

# Research on value prediction and investment strategy based on machine learning

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**Keywords:** ARIMA Model, Back Propagation Neural Network. Dynamic Programming.

**Abstract:** Quantitative investment is an investment strategy based on machine learning, which uses a specific mathematical model to find and obtain excess returns from historical data. From September 11, 2017, to September 10, 2021, the price of gold and bitcoin fluctuated, containing many attractive value investment opportunities. This paper considers the value increment, commission cost, opportunity cost, and transaction risk and discusses maximizing the value increment. To begin with, according to the historical price data of the last 50 days so far, we predict the price rise and fall of the next day based on the idea of Time Series Analysis. For gold, the price trend is found to be non-stationary time series, and the difference method is used to eliminate the trend so that it meets the condition of stability, and then ARIMA Model is used for price prediction. A three-level neural network structure, including input, hidden, and output, is designed for bitcoin. The Back Propagation Neural Network method is used to predict the price of the next day, and then the price of each day is predicted by cyclic statements. After testing, the price prediction accuracy of gold and bitcoin has reached about 99%. Next, aiming at maximizing the total return of assets, an investment model is established from the perspective of Dynamic Programming according to the predicted price of gold and bitcoin the next day, considering transaction commission, opportunity cost, and potential risk. Finally, according to the daily trading decision model, we calculated that the quantitative investment of \$1000 on September 16, 2016, would be worth \$305,579.152 on September 10, 2021, with an annual return of 314.69%.

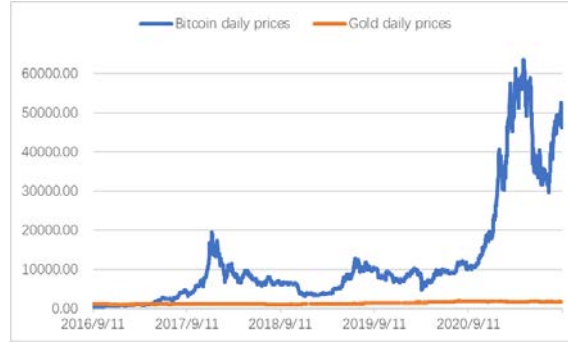
## 1. Introduction

Financial assets have volatility in a certain period. Therefore, in the investment of volatile assets, formulating reasonable trading strategies plays an important role [1] in reducing its risk. In recent 40 years, compared with other investment strategies, the significant advantages of a quantitative investment strategy with rational investment style and excellent performance have been fully reflected [2].

Quantitative investment is a trading strategy based on machine learning algorithms and using a specific mathematical model to obtain excess returns from much historical data [3]. It is increasingly used in various types of investment. Gold has always been an investment tool [4], which has high value and is not limited to any country or trade market. Bitcoin is an emerging P2P form of digital currency [5], which is not issued by specific currency institutions but generated through a large number of calculations according to specific algorithms [6]. Gold and bitcoin represent traditional and emerging volatile assets, respectively [7]. This paper considers transaction commissions, opportunity costs, and potential risks from a dynamic programming perspective [8]. By building a machine learning value prediction model and an investment model to maximize the total return on assets [9].

## 2. Establishment Of Models

Firstly, using Stata to produce a data series plot of bitcoin and gold prices, the data visualization shows that the data from September 11, 2016, to September 10, 2021, is unstable.



**Figure 1** Time series comparison of bitcoin and gold prices

### 2.1. Establishment of ARIMA Model

ARIMA Model is a linear time series prediction method with high accuracy. Time series analysis is an effective parametric time-domain analysis method for processing dynamic data. The further development and improvement of the Box-Jenkins method are established by American scholar George Box and British statistician Gwilym Jenkins in the 1970s. In this paper, we eliminate the non-stationary trend of the gold price with the difference to meet the stationary condition and then use the ARIMA model.

ARIMA (p,d,q) Model:

$$y_t' = \alpha_0 + \sum_{i=1}^p \alpha_i y_{t-i}' + \varepsilon_t + \sum_{i=1}^q \beta_i \varepsilon_{t-i} \quad (1)$$

$$y_t' = \Delta^d y_t = (1 - L)^d y_t \quad (2)$$

$$\left(1 - \sum_{i=1}^p \alpha_i L^i\right) (1 - L)^d y_t = \alpha_0 + \left(1 + \sum_{i=1}^q \beta_i L^i\right) \varepsilon_t \quad (3)$$

$$L^i y_t = y_{t-i} \quad (4)$$

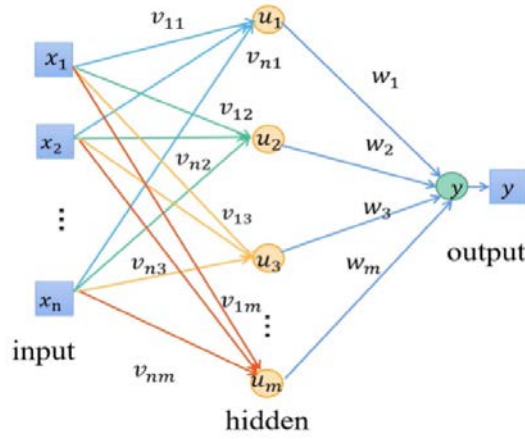
In the formula above,  $\alpha_i$  represents the autoregressive coefficient, p represents the autoregressive order,  $\beta_i$  represents the moving average coefficient, q represents the moving average order,  $\{\varepsilon_t\}$  represents the white noise sequence, d represents difference order, and L represents lag operator.

### 2.2. Bitcoin price prediction model based on BP Network

An artificial Neural Network is an information processing system based on imitating the structure and function of the biological brain. The network is composed of many neurons. Each neuron can have multiple inputs but only one output. Different connection modes between neurons constitute different neural network models.

A Backpropagation network is a typical nonlinear algorithm composed of the input layer, output layer, and several hidden layers (one or more layers), and each layer can be composed of several nodes. Various connection state between nodes is reflected by weight.

The BP neural network is composed of input, hidden, and output layers. The basic structure is shown in the figure below :



**Figure 2** Schematic diagram of the basic structure of BP neural network

To determine the structure of the BP neural network is to determine the number of input layer units, hidden layer units, hidden layer units, and output layer units. The number of units in the input and output layers is determined by the input and output data items. In this case, we take the historical gold price of the last 100 days as input, and the predicted gold price of the next day as output, that is, the number of units in the input layer is 100, and the number of units in the output layer is 1.

Then we refer to the empirical formula as follows to determine the number of hidden layer neurons in the initial network structure:

$$N = \log_2(N_1 + N_2)/2 \quad (5)$$

Where  $N_1$  is the number of input neurons,  $N_2$  is the number of output neurons, and  $N$  is the number of hidden layer neurons.

Then, the optimal number of hidden layer neurons is determined by adjusting gradually in the simulation experiment. After testing, the optimal number of hidden layer neurons in gold price prediction is 8.

MATLAB neural network toolbox integrates various training algorithms, including Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient. It is difficult to determine which kind of training algorithm in the BP network is the best. Through the test of various algorithms, we finally selected Scaled Conjugate Gradient. This algorithm requires less memory. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples.

The input-output relationship between neurons at each layer satisfies:

$$u_i = f\left(\sum_{i=0}^{n_0} x_i w_{ij}\right), x_0 = -1 \quad (6)$$

$$y^n = \frac{1}{1 + \exp\left(\sum_{j=0}^m u_j^n v_j / \lambda^n\right)}, u_0 = 0 \quad (7)$$

$$f(s) = \frac{1}{1 + e^{-s}} - \frac{1}{2} \quad (8)$$

If the local minimum relaxation  $\lambda_n > 1$  is entered, it quickly breaks out of the flat region. After leaving the flat area,  $\lambda_n = 1$ .

### 2.3. Daily transaction model based on dynamic programming

On September 1, 11, 2016, we held \$1,000 in cash. The cash holdings, the dollar value of daily gold holdings, the dollar value of bitcoin holdings, as the three core unknowns, constitute the investment

portfolio, [C, G, B], and on the first day, C+G+B = 1000. Starting from the second day, C+G+B=M, M is the total assets. Since we base our gold and bitcoin price forecasts on the last 50 days' prices, our buy and sell decisions start on day 51. The decision of each stage is generated in the changing state, which is affected by the decision of the migration stage. Therefore, this is a target revenue maximization problem from the perspective of Dynamic Programming. Dynamic Programming is a method for solving optimization problems, and its basic idea is to transform the original problem into a series of interrelated subproblems.

First, define the cash, gold, and bitcoin held at the beginning of the day as:

$$[C_n, G_n, B_n] \quad (9)$$

According to the previous prediction of the price of each day, the predicted gold amplitude rate and the predicted Bitcoin amplitude rate can be obtained:

$$\begin{aligned} rg &= \frac{prePG_{n+1}}{PG_n} \times 100\% \\ rb &= \frac{prePB_{n+1}}{PB_n} \times 100\% \end{aligned} \quad (10)$$

Due to the commission's existence, it can be inferred that when  $rg > 1\%$ , gold will be bought or sold; when  $rb > 2\%$ , bitcoin will be bought or sold. The constraints are:

$$\begin{cases} C_n + G_n + B_n = M_n \\ (G_{n+1} - G_n) \cdot \frac{prePG_{n+1}}{PG_n} + (B_{n+1} - B_n) \cdot \frac{prePB_{n+1}}{PB_n} \\ - 0.01 |G_{n+1} - G_n| - 0.02 |B_{n+1} - B_n| = K \\ - G_n < G_{n+1} - G_n < C_n \\ - B_n < B_{n+1} - B_n < C_n \\ G_{n+1} - G_n = 0 & \text{if time = weekends} \end{cases} \quad (11)$$

Where  $C_n$  represents the cash on the day,  $G_n$  represents the gold holdings on the day,  $B_n$  represents the bitcoin holdings on the day.  $G_{n+1}$  represents the gold holdings on the next day,  $B_{n+1}$  represents the bitcoin holdings on the next day,  $PG_n$  indicates the gold price of the day,  $prePG_{n+1}$  indicates the predicted gold price for the next day,  $pB_n$  indicates the Bitcoin price on the day,  $prePB_{n+1}$  indicates the Bitcoin price on the next day,  $K$  indicates the profit and loss of this transaction.

The goal is that the investment decisions of the day maximize the total assets of the next day. That is, the objective function is:

$$\begin{aligned} \max(M_{n+1}) &= \max(M_n + K_n) \\ &= \max\left(1000 + \sum_{i=1}^n K_i\right) = \max(h(G_{n+1}, B_{n+1})) \end{aligned} \quad (12)$$

It can be seen from the above formula that the function expression for maximizing the total assets is essentially only related to two variables  $G_{n+1}$ ,  $B_{n+1}$ .

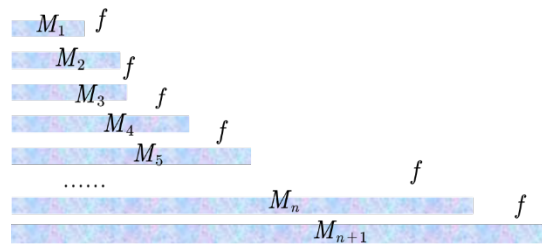
First, identify the original problem and subproblems. The key step of dynamic programming is to solve complex problems by decomposing the original problem into relatively simple subproblems. In the transaction decision model, the original problem is that the total amount of assets on the  $n+1$ th day is the largest, and the subproblem is that the total amount of assets on the first  $i$  ( $i \leq n+1$ ) days is the largest.

Second, the state is defined in terms of what it means. It may be defined that the total assets of the first  $i$  ( $i \leq n+1$ ) days are the largest, then is the answer to the original question we asked. At this point,  $i$  is all the states corresponding to the subproblems. Because there is only one parameter here, we need to define a one-dimensional DP array during programming.

Next, look for the state transition equation. Since this problem is particular, the corresponding one-dimensional DP array, the original problem to be solved, is the only element in the matrix. In the daily trading decision model, the dynamic factor is the total asset value of each day, and the total asset value of each day has a functional relationship with the asset price of the previous day. Thus, the state transition equation in the general case is found.

$$M_{n+1} = f(M_n) \tag{13}$$

Finally, the state transition function relationship can be obtained through computer modeling. Contact (12) (13) to solve  $G_{n+1}$   $B_{n+1}$ , and get the daily specific trading strategy:  $G_{n+1}-G_n>0$ , buy gold with a value of  $G_{n+1}-G_n$ ;  $G_{n+1}-G_n=0$ , do not trade gold;  $G_{n+1}-G_n<0$ , sell gold with a value of  $|G_{n+1}-G_n|$ ;  $B_{n+1}-B_n>0$ , buy a bit with a value of  $B_{n+1}-B_n=0$ , no bitcoin transaction;  $B_{n+1}-B_n<0$ , sell bitcoin with a price of  $|B_{n+1}-B_n|$ .



**Figure 3** Recursive function diagram of total assets

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### 3. Analysis Of Results

#### 3.1. The Solution of ARIMA Model

Since gold can only be traded when the market is open, this paper defines the time variable as a date variable to keep it continuous. Take the gold price in the first 50 days as the historical data, and use ARIMA Model to get the predicted value of daily gold price. Next, this paper will take the prediction of gold prices on day 51 as an example to show the process of the ARIMA model.

##### 3.1.1. Gold price forecast of day 51

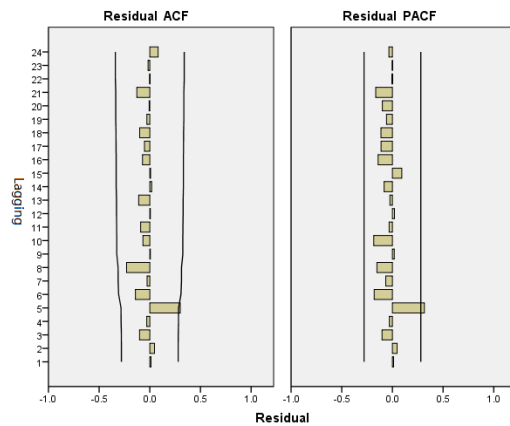
The preliminary visualization of daily gold price data found that its trend is a non-stationary time series, so it is processed by difference to eliminate the trend. After the first-order difference, the stationary Rsquare fitted by ARIMA (0,1,1) is 0.093, and Rsquare is 0.914, which are higher than those before the difference. The normalized BIC is 4.691, which decreases; The statistical significance is 0.712, which is greater than 0.05, so the residual is white noise. The significance of the ARIMA (0,1,1) model is 0.011, so the estimation result is accurate.

Obtain that:

$$\Delta y_t = \varepsilon_t - 0.369\varepsilon_{t-1} \tag{14}$$

$$y_t = y_{t-1} - 0.369\varepsilon_{t-1} \tag{15}$$

On the 51st day, the gold price is \$1208.74 per troy ounce.



**Figure 4** Residual ACF and Residual PACF

### 3.1.2. Cyclic rolling prediction of gold price of each day

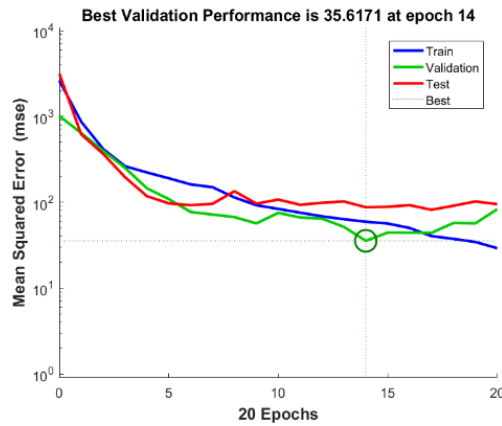
Take the gold price from day 1 to day 50 as the historical data to predict the next day, and get the predicted price of gold on day 51. By analogy, predict the next day with the historical data from day 2 to day 51 to get the predicted price of gold on day 52. Use the circular statement to realize the iteration to get the gold price from day 51(October 31, 2016) to day 1265(September 10, 2021). The predicted price and the actual price of gold are shown in the figure. The fitting degree reaches 99.31%, which has a good fitting effect.

**Table 1** Short cut keys for the template

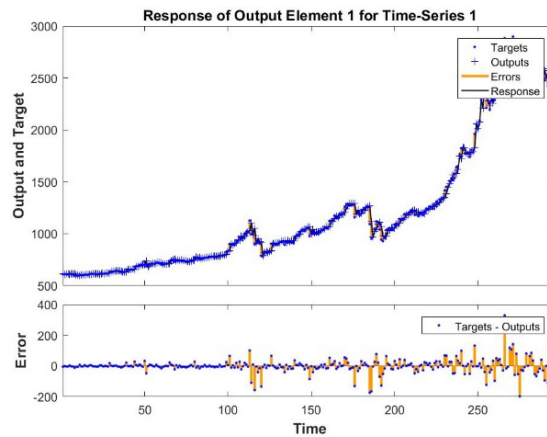
Date	USD (PM)	Predicated
09-12-2016	1324.60	1324.60
09-13-2016	1323.65	1323.65
09-14-2016	1321.75	1322.23
09-15-2016	1310.80	1320.27
09-16-2016	1308.35	1308.75
09-19-2016	1314.85	1306.85
09-20-2016	1313.80	1313.93
09-21-2016	1326.10	1312.39
09-22-2016	1339.10	1325.54
09-23-2016	1338.65	1338.57
09-26-2016	1340.50	1337.25
09-27-2016	1327.00	1339.25
09-28-2016	1322.50	1324.77
09-29-2016	1318.10	1320.85
09-30-2016	1322.50	1316.47

### 3.2. The Solution of BP Network Model

Mean Squared Error is the average squared difference between outputs and targets. Lower values are good. Zero means no error. Generally, the error decreases after more training phases, but as the network begins to overfit the training data, the error in the validation data set.



**Figure 5** Optimal response time and minimum MSE



**Figure 6** Optimal response time and minimum MSE

May begin to increase. In the default setting, the training stops after the MSE of the validation data set increases 6 times in a row, and the optimal model corresponds to the Minimum Mean Squared Error. As the picture depicts, after 14 times of epochs, the Mean Squared Error of the best validation data is 35.6167.

The historical data from day 1 to day 50 are used to predict the next day, so the predicted bitcoin price of day 51 is obtained. In this way, the historical data from the second day to the 51st day are used to predict the next day, and the predicted bitcoin price of day 52 can be obtained. The bitcoin price from day 51, namely October 31, 2016, to day 1826, September 10, 2021, can be obtained by programming the loop statement. To predict daily bitcoin price sets the stage for giving the best daily trading strategy, and this cycle meets the premise of "Based only on price data up to that day." The predicted price and actual price of Bitcoin are shown in the table. The fitting effect is good, and the fitting degree reaches 98.96%, which has a good fitting effect.

### 3.3. Presentation of dynamic programming results

According to the investment strategy model developed in this paper, the trading strategies based on the predicted values of gold and bitcoin are shown in table 2. On the last day, September 10, 2021, holding \$126.32 worth of gold, \$254,526.327 worth of bitcoin, and \$50,926.505 in cash, the total assets reached \$305,579.152, and the annualized rate of return reached 314.69%.

**Table 2** Daily trading strategy summary

Date	M	C	G	B	Predicted gold	Predicted Bitcoin
09-17-	1000	1000	0	0	-0.0011	0.002
09-18-	1000	1000	0	0	-0.0007	-0.0011
09-19-	1000	1000	0	0	-0.0004	-0.0003
01-04-	1006.958	103.423	903.536	0	0.022	-0.104
01-05-	1012.24	139.805	872.435	0	-0.0007	0.014
08-02-	1955.008	203.158	291.648	1433.202	-0.0203	0.0486
10-12-	2336.779	269.32	59.298	2008.156	-0.0008	0.1253
03-29-	4253.168	781.99	2645.39	826.671	-0.0098	-0.1281
04-11-	4428.601	310.458	715.759	3402.348	\	0.1253
02-19-	12605.007	784.462	7564.22	4256.325	\	-0.1477
02-20-	12494.347	2784.462	7564.22	2145.658	\	-0.1554
09-05-	303636.517	66557.946	642.35	236436.221	-0.001	-0.0864
09-10-	305579.152	50926.505	126.32	254526.327	-0.0213	0.0047

#### 4. Conclusion

In this paper, we use the ARIMA model and BP neural network. ARIMA model only needs internal data for prediction, and BP neural network has strong nonlinear mapping ability, self-learning ability, and adaptability. Dynamic planning can reflect the relationship between total assets in two days. Before and after the change process, the optimal solution is found by the state transfer matrix and DP array to improve the solution efficiency.

Based on the original data, the budget of gold and bitcoin is carried out through neural network and ARIMA time series to judge the daily value increase. After testing, the price prediction accuracy of gold and bitcoin has reached about 99%. In order to ensure the optimal value investment, dynamic programming is used to optimize the ternary combination of gold, bitcoin, and US dollar and judge the different decision-making methods in different stages of the investment process. Finally, the value return of \$305579.152 was obtained, and the annual income was as high as 314.69%.

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