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Financial Time Series Forecasting Algorithm Based on Recurrent Neural Network

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Abstract. A variation of recurrent neural networks (RNN) called the GRU neural network is suggested in order to address the long-term reliance of RNN network structure. GRU overcomes the long-term reliance of time series on the basis of inheriting RNN's strong memory ability of time series. This research proposes a financial time series prediction model based on difference operation and GRU neural network with a focus on the reliance of financial time series data. It also applies GRU extension to financial time series prediction. The model can handle the complicated nonlinearity, nonstationarity, and series correlation properties of financial time series data. The experimental results show that the suggested scheme can improve the GRU neural network's generalization capability and prediction accuracy. Additionally, when compared to the traditional prediction model, this model has a better prediction effect and a relatively lower calculation cost for financial time series. The experiment makes a prediction about the S&P 500 stock index's modified closing price.

Keywords: Recurrent Neural Network, Forecast of financial time series, Deep learning

1. Introduction

Making efficient market trading methods requires predicting the stock price index and its trend. However, because financial data has complicated features, such as serial correlation, nonlinearity, and non-stationarity, it is exceedingly difficult to anticipate the trajectory of the stock market. Additionally, a variety of macroeconomic factors, including political developments, company decisions, general economic circumstances, investor expectations, institutional investment decisions, stock market performance across other markets, investor psychology, etc., have an impact on the stock market. Some traditional techniques have been used to solve this challenge [1], such as linear regression, traditional time series prediction, etc. However, for financial time series analysis, the performance of these methods still needs to be improved [2]. At the same time, the focus of research in this field has expanded from linear models to nonlinear models, such as logistic regression, machine learning techniques such as random forests, and deep neural networks. Neural network has excellent nonlinear function mapping

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ability and can approximate continuous function with any desired accuracy [3]. Therefore, it can solve complex problems and has good performance. However, shallow machine learning algorithms fundamentally limit their ability to learn complex high-dimensional functions. In contrast, neural networks with deep architecture have achieved good performance and made progress in complex tasks [4]. The great success of deep learning has been demonstrated in complex time series fields such as natural language processing and speech recognition. Recently, deep learning-based approaches have been widely explored in financial time series forecasting. For example, recurrentneural networks [5] (RNN) have shown good performance in stock price prediction [6]. In addition, as a variant of RNN, long short-termmemory (LSTM) network is also applied to the problem of financial time series prediction [7].

Currently, RNN is widely used in the financial field. Nag and Mirtra set up a BP neural network model to study the currency crisis early warning system, proposed a Nonlinear regression method, broke the traditional linear fitting method, and used the black box to capture high-dimensional influencing factors [8]. The experiment proved that this model is more effective. Dieter Gramlinch used the financial risk dynamic early warning model to analyze the causes of the global financial crisis, and the research showed that the vulnerability of the financial system was the most important influencing factor that ultimately led to the crisis [9]; Sevim et al. established ANN, decision tree and Logistic models to regression analyze Türkiye's currency crisis, and analyzed the advantages and disadvantages of each regression model through regression comparison [10]. Kumar, Moorthy and Perraudin innovatively proposed that the generation of financial risks should include several important variables, such as export decline, international reserves and weak real economy, which enriched the financial risk early warning system [11].

On the basis of predecessors' work, this paper further puts forward a hybrid model combining differential operation with GRU neural network for financial time series prediction. Because the financial data is non-stationary, this paper puts forward a method to calculate the difference between continuous observations, so as to stabilize the time series. GRU is a slight but excellent variant of LSTM, and GRU also has the ability to remember historical information, and can make a good prediction of financial time series data. The experiment takes the S&P 500 stock index as an example to evaluate and analyze the performance of the proposed scheme.

Our contributions are as follows:

(1) We put forward a hybrid model combining differential operation with GRU neural network for financial time series prediction.

(2) We put forward a method to calculate the difference between continuous observations, so as to stabilize the time series

(3) Experimental results show that our method has better financial forecasting ability.

2. GRU Neural Network

It is a unique recurrent structure that was initially proposed by Hochreiter and Schmidt Huber. To enable information to selectively impact the state at each instant, it depends on the construction of specific "gates". Figure 1 depicts the repetitive structure of it.

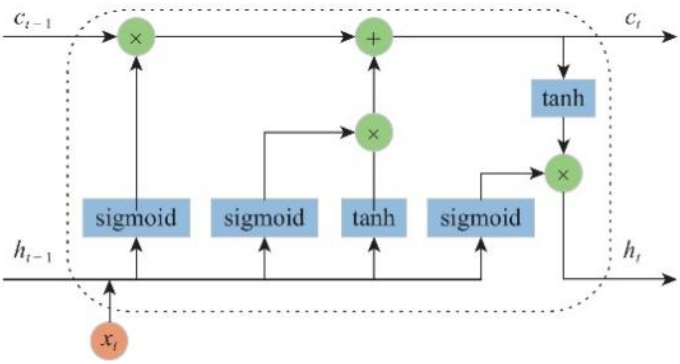

Figure 1. Schematic diagram of LSTM unit structure

In the LSTM loop body, the information removed from the loop body is determined by the forgetting gate f_t:

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right) \tag{1}$$

where σ represents the Sigmoid function, x_t represents the input vector, h_{t-1} represents the previous hidden vector, W_{xf} represents the input weight, W_{hf} represents the hidden weight, b_f represents the bias.

$$i_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + b_i\right) \tag{2}$$

In order to keep long-term memory more effectively, forgetting gate and input gate are very important. Through forgetting gate and input gate, LSTM can effectively determine which information should be forgotten or kept.

$$\tilde{S}_t = \tanh\left(W_{xs}x_t + W_{hs}h_{t-1} + b_s\right) \tag{3}$$

$$S_t = f_t S_{t-1} + i_t \tilde{S}_t \tag{4}$$

$$O_t = \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + b_o\right) \tag{5}$$

The output of the hidden layer in the current time step h_t is determined by the output gate O_t and the latest LSTM loop state S_t.

$$h_t = O_t \tanh\left(S_t\right) \tag{6}$$

GRU is a variant based on LSTM structure. Figure 2 shows the GRU structure, and it can be seen that GRU has no separate storage unit.

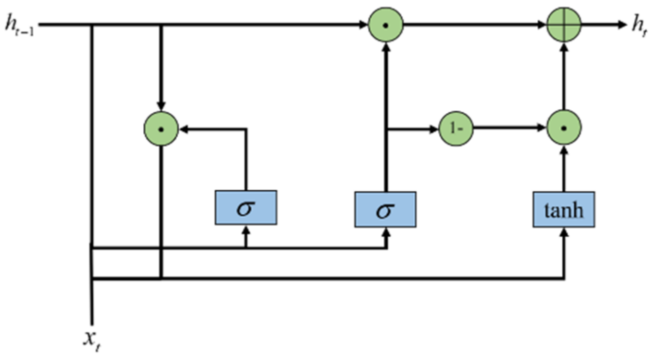

Figure 2. Schematic diagram of GRU unit structure

The hidden layer state h_t of GRU at time t is a linear interpolation between the previous state h_{t-1} and the candidate state h_t.

$$h_t = z_t h_{t-1} + (1 - z_t)\tilde{h}_t \tag{7}$$

where z_t represents the update gate.

$$z_t = \sigma\left(W_{xz}x_t + W_{hz}h_{t-1} + b_z\right) \tag{8}$$

$$\tilde{h}_t = \tanh\left(Wx_t + U\left(r_t \odot h_{t-1}\right) + b_h\right) \tag{9}$$

where r_t represents the reset gate.

$$r_t = \sigma\left(W_{xr}x_t + W_{hr}h_{t-1} + b_r\right) \tag{10}$$

3. Experiment

The S&P 500 stock index is used as the study object, and the difference operation and GRU neural network model are implemented, in order to assess the efficacy of GRU in forecasting financial time series. The data samples are S&P 500 stock index data from January 3, 1950 to July 14, 2022, and the data sampling frequency is once every trading day. The opening price, maximum price, lowest price, adjusted closing price, and trading volume are only a few of the numerous variables in the experimental dataset. In this experiment, the adjusted closing price variable is selected as the prediction target of this financial time series.

The two subsets of financial time series data are training set and test set, with 70% of the dataset being utilized for model training and the remaining 30% being used for model testing. Due to the measurement error, the original data is full of signal noise and many outliers. In order to reduce measurement errors and reduce calculation errors caused by outliers, it is necessary to standardize the raw data. The processed data is conducive to the effective learning of neural networks and speeds up the learning and convergence of neural networks. For time series $x_1, x_2, \cdots, x_n$, its standardized definition is expressed as:

$$y_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}, i = 1, 2, \cdots, n$$

$$y_{scaled} = y_i \times (\max - \min) + \min$$

where y_i is the result of standardization, ranging from 0 to 1; x_i is the value in the original time series; $x_{\max}$ and $x_{\min}$ are the minimum and maximum in the original time series; max and min are a range selected according to the effective working interval of neural network activation function; y_{scaled} is the input data of the final model after processing.

An index called root mean square error (RMSE) is frequently used to assess how well financial time series may be forecasted. Between the goal value and the actual value, it quantifies the discrepancy or residual. The forecast is more precise when this number is lower. The formula for its computation is as follows.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}$$

In order to verify the performance of our proposed method in this paper, different methods are used to predict, including ARIMA, LSTM, CNN-LSTM, and GRU. Table 1 shows prediction results of different methods.

Table 1. The comparison results of the proposed method and ARIMA, LSTM, and CNN-LSTM

Method	RMSE		
	The first trading day	The second trading day	The third trading day
ARIMA	55.30%	58.19%	60.37%
LSTM	39.72%	42.54%	45.77%
CNN-LSTM	21.61%	25.83%	27.37%
GRU	14.38%	19.35%	22.96%

ARIMA is a widely used one-step forecasting model in financial time series forecasting, and the RMSE result obtained by using ARIMA model for S&P 500 stock index is 55.3. At the same time, the LSTM and CNN-LSTM obtain better performance with RMSE of 39.72% and 21.61%, respectively. Compared the above methods (ARIMA, LSTM, and CNN-LSTM), the proposed method in this paper achieves the best performance with an RMSE of 14.38. As shown in Table 1, the RMSE of GRU forecasting model on the first trading day, the second trading day and the third trading day are 14.38%, 19.35% and 22.96% respectively, which are 40.92%, 38.84% and 37.41% lower than ARIMA model respectively. Therefore, the proposed method in this paper has better prediction performance than ARIMA. In addition, LSTM needs to train 1 036 parameters, while GRU only needs to train 781 parameters, which is 24.61% less than LSTM. Less parameter training can reduce the consumption of computing resources, and at the same time, the possibility of over-fitting will also be reduced. Because the number of training parameters is small and the calculation overhead is relatively low, the GRU model has better performance.

4. Conclusion

In this research, we provide a hybrid model that combines GRU neural network with difference operation. The experimental findings demonstrate that this method can forecast the trend of financial time series, performs better than conventional approaches (such the ARIMA model), and has a comparatively low computing overhead using the Standard & Poor's 500 stock index as the benchmark data set. Future study will develop a multi-dimensional prediction model and further optimize and enhance the performance of the suggested approach.

In the financial risk warning system, indicators exhibit temporal characteristics, so the establishment of the warning system should fully consider the influence of time factors. Unlike traditional BP neural network models, RNN recurrent network models have more temporal characteristics, which can be applied to actual financial risk warning. This article first conducts principal component analysis on the dataset to extract representative factors; Then preprocess the data to meet the needs of experimental operation, and establish a more scientific financial Systemic risk early warning model combined with RNN Recurrent neural network; Finally, using specific data from Anhui Province as a sample, the experimental results demonstrate that this method has high accuracy. By comparing the actual and predicted values, as well as the training errors of RNN and BP neural networks, the high prediction accuracy of the network is verified, providing a new approach for establishing a financial risk warning system.

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