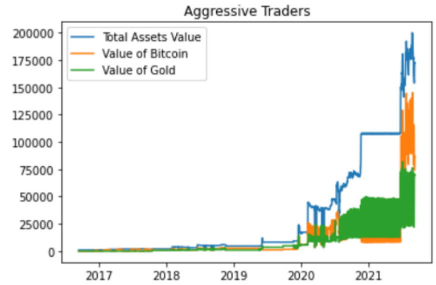


**Figure. 6** Return of aggressive trader

## 4. Conclusion

In Stage I, we adopt four technical indicators and use the composite indicator to decide the trading strategy, which earns 783 dollars for aggressive traders and 391 dollars for rational traders in this period. In Stage II, we adopt the decision tree model to better improve our strategy, which earns 277 dollars for aggressive traders and 139 dollars for rational traders in this period. In Stage III, we adopt LSTM to predict prices and use an optimization model to derive a trading strategy, which earns 170,381 dollars for aggressive traders and 7,694 dollars for rational traders in this period. Overall speaking, our strategy attains 17138.5% of return for aggressive traders and 827.1% of return for rational traders.

Our model is relatively robust on transaction rates for rational holders. After conducting regression analysis, the best transaction rates are $\alpha_{gold}$ = 0.70% and $\alpha_{bitcoin}$= 1.43% in our model.

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