

Few-Sample Traffic Prediction with Graph Networks using Locale as Relational Inductive Biases

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Abstract—Accurate short-term traffic prediction plays a pivotal role in various smart mobility operation and management systems. Currently, most of the state-of-the-art prediction models are based on graph neural networks (GNNs), and the required training samples are proportional to the size of the traffic network. In many cities, the available amount of traffic data is substantially below the minimum requirement due to the data collection expense. It is still an open question to develop traffic prediction models with a small size of training data on large-scale networks. We notice that the traffic states of a node for the near future only depend on the traffic states of its localized neighborhoods, which can be represented using the graph relational inductive biases. In view of this, this paper develops a graph network (GN)-based deep learning model LOCALEGN that depicts the traffic dynamics using localized data aggregating and updating functions, as well as the node-wise recurrent neural networks. LOCALEGN is a light-weighted model designed for training on few samples without over-fitting, and hence it can solve the problem of few-sample traffic prediction. The proposed model is examined on predicting both traffic speed and flow with six datasets, and the experimental results demonstrate that LOCALEGN outperforms existing state-of-the-art baseline models. It is also demonstrated that the learned knowledge from LOCALEGN can be transferred across cities. The research outcomes can help to develop light-weighted traffic prediction systems, especially for cities lacking historically archived traffic data.

Index Terms—Traffic Prediction; Few-sample Learning; Graph Networks; Transfer Learning; Intelligent Transportation Systems

I. INTRODUCTION

SMART traffic operation and management systems rely on accurate and real-time network-wide traffic prediction [1, 2], and it is the essential input for various smart mobility applications such as personal map services [3], connected and autonomous vehicles [4], traffic signal control

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[5], and advanced traveler information system/advanced traffic management system (ATIS/ATMS). In many megacities like Los Angeles and New York, massive traffic data have been collected and archived, which include vehicle speeds, traffic volumes, origin-destination (OD) matrices, etc., and these data are widely used to generate traffic predictions. Among different traffic prediction models, deep neural networks, especially the graph-based neural networks, such as graph convolutional networks (GCN) [6, 7], achieve state-of-the-art accuracy and have been widely deployed in various industry-level smart mobility applications. For example, Uber has been using deep learning for travel time prediction [8].

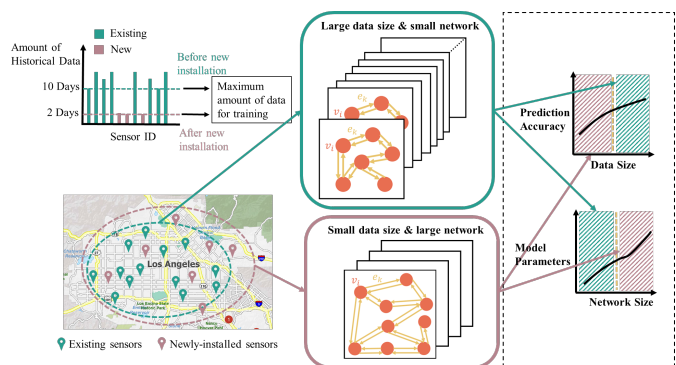


Fig. 1: Relationship of network and data size for current traffic prediction models.

To further improve the prediction accuracy on large-scale transportation networks, the model complexity and number of trainable parameters of the newly developed traffic prediction models have increased drastically in recent years [9, 10]. Most of the existing models require the historically archived traffic data for a long time period, and we define the length of the time period as the data size [11]. In contrast, the size of the transportation network is referred to as the network size. In Figure 1, many cities are gradually installing traffic sensors during the development of the Intelligent Transportation System (ITS). After the new installation, the maximum number of available training data depends on the data amount of the newest sensor. Therefore, the size of the training data for conventional traffic prediction models will be reduced dramatically, when the number of sensors keeps increasing. Every time a new installation of traffic sensors, we need to re-train the traffic prediction model with a smaller dataset and larger graph. For the majority of deep learning models, the number of model parameters is proportional to the road network size. Thus, existing traffic prediction models could

overfit on the few training data and the prediction accuracy could drop significantly.

In general, traffic prediction accuracy increases with respect to the data size, and the number of trainable parameters number increases with respect to the network size. When the network size becomes larger, more data (longer time period of historical data) is required to prevent overfitting due to a large number of trainable parameters [12]. Overall, existing well-performed deep learning models require a large data size for training to ensure good performance on the large-scale networks. However, because of the high expenses in data collection and sensor maintenance [13], it is not practical to expect every city to archive a comprehensive and long-history dataset. As shown in Figure 1, how to develop traffic prediction models with a small data size on the large-scale networks is the key research question addressed in this paper.

We further motivate this study using a practical example. Hong Kong aims to transform itself into a smart city within the next decade, and the Smart City Blueprint for Hong Kong 2.0 was released in December 2020, which outlines the future smart city applications in Hong Kong. The blueprint plans to “complete the installation of about 1,200 traffic detectors along major roads and all strategic roads to provide additional real-time traffic information” for Hong Kong’s smart mobility system. Consequently, Hong Kong’s Transport Department is gradually installing traffic sensors and releasing the data starting from the middle of 2021. The number of traffic sensors increases drastically in the recent year. The duration of the historical traffic data from the new sensors can be less than one month, making it impractical to train existing traffic prediction models. Similar situations also happen in many cities like Paris, Shenzhen, and Liverpool, as the concept of smart cities just steps into the deployment phase globally. Therefore, a network-wide traffic prediction model, which achieves state-of-the-art performance with a small size of traffic data, could enable the smooth transition and early deployment of smart mobility applications. Hence this study has practical values for many cities.

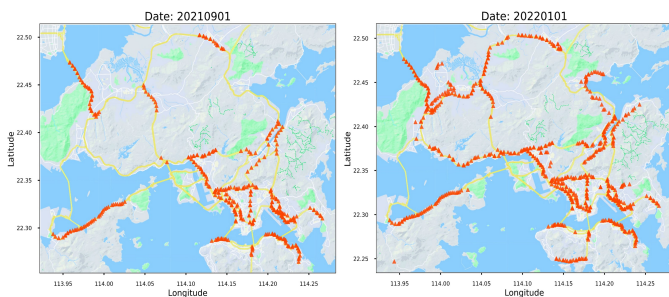


Fig. 2: Distribution of available detectors in Hong Kong in September 2021 (left) and January 2022 (right).

To this end, we define the task of few-sample traffic prediction, which aims to train on historical traffic data with a short history, and generate accurate short-term and long-term traffic prediction on the large-scale networks. This task is essentially challenging as the complicated prediction model on large-scale network is prone to overfit with limited data

[14, 15]. To address this issue, we notice that the short-term traffic state on a certain node (target node) only depends on the traffic states of its localized neighbors. More specifically, as shown in Figure 3, the traffic state at time $\tau + 1$ is mainly affected by the traffic states of itself and its neighborhoods at time τ . It is straightforward to observe that the change of traffic state on a node is attributed to the traffic (*e.g.*, vehicle, flow) exchanges, then the nodes far away from the target node cannot exchange traffic directly with the target node, and hence the impact of those nodes are indirect and marginal. We define the concept **locale** of a target node as a collection of information on its neighboring nodes, and the information includes, but is not limited to traffic states (*e.g.*, speed, flow, OD), static data (*e.g.*, road type, speed limit), and auxiliary information (*e.g.*, weather). Finally, it is safe to claim that the traffic state of the target node in the near future mainly depends on its current locale.

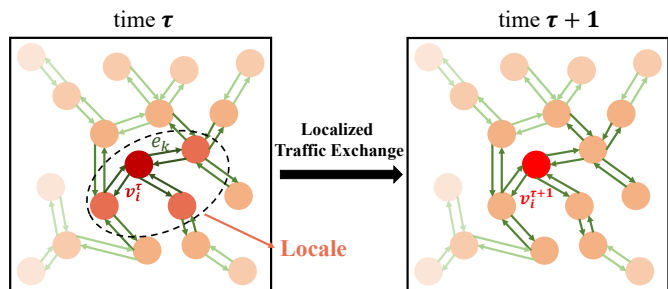


Fig. 3: Illustration of the concept of locale.

The locale of a node can be viewed as the relational inductive biases for the prediction model, which enforces the entity relations in a deep learning architecture. In our case, the connections between nodes allow the traffic exchanges, while no direct traffic exchanges are allowed if two nodes are not connected. Additionally, other static information such as location information and road properties affect the speed and frequency of those traffic exchanges. To make use of the relational inductive biases, we adopt the Graph Network (GN) to capture the dynamic and localized traffic states of a target node. The GN demonstrates great potential in modeling the relational inductive biases and has been widely used to depict the localized relationship among different entities [16]. It is also a generalized form of many existing graph-based network structures [17, 18]. In this paper, we extend the GN model to learn the *locally spatial* and temporal patterns of traffic states for generating predictions. Importantly, GN is applied to each node separately, and it can be applied to different nodes with various topologies. GN is also light-weighted with a small number of trainable parameters, making it easy to train given the limited training samples.

It is noteworthy that the similar concept of locale is widely adopted for the spatial approaches of the graph neural networks (GNN) defined in [6], and one of the representative examples is the message passing neural network (MPNN) [19]. However, current traffic prediction models overlook the properties of locale and rely on GNN to implicitly learn the locally spatial dependency of the traffic states, which also

explains why the existing traffic prediction models generally require a large amount of data. To the best of our knowledge, among the commonly used traffic prediction models, DCRNN and GRAPH WAVE NET depict the diffusion process of traffic states, which share the most similar idea to locale [20, 21]. However, due to their complex model structures, the performance of both models degrades drastically with a few data samples, which will later be shown in the numerical experiments. This observation also suggests a light-weighted structure for the few-sample traffic prediction task.

To summarize, the small data size and large network size present great challenges to existing traffic prediction models, and it is promising to utilize the localized traffic information and data (locale) to generate traffic predictions without modeling the entire network simultaneously. In view of this, this paper proposes Localized Temporal Graph Network (LOCALEGN) to model the *locally spatial* and temporal dependencies on graphs for predicting traffic states in the near future. This is the first time that GN is adopted and extended for traffic prediction tasks, and the choice of GN is attributed to its previous successful applications in predicting physical systems, such as fluid dynamics and glassy systems [16]. LOCALEGN can learn from different nodes on the large network, and hence it can be declared as a light-weighted model to make accurate short-term predictions from few training samples. The contribution of this paper can be summarized as follows:

- We propose the few-sample traffic prediction task and highlight the importance of using localized information (locale) of each node to address the issue of lacking data in the proposed task.
- We develop a *locally spatial* and temporal graph architecture LOCALEGN for the few-sample traffic prediction task. The *locally spatial* pattern is modeled by the graph network with relational inductive biases, and the temporal pattern is depicted with a modified recurrent neural network.
- We conduct experiments on three real-world traffic speed datasets and three real-world traffic flow datasets, respectively. The results show that LOCALEGN consistently outperforms other state-of-the-art baseline models for the few-sample traffic prediction. It is also demonstrated that the learned knowledge from LOCALEGN can be transferred across cities.

Source codes of LOCALEGN are publicly available at <https://github.com/MingxiLii/LocaleGN>. The remainder of this paper is organized as follows. Section II reviews the related studies on traffic prediction, few-sample learning, and graph neural networks. Section III formulates the task of few-sample traffic prediction and presents details of LOCALEGN. In Sections IV, numerical experiments are conducted to demonstrate the advantages of LOCALEGN. Lastly, conclusions and future research are summarized in Section V.

II. RELATED WORK

In this section, we first summarize the existing traffic prediction models, then applications of few-sample learning in transportation are discussed. Lastly, we review the emergence

of GN and justify the choice of GN for the few-sample traffic prediction.

1) *Traffic Prediction Models*: Traffic data as a spatio-temporal information on road networks (graphs) is a typical non-Euclidean data. There are two types of models to deal with graph data: spatial graph-based models and spectral graph-based models [6]. In smart mobility applications, GCN is a widely used spectral graph-based model to learn the complex structure of spatio-temporal data, and the representative models include T-GCN [22], ST-GCN [23], TGC-LSTM [24], STEMGNN [25] and ASTGCN [26]. The convolutional operation bases on the whole graph with its Laplacian matrix or other variants, such as dynamic Laplacian matrix [27]. In [28], it is a delicate prediction model for passenger inflow and outflow at traffic stations, such as subway or bus station. In other words, the graph consists of nodes (traffic stations) with two attributes (inflow and outflow). The graph information is further processed to obtain the subgraph for each node. This is an enlightening setting, in which spatial-temporal patterns can be learned by subgraph centered with one node. However, the spectral graph-based models do not have parameter-sharing characteristics, thus these models are tied to specific graph topologies. For example, T-GCN and ST-GCN are inflexible and impose restrictions on transfer learning tasks across different graphs [29].

For spatial graph-based models, local aggregators are explored in order to deal with the direct convolution operation with the different number of neighbors [6]. In DCRNN [20], the bidirectional random walk is introduced to model the spatial correlation of traffic flow on graphs. In GRAPH WAVE NET, an adaptive dependency matrix is adopted through the node embedding process, and the 1D convolution component is used to make the relation between entities trainable [21]. Moreover, attention-based spatial methods are developed to operate the attention mechanism on graphs. In GATCN, the graph attention network is applied to extract the spatial features of the road network [30]. We note that existing spatial graph-based models have flexible graph representations but require large historical data to achieve competitive accuracy. For example, in DCRNN, the pair-wise spatial correlation makes graph structures trainable, but its complex encoder and decoder structures also make the training data-intensive.

Methods mentioned above in the spectral and spatial domain mainly focus on modeling the spatial dependency of the traffic data. In addition to capturing spatial patterns, many other models are combined to learn temporal patterns. For example, Recurrent Neural Network (RNN) is adopted in time series prediction tasks [31, 32]. Both LSTM and GRU are two typical RNN models [33], and attention mechanism can also be used for inferring temporal dependencies (*e.g.*, AST-GAT [34], attention with LSTM [35], and APTN [36]).

In addition to deep learning, there are also other methods to deal with traffic prediction. For example, in [37], reinforcement learning is utilized to address data defect issues in traffic flow prediction. The dynamic graph is generated by the policy gradient algorithm, and the differences of the graph are used as reward signals for reinforcement learning to generate action sequences on the traffic flow transfer graph. The linear

models have more compact and simple structures, which are used in many traffic prediction settings. For example, [38] proposes to predict the short-term traffic dynamics based on the shockwave analysis and bottleneck identification. Specifically, the historical dataset is clustered by Gaussian Mixture Model and the clustering result is used for generating the congestion map bounded by shockwave speed. Besides, [39] develops a dynamic linear model with recursive coefficient updates. On top of [39], the large-scale dynamic linear model (LSDLM) further incorporates graph topological information and makes it feasible to make prediction on large scale network [40]. In general, it is difficult to adapt the above models for the traffic prediction settings with changing the number of sensors.

2) *Few-shot and Few-sample Learning in Transportation:* The majority of research applying deep learning to small datasets focuses on few-shot prediction which includes pre-training on a large dataset and fine-tuning on a small dataset [41, 42, 43]. However, works for directly learning from small datasets without external data are scarce [44]. Few-sample learning can be viewed as a specific example of few-shot learning without pre-training. Thus, it is a promising methodology to deal with the data inefficiency issue in the field of transportation. There is no direct work about few-sample learning in transportation, but some few-shot learning approaches are explored. The existing few-shot learning models can be categorized into two types: one is the gradient-based models [45] and the other is the metric-based models [46]. These methodologies work well in the case of independent and identically distributed data. However, few-shot learning in graphs is more challenging as the nodes and edges on the graph are connected and correlated with each other. Transportation data is a typical type of graph-based data. In recent years, studies explore few-shot learning with transportation applications such as vehicle detection [47] and traffic sign recognition [48]. In traffic prediction tasks, region-based transfer learning across cities is applied by matching similar sub-regions among different cities [49]. Overall, although lacking few-sample learning, the explorations of few-shot learning for traffic prediction can provide inspiration for building few-sample models without external data.

3) *Graph Networks:* Spectral GCN models and spatial GNN models can be adopted for traffic prediction tasks [7]. The inflexibility of the former one makes it unfeasible to construct few-sample or transfer prediction models. Therefore, it is worthwhile to look into spatial-based GNN models. There are many popular spatial-based GNN models such as diffusion graph convolution (DGC) [50], MPNN [19], GRAPH SAGE [51], and graph attention networks (GAT) [52]. Traffic speed or flow prediction models base on DGC, MPNN, GRAPH SAGE and GAT for short-term prediction are developed with sufficient traffic data. However, these models may fail in the cases of few data samples. In view of this, we note that Graph Network (GN) with relational inductive biases could address the issue of data intensity. In [16], the relational inductive bias is widely discussed when utilizing deep learning models to deal with structured data. In recent years, GN has been used to simulate physical systems [53, 54], predict the structure in glassy systems [55], and simulate the molecular dynamic

systems [56]. All these studies demonstrate the great potential of GN in modeling the localized relationship that is viewed as the relational inductive biases. Referring to spatio-temporal networks, GN is utilized to predict the climate data and the encoder-GN-decoder structure is developed to strengthen the representation ability in uncovering the complex and diverse connectivity of spatio-temporal networks [17]. Overall, it is worth exploring to extend GN to traffic prediction as the road network is also viewed as a typical spatio-temporal network.

III. MODEL

In this section, we formulate the few-sample traffic prediction task. The overall framework of LOCALEGN is presented and each component is introduced in detail. Lastly, the computational steps in LOCALEGN are summarized.

A. Few-sample Traffic Prediction

The traffic prediction task can be formulated as a regression problem. Various traffic data, such as traffic speed and flow, are graph-based, which can be modeled on a spatio-temporal graph. Different types of data might associate with nodes or edges. For example, the point detector data is associated with nodes, while the travel time data is associated with edges. We define the graph associated with the traffic data as a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where each node is represented by i , and the set of node indices $\mathcal{V} = \{1, 2, \dots, i, \dots, N_v\}$. N_v is the number of traffic sensors. Similarly, the set of edges is defined as $\mathcal{E} = \{1, 2, \dots, k, \dots, N_e\}$, where N_e represents the number of edges. The connectivity among nodes and edges represents the relational inductive biases on the graph.

In this paper, we formulate the traffic prediction on time-dependent (dynamic) graphs. Suppose the set of time intervals during the study period is denoted as T , for each time interval τ , we define the time-dependent data on graph \mathcal{G} as $\mathbf{G}^\tau = (\mathbf{V}^\tau, \mathbf{E}^\tau)$, where $\mathbf{V}^\tau \in \mathbb{R}^{N_v \times M}$ and $\mathbf{E}^\tau \in \mathbb{R}^{N_e \times M}$. To be precise, $\mathbf{V}^\tau = [\mathbf{v}_1^\tau; \dots; \mathbf{v}_i^\tau; \dots; \mathbf{v}_{N_v}^\tau]$, and $\mathbf{v}_i^\tau = [v_i^{\tau-M}, \dots, v_i^\tau]^T \in \mathbb{R}^{1 \times M}$, where \mathbf{v}_i^τ represents the traffic data for node i at time τ . M is the look-back window. The edge-based data $\mathbf{E}^\tau = [\mathbf{e}_1^\tau; \dots; \mathbf{e}_k^\tau; \dots; \mathbf{e}_{N_e}^\tau]$, and $\mathbf{e}_k^\tau = [e_k^{\tau-M}, \dots, e_k^\tau]^T$, where e_k^τ represents the traffic data on edge k at time τ . We note the time-dependent data in \mathbf{G}^τ can not only include conventional traffic data, but also other graph-based datasets such as weather, road properties, and so on. In this paper, without loss of generality, we suppose the nodes carry the point detector data, while the edges include the road properties (e.g., length, width, category).

Based on the above notations, existing traffic prediction models can be viewed as a function Φ , and $\Phi(\mathbf{G}^\tau) = \mathbf{V}^{\tau+1}$. Φ can be viewed as a dynamical system that evolves the graph-based traffic data from time τ to $\tau + 1$. For each τ , suppose \mathbf{G}^τ follows a certain distribution \mathcal{D} , then we have $\mathbf{G}^\tau \sim \mathcal{D}$. Given a sufficient large T , it is expected that we can use the deep learning model to approximate Φ such that the prediction error $\|\hat{\Phi}(\mathbf{G}^\tau) - \mathbf{V}^{\tau+1}\|$ is minimized, where $\hat{\Phi}$ represents the deep learning-based approximator.

In the few-sample traffic prediction task, the set of archived time interval T is relatively small, say $|T| = 10$, and then

training $\hat{\Phi}$ can easily overfit, making the existing traffic prediction models not suitable for the few-sample tasks. To address this issue, we propose to develop a function $\Psi(\mathbf{v}_i^\tau, \mathcal{L}^\tau(i)) = \mathbf{v}_i^{\tau+1}, \forall i$, where $\mathcal{L}^\tau(i)$ represents the locale of node i at time τ . For example, $\mathcal{L}(i)^\tau$ can represent all the \mathbf{e}_k and \mathbf{v}_i that are within the K -hop neighborhoods of node i . To obtain an approximator of Ψ , we notice that the available number of training data becomes $|T|N_v$. If the deep learning-based approximator $\hat{\Psi}$ could learn the *locally spatial* and temporal pattern for each node with $|T|N_v$ number of samples, then the few-sample traffic prediction task can be solved. In the following sections, we present and validate LOCALEGN as a suitable selection for $\hat{\Psi}$.

B. LOCALEGN

In this section, we introduce LOCALEGN in detail. Firstly, an overview of LOCALEGN is shown in Figure 4.

LOCALEGN mainly consists of four major components: node Gate Recurrent Unit (NODEGRU), node and edge encoders, graph network (GN) and nodes decoder. At each time τ , the input of LOCALEGN is \mathbf{G}^τ , and the node data \mathbf{V}^τ is feed into the NODEGRU for learning the temporal patterns of each node. Simultaneously, both edge data \mathbf{E}^τ and node data \mathbf{V}^τ are embedded by the edge encoder and node encoder, respectively. The GN is used to model the *locally spatial* patterns on both nodes and edges, and the edge information is aggregated to nodes. Then, the aggregated node information is further decoded by the node decoder. Lastly, the temporal patterns by NODEGRU is concatenated with the *locally spatial* patterns by GN, and a dense layer is used to generate the final prediction for $\mathbf{v}_i^{\tau+1}, \forall i$.

1) **NODEGRU:** The NODEGRU focuses on capturing the temporal correlation on \mathbf{v}_i for each node separately, as presented in Equation 1. The temporal pattern of \mathbf{v}_i is embedded in the GRU, which will be used for the inference of time $\tau+1$ in the following steps. We note that the GRU is applied for each node separately, which makes the trainable parameters dependent on the network size.

$$\mathbf{v}_i^{\tau, \text{GRU}} = \text{GRU}(\mathbf{v}_i^\tau), \forall i, \tau \quad (1)$$

2) **Node and Edge Encoder:** To encode the node and edge data in \mathbf{G}^τ , we employ two multilayer perceptron MLP^E and MLP^V for edge and node respectively, as shown in Equation 2.

$$\begin{aligned} \bar{\mathbf{e}}_k^\tau &= \text{MLP}^E(\mathbf{e}_k^\tau), \forall k, \tau \\ \bar{\mathbf{v}}_i^\tau &= \text{MLP}^V(\mathbf{v}_i^\tau), \forall i, \tau \end{aligned} \quad (2)$$

The encoded node and edge data can form the encoded graph $\bar{\mathbf{G}}^\tau = (\bar{\mathbf{V}}^\tau, \bar{\mathbf{E}}^\tau)$. In general, the two encoders can better learn the latent representations of these node and edge data, and the learned representations will be used to further mine the spatial and temporal relationship by GN.

3) **Graph Network:** The graph network (GN) is the essential component in LOCALEGN. In general, GN models the evolution of dynamic graphs using the updating and aggregating operations on nodes and edges. In particular, we aim to use GN to evolve $\bar{\mathbf{G}}^\tau$ to $\bar{\mathbf{G}}^{\tau+1}$.

In GN, two updating functions ϕ^V, ϕ^E are employed to update the per-node data and per-edge data respectively, and one aggregating function $\rho^{E \rightarrow V}$ is used to aggregate the per-edge data for each node. To provide more details, GN models the spatio-temporal propagation of the dynamic graph $\bar{\mathbf{G}}^\tau$ based on the following three steps:

- i In the first step, the edge updating function ϕ^E is applied to every single edge in the graph to calculate the per-edge updates. For each edge k , we combine the updated edge data $\bar{\mathbf{e}}_k^\tau$ and the node data for both the tail node $\text{tail}(k)$ and head node $\text{head}(k)$ of k , and then the combined data is feed into ϕ^E , as shown in the following equation:

$$\bar{\mathbf{e}}_k^\tau = \phi^E(\bar{\mathbf{e}}_k^\tau, \bar{\mathbf{v}}_{\text{tail}(k)}^\tau, \bar{\mathbf{v}}_{\text{head}(k)}^\tau), \forall k, \tau, \quad (3)$$

where ϕ^E is modeled through an MLP (MLP^{ϕ^E}).

- ii In step two, the aggregating function $\rho^{E \rightarrow V}$ is applied to all the edges that point to node i . Mathematically, we denote $\bar{\mathbf{E}}_{\rightarrow i}^\tau = \{\bar{\mathbf{e}}_k^\tau | \text{tail}(k) = i, \forall k\}$ as the set of the updated edge data pointing to i at time τ . The function $\rho^{E \rightarrow V}$ aggregates the information in $\bar{\mathbf{E}}_{\rightarrow i}^\tau$ and outputs a representation of all the edges pointing to node i , as shown in Equation 4. We note that the aggregating function should work on different size of $\bar{\mathbf{E}}_{\rightarrow i}^\tau$, and hence the element-wise mean function is chosen as $\rho^{E \rightarrow V}$.

$$\bar{\mathbf{e}}_{\rightarrow i}^\tau = \rho^{E \rightarrow V}(\bar{\mathbf{E}}_{\rightarrow i}^\tau), \forall i, \tau \quad (4)$$

- iii In step three, the node updating function ϕ^V is applied to every single node in the graph. For node i , the function ϕ^V takes the current node data $\bar{\mathbf{v}}_i^\tau$ and the representation of the edge data pointing to node i computed in the previous step as input, and the output is the updated node data $\bar{\mathbf{v}}_i^{\tau+1}$, as represented in the following equation:

$$\bar{\mathbf{v}}_i^{\tau+1} = \phi^V(\bar{\mathbf{e}}_{\rightarrow i}^\tau, \bar{\mathbf{v}}_i^\tau), \forall i, \tau, \quad (5)$$

where ϕ^V is modeled as a different MLP (MLP^{ϕ^V}).

Overall, the GN model decomposes the complex topological graph structure into updating and aggregating operations on each single node and edge, and the localized relationship on the graph can be modeled accordingly. GN is a generalized module that can be reduced to many existing GNNS, such as graph convolution neural networks, etc. Mathematically, the locale of node i can be rigorously defined as $\bar{\mathbf{e}}_{\rightarrow i}^\tau, \bar{\mathbf{v}}_i^\tau, \bar{\mathbf{E}}_{\rightarrow i}^\tau$ and all the $\bar{\mathbf{e}}_k^\tau, \bar{\mathbf{v}}_{\text{tail}(k)}^\tau, \bar{\mathbf{v}}_{\text{head}(k)}^\tau$ for all the k that are connecting to i . The aggregating function $\rho^{E \rightarrow V}$ can be applied to different numbers of edges for each node, making our model flexible for various graph typologies. Indeed, the updating and aggregating operations in GN mimic the localized traffic exchanges shown in Figure 3, and hence it is powerful in uncovering the *locally spatial* patterns of traffic data. Additionally, GN is applied to each node and edge separately, so it is independent of network size, which is another attractive feature of GN.

4) **Node Decoder:** The updated node $\bar{\mathbf{v}}_i^{\tau+1}$ from the GN model is further decoded by the node decoder. Similar to the node encoder, the node decoder is modeled through an MLP, as shown in Equation 6.

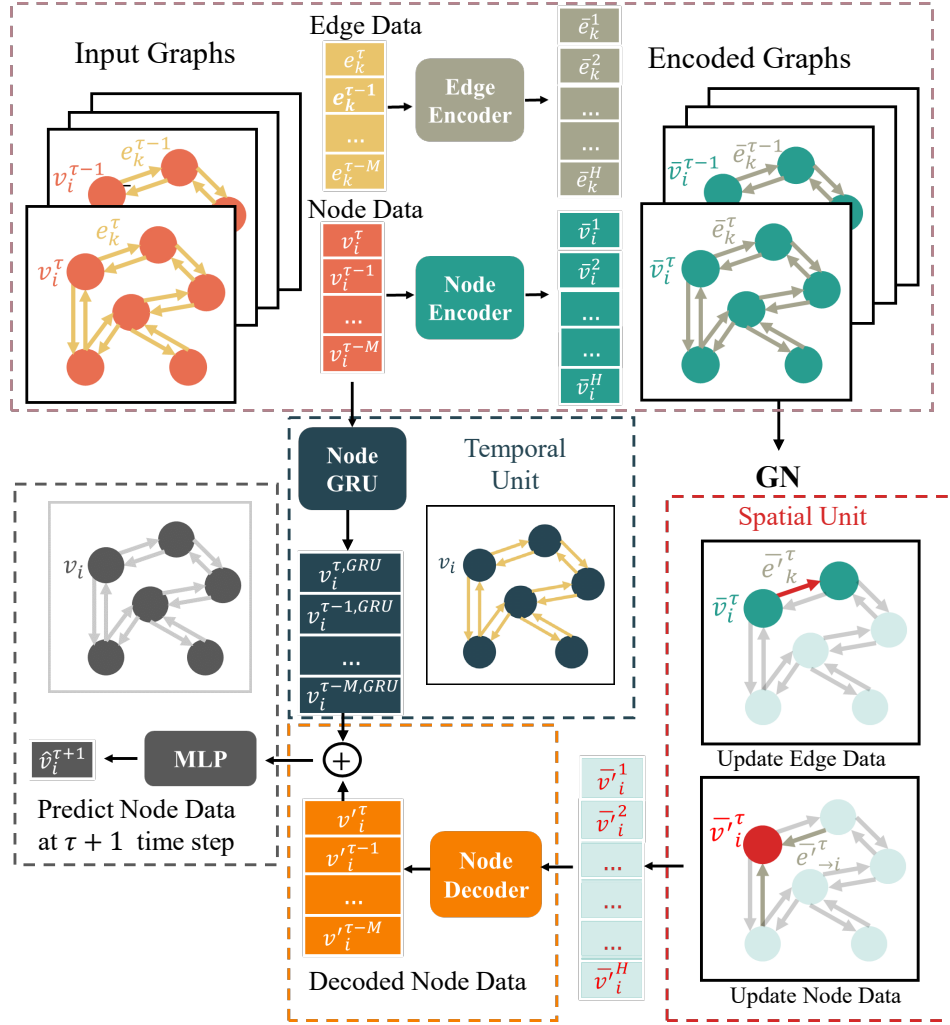


Fig. 4: An overview of LOCALEGN (H represents the size of hidden layers).

$$\mathbf{v}_i^{\prime\tau} = \text{MLP}^{V'} \left(\overline{\mathbf{v}}_i^{\tau} \right), \forall i, \tau \quad (6)$$

where $\mathbf{v}_i^{\prime\tau}$ represents the decoded data for node i at time τ .

5) *Output Layer*: In the output layer, we combine the *locally spatial* and temporal information obtained from the NODEGRU and node decoder, respectively. Mathematically, we concatenate $\mathbf{v}_i^{\tau, \text{GRU}}$ and $\mathbf{v}_i^{\prime\tau}$, the resulting vector is feed into an MLP for predicting the traffic states at time $\tau + 1$, as shown in Equation 7.

$$\hat{v}_i^{\tau+1} = \text{MLP}^{\text{Output}} \left(\mathbf{v}_i^{\prime\tau} \oplus \mathbf{v}_i^{\tau, \text{GRU}} \right), \forall i, \tau \quad (7)$$

where \oplus is the vector concatenation operator, $\hat{v}_i^{\tau+1}$ is the prediction for $v_i^{\tau+1}$, and $\text{MLP}^{\text{Output}}$ represents another MLP. To summarize, all the computational steps in the LOCALEGN are presented in Algorithm 1.

Finally, the difference between the prediction $\hat{v}_i^{\tau+1}$ and the actual data $v_i^{\tau+1}$ is measured by the ℓ_2 norm represented by $\sum_i (v_i^{\tau+1} - \hat{v}_i^{\tau+1})^2$. The error is back-propagated to update all the parameters in LOCALEGN.

In addition, the computational complexity of proposed LOCALEGN is $O(N * P + N * M)$, in which N is the number of nodes, P is the layer number of GN and M is the length of the lookback window.

C. Transferability of LOCALEGN

In this section, we discuss how LOCALEGN is different from the existing traffic prediction models in terms of transferability. The most important feature of LOCALEGN is that both GN and NODEGRU modules make use of the parameter-sharing characteristic so that the knowledge learned for traffic prediction can be transferred among nodes. Though most of the existing GNNs can be cast into the message passing neural networks and hence the parameters can be shared [19], existing traffic prediction models avoid using the parameter sharing characteristic because it could impede the prediction performance.

In this study, we particularly consider the edge data \mathbf{e}_i^{τ} , which represents road properties (e.g., road length, width, and types), location information (e.g., weather, socio-demographic factors), and so on. For node i , we define the locale of node i at time τ to be $\mathcal{L}^{\tau}(i) = \{\mathbf{v}_i^{\tau}, \overline{\mathbf{E}}_{\rightarrow i}^{\tau}\}$, and hence the information

Algorithm 1 Computational steps in LOCALEGN.

Require: graph structure $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, node data $\mathbf{V}^\tau = [\mathbf{v}_1^\tau; \dots; \mathbf{v}_i^\tau; \dots; \mathbf{v}_{N_v}^\tau]$ and edge data $\mathbf{E}^\tau = [\mathbf{e}_1^\tau; \dots; \mathbf{e}_k^\tau; \dots; \mathbf{e}_{N_e}^\tau]$.

Ensure: GRU in Equation 1, MLP^E and MLP^V in Equation 2, MLP^{ϕ^E} and MLP^{ϕ^V} in GN, $\text{MLP}^{V'}$ in Equation 6, and $\text{MLP}^{\text{Output}}$ in Equation 7 are properly initialized and trained.

for $i \in \{1, \dots, N^v\}$ **do**

Compute $\mathbf{v}_i^{\tau, \text{GRU}}$ based on Equation 1.

Compute $\bar{\mathbf{v}}_i^\tau$ based on Equation 2.

end for

for $k \in \{1, \dots, N^e\}$ **do**

Compute $\bar{\mathbf{e}}_k^\tau$ based on Equation 2.

Update the edge data using the edge updating function based on Equation 3.

end for

for $i \in \{1, \dots, N^v\}$ **do**

Form the set of the updated edges pointing to node i as $\bar{\mathbf{E}}^{\tau \rightarrow i}$.

Compute $\bar{\mathbf{e}}^{\tau \rightarrow i}$ based on Equation 4 and $\bar{\mathbf{E}}^{\tau \rightarrow i}$.

Compute $\bar{\mathbf{v}}_i^{\tau'}$ based on Equation 5.

Decode the updated node data based on Equation 6.

Concatenate $\mathbf{v}_i^{\tau'}$ and $\mathbf{v}_i^{\tau, \text{GRU}}$.

Predict $\hat{v}_i^{\tau+1}$ based on Equation 7.

end for

return $\hat{v}_i^{\tau+1}, \forall i \in \{1, \dots, N^v\}$

contained in the locale can be used to conduct traffic prediction independently. The learning of traffic states becomes inductive, *i.e.*, LOCALEGN universally learns the traffic states conditional on the locale, instead of learning the traffic states for each node separately. Later in the experimental experiments, we demonstrate that with the consideration of edge data, the node embedding can be learned through a universal encoder, *i.e.*, the GN module, and the traffic prediction can be conducted per node. Additionally, the information contained in the locale is permutation-invariant, hence LOCALEGN is suitable for different network topologies for traffic prediction.

D. Determining the number of GN layers

One can see that the GN (spatial unit) in LOCALEGN depicts the traffic states on each node, and the K layers of GN can be stacked to model the localized traffic exchanges for the K -hop neighbors. In this section, we discuss how to determine K with theoretical analysis.

In general, traffic states are formed through the traffic flow forward propagation and congestion spillover. To predict traffic states on node i for the next L time intervals, we should ensure that the traffic exchanges in the next L time intervals are within the K -hop neighbors, so that GN has the capability to capture the changes in traffic states. Without loss of generality, we assume that around node i , the free flow speed is f and the shockwave speed is w , respectively. Free-flow speed f can be obtained from the OpenStreetMap. The OpenStreetMap contains the road level information (*e.g.*, highway, local roads), which can be used to infer the free-flow speed. Similarly,

the shockwave speed w can be determined based on the road properties in OpenStreetMap. We define $d_i(j), \forall j \in \mathcal{V}$, which represents the distance from node i to node j , and K can be determined using Equation 8.

$$\begin{aligned} K &= \max_{i \in \mathcal{V}} [\mathcal{I}_i^{\text{forward}} \cup \mathcal{I}_i^{\text{backward}}] \\ \mathcal{I}_i^{\text{forward}} &= \{\text{hop}_i(j) | d_i(j) \leq Lv, \forall j \in \mathcal{V}\} \\ \mathcal{I}_i^{\text{backward}} &= \{\text{hop}_j(i) | d_j(i) \leq Lw, \forall j \in \mathcal{V}\} \end{aligned} \quad (8)$$

where $\text{hop}_i(j)$ counts the number of edges in the shortest path from i to j . $\mathcal{I}_i^{\text{forward}}$ and $\mathcal{I}_i^{\text{backward}}$ denote the sets of edge numbers to which the forward traffic flow and congestion spillover could reach from node i , respectively. Using Figure 5 as an example, the impact of a source node can spread to its directly connected neighbors in 5 minutes. It will take longer time to spread the impact further and hence it suffices to consider a small number of K based on Equation 8.

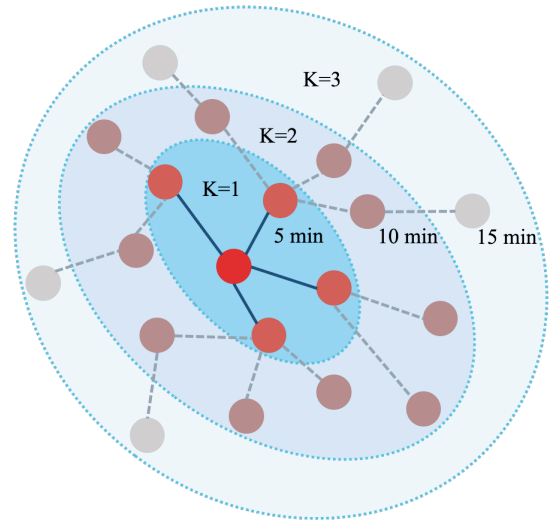


Fig. 5: Determining the number of GN layers.

IV. NUMERICAL EXPERIMENTS

In this section, the proposed model is examined in real-world flow and speed datasets to test the short-term prediction performance.

A. Datasets

We evaluate LOCALEGN and other baseline models on three traffic speed and three traffic flow datasets, respectively. The detailed dataset information is listed as follows:

1) *Traffic Speed Data:* Three speed datasets are used and the time interval is every five minutes:

- LA: The LA dataset is collected from 207 loop detectors in Los Angeles, and the data ranges from March 1st to March 7th, 2012.
- SACs: also known as PEMS7, which contains speed data from 228 detectors in the Sacramento area. The data ranges from May to June 2012.
- ST: ST contains speed data from 170 sensors in the Seattle Area. The data ranges from Jan 1st to Feb 1st, 2015.

2) *Traffic Flow Data*: Three traffic flow datasets in [57] are utilized and the time interval is every five minutes:

- **SF**: also known as PEMS04, which includes 307 sensors in the San Francisco Bay area, and the data ranges from September 1st to November 7th, 2018.
- **SacF**: also known as PEMS07, which contains traffic flow data from 883 detectors in the Sacramento area. The data ranges from January 1st to August 7st, 2018.
- **SanB**: also known as PEMS08, which contains traffic flow data from 170 sensors in the San Bernardino area, and the data ranges from July 1st to August 7st, 2016.

B. Baseline models

The following baseline models will be compared with LOCALEGN. Particularly, NODEGRU and GN are presented for ablation study.

- **GCN**: Graph Convolutional Network for graph-based data prediction [58].
- **LSTM**: Long Short-Term Memory network for time series prediction [59].
- **T-GCN**: Temporal Graph Convolutional Network [60]. Spatial dependency is captured by the GCN module and temporal correlation is abstracted by GRU.
- **ST-GCN**: Spatial-Temporal Graph Convolutional Network [23]. ChebNet and 2D convolutional network are utilized to capture the spatial and temporal correlation, respectively.
- **DCRNN**: Diffusion Convolutional Recurrent Neural Network [20].
- **GRAPH WAVENET**: Graph WaveNet for Deep Spatial-Temporal Graph Modeling [21].
- **STEMGNN**: Spectral Temporal Graph Neural Network [25].
- **LSDLM**: Large-scale Dynamic Linear Model [40].
- **NODEGRU**: Gated Recurrent Unit [61] for every single node's data in graph. This model can be viewed as LOCALEGN with only GRU component.
- **GN**: Graph network model with relational inductive bias [20]. This model can be viewed as LOCALEGN without the NODEGRU module.

C. Experimental Settings

All experiments are conducted on a desktop with Intel Core i9-10900K CPU @3.7GHz \times 10, 2666MHz \times 2 \times 16GB RAM, GeForce RTX 2080 Ti \times 2, 500GB SSD. We divide all speed and flow datasets of seven days with a ratio of 6 : 1 : 1 into training set, validation set and testing set. Since the most-commonly used historical data ranges from 7 days to 30 days, we choose 7 days' data as the minimum sufficient data for training the majority of existing prediction models. To simulate the situation of limited training samples, we randomly select 20% of the training set for training. The sufficient dataset for prediction is 7 days (including five days' lengthen of training, 1-day lengthen of validation and 1-day lengthen of testing) and we utilize 1-day data as the insufficient training data (20% of the original training dataset) and keep the validation and

testing unchanged. When constructing \mathbf{G}^τ , we set the edge data to be the normalized distance of the edges between two nodes, and the node data are the traffic speed or traffic flow from different datasets. After parameter fine-tuning with the validation set, we select one hour historical data to predict the next 5, 15, 30, 45, and 60 minutes' data, meaning $M = 12$ and $L = 1, 3, 6, 9, 12$. Hyper-parameters in LOCALEGN are determined by the validation set, and the finalized model specifications are presented in Appendix A.

D. Evaluation Metrics

Three different metrics are chosen to evaluate the prediction performance of LOCALEGN and other baseline models by comparing $\hat{v}_i^{\tau+1}$ with the ground truth $v_i^{\tau+1}$.

- **Root Mean Squared Error (RMSE)**:

$$\text{RMSE} = \sqrt{\frac{1}{N^v} \sum_{i=1}^{N^v} (\hat{v}_i^{\tau+1} - v_i^{\tau+1})^2}$$
- **Mean Absolute Error (MAE)**:

$$\text{MAE} = \frac{1}{N^v} \sum_{i=1}^{N^v} |\hat{v}_i^{\tau+1} - v_i^{\tau+1}|$$
- **Mean Absolute Percentage Error (MAPE)**:

$$\text{MAPE} = \frac{100\%}{N^v} \sum_{i=1}^{N^v} \left| \frac{\hat{v}_i^{\tau+1} - v_i^{\tau+1}}{v_i^{\tau+1}} \right|$$

E. Experimental Results

Table I and Table II present the prediction accuracy of different models with few training samples on three speed and flow datasets, respectively. One can see the proposed LOCALEGN outperforms other baseline models on the six datasets for most time. LOCALEGN outperforms the large-scale dynamic linear model-LOCALEGN in terms of testing accuracy, which show that the knowledge learned in our proposed model can be applied to unseen scenarios. LSTM utilizes temporal correlations, and GCN models the spatial dependencies; both models cannot fully take the spatio-temporal dependencies into consideration at the same time. With few training samples, the performance of the state-of-the-art models like T-GCN and ST-GCN degrades, while LOCALEGN achieves higher prediction accuracy. Besides, STEMGNN achieves acceptable prediction performance but is not as accurate as LOCALEGN. Among parameters-sharing models, LOCALEGN also outperforms DCRNN and GRAPH WAVENET. It is probably due to the complicated encoder and decoder structure of DCRNN and the specified node embedding of GRAPH WAVENET. The complicated structures make them overfit the limited available data. However, with parameters-sharing characteristics, LOCALEGN is a light-weighted model with the well-designed structure that perfectly meets the requirements of short-term traffic prediction with few samples.

We note for the flow datasets, the standard deviation is high for the baseline models, which suggests that these models may overfit with few training samples. Besides, there is a large gap between the prediction accuracy of NODEGRU and LSTM, although GRU and LSTM are similar RNN modules. It is because the complicated model is inclined to overfit on small datasets. GRU is less complicated than LSTM and LSTM is applied for all nodes' data while NODEGRU is for single node separately, which means LSTM have more trainable parameters and more complicated. The MAPE for some models (e.g.,

GCN, LSTM) in the flow datasets is very high, which is because the flow can be close to zero, resulting in an arbitrarily large MAPE if the flow prediction is not accurate.

1) *Ablation Study*: The ablation study for LOCALEGN has been incorporated in Table I and Table II by comparing with NODEGRU and GN, as both models are the essential components of LOCALEGN. In speed datasets, we observe that LOCALEGN is consistently better than the other two models. In flow datasets, NODEGRU and GN occasionally outperform LOCALEGN, which suggests that either the GRU component or GN component might dominate for a specific dataset. Overall, LOCALEGN achieves satisfactory performance for all datasets under different metrics.

2) *Justifying the use of each module*: We further conduct more experiments to justify the use of NODEGRU and GN. To this end, we try to replace each module with other modules with similar functionality. For example, NODEGRU can be replaced with a residual connection [62], and GN can be replaced with a self-attention module [63]. We find that both NODEGRU and GN outperform their counterparts, which justifies the use of both modules. Details are presented in Appendix B.

E. Number of Model Parameters

According to the few-sample experiment results, although inferior to LOCALEGN, ST-GCN achieves better prediction accuracy than other baseline models. We compare the number of trainable parameters of LOCALEGN and ST-GCN in Table III. For any network of arbitrary size, the number of trainable parameters in LOCALEGN remains the same. However, for ST-GCN, the number of its parameters is positively correlated with the network size. For example, the flow dataset SacF has a large node number of 883, and the number of trainable parameters in ST-GCN is ten times larger than that of LOCALEGN. However, the prediction performance of LOCALEGN is even better than that of ST-GCN. It further proves that the short-term traffic prediction relies on localized information, and this can be efficiently learned from few samples with graph relational inductive biases.

In the traditional graph model for spatio-temporal data prediction, the parameters sets are different for different nodes and it causes difficulty for the training process of large graphs. However, LOCALEGN makes it feasible to learn across nodes. It can be seen as the transfer learning model among different nodes on a network. One node and its neighborhoods can be interpreted as a sub-graph, and LOCALEGN is able to extract useful information from the sub-graphs. This suggests the reason why LOCALEGN requires fewer samples for training.

G. Sensitivity Analysis

Apart from evaluation in few training samples (20% of the training data), we also compare the prediction performance of LOCALEGN and other baseline models with different percentages of training data (from 20% to 100%), the results are presented in Figure 6. The prediction performance remains stable for LOCALEGN when the training ratio decreases from 100% to 20%, while the prediction performance of ST-GCN

gradually degrades when reducing the number of training samples.

Overall, LOCALEGN outperforms T-GCN and ST-GCN with all percentages of training data and the advantage is notably large when the ratio is 20% or 40%. In other words, T-GCN and ST-GCN overfit and become unstable when the training set is small. In contrast, LOCALEGN has better learning ability in capturing the localized spatial and temporal correlations than T-GCN and ST-GCN. The results further demonstrate that LOCALEGN is a powerful and efficient model for the task of the few-sample traffic prediction.

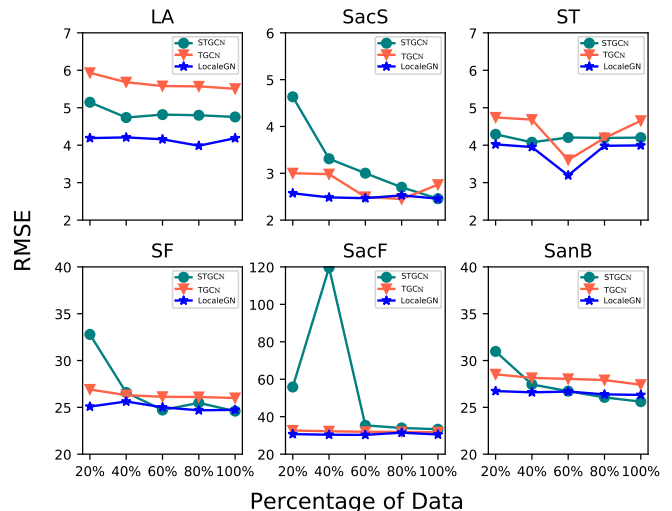


Fig. 6: Comparison of prediction performance among LOCALEGN, T-GCN and ST-GCN with the percentage of training set ranging from 20% to 100% (first row: speed data LA, ST, and SacS, unit: miles/hour; second row: flow data SF, SacF, and SanB, unit: vehicles/hour).

H. Cross-city Transfer Analysis

In this section, we consider a more challenging situation, in which traffic sensors are just installed or the traffic prediction service is just deployed in a city. In this case, we would like to use the knowledge learned from some city and directly apply it to a new city. To this end, we consider one city (target graph) that does not have historical traffic data, while some other cities (source graphs) have archived historical data. One can see this setting focuses on the transfer learning across cities. The well-performed LOCALEGN model is designed for extracting locally spatial and temporal traffic patterns, which is independent of graph structures and has the potential to be transferred to the target city. As the spectral graph-based GNN can be applied to graph structures, we compare LOCALEGN with DCRNN and GRAPH WAVE NET, the two state-of-the-art spectral graph-based models.

We compare the three models on speed and flow datasets respectively. Each model is pre-trained on a source graph with a random 20% of the training data and then directly tested on the target graph without further training. The prediction results on the target graph are presented in Table IV and Table V. One

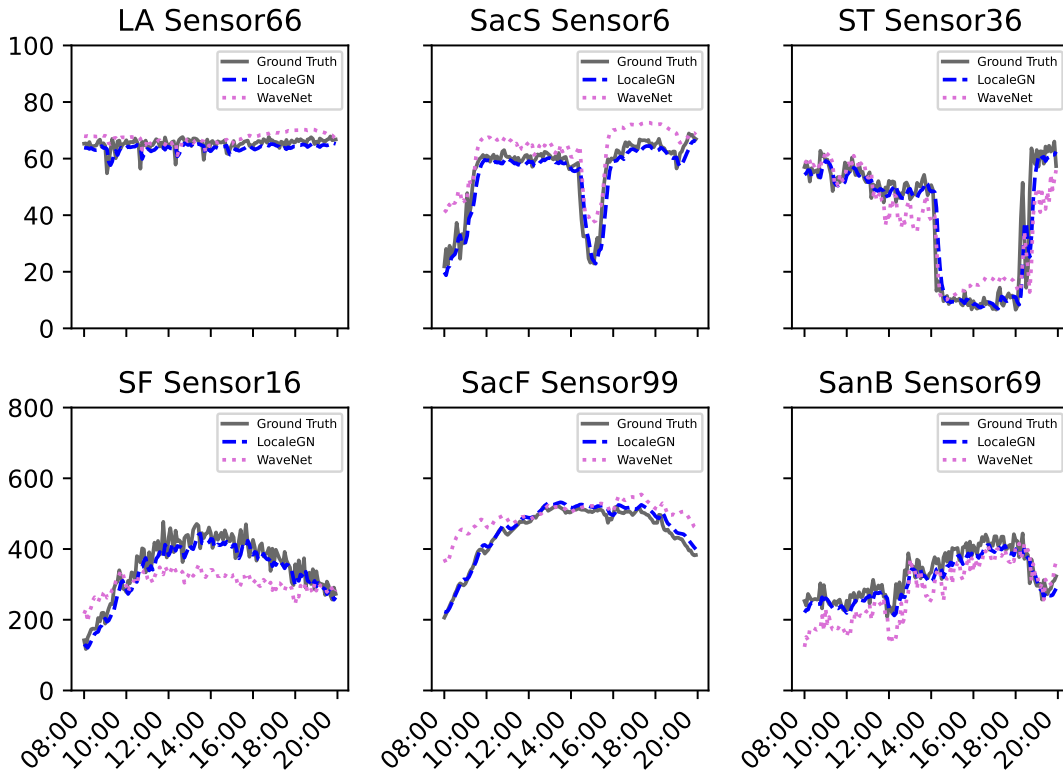


Fig. 7: Comparison of prediction performance with LOCALEGN and GRAPHWAVENET for cross-city transfer analysis (first row: speed data LA, SacS, and ST, unit: miles/hour; second row: flow data SF, SacF, and SanB, unit: vehicles/hour).

TABLE IV: Transferring Performance of DCRNN, GRAPH WAVE NET and LOCALEGN on traffic speed datasets (average \pm standard deviation across 5 experimental repeats; unit for RMSE and MAE: miles/hour).

Source/Target	DCRNN			GRAPH WAVE NET			LOCALEGN		
	RMSE	MAPE (%)	MAE	RMSE	MAPE (%)	MAE	RMSE	MAPE (%)	MAE
LA/SacS	4.52 \pm 0.39	7.56 \pm 0.74	3.30 \pm 0.39	7.34 \pm 0.65	13.73 \pm 1.48	5.88 \pm 0.65	3.84 \pm 0.31	5.56 \pm 0.69	2.79 \pm 0.47
LA/ST	4.93 \pm 0.37	7.87 \pm 0.74	3.71 \pm 0.37	6.59 \pm 0.20	10.12 \pm 0.77	4.89 \pm 0.20	4.00 \pm 0.02	5.96 \pm 0.12	2.65 \pm 0.01
SacS/LA	9.90 \pm 1.20	19.93 \pm 2.46	6.57 \pm 1.20	7.15 \pm 0.32	13.20 \pm 1.51	5.06 \pm 0.32	5.07 \pm 0.50	8.09 \pm 1.02	3.65 \pm 0.70
SacS/ST	7.29 \pm 0.43	13.44 \pm 0.98	4.98 \pm 0.43	7.34 \pm 0.82	10.78 \pm 0.87	5.42 \pm 0.82	4.57 \pm 0.45	6.80 \pm 0.89	3.24 \pm 0.59
ST/LA	8.22 \pm 1.33	15.98 \pm 3.63	5.87 \pm 1.33	6.88 \pm 0.64	12.94 \pm 1.03	4.70 \pm 0.64	4.86 \pm 0.21	7.62 \pm 0.52	3.33 \pm 0.35
ST/SacS	6.90 \pm 2.18	12.19 \pm 4.17	4.64 \pm 2.18	7.32 \pm 1.08	13.06 \pm 1.63	5.76 \pm 1.08	3.62 \pm 0.24	5.07 \pm 0.56	2.44 \pm 0.37

accuracy. Secondly, because LOCALEGN can be applied to different cities, it is interesting to develop a unified and fair framework for training and testing the LOCALEGN on multiple cities without biases. Essentially, LOCALEGN has capacities in transferring knowledge not only among nodes in a single graph, but also across different graphs. Thirdly, LOCALEGN can be further extended to predict OD demand for public transit and ride-hailing services [64, 65]. Indeed, the enlightening idea of relational inductive bias and the simple structure of LOCALEGN can be applied to learn various spatio-temporal datasets, and the localized patterns can be extracted. These datasets include human mobility patterns, social media, epidemics, and climate-related data.

APPENDIX

A. Model Specifications

In this section, we present details of the model specifications of LOCALEGN. There are four modules in LOCALEGN, which

include Encoder, NODEGRU, GN, and the Output layer. The detailed layer information of each module is listed in Table VI.

Besides, we provide hyper-parameters for model setting and training process in Table VII.

B. Additional Experiments

In this section, we provide results of some additional experiments to further justify the proposed structure of LOCALEGN.

1) *Residual Graph Network*: On top of the basic architecture of Encoder, GN, and Decoder, we also try to add residual connections to the GN module. Instead of using NODEGRU, the GN module is developed to learn the differences between the input graph and the expected output graph. The encoded data will be processed by the GN module, in which we add the residual connection to update the node attributes. The design of Residual Graph Network (RGN) model is inspired by the theory of dynamical system, in which the output at $\tau+1$ can be

TABLE V: Transferring Performance of DCRNN, GRAPH WAVE_{NET} and LOCALE_{GN} on traffic flow datasets (average ± standard deviation across 5 experimental repeats; unit for RMSE and MAE: vehicles/hour).

Source/Target	DCRNN			GRAPH WAVE _{NET}			LOCALE _{GN}		
	RMSE	MAPE (%)	MAE	RMSE	MAPE (%)	MAE	RMSE	MAPE (%)	MAE
SF/SacF	125.59 ± 9.02	571.77 ± 145.49	96.82 ± 9.02	129.38 ± 12.20	106.95 ± 27.87	108.96 ± 12.20	31.88 ± 0.87	15.26 ± 4.81	21.57 ± 1.34
SF/SanB	102.19 ± 6.23	299.38 ± 63.31	78.83 ± 6.23	90.58 ± 6.23	103.88 ± 26.38	77.27 ± 6.23	27.17 ± 0.67	14.00 ± 2.14	19.00 ± 0.88
SacF/SF	84.00 ± 5.75	659.87 ± 154.49	61.94 ± 5.75	90.76 ± 4.39	85.02 ± 8.83	78.63 ± 4.39	25.87 ± 1.01	21.71 ± 2.65	18.02 ± 1.06
SacF/SanB	95.80 ± 6.31	331.29 ± 40.89	74.75 ± 6.31	87.77 ± 5.51	90.50 ± 10.88	75.39 ± 5.51	27.93 ± 1.67	13.40 ± 0.74	19.67 ± 1.78
SanB/SF	88.32 ± 7.09	910.14 ± 140.04	63.38 ± 7.09	81.96 ± 11.46	95.34 ± 15.22	73.89 ± 11.46	26.44 ± 1.76	30.95 ± 11.12	18.97 ± 2.08
SanB/SacF	123.60 ± 10.77	591.62 ± 76.52	94.44 ± 10.77	110.59 ± 18.08	108.27 ± 23.19	99.32 ± 18.08	33.83 ± 3.51	19.19 ± 8.19	24.02 ± 4.30

TABLE VI: Functions in LOCALE_{GN}.

Module	Functions
Node Encoder	DenseLayer [12,64] with ReLU
Edge Encoder	DenseLayer [1,64] with ReLU
NODEGRU	[12,64]
Updating by ϕ_E	$\bar{e}_k^T = \phi^E(\bar{e}_k^T, \bar{v}_{tail(k)}^T, \bar{v}_{head(k)}^T), \forall k, \tau$ DenseLayer [256,64] with ReLU
Aggregating by $\rho^{E \rightarrow V}$	Element-wise average operator
Updating by ϕ_V	$\bar{v}_i^T = \phi^V(\bar{e}_{i \rightarrow i}^T, \bar{v}_i^T), \forall i, \tau$ DenseLayer [256,64] with ReLU
Node Decoder	DenseLayer [64,64] with ReLU
Output layer	Concatenation operator and DenseLayer [64,1] with ReLU

TABLE VII: Hyper-parameters in LOCALE_{GN}.

Hyper-parameters	Values
Optimizer	Adam
Learning rate	0.001
Weight decay	0.0005
Iteration	3,000
Lookback window	12
Node hidden dimension	64
Edge hidden dimension	64
Number of GRU layer	1
Number of GN layer	1

calculated based on the input at time τ as well as the evolution function GN. Mathematically, the residual connection can be presented in Equation 9.

$$\bar{G}_{\tau+1} = \text{GN}(\bar{G}_\tau) + \bar{G}_\tau \quad (9)$$

2) *Attention Graph Network*: We also try to replace the NODEGRU module in LOCALE_{GN} with the SELF-ATTENTION mechanism to capture the temporal dependency of the traffic data. Different from applying GRU for each node data separately, the SELF-ATTENTION module is applied to all the node data simultaneously. The reason we compare with the SELF-ATTENTION module is that recent studies indicate its strong potential in transferability [63, 66]. The proposed Attention Graph Network (AGN) can be represented in Equation 10.

$$\bar{G}_{\tau+1} = \text{GN}(\bar{G}_\tau + \text{SELF-ATTENTION}(\bar{G}_\tau)) \quad (10)$$

where the key, query and value in SELF-ATTENTION are embedded with historical node data. The outcome vector from SELF-ATTENTION is transformed to a lower dimension vector to obtain the compressed temporal patterns, which are then combined with the original node data. The combined vector

is fed into an encoder to generate the input of GN in order to further infer the spatio-temporal patterns at time $\tau + 1$.

3) *Results Comparison*: Using the same experiment settings as in section IV-C, the additional two models are examined on the three speed datasets and three flow datasets, respectively. The prediction errors of LOCALE_{GN}, RGN and AGN are listed in Table VIII and Table IX.

TABLE VIII: Performance of LOCALE_{GN}, RGN and AGN on traffic speed datasets.

Model	LA		
	RMSE	MAPE (%)	MAE
AGN	4.45	7.18	2.80
RGN	4.34	6.94	2.73
LOCALE _{GN}	4.24	6.88	2.70
Model	SacS		
	RMSE	MAPE (%)	MAE
AGN	2.94	4.21	1.91
RGN	2.55	3.53	1.58
LOCALE _{GN}	2.56	3.72	1.65
Model	ST		
	RMSE	MAPE (%)	MAE
AGN	4.13	6.14	2.73
RGN	4.09	6.06	2.77
LOCALE _{GN}	4.00	5.96	2.65

TABLE IX: Performance of LOCALE_{GN}, RGN and AGN on traffic flow datasets.

Model	SF		
	RMSE	MAPE (%)	MAE
AGN	25.00	40.49	17.25
RGN	25.86	34.42	18.02
LOCALE _{GN}	25.08	23.12	17.26
Model	SacF		
	RMSE	MAPE (%)	MAE
AGN	30.73	15.58	20.19
RGN	30.34	12.79	19.64
LOCALE _{GN}	30.70	10.53	20.03
Model	SanB		
	RMSE	MAPE (%)	MAE
AGN	34.97	22.60	26.56
RGN	28.23	19.30	19.77
LOCALE _{GN}	26.74	14.86	18.43

For traffic speed prediction, LOCALE_{GN} outperforms RGN and AGN on both LA and ST, but slightly under-performs

RGN on $SacS$ dataset. For traffic flow prediction, LOCALEGN outperforms RGN and AGN on all datasets regarding the MAPE, but its performance is slightly lower than RGN on $SacF$ dataset in terms of MAE and RMSE. On SF , the differences between AGN and LOCALEGN for MAE and RMSE are within the range of ± 0.01 and negligible, but MAPE of LOCALEGN is substantially smaller than that of AGN. Overall, LOCALEGN has the best and most stable performance among the three proposed models on both traffic speed and flow prediction tasks. The detailed implementation for all the three models is also available in the code repository.

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