Develop an Online Portfolio Model for Optimal Trading Strategies

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Abstract. Combined with the modeling and simulation concept, this paper considers the impact of transaction costs, long and short term risks and efficiency on the portfolio. Based on the past asset prices, this paper refers to the price trend and analyzes the buying and selling risks, and establishes a long and short term memory neural network model to predict the prices of various assets in the future. An improved non-parametric kernel-based logarithmic optimal algorithm is designed to solve the optimal online portfolio strategy. The model is tested on the dataset of gold daily price from *London Bullion Market Association, 9/11/2021* and Bitcoin daily price from *NASDAQ, 9/11/2021*. The results show that: The long short term memory neural network model predicts the known asset prices with an average root mean square error of only 1742.0421, and under the influence of Sharpe ratio of 0.8231, our algorithm can earn $214,764.78 in the future period of investment.

Keywords: Long Short-Term Memory · Online Portfolio Strategy · Risk assessment factors · Improved nonparametric kernel-based log optimal algorithm

1 Introduction

In recent years, global financial markets have experienced huge price fluctuations due to the persistence of uncertainties such as real economic recession and international political conflicts. In order to cope with the increase of financial market volatility and risks, market traders often choose assets such as gold, US dollar and bitcoin to offset risks and lock in profits [1]. So to stay competitive at work, market traders desperately need a way to help them develop the best daily portfolio strategy.

At present, the research of portfolio strategy can be divided into two fields: traditional statistics and econometrics and machine learning. In the field of traditional statistics and econometrics, Lin-lin Zhang et al. [2] based on the five most common portfolio strategy, found in the traditional portfolio to add commodity futures can effectively reduce portfolio risk and improve returns, Zhong-bao Zhou et al. [3] in the classical economics, the efficiency of the investment portfolio is given a clear definition; In the field of machine learning, Xu Jie et al. [4] classified the methods of machine learning asset pricing into

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machine learning methods based on feature processing and deep learning methods based on end-to-end processing, and compared the differences of different algorithms in principle and application scenarios. Li Bin et al. [5] systematically used machine learning to improve the stock return prediction module in fundamental quantitative investment.

To sum up, the key to finding the best portfolio strategy is to avoid risks and efficiently obtain the maximum investment benefits. However, most of the existing studies lack clear risk assessment indicators and specific trading strategies. In this paper, based on the modeling and simulation concept, a neural network model of long and short term memory is constructed to predict the daily price of each asset from three aspects of transaction costs, long and short term risk indicators and efficiency. Then, an improved non-parametric kernel-based logarithmic optimal algorithm is used to solve the online portfolio strategy problem.

2 Problem Description

Market traders frequently buy and sell volatile assets to maximize their total returns. Among the many traded assets, the two most promising assets are gold and bitcoin. Since every transaction involves paying transaction costs, buying too often when asset prices are about to rise and selling too often when asset prices are about to fall is not advisable. It is essentially a kind of portfolio strategy problem. From a macro perspective, we need to formulate an optimal trading strategy, which can not only avoid the loss of trading costs through greater profits, but also accumulate greater wealth for subsequent trading with less risk impact.

The daily price movements of gold are plotted against the given gold and Bitcoin datasets in Fig. 1, and the daily price movements of Bitcoin are shown in Fig. 2.

2.1 Construct Long Short-Term Memory Neural Network Model

Assumptions of the Model

1. Suppose that gold has a price during the period when the market is not open, and the price of gold in this period is the price of the last trading day;

Fig. 1. The daily price chart of gold [London Bullion Market Association, 9/11/2021]

Fig. 2. Daily price chart of bitcoin [NASDAQ, 9/11/2021]

2. Assume that there is no margin trading in the whole market and short selling is not allowed.

Symbol Description

- s_t: Day return ratio on day t;
- S_t: The wealth accumulated in period t, where $S^t = S^{t-1} * s^t$;
- P_i^t: The price of the i th asset at day t, $i = 1, 2, 1 \leq t \leq n$;
- x_i^t: The ratio of the price of the i th asset on day t to the price of the i th asset on day $t - 1$,
- where $x_i^t = P_i^t \Big/ P_i^{t-1}$, $i = 1, 2, 1 \leq t \leq n$;
- λ: Long-term risk assessment factors, $0 \leq \lambda \leq 1$;
- η: Short-term risk assessment factors, $0 \leq \eta \leq 1$;
- b_i^t: On day t, the proportion of the i th asset allocated in the portfolio,$i = 1, 2, 1 \leq t \leq n$;
- W_t: Transaction costs at day t.

Mathematical Model

(1) Hyperparameter Setting

First, the number of hidden layers was set as 3, and then the number of neurons in each hidden layer was set as 350. Then, the learning rate was initialized as 0.02 and linearly decreased. Finally, the size of time window was set as 7, and the number of iterations of the model was set as 30.

(2) Training of Model

After doing some preprocessing on the original data, input it into the LSTM model, and then borrow Pytorch tool in Python to build the LSTM model and the model has been well trained. In the training process, the loss function we use is the improved average root mean square error, which is calculated by the following formula:

The calculation formula of the universal root mean square error is:

$$RMSE^{(i)} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(P^t_{i,prediction} - P_{\mathrm{i}}^t)^2} \tag{1}$$

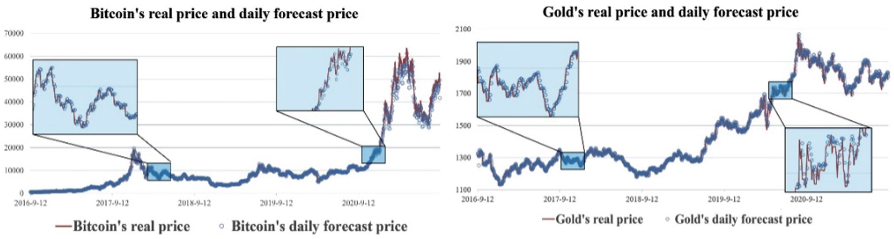

Fig. 3. Comparison between model prediction and real results [Owner-draw]

The calculation formula of average root mean square error is:

$$\overline{RMSE} = \frac{1}{m}\sum_{i=1}^{m} RMSE^i \tag{2}$$

(3) Analysis of Training Results

As shown in Fig. 3, the real curve and prediction curve of the result trend of gold and bitcoin are basically consistent with the trend. Furthermore, we obtained that the average root mean square error of the training set was 183.1624, and the average root mean square error of the test set was 1742.0421, which shows that the training effect of this model is very good and can be used to predict the future trend of these assets.

3 Improved Nonparametric Kernel-Based Log Optimal Algorithm

Suppose the financial market has m assets and n trading days, and we invest our wealth in all m assets in the market for n trading days. We use $X_i^n = \{x_1, x_2, ..., x_n\}$ to represent the sequence of market price changes of asset m from 1 to n time Windows, and use vector $B^t = [b_1, b_2, .., b_m]$ to represent the proportion of each asset in our portfolio at time t, where $B^t = \Delta m$, $\Delta m = \{B : B >= 0, B^T 1 = 1\}$. Since the portfolio vector on day t is related to the sequence of past market price changes, a portfolio strategy from day 1 to day n can be expressed as:

$$B^1 = \frac{1}{m}, B^t = B^t(X_i^{t-1}) \in \Delta\text{m} \tag{3}$$

3.1 The Main Algorithm

The main idea of this method is to first determine the time series that is similar to the upcoming time series, and then use this similar time series to obtain the maximum wealth accumulation and optimal daily investment decisions.

Firstly, the similarity is solved by Euclidean distance:

$$B^{t+1} = \underset{B\in\Delta\text{m}}{\arg\max} \prod_{i\in C(X_1^t)} BX_1^i \tag{4}$$

The formula for calculating the range of time window i is as follows:

$$C_K(X_1^t, w) = \{w < i < t+1 : ||X_{t-w+1}^t - X_{i-w}^{i-1}|| \le \frac{c}{l}\} \tag{5}$$

3.2 Introducing Transaction Costs

Because of the transaction costs of gold ∂_{gold} is 1%, the Bitcoin transaction costs $\partial_{bitcoin}$ is 2%, Not every trading day is a trading day, so not every trading day is a trading cost. To this end, we find that transaction costs only take effect when one of the following occurs:

When investors need to purchase part of the assets, it will take effect only when the following calculation is met, that is, the interest generated after the purchase of the assets will be no less than the transaction cost and cost of the assets:

$$\begin{aligned} &\mathrm{S}_t(b_i^t - b_i^{t-1})(x_i^{t+1} - 1) \ge \partial_\mathrm{i} S_t(b_i^t - b_i^{t-1}) \\ &+k[\alpha_\mathrm{j} S_t(b_i^t - b_i^{t-1}) + S_t(b_i^t - b_i^{t-1})(x_j^{t+1} - 1)] \end{aligned} \tag{6}$$

where, i = 1 represents the asset gold, and j = 2 represents the asset bitcoin.

When the investor needs to sell part of the assets, it will take effect only if the following calculation is satisfied, that is, the loss of interest before selling the assets is not less than the loss of interest after selling the assets:

$$S_t(b_i^t - b_i^{t-1})(1 - x_i^{t+1}) \ge \partial_i S_t(b_i^t - b_i^{t-1});\ \mathrm{i} = 1, 2 \tag{7}$$

Therefore, the transaction cost spent on trading day T is as follows:

$$W_t = \sum \partial_\mathrm{i} S_t |b_i^t - b_i^{t-1}|;\ \mathrm{i} = 1, 2 \tag{8}$$

3.3 Introduce Short - and Long-Term Risk Factors

In order to consider the risk behind the maximization of benefits, we introduce two risk assessment factors λ and η, $0 \le \lambda, \eta \le 1$. Where λ is the long-term risk assessment factor, it learns the long-term risk of the market. According to the mean reversion theory, this parameter will change slowly with the market; η is the short-term risk assessment factor, it can sense the short-term risk of the market, and make a quick response to asset adjustment.

After considering the possible long and short term risks of investment, the more reliable portfolio strategy at time T is modified as follows:

$$\widehat{B^t} = \lambda\eta e_1 + (1 - \lambda\eta)(1 - e_1) \odot B^t \tag{9}$$

where e_1 is a column vector whose first element is 1 and all other elements are λ.

Finally, after n trading days, according to the online portfolio strategy in this paper, the maximum cumulative return obtained within a certain risk range is as follows:

$$S_n(B^n, X^n) = S_0 \prod\nolimits_{t=1}^{n} \widehat{B^t}^T X^t - \sum_{t=1}^{n} W_t \tag{10}$$

Of which, the initial economy for the investor is \$1000.

3.4 Algorithm to Solve the Concrete Steps

Step1: Initialization parameters $w = 7, \alpha = \beta = 2, k = 0, \eta = 1, \phi = 1.1, z = 0.08$, $\tau = 1$ and the historical true price series $\{P_t\}$;

Step2: Load and instantiate the trained long short-term memory neural network, With the sequence $\{P_t\}$ as input, the price trend of each asset is predicted in the time window $w = 7$ and the price change sequence $\{X^t\}$ of each asset is obtained;

Step3: Initialize the $t = 1$;

Step4: An improved non-parametric kernel-based log optimal algorithm is used to obtain the B^t and s_t, where $s_t = (B^t)^T * X^t$;

Step5: Through the equation $q = \phi - S_t - z$ Find the number q that fits the Beta distribution;

Step6: Judge $q \le 0$? If yes, enter **Step7**, otherwise enter **Step10**;

Step7: Make $k = k + 1$, $v = 0$;

Step8: Update the short-term risk assessment factor $\eta = 1/[1 + \exp(k + \tau)]$;

Step9: Through the posterior probability formula $P(q, t - v) = P(q; \alpha + 1, \beta)$ to update parameter α and β, enter **Step14**;

Step10: Make $k = 0$,$v = v$+1;

Step11: Update the short-term risk assessment factor $\eta = 1$;

Step12: Find the transaction costs $W_t = \sum \partial_i S_t |\mathrm{b}_i^t - b_i^{t-1}|$,$i = 1, 2$;

Step13: Through the posterior probability formula $P(q, t - v) = P(q; \alpha, \beta + 1)$, $P(q, t - v) = P(q; \alpha + 1, \beta)$ to update para meter α and β, enter **Step14**;

Step14: Update long-term risk assessment factors $\lambda = (\alpha + 1)/(\alpha + \beta + 2)$;

Step15: Update the weight vector of the portfolio strategy $\widehat{B^t} = \lambda\eta e_1 + (1 - \lambda\eta)(1 - e_1) \odot B^t$;

Step16: Update the payoff ratio $s^t = \widehat{B^t}^T * X^t$ on day t and the cumulative maximum return $S^t = S^{t-1} * s^t - W^t$, $t = t + 1$;

Step17: Judge $t == n$? If yes, the algorithm is terminated and output S^n and sequence $\{B^t\}$; otherwise return **Step4**.

4 Algorithm Solution and Analysis

We implemented the portfolio model solver in Matlab software to obtain the results of the algorithm program. Then, the improved non-parametric kernel-based logarithmic optimal algorithm is compared with other four OLPS strategies and the line chart of accumulated maximum wealth over n trading days within a certain risk range is drawn, as shown in Fig. 4. It can be seen that the final cumulative wealth of this algorithm strategy is as high as 214764.78 dollars under a certain risk range, which is much better than the other four strategies.

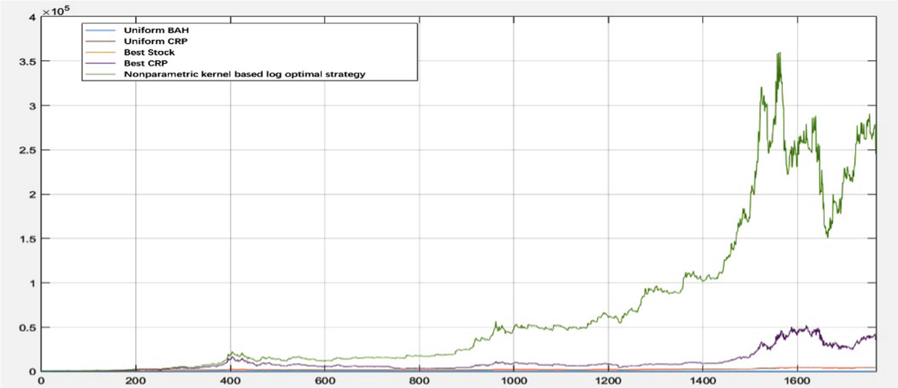

Fig. 4. Compare our algorithmic strategy with four other online portfolio strategies [Owner-draw]

5 Conclusion

We develop a model in this paper to solve the asset allocation problem on each trading day to maximize cumulative returns with low risk.

First of all, we constructed a long short-term memory neural network prediction model. Next, we apply the improved non-parametric kernel-based logarithmic optimal algorithm to the online portfolio strategy, and combine it with the long short-term memory neural network prediction model to obtain the optimal daily asset allocation scheme considering the maximum risk that rational people can bear. On this basis, We conclude that the maximum accumulated wealth can reach $214,764.78 with a Sharpe ratio of 0.8231.

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