Research on Quantitative Trading Decision Based on BP Neural Network and Circular Decision Model

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Abstract. Market traders usually buy risky assets in order to achieve rapid asset appreciation. In this paper, we build a BP Neural Network Model (BPNNM) and Ci. color Decision Model (CDM) provides investors with optimal strategies by analyzing historical prices, risks, and other factors of gold and bitcoin. Firstly, we build a BP neural network to predict the closing price of gold and bitcoin. We make full use of all available data up to that day. Eight consecutive days of closing price are selected as training data (the closing prices of the first to seventh days are used as input data and the eighth day as output data). Accordingly, we utilize the BP neural networks to predict the next day's closing prices of gold and bitcoin, respectively, passing the reliability and validity tests (R2 > 0.99). Multi-objective nonlinear programming was established with the data predicted by the BP neural network. The objective is to maximize the next day's return and minimize the risk. Subsequently, we looped the multi-objective nonlinear programming daily to build a CDM which is solved to obtain the optimal strategy. The results show that we have an average annualized return of 172.73%.

Keywords: Circular Decision Model, BP Neural Network, Multi-objective nonlinear programming

1. Introduction

Gold and bitcoin are the most frequently traded volatile assets for market traders in recent years. [1] Especially after the outbreak of the novel coronavirus (COVID-19), more and more investors are choosing gold and bitcoin as safe-haven assets, which has brought gold and bitcoin to the attention of the community. [2][3][4].

Any investor wants to maximize the return on trading in volatile markets, i.e., to use the least amount of capital to maximize returns by making investment decisions to buy or sell. However, investors cannot know the future price movements. [5] Therefore, predictions can only be made from past data.

2. Price Prediction Model Based on BP Neural Network

Before building mathematical models and finding their solutions, the data needs to be pre-processed. It enables better identification of data rules and optimizes the process of dealing with subsequent data.

According to data, we can get the information as follows:

a) Daily Bitcoin Closing Prices (R_{bi}) from September 11, 2016, to September 10, 2021.

b) Daily Gold Closing Prices (R_{gi}) from September 11, 2016, to September 10, 2021.

c) Date when the gold market opened (M_i) from September 11, 2016, to September 10, 2021.

d) There is a commission for each transaction that costs α% of the amount traded.

e) Starting assets were [1000,0,0] (1000 dollars, 0 gold, 0 bitcoins) in 11 September 2016 to 10 September 2021.

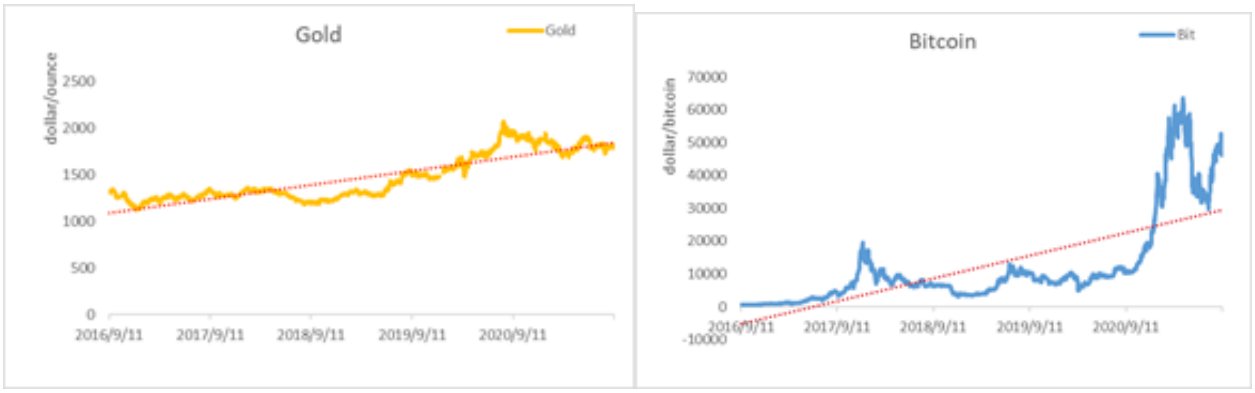


Figure 1. Trend of gold & bitcoin

BP network was proposed by a team of scientists led by Rumelhart and McClelland in 1986. It is a multilayer feedforward network trained by an error backpropagation algorithm. It is one of the most widely used neural network models at present. BP network can learn and store many input-output mode mapping relationships without revealing the mathematical equations describing this mapping relationship in advance. Its learning rule is to use the steepest descent method and continuously adjust the weight and threshold of the network through backpropagation to minimize the sum of squares of the network error. The topology of the BP neural network model includes the input layer, hidden layer, and output layer.

We need to simplify the model as much as possible and make the comparative analysis as many times as possible. In the prediction of the gold price, we build a hidden layer. The hidden layer consists of three neurons and a bias unit. In predicting bitcoin price, we also construct a hidden layer containing two neurons and a bias unit. The prediction model of bitcoin price is shown here. Figure 2 shows the construction of the bitcoin neural network.

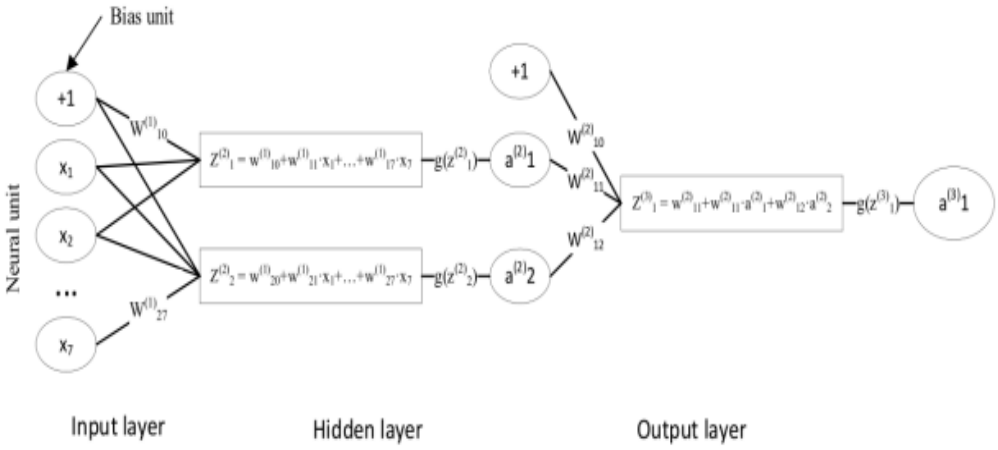


Figure 2. Construction of bitcoin neural network

The activation function in the above-hidden layer adopts the sigmoid function, and the activation function in the output layer adopts a linear function.

Because the amount of data is different every day, we need to retrain the neural network every day according to all the data we have on that day.

Here, we only select the construction process of the last day to explain. We can get 1820 groups of bitcoin training data and 1248 groups of gold training data by processing the data.

In order to improve the generalization of the model and avoid overfitting and underfitting, we divide the data into 50% training data, 30% cross-validation data, and 20% validation data.

Training the model of the loss function model in machine learning is the process of optimizing the cost function. The partial derivative of the Loss function to each parameter is the gradient mentioned in gradient descent. The Loss function of this model is as follows.

$$f\left(w_{jk}^{(i)}\right) = \frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{P}\left(y_k(i) - a_k(i)\right)^2 \tag{1}$$

Where, $y_k{}^{(i)}$ presents the true value of the i^{th} sample at the k^{th} the neuron of the output layer, $a_k{}^{(i)}$ presents the predicted value of the i^{th} sample at the k^{th} the neuron of the output layer.

For ease of expression, the Loss function can be defined as follows.

$$f\left(w^{(i)}{}_{jk}\right) = \frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K}\cos t_k(i) \tag{2}$$

Gradient descent is currently the main way to solve the neural network, and its steps are as follows.

Step 1: initialize $w^{(i)}{}_{jk}$

In machine learning, the initial parameters of the model are always generated by random. Therefore, first the parameters of the model need to be initialized.

Step2: update $w^{(\,)}{}_{jk}$

In the process of optimizing the cost function, the partial derivative of the loss function concerning each parameter is the gradient mentioned in gradient descent. So we need to obtain the partial derivatives of the cost function to each parameter and then update the iterations using the following equation.

$$\text{tem}\, w^{(i)}{}_{jk} = w_{jk}^{(i)} - \alpha\frac{\partial f}{\partial w_{jk}^{(0)}} \tag{3}$$

In the above equation, α is the learning efficiency of machine learning. Usually, the learning efficiency of machine learning depends on the speed of gradient descent. When the learning efficiency is large, the accuracy of machine learning will be reduced. When the learning efficiency is small, the iteration time will increase, and the load of the computer will be aggravated. We need to determine the learning efficiency in one attempt.

It is more complicated to calculate the above bias derivatives. In order to reduce the load on the computer and speed up the machine learning, we use the backpropagation algorithm to calculate the following equation, which splits the partial derivative into two separate calculations

$$\frac{\partial f}{\partial w^{(i)}{}_{jk}} = \frac{\partial f}{\partial z^{(i+1)_k}} * \frac{\partial z^{(i+1)_6}}{\partial v^{(i)}{}_{jk}} \tag{4}$$

It can be divided into two calculations, as follows

$$z_k^{(i+1)} = w_{k0}^{(i)} + \sum_{p=1}^{p} w_{kp}^{(i)} * a_p^{(i)} \tag{5}$$

$$a_k^{(i+1)} = g\left(z_k^{(i+1)}\right) \tag{6}$$

$$\frac{\partial f}{\partial z_k^{(i+1)}} = \frac{\partial f}{\partial a_k(i)} * \cdots \frac{\partial z^{(i+2)}k}{\partial z_k^{(i+1)_k}} \tag{7}$$

$$\frac{(T-n)k}{(T-n-1)k} = w^{(T-n-1)}{}_{kp} * g^{(T-n-1)} \tag{8}$$

Therefore:

$$\frac{\partial z^{(i+1)}\big)_k}{\partial w^{(i)}} = a^{(i)}k\ \frac{\partial a^{(i+1)}k}{\partial z^{(i+1)}{}_k} = g^{(i+1)} \tag{9}$$

$$\frac{\partial f}{\partial Z^{(i+1)_k}} = \cos\ t_k'(i)^* \prod_{i=i+1}^{T}\ g^{g^{(i)*}*} \prod^{w} \tag{10}$$

Multiply the above two results to get the result.

Step3: Determining convergence or not

In machine learning, the number of iterations is also an important factor. Generally, the iterations will be stopped when the accuracy reaches the user's requirement or when the number of iterations reaches the user's setting so that the machine learning will not fall into a dead loop.

In this model, the iterative approach is as Eq.11, as long as we can get a smaller cost than before, we will continue to iterate to learn

$$\begin{cases} w^{(i)}{}_{jk} = \text{ tem } w^{(i)}{}_{jk}, f\left(tem\, w^{(i)}{}_{jk} \cdots\right) < f\left(w^{(i)}{}_{jk} \cdots\right) \\ End\ of\ study, otherwise \end{cases} \tag{11}$$

Through MATLAB programming to find out the solution. After several runs of the solution, the model for predicting bitcoin always converges around 100 times, and the R-squared of the training set, cross-validation set, and validation set are around 0.99, which means that the model fits much better.

3. Circular Decision Model Based on Multi-objective Nonlinear Programming

After using neural networks to predict future ups and downs over a certain period, it is necessary to use a trading strategy model to determine the exact amount of bitcoin and gold to buy or sell. [6] The trading strategy model is based on basic financial investment theory, taking cost, profit, risk, and market performance into account to arrive at the best recommendation for each day.

It is noticed that whether to buy or sell and whether the amount bought or sold will result in a loss, which is closely related to the accuracy of the forecast. With this risk in mind, our trades always follow the general rule of trading, which is the highest priority and the basic of trading strategy. The application of this general rule may reduce gains in a successful forecast, but it will also reduce losses in the event of a failed forecast.

The research results indicate that the stop-loss and take-profit point method originating from the investors' experience has some theoretical basis in the volatile assets market. [7] The establishment of take-profit and stop-loss points ensures the safety of the principal in market trading. Based on the revised article, we establish the general rules as follows:

a) Take-profit point set at k%: sell the profit when it exceeds k% of the investment amount.

b) Stop-loss point set at k%: sell all the assets volatile and stop trading for 7 days when the loss exceeds k%.

c) cooling-off period[8] set at 7 days: If the investment is restarted, it will take 7 days to watch the market and validate the model

Our goal is to maximize the return on day i+1 after deciding on the day i

$$max\ D_{gi+1} \cdot P_{gi+1} + D_{bi+1} \cdot P_{bi+1} + USD_{i+1} - \left(\alpha_{gold} \cdot x_{1i} \cdot x_{3i} \cdot R_{gi} \cdot M_i + \alpha_{bitcoin} \cdot x_{2i} \cdot x_{4i} \cdot R_{bi}\right) \tag{12}$$

Where D_{gi} denotes the gold holdings at day i, P_{gi} denotes the prediction of the closing price of gold at day i, D_{bi} denotes the bitcoin holdings at day i, P_{bi} denotes the prediction of the closing price of bitcoin at day i, USD_i denotes the dollar holdings at day i, x_{1i}, x_{2i}, x_{3i}, x_{4i} denote whether gold is bought, sold or held, whether bitcoin is bought, sold, or held, the volume of gold transactions, and the volume of bitcoin transactions, respectively.

Based on setting a stop loss of k% to make the minimum risk, the daily gold & bitcoin trading value shall not exceed k% of the principal. Even if the forecast is wrong, it will not directly lead to serious losses, with a maximum loss of 10%. At the same time, the profit will be correspondingly reduced, which means the maximum profit will not exceed 10%.

$$\frac{x_{1i} \cdot x_{3i} \cdot R_{gi} \cdot M_i}{USD_i} \leqslant k \tag{13}$$

$$\frac{x2_i \cdot x4_i \cdot R_{bi}}{USD_i} \leqslant k \tag{14}$$

Where M_i indicates whether gold can be traded on the day i.

We can get the stop loss setting rules according to the lottery stocks and stop loss rules [9] published by Dai and Bochuan in 2021. The value of the stop loss point is different for different investors and different markets. The average stop loss point of the industry is between 5% and 10%. Then, the relationship between the level of stop-loss point, risk, and return is as Figure 3.

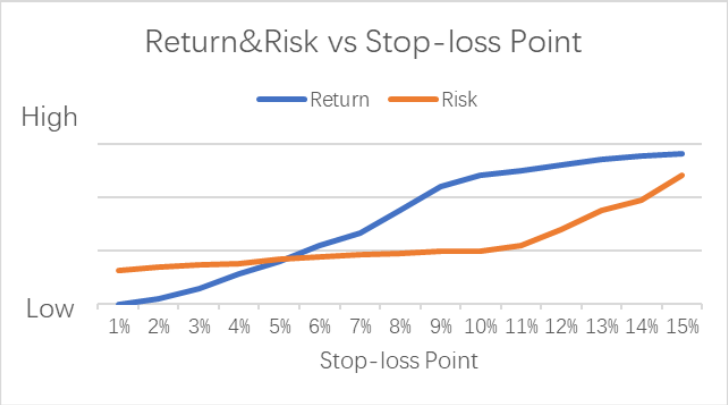


Figure 3. Return & Risk vs Stop-loss Point

According to Figure 3, when the stop loss point is small, the investment risk is low, but the return is low. When the stop loss point is large, the investment risk is high, and the return is also high. The investment return has an inflection point between 10% and 12% of the stop loss point. The investment return on the right side of the inflection point is not sensitive to the stop loss point, resulting in the flattening of the return curve. The investment risk has an inflection point between 9% and 10% of the stop loss point. The investment risk on the left side of the inflection point is not sensitive to the stop-loss point. The risk curve can be seen as a straight line with a small slope. To sum up, the best strategy is to select a 10% stop loss point. When the stop-loss point is more than 10%, the growth rate of investment return is much less than that of investment risk; When the stop-loss point is less than 10%, the opposite is true.

So we take k as 10%

If we want to sell gold or bitcoin, the amount sold must be less than the amount originally held. That is, on day i+1, the holdings of US dollars, gold, and bitcoin must be greater than 0

$$D_{gi+1} \geqslant 0 \tag{15}$$

$$D_{bi+1} \geqslant 0 \tag{16}$$

$$USD_{i+1} \geqslant 0 \tag{17}$$

Daily gold and bitcoin holdings are equal to the closing holdings of the previous day plus today's trading volume. The amount of dollars held per day is equivalent to the closing holding of the previous day, plus the trading volume of bitcoin and gold today

$$D_{gi+1} = D_{gi} + M_i \cdot x_{3i} \cdot x_{1i} \tag{18}$$

$$D_{bi+1} = D_{bi} + x_{4i} \cdot x_{2i} \tag{19}$$

$$USD_{i+1} = USD_i - M_i R_{gi} x_{3i} x_{1i} - R_{bi} x_{4i} x_{2i} \tag{20}$$

In conclusion, the decision model of day i-1 is given as follows

$$max\ D_{gi+1} \cdot P_{gi+1} + D_{bi+1} \cdot P_{bi+1} + USD_{i+1} - \left(\alpha_{gold} \cdot x_{1i}^2 \cdot x_{3i} \cdot R_{gi} \cdot M_i + \alpha_{bitcoin} \cdot x_{2i}^2 \cdot x_{4i} \cdot R_{bi}\right) \quad (21)$$

$$s.t. \begin{cases} \dfrac{x_{1i} \cdot x_{3i} \cdot R_{gi} \cdot M_i}{USD_i} \leq k, j = 1,2 \\ \dfrac{x_{2i} \cdot x_{4i} \cdot R_{bi}}{USD_i} \leq k, j = 1,2, k = 0.1 \\ D_{gi+1} = D_{gi} + M_i \cdot x_{3i} \cdot x_{1i} \\ D_{bi+1} = D_{bi} + x_{4i} \cdot x_{2i} \\ USD_{i+1} = USD_i - M_i R_{gi} x_{3i} x_{1i} - R_{bi} x_{4i} x_{2i} \\ x_{ji} \cdot (x_{ji} + 1) \cdot (x_{ji} - 1) = 0, j = 1,2 \\ x_{3i}, x_{4i} \geq 0 \\ D_{gi+1}, D_{bi+1}, USD_{i+1} \geq 0 \end{cases} \quad (22)$$

Bring US dollars, gold, and bitcoin holdings on day i into the one-day decision model. We can get the best strategy on day i and the number of dollars, gold, and bitcoin on day i+1 after making the best strategy. The daily cycle can build a Circular Decision Model (CDM).

The one-day model is a nonlinear programming problem. The Lagrange multiplier method is generally used to solve this problem. Here, we use MATLAB programming to solve it. By constructing a cycle, we can achieve the best strategy for each day of 1826 days and return from the initial investment value of $1000 on September 10, 2021.

The change of US dollar volume over time is shown in Figure 4.

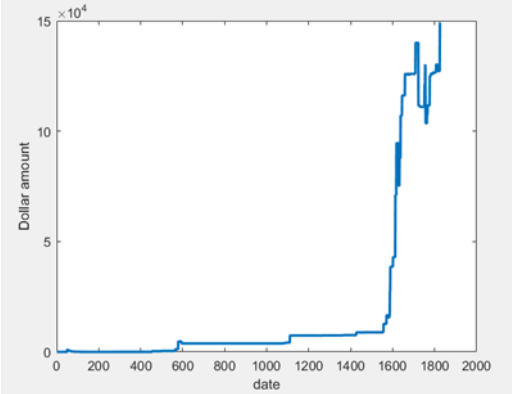


Figure 4. Change of US dollar volume over time

As can be seen from Figure 4, US dollar holdings rose slowly before day 1600 and rose sharply after day 1600. Compared with the daily price change of gold and bitcoin (Fig.8), the price of bitcoin increased rapidly after day 1600, while gold was relatively flat. At this time, selling the previously purchased gold and bitcoin will obtain a large return.

The change chart of gold and bitcoin holdings over time is as follows.

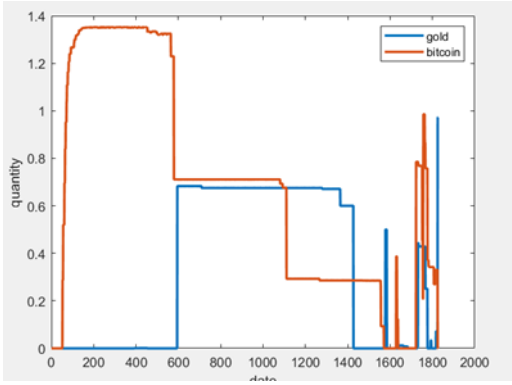


Figure 5. Daily price change of gold & bitcoin

It can be seen from Figure 5 that when the price of gold and bitcoin fluctuates greatly, transactions are frequent; When gold and bitcoin prices fluctuate less, the opposite is true. It is because there is a certain handling fee for the transaction. At the same time, this also reflects our consideration of risk: when the US dollar holdings are low, transactions will not be too frequent.

The average annualized rate of return (γ) is a theoretical rate of return calculated by converting the current rate of return into the annual rate of return. It is an important index to evaluate the quality of investment. This paper holds assets [149151.6116, 0.972175413, 0] at the closing on September 10, 2021, which can be converted into USD 150878.83 after deducting handling fees.[10]

Therefore, the formula of annualized interest rate is:

$$C_i = C_0(1+\gamma)^i \tag{23}$$

The average annualized rate of return is:

$$\gamma = \sqrt[i]{\frac{C_i}{C_0}} - 1 = \sqrt[5]{\left(\frac{150878.83}{1000}\right)} - 1 = 1.727254 = 172.73\% \tag{24}$$

γ is much higher than the benchmark interest rate of bank deposits (2% ~ 5%) and the benchmark yield of the industry (30%). It is worth noting that such a large annualized rate of return is the existence of bitcoin, an asset with high uncertainty. Bitcoin increased by 74.59 times from $621.65 on Day1 to $46368.69 on day1826. Although γ lower than the average annual yield of bitcoin, few investors will hold bitcoin for a long time as a high-risk asset. It is returned result can be obtained precisely because the machine correctly predicted bitcoin's sharp rise and fall several times and made buy and sell decisions through the strategy model. Of course, we manually add risk operators because of the inaccuracy of machine prediction. Its existence ensures the safety of funds and will not lead to large losses due to a wrong prediction. Therefore, the strategy obtained through the model is the best strategy model rather than the maximum return model.

4. Conclusion

The neural network model accuracy-test provides a rock-solid guarantee of the reliability of the predicted data. The analysis of holding length leads to the conclusion that frequent buying and selling has little impact on the final return versus a large one-time buy and sell. Bitcoin can have sudden ups and downs due to policies and other reasons in the actual market. It is the reason why we have to consider issues such as trading risk. We have established a take-profit point and a stop-loss point in the model. We protect the capital from losing much money by sacrificing some of the benefits due to the allowed forecast errors. Ultimately, we calculated the annualized rate of return, which is much higher than the average rate of return for solid investments and the liquid asset market. Therefore, we get the optimal return with a combination of risks, not the maximum return.

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