

Bayesian Neural Network-Based Demand Forecasting for Express Transportation

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Abstract. The rapid development of e-commerce in recent years has driven the growth of the logistics service industry, which in turn has led to a significant increase in express delivery volume. Predicting express delivery volume accurately and in advance can help companies allocate various resources reasonably and provide the basis for predicting express delivery demand. To predict the specific transport volume of XX Express Company's logistics routes on April 28th and 29th, 2023, this article builds two Bayesian prediction models based on the company's historical transportation data as the training set, one for predicting the opening of logistics routes and the other for predicting express delivery quantity. This approach reduces the impact of inaccurate predictions due to logistics routes not being opened properly and improves the accuracy of the prediction model. It provides decision support for optimizing resource layout for express delivery companies.

Keywords: Express delivery quantity prediction, Neural network, Bayesian prediction model.

1. Introduction

In recent years, the explosive growth of online shopping has greatly promoted the development of e-commerce logistics services, making it an important channel for social commodity circulation. In the logistics market, the layout of express delivery enterprises' warehouses and stations, cost savings in warehousing, and route planning all depend on the quantity of express delivery demand. Therefore, accurate prediction of express delivery demand is of great significance for the reasonable allocation of express delivery enterprise resources, abnormal situation monitoring, and improving express delivery service quality [1]. With the rapid development of express delivery industry, domestic and foreign scholars have conducted a series of researches on express delivery demand forecasting. For example, Xue Rongna [2]. proposed a daily average express delivery business volume forecasting model based on GRU deep learning algorithm to overcome the weakness of traditional methods in processing time series data. Huang [3] constructed the Guangdong Logistics Demand Forecast Index System from the perspective of e-commerce to solve the problem of low match between e-commerce and logistics demand growth, and used GM (1,1) model and BP neural network model to simulate and forecast logistics demand. A zhiyuan and He Enqiu [4]. considered the obvious seasonal characteristics of express delivery volume time series data and used SARIMA model to predict the express delivery quantity from December 2022 to May 2023 in Jiangsu Province. Li [5] studied and predicted the express delivery business volume using the CEEMD-SVM combined model, aiming at the characteristics of large time series fluctuations, chaos, and nonlinearity of express delivery business volume. Xu Rongbin et al. [6] This paper studies the forecasting problem of daily express business volume of logistics company, and improves the inertia weight of particle swarm optimization algorithm, and combines the combination model of back propagation neural network model to forecast the express business volume. Zhang Zhongfei et al. [7] Using ARIMA model, the quarterly cross-border express delivery volume of four express delivery companies is predicted. Yu, etc. [8] The ant colony algorithm is introduced into the modeling process, and the improved ACO-SVM prediction model is established to forecast the logistics demand of Qingdao City. Zhang Fan (2020) [9] Using the grey relational analysis method to analyze the factors affecting the volume of express delivery.

The above-mentioned scholars have enriched the research content of express delivery prediction, there are three main differences: prediction time dimension, research object and modeling method [6], but there are still some problems. For example, the impact of sudden events on express delivery affecting some routes cannot be considered, and the prediction accuracy is insufficient. Therefore, from the perspective of expanding data diversification and improving model prediction accuracy, this paper quantifies the express delivery data of a certain company, and uses the historical data of the shipment-receiving location as the training set to establish a Bayesian neural network. The "whether normal transport" index is added, and the data is divided into two prediction model training data and predicted input data. Bayesian predictive models for whether the route can be open normally and for transportation quantity are established.

2. Basic Principles and Model Construction of Bayesian Neural Network

2.1. Basic Principles of Bayesian Neural Networks

Bayesian neural network is a type of stochastic artificial neural network trained via Bayesian inference, which is highly effective in inference and uncertain knowledge representation [10]. The structure of BNN is similar to that of standard neural networks, but with additional elements that enable it to learn in a Bayesian way. Its main components include an input layer, one or more hidden layers, and an output layer. The network structure is shown in Figure 1.

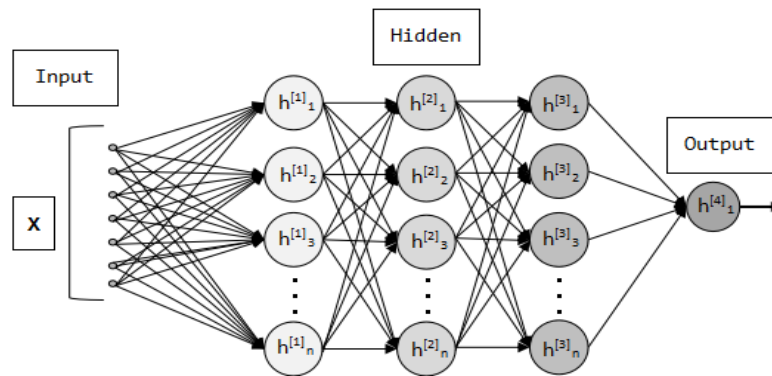


Figure 1. Neural network structure

The input layer of BNN receives external data, and the hidden layers form complex nonlinear mapping relationships between the input and output through neurons. In BNN, the weights are modeled as normal distributions with mean μ and variance δ , where each weight is assumed to follow a different normal distribution. The optimization target for BNN is the mean and variance of the weights. During inference, BNN samples from each normal distribution to obtain a weight value. At this point, BNN becomes equivalent to a BP neural network. Multiple samples can be obtained to obtain multiple prediction results, which can then be averaged to obtain the final prediction result.

2.2. Model Construction

Next, we construct a specific model for training the Bayesian neural network:

Suppose the training set is $\{x_i, y_i\}$, where $0 < i < N$ and the i -th weight ω_i follows a normal distribution with mean μ_i and variance δ_i . $\theta = \{\mu_i, \delta_i\}$ represents the parameter of the distribution, y_p is the output value of the BNN, and there are n weights in the BNN. The loss function of the BNN can be expressed as:

$$L(x_j) = \sum_{i=1}^n [\log q(\omega_i | \theta_i) - \log p(\omega_i)] - \log p(y_j | W, x_j) \quad (1)$$

$$\log q(\omega_i | \theta_i) = \log \frac{1}{\sqrt{2\pi}\delta_i} - \frac{(\omega_i - \mu_i)^2}{2\delta_i^2} \quad (2)$$

$$\log p(\omega_i) = \pi \left(\log \frac{1}{\sqrt{2\pi}\delta_1} - \frac{(\omega_i)^2}{2\delta_1^2} \right) + (1 - \pi) \left(\log \frac{1}{\sqrt{2\pi}\delta_2} - \frac{(\omega_i)^2}{2\delta_2^2} \right) \quad (3)$$

$$\log p(y_j|W, x_j) = \log \frac{1}{\sqrt{2\pi}\delta} - (y_j - y_p)^T \delta^{-1} (y_j - y_p) \quad (4)$$

The Bayesian neural network assumes that the distributions $p(\omega_i)$, $q(\omega_i|\theta_i)$, and $\log(y_i|w_i, x_i)$ all follow normal distributions, which is reasonable due to the central limit theorem. The parameters of the distributions need to be specified by the user.

By sampling the specific values for ω_i , the result is then calculated using the formula for the loss function. Since it is difficult to directly sample from $q(\omega_i|\theta_i)$, samples are first drawn from a normal distribution with ϵ_i , and $\mu_i + \epsilon_i \delta_i$ is then computed to obtain a sample that follows $q(\omega_i|\theta_i)$ distribution.

Note that $L(x_i)$ is calculated for one training sample $\{x_i, y_i\}$, and the project team can optimize θ_i via backpropagation. However, backpropagation may cause δ_i to be less than 0, so Bayes is used to handle δ_i in a special way.

$$\delta_i = \log(1 + e^{p_i}) \quad (5)$$

As a result, the Bayes parameter becomes $\theta_i = \{\mu_i, p_i\}$.

3. Empirical analysis

3.1. Data sources and processing

Based on the previously established Bayesian neural network prediction system, XX express records of delivery transportation data from April 28, 2020 to April 27, 2023 were selected. It is known that due to unexpected events, some express transportation routes between cities cannot be operated normally, leading to inability to ship or receive goods between certain station cities. In this study, two Bayesian neural network prediction models were established: one based on whether the route could be opened and the other based on the amount of transportation. The data were divided into training data and prediction input data for each model. The prediction input datasets for each model were the predicted data for April 28 and 29, 2023, respectively, yielding a total of six datasets for establishing prediction models. After importing the processed data into MATLAB, the date and shipping-receiving city were used as input parameters along with "whether the route was opened" as output for predicting in the Bayesian neural network model based on whether the route could be opened, while the date and shipping-receiving city were used as input parameters along with "express transportation quantity" as output for predicting in the Bayesian neural network model based on the amount of transportation.

3.2. Bayesian Network Structure and Parameter Selection

Import the preprocessed data into MATLAB, and use date and the station city pair (shipping city - receiving city) as input variables, and cargo volume as output for training. Divide the standardized data into training, validation, and testing sets to obtain a schematic diagram of the Bayesian neural network structure as shown in figure 2.

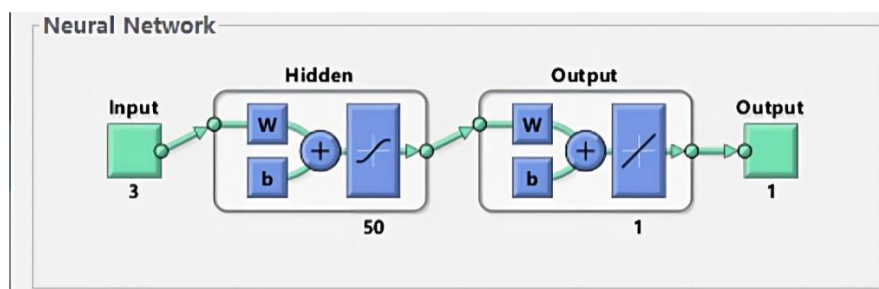


Figure 2. Bayesian neural network structure diagram

We need to set the parameters of the Bayesian neural network model, which mainly include: number of iterations, learning rate, target accuracy for learning, and number of hidden nodes.

3.3. Bayesian neural network prediction model based on whether the route can be opened

Validation and gradient analysis of the predictive model were performed using the aforementioned Bayesian neural network, as shown in Figure 3.

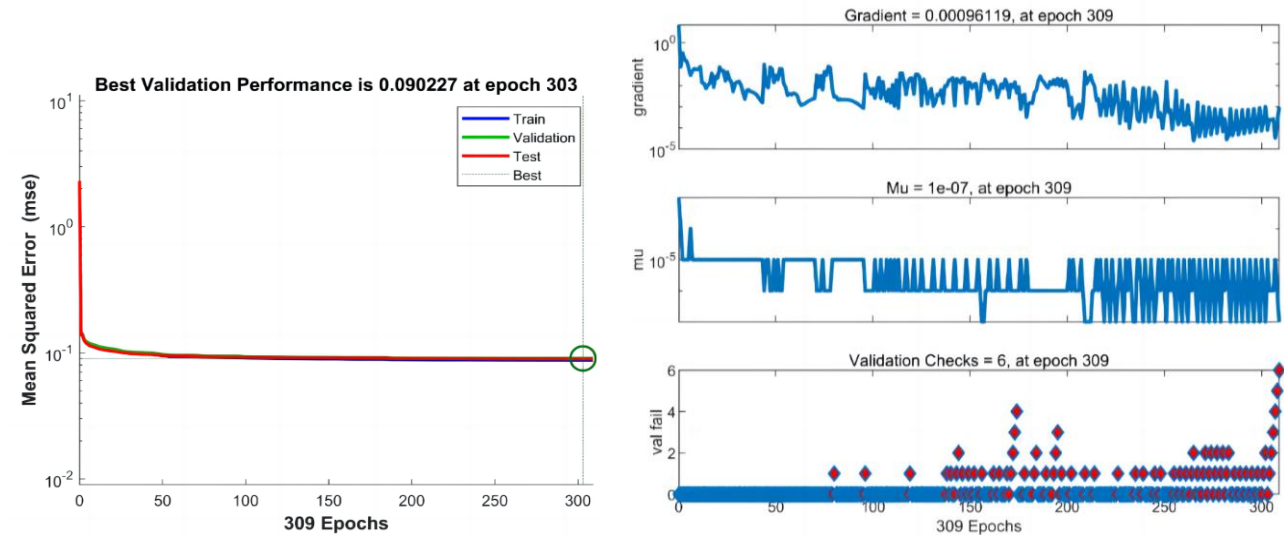


Figure 3. Performance curve, gradient, and validation of prediction model one

The following Figure 4 shows the regression curve of the training set, validation set, and test set of the Bayes neural network prediction model with a correlation coefficient of 0.64654. This indicates that the training results have reached the target error and yielded satisfactory performance.

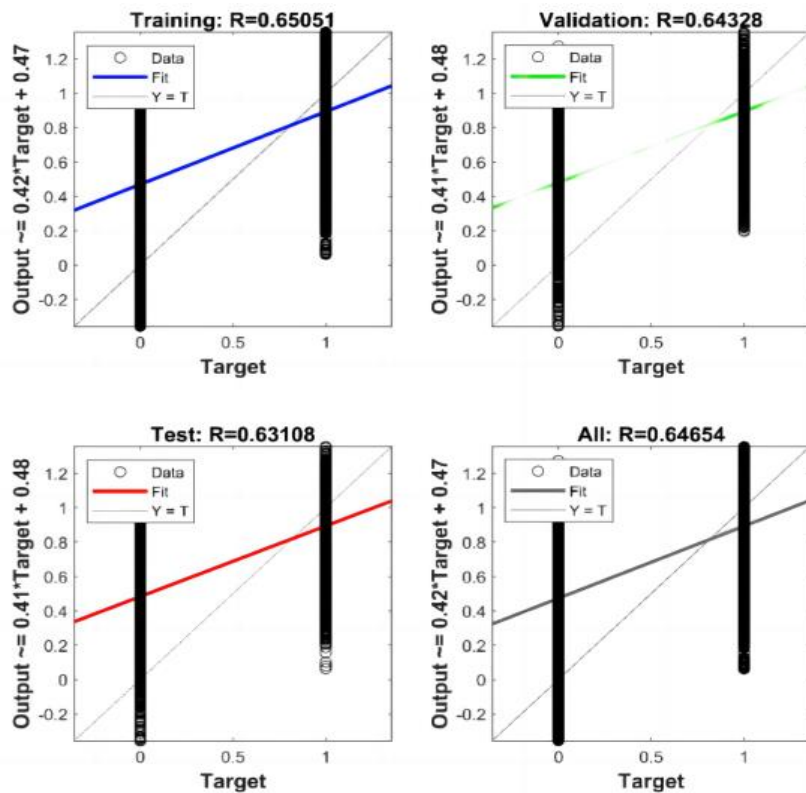


Figure 4. Regression curve of prediction model one

3.4. Bayesian neural network prediction model based on transportation quantity

Similarly, validation and gradient analysis were conducted for the Bayesian neural network prediction model. The model performance curve, gradient, and validation are shown in Figure 5 below.

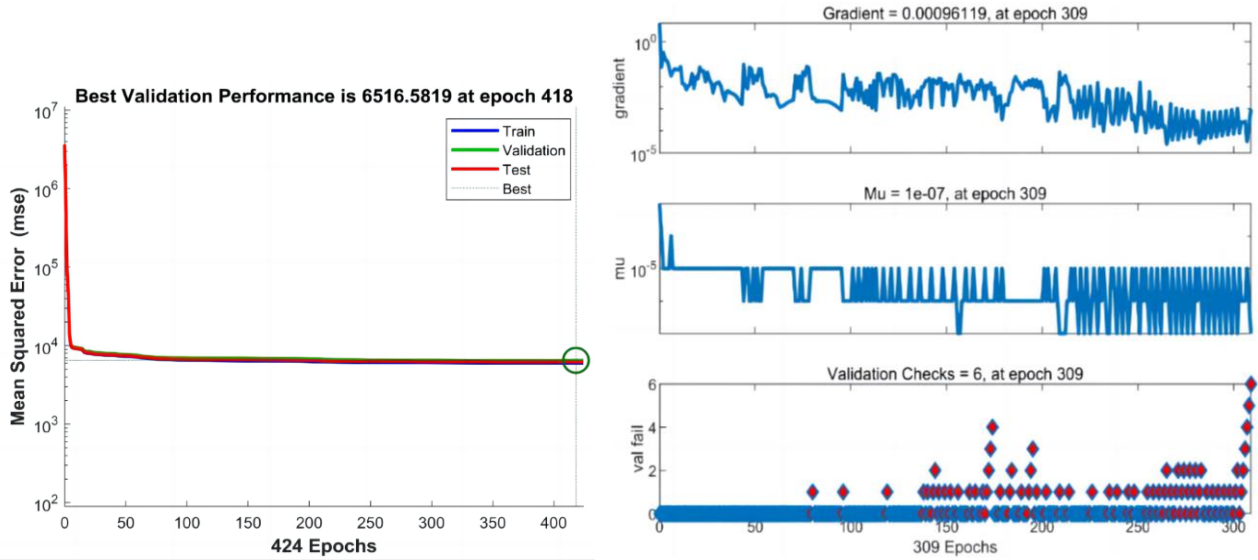


Figure 5. Performance curve, gradient, and validation of prediction model two

The following Figure 6 shows the regression curve of the training set, validation set, and test set of the Bayes neural network prediction model with a correlation coefficient of 0.64654. This indicates that the training results have reached the target error and yielded satisfactory performance.

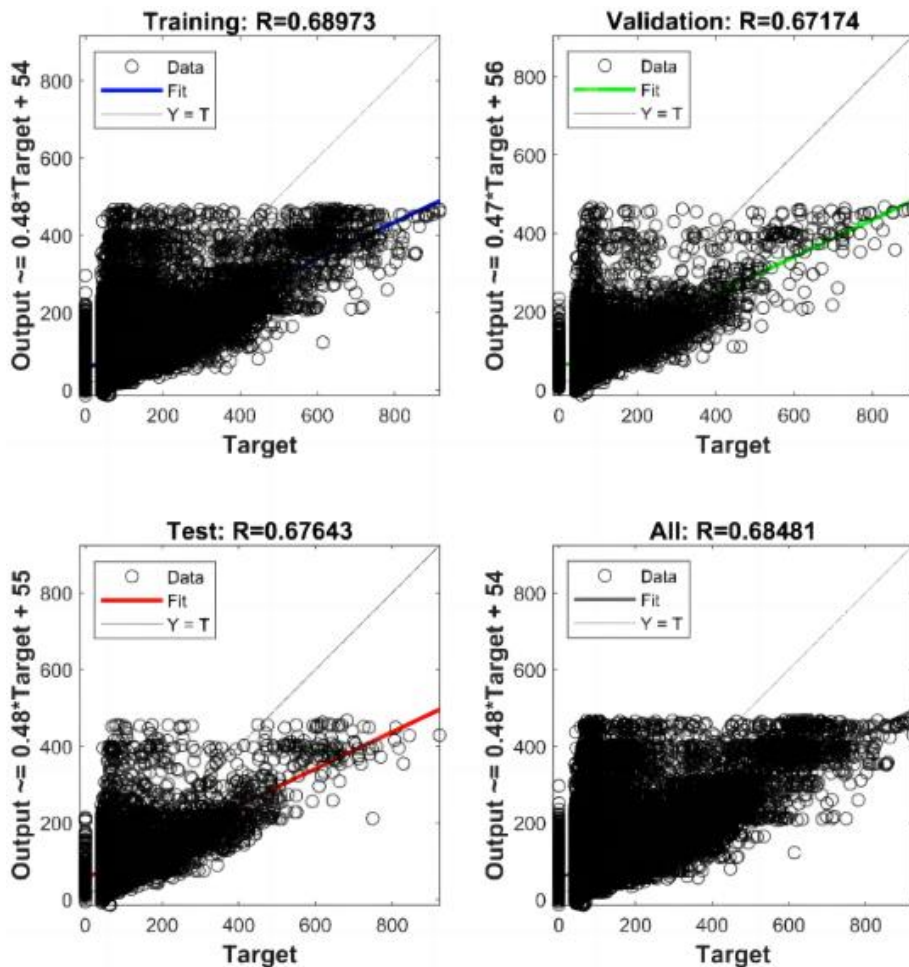


Figure 6. Regression curve of prediction model one

4. Results

The two models were run and solved in MATLAB software, and the predicted results were obtained as shown in Table 1 below.

Table 1. Predicted results

Date	"Shipping-Receiving" station city pairs	Whether shipping can be carried out normally	Express transportation quantity (Unit: pieces)
April 28, 2023	I-S	yes	42
	M-G	yes	45
	S-Q	yes	45
	V-A	yes	42
	Y-L	no	/
April 29, 2023	D-R	yes	20
	J-K	yes	167
	Q-O	yes	56
	U-O	yes	35
	Y-W	no	/

5. Conclusion

In order to predict express transportation demand, a Bayesian neural network-based prediction model is proposed in this paper. Based on the transportation data of actual logistics companies, the historical daily data of shipping-receiving city pairs are collected as the training set, and a Bayesian neural network is established to predict the specific transportation quantity for 10 routes (receiving-shipping city pairs) on April 28th and April 29th. Considering that there are many unexpected situations during transportation, a Bayesian prediction model is established before predicting the transportation quantity, with the addition of the "whether normal transportation can be carried out" index. The data is divided into two prediction model training data and prediction input data, and a Bayesian prediction model based on whether the route can be opened and a Bayesian prediction model for transportation quantity are established to predict whether the route can be opened and the transportation quantity of the current day. Experimental results show that the Bayesian neural network prediction model can accurately predict the opening status of transportation routes and the corresponding transportation quantity. It is suitable for incremental training and can handle multi-classification tasks, especially when the amount of data exceeds memory, batch training can be conducted.

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