Intelligent Urban Rail Transit Based on Big Data Analysis and Application

Wei Sun*
Southampton International College, Dalian Polytechnic University, Dalian, China

Corresponding author e-mail: sunwei23@gjjyxy.dep.dlpu.edu.cn

Abstract. It is an intelligent information system developed in recent years to manage and control the traffic system with modern and intelligent technology. It plays an important role in alleviating traffic congestion, reducing traffic accidents and reducing energy consumption. This paper mainly studies the smart urban rail transit based on big data analysis and application. According to the characteristics of complex spatial correlation and time dependence of passenger flow, a deep learning model-temporal attention network is proposed, and multi-input multi-output multi-step forecasting strategy is used to solve the problem of error accumulation in long-term forecasting of passenger flow. Experimental results show that the prediction performance of our method in each time step is better than the traditional linear model, machine learning model and deep learning model, and the error is reduced by 7%-9% compared with the benchmark model. Moreover, the multi-input multi-output multi-step prediction strategy can effectively reduce the error accumulation of the traditional iteration strategy.

Keywords: Big Data, Smart City, Rail Transit, Passenger Flow Prediction

1. Introduction
Intelligent Transportation System (ITS) provides effective service guarantee for improving the operation efficiency of traffic system, improving travel safety and improving travel experience, and traffic flow prediction is one of the most important research issues in ITS. The traditional traffic flow research mostly adopts model-driven research method to establish simulation model to predict traffic flow. The shortcoming of this kind of method is the lack of analysis and verification of real data, so it is difficult to capture some travel behaviors of passengers, so the prediction has a certain limitation. In recent years, with the popularization of urban infrastructure and the increase of urban sensor network, various sensing technologies are becoming more and more mature, and multi-source big data emerges quietly in cities. Therefore, the effective use of multi-source mass data plays a positive role in promoting the development of intelligent transportation system, making the intelligent transportation system change from the traditional model-driven system to a more powerful data-driven system [1]. In addition, the development of distributed computing allows us to process more massive amounts of data more quickly. Therefore, the multi-source spatiotemporal data in the city provides the basis for
the pattern analysis of traffic flow and the mining of passenger behavior, which can make the passenger flow prediction and early warning in the urban rail transit system achieve better results.

The method based on time series has been widely used in traffic flow prediction. Most of the models are based on the classic Box & Jenkins auto-regressive integrated moving average model for road traffic flow prediction. Based on the variable of historical traffic flow, Getanda introduces other exon variables and uses AriMax model to predict the traffic flow [2]. Agafonov proposed the space-time ARIMA model, which also considered the Time and Space information and integrated them into the model as the weight information of linear combination, thus achieving high robustness [3].

This paper focuses on the study of passenger flow in urban rail transit system, including analysis, prediction and early warning of passenger flow in rail transit system. The characteristics of passenger flow in urban rail transit system are analyzed macroscopically, and the spatiotemporal behavior of passengers, including individual and group, is analyzed microscopically. The normal and abnormal patterns of passenger flow and the characteristics of passenger travel behavior are excavated to provide insight for the understanding of traffic flow and subsequent prediction and early warning.

2. Multi-step Prediction of Rail Transit Passenger Flow Based on Spatio-temporal Attention Network

2.1. Relevant Summary

In the past few decades, the development of science and technology and the advancement of urbanization have brought convenience to People's Daily life, but at the same time, the increase of urban population has also brought a series of traffic problems, such as traffic congestion, excessive energy consumption and carbon emissions. In recent years, intelligent transportation system (ITS) has become a very effective solution to improve transportation management and service, and ITS success depends on accurate and timely traffic flow status information. Reliable and accurate traffic flow prediction can provide and support for route guidance, traffic control, and effectively reduce the traffic congestion and traffic accidents, because of its practical application in many ways brought the huge potential, traffic forecasting has become a hot research topic, has been also plays an important role in modern traffic system [4].

According to the length of Prediction Horizon, passenger flow Prediction problems can be divided into the following two categories:

- Short-term forecast, the passenger flow forecast for the next 5 minutes to 30 minutes.
- Medium- and long-term forecast, for the next 30 minutes and more passenger traffic forecast.

Some traditional statistical models can perform well in short-term forecasting, but due to the uncertainty and complexity of traffic flow, these methods are less effective for medium- and long-term forecasting. Generally speaking, for the short-term traffic forecast, the single-step forecasting method is used, while for the medium and long-term forecast, the multi-step forecasting method is needed. Compared with single-step forecasting, multi-step forecasting of passenger flow has more significance in practical application [5-6]. For example, for traffic managers, multi-step prediction information is helpful to develop more effective traffic control strategies to alleviate traffic congestion and thus improve the efficiency of resource allocation. For passengers, the multi-step prediction information is beneficial to route planning and transportation choice before travel. In this study, we hope to predict the mid-term and long-term passenger flow of each subway station in the future based on the historical passenger flow of each subway station in the urban rail transit system.

The existing research on medium- and long-term traffic flow prediction can be roughly divided into two categories: model-driven approach and data-driven approach. Model-driven approaches use mathematical tools (such as differential equations) and physical models to solve traffic problems through computational simulations. However, the simulation process requires not only complex system design, but also high mathematical foundation, and unrealistic assumptions and simplification in modeling will reduce the prediction accuracy. Therefore, with the rapid development of traffic data
collection and storage technology, a large number of researchers are turning their attention to data-driven approaches [7]. Classical statistical model and machine learning model are the two main representatives of data-driven methods. Among the classical statistical models, time series models such as ARIMA and its variants are one of the most commonly used methods. However, this model is limited by the assumption of stationarity of time series and does not consider the spatiotemporal correlation, so the representation of nonlinear features is limited and the classical statistical model is challenged by machine learning methods. The machine learning model can achieve higher prediction accuracy and more complex data representation, and the commonly used algorithms include the nearest neighbor algorithm (KNN), support vector machine (SVM), etc.

2.2. Prediction Model

(1) Spatial and Temporal Attention Network Architecture

We propose a spatial-temporal attention network (STAN) as a multi-step prediction model for the ridership of urban rail transit system, which assumes that the future ridership of a subway station will not only be affected by its past ridership, but also by the ridership of neighboring stations. In this section, we elaborate on the architecture of the proposed space-time cylindrical force network. The spatial and temporal implication network is composed of two parts. The first is the spatial correlation fitting module, which is composed of a spatial subnetwork, namely the graph annotation force network (GAT), which is mainly used to capture the correlation between the width of the space near the subway station. Followed by time dependence fitting module, by the time the child network structure, the short - and long-term memory network (LSTM), is mainly used to capture the subway station traffic temporal correlation of the prediction framework is e sequence based on neural network to the sequence architecture (Seq2Seq), input is a sequence of output as well as a sequence, which is consistent with the input and output structure of MIMO strategy [8-9].

We input is multiple sites in the past, r the flow of a time step, for each time step, the first to use the space of spatial correlation network capture multiple site traffic, will be the result when the input to Anthony refrained network capture the dependencies between each time step, the Encoder (Encoder) coding, after the output to the Decoder (Decoder), and in every time step access all connect to the Internet (Full Connected Networks) step 7 time of traffic forecast for the future.

(2) Spatial Subnetwork

To each node of the input features for the output mapping, we first use a Shared role in t time interval linear transformation matrix of each station characteristics, using the Shared attention mechanism to calculate weight between each site's attention, and attention between ej representative site I and j weights, a representative of attention mechanism mapping:

\[ e_{ij} = a(W^{T}x_{i}, W^{T}x_{j}) \] (1)

We use a single-layer forward neural network to map our attention mechanism A, specifically by first splicing an inner machine with a vector and then introducing the nonlinear activation function LeakyRelu. So eij

\[ e_{ij} = \text{LeakyReLU}(a \left[W^{T}x_{i}, W^{T}x_{j}\right]) \] (2)

Represents the influence of the characteristics of subway station j on subway station I. Here r transposed, \(||\) for splicing operator. In order to make the learning process more stable, we introduced the multi-head attention mechanism, and used k independent attention mechanisms to calculate, and then took the mean value of k independent calculation results, and connected to the nonlinear activation function.

(3) Time Subnetwork

Traffic flow data is significantly time dependent, and flow patterns from a few hours ago can have a long-term impact on the current state. We use the spatial subnetwork to capture the spatial
correlation of passenger flow. Based on the output of the spatial subnetwork, we use the temporal subnetwork to capture the time dependence of passenger flow, especially the long-term dependence [10].

Cyclic neural network (RNN) is a feature mapping function containing at least one feedback loop, which is often used to fit time-dependent relationships. The input vector at time \( t \) is expressed as \( X_T \), the hidden layer vector is expressed as \( H_T \), the weight matrix is expressed as \( WH \) and \( UH \), and the deviation term is expressed as \( BH \).

However, the cyclic neural network usually has gradient explosion and gradient disappearance when the sequence is long, so the fitting effect of long sequence is poor. In order to solve this problem, related scholars put forward the Long Short-Term Memory Network (LSTM), a special type of RNN, aiming to avoid the problems in the original RNN model. The key to LSTM is the unit state, which allows information to flow along the network. LSTM can remove or add signals to the cell state, regulated by structures called "gates", including Input Gate, Forget Gate and Output Gate.

The predicted value of time \( t \) to the target subway station \( k \) is obtained by nonlinear transformation of \( HT \) through a fully connected nerve two channels, i.e

\[
\hat{x}^k_i = \sigma(W_o h_i + b_o) \\
\text{(3)}
\]

Correspondingly, the sum of \( T \) future time steps of subway station \( k \) is

\[
\hat{x}^k = (\hat{x}^k_1, \hat{x}^k_2, ..., \hat{x}^k_T) \\
\text{(4)}
\]

3. Experimental Evaluation

3.1. Data Preparation
In this paper, the traffic flow data of all subway stations in the municipal rail transit system in a certain month is used for verification. The data set contains 13 million users and 240 million transactions, covering multiple subway stations. A more important problem is the selection of sink time interval. Generally speaking, a time interval of less than 5 minutes will make the sink flow fluctuate greatly, which is not conducive to prediction. If the sink time interval is set too long, it will also lead to the loss of recent information. Considering our practical application, we set the convergence interval as 10 minutes. We aggregate the transaction records of each subway station in a time interval of 10 minutes, calculate the total number of people passing through each subway station in every 10 minutes, and form the passenger flow of each subway station. Considering the running time of the subway, we filter out the passenger flow in invalid time periods, such as the passenger flow in the middle of the night and the early morning, and extract the passenger flow from 6 am to 23 PM at each station. Considering the limitation of computing resources and time, we randomly selected 80 subway stations to test the model.

3.2. Parameter Setting
There are a total of 5 parameters in our model, including the time step length \( T \) of the input sequence, the time step length \( T' \) of the prediction sequence, the distance threshold \( D \) near the subway station, the number of multi-head attention mechanisms \( K \) of the spatial subnetwork, and the hidden state dimension \( M \) of the time subnetwork. We set \( T=18 \), \( T'=6 \), that is, the passenger flow of multiple stations in the past 3 hours is used to predict the passenger flow of one subway station in the future 1 hour. The distance threshold of a subway station is set as 1000m, that is, when predicting the future passenger flow of a station at a certain location, the influence of the passenger flow of a subway station within 1000m on it is taken into account. The number of multi-head attention mechanisms \( K \) and the hidden state dimension \( M \) of the time subnetwork are both set to 16.
4. Experimental Result

4.1. Comparison of Different Models

Table 1. Comparison of multi-model multi-step prediction effect

| T     | Metrics | ARIMA | SVR  | RF   | DNN   | RNN   | LSTM  | STAN  |
|-------|---------|-------|------|------|-------|-------|-------|-------|
| 10 min| MAE     | 23.37 | 25.01| 25.5 | 18.63 | 17.93 | 17.49 | 16.15 |
|       | RMSE    | 45.41 | 38.36| 46.36| 35.71 | 33.51 | 33.2  | 29.98 |
| 20 min| MAE     | 23.39 | 34.61| 30.51| 19.62 | 19.34 | 18.36 | 17.21 |
|       | RMSE    | 45.44 | 53.29| 58.6 | 38.48 | 37.28 | 34.73 | 31.17 |

As shown in Table 1, the DNN here uses a MIMO strategy. It can be seen that the prediction indexes MAE and RMSE of the Stan model are basically the lowest among all the models under each prediction step size. SARIMA model considers periodicity of sequence, so its prediction accuracy has a low correlation with step size. However, its performance is lower than that of STAN and other deep learning models. This is because although SARIMA considers periodicity, it has a weak representation ability, so it is not as good as deep learning models in data fitting ability. In addition, due to the complex nonlinear characteristics of subway passenger flow, the performance of deep learning models with strong characterization ability is better than that of traditional machine learning models. The performance of LSTM is better than DNN by introducing time dependence. However, our STAN model can not only fit the time dependence, but also fit the spatial correlation, so its performance is better than other models.

4.2. Comparison of Multi-step Prediction Strategies

Figure 1. Within DNN iteration strategy compared with multiple input multiple output strategy within DNN

As shown in Figure 1, although the performance of the iterative strategy and the MIMO strategy is similar when the step size is small, the effect of the MIMO strategy is significantly better than that of the iterative strategy as the step size increases. This is because iterative strategies generate cumulative errors in the process of prediction, while MIMO strategies do not have this problem.

4.3. Impact of Spatial Information Introduction on Prediction
As shown in Figure 2, the prediction effect of the spatial information is better than that of the MIMO_DNN in each step size, which indicates that the introduction of the passenger flow near the subway station in the space is conducive to the improvement of the prediction effect. You can also see the comparison between the prediction effects of Spatial_DNN and STAN, where STAN is superior to Spatial_DNN for all step sizes. On the one hand, STAN can fit the time dependence, and on the other hand, STAN's spatial subnetwork can fit the space information more effectively than Spatial_DNN.

5. Conclusions
The variation of passenger flow in the urban rail transit system is complex and highly nonlinear, and the traditional linear model is difficult to fit its characteristics. However, the deep learning model can fit the nonlinear characteristics of passenger flow in the rail transit system due to its strong representation ability. But in general the depth of the neural network is difficult to characterize spatial correlation and time dependence of metro traffic, so we put forward the space-time network STAN attention to fitting the space-time characteristics of traffic, use the empty Qing figure note ZhangLi network based on fitting since network spatial correlation, time that use based on the length of the memory of the subnet to fitting time dependence. We use the MINO strategy for multi-step prediction. The results of experiment on real urban subway traffic data indicate that the performance of the model is better than that of the traditional machine-learning hazel-model and the general deep learning model, and the introduction of spatial information does improve the prediction performance. The model can achieve a good fitting effect for both urban and suburban subway stations with regular passenger flow.

Acknowledgements
This work was sponsored by Dalian Academy of Social Science, Liaoning Province. Project: Study on optimization strategy of intelligent Dalian rail transit. Project No. 2020dlsky095.

References
[1] Zhang Z, Zhang A, Sun C, et al. Research on Air Traffic Flow Forecast Based on ELM Non-Iterative Algorithm [J]. Mobile Networks and Applications, 2020(2):1-15.
[2] Getanda V B, Oya H, Kubo T, et al. DATA GROUPING TECHNIQUES’ PERFORMANCE ANALYSIS IN GM(1,1)'s PREDICTION ACCURACY IMPROVEMENT FOR FORECASTING TRAFFIC PARAMETERS[J]. Control and Intelligent Systems, 2020, 48(1):25-34.
[3] Agafonov A A, Myasnikov V V. Method for the reliable shortest path search in time-dependent stochastic networks and its application to GIS-based traffic control[J]. Computer Optics, 2016, 40(2):275-283.

[4] Song X, Li W, Ma D, et al. A Match-Then-Predict Method for Daily Traffic Flow Forecasting Based on Group Method of Data Handling [J]. Computer Aided Civil & Infrastructure Engineering, 2018, 33(11):982-998.

[5] Si-Yan L, De-Wei L, Yu-Geng X, et al. A short-term traffic flow forecasting method and its applications [J]. Journal of Shanghai Jiaotong University, 2015, 20(002):156-163.

[6] Zhu H, Xie Y, He W, et al. A Novel Traffic Flow Forecasting Method Based on RNN-GCN and BRB [J]. Journal of Advanced Transportation, 2020, 2020(24):1-11.

[7] Wang X, Shao C, Yin C, et al. Short term traffic flow forecasting method based on ARIMA-GARCH-M model[J]. Beijing Jiaotong Daxue Xuebao/Journal of Beijing Jiaotong University, 2018, 42(4):79-84.

[8] Li W, Guo D, Fang X. Multimodal Architecture for Video Captioning with Memory Networks and an Attention Mechanism [J]. Pattern Recognition Letters, 2017, 105(APR.1):23-29.

[9] Ji H, Xue F, Zhang W, et al. Attention-based spatial–temporal hierarchical ConvLSTM network for action recognition in videos[J]. IET Computer Vision, 2019, 13(8):708-718.

[10] Xu L, Wang Z, Liu Y. The spatial and temporal variation features of wind-sun complementarity in China [J]. Energy Conversion and Management, 2017, 154(DEC.):138-148.