# A Passenger Flow Prediction Method Using SAE-GCN-BiLSTM for Urban Rail Transit

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### **ABSTRACT**

To address the problems of existing passenger flow prediction methods such as low accuracy, inadequate learning of spatial features of station topology, and inability to apply to large networks, a SAE-GCN-BiLSTM-based passenger flow forecasting method for urban rail transit is proposed. First, the external features are extracted layer by layer using stacked autoencoder (SAE). Then, graph convolutional network (GCN) is used to capture the spatial features of station topology, and bi-directional long and short-term memory network (BiLSTM) is used to extract the bi-directional temporal features, realizing the extraction of the spatio-temporal features. Finally, external features and spatio-temporal features are fused for accurate prediction of urban rail transit passenger flow. The experimental results show that the proposed method is higher than several other advanced models in the evaluation indexes under different granularities, indicating that the model effectively develops the accuracy and robustness of urban rail transit passenger flow prediction.

#### **KEYWORDS**

Bi-Directional Long and Short-Term Memory Network, External Features, Feature Fusion, Graph Convolutional Network, Passenger Flow Prediction, Rail Transit, Spatial-Temporal Features, Stacked Autoencoder

### INTRODUCTION

As the result of the accelerated development of urban rail transit (Z. Cheng et al., 2021), the flow of passenger data is exploding and the data structure is becoming increasingly more complex, so the task of constructing a city rail-transit passenger flow forecast is imminent. Traditional prediction models based on statistical theory show disadvantages, such as low prediction accuracy and difficulty in prediction when dealing with prediction tasks of large-scale complex data (Zhang, Z., et al., 2023). The emergence of prediction approaches utilizing machine learning has well solved the previous problem of traditional prediction methods centered on statistical theory being difficult to deal with when working with large-scale complex data, and machine learning approaches can complete data processing tasks more accurately and efficiently to achieve the expected results.

To learn the feature information of passenger flow data more comprehensively, many scholars have proposed a prediction model that combines multiple models. Zhang, Z., et al. (2020) suggested

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a multilayer long- and short-term memory network (LSTM)-based passenger flow prediction method, which integrates multiple sources of traffic data and various techniques to refine the expression of passenger flow prediction. In the above studies, forecasting is mainly done for the historical information data of passenger flow, but the urban rail transit passenger flow is additionally impacted by some external factors, including weather conditions, holidays, surrounding stations, and other factors. Therefore, Jing et al. (2020) incorporated the data of external characteristic factors that affect passenger flow into the model's input data, used the method of learning and updating the step rate to predict the number of incoming passengers in a certain time period, and weighted it with the historical data to predict the passenger flow for the subsequent interval.

However, considering the complexity, diversity, and large scale of urban rail transit passenger flow data, traditional prediction models often have some limitations, such as difficulty in fully extracting both temporal and spatial features, and difficulty in fully extracting deep features. To address these issues, a SAE-GCN-BiLSTM-based city rail traffic passenger-flow prediction method that combines a stacked autoencoder (SAE), a graph convolutional network (GCN) and a bi-directional long- and short-term memory network (BiLSTM) is suggested to enhance the reliability of the short-term passenger flow prediction model. The innovations of this article can be summarized in four points:

- To solve the drawbacks of convolutional neural network in passenger flow prediction, the GCN
  is introduced, which enhances the extraction ability of spatial feature information of station
  topological structure map and fits the real passenger flow data better.
- 2. To fully learn the historical passenger flow time series data, BiLSTM is employed to completely exploit the global features of time series and enhance the extraction ability of temporal features.
- 3. To enhance the extraction ability of the model in the spatial structure and time series features, the GCN-BiLSTM method is proposed, and the features of GCN and BiLSTM models are fused to achieve efficient extraction of the whole passenger flow data representation.
- 4. To fully extract the deep features of external factors affecting passenger flow, this paper selects 15 external factors data and proposes to use the stack autoencoder model to extract external features layer-by-layer for external factor information to enhance the precision of passenger flow prediction.

## **RELATED WORKS**

According to model development history, short-time traffic forecasting methods mainly include statistical learning-based forecasting models, machine learning-based forecasting models, and deep learning-based forecasting models (Zhang, J., et al., 2020). These three stages are described in detail in the following paragraphs.

Statistical learning-based forecasting models primarily contain the moving average (MA) model (Abellana, 2021), the Autoregressive Integrated Moving Average (ARIMA) model (Su, C., 2020), the variant ARIMA model (Zhang, J., et al., 2024), the Seasonal Autoregressive Integrated Moving Average (SARIMA) model (Liu, S., et al., 2021), and the Kalman filter model, etc. Although these models are theoretically clear and simple to implement, they have poor prediction accuracy when dealing with large-scale complex data tasks.

The main machine learning-based prediction models are the Bayesian algorithm, support vector machine, random forest, decision tree model, and so on. Wu et al. (2020) suggested a novel scaled stacking-gradient boosting decision tree (SS-GBDT). The gradient boosting decision tree (GBDT) model, with data stacking for passenger flow prediction, improves prediction performance. Zhou and Tang (2020) constructed a support vector machine model-based passenger flow prediction model for city rail transit holidays, and they analyzed the characteristics of station passenger flows during holidays by comparing the features of different prediction models. The hybrid prediction models constructed using machine learning have higher prediction accuracy than the traditional mathematical statistics-

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