

Problem Chosen

A

**2022
MCM/ICM
Summary Sheet**

Team Control Number

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The L^AT_EX Template for MCM Version v6.3.1

Summary

Keywords: keyword1; keyword2

The L^AT_EX Template for MCM Version v6.3.1



February 21, 2022

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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:

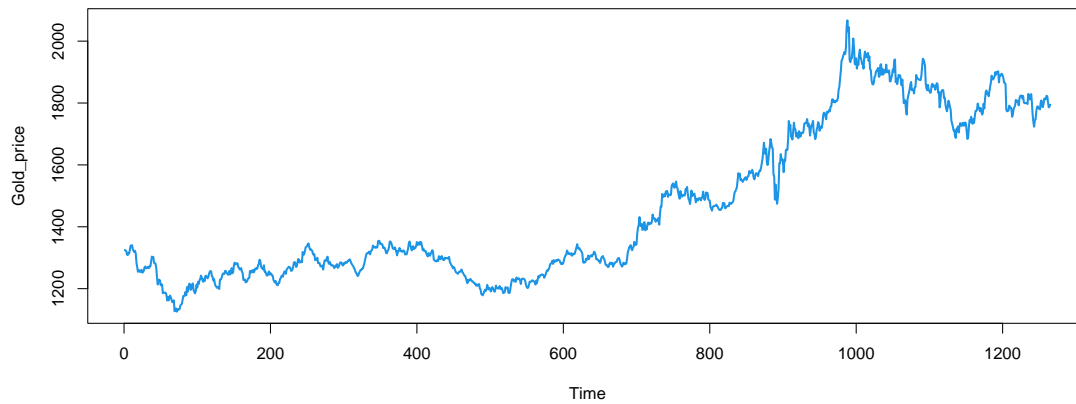
For the missing data in LBMA-GOLD.csv, we fill in the date according to the average of the day before and the day after.

3.2 Data Visualization

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

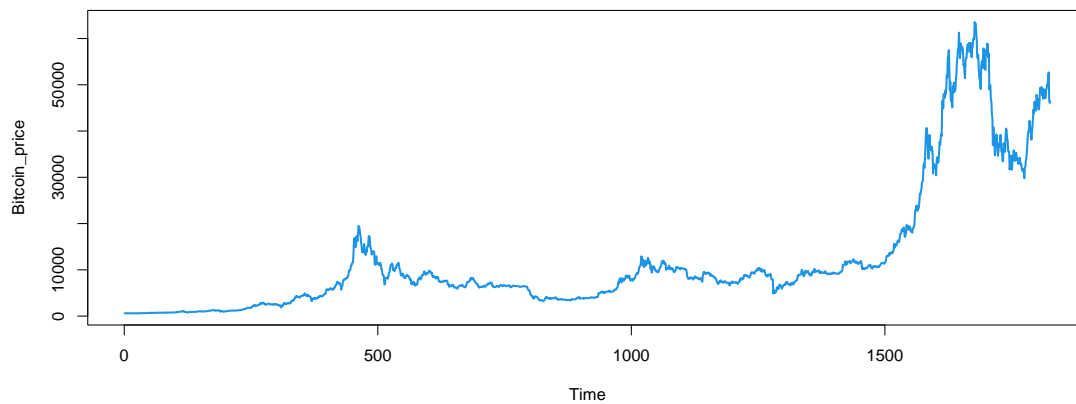
3.3 Mining Time Series

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 root and 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 above 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

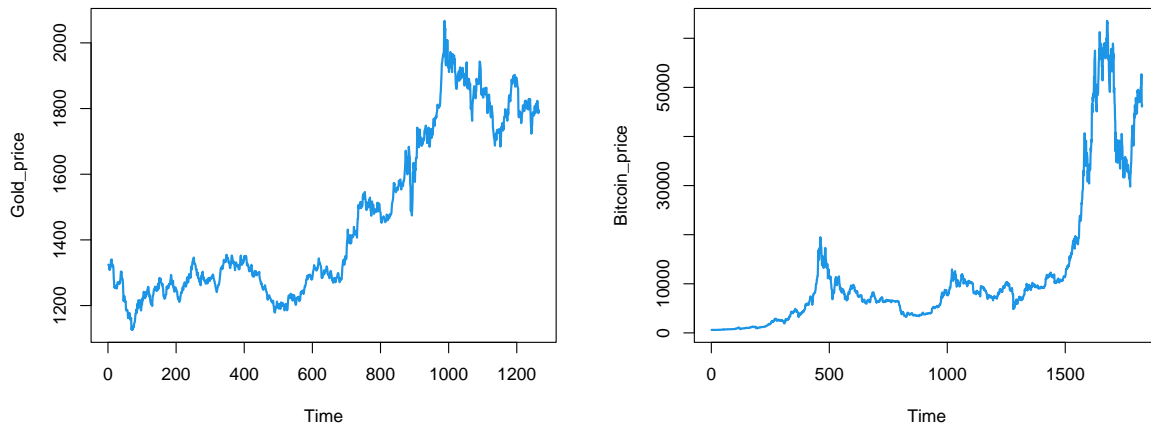


Figure 3: Raw data visualization

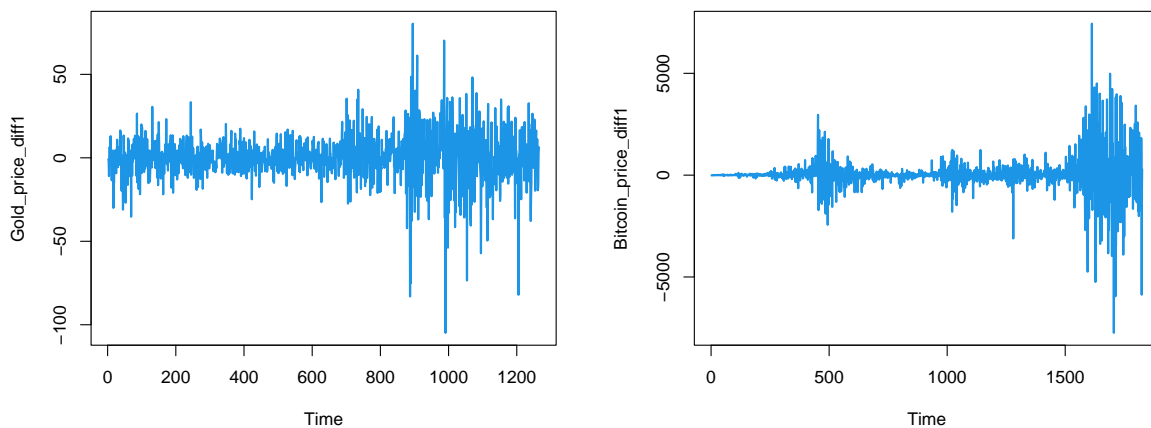


Figure 4: first order difference data

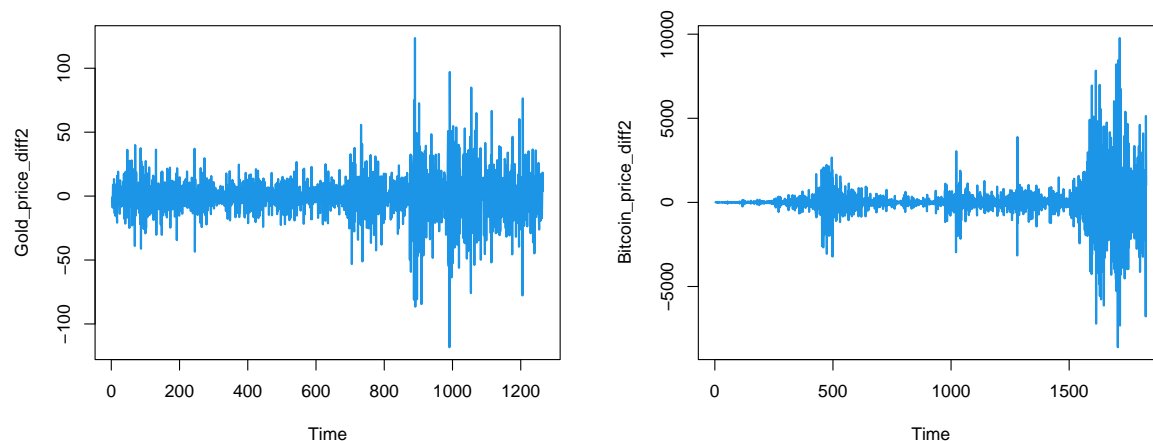


Figure 5: second order difference data

4 PartModel Development

4.1 Time Series Model ARIMA - Data Forecasting

4.1.1 Model Theory

Autoregressive Integrated Moving Average model is the differential integrated moving average autoregressive model, also known as the integrated moving (or sliding) 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 4 and 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.

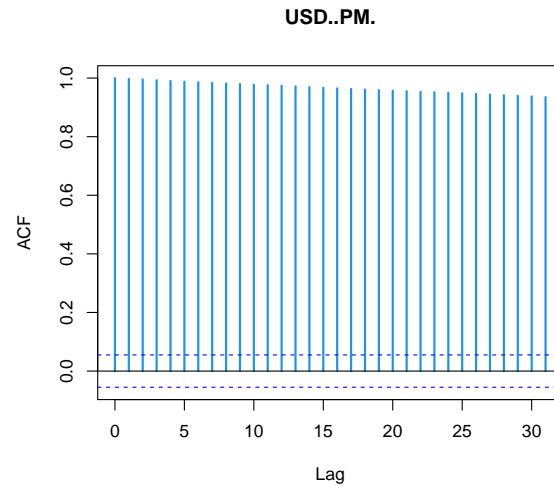


Figure 6: Autocorrelation diagram

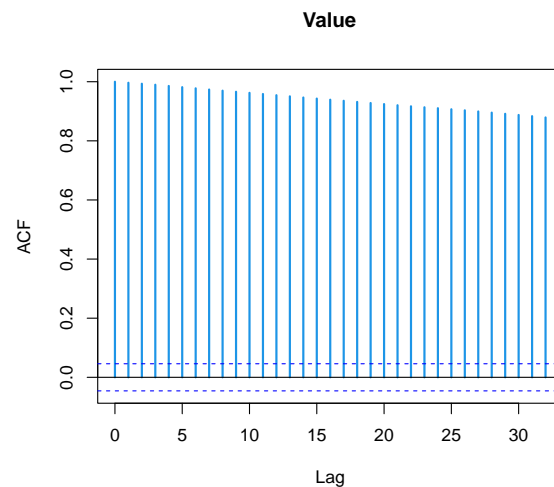


Figure 7: Partial autocorrelation diagram

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:

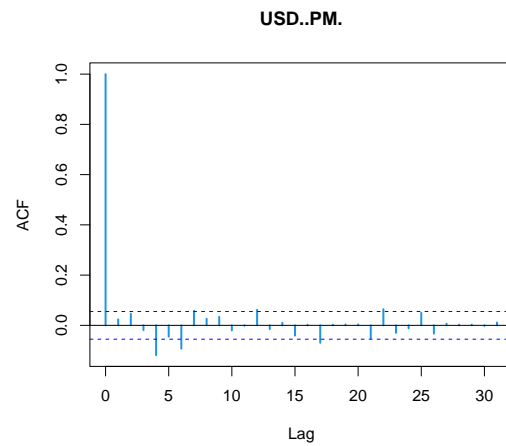


Figure 8: First order differential autocorrelation diagram-gold

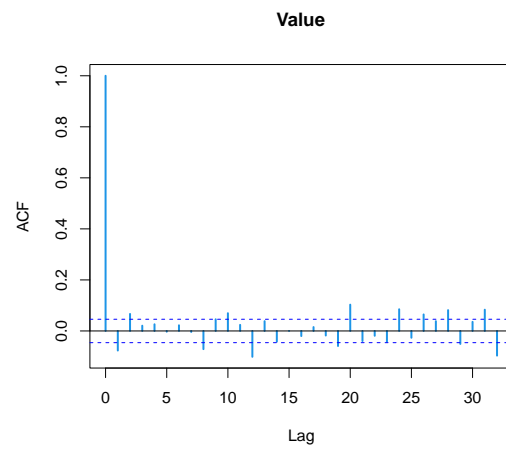


Figure 9: First order differential partial autocorrelation diagram-bitcoin

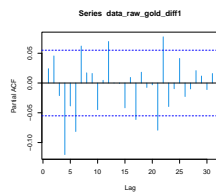


Figure 10: First order differential autocorrelation diagram-gold

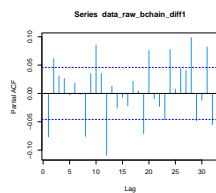


Figure 11: First order differential partial autocorrelation diagram-bitcoin

4.1.4 Model Validating

4.1.5 Model Prediction and Visualization

4.1.6 Batch prediction of data

4.2 Investment Decision Model - Dynamic Programming

4.2.1 Buy and Sell Standard Setting

4.2.2 Portfolio Optimal Ratio Identification

4.2.3 Positioning Standard Identification

4.2.4 Daily Portfolio Determinations

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 \TeX book 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
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;
}
```

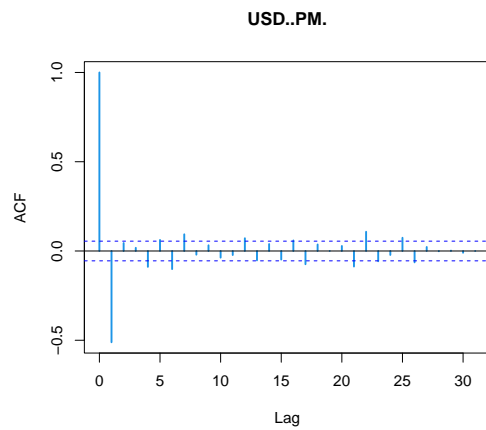


Figure 12: Second order differential autocorrelation diagram-gold

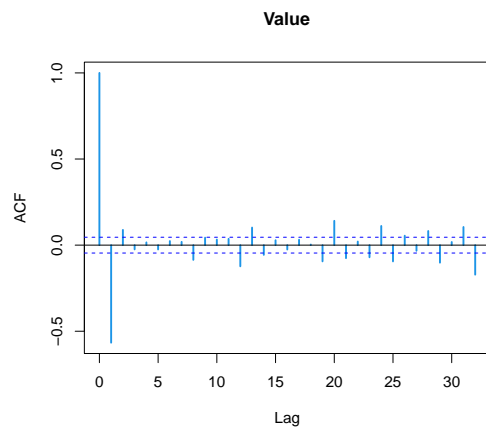


Figure 13: Second order differential partial autocorrelation diagram-bitcoin

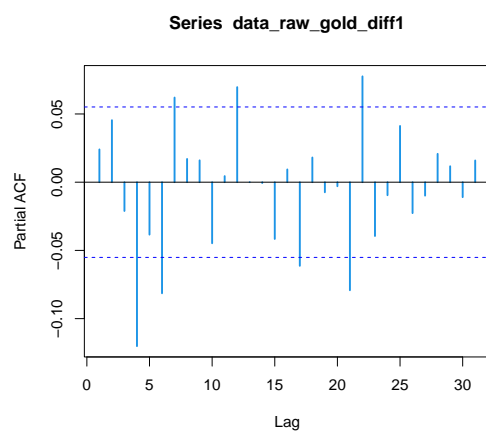


Figure 14: Second order differential autocorrelation diagram-gold

