Application of Artificial Intelligence Technology in Traffic Flow Forecast

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Abstract. In recent years, China's urbanization process has been accelerating, the number of motor vehicles has been increasing, and the problems of traffic congestion, traffic noise and environmental pollution have become increasingly prominent. The application of artificial intelligence system in the field of transportation provides a good idea to solve the above problems. Traffic flow prediction is to estimate the traffic flow in a period of time according to historical traffic data. This technology can provide decision-making basis for traffic guidance and path planning. In this paper, the deep learning theory of artificial intelligence technology is used to predict the short-term traffic flow, and the LSTM prediction model is constructed. On the basis of preprocessing the original data, through correlation analysis, compression matrix construction and other steps, a more accurate short-term traffic flow prediction is realized. According to the model, this paper also discriminates the actual road congestion, and the prediction results are basically consistent with the actual situation.

Keywords: Artificial Intelligence; Deep Learning; Short Traffic Flow Prediction; LSTM

1. Introduction

After a large number of literature search and analysis, it is found that the current research in the field of traffic flow prediction is relatively lively. Many scholars have put forward their own research theories, thus forming a relatively rich research method [1-3]. Generally speaking, there are the following major types of forecasting methods: prediction methods based on statistical analysis theory, prediction methods based on nonlinear theory, prediction methods based on intelligent algorithm theory, prediction methods based on deep learning theory and prediction methods based on combination model, etc. The prediction method based on statistical analysis theory is very limited in the number of calculation units and samples, and also involves a large number of complex function operations, so the efficiency is low; the nonlinear theory prediction method ignores the nonlinear characteristics of traffic flow data, although the process is
simplified, the accuracy is affected. The theoretical model of intelligent algorithm has strong data fitting ability and high prediction accuracy, but in large-scale training, the structure of the model is complex and the training time is long, so the real-time performance is poor. The combination model prediction method mainly uses the advantages of one or several models to improve the shortcomings of the other model, so as to improve the prediction ability of the combination model. However, the modeling process is too complex and the prediction is too complex. The results are greatly affected by the performance of a single model.

It can be seen that some of the existing models based on deep learning have many shortcomings when facing the massive traffic data with the characteristics of complexity, diversity and high dimension. In this paper, a short-term traffic flow prediction method based on LSTM prediction model is proposed, which optimizes the prediction accuracy and computational complexity.

2. Analysis of traffic flow data characteristics
Since some variation characteristics of traffic flow have great influence on the prediction, the similarity and periodicity characteristics of traffic flow data should be analyzed first [4, 5]. According to the historical statistical data we collected, the daily data is calculated by 30s. It is found that the overall traffic flow in a week is relatively large, and the change trend of daily traffic flow is basically the same, especially in peak and low peak periods. In addition, the peak value of traffic flow on weekdays is higher than that on holidays.

In terms of space, any location on the road network has spatial accessibility. The cross-correlation of traffic flow is a function of spatial distance. With the increase of traffic load, the spatial correlation between two road sections in the same road network will increase. The road structure in the road network is complex, and the characteristics of road traffic flow are particularly obvious at the intersection.

From the perspective of time, traffic flow time series has fractal characteristics, that is, the future change trend of traffic flow series is positively correlated with the historical change trend, and it shows strong regularity in the same period, and has differences in different time periods. Therefore, in order to predict the traffic flow in the next period by analyzing the time characteristics of the traffic flow parameters of the target road section, it is necessary to consider not only the flow in several periods related to the previous period, but also the flow of multiple observation periods flowing into the predicted section through other intersections.

3. Preprocessing of traffic flow data

3.1 Repair of Abnormal Data
The repair of traffic flow abnormal data mainly aims at data error and data missing. The data with obvious errors in the data set can be directly deleted. For the missing data, the historical trend method is used to repair the missing data. The method is to fill in the weighted value of the traffic data of the previous time and the current time, and control the weight of each individual through a smoothing coefficient.

3.2 Normalization of Data
When constructing the neural network model for traffic flow data, in order to avoid the phenomenon of neuron saturation, the data should be normalized. Because the traffic flow cannot be negative, we limit the number of traffic flow to the interval [0, 1]. The Min-Max method is used to normalize. Assuming that the original sequence is , then it becomes \( y_1, y_2, \ldots, y_n \) after normalization as below:

\[
y_j = \frac{x_i - \min(x_j)}{\max(x_j) - \min(x_j)}
\]
Where $a$ is the maximum value in the sequence and $b$ is the minimum value in the sequence.

### 3.3 Construct Data Compression Matrix

Let two variables $x$, $y$, define the correlation coefficient between the two variables as $R$. In the above formula, $x_i$ and $y_i$ are the observed value respectively. For two variables $n$, we have $i=1,2,3,\cdots,n$. The mean value of $n$ is $x,y$. Where $R$ shows the relationship and closeness of variables. The greater $R$ is, the stronger the closeness between variables is, and vice versa.

If the road network in the study area is regarded as a network graph $G$, then $G=(V,E)$, where $V$ represents the number of nodes in the road network, and $E$ is the collection of all road sections in the whole network, then the corresponding relationship between the traffic flow data of all sections in the actual road network and the mathematical formula can be established [5]. If there are $p$ sections in the network, and $N$ is the time lag of historical traffic flow data, then

$$E = \{S_i, i = 1,2,3,\ldots,p\}$$

For any section $S_i$ contain a continuous time series, denoted as a matrix

$$F_{X_{n}} = \begin{bmatrix}
    F_1 \\
    F_2 \\
    \vdots \\
    F_p
\end{bmatrix} = \begin{bmatrix}
    s(s_1, t-N+1)s(s_1, t-N+2)\cdots s(s_1, t) \\
    s(s_2, t-N+1)s(s_2, t-N+2)\cdots s(s_2, t) \\
    \vdots \\
    s(s_p, t-N+1)s(s_p, t-N+2)\cdots s(s_p, t)
\end{bmatrix}$$

### 4. LSTM short term traffic flow prediction mode

#### 4.1 LSTM model structure

LSTM is improved on the structure of RNN to improve the ability of long-term information memory [6]. The internal structure of its single information unit is shown in the Figure 1.

![Figure 1. LSTM unit structure](image-url)

RNN is a chain form, with repetitive neural network module, which has a very simple structure [7]. LSTM is the same structure, but repeated modules have a different structure that interacts in a very special way. The key of LSTM structure is cell state, which runs directly on the whole chain with only a small amount of linear interaction, which makes the information remain unchanged during transmission. The LSTM unit structure sets three “gate” structures, which remove or increase the ability of information to the cell state [8]. Gates are a way to let information through selectively. They contain a sigmoid neural network layer and a multiplication operation. This “gate” structure solves the problem of long-term dependence of RNN network. For short-term traffic flow prediction, LSTM structure is essentially the processing process.
of continuous time series, so its structure has unique advantages in short-term traffic flow prediction. LSTM improves RNN model structure by adding LSTM unit structure in hidden layer.

4.2 LSTM model construction

According to the LSTM unit structure in Figure 1, the input gate can be represented as:

$$\tilde{o}_t^l = \sum_{i=1}^{I} w_{il} x_t^l + \sum_{h=1}^{H} w_{hl} g_{t-1}^l + \sum_{c=1}^{C} w_{cl} f_{t-1}^l$$

Where the subscript I denotes the input gate; $o_t^l$ represents the input of neurons l at time t; I represents the total number of neurons in the input layer, H represents the total number of memory modules; C represents the total number of memory units in each memory module; if i is the input neuron and j is the next layer of neurons, then $w_{ij}$ is the connection weight of neurons i to j, then $w_{hl}$, $w_{hl}$ and $w_{lj}$ represent the connection weights of i to l, h to l, c to l, respectively $x_t^l$ is the historical sequence data of short-term traffic flow with time span n at time t, $g_{t-1}^l$ is the output of hidden layer at time t-1, $f_{t-1}^l$ is the state value of memory cells at time T-1. The output value of input gate at time t can be expressed as follows:

$$o_t^l = \text{sigmoid}(o_t^l)$$

From the above analysis, it is not difficult to see that the model proposed in this paper consists of input layer, output layer and intermediate layer. Each layer is superimposed in sequence. The network between layers is fully connected, and the first two hidden layers are LSTM layer. After selecting features, the traffic flow feature compression matrix of training set after preprocessing is directly sent to LSTM from input layer. The input tensor dimension and output tensor dimension of each LSTM layer are set respectively. Then all the extracted features are sent to flatten layer to flatten into one-dimensional vector. The vector is used as the input of the last two layers of fully connected layer, and the fully connected dense layer is used as the output layer. Finally, the traffic flow data of the next moment are output from the model.

4.3 LSTM model training

The training parameters of deep learning model are generally more, if the training samples are less, the training model is easy to produce over fitting phenomenon [9]. Over fitting is shown in the following aspects: the loss function of the model on the training data is small, and the prediction accuracy is high; but on the test data, the loss function is relatively large, and the prediction accuracy is low. The model trained in this way has poor practicability [10]. In order to solve the problem of over fitting, dropout parameter is introduced, which can achieve the effect of regularization to a certain extent. In the training phase, dropout constraints are added to the hidden layer of the model, so that the information on the input connection of each LSTM network module will be temporarily inactivated in the process of forward activation and back propagation weight update with a certain probability. The hidden layer nodes appear randomly with a certain probability in each iteration, and the updating method of weights no longer depends on the joint action of hidden nodes with complex relationships, which enhances LSTM. The learning ability of network model under the condition of lack of individual connection information avoids the situation that some data features are effective only in specific cases, which greatly improves the generalization ability of the model.

The LSTM model used in this paper is trained by BPTT algorithm. In the process of model training, various parameters such as iteration number, number of neurons, discarding rate, optimizer, intermediate activation function, output activation function, number of structural layers are optimized. With the increase of the number of iterations, the root mean square error of the whole model gradually decreases, which indicates that the more iterations, the better the prediction efficiency. However, considering that too many iterations will lead to the increase of the training and prediction time and complexity of the model, the iteration number in this paper is 250.
5. Traffic congestion prediction experiment

Traffic congestion refers to the phenomenon of slow driving of vehicles due to various factors on the road. This phenomenon has been widespread in urban roads, and urban residents are troubled by traffic congestion in rush hours of work and off duty. Traffic congestion is usually differentiated by traffic density, road saturation and other indicators.

5.1 Traffic Congestion Discrimination Index

Traffic density refers to the density of vehicles on a single lane, that is, the number of vehicles in a certain unit length at an instant, also known as traffic density. The results show that the traffic density is proportional to the traffic volume, and the traffic volume increases from zero. The optimal traffic density reflects the density when the traffic volume is maximum. When the density continues to increase, when all vehicles cannot normally pass, the speed tends to zero, and the density is called blocking density. Therefore, traffic density can be used to judge whether the road is congested and the degree of congestion. The traffic density division criteria are shown in Table 1.

| Density   | 1  | 2    | 3    | 4    | 5    |
|-----------|----|------|------|------|------|
| Density   | <10/km | 10-20/km | 20-30/km | 30-40/km | >40/km |

The calculation of road saturation should mainly consider road traffic volume and road capacity. Generally, urban road saturation is calculated by the ratio of daily peak hour traffic volume to maximum design traffic capacity. The higher the saturation value, the lower the road service level. Because the degree of congestion and road service level are restricted by many road factors, the saturation value is taken as one of the main indicators to evaluate road service level. In China, the road service level and congestion classification standards are shown in Table 2.

| Service level | Congestion level | Traffic conditions      | Value       |
|---------------|------------------|-------------------------|-------------|
| 1             | T1               | unobstructed and excellent | [0,0.6]    |
| 2             | T2               | a little congested and better | [0.6,0.8]  |
| 3             | T3               | traffic jam and relatively poor | [0.8,1]     |
| 4             | T4               | serious and bad | [1, +∞) |

5.2 Identification Process of Road Congestion

In this paper, the traffic density and road saturation are taken as the main evaluation indexes, and a set of congestion discrimination system is established.

(1) According to the LSTM model prediction process proposed in this paper, the subsequent traffic flow of a certain section at a certain time is obtained.
(2) According to the obtained traffic flow, saturation is calculated respectively. In the calculation of saturation, because this is the simulation section discrimination, the fixed maximum capacity of the road is set according to the situation.

(3) Firstly, according to the calculated road saturation, the corresponding relationship in table 1 is used to partition the congestion situation. Then, according to the calculated road saturation, the congestion classification is given in table 2. Finally, the road congestion is divided into six grades: serious road congestion (T1), road congestion (T2), relatively congested road (T3), relatively smooth road (T4), smooth road (T5) and very smooth road (T6).

5.3 Identification of Actual Road Congestion
In order to test the congestion discrimination system proposed in this paper, the LSTM model is used to predict the traffic flow of No.1, No.2, No.3, No.4, No.5 selected by road network correlation coefficient calculation, and the traffic flow of No For the forecast traffic flow on the November 20, 2020 (12:00-18:00), this paper uses the identification system proposed in this paper to identify the congestion. The traffic flow of the actual road network is reflected by the identification of the congestion of the small road network composed of the five roads.

As the road sections are divided into equal lengths and this is only simulation calculation, the length (L) of five sections is determined to be 15km, and the maximum traffic capacity (a) is proposed to be set as 1000 vehicles. The congestion situation of the five sections is determined by calculating two judgment indexes. According to the discriminant system in this paper, the congestion judgment results of section No.2 are shown in table 3 and Figure 2.

### Table 3. Congestion judgment results of No.2

| Time slot | 12:00 | 12:30 | 13:00 | 13:30 | 14:00 | 14:30 | 15:00 | 15:30 | 16:00 | 16:30 | 17:00 | 17:30 |
|-----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Traffic flow | 1208  | 3207  | 1311  | 672   | 496   | 538   | 327   | 630   | 455   | 573   | 787   | 1253  |
| Congestion level | T4     | T4     | T4     | T2     | T2     | T2     | T1     | T3     | T1     | T3     | T3     | T4     |

![Figure 2. Visualization of No.2 congestion level](image)
From the Figure 2, it can be seen that during the two time periods of (12:00-13:30) and (17:00-18:00), obvious congestion occurred in all five sections, which may be caused by rush hour. In the future, section No.3 is the most congested and section No.1 is the most unobstructed.

To sum up, it can be judged by the traffic flow predicted by LSTM model in the next period In the six hour time period of November 20, 2020 (12:00-18:00), the five numbered road sections constitute the overall traffic situation of the road network. In practical application, the traffic control department can take this as a reference to implement traffic control and guidance for the next time period, so as to avoid the traffic problems in advance.

6. Conclusions
In view of the problems existing in some existing prediction models, this paper makes specific research and analysis in the following aspects: (1) analyzes the various characteristics of traffic flow, puts forward a complete set of data preprocessing process, improves the utilization rate of model training set data; (2) carries out traffic flow prediction at the road network level, selects the actual road network structure, and proposes the construction method of compression matrix By calculating the correlation between the road sections, the correlation coefficient matrix is constructed; (3) the LSTM deep learning model is constructed and the parameters of the model are optimized; (4) the application of artificial intelligence technology in the identification of traffic congestion on the communication road is studied, and the results for decision analysis are given through the discriminant analysis of the traffic volume predicted by the LSTM model.

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