Research on Portfolio Model Based on LSTMIS-AMTM and Improved Markowitz

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Abstract. With the development of financial market, portfolio investment has become a new hotspot in the field of quantitative investment. We develop a model to propose the best strategy of gold and bitcoin portfolio investment. We first use LSTMIS to predict the value of gold and bitcoin with input sequence consisting of last 30 days data. Then we use the predicted data and the mean value of last 5 days as long- and short-term moving average input of AMTM model respectively, hence judging whether to buy or sell. Then we improve and modify the existing Markowitz portfolio model by treating gold and bitcoin as two different stocks and completing the matching of the two through the model, so as to make quantitative investments and reduce the risk while satisfying a higher rate of return.

Keywords: LSTMIS, Markowitz, The Moving Average Trading Strategy.

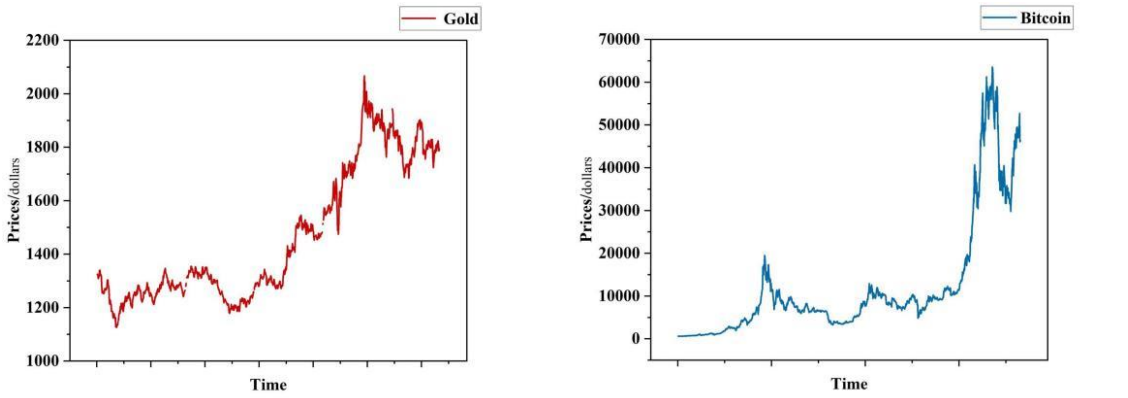
1. Introduction

As the financial markets evolve, how investors construct the right portfolio has become an important topic of study in economics, and the rise of quantitative investing has gone some way to solving that problem [1]. Quantitative investment is an investment method based on data, programmed trading, strategy models and the pursuit of absolute returns. Compared with traditional investment, it relies entirely on massive data and models and can fully realize the risk diversification of the strategy. It has a wide range of information sources, a short investment cycle, and issues buy and sell orders through a computer program, which excludes human cognitive bias and subjective judgment, and therefore has more stable returns. Therefore we need to use quantitative investment as the core to provide investors with the best portfolio strategy.

Traditional Markowitz Mean Variance Model provides the optimal portofio, given two types of risk venture and one risk-free investment, which achieving the minimum of risk and the maximum of profit simultaneously [2]. But can only give strategy of one day. Traditional Average Moving Trading Strategy judges the gold cross point and death cross point, through long-time and short-time average line. We creatively integrates the above two model, using AMTS to give trade signals and MOP to determine accurate volume of trade each day [3]. Moreover, we substitute LSTM into the AMTS as long-time prediction, and develop strategies for the commission α and close day of gold respectively. The specific algorithmic process is shownbelow.

2. Data Pre-processing and Visualization

First, we need to process the data in the two official price data tables LBMA-GOLD.csv and BCHAIN-MKPRU.csv. provided by Metsä about gold and bitcoin between 2016 and 2021, and after unifying the formats we can get the graphs of gold and bitcoin prices over time respectively as shown in Figure 1 [4].



(a) Gold price fluctuations between 2016 and 2021 (b) Bitcoin price fluctuations between 2016 and 2021

Figure 1. Gold and Bitcoin price fluctuations between 2016 and 2021

As we can see from Figure 1, the price curve for gold is not continuous, which is in line with the market rule that gold is not traded every day. In contrast, the curve for Bitcoin is continuous, indicating that Bitcoin is not affected by trading hours. Based on the data and the images obtained, it is easy to see that the two datasets are extremely nonlinear, so we can use AI prediction algorithms such as neural network algorithms to model and analyze [5].

3. LSTMIS: LSTM-based Investment Strategy

3.1. LSTM Structure

LSTM, short for long-short term memory recurrent neural network, is a powerful and effective tool to process sequence data [6]. Based on LSTM, we create a prediction model named LSTMIS, which uses the most recent 30 days to predict tomorrows bitcoin value or gold value, so that we can wisely invest our money. The whole structure is portrayed in figure 2.

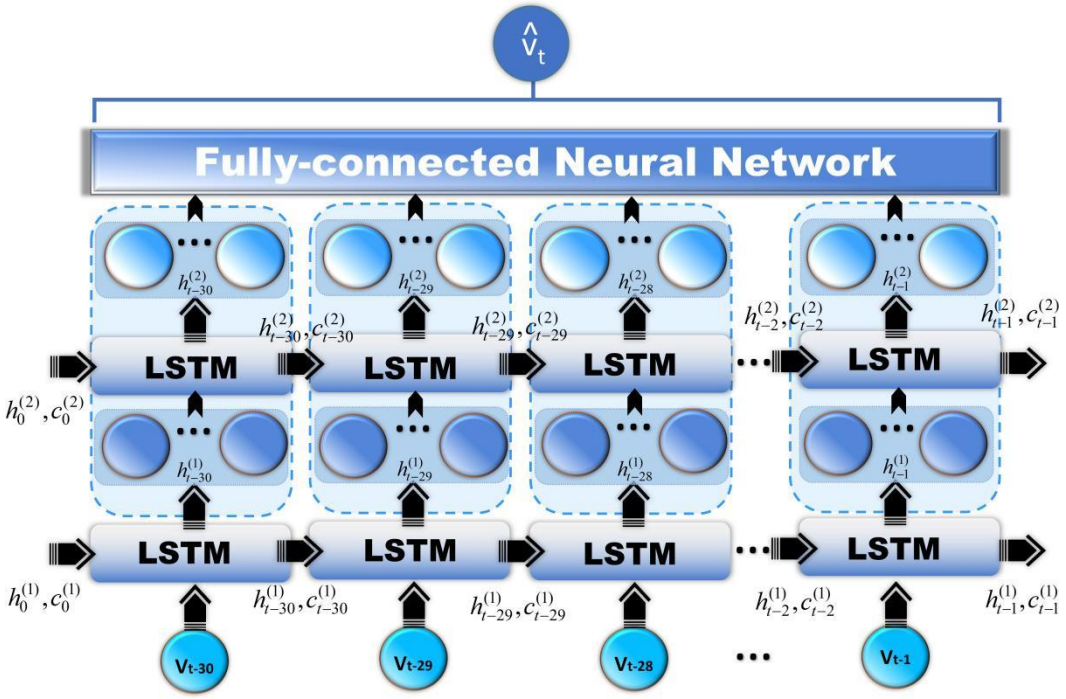
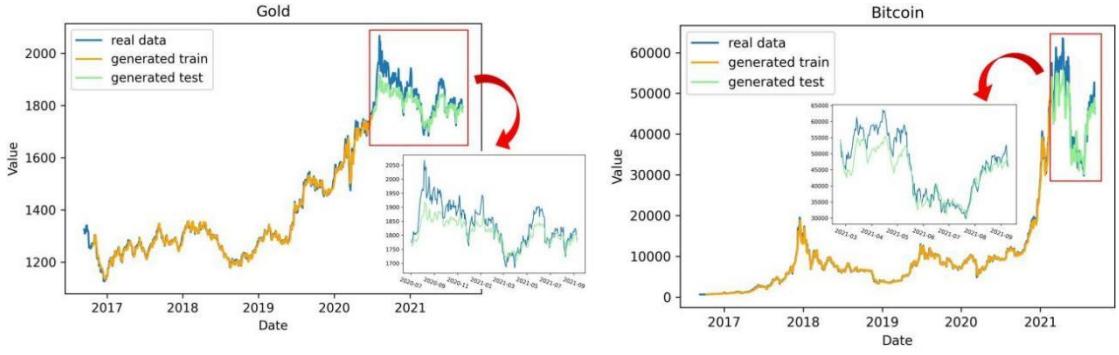


Figure 2. Fully-connected neural network (FCN)

Based on mean square error loss and Adam optimizer, the model is trained using back propagation (100 epochs, batch size=10) and tested. We use data of the last 200 days as the test set for bitcoin value and data of the last 300 days as the test set for gold value, while the rest data as their training set respectively. The results are shown in figure above. We can see that our model makes predictions that

are very accurate in the beginning. Even if the gap between generated data and real data widens gradually as time passes by, it still accurately predicts the trend value changes, with acceptable minor delays [7]. Gold and Bitcoin price fluctuations between 2016 and 2021 is shown as figure 3.



(a) Forecast of gold price trend **(b) Forecast of bitcoin price trend**

Figure 3. Gold and Bitcoin price fluctuations between 2016 and 2021

In practice, when making a daily trading strategy, we can only get data up to that day [8]. It means we cannot use the all the data in this 5-year period to make a perfect regression and use it to make a daily strategy. Given this fact, we use data of all days prior to the day we want to predict as the training set, and train the LSTMIS model for 100 epochs our model daily. When it comes to the next day, we add that days data to our training set and update the model, in a bid to better predict the value of gold and bitcoin in the future.

When conducting our strategy, we can not only use next days predicted value, but also use predicted value on days after tomorrow, which can be calculated using real data and predicted data, to obtain a likely change trend, therefore helping us better our strategy. And since the model is updated daily, the trend it predicts is more valid and grounded since it learns up-to-date information [9].

3.2. Moving Average Trading Strategy

The Moving Average Trading Strategy (MATS) forecasts the future trend of the price or price index by selecting the long and short time periods (abbreviated as L, S) respectively, and then generates trading signals and implements the trading strategy based on the results of L and S forecasts.

The short-term forecast is used to track the short-term price trend of the market, and the average of the above m = 5 days is used in this study; the long-term forecast is used to track the long-term price trend and possible price reversal of the market, and the forecast result of the LSTM of the above n days is used in this study. In the moving average trading strategy, when the fast average breaks upwards through the slow average as a golden cross, it is considered as an ideal buying point to open a position as the price may rise significantly at a future date. When the fast SMA breaks down the slow SMA, a death cross is formed and the price is considered to have a tendency to fall in the future, which is considered to be the ideal point to sell short. The timing of both buying and selling is the opening price on the second day of the signal. The rules for calculating the moving average are [10]:

$$\text{Fast average: } \mathrm{MA(t,m)} = \frac{\sum_{i=1}^{m} r_i}{m}, m = 5; \text{ Slow average: } \mathrm{MA(t,n)=LSTM(n=30)}$$

Considering the existence of handling fees for actual transactions: $\alpha_{gold} = 1\%, \alpha_{bitcoin} = 2\%$, When $MA(t,m) > (1+\alpha) * MA(t,n)$, buy to open a position at the opening price of T+1 When $MA(t,m) < (1+\alpha) * MA(t,n)$, sell the short position at the opening price of T+1.

We use MATS to get the golden cross point and death cross point, and judge whether to trade or not. Then we will introduce the MOP to determine the accurate volume of trade.

4. Markowitz Optimal Portfolio

4.1. Optimal Hedge Portfolio

Portfolio theory refers to a portfolio of several securities whose return is the weighted average of the returns of these securities, but whose risk is not the weighted average risk of the risks of these securities. The portfolio reduces the unsystematic risk, and we improve and modify the existing Markowitz portfolio model by treating gold and bitcoin as two different stocks and completing the matching of the two through the model, so as to make quantitative investments and reduce the risk while satisfying a higher rate of return.

Table 1. The Optimal Risk of Gold and Bitcoin

Category	Earnings Value	Risk	Investment ratio
Cold	$\mathrm{E}(r_g)$	σ_g	ω_g
Bitcoin	$\mathrm{E}(r_b)$	σ_b	$\omega_b = 1 - \omega_g$

When the investment ratio ω_g is reasonably chosen, better portfolio returns and lower portfolio risk can be obtained. We use the maximum Sharpe ratio and the minimum value at risk as the optimization objectives, respectively, and thus jointly build an optimization model with two sets of equations as the core.

We developed an optimization model with the objectives of maximum Sharpe ratio and minimum value-at-risk.

$$\begin{cases} \max\ (\omega_g)\frac{\mathrm{E}(r_g)-r_f}{\sigma_p} \\ min\sigma_g^2 \end{cases} \tag{1}$$

The restrictions are

$$\text{s.t.}\begin{cases} \omega_g + \omega_b = 1 \\ 0 \le \omega_g \le 1 \\ E(r_p) = \omega_g E(r_g) + \omega_{bE(r_b)} \\ \sigma_p^2 = \omega_g^2\sigma_g^2 + \omega_b^2\sigma_b^2 + 2\omega_g\omega_b \\ E(r_g) = mean[r_b^{(T-N)}: r_g^{(T-1)}] \\ E(r_b) = mean[r_b^{(T-N)}: r_b^{(T-1)}] \\ \sigma_g = var[r_g^{(T-N)}: r_g^{(T-1)}] \\ \sigma_b = var[r_b^{(T-N)}: r_g^{(T-1)}] \end{cases} \tag{2}$$

Among the restrictions we have the following points to note

cov(G, B) is the covariance of r_b and r_g

When ω_g>1 or ω_g<0, we take the boundary value

N is the data period, where N is taken as the period of 7 days

Maximum Sharpe Ratio According to the above formula, we can solve for

$$\omega_g^* = \frac{E(R_g)\sigma_b^2 - E(R_g)cov(G,B)}{E(R_g)\sigma_b^2 + E(R_b)\sigma_g^2 - [E(R_g)+E(R_b)]cov(G,B)} \tag{3}$$

And among these equations.

$$E(R_g) = E(rg) - r_f; E(R_b) = -r_f \tag{4}$$

$$\omega_b^* = 1 - \omega_g^x \tag{5}$$

Minimum total risk value.

$$\omega_g^* = \frac{\sigma_b^2 - COV(G,B)}{\sigma_g^2 - 2COV(G,B) + \sigma_b^2} \tag{6}$$

4.2. Markowitz Mean Variance Model

People make investments, essentially choosing between uncertain returns and risks. Portfolio theory uses mean-variance to portray these two key factors. By mean, we mean the expected return of a portfolio, which is a weighted average of the expected returns of individual securities, weighted by the corresponding percentage of the investment. Of course, the return of a stock includes both dividend payout and capital appreciation. By variance, we mean the variance of the portfolio's return. We refer to the standard deviation of returns as volatility, which portrays the risk of a portfolio. How should people choose the combination of return and risk in their portfolio investment decisions? This is the central question in the study of portfolio theory. Portfolio theory is the study of how "rational investors" choose the optimal portfolio. A rational investor is an investor who maximizes expected return for a given level of expected risk or minimizes expected risk for a given level of expected return.

Therefore, based on the above knowledge of finance, we created a flow analysis of the portfolio as shown in the figure 4 below.

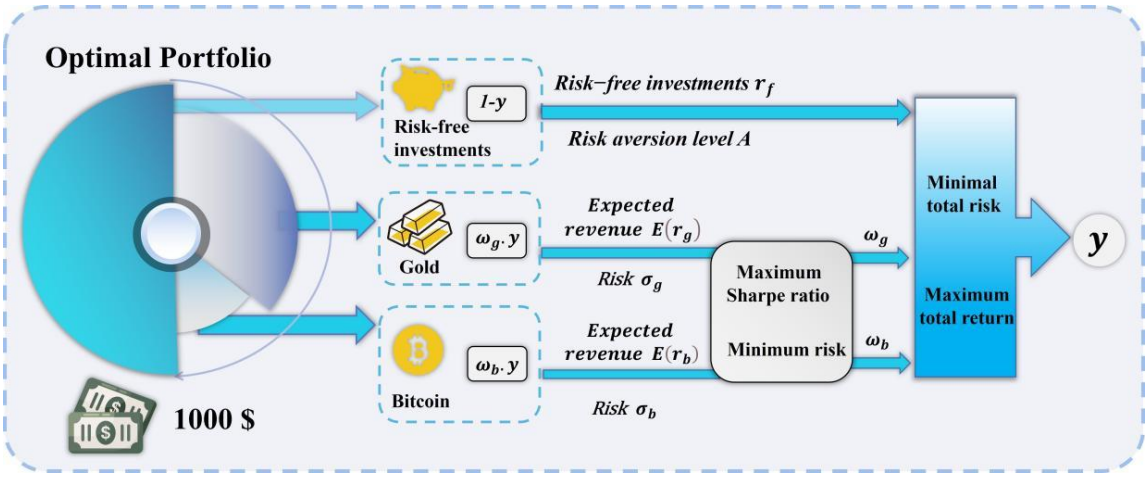


Figure 4. Process analysis of the optimal portfolio

Non-differential curve Now introduce the risk aversion index A, where the value of A is taken to be 2. Considering the total benefit and total risk, the utility function u is constructed, where the contour of the utility function is the undifferentiated curve. The undifferentiated curve is a portfolio that has the same attractiveness to investors. Portfolios located on the undifferentiated curve have the same attractiveness to investors.

Capital Allocation Line CAL CAL denotes all feasible risky portfolios of the investor (determined by ω_g), with a slope S (Sharpe ratio) equal to the expected return that rises for each unit increase in the standard deviation of the chosen asset portfolio. That is, the degree of additional return generated by each unit of additional risk.

Introduction of optimization models the system of equations for the optimization model is as follows

$$\max(u) = E(r_c) - \frac{1}{2} A\sigma_c^2 \tag{7}$$

$$\text{S.t.} \begin{cases} E(r_c) = r_f + y[E(r_p) - r_f] \\ \sigma_c^2 = y^2 \sigma_p^2 \\ 0 \le y \le 1 \end{cases} \tag{8}$$

From equations above, we can easily find the solution.

$$y^* = \frac{E(r_p) - r_f}{A\sigma_p^2} \tag{9}$$

Visual Analysis of Optimal Portfolio We visualize the above optimal portfolio in the feasible set by using the relevant functions in matplotlib.pyplot in order to illustrate more intuitively the value area and rationality of the portfolio. We use the relevant function in matplotlib.pyplot to visualize the position of the above optimal portfolio in the feasible set, and the obtained image is shown in figure 5.

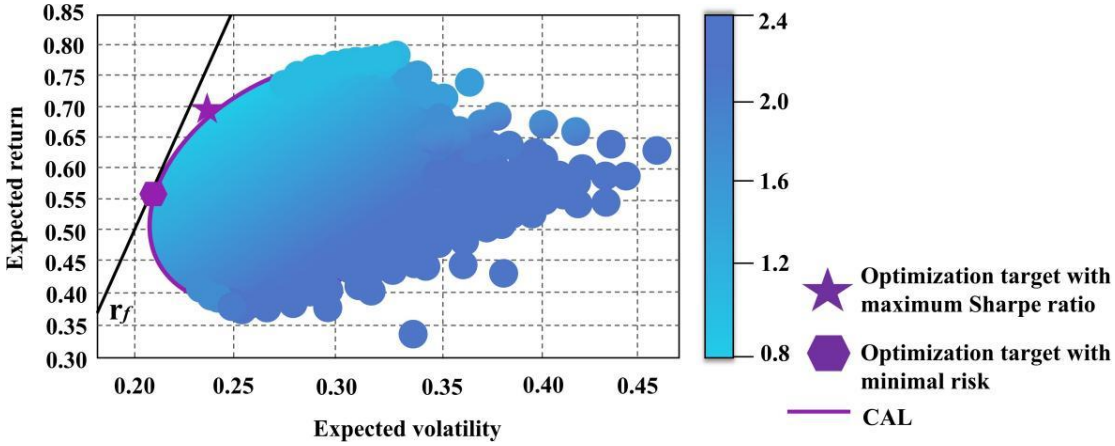


Figure 5. Modeling process

In the chart above, the pentagon marks the portfolio with the highest Sharpe ratio (i.e. risk-return equilibrium point), and the positive hexagon marks the minimum variance portfolio. We use the minimum variance portfolio as the boundary and divide the feasible set into the upper and the edge of the upper half is the effective boundary, which we represent by the purple curve. The image illustrates the feasible region of the portfolio and gives options that can reduce the risk while guaranteeing a certain rate of return, proving that the model can achieve the unity of risk and return for the client.

5. Sensitivity Analysis

To test the sensitivity of our model, we change the number of most recent days that are used to predict future value. We use data before 7/2/2019 to predict the value of bitcoin on 7/3/2019 and 4/27/2020 respectively, and records the absolute error between real and predicted value. Since the result of neural network is highly related to parameter initialization, which are random variables following Gaussian distribution, we train our model for several times given different number of most recent days and use the average absolute error as the yardstick. The relationship between absolute error and the number of most recent days are shown in figures above. As can be seen, our model is highly sensitive to the number of most recent days.

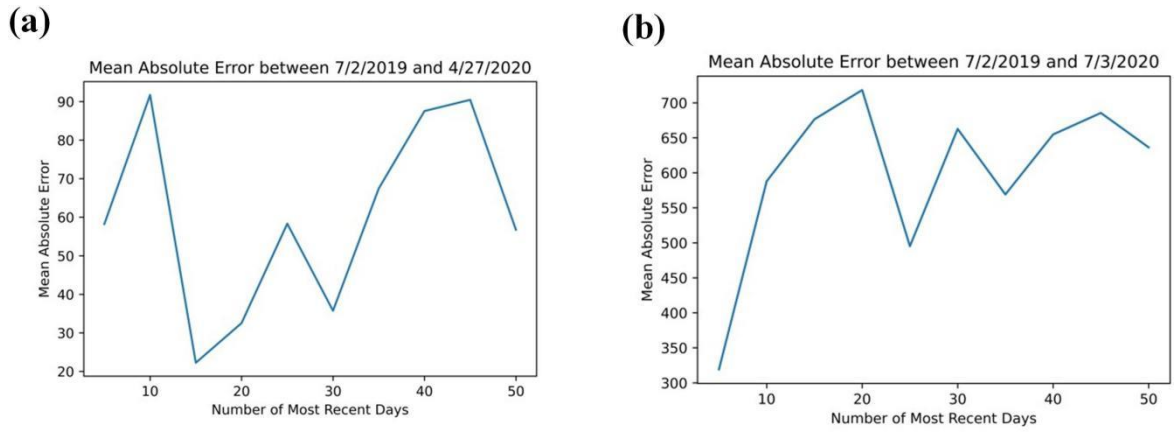


Figure 6. The relationship between absolute error and the number of most recent days

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