Paper ID:CS 805

2024 International Conference on Applied Mathematics, Modeling and Computer Simulation (AMMCS 2024)

Internet taxi trip prediction based on multi-source data fusion

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Supported by Xi'an Siyuan University President's Fund Research Project Natural Science Project (NO.XASYZD-B2302).

INTRODUCTION

With the widespread popularity of online ride-hailing services such as Uber and DDT, massive amounts of offline and online car GPS data provide rich resources for demand forecasting. Accurately predicting traffic demand has become the key to ITS research.

This paper proposes a prediction method based on CNN-BiLSTM-Attention. The method employs a grid segmentation strategy to transform the urban network car GPS data into a collection of static image snapshots, where each pixel reflects the traffic flow of a single or multiple roadway area. Through a deep convolutional neural network (CNN), we effectively mine the spatial features in the entire traffic network. Further, by combining the bidirectional long and short-term memory network (BiLSTM) and the attention mechanism, the model is able to accurately capture the spatio-temporal dependence and significance of the changes in the traffic flow, which leads to more accurate traffic flow prediction.

RESEARCH OBJECTIVIES

Using long-term accumulated historical GPS data of ride hailing taxis, accurately predict the demand of urban residents for ride hailing services in the coming hours.

A typical spatiotemporal series prediction problem is studied, including temporal trends, capturing spatial distribution characteristics, and the dynamic relationship between the two.

METHODS

1. Traffic flow matrix based on spatio-temporal sequence features
2. Characterization of spatial and temporal trajectory data
3. Model network structure

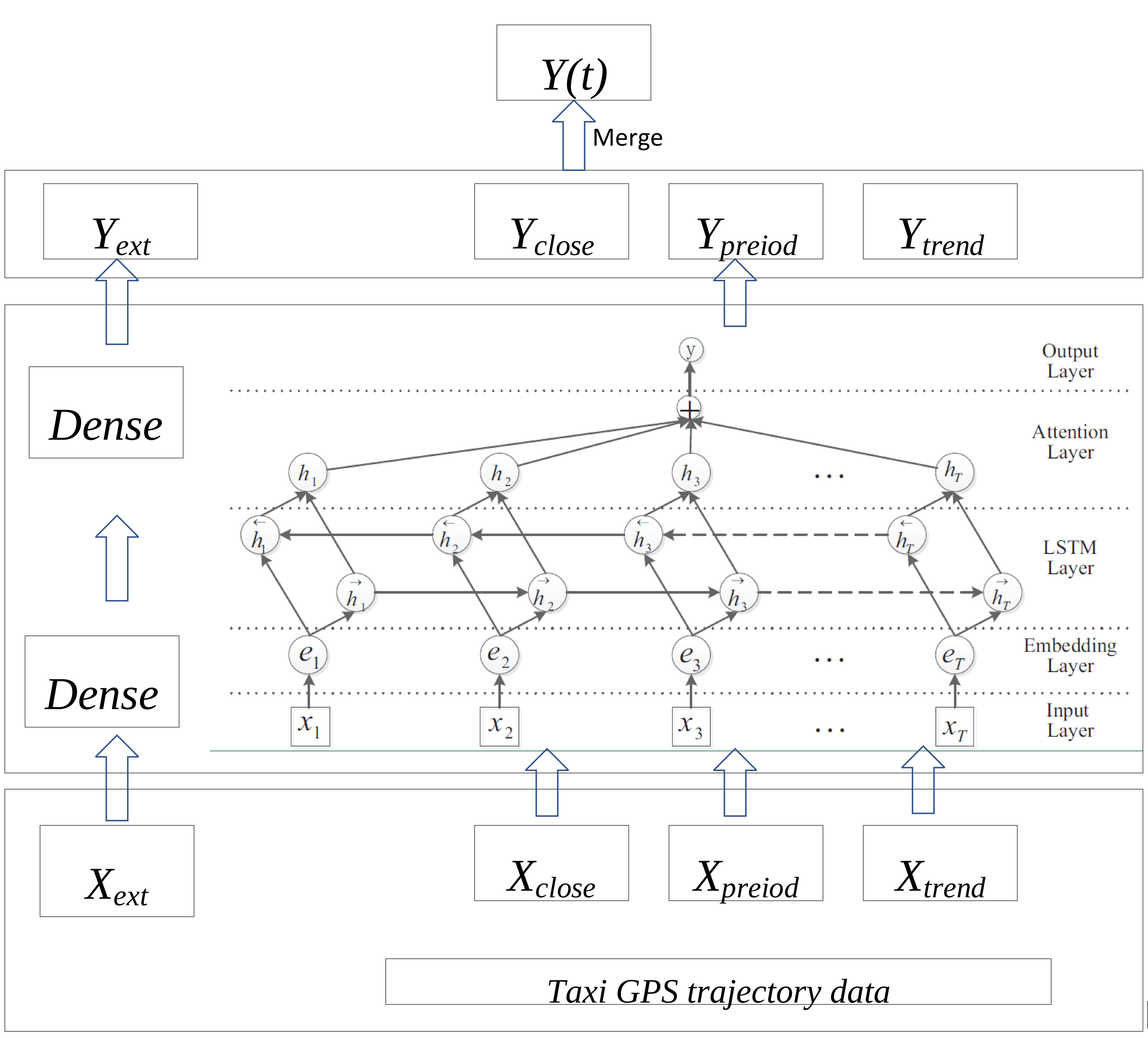

Fig.1 Schematic diagram of the model in this paper

$$\begin{cases} x_t^{getUp,i,j} = \sum_{Tr\in Ts} \left| n>1 \middle| p_{n-1} \notin (i,j) \wedge p_n \in (i,j) \right| \\ x_t^{getDown,i,j} = \sum_{Tr\in Ts} \left| n>1 \middle| p_n \notin (i,j) \wedge p_{n+1} \in (i,j) \right| \end{cases}$$

$$A_t = \begin{bmatrix} X_{lon_1,lat_1} & \cdots & X_{lon_1,lat_j} \\ \vdots & & \vdots \\ X_{lon_i,lat_1} & \cdots & X_{lon_i,lat_j} \end{bmatrix}$$

$$Y_c^{(1)} = f\left(\sum_{j=1}^{l_c} W_{cj}^{(1)} \cdot X_{t-j} + b_c^{(1)} \right)$$

$$Y_{tr}^{(1)} = f\left(\sum_{j=1}^{l_{tr}} W_{trj}^{(1)} \cdot X_{t-j} + b_{tr}^{(1)} \right)$$

$$Y_{tr}^{(1)} = f\left(\sum_{j=1}^{l_{tr}} W_{trj}^{(1)} \cdot X_{t-j} + b_{tr}^{(1)} \right)$$

$$H^{(2)} = f(W_c^{(2)} \cdot H_c^{(1)} + W_p^{(2)} \cdot H_p^{(1)} + W_{tr}^{(2)} \cdot H_{tr}^{(1)})$$

$$Y_t = f(X_{Res}, X_{Ext})$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^{N} (Obs_t - Pre_t)^2}$$

QUALITATIVE INORGANIC ANALYSIS

Table 1. Comparison of models

Model	Setup	RMSE	Weekly RMSE	Weekend RMSE	Weekly/Weekend
HA		46.54			
ARIMA		48.32			
CNN	2-layer CNN	8.66	6.11	5.66	7.95%
LSTM-Attention	Integration of external factors	8.73	8.34	8.67	3.80%
BiLSTM-Attention	Integration of external factors	8.61	8.62	8.27	4.23%
CNN-BiLSTM-Attention	Integration of external factors	8.05	7.93	8.32	4.69%

CONCLUSIONS

As shown in Table 1, the CNN with the smallest error for both weekdays and holidays, but only predicts the spatial features of vehicle GPS data and ignores the temporal features. More importantly, BiLSTM combined with the attention mechanism can learn to memorize historical data in a deeper and long-term way, so the prediction (without distinguishing between weekdays and holidays) error of the proposed model in this paper is only 8.05, and its relative error between holidays and weekdays is smaller than that of LSTM-Attention and BiLSTM-Attention.

ACKNOWLEDGEMENT

Thanks for the support of Xi'an Siyuan University President's Fund Research Project. （NO.XASYZD-B2302）

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