Learning to Generate Temporal Origin-destination Flow Based on Urban Regional Features and Traffic Information

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Origin-destination (OD) flow contains population mobility information between every two regions in the city, which is of great value in urban planning and transportation management. Nevertheless, the collection of OD flow data is extremely difficult due to the hindrance of privacy issues and collection costs. Significant efforts have been made to generate OD flow based on urban regional features, e.g., demographics, land use, and so on, since spatial heterogeneity of urban function is the primary cause that drives people to move from one place to another. On the other hand, people travel through various routes between OD, which will have effects on urban traffic, e.g., road travel speed and time. These effects of OD flows reveal the fine-grained spatiotemporal patterns of population mobility. Few works have explored the effectiveness of incorporating urban traffic information into OD generation. To bridge this gap, we propose to generate real-world daily temporal OD flows enhanced by urban traffic information in this paper. Our model consists of two modules: *Urban2OD* and *OD2Traffic*. In the *Urban2OD* module, we devise a spatiotemporal graph neural network to model the complex dependencies between daily temporal OD flows and regional features. In the *OD2Traffic* module, we introduce an attention-based neural network to predict urban traffic based on OD flow from the *Urban2OD* module. Then, by utilizing gradient backpropagation, these two modules are able to enhance each other to generate high-quality OD flow data. Extensive experiments conducted on real-world datasets demonstrate the superiority of our proposed model over the state of the art.

CCS Concepts: • **Applied computing**;

Additional Key Words and Phrases: Urban mobility, origin-destination, traffic flow, spatiotemporal graph learning

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1 INTRODUCTION

Urban simulation and digital twins have been attracting increasing attention for their vital supporting role in policy formulation and development planning [8, 27]. **Origin-destination (OD)** flow data is critical to these leading-edge technologies, because it portrays the population movements between regions in the city [33, 45]. However, high cost and privacy issues may obstruct the large-scale city-wide OD flow data from being collected, which drives researchers to construct models to generate the OD flow data [2, 28, 40, 41, 56].

In urban science, long-standing efforts have been made on OD generation problem from classic physics-derived methods [2, 41, 56] to recent data-driven models [31, 32, 35, 36, 40, 54]. In these works, it is widely adopted that the spatial heterogeneity of the city is the primary cause that drives people to move from one region to another [55]. Therefore, the models proposed in these works take the urban regional features, e.g., demographics and POI distribution (the number of points of interest in different categories), as input and output of the predicted OD flows between regions. From another perspective, the OD flows also have an effect on urban traffic. For example, a huge flow of population movements between two regions will lead to traffic congestion on the roads between the origin and the destination. However, existing works only consider the cause, i.e., urban regional features, but ignore the effects caused by OD flows. Our key observation is that OD generation could benefit from introducing the effect, i.e., the urban traffic, caused by OD flows. Fortunately, with the development of **ICT (Information and Communications Technology)** and **ITS (Intelligent Transportation Systems)**, massive fine-grained traffic data, such as road level traffic speed, has been accumulated by sensors deployed on the road networks [1, 6, 48], which provides a solid foundation for enhancing OD generation models with traffic information [30]. More than that, existing works [17, 21, 49, 53] have demonstrated the feasibility of generating OD flows given the observed traffic information.

Still, it is challenging to generate city-wide daily temporal OD flows with regional features and urban traffic. **First**, there is an obstacle hindering directly combining the OD generation models with the methods which predict traffic information based on OD flows. Since the traditional approaches [55] are based on a simulator to model the relationship between OD flows and urban traffic, they are not differentiable leading to the incapability of optimization with gradients. But the state-of-the-art OD generation models are optimized using the gradient-based technique [28, 40] proved to be effective. **Second**, the impact of temporal OD flows on traffic speed of roads is very difficult to capture due to both spatial and temporal factors [25, 47]. From the spatial perspective, people moving between a pair of specific origin and destination may travel on different routes considering multiple factors [14], such as individual preferences and path distance, which is compounded by the fact that OD pairs and roads are in a many-to-many relationship. The high time sensitivity of the relation between OD flows and urban traffic makes it even harder to capture.

To address above two challenges, we propose a special designed model named **Generating Origin-Destination flows with regional features and Urban Traffic (GODUT),** which consists of two modules: *Urban2OD* and *OD2Traffic*. To overcome the first challenge, we design a cascaded multitask learning framework to integrate the Urban2OD and OD2Traffic modules end-to-end. Specifically, the *Urban2OD* module generates daily temporal OD flows based on regional features, and then the *OD2Traffic* module predicts urban traffic given the OD flows generated from the *Urban2OD* module. In this framework, the two modules will enforce each other during the gradient-based training strategy. In the *Urban2OD* module, we utilize a special designed spatiotemporal graph neural network to model the complex dependencies between urban space and OD flow. In the *OD2Traffic* module, as a solution to the second challenge, we leverage attention mechanism on both OD pair level and time level to predict the urban traffic by automatically capturing the dynamic relations between OD pairs and road networks.

Our primary contributions are three-fold:

— We propose a multitask learning framework, which utilizes the urban traffic information to improve the OD generation results. To the best of our knowledge, we are the first to investigate the feasibility of combining urban regional features and urban traffic in the OD generation task.
— We design a model named **GODUT** to integrate the modeling of the cause and the effect of OD flow: the relationship between regional features and daily temporal OD flow; the dependencies between OD flow and urban traffic.
— Extensive experiments conducted on real-world datasets demonstrate the superiority of our model.

The organization of the remaining part of this paper is detailed as follows. In Section 2, the related works on OD generation and graph neural networks are introduced for convenient understanding and comprehension. Next, the preliminaries of some necessary notations and problem definitions of OD generation will be given in Section 3. Following this, the details of our proposed model are described completely in Section 4. After, the experiments and results are revealed in Section 5. Finally, we give a conclusion to this work and look ahead to future directions in Section 6.

2 RELATED WORKS

2.1 Origin-destination Generation

Recently, researches related to OD generation have been very active, which can be categorized into two groups: physics-based methods and machine learning methods. Traditionally, numerous works [2, 41, 56] utilized physics-inspired traditional methods to model human mobility. The gravity model [56] is motivated by Newton's law of Gravitation and compares population mobility to the universal gravitational force between objects. The Radiational [41] model analogizes population mobility between regions to the process of physical radiation and absorption. These physics-based methods are dedicated to leveraging physical models to explain the underlying mechanisms of human mobility behaviors in urban areas. Based on formulaic models and the spatial distribution information of population in cities, they predict population mobility, i.e., OD flows. However, since these models take into account relatively simplistic factors and are unable to effectively model the complex urban factors impacting human mobility behaviors, their performance is subpar. Recently, machine learning techniques have been introduced into the human mobility modeling domain and achieved the state of the art. The tree-based machine learning models have shown great generalization ability in modeling the dependencies between urban regional features and population mobility [31, 32]. Deep learning methods, including **CNNs (convolutional neural networks)** and **GNNs (graph neural networks)**, have also been reported in the study of human mobility with good performance [34–36, 40]. GMEL adopts GNNs to learn geo-contextual embedding, which enhanced the performance of the tree-based mobility model. However, these works that model the relationship between static urban features and OD flows based on data-driven schema do not incorporate the temporal dynamics, thus they can only assist in obtaining static, regular OD flows and fail to capture the temporal OD dependencies, which our work strives to achieve. While they could use a multimodel-based approach to separately model OD flows at different times in order to capture time-dependent information, due to the lack of modeling of temporal correlations, their performance is also poor, as can be seen from the experimental results in the later sections. However, few works [16] have exploited the effect of OD flows on urban traffic. The reason might be that the relationship between OD flows and traffic is primarily modeled using a simulator-based method [15] which is unable to incorporate with a machine learning model. In this work, we bridge this gap by designing an attention-based neural network that is easy to stack with a neural network-based OD generation module.

2.2 Spatiotemporal Graph Neural Network and Attention Mechanism

Spatiotemporal graph neural networks (STGNN) have been exploited to model the spatiotemporal dependencies in many fields. Recently, STGNN have been applied to model the behavior of particles and simulate complex processes in physics [23, 38]. Moreover, STGNN have been widely used to model the human behavior in urban applications, such as the traffic prediction problem [9, 13, 22, 26, 43, 46, 52] and ride-hailing demand prediction [12, 39]. However, existing works are limited to focusing on partial human movements and do not exploit the potential of STGNN in modeling the spatiotemporal dependencies of city-wide OD flows.

Recent works have successfully applied attention mechanisms to model human movement behavior. Feng et al. utilize attention-based **RNNs (recurrent neural networks)** to predict the next location of individual trajectories [10]. ASTGCN [13] integrates attentions with graph convolutions and temporal convolutions to do the traffic forecasting of flow volumes and speed of vehicles on the road network. Liu et al. [28] utilize **GAT (graph attention networks)** to learn spatial embeddings for regions and predict the commuting flow for a city. Zheng et al. [53] use the attention mechanism to model the relationship between OD flows of vehicles and road traffic volume, which is different from ours. However, none of these works solve the problem of generating the daily temporal OD flows.

3 PRELIMINARIES

3.1 Notations

Regions. The urban space of a city is partitioned into a set of regions, one of which is denoted as $r \in \mathcal{R}$, by certain rules, e.g., road networks and the latitude and longitude. Regions serve as the basic geographic unit of human movement in this paper.

OD Pairs. Origin-destination pairs, denoted as $\{(r_i, r_j)|r_i, r_j \in \mathcal{R}\}$, stand for the two different regions between which human mobility comes up.

OD Flows. OD flow denotes the population of mobility of an OD pair. We use $F^t_{r_i,r_j}$ to represent the temporal OD flow from region r_i to region r_j at t^{th} time slice. Daily temporal OD flow is the regular human mobility at different times on an ordinary day of the year.

Geographic Features. Geographic features reflect the function and attributes of regions in the city, such as demographics of regions and **POIs (point of interests)** located in regions. We use $\{\mathbf{X}_r|r \in \mathcal{R}\}$ to denote the geographic features for regions.

Urban Traffic. The urban traffic are the traffic observation on road networks, such as traffic flows and the traffic speed. In this paper, we adopt the vehicle speed of roads, which represents as $\mathcal{S}^t_k$, where k denotes the identification of road and t means at t time slice.

3.2 Problem Definition

The definition of the problem is to construct a model. The inputs of the model are urban regional features $\{\mathbf{X}_r|r \in \mathcal{R}\}$ and traffic observation $\{\mathcal{S}^t_k|k = 1, 2, \ldots, K \, and \, t = 1, 2, \ldots, T\}$ on road networks in the city. The outputs are daily temporal OD flows $\{F^t_{ij}|r_i, r_j \in \mathcal{R} \, and \, t = 1, 2, \ldots, T\}$. And the model is used to generate the temporal OD flows for region pairs of interest, where the flows are not available.

4 METHODS

4.1 The Framework of GODUT

We will introduce the multitask learning framework of *GODUT* in this part. As shown in Figure 1, this framework includes two modules: *Urban2OD* and *OD2Traffic*. As their names suggest, the

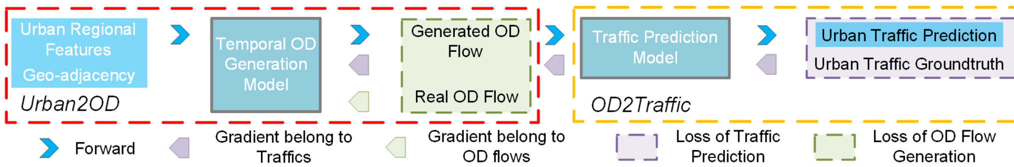


Fig. 1. Framework of our proposed model, i.e., **GODUT**.

Urban2OD module takes pairwise regional features as input and outputs the predicted OD flows between regions, while the *OD2Traffic* module predicts the urban traffic given the OD flows from *Urban2OD* module. Traditionally, the process from OD flows to urban traffic is obtained by traffic simulators, such as MATSim [42] and SUMo [4], of which the simulation process is not differentiable, and thus, it is hard to integrate directly with *Urban2OD* models. The neural network-based *OD2Traffic* module bridges this gap in that the two processes can be modeled under a holistic framework and the models can be optimized through gradient-based techniques, as shown in Figure 1.

In more detail, we leverage a particular designed spatiotemporal graph neural network as the spatiotemporal embedding learner in the *Urban2OD* module, which is composed of **GNNs (graph neural networks)** and RNNs to capture the spatiotemporal dependencies of human mobility. Specifically, GNNs jointly extract the spatial features of a region based on its own features and the surrounding neighborhoods, and RNNs model the daily temporal pattern between human mobility and urban space. After the processing of the spatiotemporal embedding learner, the spatiotemporal features of regions in the city could be captured into the embeddings. Then, the spatiotemporal embedding of an OD pair concatenated with the spatial interaction features, i.e., distance, between origin and destination is used to predict the OD flows through a flow predictor. In the *OD2traffic* module, we aggregate the historical OD flow information belonging to a specific road utilizing the attention mechanism from two levels, OD pairs level and temporal level, and predict the corresponding urban traffic of this road with the aggregated information.

4.2 Urban2OD Module for Generating OD Flow from Urban Regional Features

The spatial distribution of urban functions, which could be reflected by regional features, e.g., demographics and POI locations, causes the spatiotemporal heterogeneity of population mobility in the city. For example, on weekdays, people often travel from residential places to employment places for work in the morning and opposite at nightfall. More specifically, the OD flow volume is affected by the features of origin and destination. What's more, the urban functions of the origin and destination are influenced by not only the interior content but also the neighbors. Besides that, the distance between origin and destination greatly influences the volume of OD flow. Considering the above characteristics of OD flows, we propose the *Urban2OD* module, which produces the OD flow for every OD pair based on urban regional features.

As shown in the Figure 2, the *Urban2OD* module includes two parts, a spatiotemporal embedding learner and an OD flow predictor. Specifically, the first part, i.e., embedding learner is comprised of several Graph Enhanced **GRU (gated recurrent units)**, the structure of which is shown in the upper right of Figure 2. In each unit, the reset gate and the update gate decide whether to retain more long memory or receive more new coming information. The Graph Enhanced GRU is recurrently used to model the temporal pattern of OD flow in daily life. The input of each time step is the temporal embedding of time-of-day with regional features of all regions and the output is the hidden states of current time, i.e., spatiotemporal embedding, which is used to predict the OD flow between every two regions. The computation formula of Graph Enhanced GRU is shown below,

$$\mathbf{r} = \sigma(GCN^r(\mathbf{x}^t \oplus \mathbf{h}^{t-1})), \tag{1}$$

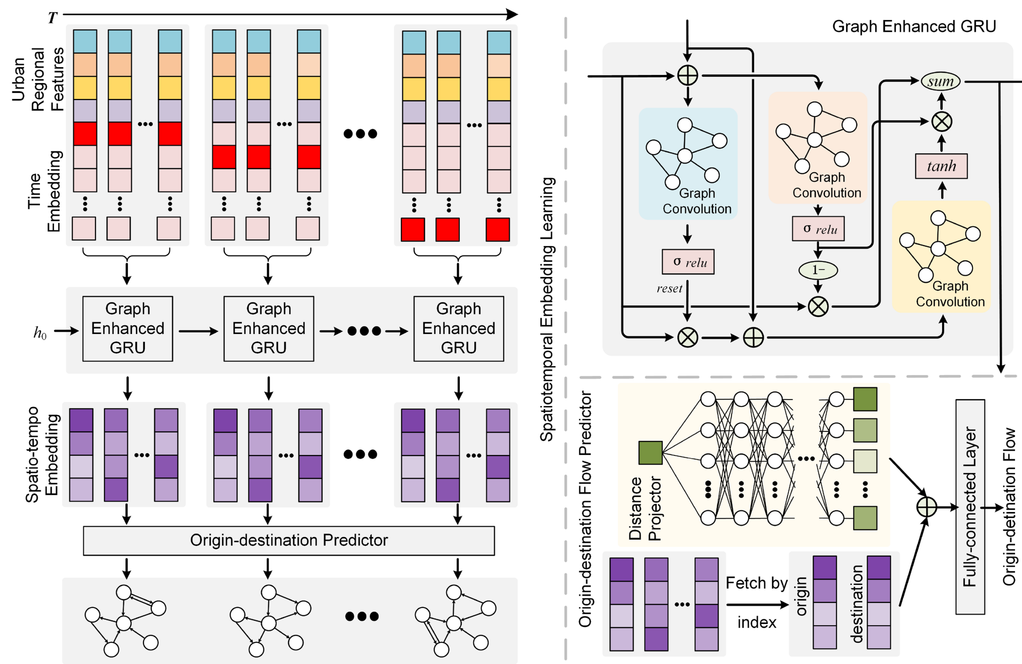


Fig. 2. The architecture of *Urban2OD* module.

$$\mathbf{z} = \sigma(GCN^{z}(\mathbf{x}^{t} \oplus \mathbf{h}^{t-1})), \tag{2}$$

$$\mathbf{h}^{t-1\prime} = \mathbf{h}^{t-1} \odot \mathbf{r}, \tag{3}$$

$$\mathbf{h}' = tanh(GCN(\mathbf{x}^{t} \oplus \mathbf{h}^{t-1\prime})), \tag{4}$$

$$\mathbf{h}' = (1 - \mathbf{z}) \odot \mathbf{h}^{t-1} + \mathbf{z} \odot \mathbf{h}' \tag{5}$$

where $\mathbf{r}$ and $\mathbf{z}$ stand for the output of reset gate and update gate respectively, σ and $tanh$ indicate the activation functions of **ReLU (Rectified Linear Unit)** and the tanh function, $\oplus$ denotes concatenation, $\odot$ denotes Hadamard product, $\mathbf{h}^{t}$ denotes the hidden states of time t and *GCN* stands for the graph convolution computation.

In order to comprehensively model the heterogeneity spatial distribution of urban functions, we utilize graph to represent the topology of urban space and leverage graph convolutional networks to model the spatial dependencies. The urban graph $\mathcal{G} = \{\mathcal{N}, \mathcal{E}\}$ is constructed by adjacency of regions in a city, where nodes $n \in \mathcal{N}$ represent regions and edges $e \in \mathcal{E}$ announce whether two regions are geographically adjacent or not. The features of every region are working as the node attributes jointly with temporal embedding. The graph convolution we adopt is proposed by Kipf and Welling [18]. The computation of one graph convolution layer is shown as follows,

$$\mathbf{X}^{(l+1)} = f(\mathbf{A}, \mathbf{X}^{(l)}) \tag{6}$$

$$\mathbf{D}_{ii} = \sum_{j} A_{ij} \tag{7}$$

$$\hat{\mathbf{A}} = \mathbf{A} + \mathbf{I} \tag{8}$$

$$f(\mathbf{A}, \mathbf{X}^{(l)}) = \sigma(\hat{\mathbf{D}}^{-\frac{1}{2}} \hat{\mathbf{A}} \hat{\mathbf{D}}^{-\frac{1}{2}} \mathbf{X}^{(l)} \mathbf{W}^{(l)} + \mathbf{b}^{(l)}), \tag{9}$$

in which $\mathbf{A}$ denotes the adjacency matrix of the urban graph $\mathcal{G}$, $\mathbf{X}^{(l)}$ represents the node embedding of l^{th} layer, $\mathbf{D}$ indicates the degree matrix of $\mathbf{A}$, $\mathbf{I}$ denotes the Identity Matrix. The GCN computation is stacked by several graph convolutional layers and the last layer is not activated. After each time step in Graph Enhanced GRU, the node embeddings will contain the spatial-temporal information for each region, which are used to give a prediction for the OD flow of every OD pair next.

Then, the OD flow predictor will predict the flow volume for OD pairs based on the spatiotemporal embeddings learned previously. The structure of the flow predictor is shown in Figure 2 at the bottom right. As we can see, the distance feature is mapped into a high-dimensional space to exploit corresponding transition pattern of human mobility. This is because human mobility exhibits the law of distance-decay, which has the property of extremely stiff non-linearity, according to existing works [2, 19, 28]. In detail, there are many published forms of the distance decay function, such as power-decay and exponential-decay, and the like [3, 5, 7, 11, 20]. It is not reasonable and elegant to handcraft the distance function for human mobility due to its variation in different settings. Some works [40] directly concatenate the distance feature with the regional features of origin and destination. We will show that it cannot correctly model the relationship between distance and human mobility well owing to the extremely stiff non-linearity in experiments. Consequently, we use an **MLP (multi-Layer Perceptron)** as the distance projector to automatically learn the map for the distance feature from one dimension to a high dimension feature space to thoroughly build the relationship between the distance and the OD flow. After that, the projected high-dimensional distance features are concatenated with spatiotemporal embeddings of OD pairs to predict the OD flows through the following fully-connected layer.

4.3 OD2Traffic Module for Enhancing the Generation with Urban Traffic

With the OD flows generated from the *Urban2OD* module, one way to verify its reliability is to use the traffic simulator to see if it can recover the real-world urban traffic [37, 51]. This is natural since OD flows are significant causes of urban traffic [16, 29, 50] and the spatiotemporal features of the OD flow both affect the urban traffic on the road extensively. For example, during the morning rush hour, the roads between residential places and workplaces tend to be congested due to the increased number of vehicles. Moreover, empirically, the larger the OD flow and the closer the distance, the more vehicles on the road [50]. Therefore, we build a model to predict urban traffic based on the OD flows generated and calibrate the flows by adapting the *Urban2OD* module, which is an OD generation model based on regional features proposed above. Thus, the *Urban2OD* module will be improved by *OD2Traffic* to make the generated OD flows more practically. Urban traffic is the real-time status of the roads, such as the traffic flow and traffic speed.

We first construct the relation between OD pairs and roads. Empirically, people usually choose the lowest cost path to the destination when they travel. However, in reality, there are paths with similar distances and travel times, and people usually choose one of them depending on the condition of the roads at the time, as shown in Figure 3(a). Accordingly, we design a method to establish the relation between OD pairs and roads. As shown in Figure 3(b), we mark the road located in the rectangular area between origin and destination having relation with the corresponding OD pair. Through this approach, we can include as complete as possible the dependencies between OD pairs and roads and thus consider them in our model design sufficiently. OD pairs and roads are a many-to-many relationship, where each OD pair affects multiple roads, and each road is also affected by multiple OD pairs. Then, we use the dependencies between OD pairs and roads to construct a bipartite graph to describe their relationship, as shown up in Figure 4, where the nodes colored blue stand for OD pairs and the green nodes denote the roads.

Based on the constructed bipartite graph, we design a model with an attention-based mechanism to predict the urban traffic given the historical information of related OD pairs. For one specific

(a) Routing preference of people.

(b) Roads related to Origin-destination pairs

Fig. 3. Relation between Origin-destination pairs and roads.

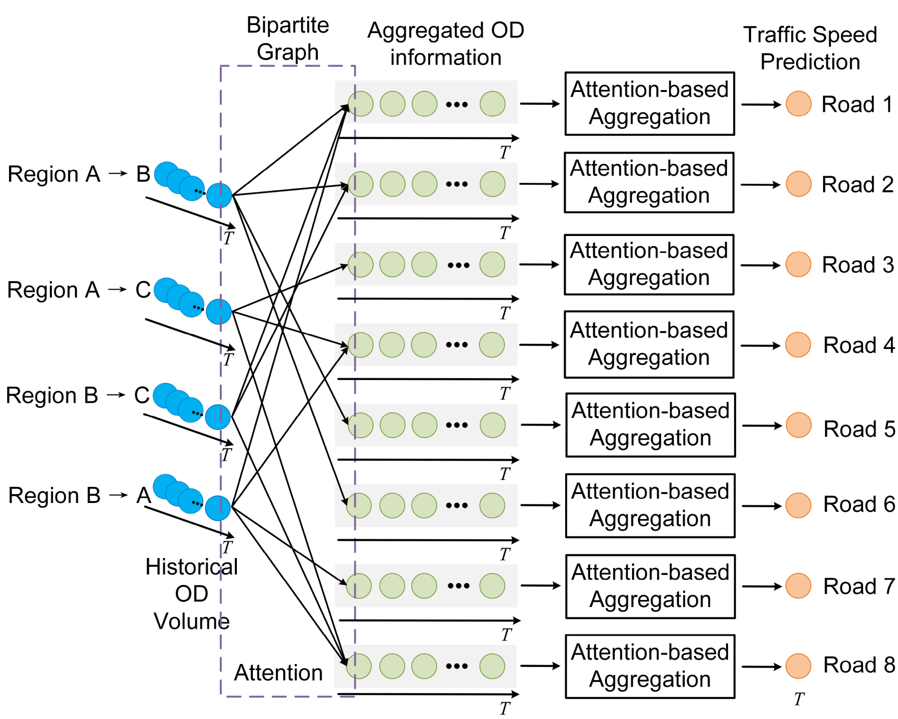


Fig. 4. The architecture of *OD2Traffic* module.

road, the more recent historical information of the closer origin will have a more significant impact. In contrast, the older history will have a greater impact if the distance is farther. Attention mechanism, which automatically gives weights to aggregate the information from different OD pairs and at different historical time slices, is suitable to model this sophisticated and dynamic relation between historical OD flows and urban traffic. The OD pair and temporal levels have their own attention mechanisms for information extraction, respectively, designed as two attention layers in the model. As shown in Figure 4, the first attention layer in the dashed box decides which OD pairs have high weights. The second attention layer works for the aggregated OD flow information on the road level at different historical time slices. The computation of the first attention layer is shown below,

$$e_{ij}^t = \sigma(W(\hat{F}_{ij}^t \oplus v_k) + b), \tag{10}$$

$$\alpha_{ij}^t = softmax(e_{ij}^t) = \frac{exp(e_{ij}^t)}{\sum_{ij} exp(e_{ij}^t)}, \tag{11}$$

$$l_k^t = \sum_{ij} \alpha_{ij}^t \hat{F}_{ij}^t, \tag{12}$$

where $\hat{F}_{ij}$ means the generated OD flow from region r_i to region r_j, v_k means the one-hot embedding of k^{th} road, α_{ij} means the attention weight for OD flow F_{ij}, l_k means the aggregated features for k^{th} road and W and b are the learnable parameters. The computation of the second attention layer is presented as follows,

$$e^t = \sigma(Wl^t + b), \tag{13}$$

$$\alpha^t = softmax(e^t) = \frac{exp(e^t)}{\sum_t exp(e^t)}, \tag{14}$$

$$S^T = \sum_t \alpha^t l^t, \tag{15}$$

where l^t means the aggregated information at time t for one specific road and S_T means the predicted urban traffic of time T.

4.4 End-to-End Training of *Urban2OD* and *OD2Traffic*

The training of *Urban2OD* and *OD2Traffic* all adopt **MSELoss (Mean squared Error loss)**. The formula is given as follows,

$$\mathcal{L}_{generation} = \frac{1}{|T|} \frac{1}{|\mathcal{R}|^2} \sum_t \sum_{ij} (F_{ij}^t - \hat{F}_{ij}^t)^2, \tag{16}$$

$$\mathcal{L}_{inference} = \frac{1}{|T|} \frac{1}{|l|} \sum_t \sum_k (Vel_k^t - \hat{Vel}_k^t)^2, \tag{17}$$

$$\mathcal{L} = \mathcal{L}_{generation} + \mathcal{L}_{inference}. \tag{18}$$

We train our proposed model using the **SGD (stochastic gradient descent)** optimization technique to minimize the loss $\mathcal{L}$ mentioned above.

5 EXPERIMENTS

We will answer the following research questions in this section based on the results of experiments conducted on real-world datasets.

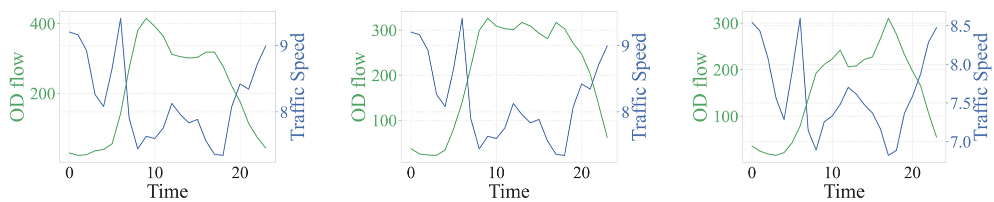
- **RQ1:** Can our model generate daily temporal practical OD flow data?
- **RQ2:** Does the *OD2Traffic* module improve the generation results of OD flows?
- **RQ3:** How do the hyper-parameters influence the model's performance?

5.1 Data Description and Analysis

The datasets, collected from Beijing, contain three parts: urban regional features, OD flows and urban traffic. The space within Beijing's Fifth Ring Road is divided into 343 regions by second-grade highways. The urban traffic are the real-time traffic speed records of all roads within the 5th Ring Road. The datasets are given a detailed introduction below.

Table 1. Statistics of the OD Flow Dataset and Traffic Dataset used in Our Experiments

Dataset	City	Time Span	T-granularity	#Units
OD flows	Beijing	2021.07.01-2021.07.31	One hour	342 regions
Traffic A	Beijing	2022.07.01-2022.07.31	5 minutes	29,418 road segments
Traffic B	Beijing	2017.04.01-2017.05.31	15 minutes	15,073 road segments



(a) From West Chang 'an Avenue Sub-district to Temple of Heaven Subdistrict. (b) From Temple of Heaven Subdistrict to West Chang 'an Avenue Subdistrict. (c) From Temple of Heaven Subdistrict to Taipingqiao Subdistrict.

Fig. 5. Case analysis of effects of OD flows on traffic.

5.1.1 Urban Regional Features. Regional attributes, provided by one of the biggest Chinese **Internet service provider (ISP)** corporations, include demographics, e.g., the number of people with different ages and genders, and POIs distribution, e.g., POIs quantities of different categories. The features we adopt in experiments are collected in 2021.

5.1.2 OD Flows. OD flow is also provided by the ISP corporations, which contains the daily average number of people moving between every two regions per hour in July 2021.

5.1.3 Urban Traffic. We use two traffic datasets to validate the superiority of our method. One of the urban traffic datasets, which comes from the biggest Digital Map Service Provider, gathered every 5 minutes traffic speed for each road in the same period with OD flow data. The other is a public traffic dataset named Q-Traffic [24] which is a popular benchmark dataset in traffic prediction task.

5.1.4 Statistics and Analysis of OD flow Dataset and Traffic Dataset. In order to provide a detailed overview of the data, we have conducted statistical analyses on the utilized OD flow dataset and the traffic dataset, and introduced their important indices, as shown in Table 1.

Additionally, we conducted an in-depth analysis of the data to explore the connection between changes in OD flows and traffic status. As shown in Figure 5, we selected three representative region pairs for analysis. The results demonstrate a strong influence of OD flow volume on traffic conditions. Specifically, an increase in OD flows tends to intensify road congestion, consequently reducing road traffic speed.

5.2 Baselines

We conduct experiments on two classes of baseline methods to validate the superiority of our model.

- **GM.** Gravity model [56] is a widely-used physics-derived model motivated by Newton's law of gravitation.
- **RF.** Random forest is a kind of robust tree-based traditional machine learning technique. In recent works [31, 32], tree-based methods represented by the random forest were claimed to be the state of the art of population mobility modeling.

- **DG. DG (DeepGravity)** [40] introduced the deep learning technique to enhance the gravity model and handle more features.
- **GNN.** Graph neural networks have been reported to achieve excellent performance in many applications. GMEL [28] points out that utilizing GNN to extract topology features could improve mobility modeling.

The baselines mentioned above use a single model and the one-hot time embedding (the hour of a day) to predict OD flows. The second class includes methods that consist of multi-models, which handle the relation between urban attributes and population mobility at different times in a day.

- **Multi-GM.** Multi-GM utilizes several gravity models to predict OD flow at different times. In this work, we use 24 gravity models to model the mobility apart at 24 hours in one day.
- **Multi-RF.** This baseline builds 24 random forest models without the time embedding to predict 24 hours OD flow between two regions.
- **Multi-DG.** Like the other baselines introduced above, this baseline consists of 24 DeepGravity models.
- **Multi-GNN.** Similarly, this method includes 24 GNNs.

5.3 Metrics

we choose **Root Mean Squared Error (RMSE)**, **Normalized Root Mean Squared Error (NRMSE)** and **Common Part of Commuting (CPC)** as evaluation metrics to validate the performance of our proposed model. CPC is positive and located in the closed interval between 0 and 1, where 1 means the generated OD flow and the ground truth coincide exactly and 0 means there is no overlap between the generation and ground truth at all.

$$RMSE = \sqrt{\frac{1}{|T|}\frac{1}{|\mathcal{R}|^2}\sum_t\sum_{ij}||\mathbf{F}_{ij}^t - \hat{\mathbf{F}}_{ij}^t||_2^2}, \tag{19}$$

$$NRMSE = \frac{RMSE}{\sqrt{\sum_t\sum_{ij}\frac{1}{|T|}\frac{1}{|\mathcal{R}|^2}||\mathbf{F}_{ij}^t - \overline{\mathbf{F}}||_2^2}}, \tag{20}$$

$$CPC = \frac{2\sum_t\sum_{ij} min(F_{ij}^t, \hat{F}_{ij}^t)}{\sum_t\sum_{ij} F_{ij}^t + \sum_t\sum_{ij}\hat{F}_{ij}^t}, \tag{21}$$

where F_{ij}^t means real OD flow from region r_i to region r_j at time t and $\hat{F}_{ij}^t$ means the generated OD flow.

5.4 Experiment Settings

We split the OD pairs into 8 : 1 : 1 as the training, validation and test set randomly. We follow the same hyper-parameter settings for all methods of the same type for a fair comparison. For the gravity model, the residential and work population are the input and the model takes 4 learnable parameters. For the tree-based models, the number of estimators is set to 30, where the increment will not provide more improvement. For all GNNs, the number of layers is set to 3 and filters is set to 64. In our model, the layer of distance projector is set to 5 and the number of neurons of each layer is set to 64. The size of learned regional spatial-temporal embedding is set to 64. The length of historical OD flow information used in the *OD2Traffic* module is set to 2.

We implemented the experiments of our proposed model and baselines through Pytorch v1.10 and Deep Graph Library v0.8 [44]. The hardware used are Intel(R) Xeon(R) 8358 2.60GHz, 500 GB of RAM, and NVIDIA GeForce RTX 3090 Ti with 24GB of RAM.

Table 2. Overall Performance Comparison with Baselines

Model	RMSE↓	NRMSE↓	Imp.	CPC↑	Imp.
GM	54.275	0.912	−32.57%	0.349	+81.66%
DG	53.532	0.900	−31.67%	0.402	+57.71%
GNN	47.795	0.797	−22.84%	0.560	+13.21%
RF	48.499	0.815	−24.54%	0.624	+1.60%
multi-GM	52.142	0.876	−29.79%	0.387	+63.82%
multi-DG	52.197	0.877	−29.87%	0.432	+46.76%
multi-GNN	47.411	0.797	−22.84%	0.556	+14.03%
multi-RF	49.502	0.830	−25.90%	0.537	+18.06%
ours-B	38.615	0.649	−5.23%	0.617	+2.75%
ours-A	**36.571**	**0.615**	–	**0.634**	–

5.5 Results and Analysis

5.5.1 Overall Performance (RQ1). In this section, we will give a detailed introduction and systematic analysis of the experiment results of the performance of GODUT compared with all baselines. To more comprehensively evaluate and compare with different baselines, we run five experiments for each model, each time using different initial weights set by different random seeds. We collected the results from each experiment and run an ANOVA test to determine if the performance differences were significant. The test results showed that the p-value is less than 0.05, indicating that the performance differences we observed are significant. Combined with Table. 2, it suggests that our method significantly outperforms other baselines, and this result is not merely due to the randomness of weight initialization.

The overall performance of our model and baselines are shown in Table. 2. As we can see, the proposed model outperforms all baselines referring to all metrics with a significant margin of more than 20% according to *RMSE* based on the complementary traffic information from the Traffic A dataset. The performance improvement brought about by the Traffic B dataset is limited due to the considerable time gap between its collection and that of the OD flow dataset. This could potentially be attributed to the gradual changes in OD flows as time progresses. This method exhibits robustness to gaps in the time period of traffic data. The classic method gravity model [56] performs unwell due to its simplicity, e.g., comparing the population mobility with Gravitation between objects. Random forest [31] has a strong capability of fitting non-linearity and generalization power. However, it cannot take urban topology information and the association between human mobility at different times of the day into consideration, which leads to unimpressive performance. DeepGravity [40] takes lots of urban attributes into account but neglects the stiff non-linearity and urban topology. So DeepGravity performs better than the naive gravity model but worse than random forest and GNNs. GNNs bear the urban topology and regional neighbors' information in mind without fully exploiting distance features and temporal patterns. From the experiment results of all multiple models method, we can see that using multiple models to handle different patterns of human mobility at different times of a day could slightly improve the performance but is still not good enough. Our proposed model thoroughly models spatial-temporal dependencies between human mobility and urban space. What's more, the urban traffics caused by OD flow is also applied in the *OD2Traffic* module of our model to make the generation results more practical.

Furthermore, we performed an analysis of time and computational complexity for our method, and compared it with the baselines, as shown in Table 3. It can be observed that both our method and the baselines primarily consume more time during the training process. However, during inference, as the structure of the models are fixed, the computational complexity is proportional to

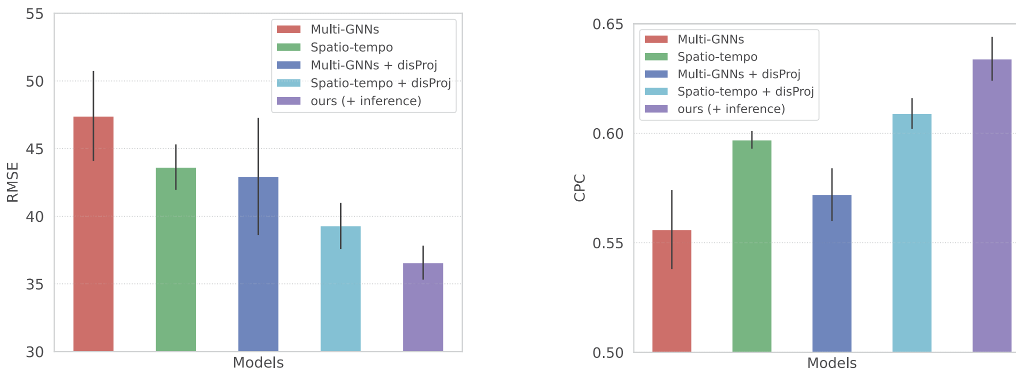
Table 3. Analysis of the Computational Complexity of Our Method and All Baselines

Methods	#Para	Training Time	Inference Time
GM	4	~5min	<1s
DG	~41k	~5h	<1s
GNN	~29k	~12h	<1s
RF	~3k	~12min	<1s
Multi-GM	96	~20min	<1s
Multi-DG	~1m	~10h	<1s
Multi-GNN	~700k	~20h	<1s
Multi-RF	~72k	~18min	<1s
ours	~1m	~20min	<1s

the number of region pairs, i.e., the computational complexity is O(N). It's worth noting that existing computing devices fully utilize the parallel computation of CPU and GPU to accelerate the computation process, thus further improving computational efficiency. As concluded from the experiments, the inference time for both our method and the baselines is less than 1 second on about 150k temporal OD flow records. In terms of the number of parameters, the parameter count of all multimodal-based methods will be a multiple of the time steps of their corresponding single model-based methods. Our method uses a complex spatio-temporal graph convolution network and an additional OD2traffic module to further utilize traffic information for performance enhancement, resulting in a higher number of parameters.

5.5.2 Ablation Study (RQ2). We give the analysis of results of ablation experiments to check the validity of our designs in this section. The multi-GNNs method is set as the basic model and we add the design of spatiotemporal embedding learner, distance projector and the *OD2Traffic* module with traffic information one by one. According to the metric of *RMSE*, the result is shown in Figure 6. The results demonstrate that each part of our method brings a performance gain with a considerable margin. With the comparison between **Multi-GNNs** and **Spatio-tempo**, we can see that spatial-temporal embedding learning could lead to around 8% improvement in performance. From the difference between **Multi-GNNs** and **Multi-GNNs + disProj**, we get that the distance projector provides a robust performance improvement. And **disProj** (**distance projector**) could decrease the generation error up to 10%. It can be seen from the rightmost bar that the *OD2Traffic* module will substantially improve the quality of OD generation, e.g., a 7% decrease of *RMSE*. From these results, we can see that each part of our model design has improved the performance of OD generation.

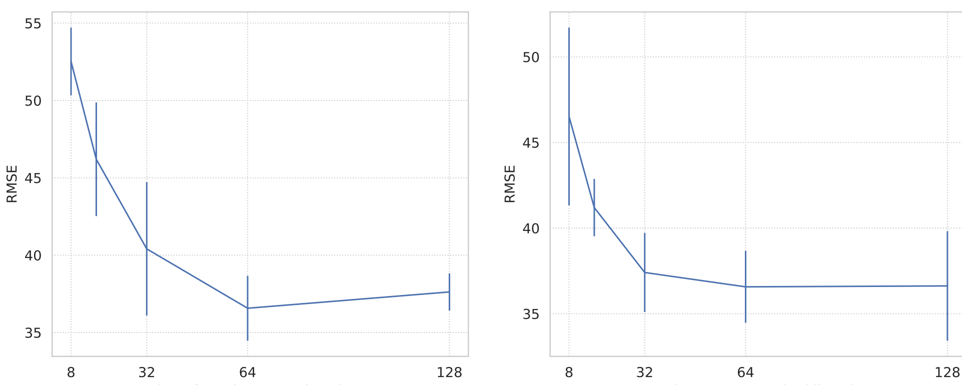
5.5.3 Hyper-parameters Learning (RQ3). In this section, we present a systematic analysis of four important hyper-parameters. Figure 7(a) shows the impact of the number of graph convolutional channels in the spatial-temporal embedding learning process, where the x-axis is the number of channels and the y-axis is the generation error. We can see that the performance will increase with the number of channels but will stop growing when it reaches 64. It means that too few channels will lead to the poor fitting ability of the model. Figure 7(b) shows the effect of the size of spatial-temporal embedding, where the y-axis is the generation error and the x-axis is the spatial-temporal embedding size. Results show that a small embedding size will lead to less information. From Figure 7(c), we can see that the distance feature requires sufficient dimensionality to be adequately modeled. The effect of a given length of historical OD flows in the *OD2Traffic* module is shown in Figure 7(d). Results show that 2 hours of historical OD information will support the



(a) Ablation study in terms of *RMSE*.

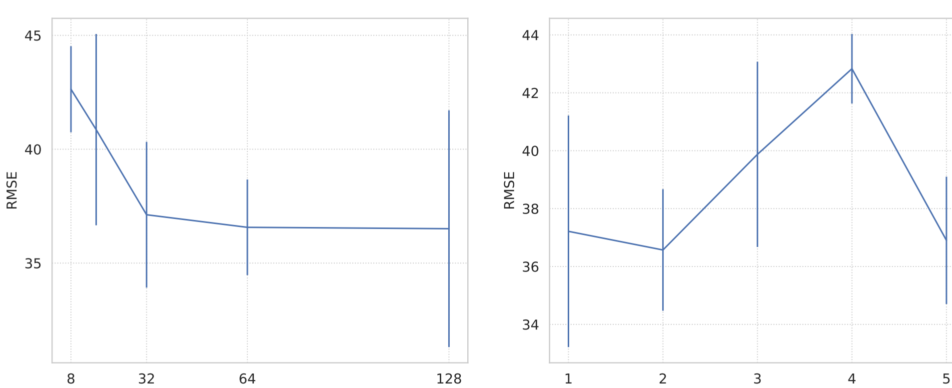
(b) Ablation study in terms of *CPC*.

Fig. 6. Ablation study.



(a) Effect of number of graph convolutional channels.

(b) Effect of spatial-temporal embedding size.



(c) Effect of dimension of distance projector.

(d) Effect of length of historical OD flows.

Fig. 7. Effects of hyper-parameters.

best prediction of urban traffic. This may be because long historical information will bring noise, which reduces the modeling ability.

6 CONCLUSION

The rapid development of ICT and ITS allows us to collect huge amounts of traffic data in the city, which provides the conditions to utilize urban traffic information to enhance the performance of OD flow generation. This work proposes a novel model named *GODUT* to solve the OD generation problem. Different from traditional methods, *GODUT* not only considers the cause of OD flows, e.g., the spatial heterogeneity of the city but also models the effect of OD flows on urban traffic. As such, *GODUT* consists of two modules: *Urban2OD* and *OD2Traffic*. *Urban2OD* takes urban regional features as input to generate OD flows between regions. *OD2Traffic* predicts urban traffic based on the OD flows given by the *Urban2OD* module. Two modules are integrated into one holistic framework to improve the results of OD generation. Extensive experiments conducted on real-world data demonstrate that our model *GODUT* outperforms all baselines, which proves the validity of the idea of solving the OD generation problem by considering both the causes of OD flows and the effects of OD flows. The code is public at https://github.com/tsinghua-fib-lab/Traffic_Enhance_OD.

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