

The Best Decision-Making Scheme Based on Bitcoin and Gold Stock Market

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Keywords: Unstable Assets, Bull and Bear Market Judgment Model, Risk Model, Time Series Prediction Model, Xgboost Regression Model.

Abstract: Market traders frequently buy or sell their volatile assets, Bitcoin and gold, in order to maximize their returns, and each purchase and sale of these two assets requires a commission. In order to study this economic management problem, we made certain assumptions and established a prediction model to achieve the best rate of returns. We construct bull and bear market judgment models, risk models and time series prediction models to help traders make the best decisions every day in order to maximize profits. Find the total assets in the hands of traders as of 9/10/2021. To demonstrate the feasibility of our strategy, we use XGboost regression model to fit the predicted data and the real data. After determining the sensitivity of the model and analyzing the impact of market price fluctuations on our model, we communicated our decisions, models, and results to traders in the form of memos. In summary, when you have \$1000 on September 11, 2016, through our model based on five years' market data, you will have \$184659.88 on September 10, 2021.

1 INTRODUCTION

Market traders often buy or sell their volatile assets - bitcoin and gold - to maximize their returns. Each purchase or sale of these two assets requires a commission, and while gold is not open every day, bitcoin can be bought and sold daily. The trader would have a principal of \$1,000 on November 9, 2016, and would use that money to invest and trade gold and bitcoin over a five-year period from November 9, 2016, to September 10, 2021, to maximize their returns. We categorize this problem as a quantitative economic investment strategy analysis problem (Tang, 2021), quantitative investment is a type of trading with quantitative statistical analysis tools at its core and programmed trading (Guo, 2014; Hou, 2021). We use data from the past five days to predict the future day's gold and bitcoin prices and build a dynamic programming model to determine the objective function (Gou, 2022). Specifically, our work starts with data preprocessing of the trading market amounts for the last five years of trading, and since traders cannot determine the market stock movements for the day after, we form our total model

part by building three models: a bull and bear market model, a risk forecasting model and a time series forecasting model. It is used to forecast the economic conditions of the market stocks on a 5-day basis. This model is used to determine daily trading decisions and to calculate total assets on hand on 10/9/21. Next is to use our regression model using machine learning XGboost to learn all the transaction amounts over the five years and fit them to the data obtained from our model to test the accuracy of the decision model. Finally starting with the commission collection for each trade, we determine the sensitivity of the trade and analyze the impact of price fluctuations on us.

2 RELATED WORK

As we provide traders with a daily decision-making solution, it is important to forecast the direction of the market. It is difficult to predict the trend of the stock market because of the many factors and complex relationships that influence it. In this regard, we have made progress in understanding the development of a good prediction model by consulting the literature on

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stock market prediction models. Based on the neural network integration theory, we developed a stock market forecasting model. The "Basic Data Model", "Technical Indicator Model" and "Macro Analysis Model" were developed and finally a simple average was used to create an integrated system (Zhang, 2003). The corresponding BP algorithm network forecasting model and ARCH (1) and GARCH (1,1) forecasting models are also developed to forecast the volatility of the closing price of the Shenzhen Stock Index at each weekend using the actual data of the Shenzhen stock market in China (Pang, 2006). In addition, a stock-specific forecasting estimation method is proposed based on a specific state space form consisting of a combination of trend, smooth autoregressive and nonlinear heteroscedastic random variables (Wang, 2010). Drawing on the advantages of spatial reconstruction techniques and visual data analysis techniques for expressing the patterns and characteristics of complex systems, graphical methods for forecasting stock market trends based on minute-by-minute stock market trading information have been proposed (Hu, 2014). A stock-specific forecasting estimation method is proposed based on a specific state space form consisting of a combination of trend, smooth autoregressive and nonlinear heteroskedastic random variables (Zhu, 2006). The new XGBoost-ARIMA hybrid forecasting model is also suitable for forecasting about daily average data (Liu, 2022). In order to optimize various forecasting models, the Realized GARCH model is a good choice. In addition, the study ignores the impact of the information contained in the exchange volume on the stock price volatility, which may lead to biased estimation of the model parameters. Stochastic volatility models based on Poisson distribution can not only effectively solve the problem of underutilization of volume information by traditional practices (Sun, 2019). The analysis and judgment of the stock market is also crucial to the proposed decision. Using parametric and semiparametric methods, we judge and predict the bull and bear market cycles of the stock market (Ye, 2021). In the case that short selling is not allowed, a log-optimal portfolio model with conditional value-at-risk as the risk measure can be established based on the conditional value-at-risk proposed by Rockefeller (Moazeni, 2015). In order to optimize various forecasting models, the Realized GARCH model is a good choice. In addition, the study ignores the impact of the information contained in the exchange volume on the stock price volatility, which may lead to biased estimation of the model parameters (Shi, 2019). A new multifractal volatility forecasting model was

constructed based on the HAR model, taking into account the intra-day effects of high frequency stock market data and the measurement error of realized volatility to revise the existing multifractal volatility indicator construction method. The models were evaluated using the Diebold-Mariano test and the "model confidence setting" test (Yuan, 2020).

3 EXPERIMENT

According to the daily price of gold and bitcoin in the past five years, this method forecasts the price of gold and bitcoin in a certain period of time, and finally makes the most profitable measure according to the assumption of bull and bear market. From the table, we find that the prices of gold and bitcoin are increasing in the general situation, and the prices themselves are related to the prices of the previous year; In the short term, it will be affected by the local market policies and other uncertain factors and will increase or decrease. According to the above two characteristics, we choose to use AR autoregressive model to simulate and forecast the amount of money we need in the time period according to the known data. First of all, we need to test the data to see if they are stable, if not, then we need to make small changes and debug them until the conditions are met. We use the method called Daniel test, which is mainly around the Spearman correlation coefficient. Spearman correlation coefficient q_s and statistical variables T The formula is as follows:

$$q_s = 1 - \frac{6}{n(n^2-1)} \sum_{\tau=1}^n (t - R_t)^2 \quad (1)$$

$$T = \frac{q_s \sqrt{n-2}}{\sqrt{1-q_s^2}} \quad (2)$$

After knowing the above two quantities, we can start the test.

For a set of data, there will be the rank of the time series (sort the data from small to large, and the rank of each data is its serial number). We use MATLAB's own algorithm to calculate the rank of the data. Rt ; For significant levels α From the time series (the matrix of data in the file), calculate (t_0, Rt) , $t_0 = 1, 2, \dots$, the correlation coefficient of n . If $|T| \leq t_0$, then the sequence is stationary; Conversely, if $|T| \geq t_0$, it is not stationary and $q_s > 0$, showing an upward trend. The specific operation is shown below:

```

clc, clear;
[a]=xlsread('BCHAIN-MKPRU','B3:B1827');
a=a';
Rt=tiedrank(a);
n=length(a); t=1:n;

```

```
Qs=1-6/n*(n^2-1)*sum((t-Rt).^2);
T=Qs*sqrt(n-2)/sqrt(1-Qs^2);
t_0=tinv(0.995,n-2);
```

To debug data, we take to do the first-order difference operation, that is, the new sequence $b_k = a_{k+1} - a_k$, then you can easily get $a_{k+1} = b_k + a_k$, and here aa_{k+1} is the prediction value we calculated, b_k is the new sequence we will a_k for change to get, that is, to meet the use of smooth time series conditions of the sequence, here We subject the new series to another Daniel's test.

```
b=diff(a);
[Tb,t_00]=spearman(b);
```

The Spearman function is the function that we check whether the sequence is stationary. To put it simply, we will summarize our previous work and see them written into a new function.

```
function [T,t_0]=spearman(a)
a=a'; a=a(:); a=a';
Rt=tieddrank(a);
n=length(a); t=1:n;
Qs=1-6/n*(n^2-1)*sum((t-Rt).^2);
T=Qs*sqrt(n-2)/sqrt(1-Qs^2);
t_0=tinv(0.995,n-2);
```

The debugged data is the precondition of AR autoregressive model. At this time, we put the debugged data into the model.

According to the theory, we know that the formula of AR autoregressive model is as follows:

$$y_t = c_1 y_{t-1} + c_2 y_{t-2} + \dots + c_p y_{t-p} + \varepsilon_t \quad (3)$$

It can be clearly seen that the regression equation y_t is composed of the first p terms and the last ε_t (i.e., the random perturbation term with a mean of 0), and the theory of this AR autoregressive model is that the data of the t^{th} year is expressed with the data of the previous p years, and finally the AR(p) is formed, and this p , we use the AIC criterion to seek, and finally our $p = 6$, as follows.

```
m=ar(b,6,'ls');
bhat=predict(m,[b';1000:]);
ahat=[a(1),a+bhat'];
delat=abs((ahat(end-1)-a)./a);
```

There are several unknown representations above: m is a vector composed of c_1, c_2, \dots , will find him, we can get to the expression of the function AR (p), the completion of the expression will mean that we can find the new sequence b , and then we will calculate the $ahat$ (the first few fitted values and the $n+1$ predicted value, the first fitted value may have a difference with the But the final $delat$ is the algorithm for calculating the relative error, where our relative error is very small, probably only about 0.00008), and the final result is our predicted value.

We need to judge whether it is the best way to judge whether it is the best way to make a profit by buying or selling gold in the bull market or in the bull market every day. After making this judgment, according to the price of the previous few days, judge whether to trade on the same day. The specific judgment methods of the model are as follows.

We assume that if the average amount of the current cycle is higher than 20% of the previous cycle, it is considered as a "bull market", and we will sell it in full. Assuming that the average amount in the current cycle is less than 80% of the previous cycle, we consider it a "bear market" and we will buy gold or bitcoin. Based on the average amount of each period obtained from the previous data analysis, Establish the judgment model of "bear market" and "bull market" in each cycle.

```
NUM=xlsread('C:\Users\wyf\Documents\
WeChat Files\wxid_uknuh3yjrrhv2\ File\2022-
02\333.xlsx');
a=NUM'
a=round(a);
disp(a);
for ii=2:length(a)
if a(1,ii)>=1.05*a(1,ii-1)
disp('This was the bull market.')
elseif a(1,ii-1)*0.95>=a(1,ii)
disp('This was the bull market.')
else
continue
end
end
```

Second, we need to judge whether traders will buy, hold or sell gold and bitcoin on a certain day. Here, we simply use MATLAB to realize our hypothesis. First of all, let's assume that a certain day is an unknown day in the 21st century, then we input the number into MATLAB and bring it into the code. We can get the conclusion that $a = 1 \setminus 0 \setminus 2$.

Assuming that the date we input is September 20, 2017, we can clearly see that this day is the 368th day from September 12, 2016, and the final conclusion is $a = 0$ (buy). We use the data given in the title and further optimize it to form a new table and bring it into MATLAB. The specific operation code is shown in the following:

```
clc, clear;
y=input('input years:');
m=input('input months:');
t=input('input dates:');
date=(y-2016)*360+(m-9)*30+(t-12);
[NUM]=xlsread('BCHAIN-MKPRU',1);
b=NUM(date-4:date);
ave=mean(v)
```

```

if b-ave>=0.2*ave
    a=1;
elseif ave-b>=0.2*ave
    a=0;
else
    a=2;
end

```

4 RESULTS AND EVALUATION

In this section, we will show the results of our model. The first is our data detection results. If the two Excel data mentioned above are not stable, AR autoregression is not possible. According to the programming results, $|T| \geq t_0$, and $q_s > 0$. Therefore, we have verified our previous idea that it is unstable, so our later step is to make the data stable, and then run the AR autoregressive model.

Secondly, we put the above debugged data into the programming system of AR model. In the middle, we interspersed the verification that the debugged data is stable. Taking bitcoin as an example, its result is $t = 0.000000$ million+42.696604080418390i, $t_0 = 2.578528918212297$, which obviously satisfies $|T| \leq t_0$. Therefore, the new sequence B created is the data sequence satisfying AR autoregressive model. Finally, sequence B is brought into the MATLAB programming function of AR autoregressive model. The result is that the price of bitcoin on September 10, 2021 is \$46161, while the price of gold is \$1796.5.

Finally, the most important result is the result of solving the problem. While judging the bull and bear market, we combine the results of each cycle with the price of gold bitcoin to calculate the final profit we get. Here we start with three assumptions about how to allocate the \$1000.

4.1 Suppose You Cost All \$1000 for Gold

Purchase price: \$1324.6
 Selling price (assuming last day sell): \$1796.5
 Ultimate Assets: \$1356.3

4.2 Suppose You Cost All \$1000 for Bitcoin

Purchase price: \$621.65
 Selling price (assuming last day sell): \$ 46161
 Ultimate Assets: \$74255.6

4.3 Suppose You Cost \$500 for Gold and \$500 for Bitcoin

Bitcoin purchase price: \$621.65
 Bitcoin selling price (assuming last day): \$46161
 Gold buying price: \$1324.6
 Gold selling price (assuming last day): \$1796.5
 Ultimate Assets: \$86734.7

We decided to start the investment plan in the form of 50% investment, that is, half of the money to buy gold, half of the money to buy bitcoin. In this way, we can get the most cost, which is our best trading plan.

We choose to put the average bitcoin price of the previous five-day line and the average price of gold on the 15th day line into MATLAB for analysis. Using the code of "the price of the day and the judgment of the previous cycle", we classify the needs of buying, selling and holding, and then further calculate and distribute the money in proportion. The specific operation is as follows:

```

[NUM]=xlsread('liangbaihebing(1)',1,'C2:C1827'
);
NUM(isnan(NUM(:,1))=1)=[];
NUM=NUM';
A=A';
l=length(NUM);
i=1;
while(i<=l)
    if NUM(i)-NUM(i+1)>=0.1*NUM(i)
        a=1;i=i+1;
    elseif NUM(i+1)-NUM(i)>=0.1*NUM(i+1)
        a=0;i=i+1;
    else
        a=2;i=i+1;
    end
    A(i)=a;
end

```

According to the above method, the final result is: from September 10, 2016 to September 10, 2021, the final amount is \$184659.88.

In the previous model part, we established AR autoregressive model to predict the future stock price trend of bitcoin and gold. Through the establishment of risk model and bull bear market model, we got our best plan. In order to prove the feasibility of the strategy, it is necessary to test the fitting degree between the time series prediction and the reality. With the return of XGboost, we simulated the trend of bitcoin and gold and compared it with the actual situation.

Since the amount of data is too large (more than 1000 lines), and the results of each simulation will change due to the debugging of simulation parameters

of XGboost regression, we consider the operation of the program, that is, bitcoin is divided into two parts by 5/31/19, that is, the first 993 days and the last 833 days. Gold is divided into the first 1000 days and the last 266 days by 8/24/20.

The first analysis is the two parts of Bitcoin. First, we can see the first 993 days, as shown in the Figure below, which is the quantitative Y of time series analysis and some data of X1, X2, X3, X4 and X5 (due to the large number of data, we can't show them one by one).

	A	B	C	D	E	F	G
1	Prediction result Y	Time series variable conversion Y	Time series variable conversion X1	Time series variable conversion X2	Time series variable conversion X3	Time series variable conversion X4	Time series variable conversion X5
2	6970.272	6993.513333	6718.23	7394.499167	7247.769167	7011.28	6988.079167
3	6728.27	6718.23	6396.7725	7247.769167	7011.28	6988.079167	6993.513333
4	6443.179	6396.7725	6396.494667	7011.28	6988.079167	6993.513333	6718.23
5	6378.84	6396.494667	6138.96	6988.079167	6993.513333	6718.23	6396.7725
6	6171.4604	6138.96	6311.131667	6993.513333	6718.23	6396.7725	6396.494667
7	6303.693	6311.131667	6347.07	6718.23	6396.7725	6396.494667	6138.96
8	6325.2783	6347.07	6252.13	6396.7725	6396.494667	6138.96	6311.131667
9	6313.986	6252.13	6362.676923	6396.494667	6138.96	6311.131667	6347.07
10	6337.5664	6362.676923	6342.629231	6138.96	6311.131667	6347.07	6252.13
11	6329.344	6342.629231	6312.75	6311.131667	6347.07	6252.13	6362.676923
12	6355.935	6312.75	6436.720833	6347.07	6252.13	6362.676923	6342.629231
13	6401.6357	6436.720833	6404.063333	6252.13	6362.676923	6342.629231	6312.75
14	6454.348	6404.063333	6486.58	6362.676923	6342.629231	6312.75	6436.720833
15	6473.4307	6486.58	6401.246154	6342.629231	6312.75	6436.720833	6404.063333
16	6445.279	6401.246154	6575.229167	6312.75	6436.720833	6404.063333	6486.58
17	6501.067	6575.229167	6354.57	6436.720833	6404.063333	6486.58	6401.246154
18	6411.334	6354.57	6543.645714	6404.063333	6486.58	6401.246154	6575.229167
19	6568.079	6543.645714	6719.429231	6486.58	6401.246154	6575.229167	6354.57
20	6693.647	6719.429231	6738.27	6401.246154	6575.229167	6354.57	6543.645714
21	6738.17	6738.27	6719.266154	6575.229167	6354.57	6543.645714	6719.429231

Figure 1: XGboost model testing data (partial).

Then the regression simulation of 993 before Bitcoin is:

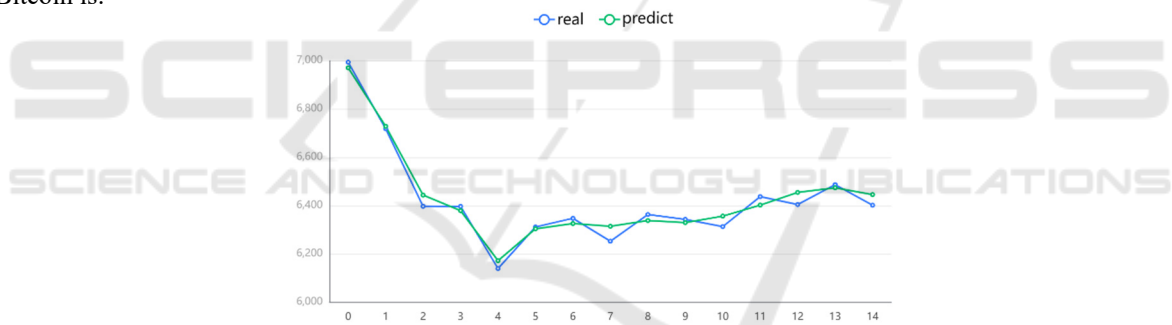


Figure 2: First 993 days for Bitcoin.

Using the same analysis method, we also get the fit between the predicted value and the actual value of the second half of Bitcoin:

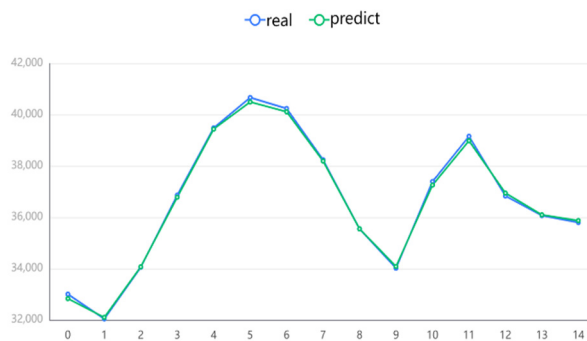


Figure 3: The last 833 days for Bitcoin.

Through this fitting, we can clearly see that although there is a slight deviation in the first half of the forecast trend, it will not be very serious. The error range is controlled around 100, which has no obvious impact on our final results. The second half of the

simulation is perfect, which shows that our timing forecast is very suitable for the market trend of Bitcoin. The next step is the simulation of gold. The simulation of gold is as Fig.3 and Fig.4.

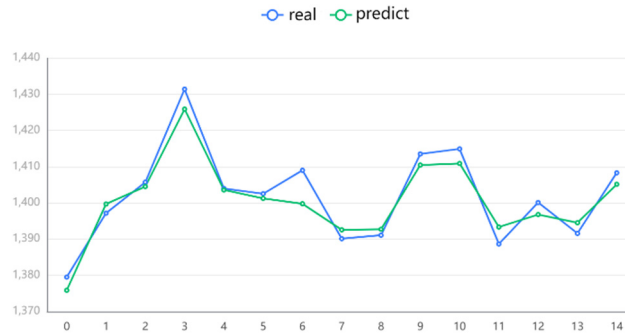


Figure 4: First 993 days for gold.

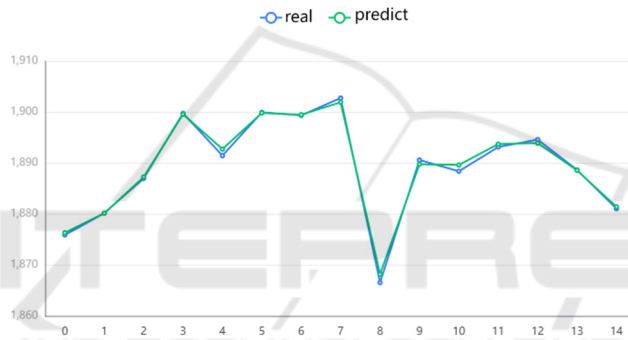


Figure 5: The last 833 days for gold.

As can be seen from the two fitting curves in the above chart, although there are some deviations in the trend prediction of the first half of gold, the maximum value is not more than 10. Combined with the simulation of the second half, it can be said that our simulation results are very impressive. To sum up, our decision-making model is very precise and reasonable.

5 DISCUSSION AND CONCLUSION

Based on the data of gold and bitcoin trading markets in the past five years, we have constructed the judgment model, risk model and time series prediction model of bull and bear markets to help traders make the best decisions every day in five years, so as to maximize profits. From September 10, 2016 to September 9, 2021, the total assets held by traders increased from \$1000 to \$184659. At the same

time, XGboost regression model is used to fit the predicted data and the real data, and the better fitting results are obtained. The advantages of our decision-making are obvious. The three models comprehensively analyze the fluctuation of stock market price. When verifying the fitting degree of time series prediction, we choose XGboost to fit to achieve better results. But unfortunately, the risk indicators in the model still need to be considered comprehensively. In a word, our decision-making model provides a good reference for traders' decision-making.

REFERENCES

Guo Xicai. The development and supervision of quantitative investment[J]. Jiangxi Social Sciences, vol. 3, pp. 58-62, 2014.
 Hou Xiaohui, Wang Bo. Quantitative investment based on fundamental analysis: Research Review and

- prospect[J]. Journal of Northeast Normal University, vol. 3, pp. 124-131, 2021.
- Hu Min, Sun Yufeng. Visual prediction of stock market trend based on state evolution[J]. Journal of computer aided design and graphics, vol. 02, pp. 302-313, 2014.
- Liu Yongmin, Luo Haoyi, Xie Tieqiang. PM based on XGboost Arima method_(2.5) research and application of mass concentration prediction model[J]. Journal of safety and environment, vol.3, pp. 1-13, 2022.
- Moazeni S, Powell W B, Hajimiragha A H. Mean-Conditional Value-at-Risk Optimal Energy Storage Operation in the Presence of Transaction Costs[J]. IEEE Transactions on Power Systems, vol. 30(3), pp. 1222-1232, 2015.
- Pang Sulin, Xu Jianmin, Li Rong. The empirical comparison of BP algorithm and symmetric arch model for Stock Market Volatility Prediction[J]. Control theory and response, vol. 04, pp. 658-662, 2006.
- Shi Yanlin, AI Chunrong. The intra week characteristics of volatility in China's stock market and its prediction model[J]. System theory and practice, vol. 04, pp. 935-945, 2019.
- Sun Yanlin, Chen Shoudong, Liu Yang, Stock Price Volatility Prediction Based on stock market and foreign exchange volume information[J]. System theory and practice, vol. 04, pp. 935-945, 2019.
- Wang Wenbo, Fei Fusheng, Yi Xuming. Prediction of China's stock market based on EMD and neural network[J]. System theory and practice, vol. 06, pp. 1027-1033, 2010.
- Xianwei Gou. Analysis of Quantitative Economic Investment Strategy[J]. Scientific Journal of Intelligent Systems Research, vol. 4(4), pp.34-54, 2022.
- Ye Lu, Wang Zhizheng. Identification and prediction of bull and bear market in Chinese stock market [J] Statistics and decision making, vol. 37(20), pp. 161-165, 2021.
- Yuan Ying, Chen Shoudong, Liu Xin. Research on multifractal modeling and prediction of China's stock market [J]. System theory and practice, vol. 09, pp. 2269-2281, 2020.
- Zihe Tang and Yanqi Cheng and Ziyao Wang. Quantified Investment Strategies and Excess Returns: Stock Price Forecasting Based on Machine Learning[J]. Academic Journal of Computing & Information Science, vol. 4, pp.24-34,2021.
- Zhang Xiuyan, Xu Benben. Stock market forecasting model based on neural network integrated system[J]. System theory and practice, vol. 09, pp. 67-70, 2003.
- Zhu Yu, Shi Zhongke. The spatial trend method of stock market[M], vol. 05, 2006, pp. 567-570.