Multi-Graph Convolutional Network for Short-Term Passenger Flow Forecasting in Urban Rail Transit

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Abstract: Short-term passenger flow forecasting is a crucial task in the operation of urban rail transit. Emerging deep-learning technologies have become effective methods to overcome this problem. In this study, we propose a deep-learning architecture called Conv-GCN combining graph convolutional network (GCN) and 3D convolutional neural network (3D CNN). First, we introduce a multi-graph GCN to deal with three patterns (recent, daily, and weekly patterns) of inflow and outflow separately. Multi-graph GCN network can capture spatiotemporal correlations and topological information in a whole network. Then, a 3D CNN is applied to deeply integrate the inflow and outflow information. High-level spatiotemporal features between different patterns of inflow and outflow, and between stations nearby and far away can be extracted by 3D CNN. Finally, a fully connected layer is used to output results. The Conv-GCN model is evaluated on smart card data of Beijing subway under the time interval of 10 min, 15 min, and 30 min. Results show that this model performs the best among seven other relative models. In terms of the RMSE, the performances under three time intervals have been improved by 9.402%, 7.756%, and 9.256%, respectively. This study can provide critical insights for subway operators to optimize the operation.

Keywords: Multi-Graph; GCN; 3D CNN; short-term; passenger flow forecasting; urban rail transit; deep learning

1. Introduction

Short-term passenger flow forecasting (STPFF) is of critical importance in urban rail transit (URT). For passengers, they can schedule their travels in advance utilizing forecasting results. For operators, they can take immediate measures to avoid traffic congestions. However, it is a challenging task for a citywide prediction because it is easily affected by many factors, such as spatiotemporal dependencies, topological information, incidents, and weather conditions. Models for STPFF range from statistics-based models, such as historical average and autoregressive integrated moving average (ARIMA) [1,2], to machine-learning-based models, such as neural networks and support vector machine [3-5]. Recently, deep-learning-based models have been widely introduced to tackle this problem and have been proved to have great advantages than previous models. For example, they have favorable prediction precisions and can meet real-time requirements. We can also use one model to make predictions in a citywide network [6,7]. Deep-learning-based models can be summarized into four categories as follows.

The first category is the recurrent-neural-network (RNN)-based models. Ma et al. [8] introduced the long short-term memory (LSTM) network for traffic speed prediction for the first time. Fu et al. [9] applied gated recurrent unit (GRU) to perform traffic flow prediction for the first time. However, they only considered the temporal dependencies. Zheng et al. [10] proposed an LSTM architecture via a two-dimensional network which can consider spatiotemporal correlations for short-term traffic forecast. Zhang et al. [7] built a cluster-based LSTM model to conduct STPFF in URT, which can be used especially when the available data is pretty less. Generally, RNN-based models cannot consider overall spatial correlations in a citywide network. Moreover, it will take a longer training time because parallel computing cannot be utilized during training processes.

The second category is the convolutional-neural-network (CNN)-based models, which can extract spatial dependencies even when stations are far away from each other. CNN-based models always treat passenger flows as images so that the convolution operation can be conducted [11]. Residual network (ResNet) [12] is a typical framework using skip-connection between CNN layers and has been proved to be effective in STPFF such as spatiotemporal ResNet models [13,14]. However, CNN-based models can only be used for Euclidean data. All traffic data, which are actually Non-Euclidean data, must be transformed into structural data with a fixed form so that they can be input into CNN-based models. Therefore, some structural information in a network will be lost during preprocessing.

The third category is graph-convolutional-network (GCN)-based models [15]. These models can capture spatiotemporal correlations and topological information between stations or areas. The structural information of Non-Euclidean data can be fully utilized. Moreover, they have faster training speed and fewer parameters than RNN and CNN-based models. Some models considered recent, daily, and weekly patterns during the graph convolutional process [6,16,17]. Recent studies constructed multi-graph networks to capture several kinds of adjacent information, such as proximity, connectivity, and functionality, to improve precision [18,19]. Yu et al. introduced STGCN model [20], enabling much faster training speed with fewer parameters and performing better than many models. The GCN-based models, however, generally use one to four GCN layers. They cannot go as deep as CNN-based models [21]. Therefore, some deep spatial correlations cannot be effectively captured.
The last category is hybrid models, which are complex architectures involving RNN, CNN, or GCN, etc. For example, Zhao et al. [22] integrated GCN and GRU to make traffic prediction. Cui et al. [23] introduced a model combining GCN and LSTM. Park et al. [24] used the transformer model [25] and self-attention mechanism under an encoder-decoder architecture. Zhang et al. [26] designed an architecture including attention mechanism, GCN, and sequence-to-sequence model to conduct multistep speed prediction. After ConvLSTM was firstly introduced [27], CNN and LSTM are often integrated together to perform traffic predictions [28, 29]. Recently, generative adversarial network has begun to attract researchers’ attention and has been applied to traffic time estimation [30]. Generally, these hybrid models are so complicated that it is difficult to reproduce or transplant. Moreover, they cost lots of computing resources and training time.

Overall, existing models present several drawbacks. First, some models cannot capture spatial and temporal dependencies simultaneously. Second, overall topological information was neglected sometimes. Third, Models are so complicated that a lot of computing resources and time will be cost during the training process. Models are not the more complicated the better. How to improve prediction precision using a relatively simpler while more efficient model is also pretty important. To overcome these shortcomings, we proposed a deep learning architecture called Conv-GCN based on multi-graph GCN and 3D convolutional network (3D CNN), which are relatively simple while more effective. The main contributions of this model are as follows.

1. The multi-graph GCN can capture spatiotemporal and topological correlations in a whole network. Three patterns (recent, daily, and weekly) both in inflow and outflow are involved in this model.

2. The 3D CNN can effectively integrate the inflow and outflow information via 3D filters. It can also capture high-level spatiotemporal features between three patterns of inflow and outflow, as well as between stations nearby and far away.

3. The model is evaluated on smart card data from Beijing subway under three time intervals. The model performance always shows the best in all cases among seven other models, showing strong robustness.

The remainder of this study is organized as follows. In section 2, we define the problem and present the model architecture. The multi-graph GCN and 3D CNN used in this model are also described. In section 3, the experimental details and results are discussed. The conclusion is drawn in section 4.

2. Methodology

In this section, the methodological framework is formulated. First, we define the problem to be solved. Second, the model architecture is built. Third, one part of the architecture, the multi-graph GCN, is summarized in detail. Another part, 3D CNN, is introduced finally.

2.1. Problem definition

The goal of this study is to predict the tap-in ridership in URT network using historical smart card data. The historical tap-in ridership can be extracted from smart card data and can be aggregated in different time intervals, such as 10 min, 15 min, and 30 min.

We define the URT network as a graph $G = (V, E, A)$, where $V$ is the vertices representing subway stations. $V = (V_1, V_2, V_3, \ldots, V_n)$, where $n$ is the station number. $E$ is the edges between stations. $A \in \mathbb{R}^{n \times n}$ is the adjacent matrix whose elements are all 1 and 0, denoting if there is a link between the two stations. The feature matrix $F \in \mathbb{R}^{n \times m} = (X_r, X_{t-1}, X_{t-2}, \ldots, X_{t-m+1})$, where $n$ is the station number that is ordered according to subway line number; $m$ is the past several time intervals used to predict ridership in the next time interval; and $X \in \mathbb{R}^{n \times 1}$ is the tap-in passenger flow vector in a specific time interval. Each time interval will generate a feature matrix. Therefore, the problem can be defined as Equation (1), where $f(\cdot)$ is the mapping function to be learned using the proposed deep learning architecture.

$$X_{t+1} = f(A; X_t, X_{t-1}, X_{t-2}, \ldots, X_{t-m+1})$$

2.2. Model architecture

The Conv-GCN model architecture is shown in Fig. 1. There are mainly three parts of the model. One is the multi-graph GCN, including the inflow graph and outflow graph, which can easily capture spatiotemporal and topological information. In each graph, three travel patterns, the recent, daily, and weekly patterns, are taken into account to capture temporal correlations. The recent pattern is the passenger flow volumes in the last several time intervals. The daily and weekly patterns are the corresponding information in the same time interval on the last day and on the same day during last week, respectively. Another two parts comprise the 3D CNN layer and fully connected layer, respectively. The 3D CNN layer is used to deeply integrate the inflow and outflow information obtained from the GCN layer. Then, the high-level spatiotemporal information can be extracted. The fully connected layer is used to reduce the dimension of flattening layer, as well as capture the non-linear relationship between high-level features and predicted results.
2.3. Introduction of Multi-graph GCN

The GCN plays a critical role in our proposed Conv-GCN model because of its powerful ability to capture spatiotemporal and topological information. In this study, we apply two graphs, dealing with inflow and outflow, respectively. In recent years, GCN has received great attention. From spectral graph filter [31] to Chebyshev polynomials filter [32], then to first-order filter [15], the GCN layer has experienced significant improvement. The stack of GCN layer with first-order filter can achieve similar effects with k-Chebyshev polynomials filter [20] while it can allow significantly faster training speed and prediction accuracy in most cases [15]. Therefore, we use the GCN proposed by Kipf et al as shown in Equation (2).

\[
X^{i+1} = \sigma \left( \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} X^i W^i + b \right), \quad \tilde{A} = A + I \tag{2}
\]

where \(A \in \mathbb{R}^{n \times n}\) is the adjacent matrix. \(I \in \mathbb{R}^{n \times n}\) is the identity matrix. \(\tilde{D} \in \mathbb{R}^{n \times n}\) is the diagonal node degree matrix of \(\tilde{A}\). \(X^i \in \mathbb{R}^{n \times m}\) is the feature matrix of the \(l_0\) layer, in which \(m\) represents the time steps used to predict ridership in the next time step. \(W^i \in \mathbb{R}^{m \times k}\) is the weight matrix of the \(l_0\) layer, in which \(k\) is the kernel number, namely the output feature number per node. \(b \in \mathbb{R}^{k \times 1}\) is the bias vector. \(\sigma\) is the activation function.

The GCN diagram used in this study is shown in Fig. 2 and Fig. 3. Let’s take station \(E\) as an example. If there is only one subway line as shown in Fig. 2, for the passenger flow prediction of station \(E\), the first GCN layer will capture the influences of adjacent stations \(D\) and \(F\). After stacking another GCN layer, the influence of stations \(C\) and \(D\) will also be integrated into its prediction process. Similarly, in subway network, if \(E\) is an interchange station of two subway lines, it will capture the influence of four adjacent stations in the first GCN layer and the influence of stations adjacent to these four stations in the second GCN layer.

Moreover, we also consider three passenger flow patterns, recent, daily and weekly patterns. In each pattern, the same time steps are applied. This kind of organizing method benefits the prediction precision in three aspects. First, it can capture the temporal correlation between different patterns. Then, the spatial correlations between stations nearby and far away can be considered as well. Finally, the topological information between adjacent stations can also be fully utilized. Two branches deal with inflow and outflow separately. Their results are concatenated together before being input into 3D CNN to deeply integrate inflow and outflow information together as shown in Fig. 1.
2.4. Introduction of 3D Convolutional Network

In our Conv-GCN model, we use the 3D convolutional network (3D CNN), as shown in Fig. 4, rather than a general 2D convolutional network (2D CNN). The 3D CNN was widely applied to computer vision, such as medical image analysis, abnormal event detection and human action recognition [33-35]. It has also been proved to be effective in learning spatiotemporal features [34] for several reasons. First, the 3D convolution kernel can effectively integrate information from different channels together. Second, 3D CNN can model spatiotemporal features better than 2D CNN because 3D convolution is performed spatiotemporally while 2D convolution can only be done spatially. Therefore, we apply a 3D CNN to aggregate the inflow and outflow information output by the GCN layer so that the outflow information can be fully utilized. High-level spatiotemporal features between different patterns of inflow and outflow, as well as between stations nearby and far away, can be extracted.

The output of 3D CNN is flattened and input into a fully connected layer as shown in Fig. 5. The fully connected layer is used to reduce the data dimension, as well as capture the non-linear correlation between high-level features and outputs. By trial and error, we use only one fully connected layer to reduce the dimension of flattening layer to the dimension we used.

![Fig. 4 Diagram of 2D CNN (Top) and 3D CNN (Bottom)](image)

![Fig. 5 Diagram of fully connected layer](image)

3. Experiment

In this section, we will describe the dataset used in our study at first. Then, the evaluation metrics are presented. Several popular models are chosen as baselines. The detailed experimental settings are also discussed. Finally, we analyse the predicted results.

3.1. Dataset description

The Conv-GCN model performance is evaluated on smart card data of Beijing Subway from February 29, 2016 to April 3, 2016. Each record contains card number, tap-in time, tap-in station name, tap-out time, and tap-out station name. The records are integrated into specific time intervals, 10 min, 15 min, and 30 min. We only use the data on weekdays to evaluate the model. The data in the first four weeks are used to train the model and the remaining data in the last week are used to test the model. There are 276 stations in March 2016. Therefore, the adjacent matrix is $A \in \mathbb{R}^{276 \times 276}$. The passenger flow information, namely the feature matrix is aggregated into $F \in \mathbb{R}^{276 \times m}$. Each row of the feature matrix represents a subway station and each column represents the ridership in the specific time interval. All data are normalized to (0, 1) using min-max scaler. The result evaluation is conducted after the predicted results are rescaled to its original scale.

3.2. Evaluation metrics and loss function

We choose the Mean Square Error (MSE) as the loss function. Three indicators, the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and weighted Mean Absolute Percentage Error (WMAPE), are used to evaluate model performances as shown in Equation (3) to (6).

\[
\text{Loss} = \text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (\hat{X}_i - X_i)^2 \quad (3)
\]
\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{X}_i - X_i)^2} \quad (4)
\]
\[
\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |\hat{X}_i - X_i| \quad (5)
\]
\[
\text{WMAPE} = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{\hat{X}_i - X_i}{X_i} \right) \quad (6)
\]

where $\hat{X}_i$ is the predicted value and $X_i$ is the actual value. $N$ denotes the total number of values to be predicted.

3.3. Comparison with state-of-the-art models

We compare the performance of Conv-GCN model with the following models [36]. All models are conducted on a desktop computer with Intel i7-8700K Processor (12M Cache, up to 4.7 GHz), 8 GB memory, and NVIDIA GeForce GTX 1070 Ti.

**HA:** Historical average model. We use the average values in the last time step of three patterns to predict the value in next time step.

**ARIMA:** Autoregressive Integrated Moving Average Model. We use the Expert Modeler in Statistical-Package-for-the-Social-Sciences (SPSS®) software (IBM Corp., USA) to get ARIMA results.

**LSTM:** LSTM was firstly applied to traffic field in 2015 [8]. We apply an LSTM model with two hidden layers.

**ConvLSTM:** We apply a general 2D CNN model with two layers. ConvLSTM was proposed by Shi et al. [27]. It achieved great success in 2015. We also apply a ConvLSTM model with two hidden layers.
ST-ResNet: It was proposed by Zhang et al. [14]. Here, we only adopt three branches of this model and do not use weather data.

ResLSTM: A deep-learning architecture comprises GCN, ResNet and attention LSTM [36].

3.4. Experimental settings

We used Keras and TensorFlow to implement our model. By trial and error, we applied one GCN layer both for inflow and outflow, and one 3D CNN layer after the concatenation of two GCN branch. There are several hyperparameters, the time steps, batch size, kernel number of GCN layer, and filter number of Conv3D layer. To get the best parameter combination, we set time steps as [3, 17], batch size as (4, 8, 16, 32, 64, 128, 256), filter number of Conv3D layer as (1, 2, 4, 8, 16, 32, 64), and kernel number of GCN layer as (6, 9, 12, 15, 18, 21, 24). During parameter tuning, we used the control variate method. The testing results are shown in Fig. 6. According to the variation of RMSE and MAE, the time step, batch size, filter number, and kernel number are set as 10, 64, 16, and 15, respectively. For the time step, we use 30, 20, and 10 time steps for the time interval of 10 min, 15 min, and 30 min, respectively.

3.5. Result analysis

The results are shown in Table 1 and Fig. 7. As is shown, the Conv-GCN always performs best whichever the time interval is. Conventional HA and ARIMA performs the worst no matter in short-term or long-term scenarios. RNN and CNN based models like LSTM and 2D CNN perform better than conventional models. As we can see, hybrid models like ConvLSTM, ST-ResNet, and ResLSTM show more favorable results than single models in most cases. The proposed Conv-GCN gives the best precision in all cases, showing great robustness. In terms of RMSE, the improvements comparing with best existing models are 9.402%, 7.756%, and 9.256% for the three time intervals, respectively. As for MAE, the result improvements are 6.692%, 4.836%, and 5.602%, respectively. The corresponding improvements for WMAPE are 3.946%, 1.627%, and 2.804%.

![Fig. 6 Testing results for choosing hyperparameters](image)

![Fig. 7 Model performance comparison under different time intervals](image)
Table 1 Model performance comparison under different time intervals

| Time Interval | RMSE | MAE | WMAPE | RMSE | MAE | WMAPE | RMSE | MAE | WMAPE |
|---------------|------|-----|-------|------|-----|-------|------|-----|-------|
| HA            | 59.4652 | 29.2990 | 16.60% | 100.8358 | 50.1607 | 18.93% | 317.1108 | 158.6099 | 29.88% |
| ARIMA         | 50.5436 | 27.3968 | 15.53% | 79.9580 | 42.2139 | 15.95% | 189.3329 | 100.3590 | 18.95% |
| LSTM          | 37.1903 | 21.9925 | 12.71% | 53.9216 | 29.5340 | 11.29% | 96.3534 | 55.8265 | 10.76% |
| 2D CNN        | 29.8125 | 18.5460 | 10.43% | 40.2673 | 25.1231 | 9.375% | 64.0458 | 39.6667 | 7.472% |
| ConvLSTM      | 28.7943 | 17.4780 | 9.814% | 37.0923 | 22.4236 | 8.380% | 61.4978 | 36.9768 | 6.962% |
| ST-ResNet     | 28.8943 | 17.4224 | 9.812% | 37.3432 | 22.8570 | 8.545% | 59.3686 | 33.5018 | 6.309% |
| ResLSTM       | 28.3686 | 16.6318 | 9.352% | 36.0444 | 20.7830 | 7.810% | 52.5819 | 32.5819 | 6.134% |
| Conv-GCN      | 25.6992 | 15.5188 | 8.983% | 33.2488 | 19.8687 | 7.678% | 51.6925 | 30.7568 | 5.962% |
| Improvement   | 9.402% | 6.692% | 3.946% | 7.756% | 4.836% | 1.627% | 9.256% | 5.662% | 2.804% |

4. Conclusion

This study proposed a deep learning architecture called Conv-GCN to conduct STPFF in URT. The Conv-GCN was combined with multi-graph GCN and 3D CNN. The multi-graph GCN was used to capture spatiotemporal and topological correlations. The 3D CNN was used to innovatively integrate the inflow and outflow information as well as extract high-level correlations between three patterns of inflow and outflow, and between stations nearby and far away. This model was evaluated on the smart card data from Beijing subway and obtained better performance than HA, ARIMA, LSTM, 2D CNN, ConvLSTM, ST-ResNet, and ResLSTM. Results always show the best no matter in which time interval, indicating strong robustness of this model. Model architecture can also be transplanted to other scenarios such as taxi and bike-sharing systems.

5. Conflicts of Interest

The authors declare no conflict of interest.

6. Acknowledgments

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