Quantitative Trading Model of Two Shares Based on NARX Neural Network and Dynamic Programming

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Abstract. This paper focuses on the quantitative trading of two shares based on historical data. In modern financial research, quantitative transaction is an important research topic. With the rapid development of the financial market, it is of great practical significance to accurately predict the future data through historical data and make reasonable decisions. This paper aims to help traders improve their decision-making ability and optimize asset allocation by building a quantitative trading decision-making model. This paper analyzes the advantages and disadvantages of the model, and proves that the established model has high robustness, accuracy and popularization significance. According to the experimental results and research conclusions, the memorandum provides information and suggestions for investors' investment choices.

Keywords: Quantitative transaction; NARX neural network ;Dynamic programming; Particle.

1. Introduction

1.1 Problem Background

In the case of limited funds, how to maximize the return is an important issue for the majority of market traders. Maximizing the return depends on making a reasonable trading strategy, and the precondition of making a reasonable trading strategy is to make a reasonable forecast of the price of financial assets[1-2]. Nowadays, the financial market is unpredictable, and the prices of various assets such as gold and bitcoin fluctuate greatly[3]. Traditional investment, based on people's experience and judgment, can't meet the market demand[4-5].

At present, a hot field of financial market research is quantitative investment. The methods of forecasting the price of financial assets can be roughly divided into two categories[6]. One is the time series prediction model based on statistical methods, such as differential integration moving average autoregressive model (ARIMA). The other is a time series prediction model based on machine learning algorithm, such as RNN[7] Compared with traditional investment methods, quantitative investment has the advantages of big data, quick response and objectivity. The research of quantitative investment and the analysis of trading strategies are aimed at making the best investment decisions for investors, which is of far-reaching significance to the stable development of financial markets.

1.2 Our Work

We need to build a quantitative trading decision model. The model can be disassembled into prediction and planning models. First of all, we need to preprocess the original data set, such as the completion of missing values, so that it can be directly used later. And observe and analyze the basic characteristics of the data set[8]. Then, we train the data based on NARX neural network and build a prediction model. Then, based on the predicted data, dynamic planning is carried out, and the particle swarm optimization model is used to optimize the model, so as to maximize profits under certain risks[9]. This paper studies the influence of transaction cost on the best strategy by adjusting the transaction rates of gold and bitcoin. We increase and decrease the transaction rates by 12.5%, 25%

and 50% respectively, and analyze the influence of transaction costs on the strategy according to the results[10].

2. Assumptions

Assume the trader knows the gold/bitcoin price data up to the nth day when trading on the nth day.

Assume that the handling fee to be paid for each transaction is $\alpha\%$ of the transaction amount, and $\alpha_{\text{gold}} = 1\%$, $\alpha_{\text{bitcoin}} = 2\%$。Traders hold assets without cost.

Assume that the transaction fee is settled on the day of the transaction, and the revenue is calculated on the next day after the gold/bitcoin is bought.

Assume that the future value depends on the historical value. In the short term, the policy and economic situation are generally consistent. There is no economic crisis or systemic risk.

3. Notations

The key mathematical notations used in this paper are listed below. As shown in Table 1.

Table 1 The key mathematical notations used in this paper

Symbol	Description
α	commission rate
$E(r_p)$	expected rate of return
σ_p	standard deviation
r_f	Return on risk-free assets
SR_p	sharpe ratio
$[c_t, g_t, b_t]$	Proportion of cash, gold and bitcoin
P_i	personal best value
P_g	global extreme value

4. Price Data Prediction Based on NARX Neural Network

4.1 Data Description

Before building the model, we need to preprocess the two data sets provided by the topic. There are a few null values in the data set, which will affect the final result of the model. Therefore, we need to process the known price data sets of gold and bitcoin with null value, so as to reduce the error of subsequent calculation and improve the robustness of the model. Considering the influence of the opening day of gold, we use the data from the previous line to fill in the blank values. In order to avoid getting the non-trading day data in the forecast, we designed the sort program, so we won't get the non-trading day in the forecast. As shown in Figure 1.

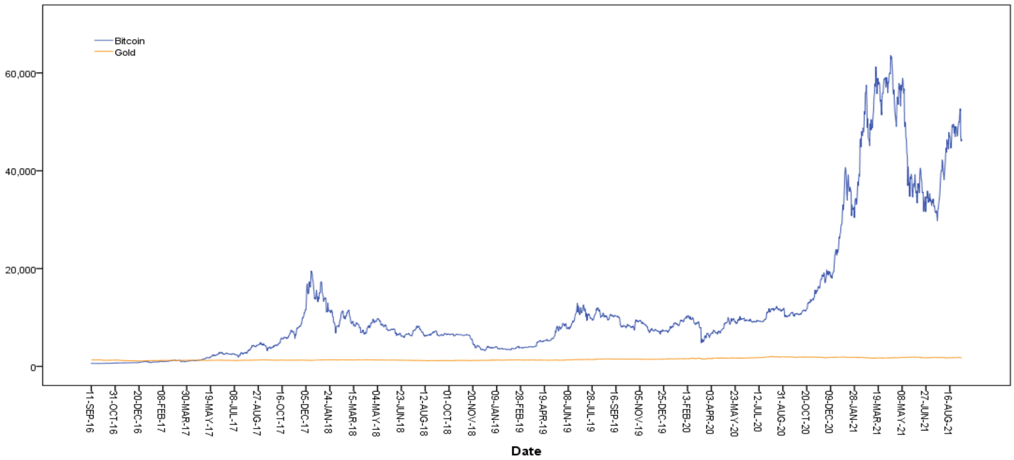

Figure 1. Price Data Chart

According to the above figure, we can see that there are fluctuations in both gold data and bitcoin data, among which bitcoin fluctuates greatly.

4.2 The Establishment of Model 1

The precondition of making the best decision is to accurately predict the price data of the future trading day, so as to make the best decision based on the predicted value. There-fore, it is very important to make a reasonable prediction for the future to solve the problem. Through the price charts generated by the data sets ‘LBMA-GOLD.csv’ and ‘BCHAIN-MKPRU.csv’, we can clearly understand that the price of gold and bitcoin is non-linear with time. Because the premise of the model based on statistical method is that the time series satisfies the linear relationship, it is not applicable. Through literature, we know that the nonlinear time series can be established by nonlinear autoregressive model, and the formula is as follows[2]:

$$y(t) = h\,(y\,(t\,-\,1)\,, y\,(t\,-\,2)\,, \cdots, y\,(t\,-d))\,+\,x\,(t) \tag{1}$$

Among them, it is the time series value of t days, and it is an exogenous variable. Predict the value of t day according to the value of t-1, t-2,⋯, t-d.

In order to make the model more comprehensive, the output results are not only related to the past output, but also related to the past input. We establish a time series NARX feedback neural network model for time series prediction based on dynamic neural network. The model can be expressed as follows:

$$y(t) = f(y(t-1), \cdots, y(t-d), x(t-1), \cdots, x(t-d)) \tag{2}$$

In NARX model, the future value of y(t) is predicted by the past value of time series y(t) and another time series x(t). As shown in the Figure 2.

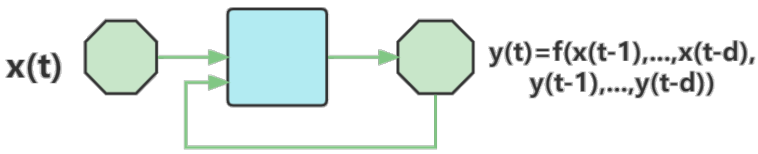

Figure 2. NARX Neural Network

Time series NARX feedback neural network is one of dynamic neural networks, which is characterized by double-layer feedforward. Therefore, we can better train the model by learning the price data of gold and bitcoin. The transfer function in the hidden layer is sigmoid, which can convert the weighted sum into a value between (0,1), and there is a linear transfer function in the output layer. NARX network saves the input value and output value of price data time series through tapped delay line. In addition, the output of NARX network will be used as the input of the network to get new output, forming an open-loop network, so as to train the model more effectively. When the network is trained, it will be transformed into a closed-loop architecture, so as to make time series prediction.

4.3 The Solution of Model 1

4.3.1 Model Training

The data used in NARX feedback neural network is the time series data after data processing. First, we import data, and specify forecast variables (historical price data) and response variables (future price data). In order to prevent the model from over-fitting or poor effect, we divide the data into training set and test set, and the machine learning data set is usually set with the common ratio of 7:3. Therefore, we split the data into training set (70%), verification set (15%) and test set (15%). After analysis and comparison, the number of neurons in the hidden layer is set to 10, and the output value is set to 1 each time. This means that we predict the price of the next trading day based on the price data of the past ten days, and so on, and predict the data of the future trading day.

4.3.2 Forecast Result

According to the model obtain ed by our training mentioned above, we can predict the data of the next trading day according to the price data of the last 10 days, so that we can adjust and optimize our investment portfolio according to the predicted results. The accuracy of the predicted results is very important for us. Through model calculation, we can get the following prediction results. As shown in Table 2.

Table 2 Forecast Results of Golden Section

Date	Realty	Predict
2016/9/12	1324.60	-
2016/9/13	1323.65	-
2016/9/14	1321.75	1323.09
2016/9/15	1310.80	1321.06
2016/9/16	1308.35	1309.48
2016/9/19	1314.85	1307.32
2016/9/20	1313.80	1314.93
2016/9/21	1326.10	1312.97
2016/9/22	1339.10	1327.43
2016/9/23	1338.65	1340.95
2016/9/26	1340.50	1338.77

According to the data, we can conclude that the fitting effect between the predicted result and the actual value is good. For example, we can forecast the price data on September 26th, 2016 based on the price data from September 12th, 2016 to September 23rd, 2016. The predicted result is 1338.766, and the actual value is 1340.5, with a difference of 1.734 and an accuracy of 0.999. We can predict the gold price data of September 21st, 2016 through the gold price data of September 11th, 2016 to September 20th, 2016. The predicted result is 624.5296, the actual value is 598.88, the difference between them is 25.65, and the prediction accuracy is 0.957. Through the calculation of accuracy, we can conclude that the prediction effect of the above model is better. As shown in Figure 3.

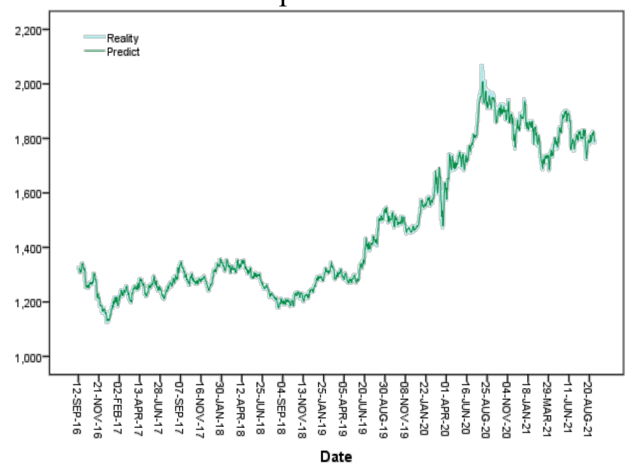

Fig.3a Fitting Chart of Gold Price Forecast

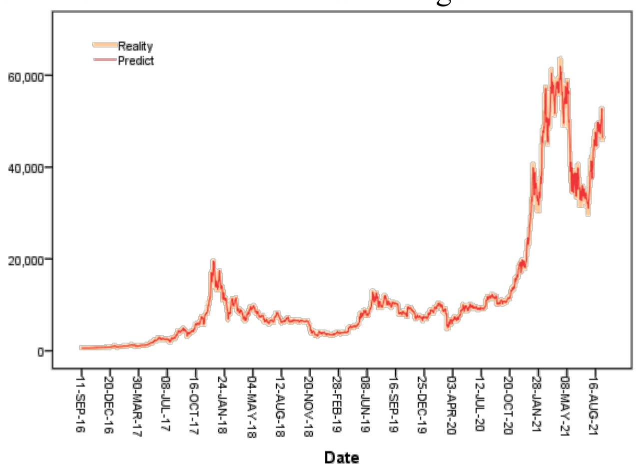

Fig.3b Bitcoin Price Prediction Fitting

Figure 3.Price Forecast Chart

In addition, we should prevent the over-fitting problem when using the neural network model, that is, the model performs well on the training set. Did not perform well on the test set. To prevent this problem, we use 70% of the data for training and 30% for verification and testing. After training, the model is constantly corrected, so that the error is constantly reduced. The abscissa of the above figure is our target value, and the ordinate is the output of our model. It can be seen that each data point is roughly concentrated near the diagonal line, which shows that the model has a good fitting effect, and the historical data of the next trading day can be well predicted through the data of nearly ten days. As shown in Figure 4.

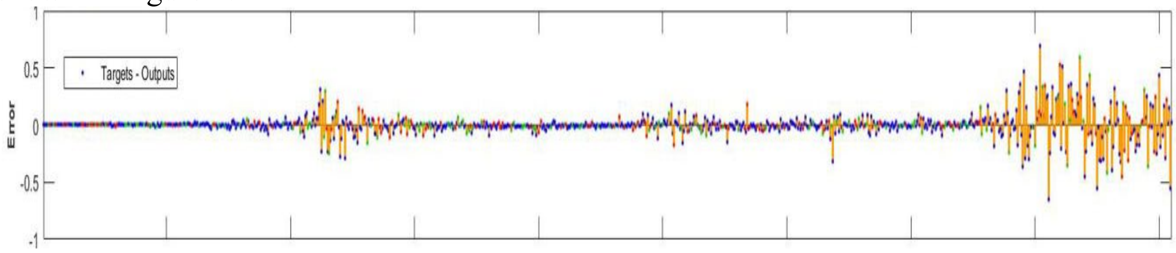

Figure 4. Model Fitting Residual Fiagram

The figure above shows the difference coefficient between the target value and the output value. It can be clearly seen that the difference coefficient is basically zero most of the time, indicating that the output value is approximately equal to the target value.

5. DP Model of Quantitative Transaction

5.1 Problem Analysis

The topic requires us to make future decisions based on past data, for example, on the nth day, we have the data of the first n days, including the nth day, and make decisions on the nth+1st day based on these data. On the n+1 day, we not only have the previous data, but also the data of the n+1 day, according to which we make the trading decision of the n+2 day. Recursion until the last day. This is a typical dynamic programming problem, so we set up a dynamic programming problem to get the optimal solution.

5.2 Establishment of Model

There are many factors that will affect the pros and cons of trading strategies. Normally, we will judge by the rate of return. But in fact, the investment strategy should not only depend on the rate of return. The investor's goal is to get the maximum profit with the least risk. Here we introduce "Sharp Ratio".

$$SR_p = \frac{E(r_p) - r_f}{\sigma_p} \tag{3}$$

Among them, $E(r_p)$ is the expected rate of return of portfolio P during the observation period, the standard deviation of portfolio and the rate of return of risk-free assets. σ_p is the standard deviation of portfolio, and r_f is the rate of return of risk-free assets.

The constraints of our planning model are as follows:

$$s.t. = \begin{cases} (1+\overline{C_t})c_t + (1 \pm 0.01)\Delta G_t + (1 \pm 0.01)\Delta B_t \geq 0 \\ (1+\overline{G_t})g_t - \Delta G_t \geq 0 \\ (1+\overline{B_t})b_t - \Delta B_t \geq 0 \end{cases} \tag{4}$$

Among them, $\overline{C}_t$、 $\overline{\ }_t$、 $\overline{B}_t$ are the increase of cash, gold and bitcoin on T day. We need to find the best trading point when the risks and benefits are balanced under this constraint.

5.3 Model Optimization

In PSO algorithm, the position of particles represents the solution of the optimization problem to be solved, and the fitness value determined by the objective function of the op-timization problem determines the performance of each particle. In a D-dimensional target search space, there are n particles forming a group, where the position of particle I in the m-th iteration is expressed as:

$$\mathrm{X_i(m) = (x_{i1}(m), x_{i2}(m), \cdots, x_{id}(m))} \tag{5}$$

The corresponding flight speed i

$$V_i(m) = (v_{i1}(m), v_{i2}(m), \cdots, v_{id}(m)) \tag{6}$$

5.4 The Solution of Model 2

We can see that the accumulated investment income based on our investment strategy shows a steady upward trend. Among them, bitcoin has increased greatly. Because of our limited funds in the early stage, and considering the existence of transaction fees, we reduce the transaction frequency. When the capital reaches a certain level, we can increase the transaction frequency, optimize the asset allocation and improve the income level.

At the same time, in the formulation of trading strategy, we should give consideration to both risks and interests, and seek a balance between them.

6. Quantify Investment Risk

In actual investment, investors not only pursue the maximization of interests, but also need to consider the investment risks. Different people have different investment preferences, which will also affect the choice of portfolio. From this, we analyze the mean-variance effective frontier according to the financial risk indicators, and draw the risk-return curve.

According to investors' different preferences for risks, they can be divided into risk avoiders, risk pursuers and risk neutrals. When the expected returns are the same, risk seekers usually actively pursue risks and seek to obtain excess returns. For those who avoid risks, they will avoid risks and are unwilling to bear possible losses. Risk neutrals don't avoid risks, and they don't pursue risks at the same time. They only care about the expected return.

In the formulation of quantitative trading strategies, different traders may have different strategy choices for the same set of data. Therefore, in the formulation of the objective function of the programming function, we use Sharp ratio to give consideration to both risks and benefits, and seek the maximum benefits under reasonable risks.

7. Optimal Test

In this paper, we set a certain disturbance to the model to prove that our strategy is optimal. If the results after disturbance are all less than the maximum profit we calculated above, it can be proved that our scheme is the optimal strategy. The result shows that the maximum value is 6618421.8, which is less than the maximum value of 6709457.2 calculated based on our strategy. Based on the analysis of the above forecast and planning links, it can be proved that our trading strategy is the best scheme, which can maximize the profits.

8. Sensitivity Analysis

In order to test the influence of transaction cost changes, we adjust the parameters α_{gold} and $\alpha_{\mathrm{bitcoin}}$ bring in the model to make the corresponding best strategy and generate the results. The results are shown in the Figure 5.

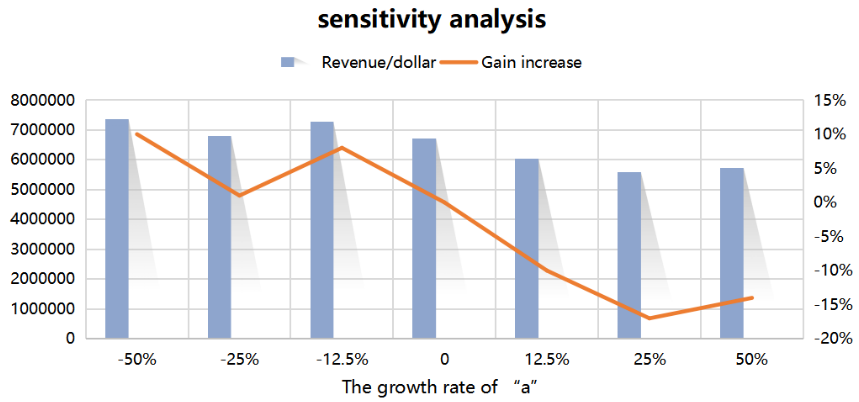

Figure 5. Influence of Transaction Cost on Decision-making Results

We reduce the transaction rates by 12.5%, 25% and 50% respectively, and increase them by 12.5%, 25% and 50% respectively. According to the results, when the transaction rates are reduced, the benefits are higher, and when the transaction rates are increased, the benefits are lower. There is no obvious linear relationship between transaction cost and income.

9. Model Evaluation and Further Discussion

9.1 Strengths

Taking both risks and benefits into account: We take Sharp's ratio as the objective function, seek its maximum, find the balance between benefits and risks, and help us make better decisions. Wide applicability: Our model can be widely applied to stock data, and can help investors make reasonable decisions under relatively accurate prediction.

9.2 Weaknesses

Insufficient data volume: Because we only have one data dimension of closing price, the training of neural network model may not be sufficient, and there is a certain error between the predicted value and the actual value.

9.3 Further Discussion

In the establishment of the standardized model, the convergence speed of the model is too slow and takes a long time. Therefore, we use the intelligent algorithm to speed up the convergence of the planning model, which leads to certain errors in the output results and cannot be avoided. However, in the actual process of quantitative trading decision-making, we can optimize the asset allocation through minor adjustments and improve the decision-making ability.

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