LSTM-Based MACD Strategy Parameter Restructuring

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Abstract. Moving average convergence divergence (MACD) strategy has been applied in much research in financial area. Studies has demonstrated the excellent performance of the MACD strategy in quantitative investment. However, traditional parameter set (12, 26, 9) performs differently in various regions and market environments. Hence, we propose a LSTM-based method to optimize MACD strategy parameters. The proposed method offers the ability to predict advanced MACD strategy parameters in any time interval. We use all stocks from China A-Shares over the period of 2015–2020 as experiment data. We find that after applying different MACD parameter sets produced by our model, balance outperforms than the non-optimized parameter set. Our model provides an easy-to-use investment tool that discovers potential positive returns.

Keywords: MACD · Parameters optimization · LSTM · China A-Shares

1 Introduction

With the advent of the era of big data and the development of artificial intelligence, machine learning methods have become an advanced means of solving problems. Therefore, the financial field has set its sights on the field of machine learning to realize the commercialization of big data and artificial intelligence in financial markets and institutions, such as quantitative trading and other applications.

The MACD strategy is a commonly used and effective technical analysis method in the financial market. It uses the convergence and divergence of the long- and short-term exponential moving averages of the closing price to determine the timing of buying and selling. Prior experience has used fixed parameters (12, 26, 9) for a long time. However, the market is volatile, and the efficiency levels of the excess returns obtained by using the MACD strategy in different regions are different [1]. Therefore, we consider dynamically adjusting parameters to adapt to different market environments in order to obtain greater economic benefits [2]. Marques et al. [3] used genetic algorithms and fuzzy logic to test

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the MACD strategy and improved the MACD parameters, proving the potential benefits of adjusting the MACD parameters.

We proposes a neural network based on LSTM to optimize and restructuring the parameters of the MACD strategy to make it more adapted for different market environments. The experimental results prove the advantages of using neural network method and the possibility of bringing more benefits.

The rest of this paper is structured as follows. In Sect. 2 we review the related work. Section 3 introduces the proposed method. Then, in Sect. 4 we present and analyze the experimental results. Section 5 concludes.

2 Related Work

Moving average convergence divergence (MACD) is a trading indicator for stock price technical analysis created by Gerald Appel in the 1970s. By revealing the strength, direction, momentum and continuous direction changes of the stock price trend, it guides investors to buy or sell for returns. The formula is as follows [2,4,5]:

$$EMA_{Nt} = EMA_{Nt-1} * \frac{N-1}{N+1} + \frac{2 * Close_t}{N+1} \tag{1}$$

$$EMA_{Mt} = EMA_{Mt-1} * \frac{M-1}{M+1} + \frac{2 * Close_t}{M+1} \tag{2}$$

$$DIF_t = EMA_{Nt} - EMA_{Mt} \tag{3}$$

$$DEA_{Pt} = DEA_{Pt-1} * \frac{P-1}{P+1} + \frac{2 * DIF_t}{P+1} \tag{4}$$

$$MACD_t = 2(DIF_t - DEA_{Pt}) \tag{5}$$

where $Close_t$ is the closing price of t_{th} time. By drawing MACD and signal curves, triggering buy and sell signals are revealed.

The optimization methods of MACD parameters can be divided into two categories, model-based methods and data-driven methods. The model-based method finds the optimal parameter sets through existing mathematical methods. Marques et al. [3] used genetic algorithms to establish an optimal window value based on the MACD model, and fuzzy logic to indicate the best time to buy and sell, which can generate higher profits. It revealed the potential returns of adjusting MACD parameters. Based on the Nikkei 225 futures market, Kang [6] evaluated the potential positive returns brought by changes in MACD parameters through the establishment of traditional MACD models, comparative models and optimized models. The data-driven method selects and analyzes a large amount of data through machine learning methods to find the potential relation between the optimal parameters and the data. Yang [5] used SVM and RVM methods to optimize trading signals in MACD, and added indicators such as market activity, volatility, and deviation. Javan et al. [7] established a SeroFAM network based on the MACD model, and added its predicted value to the MACD signal to reduce the lagged effect of MACD.

Predicting methods based on time series are of great significance in various knowledge fields. In the financial field, more and more scholars have begun to use time series analysis methods. Yu et al. [8] used BP network and fuzzy logic to predict the value of TAIEX (Taiwan Stock Exchange Capitalization Weighted Stock Index) price series. Sidra et al. [9] used CNN to build a regression model and predict the future index value based on the NIFTY50 of the National Stock Exchange (NSE) of India. Inspired by the above work, we propose a neural network based on LSTM, which optimizes the parameters of the MACD strategy from time series stock data.

3 Method

The network structure constructed in this paper mainly includes LSTM and two fully connected layers. The input stock data is preprocessed and then input to the LSTM. After Dropout, the hidden layer output h_t is obtained. The predicted values of the MACD strategy parameters are calculated through the two-layer full connection as the final result (see Fig. 1).

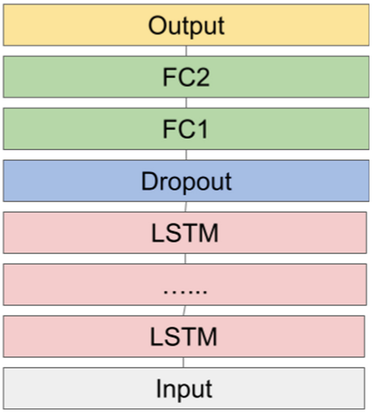

Fig. 1. The overall structure of the network.

3.1 Network

Recurrent Neural Network. RNN is a common artificial neural network, which specializes in processing sequence problems. Sequence usually refers to a piece of text or audio. For this paper, it refers to stock data in a certain time window. A simple feed-forward neural network usually contains an input layer, a hidden layer and an output layer. RNN has more loops on the hidden layer based on it. The output of the hidden layer at the t_{th} time and the input of the next time are calculated as the input of the hidden layer together, so as to realize the preservation of information. But RNN has a hidden short-term memory problem, which is caused by the nature of back propagation. In order to solve this problem, LSTM is introduced.

Long Short-Term Memory. The core of LSTM is the cell state c_t, which carries relevant information (memory). Similar to the hidden state h_t, but it will not be passed to the next layer of the network. In addition, three new gate components are added to the hidden layer, the forget gate f_t, the input gate i_t and the output gate o_t [10]. The formula is as follows:

$$f_t = \sigma(U_f x_t + W_f h_{t-1}) \tag{6}$$

$$i_t = \sigma(U_i x_t + W_i h_{t-1}) \tag{7}$$

$$o_t = \sigma(U_o x_t + W_o h_{t-1}) \tag{8}$$

$$\hat{c}_t = tanh(U_c x_t + W_c h_{t-1}) \tag{9}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \hat{c}_t \tag{10}$$

$$h_t = o_t \odot tanh(c_t) \tag{11}$$

Different gates determine whether information needs to be saved or forgotten, and selective control of memory is achieved through the superposition of multiple gated units, thereby solving the problem of short-term memory.

3.2 Data Preparation

The source of the data in this article comes from Sina Finance and Tonghuashun Finance. It contains all the stocks of China A-shares, that is, common stocks issued by companies registered in China and listed in the country for a variety of investors to subscribe and trade in RMB. A total of about 3800 stocks and data over the period of 2015–2020. In units of days, it contains data such as opening and closing prices.

At the same time, we used vn.py, a Python-based open source quantitative trading system development framework. It integrates a variety of trading interfaces, and provides a simple and easy-to-use API for specific strategy algorithms and function development. Based on the MACD strategy, through the Enumeration method, with the annualized rate of return as an indicator, the optimal parameters of the corresponding MACD strategy under each time window are calculated as our training data.

There are missing data values in the acquired data, and we performed padding operations on them. In addition, the characteristics of stock data may also affect the training of the model (see Fig. 2). The price per share of different stocks varies greatly. The price of some stocks may be a few yuan, while others may be in the hundreds or even thousands. In order to avoid problems such as potential gradient explosion caused by too large numerical differences, and at the same time maintain the data distribution, we used the z-score standardization method to map them to the same interval. The formula is as follows:

$$z = \frac{x - \mu}{\delta} \tag{12}$$

where μ is the population mean, and δ is the population standard deviation.

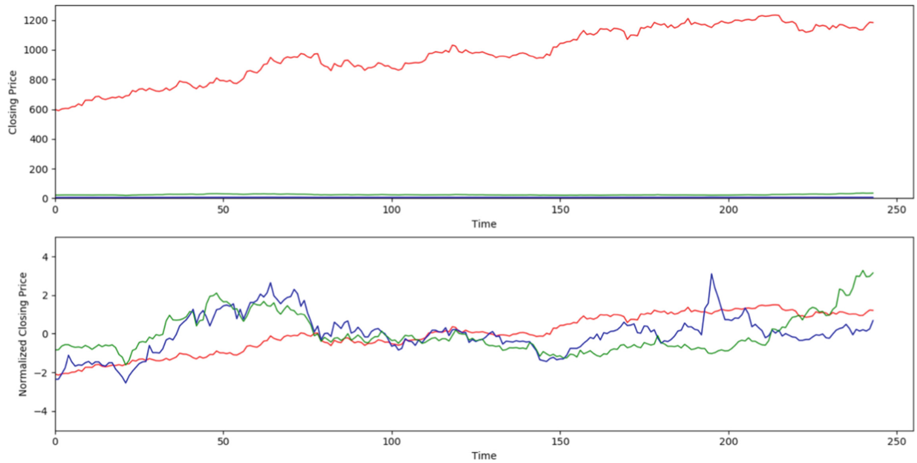

Fig. 2. Original and normalized data after applying z-score.

The z-score standardization method is suitable for situations where the maximum and minimum values of features are unknown, or there are outliers that exceed the value range. After using the z-score method, the model losses converges steadily and promptly during the training. While improving the accuracy of the model, the gradient explosion problem is avoided.

4 Results

4.1 Experiments

We use 200 stocks of all stocks for testing, and the rest for model training. Training data includes stock code, date, opening price, highest price of the day, lowest price of the day, closing price, volume and amount values. There is also the optimal parameter value of the MACD corresponding to each stock under the time window, which is given by Enumeration method and backtesting. When calculating the optimal parameter value, the parameter value ranges between (2, 31). We used a two-layer LSTM network with 1024 units in each layer. In the end, the hidden layer output is mapped to 3 dimensions through the fully connected layer. In the training process, we used the K-fold method for validation to evaluate the training effect of the model, where K = 10. In addition to Dropout, we also use the Early Stopping method to control the suspension time of model training, in order to obtain a model with relatively good generalization performance, while reducing training costs. Exponential decay is used to control the learning rate. At first, a larger learning rate is used to obtain a better solution, and then the learning rate is gradually reduced to control the stability of the model in the later stage of training. We use the Xavier initializer method to effectively initialize the network to ensure the training effect. RMSE and MAE are used as the evaluation methods of MACD optimal parameter prediction performance.

RMSE (Root Mean Square Error) reflects the degree of dispersion between the actual value and the predicted value. The formula is as follows:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \tag{13}$$

MAE (Mean Average Error) is the average of the absolute value between the actual value and the predicted value, which can avoid the errors from canceling each other out, thereby accurately reflecting the size of the actual prediction error. The formula is as follows:

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|y_i - \hat{y}_i| \tag{14}$$

where y_i is the actual value, and $\hat{y}_i$ is the predicted value. We use MSE as the loss function and Adam as the optimizer.

Table 1 shows the RMSE and MAE of the prediction of MACD parameters, using linear regression, GRU and LSTM. Where fast, slow and signal are the three parameters of the MACD strategy. It can be seen that LSTM achieves the lowest RMSE and MAE among the three methods, especially on MAE. GRU is slightly inferior to LSTM method. The linear regression method performs the worst, which proves that the neural network method has more advantages than the traditional linear method.

Table 1. RMSE and MAE of MACD parameters prediction with 3 methods

	RMSE			MAE		
	Fast	Slow	Signal	Fast	Slow	Signal
LR	7.91	4.75	6.99	7.17	4.14	6.2
GRU	7.41	4.19	6.47	6.33	3.24	5.34
LSTM	**7.19**	**3.93**	**6.29**	**5.78**	**2.71**	**4.93**

Figure 3 shows the balance, drawdown, daily profit & loss (PnL) and its distribution. The daily PnL begins to produce large deviations and fluctuations in November 2017, but the overall balance is positive. From the distribution of daily PnL, we can see a more detailed profit and loss value. For more than 400 days, it remained near the zero line, the maximum profit is close to 1000 and the maximum loss is close to 750. The population is normally distributed. Figure 4 shows the balance of trades using MACD parameters (12, 26, 9) and (2, 20, 20). Where parameter set (2, 20, 20) are the optimal value predicted by our model. During 2015–2018, we set an initial capital of 10,000 yuan. In 752 trading days, in comparison, the latter's closing funds are much higher than those of the default MACD parameter settings (12, 26, 9), and the overall balance is better than the former. This proves that dynamic adjustment of MACD strategy parameters can adapt to different market environments and obtain greater economic efficiency.

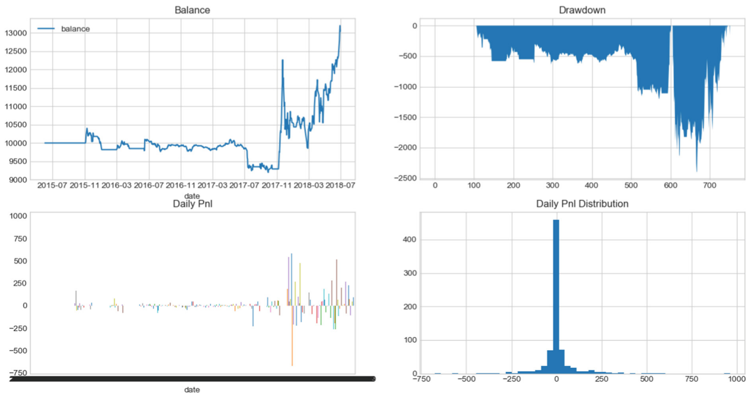

Fig. 3. Balance, drawdown and PnL.

4.2 System

We have built a prototype system to provide investors with a simple and easy-to-use investment tool. We built the back-end part of the prototype system based on the Django framework, and then integrated the algorithm module into the system. The back-end part provides user management and back-testing modules, and the algorithm provides asset allocation recommendation functions. The front end uses Javascript and Vue framework. The database storage uses MySQL, Redis and MongoDB databases and related technologies. Workflow is shown in Fig. 5.

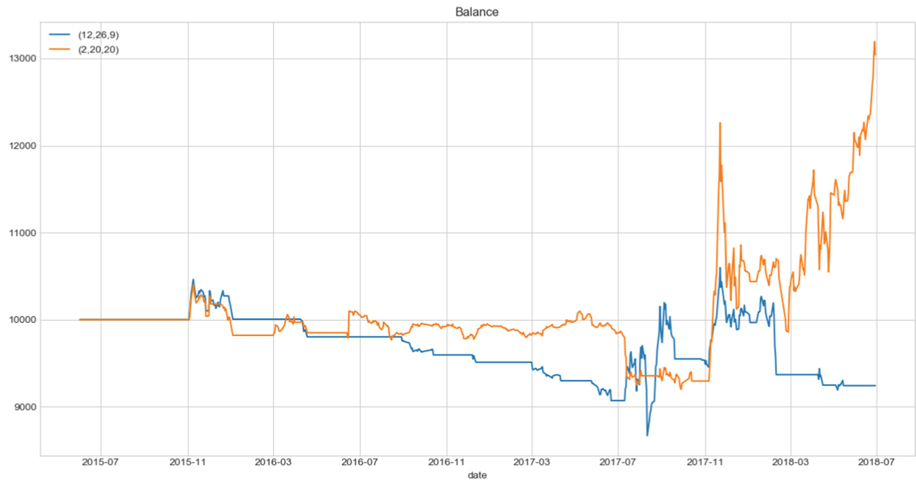

Fig. 4. Balance with different MACD parameter sets.

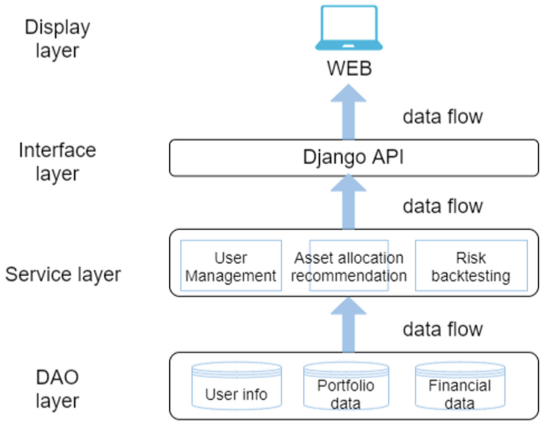

Fig. 5. System workflow.

We use the form of risk questionnaires to evaluate investors' risk-bearing ability to facilitate rating, and then according to the MACD strategy, we recommend a set of appropriate asset allocation based on the user's investment principal.

5 Conclusion

In this work we contribute to MACD strategy parameters restructuring by building a deep learning method using LSTM network. We investigate in MACD strategy and devise a new way of optimizing the gains of trades using MACD strategy. It is clear that balance improves after applying deep learning architectures to capture the information between statistics. LSTM network predicts the advancing MACD parameters, which could be used between any time periods, providing an easy-to-use investment instrument. Overall, this yields a new perspective to operate traditional MACD strategy, makes it more adapted to different market environments while brings more possibilities of potential returns. Future work will mainly focus on mining deeper stock statistics, constructing more effective features and denoising. At the same time trying more new neural network methods.

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