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Research on e-commerce sales forecast based on BP neural network

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Abstract: *Over the last few years, the widespread adoption of various 4G and 5G networks, along with residents' acceptance of innovative online shopping methods, has positioned e-commerce as a primary operational model for numerous businesses. Accurate forecasting in e-commerce has become a crucial foundation for informed business decisions. This paper presents a system model that analyzes the factors influencing online sales, such as customer unit price, user page views, and transaction conversion rates. Additionally, the training error curve and correlation coefficient curve are generated using the BP neural network prediction model. The results indicate a correlation coefficient of 0.99804, a mean squared error of 0.0021458, an average absolute error of 0.0035446, and a minimal relative error of 0.0034991. These findings suggest that the forecasting results are highly accurate, enabling enterprises to develop more effective sales strategies and enhance their online marketing performance.*

Keywords: *Business Decision, E-commerce Sales, BP Neural Network, Sales Forecasting*

1. Introduction

In the modern economic environment, e-commerce has become an effective means to enhance urban comprehensive strength and gain access to global resource allocation. As the leader of fresh strategic industries and internet, e-commerce has always been an essential portion of the city's economy and a key element of urban development. In e-commerce, the BP neural network can deal with complex and non-linear market data, which allows the enterprise to detect hidden market trends and trends. This makes it possible for firms to make greater efficient decisions in volatile markets.

In the existing research on e-commerce sales forecast, BP Neural Networks[1] and other machine learning models have been widely applied. For instance, LiZhenhong[2] combines BP neural networks with random forest, GBDTand XGBoost algorithms to achieve the sales prediction of e-commerce products, and uses each commodity cost data to finely weigh the sample. Jiang Yanjun, et al.[3] put forward a GDP prediction model in Guilin, and the consequences illustrate that the forecasting precision of this method is high. Geng Baoguang et al.[4] A novel methodology for diagnosing faults in rolling bearings is proposed, grounded in the integration of wavelet analysis and backpropagation neural networks. Zhuying et al[5] used BP Neural Network to measure the level of food security and cultivated land ecological security in different provinces and cities in the area, and visualized the temporal features of the YangtzeRiver Economic Belt's coupling and coordination. Geng Zhenduo et al.[6] Established a simplified model of obstacle avoidance for a mobile robot in two-dimensional coordinate system.Liu Xiaojie, et al.[7] put forward a method for predicting pressure difference in blast furnace based on XGBoost and BP fusion model based on SSAoptimization. With the development and breakthrough of machine learning, the algorithm has been widely applied in economics, finance and other areas, such as Li et al.[8] proposed an ensemble prediction model rooted in deeplearning. Tkaczet[9] studied Canadian GDP data with an ANN model and found that it had about 25% fewer errors compared to the linear predictive model. Established on the Granger causality test and the Bayes-BP algorithm, Sun Tong et al.[10] realized the prediction of the sales volume of food, clothing and cosmetics and related influencing factors on the purchase volume of cross-border e-commerce platforms.

This paper predicts e-commerce sales grounded in BP Neural Network Prediction Model, which can better analyze and forecast the trend of e-commerce sales. By examining the different factors influencing the sales of electronic commerce, the model can analyse in detail the various influencing factors and provide exact results for sales forecasts. Through constant adjustment of the model weights and feedback

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the forecast error, the specific effect of the eachfactor on sales is revealed. The results of this study can be used as a scientific basis for the decision of electronic commerce enterprises, such as resource allocation, market strategy adjustment, and so on.

2. Preprocessing of data

2.1 A brief introduction to the data

This article uses 1,953 pieces of data from Alibaba Cloud Tianchi. The diversity and scale of the data makes the model's predictions more exact and adaptable to a variety of scenarios. Table 1 presents the forecast characteristics of e-commerce sales.

Table 1: E-commerce sales forecast features

Feature type	Feature number	Feature name	Feature description
Users feature	x_1	Unit value	The average transaction amount of the users
	x_2	Number of deals	The total number of commodities sold by the users
	x_3	Number of transacted users	The total number of users who successfully traded
	x_4	Number of users browses	The total number of commodities browsed by the users
	x_5	Closing conversion rate	The ratio of the number of users who visited the product to the number of users who actually transacted

2.2 Preprocessing operations

Because there are large differences in the magnitude and units of input and output data, all data need to be normalized by equation (1) before the neural network learns.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

where: X and X' represent the e-commerce data before and after the standardized processing. X_{min} and X_{max} which represent the minimum and maximum values in the original e-commerce data, respectively. The original e-commerce user behavior data is preprocessed by using the above content in this paper, so that it is suitable for training deep neural networks.

3. Establishment of the model

3.1 Introduction to the model

BP neural network owns powerful nonlinear modeling capabilities. Compared with traditional regression model, AHP and gray forecast, the BP neural network has better fault tolerance, precision, self-organization and self-learning properties. Although traditional models can make predictions based on setvariables, BP neural networks are more suitable for predicting e-commerce sales due to the complexity and variability of sales influencing factors, because it does not rely on fixed mathematical models and can effectively avoidoverfitting. The adaptive capacity of BP neural networks enables the BP neural networks to be able to predict effectively the effects of competition, consumer preferences and economic cycles, and to optimise the adjustment to changing market conditions by means of recurrent training. Figure 1 illustrates the structural diagram of the BP neural network.

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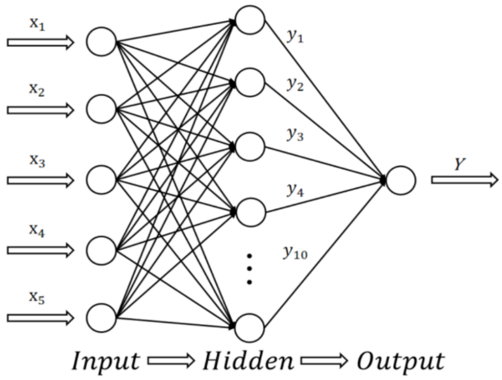

Figure 1: BP neural network structure

3.2 Establishment of BP neural network model

In the e-commerce sales forecast, the BP neural network can effectively process complex time series data, continuously correct the weight coefficients by using the gradient descent method. By repeatedly training a lot of historical sales data, the BP network can optimize the weights and thresholds for each tier, so that it can exactly predict future sales trends in the light of new data. Figure 2 illustrates the flow chart of the BP neural network algorithm.

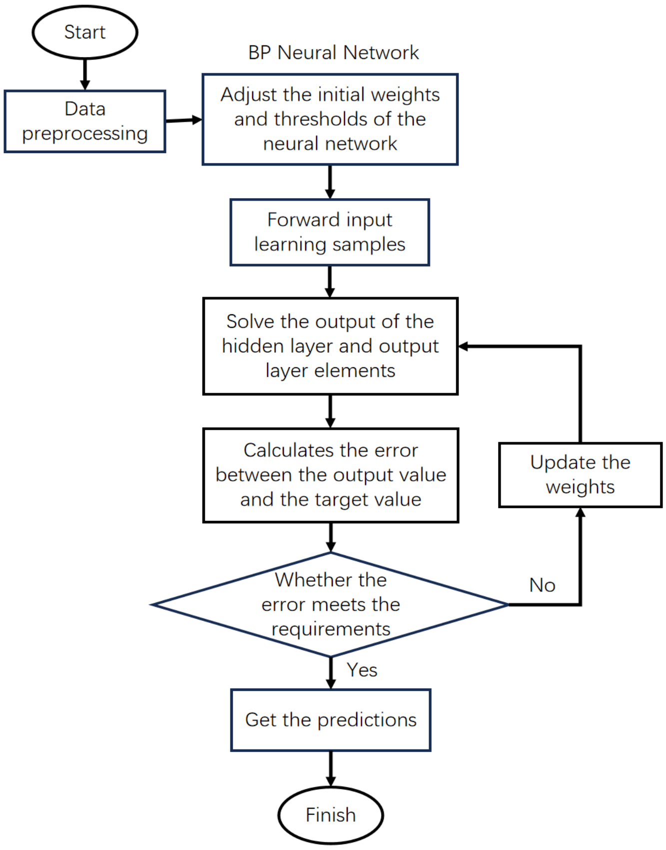

Figure 2: BP neural network algorithm flow diagram

The specific steps are as follows:

Step 1: Set the relevant parameters

Used as the training set is the first 80% of the data, while the last 20% is used as the test set.Set 10 hidden layer neurons, 1000 iterations, 10-6 error thresholds, and 1% learning rate. Five is the number of input neurons, and one is the number of output layer neurons.

Step 2: Data preprocessing

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Because there are large differences in the magnitude and units of input and output data, all data need to be normalized by equation (1) before the neural network learns. Make the final prediction more precise.

Step 3: Adjust the initial weights and thresholds of the neural network

Adjust the numerical value to prepare the forecast.

Step 4: Forward input learning sample

The learning process is:

① Positive propagation

The input signal propagates from the input layer through each hidden layer to the output layer, and the actual response value is obtained in the output layer.

② Backpropagation

Based on the gradient descent method, the connection weights and thresholds of each neuron are continuously adjusted from the output layer to the hidden layer, and the connection weights and thresholds of each neuron are continuously adjusted and repeated until the error of the network output is reduced to an acceptable level, or the pre-set learning time is performed.

BP neural networks are practiced and learned through a guided learning approach. Minimized is the mean square error between the design output value of the network and the expected output value, as the standard BP algorithm learns using the error function according to the gradient descent method. Adopted usually is the sigmoid function as the transfer function of BP neural networks, while the linear transfer function is used in the output layer.

Step 5: Hide the output of the layer and output layer unit

The output of the j neuron:

$$\beta_j = \sum_{h=1}^{q} w_{hj} b_h \tag{2}$$

The connection weight between the h neuron of the hidden layer and the first neuron of the output layer is w_{hj}. b_n is the output of the h neuron in the hidden layer.

The output of the h neuron:

$$\alpha_h = \sum_{i=1}^{d} v_{ih} x_i \tag{3}$$

The connection weights between the i neuron of the input layer and the h neuron of the hidden layer is v_i.

Step 6: Calculate the error between the output value and the target

The error between the output value and the target is calculated by error formulas (6), (7), and (8).

Step 7: Check whether the error meets the requirements

Less than the acceptable range is the final output error for each sample, or if the number of iterations reaches a certain threshold, the next sample is selected, and Step 5 is continued. Otherwise, increased by 1 is the number of iterations, and then Step 5 is moved to continue training with the current sample.

Step 8: Update the metric value

An iterative learning algorithm is BP, which uses generalized perceptron learning rules to refresh and appraise parameters during each iteration cycle. The formula for estimating any parameter after the update is as follows:

$$v \leftarrow v + \Delta v \tag{4}$$

Step 9: Get the expected result

The weights of the input and output layers and the hidden layer to the output layer are calculated, and the values of the mean, determination, average, and minimum are calculated.

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4. Solving the model

4.1 Evaluation index

(1)Coefficient of determination R^2

The nearer the coefficient of determination is to 1, the better the goodness of fit, indicating a higher degree of interpretation of the independent variable on the dependent variable and a more accurate prediction result.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2+\sum_{i=1}^{n}(y_i-\hat{y}_i)^2} \tag{5}$$

(2)Mean square error MSE

Mean square error represents the average magnitude of the difference between the model's predicted value and the target value. A smaller value signifies a smaller difference between the predicted and objective values, reflecting a better fit of the model.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{6}$$

(3)Mean absolute error MAE

The average absolute error represents the average error amplitude of the forecasted value. The smaller the value, the smaller the difference between the forecasted value of the model and the target value, and the better the fitting degree of the model.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{7}$$

(4)Mean relative error MRE

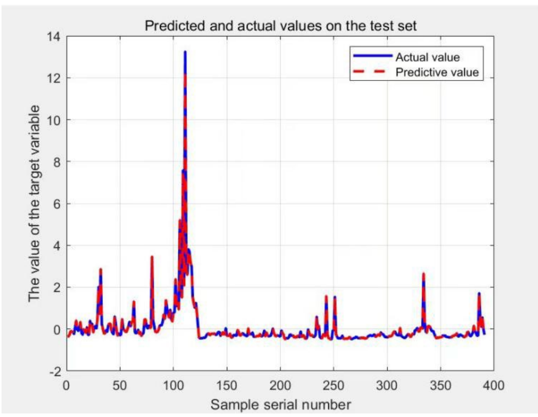
The average absolute error represents the average error amplitude of the predicted value. The smaller the value, the smaller the difference between the predicted value of the model and the target value, and the better the fitting degree of the model.

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

Where n is the number of sample points, y_i is the target value of the i th sample point, and $\hat{y}_i$ is the predicted value of the model for the i th sample point.

4.2 Analysis of Model Solving

In Figure 3 and Figure 4, the predicted sales curve output by the BP neural network model are able to well fit the actual sales curve, revealing that the model has a fairly ideal prediction of e-commerce sales with a high accuracy, and can be used to predict e-commerce sales.



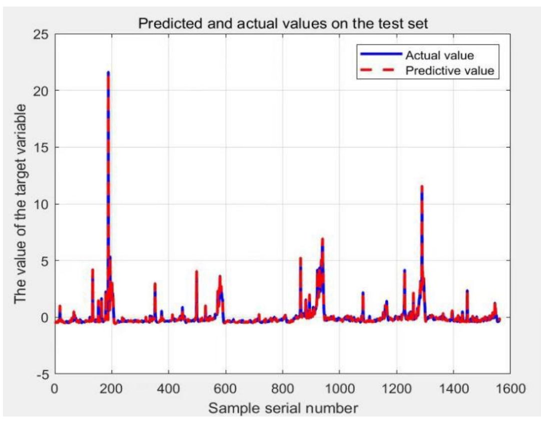


Figure 3: Simulation curve of e-commerce sales training sample A (Left)

Figure 4: Simulation curve of e-commerce sales training sample B (Right)

As can be seen from the linear regression results of the neural network in Figure 5, the predictive output has an owesome tracking ability for the real sales volume, and the fitting accuracy of the neural

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network is 0.99804, that is, the model can reproduce the output of the training data extremely precisely. Therefore, using this model to predict e-commerce sales can get reliable results.

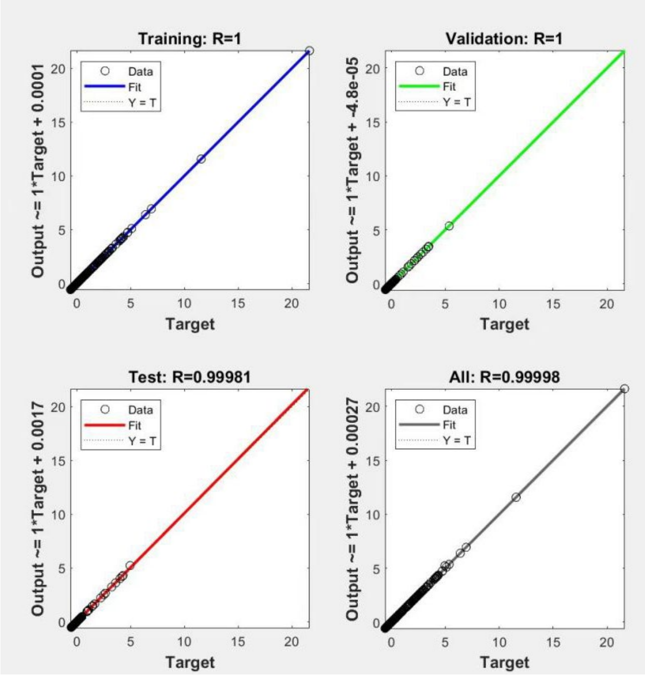

Figure 5: Regression fitting diagram

As can be seen from the error variation chart in Figure 6, the error decreases with the elevate of the number of iterations. Between the 185th and 190th iterations, the target error exceeded 10-6, and finally reached the error accuracy meeting the target requirements at the 187th iteration, and the training was terminated.

Figure 7 can reflect the whole change process of gradient and step length during training. In general, the gradient and step size continue to decline, indicating that the training has entered a relatively flat area on the error surface with the increase of the number of training times.

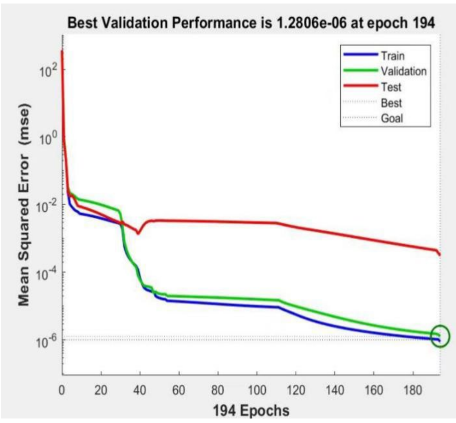

Figure 6: Error variation

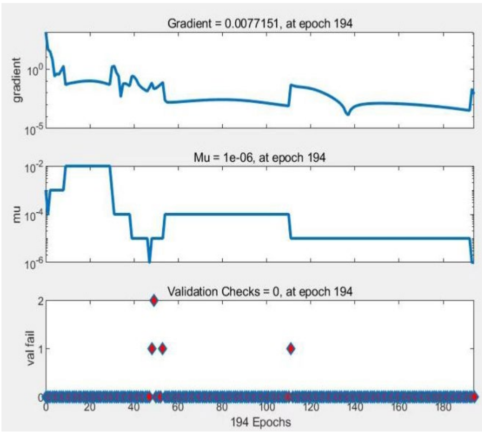

Figure 7: Gradient and step size variation diagram

The training results of sample data are shown in table 2. According to the data in table 2, bp neural network has a high prediction accuracy, which can provide Suggestions for merchants to formulate sales strategies.

Table 2: Training results of sample data

Evaluation index	Data
Mean square error	0.0021458
Mean absolute error	0.0035446
Minimum relative error	0.0034991

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4.3 Conclusion of the experiment

The data set is from Ali Tianchi, and it is a true dataset with 1953 data sets, which can refine the forecasting accuracy of the model.

The BP network has strong non-linear modeling capability. By means of its structure and non-linear activation function, it can effectively capture the non-linear relation of e-commerce sales and construct a highly non-linear forecasting model. Compared with the traditional regression model, AHP and gray forecast, the model is more robust, accurate, self-organized and self-learning. BP Neural Network is more suitable for pre-business sales forecasting, because it doesn't depend on a fixed mathematical model, and can avoid overfitting effectively.

The mean square error, average absolute error, and smallest relative error of the model are all notably low. At the same time, the fitting precision of ANN is up to 0.99804, which exhibits that this model has splendid performance in the field of e-commerce. Exact predictions can greatly improve the consumer experience, enabling traders to precisely grasp the timing of changes in demand and deliver the right products in time to meet the needs of consumers and raise customer satisfaction. In the long term, accurate forecasting will not only help businesses stay at the forefront of the competitiveness of the Competitiveness of the European Union, but also contribute to the sound and sustainable development of the electronic commerce sector, which will help to reduce economic losses and enhance the overall competitiveness of the market.

5. Conclusion

The BP neural network adopts the gradient descent method to continuously modify the weight coefficient by simulating the connection and inverse propagation of the biological neurons, so as to predict the future sales. The results demonstrate that the backpropagation neural network achieves a low mean square error, an average absolute error and the lowest relative error, which accurately reflects the actual sales trend. Although some preliminary results have been achieved, BP Neural Network Algorithm Model is only applicable due to constraints. It is necessary to consider these optimization techniques so as to increase the forecasting precision of BP neural network.

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