LSTMGA-QPSBG: An LSTM and Greedy Algorithm-based Quantitative Portfolio Strategy for Bitcoin and Gold

Leyi Zhang

3221000862@mail2.gdut.edu.cn

Guangdong University of Technology, No.100, Huanchengxi Road, University Town, Guangzhou, Guangdong Province, P.R.China

Abstract. Quantitative trading plays a pivotal role in financial markets. Over the past decade, quantitative trading has made remarkable improvements. Due to instability and nonlinearity in financial markets, it is still challenging to formulate high-return trading strategies to address the problem of long-term time series forecasting in financial markets. To tackle this issue, we propose an LSTM and Greedy Algorithm-based quantitative portfolio strategy in this work. First, an LSTM-based price prediction model is presented to forecast the closing price on the final trading day. Subsequently, a greedy algorithm is employed to identify the optimal daily trading strategy to pursue the overall optimal solution and achieve maximal profits. The experimental results show that the maximum value of the VaR percentage is about 9.1%, proving that the proposed strategy is feasible and effective.

Keywords: quantitative trading, LSTM, Greedy Algorithm, Bitcoin, gold

1 Introduction

Forecasting the trend of financial assets is a critical step before making the decision on a portfolio in quantitative trading theory. In the early days of economic forecasting, people mainly built linear models through statistical methods to forecast the future price of stocks[1, 2]. However, the financial market is a noisy and non-parametric dynamic system, which is difficult for traditional statistical models to accurately analyze and forecast the nonlinear parts of stock data[3]. Hochreiter et al.[4] proposed an LSTM network, an improvement on the RNN structure, which can better characterize the long memory of time series data. Later, Graves et al.[5] improved the LSTM model and compared the accuracy of the LSTM model with the traditional RNN, finding that the former has better predictive performance. Long short-term memory network has become a mainstream model in the field of time series prediction, for it solves the above problems by adding three control units of forget gate, input gate, output gate, and cell state to RNN. Therefore, LSTM is applied to predict the future prices of Bitcoin and gold in this paper.

After establishing the forecasting model, designing an optimal trading strategy for the portfolio is another essential task to achieve maximum returns. In recent years, dynamic programming [6] has been extensively utilized to address optimization problems, particularly in the domain of quantitative portfolios. Nonetheless, in quantitative trading where investment

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cycles are prolonged, dynamic programming's time and space complexity exceeds that of greedy algorithms. The greedy algorithm embodies a greedy approach that attains global optimum by implementing local optimal strategies. Each step in the greedy algorithm chooses the present optimal solution without considering its future implications, leading to significant time savings. In the volatile trading market, swift and efficient model-solving can yield considerable economic benefits.

Motivated by the above analyses, we present an LSTM and Greedy Algorithm-based model to devise the best daily trading strategy for Bitcoin and gold. In general, our contributions are summarized in three aspects:

1) LSTM is utilized to forecast the future price of bitcoin and gold so that the network can converge better and faster, efficaciously improving forecast accuracy.

2) By utilizing the greedy algorithm, a superior trading strategy for Bitcoin and gold is developed to rapidly achieve maximal investment returns.

3) The data predicted by the LSTM model fits well with the original data. In addition, the risk evaluation of the greedy algorithm model, assessed by VaR, confirms that the model possesses a low-risk advantage.

2 Method

2.1 Long Short-Term Memory

LSTM (long short-term memory neural network) is a special recurrent neural network. What distinguishes LSTM from RNN is that it adds a "processor" to the algorithm to determine whether the information is useful or not[7]. The structure of the processor is called a cell. There are three gates placed in a cell, an input gate, an output gate, and a forget gate network. The detailed internal structure of LSTM is shown in Fig.1.

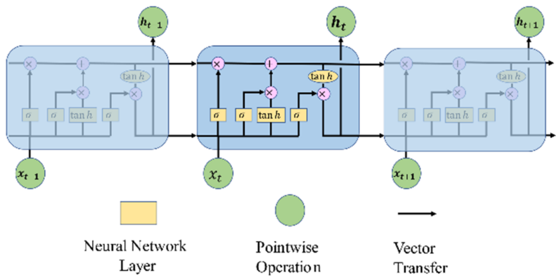


Fig.1. Diagram of the internal structure of LSTM. Where $\boldsymbol{h_{t-1}}$ is the output of the previous unit, $\boldsymbol{x_t}$ is the input of this unit, σ is the sigmoid function, and $tan\,h$ is the tangent activation function.

LSTM controls the transmission state through the gated state, remembering information that needs to be retained for a long time and forgetting unimportant information. It is unlike ordinary RNNs with only one way of memory superposition. This is especially useful for historical data like Bitcoin and gold in this experiment that require long-term memory.

2.2 Greedy Algorithm

A greedy algorithm is an approach to solving an optimization problem, whereby the ultimate global optimal solution is attained by iteratively selecting the locally optimal solution at each step[8]. The specific steps of the greedy algorithm are shown in Fig.2.

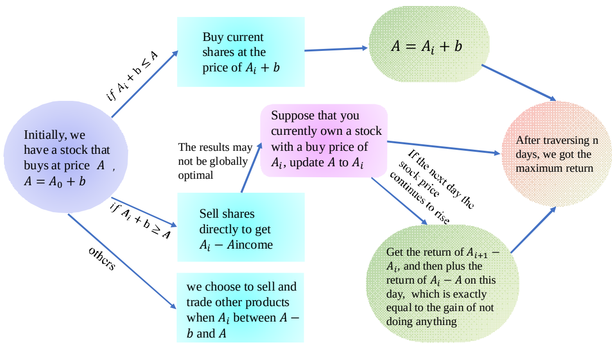


Fig.2. The main idea of the greedy algorithm.

In the beginning, suppose we have a stock with the price of A, in which case $A = A_0 + b$ and b is the commission. When we invest to day i: if $A_i + \mathrm{b} \leq A$, then buy the current stock at the price of $A_i + b$; if $A_i + \mathrm{b} \geq A$, then sell stock directly to get $A_i - A$ income. But the return on our stock sale at this time may not be globally optimal in reality, for example, the stock price continuing to rise the next day. So, we can provide a repentance operation that treats the stock we currently have as buying at A_i and updates A toA_i. If the stock price continues to rise the next day, we will receive the return of $A_{i+1} - A_i$. After adding the return of$A_i - A$ on this day, the benefit is exactly equal to the gain of selling the stock the next day without doing anything on this day.

3 Experiment

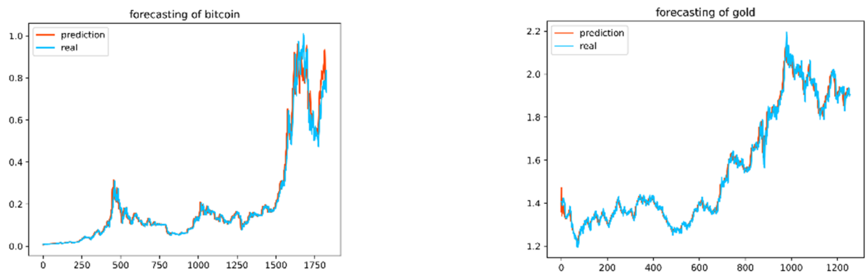
In this paper, the focus is on quantitative trading, which can be divided into three primary components. Firstly, the forecasting of future price trends of Bitcoin and gold. Next, the development of a trading strategy through the use of dynamic programming and the greedy algorithm. Lastly, the effectiveness of the strategy is evaluated through the use of VaR (Value-at-Risk)[9].

3.1 Detailed Introduction of the Datasets

The two datasets used in this paper, Bitcoin Daily Price and Gold Daily Price, respectively, come from NASDAQ, 9/11/2021, and London Bullion Market Association, 9/11/2021. The two datasets enumerate the daily prices of bitcoin and gold from 2001 to 2021 separately. According to the regulations of the trading market, bitcoin can be traded every day, but gold is only sold on days the market is open. 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.

3.2 Result of the LSTM-based forecasting models

We first import the data of Bitcoin and gold from 2001 to 2021 and then use Newtonian interpolation to impute null values. The cleansed data is normalized as input. Regarding parameter settings, we set the sliding window value to 7 after many tests and used single-step prediction to predict one-day data with seven days of data. The number of hidden layers in LSTM is set to 4, and the hidden layer size is 25. Considering the financial timing noise and a large number of data, we choose to use the ADAM (Adaptive Moment Estimation) optimizer with the advantages of fast convergence speed and easy parameter adjustment and then set the learning rate to 1e-2. After training and testing, the forecasting result of Bitcoin and gold is shown respectively in Fig.3. (a)(b) below. We can see that the prediction fits the actual curve well.



(a) (b)

Fig.3. (a) Bitcoin's predicted curve compared to the actual value curve. (b) Gold's predicted curve compared to the actual value curve.

3.3 Portfolio Results

Our investment strategy is shown in Fig.4. Among them, A_{bi} is the price of bitcoin on day i, and $A_{gi}$is the price of gold on day i; A_b, A_g is the initial price of bitcoin and gold respectively, which changes with the program. b_1, b_2 is the handling fee of bitcoin and gold respectively; $P_1, P_2$is the income of bitcoin and gold respectively; P is the total income after n days. At the same time, to prevent the emergence of local optimal solutions as much as possible, we add repentance operations to the program.

In this experiment, we use the two datasets of bitcoin daily price and gold daily price which respectively come from NASDAQ, 9/11/2021, and London Bullion Market Association, 9/11/2021. we will start with $1000 on 9/11/2016 and use the five-year trading period, from 9/11/2016 to 9/10/2021 to obtain the result that how much is the initial $1000 investment worth on 9/10/2021.

First, we set the daily transaction ratio of bitcoin and gold to c, d.

Initially:

$$A_b = 1000 * c + b_1 \tag{1}$$

$$A_g = 1000 * d + b_2 \tag{2}$$

Then according to the algorithm above, the experimental result shows that we receive a profit of approximately $113,313.7080 on 9/10/2021 and the investment ratio of bitcoin and gold is 0.3 and 0.7 respectively.

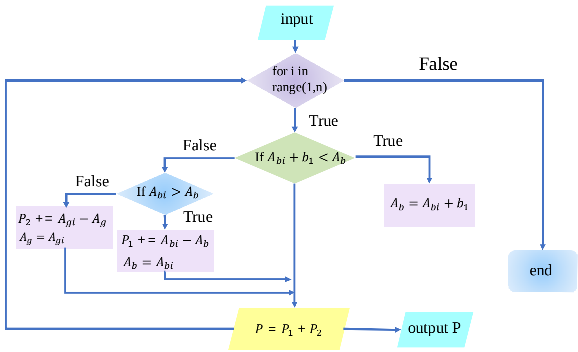


Fig.4. Flowchart of quantitative trading strategy using dynamic programming and greedy algorithm.

3.4 Evaluating Indicator

To make the above model more convincing, we introduce the VaR model to plot the maximum loss amount that the portfolio model will face to visualize the suitability of the model. VaR refers to the value at risk, i.e., the maximum loss a financial instrument or its portfolio will meet in future asset price fluctuations at a certain confidence level and over a specific holding period [10]. Suppose the asset portfolio has a VaR value of 1000 at a confidence level of 95%. It means that the probability that an investor will suffer a loss in the coming day simply due to a change in market prices is 95% and that the loss will not exceed 1000. The smaller the VaR value, the smaller the loss value of the portfolio. The VaR values of the portfolio are shown in Fig.5.

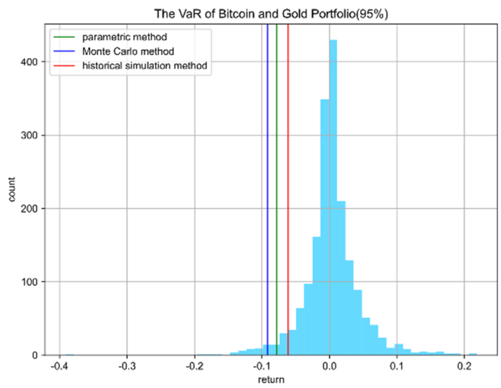


Fig.5. Distribution of VaR values of Bitcoin and gold portfolio in a five-year holding period with 95% confidence. Horizontal coordinates represent the VaR value as a percentage of the total value of funds, and longitudinal coordinates represent the frequency.

The experimental results show that the percentages of VaR value under the Monte Carlo method, parametric method, and historical simulation method are respectively about 9.1%,7.8%, and 6.1%, which means the maximum loss will not exceed 9.1%,7.8%, and 6.1% of the total funds under the 95% confidence level separately. In our hypothesis, our initial capital is $1,000. Under the calculation of the three methods of VaR, our loss value in this portfolio will not exceed $91, $78, and $61, which is considerable, indicating that our portfolio results are excellent.

4 Conclusion

In this work, we propose an LSTM and greedy algorithm-based quantitative portfolio strategy. First, LSTM is utilized to analyze the long-term dependencies of time series to forecast future financial product prices. Then, the greedy algorithm is applied to find the optimal solution for trading strategies. VaR is employed to evaluate our trading strategy, and the results show that the proposed quantitative trading strategy has excellent profitability.

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