Problem Chosen	2022	Team Control Number
C	MCM/ICM Summary Sheet	2215361

Multi-dimension Trade Solution Based On ANNs and Chaos Theory

Summary

For the *TASK1*, we first analyzed the indicator needed for strategy making, extracted the prediction features by using the sliding window method, and selected the appropriate window size 5 by using the f-score sorting. We build a Fully connected neural network and train it with the feature vector selected by the sliding window. The average error of its prediction on the sixth day was 2% for gold and 9% for Bitcoin when the data of the past five days were known. Then we analyzed the financial indicators that could be obtained from the data and converted the price data into price changing rate to better analysis the market trend. Finally,we build an Adaptive portfolio investment strategy model based on incentive optimization. **Our 5 year return was 1544608 USD eventually.**

For the *TASK2*, we discussed the defination of optimal strategy in the given senario,and analyzed our model from the perspective of details and comparison. We come up with the following evidence that our model works well:

- Our strategy of using the price rate of change as the basic data achieves great results in the experiment, and can make accurate investment strategy according trend of the price change.
- The combined model dominated by the conservative strategy model is effective for short-term price fluctuation filtering, along with good profitability and good balance.

For the *TASK3*, we visualized the relation between the strategy return and the transaction cost with heatmap. We discovered that there are negative correlations between transaction cost and return, as our strategy is sensitive to the transaction cost. We also found that the model is more sensitive to the transaction cost of Bitcoin, as the Increase of transaction cost will mainly affect Profolio, which had higher return and more transactions in the original strategy. On the other hand, by sensitivity analysis toward our strategy model, it is relatively adptable to new situations.

For the *TASK4*,We wrote an memorandum to give the traders an overview to our model, strategy and results.

Keywords: Neural Network; Comprehensive Model; Sliding Window;Chaos Theory;MACD;KDJ lines

Contents

1 Introduction

1.1 Problem Restatement

To maximize the total return, market traders set strategies to buy and sell their different assets considering the trading price,cost of commissions etc. In this case, we are asked to develop a model to give trading strategy with the previous price data of Gold and Bitcoin.

The initial status starts with 1000 USD on 9/11/2016, as the trading period will last 5 years till 9/11/2021. On each trading day, the trader will have a portfolio consisting of cash, gold, and bitcoin, and need to determine trade strategy on days according to the trading schedule. The commission for each transaction costs percentage of amount traded, 1% for gold and 2% for Bitcoin.

In our work, we need to solve the following tasks:

- ***TASK1:***Develop a model that gives the best daily trading strategy based only on previous price data, and come out with the final return of the initial 1000USD after the 5 year period on 9/11/2021.
- ***TASK2:***Prove that the model gives the best trading strategy.
- ***TASK3:***Analyze the sensitivity of trading strategy to the transaction costs, and reveal how transaction costs impact the strategy and the result.
- ***TASK4:***Communicate your strategy, model, and results to the trader in a memorandum.

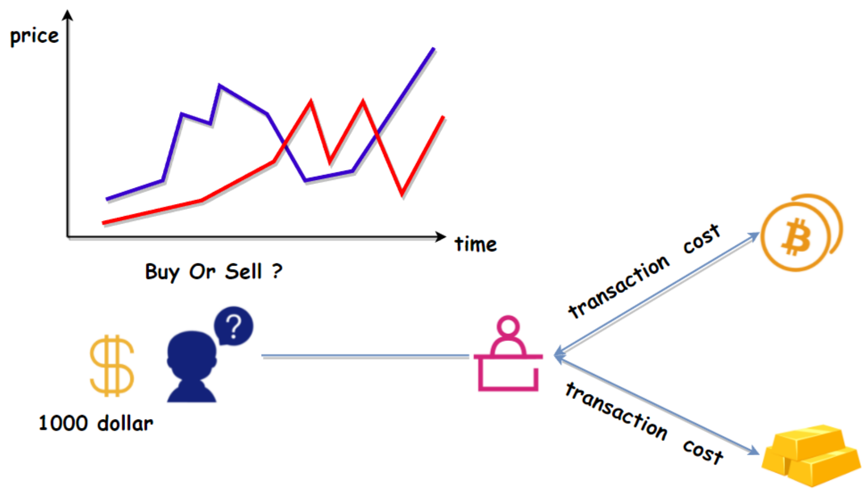
1.2 Our Work

After reading the question, the three members of the group discussed seriously and considcer that the key to solve the problem was to combine the commonly used stock market judgment strategies with the knowledge of mathematical models. Among them, the establishment of mathematical model must be based on known data , rather than create an excellent investment plan that fits the data set. We need a investment strategy suitable for the general situation.

We first use neural network to train some data in the data set to do accurate prediction. The accuracy should be analyzed carefully.

After then, we have a broad understanding of the common judgment methods in the investment market, such as MACD,KDJ,PSY, etc. and more common decision patterns in investment, such as portfolio optimization. We also viewed papers of chaotic theory. Eventually, we decided to use a combination of these methods,as to absorb the good points of each method, and avoid the loss-prone points of each method. A well strategy can steadily increase assets while still keenly aware of the timing of bottom hunting and selling.

Figure 1: Problem description



2 Assumptions and confirmation

- While training neural network, we assume that the user can get a history data before the given datasheet, at the begining of investment.
- Gold market is closed at weekens, and December 24/30th
- Considering the reality, we keep two decimal places.

3 Notations

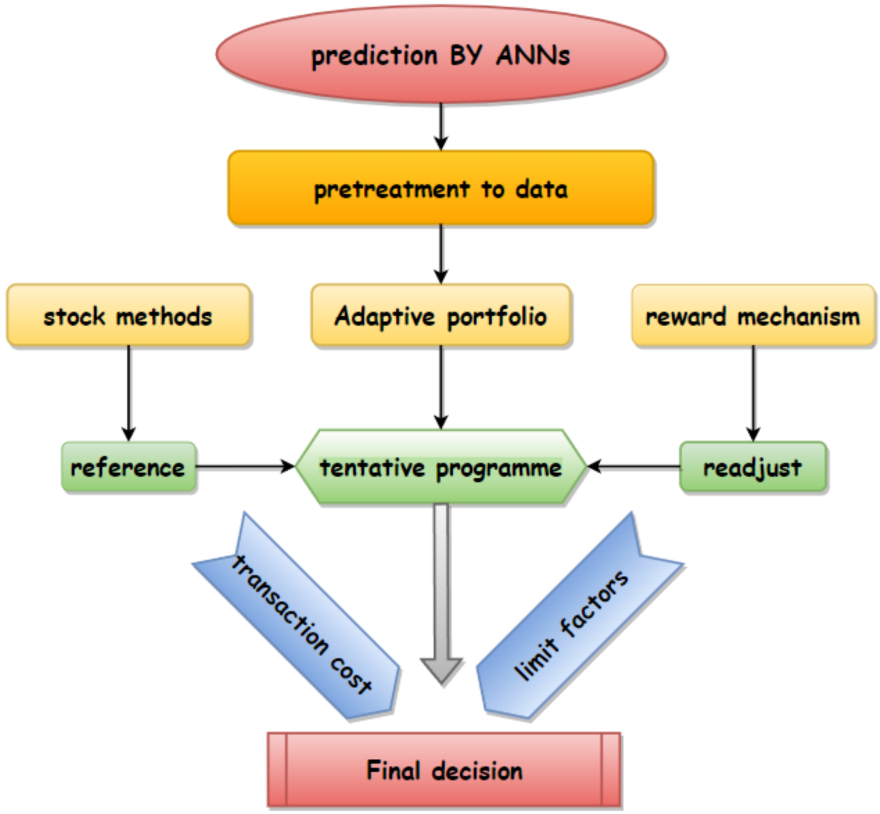
Notations are defined as the Table 1 below.

Table 1: Notations

Symbol	Definition
k	The size of sliding window
X_i	The price of profolio on day i
EMA	Exponential Moving Average
RSV	Indicator of Raw Stochastic Value
K	K Line of KDJ indicator
D	D Line of KDJ indicator
J	J Line of KDJ indicator
ROI_i	Rate of interest of day i
S_i	Short EMA on ROI of day i
L_i	Long EMA on ROI of day i
β_i	Breakout rate of day i
β_0	Limitation of breakout rate
α_{bit}	Transaction cost of bitcoin
α_{gold}	Transaction cost of gold

4 *TASK1*:Establishment of Trading Strategy Model

Figure 2: Model Overview



4.1 Trading Price Prediction

Only when we know the trend of the trading price in the future, we can specify the strategy, calculate the short-term and long-term returns and evaluate the merits and disadvantages of the strategy. First, we need to make a reasonable prediction of the price of bitcoin and gold in the next few days.

4.1.1 Data Preperation

First, we processed the data to ensure that subsequent steps are not affected by defects in the data itself.

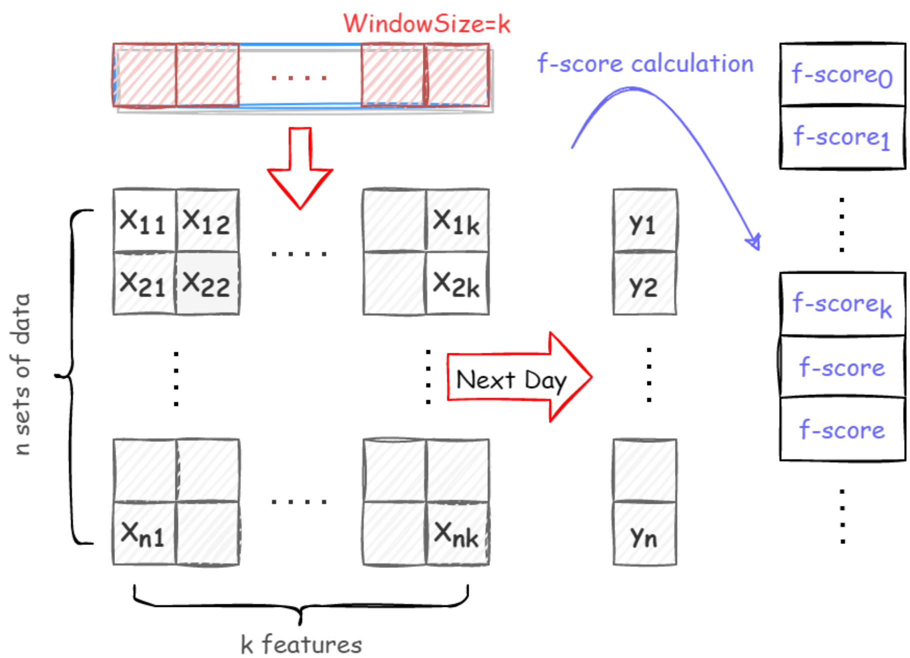
For the trading price given in the datasheet, we can make artificial analysis of its characteristics by using financial indicators. For example, moving average (aka.MA) is one of the most common analysis methods in the investment market, which was proposed by the famous American investment expert Joseph E.Granville in the mid-20th century.From the existing price data, we can use the sliding window method to select and calculate the data,while windows of different sizes can extract the characteristics of moving averages at different scales;

At the same time, the price trend of gold and bitcoin in reality is affected by many social factors. Such a complex influence system makes it difficult to analyze simply from the characteristics of financial indicators. For example, the price of Bitcoin increases significantly or falls abnormally due to the power supply problems of Bit-mine or its legitimacy as a currency. These changes are different from the general price fluctuations caused by investors, but the price trend within a few days of the event also has its own characteristics. Selecting the specific price changes of the past k days as the overall feature would give a better performance in the price prediction step.

Further, we need to determine the length of the selected period —— selecting a overlong period may lead to poor feature differentiation, while overshort period may lead to an obscure feature and bad prediction result.

4.1.2 Feature Selection

Figure 3: f-score calculation



The above Figure 2 shows the mechanism to calculate the f-score and subsequently find the proper size k of the sliding window.f-score[1] is a method to measure feature resolution ability. Through this method, features can be evaluated and the most effective features can be selected to train the prediction model. First, each feature $X_{i1}, X_{i2}..., X_{ik}$ is normalized:

$$X_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{1}$$

After normalization, the correlation coefficient r_i between feature variable and dependent variable in regression fitting was calculated :

$$r_k = \frac{\sum_{i=1}^{n} \left[X_{ik} - \operatorname{mean}(X_k)\right] \cdot \left[Y_i - \operatorname{mean}(Y)\right]}{\operatorname{std}(X_k) \cdot \operatorname{std}(Y)} \tag{2}$$

The F-score in fitting is defined as:

$$f_k = \frac{r_i^2}{1 - r_i^2} * (n - 2) \tag{3}$$

The larger the value of f is, the larger the relationship between feature X and variable Y is. We calculate the F-score of window size from 0-13 days, which follows the F distribution. The result is shown in the table below: It can be seen that as the window increases, the correlation of features

Table 2: f-score per window size

Days to today			
Day	**F-Score**	**Day**	**F-Score**
0	396993.83	**7**	54180.23
1	193731.30	**8**	48852.34
2	124244.94	**9**	44155.23
3	92042.19	**10**	40498.39
4	76546.46	**11**	37442.86
5	66473.40	**12**	34428.67
6	60298.21	**13**	31957.86

decreases, which is consistent with common sense.

4.1.3 Prediction Model Using Sliding Window and Neural Network

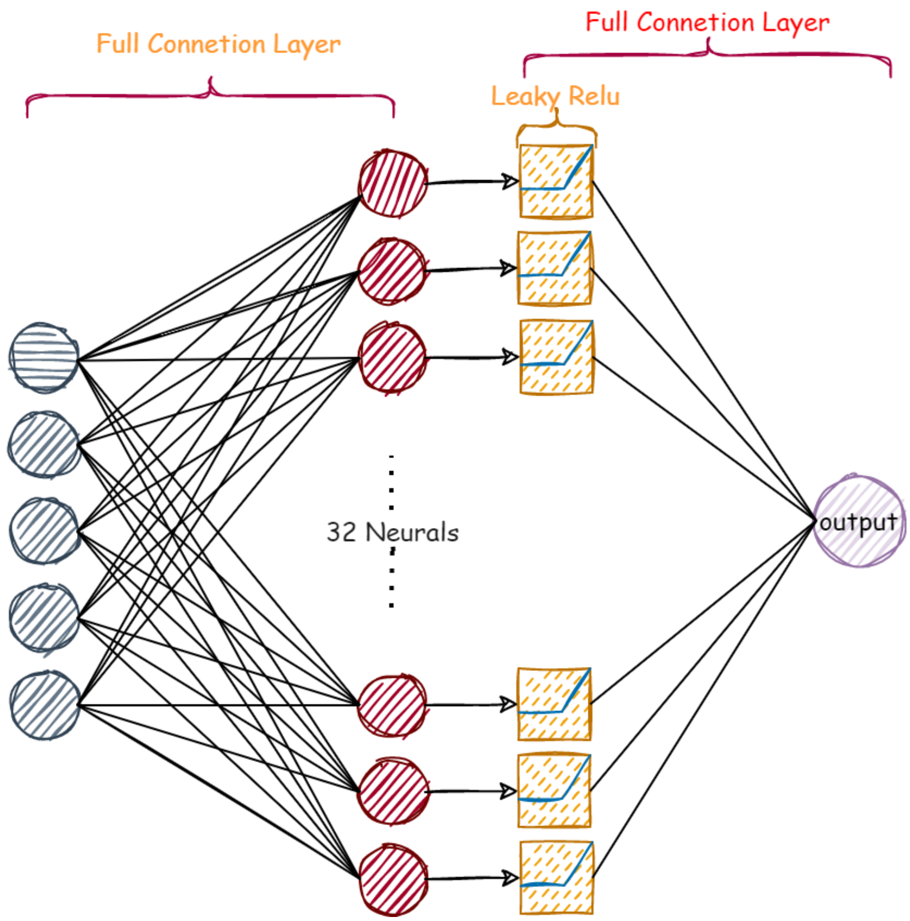
Single Day Prediction:

As mentioned above, the price trend of gold and bitcoin in reality is affected by many social, political and even natural factors. As the value of trading price is a complex time series, it is difficult to analyze its rules, so we choose to use neural network to mine its change rules and make accurate predictions.

The advantages of using neural networks in this case are:

- Compared with other nonlinear prediction models, time series do not need to be pre-analyzed. A large number of neurons in the network structure can extract hidden features from time series, which has a relatively high accuracy in price prediction of assets affected by complex factors in reality such as Bitcoin. At the same time, the trained neural network can solve such problems with high speed.The optimal results can be obtained quickly.
- Complex time series contain linear and nonlinear components. Neural network has a better fitting effect for complex nonlinear components, and can filter the inefficient features when extracting from data. At the same time, the developed steps as Dropout and Normalization in training can effectively alleviate the problems of over-fitting and gradient disappearance, which has a relatively good balance.

Figure 4: Structure of a fully-connected Neural Network



We used Pytorch to build a simple neural network with the structure shown below:

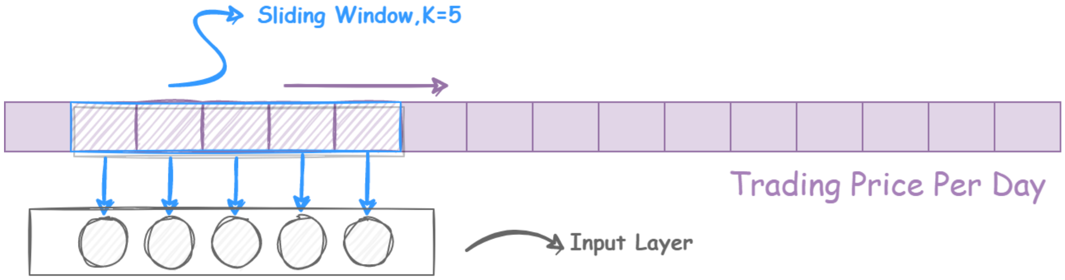
The data vector selected by the window is input by the input layer of the neural network, and the output layer is one-dimensional, that is, the price prediction of a single day.The mechanism is shown in figure below:

Multiple Day Prediction:

It is mentioned in the question that each transaction requires a certain fee, and it is not possible to formulate strategies based on the prediction results of only one day by using the method similar to greedy algorithm, because it may lead to repeated transactions and ultimately reduce profits.

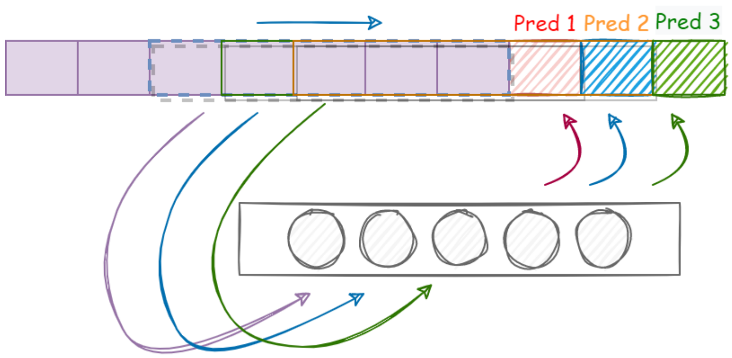
Thus, we also hope to comprehensively consider the price prediction in the next few days. We can use the iterative method: input the prediction result of each time into the window as the new component in input vector, and get the prediction result of the next day, while repeating the cycle. The drawback of this method is that as the number of predicted days increases, it differs from the

Figure 5: Model mechanism



real value and the bias increases rapidly, so we need to determine the maximum valid prediction we can get.

Figure 6: Predicting multiple days

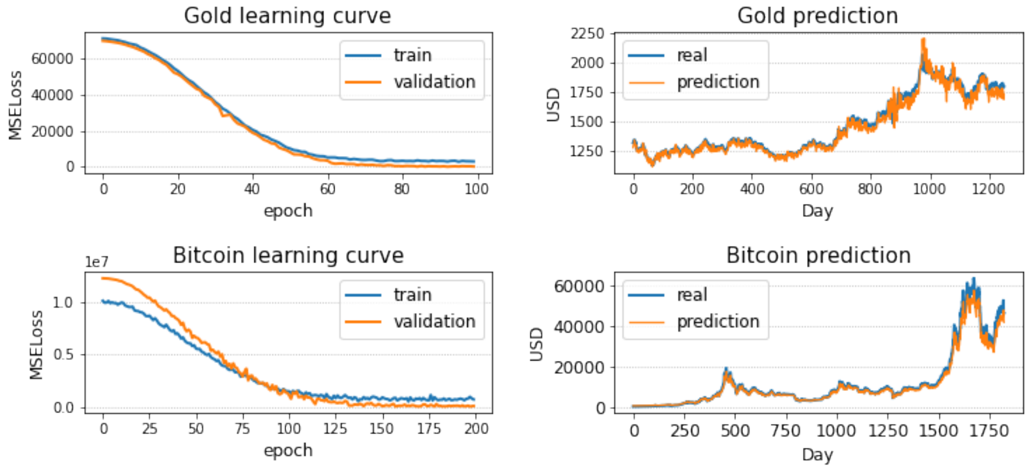


4.1.4 Model Training and Evaluation

We use SGD(Stochastic Gradient Decent) to train our network, and the loss funtion is set to be MSE. Our dataset is divided into train,validation,testing set at a ratio of 5:3:2, the learning kurve shown below reveals that our model has a relatively high accuracy and is not over fitting.

We also tested the result, getting prediction by every 5 past trading price, the visualization shown below reveals that our model works relatively well in single day prediction.

Figure 7: Learning Curve and Prediction Result



Meanwhile, for multi-day prediction, we use mean standard error as evaluation index and define it as:

$$\epsilon = \frac{\sum_{i=1}^{n} \mid pred - real \mid}{real \cdot n} \tag{4}$$

By analyzing the results of single-day prediction and that of iterations, we find that the volatility of bitcoin's trading price is much unstable and in disorder, thus the error is too large after multi-day iteration. Therefore, we need to adopt different evaluation criteria for two assets in the subsequent strategy model. We calculated the average standard error AE of gold for 5 interations and bitcoin for one, and the results are as follows.

Table 3: Average standard error of continuous prediction

Days	Average standard error
+1	0.02025754
+2	0.03541885
+3	0.03395198
+4	0.05497369
+5	0.08606456
+1	(Bitcoin)0.09486453

Finally, for the gold price with relatively stable price trend, we select five days from the test set and predict the price of the following five days, which are drawn in the line chart.

Troughout the variance-mean analysis with sliding window, it can be seen that the price of gold and bitcoin fluctuate greatly in the middle and late period, and the prediction accuracy decreases significantly.

Figure 8: Example prediction result and glabal average error

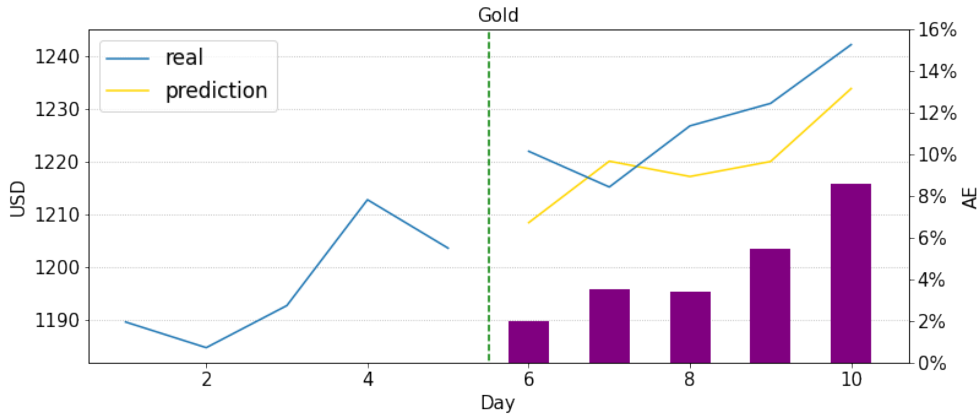
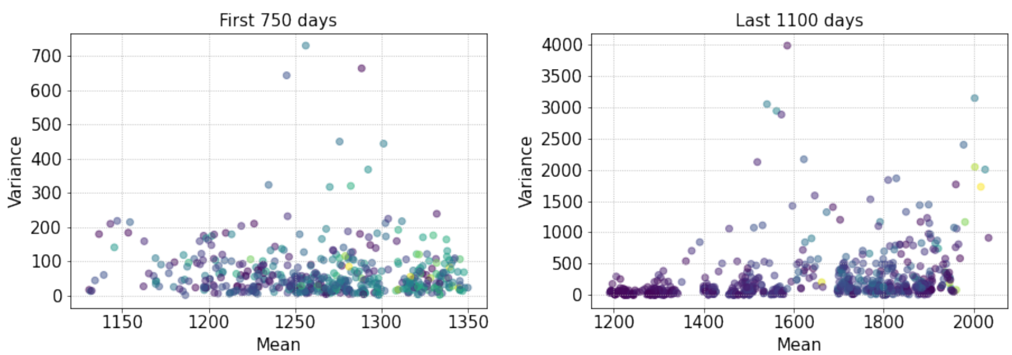


Figure 9: Variance-mean distribution



4.2 Model Preparation

Firstly, we need to identify the valid indicators that can be used and expand the dimension of features. From the existing data, we can obtain the following financial indicators:

MACD: The MACD(Moving Average Convergence/Divergence) is developed from the double exponential moving average. Its significance lies in revealing revealing possible moving trend with the combined feature of long/short moving average.

- ***EMA:*** The indicator we need to use is EMA. Calculate the moving average EMA_{12} and EMA_{26} of 12 and 26 days, and its definition is as follows:

$$EMA_k(n) = \sum_{i=1}^{k} \frac{X(n-i)}{k} \tag{5}$$

$$EMA_k(n) = \frac{k-1}{k+1} EMA_k(n-1) + \frac{2}{k-1} X(n) \tag{6}$$

variable X refers to the price data of day n.

KDJ random index:Initially used for the analysis of market prediction, KDJ index now is widely used for short-term trend analysis in the investment field.

The highest, lowest, and final prices that have occurred during a particular period is used to calculate the random value RSV of the last calculation period, The method of moving average line is used to calculate K value, D value and J value to judge the stock trend.

- RSV is defined as:
$$RSV = \frac{X - L_k}{H_k - L_k} \times 100 \tag{7}$$
where variable H_k and L_k refers to the highest price in the past k days.

- The K value on a certain day is determined by the RSV value of that day and the K value of the previous day while the initial value of K is set as 50. K is defined as:
$$K_i = \frac{2}{3}K_{i-1} + \frac{1}{3}RSV_i \tag{8}$$

- The D value on a certain day is determined by the K value of that day and the D value of the previous day while the initial value of D is set as 50. D is defined as:
$$D_i = \frac{2}{3}D_{i-1} + \frac{1}{3}K_{r_i} \tag{9}$$

- The J value on a certain day is determined by the K and D values of that day, which is defined as:
$$J_i = 3K_i - 2D_i \tag{10}$$

A key decision-making methods in the strategy model can be derived from the above two financial indicators: Death cross and a golden cross are stock market terms. A golden cross represents a shorter-term moving average on the rise, moving from below tosurpass a longer-term moving average,that is,the J line goes up through the K line and the D line from below while using KDJ indicator.This stated that prices would continue to rise

A death cross represents a falling shorter-term moving average moving down through a longer-term moving average, this stated that prices will continue to fall.

4.3 Adaptive portfolio investment strategy model based on incentive optimization

4.3.1 Logical and parameter settings

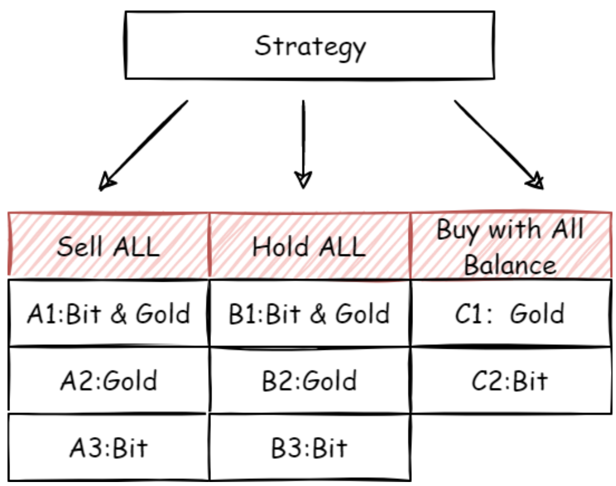
In the actual modeling, we found that the comprehensive investment of gold and bitcoin has its particularity: the price of gold is far more stable than that of Bitcoin, and the return of bitcoin investment is much higher than gold. In fact, if you view it from a global perspective, bitcoin investing is the main source of interest, while gold investing is similar to an interest-bearing currency, acting as a switching pool between large bitcoin investments.

The characteristics of both assets and the existence of trading commissions allow stable, long-term investment strategies to achieve better returns; On the other hand, bitcoin, which is mainly profitable, is influenced by many social factors and random events in reality. This leads to the large amount of noise contained in its time series, thus the prediction model can not predict with considerable accuracy for a long enough period.

The decision model we need is relatively stable and robust. Overly complex decision operations will lead to sensitive model and would be seriously affected by noise, which will lead to losses in the five-year long-term investment. Therefore, we limit the minimum step of decision making to minimize the unnecessary trade.

Buying all or selling all of an asset is the unit operation of our decision model, as shown in figure below:

Figure 10: Basic act of strategy



4.3.2 Asset division of multiple judgment schemes

In the preparation stage of the above model, we carried out future prediction using machine learning and data processing based on financial indicators, and obtained three main types to determine the strategy, we first consider their characteristics in a single investment task:

- The judgment scheme using Golden/Death crossover line has good stability, but at the same time has lag and poor ability to capture opportunities.
- The judgment scheme using J-line responds faster to market changes, but its stability is poor, leading to a greater possibility of investment failure.
- The judgment scheme predicted value of the trading price in the next few days. The scheme can obtain better results in the short term when the forecast is correct, but there are risks to accuracy in predicting bitcoin in particular, and short-term solutions may not be optimal for long-term investments.

Each of the three judgment methods has its advantages and disadvantages. In different investment situations, all three may obtain optimal results at certain stages. Therefore, in order to achieve higher returns, we want to build a comprehensive model to deal with different market fluctuations.

4.3.3 Conservative investment strategy model based on price change rate and prediction

Based on the above analysis, we need a stable model to lead investment in long-term investment, which should be able to filter the interference of short-term market price fluctuations and give a sound investment strategy.Since the price gap between gold and bitcoin is very wide in some periods of time, such a gap will lead to a bias towards bitcoin in return-oriented decision making process, which has a negative impact on the filtering of short term fluctuate. Therefore, we first convert the price data into the price changing rate, which is defined as Rate of Interest ROI:

$$ROI_i = \frac{X_i}{X_{i-1}} \tag{11}$$

Such indicator will take the place of daily price X_i in this model, which can help the model better measure and compare the trend of two kinds of assets. Furthermore, we set 3 pairs of constraint parameters for the model to specify the conservative policy:

- S_i: Short time average calculated on ROI with the same method of EMA.
- L_i: Long time average calculated on ROI with the same method of EMA.
- β: Breakout rate β is defined as:

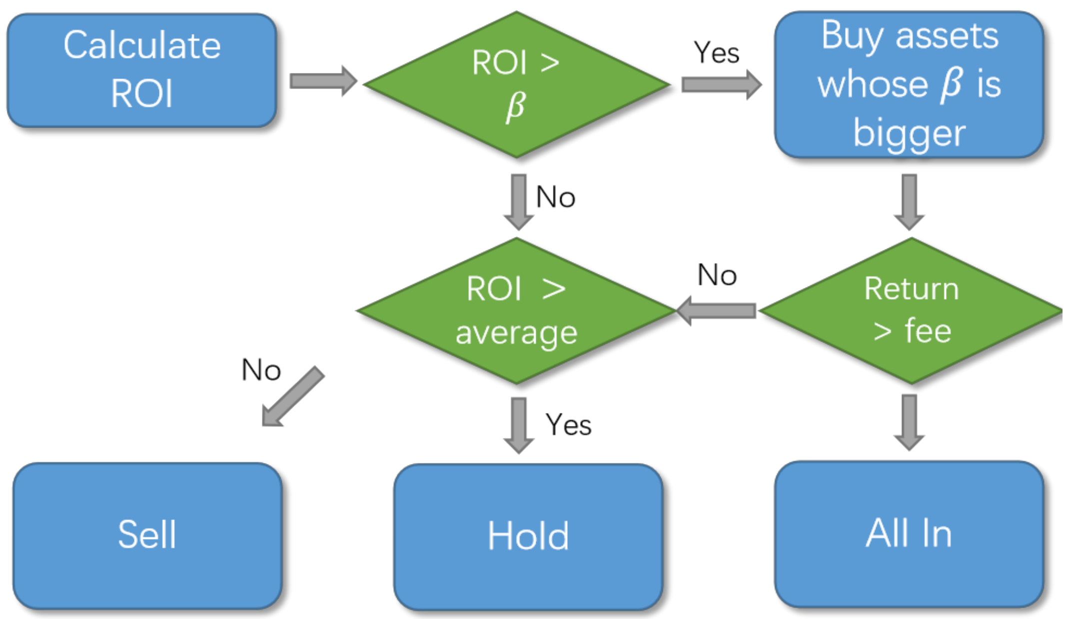
  $$\beta = \frac{S_i}{L_i} - 1 \tag{12}$$

  A constant value β_0 is set to be a judgeline for strategies.

For each transaction in both profolios, we follow the following guidelines:When the breakout rate β_i exceeds β_0 , the model tends to convert balance to profolio. When the breakout rate β_i falls below -β_0, the model tends to convert profolio to balance.

The model works as follows in a daily basis:

Figure 11: Model Overview



- ***Step1***: Calculate whether the ROI of each profolio on that day is higher than β_0. If ROI of both assets is greater than $beta$, **go *StepA***, if one of them is greater, **go *Step2***, else **go *Step3***
- ***StepA***: Select the profolio with higher
- ***Step2***: Judge whether the return is higher than transaction fee. If so, convert all balance to it.
- ***Step3***:If the prediction result still shows the trend of falling, convert profolio to balance.

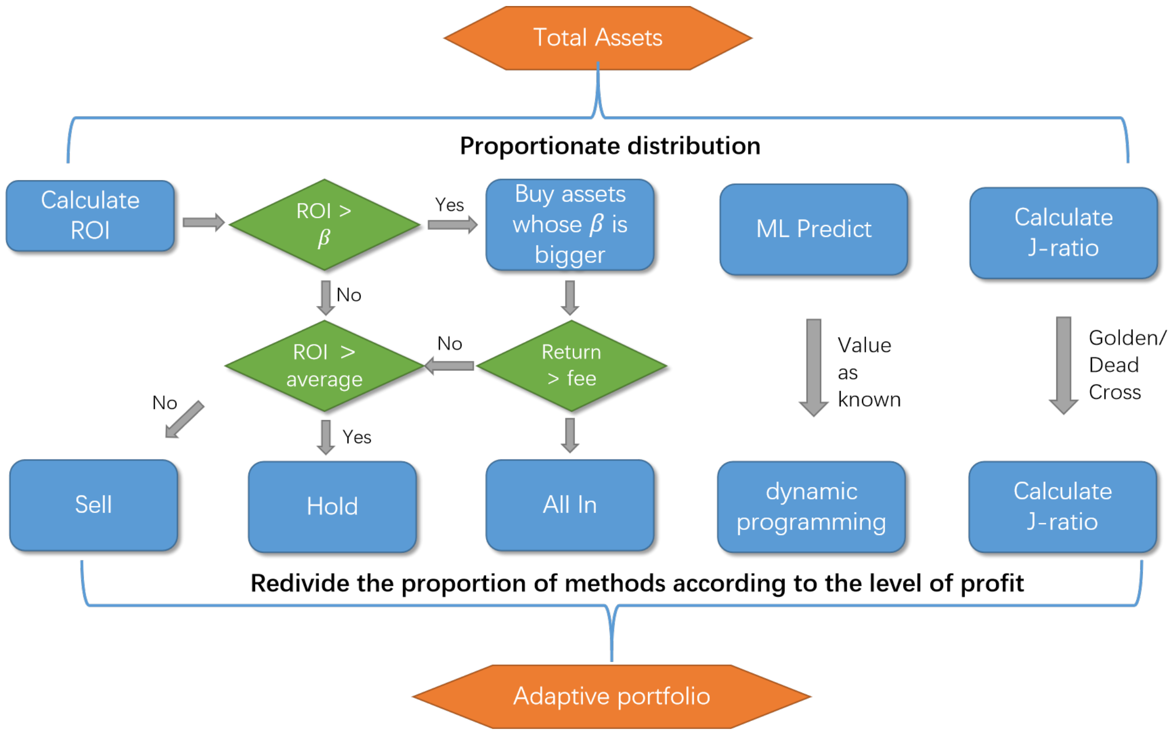
4.3.4 Incentive Adjustion

Finally, the proportion of total assets allocated to 3 models will change dynamically in month basis, in order that it can adapt to the market.

At the beginning of KDJ line and further prediction ,we distribute them 1 part of assert respectively to let them make their own decision.If next day,the result proves that their decision is right,the parts they control will increase,or their parts will be decrease.The count will be restart when our main part choose to buy.This regulation will help us to make further decision with less part to loss.

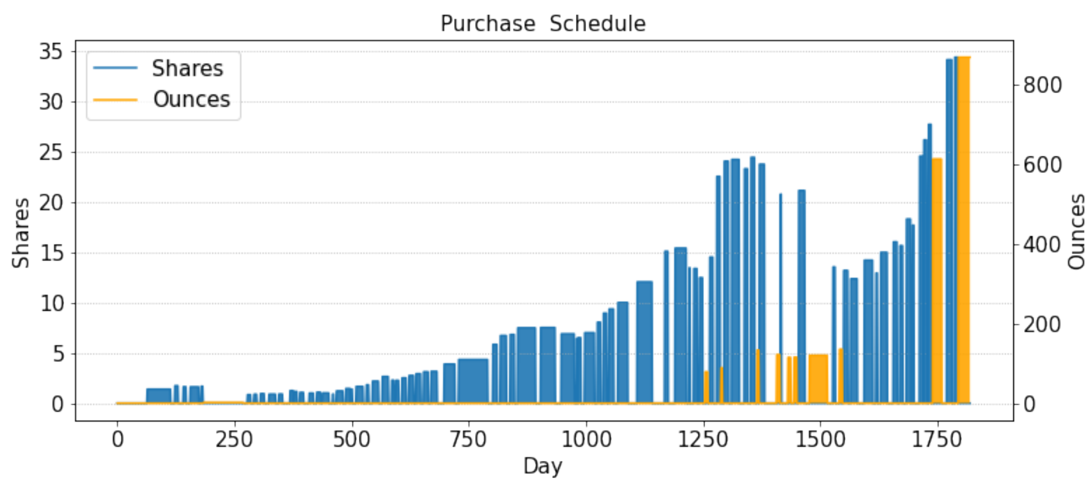
The model overview is shown as the below figure:

Figure 12: sensitive analysis of β



4.4 Model Results

Figure 13: Trading Overview



With the operation series given by our model ,**we end up with the final balance of 1544608 Dollars**.The example period of our Buy&Sell strategy is shown in table below;An overview of our trading strategy can be revealed with the figure 9 above:

Table 4: Excerpt of Bitcoin Buy&Sell

Day	Bitcoin Value	Operation	Dollar	Shares
11/14/16	706.46	Buy	0	1.39
1/3/17	1013.42	Sell	1377.70	0
1/12/17	780.92	Buy	0	1.73
1/21/17	895.64	Sell	1517.78	0
1/30/17	912.19	Buy	0	1.63
2/5/17	1034.07	Sell	1652.44	0
2/14/17	1001.20	Buy	0	1.62
3/4/17	1287.00	Sell	2040.03	0
...	...	...	...	...
2/27/21	46340.31	Buy	0	14.97
3/13/21	57253.28	Sell	839738.62	0
3/26/21	51415.92	Buy	0	16.01
4/3/21	59031.32	Sell	925936.41	0
4/9/21	58048.59	Buy	0	15.63
4/15/21	62969.12	Sell	964648.87	0
...	...	...	...	...

Table 5: Excerpt of Gold Buy&Sell

Day	Gold Price	Operation	Dollar	Ounces
3/13/17	1204.2	Sell	2017.1	0
3/14/17	1204.6	Buy	0	1.65
6/7/17	1291	Sell	2118.76	0
...	...	...	...	...
2/18/20	1589.85	Buy	0	78.7
2/24/20	1671.65	Sell	130237.8	0
3/23/20	1525.4	Buy	0	89.12
3/24/20	1634.8	Sell	144248.54	0
...	...	...	...	...

5 *TASK2:* Result Verification and Analysis

5.1 Defining the good strategy

In this task, we first need to define a good policy. In reality, algorithms that learn historical market data and automatically invest or give suggestions, such as deep reinforcement learning algorithms trained by abundant data with sufficient dimensions, can achieve excellent results in investment simulation. At the same time, people's strategy in reality can also take social reality and realtime information into consideration.

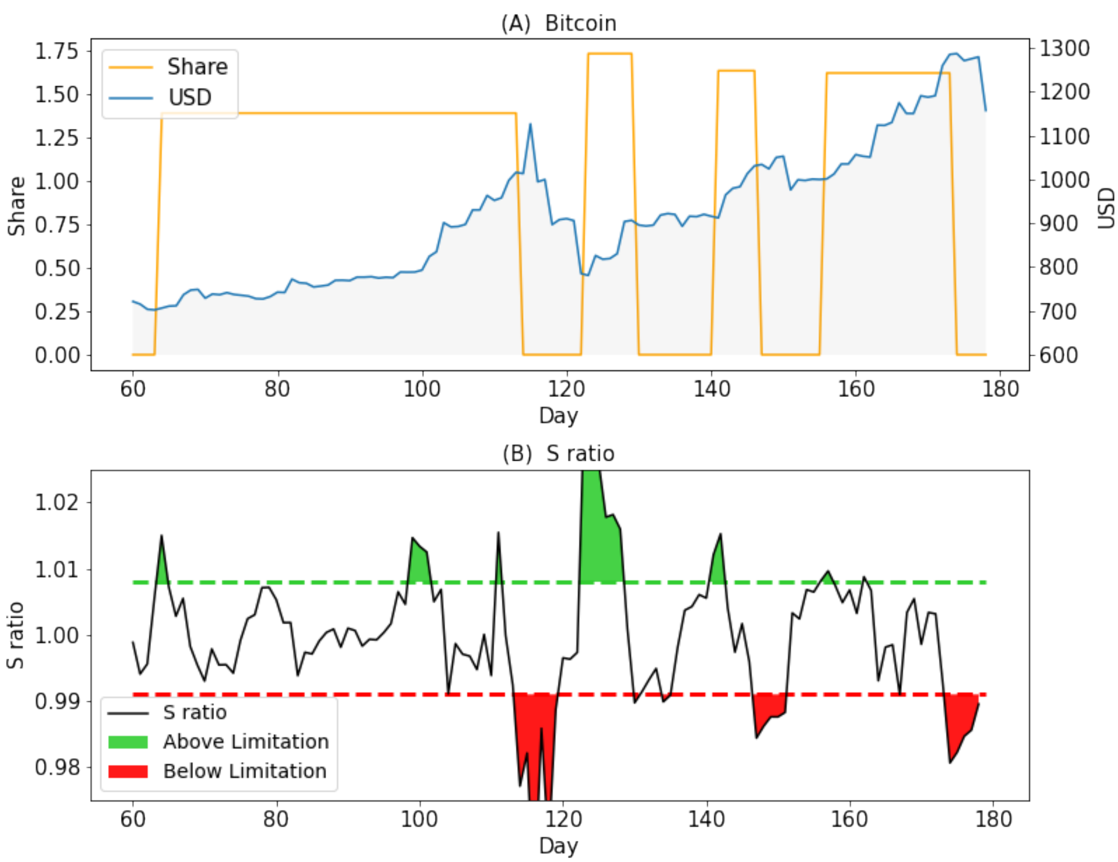
In this case, the data we can use are limited compared with the actual situation, especially in terms of its dimension, and there are relatively few financial indicators available. In this case, the optimal result that the model can obtain through its own mechanism is different from the optimal result that we can obtain from a broader viewpoint.

Therefore, in this section, we will analyze the success of its mechanism from the perspective of the model and judge whether the strategy is optimal.

5.2 Result Analysis

Let's start with an excerpt example of bitcoin investment by our model:

Figure 14: Excerpt Example



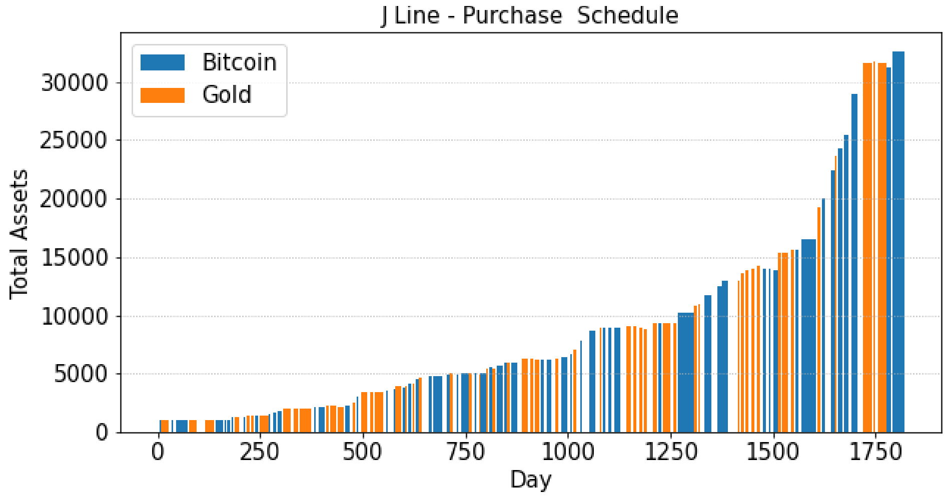
It can be seen that there are strong correspondence between the number of shares hold and the up-down pulse colored in red and green. An appropriate S value can select an appropriate trading time,as in this six-month trading example of Bitcoin, we can see that the model makes a decision to buy bitcoin after the parameter $S-ratio$ breaks through the upper limit t and to sell after $S-ratio$ breaks through the lower limit.

By comparing the decision with the price trend of Bitcoin, our model will choose to buy shares when the overall price trend increases greatly, but not when the overall price trend increases little, in order that the trasaction cost will not cause actual long term lost.The model achieves our goal of taking conservative investment model as the leading factor —— to better analyze the long term price trend and filter the short term noises of price fluctuations.

5.3 Comparison Analysis

The second mechanism we foucus on is how our comprehensive model works.To measure the strategy, we compared the results of the combined model with those of the KDJ single indicator model:

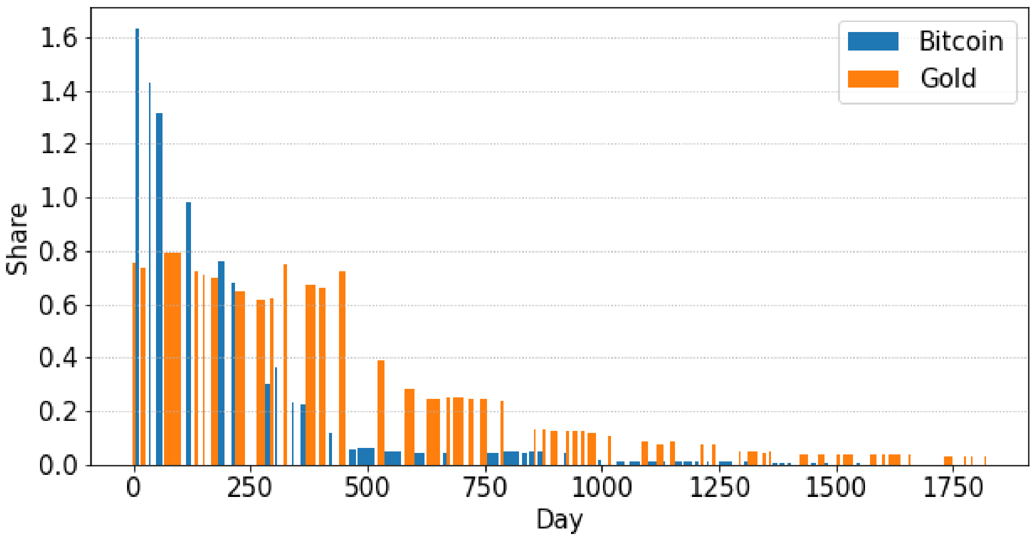
Figure 15: Total Assets Balance of single model



It can be seen that the decision-making of the model under a single indicator is greatly affected by short-term fluctuations, so that it is converted between holding and bitcoin for many times. In the total assets change curve, transaction cost decreases the total assets. In our model, parameter B is used to limit and select the mechanism of the highest short-term return, which makes the model automatically invest in high-yield bitcoin in most of the time, thus achieving better results.

We also compared the result of the model using the raw price as the base data, which even cause deficits as the judgement is completely biased due to the scale difference of the price of Gold and Bitcoin. This makes it unable to do valid trend analysis and the following steps.

Figure 16: Total Assets Balance of single model



6 *TSAK3:*Sensitivity analysis toward changing transaction cost

6.1 Data visualization

We adjusted transaction cost of the two profolio and obtained the total benefit of the model under the new situation. We visualized the above data using heatmap and got the following results:

Figure 17: Heat map of $Return - \alpha$

It can be seen that transaction cost of both gold and Bitcoin is negatively correlated with total return.The higher transaction cost is, the lower the total return is, which is an intuitive result. Meanwhile, we find that total return R is more influenced by Bitcoin transaction Cost than gold transaction cost, that is:

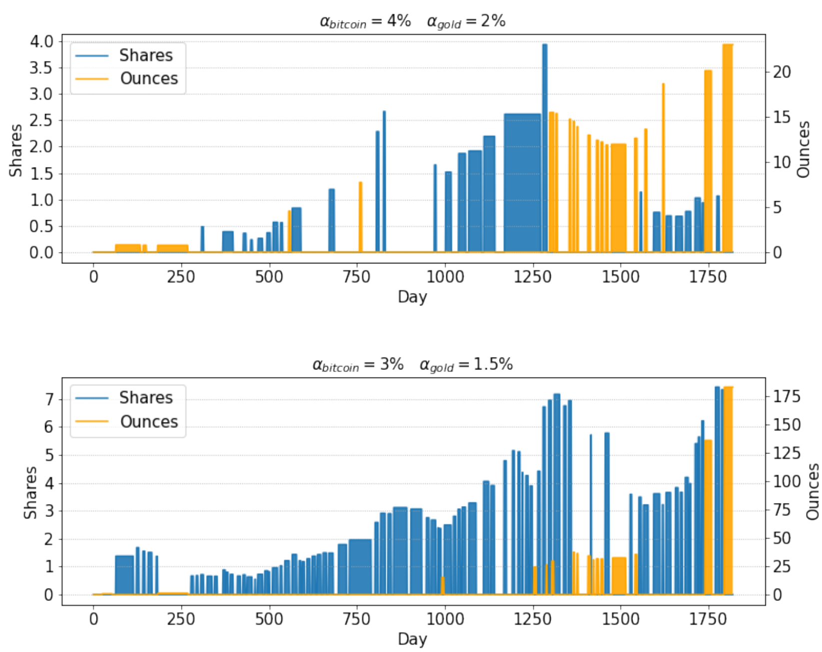
$$\frac{\partial R}{\partial \alpha_{bit}} > \frac{\partial R}{\partial \alpha_{gold}} \tag{13}$$

It can be inferred that bitcoin has a greater impact on investment strategy than gold due to its larger price increment and wider floating range, which is consistent with the rule we found in the section above. Finally, as for ***TASK3***, we found our strategy highly sensitive toward the change of transaction cost.

6.2 Impact toward strategies

Finally, we analyze the esay transaction cost change impacts ther model strategy. We select $\alpha_{gold} = 2\%, \alpha_{bit} = 4\%$ as the case parameter and use the model for strategic planning.We hope to analyze the changing rule of both profolio. The results under the new parameter are compared with those in ***TASK1*** as the figure 12 shown below.

Figure 18: Strategy camparison



As mentioned in the above analysis, the model is more sensitive to Bitcoin transaction cost, so it can be seen from the result that the number of bitcoin transactions in the strategy decreases significantly. Meanwhile, when bitcoin price have a low growth rate in first 200 days, Gold became the main investment profolio, which has a big impact to the following strategy when the bitcoin's price booms suddenly in the near future. It can be inferred that the increase of transaction cost will mainly affect Profolio, which originally had higher income and more transactions.

7 *TASK4*:Memorandum to traders

TO:Trader
FROM:Group 2215361
DATE:2022/2/21
Subject:Purchase Model For
Gold and Bitcoin

Dear trader, after careful analysis, we finally came to the following trading scheme. Taking the principal 1000 as an example, our final result is 1544609 dollar, which has increased 1544 times compared with the principal, and there are few losses in the trading process. The profit has increased steadily, taking into account high income and low risk. It is a very excellent trading strategy, The following is the details of the transaction method.

First of all, we introduce you to the investment strategy. Before investing at the benning of one day, the most important thing is to predict the possible price and future trend of gold and bitcoin. Through accurate prediction, we can have the most important and intuitive judgment for decision-making. However, even if we are able to get a better prediction value, we can't make the decision all depend on that result. The reason is that there is still uncertainty in the prediction and the transaction costs of the operation: the uncertainty of the prediction may reduce the income or even make a loss, and the transaction costs will completely erase the mediocre income. The second is the chaotic trading model, which divides the long-term and short-term averages of each stock market to determine the yield breakthrough rate. When the rate of short-term and long-term average returns on that day is greater than the breakthrough rate, it is considered that the stock can be bought, otherwise it is not recommended to buy. Then, the situation of one day can be divided into the following situations:if buying is not recommended in both markets, we transact gold and bitcoin into cash. There is a market which recommends buying. Judge whether the profit will be reduced due to the transaction costs after buying all of the market. If buying is recommended in both markets, judge which market has higher income,and after judgment, you can use the second case to make decision. At the same time, in order to make the transaction conservative, in addition to the above methods, we also calculate the KD line and MACD line. When either of them has a gold cross or a death cross, all of them will be bought or sold. The purpose of this is to set the last insurance for assets, because the cross line often has a certain lag, but it is also stable in most cases. Using this method as the bottom guarantee can stabilize the trading strategy. The above is our trading strategy.

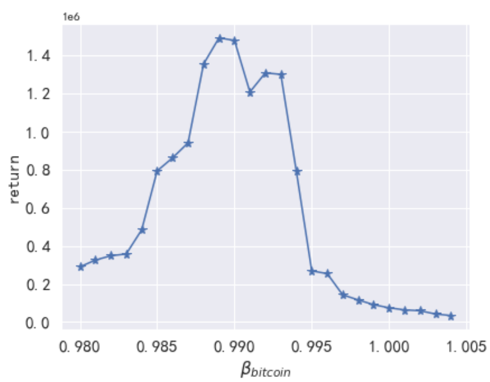
The second is the model we established. Corresponding to the previous paragraph, let's first introduce the prediction model. For the complex time series such as the rise and fall of stock price, the result will be greatly reduced only by relying on linear components; The artificial neural network has a good effect in nonlinear prediction, so we decided to use the neural network to train some selected data, and achieve better prediction effect by superimposing the layers of the network. After such analysis and prediction, we finally get the following results: the prediction accuracy of gold price is 2.02% and that of bitcoin price is 9.4%. Secondly, when making decisions, compared with the traditional "bringing prices into the analysis process", we choose to use the profit rate of each market for analysis. On the one hand, the introduction of the rate of return can avoid the problem that stocks with different prices lead to changes in the same value and different sensitivity. On the other hand, it can smooth the calculation process, making the data swing around 1 most of the time, and avoid the problem of handling fee explosion caused by too many transactions when the stock price fluctuates seriously. Thirdly, through the six variable parameters in the chaotic model, we can flexibly reflect the characteristics of different markets, achieve agile response and suit the remedy to the case.

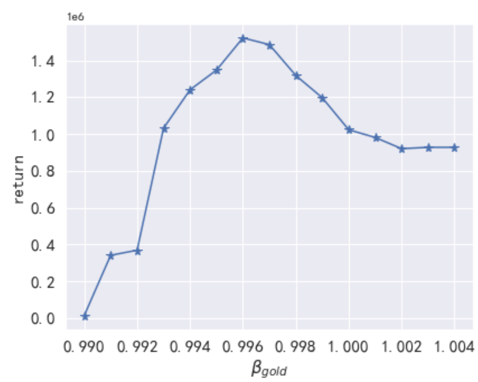
Our final result is 1544609. See the appendix for detailed step-by-step transaction information.

8 Model Sensitivity Analysis

The main controllable variable in our model is the limit of β_0 of gold and Bitcoin. Thus we apply a sensitive analysis to such variable to see how it impacts the total return of our model. At a state of $\alpha_{bit} = \%$, $\alpha_{gold} = 1.5\%$, the results is as the figure below:

Figure 19: sensitive analysis of β





Both curve shows grading regularity, making it availible to optimize the model parameter easily when applying it to new environment.

9 Strengths and weaknesses

9.1 Strengths

- The results of prediciton model are accurate, which can reflect the future price trend well.
- A variety of methods are used and combined as a comprehensive model, which alleviates the defect of any single method and strengthen the stablity.
- In the chaotic model, personalized parameters are arranged for different markets to improve the accuracy.
- Using yield rate rather than price directly in order to avoid the bias caused by the numeric scale difference between the profolio data.

9.2 Weakness

- The decision of the subsequent method is based on the prediction model, as the prediction model will increase the error when the real price changes dramatically. This may lead to problematic strategy.
- The strategy model is sensitive to parameter change, which may need frequent update.
- The lack of the use of bottom - fishing phenomenon.

References

[1] Sergey Ioffe, Christian Szegedy, Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift

[2] Zhang Ning, Fang Jing-wen and Zhao Yu-xuan, Bitcoin price prediction based on LSTM hybrid model. Computer Science ZTP183 Addison-Wesley Publishing Company, 1986.

[3] https://kns.cnki.net/kcms/detail/detail.aspx?dbcode=CMFD&dbname=CMFD202102&filename=1021590191.nh&uniplatform=NZKPT&v=I_2ak431_rjnznv6FlZMdhBwphIRdfwyKCAumWTyIril95zMwjsyOq7iIifYmVgx

[4] https://blog.csdn.net/jetFlow/article/details/78884619

[5] Ge Hinton, N Sriivastava, A Krizhevsky, I Sutskever, RR Salakhutdinov, Improving neural networks by preventing co-adaptation of feature detectors. Computer Science arxiv: 1207.0580, 2014

[6] Wang Yi, Wang Teng-fei, Research on investment decision of the financial market based on Chaos Theory. Times Finance No.9.636, 2016

[7] Liu Man-zai, Research on quantitative trading strategy Master Dissertation. Master Dissertation April, 2015

[8] Yu Tong, Analysis of stock quantitative trading strategy based on artificial intelligence and visualization technology. Financial Minds, F830.91

[9] Liu Li-jun, Research on quantitative trading strategy system model. Chinese economics JSXJKT2007

[10] Ioffe, Sergey, Szegedy, Christian, Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift. Computer Science arXiv:1207.0580