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Road traffic flow prediction based on neural Network

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Abstract: The key to the implementation of urban traffic flow guidance system is to forecast the road traffic flow. This thesis mainly studies the prediction of traffic flow by neural network and the logical prediction of traffic flow. When the traffic flow information is regarded as a time series, the traffic flow can be regarded as a random time series, using the correlation between the data and the internal connection between the adjacent data. BP algorithm has a strong ability to deal with nonlinear problems, imitate bionic learning and self-organization, and occupies a certain advantage in dealing with nonlinear and uncertain traffic information. This paper mainly uses BP algorithm to build a traffic flow prediction model. In this paper, the traffic flow data of Minneapolis from 2012 to 2018 are preprocessed, and the traffic flow prediction model is used to make a better prediction of the traffic flow data of Minneapolis.

Keywords: Traffic flow forecasting ; neural networks ; data preprocessing ; correlation.

1. Introduction

Transportation plays a pivotal role in the city, and the development of its industry is related to the development of a city. Its progress can promote the development of the urban economy and have an impact on the urban pattern. my country's urban construction has made rapid progress, followed by increasingly severe traffic problems and people's increasing emphasis on urban transportation. Only by mining effective information from a large amount of traffic data can we achieve the purpose of predicting road traffic flow, providing information on congestion conditions for urban residents, improving travel efficiency, and saving travel time[0].

At present, there are studies on traffic flow prediction at home and abroad, mainly including regression model method, time series method, gray model prediction method, etc. The more famous one is the autoregressive comprehensive mobility model proposed by Pitakrat et al[2]. The structure of this model is relatively simple, and the data will be affected by external factors, so the effect of this model is relatively poor. In order to solve the difficulty of nonlinear traffic data, Cao Jie et al. [3] proposed a BP neural network based on wavelets and multi-dimensional reconstruction, which smoothed the initial data to slow down the convergence speed of the original BP neural network and further Solve the problem of nonlinearity. The method used by Zhu Yongqiang et al. [4] is the least square method of genetic algorithm optimization parameters to process complex traffic data. This algorithm improves the accuracy and stability of prediction. Xie Haihong et al. [5] used the K-nearest neighbor algorithm to predict traffic conditions and compare them with known similar road conditions to achieve prediction. However, machine learning algorithms have limitations and lack of universality. [6] With the development of deep learning, Li Juan et al. [7] established a traffic accident prediction model based on BP neural network, with good prediction accuracy; Zhan Wei et al[8] By studying the combined model and the single model, it was found that the prediction results of the combined model are better than Single model.

This article discusses logical prediction of traffic flow. Therefore, when the information of traffic flow is regarded as a time series, the traffic flow can be regarded as a random time series, there is correlation between the data, and there are internal connections between adjacent data. Based on the fact that changes in current traffic flow are affected by traffic flow in the previous period, traffic flow prediction can achieve prediction of traffic flow by analyzing past and current data and finding internal correlations.

2. BP neural network

BP neural network is a nonlinear function network composed of multiple hidden layer nodes and several output layer nodes. The output layer nodes are connected through the transfer of weights. To a certain extent, BP neural network can replace the human nervous system and complete many complex tasks without human intervention. It uses the forward propagation process to update the connection weights of other neurons i the entire network through learning of the current neuron. Its topology is shown in Figure 1.

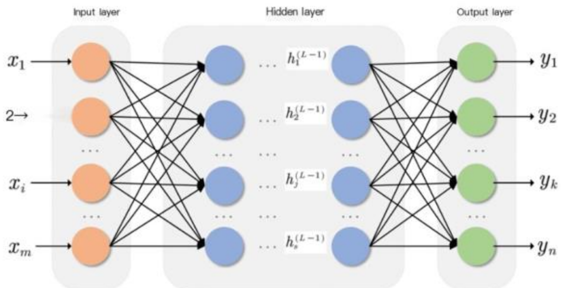

Figure 1 Neural network topology structure

The BP algorithm implementation process is as follows:

1. Selection of hidden layer

Determine the number of hidden layer nodes h of the neural network based on the input and output data to determine the number of hidden layer nodes.

$$h = \sqrt{m + n} + b \qquad \text{(Formula 1)}$$

In the formula: b is a constant between 1-10.

2. Forward transfer sub-process

The output value of each node is realized based on the output values of all nodes in the upper layer, the weights of the current node and all nodes in the previous layer, thethreshold of the current node, and the activation function. The algorithm is as follows:

$$S_j = \sum_{i=0}^{m-1} w_{ij}\, x_j + b_j \qquad \text{(Formula 2)}$$

$$x_j = f(S_j) \qquad \text{(Formula 3)}$$

Among them,f is the activation function, usually S-shaped function or linear function is selected

Reverse transfer sub-process

Assuming that all results of the output layer are d_j , the error function is as follows:

$$\mathrm{E}(\mathrm{w},\mathrm{b}) = \frac{1}{2}\sum_{\mathrm{j}=0}^{\mathrm{n}-1}(\mathrm{d_j}-\mathrm{y_j})^2 \qquad \text{(Formula 4)}$$

According to the gradient descent method, the correction of the weight vector is proportional to the gradient of E(w,b) at the current position. For the j-th output node:

$$\Delta\mathrm{w}(\mathrm{i},\mathrm{j}) = -\beta\frac{\partial \mathrm{E}(\mathrm{w},\mathrm{b})}{\partial \mathrm{w}(\mathrm{i},\mathrm{j})} \qquad \text{(Formula 5)}$$

Assume that the activation function is selected as:

$$\mathrm{f}(\mathrm{x}) = \frac{\mathrm{A}}{1+\mathrm{e}^{-\frac{\mathrm{x}}{\mathrm{B}}}} \qquad \text{(Formula 6)}$$

Then take the derivative of the activation function and get:

$$\mathrm{f}'(\mathrm{x}) = \frac{f(x)[A-f(x)]}{AB} \qquad \text{(Formula 7)}$$

Next for w_{ij} there are

$$\frac{\partial E(w,b)}{\partial w_{ij}} = \frac{1}{\partial w_{ij}} \cdot \frac{1}{2}\sum_{j=0}^{n-1}(d_j - y_j)^2 = \delta_{ij} \cdot x_i \qquad \text{(Formula 8)}$$

Assume w_{ki} is the weight between the k-th node in the input layer and the i-th node in the hidden layer, then we have

$$\frac{\partial E(w,b)}{\partial w_{ki}} = \frac{1}{\partial w_{ki}} \cdot \frac{1}{2}\sum_{j=0}^{n-1}(d_j - y_j)^2 = \delta_{ki} \cdot x_k \qquad \text{(Formula 9)}$$

According to the above formula and gradient descent method, adjust the weights and thresholds between the hidden layer and the output layer

$$w_{ki} = w_{ki} - \beta_1 \cdot \frac{\partial E(w,b)}{\partial w_{ki}} = w_{ki} - \beta_1 \cdot \delta_{ki} \cdot x_k \qquad \text{(Formula10)}$$

$$b_i = b_i - \beta_2 \cdot \frac{\partial E(w,b)}{\partial b_i} = b_i - \beta_2 \cdot \delta_{ki} \qquad \text{(Formula11)}$$

3. Establishment of traffic flow prediction model

3.1. Traffic flow prediction method

Traffic flow is determined by many factors, including different time factors, weather, road emergencies, road conditions, etc., temporary traffic control, holidays, morning and evening peak periods, etc. Because traffic changes are dynamic, they also exhibit strong randomness. The urban transportation system is mainly participated by people. Travelers are greatly affected by travel purposes, weather conditions and other factors. Road congestion and other factors show random changes and are difficult to control.The road traffic flow prediction in this article includes the following steps, as shown in Figure 2:

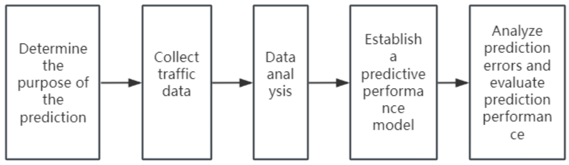

Figure 2 Traffic flow prediction flowchart

3.2. Traffic flow prediction model

3.2.1. Principles of establishing traffic flow prediction model

The prediction model is composed of time series. To accurately predict traffic flow, the

characteristics of the time series must betaken into account. If we only use the traffic flow within a certain period of time as the prediction object, we cannot accurately reflect the traffic flow of the entire road or the entire road network.

The prediction model should accurately reflect the changes in traffic flow over time. When establishing the model, the interaction between factors affecting traffic flow changes should be fully considered.

3.2.2. Traffic flow prediction evaluation indicators

In recent years, short-term traffic flow prediction research has increasingly become the focus of experts and scholars from all walks of life, and prediction methods are increasing day by day. Among these results, many are very effective and have higher accuracy to establish prediction models. Various prediction methods Various influencing factors have been taken into consideration, so its scope of application is not completely consistent with the conditions of use. Let x_i be the actual traffic flow sequence, and the M_i prediction result is defined as follow.

(1) Mean square error: It is a commonly used statistic used to describe the relationship between the mean and variance of each point in a data set.

$$MSE = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(x_i - M_i)^2} \qquad \text{(Formula 12)}$$

(2) Mean absolute error: It is the standard deviation obtained by comparing the arithmetic mean of two or more measured values with the original measured values, which can better reflect the error of the predicted value.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - M_i| \qquad \text{(Formula 13)}$$

(3)R^2 (RMSE): used to express the difference betwe en two variables. It is one of the most commonly u sed indicators to measure the difference between two va riables. In many studies, it is an evaluation index.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - M_i)^2}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \qquad \text{(Formula 13)}$$

3.2.3. Selection of traffic flow prediction model

This article discusses logical prediction of traffic flow.

Therefore, when the information of traffic flow is regarded as a time series, the traffic flow can be regarded as a random time series, there is correlation between the data, and there are internal connections between adjacent data. Based on the fact that changes in current traffic flow are affected by traffic flow in the previous period, traffic flow prediction can beachieved by analyzing past and current data and finding internal correlations.

The analysis of traffic flow characteristics and the comprehensive comparison of existing prediction models show that the neural network model is relatively more suitable for the characteristics of traffic data. The neural network model is characterized by high nonlinearity, strong self-learning ability, and relatively high prediction accuracy. It can predict nonlinearly changing data sequences without establishing an accurate model. This feature is a response to the stochastic nature of traffic data and the difficulty of building accurate models.

3.3. Experimental data set

3.3.1. Collection of data sets

The data set used in this article is Minneapolis traffic flow data, which is the city 's traffic flow data from 2012 to 2018. It contains variables such as whether holiday is a holiday, temp average temperature (Kelvin),rain_1h that occurs within one hour Rainfall (mm), snow_1h snowfall amount in one hour, clouds_all cloud cover (percentage), weather_main short text description of the current weather,weather_description longer text description of the current weather, date_time date and time of the data collected in local CST time and traffic_volume Numbers Westbound traffic volume reported on I-94 ATR 301 per hour.

3.3.2. Data preprocessing

(1) Outlier processing: Due to data acquisition errors or abnormal situations (such as brake failure and other events that cause the vehicle to be too fast), the data set may be abnormal. If the outliers are ignored to build the model, the model prediction may be caused. Performance is poor, so it is necessary to detect and handle anomalies in the data before leveraging it. The most commonly used detection method at present is to determine the value range of statistics and judge the rationality of variable values. Gaussian distribution can also be used as the judgment standard. Gaussian distribution is also called normal distribution. The highest point of the curve is the position of the mean. With the position of the mean as the center, it shows complete symmetry on the left and right, and tends to the horizontal axis without restriction. The Gaussian distribution function is shown in Equation 15:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \qquad \text{(Formula 15)}$$

(2)Missing value filling: It is very common for missing values to occur in data sets due to sensor failure, traffic accidents and other reasons. For missing values, the mean interpolation method can be used to fill them.

3.4. BP neural network trains traffic flow prediction model

By using the first 80% of weather and temperature data as independent variables and traffic flow as dependent variables for model training, the traffic flow in Minneapolis for the next period of time is predicted, and then compared with the actual flow.

BP neural network training process Step 1: Initialize parameters

In order to avoid excessive fitting of the network, the number of nodes is usually set to 1 so that the model cannot enter a local minimum after training.

Step 2: Selection of learning rate

When we train the input data, we divide it into 10 samples. When we choose the learning rate 0.1, the data will be divided into 10 parts during training; when we choose the learning rate 1, then during training Divide the data into 1 parts.

Step 3: Activation function

In the neural network, we use the sigmoid function for activation. The larger the value, the closer the neural network is to the way the human brain nervous system works.

This system uses the small-batch stochastic gradient descent method and continuously iterates through the for loop for learning and training. The model training results are shown in Figure 3:

Figure 3 Model training

4. Experimental testing of prediction models

4.1. Trends of influencing factors

The main factors that affect traffic flow are cloud density and temperature. By drawing a line chart, you can intuitively see the daily temperature and cloud changes, as shown in Figure 4. Put the cloud data and temperature data in the same line chart. The coordinates represent time in days, the vertical coordinate is in Kelvin when looking at temperature, and the unit is in percent when looking at cloud cover. It can be seen that the annual temperature trend is similar, and the cloud cover fluctuates greatly.

4.2. Impact of weather (temperature) on traffic flow

Normalize the data and map the average traffic flow and cloud volume data (average traffic flow and temperature) to decimals between 0 and 1 for processing, which is more convenient and faster [6]. As shown in Figure 5, overall, when the average cloud density accounts for a large proportion, the traffic flow is also greater, indicating that traffic flow is positively correlated with the amount of clouds. As shown in Figure 6, it can be seen that when the average temperature is lower, the average traffic flow is larger, indicating that traffic flow and temperature are inversely related.

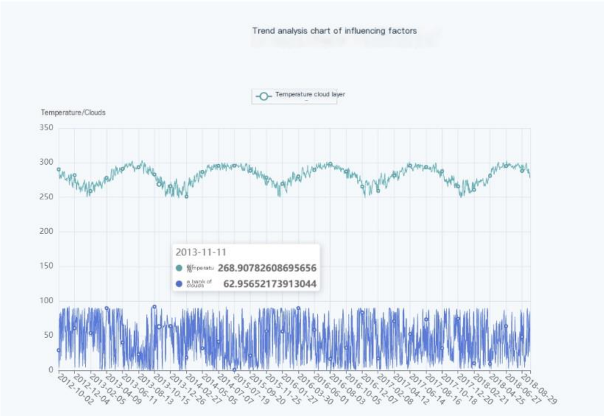

Figure 4 Analysis chart of influencing factors

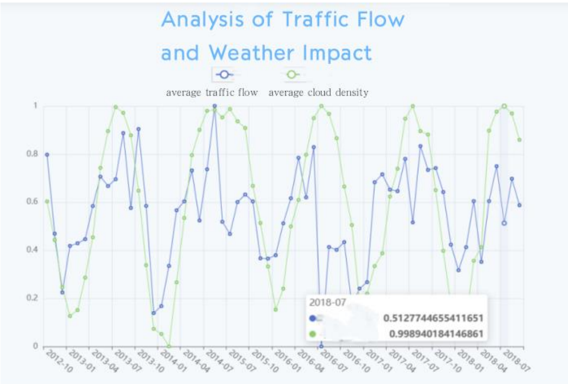

Figure 5 Traffic flow and weather impact analysis

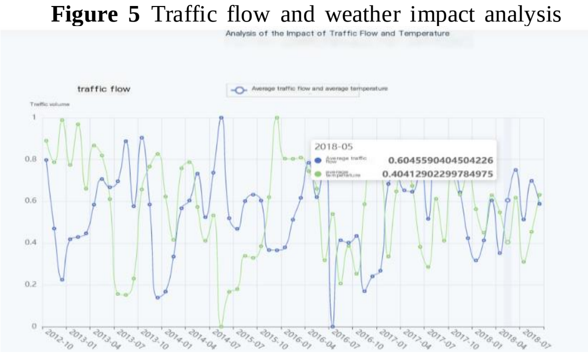

Figure 6 Traffic flow and temperature analysis

The data in Table 1 clearly show that there is a positive correlation between average cloud density and traffic flow, and an inverse correlation between average temperature and traffic flow. Through internal analysis of different factors, the prediction effect is

improved.

Table 1 Effects of temperature and weather on traffic flow

time	average traffic volume	average temperature	average cloud density
201210	0.80	0.89	0.60
201301	0.43	0.99	0.18
201304	0.70	0.83	0.77
201307	0.90	0.18	0.98
201310	0.91	0.63	0.62
201401	0.37	0.40	0
201404	0.60	0.80	0.80
201407	1	0	1
201507	0.60	0.37	0.98
201510	0.60	0.39	0.97
201601	0.38	1	0.23
201604	0.79	0.78	0.62
201607	0.89	0.57	0.99
201707	0.51	0.24	0.96
201710	0.81	0.61	0.90
201801	0.31	0.42	0.10
201804	0.40	0.61	0.38
201807	0.70	0.43	0.99

It can be seen from the table that data from January, July, and October of 2013, January of 2016, and January of 2017 show that the average cloud density is positively.correlated with traffic flow, and the average temperature is inversely correlated with traffic flow. relationship. Especially in July 2014, when the average traffic volume was about 1 unit, the average temperature was about 0 units, and the average cloud density was about 1 unit. Looking at the data in January 2016, when the average traffic flow is 0.38 units, the average temperature is about 1 unit, and the average cloud density is about 0.23 units. Multiple data reflect the changing trends of traffic flow, weather and temperature.

4.3. Correlation of influencing factors

The correlation between each two factors is analyzed anddisplayed in the heat map. The

closer the value is to 100, the higher the positive correlation. As shown in Figure 7, it can be seen that the heat map is completely symmetrical, and the abscissa is car When the traffic flow is high, the correlation coefficient between cloud volume and temperature is relatively large, that is, the impact on the traffic flow is relatively large, and can be analyzed separately with the traffic flow.

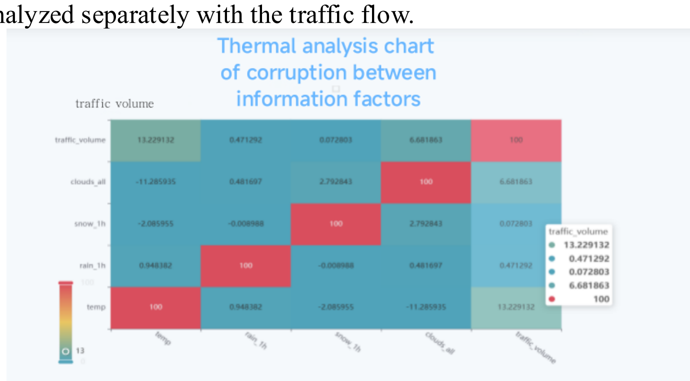

Figure 7 Thermal analysis related to influencing factors

4.4. Display of model prediction results

The prediction results of the neural network are shown in Figure 8. The blue curve is the predicted traffic flow and the green curve is the real traffic flow. It can be seen that the curve trend of the overall predicted value and the size of the vertical coordinate traffic flow are smaller than the real traffic flow. The prediction is more accurate.

Figure 8 Model fitting results

The results predicted by the model are shown in Table 2, which shows the prediction effect of the model through obvious data comparison.

Table 2 Data fitting results

time	actual value	Predictive value
201704	0.72	0.57
201705	0.63	0.58
201706	0.62	0.59
201707	0.79	0.63
201708	0.56	0.61
201709	0.81	0.60
201710	0.71	0.61
201711	0.77	0.58
201712	0.61	0.58
201801	0.41	0.40
201802	0.37	0.39
201803	0.40	0.39
201804	0.60	0.51
201805	0.39	0.57
201806	0.60	0.61
201807	0.78	0.60
201808	0.50	0.61
201809	0.64	0.61

It can be seen from the data in the table: the real value in May 2017 is 0.63 units, and the predicted value is 0.58 units; the real value in June 2017 is 0.62 units, and the predicted value is 0.59 units; the real value in February 2018 The value is 0.37 units and the predicted value is 0.39 units. In particular, the prediction effect is more obvious when the real value in January 2018 is 0.41 units and the predicted value is 0.40 units and in June 2018 when the real value is 0.60 units and the predicted value is 0.61 units. From the overall data point of view, the model has achieved good results in traffic flow prediction.

5. Summary

The rapid development of the transportation industry, which can effectively organize production within a certain range, has promoted the rapid development of the national economy, but has brought many benefits. At the same time, we are also facing many traffic problems, such as traffic congestion, waste of resources, and environmental pollution. serious. This paper mainly studies road traffic flow prediction, a hot issue. Based on actual traffic flow data, the influencing factors of road traffic flow are studied and forecasted.And BP neural network was selected as the prediction model. Now we make the following summary of the full text research work:

(1) This article introduces the current development status of traffic flow prediction.

(2) Preprocessing the collected traffic flow data.

(3) Through analysis and related research, it is found that the BP algorithm has strong processing capabilities for nonlinear problems and imitates bionics learning and self-organizing capabilities. It has certain advantages in dealing with nonlinearity and uncertainty in traffic information. Therefore, the BP neural network is determined as the prediction model of this system, and the traffic flow in Minneapolis is predicted more

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