Problem Chosen	2022 MCM/ICM Summary Sheet	Team Control Number
C		2217034

Trading Strategy Model:MA-FTM Based on Apriori Algorithm

Summary

Market traders often profit by buying and selling gold and bitcoin. This paper puts forward a comprehensive strategy MA-FTM, which can help traders to take the existing data as the reference for the next operation, so as to obtain more profits more stably.

We first introduced the Fuzzy Trading Model (FTM), the core Model of our Trading strategy. FTM is a model that needs training. In the process of training, FTM uses the concept of fuzzy set to process data, and then uses Apriori Algorithm to establish the mapping relationship between buy and sell signals and the current rise. When FTM is used for judgment, FTM can map directly to an operation through data from the previous days.

In order to train FTM and make better decisions at the same time, Moving Average(MA) model was introduced in the early stage. MA model uses Moving Average Convergence Divergence as an indicator to make decisions, which requires a small amount of previous data, so it is suitable for making initial decisions. Based on the characteristics of MA model and FTM, we established a MA-FTM comprehensive decision model and conducted experiments using five years' data. The change curve of the asset and the final result are obtained.

Then, we analyze and design the parameters of the model. From the qualitative point of view, we discuss the design method of parameters, give the basis of parameter assignment, and analyze how parameters affect the model. From the quantitative point of view, we conducted a comparative experiment on transaction cost, analyzed the experimental results and data, and got the conclusion of sensitivity analysis on transaction cost. We also designed parameters for fine-tuning model maturity and risk measurement.

After that, we present evidences that our model provides the best strategy. We compared some other models and provided some good evidence for our model from the perspective of error analysis and economic analysis. We also analyzed the strengths and weaknesses of our model, which can make you a better understanding of this model.

Finally, we present our strategy in the form of a memo to market traders for their reference.

Keywords: Fuzzy Trading Model, Fuzzy Set, Apriori Algorithm, MA model

Content

1 Introduction

“All good things come to an end. ”

——Geoffrey Chaucer

As the saying goes, the value of the “good things” — both physical gold and bitcoin, the so-called "digital gold" — rises and falls. Market traders tend to profit by trading these assets frequently. Therefore, a good trading strategy can help traders maximize profits quickly and safely.

1.1 Problem Restatement

In this topic, we were asked to develop a model that used the prices of gold and bitcoin up to that day to determine whether traders should buy, hold or sell each asset each day.

We need to

- Develop trading models, formulate trading strategies, use those models and strategies, and figure out what the first 1000 dollars will be worth in five years.
- Provide evidence that our model provides the best strategy.
- Determine the sensitivity of our strategy to transaction costs.
- Write a memo of our strategy to the trader.

1.2 Literature review

We investigated the investment decision making methods in today's popular quantitative trading, which can be roughly divided into the following two categories. Traditional empirical strategies based on historical data analysis have distilled subjective trading rules (represented by riding the wind and trend tracking strategies proposed by Wang [1]) and investment strategies based on neural networks (represented by ANN applied by Rajashree [2]). The first kind of method has a good performance at present, but it is criticized for its high subjective participation. And because the second type of method is limited by poor interpretability, there is no way to prove the effectiveness of the strategy in principle.

Based on this, we propose a MA-Fuzzy trading model. By referring to the relevant definitions and properties ([3] [4]) and the fuzzy method of technical indicators proposed by Yao [5], the paper establishes its own fuzzy indicators, uses Aproori algorithm to generate association rules and obtain buy and sell judgment signals. Finally, we evaluated our model by referring to some common indicators [6] [7].

1.3 Data Processing and Analysis

Through data processing of the two files BCHAIN-MKPRU.csv and LBMA-GOLD.csv, there are 1826 items of bitcoin transaction price data and 1255 items of gold transaction price data.

Since gold is only traded on trading days and data on weekends and other holidays are empty, in order to simplify the processing process, we use the method of forward filling to fill the blank of gold trading price on non-trading days.

After aligning the gold and Bitcoin transaction data, we get Figure 1 below. You can see that gold and bitcoin as a whole have been on the rise over the past five years, while Bitcoin has risen much more than gold.

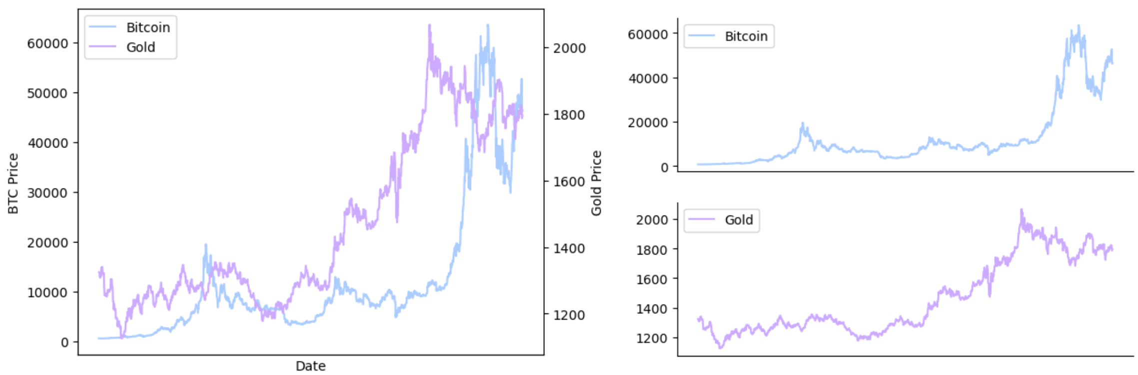


Figure 1 Gold and Bitcoin transaction data

To further explore the characteristics of the data, we calculate SMA, the simple moving average. The simplest use of SMA in technical analysis is to use it to quickly determine whether a price curve is in an upward or downward trend. We set the window size to 15. The obtained Figure 2 shows a basically consistent trend with the original data curve.

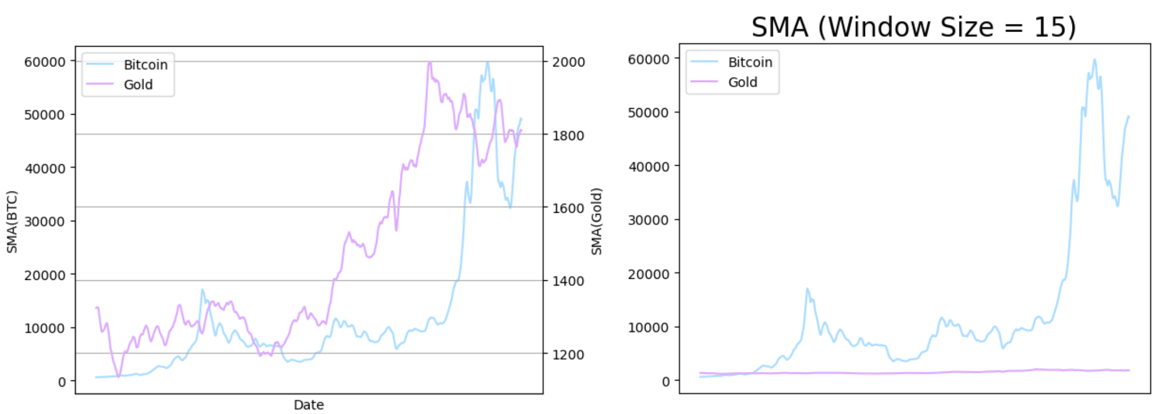


Figure 2 SMA of Gold and Bitcoin

In order to analyze the rising trend of gold and bitcoin and compare them, we draw the first derivative[1] diagram of their moving average in Figure 3, which shows that the trend of the two is

[1] We use difference here to compute the derivative.

not closely related. Further calculation of the correlation coefficient of the two, the result is about 0.0081247.

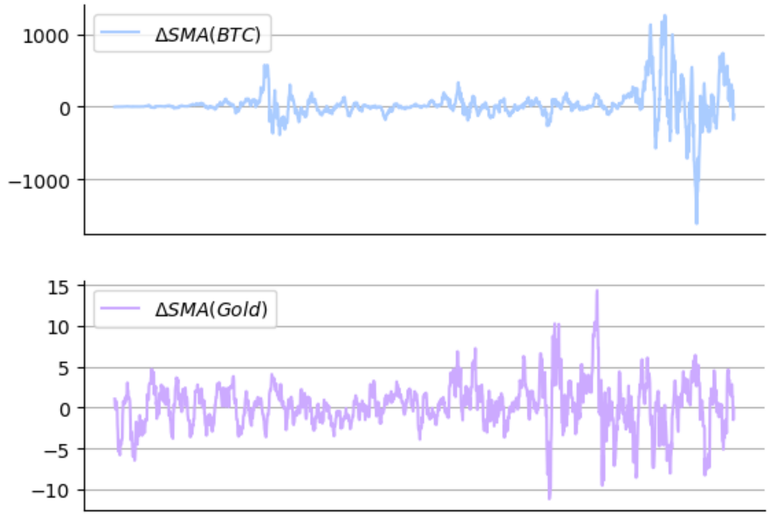


Figure 3 Derivative of SMA

2 Assumptions and Nomenclature

Before formally introducing our model, in order to better explain the model, we will put forward some assumptions in Section 2.1, and give the parameters and nomenclatures used in the model and their descriptions in Section 2.2.

2.1 Assumptions

- ✧ Asm1. We divide market traders into "risk aversion[2]" and "risk taker". The model takes traders as "risk aversion".
- ✧ Asm2 Based on data processing, the model believes that there is no relationship between the price curve of gold and the price curve of bitcoin, that is, they can be considered independent of each other.

[2] See more details on https://en.wikipedia.org/wiki/Risk_aversion

2.2 Nomenclature Table

Parameters and Nomenclatures	*Description*
t	**Date ordinal (start date 1)**
α	**The commission on each transaction is α % of the**
PTS	**Price Trend Set**
$BSSS$	**Buy-Sell Signal Set**
x	**price fluctuation variable**
$\mu_m(x_t)$	**Membership function of m on day t**
ω	**Sensory threshold parameter**
β	**Transaction sensitivity parameter**
ϕ	**Price volatility vector, a seven-dimensional vector**
ψ	**Buy-Sell signal vector, a seven-dimensional vector**
ed	**Buy-Sell signal strength variable**
θ	**Model usage parameter**
γ	**Risk parameter**

3 Fuzzy Trading Model

3.1 Model Overview

In this model, we use the idea of establishing fuzzy sets to quantify the state of the current price curve and the Buy-Sell signal into two vectors by using the trigonometric membership function of fuzzy sets, and use the Apriori algorithm to build the mapping relationship between the two vectors. In this way, we can generate a set of fuzzy trading rules and establish a decision system. This allows us to use the current price curve mapping to get the actions and weights we should take. Finally, the ratio of buy and sell is adjusted by stability analysis. The model framework is shown below.

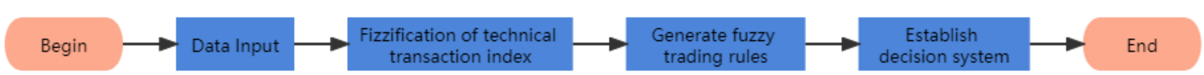


Figure 4 Fuzzy Trading Model

As you may have noticed, this model requires training. Therefore, the above process can also be regarded as a training model using training sets.

3.2 Fuzzification

In this section, we fuzzily process the commonly used trading indicators in the market to form the natural language set (PS and BSSS) of the fuzzy system, and then get the vector representation of the fuzzy set according to the membership function. First we introduce the concepts of fuzzy set and membership function.

Given a domain U, then a mapping from U to the unit interval [0,1] is called a fuzzy set on U, or a fuzzy subset of U. The fuzzy set can be called D. The map (function) $\mu_D(\cdot)$ or simply $D(\cdot)$ is called the membership function of the fuzzy set D. For each $y \in U$, $\mu_D(x)$ is called the membership degree of element y to the fuzzy set D. The membership degree of each fuzzy set on U can be jointly written as a vector.

The moving average p is the average of the previous n days at the time of t

$$p_{t,n} = \frac{1}{n}\sum_{i=0}^{n-1} p_{t-i} \tag{1}$$

Take $m < n$ and calculate the relative change of MA of length m with respect to MA of length n.

$$x_{1,t}^{(m,n)} = \ln\left(\frac{p_{t,m}}{p_{t,n}}\right) \tag{2}$$

From this formula, we can see that when $x > 0$, the current price is in the mode of increase; when $x < 0$, the current price is in the mode of decline, and the absolute value of x indicates the fluctuation range. So x reflects the current price fluctuation.

We use the concept of fuzzy sets to quantify the price trend and Buy-Sell signal as vectors. Therefore, we construct the price trend set PTS, the Buy-Sell signal set $BSSS$, the price trend vector φ, and the B-S signal vector ψ.

3.2.1 PTS *and* φ

First, we focus on PTS, the price trend set, which consists of seven fuzzy sets. We define these seven fuzzy sets according to the percentage change amplitude of $x_{1,t}^{(m,n)}$

PS	**Positive small**
PM	**Positive middle**
PL	**Positive large**

NS	**Negative small**
NM	**Negative middle**
NL	**Negative large**
AZ	**Zero**

and construct their trigonometric membership function. Take PL, for example, whose membership function is

$$\mu_{PS}\left(x_{1,t}^{(m,n)}\right) = \begin{cases} 0 & if\ x_{1,t}^{(m,n)} < 2\omega \\ \dfrac{x_{1,t}^{(m,n)} - 2\omega}{\omega} & if\ x_{1,t}^{(m,n)} \in [2\omega, 3\omega] \\ 1 & if\ x_{1,t}^{(m,n)} > 3\omega \end{cases} \tag{3}$$

Among them, ω is called sensory threshold function, which is a controllable variable used to reflect the scale of volatility perceived by traders. We will examine this in detail in the next section.

The membership function images of the seven fuzzy sets in PTS are shown in the figure

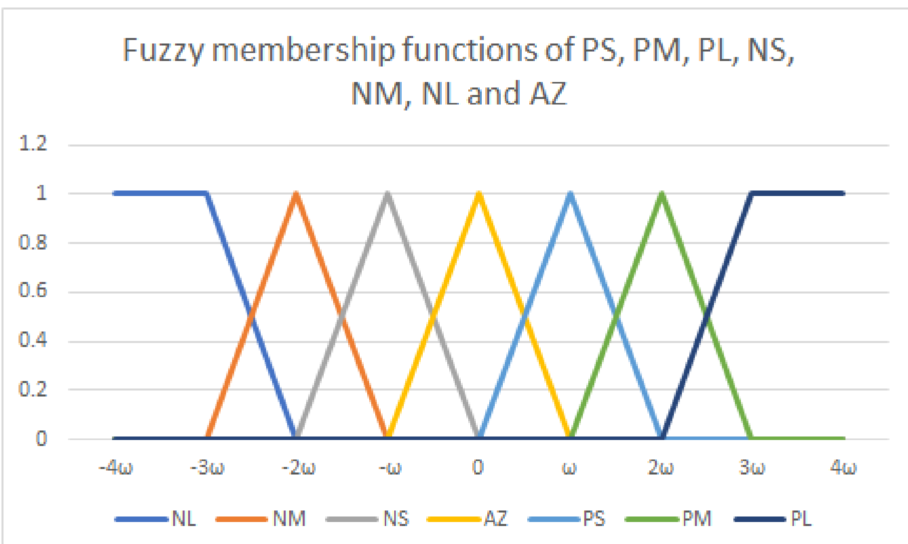


Figure 5 Membership function of PTS

So, for every $x_{1,t}^{(m,n)}$ we get, we can plug it into these seven functions, and we get a seven-dimensional vector. For example, on day 5, if ω is set to 0.01 and $x = 0.01$, the resulting vector φ_5 is (1,0,0,0,0,0,0).

3.2.2 $BSSS$ *and* ψ

Let's look at the B-S signal set. Likewise, $BSSS$ is made up of seven modes of signal

BS	**Buy small**
BM	**Buy middle**
BB	**Buy big**
SS	**Sell small**
SM	**Sell middle**
SB	**Sell big**
N	**No operation**

They are both fuzzy sets and have their own membership functions. To assess the strength of the buy and sell signal, we define a new concept, ed[3], which represents the ratio of the price of the following day to that of the current day. When $ed > 0$ is large, the signal of buy operation can be considered strong, and so on. So we have seven membership functions, as shown here

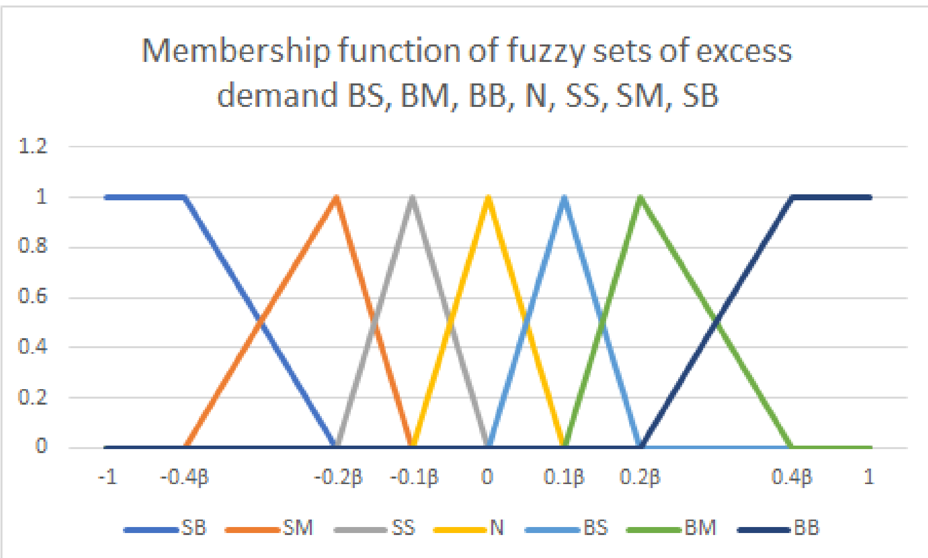


Figure 5 Membership function of BSSS

For example, the membership function of BB is

$$\mu_{BB} = \begin{cases} \dfrac{ed-\beta}{\beta} & if\ ed \in [\beta, 2\beta] \\ \dfrac{(4\beta - ed)}{2\beta} & if\ ed \in [2\beta, 4\beta] \\ 0 & otherwise \end{cases}$$

[3] The calculation method of ed is at the trader's discretion. The calculation method we choose in our model is (tomorrow's price - today's price) / today's price

Similarly, we have a Transaction sensitivity parameter β. For every ed we get, we can plug it into these seven functions, and we get a seven-dimensional vector ψ.

From this section we can see that $x_{1,t}^{(m,n)}$ and ed are the so-called common trading indicators, and after blurring they become vectors φ and ψ.

3.3 Apriori algorithm

Now that we have fuzzy the data, we need to extract the trading rules from them. The algorithm we use is Apriori algorithm. Here's an overview of the algorithm.

Purpose: This algorithm is used to establish fuzzy association rules from $x_{1,t}^{(m,n)}$ to ed, that is, to establish the mapping relationship between φ and ψ.

Apriori algorithm

Algorithm input: set of vectors φ and ψ

Algorithm output: fuzzy association rules

Algorithm process:

① Input processing. Associate two vectors of the same day to form a 14-dimensional vector $(\varphi_t,\ \psi_t)$ and simplify it to a list. For example, a 14d vector is [0,0,0.5,0.5,0,0,0,0,0,0,0,0,0,1], is reduced to a list of [3,4,14].

② Look for frequent sets. A frequent set, as the name suggests, is a collection of items that appear together frequently. We use the $support$ to show the proportion of entries containing this item set in the selected fixed data set. The higher the support degree is, the greater the probability of becoming frequent set. We can set a minimum level of $support$. (P is the probability of occurrence.)

$$Support\ = P\ (A \cup B) \tag{4}$$

In step ①, we generate all the lists, iterate through them, and find all the itemsets in increasing order of dimension, such as {1}, {2}, {3}, ..., {1,2}, {1,3} ..., {1,2,3}, ... Record the number of items. If the number of items in a set is greater than $the\ minimum\ support \times the\ total\ number\ of\ sets$, the set is considered to be a frequent item set. A list of frequent sets is a list of possible rules.

③ The $confidence$ degree of a rule $A \rightarrow B$ can be quantified as

$$Confidence = \frac{support(A \cup B)}{support(A)} \tag{5}$$

The higher the confidence, the stronger the correlation. We specify the minimum confidence and delete the rules that do not satisfy the confidence in frequent sets. We end up with a set of trading rules.

4 Trading Strategies

In the previous section, we introduced the Fuzzy Trade Model (FTM), which is our core model. FTM does not have enough training sets in the early stages, given that we only have data from the trading day to the day when we make daily decisions. In order to accumulate training data while making rational decisions, we used MA-FTM comprehensive strategy.

4.1 Overview

We divide the strategy into several sections by year. As shown in Figure 7, in the first two years, we used MA model, which does not require training and can obtain relatively robust judgments through a small amount of data. For details, see Section 4.2. Meanwhile, we accumulated the data of the previous two years as a training set to train FTM model. In the third and fourth years, we used THE FTM model to determine the trading strategy, and updated the training set to train the FTM model again. In the fifth year, we used the updated FTM model to determine the strategy.

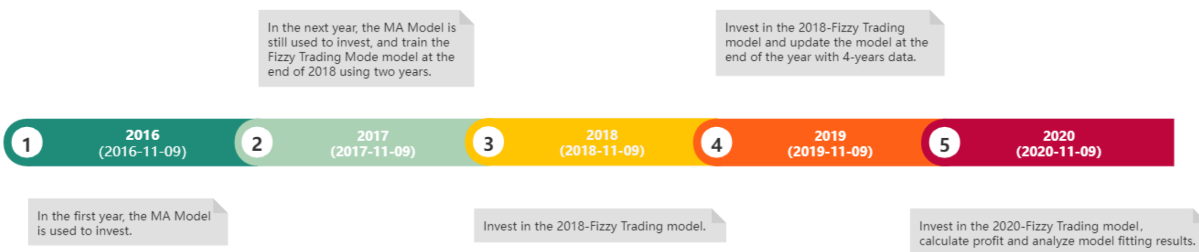


Figure 7 The timeline

After the trader has the day's data, the MA-FTM comprehensive strategy flow chart is shown as Figure 8

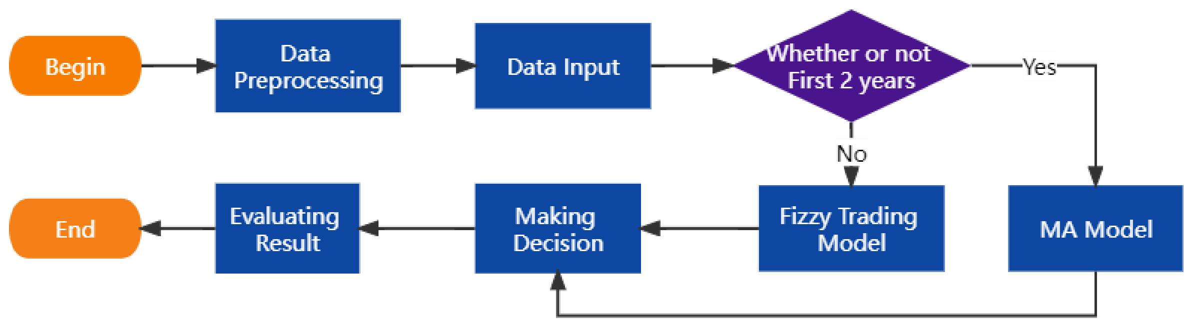


Figure 8 Trading Strategies

4.2 MA Model-based decision making

Firstly, we calculate MACD[4] index, and the process is as follows:

① Calculate fast moving average EMA12 and EMA26

② The difference value DIF is obtained by subtracting EMA12 and EMA26

③ Calculate the mean value of 9-day DIF (mean deviation is MACD)

In five years, we can calculate the MACD value of the day (as shown in Figure 9), and make decisions according to the DIF value and MACD value calculated on the day. Specific decisions are made in the following table.

Current MACD > Last MACD, and DIF， MACD>0	**BM**
Current MACD < Last MACD, and DIF， MACD>0	**SS**
Current MACD > Last MACD, and DIF， MACD<0	**BM**
Current MACD< Last MACD, and DIF， MACD>0	**SS**
Current MACD and DIF are inconsistent	**N**

The BM in the table refers to Buy Middle, using 20% of the current cash to Buy an asset. SS means to Sell Small, to sell 10% of your assets. N indicates no operation.

[4] See more on https://en.wikipedia.org/wiki/MACD and https://en.wikipedia.org/wiki/EMA

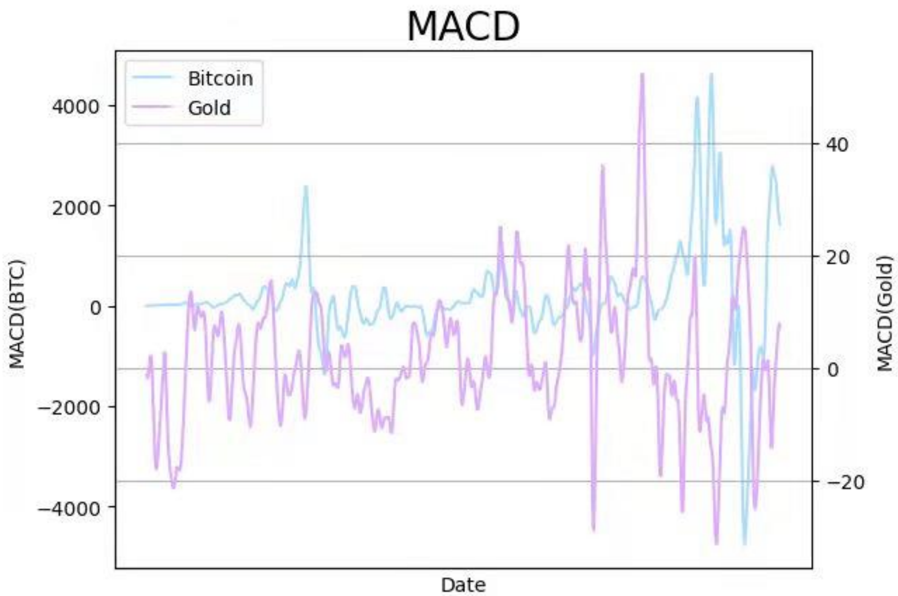


Figure 9 MACD

4.3 FTM-based decision making

In section 3 (3.1-3.3), we introduced the training process of FTM in detail. Next, we introduce the use of FTM and how to make decisions with FTM. Figure 10 shows us the FTM-based decision flow. When we got the data for the day, we of course first processed the data to get $\boldsymbol{x}$. Our ultimate goal is to map x to the B-S signal ed through the trained FTM, and then substitute $\widehat{\boldsymbol{ed}}$ into the membership function to get a vector. Specific strategies can be calculated according to the buying and selling intensity and weight represented by each dimension of the vector.

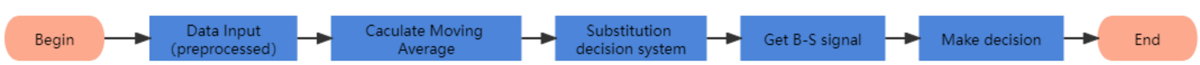


Figure 10 FTM-based strategy

Next we calculate $\widehat{\boldsymbol{ed}}$. After training we get a set of rules, which are like PS→BB from PTS to $BSSS$. We define the set of these rules as fuzzy transaction library. Then the function relation of $\widehat{\boldsymbol{ed}}$ to $\boldsymbol{x}$ is:

$$\widehat{ed} = \frac{\sum_{i=1}^{M} c_i \mu_{Ai}(x)}{\sum_{i=1}^{M} \mu_{Ai}(x)} \tag{6}$$

where c_i represents each fuzzy center in BSSS. When $\beta = 0.1$, c_i is [-0.4,-0.2,-0.1,0,0.1,0.2,0.4]. Here we show the rules generated from the previous two years of data and the generated function $\widehat{ed}\ (x)$.

GOLD：*PL*→*BM* *PM*→*BM* *NL*→*SM* *NM*→*SM*

$$\widehat{ed}\,(x) = \frac{2\beta\mu_{PL}(x) + 2\beta\mu_{PM}(x) - 2\beta\mu_{NL}(x) - 2\beta\mu_{NM}(x)}{\mu_{PL}(x) + \mu_{PM}(x) + \mu_{NL}(x) + \mu_{NM}(x)} \tag{7}$$

BITCOIN：PL→BB NL→SB

$$\widehat{ed}\,(x) = \frac{4\beta\mu_{PL}(x) - 4\beta\mu_{NL}(x)}{\mu_{PL}(x) + \mu_{NL}(x)} \tag{8}$$

4.4 Some details

(1) Forward alignment is adopted in our data processing, so traders do not need to do anything on non-gold trading days. In the new gold opening day data and the previous gold trading day can be linked.

(2) Based on Asm.2, we believe that gold and bitcoin are independent of each other. So, we apply the above strategy to gold and bitcoin respectively, and get two decisions. The order in which decisions are executed is at the trader's discretion. Due to Asm.1, our default trader is robust, and for the convenience of operation, we adopted the method of "buy > sell" and "gold > bitcoin" in these 5 years. “>” indicates the execution priority.

5 Results and Analysis

5.1 The Results Show

Using the MA-FTM synthesis strategy proposed in the previous section (see Figure 8), we conducted experiments using only data from the files LBMA-GOLD.csv and BCHAIN-MKPRU.csv. After parameter adjustment, we finally get the following results.

In the first two years (9/11/2016 -- 9/10/2018), we used the MA model to get the following asset change picture

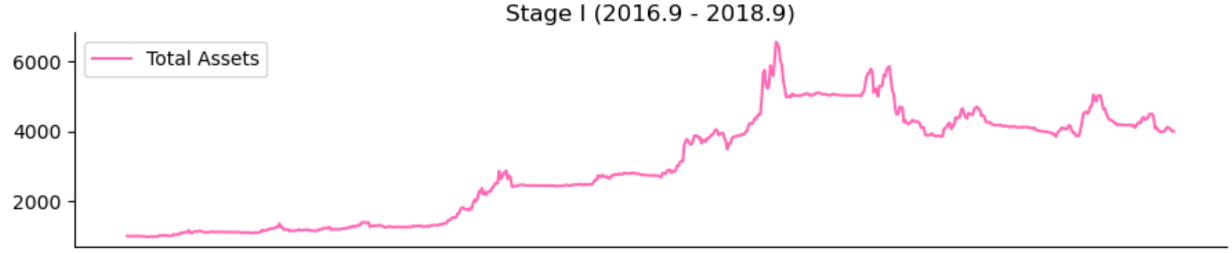


Figure 11 Asset Change Ⅰ

and the annual change in assets statement.

	(C,G,B)(Units: U.S. dollars, Troy ounces, bitcoin)	Asset value (in US dollars)
9/11/2016	(1000, 0, 0)	1000
9/10/2017	(163.706, 1.941, 0.00734)	2785
9/10/2018	(366.818, 0.5094, 0.5046)	3996

In the third year and the fourth year (9/11/2018-9/10/2020), we trained the first version of FTM with the data of the previous two years, and obtained the following asset change chart

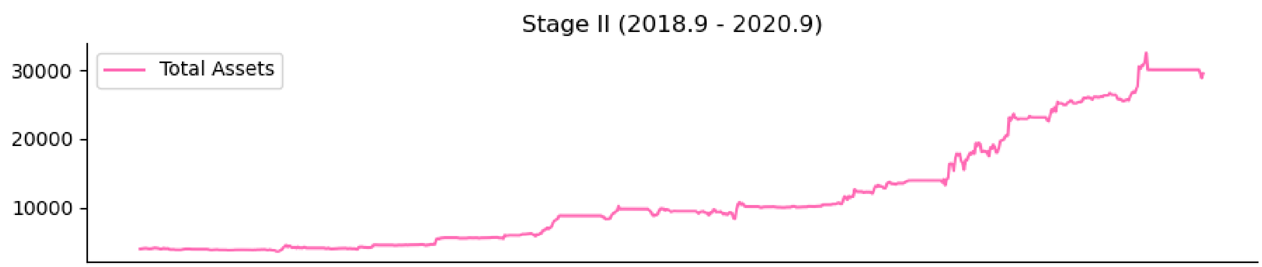


Figure 12 Asset Change Ⅱ

The table below is the annual change in assets statement.

	(C,G,B)(Units: U.S. dollars, Troy ounces, bitcoin)	Asset value (in US dollars)
9/10/2018	（366.818，0.5094，0.5046）	3996
9/10/2019	(5.38509,0.122,0.9254)	8890
9/10/2020	(18613,1.8124,0.6744)	30084

In the last year (9/11/2020-9/10/2021), we added the data of the third and fourth years as a training set, trained the second version of FTM, and obtained the following asset change images

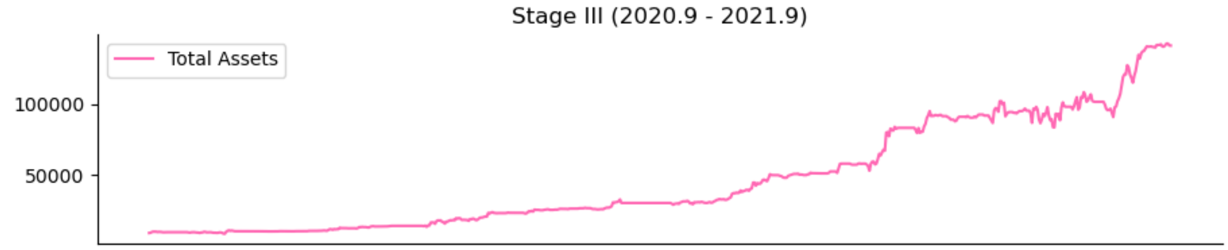


Figure 13 Asset Change III

The table below is the annual change in assets statement.

	(C,G,B)(Units: U.S. dollars, Troy ounces, bitcoin)	**Asset value (in US dollars)**
9/10/2020	(18613,1.8124,0.6744)	30084
9/10/2021	(126173,2.1965,0.232)	140873

According to the calculation formula: (total assets on the last day - 1000) / 1000)/(total days / 365) * 100) %, we can calculate the annualized rate of return: 1712%

To sum up, using our MA-FTM model, the trader went from $1000 in assets to $140,873 with an annualized return of 1712%

5.2 Parameter Analysis and Design

Many very important parameters appear in our model, they are sensory threshold parameter ω, transaction cost α% and transaction sensitivity parameter β. In addition, we added two parameters for fine tuning: the model usage parameter θ and the risk parameter γ. Here we design and analyze them one by one.

Sensory threshold parameter ω

The so-called sensory threshold is the boundary value of some kind of classification that refers to traders' range of change. In the face of the same rise, investors with lower sensory threshold are more inclined to buy/sell when the market fluctuates greatly. In other words, investors with lower sensory threshold will trade more frequently.

We evaluate the price fluctuation range of gold and bitcoin by calculating the standard deviation of the x value of gold and bitcoin in the first stage (the first five days and the first ten days) respectively, and set the ω value of gold to 0.01 and the ω value of bitcoin to 0.05.

Transaction cost α & transaction sensitivity parameter β

Firstly, we perform quantitative sensitivity analysis for α.

α%（GOLD）	α%（Bitcoin）	Ultimate asset（US dollar）
0.5%	1%	342395
1%	2%	140873
2%	4%	24034
1%	0.5%	368508
2%	1%	163921
4%	2%	32501
0.5%	0.5%	471114
1%	1%	267916
2%	2%	86580
4%	4%	9065

As can be seen from the table above, when $\alpha\%\ (Bitcoin)\ = 1$, $\alpha\%\ (GOLD)\ = 0.5\%$ 1% 2%, the results decrease from 300000+ to 200000+ to 100000+ with a relatively stable range. If the change of the final asset is considered as linear, the results and $\alpha\%\,(GOLD)$ have an approximately negative logarithmic relationship. Fixed $\alpha\%\ (GOLD)$ gave similar results. This shows that the model has strong robustness and can deal with the change of $\alpha\%$ well.

For higher cost, investors tend to reduce the trading frequency and increase the training concentration of trading sensitivity parameter β, thus α and β show a positive correlation. Therefore, we associate α with the trading sensitivity parameter β, allowing different α to influence our investment model by influencing β.

In the training set, investors with higher β were more likely to make a hold decision for the same buy and sell signal Ed. Based on the above inference, we use the modified $\widehat{\beta} = \beta + \alpha$ instead of β.

The model uses the parameter θ

We believe that the model may be immature due to insufficient training data, and the supplied buy and sell signals are weakened by multiplying the corresponding θ values between 0 and 1.

By measuring the estimation error parameter R2 of the first stage and the second stage, we set θ1 as 0.85 and θ2 as 0.95 in reference to part of the investment advice.

Risk parameter γ

We relate the risk of an investment to the volatility of the market. In order to add a risk control mechanism into the model, we designed the risk parameter γ. So we get our new buy and sell quantity $\widehat{W} = \gamma W$

We use moving standard deviation (MSD) to determine γ as follows:

$$\gamma = 0.9 + 0.1 \times e^{-|MSD|} \tag{9}$$

6 Validating the Model

We are going to argue that our model is the best from two perspectives.

6.1 Error Analysis

The model error was evaluated and the correlation coefficients were calculated using the well-trained fifth year data. R is calculated as follows

$$R^2 = \frac{MSE}{Var(ed)} = \frac{\sum\left(\widehat{ed} - ed\right)^2}{Var(ed)} \tag{10}$$

Here $\widehat{ed}$ is the test set label output and ed is the actual value using tomorrow's data.

The calculated result is 0.73, which is relatively close to 1. That is to say, our model has a small error after four years of data training.

6.2 Economic Analysis

Annualized return: Earn more

If only referring to MA model to make trading decisions within five years, the annual interest rate can reach 101.74%, which is far higher than various popular financial investment means. Even more surprising, our coupled model ended up yielding a staggering 1712% annual return, about 17 times higher than the MA model alone.

The annualized rate of return is calculated as follows

$$Annual\ rate\ of\ return = \frac{Investment\ income/principal}{Days\ of\ investment\ /365}$$

To facilitate comparison, we used MA model to conduct experiments on the data of five years (see Figure 14), and the annual return rate was 101.74%, far lower than our model.

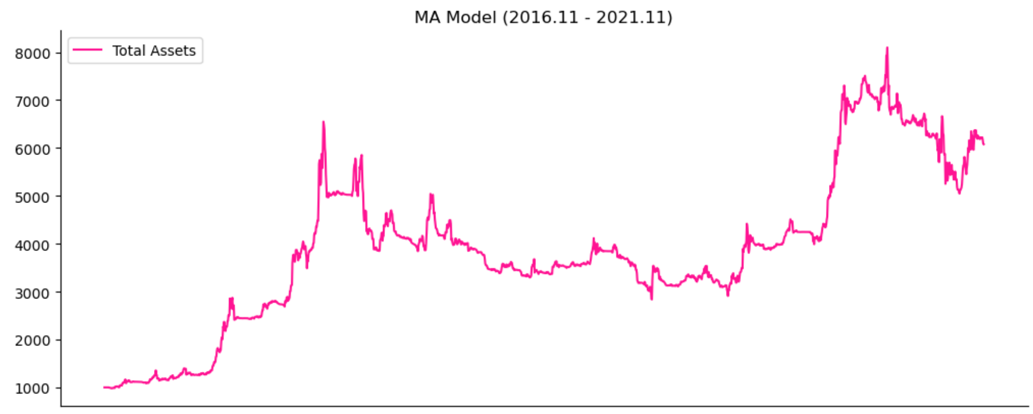


Figure 14 Asset Change -MA

Sharpe ratio: Earn it safely

By calculating the Sharpe ratio, we got a pretty impressive result. The Sharpe ratio of our proposed model is about 1.5 times that of the MA model alone, which means that our model will get more profit than the traditional MA model with the same risk.

The Sharpe ratio is calculated as follows

$$SR = \frac{\bar{r}}{std} = \frac{\sum_{k=1}^{N} \frac{p_k^{sell}}{p_k^{buy}} (1-\alpha)}{\sqrt{\frac{1}{5 \times 365} \left(\frac{p_k^{sell}}{p_k^{buy}} (1-\alpha) - \bar{r} \right)^2}} \tag{11}$$

Where $\bar{r}$ refers to average return rate and std refers to standard deviation.

7 Strengths and weaknesses

7.1 Strengths

The strengths of this model are:

- Fuzzy system theory is used to simplify the complex dynamic price model into an easy-to-understand analysis to determine technical indicators
- The Apriori algorithm is adopted to generate the mapping relationship between fuzzy sets by means of machine learning, that is, objective trading rules, which remove the subjective restrictions existing in the original relevant rules proposed by field experts, so that the data speak, and make the results more real and reliable
- The process can be explained, with complete mathematical reasoning and logical demonstration
- Many calculation parameters are designed to perform their respective functions, so that the model has stronger practicability, universality and robustness, which can weaken the

influence of prediction errors to a certain extent and help investors make more favorable decisions. For example, investors can improve or reduce the sensitivity of the model to market changes by adjusting the sensory threshold parameter Omega, and adjust the investment proportion by evaluating the risk parameter Gamma to better avoid risks.

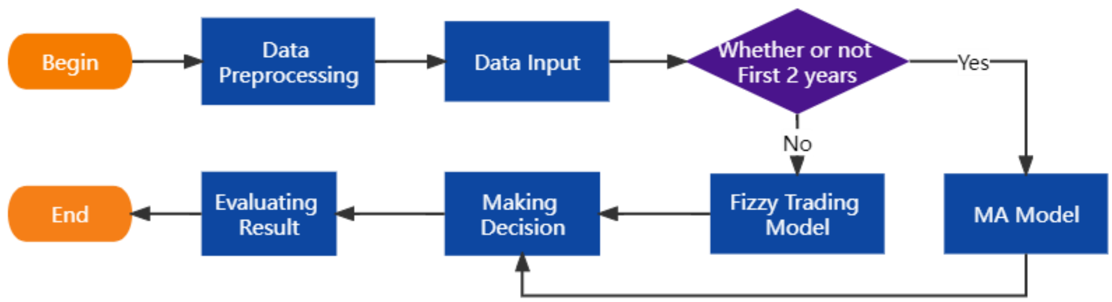
7.2 Weaknesses

The weaknesses of the model are:

- The position management was considered in the design of buy and sell strategy, and only 40% of the current purchasing power was used, which may be excessively conservative and lose some profits. The future research direction will be to continue to find a balance between profit pursuit and risk avoidance.
- In parameter design, only the correlation between parameters is considered, without establishing a strict function model, the effectiveness of each parameter may not be played to the maximum extent, which will also become our future research direction.

8 A Memorandum to the Trader

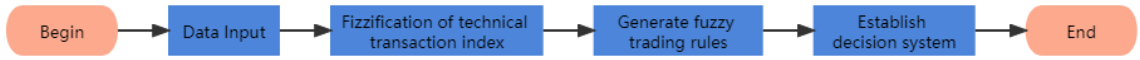
First, let's look at our strategy flow chart.



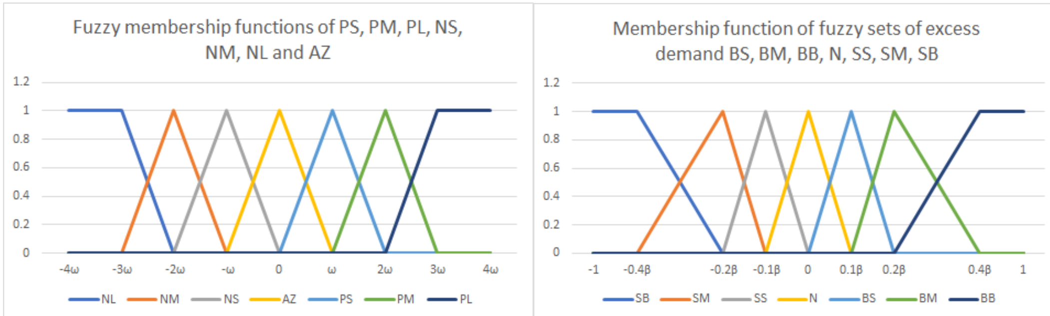
From this figure we can see that the models we used in the first two years and the last three years are different. We used a more mature MA model for the first two years. Of course, if you use this model, you will have an adequate training set, so you just need to use FTM.

Let's talk about how to train and use FTM model in detail

- Model training



As shown in the figure, after we finish processing the data, we should first carry out fuzzy processing. Firstly, the following fuzzy sets are established to determine the membership function of each fuzzy set.



By fuzzifying the existing data x, which represents price fluctuation, the buying and selling signal ed is fuzzified. Then, Apriori algorithm is used to find the relationship between x and ed, and a set of fuzzifying rules is obtained. For example,

$$GOLD: \; PL \rightarrow BM \quad PM \rightarrow BM \quad NL \rightarrow SM \quad NM \rightarrow SM$$

Use the rules to establish the functional relationship between X and Ed, for example

$$\widehat{ed}\,(x) = \frac{2\beta\mu_{PL}(x) + 2\beta\mu_{PM}(x) - 2\beta\mu_{NL}(x) - 2\beta\mu_{NM}(x)}{\mu_{PL}(x) + \mu_{PM}(x) + \mu_{NL}(x) + \mu_{NM}(x)}$$

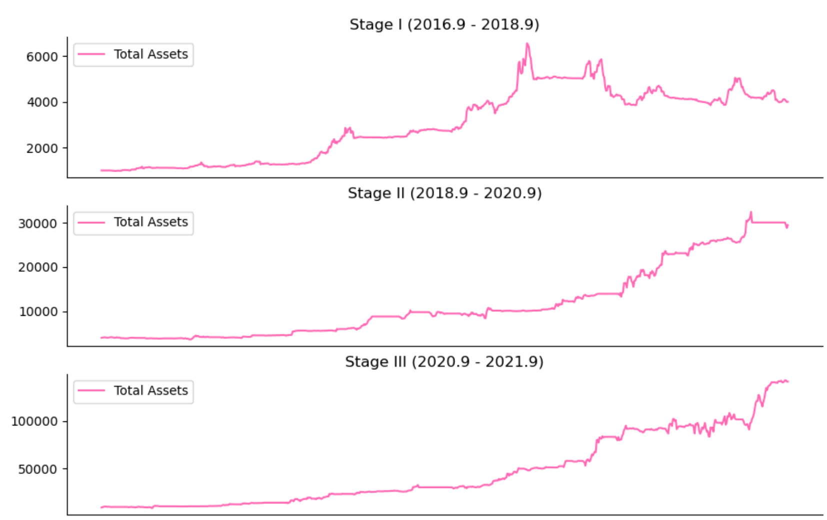
That's what we're training for.

- Use of models

Now we get x again by processing the data, and then we can substitute it into the trained function to get an ed, and then we can substitute ed into the designed fuzzy set membership function to find the corresponding operation.

- Our results

Using the five-year data given by the question, we finally get the following results



Five years later, the annualized return was 1712%.

- Tips

1. Many parameters are used in our model. There are sensory threshold parameters, trading sensitivity parameters, risk parameters and so on. You can use these parameters to adjust your trading strategy because you may be a risk-tolerant trader.

2. The robustness of our model is relatively strong, and it can play a stable role in different transaction fees, so there is no need to worry about it.

3. If you have enough training sets, you can train FTM with more training sets and use it alone.

Use our strategy and good luck making more money!

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