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Forecasting of Forex Time Series Data Based on Deep Learning

Lina Ni[a,b,c], Yujie Li[a], Xiao Wang[a], Jinquan Zhang[a,b,*], Jiguo Yu[d,e], Chengming Qi[f]

[a]*College of Computer Science and Engineering, Shandong University of Science and Technology, Qingdao,266590, China*
[b]*Shandong Province Key Laboratory of Wisdom Mine Information Technology, Shandong University of Science and Technology, Qingdao, 266590, China*
[c]*The Key Laboratory of Embedded System and Service Computing, Ministry of Education, Tongji University, Shanghai, 200092, China*
[d]*Qilu University of Technology (Shandong Academy of Sciences), Jinan, Shandong, 250014, China*
[e]*Shandong Computer Science Center (National Supercomputer Center in Jinan), Jinan, Shandong, 250014, China*
[f]*Beijing Union University, Beijing, 100101, China*

Abstract

This paper proposes a C-RNN forecasting method for Forex time series data based on deep-Recurrent Neural Network (RNN) and deep Convolutional Neural Network (CNN), which can further improve the prediction accuracy of deep learning algorithm for the time series data of exchange rate. We fully exploit the spatio-temporal characteristics of forex time series data based on the data-driven method. On the exchange rate data of nine major foreign exchange currencies, the experimental comparison of the forecasting method shows that the C-RNN foreign exchange time series data prediction method constructed in this paper has better applicability and higher accuracy.

Keywords: Deep learning; Recurrent neural network; Convolutional neural network; Foreign Exchange Rate; Time series analysis

1. Introduction

The flourish of Internet of Things (IoT) has brought about enormous IoT applications to facilitate our daily life [1, 2, 3, 4, 5, 6, 7]. It connects tremendous devices, such as sensors and smartphones, to a seamless world [8, 9, 10, 11, 12, 13], and enables them to sense, store, and interpret information in an opportunistic and loosely-coupled manner. A huge volume of data are processed and used by various IoT-based applications to satisfy human needs, interests, and objectives [14, 15, 16, 17, 18, 19, 20].

* Corresponding author. Tel.: +86-532-88032909; fax: ++86-532-88032909.
E-mail address: nln2004@163.com, ldy1025m@163.com, waxi2016@163.com, tjzhangjinquan@126.com, jiguoyu@sina.com, qicm@163.com

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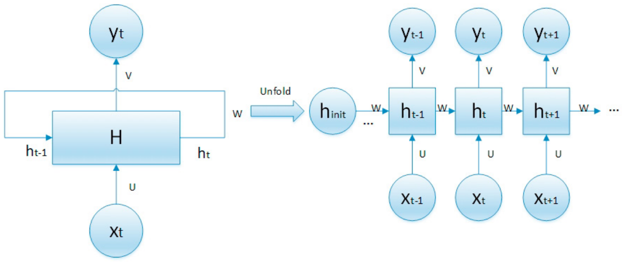

Fig. 1 Schematic of the network structure of our prediction method.

As the world's largest financial market, the foreign exchange market has increased its daily trading volume to Six trillion dollars, of which 45% of the transaction volume comes from terminal retail customers [21]. For the majority of investors in China, foreign exchange has become another major investment area after stocks, futures, funds and bonds. Investors can obtain high profits at low cost in the environment of frequent changes of exchange rate. Therefore, the prediction of time series data for exchange rate has become a hot issue in financial market research [22]. With the deepening of research, the researchers found that the changes of exchange rate have the typical characteristics of nonlinear dynamic system whose factors are very complicated to affect their changes. Based on linear thinking, the analysis method can't predict the trend of exchange rate, so it is urgent for a nonlinear method to predict the exchange rate with a better predictive ability for nonlinear systems to meet the market demand for the forecasting of exchange rate at this stage.

Deep learning has achieved great success in the fields of image recognition, natural language processing, speech recognition, video processing, etc. Therefore, the application of deep learning algorithms in exchange rate prediction has also received extensive attention [23, 24, 25, 26, 27, 28, 29, 30, 31].

Convolutional neural network (CNN) can effectively exploit the spatial characteristics of data and have been widely used in the field of image recognition, but they cannot mine the temporal characteristics of data. Therefore, combining the advantages of two deep learning algorithms, such as cycle and convolution, in this paper, we fully exploit the spatio-temporal characteristics of forex time series data. We construct a foresight time series data prediction method based on deep learning, in order to further improve the prediction accuracy of deep learning algorithm in exchange rate time series data. It provides a certain theoretical and practical value for the application of deep learning algorithm in the foreign exchange market, and provides some reference significance for sample characteristics and network parameter selection in the process of deep learning modeling.

2. Related Work

In this section, we briefly introduce the principles of the recurrent neural network (RNN) [32] and convolutional neural network (CNN) [33, 34].

2.1. *Recurrent neural network*

Fig. 1 is the schematic diagram of the network structure of our prediction method. As shown in Fig. 1, x_t is the input of RNN at time t, h_t is the hidden state of RNN at time t, y_t is the output of RNN at time t, and U,V,W are the parameter matrices shared by RNN [32].

For any time t, the hidden state h_t of the moment is calculated from the input x_t of the current moment and the hidden state h_{t-1} of the previous moment. The calculation formula is as follows.

$$h_t = f(Ux_t + Wh_{t-1} + b) \tag{1}$$

where f is the activation function of the RNN, and b is the offset of the linear relationship.

Knowing the hidden state h_t of the current time, the calculation formula of the predicted output value y_t of the RNN at the current time is as follows.

$$y_t = f(Vh_t + c) \tag{2}$$

where c is the offset of the linear relationship, and f is the activation function of the RNN. According to different application problems, different activation functions can be selected. For example, in the classification problem, the $softmax$ activation function is generally selected.

2.2. Convolutional neural network

The basic structure of CNN consists of input layer, convolution layer, pooling layer, fully connected layer and output layer [33, 34]. The convolutional layer and the pooling layer are generally taken several times and alternately arranged, that is, one convolutional layer is connected to one pooling layer, the pooling layer is connected to one convolutional layer, and so on. Since each neuron of the output feature surface in the convolutional layer is locally connected to its input, and the weighted sum is added by the corresponding connection weight and the local input, and the offset value is obtained, the input value of the neuron is obtained. This process is equivalent to the convolution process, and CNN is named after it.

The convolutional layer is composed of a plurality of characteristic faces, each of which is composed of a plurality of neurons. Each of its neurons is connected to a local region of the upper feature plane through a convolution kernel, which is a weight matrix. CNN's convolutional layer extracts different features of the input through convolution operations.

In the CNN structure, the deeper the depth and the greater the number of feature surfaces, the larger the feature space that the network can represent and the stronger the network learning ability. However, the calculation of the network is more complicated and it is easy to over-fit. The pooled layer is immediately followed by the convolutional layer, and is also composed of a plurality of characteristic faces, each of which has a feature face uniquely corresponding to a feature face of the upper layer thereof, and does not change the number of feature faces. In the CNN structure, after multiple convolutional layers and pooling layers, one or more fully connected layers are connected.

3. C-RNN foreign exchange time series data prediction method

Since the transaction volume in the foreign exchange market is difficult to obtain accurately, this paper selects four of the most representative characteristic attributes of the foreign exchange rate including opening price, closing price, highest price and lowest price to predict the closing price of the daily exchange rate.

The overall framework of the C-RNN foreign exchange rate forecasting method includes five functional modules: input layer, hidden layer, output layer, network training and network prediction.

1) **Input layer**. Firstly, the pre-processed and standardized exchange rate data is divided into training set and test set by a ratio of 10:1. The training input is a time-delay exchange rate historical data, and the output is the predicted closing price of the training input after a certain time lag.
2) **Hidden layer**. The size of the hidden layer, i.e., the number of neurons in the hidden layer, has an important influence on the learning ability of the algorithm. Too few numbers can lead to insufficient learning, and too many numbers can lead to overfitting. Therefore, when determining the number of hidden layers, it is necessary to ensure the implied law of the better learning training data sequence, and to prevent the over-fitting problem caused by the network being too complicated.
3) **Output layer**. The number of output neurons is determined by the number of output variables. The academic community agrees that when the algorithm has only one output neuron, the output will be optimal. Therefore, the number of output neurons in this paper is set to 1.
4) **Network training**. According to the batch gradient descent method, the training data set D_{train} is divided into batches, and each batch size is m. Then divide the data window according to the number of lag periods n and enter the hidden layer. In the hidden layer, the data is first processed by the convolution layer, and the spatial feature information in a single input data is extracted, and then the information is input into the loop layer for processing.

5) **Network forecasting**. The trained network $CRNN_{train}$ is used for prediction. The iterative method is used to predict the predicted value at each moment. The prediction process involves only the forward computation process of the network, similar to the forward computation process of network training.

4. Experimental Evaluation

The software and hardware configuration of the experimental environment is shown in Table 1.

Table 1. Experimental environment configuration.

configuration items	**Configuration parameter**
CPU	CPU i7-7700HQ @ 2.80GHz
GPU	NVIDIA GeForce GTX 1060
RAM	16GB
Programming language	Python3.6.4
Deep learning framework	TensorFlow1.4.0

4.1. Data processing

Data is the basis of model method research. The data of different financial varieties are very different in nature. The data surface is too broad and the research difficulty of this topic is increased. In order to enable more targeted research, this paper takes foreign exchange as the research object. The raw data is mainly downloaded from the historical data center of the foreign exchange trading platform Meta Trader 4 and the foreign exchange tester website to collect data on the hour and day cycle in the last ten years. Through the statistical analysis of the original data, it is found that the original data mainly has three defects.

(1) The missing data is incomplete.

(2) The irregular data format.

(3) There is strong noise in the data.

In view of the above problems, this paper makes the following three aspects of data preprocessing operations on the original data.

a. *Data cleaning*: The missing data in the original data is compensated. The compensation method is to make up the data at the moment before the missing data.

b. *Data integration*: Store raw data in a *csv* file with time as an index and eliminate redundant data.

c. *Data reduction*: Eliminate unwanted feature attributes from the original data.

4.2. Results

The experimental data used the daily exchange rate data of nine volatile currency pairs in the data set for the past 10 years (June 2008 to May 2018). The prediction algorithm constructed in this paper is compared with the prediction algorithm based on LSTM or CNN deep neural network. The training data set has 2000 data, each of which is a 24*4 feature matrix. The predicted value is the daily closing price of the foreign exchange rate, and the volume of test set data is 200.

Through our algorithm, the mean square error of the predicted value and the true value and the prediction effect fit map are used as the evaluation criteria of the algorithm prediction effect. The specific experimental results are compared and analyzed as follows. For the nine exchange rate data of foreign exchange currency pair, the comparison of the predicted mean square error of the three prediction methods is shown in Fig. 2.

It can be seen from Fig. 2 that the mean square error of the C-RNN foreign exchange rate prediction method based on CNN and RNN is the smallest, so the prediction effect is relatively good.

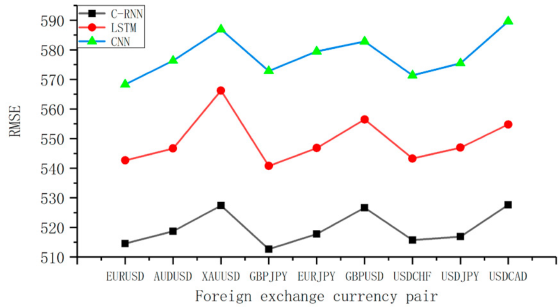

Fig. 2 Comparison of mean squared errors of predicted values by different forecasting algorithms.

5. Conclusions and Future Work

In this paper, based on the two deep learning algorithms of cycle and convolution, the prediction method of C-RNN forex time series data is constructed. The experimental comparison and analysis proves the effectiveness of the prediction method. It provides certain theoretical and practical value for the application of deep learning in the foreign exchange market. Based on the current work, the follow-up can be further studied in the following areas. In the future, we will expand the network scale, improve the network structure, increase the attention mechanism, and test the application effect of more complex network structures.

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