Online Product Sales Prediction Based on Elman Neural Network

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***Abstract*—The prediction of online product sales affects the decision-making process of enterprise online sales. The academic community has conducted numerous studies on product sales prediction, and the vast majority of existing literature uses feedforward neural networks for sales prediction. As sales belong to time series data, recurrent neural networks with memory function may be more suitable for online product sales prediction. Therefore, this paper constructs the Elman neural network model as a representative of recurrent neural networks, and constructs the BP (Back Propagation) neural network model as a representative of feedforward neural networks. By using the same data to train and test the Elman neural network and the BP neural network, the error between the two network networks is compared and analyzed. The results show that the Elman neural network's prediction of online product sales is closer to the actual value. The mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE) of the BP neural network are 8.03 times, 8.12 times and 8.24 times of the corresponding values of the Elman neural network, respectively. The error value of the BP neural network is much larger than that of the Elman neural network, and the Elman neural network has more stable and less fluctuating prediction. Therefore, compared with the BP neural network, the Elman neural network has higher prediction accuracy, more stable prediction, better prediction effect and more accurate prediction of online product sales.**

Keywords—Elman neural network; Online product; Sales; Prediction; BP neural network

I. Introduction

With the vigorous development of the Internet economy, more and more enterprises have opened up online sales channels. Because online shopping has the advantages of saving shopping cost and shopping time, and has certain convenience and security, online shopping also attracts more and more consumers' shopping methods. In addition, compared with offline sales, online sales have special sales methods and unique ways of attracting customers. How to effectively predict online product sales is of great strategic significance to major business decisions such as investment and promotion of online sales channels.

At present, the academic circle has carried out a series of research on the prediction of product sales. In terms of research methodology, the existing literature is primarily divided into the following two categories.

The first category of literature adopts neural networks as the research methodology. Dai, Fu, and Hua constructed a sales prediction model based on the BP (Back Propagation) neural network [1]. Zhang et al. used the BP neural network to carry out sales of auto retail parts [2]. Thiesing and Vornberger used the BP neural network to predict sales [3]. Lyu et al. used the BP neural network to predict sales [4]. Sun et al. built a sales prediction model combining the genetic algorithm and the BP neural network [5]. Koochakpour and Tarokh combined particle swarm optimization algorithm and the BP neural network to predict sales [6]. Wang et al. used a two-stage method combining structural equation model and artificial neural network to predict the sales of fresh food [7]. Zhu and Liao built a sales prediction model of grey BP neural network [8]. Yang adopted a big data controllable clustering algorithm to predict cross-border e-commerce product sales [9]. Gao et al. constructed a sales prediction model based on singular spectrum analysis and support vector regression [10]. Nebri, Moussaid, and Bouikhalene used the gradient boosting regressor algorithm to predict the sales of agricultural products [11]. Li et al. introduced genetic algorithm to fit the modified Bass model and predicted the sales of electric vehicles [12]. Qu et al. proposed a vehicle sales prediction model based on gray wolf optimization algorithm to optimize support vector regression [13]. Hasheminejad, Shabaab, and Javadinarab built an algorithm combining hybrid clustering, adaptive network fuzzy inference system and particle swarm optimization to predict automobile sales [14]. Zhao, Xiong, and Jin established the sales prediction model of linear regression model and the support vector regression model [15]. Sbrana and Antonetti built a sales prediction model based on the state-space model [16]. Liu et al. built a multi-angle feature extraction and sentiment analysis prediction model for electric vehicle sales [17].

The second category of literature adopts time series analysis as the research methodology. Hyndman and Khandakar used time series to predict sales [18]. Wang and Aviles compared univariate and multivariate sales prediction methods based on time series [19]. Lian, Liu, and Li proposed a fuel sales prediction method based on variational Bayesian structural time series [20]. Li et al. studied the differences among different time series in multivariate time series [21].

To sum up, the academic research on sales prediction is mainly divided into two categories: neural networks and time series analysis. Most of the literature focuses on the research of neural networks, which are mainly divided into feedforward neural networks and recurrent neural networks. The characteristics of feedforward neural networks are that the output of any layer does not affect the peer layer, and there is no feedback in the data transmission of the entire network. Data is input from the input layer, then data is passed to the hidden layer, and finally output from the output layer, the data is a single flow. Common feedforward neural networks include the BP neural network, RBF neural network, convolutional neural network and so on. The characteristic of recurrent neural network is that neurons in the same layer not only receive the input of the previous layer of neurons, but also receive their own feedback signals. Neurons have memory function, and data can be one-way or two-way propagation. Common recurrent neural networks include the Elman neural network, the Hopfield neural network and so on. Since sales belong to time series data, it is more suitable for the application of recurrent neural networks. The existing literature mainly focuses on the research of feedforward neural networks such as the BP neural network. The differences between this paper and the existing literature are as follows: First, this paper uses the Elman neural network as recurrent neural network to predict sales, which is an innovative attempt of the Elman neural network to predict online sales; Secondly, this paper makes a comparative analysis of the Elman neural network and the BP neural network to analyze the difference of their prediction effect.

II. ELMAN NEURAL NETWORK

The Elman neural network is a recurrent neural network. The Elman neural network is composed of input layer, hidden layer, undertaking layer and output layer. Compared with the BP neural network, the Elman neural network has an additional inheriting layer. The function of the inheriting layer is to store the output data of the hidden layer at the previous time and return it to the input. Together with the input at the current time, the inheriting layer serves as the hidden layer input, acting as a delay operator and having the function of memory. Therefore, the Elman neural network has the ability to deal with time-varying features, and can better deal with dynamic data with time series properties. The structure of the Elman neural network is shown in Figure 1.

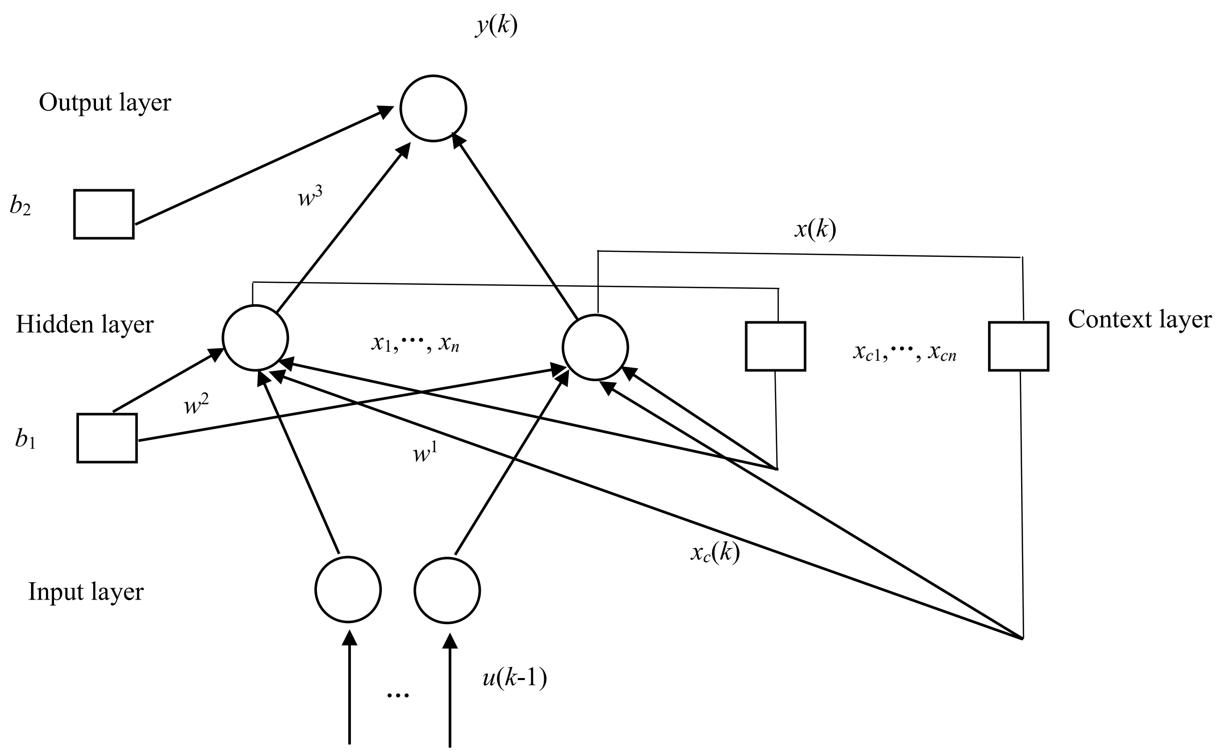

Fig. 1. Structure of the Elman neural network

The expressions of the Elman neural network are shown below.

$$x(k) = f\left(w_1 x_c(k) + w_2\big(u(k-1)\big)\right) \quad (1)$$

$$x_c(k) = x(k-1) \quad (2)$$

$$y(k) = g\big(w_3 x(k)\big) \quad (3)$$

Among them, y is the output layer vector, x is the hidden layer vector, u is the input vector, x_c is the context layer vector, w_1 is the weight matrix from the context layer to the hidden layer, w_2 is the weight matrix from the input layer to the hidden layer, w_3 is the weight matrix from the hidden layer to the output layer, k is the current time, $f(\bullet)$ is the hidden layer transfer function, and $g(\bullet)$ is the output layer transfer function.

III. ONLINE PRODUCT SALES PREDICTION

A. Data preprocessing

Online product sales are non-linear and dynamic. In this paper, the daily sales of an online product are selected as a time series, and the data of the past n days is used to be the data of the future m days, that is, each piece of data includes the data of the past n days as the input layer data of the neural network and the data of the future m days as the output layer data of the neural network. Further, the whole time series can be divided into k groups of data according to the above rules, as shown in Table I.

TABLE I. DATA PARTITIONING RULES

Input	Output
$x_1, x_2, \ldots, x_n$	$x_{n+1}, x_{n+2}, \ldots, x_{n+m}$
$x_2, x_3, \ldots, x_{n+1}$	$x_{n+2}, x_{n+3}, \ldots, x_{n+m+1}$
……	……
$x_k, x_{k+1}, \ldots, x_{n+k-1}$	$x_{n+k}, x_{n+k+1}, \ldots, x_{n+k+m-1}$

In order to improve the accuracy of the prediction model, the data used in this paper is to predict the sales data of the next day from the sales data of the past five days, that is, there are 5 nodes in the input layer and 1 node in the output layer. The number of nodes in the hidden layer is determined by formula (4), where m is the number of nodes in the output layer, n is the number of nodes in the input layer, a is an arbitrary integer in [1,10], and k is the number of nodes in the hidden layer.

$$k = \sqrt{m+n} + a \tag{4}$$

The data selected in this paper is from an online product sales data from February 2023 to April 2023. The first 50 groups are selected as training samples, and the last 5 groups are selected as test samples.

In order to unify the dimension of data, all the data used in this paper is normalized. The normalization formula (5) is shown, where $\hat{x}$ is the processed value, x is the original value, x_{min} is the minimum value of the original data, and x_{max} is the maximum value of the original data.

$$\hat{x} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{5}$$

B. The establishment of the Elman neural network

The Elman neural network has 5 nodes in the input layer and 1 node in the output layer. Through calculation, the number of hidden layer nodes is determined to be 10, and the number of context layer nodes is 1.

In this paper, three error indicators are used to evaluate the prediction accuracy of the neural network model: mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{7}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{8}$$

Among them, $\hat{y}_i$ represents the predicted value and y_i represents the actual value. The smaller the values of MAE, RMSE, and MAPE, the higher the prediction accuracy.

The training goal error of the Elman neural network is 0.0001, and the maximum training epochs are 10000.

C. The results of neural network calculation

After establishing the Elman neural network structure, this paper uses MATLAB to train the normalized data and predicts online product sales. The predicted values are compared with the actual values to obtain the corresponding errors. In order to further compare the prediction performance of the Elman neural network and the BP neural network, according to relevant literature [22-24], this paper constructed the Elman neural network model and the BP neural network model based on the same raw data, and compared the prediction accuracy and error of the two models. The prediction performance of the two models is shown in Figure 2.

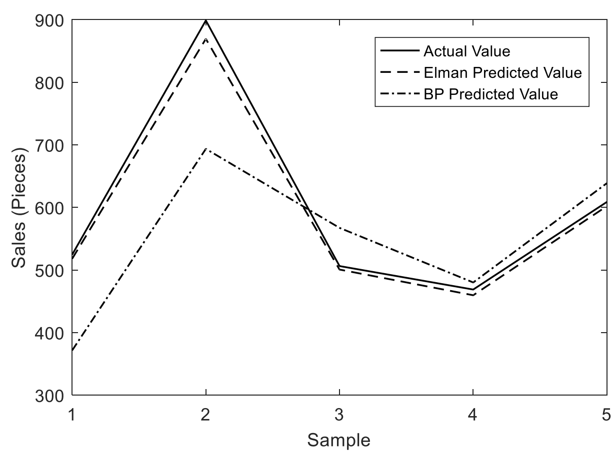

Fig. 2. Comparison between the predicted value and the actual value of the Elman neural network and the BP neural network

TABLE II. ABSOLUTE ERROR OF THE ELMAN NEURAL NETWORK AND THE BP NEURAL NETWORK

Actual value (Pieces)	Elman Predicted value (Pieces)	Elman Absolute error (Pieces)	BP Predicted value (Pieces)	BP Absolute error (Pieces)
524.527	517.96	-6.567	371.51	-153.017
898.723	869.35	-29.373	693.53	-205.193
506.242	500.66	-5.582	567.30	61.058
468.734	459.62	-9.114	480.05	11.316
608.731	602.06	-6.671	638.72	29.989

As shown in Figure 2, the Elman neural network has better prediction performance than the BP neural network. The predicted values of the Elman neural network are closer to the actual values, while the deviation between the predicted values of the BP neural network and the actual values is greater.

The absolute errors of the Elman neural network and the BP neural network are further calculated, as shown in Table II. It can be found that the absolute errors of the Elman neural network are all smaller than the absolute errors of the BP neural network, and Figure 3 shows that the relative errors of the Elman neural network are all smaller than the relative errors of the BP neural network. In addition, the minimum relative error of the Elman neural network is 1.10%, the maximum is 3.27%, and the range is 2.17%. The relative error of the Elman neural network fluctuates little and is relatively stable. On the other hand, the minimum relative error of the BP neural network is 2.41%, the maximum is 29.17%, and the range is 26.76%. The relative error of the BP neural network fluctuates greatly and its stability is poor.

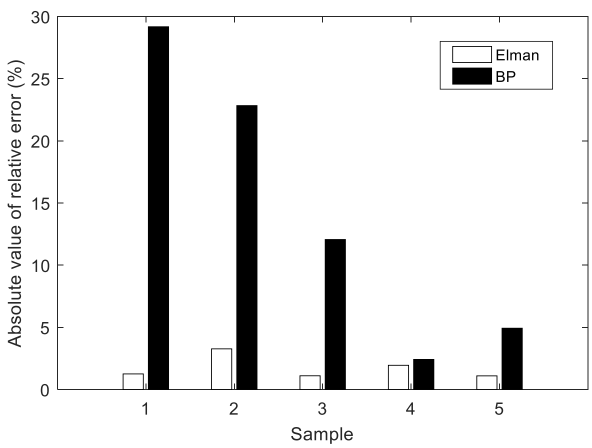

Fig. 3. Comparison of absolute values of relative errors between the Elman neural network and the BP neural network

Finally, the MAE, RMSE and MAPE of the Elman neural network and the BP neural network can be obtained through calculation. As shown in Table III, the MAE, RMSE and MAPE of the BP neural network are 8.03 times, 8.12 times and 8.24 times of the corresponding values of the Elman neural network, respectively. This shows that the prediction accuracy of the Elman neural network for online product sales is much better than that of the BP neural network.

TABLE III. COMPARISON OF ERROR VALUES BETWEEN THE ELMAN NEURAL NETWORK AND THE BP NEURAL NETWORK

	Elman	BP
MAE	11.4614	92.1146
RMSE	14.5919	118.5528
MAPE(%)	1.7326	14.2811

In summary, compared with the BP neural network, the predicted value of online product sales by the Elman neural network is closer to the actual value, and the relative error of the Elman neural network is lower, the fluctuation is smaller, and the prediction accuracy is higher. Therefore, the prediction effect of the Elman neural network is better, and it can predict the sales of online goods more accurately.

IV. CONCLUSION

In sales prediction, most of the existing literature uses neural network for prediction. As an excellent sales prediction tool, neural network is attracting more and more attention. In the existing literature, the feedforward neural network method is more used, while the recurrent neural network is less used. Therefore, this paper studies the representative of recurrent neural network, Elman neural network.

In this paper, the Elman neural network model is constructed, and the sales data of an online product is selected to carry out the training and testing of the neural network. Based on the same raw data, the representative BP neural network model of feedforward neural network is constructed, and the prediction effect of the Elman neural network model and the BP neural network model is further compared and analyzed.

The prediction results show that compared with the BP neural network, the Elman neural network's prediction value of online product sales is closer to the actual value, and its prediction effect is better, the prediction accuracy of online product sales is higher, and the prediction is more stable.

In addition to the Elman neural network, the recurrent neural networks also include the Hopfield neural network, LSTM neural network, and Bi-RNN neural network, so future research will focus on exploring these other types of recurrent neural networks. Besides, the Elman neural network takes a relatively long time to train, and improving algorithms to further reduce training time is also the next research direction.

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