Quantitative Trading Optimization Model Based on Moving Average and Risk Prediction

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Abstract:Quantitative investment can bring very large returns to investors and is increasingly popular among investors. Based on this, a quantitative trading model of averaging strategy is constructed for both gold and bitcoin products, and then the market risk model and trading frequency model based on multi-prediction model is constructed based on the optimization of the lagging loss that exists in the averaging strategy when the market is in a period of oscillation. The market risk and trading frequency are taken into account in the averaging model, and the trading ratio is dynamically changed to adapt to different market patterns on the basis of constant trading dates to achieve the optimization of the averaging strategy. The model integrates the impact of historical prices on the trading strategy. Here, the daily trading prices of gold and bitcoin from September 2016 to October 2021 are used as experimental data, and the experimental results show the effectiveness of the model.

Keywords: The Averaging Model; Coefficient of Variation; Trading Strategy Optimization

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Introduction

In recent years, with the development and improvement of finance theory and mathematical and statistical theory, especially with the development and innovation of computer technology and optimization algorithms, quantitative trading methods that rely on information technology and financial engineering modeling to achieve investment decisions are affecting the financial market and have become a major focus of attention in the global financial field.

Among the existing studies on quantitative trading decisions, WangJuJie et al. (2022) constructed a stock selection model and designed a quantitative investment strategy using a gated recursive unit (GRU) neural network based on the cuckoo search (CS) optimization algorithm, and the results showed that the stock selection model achieved better backtest performance[1].QiaoXuQin et al. (2018) used PCA and logistic regression as the theoretical basis to establish a quantitative trading strategy for futures and back-tested using some futures data from 2014-2015, and the results showed that the strategy achieved better returns and provided a new investment perspective for futures market investors[2].LiZiYu et al. (2017) established a quantitative trading strategy through BP neural network algorithm and Fisher linear discriminant method, and the results showed that that the training optimization by neural network and Fisher linear discriminant improved the profitability and risk control of the trading system[3].

From the above research status, it is not difficult to implement quantitative trading strategies based on technical indicators using artificial intelligence algorithms. However, in most cases, the performance of quantitative trading strategies based on technical indicator parameters is rather mediocre, and it is difficult to adapt to different market and time trends[4]. By optimizing the parameters of the quantitative trading strategy based on technical indicators, it is possible to adapt to the market trend of specific trading targets, improve the profitability of the quantitative trading strategy, reduce the risk, and maximize the utility of the quantitative trading strategy.

1. Methodology

1.1 Source of data

The data used in this study is the average daily price of bitcoin and gold from September 2016 to October 2021. The trade start with $1000 on 9/11/2016. We use the five-year trading period, from 9/11/2016 to 9/10/2021. On each trading day, we have a portfolio consisting of cash, gold, and bitcoin [C, G, B] in U.S. dollars, troy ounces, and bitcoins, respectively. The initial state is [1000, 0, 0]. The commission for each transaction (purchase or sale) costs α% of the amount traded. Assume αgold = 1% and αbitcoin = 2%. There is no cost to hold an asset.The data derives from question C of the 2022 U.S. Collegiate Mathematical Modeling Contest.

2. Quantitative portfolio analysis

2.1 Multiple Investment Forecasting Model

Before building a daily trading strategy model, we need to predict the daily trading prices of gold and bitcoin. We can divide them into traditional prediction models and nonlinear prediction models regarding prediction methods. The traditional forecasting models include SMA, EMA, ARIMA, GARCH and LSTM models.

The SMA model equation is as follows:

$$SMA = \frac{P_1 + P_2 + \cdots + P_n}{n}$$

where n is the moving average period and P is the gold or bitcoin price.

The EMA model equation is as follows:

$$EMA = P_t \times \beta + P_t \times (1 - \beta)$$

where β is the multiplier, $\beta = \frac{2}{(n+1)}$, Pt is the current day's trading price, and P_{t-1} is the price the day before the trade.

We use Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Average Percentage Error (MAPE), and Fitting Degree (R^2) to judge the prediction results.

2.2 Investment Risk Quantification Model

For analyzing this data, we use the coefficient of variation to measure the degree of dispersion of the prediction. The coefficient of variation formula is as follows:

$$C.V = \frac{SD}{Mean}$$

$$Mean = \sum_{i=1}^{5} P_{it}$$

$$SD = \frac{\sum_{i=1}^{5} SD_{it}}{5}$$

P_{it} denotes the daily predicted trading price for each forecasting model in 2.1, and SD denotes the standard deviation of the daily predicted price for each forecasting model.The coefficient of variation is a dimensionless quantity that is typically used to compare the degree of dispersion of data with different ranges. We analyze the magnitude of the coefficient of variation of the daily predictions. If the coefficient of variation is higher, we consider that the more unreliable it is to predict the price on that date.

2.3 Moving Average Strategy - Oscillation Period Optimization Based on Predicted Risk and Trading Frequency

2.3.1 Moving Average(MA) Strategy Construction

We use MA to determine the buying and selling times. MA is calculated as follows:

$$L_i = \frac{\sum_{t=i-n}^{i} p_i}{n}$$

Where n is MA length, Pi is the market price on the day i, and L_i is MA value on the day i. MA reflects the average trend of prices over time. The longer the length n of MA, the longer the historical period considered, and the better it reflects the long-term trend, but with a significant lag. The shorter the n, the shorter the historical period considered, the better it reflects instantaneous market price movements but is vulnerable to volatility. We take n to be 10, which mainly reflects the mid-to-long-term trend.

Buying and selling strategy is to sell when MA turns up to down while buying the opposite. This strategy enables you to buy at the lows and sell at the highs for profit when the market has a long-term trend.

2.3.2 Moving Average Strategy Optimization

Oscillations in market prices exist, resulting in frequent buy and sell points. MA has a lagging effect, and when buying, the market price may have increased; while selling, the price may have decreased, thus generating frequent losses.

Therefore, we consider the market risk and short-term shocks and optimize the buy and sell ratio with the same buying and selling dates. Set the buy-sell ratio to α. The value of α ranges from 0 to 1. If α is higher, it indicates a higher proportion of buying and selling and vice versa.

$$\alpha = \frac{1}{1+e^{-Z}}$$

$$z = \frac{d}{n} \times \frac{1}{c.v}$$

$$C.V = \frac{SD}{Mean}$$

Where d is days since the last transaction. n is MA length, which reflects the time interval since the last buying and selling. If d is small, it means that buying and selling occur frequently. At this point, the market is more likely to be in an oscillation period, which should reduce the proportion of buying and selling α. C.V is the coefficient of variation. α takes into account market risk and transaction frequency. The buy-sell ratio α decreases when the market is unpredictable, or when the trading frequency is too high, while α is higher when the market risk is low and the trading frequency is low. The optimization reduces losses when markets are in oscillation periods.

3. Results

3.1 Multiple investment forecasting models do not predict well

From Table 1, we can see that traditional time series models have difficulty accurately forecasting the gold and bitcoin markets.

Model	Accuracy	MAE	MAPE	RSME	R^2
Simple Moving Average	0.4893	592.4706	4.4096%	1179.8188	0.9929
Exponential Moving Average	0.4937	536.5568	3.9847%	1073.8767	0.9936
ARIMA Model	0.5316	367.1110	2.6638%	805.7475	0.9958
GARCH Model	0.5402	367.8153	2.6642%	807.9065	0.9967
LSTM Model	0.5576	365.8225	2.5984%	809.3218	0.9983

Table 1: Prediction Accuracy

3.2 Gain after optimization of MA strategy

With the daily average length set to 10, we traded the decision using the optimized averaging strategy for Bitcoin and gold 16 to 21 years of data. The final return is obtained as $17,996.

With a daily stochastic trading strategy, the final return obeys a normal distribution with a mean of $7399 and a standard deviation of 4821. It can be seen that the optimized daily mean strategy is significantly better than the stochastic strategy.

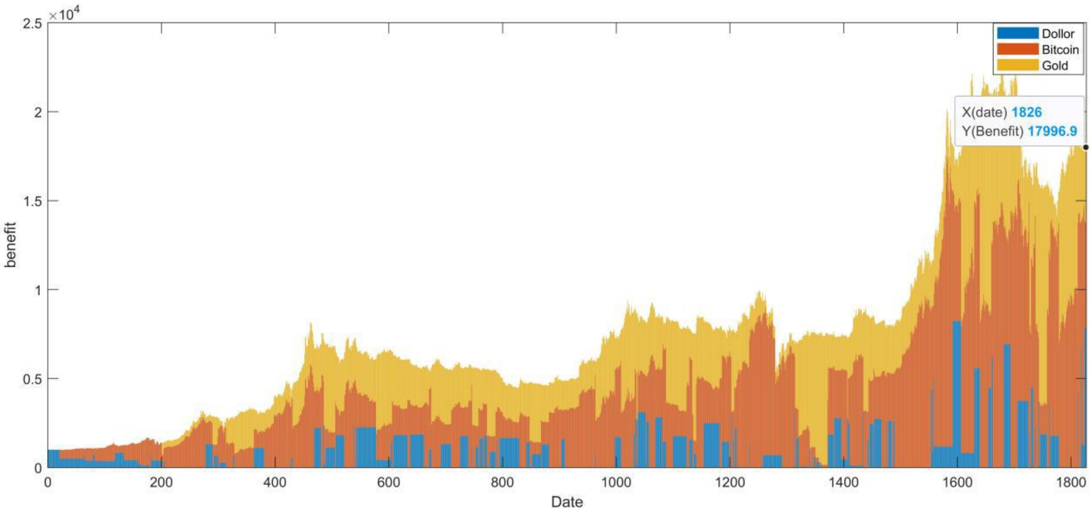

Figure 1: Gains from the ratio of gold, Bitcoin and USD holdings

The length of the daily average has a significant effect on the final return. With a daily average length of 3, the ultimate return is the largest, at $82,833, but that return is not stable. With a daily average length of about 2 to 30 days, the average return is $35,790. And when the length of the daily average is higher than 90 days, the return is lower than the stochastic strategy.

3.3 Sensitivity of the Strategy to Transaction Costs

We vary the trading ratio αgold and αbitcoin to observe the change in decision and the final profit. The final return changes by 0.4610% with a 10% change in αbitcoin and by 0.9635% with a 10% change in αgold. It demonstrates that our model is insensitive to changes in transaction costs.

Conclusion

In this study, we first constructed a quantitative trading strategy model based on the mean line strategy. Then, based on the optimization of the lagging loss that existed in the mean line strategy when the market was in an oscillation period, a market risk model and a trading frequency model based on a multi-prediction model were constructed. The market risk and trading frequency were taken into account in the averaging model, and the trading ratio was dynamically changed to achieve optimization of the averaging strategy on the basis of constant trading dates. The model took into account the influence of historical prices on the trading strategy. The trading ratio was dynamically changed to accommodate different market patterns when there was a long-term trend in the market price and it is in a period of oscillation.

We viewed the problem as a portfolio investment strategy case when building the Model. By using the portfolio investment strategy approach to construct the model, the model applicability was favorable and generalized well to investment decisions in other assets.

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