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A RAPID PREDICTION SUBWAY PASSENGER FLOW FORECASTING BASED ON MULTI-STATION AND MULTI FACTORS IN RAIL TRANSIT

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ABSTRACT:

With the rapid development of urban rail transit, more and more people choose to travel by subway. Therefore, accurate passenger flow forecasting is of great significance for passengers and municipal construction, and contributes to smart city services. In this paper, we propose a multi-type attention based network to forecast the subway passenger flow with multi-station and external factors. The proposed network has different types of attention mechanisms to adaptively extract relevant features including multi-station, external factors and historical data. In addition, the hierarchical attention mechanism is used to model the hierarchical relationship between subway lines and stations. And the embedding method is applied to better combine the different kinds of data. Experiments on real subway passenger flow data in a city in China demonstrate that our method outperforms five baseline methods. Moreover, our method can visualize the impact of different stations and other factors on traffic, which plays an important role in passenger travel and subway dispatch.

INDEX TERMS Passenger flow forecasting, attention mechanism, recurrent neural networks.

I. INTRODUCTION

In recent years, rail transit has developed rapidly. As an important part of rail transit, the subway has become the main choice for people's travel with its timely and efficient advantages. Therefore, reliable and accurate subway passenger flow forecasting is significant for passengers, transit operators, and public agencies [1], [2]. Moreover, the study of subway passenger flow is also an important part of the smart city domain [3], [4].

We define passenger flow as the number of passengers passing through the target station per unit time. For subway companies and passengers, passenger flow in the subway station is more concerned, including all inbound and outbound passengers. Metro managers can adjust the number of subway gates and the running interval of the subway according to the passenger flow in the station, and passengers can adjust their own travel routes to avoid crowding. Therefore, this paper focuses on the trend of passenger flow in subway stations. From the time dimension, the forecasting of passenger flow can be regarded as the prediction of time series data, and there have been many studies on it. These studies focus on the prediction of a single source of time series data, and try to find the interconnection in the time dimension. However, The associate editor coordinating the review of this manuscript and approving it for publication was Miltiadis Lytras.

the subway passenger flow forecasting can be considered as a typical time-space problem, so it is not enough to consider only the information of the time dimension. Taking into account the characteristics of urban subway, we divide all the factors affecting passenger flow into three parts: the influence of subway stations on each other, external factors and historical data.

A. THE INFLUENCE OF SUBWAY STATIONS ON EACH OTHER

Urban subway can be regarded as a network system with the spatial topological relationship, nodes of which are subway stations. Passengers' travel and transfer make the subway stations interact with each other. An intuitive example is the impact among sites on the same subway line. If the passenger flow of the upstream site is large, after a period of time, the

passenger flow of the downstream site will increase accordingly. In addition, due to the division of urban functional areas [5], stations that are not on the same line would also interact with each other. For example, during the morning rush hour, passengers near a residential area flood into the central business district (CBD) to work. Similarly, during the evening rush hour, passengers return to the residential area from the commercial area. We show the inbound passenger flow of a site in the residential area and the outbound flow of a site in the commercial area in Fig. 1(a). It can be seen fromthe graph that the trend of the two curves is roughly the same during the morning rush hour. A schematic diagram of this phenomenon is shown in Fig. 1(b).

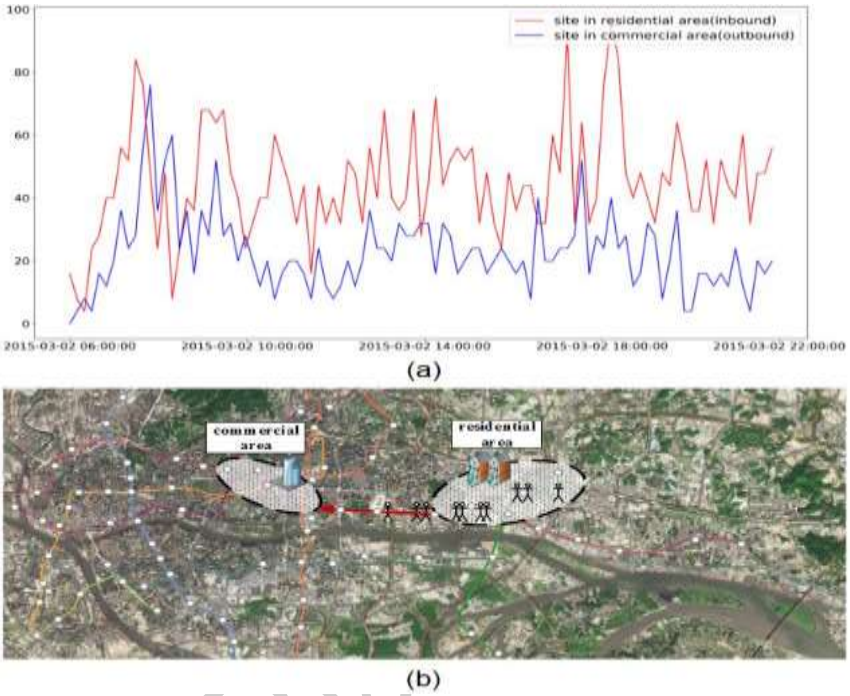

FIGURE 1. (a) Inbound and outbound passenger flow in residential and commercial area during 2019-03-02 10:00 to 2019-03-02 22:00.

(b) Schematic diagram of passenger flow distribution during morning rush hour.

It can be seen from the above analysis that the relationship between the stations will also be affected by the subway lines. In general, for a target station, all the other stations, namely common stations, have different effect at different time. And the traffic data of the entire subway can be regarded as a hierarchical structure due to the inclusion relationship between the line and the site.

B. THE INFLUENCE OF EXTERNAL FACTORS

In addition to the subway stations, there are many factors that affect the passenger flow of the target station, including the properties of the station itself and environmental factors. For predicting time series data, the properties of the target station do not change over time, so these properties do not affect trend prediction. Environmental factors, such as weather and season, are characteristics of the time dimension and have a certain impact on passenger flow. Considering the passengers' age and occupation distributions, the traffic flow is related to the workday [6], i.e., passenger flow during the weekend and the working day are different. In addition, some studies have shown that holidays also have a certain impact on passenger flow. For example, during the Spring Festival, the passenger flow present a special form [7]. Moreover, different seasons and months also have some impact on passenger flow. All of these related factors are called external factors.

C. THE INFLUENCE OF HISTORICAL DATA

For urban subway, the daily passenger flow is basically the same, which can be considered as a time series data with a daily cycle. And for time series data, historical data contains important information.In

this paper, we propose a Multi-Type Attention-based Network to forecast the subway passenger flow with multi-station and external factors (subMTAN).

The proposed network has different types of attention mechanisms for multi-station, external factors and historical data. It consists of two parts: passenger flow representation and passenger flow forecasting. In the representation part, we use relevant factors to represent the passenger flow at a certain moment.

Different attention mechanisms are used to model different data structures and dynamically adjust the weights among different factors. In the forecasting part, we use a temporal attention mechanism to select relevant states across all the timestamps. These two parts can not only adaptively select the most relevant features, but also capture the long-term temporal dependencies of the passenger flow appropriately. Specifically, the attention vector for multi-station in the first part can be used to represent the influences of common stations on the target at different time. This plays an important role in the early warning and dispatch of subway passenger flow

II. RELATED WORK

A. SUBWAY PASSENGER FORECASTING

Auto regression-based models (e.g., ARIMA and VAR) are widely used in subway passenger forecasting. They show their effectiveness on various real world applications, but they cannot model nonlinear relationships and show poor performance on long-term prediction. In recent years, there have been some traffic prediction studies that have developed the spatial-temporal prediction approaches. Xu *et al.* [8] proposes a method that can forecast complex data with both spatial and temporal attributes. Xie *et al.* [9] proposes a hybrid temporal patio forecasting approach to obtain the passenger own status in HRTH. The approach combines temporal forecasting based on radial basis function neural network (RBF NN) and patio forecasting based on spatial correlation degree. Zou *et al.* [10] also proposes a space-time diurnal method to predict short-term freeway travel times which considers spatial and temporal correlation and diurnal pattern of travel times. These studies take into account spatial and temporal travel time information simultaneously in the prediction approach. With the development of deep learning, recurrent neural networks (RNNs) [11], [12], a type of deep neural network specially designed for sequence modeling, have received a great amount of attention due to their edibility in capturing nonlinear relationships. Traditional RNNs, however, suffer from the problem of vanishing gradients and thus have difficulty capturing long-term dependencies. Recently, long short-term memory units (LSTM) [13] and the gated recurrent units (GRU) [14] overcome this limitation and achieve great success in various applications. In recent years, the use of deep learning models for passenger row prediction has increased. Toque *et al.* [15] uses the LSTM to forecast dynamic public transport origin-destination matrices, and suggests that future research should consider the impact of exogenous variables such as weather and traffic accidents. Polson and Sokolov [16] uses deep learning methods to predict short-term traffic row in Chicago and takes into account the effect of extreme weather to improve the accuracy of forecasting results. For external factors, in addition to the weather and traffic accidents mentioned in the two papers above, Li *et al.* [6] take into account the in faience of weather, holidays, peak hour and other factors in the forecasting process. Zheng *et al.* [17] proposes a semi-supervised learning approach based on a co-training framework that consists of two separated classifiers. One is a spatial classifier based on an artificial neural network. The other is a temporal classifier based on a linear-chain conditional random field. These models do not take into account the different degrees of influence between features.

B. ATTENTION MECHANISM

Recently, attention mechanism has become popular due to its success in general sequence-to-sequence (seq2seq) problems. Bahdanau *et al.* [18] first introduces a general attention model in translation task. Later, researchers developed a number of multilevel attention-based models to select the relevant features and hidden states in different applications [19], [20]. For the hierarchical structure of documents, Yang *et al.* [21] propose a hierarchical attention network for document classification. It has two levels of attention mechanisms applied at the word and sentence-level, enabling it to attend differentially to more and less important content when constructing the document representation. This hierarchical structure is also suitable for subway

passenger flow data. Tao *et al.* [22] propose a hierarchical attention-based Recurrent Highway Network (HRHN), which incorporates spatiotemporal feature extraction of exogenous variables and temporal dynamics modeling of target variables into a single framework. Moreover, by introducing the hierarchical attention mechanism, HRHN can adaptively select the relevant exogenous features in different semantic levels. To forecast the time series data, Qin *et al.* [23] pro-poses a dual-stage attention-based recurrent neural network (DA-RNN) to select the relevant driving series at each time interval and select relevant states across all the timestamps. These attention-based seq2seq models are widely used in general sequence-to-sequence applications, but the actual situation needs to be considered in passenger flow prediction, and the accuracy needs to be improved. In this paper, we follow these ideas, and propose an attention-based network to better forecast the subway passenger flow using spatial and temporal travel time information simultaneously.

The daily passenger flow is basically the same, which can be considered as a time series data with a daily cycle. And for time series data, historical data contains important information. In this paper, we propose a Multi-Type Attention-based Network to forecast the subway passenger flow with multistation and external factors. The proposed network has different types of attention mechanisms for multistation, external factors and historical data. It consists of two parts: passenger flow representation and passenger flow forecasting. In the representation part, we use relevant factors to represent the passenger flow at a certain moment. Different attention mechanisms are used to model different data structures and dynamically adjust the weights among different factors. In the forecasting part, we use a temporal attention mechanism to select relevant states across all the timestamps. These two parts can not only adaptively select the most relevant features, but also capture the long-term temporal dependencies of the passenger flow appropriately. Specifically, the attention vector for multi-station in the first part can be used to represent the influences of common stations on the target at different time. This plays an important role in the early warning and dispatch of subway passenger flow.

We first review the related work in Section Then we introduce the notations used in this work and the problem we aimed to study. we introduce the proposed network in detail. we collect real subway passenger flow data for forecasting, and use experimental results to demonstrate the effectiveness of our proposed method.

III. PROPOSED SYSTEM:

Rail transit has developed rapidly. As an important part of rail transit, the subway has become the main choice for people's travel with its timely and efficient advantages. Therefore, reliable and accurate subway passenger flow forecasting is significant for passengers, transit operators, and public agencies Moreover; the study of subway passenger flow is also an important part of the smart city domain We define passenger flow as the number of passengers passing through the target station per unit time. For subway companies and passengers, passenger flow in the subway station is more concerned, including all inbound and outbound passengers. Metro managers can adjust the number of subway gates and the running interval of the subway according to the passenger flow in the station, and passengers can adjust their own travel routes to avoid crowding. Therefore, this paper focuses on the trend of passenger flow in subway stations. From the time dimension, the forecasting of passenger flow can be regarded as the prediction of time series data, and there have been many studies on it.

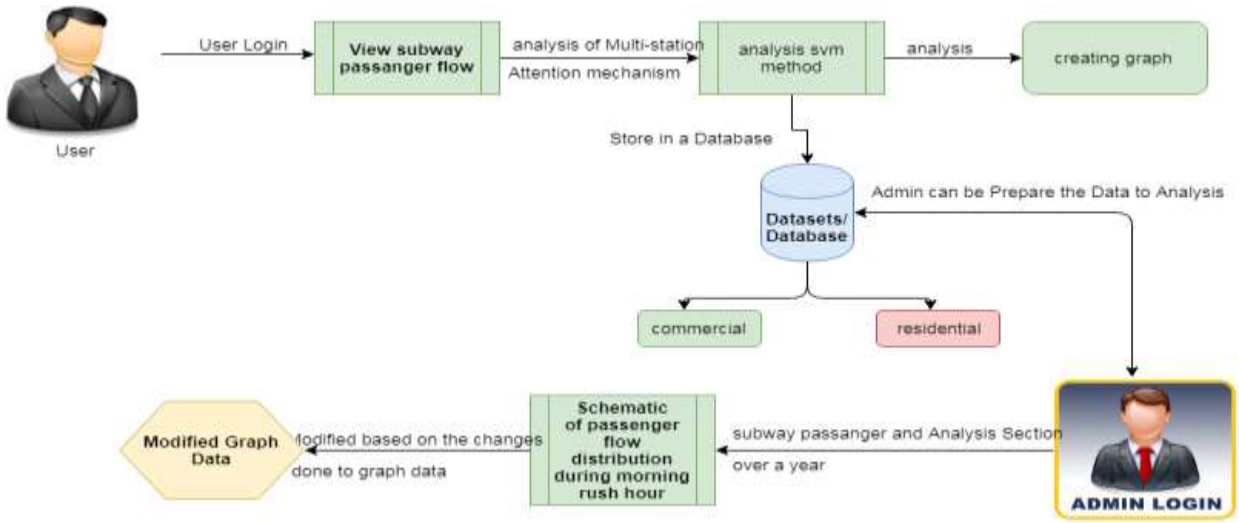

FIG 2: PROPOSAL FRAMEWORK

1. **DATASET**

We conduct our experiments on real subway passenger flow dataset of containing the information on passenger inbound and outbound. For each common station, we sum the number of passengers entering and leaving the station to indicate the passenger flow and sample it at 10-minute intervals.

2. **MODEL COMPARISON AND PREDICTION RESULTS**

The basic idea of the is to treat the data sequence formed by the predicted object over time as a random sequence, and use a mathematical model to approximate the sequence. In this paper, we do stationary processing and test the order of the model models a data set based on relevant features and predicts the time series using the tree model. In this paper, we use common stations and external factors as relevant features

3. **VISUALIZATION**

we can find where the network is focused on most at each time step We find that each station has a different impact on the target at different time. We represent the weights as different colors and draw them on the city map; It is found that stations that have a strong influence in the morning are almost all in residential areas. This is consistent with our previous analysis.

4. **GRAPH ANALYSIS**

Graph analysis is the part where admin can knows the statistics about process of details. The data are taken from the project flow and it shows until updated value. The data are gives clear solution to admin that part of improvement and user satisfaction and other factors.

These studies focus on the prediction of a single source of time series data, and try to find the interconnection in the time.

ALGORITHM:

SUPPORT VECTOR MACHINE (SVM)

"Support Vector Machine" (SVM) is a supervised machine learning algorithm which can be used for both classification and regression challenges. However, it is mostly used in classification problems. In this algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiate the two classes very well (look at the below snapshot). The SVM algorithm is implemented in practice using a kernel. The learning of the hyper plane in linear SVM is done by transforming the problem using some linear algebra, which is out of the scope of this introduction to SVM. A powerful insight is that the linear SVM can be rephrased using the inner product of any two given observations, rather than the observations themselves. The inner product between two vectors is the sum of the multiplication of each pair of input values. For example, the inner product of the vectors [2, 3] and [5, 6] is 2*5 + 3*6 or 28. The equation for making a

prediction for a new input using the dot product between the input (x) and each support vector (xi) is calculated as follows:

$$f(x) = B0 + sum (ai * (x, xi))$$

It can be seen from the above analysis that the relationship between the stations will also be affected by the subway lines. In general, for a target station, all the other stations, namely common stations, have different effect at different time. And the traffic data of the entire subway can be regarded as a hierarchical structure due to the inclusion relationship between the line and the site.

CONCLUSION

In this paper we propose a multi-type attention-based network for forecasting the subway passenger flow with the multi-station and external factors. The model contains three different attention mechanisms to adaptively select the relevant spatial and temporal features for the target passenger flow. With this weighted representation, we use encoder decoder architecture to predict the passenger flow. In order to include more different kinds of data, we bucket the numerical data and add an embedding layer to unify categorical and numerical data. In the future, we will expand more relevant features, including some text or image information. We believe that more information will help with the prediction. Moreover, we will explore more efficient encoder unit and better model structures. Accurate passenger row forecasting is important for both cities and passengers, and has a positive impact on the construction of smart city.

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