Long-term Spatio-Temporal Forecasting via Dynamic Multiple-Graph Attention

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Abstract

Many real-world ubiquitous applications, such as parking recommendations and air pollution monitoring, benefit significantly from accurate long-term spatio-temporal forecasting (LSTF). LSTF makes use of long-term dependency structure between the spatial and temporal domains, as well as the contextual information. Recent studies have revealed the potential of multi-graph neural networks (MGNNs) to improve prediction performance. However, existing MGNN methods do not work well when applied to LSTF due to several issues: the low level of generality, insufficient use of contextual information, and the imbalanced graph fusion approach. To address these issues, we construct new graph models to represent the contextual information of each node and exploit the long-term spatio-temporal data dependency structure. To aggregate the information across multiple graphs, we propose a new dynamic multigraph fusion module to characterize the correlations of nodes within a graph and the nodes across graphs via the spatial attention and graph attention mechanisms. Furthermore, we introduce a trainable weight tensor to indicate the importance of each node in different graphs. Extensive experiments on two large-scale datasets demonstrate that our proposed approaches significantly improve the performance of existing graph neural network models in LSTF prediction tasks. The code is available at https://github.com/swsamleo/MLSTGCN.

1 Introduction

Recently, various spatio-temporal prediction tasks have been investigated, including traffic flow [Li et al., 2018; Huang et al., 2020; Yu et al., 2018], parking availability [Zhang et al., 2020a], and air pollution [Wang et al., 2020b; Wen et al., 2019; Liu et al., 2021]. All the scenarios above benefit from an accurate forecast by leveraging historical data in the long run, namely, long-term spatio-temporal forecasting (LSTF).

One main challenge in LSTF is to effectively capture the long-term spatio-temporal dependency and extract contextual information. Recently, multi-graph neural networks (MGNNs) [Wang et al., 2021] have received increasing attention for spatio-temporal forecasting problems. Specifically, as shown in Figure 1, each node's value $V_i$ is estimated in the long run using historical data and correlations across nodes of a distance graph, where each edge denotes the correlation or dependency between two different nodes. Furthermore, the functionality similarities of surrounding areas, which represent contextual information, can also be used...
for prediction purposes. Compared to the single graph approach, which may not comprehensively capture all the relationships, the MGNN-based approach is appropriate for leveraging more information and features by integrating different graphs. Thus, in this work, we choose the MGNN-based approach to infer how information about each node evolves over time.

Although MGNNs show potential for extracting contextual information around prediction sites, four significant limitations remain when solving the LSTF problem:

1. **Most existing MGNN studies consider only the spatial similarity of nodes, such as the distance similarity and neighborhood correlation.** Previous studies have shown that the distance similarity is insufficient to represent correlations among nodes with spatio-temporal attributes [Geng et al., 2019]. Wu et al. [Wu et al., 2019] proposed an adaptive adjacency matrix to discover hidden spatial dependencies directly from historical records of each node in an end-to-end fashion by computing the inner product of the nodes’ learnable embedding. However, these works did not utilize well the existing prior knowledge encoded as an adjacency matrix, which may result in missing vital information.

2. **Fusing different graph models is challenging.** For multi-graph-based problems, the graph models differ with different scales; thus, it is inappropriate to simply merge them using weighted sum or other averaging approaches. Additionally, how to align each node in different graphs is challenging since nodes in different graphs are associated with different spatio-temporal information.

3. **Existing multi-graph fusion approaches rely heavily on specific models.** The current MGNNs lack generalizability. Specifically, the existing graph construction approaches and fusion methods need to be strictly bonded, assuming specific graph neural network structures. Although such an end-to-end framework provides a convenient method, it induces various difficulties in examining the importance of each graph to find a better combination of each module.

4. **Long-term spatio-temporal dependency is not considered.** Usually, MGNNs tend to learn the spatio-temporal dependency by projecting mapping from data within the observation window and the prediction horizon. However, due to the limitation of data sources, existing graph models, such as the distance graph [Li et al., 2018] or the neighbor graph [Geng et al., 2019] represent only the static spatial information, which cannot capture the long-term spatio-temporal dependency.

To address the issues above, we investigate graph construction and fusion mechanisms, and make improvements to each component. Specifically, we take advantage of human insights to build a new graph model namely ‘heuristic graph’, which can represent the long-range distribution of the collected spatio-temporal data. Aiming to align various graphs with different information, we then employ the spatial and graph attention mechanisms to integrate nodes in the same graph and different graphs. Furthermore, to dynamically capture the contextual information and temporal dependency of each node in different graphs, we construct an adaptive correlation tensor to indicate the importance of each node. In summary, the main contributions of this paper are as follows:

- We propose a new graph model namely ‘heuristic graph’, for the LSTF problem, which can represent the long-term spatio-temporal dependency from historical data or human insights and can be widely used for various graph neural networks.
- We design a novel graph model fusion module called a dynamic graph fusion block to integrate various graph models with graph attention and spatial attention mechanisms, aiming to align nodes within graphs and across different graphs. We further construct a learnable weight tensor for each node to flexibly capture the dynamic correlations between nodes.
- We conduct extensive experiments on two large-scale public real-world spatio-temporal datasets. We validate the effectiveness of the proposed new graph models and fusion approaches using ablation studies.

## 2 Methodologies

As shown in Figure 2, the proposed framework consists of three major components: the graph construction module, the dynamic multi-graph fusion module, and the spatio-temporal graph neural network (ST-GNN). We designed five graphs to represent different aspects of the spatio-temporal information in the graph construction module. In the dynamic multi-graph fusion module, we align spatial and temporal dependency using an adaptive trainable tensor and introduce graph and spatial attention mechanisms to calculate the correlations among nodes located in different graphs. We then obtain the prediction results with existing ST-GNN models.

### 2.1 Graph Construction

In this section, we describe in detail two new graph models we proposed named the heuristic graph $G^H = \{V, E, W^H\}$ and the functionality graph $G^F = \{V, E, W^F\}$, combined with other three existing graphs, the distance graph $G^D = \{V, E, W^D\}$, neighbor graph $G^N = \{V, E, W^N\}$, and temporal pattern similarity graph $G^T = \{V, E, W^T\}$, into a multiple graph set $G = \{G^D, G^N, G^F, G^H, G^T\}$.

**Distance Graph.** The element of distance matrix $W^D$ is defined with a thresholded Gaussian kernel as follows [Shuman et al., 2013]:

$$W^D_{ij} := \begin{cases} \exp \left(-\frac{d^2_{ij}}{\sigma^2_D}\right), & \text{for } i \neq j \text{ and } \exp \left(-\frac{d^2_{ij}}{\sigma^2_D}\right) \geq \varepsilon, \\ 0, & \text{otherwise.} \end{cases}$$  

(1)

where $d_{ij}$ is the Euclidean distance between $v_i$ and $v_j$, $\varepsilon$ and $\sigma^2_D$ are used to control the sparsity and distribution of $W^D$.

**Neighbor Graph.** The element of neighbor matrix $W^N$ is defined as follows:

$$W^N_{ij} := \begin{cases} 1, & \text{if } v_i \text{ and } v_j \text{ are adjacent}, \\ 0, & \text{otherwise.} \end{cases}$$

(2)
Functionality Graph. Usually, places with similar functionalities or utilities, such as factories, schools, and hospitals, have strong correlations. In this paper, different from the functionality graph proposed by [Geng et al., 2019], we propose a new functionality graph using Pearson correlation coefficients to capture the global contextual function similarity. Denote the total number of functions is $K$; then the vector of the number of these functions of vertex $v_i$ is denoted as $F_i = \{f_{i,1}, f_{i,2}, \ldots, f_{i,k}, \ldots, f_{i,K}\}$. The functionality matrix can be obtained using Pearson correlation coefficients [Zhang et al., 2020b] by

$$W^F_{ij} := \begin{cases} \frac{\sum_{k=1}^{K} (f_{i,k} - \overline{F}_i)(f_{j,k} - \overline{F}_j)}{\sqrt{\sum_{k=1}^{K} (f_{i,k} - \overline{F}_i)^2} \sqrt{\sum_{k=1}^{K} (f_{j,k} - \overline{F}_j)^2}}, & \text{if } i \neq j, \\ 0, & \text{otherwise.} \end{cases}$$

(3)

Heuristic Graph. To leverage heuristic knowledge and human insights, we propose a new graph model called the heuristic graph. We create a histogram to represent the overview of the spatio-temporal training data, where each bin indicates a predefined temporal range, and the bar height measures the number of data records that fall into each bin. Then we apply a function $f(x) = \alpha e^{-\beta x}$ to approximate the histogram. For a vertex $v_i$, we can obtain its fitted parameters $\alpha_i$ and $\beta_i$. The distribution distance is calculated using the Euclidean distance $d_{ij}^H = \sqrt{(\alpha_1 - \alpha_2)^2 + (\beta_1 - \beta_2)^2}$. The element of the heuristic matrix $W^H$ can be defined as follows:

$$W^H_{ij} := \exp\left(-\frac{\|d_{ij}^H\|^2}{\sigma_H^2}\right), \quad \text{for } i \neq j, \quad 0, \quad \text{otherwise}. \quad (4)$$

where $\sigma_H^2$ is a parameter to control the distribution of $W^H$. Kullback-Leibler (KL) divergence [Van Erven and Harremos,
2014] can be also used to create this graph, which usually quantifies the difference between two probability distributions.

**Temporal Pattern Similarity Graph.** For a vertex \(v_i\), the vector of the time-series data used for training is described as \(T_i = \{t_{i,1}, t_{i,2}, \ldots, t_{i,L}, \ldots, t_{i,P}\}\), where \(P\) is the length of the series, and \(t_{i,p}\) is the time-series data value of the vertex \(v_i\) at time step \(p\). We also use the Pearson correlation coefficients [Zhang et al., 2020b] to define the elements of the temporal pattern similarity matrix \(W^T\) as follows:

\[
W^T_{ij} := \begin{cases} 
\frac{\sum_{p=1}^{P} (t_{i,p} - \bar{T})(t_{j,p} - \bar{T})}{\sqrt{\sum_{p=1}^{P} (t_{i,p} - \bar{T})^2 \sum_{p=1}^{P} (t_{j,p} - \bar{T})^2}}, & \text{if } i \neq j, \\
0, & \text{otherwise.}
\end{cases} \tag{5}
\]

### 2.2 Dynamic Multi-graph Fusion

The graph fusion approach plays a key role in multi-graph neural networks as multi-graphs cannot simply be merged with the average sum or the weighted sum [Wang et al., 2020a]. In this paper, a dynamic graph fusion method is proposed; the whole process of this method is shown in Figure 2 and Algorithm 1. We construct a trainable weight tensor as the input of a dynamic multi-graph attention block (DMGAB). Moreover, we incorporate the spatial and graph information into multi-graph spatial embedding (MGSE) and add this embedding to the DMGAB. To facilitate the residual connection, all layers of the DMGAB produce outputs of \(D\) dimensions, and the block can be expressed as DMGAB \(\mathbb{R}^{(G) \times N \times D}\).

**Multi-graph Spatial Embedding**

We apply the spatial embedding \(E^S_{v_i} \in \mathbb{R}^D\) to preserve the graph structure information. To represent the relationships of the nodes in different graphs, we further propose graph embedding to encode five graphs into \(\mathbb{R}^{(G)}\). Then we employ a two-layer fully-connected neural network to transform the graphs into a vector \(\mathbb{R}^D\) and obtain the multi-graph embedding \(E^M_{G_i} \in \mathbb{R}^D\), where \(G_i\) is any graph. To obtain the vertex representations among multiple graphs, we fuse the spatial embedding and the multi-graph embedding as the multi-graph spatial embedding (MGSE) with \(E_{v_i,G_i} = E^S_{v_i} + E^M_{G_i}\),

![Figure 3: The attention mechanisms adopted in this paper.](image-url)
functions in the Graph Attention. We employ graph attention to obtain the multi-head method to calculate the correlations. For each node in different graphs (as shown in correlation between graph $G_i$ and $G_j$), we further create a spatial-graph attention (SG-ATT) mechanism to extend them to the multi-head attention mechanism [Zheng et al., 2020] to consider both effects. The spatial attention $H_{S}^{l}$ is calculated by:

$$H_{S}^{l}(v_i) = \frac{1}{d} \sum_{n=1}^{N} \alpha_{v_i,v_n}^{(m)} \cdot f_{s,3}(h_{v_i,G_i}^{(l)}, h_{v_n,G_n}^{(l)}),$$

where $\alpha_{v_i,v_n}^{(m)}$, $f_{s,3}(\cdot, \cdot)$, and the ReLU functions are different ReLU functions serving as nonlinear projections in $m$-th head attention. $\alpha_{v_i,v_n}^{(m)}$ is calculated with a softmax function in the $m$-th head attention and $h_{S}^{l}(v_i)$ is the hidden state of $v_i \in G_i$.

**Graph Attention.** We employ graph attention to obtain the self-correlations of a node in different graphs (as shown in Figure 3b). Similar to the spatial attention mechanism, we concatenate the hidden state with MGSE and employ the multi-head method to calculate the correlations. For $v_i$, the correlation between graph $G_j$ and $G_k$ is defined as:

$$u_{G_j,G_k}^{(m)} = \frac{1}{d} \sum_{k=1}^{G} \beta_{G_j,G_k}^{(m)} \cdot f_{s,3}(h_{v_i,G_j}^{(l)}, h_{v_i,G_k}^{(l)}),$$

where $\beta_{G_j,G_k}^{(m)}$ calculated with a softmax function is the attention score in the $m$-th head, indicating the importance of graph $G_k$ to $G_j$. $f_{s,1}(\cdot)$, $f_{s,2}(\cdot)$, and $f_{s,3}(\cdot)$ are the ReLU functions in $m$-th head attention.

**Gated Fusion.** To further extract the correlations of nodes on different graphs, we adopt the gated fusion method [Zheng et al., 2020] to consider both effects. The spatial attention $H_{S}^{l}(\cdot)$ and the graph attention $H_{G}^{l}(\cdot)$ in the $l$-th block are fused with:

$$H^{l}(\cdot) = z \odot H_{S}^{l}(\cdot) + (1 - z) \odot H_{G}^{l}(\cdot),$$

where the gate $z$ is calculated by:

$$z = \sigma(H_{S}^{l}(W_{z,1} + H_{G}^{l}(W_{z,2} + b_z),$$

where $W_{z,1} \in \mathbb{R}^{D \times D}$, $W_{z,2} \in \mathbb{R}^{D \times D}$, and $b_z \in \mathbb{R}^{D}$ are the learnable parameters, $\odot$ indicates the element-wise Hadamard product, and $\sigma(\cdot)$ is the sigmoid activation function. By combining the spatial and graph attention mechanisms, we further create a spatial-graph attention (SG-ATT) block, which is shown in Figure 2.

3 Experiments

3.1 Datasets

**Parking:** The Melbourne parking dataset, collected by the Melbourne City Council in 2019, contains 42, 672, 743 parking events recorded by the in-ground sensors every five minutes located in the Melbourne Central Business District (CBD) [Shao et al., 2017]. All sensors have been classified into 40 areas.

**Air Quality:** The Ministry of Ecology and Environment of China (MEE) published a large-scale air quality dataset [Wang et al., 2020b], comprising 92 air quality monitoring stations, to assess the hourly PM$_{2.5}$ concentration in Jiangsu province in 2020.

3.2 Experimental Details

**Baselines.** We selected five state-of-the-art ST-GNN models as baselines: STGCN [Yu et al., 2018], ASTGCN [Guo et al., 2019], MASTGCN [Guo et al., 2019], ST-MGCN [Geng et al., 2019], and Graph WaveNet [Wu et al., 2019].

**Platform.** All experiments were trained and tested on a Linux system (CPU: Intel(R) Xeon(R) Gold 6240 CPU @2.60GHz, GPU: NVIDIA GeForce RTX 2080 Ti).

**Hyper-parameters.** All the tests used a 24-time step historical time window, and the prediction horizons ranged from three to 24 steps. The proposed methods were optimized with the Adam optimizer. The learning rate was set to $1 \times 10^{-4}$. The L1 loss function was adopted to measure the performance of the proposed model. The batch size was 32, and the global seed was set to 0 for the experiment repeat. All the tests were trained for 40 epochs. The number of attention heads $M$ and the dimension $d$ of each attention head were set to 8 and 8 in the Parking dataset and set to 24 and 6 in the Air Quality dataset.

**Evaluation Metrics.** In our study, mean absolute error (MAE) and root mean square error (RMSE) were used.

3.3 Results and Analysis

Table 1 summarizes the results of all ST-GNN models based on the two datasets. The prediction horizon ranged from three time steps to 24 steps. The best evaluation results are highlighted in boldface. The number of highlighted values is also recorded (i.e., the winning counts) to compare the performance of different models.

Table 1 shows the following: (1) When the proposed dynamic multi-graph fusion approach (marked with ‘*’) was used, the prediction performances significantly improved. For example, when the STGCN method was used, our method had an average RMSE decrease of 9.5% (over all prediction horizons). This indicates that our multi-graph fusion methods can extract more information and are effective for various

https://data.melbourne.vic.gov.au/
https://english.mee.gov.cn/
| Datasets | Methods | Metric | STGCN | STGCN* | ST-MGCN | ST-MGCN* | ASTGCN | ASTGCN* | MSTGCN | MSTGCN* | Graph WaveNet | Graph WaveNet* |
|----------|---------|--------|-------|--------|---------|---------|--------|---------|--------|---------|----------------|----------------|
| Parking  | 3       | RMSE   | 0.0607 | 0.0514 | 0.0538 | 0.0533 | 0.0524 | 0.0517 | 0.0493 | 0.0604 | 0.0479       | 0.0477     | 0.0483 |
|          | 6       | MAE    | 0.0751 | 0.0658 | 0.0677 | 0.0677 | 0.0646 | 0.0642 | 0.0611 | 0.0724 | 0.0607       | 0.0608     | 0.0694 |
|          | 9       | RMSE   | 0.0869 | 0.0787 | 0.0794 | 0.0794 | 0.0748 | 0.0748 | 0.0702 | 0.0833 | 0.0706       | 0.0709     | 0.0684 |
|          | 12      | MAE    | 0.0992 | 0.0903 | 0.0900 | 0.0900 | 0.0839 | 0.0843 | 0.0776 | 0.0939 | 0.0796       | 0.0801     | 0.0762 |
|          | 15      | RMSE   | 0.1107 | 0.1007 | 0.0999 | 0.0999 | 0.0924 | 0.1115 | 0.0850 | 0.1041 | 0.0875       | 0.0883     | 0.0832 |
|          | 18      | MAE    | 0.1210 | 0.1105 | 0.1092 | 0.1092 | 0.1002 | 0.1228 | 0.0915 | 0.1140 | 0.0947       | 0.0965     | 0.0893 |
|          | 21      | RMSE   | 0.1301 | 0.1194 | 0.1178 | 0.1178 | 0.1075 | 0.1308 | 0.0977 | 0.1229 | 0.1017       | 0.1040     | 0.0946 |
|          | 24      | MAE    | 0.1393 | 0.1276 | 0.1259 | 0.1259 | 0.1143 | 0.1410 | 0.1035 | 0.1318 | 0.1071       | 0.1114     | 0.0996 |

| Air Quality | 3       | RMSE   | 6.6843 | 6.3609 | 6.7802 | 6.3255 | 6.3958 | 6.9846 | 7.0427 | 6.3729 | 6.4878       | 6.1353     |
|             | 6       | MAE    | 8.3989 | 7.7995 | 8.7083 | 7.6470 | 7.7519 | 8.1628 | 8.4449 | 7.6549 | 8.2323       | 8.5556     |
|             | 9       | RMSE   | 9.7762 | 8.6881 | 10.3522 | 8.6431 | 9.0522 | 9.4715 | 9.3188 | 8.7717 | 10.3232      | 10.8160    |
|             | 12      | MAE    | 10.8079 | 9.5392 | 11.5615 | 9.5453 | 10.7794 | 10.2963 | 10.7145 | 9.6747 | 12.9487      | 13.1379    |
|             | 15      | RMSE   | 11.7172 | 10.1575 | 12.3340 | 10.3465 | 11.9669 | 10.9218 | 11.4235 | 10.7134 | 15.7093      | 15.0418    |
|             | 18      | MAE    | 11.9014 | 10.4241 | 12.7944 | 10.9299 | 13.2015 | 11.3600 | 12.3950 | 11.1146 | 19.2325      | 14.1381    |
|             | 21      | RMSE   | 12.5268 | 11.3408 | 13.1333 | 11.2794 | 14.4416 | 11.6768 | 13.1675 | 10.7613 | 21.1240      | 13.4125    |
|             | 24      | MAE    | 12.9587 | 11.8283 | 13.4853 | 11.3442 | 14.6557 | 10.7624 | 13.3226 | 11.3835 | 21.2758      | 12.0525    |
| Count      | 0       | 32     | 0      | 32     | 6       | 26      | 0      | 32     | 5       | 27     |                |            |

Table 1: The prediction results with five ST-GNN models with or without multi-graph modules on two datasets. (**"** indicates the ST-GNN model with the proposed dynamic multi-graph fusion method.)

| Model | STGCN | ASTGCN | MSTGCN | ASTGCN* | ST-MGCN | MST-MGCN | Graph WaveNet |
|-------|-------|--------|--------|---------|---------|----------|---------------|
| 12    | 0.0648 | 0.0648 | 0.0579 | 0.0612 | 0.0579 |
| 24    | 0.0964 | 0.0964 | 0.0957 | 0.0979 | 0.0957 |
|       | 0.0961 | 0.0961 | 0.0890 | 0.0887 | 0.0890 |
|       | 0.0934 | 0.0934 | 0.0868 | 0.0916 | 0.0868 |
| 24    | 0.0901 | 0.0901 | 0.0882 | 0.0860 | 0.0882 |
|       | 0.0903 | 0.0903 | 0.0976 | 0.0984 | 0.0976 |
|       | 0.1206 | 0.1206 | 0.1099 | 0.1281 | 0.1099 |
|       | 0.1276 | 0.1276 | 0.1035 | 0.1139 | 0.1035 |

Table 2: The predicted RMSE of each model in the Parking dataset. "†" and "‡" indicate the ST-GNN model that applies multi-graph fusion using the functionality graph proposed by [Geng et al., 2019] or the proposed functionality graph, respectively.

Specifically, with the increase in prediction horizons, the gaps between vanilla ST-GNN models and our proposed models become larger. Figure 4 illustrates the trends of the proposed model and existing ST-GNN models with various prediction horizons. We found that the performance of the proposed models (green line) did not show a significant drop with the increasing prediction horizons while existing ST-GNN models (red line) underperformed in a long-run prediction.

3.4 Ablation Study

To validate the performance of each component, we further conducted ablation studies on the Parking dataset.

The Performance of Functionality Graphs. Table 2 shows that (1) most ST-GNN models using the proposed functionality graph (marked with ‘†’) outperformed those using the functionality graph proposed by [Geng et al., 2019], (2) The results using the proposed functionality graph showed less drop when the prediction horizons changed from 12 to 24, which suggests that our proposed functionality graph performs well in LSTF tasks.
Figure 4: The predicted RMSE of each model on the Parking dataset over all time steps. The red line indicates the prediction errors of vanilla ST-GNN models, the blue line (*) shows the results of models using the proposed graph fusion methods but without SG-ATT, and the green line (**) shows the results of models with multiple graphs with the proposed dynamic graph fusion approach.

The Performance of Heuristic Graph. Figure 5 shows that graphs generated by exponential approximation function in general outperformed other approaches with prediction horizons 12 and 24, while graphs generated by the KL divergence outperformed graphs without heuristic graphs.

The Performance of SG-ATT. Figure 4 shows the performance of the framework with (marked with ‘***’) and without SG-ATT (marked with ‘**’). We observe that the SG-ATT mechanism contributes considerably to the proposed framework, especially in long-term prediction.

4 Related Work

Graph convolution networks (GCN) attracts much attention in spatio-temporal data prediction tasks recently. Bruna et al. [Bruna et al., 2013] proposed convolutional neural networks on graphs for the first time, which Defferrard et al. [Defferrard et al., 2016] extended using fast localized convolutions. Using graph-based approaches, we can easily model spatial data. However, the observation from a single graph usually brings bias, while multiple graphs can offset and attenuate the bias. Chai et al. [Chai et al., 2018] designed a multi-graph convolutional network for bike flow prediction. Geng et al. [Geng et al., 2019] encoded non-Euclidean pairwise correlations among regions into multiple graphs and then modeled these correlations using multi-graph convolution for ride-hailing demand forecasting. Lv et al. [Lv et al., 2020] encoded non-Euclidean spatial and semantic correlations among roads into multiple graphs for traffic flow prediction. However, the relationships among graphs are ignored. Moreover, the input graphs are fixed and cannot be adapted to change during training and long-term temporal information is rarely considered.

5 Conclusion

In this paper, we try to solve the LSTF problem with multi-graph neural networks. We propose two new graphs to extract heuristic knowledge and contextual information from spatio-temporal data. Specifically, we designed a heuristic graph to capture the long-term pattern of the data and a functional similarity graph to represent the similarity of functionality between two areas. To align nodes in graphs and timestamps, we designed a dynamic graph multi-graph fusion module and fed them to various graph neural networks. Extensive experiments on real-world data demonstrated the effectiveness of the proposed methods for enhancing the prediction capacity in LSTF problems. In the future, we will apply the proposed framework to additional graph-based applications.
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