Advances in Computer, Signals and Systems (2021) 5: 23-27
Clausius Scientific Press, Canada
DOI: 10.23977/acss.2021.050103
ISSN 2371-8838

Traffic congestion index calculation based on BP neural network

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Keywords: BP Neural network, traffic congestion, Z-score, Bayesian Regularization

Abstract: Aiming at the problem of traffic congestion, the paper analyzed a large number of traffic congestion data in different regions. After analyzing the data, took speed, day of week, bus count, weather and visibility as the most significant factors of traffic congestion time. These factors were preprocessed with Z-score to unify their dimension. In addition, the Bayesian Regularization training algorithm is selected in the BP neural network model to generate the code for predicting traffic congestion time. There is a high correlation between the result of the model and the real record as expected. Then using the BP neural network to analyze the results, get the prediction results and explore the actual deviation to get the advantages and disadvantages of the model, and put forward the improvement and improvement methods in the future.

1. Introduction

In the Internet era, electronic maps have penetrated into every aspect of people's lives. People can get real-time local traffic information with a tap of their smart-phone. Artificial intelligence self-driving car is also a hot research direction, and has a high application prospect in the future traffic [1]. One of the macro way-finding approaches for many self-driving cars is often to connect to specific electronic maps to get real-time information about road congestion, so as to better plan driving routes.In most of the existing navigation software [2], it is a decisive solution to obtain the GPS data of taxi or other vehicles in real time to estimate the congestion of the road where the vehicle is located [3].

However, in the real situation, driving speed is extremely slow in extreme traffic congestion, so the prediction of navigation software on data is also extremely inaccurate. As a result, navigation software is very inaccurate in predicting the time of traffic congestion. The actual traffic jam may be several or even dozens of times as long as the software predicts. This serious problem not only affects the practical value of navigation software, but also has to be overcome in the development of intelligent driving vehicles.

2. Data preprocessing

The indicators are in the same order of magnitude, suitable for a comprehensive comparative evaluation [4]. Therefore, before simultaneously considering factors such as speed, weather, visibility, week number and predicting the congestion time, use the Z-score standardization to pre-process the relevant data. .Z-score standardization is the standardization of data based on the mean and standard deviation of original data. Here is the z-scores formula:

$$z = \frac{x-\mu}{\sigma} \tag{1}$$

3. The body of the model

The utility function Input net_i of the i_{th} of hidden layer:

$$net_i = \sum_{j=1}^{M} w_{ij} x_j + \theta_i \tag{2}$$

Input y_i of the i_{th} node of hidden layer:

$$y_i = \phi(net_i) = \phi\left(\sum_{j=1}^{M} w_{ij} x_j + \theta_i\right) \tag{3}$$

Input net_k of the k_{th} node in the input layer:

$$net_k = \sum_{i=1}^{ij} w_{ki} y_i + a_k = \sum_{i=1}^{ij} w_{ki} \phi\left(\sum_{j=1}^{M} w_{ij} x_j + \theta_i\right) + a_k \tag{4}$$

Input o_k of the k_{th} node in the output layer:

$$o_k \psi(net_k) = \psi\left(\sum_{i=1}^{ij} w_{ki} y_i + a_k\right) = \psi\left(\sum_{i=1}^{ij} w_{ki} \phi\left(\sum_{j=1}^{M} w_{ij} x_j + \theta_i\right) + a_k\right) \tag{5}$$

The quadratic error criterion function of each sample p is:

$$E_p = \frac{1}{2} \sum_{k=1}^{L} (T_k - O_k)^2 \tag{6}$$

The total error criterion function of the system for P training samples is:

$$E = \frac{1}{2} \sum_{P1}^{P} \sum_{k=1}^{L} \left(T_k^P - O_k^P\right)^2 \tag{7}$$

According to the error gradient descent method, the correction quantity Δw_{ki} of the output layer weight, the correction quantity Δa_k of the output layer threshold, the correction quantity Δw_{ij} of the implicit value weight, and the correction quantity Δθi of the implicit value threshold are corrected in order.

$$\begin{aligned} \Delta w_{ki} &= -\eta \frac{\partial E}{\partial w_{ki}} \\ \Delta a_k &= -\eta \frac{\partial E}{\partial a_k} \\ \Delta w_{ij} &= -\eta \frac{\partial E}{\partial w_{ij}} \\ \Delta \theta_i &= -\eta \frac{\partial E}{\partial \theta_i} \end{aligned} \tag{8}$$

The following formula is obtained:

$$\Delta w_{ki} = \eta \sum_{P=1}^{P} \sum_{k=1}^{L} \left(T_k^P - O_k^P\right) \cdot \psi'(net_k) \cdot y_i \tag{9}$$

$$\Delta a_i = \eta \sum_{P=1}^{P} \sum_{k=1}^{L} \left(T_k^P - O_k^P\right) \psi'\left(net_k\right) \tag{10}$$

$$\Delta w_{ij} = \eta \sum_{P=1}^{P} \sum_{k=1}^{L} \left(T_k^P - O_k^P\right) \cdot \psi'\left(net_k\right) \cdot w_{ki} \phi'\left(net_i\right) x_j \tag{11}$$

$$\Delta \theta_i = \eta \sum_{P=1}^{P} \sum_{k=1}^{L} \left(T_k^P - O_k^P\right) \psi'\left(net_k\right) w_{ki} \phi'\left(net_i\right) \tag{12}$$

After the above modeling process, the paper obtained various factors affecting traffic congestion in the city through correlation analysis [5] [6], and obtained the relationship between the above factors and traffic congestion index through the bayesian neural network algorithm. The following picture shows how many times the neural network circulates. The fitting result of relevant data is shown below. We obtained the function of traffic congestion index by fitting the traffic congestion index and its related influencing factors, and the relevant MATLAB code has been attached in appendix I. Finally, the paper got the comparison between the predicted results and the actual values.

4. Survival analysis

Survival analysis is an algorithm that studies survival phenomena and response time data and their statistical rules. It has important applications in biology, medicine, insurance, reliability engineering, demography, sociology, economics and other aspects. Survival analysis is an algorithm

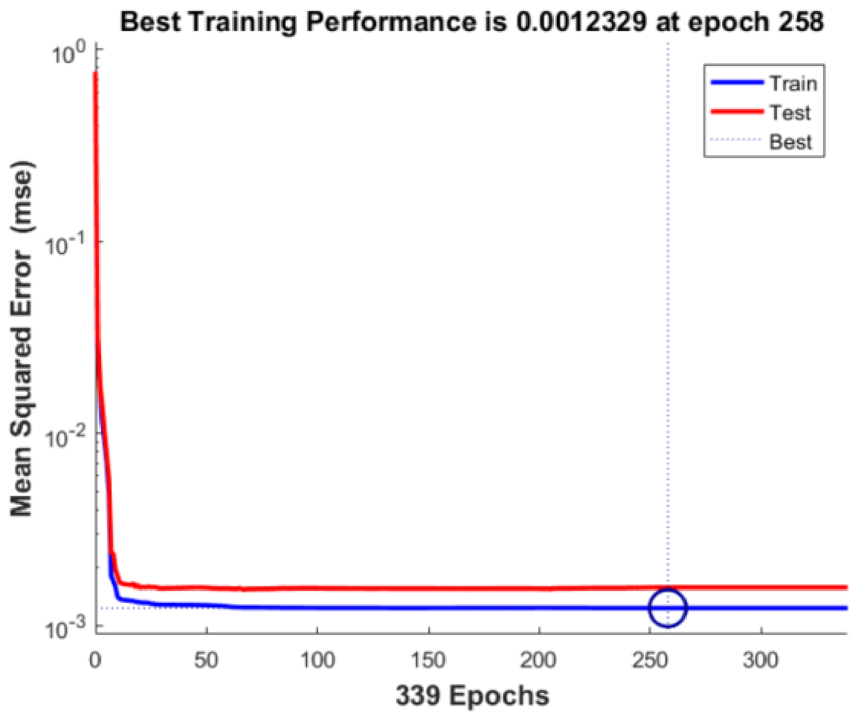

Figure 1: Number of calculations

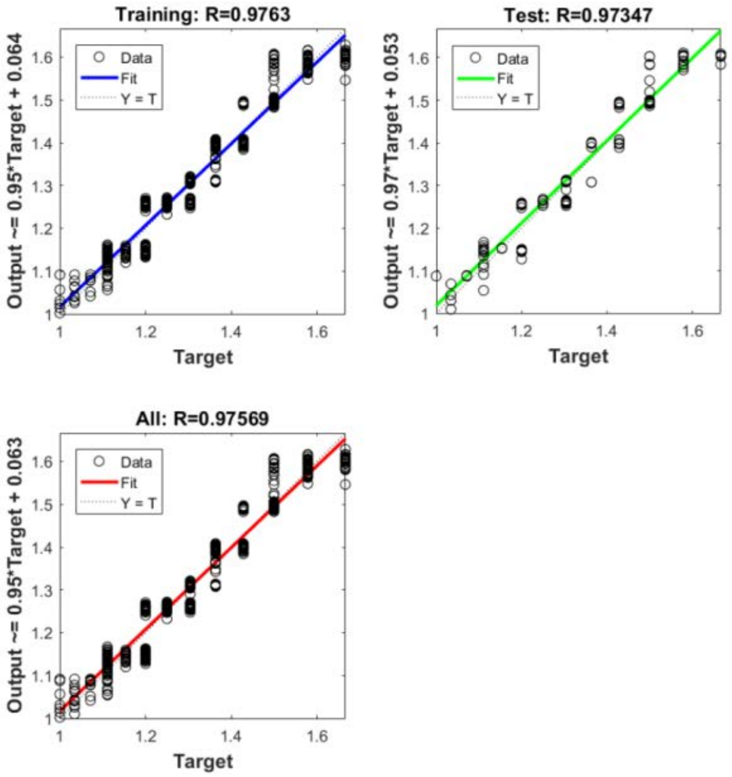

Figure 2: The fitting result is obtained by BP neural network

KM method is a non-parametric method to estimate the survival probability from the observed survival time. For tn, the nthtime point in the study, the survival probability can be calculated as follows:

$$S\left(t_n\right)=S\left(t_{n-1}\right)\left(1-\frac{r_n}{d_n}\right) \tag{13}$$

Through the survival analysis, the paper found that Sunday and Tuesday contributed significantly to the traffic congestion index, while other days did not contribute significantly to the traffic congestion index.

5. Conclusion

By using BP neural network based on speed, day of week, weather and visibility, bus count, we obtain the model to predict traffic congestion time. After comparing their different impacts on traffic congestion time, we figure out day of week is the most effective factor. Finally, use the model to test a series of different sets of data, based on the neural network algorithms generated by using a lot of data. By comparing the prediction results obtained with other data, know that the function fitted by neural network is relatively accurate. It can be concluded that BP neural network is very effective in modelling traffic congestion index and its related influencing factors. This also provides a new idea for the follow-up traffic jam research and the solution of the disease in big cities.

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