Problem Chosen	2022	Team Control Number
C	MCM/ICM Summary Sheet	2204935

The Wisdom of Trading

Summary

Over the past two thousand years, gold has acted as both a currency and an investment asset. New asset bitcoin has also set off an upsurge of new asset investment in recent years. Using ECM Model could better verify the correlation between the price data of two assets. New quantitative indicators are obtained by using the KDJ Model, which can provide us with the specific trend of data and its meanings. The data provided by the two models above could facilitate us to make corresponding decisions in the later strategy model. Based on the two methods above, we could determine that the two sets of data did affect each other. We first try the $DDPG$ algorithm in the field of reinforcement learning, integrate the two groups of data, simulate the trading process of the model in the real environment, and achieve good benefits. However, there is still some room for improvement in the model, that is, the super parameters could be further adjusted to be more suitable for the data, and this can get better results. We also see some trends and possibilities of the development of such models from this model. Finally, we refer to a large number of well-known trading strategies that only consider the price. Integrate and summarize a series of algorithms, integrate the short jump trading strategy, 123 rule trading strategy, and other trading strategies based on $Fiali$ trading strategy, and use the Dual thrust strategy to supplement the original $Fiali$ strategy, add some adjustments, and finally get a comprehensive $Fiali$ Model. We are very satisfied with the benefits of this model. And we firmly believe that if there are more sufficient data and more objective factors involved in the construction of the model, we could achieve better results.

Keywords: Gold ; Bitcoin ; $DDPG$; $Fiali$ Model ; ECM ; KDJ

Contents

1 Introduction

1.1 Background

For more than 2000 years, gold has been known as a high-quality liquid asset that has served as a hedge and safe haven for exchanging commodities. In ancient times, gold occupied a large number of circulation markets for a long time. As a currency, gold has long performed the functions of value scale, circulation means, storage means, payment means and world currency. By the 18th century, the gold standard was implemented in Europe, and standardized gold coins appeared in various countries. Currencies can be freely minted, freely convertible and freely imported and exported. At that time, gold was used uniformly in monetary reserves and international settlement, and the monetary attribute of gold reached its peak.In addition, gold also has investment properties. Investors can earn spread income by buying and selling gold in the gold market. From the perspective of large asset allocation, gold, like stocks, bonds, bulk commodities, foreign exchange and alternative investments (including real estate, art, etc.), is an investment variety that investors can choose. But the difference of gold is that gold is more risk averse as an investment.

Bitcoin, which is one of all types of cryptocurrencies, is regularly referred to as new gold, digital gold or gold 2.0. Cryptocurrencies are digital currencies that belong to a decentralized system still classified in the nascent asset class. Their prices are very sensitive to good and bad news with significant instability leading to high volatility and making the predictions hard and challenging, especially under adverse market conditions. Thus, investments in cryptocurrencies are, often, equated to investments in gold, where cryptocurrencies may benefit from higher allocations to gold and vice-versa.Dirk G. Baur et al. estimate the correlation of bitcoin and gold across time, across different return frequencies and across quantiles and find a near-zero correlation inconsistent with the claimed similarity. They offer two explanations for this puzzle: either the similarity is only a narrative and not accepted by investors or there are other forces at play that depress the true correlation. Such forces could be a substitution effect, investors sell gold and buy bitcoin, and a catching up effect, investors buy bitcoin to catch up with the market weight of gold[1].

With the continuous development of machine learning, compared with econometric quantitative models and other technologies, machine learning can deeply mine hidden information in huge data, and has also been applied to financial market transactions by many scholars.Tay et al. took the time series data of five futures as samples to prove that support vector machine(SVM) and BP neural network have good effects in financial time series prediction[2].Mc Donald et al. combined linear statistical model with nonlinear machine learning, which can effectively predict the time series of financial data[3].Heaton et al. constructed the deep portfolio theory and explored the deep mapping relationship between the portfolio and the objective function by setting the objective function of neural network, which showed the effectiveness of deep learning in asset price prediction and asset allocation[4].Wang et al. proposed a hybrid method composed of LSTM network and mean variance. Firstly, they use LSTM network to predict asset returns, and select assets with high potential for asset pre selection to optimize the assets of the portfolio. After that, the mean variance model is used in the portfolio, which has achieved good performance in the UK stock market[5]. In 2016, DeepMind Team made a breakthrough by combining DQN and DPG algorithm. They also proposed a deep deterministic strategy gradient ($DDPG$), which can solve the continuous action space problem, which improves the stability and convergence[6].

1.2 Problem Restatement

1. Create a model based on the daily data provided by the price data on that day. This model could help you buy and sell assets. When you are given the initial investment value of 1000 dollars, how much value could you gain on October 9, 2021.

2. Please use data or illustrations to prove that your model could make your earnings positive, and prove that your investment strategy could make your income the highest.

3. Determine the impact of changes in transaction costs on our strategy. When the transaction cost becomes larger or smaller, how will your strategy and the results under this strategy change.

4. In the form of memorandum, write a letter to help you understand the advantages and disadvantages of your strategy clearly and easily, the logic, process and results of the model to investors.

1.3 Overview of Our Work

Our goal is to build a mathematical model which could help trader automatically buy or sell assets and achieve the highest return in five years. And we hope that this model to some extent could be universal, rather than the data of two groups of assets given by a single over fitting asset.

Our specific work includes:

1. In order to verify that there is a certain relationship between the price of gold and the price of bitcoin, we use KDJ Model and ECM Model to explore the relationship between the two commodities. The price line chart given in the title is not enough to conclude the relationship between the two sets of data. Using ECM Model could better verify the correlation between the two asset price data. New quantitative indicators are obtained by using KDJ model, which can provide us with the specific trend of data and its meanings. The data provided by the two models above could facilitate us to make corresponding decisions in the later strategy model.

2. Based on the two methods above, we could determine that the two sets of data did affect each other and have a certain correlation. We first try the $DDPG$ algorithm in the field of reinforcement learning, integrate the two groups of data together, simulate the trading process of the model in the real environment, and achieve good benefits.

3. Finally, we refer to a large number of well-known trading strategies that only consider price. Integrate and summarize a series of algorithms, integrate the short jump trading strategy, 123 rule trading strategy and other trading strategies on the basis of $Fiali$ trading strategy, and use the Dual thrust strategy to supplement the original $Fiali$ strategy, add some adjustments, and finally get a comprehensive $Fiali$ Model. We are very satisfied with the benefits of this model.

4. In order to explore the impact of transaction cost on trading strategy, we adjusted the transaction cost ratio by one percentage point up and two percentage points down respectively on the basis of the original comprehensive $Fiali$ model, and kept other parameters unchanged. We find that changes in transaction costs could make a huge difference in returns.

5. The model we adopted and the results obtained are written into a memorandum to our trader to introduce the advantages and disadvantages of the model.

2 General Assumption and Variable Description

2.1 Assumptions

1. In the given data set, due to data vacancy, the filtered part of the data has no impact on the overall performance of the established model.
2. When ECM model is used to study the hedging ratio between gold market value and bitcoin market value, the impact of realistic factors such as Covid-19 and policy on the two commodity markets is ignored.
3. When the concept of cycle is involved in the modeling, the trading days of two commodities in a week are taken as a round by default. Gold is traded every five days and bitcoin is traded every seven days.

2.2 List of Notation

Table 1: List of Notation

Symbol	Definitation
$open$	opening price
$high$	highest price
low	lowest price
$close$	closing price
$volume$	volume of business
$amount$	turnover
$adjustflag$	rehabilitation of right state
$tradestatus$	transaction status
$pctChg$	fluctuation range(percentage)
$peTTM$	price earnings ratio -trailing twelve months
$pbMRQ$	price to book ratio-most recent quarter
$psTTM$	price to sales ratio
$balance$	current money
$maxnetworth$	maximum net asset value
$sharesheld$	number of hands held
$costbasis$	immediate buying price
$totalsharessold$	total number of hands thrown
$totalsalesvalue$	total value thrown
RSV_t	the probability for current price

3 Model Establishment and Solutions

3.1 Model premise

3.1.1 KDJ Model

(1)Model Establishment

In captial market, KDJ is a derived form of the Stochastic Oscillator Indicator which performs well in short term. George Lane developed this indicator in the late 1950s[7].This indicator uses stochastic method to forecast the price and trend of a certain asset, which not only bases on former data, also uses some random variables to achieve a accurate result. This method attempts to predict price turning points by comparing the closing price of a captial to its price range.

First we define Row Stochastic Value (RSV), which means the probability for current price. The formula of RSV is:

$$RSV_t = \frac{c\,\text{lose}_t - \text{low}_{t(n)}}{\left(high_{t(n)} - \text{low}_{t(n)}\right)} 100 \tag{1}$$

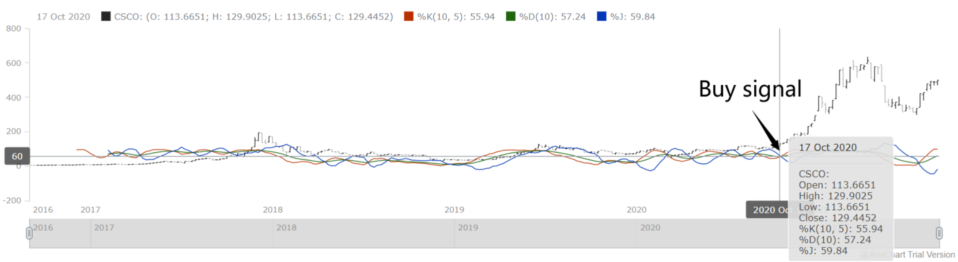
The standard value for RSV is 50, which means the future price will stay stable. If we get a value greater than 50, that means the probability of rising is higher than falling; and vice versa for RSV is less than 50. Using RSV, we make up three line K, D and J as below:

$$\begin{cases} K_t = \frac{2}{3}K_{t-1} + \frac{1}{3}RSV_t \\ D_t = \frac{2}{3}D_{t-1} + \frac{1}{3}K_t \\ J_t = 3K_t - 2D_t \end{cases} \tag{2}$$

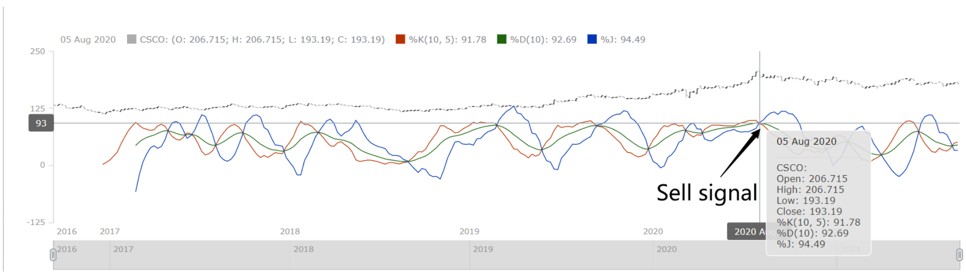
K is the function about RSV and itself, D is calculated from K and J is calculated from K and J. In practice, J is the fastest line, then the line K, and D line is the slowest line. Correspondingly, J is most sensitive to the variation of price and D is the dullest one.

(2)Model Solving

Using KDJ, we import the preprocessed dataset. For gold trading, we get $open_t$, $close_t$, $high_t$, low_t on a five-day cycle, for bitcoin trading, the cycle is extended to seven days. Then there are 250 and 260 pieces of data respectively, based on which we used Anychart to calculate above formulas. In order to calculate moving average of K line and D line, we used Exponential Moving Average (EMA) and Simple Moving Average (SMA) while detailing those two indicators.



(a) The KDJ Indicator of Gold Price



(b) The KDJ Indicator of Bitcoin Price

Figure 1: The KDJ Indicator of Two Assets' Price

(3)Analysis and Evaluation of Results

According to the KDJ graph, we summarized the following trading strategies:

· Values of %K and %D lines show if the security is overbought (over 80) or oversold (below 20).

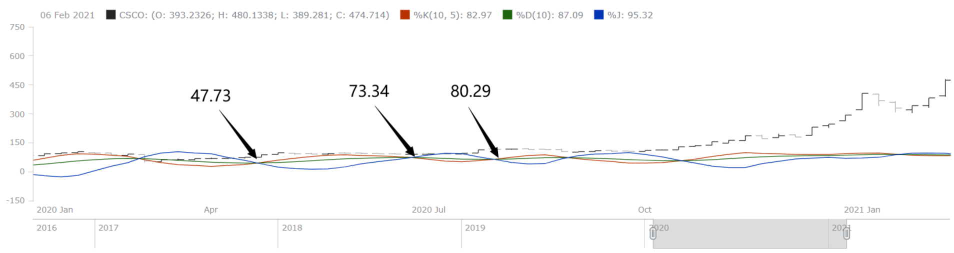
· The moments of %K crossing %D are the moments for selling (As Figure1(b)) or buying (As Figure1(a)).

· If K line above D line, it means that it is in a rising trend, sending a buy signal; conversely, it is in a declining trend, sending a sell signal.

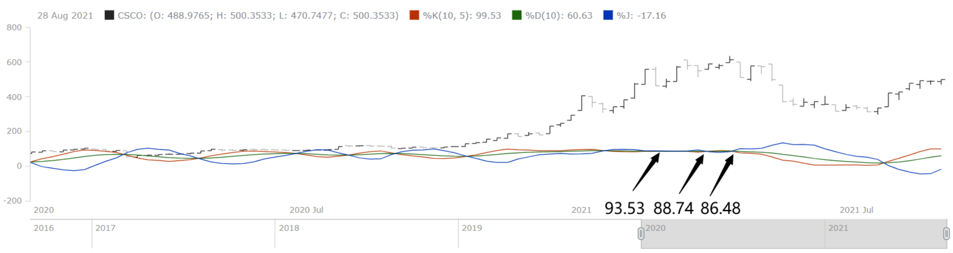
· The J line represents the divergence of the %D value from the %K value.

· In the process of the value of asset climbing, while KDJ indicator getting lower, it means that the price of asset is rising but buyers' power is weakening (As Figure2(b)), at this time the asset should be sold with the least delay possible.

· Conversely, when the value of asset getting lower and the KDJ indicator rising gradually (As Figure2(a)), it means that buyers' power is gradually increasing, the likelihood of a subsequent reversal up increases.



(a) Rising Trend with K Increasing



(b) Declining Trend with K Decreasing

Figure 2: From K Indicator Analyse Line Trend

As mentioned above, KDJ indicator could provide an important reference for the trading timing and measure. Meanwhile, the strategy proposed by KDJ could reflect the short-term situation of the trading market, which is of great significance for short-term investment.

However, the sensibility of KDJ might appears to be a weakness. In figure below, we can see 4 crosses in 17 cycles (As Figure3), which leads to frequent trading. Take transaction costs into consideration, the transaction costs will be high so it is hard for investor to earn money[8]. On this basis, we need to find a model which can earn a more steady income to guide our investment.

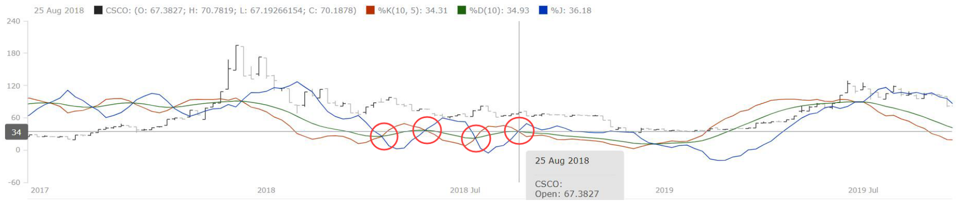


Figure 3: KDJ Graph Which Show 4 Crosses in 17 Cycles

3.1.2 ECM Model

(1)Model Establishment

In the context of the this problem, money we held flows between both gold and bitcoin assets. Therefore, in addition to separate analysis of the trading strategies of each asset, it is also necessary to examine the correlation between the two assets of gold and bitcoin.

Bouri et al. (2018) examined the nonlinear and asymmetric effects of aggregate commodity index and Gold prices on bitcoin prices. They reported that price information from the aggregate commodity index and Gold prices could be used to predict bitcoin price movements[9]. Bri‘ere et al. (2015) reported low connectedness between bitcoin, traditional assets and commodities based on correlation coefficient[10]. Analyzing the inter linkages between different assets could be equally important from a portfolio perspective. Indeed, it can help investors to determine if gold and bitcoin can hedge against each other.

The theory of $Cointegration$ was proposed by Engle and Granger in 1978. Stationarity is a very important premise for time series analysis. Many models are based on stationarity. But in fact, many time series are not smooth, and $Cointegration$ starts from analyzing the non-stationarity of time series.

The content of the $Cointegration$ is as follows:

Record X_t as $\mathrm{X}_t \sim I(d)$ if it is a integrated d-order series. If there exists a nonzero vector β which makes $Y_t = \beta X_t \sim I(d-b)$, X_t is thought to have d, b-order $Cointegration$ relationship, β is called $Cointegration$ vector. When X_t and Y_t both are integrated order series, there linear combination $Y_t - \beta X_t$ is a integrated order series as well. In other words, if both sets of series are non-stationary, but are stable after a first-order difference, and the two sets of series are also stationary after linear combination, then there is a $Cointegration$ relationship between them, the ECM model is:

$$A(L)\Delta Y_t = \alpha + B(L)X_t + \gamma\varepsilon_t + \theta(L)u_t \tag{3}$$

The ECM(Error Correction Model) Model is extension of the $BVAR$ Model(Bayesian Vector Autoregressive), which brings residual series into a new equation based on the expression of $BVAR$. The model can considers both the long-term stable relationship of the logarithmic yield series of two assets and the process of adjusting the short-term unstable series to a stable series in real time.

If regression of the following EMC model includes a stationary residual ε_t, indicating a $Cointegration$ relationship between the yield rates of gold and bitcoin.

$$\Delta r_{3t} = \Delta r_{1t} + u_{t-1} \tag{4}$$

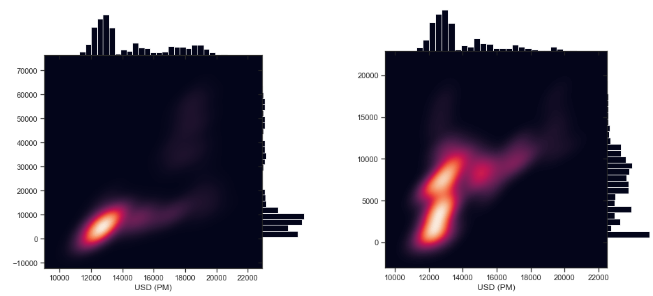
(2)Model Solving

According to $Cointegration$, we first analyze the intuitive correlation between gold and bitcoin assets with all data. It can be seen from that due to the greater impact of real factors on bitcoin, it is not possible to show a good correlation in the long term. The data set covers five years, during which bitcoin ban in 2017 and Covid-19 in 2021 all contributed to wild price swings. In view of the uncertainty over these two periods, we gradually narrowed the scope of our data from No.350 to No.1000 as (Figure4) shows, that is from Sep, 2017 to July, 2019.

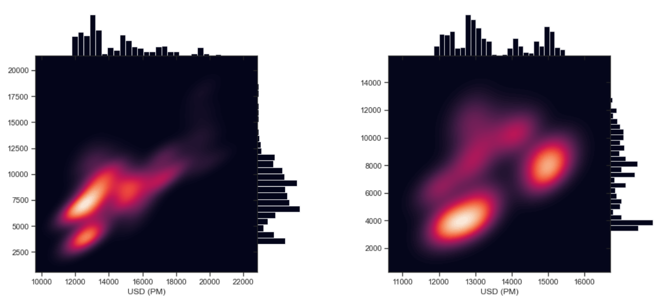
(a) Price Trend from Overall Data (b) Price Trend from Filtered Data

Figure 4: Contrast of Price Trend Before and After Data Filter

We use jointgrid to analyze the price relationship between the two assets, as (Figure5) shows. Re-analyzing the correlations, we gain a better result, and both pirce series are unstable.



(a) Data from 1 to 1190 (b) Data from 1 to 1000



(c) Data from 200 to 1000 (d) Data from 350 to 1000

Figure 5: Jointgrid for Analyzing Price Relationship

We then use ADF test to determine whether the two series are integrated of order 1, assuming that there is a root of unity makes the significance test statistic less than confidence levels (10%, 5%, 1%), then there probability (90%, 95%, 99%) to reject null hypothesis.

The results of the following table could be obtained by ADF tests using statsmodels in Python. It can be seen that both series are integrated of order 1.

Table 2: ADF Test Results

asset	t-statistic	pvalue	usedlag	nobs	level		
					1%	5%	10%
Gold	-12.443	3.705e-23	6	988	-3.436	-2.864	-2.568
Bitcoin	-5.453	2.613e-06	20	978	-3.437	-3.885	-2.569

Further, we use function coin in this module to detect the $Cointegration$ relationship between two series based on the EG $Cointegration$.

Table 3: EG $Cointegration$ Test Result

coint	pvalue	crit-value		
		1%	5%	10%
-0.453	0.968	-3.913	-3.346	-3.051

From results, it can be seen that the t-statistic value is less than 1 confidence, so there is a 99% confidence to reject the null hypothesis, and the value of p-value is quite small, so there is a $Cointegration$ relationship between the price of gold and bitcoin in time series excluding factors under certain significant practical influence.

If there is a $Cointegration$ relationship between the logarithmic prices of the two assets, it is possible to obtain stationary return by constructing a linear assets portfolio. This conclusion can provide a theoretical basis for subsequent discussion and establishment of major models.

3.2 $DDPG$ Model

3.2.1 Model Establishment

The last two decades were marked by increasing integration of international markets, which has resulted in crashes and financial crises,including the global financial crisis in 2008 and the European debt crisis in 2012. The increase in cross-market linkages or spillovers has increased portfolio riskiness and decreased diversification benefits, pushing investors and portfolio managers to find alternative assets that help to hedge exposure risk. In the last two years, the impact of the COVID-19 on the trading strategies between different types of cryptocurrencies, gold, exchange market,portfolio diversification, and macroeconomic policy has attracted a great deal of interest in the financial market.

Investment strategy portfolio is a subject of in-depth research in the financial field, but various models are based on certain assumptions. In the actual assets market, it is often difficult to achieve because of its complexity and high cost. Deep reinforcement learning has many advantages and has been able to outperform human players in many challenging video games. Using the deep learning algorithm, its advantages are applied to the research of portfolio strategy, which can disperse the risk and maximize the number at the same time. Firstly, this paper defines the MDP model of assets portfolio trading. In order to disperse the weight of investment, entropy is introduced to improve the $DDPG$ algorithm, optimize the portfolio strategy, and take the assets price information, assets share and capital amount as the input to output the portfolio value. Compared with the $DDPG$ strategy studied in the past, the income of the improved strategy in this paper is significantly improved.

(1)$Actor - Critic$ Algorithm Framework

The $DDPG$ algorithm is an improved version of the DPG algorithm.DPG combines Q-learning and strategy gradient framework.Compared with DPG, $DDPG$ uses neural network as function approximator. $DDPG$ includes $Actor$ network and $Critical$ network.The actor network $\mu\left(\mathrm{s} \mid \theta^{\mu}\right)$ maps states to actions.Where θ^{μ} is the set of actor network parameters, while critical network $Q\left(s, a \mid \theta^{Q}\right)$ is the output of action values in this state, where θ^{Q} is the set of critical network parameters.In order to explore better actions, Noise is added to the output of $Actor$ network, which is sampled from random process N[11].

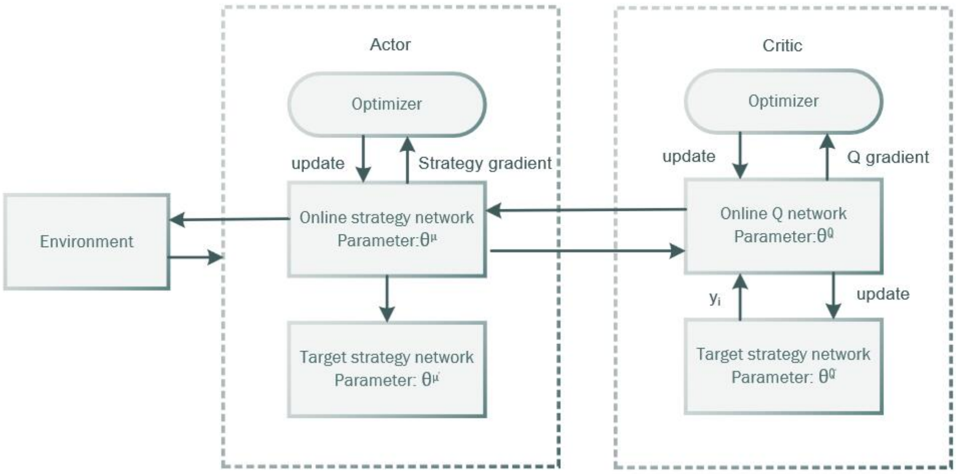


Figure 6: $DDPG$ Flow Chart

(2)Experience Replay Technology

Using experience pool R to store state transition experience and update the model, which can effectively reduce the correlation between experiential samples.Create target $Actor$ network Q' and μ' by copying $Actor$ network and $Critical$ network respectively to provide consistent time differential backup.Both networks are updated iteratively.Each time, the $DDPG$ agent takes action s_t at a_t, and then receives a reward according to s_{t+1}.The conversion experience (s_t, a_t, s_{t+1}, r_t) is then stored in the experience pool R.The conversion experience of N samples is taken from R and calculated $y_i = r_i + \gamma Q'\left(s_{i+1}, \mu'\left(s_{i+1} \mid \theta^{\mu'}, \theta^{Q'}\right)\right), i = 1, \ldots, N$.The critical network is then updated by minimizing the expected difference $L\left(\theta^{Q}\right)$ between the outputs of the target $Critica$ network Q' and $critical$ network Q[11].

$$L\left(\theta^{Q}\right)=\mathbb{E}_{s_t, a_t, r_t, s_{t+1} \sim buffer}\left[\left(r_t+\gamma \mathrm{Q}'\left(s_{t+1}, \mu\left(s_{t+1} \mid \theta^{\mu}\right) \mid \theta^{Q'}\right)-Q\left(s_t, a_t \mid \theta^{Q}\right)\right)^2\right] \quad (5)$$

The parameters of the participant network θ^{μ} are as follows

$$\begin{aligned}&\nabla_{\theta}\mu\mathcal{T} \approx \mathbb{E}_{s_t,a_t,r_t,s_{t+1}\sim buffer}\left[\nabla_{\theta}\mu Q\left(s_t,\mu\left(s_t\mid\theta^{\mu}\right)\mid\theta^{\mathrm{Q}}\right)\right]\\&=\mathbb{E}_{s_t,a_t,r_t,s_{t+1}\sim \mathrm{buf}\,f\,\mathrm{er}[\nabla_a Q(s_t,\mu(s_t)|\theta^{\mathrm{Q}})\nabla_{\theta}\mu\mu(s_t|\theta^{\mu})]}\end{aligned} \tag{6}$$

After updating the $Critical$ network and $Actor$ network through the transferred experience in the experience pool, the target $Actor$ network and target $Critical$ network are updated as follows:

$$\begin{aligned}&\theta^{Q'} \leftrightarrow \tau\theta^{Q}+(1-\tau)\theta^{Q'}\\&\theta^{\mu'} \leftarrow \tau\theta^{\mu}+(1-\tau)\theta^{\mu'}\end{aligned} \tag{7}$$

Where τ is the learning rate.

(3)Decentralized Weight Mechanism

The action behavior in the portfolio strategy problem is to allocate the weight on the assets, and the sum of the weights of the left and right stocks is 1. asset trading is modeled as Markov Decision Process (MDP), and the trading goal is to maximize the final portfolio return.After the strategy network's result was printed out, the transaction with a certain amount of power was finally realized. In view that the weight of the previous research's output was usually concentrated in one or several assets, this article introduced the risk division mechanism in the training process, so that the intelligence agency could distribute the weight in the training process and reduce the investment risk. In the target function of the strategy network, the entropy of the current strategy was introduced as a regular term, so that the agent could learn to distribute the investment[11].

In information theory, information entropy enables the measurement of system complexity. The expression is as follows:

$$H=-\sum p\left(x_i\right)\log_2 p\left(x_i\right) \tag{8}$$

Suppose that for a portfolio of 10 assets, all funds can be invested in one of the assets with the highest return. The weight of this asset is 1 and the weight of other assets is 0. In this case, the entropy is 0, that is, the system is deterministic and invariant, and there is no randomness.The fund can also be divided into 10 assets on average, and the weight of each asset is 0.1. In this case, the randomness of the system is the largest, and the entropy is also the largest in all distribution methods.

Therefore, funds can be dispersed as much as possible by maximizing entropy. The entropy of strategy network is defined as follows:

$$H(\mu(s))=-\sum_{k=1}^{n}\mu(s)_k\log\mu(s)_k \tag{9}$$

Where $\mu(s)$ is the output of the policy network and K is the output of $\mu(s)_k$.

The entropy of the policy is taken as the regular term of the objective function of the policy network. The influence of the regular term is controlled by the constant C. after adding it to the objective function, the gradient becomes:

$$\nabla_{\theta^{\mu}} \mathcal{T} \approx \frac{1}{N} \sum_{i} \nabla_{a} Q\left(s, a \mid \theta^{Q}\right)\Big|_{s=s_{i}, a=\mu\left(s_{i}\right)} \nabla_{\theta^{\mu}} \mu\left(s \mid \theta^{\mu}\right)\Big|_{s_{i}}+c \frac{1}{N} \sum_{i} \nabla_{\theta^{\mu}} H\left(\mu\left(s \mid \theta^{\mu}\right)\right)\Big|_{s_{i}} \tag{10}$$

(4)Construction of Asset Market Environment

Before training and strengthening the asset portfolio trading agent, we need to carefully build the environment to simulate the asset trading in the real world, so that the agent can interact and learn.

State space:

The multi-dimensional vector composed of three parts of information is used to represent the state space of multiple asset trading environment:$[b_t, p_t, h_t]$.Some definitions are as follows:

Fund balance $b_t \in \mathbb{R}_{+}$:Available fund balance in trading account at current time step t.

Price $p_t \in \mathbb{R}_{+}^{D}$:Price information of each asset.

Share of asset $h_t \in \mathbb{Z}_{+}^{D}$:Number of shares per asset.

Action space:

Action space describes the actions allowed by the interaction between agent and environment. Usually,$a \in A$ includes three actions: $a \in \{-1, 0, 1\}$,where - 1, 0 and 1 respectively represent the sale, holding and purchase of an asset. For one asset, action space can be defined as $\{-k, \ldots, -1, 0, 1, \ldots, k\}$, where K and $-K$ represent the number of assets that can be bought and sold,$k \leq h_{\max}$,$h_{\max}$ is a predefined parameter, this parameter is set to the maximum number of assets that can be bought for each buy operation,$h_{\max} = 100$.Therefore, the size of secant action space is $(2k+1)^D$.Then standardize the action space into $[-1, 1]$[11].

Reward function:

$$r\left(s, a, \mathrm{~s}'\right)=v'-v \tag{11}$$

v' and v respectively represent the value of the portfolio s' and s in the state.

3.2.2 Model Solving

Based on the Reinforcement learning model of $DDPG$, aiming at the trading environment of gold and bitcoin, we take the whole trading market as the environment in which we experiment, and take the trading strategy as the agent in the environment. After interacting with the environment through the agent,Basing on a state provided by the environment, we can obtain the corresponding reward and punishment and update the trading strategy based on the corresponding punishment.

This involves several main aspects, specifically: ① Construction of model environment ② Update the environment itself when the termination condition is not triggered ③ Update the reward obtained value after triggering the termination condition. The specific implementation process is:First, according to the current state, substitute it into the environment corresponding to $DDPG$ and take corresponding actions. Secondly, interact according to the specific action and environment, so as to get the corresponding interactive feedback. Positive feedback will make the agent get the corresponding reward. The reward value here is set as 1000 times of the benefit ratio of this action. The specific formula of the benefit ratio is:

$$Profitratio = \frac{currentamount - capital}{capital} \tag{12}$$

The penalty value brought by negative feedback is - 100.The environment itself is updated based on the actions obtained in this operation, and this operation is recorded in the model environment experience pool to assist the actions in the subsequent environment.

3.2.3 Analysis and Evaluation of Results

Finally, by applying the constructed model back to the value itself, the total reward obtained by the intelligent agent is 11356.588 dollars. It can be seen that we can also obtain good income through this method. The final yield curve is shown in the (Figure 7) below:

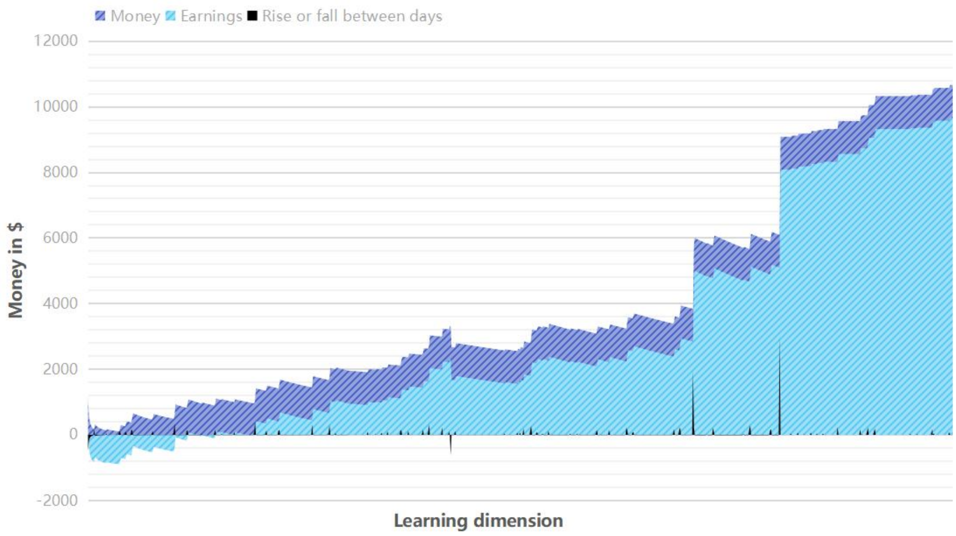


Figure 7: $DDPG$ Yield Curve Chart

As can be seen from the above figure, the $DDPG$ model can indeed steadily obtain benefits, but there are still certain data fluctuations. In addition, due to the limitation of the number of iterations of the model, it can be found that the decision made by the current model is not the optimal decision of the model, but only a feasible decision. But what we know from the rising curve is that the model is sufficiently sensitive to the increment of goods, thanks to the reward mechanism of reinforcement learning. Of course, this model can also achieve more satisfactory results by improving parameters and increasing training times and training markets.

3.3 Comprehensive $Fiali$ Model

3.3.1 Model Establishment

$Fiali$ trading strategy is summarized from "1000% men - trading method of futures champion miracle" written by $Fiali$. $Fiali$ one of the authors of the book, is the champion of Japan's first "robbins-taicom futures championship competition". He created an amazing record of

1089% times earnings and won the championship of the competition. This trading strategy is extracted from his articles.

The difference between the $Fiali$ trading strategy and the general trading strategy is that the $Fiali$ trading strategy requires less data support. Now the general trading strategy often needs the comprehensive consideration of market income, industry status and other factors. However, $Fiali$ trading strategy is the trading strategy obtained by studying the price change trend, which is very consistent with our data scale and data type. The specific content of $Fiali$ trading strategy is: yesterday's high is on track and yesterday's low is off track. When the price breaks the on track, buy; When the price breaks down the off track, sell. Roughly as shown in the K-line diagram below,

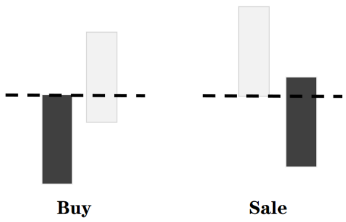


Figure 8: K-line Diagram of $Fiali$ Trading Strategy

3.3.2 Model Solving

Due to our own data, we have made some improvements on this basis. We change the time cycle from one day to one week, and deploy the trading strategy on a weekly basis. As for the purchase of gold and bitcoin, we choose to compare the growth rate at last week and the short-term benefit value of the two, and choose the one with the higher benefit as the purchase choice for this week. The final revenue results and the basic asset selection strategy are shown in the (Figure 9) and (Figure 10) below:

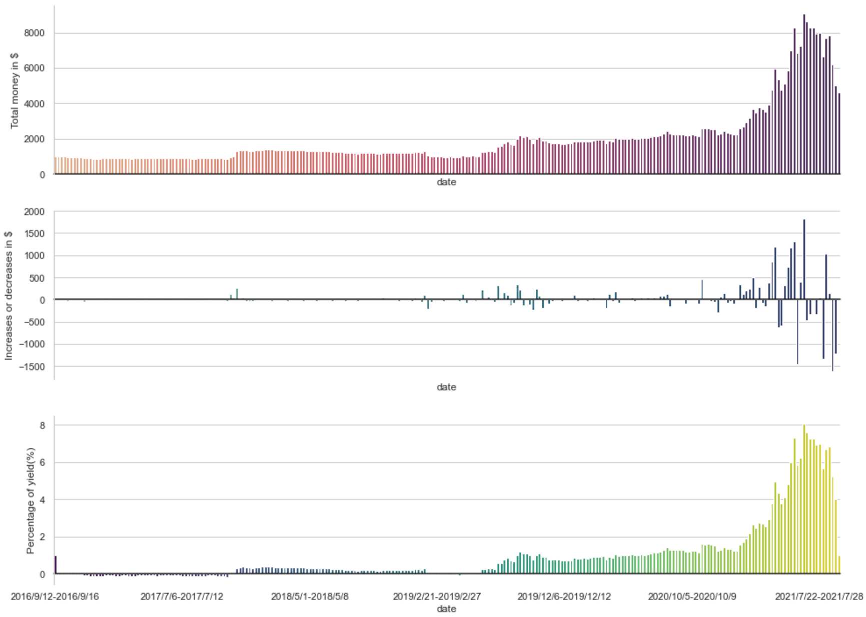


Figure 9: $Fiali$ Yield Graph before Improvement

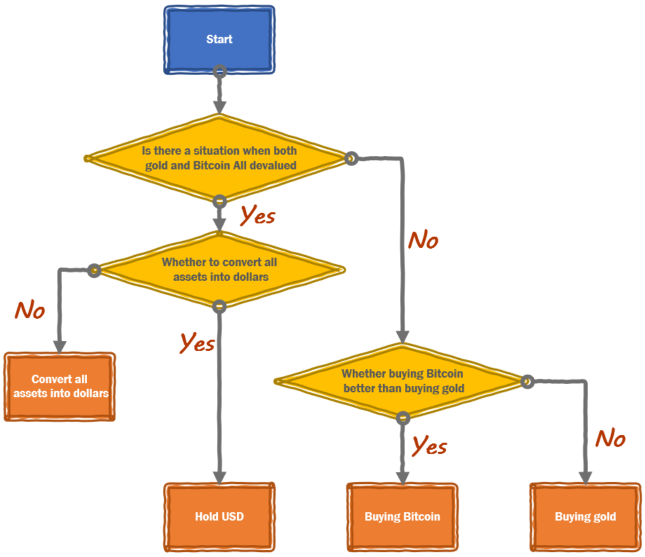


Figure 10: $Fiali$ Method Flow Chart

We can see from the (Figure 9) above that the application of $Fiali$ trading strategy could indeed bring good benefits, but it is far from meeting our expectations. We found several problems by observing the images. First, there are few optional commodities, when the income of holding bitcoin is much greater than that of holding gold. The strategy will not change existing assets into US dollars for hedging or gold for appreciation when bitcoin depreciates. Secondly, the response of the strategy to price fluctuations is too strong. The strategy hope to purchase frequently, ignore the relationship between income and commission. It is too sensitive to fluctuations, so we improve the basic $Fiali$ trading strategy based on other models.

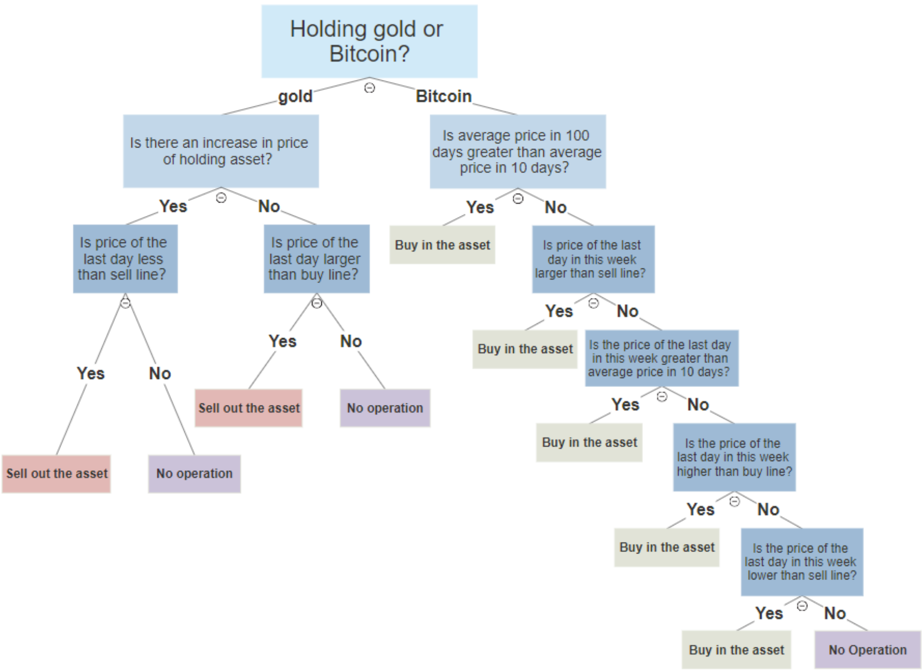


Figure 11: $Fiali$ Method Decision Tree Flow Chart

We refer to the well-known relevant trading strategies that only consider the price, add the short jump trading strategy, 123 rule trading strategy and other trading strategies on the basis of the $Fiali$ trading strategy[12]. We use the Dual thrust strategy to supplement the original Fiali strategy[13], and add some adjustments. The final decision model is above.

3.3.3 Analysis and Evaluation Results

Through the above Decision tree method, we have achieved the final result of earning 163230 dollars with the principal of 1000 dollars. It could be seen that the result obtained by the model is still satisfactory. We present the income in the form of time series, and we can get the following income chart (Figure 12) as follows:

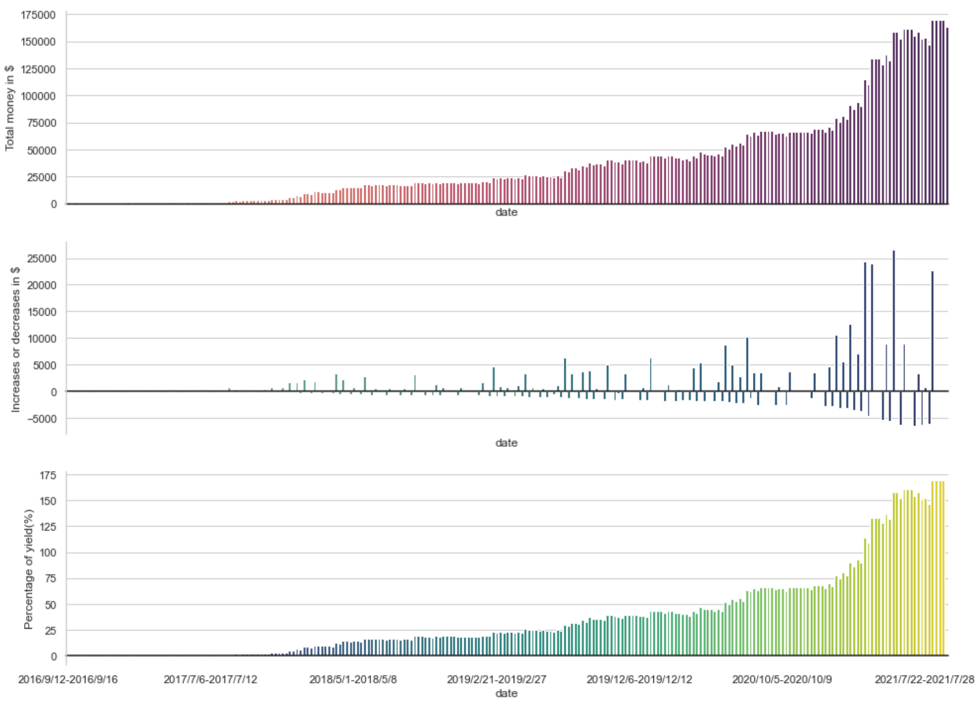


Figure 12: Income Time Series Chart

From the (Figure 12) above, we could see that after the modification of the $Fiali$ Model, its sensitivity to price fluctuation is far less than that of the original model, and its grasp of the development trend is more diversified, and its impact on the transaction cost is more accurate. Since the decision-making is based on the data before the time point, it is impossible to predict the future trend and the impact of policy changes and external factors, so it will lead to deviation in the prediction of the future trend, which is difficult to avoid. But the overall result is very satisfactory to us.

4 Impact of Transaction Cost Change on Strategy

In order to explore the impact of transaction cost on trading strategy, we adjusted the transaction cost ratio by one percentage point up and two percentage points down respectively on the basis of the original comprehensive model, and kept other parameters unchanged. The time series chart corresponding to the specific results is shown in the (Figure 13) below:

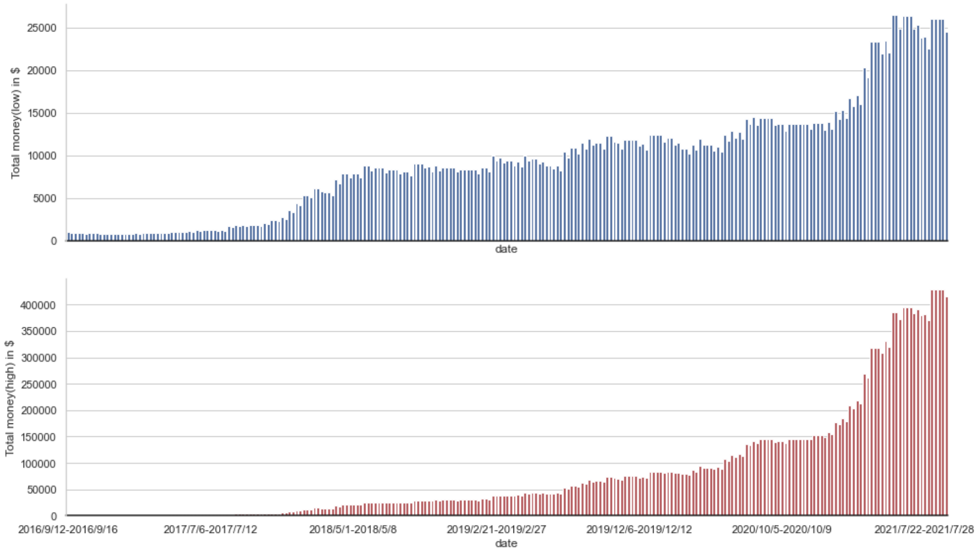


Figure 13: Time Series Chart after Changing Transaction Cost

Through the (Figure 13) above, we could clearly find that after changing the transaction cost ratio, not only the trading strategy has changed, but also the final amount has a gap of nearly five times. After increasing the transaction cost percentage point, we can see that when the strategy makes a wrong decision, the losses suffered are reduced, and from the operational level, the operation frequency of the strategy is also relatively reduced, and we finally obtain a profit of more than 400000 dollars. On the contrary, after the transaction cost percentage point is reduced, the fault tolerance value of misoperation is reduced, and due to the increased loss caused by the transaction, the model will give up the transaction because of the immediate excessive loss, and then choose the transaction later when the currency appreciates, further increasing the lag of the transaction. So we only get $20000 in the end.

On the other hand, due to the above reasons, there are some differences between the two revenues in the first few years when the value of bitcoin did not increase. The difference was small at first, but with the increase of bitcoin value, the difference between the two will further increase, resulting in a difference of nearly 20 times. It can be seen that small changes in transaction cost will have a certain impact on trading strategy, and the impact will gradually increase with the growth of time.

5 Sensitivity Analysis

For the final comprehensive strategy model, the focus of our future research is whether it has universal adaptability to the data, rather than the over fitting model. We made some changes to the original data: we adjusted the monetary value data of some days from 2016 to 2017 and 2020 to 2021 by $300, so as to increase the uncertainty of the data. On this basis, the model is used for decision-making. The final income is shown in the (Figure 14) below:

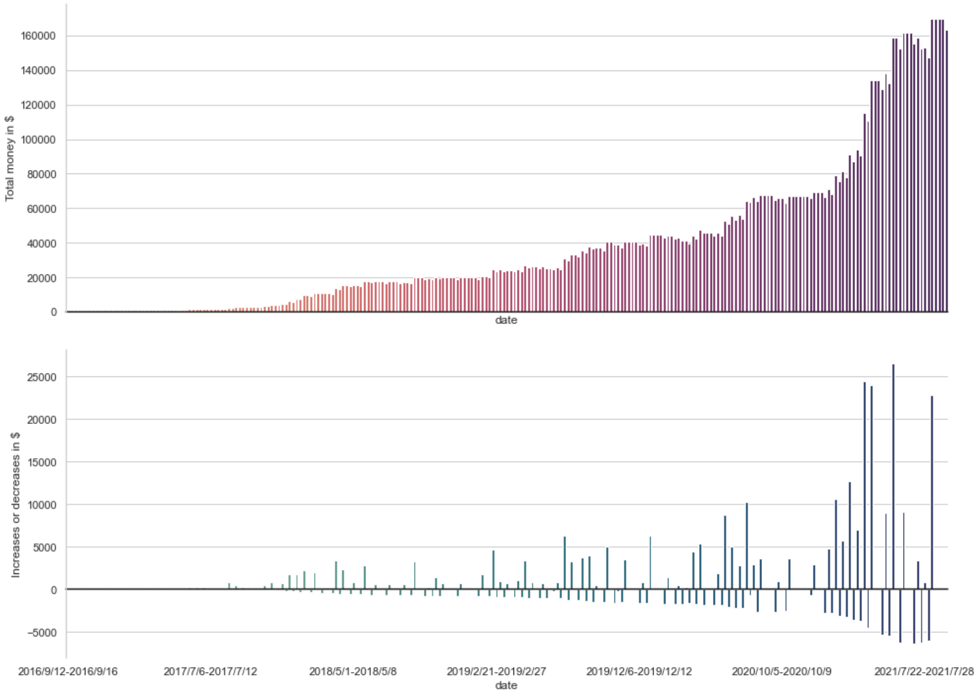


Figure 14: Sensitivity Analysis Income Chart

It could be seen from the above (Figure 14) that after a certain level of data fluctuation, the income obtained has not been greatly affected, indicating that the model itself has good anti-interference ability and could deal with certain data fluctuations.

6 Strengths and Weakness

6.1 $DDPG$ Model

Through the implementation of the model and the analysis of the time results, we find that $DDPG$ Model could get good results in decision-making by setting the manipulation agent to learn with reward and punishment mechanism in the learning environment. And this effect could get an excellent result with the increase of training time and the adjustment of parameters.

However, its disadvantages are also very obvious. Because it relies heavily on parameters and data volume, the effect is very limited when the data volume is insufficient or the parameters are insufficient. This deficiency is also reflected in the model results.

6.2 Comprehensive $Fiali$ Model

After optimizing the $Fiali$ Model, we can find that the income has been significantly improved, and the anti-interference ability of the model is also very excellent. However, the model cannot deal with complex situations because its rules are too simple. And it will perform poorly for multivariate data that are not only commodity prices. Moreover, there is still a certain optimization space for this model, and its income level could be further increased.

7 Conclusion

In the face of gold and bitcoin, two assets with large capital fluctuations, this paper exposes the $Cointegration$ relationship between the value time Chart of gold and bitcoin through

ECM. The KDJ Model is used to quantify the trend of its growth sequence. It reveals the trading laws of two kinds of money and a benchmark for us to make decisions under this law as consumers. Based on the above relations and criteria, we preliminarily realized the simulation decision model through the reinforcement learning model called $DDPG$, which further verify the rationality of the above criteria, and also provided a certain logical reference for the construction of our final Comprehensive $Fiali$ Model. Finally, based on the $Fiali$ trading model, we integrate the landing trading strategy and Dual Thrust trading strategy into the above premise, and then realize the trading decision model for such volatile value assets, and find that the transaction cost has a profound impact on it. Although the model itself can be further optimized, the final simulation results are satisfactory.

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[13] $https : //blog.csdn.net/The_Time_Runner/article/details/$88762963.

Memorandum

To: Trader
From: Team 2204935
Date: February 21, 2021
Subject: Memorandum

From the beginning, we used a different disintegration idea from the past. We believe that the data affect each other, while having a certain correlation, both in the virtual experiment and in the real world. After searching the articles, we found that the prices of gold and bitcoin are correlated, and to some extent, investing in bitcoin is another type of investment in gold.

In order to verify that there is a certain relationship between the price of gold and the price of bitcoin, we use KDJ Model and ECM Model to explore the relationship between the two commodities. The price line chart given in the title is not enough to conclude the relationship between the two sets of data. Using ECM Model could better verify the correlation between the two asset price data. New quantitative indicators are obtained by using KDJ Model, which can provide an important reference for the trading timing and measure. Meanwhile, the strategy proposed by KDJ can reflect the short-term situation of the trading market, which is of great significance for short-term investment.The data provided by the two models above could facilitate us to make corresponding decisions in the later strategy model.

Based on the two methods above, we could determine that the two sets of data did affect each other and have a certain correlation. We first try the $DDPG$ algorithm in the field of reinforcement learning, integrate the two groups of data together, simulate the trading process of the model in the real environment. Finally, the total reward obtained by the agent converted into USD is 11356.588\$. $DDPG$ Model can indeed obtain benefits steadily, but there are still some data fluctuations. Due to the number of iterations of the model, it could be found that the decision made by the current model is not the optimal decision of the model, but only a feasible decision.

We refer to a large number of well-known trading strategies that only consider price. Integrate and summarize a series of algorithms, integrate the short jump trading strategy, 123 rule trading strategy and other trading strategies on the basis of $Fiali$ trading strategy, and use the Dual thrust strategy to supplement the original $Fiali$ strategy, add some adjustments, and finally get a comprehensive $Fiali$ Model. Through the above Decision tree method, we have achieved the final result of earning 163230 dollars with the principal of 1000 dollars. It could be seen that the result obtained by the model is still satisfactory. After the modification of the $Fiali$ Model, its sensitivity to price fluctuation is far less than that of the original model, and its grasp of the development trend is more diversified, and its impact on the transaction cost is more accurate. Since the decision-making is based on the data before the time point, it is impossible to predict the future trend and the impact of policy changes and external factors, so it will lead to deviation in the prediction of the future trend, which is difficult to avoid. We are very satisfied with the benefits of this model. And we firmly believe that if there are more sufficient data and more objective factors involved in the construction of the model, we could achieve better results.

In general, the result of Comprehensive $Fiali$ Model is better than that of $DDPG$ Model. I hope our strategy could help you make investment decisions.

Appendices

Here are simulation programmes we used in our $Fiali$ Model as follow.

```
def Step1(num , i):
    K1=0.05
    K2=0.05
    if (num == 1):
        HH=0
        LC=0
        HC=0
        LL=0
        if (i>=1):
            for j in range(1,2):
                HH = max(HH,data1['high'][j])
                HC = max(HC,data1['close'][j])
                LC = min(LC,data1['close'][j])
                LL = min(LL,data1['low'][j])
            rang=max((HH-LC),(HC-LL))
            Buyline = data1['open'][i]+K1*rang
            Sellline = data1['open'][i]-K2*rang
        else:
            Buyline = data1['high'][i-1]
            Sellline = data1['low'][i-1]*0.99
        min_ = 0
        if (i>=14):
            for j in range(2,15):
                min_ = min(min_,data1['low'][i-j])
        else: min_ = data1['low'][0]
        min_1 = 0
        if (i>=30):
            for j in range(0,14):
                min_1 = min(min_1,data1['low'][i-j])

        average = (data1['low'][i]+data1['high'][i]+data1['open'][i]+data1[
                                                  'close'][i])/4

        if ((wallet['gold'] == 0 )&( wallet['bitc'] == 0)):
            if (
                (min_1>min_)|
                (data1['close'][i] >= min_)|
                (data1['close'][i] >= Buyline) |
                (data1['close'][i] <average*0.98)
               ):

                money = wallet['USD']
                wallet['USD']=0
                wallet['bitc']=money*(1-0.02)/data1['open'][i]
            elif ((data1['open'][i] <= Sellline)):
                money = wallet['USD']
                wallet['USD']=0
                wallet['bitc']=money*(1-0.02)/data1['open'][i]
            return

        if (data1['close'][i-1]>data1['open'][i-1]):
            if (data1['close'][i] < Sellline):
```

```
                money = wallet['bitc']
                wallet['bitc']=0
                wallet['USD']=money * data1['open'][i] * 0.98
                return
        elif (data1['close'][i-1]<data1['open'][i-1]):
            if (data1['close'][i] > Buyline):
                money = wallet['bitc']
                wallet['bitc']=0
                wallet['USD']=money * data1['open'][i] * 0.98
                return
wallet = {'USD':1000 ,'gold': 0 , 'bitc': 0}
final = []
final.append(wallet['USD'])
print(wallet,'USD:' ,wallet['USD'])
for i in range(1,min(len(data1),len(data2))):
    if ((data1['close'][i]-data1['open'][i]<0)&(data2['close'][i]-data2['
                                          open'][i]<0)&(wallet['USD']!=0)):
        final.append(wallet['USD']+wallet['gold']*data2['open'][i]*1+wallet
                                              ['bitc']*data1['open'][i]*0.
                                              98)
        print(wallet,'USD:' ,wallet['USD']+wallet['gold']*data2['open'][i]*
                                              1+wallet['bitc']*data1['open'
                                              ][i]*0.98)
        continue
    if (wallet['bitc']!=0 & (wallet['USD']==0 & (data1['open'][i]>data1['
                                          open'][i-1]))):
        money = wallet['bitc']
        wallet['bitc']=0
        wallet['USD']=money * data1['open'][i] * 0.98
        final.append(wallet['USD']+wallet['gold']*data2['open'][i]*1+wallet
                                              ['bitc']*data1['open'][i]*0.
                                              98)
        print(wallet,'USD:' ,wallet['USD']+wallet['gold']*data2['open'][i]*
                                              1+wallet['bitc']*data1['open'
                                              ][i]*0.98)
        continue
    elif(wallet['gold']!=0 & (wallet['USD']==0 & (data2['open'][i]>data2['
                                          open'][i-1]))):
        money = wallet['gold']
        wallet['gold']=0
        wallet['USD']=money * data2['open'][i] * 0.99
        final.append(wallet['USD']+wallet['gold']*data2['open'][i]*1+wallet
                                              ['bitc']*data1['open'][i]*0.
                                              98)
        print(wallet,'USD:' ,wallet['USD']+wallet['gold']*data2['open'][i]*
                                              1+wallet['bitc']*data1['open'
                                              ][i]*0.98)
        continue
    if ((data1['close'][i]-data1['open'][i])/data1['close'][i] >= (data2['
                                          close'][i]-data2['open'][i])/
                                          data2['close'][i]):Step1(1,i)
    else :
        Step1(2,i)
    final.append(wallet['USD']+wallet['gold']*data2['open'][i]*1+wallet['
                                          bitc']*data1['open'][i]*0.98)
    print(wallet,'USD:' ,wallet['USD']+wallet['gold']*data2['open'][i]*1+
                                          wallet['bitc']*data1['open'][i]*0
                                          .98)
```