Neural network model based on travel planning for travel time prediction

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Abstract. The development of smart cities presents new challenge to more convenient and intelligent transportation, while the advent of big data era promotes the sharing of travel data, which provides powerful data support for the development of smart travel. As an important part of smart travel, accurate travel time prediction is definitely crucial. Different from traditional passive forecasting methods which is only based on historical data, this paper proposes a Conv-LSTM network model based on travel planning data for travel time prediction from the perspective of user travel. This model can actively predict the upcoming traffic state according to the upcoming data generated by the user’s travel planning information released before travel. Specifically, we first introduce the definition of travel plan and how to calculate the future planned flow according to travel planning information. Then, the future planned data and the corresponding segment historical data are introduced into the designed Conv-LSTM model to extract spatial-temporal features and then realize the prediction of road travel time. In this study, specific travel path is taken as the research object. Extensive experimental results demonstrate that this method has high accuracy, and remarkably outperforms benchmark methods in various metrics.

1. Introduction
With the acceleration of the process of smart city, people’s travel demand and travel mode have undergone disruptive changes, the problem of travel difficulty has been greatly improved. However, the contradiction between people’s growing high-quality travel demand and the unbalanced inadequate development of smart travel field has become increasingly prominent. People cannot grasp the actual situation of the specific travel segment, cannot reasonably choose the travel mode and arrange travel time is one of the burning issues in smart travel. Reasonable travel time estimation of the travel path is one of the important solutions.

Travel time prediction values the accuracy of the prediction and the real-time performance of the data. However, the traditional travel time prediction methods are based on the historical data, ignoring the real state of the road. The forecasting methods can be summarized into three categories, namely, mathematical statistical method, machine learning method and combination forecasting method [1]. Models based on mathematical statistics include time series models, Kalman filter models, parameter regression models and so forth. Machine learning method is to learn the correlation characteristic of data features, and then predict the change of traffic state through continuous optimization of model parameters. Combination forecasting method combines the advantages of various models to achieve
higher accuracy. However, with the advent of the era of big data, massive data sources make the above method training increasingly difficult.

Deep learning method occupies an important position in the field of intelligent transportation, and it has gradually become the mainstream of research due to its advantages in spatiotemporal feature extraction of big data. Ma et al. proposed a traffic flow prediction model based on LSTM model [2]. Ma et al. regards the traffic network as an image, and use CNN model to extract the spatial features, so as to realize the traffic speed prediction [3]. Shi et al. proposed a Conv LSTM network, this method combines CNN and LSTM to extract spatial and temporal features simultaneously [4].

All the deep neural network models mentioned or unmentioned above are based on the training of historical data to passively predict the evolution of future traffic states. However, due to the randomness of emergencies and the variability between contexts, passive prediction through historical data alone cannot guarantee the permanent accuracy of the model. To explore this question, Hua et al. proposed to construct city brain and use massive video processing technology of cloud platform to evaluate and guide traffic flow in real time [5]. Dai et al. proposed a H-STGCN model, which can predict the future state use future data [6]. With the support of NSFC, Xu et al. proposed a traffic flow calculation idea based on travel plan. Through calculation, we will accurately perceive the dynamic trend of future traffic flow [7].

Currently, there are few research methods for applying travel planning idea to traffic flow prediction. In this paper, a deep neural network model based on travel planning is proposed for travel time prediction by combining travel planning idea with Conv-LSTM neural network model. Taking the special travel path as the research object, we first calculate the traffic flow in the future segment according to travel planning data. Then, the input data of the model is divided into historical data and future planned data. The convolution network is used to extract the spatial dependence and temporal correlation and LSTM is used to predict the future travel time.

2. Travel plan

2.1. The definition of travel plan
The complete travel plan is generated under the condition of data sharing, which means that user releases travel plan information through the navigation engine before traveling, including: origin information, destination information and departure time, etc., then the navigation engine transmits it to the travel database. Finally, the database calculates the total number of vehicles on a certain road segment in the future by aggregating all travel plan information in the road network, and provides real-time feedback to users through the navigation engine.

2.2. Constraints and Solutions
Since the relevant policies are in the implementation stage, complete data sharing cannot be achieved, so all the travel plan data cannot be completely obtained. We choose the road network trajectory data set to simulate the generation of travel plans. Specifically, we regard a complete trajectory data in the data set as a complete travel plan data and the corresponding travel plan information is processed as follows: the first trajectory point is O and the last trajectory is D, the time of the first trajectory point is the departure time, and the trajectory is planned by navigation by default.

Travel plan information is formally organized as $
\psi = \{ r, (\rho_{r,l_1}, \delta_{r,l_2}, t_0) \, | r \in N_\psi \},
$ (1)
where r is a trajectory, $\rho_{r,l_1}$ is the road segment where user publishes the travel plan, $\delta_{r,l_2}$ is the road segment where user plan to arrive at destination, $t_0$ is the time interval of issuing travel plan and $N_\psi$ denotes the total number of trajectories.

2.3. Basic assumption
In order to achieve the research purpose, ensure the strictness of the algorithm and the privacy of the data, we make the following assumptions for the travel plan information:
Assume that all travel planning data can be obtained in real time;
Assume that the vehicle runs in strict accordance with the navigation route;
Since we are currently only studying a specific travel route, we assume that other road vehicles in the road network will drive strictly at the average speed corresponding to their road class and traffic flow when entering the research route.

2.4. Calculation
Based on the above assumptions, we can calculate the traffic volume in a specific road segment at a certain time in the future.

Firstly, the average speed of the trajectory \( r \) in segment \( l_s \) is calculated by using the speed-flow formula:

\[
\bar{v}_{l_s} = v_f (1 - \frac{K_j}{K_f})
\]

Before entering the study travel path, trajectory \( r \) will pass through \( m \) road segments according to the navigation path, and the estimated arrival time is:

\[
T_e^r = \sum_{l=1}^{m} \frac{d_{l_s}}{\bar{v}_{l_s}},
\]

where \( d_{l_s} \) is the distance of segment \( l_s \).

Considering that the length of urban road segment is short and the driving time is less, we take one minute as the time interval and divide the day into 1440 intervals, then the time interval when the trajectory \( r \) enters the study segment \( i \) after the estimated arrival time \( T_e^r \) is:

\[
t_k = t_0^r + \frac{T_e^r}{60},
\]

Finally, by aggregating all the trajectory data in the road network, we can get that the planned traffic volume entering the study section \( i \) at the time interval \( t_k \):

\[
V_{t,k,i} = \begin{cases} \sum_r \psi_r & \text{if } t_0^r + \frac{T_e^r}{60} = t_k, \\ 0 & \text{else}. \end{cases}
\]

The calculated travel plan information is formally organized as

\[
\Psi = \{ r, \{(\rho_{r,l_s}, \delta_{r,l_s}, t_0, t_{k,r}, i) | i \in S \} | r \in N_r \}
\]

where \( t_{k,r} \) represents the time slot when the trajectory \( r \) is estimated to arrive at the research segment, \( i \) is the \( i \)th research segment entered by \( r \), and \( S \) is the collection of road segments in the research path.

After the calculation of travel plan information, we transfer the data into Conv-LSTM model to predict the travel time.

3. Conv-LSTM model based on travel plan for travel time prediction

3.1. Input data preprocessing
In this section, we set the time slot \( t_0 \) when users publish travel plan information as the present time, and divide the input data into two parts: the historical data \( X_p \) before \( t_0 \), and the calculated future travel plan data \( X_f \) after \( t_0 \). The historical data \( X_p \) is the trajectory data of the completed travel plan in the road network, and the future travel plan data \( X_f \) is the flow information calculated by travel plan information.

3.2. Convolution neural network module
Convolutional neural network is widely used in the field of computer vision. It can capture the spatial correlation of data efficiently by strengthening the local connection and weight function sharing between neural network nodes. We introduce CNN model to extract the spatial dependence and temporal correlation of research data. The module architecture is shown in the figure 1:
In Figure 1, we first perform spatial convolution and temporal convolution on the spatial and temporal dimensions of the two datasets to extract the spatial dependence and temporal correlation features, where the historical data $X_p$ uses dual channel input, which is characterized by flow and travel time, and travel plan data $X_f$ uses a single channel input, characterized by planned traffic.

After extraction, we combine temporal and spatial features:

$$X_{p}^{out} = \text{pool2d}(X_{p}^{s} + X_{p}^{t}), \quad (7)$$

$$X_{f}^{out} = X_{f}^{s} + X_{f}^{t}, \quad (8)$$

where $X_{p}^{s}$ and $X_{f}^{s}$ is the extracted spatial feature, $X_{p}^{t}$ and $X_{f}^{t}$ is the extracted time feature, and pool2d is the pooling layer function.

We input $X_{p}^{out}$ to the hidden layer of LSTM unit as the historical time state, and the travel plan data $X_{f}^{out}$ as the input LSTM unit to predict the future traffic state.

### 3.3. LSTM module

LSTM is a special RNN structure, which solves the gradient explosion and gradient vanishing problems that may exist in the traditional RNN in the long-term prediction by means of the unique gate control structure. LSTM has excellent performance in the long-term prediction, and is very suitable for the field of traffic flow prediction.

Figure 2 shows the overall structure of this module. $X_{p}^{out}$ is activated and dimension transformation by the transformer layer, and then passed into the LSTM Cell as the state of the hidden layer. At the same time, the flow data of each time slot in the planned data $X_{f}^{out}$ is converted by the transformer layer and then input into the LSTM Cell. After the prediction layer, the travel time at the future moment based on the travel plan data is obtained.
4. Experiments

The experimental data of this study comes from Didi Gaia data open platform, which includes the whole day travel trajectory data of Chengdu. The vehicle position is located every three seconds by GPS positioning system to ensure the continuity of the trajectory. The time span of the selected data is from October 10, 2018 to October 31, 2018. We select the data of the first 15 days as the training set, and the remaining data as the test set.

We choose the North Second Ring Road of Chengdu as a planned travel path, which will be divided into 20 road segments according to the entrances and exits, and 1440 intervals with one minute as the time interval. In the training process, we set the initial learning rate to 0.01, and reduce the learning rate adaptively with the training process. Batch size is 32, the number of iterations is 1000, and Adam (adaptive motion estimation) gradient descent is used as the optimizer. We use validation set to verify the model every 10 training sessions to improve the generalization ability of the model.

Due to the short segment and fast speed of urban expressway, the time required to complete a travel path will not be so long, and the vehicles that have completed the travel path will no longer affect the road network. Therefore, we select the historical data of the past 20 minutes and calculate the planned flow data of the next 5 minutes as the model input.

We use Mean Absolute Error (MAE) and Root-mean-square error (RMSE) as the evaluation indexes of the model, and the curve of loss function during training is shown in Figure 3.

Figure 2. LSTM structure based on travel plan

Figure 3. The curve of loss function during training
From Figure 3, we can see that the training error gradually decreases with the training times. After 1000 times of training, the error between the actual value and the predicted value has been reduced to less than 1s, which proves that the model has high accuracy.

In this paper, the traditional CNN, LSTM and Conv-LSTM models based on historical data are selected as benchmark models for comparison, and the comparison results are shown in Table 1. The results shown that this model is superior to other traditional models.

| Method       | MAE  | RMSE  |
|--------------|------|-------|
| LSTM         | 0.852| 1.376 |
| CNN          | 0.961| 1.601 |
| Conv-LSTM    | 0.674| 0.945 |
| TP-ConvLSTM  | 0.532| 0.798 |

5. Conclusion
In this paper, travel planning data is applied to travel time prediction. Firstly, travel planning is introduced and travel planning data is used to calculate the planned travel flow in the future. Then, convolution module is designed to extract the time and spatial characteristics of the road section by combining the calculated data with historical data. Then LSTM module is introduced to realize the future travel time prediction considering travel planning. In a word, this paper proposes a deep neural network based on travel planning and applies it to travel time prediction. Although it only uses a travel path as the research section, it also verifies the accuracy of the model. In the future, the model which based on travel plan will be considered in multiple travel paths or even in the road network. Although the model algorithm will be more complex, it is believed that it will also achieve very good results.

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