Computer Intelligent Investment Strategy Based on Deep Reinforcement Learning and Multi-Layer LSTM Network

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***Abstract*—Investors frequently make business about volatile assets with the goal of maximizing their profits. This aim of this article is to establishes a model to study the investment strategy of bitcoin and gold. It's not always accurate to use algorithm based on traditional time series model to predict the prices. Therefore, The multi-layer LSTM weighted model of multi-layer LSTM network this article puts forward is used to study the input time span to factor the influence of output time span. By using the embed approach, this model can achieve higher accuracy compared with LSTM model by influencing the stacking sequence generation cycle and training model. Meanwhile, this model introduced the Attention mechanism and can make short-term and long-term forecasts continuously. It also quantified the fluctuation of MACD, RSI, Apriori and other parameters to construct the risk measurement index. The higher the periodic price fluctuation is, the greater the risk can be. The results show that timely business maximizes profits. An initial $1,000 investment on September 10, 2021 can even profit more than $900,000. In order to prove the model provides the best strategy, depth of reinforcement learning model is set up. Bitcoin and gold history feature information of state data matrix and agent within the depth of neural network is utilized to extract the stable characteristics of data expression. Based on these features, this model utilized optimized strategy method of three reinforcement learning algorithms. Combined with the current reward, it optimized the relevant parameters of the deep neural network to obtain the optimal investment strategy in exploratory ways. Moreover, the model will be ran twice to test the sensitivity under different transaction costs (investment decision results) by setting points of 0.5%, 1%, 1.5% and 2% according to the percentage of increase and decrease of transaction costs. The results show that the model has good robustness, which means the model constructed in this paper has good results under different transaction costs.**

Keywords—Support vector machine, Random forest algorithm, Deep reinforcement learning model, Sensitivity analysis, Portfolio optimization

I. Introduction

A. Background and Literature Review

Portfolio management is a decision-making process that allocates a certain amount of capital to multiple financial assets. It improves profits and reduces risks by changing the weight of allocation constantly. This article takes bitcoin and gold markets as examples for portfolio management[1]. Bitcoin is a virtual currency that just has born for decades. Although it has only existed for a short time so far, now it has become the mainstream of the investment community and predicated to become the universal currency of El Salvador in 2021[2].Gold is a traditional investment project with a long investment history and a high preservation rate [3]. How to obtain maximum returns by using limited funds has been the capital question of investors, and it is also one of the major topic issue in financial academic research[4].

Classic portfolio optimization model using historical returns as the expected return on average, which will make low-pass filtering effect on the behavior of the stock market. Then it will cause the deviated estimation of short-term return. Additionally, it's not reasonable to take average annual return as short-term expected return because the subjective emotions of investors can influence the short-term price of stock.[5]. Therefore, stock return prediction should be combined with portfolio optimization model in financial investment. In this regard, many scholars apply forecast return as expected return to construct portfolio optimization model[6]. Moreover, some researches try to make more prediction results combined to form objective function in the portfolio optimization model and further improve the performance of the original portfolio optimization model[7].

Chen Menggen and Cao Fengqi (2005) put forward a shock transmission mechanism. They believe that the convergence of policy expectations, decisions and behaviors will have an impact on investors, then lead to shock

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transmission in the market and showing the characteristics of plate linkage [8]. Finally, in terms of fundamentals, researchers mainly use valuation indicators to test investment. Lu Dayin, Lin Chengdong and Yang Chaojun (2006) use a series of valuation indicators to study and find that value portfolio has a higher rate of return than growth portfolio[9].Overall, fundamentally, the research reflects the satisfying performance of value investing. The situation that value investing in the market have a larger probability to produce positive returns is understandable. Value investment index reflects the valuation and financial ability, which can predict the future profits better and then it can point to more positive return on investment better.

From the perspective of research subject, the value of bitcoin changes just like a stock, but the parameters that affect bitcoin are different[10].The difference between the stock market and bitcoin is that the price of bitcoin does not depend on commercial events or government intervention[11]. Therefore, indicators need to be screened to build the most suitable factor for model input.

Due to the uncertainty and high noise characteristics of bitcoin time series, it is still very difficult to make accurate prediction. In addition, the relationship between independent and dependent variables usually changes dynamically over time, which makes it difficult for traditional time series models to predict stocks and financial markets effectively. Therefore, this paper uses deep learning to predict the price of bitcoin and gold, as shown in Figure 1 and Figure 2.

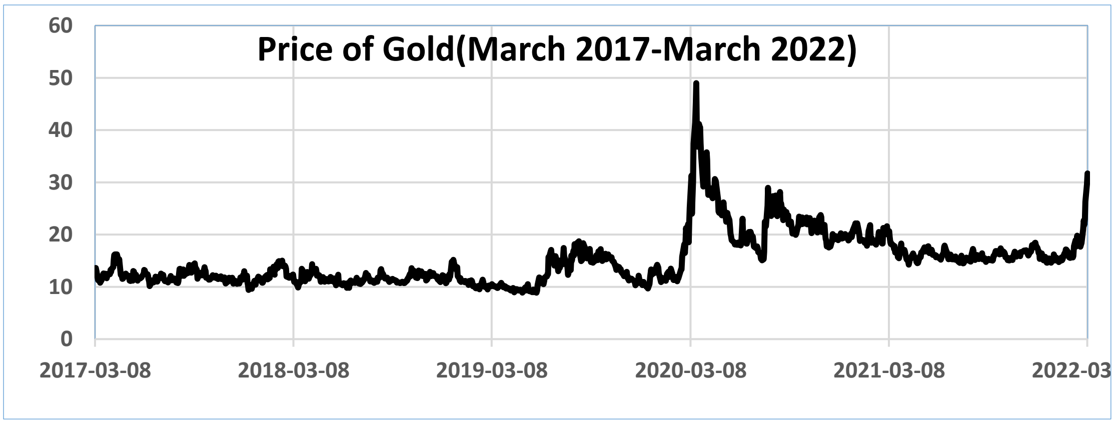

Figure 1 Gold daily prices. Source: Chicago Board Options Exchange (the horizontal axis represents the date, and the vertical axis represents gold in grams)

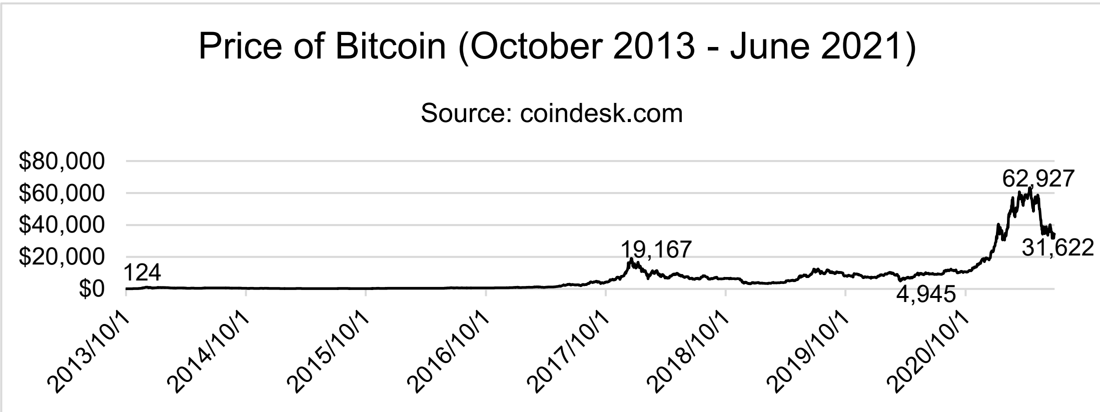

Figure 2 Bitcoin daily prices, U.S. dollars per bitcoin. Source: Coinbase(the horizontal axis represents the date and the vertical axis represents the price per bitcoin)

On September 11, 2016, it will start at the point of $1,000 and use a five-year trading period from September 11, 2016 to September 10, 2021. On each trading day, traders will have a portfolio of cash, gold and Bitcoin [C, G, B] in U.S. dollars, Troy ounces and Bitcoin, respectively. The initial state is [1000, 0, 0]. The commission cost for each transaction (purchase or sale) is alpha % of the transaction amount. Assume α gold = 1% and α Bitcoin = 2%. Holding assets costs nothing. Bitcoin can be traded all the time while gold is only traded on opening days.

Firstly, Bitcoin is a digital virtual currency in the form of P2P. Different from traditional currency, bitcoin does not need to be issued by a specific monetary institution, but is generated by a specific algorithm of a branch. Since 2013, the price of Bitcoin has risen sharply, from an initial 13 DOLLARS to 1200 dollars, which has increased for nearly 80 times. In 2017, bitcoin peaked at the point of $20,000 and then fell below $10,000. In 2021, the price of Bitcoin has successfully broken through the $60,000 mark and the market value has reached $1.2 trillion, which is more than the sum of the market value of two Teslas. Thus bitcoin has become the mainstream of investment and the price prediction of Bitcoin has also become a key research topic.

Among many prediction model tools, deep learning is outstanding with its powerful learning and performance ability and becomes the preferred tool for time series prediction in the financial field. Donaldson has used artificial neural network (ANNs) to predict S&P500 stock price and cross-verified the advantages of neural network compared with traditional methods such as weighted least squares in the end of the 20th century[12].

Takeuchi and Lee used an autoencoder based on stack limit Boltzmann machine to extract stock price characteristic information and predict which stocks would have higher or lower monthly returns than the median. finally they obtain 53% accuracy and 45.93% annual returns [13]. Yelowitz A and Wilson (2015) [14] studied bitcoin from different angles. They analyzed the characteristics of bitcoin users and found that computer programming and search terms for illegal activities were positively correlated with interest in Bitcoin, while liberals and investment terms were not. Dyhrberg (2015) [15] applied the asymmetric GARCH method used in gold research to explore the hedging ability. He found that bitcoin has the same hedging capacity as gold, and the scale can be divided between a pure exchange advantage and a pure value advantage into some kind of hedging capacity between gold and the dollar.

LSTM gained attention and was widely applied in the financial field after the great success of LSTM algorithm in the field of machine translation in 2014. Sutskever et al, in the application of processing financial time series, Murtaza used the two-layer LSTM network to predict NIFTY50 stock prices and obtained results with RVSE of 0.00859, which has significantly higher prediction accuracy than the econommetric model [16]. n terms of the improvement of LSTM model, Bao et al, first combined wavelet transform and stack coding with LSTM, and used six stock market index futures to verify the performance of the model. Then they found that its prediction accuracy and profitability are better than similar models [17].

In the research of bitcoin price prediction, the correlation model between deep learning and LSTM has gradually occupied the mainstream. In the early stage when Bitcoin came into the public view, Shah et al. applied the potential source model in Bayesian regression to the prediction of bitcoin and achieved good returns on bitcoin investment through binary classification [18]. Yang et al. established the joint dynamic relationship between these complex measures and bitcoin yield and volatility by studying the complex measures of bitcoin transaction flow network. And they used one of the special complexity variables, which is the residual diversity variable of bitcoin network traffic, to improve the predictability of bitcoin volatility [19]. Subsequently, McNally et al. predicted the bitcoin price index through bayesian optimization recursive neural network and short and long memory network. Comparing the prediction results with the commonly used prediction method ARIMA, they found that the performance of nonlinear deep learning was significantly better than the latter. Stenqvist predicted the price by analyzing 2.72 million comments related to bitcoin, with a prediction accuracy of 83% [20].

In conclusion, deep learning methods are more and more widely used in the prediction of bitcoin and gold prices while LSTM has certain advantages in the prediction because of its effective solution to the problem of long-term dependence. In terms of specific effects, the high complexity of bitcoin price makes it difficult for a single prediction model to achieve ideal results. Multiple model integration can effectively extract features of different dimensions of bitcoin price time series and enhance the accuracy of prediction. Therefore, this paper takes SVM and LSTM deep learning prediction model as the core to build a model to evaluate the prediction results of the model.

This study enriches the theoretical research of portfolio optimization and return prediction. First of all, this paper uses the deep learning model in the process of investment return prediction to ensure the selection of high-quality investment objects before establishing the portfolio optimization model. Specifically, this study enriches the gated cyclic neural network mainly from the aspect of model construction. Neural network has gradually developed from the original single-layer perceptron into the popular recurrent neural network and convolutional neural network in deep learning. Compared with the basic neural network, the advantage of recurrent neural network is that it breaks the independent boundary between elements and established the connection between input and output, which solved the disadvantage of artificial neural network that can not remember the distant information. And the gated neural network further develops its advantages. Its core is that the amount of memory information can be determined by the gating parameters, which realize the effective information control problem. This paper based on the traditional door control model based on the improved model is more concise and efficient, which reduced the amount of calculation information at the same time and further enhanced the efficiency of information transmission then enrich the development of neural network. All of these fill the gaps in the existing literature research. This paper shows that the predicted effect of mixed forecasting model is superior to the single model. It is helpful for investors to carry out investment portfolio.

This paper develops a model that gives the best daily investment trading strategy based on the day's price data merely and estimate the value of the initial $1,000 investment on September 10, 2021 by using models and strategies. At the same time, this paper proves that the model provides the optimal strategy to determine the sensitivity of the strategy to investment transaction costs and how transaction costs affect the strategy and results.

B. Date description

Compared with traditional financial products investment, Bitcoin’s trade can run all the time and it even don’t stop on holidays so there’s no distinguish between day trading and trading data.[21],the researchers compiled Bitcoin daily closing price from 1,10,2013 to 2,28, 2022. The Data from FRED website (Federal Reserve Economic Data | FRED | st. Louis Fed (stlouisfed.org)), is the currency daily price changes (in dollars)and gold open at the same time is also selected. Although gold prices change daily, gold is only traded on trading days. Data on gold trading days also comes from FRED.

At the end of 2017, Bitcoin generally became the most dominant cryptocurrency, peaking at $19,511 on December 17, 2017, with a market cap of over 42%. As a result, the researchers observed a steady upward increase in the price of bitcoin during this period. From 2018 to 2019, the bitcoin market returned to rationality, and the emergence of bitcoin futures provided a channel for investors to short bitcoin, which was mixed with investors' doubts about the implementation of block chain technology and investment value, so the overall state was relatively depressed[22].As cryptocurrencies gradually shift to digital gold, digital currencies are becoming the choice of more and more investors. At the end of 2020 and 2021, bitcoin will return to the view of investors and the price will rise sharply. Coupled with the attention of governments of various countries, many countries will continue to promote the process of issuing digital currency and the value of bitcoin will therefore continue to rise. Therefore, we consider the research phase to include distinct normal, bullish and bearish phases. Table I describes the descriptive analysis of Bitcoin.

TABLE I DESCRIPTIVE ANALYSIS OF BITCOIN

Variable(year)	2017-2018	2018-2019	2019-2020	2020-2021
mean	3980.40	7505.97	7373.63	10461.54
min	788.81	3179.54	3359.33	4841.67
max	19187.18	17149.67	12920.54	19700.19
poor	18398.97	13970.13	9561.21	14858.52
Standard deviation	3972.00	2407.58	2648.39	3153.29
variance	1820263.63	5812431.45	7033363.99	9943251.25
kurtosis	3.61	2.15	-1.23	1.44
Partial degrees	2.00	1.04	-0.092	1.27
The number of variation	0.99	0.32	0.36	0.30

Financial time series is a basic technology in quantitative investment, which means to analyze the value sequence of a variable measured by time series in a certain period of time, so as to predict the future[23] .However, according to historical studies, the financial time series of Bitcoin shows traces of non-stationary, non-parametric and chaos. It is difficult to capture these characteristics with visualization of temporal evolution patterns merely[24]. Therefore, the researchers rely on statistical and econometric tests to decode these characteristics, and the current work follows the same principles to understand the basic temporal properties of bitcoin prices. Because bitcoin's daily closing price does not conform to a normal distribution. The time series considered is non-stationary and the complex evolution pattern of the selected time series means that the traditional predictive econometric model is not suitable for deducing predictions.

NOMENCLATURE

symbol	illustration	unit
PB	Price-to-book ratio	-
EPS	earnings per share	-
NPG	net profit growth rate	-
ROA	return on equity	-
RPCE	Cost and expense profit margin	-
a_i	The weight of the index	-
x_i	Predicted value for the next phase	-
y	Ratings of securities companies	-

C. Research methodology

Taking bitcoin and gold prices as examples, the main purpose of this paper is to study the return prediction of machine learning (SVR) and deep learning (LSTM) models to promote the performance of portfolio optimization models. These models have an overwhelming performance over traditional time series models, which ensures the selection of high-quality investment plans before building a portfolio optimization model.

II. QUANTITATIVE INVESTMENT MODEL BASED ON MACHINE LEARNING

In this paper, the model is assumed to exclude low-probability events in life (such as black swan events, abnormal situations). It only consider the core factors in the problem and doesn't consider the influence of secondary factors. It is assumed that the trend of investment market can be roughly predicted after full analysis of historical data and the prediction results do not consider the impact of emergencies. Markets are efficient markets and information flows freely as well as investors are rational.

A. Model building

1) Feature reconstruction of GBDT model

To understand the feature refactoring of GBDT, Figure 3 shows a simple GBDT and FFM merge model with only three subtrees, t=3. So let's say I have some sample x; Enter the GBDT model, and the sample is divided into two leaf nodes: the second leaf node of the first subtree, the second leaf node of the second subtree and the first leaf node of the third subtree, as shown in the red node.

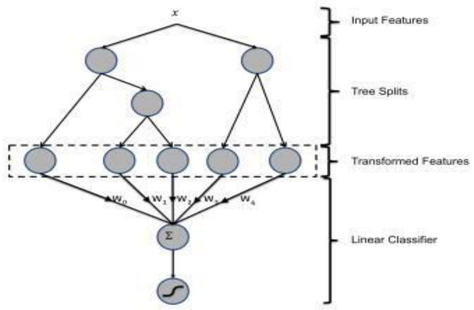

Figure 3 GBDT model

The formation process of GBDT model, namely the establishment process of subset, is actually the process of continuous combination of original individual features, and feature combination is usually superior to individual features. New features of GBDT reconstruction usually have strong expressiveness.

If the number of candidate factors of the multi-factor model is N and the feature names are encoded by natural numbers, then the original feature set of the dataset is $\ell = \{c_1, c_2, \ldots c_N\}$.

The original eigenvector of the data set input sample x_i, so:

$$x_i = \{x_1, x_2, \ldots x_N\} \tag{1}$$

$$y_i = \{y_1, y_2, \ldots y_N\} \tag{2}$$

GBDT will then input the vector $x_i \in R^N$ Map to something called $\omega_i \in R^T$ t-dimensional vector, namely, feature reconstruction process, namely:

$$GBDT : x_i \rightarrow \omega_i \tag{3}$$

Among them $x_i \in R^N$:

$$\omega_i = \{\omega_1, \omega_2, \ldots, \omega_T\}, \omega_k \in L_K \tag{4}$$

2) FFM model input

FFM model input is shown in Figure 4.

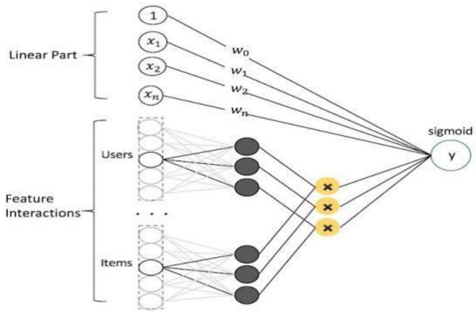

Figure 4 FFM model input

The input vector of FFM model must contain fields, features under the fields and values corresponding to the features. Here, the new features reconstructed by GBDT need to be further transformed into the acceptable form of FFM model.

Here, it is also necessary to take the model in Figure 4 as an example. After independent thermal coding of the output feature vector of the current GBDT model, the elements at each position of the extension vector correspond to the leaf node of the GBDT subtree one by one. Therefore, it is natural to divide the vectors corresponding to the same subtree into corresponding fields. The FFM model in the figure has three fields. Obviously, the number of subtrees is the same as the number of GBDT and the dimension of the input vector is exactly equal to the sum of the leaves of all the GBDT subtrees.

In short, it can be expressed as a linear regression problem:

$$r_{i,t} = \alpha_i + \beta_i^{(1)} F_t^{(1)} + \beta_i^{(2)} F_t^{(2)} + \cdots + \beta_i^{(k)} F_t^{(k)} + \varepsilon_{i,t} \tag{5}$$

Generally speaking, $r_{i,t}$ represents the rate of return of risky asset i at time t, F is called factor return, and β represents factor exposure. namely:

$$r_t = \alpha + \beta^{(1)} F_t^{(1)} + \beta^{(2)} F_t^{(2)} + \cdots + \beta^{(k)} F_t^{(k)} \tag{6}$$

At this point, a multi-factor model equation (4.6) will be written to represent the sensitivity of stock i to a specific risk at time t

$$r_{i,t} = \beta_t + X_{i,t}^{(1)} f_t^{(1)} + X_{i,t}^{(2)} f_t^{(2)} + \cdots + X_{i,t}^{(k)} f_t^{(k)} + \varepsilon_{i,t} \tag{7}$$

B. LSTM

A typical LSTM unit consists of one or more internal state storage units, front doors, forget doors, and output gates, as shown in Figure 5. Assuming the state of the storage unit at time t, the calculation of the LSTM unit at time T is as follows:

$$\begin{cases} s_t = s_{t-1} f_t + i_t g_t \\ o_t = sigmoid\left(W^{xo} x_t + W^{ho} x_{t-1} + b_o\right) \\ h_t = o_t \tan\left(s_t\right) \end{cases} \tag{8}$$

In this paper, the multi-layer LSTM network is used to learn the time correlation of time series data, and the historical input is used to predict the value of current data. The multi-layer LSTM network is shown in Figure 6. The input vector $U \subseteq V$

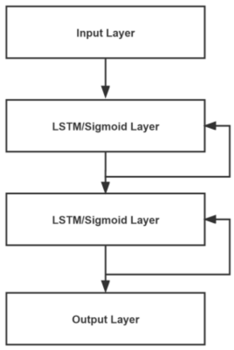

Figure 5 LSTM unit structure

There is a certain time correlation between each component, and the i index represents a specific time step i. $\tilde{U}_i$ is the predicted value $\tilde{U}_i$ in all or part of the first stage; H_j represents the hidden layer j, and during deployment, H_j j and the LSTM layer in the i step; and the input time step is used as the input data for the predicted step length; s is the input time step, that is, the data of step $i-s, i-s+1, \cdots, i-1$ is used to predict the input data of step i.

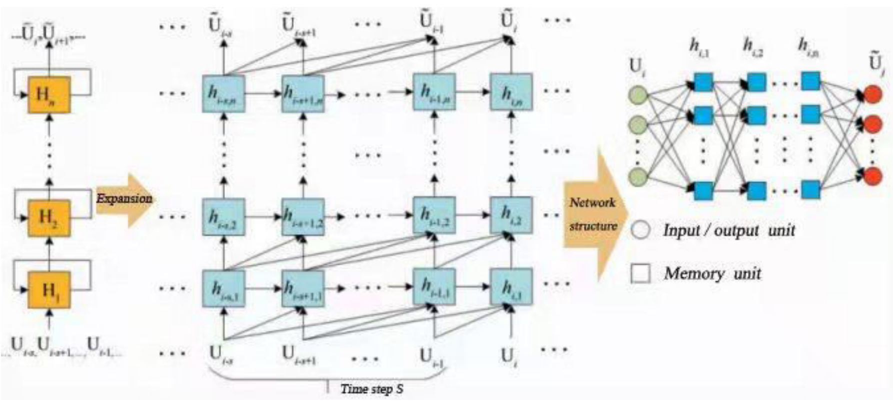

Figure 6 Multilayer LSTM Network(Source:Internet)

Sequence prediction is essentially a regression problem. For the anomaly detection task, the number of normal samples is much larger than the number of abnormal samples and the time step i and $U_{i-s}, U_{i-s+1}, \cdots, U_{i-1}$ serve as the input of the multi-layer LSTM network U'_i. is used as the target output and the loss function is minimized (as shown below)

$$Loss = \frac{1}{2}\left(U'_i - \tilde{U}_i\right)^2 \tag{9}$$

The backward propagation algorithm is used for training.

III. DEEP REINFORCEMENT LEARNING MODEL

A. Model establishment

1) Correlation analysis

(a) The principle of correlation analysis

Assume p variables $X_i(i = 1,2,\cdots,p)$,if expressed as

$$X_i = u_i + a_{i1}F_1 + \cdots + a_{im}F_m + \varepsilon_i, (m \le p) \tag{10}$$

or

$$\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_p \end{bmatrix} = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_p \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & & \vdots \\ a_{p1} & a_{p2} & \cdots & a_{pm} \end{bmatrix} \begin{bmatrix} F_1 \\ F_2 \\ \vdots \\ F_m \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_p \end{bmatrix} \tag{11}$$

or

$$X - u = AF + \varepsilon \tag{12}$$

Among them,

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_p \end{bmatrix}, u = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_p \end{bmatrix}, A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{12} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & & \vdots \\ a_{p1} & a_{p1} & \cdots & a_{pm} \end{bmatrix}, \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_p \end{bmatrix} \tag{13}$$

While $F_1, F_2, \cdots, F_p$ is the common factor, such variables are not estimable, and the loading factor is their expression coefficient. ε_i is a special factor, which cannot be contained by the first m common factors. And meet

$$E(F) = 0, E(\varepsilon) = 0, Cov(F) = I_m,$$

$$D(\varepsilon) = Cov(\varepsilon) = diag\left(\sigma_1^2, \sigma_2^2, \cdots, \sigma_m^2\right), Cov(F, \varepsilon) = 0。$$

(b) Properties of correlation analysis models

a) Decomposition matrix of the covariance of the original variable X

The correlation coefficient between the i variable and the j common factor is factor load a_{ij} , which reflects the important correlation between the j common factor and the i variable. The greater the absolute value is, the higher the correlation.

b) Statistical significance of common degree of variables

The sum of squares of the elements in row i of the factor loading matrix is called the degree of commonality of variable X_i. Remember to

$$h_i^2 = \sum_{j=1}^{m} a_{ij}^2 \tag{14}$$

Seek the variance on both sides of the formula

$$Var(X_i) = a_{i1}^2 Var(F_1) + \cdots + a_{im}^2 Var(F_m) + Var(\varepsilon_i) \tag{15}$$

$$1 = \sum_{j=1}^{m} a_{ij}^2 + \sigma_i^2 \tag{16}$$

It follows from the above formula that the output of all special and common factors on variable X_i is 1. If σ_i^2 is very small and $\sum_{j=1}^{m} a_{ij}^2$ is close to 1, the result of the factor analysis is good.

The sum of squares of the columns of the subload matrix $F_j(j = 1,2,\cdots,m)$ and the sum of variance contributions to all X_i is called $S_j = \sum_{j=1}^{p} a_{ij}^2$. This is the variance contribution of the statistical significance of the common factor D and the important relativity of measuring F_j.

Because the sum of squares of the common factor coefficients of other special factors is equal to the corresponding eigenvalue root, that is, the variance of the common factor. So F_j.

Because the sum of squares of the common common factor coefficients of other special factors is equal to the corresponding eigenvalue root, the variance of that common factor. so, $S_j = \sum_{j=1}^{p} a_{ij}^2 = \lambda_j$

B. Analysis of the association rules S

The Apriori algorithm is a classical algorithm for mining association rules that adopts the idea of 2-stage mining and scans the transaction database multiple times for the mining of frequent item sets.It has 2 basic definitions:

Frequent item set L_k of order k is a set composed of elements whose support degree is greater than the minimum. Each element in L_k is composed of k data items in the database. For example, the form of frequent item set of order 3 is $L_3 = \{(l_1, l_2, l_3), (l_1, l_3, l_4), (l_2, l_3, l_4), \cdots\}$, where the g item in the database of table i is substituted.

k order candidate item set : C_k the e-order candidate item set can be obtained by combining $L_{k\text{-}1}$ and L_1. The part of C_k with greater than minimum support is L_k.

2) State cloud concept extraction

For continuous data, it needs to be discretized before the Apriori algorithm is used.Cloud theory can make the transformation from continuous numerical interval to discrete concepts, transforming quantitative data into qualitative concepts possible, which is an uncertainty transformation model that integrates probabilistic statistical theory and fuzzy theory.

The main steps of the cloud transformation are:

(a) Normize the collected investment data set and analyze the frequency distribution in different numerical sections, then draw the frequency distribution curve according to the statistical results.

(b) The frequency distribution curve of the peak-based cloud transformation algorithm is used to process the data to obtain the cloud concept distribution in the sample data, whose principle is expressed as:

$$\begin{cases} f(x) \to \sum_{i=1}^{z} (a_i C_i) \\ 0 < \left| f(x) - \sum_{i=1}^{z} (a_i C_i) \right| < \varepsilon \end{cases} \quad (17)$$

3) Association rule mining between state parameters and states

In this paper, state cloud concepts are extracted for five state parameters, namely country, type, director, actor and screenwriter. Each cloud concept of each state parameter is named as C_{ij}, where i represents the serial number of the state parameter, and j represents the serial number of the cloud concept of the state parameter.

When cloud concepts are extracted from state parameters and states, the Apriori algorithm can be used to mine association rules for data. Firstly, the data item set $H = \{E_i, D_j\}$ is established, where E_i is the membership cloud concept set of the 9th state parameter i. $D_j \left(j = 1, 2, \cdots, 6\right)$ is the cloud concept of one of the six states of the investment transaction data set. Then, the Apriori algorithm is used to scan the data set and generate frequent item sets and their confidence.

The diagram of association rules between state parameters and states is shown in Figure 7.

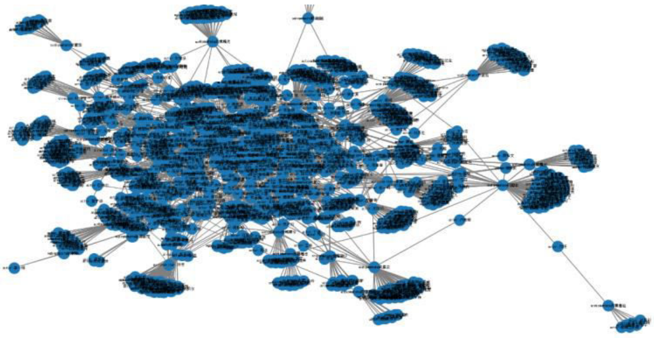

Figure 7 Partnership diagram

4) Association rule mining between states

For the mining of association rules between states, item set $I = \{D_a, D_b\}$ is established first, where D_a is the current state of investment transaction data set and D_b is the next state of investment transaction data set. Apriori algorithm is used to scan the data set and generate frequent item set and its confidence degree.

The association rules between states are shown in Figure 8.

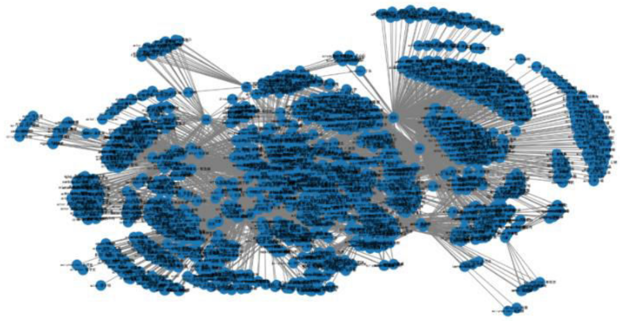

Figure 8 The association rules between states

IV. Results

This paper uses two LSTM models to predict the abnormal data at the same time. Through weighting, it aims to improve the accuracy of abnormal value 1 and normal value 0 at the same time.

The weighting formula is: $o_t = sigmoid\left(W^{xo} x_t + W^{ho} x_{t-1} + b_o\right)$

The comparison of accuracy between single LSTM model and improved LSTM model is shown in Table II.

TABLE II Comparison of Accuracy

	Acc_0	Acc_1	Acc_all
Single LSTM model (1 day)	0.753	0.619	0.751
Improved LSTM model (1 day)	0.831	0.846	0.847

Through the above comparison, researchers can conclude that the improved LSTM model not only predicts whether there will be abnormal values in the future on the basis of considering the time span of model input and model output, but also predicts that the F1 value of the model is 0.816, which greatly improves the accuracy of the traditional LSTM model, as shown in Figure 9.

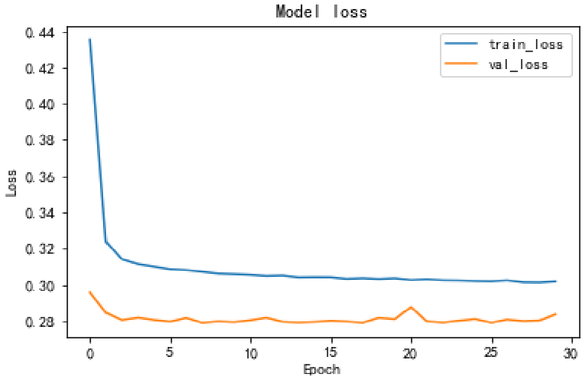

Figure 9 Convergence curve

Therefore, this paper proposes a multi-layer LSTM weighted model. The multi-layer LSTM network is used to learn the influence factors of the input time span on the output time span. By embedding approaches, it influences superposition; generates periodic sequence and train the model so as to achieve higher accuracy than the LSTM model. The framework uses the closing price of bitcoin in one day, two days, three days, four days and one day as the explanatory feature. The partial autocorrelation function proves the rationality of the selection. Subsequently, it shows a gradual upward and downward movement. Then, it builds a risk measurement index. The greater the cycle price fluctuation is, the greater the risk there is. The results show that timely trading will maximize the return, and an investment of $1000 will eventually yield a return of $900000.

A. Correlation analysis

This paper studies the correlation of six influencing factors: Event 1, event 2, event 3, event 4, event 5 and event 6.

Through SPSS analysis, the following results can be obtained:

TABLE III CORRELATION ANALYSIS

	Event 1	Event 2	Event 3	Event 4	Event 5	Event 6
Event 1	1					
Event 2	-.955**	1				
Event 3	-.150	.251	1			
Event 4	-.964**	.972**	.268	1		
Event 5	.899**	-.897**	.151	-.886**	1	
Event 6	-.665	.578	-.345	.490	-.733	1

It can be seen from the above table III that there is a very close correlation between the six influencing factors of event 1, event 2, event 3, event 4, event 5 and event 6. The following regression analysis can be carried out.

B. Regression analysis

Multiple nonlinear regression analysis is used to study the influence relationship of six influencing factors of event 1, event 2, event 3, event 4, event 5 and event 6 on "time". The analysis is as follows:

TABLE IV MODEL SUMMARY

Model	R	R-square	Adjusted R-square	Error of standard estimation	Debin Watson
1	.575^{a}	.119	.082	.433	1.910

The R-square in the table IV is 0.575, greater than 50%, which indicates that the model prediction is accurate and the study of the model is meaningful.

TABLE V ANOVA

Model		Sum of squares	degree of freedom	mean square	F	Significance
1	regression	3.648	6	.608	3.236	.005^{b}
	residual	27.054	144	.188		
	total	30.702	150			

This table V considers whether the regression equation is meaningful. The significance is 0.005 < 0.05, so the equation is meaningful.

TABLE VI VIF DIAGNOSIS

parameter	estimate	standard error	95% confidence interval lower limit	95% confidence interval upper limit	95% range after clipping lower limit	95% range after clipping upper limit
a	-60.167	.000	-60.167	-60.167	-60.167	-60.167
b	-1.065	.000	-1.065	-1.065	-1.065	-1.065
c	-25.936	.000	-25.936	-25.936	-25.936	-25.936
d	-23.591	.000	-23.591	-23.591	-23.591	-23.591
e	-33.704	.000	-33.704	-33.704	-33.704	-33.704
f	-5.525	.000	-5.525	-5.525	-5.525	-5.525
g	1.496	.000	1.496	1.496	1.496	1.496
h	12.833	.000	12.833	12.833	12.833	12.833
i	-1.017	.000	-1.017	-1.017	-1.017	-1.017
j	27.320	.000	27.320	27.320	27.320	27.320
k	1.753	.000	1.753	1.753	1.753	1.753
l	32.772	.000	32.772	32.772	32.772	32.772
m	-.245	.000	-.245	-.245	-.245	-.245

Based on the three features that establishing a deep reinforcement learning model, normalizing the original data by using mathematical statistical methods to obtain the state data matrix containing the historical feature information of gold and bitcoin, and extracting the robust and effective feature expression in the state data by using the deep neural network inside the agent; the respective strategy optimization methods of the three reinforcement learning algorithms are used. Combined with the current reward value, the relevant parameters of deep neural network are optimized to obtain the optimal investment and trading strategy in an exploratory way, as shown in Table VI.

V. DISCUSSION

Sensitivity analysis is a method to study and analyze the sensitivity of system (or model) state or output changes to system parameters and surrounding conditions. Sensitivity analysis is usually used to study the stability of the optimal solution when the original data is inaccurate or changing. There are two conversion methods: the first is the factor change method, if the pre-analysis parameters increase by 10% or decrease by 10%; Another method is to modify the deviation, for example, by adding or reducing the standard deviation in the pre analysis parameters. The overall sensitivity analysis quantitatively determines the contribution of model parameters to fix the error of model results. The main methods are Sobol method [25] and Fourier amplitude sensitivity test expansion method, both of them are based on variance[26]. The variance of the model results can fully reflect the uncertainty of the model results. Not only can it calculate the individual influence of parameters on the model results, but also calculate the influence of parameter interaction on the model results. Through qualitative global sensitivity analysis, the parameters that have little impact on the model results are selected.

The principle of the improved LSTM model is shown in Figure 10.

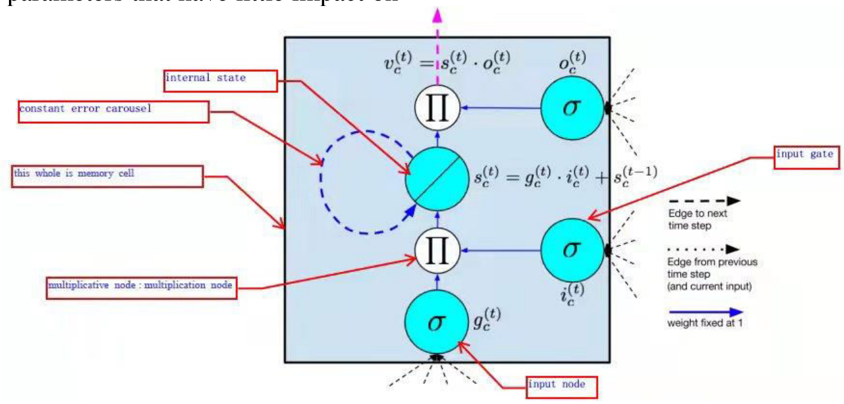

Figure 10 The principle of the improved LSTM model

By setting 0.5%, 1%, 1.5% and 2% as the percentage of increasing or decreasing transaction costs, this paper runs the model again to test the sensitivity (investment decision results) under different transaction costs. The results show that the model has excellent robustness, that is to say the model constructed in this paper has good results under different transaction costs. The accuracy is shown in the figure 11.

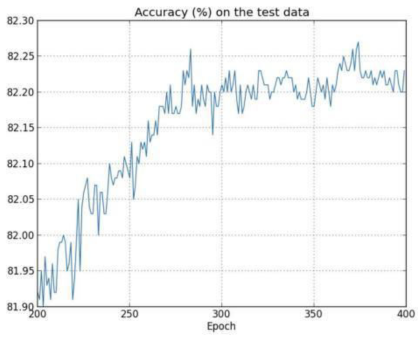

Figure 11 Accuracy

The model has certain advantages in sequence modeling and has long-term memory function. Additionally, It is also simple to implement. The model solves the problems of gradient disappearance and gradient explosion in the process of long sequence training[27].Regression analysis showed that there was a significant relationship between independent variables and dependent variables; It indicates the influence intensity of multiple independent variables on a dependent variable. However, there are disadvantages in parallel processing. Compared with some of the latest networks, the effect is general. The stock factor selection model is further studied[28]. In the first simulation test, the yield of a single model is often lower than that of multiple models. This idea is called model integration, and its basic idea is to use multiple models with different branches[29]. Then vote according to the results of all models to complete the final filtering of factor combination. Therefore, researchers can try more different models, which includes gbdt, FFM, RF and DNN. However, the screening effect of these stock factors is worrying. The increase cost of multi-modal transport training is also a factor needs to be considered. In the process of writing this paper, we constantly consult and learn journals related to machine learning and quantitative trade, hoping to establish a synchronous relationship between theory and practice. In order to solve the problems existing in the increasingly fierce industry competition. It is very difficult to understand and improve the quantitative impact of capital investment and application.

VI. Conclusion

(1) Quantitative investment is a popular investment method nowadays. Compared with traditional investment, this method is based on the high-performance data processing ability of the computer and a large amount of market data. It uses mathematical model and computer programming technology to write the investment strategy into the computer for high-speed data processing[30] so that investors can find securities in line with the market law in a large number of data for investment. Traditional quantification is a strategic model based on data and model. Its ultimate goal is to achieve stable long-term benefits through automated transactions. Traditional quantification has derived many types of strategies, and different strategies also focus on different investment targets[31]. Through the observation of the investment subject matter and long-term staring at the market, we can find the rise and fall law from the data, so as to form a strategy model. This strategy needs to be tested back to the historical data. When the return and risk of back testing are within the tolerance range, it can be recognized as a feasible strategy. However, this back test result is likely to be based on the result of an optimization, so it may be over fitting. It is necessary to further detect the moving time window of the strategy to test the prediction ability of the strategy in the long-term environmental changes and the recommended fund allocation of the strategy for a certain object. Traditional quantification provides investors with trading suggestions and investment recommendations in this digital way, which not only improves the investment income, but also greatly saves time investment.

(2) Due to the highly nonlinear and non-stationary characteristics of bitcoin price, LSTM has advantages over traditional prediction models[32]. However, when we only use a single LSTM model for prediction, there is still a great room for improvement in the final accuracy due to the difficulty in capturing multi-scale periodic features. Therefore, this paper constructs an LSTM hybrid model for

prediction[33].Bitcoin has the ability to provide investment security in difficult times. These characteristics of bitcoin can help to estimate its trend in the short and long term accurately. The proposed framework shows high flexibility in accomplishing this task. Therefore, it will help investors reduce risk by estimating the future price of bitcoin. The effectiveness of the proposed framework for alternative series proves the ability of the prediction framework to obtain significant returns in times of crisis. The first mock exam results show that the prediction results of hybrid forecasting model are better than that of single model. It is helpful for investors to make investment portfolio.

(3) Based on AI quantification, a series of characteristic factors are generated, which represents the basic attributes of the investment object, such as the volatility of a stock in a certain period of time, 5-day average return and so on. As an attribute of the subject matter, these factors can reflect the future profitability and potential risks of the subject matter in a certain level. The first thing to do is to select the factor that can describe a subject matter best and make this factor close to the subject matter itself as possible as it can, so as to facilitate the later investment choice. Secondly, we need to build an appropriate scoring model and select the one with the highest score from some investment objects to invest. The characteristics of these factor attributes include the exposure value of the factor, the correlation with other factors, the return of the factor and so on. Through the study of these attributes, we can work on factor analysis better.

(4) Deficiency and follow-up studies: this article is based on the degree of data to explore the strategies to improve and prediction model. It gets no involved in hours or minutes data and there may also be some error about the results for different frequency data. In terms of strategy, the strategy it takes is very conventional technical indicators and the addition of forecast data is the basis of business. In the future, more application scenarios of predicted data can be explored.

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