LSTMcon: A Novel System of Portfolio Management Based on Feedback LSTM with Confidence

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***Abstract*—Trading carries a substantial amount of risk and making adequately informed decisions cannot be overemphasized. In order to propose a more reasonable strategy on portfolio arrangement, we design LSTMcon, a two-stage system that consists of a assets price prediction model and a decision-making strategy based on ensemble rules. As for next-day price prediction, we implement an LSTM model with feedback mechanism and devise a series of training settings. The feedback mechanism uses the deviation between predicted price and actual price to correct the prediction result from LSTM. To decrease the transaction cost, we design a three-day trading period and adopt an iterative prediction approach. Our model achieves the accuracy of 98.5% on GOLD and 98.8% on BTC finally. In addition, we devise a decision-making system after getting the predicted data. We modify the predicted price by giving everyone a certain confidence level based on three approaches (reward and punishment mechanism, sequential days rules, historical price relying). We combine these rules and give a comprehensive confidence level to weigh the predicted price. Subsequently, we summarize the transactions into 8 trading operations, input the modified price and automatically compare the hypothetical return of these eight operations. Then, output the operation with largest return as today's decision. We compare the returns and transaction costs of comparative systems, and demonstrate our strategy with effectiveness.**

***Index Terms*—Price Prediction, Decision-making, LSTM, Portfolio Management, Knowledge Engineering**

I. Introduction

Market traders buy and sell volatile assets frequently, with a goal to maximize their total return. Nowadays, it is not difficult for us to find trading strategies suitable for our preferences in many academic articles or forums [1]. However, it is still a problem of how to distinguish the good and bad of these strategies and avoid making some common mistakes, such as survivorship bias, look-ahead bias, and trading cost [2].

With the popularity of Internet resource search, quantitative trading emerges as the times require [3]. It refers to using advanced mathematical models to replace human subjective judgment, and selecting a variety of high probability events that bring excess returns from huge historical data to formulate strategies. For example, in some simple quantitative analysis [4], some statistical tests are carried out on the close price of financial instruments. More complex systems consider more information to improve the accuracy of price prediction [5].

In this paper, we deliver a novel system of portfolio management based on a two-stage model consisting of a financial assets price prediction model and decision-making strategy based on ensemble rules (Fig. 1). We apply a LSTM with Feedback Mechanism for prediction and set aside a period of half a year used to train a preliminary LSTM which constantly carries out training with real assets price of the days we have predicted and modifies its parameters. It can be generalized to other asset datasets in addition to gold and bitcoin. As for decision-making, we introduce several rules to modify the predicted assets price by giving everyone a certain confidence level in order to propose a more reasonable strategy. The remainder of this paper is organized as follows: After concluding related work in Sec. II, Sec. III discusses details of our portfolio management system. Experiment settings and results analysis are revealed in Sec. IV and we summarize this paper with future work discussed finally.

II. Related Work

There are some traditional time series models applied to portfolio management based on typical methods in mathematics. These methods include multivariate analysis [6], dependence learning [7] and transitional models [8]. In spite of their widely use in scientific experiments, they were proposed early and incapable of modeling the aforementioned huge data and complex features.

Recently, researchers apply more deep learning models for time series prediction tasks, such as recurrent neural networks (RNN) based method with a dual-stage attention [9] to select relevant driving series, and convolution neural network (CNN) based method like TCN [10] to capture effective historical data of price fluctuation. They are regarded as good trials on assets price prediction. Related work also pays attention to improve the accuracy by utilizing external information which may influence the market and effect assets price [5]. Clearly, a deep learning model does show a better performance on big data and take more factors into consideration.

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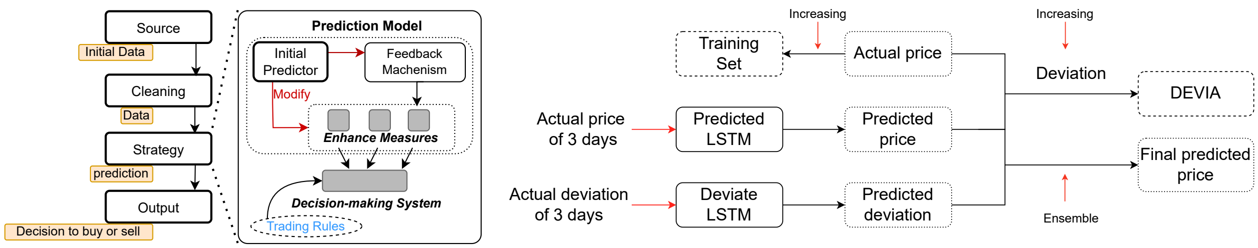
DOI reference number: 10.18293/SEKE2022-160



(a) (b)

Fig. 1: The framework of our system: (a) Quantitative trading process we simulate in this paper: data flows in the prediction model and decision-making strategy; (b) The detail process of our financial assets price prediction model: LSTM with Feedback Mechanism and utilised datasets.

We conclude with these SOTA models from both computer scientists and economists in real-world investment, but they are difficult to be directly formed as a strategy. Among them, RNN[11], [12], [13] is one of the most powerful models. Compared with other neural network, results of each layer in RNN are not independent, but relate to results of the previous layer and current input. However, computational complexity would increase exponentially, resulting in a significant increase of model training consumption. Due to the assumption that cash from selling gold or bitcoin could be used to buy assets on the same day, there is no necessity to consider multi-step prediction. In this paper, we start with the variant of RNN: Long Short-Term Memory (LSTM) [14] and some measures are taken on the single LSTM for improvements.

III. Method

A. Financial Assets Price Prediction System

1) LSTM with feedback mechanism: LSTM is specially designed to solve the long-term dependence problem of general RNN, thus it helps with prediction of sequential data, of which a good example is constituted by daily price of financial assets.

We set the training rules as follows:

- Considering the transaction cost, we design a three-day trading period, that the trader buys or sells assets using data of every three days. Therefore, we choose the iterative prediction approach. Our model predicts the daily rise or fall of three days at a time and we make one trading decision based on these data (the reason for choosing 3 is in Sec. IV-E with experiments).
- Due to prediction based on data up to that day, we cannot use the later data to train our model. We set aside a stable period of half a year. For example, we use data from September 2016 to February 2017 to preliminarily train an LSTM but the training set size increases day by day.
- The maximum return may be closely related to the exact predicted price. Therefore, we device Feedback Mechanism to modify our model. After comparing the predicted value with the real value, we return the deviation to LSTM by Feedback Mechanism, and modify parameters.

The final structure of our prediction model is shown in Fig. 1 (b). Feedback Mechanism is actually a deviate LSTM. Based on the predicted LSTM, we add it to return the deviation between predicted price and actual price. First, we train a preliminary LSTM for predicting future prices from six-month data for iterative prediction. Its training set is increasing day by day, and it constantly carries out training, that is, modifying parameters to improve the prediction performance. Next, we accumulate the deviation between the predicted price and the actual price to form a training set named DEVIA. DEVIA is used to train the deviate LSTM to input the deviation of several days and obtain the deviation of the next day, which is used to correct the prediction result of the predicted LSTM. The outputs of the two models are added together, i.e. predicted price + predicted deviation, as our final predicted value.

B. Decision-making Strategy Based on Ensemble Rules

1) Predicted Price Modification: In order to reduce potential risks of prediction models, we consider how much confidence is given to predicted results. To evaluate the confidence, we introduce several approaches which help filter opportunities with low winning rate, which is very difficult for machines.

Since we have adjusted the predictor by Feedback, the results are actually reliable and we set the lowest confidence as 0.94 (the reason for choosing 0.94 is in Sec. IV-E with experiments). with the maximum confidence of 1. Each evaluation method gives a confidence to predicted results. We combine these confidences to give a comprehensive one to weigh the results for next decision-making. Confidence of different days would continuously change in [0.94, 1].

(a) Reward and Punishment

We study the process of real neural networks generating strategies through neural circuits. After animals successfully hunts with a certain method, they would incline to use this method in the next hunt, and abandon the failed one. It mainly depends on the reward and punishment mechanism.

We manage to set **Reward and Punishment** in our model, which rewards and punishes the confidence of predicted price. At the beginning, confidence is relatively low. As the number of correct predictions increases, it would rise linearly; otherwise, reduce it appropriately.

(b) Transaction rules

TABLE I: Model Comparsion

Technique	RP Mechanism	Sequential Days	Historical Price
Range	[0,2000]	[1000,2000]	[0,2000]
Initial Value	0	2000	2000
Change per day	±100	±100	±100

From the perspective of economics, we directly incorporate some summarized laws into our system, such as the two famous economic principles in the follows [15]:

- People make decisions after comparing costs and benefits. When costs and benefits change, people's decisions also change. So they respond to incentives, which can be either artificial or the result of natural change.
- The market fluctuates and the fluctuation has a direction. Although there are differences between strong and weak fluctuations, fluctuations is cyclical in a long term.

As for the first principle, we believe that the trader's mentality of buying, holding, or selling his assets is in a dynamic process of days, even if the change ratio is the same. When the price rises (falls) for several **Consecutive Days**, traders are more likely to sell (buy) than on the first day, which is a right way to invest. We suppose the predicted price is rising continuously for several days. On the first day, we give almost full confidence, because it is a normal fluctuation. Confidence would decrease with days passing, since it is difficult to imagine that an asset will rise for ten days or more.

For next principle, we adjust confidence according to **Historical Price** since the fluctuation is cyclical. If the price falls to historical bottom (all-time low), we tend to think that it would rise. Stay alert to consider whether we sell the assets or hold on when the predicted price is close to historical peak.

(c) The combination

We write a scoring program with three indicators that we proposed: **Reward and Punishment (RP)**, **Conservative Days** and **Historical Price**. The rules are shown in Table I and these parameters are the best determined by repeated tests in subsequent experiments.

As for **RP**, the initial value is 0 and it increases by 100 every time the prediction is correct, and decrease when false. For **Consecutive Days**, experimental results give it a large minimum value, which means we rely on it very much. On the first day of rising, it is 2000 but decreases by 100. For **Historical Data**, when it is between historical maximum and minimum, we give it 2000. Every time it falls outside the range, 100 points are deducted.

The total score is within [1000, 6000]. We map them to [0.94, 1] to obtain a confidence in [0.94, 1]. Let RP be the score given by **RP**, Seq be the score of **Consecutive Days** and His of **Historical Data**. The mapping relationship is:

$$Conf = (His + Seq + RP - 1000)/50000 + 0.94 \tag{1}$$

Experiments show that the composition of the confidence is very reasonable. At the initial stage of prediction, the proportion of scores given by constructive days is the highest because of the lack of samples, on which RP mechanism and historical data bases. In the medium term, the proportion of RP mechanism rises quickly. When predicting the final data, the score of confidence is almost determined by historical price.

2) Decision Tree: We summarize the transactions in each day into 8 trading operations as follows:

- $B \rightarrow G$, sell bitcoin and buy gold
- $G \rightarrow B$, sell gold and buy bitcoin
- $B\downarrow$, $G\downarrow$, all sold
- B— , G— , no operations
- $B\uparrow$, G— , buy bitcoin, no operations on gold
- B— , $G\uparrow$, no operations on bitcoin, buy gold
- $B\downarrow$, G— , sell bitcoin, no operations on gold
- B— , $G\downarrow$, no operations on bitcoin, sell gold

We simulate these eight trading operations, as shown in the following formulas. On the left of the equation is the hypothetical return. In each case, the whole return from the operation is subtracted from the cost of the corresponding operation (transaction cost and income that can be obtained if the operation is not carried out), and then the hypothetical return are obtained. After getting the predicted price of the next day, our algorithm automatically compares the hypothetical return of these eight operations. Then, output the operation with largest return as today's decision.

- $B_1 = (P_{G_{d+3}} - R_{G_d}) * (T_{B_d} - 0.02 * T_{B_d} - 0.01 * 0.98 * T_{B_d})/R_{G_d} - (0.02 * T_{B_d} + 0.01 * 0.98 * T_{B_d} + (P_{B_{d+3}} - R_{B_d}) * H_B) + (P_{G_{d+3}} - R_{G_d}) * H_G$
- $B_2 = (P_{B_{d+3}} - R_{B_d}) * (T_{G_d} - 0.01 * T_{G_d} - 0.02 * 0.99 * T_{G_d})/R_{B_d} - (0.01 * T_{G_d} + 0.02 * 0.99 * T_{G_d} + (P_{G_{d+3}} - R_{G_d}) * H_G) + (P_{B_{d+3}} - R_{B_d}) * H_B$
- $B_3 = -1 * (T_{G_d} * 0.01 + T_{B_d} * 0.02)$
- $B_4 = (P_{B_d} - R_{B_d}) * H_B + (P_{G_d} - R_{B_d}) * H_G$
- $B_5 = (P_{B_{d+3}} - R_{B_d}) * 0.98 * H_D/R_{B_d} + (P_{B_{d+3}} - R_{B_d}) * H_B + (P_{G_{d+3}} - R_{G_d}) * H_G$
- $B_6 = (P_{G_{d+3}} - R_{G_d}) * 0.99 * H_D/R_{G_d} + (P_{B_{d+3}} - R_{B_d}) * H_B + (P_{G_{d+3}} - R_{G_d}) * H_G$

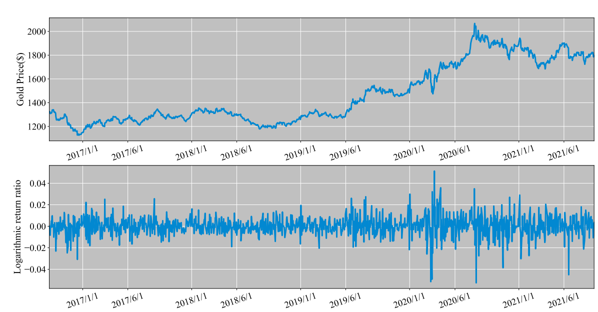


Fig. 2: A example: the price fluctuation curve of Gold and the corresponding Logarithmic return ratio of each day.

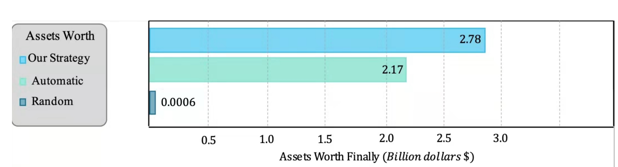
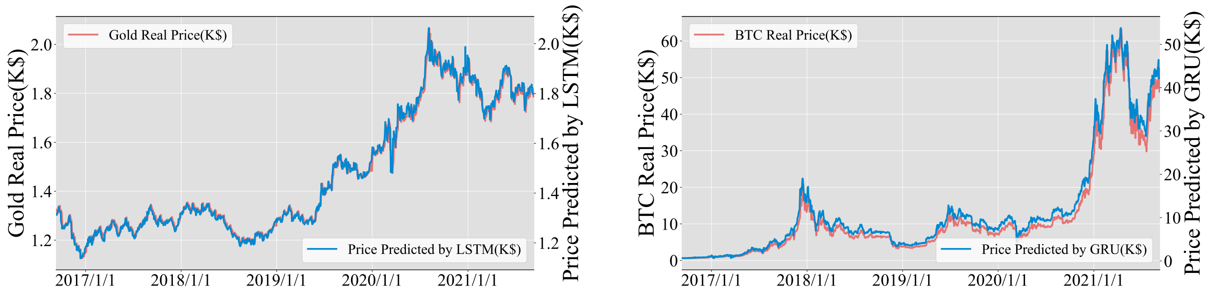
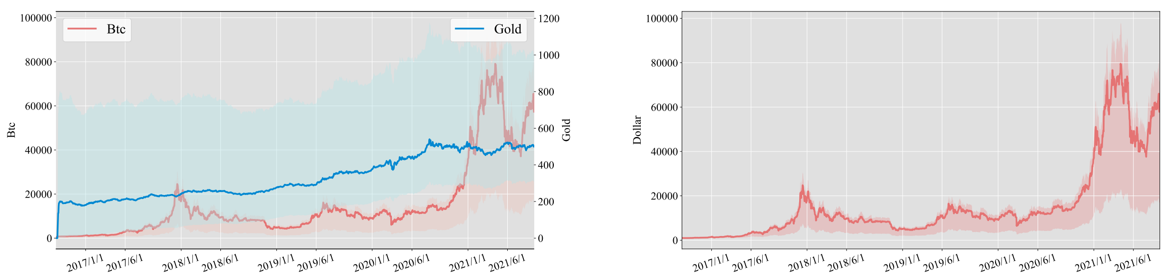


Fig. 3: Assets Worth Finally on three systems.



(a) (b)

Fig. 4: Predicted price fluctuation curves of (a) LSTM with feedback on GOLD, (b) LSTM with feedback on BTC.



(a) (b)

Fig. 5: In the random system, (a) amount of gold and bitcoin we hold in a timeline; (b) assets worth in a timeline

- $B_7 = (P_{G_{d+3}} - R_{G_d}) * H_G - 0.02 * T_{B_d}$
- $B_8 = (P_{B_{d+3}} - R_{B_d}) * H_B - 0.01 * T_{G_d}$

Take $Branch_8$ as an example which represents no operations on bitcoin and selling gold. The final predicted return (assuming no operations on holding assets and all surplus cash to buy gold in the next three days) is equal to the three-day return on buying gold, and holding gold and bitcoin.

Suppose the situation: the assets price falls next day with the decline just greater than transaction cost, but it rises immediately the day after. In these cases, the decision from models directly using predicted price causes repeated jump and consumption, and our model effectively avoids the problem.

C. Comparative Systems

Although we already devise a decision-making strategy, we think it necessary to design two other simple decision-making systems for comparison. After leveraging existing predictor, we get a set of price fluctuation prediction results. We put these results into these systems and calculate the income.

The first is **Random System** that we devise based on our prediction model. We design a random algorithm as follows: after we gain the prediction results, we input them into the algorithm and get a random value, the asset value we decide to buy or sell. We aim to make money and would not trade against price fluctuation, but are eager to get a return under random circumstances. In the experiment below, we run the program 1000 times to obtain the random mean return.

Next comes a simple **Automatic System**. This system is hardly added with any decision-making strategy. As long as the predicted decline next day exceeds transaction cost, we sell the assets, and vice versa. Unless both assets fall, we do not keep cash in wallets. If both assets rise or other complex conditions, we would allocate the percentage of each asset according to rules in Sec. III-B2.

IV. Experiments

A. Experimental Setup

1) Datasets: In this paper, we only take two assets: gold and bitcoin as examples. To predict the price based on data up to that day, we collected the price of gold and bitcoin during a five-year trading period from September 11, 2016 to September 10, 2021, and name them as GOLD and BTC. We supplement the default data of GOLD to improve the accuracy of subsequent prediction, and calculate the specific fluctuation ratio of assets price each day.

To gain a more intuitive understanding of price changes, we create a column that indicates the Logarithmic return ratio of each day. The price fluctuation follows a log-normal distribution with a more stationary characteristic [16].

2) Index: Based on the two comparative systems mentioned in Sec. III-C, we mainly use two indexes as follows.

Return: Assume that we have $1000 in the beginning as the initial capital, and we calculate how much our assets is worth after five-year prediction and decision-making.

Accuracy: Since the exact changing range is difficult to predict, the accuracy in this paper refers to whether we correctly predict it rises or falls.

TABLE II: Model Modify

Models	Accuracy_GOLD (%)	$Training\ MSE_{GOLD}$	$Test\ MSE_{GOLD}$
LSTM	98.2	1373.836482	1378.41921
LSTM with Feed Back	98.5	1321.472946	1299.382565
Models	Accuracy_BTC (%)	$TrainingMSE_{BTC}$	$TestMSE_{BTC}$
LSTM	98.5	7132.357321	31232.64239
LSTM with Feed Back	98.8	7037.683933	29475.83646

B. Assets Price Prediction

We assume that the real data has a certain law, and believe that LSTM learns some laws from the training set, but previous experiments indicate that there are some deviations between the laws contained in real data and learned by LSTM. Accordingly, we speculate that the gap between prediction results and real data also forms a certain law. Therefore, we add Feedback Mechanism (deviate LSTM in Sec. III-A) for predicting the gap to correct the predicted price.

As shown in Fig. 4, LSTM with Feedback simulates the whole price fluctuation almost perfectly even on BTC with exaggerated fluctuations. Table II better shows the performance of LSTM with Feedback and it behaves very improvement on all metrics compared to a single LSTM. Our model achieves the accuracy of 98.5% on GOLD and 98.8% on BTC, which demonstrate Feedback mechanism with highly effectiveness.

C. Three Decision-making Systems and Who is the Best

In general, we calculate how much our assets is worth finally. According to the prediction, **Random System** achieves \$0.0006 billion in five years, which is too little to show on the Fig. 3. **Automatic System** which makes decisions only based on the relationship between prediction and transaction cost shows a good performance of \$2.17 billion.

However, the market is difficult to predict and untenable to directly rely on computer models. Therefore, we introduce mature market rules in our decision-making model to modify the predicted price, and finally get \$2.78 billion.

1) The random system: The performance of **Random System** is worth mentioning (Fig. 5 in a timeline). After experimental data of 1000 random trials are averaged, the solid line is obtained. The shaded part indicates the fluctuation range of 1000 randomized trials. The assets value almost completely follows bitcoin. We guess the reason is the price of bitcoin fluctuates more suddenly and steeply than that of gold. Bitcoin has risen greatly in recent years, so the results are better. However, there are also great disadvantages. When bitcoin plummeted, our total assets decreased sharply. It shows that blind investment is problematic even with a correct prediction.

2) Our strategy: Fig. 6 shows the performance of our strategy with assets worth and different assets' ratio in a timeline. Since the effect of the other two models is relatively weak, we mainly compare our model with **Automatic System**.

The final assets value of our strategy is 28.1% higher than that of Automatic System, which fully shows the effectiveness of the laws we designed from different disciplines. As is shown in Fig. 6, the overall worth is rising almost consistently and the ratio of different assets is relatively uniform. Each color lasts a certain distance that indicates the ratio is relatively stable. There is no problem of frequent buying and selling of Automatic System, which leads to a large amount of handling charge.

TABLE III: The transaction cost and ratio of two models.

Models	Transaction cost	Return	Ratio (%)
Decision-making system	1.68	2.78	60.43
Automatic system	1.78	2.17	82.04

In addition, with the addition of well-designed decision-making methods, we can well avoid the characteristic that the value follows bitcoin in the random system. We discover that the value of assets has been rising over time without any decline, which shows our strategy the most stable one. Unlike the random system that always invests in bitcoin, when the predicted price of bitcoin falls, our strategy will buy a lot of gold to ensure that assets value are not lost.

D. Influence of Transaction Cost

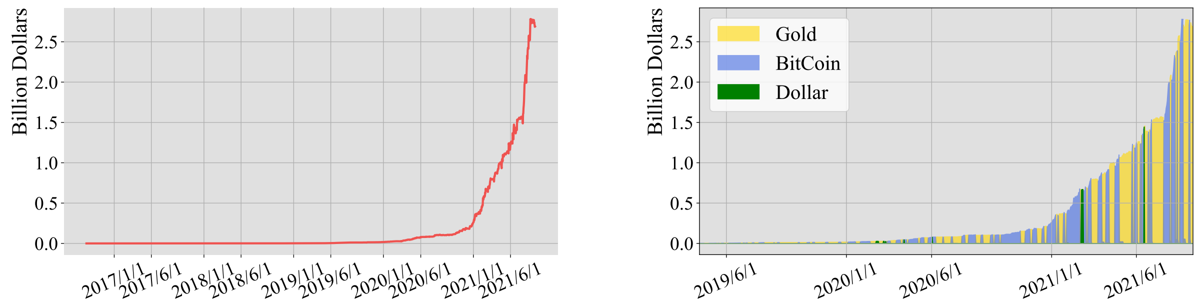
In this part, we compare our model mainly with **Automatic System**. We get the transaction cost through programming, and calculate the ratio between it and the actual return of the model. Table III below includes these information.

In this table, Automated System spends more on transaction fees during the investment period, meaning more daring actions. After introducting market rules, we spent less fees and achieved 27% higher profits than the automatic system. We conclude that machines tend to short-term benefits, while decision-making systems pay more attention to long-term benefits, which is also what economic principles tell us. It indicates that decision-making is significantly effective in portfolio management.

E. Parameters chosen

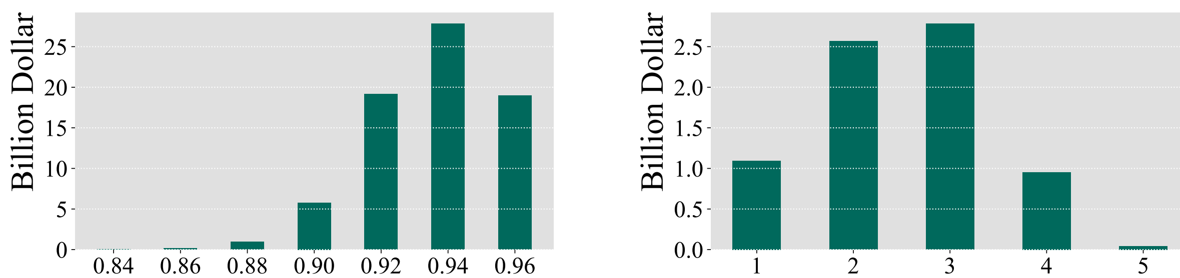
Fig. 7 (a) shows how much the assets worth finally under different lower confidence limits. In Sec. III-B, based on the predicted results of LSTM with a feedback mechanism, we set a confidence level for the predicted price by combining some economic principles and other methods. Confidence levels would inevitably effect the final results, so we need to find the most appropriate value. Experimental results show that when the confidence level is 0.94, the final assets price maximized.

For portfolio management, we make decisions with reference to predicted prices. In reality, there are often frequent changes in prices in a short term, which leads to unnecessary trading operations and increases the transaction cost. The problem can be effectively avoided by predicting prices of several days in the future, but it leads to inaccurate prediction when we predict prices for too many days. We conduct repeated experiments and finally discover in Fig. 7 (b) that predicting the price of next three days brings the best results.



(a) (b)

Fig. 6: In our strategy, (a) red line indicates how much is our assets worth in a timeline of five years; (b) ratio of different assets in our portfolio management during the same time.



(a) (b)

Fig. 7: Our assets worth under different parameters: (a) different lower confidence limits range in [0.84, 0.96]; (b) different number of days of which we predict assets prices and train iteratively.

V. Conclusion

For better portfolio arrangement, we established a novel system which contains a price prediction model and a decision-making model. We applied an LSTM model with Feedback Mechanism and achieved an excellent accuracy on two datasets. As for decision-making, we devised an ensemble method based on three approaches (reward and punishment mechanism, sequential days rules, historical price relying). to modify the predicted price by giving a confidence level. We summarized transactions into 8 trading operations and designed an algorithm to automatically output the operation with largest return. We calculate the returns and transaction costs of comparative systems, to demonstrate that our strategy is more reasonable. For future work, we can further combine external information, such as policies to enhance the system.

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