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Research on Optimal Strategy Scheme based on Neural Network Prediction Model

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Abstract:This paper focuses on the investment plan with the maximum return around the fluctuation of the stock market. First of all, this paper is based on the neural network model price trend line, and then uses the reverse Bollinger band strategy (CBB model). We calculate the error of the price forecast, draw the residual diagram, and find that the error level of the prediction is within an acceptable range. The model in this paper has strong expansibility and good robustness. Finally, we summarize the strategies and results of the model.

Keywords: Quantitative Investment; Neural Network Model; CBB Strategy

0. Introduction

Portfolio optimization is one of the origins and motivations of modern financial theory research. In short, its idea is to distribute wealth among different assets in order to achieve the purpose of spreading risks and ensuring returns. In 1952, Markowitz proposed the mean-variance model, which is the basis of modern investment theory. The theory studies and discusses the theories and methods of investment portfolio from a static point of view. However, the actual portfolio problem has dynamic characteristics. Because the return rate of assets is different in different periods and investors' preference for risk and return will change[1], investors will consider establishing a multi-stage portfolio strategy to maximize terminal wealth and periodically balance the proportion of asset investment.

Combined with the CBB strategy, this paper establishes a dynamic goal programming model, uses particle swarm optimization algorithm to solve the new multi-stage portfolio optimization model, and puts bitcoin and gold asset data into the model to conduct empirical analysis and verify its effectiveness.

1. Neural Network Model Establishment

The connection structure between neurons constitutes the neural network structure. In this paper, a four-layer fully connected neural network is constructed to predict the price of gold and Bitcoin[2]. The structure is "1-3-2-1", and the graph is as follows:

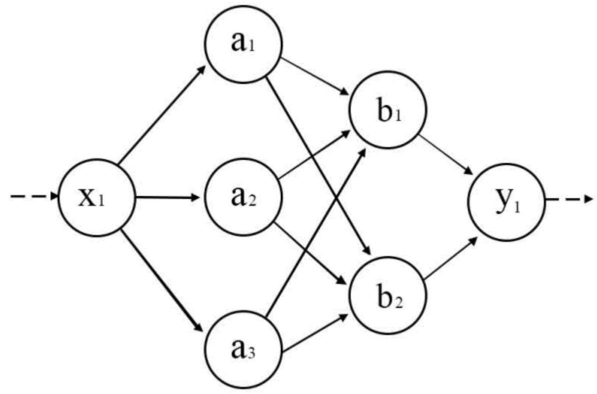

Fig.1 Four-layer fully connected neural network

The prediction accuracy is improved by optimizing the loss function. In order to judge the loss size[3-5], it is necessary to define a function to describe the corresponding loss value quantitatively, namely, the loss function.

$$MSE(y_i, y_i') = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2 \qquad (1)$$

y_i is the correct answer to the ith data in a batch (i.e. a small part of training data),y_i' and is the predicted value of the neural network.

Forecasting principle are generally as follows: First of all, according to the x_t moment price data and historical data to predict x_{t+1} moment, secondly according to the actual moment of x_{t+1} data reverse revision x_{t+1} data, then the historical data update iteration, continue to predict the x_{t+2} moment data, repeat the above steps, eventually get the price of gold and Bitcoin forecast figure.

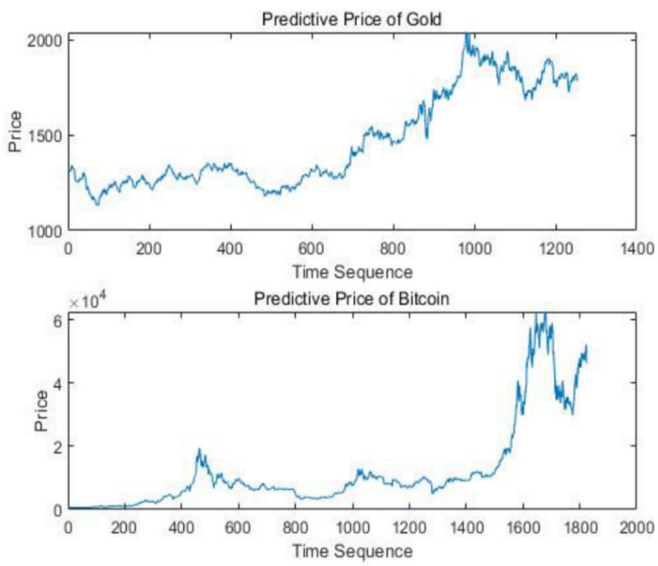

Fig.2 Predictive Price of Gold and Bitcoin

2. CBB Model

BOLL index is a very practical and intuitive technical analysis index[6]. The calculation method of BOLL index introduces the standard deviation in statistics, including the calculation of MA(middle rail),UP(upper rail) and DN(lower rail). BOLL indexes include daily BOLL index, weekly BOLL index and annual BOLL index due to different calculation cycles. Here, daily BOLL index is selected. Calculation formula of daily BOLL index is as follows: The value of MA is 20-day average daily closing price.

The value of MA at time t:

$$MA_t = \frac{\sum_{i=0}^{N-1} P_{t-i}}{N} \qquad (2)$$

(N=20)

The value of MD at time t:

$$MD_t = \sqrt{\frac{\sum_{i=0}^{N-1} (P_{t-i} - MA_t)^2}{N-1}} \qquad (3)$$

UP = MA+2MD, DN = MA−2MD

When the price line breaks the upper rail,the buying point arises. When the price line breaks the lower rail, the selling point arises.

Fig.3 Trading Points of Gold Based on Bollinger band

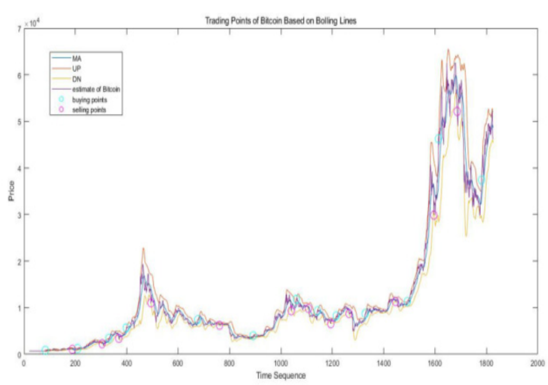

Fig.4 Trading Points of Bitcoin Based on Bollinger band

According to the CBB strategy, we can get the cumulative return of gold and Bitcoin over time.

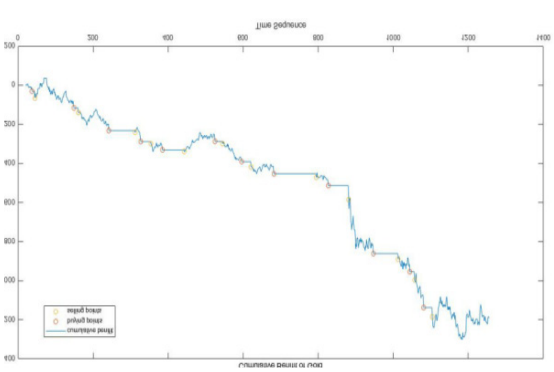

Fig.5 Cumulative benifit of Gold

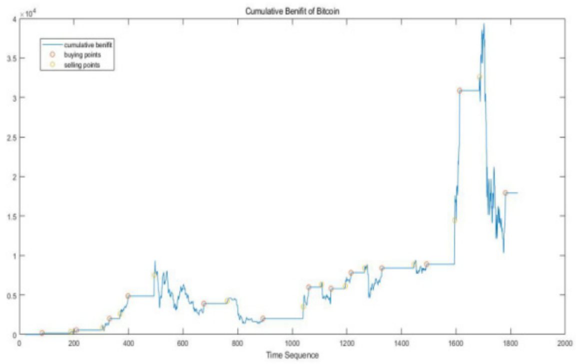

Fig.6 Cumulative benifit of Bitcoin

3. M-V Model

Now the existing assets are divided into risky assets and risk-free assets. In this paper, the risk-free assets can be viewed directly as cash. It is assumed that the investment ratio of risky assets is γ, then the investment ratio of cash is $1-\gamma$.The expected return on the risky asset is $E(r_p)$, the expected return on cash is r_f. The risk of the risky asset is σ_p, and the risk of cash is σ_f ($\sigma_f=0$)[4]. The correlation coefficient of the two assets is ρ,and now assuming that $\rho=0$. Then we can easily get the combined expected return between risky assets and cash:

$$E(r_c)=r_f+\gamma[E(r_p)-r_f] \qquad (4)$$

The variance between risky assets and cash is:

$$\sigma_c^2=\gamma^2\sigma_P^2+(1-\gamma)^2\sigma_f^2+2\rho\sigma_P\sigma_f \qquad (5)$$

We plug $\sigma f=0,\rho=0$ into equation, and then simplify this equation to

$$\sigma_c{}^2=\gamma^2\sigma_p{}^2 \qquad (6)$$

According to the equation(6),the transformation of this equation is obtained:

$$\gamma=\frac{\sigma_c}{\sigma_p} \qquad (7)$$

We plug equation(7) into equation (4), and then simplify this equation to:

$$E(r_c)=r_f+\frac{\sigma_c}{\sigma_p}[E(r_p-r_f)] \qquad (8)$$

This equation can be viewed as a function of σ_c. In addition, we need to build the combined effect function:

$$U(\sigma_c)=r_f+\frac{\sigma_c}{\sigma_p}[E(r_p)-r_f]-\frac{A}{2}\sigma_c{}^2 \qquad (9)$$

Now assuming that there are two risky assets, they are gold and Bitcoin. It is assumed that the investment ratio of gold is w1, then the investment ratio of Bitcoin is w_2.The expected return on the gold is $E(r_1)$, the expected return on Bitcoin is $E(r_2)$.The risk of the gold is $\sigma 1$, and the risk of Bitcoin is σ_2. Then we can easily get the combined expected return between gold and Bitcoin:

$$E(r_p)=w_1E(r_1)+w_2E(r_2) \qquad (10)$$

According to the calculation, the proportion of each asset at the time of initial transaction is shown in the table below.

Tab.1 Proportion of assets at the time of initial transaction

Category	Type	Date	Percentage of cash	Percentage of gold	Percentage of Bitcoin
Gold	buy	2016/10/5	0	75.65%	24.35%

4. Conclusion

Due to the great volatility of the stock market, good trading strategies determine that investors get higher net returns. Therefore, in order to maximize the investment return after five years, this paper first quantifies the investment model, and uses the neural network model to predict the price trend line of the two. Secondly, the adverse Bollinger band strategy (CBB model) is adopted. Similarly, the intersection of the predicted price line and the lower rail line is the selling point to determine the trading time and the corresponding transaction type of gold and bitcoin respectively. Finally, the accuracy of the model is analyzed, and it is found that the prediction error level is within an acceptable range, and the model is good.

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