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Investment Return Forecast and Risk Avoidance Analysis Based on Quantitative Trading

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***Abstract* – Quantitative trading is based on professional financial knowledge. With the help of statistical and mathematical tools, the quantitative model is solidified from the data, and the transaction is simulated by computer technology to obtain excess returns. This paper uses data on a five-year trading period in the United States from 11 September 2016 to 10 September 2021. We first establish a time series model to predict the follow-up price of gold coins and gold, and then introduce the Sharp ratio to establish a risk model to simulate and predict the risk of the market, and then use the particle swarm optimization method to modify the parameters of the model. Finally, sensitivity tests and analysis are carried out to ensure that the profit is maximized under the model conditions. In the course of the analysis, we found that with the increase in fees, gold and bitcoin trading volume significantly reduced, the final value of the decline. With fees falling, gold and bitcoin's large trading volumes have increased dramatically, with final value rising. The scheme has good predictability, and the heuristic algorithm greatly accelerates the convergence speed of the model.**

***Keywords* – Quantitative Trading, Sharp Ratio, Particle Swarm Optimization, Sensitivity Analysis.**

I. INTRODUCTION

In China's financial market, whether it is the securities market or futures market, and whether different investors adopt the basic analysis, technical analysis or the popular quantitative analysis method in recent years, their same investment goal is to obtain more than the market average income. Attracted by high returns in financial markets, a large number of related research has spawned the research discipline of quantitative analysis, which has gradually expanded from the initial field of financial economics to statistics, computational science, information science and biology [1]. There are three basic analysis methods to summarize the current trend of financial asset prices: fundamental analysis, technical analysis and quantitative analysis. Reviewing the three main investment methods, the fundamental analysis method and the technical analysis method are relatively mature, and the quantitative analysis method has only begun to rise in recent years. Many application studies of quantitative analysis are still in the exploratory stage, and are not fully mature in general. With the increasing popularity of machine learning research and the improvement of computer hardware computing power in recent years, quantitative analysis theory has begun to be popular among investors. Some quantitative analysis frameworks are derived from the accumulation of experience in technical analysis theory, which also makes quantitative analysis theory easy to be accepted by investors.

Quantitative transaction refers to taking a large number of investment-related data as samples, establishing appropriate mathematical models and formulas by quantitative means, and using computer technology to develop efficient procedures to study and analyze the future returns and risks of financial products, and to determine the probability of occurrence of various market trends to achieve investment [2]. Quantitative trading plays an increasingly important role in today's global financial markets, because it has the advantages of automation and scientific quantitative decision-making [3].

Based on this background, this paper uses gold and bitcoin data from 11 September 2016 to 10 September 2021 to establish a quantitative investment model and design investment strategies.

II. Related Work

Back in 2012, Lu selected the closing price data of CSI 300 stock index futures every five minutes in the day as the research object, and selected the holding cost model and the cointegration model to establish the model for empirical analysis. The analysis shows that both models are effective, but the co-integration model is more accurate and sensitive, and can find more subtle arbitrage opportunities [4].

In 2014, Wang proposed a quantitative trading intelligent system based on Lasso method and neural network model. The results show that the trading system has high yield and risk control ability [5]. Based on empirical mode decomposition, Yu uses autocorrelation function and wavelet soft threshold to denoise the data sequence of Shanghai and Shenzhen 300 stock index futures, and establishes the Brin channel trading model, which effectively reduces the number of false triggers of trading model caused by interference signals in the market [6].

In 2015, Ye took Shanghai Composite Index as the research object to verify the short-term and long-term performance of simple moving average and exponential moving average time series momentum models in A-share market. Finally, it is found that the main profit periods of the time series momentum model are concentrated in the oscillating bear market [7].

In 2016, Lin explained the Alpha strategy in theory, analyzed the characteristics of Alpha strategy and provided multiple methods for seeking Alpha strategy, helping investors to explore effective strategies that can exceed market returns. In the empirical test, select from January 1,2010 to December 31,2015 this period of time in Chin 's stock market all A shares, design a multi-factor system [8].

In 2017, Shen processed daily trading data of CSI 300 stock index futures, and used support vector machine theory to design quantitative trading strategy model for fitting and forecasting. The annual rate of return was 63.91 per cent and the maximum withdrawal rate was 12.33 per cent [9].

In 2019, Jia used GARCH model to analyze volatility, and established mean equation and variance equation. Finally, according to the GARCH model of residual volatility analysis results, design a set of practical reference value of intraday quantitative trading strategy [10]. Zheng use the split and merger structure to build the depth model with the long and short term memory network (LSTM) as the core, and use a variety of loss functions to train and realize the automatic rolling update of the model. The historical data of China’s A-share market from 2010 to 2018 are used for model construction and retest analysis. The model obtained 265.7% cumulative income and 32% annualized income during the retest period, which was significantly ahead of the 43% cumulative income and 8.1% annualized income of the benchmark Shanghai and Shenzhen 300 [11].

In 2020, Xu uses multi-factor and machine learning theory, uses historical data to train and trace back various machine learning algorithms, and selects the best algorithm through scoring and evaluation. Finally, it is concluded that the multi-factor strategy optimized by xg boost is the optimal quantitative algorithm strategy [12]. Liao focuses on the A-share investment strategy based on ensemble learning algorithm. The main work includes extracting relevant stock data from the concentration trading platform, and selecting 50 variables that usually affect the stock price to construct the feature factor library. Random Forest and Ada Boost are combined with the feature factor library respectively to construct the stock selection model of ensemble learning algorithm. After analysis, the stock selection model constructed by these two machine learning algorithms is suitable for the A-share market. The selected portfolio has achieved good returns in the test interval, and can beat the market index, which has reference significance for the majority of investors [13].

In 2021, Lu constructs a quantitative stock selection trading strategy based on the price-earnings ratio interpretation model and random forest algorithm. The total return rate of the strategy reached 143.94%, which was higher than 14.57% of the benchmark return rate of Shanghai and Shenzhen 300 [14]. Wang combined with the neural network model under the framework of deep learning to analyze and predict the trend of the selected opening and closing price data of CSI 300 index futures, and finally obtained high prediction accuracy. The results show that the deep learning recurrent neural network has a good performance in futures price prediction and has great development potential [15]. Tang proposed a turtle trading model based on LSTM neural network optimization, which improved the channel breakthrough system of the traditional turtle model. At the same time, based on the DTW dynamic time warping algorithm, an algorithm index was proposed to detect whether the model was invalid. The results show that the overall profitability of the model is increased by more than 20 %, and the problem of gradual failure of the traditional turtle model in recent years is solved [16].

III. Investment Return Forecast

A. *Data Sources*

The training set of experimental data uses us daily gold settlement price data from January 02, 2008 to May 16, 2018 for a total of 2,290 days, and daily Bitcoin settlement price data from April 28, 2013 to August 14, 2018. Then verify the data from September 11, 2018 to September 10, 2021, as shown in Table 1. Prices have different dimensional and dimensional units, which will affect the results of data analysis. In order to eliminate the dimensional influence between prices, data standardization is needed to solve the comparability between data. Therefore, for the price of gold and bitcoin, we use today’s price/yesterday’s price instead of today’s price for follow-up prediction, which can make the data more substantial.

Table 1. Experimental data (first five).

Date	Gold Price	Date	Bitcoin Price
2009/12/16	1324.6	2009/11/16	621.65
2009/13/16	1323.65	2009/12/16	609.67
2009/14/16	1321.75	2009/13/16	610.92
2009/15/16	1310.8	2009/14/16	608.82
2009/16/16	1308.35	2009/15/16	610.38
...	...	...	...

B. *COINS and Gold Prices Prediction Based on ARIMA Time Series Model*

When the data preprocessing is completed, we USES the time series analysis method, using the data from the previous single variable prediction, respectively of late COINS and predict the price of gold and get the predicted value, then you can compare price growth, with both make the selection of the initial investment decision, this is the basis of the subsequent risk model and choose. The price data for bitcoin and gold comes in the form of a time series, meaning that our data exists over a continuous time interval, with equal intervals between every two consecutive measurements for Bitcoin and equal intervals between measurements on weekdays for gold. In R, we can use create a time series object for our data vector. To do this, we adjust the start (start time) parameter and the FREq (frequency) parameter. Time series data is stored in the variable Bitcoin by calling our newly created time series object. Then we draw the timing diagram of the sequence. From Figure 1, we can intuitively feel that the sequence is non-stationary.

Then we use ARIMA model to predict this sequence. ARIMA model is a differential integration moving average autoregressive model, also known as integration Moving average autoregressive model is one of the predictive analysis methods of time series. Usually For a linear trend you can use a first order difference to stabilize it, for a second order curve Second order difference. In practical application, data may be lost due to over difference True. Therefore, fractional difference is generated for optimization. First-order difference is used in this paper. After examination, the sequence was found to be stable with p value less than 0.05. We build time series models and diagnose them. The residuals do approximate a normal distribution.

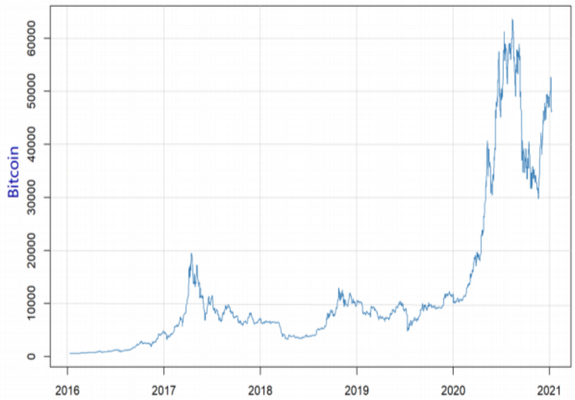

Fig. 1. The timing diagram of the sequence.

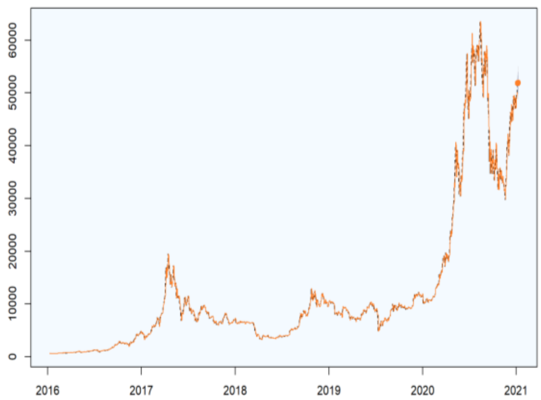

Fig. 2. Forecasts from ARIMA (0, 1, 0) with drift.

If our model works well, its corresponding residual should be white noise that is approximately normally distributed, fluctuating randomly up and down the predicted value of the model. Therefore, in order to diagnose the model, we need to perform a residual test on it, and the residuals do approximate a normal distribution.

Finally, we predict the results. Data after 2015 were taken as the test set of the model to judge the prediction effect and accuracy of the model, the data of the test set was imported by us into the variable, and the time series model trained by the previous training set was used for fitting. The predicted results are shown in Figure 2.

IV. Risk Avoidance Analysis

A. *Model Assumption*

Since the capital held is composed of cash, gold and bitcoin, we assume that cash is c_n on the NTH day, gold is g_n, and Bitcoin is b_n, denoted as $[c_n, g_n, b_n]$ and it is easy to get their relationship: $c_n + g_n + b_n = 1$.

We set the decision variables $[\Delta G_n, \Delta B_n]$ as the change of gold and bitcoin respectively. Suppose, on day *n*, the increase of cash, gold and bitcoin is $[0.00547\%, \overline{G_n}, \overline{B_n}]$, according to the predicted results, on day *n*, we will have the data of day *Kn* and the predicted results of day *n*. In order to better quantify the relationship between investment risk and return on a daily basis, we introduce sharpe ratio. Sharpe ratio (Sharpe,1966) proposed Sharpe ratio on the basis of modern portfolio theory. Sharpe ratio not only focuses on the return of assets, but also the risk of assets. It measures the return of assets adjusted for risk and is the price display of unit risk. Because Sharpe ratio comprehensively reflects the risk-return characteristics of the capital market, it has been widely used to evaluate the performance of asset portfolio, evaluate the operating efficiency of the capital market, construct effective asset portfolio, and guide investment decisions. Its mathematical expression is:

$$SR_p = \frac{E(r_p - r_f)}{\sigma_p}$$

Where $E(r_p)$ is the expected rate of return of portfolio P during the observation period; σ is the standard deviation of return rate; r_f is the rate of return on a risk-free asset.

B. *Establishment of Planning Model*

According to the planning model, on the NTH day, the objective function *F(n)* is set as the sharpe ratio of the third day when positions are adjusted today and the next three days remain unchanged. When this objective function reaches its maximum, it is the state in which risk and return are balanced. Take *n* day as an example, the proportion of cash, gold and bitcoin in total assets is $[c_n, g_n, b_n]$. At the end of day *n*, you have to settle up or down. If the increase rate of cash, gold and bitcoin on that day is $[0.00547\%, \overline{G_n}, \overline{B_n}]$ respectively, then the proportion will become $[1+0.00547\%, (1+\overline{G_n})g_n, (1+\overline{B_n})b_n]$. Since the sum of the proportion is not *1* due to the change of the total amount, we will normalize it again so as to repeat the operation on the *n+1* day.

Since there are trading fees, we need to adjust trading positions and calculate trading costs. Here, we divide it into gold only and bitcoin only. When only buying gold, the change in the proportion of gold amount is $\Delta G_n > 0$, at this time, the change of cash proportion is $1.0101 * \Delta G_n$ (buying rate is 1%, 101 pieces can not buy 100 pieces of gold). When only selling gold transaction, the change of gold proportion is $DeltaG_n < 0$, at this time, the change of cash proportion is $0.99 * \Delta G_n$.

When only buying bitcoins, the change in the proportion of bitcoins is $\Delta B_n > 0$, at this time, the change of cash proportion is $1.0204 * \Delta B_n$. When only selling bitcoin transactions are conducted, the change in the proportion of the amount of bitcoin re membered is $\Delta G_n < 0$, at this time, the change of cash proportion is $0.98 * \Delta G_n$.

The percentage of total assets in cash, gold and Bitcoin is as follows on the last day after transaction fees are settled: $[(1+0.00547\%)c_n - (1\pm 0.01)\Delta G_n - (1\pm 0.02)\Delta B_n, (1+\overline{G_n})g_n + \Delta G_n, (1+\overline{B_n})b_n + \Delta B_n]$

C. *Parameter Optimization*

Notice that in the process of establishing the model above, when setting the objective function, it is assumed that the positions will be adjusted on one day and remain unchanged for the next three days. However, in the actual transaction, such decision will cause problems in the subsequent investment. If only three days are considered, arbitrage space will be generated and subsequent arbitrage behaviors will be induced. Therefore, we should constantly adjust the investment plan after each day according to the forecast results to strive for higher profits. In the optimization process, we should set the value $[\Delta G_{n+1}, \Delta B_{n+1}, \Delta G_{n+2}, \Delta B_{n+2}]$ in the middle of the optimization process without changing the constraint conditions, and continue to use the above model to solve again. We introduce Particle swarm optimization (PSO) to modify parameters.

Particle swarm optimization (PSO) is a random search algorithm based on swarm cooperation developed by simulating the foraging behavior of birds. It is a type of swarm intelligence (SI) and can be incorporated into multi-agent optimization systems(MAOS). PSO is inspired by models that simulate the predation behavior of flocks of birds and used to solve optimization problems. In PSO, the solution of each optimization problem is a bird in the search space, which is called a "particle" in formal terminology. All particles have an adaptation determined by the optimized function, each particle has a velocity that determines the direction and distance they fly, and then the particles follow the current optimal particle in the solution space. Therefore, in a nutshell, PSO optimization method is to initialize a group of random solutions, find the optimal solution through iteration, and constantly update itself according to individual extremums, local extremums and global extremums.

D. *Model Modification*

In the process of the above model, we adopted the financial Sharpe ratio as the objective function, and the investment strategy was too conservative. We invested as much as possible in gold instead of bitcoin. This is because bitcoin is different from traditional financial projects, its daily fluctuation range is huge, the variance will be large, as a Sharpe rate will reject such a large risk. Therefore, the final yield is not high.

When establishing the risk model above, we chose the financial index Sharpe ratio as the measurement index. However, in the investment decision, in addition to the objective market environment will affect the decision of investors, investors' risk preference is also an important factor. Risk preference can be roughly divided into three types, namely, risk-averse type (choosing the scheme with the highest return rate under the same risk), risk-neutral type (the choice of investment scheme is not affected by the risk) and risk preference type (choosing the scheme with higher risk under the same investment return rate). It is obvious that investors with different risk preferences will choose different schemes even if they are faced with the same investment decision. Therefore, we should develop different indicators for them to get the most suitable scheme for them.

The standard deviation of the predicted value σn in the next three days is used as the risk evaluation value. If the predicted price fluctuation in the next three days is relatively large, it means that the risk in the future is relatively large.

In the building of a model for risk averse investors, we will set the target function fn as the largest sharpe ratio after three days, investors for the risk neutral type, we set the target function fn to the earnings minus 0.8 times the risk assessment of the value after three days, and finally, investor appetite for risk, we will set the target function fn as the biggest gains after three days.

Finally, the investment plan and daily rate of return are as follows. Finally, the total value of the investment of the aggressive type is 20560265.49, the total value of the investment of the stable type is 1237.22, and the

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total value of the investment of the intermediate type is 4253.99.

E. *Sensitivity Analysis*

In order to prove that our scheme is the local optimal solution, we conducted sensitivity analysis on the parameters, disturbed the buying ratio of bitcoin and gold in our model within the range of 5%, and made a new buying and selling scheme. The final result is shown in the following Table:

Table 2. Adujusted result 1.

	1(No disturbance)	2	3	4	5	6
Returns	4253.989	4014.187	4328.010	4099.514	4303.118	4248.701
Std	1112.463	1123.794	1182.513	1146.448	1175.422	1164.930
Sharpen	3.823	3.571	3.660	3.575	3.660	3.648

It is concluded from this evaluation that our model is not sensitive to the changes of parameter values, that is, the model has a considerable degree of high robustness.

In order to study how much influence the change of transaction cost will have on the strategic plan, the parameters a gold and a bit are adjusted appropriately to obtain the following table for scientific investment.

Table. 3. Adjusted result 2.

a_gold	1.00%	1.50%	0.50%	1.00%	1.00%	0.50%
a_bit	2.00%	2.00%	2.00%	1.50%	2.50%	1.00%
returns	4240.895	4250.74	3992.134	5655.804	2787.148	5918.263
std	1171.802	1089.679	1059.261	1306.455	825.942	1440.177
g_tans_times(>1)	118	65	238	122	90	285
bits_trans_times(>=1)	633	620	641	712	533	850

According to the results, the number of transactions for gold and bitcoin decreased with the increase in fees, while the number of transactions for gold and bitcoin increased significantly.

V. Conclusion

Finance is an important part of the world economy. With the continuous opening up of China’s financial market and the progress of science and technology, the market demand for financial science and technology will gradually increase. Quantitative trading has important research and application significance for both institutional and individual investors because of its all-weather automatic trading, scientific quantitative retest method, avoiding human weakness, and easy construction of portfolios.

This paper uses data from September 11, 2016 to September 10, 2021 for a five-year trading period in the United States, starting at $1,000, estimated investment value on September 10, 2021. We first establish time series models to predict subsequent COINS and gold prices, and introducing the sharpe ratio to build risk model to simulate and predict the risk of market, and then use the particle swarm optimization method to modify parameters, such as model, finally sensitivity test and analysis, make sure that under the condition of model to maximize returns. Finally, the specific daily invest ment plan of the three personalities is given, and the total value of the investment of the radical type is 20560265.49, the total value of the investment of the stable type is 1237.22, and the total value of the investment of the intermediate type is 4253.99. Finally, we test the sensitivity of the previous model and find that if the investment scheme is disturbed, the objective function will no longer be the maximum, which means it does not meet the psychological expectations of investors. Therefore, the proposed scheme is an optimal one. Then, a series of changes were made to trans action fees, and it was found that with the increase of commission fees, the number of large transactions of gold and Bitcoin decreased significantly, and the final value decreased. With the decrease of commission fees, the number of large transactions of gold and Bitcoin increased significantly, and the final value rose. The scheme has good predictability, and the heuristic algorithm greatly speeds up the convergence of the model.

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