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Trading Strategies: How to Buy Gold and Bitcoin Correctly to Make a Fortune Summary

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Abstract

In this paper, we examine the price volatility of gold and Bitcoin. Specifically, we calculate the expected upside data for gold and Bitcoin separately through the Autoregressive Integrated Moving Average Model (ARIMA) algorithm, we build bull market data for gold and Bitcoin and build a purchase-ability model, in addition, we The analysis hierarchy process (AHP) is used to correspond to these data, and the strategy model of the final transaction result is obtained. Finally, we build a simple algorithm for profit maximization for known time series data by programming and combining dynamic programming.

Keywords

ARIMA; Data Processing; AHP; Trading Strategies; Quantitative Trading.

1. Introduction

Since the establishment of the gold market in the 19th century, the gold market has become a common concern of investors, managers, and economic management scholars. With the development of gold investment in China, its influence is increasing [1]. Bitcoin was proposed in November 2008 and officially born in January 2009. Bitcoin is the first distributed virtual currency where the entire network is made up of users [2], without a central bank, and is very secure and free. However, how to use the balance in the hands of reasonable gold and bitcoin transactions to achieve the maximum personal profit is a solution that people have been pursuing for many years.

A trader asked me to develop a model that uses only past daily price streams to decide whether a trader should buy, hold or sell an asset in a portfolio each day. Every transaction requires a commission, and there is no cost to the assets we hold. Bitcoin can be traded on a daily basis, but gold can only be traded on days when the market is open given the data file. In the end, we can only use the data from these two spreadsheets to develop our model. In this article, based on the given dataset, we cleaned its data and added some needed data. Additionally, a model is built that gives the best daily trading strategy based only on current price data. Finally, determine the sensitivity of strategies to transaction costs and how they affect decisions and outcomes.

2. Data Preprocessing and Corresponding Expansion

Interpolation algorithm is to interpolate continuous function on discrete data so that the continuous curve passes through all the given discrete data points [3]. We use cubic spline interpolation to fill in the missing data in this problem.

Since gold does not trade every day, we defined its non-trading price as the same as the previous day, and we added a new column named "whether gold can be traded on that day" – if dealed, where 0 means that it can not be traded and 1 means that it can be traded, and finally

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merged the two tables to form a new table labeled as date-USD(PM)-value-if dealed. And we plotted the price of gold and bitcoin, which is shown in Fig.1.

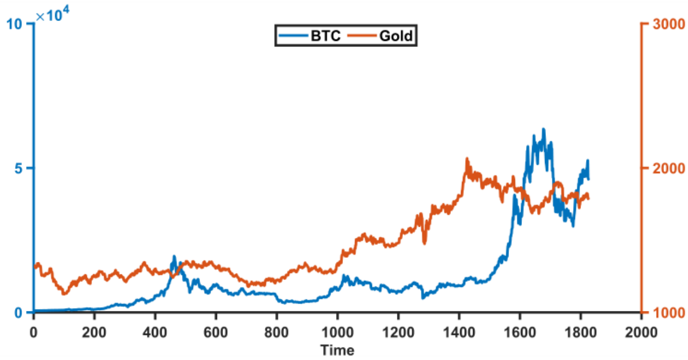

Figure 1. Gold and bitcoin price trend chart

Then, we conduct descriptive statistics and plotted the exchange rates of gold and bitcoin, which is shown in table 1.

Table 1. Descriptive statistical table

Descriptive Statistics	Mean	Median	Standard Deviation	Minimum	Maximum
BTC	12206.0683	7924.4600	14043.8916	594.0800	63554.4400
USD(PM)	1463.6445	1327.8250	249.3299	1125.7000	2067.1500

We calculate the gains in gold and bitcoin, which can be expressed as:

$$\beta = \frac{\alpha_i - \alpha_{i-1}}{\alpha_{i-1}} \times 100\% \tag{1}$$

We plot the rise of gold and bitcoin, which is shown in Fig.2 and Fig.3.

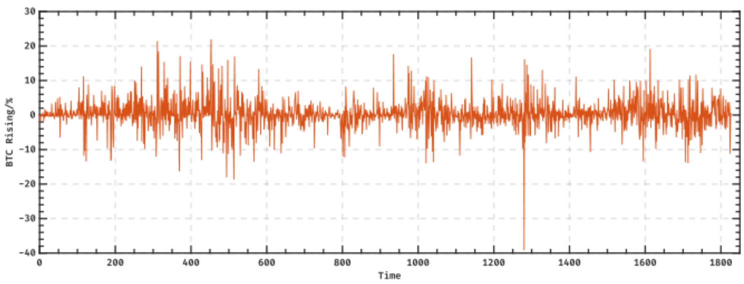

Figure 2. Bitcoin gains chart

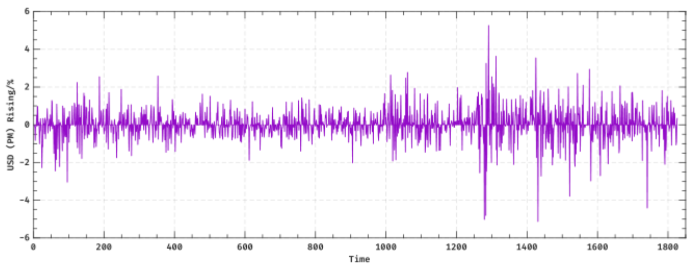

Figure 3. Gold gains chart

In economics and statistics, buying strategies for gold and bitcoin are different [4]. As can be seen from the Fig. 2 above, the price fluctuation of bitcoin is huge, which is not conducive to medium and long term trading and easy to cause great risks. Therefore, we choose the 5-day moving average method. It can be seen from Fig. 3 that the increase of gold is between negative 4% and positive 4%, which is relatively stable. Therefore, we use the 15-day moving average method and the 20-day moving average method, which are better for gold with relatively stable prices, which can be expressed as:

$$MA_n = \frac{1}{n}\sum_{i=n-5}^{n} V_i \tag{2}$$

The calculation formula of convergence divergence is:

$$B = \frac{(P-A_n)}{A_n} \times 100\% \tag{3}$$

We use Z-score standardization to normalize the data to convert original data into a data set with a mean of 0 and variance of 1, which can be expressed as:

$$Z = \frac{MAX-MIN}{MAX-MIN} \tag{4}$$

where MIN represents the minimum value of the data set, and MAX represents the maximum value of the data set. And X is the current data.
We draw the 5-day average chart of bitcoin and 15-day average chart of gold, which is shown in Fig.4 and Fig.5.

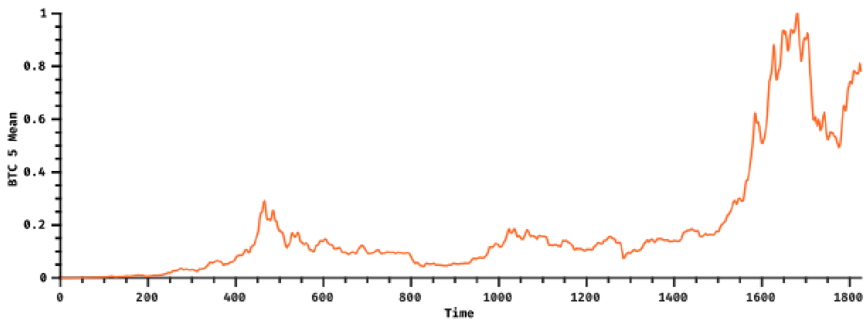

Figure 4. The normalized 5-day average of bitcoin, used to determine whether it is a bear or bull market

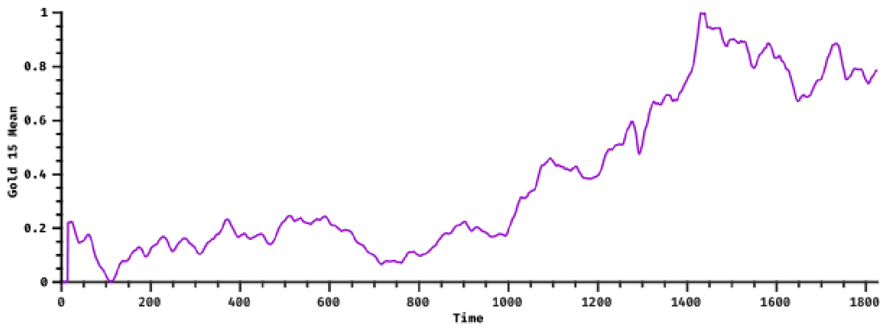

Figure 5. The normalized 15-day average of gold, used to determine whether it is a bear or bull market

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3. Model Establishment

After reviewing the data and analyzing the data artificially, we have come up with the following properties: Bitcoin is highly volatile in value over a short period of time and is suitable for short-term trading, while gold is less volatile and suitable for medium to medium long term trading. So we use 15 days for bitcoin and 60 days for gold as the basis for bullish decisions, which can be expressed as:

$$\epsilon_g = \frac{61}{100} \times \lambda_g + \frac{39}{100} \times \theta_g \tag{5}$$

$$\epsilon_b = \frac{3}{5} \times \lambda_b + \frac{2}{5} \times \theta_b \tag{6}$$

where ϵ_b and ϵ_b represent the bull market probabilities for bitcoin and gold.

We establish the Purchasability model of gold and bitcoin through artificial adjustment, which can be expressed as:

$$\rho_b = \frac{61}{100} \times \epsilon_b + \frac{39}{100} B_b \tag{7}$$

$$\rho_g = \frac{3}{5} \times \epsilon_g + \frac{2}{5} B_b \tag{8}$$

We use difference methods (DM) for its time series data smoothing. To ensure the reliability of the judgment, we use ADF to test the smoothness of the original time series data, which is shown in table 2.

Table 2. ADF test table

Variable	Result	Coefficient	Std. Error	t-Statistic	p-Value
BTC	0	1.001	0.001	983.092	0.876
USD(PM)	0	1.000	0.000	5501.300	0.891

As shown in table 2, we can find that both BTC and USD (PM) cannot reject the null hypothesis, and the series has a unit root, which is non-smooth time series data.

Due to the non-smoothness of the time series data, the series are processed using DM, and the results are checked for smoothness. After several experiments, we learned that the first-order difference for both time series data is smooth, which is shown in Fig.6 and Fig.7.

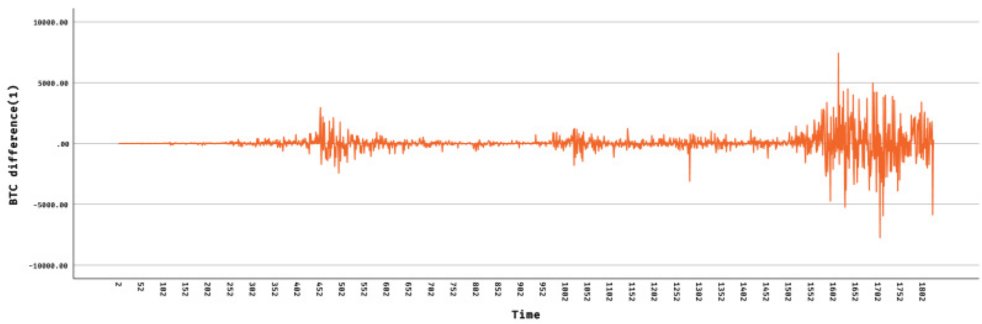

Figure 6. BTC data values after first order difference.

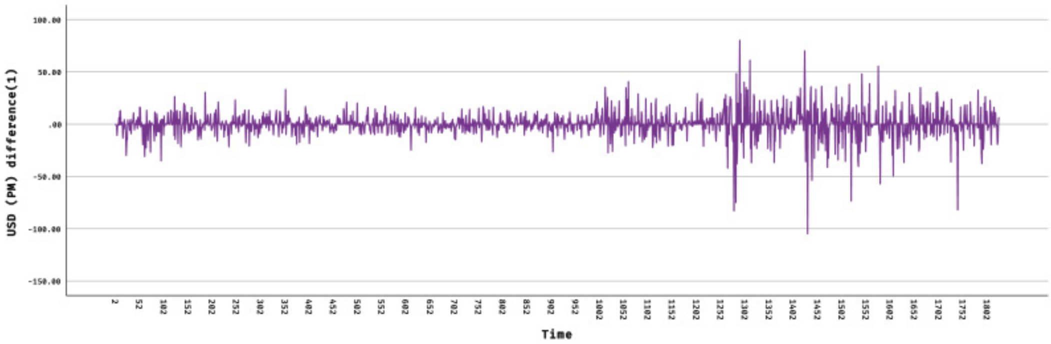

Figure 7. USD (PM) data values after first order difference.

We conduct a series of explorations on selecting parameters for ARIMA, varying p, q in ARIMA (p, 1, q) based on first-order differences, and obtained the best parameters to fit the two time series data by comparison. The data are presented in table 3.

Table 3. The model used and the parameters

Variable	Model Type	Std. R^2	LBQ(18) Statistics	LBQ(18) Sig.
BTC	ARIMA (0,1,2)	0.238	17.057	0.450
USD (PM)	ARIMA (0,1,17)	0.351	26.331	0.092

After using the data obtained from ARIMA model of, we drew the predicted rise of gold and the predicted rise of bitcoin, which is shown in Fig. 8.

Figure 8. Results of USD (PM) and BTC time series data using ARIMA forecasts.

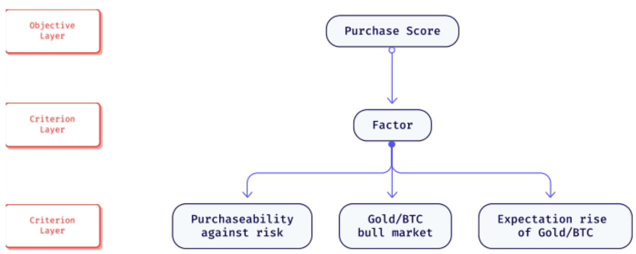

Figure 9. Hierarchy diagram.

We use gold bitcoin expected to rise, gold bitcoin purchase-ability; gold bitcoin is bull market, gold bitcoin Bias these indicators to build an indicator called purchase value, and we use analytic hierarchy process (AHP) [5] to set the weights to create the purchase score indicator, and constructed a Hierarchy diagram as shown in Fig 9.

We need to consider not only the purchased score but also the amount of purchase. The formula of Purchase amount and Sell amount is as follows:

$$P_{ib} = \frac{((1-\alpha_{bitcoin})\times P_{ib-1}\times S_b)}{P} \tag{9}$$

$$P_{ig} = \frac{((1-\alpha_{gold})\times P_{ig-1}\times S_g)}{P} \tag{10}$$

We add our cash, gold, and bitcoin, which are the total assets we own. The total property chart is shown in Fig. 10. The final total assets obtained through our trading model were $564,563.410.

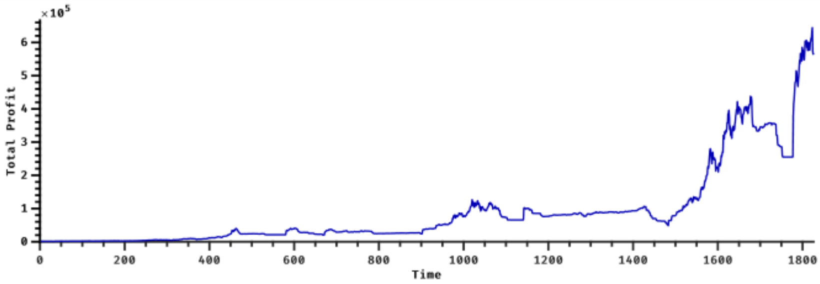

Figure 10. The total property in our trading model

4. Model Analysis

Based on the above idea, we have built a simple algorithm for solving the maximum profit for known time series data by programming and combining it with the knowledge of dynamic programming. To simplify the calculation and reduce the difficulty of thinking, we do not take into account the loss of profit due to commissions, and we assume that the maximum profit obtained by such an algorithm is not very different from the case where commissions are actually taken into account. To better illustrate this algorithm, some notation is agreed upon as follows. $\mathrm{d}p_i$ is the maximum return on day i when selling, P_i is the value on day i. $\max\{x_1, x_2, \ldots, x_n\}$ is an algorithm that serves to return the maximum of $x_1, x_2, \ldots, x_n$. Clearly, $\mathrm{d}p_i$ is a monotonically increasing array, and by analysis, we obtain the state transfer equation as follows:

$$\mathrm{d}p_i = \mathrm{d}p_{i-1} + max\{P_i - P_{i-1}, 0\} \tag{11}$$

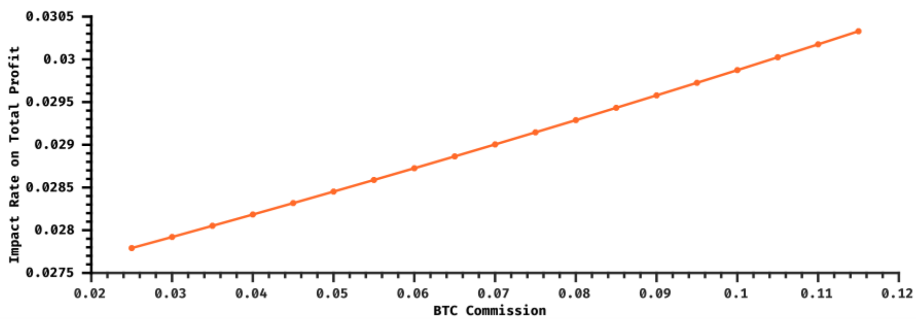

Figure 11. The impact curve of changes in bitcoin commissions on total property

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Using this algorithm, we calculate a theoretical maximum profit of $358,499.29 for BTC and $6,032.85 for gold. Fig. 11 and Fig. 12 show the impact on the total profit when we change the commissions for Gold and BTC. From this, we can conclude that the impact of the gold commission is much greater than the impact of the bitcoin commission. As can be seen from the Fig. 11 and Fig. 12, with the increase of commission, the impact on the decrease of total property is also getting higher and higher. Moreover, the gold commission occupies an important position in influencing property. Also, when it is between 0.08-0.09, the property reaches the lowest and does not change, so it shows a downward trend.

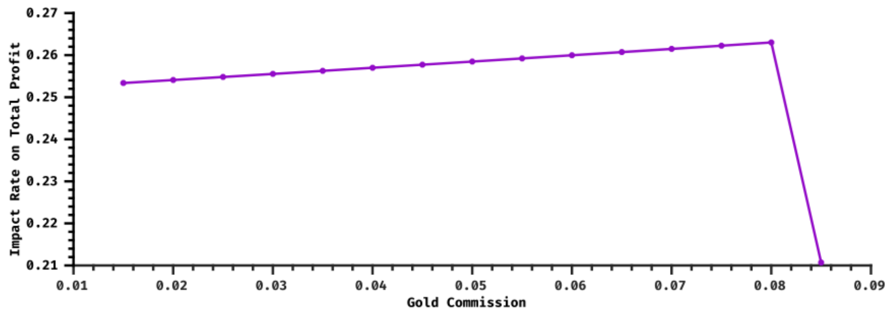

Figure 12. The impact curve of changes in gold commissions on total property

5. Conclusion

In this paper, we preprocess the given data and add some indicator transactions. Additionally, we use the ARIMA time series prediction model to predict gold and bitcoin prices, and calculate the gold/bitcoin bull market indicators and gold/bitcoin purchase-ability. Then, we use AHP to calculate the proportionality coefficient of bull market/purchase-ability/expectation rise to build a purchase score indicator to finish the final model. Moreover, two other strategies were established to compare with ours, proving that our strategy is much better. Finally, we modify the commission size to show the sensitivity of total property to the commission by comparing the total property.

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