Problem Chosen	2022 MCM/ICM Summary Sheet	Team Control Number
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The LaTeX Template for MCM Version v6.3.1

Summary

Keywords: keyword1; keyword2

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LaTeX Studio

February 22, 2022

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Contents

1 Introduction

1.1 Background

which means , to develop a model that uses only the past stream of daily prices to date to determine each day if the trader should buy, hold, or sell their assets in their portfolio.

1.2 Problem Statement

1.
2.
3.
4.
5.
6. Determine how sensitive the strategy is to transaction costs

1.3 Problem Analysis

ARIMA ARIMAARIMA

2 Assumption

3 Data Processing

3.1 Data Screening

We analyzed the raw data in the LBMA-GOLD.csv and BCHAIN-MKPRU.csv files,final data status is as follows:

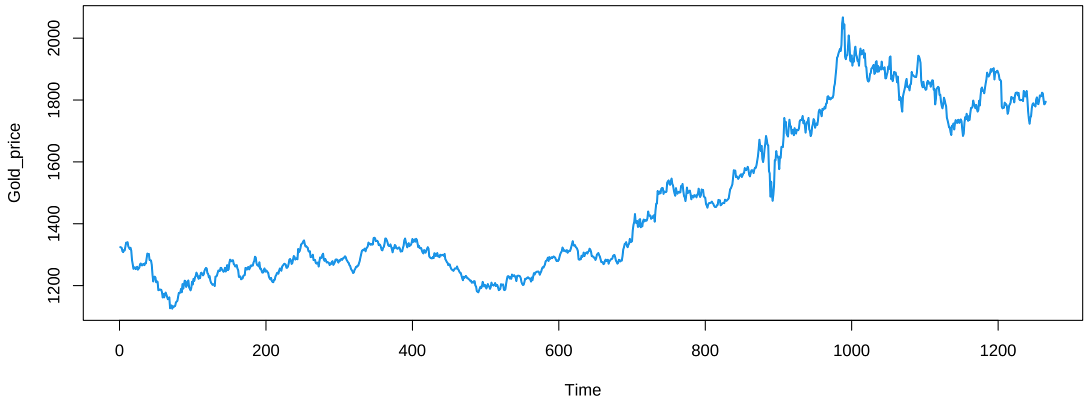
For the missing data in LBMA-GOLD.csv, we fill in the date according to the average of the day before and the day after.

3.2 Data Visualization

To observe the price trends of gold and bitcoin more visually, we visualize the given data and draw figure1and2

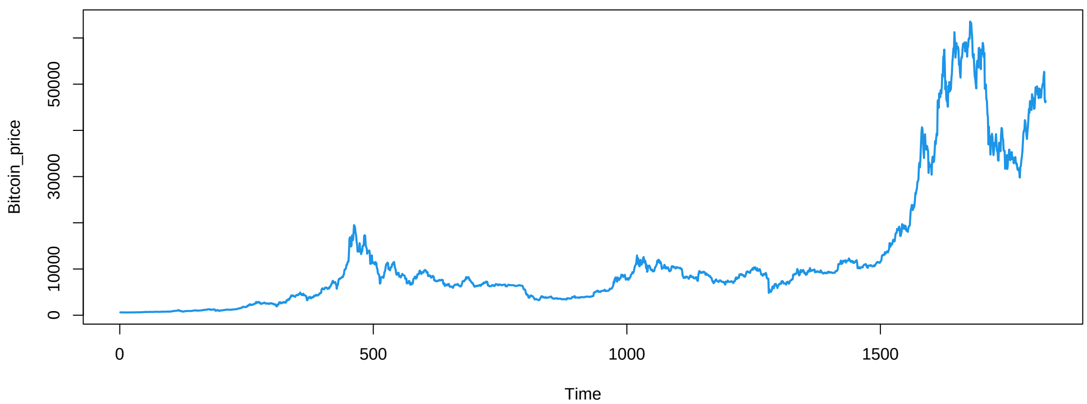
3.3 Mining Time Series

For subsequent data prediction using the time series model ARIMA, We perform stability test and white noise test on the raw data and processed data as a way to mine meaningful time series.



(a) 1

Figure 1: Gold price tendency



(a) 2

Figure 2: Bitcoin price tendency

3.3.1 Stability Test

First,we test the stability of the original data by comparing two methods, the image observation and the unit root test.

Testing unit rootand result is shown below:

Secondly,the first-order difference data is obtained according to the first-order difference of the original data, and the two methods abrove are also used to test.The result is as follows.4

Thirdly,utilizing second order difference we obtained second order difference data with two methods testing The result is shown in5.

3.3.2 White Noise Test

We need to evaluate whether the data is white noise or not, and will discard the one that is white noise because it has no research significance. So We chose Ljung-Box test to meet the demands.

The first step is to examine the raw data,The test yielded the following graph

The second step,we test first order difference data,result can be seen below

Third,we test second order difference data,result is shown below

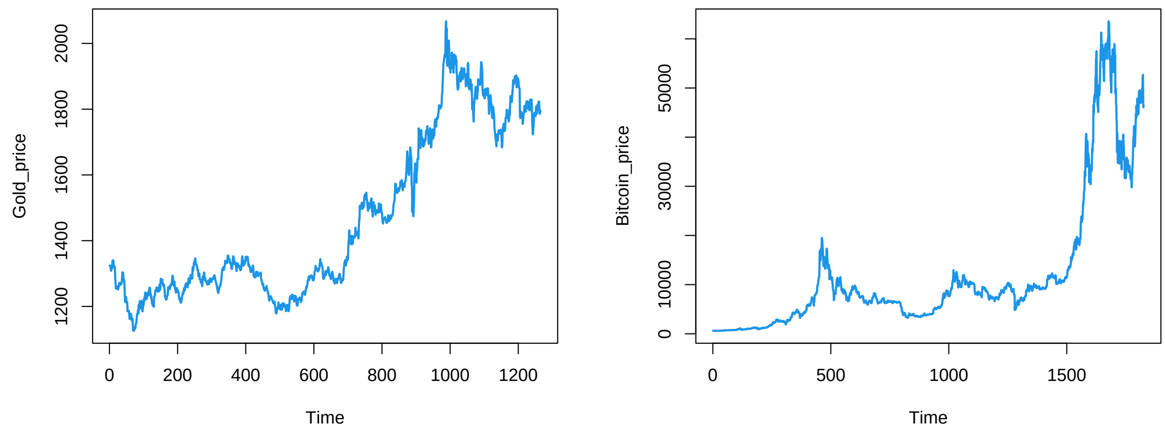


Figure 3: Raw data visualization

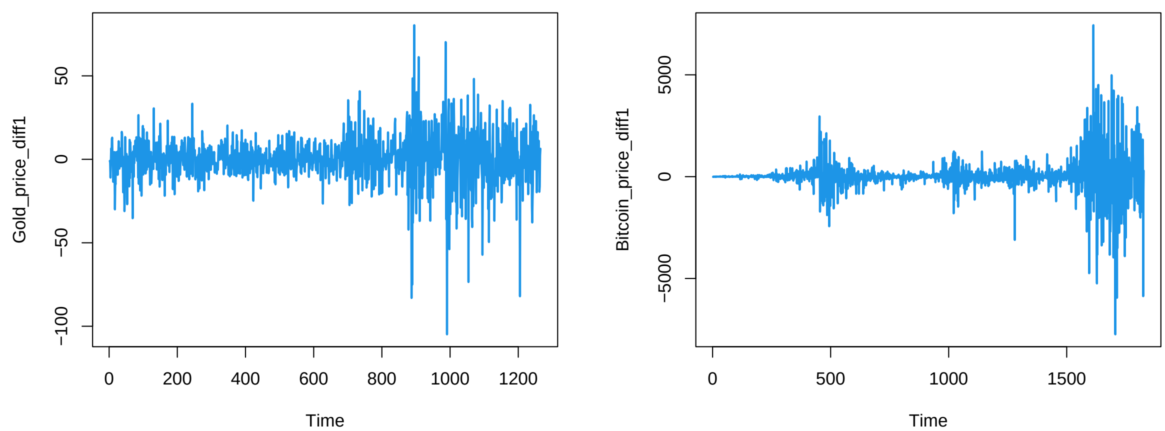


Figure 4: first order difference data

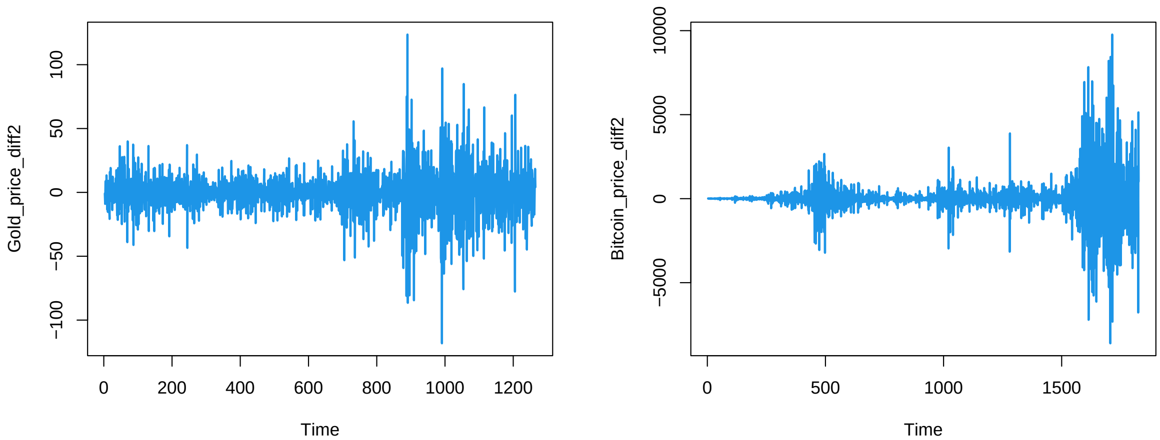


Figure 5: second order difference data

4 PartModel Development

4.1 Time Series Model ARIMA - Data Forecasting

4.1.1 Model Theory

AutoregressiveăIntegratedăMovingăAverage model is the differential integrated moving average autoregressive model, also known as the integrated moving(or slilding)average autoregressive model, is one of the time series forecasting analysis methods. In ARIMA(p, d, q),AR is "autoregressive", p is the number of autoregressive terms; MA is "sliding average ",q is the number of sliding average terms, and d is the number of differences (order) made to make it a smooth series. Although the word "difference" does not appear in the English name of ARIMA, it is a key step to analyse time series.

4.1.2 Determining the parameters p, q

We take advantage of the autocorrelation and partial autocorrelation plots to find out the parameters p, q. The following figures show the the format of autocorrelation and partial autocorrelation plots.

In theory Tail-dragging: always have non-zero values, not constant equal to zero after k is greater than some constant (or fluctuate randomly around 0).

Truncated tail: After greater than a constant k, it quickly tends to 0 as a k-order truncated tail when both autocorrelation and partial.

By figure 4and 5, it can be seen that the first order difference data and the second order difference data are meaningful time series. Therefore,we use the same methods in the subsequent section.The analysis charts are as follows.

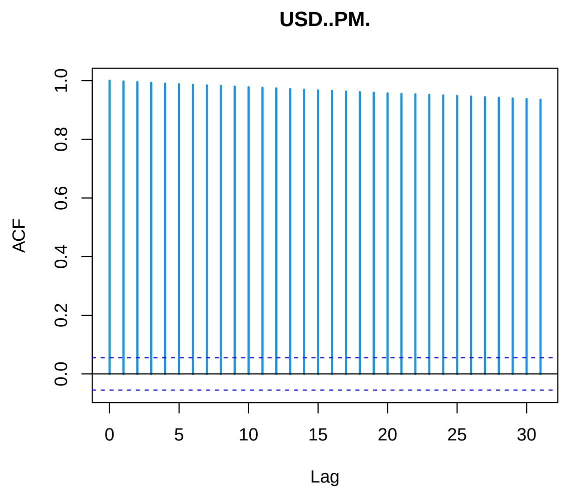


Figure 6: Autocorrelation diagram

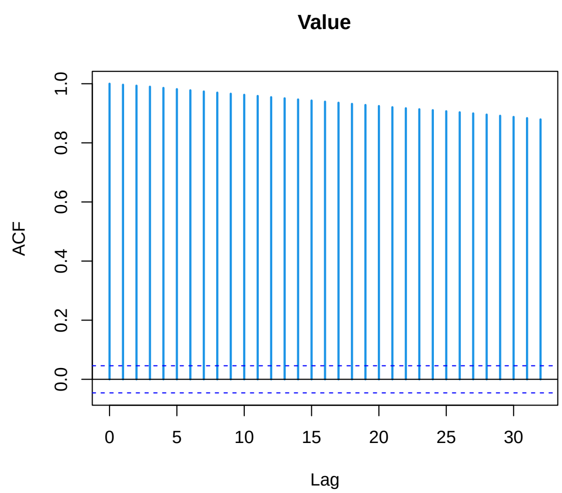


Figure 7: Partial autocorrelation diagram

4.1.3 R Language Determines the Optimal Parameters p, d, q

Given that only the price data as of the day can be used each day, i.e., the training data used each day are inconsistent, it is not practical to determine the optimal parameters for the model through autocorrelation and partial autocorrelation plots, so we use the auto.arima function in R language to automate the parameter determination.

The best model information was obtained after using the auto.arima function with all given data. And the model is as follows:

4.1.4 White noise test for model residuals

It is usually assumed that the model residuals of a reasonable model should be white noise. logically we conducted a white noise test on the residuals of the resulting model. The results are as follows.

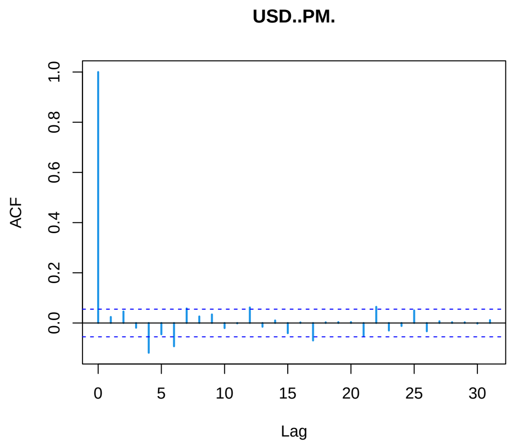


Figure 8: First order differential autocorrelation diagram-gold

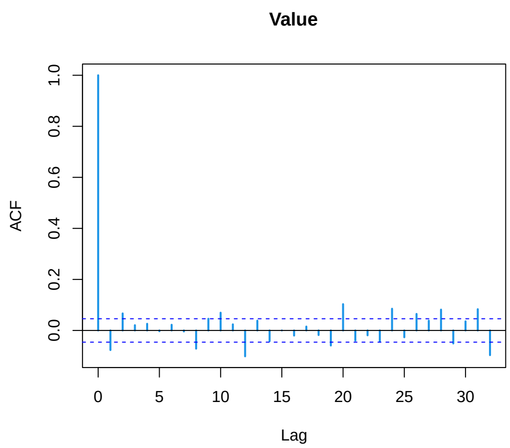


Figure 9: First order differential partial autocorrelation diagram-bitcoin

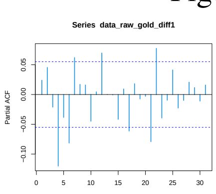


Figure 10: First order differential autocorrelation diagram-gold

Figure 11: First order differential partial autocorrelation diagram-bitcoin

4.1.5 Model Prediction and Visualization

To make the results more intuitive,we use the model to calculate and predict the historical data. And the visualization results are shown in the figure

The reason for the large overlap of lines in Figure 6 is that the data sample is too large. So we choose 100 of these samples and make graph7.

4.1.6 Batch prediction of data

Based on the price data as of the day,we predicted gold and bitcoin price for the next 7 days and the same automated arima modeling is performed using the auto.arima function to obtain the price data for the next 7 days. By analyzing the forecast data, we observed a roughly linear variation. Then,we integrated these data using linear regression to clarity the future price trend and fitted slope quantifies the trend to make the better investment decisions.

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4.1.7 Batch prediction of data

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4.2 Trading Strategy Model - Dynamic Programming

Notation: w_G:Gold holding ratio w_B:Bitcoin holding ratio r_G:Gold expected return r_B:Bitcoin expected return α_G:Commission ratio of gold transaction α_B:commission ratio of bitcoin transaction σ_G:Gold lower semi-variance of historical yield σ_B:Bitcoin lower semi-variance of historical yield β:Risk aversion coefficient of trader T:The average number of days held after each purchase of assets

4.2.1 Expected return on assets

Traders pay a percentage of commission when they buy and sell assets, in other words, there is hidden cost to holding assets every day. We use$\alpha \div T$ to represent such costs.

We determine trading behavior by comparing the expected benefit with the size of that cost. When expected revenue is large enough to offset this cost,model decide to buy; When the expected return is less than the negative cost, it represents maintaining; When the asset is about to lose more than commission cost,model needs to sold Holding share immediately to stop loss.

If$r > (1+\beta)\alpha \div T$it means that the asset will appreciation in the future,so trader can be buy in.

If$r < -(1-\beta)\alpha \div T$it represents that the asset will depreciation in upcoming period,so trader must sell them out .

If$-(1-\beta)\alpha \div T < r < (1+\beta)\alpha \div T$,it indicates that recent prices are stable,trader can either buy or sell.

moreover,due to the difference in investors and investment products, We introduceβ to characterize the diffrent degree of risk aversion.

The larger the β,refers to the more conservative the investors is,stricter restrictions on buying and more lenient restrictions on selling. On the contrary,thr smaller β indicates that the more aggressive the investor is, who has more lenient buying criteria and more stringent selling criteria.

Additionally,we have to consider the following two situations when purchasing: ,

1. If only one of gold and bitcoin meets the upside condition, then we simply buy all of our currently available funds into that asset.
2. Whereas if gold and bitcoin rise at the same time,there is a need to consider how to allocate the available funds. In this case, we use the Sharpe ratio to measure the different proportional investment groups

$$Sharpe\ Ratio = \frac{w_G \times r_G + w_B \times r_B}{\sqrt{w_G^2\sigma_G^2 + w_B^2\sigma_B^2 + 2Cov_{w_Bw_G}}}$$

We use the lower semi-variance as a quantitative index of risk, as the portion of the standard deviation that represents fluctuations less than the mean. which is more indicative of the risk of asset losses. We divide the expected return by the following half standard deviation yields the Sharpe ratio,which implies the magnitude of the return per unit of risk of the current portfolio. When the Sharpe ratio is maximum, it undoubtedly means that the current proportion of the portfolio is optimal

Based on the assumptions that "All cash is consumed at each purchase" and "The price fluctuations of gold and bitcoin are independent of each other", We simplify the problem of solving the optimal investment ratio as an optimization problem. And we can use the computer to find its numerical solution.

$$\begin{aligned} max \quad & \frac{w_G \times r_G + w_B \times r_B}{\sqrt{w_G^2\sigma_G^2 + w_B^2\sigma_B^2}} \\ s.t. \quad & w_G + w_B = 1 \\ & 0 \le w_G \le 1 \end{aligned}$$

4.2.2

	cash	gold	bitcoin
$2^3-2=6()$	●	○	○
	●	○	●
	●	●	○
	○	○	●
	○	●	○
	○	●	●

4.2.3

9 654546

1. one maintain,the other appreciate:
2. one maintain,the other depreciate:
3. one appreciate,the other depreciate:
4. both maintain:
5. both appreciate: 4.2.1 10
6. both depreciate:

4.2.4

- 4.2.14
-

4.2.5

$\beta = 0.2$

5 Part:Strategy Evaluation

5.1 Set Perturbation Terms

5.2 Comparison Illustrates the Best Strategy

6 Part:Sensitivity Analysis

6.1 Assuming Changes In Commission

6.2 Visualization Results

7 Evaluate of the Model

7.1 Strengths and weaknesses

7.2 Sensitivity Analysis

8 Conclusions

9 A Memo

References

[1] D. E. KNUTH The TEXbook the American Mathematical Society and Addison-Wesley Publishing Company , 1984-1986.

[2] Lamport, Leslie, LATEX: " A Document Preparation System ", Addison-Wesley Publishing Company, 1986.

[3] `https://www.latexstudio.net/`

Appendices

Appendix A First appendix

In addition, your report must include a letter to the Chief Financial Officer (CFO) of the Goodgrant Foundation, Mr. Alpha Chiang, that describes the optimal investment strategy, your modeling approach and major results, and a brief discussion of your proposed concept of a return-on-investment (ROI). This letter should be no more than two pages in length.

Dear, Mr. Alpha Chiang

Sincerely yours,

Your friends

Here are simulation programmes we used in our model as follow.

Input matlab source:

```
function [t,seat,aisle]=OI6Sim(n,target,seated)
pab=rand(1,n);
for i=1:n
    if pab(i)<0.4
       aisleTime(i)=0;
    else
        aisleTime(i)=trirnd(3.2,7.1,38.7);
    end
end
```

Appendix B Second appendix

some more text **Input C++ source:**

```
//===================================================================
// Name        : Sudoku.cpp
// Author      : wzlf11
// Version     : a.0
// Copyright   : Your copyright notice
// Description : Sudoku in C++.
//===================================================================

#include <iostream>
#include <cstdlib>
#include <ctime>

using namespace std;

int table[9][9];

int main() {

    for(int i = 0; i < 9; i++){
        table[0][i] = i + 1;
    }

    srand((unsigned int)time(NULL));

    shuffle((int *)&table[0], 9);

    while(!put_line(1))
    {
        shuffle((int *)&table[0], 9);
    }

    for(int x = 0; x < 9; x++){
        for(int y = 0; y < 9; y++){
```

```
            cout << table[x][y] << " ";
        }

        cout << endl;
    }

    return 0;
}
```

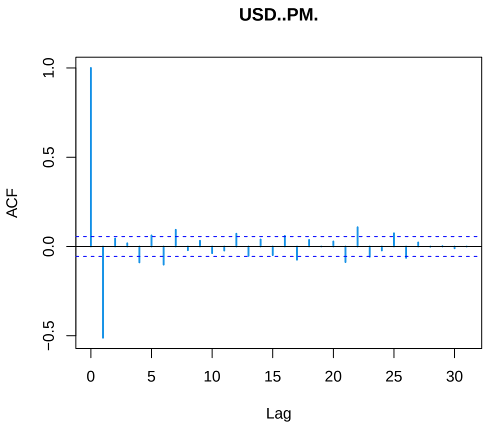

Figure 12: Second order differential autocorrelation diagram-gold

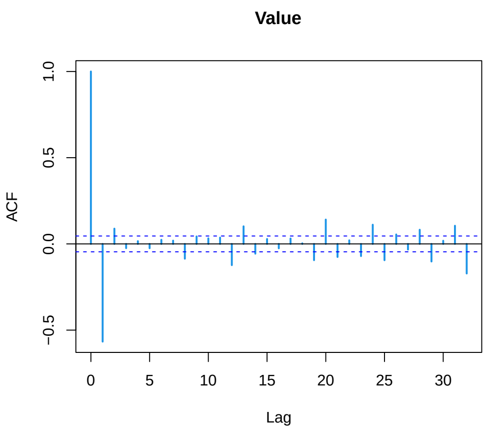

Figure 13: Second order differential partial autocorrelation diagram-bitcoin

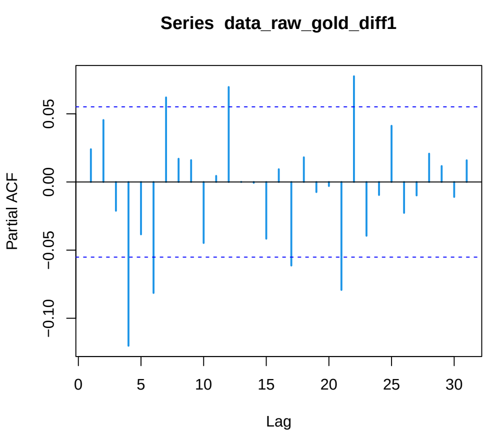

Figure 14: Second order differential autocorrelation diagram-gold