Incorporating Reachability Knowledge into a Multi-Spatial Graph Convolution Based Seq2Seq Model for Traffic Forecasting

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Abstract—Accurate traffic state prediction is the foundation of transportation control and guidance. It is very challenging due to the complex spatiotemporal dependencies in traffic data. Existing works cannot perform well for multi-step traffic prediction that involves long future time period. The spatiotemporal information dilution becomes severe when the time gap between input step and predicted step is large, especially when traffic data is not sufficient or noisy. To address this issue, we propose a multi-spatial graph convolution based Seq2Seq model. Our main novelties are three aspects: (1) We enrich the spatiotemporal information of model inputs by fusing multi-view features (time, location and traffic states) (2) We build multiple kinds of spatial correlations based on both prior knowledge and data-driven knowledge to improve model performance especially in insufficient or noisy data cases. (3) A spatiotemporal attention mechanism based on reachability knowledge is novelly designed to produce high-level features fed into decoder of Seq2Seq directly to ease information dilution. Our model is evaluated on two real world traffic datasets and achieves better performance than other competitors.

Index Terms—Graph Neural Networks, Graph, Deep Learning, Traffic Forecasting, Seq2Seq

I. INTRODUCTION

Traffic forecasting is a key component of advanced traffic management systems, aiming to predict the future traffic states (e.g. traffic flow [1], traffic speed [2], traffic time [3]) in the traffic network. Accurate prediction can contribute to control traffic flow, allocate traffic resources, and ease traffic congestion [4].

Multi-step traffic forecasting is a typical spatial-temporal forecasting problem and it has two main challenges. The first challenge is the complex spatiotemporal dependencies. The future traffic state of a region is influenced by many factors, such as its historical observation, the correlation with other regions, external factors (e.g. holiday, special events) and so on [5]. The correlations among regions are quiet complex. Although prior knowledge such as distance or travel time between regions might help to capture the spatial correlation, there are still some hidden patterns that need to be detected by data-driven methods. In addition, compared with one-step prediction task, long-term spatiotemporal correlation between input and output steps in multi-step scenario is more complex for that it changes as region, step and time gap between steps change [6]. The second challenge is the model performance deterioration with insufficient qualified traffic data. Although we can collect more traffic data due to the update of transportation infrastructures, in many cases, the collected data is low quality with noise and some key features are missing. The available qualified traffic data is still insufficient. To the best of our knowledge, the traffic data used in most previous studies are less than one year [7–9], even one or two months [10].

Recently, various deep learning based methods have been successfully applied to traffic prediction due to their superior capacities to capture complex traffic patterns. Graph neural networks (GNNs) are popular in extracting spatial dependency in traffic network [5], [8], [11], [12]. Recurrent neural networks (RNNs) [13], [15] and Temporal convolution networks (TCNs) [8], [16], [17] are often adopted to capture the temporal dependency. Seq2Seq model is widely utilized in multi-step forecasting [18]–[20]. However, these previous works have the following limitations.

First, most existing works didn’t capture the complex spatial correlations sufficiently. Many researchers pre-defined a matrix to reflect spatial correlation based on prior knowledge such as geometrical proximity, function similarity, transportation connectivity [5], [21], [22]. However, any prior knowledge is limited and is not able to reflect some hidden traffic correlations among traffic regions. Some works designed an adaptive matrix to dig out spatial correlation on a data-driven basis [12], [16], [23]. However, when the data is not sufficient or noisy, the efficiency of data-driven method is deprecated and accurate prior knowledge might enhance the model performance in such situation. But most works only focus either pre-defined correlation or data-driven correlation for prediction.

Secondly, Seq2Seq model generally adopted in multi-step prediction has the information dilution problem [6], [18], [19]. When the original information on each input step arrives at a given output step, it has been diluted several times by both the encoder and decoder cell in Seq2Seq. Sufficient data might ease the dilution problem while insufficient data might amplify the dilution severity and decrease prediction performance. Therefore, modeling the long-term temporal correlation of traffic state between input and output steps to releviate dilution is particularly important.

In addition, each observed traffic feature (e.g. traffic speed, traffic flow) has both spatial attribute (i.e. its location) and temporal attributes (e.g. its time slot and week attribute). Most works [9], [10], [24]–[27] extracted the spatiotemporal patterns

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purely from traffic feature without making full use of its spatiotemporal attributes. However, such attributes can directly help model better identify spatiotemporal correlation among traffic states. They can also enrich the available spatiotemporal information when feature data is insufficient.

To overcome the challenges and limitations above, this paper proposes a model MSGC-Seq2Seq, which mainly leverages the graph convolution and GRU based Seq2Seq to learn the complex spatiotemporal dependency from traffic data. Specifically, we fuse the traffic feature with its spatial attribute and temporal attribute to augment the spatiotemporal information of model input. To capture spatial correlation sufficiently, we first pre-define a matrix based on prior knowledge (i.e. geographical proximity and feature trend similarity) to extract the spatial correlation. Then, inspired by self-attention mechanism in transformer [28], we calculate dynamic semantic attention between any two locations in the network on a data-driven basis. To tackle the dilution in Seq2Seq, we novelty design an attention mechanism based on reachability knowledge to model the cross-step spatial correlation. The high-level features produced are fed into the decoder at given output step directly without dilution by encoder. In addition, we integrate features produced are fed into the decoder at given output step to model the cross-step spatial correlation. The high-level design an attention mechanism based on reachability knowledge driven basis. To tackle the dilution in Seq2Seq, we novelly design a attention mechanism based on reachability knowledge to model the cross-step spatial correlation. The high-level features produced are fed into the decoder at given output step directly without dilution by encoder. In addition, we integrate a multi-head temporal attention mechanism into Seq2Seq to allow the decoder to focus on the most relevant input steps related with the predicted output step, augmenting the useful input information for each output step prediction.

The main contributions of this paper are as follows:

- We enrich the spatiotemporal information of model inputs by integrating the traffic state with its explicit spatiotemporal attributes via graph embedding methods.
- We capture spatial correlations sufficiently from prior knowledge perspective (i.e. geographical proximity and feature trend similarity) and data-driven perspective (i.e. semantic similarity related with flow pattern).
- We novelty design a reachability based attention mechanism to construct output step related high-level features and feed them directly into the decoder to avoid the dilution by the encoder in Seq2Seq.
- Our MSGC-Seq2Seq model is evaluated on two real-world traffic datasets and performs better than other baselines, especially when data is insufficient and noisy. Our codes and datasets are public in https://github.com/start2020/MSGC-Seq2Seq.

II. PRELIMINARIES

1) Traffic Network as Graph: Traffic network is modeled as a graph $G = (V, E, A)$, which can be weighted or unweighted, directed or undirected. Each node in the graph represents a traffic region, such as a road sensor [9], a road segment [14], a road intersection [11]. $V = \{v_1, \ldots, v_N\}$ refers N traffic nodes on the traffic network. $E$ is the edges set and each edge refers the connectivity between regions, which reflects some kind of spatial correlation, e.g. geographical proximity, semantic connectivity and reachability correlation.

2) Traffic Prediction Formulation: Assume that we can observe $F_t$ features of each node in the traffic graph during each given time period. The features of the whole network at time slot $p$ can be represented by a matrix $X_p = [x_{p,1}, x_{p,2}, \ldots, x_{p,N}] \in \mathbb{R}^{N \times F_t}$. Further, the historical features of the whole network over the past P time periods can be denoted as $[X_1, X_2, \ldots, X_P] \in \mathbb{R}^{P \times N \times F_t}$. In this paper, we aim to predict the future status of the whole network over Q time period, denoted as $[Y_1, Y_2, \ldots, Y_Q] \in \mathbb{R}^{Q \times N \times F_o}$, where $Y_q = [y_{q,1}, y_{q,2}, \ldots, y_{q,N}] \in \mathbb{R}^{N \times F_o}$ and $y_{q,j} \in \mathbb{R}^{F_o}$ represents the ground truth of region $j$ at future time period $q$. $F_o$ is the number of output features. We focus on multi-step prediction, therefore $Q > 1$. This paper aims to find a function $f$ mapping the historical observations of the graph-based traffic network over past P time slices to its future observations over Q time slices as follows:

$$[\hat{Y}_1, \ldots, \hat{Y}_q, \ldots, \hat{Y}_Q] = f([X_1, \ldots, X_p, \ldots, X_P]) \quad (1)$$

where $\hat{Y}_q$ is the prediction output and its ground truth is $Y_q$.

III. MODEL

A. Overview

Our model MSGC-Seq2Seq (Multi-Spatial Graph Convolution based Sequence to Sequence) (as shown in Figure 1) can be roughly divided into three stages. The first stage is to construct the model input with rich spatiotemporal information. We fuse the traffic feature with the spatiotemporal information extracted from its spatial attribute and temporal attribute via graph embedding methods. The second stage is to capture spatial correlations from multiple perspectives. We pre-define a spatial matrix based on geographical proximity and feature trend and we also develop a global spatial matrix on a data-driven basis. Both of them are both one-step correlation. In addition, a cross-step spatial correlation based on reachability knowledge is designed. Three graph convolution networks are leveraged to extract spatial correlations based on these spatial matrices. The third stage is to learn temporal dependency from the high-level features produced by graph convolution networks. High-level features based on one-step spatial correlations are merged and projected into the encoder of a Seq2Seq model to capture the temporal properties from these features. In addition, high-level features based on cross-step spatial correlation (i.e. reachability correlation) are fed into decoder directly to alleviate the information dilution problem. A temporal attention mechanism with multiple heads is integrated into Seq2Seq to enable the model focus on the most relevant input information. The details of our model is elaborated in the following sections.

B. Spatiotemporal Attributes Fusion

The traffic conditions in a traffic network have both spatial attribute and temporal attribute. The former refers to where the traffic data is observed (e.g. a sensor) and the latter refers to when the traffic data is collected (e.g. time of day, day of week). Such spatiotemporal attributes of traffic data carry spatiotemporal information explicitly and are obviously valuable for traffic state prediction. In this paper, we want to enrich the model input by considering not only the traffic
the sequential temporal information. I can observe its traffic states $X_i$ for all the time slots in a week. TP

where $\mathbf{A}$ is the adjacency matrix representing the topology of traffic network. SP $\in \mathbb{R}^{N \times F_S}$ and $\mathbf{SP}_t \in \mathbb{R}^{F_S}$ is the spatial embedding for traffic node $i$ and it has preserved the local structure information of this traffic node.

Temporal Embedding. Some works \cite{19} utilized one-hot embedding to learning temporal vector for each time slot. However, one-hot embedding method can only distinguish time slots but overlooks the sequential correlation between time slots. Different from previous works, we novelty flatten the time slots in a week and connect them sequentially as a line graph (as shown in Figure 2). We utilize DeepWalk \cite{30} to learn embedding for each node (i.e. time slot) in the line graph. In this way, the temporal correlations among time slots are reserved in the embedding vector. The embedding method is as follows:

$$\mathbf{TP} = \text{DeepWalk}(\mathbf{A}_T)$$

where $\mathbf{A}_T \in \mathbb{R}^{7T \times 7T}$ is the matrix of temporal line graph and $T$ is the number of total time slots in one day. $T$ refers to seven days in a week. $\mathbf{TP} \in \mathbb{R}^{7T \times F_T}$ is the embedding matrix for all the time slots in a week. $\mathbf{TP}_{dT+i} \in \mathbb{R}^{F_T}$ is the temporal embedding for time slot $i$ in $d_{ih}$ day of a week which carries the sequential temporal information.

Features Fusion. For each traffic node $i$ in time slot $t$, we can observe its traffic states $X_i^t \in \mathbb{R}^{F_I}$. The spatial attribute of traffic node $i$ is represented by $\mathbf{SP}_t$ and the time slot $t$ has been assigned a temporal vector $\mathbf{TP}_t$ according to its time of day and day of week attributes. We align them to the same dimension space through three fully connected layers respectively and then concatenate them together to get the fusion of all features as follows:

$$\text{XST}_t^i = \rho(W_xX_i^t)\rho(W_i\mathbf{TP}_t)\rho(W_i\mathbf{SP}_t)$$

where $\text{XST}_t^i \in \mathbb{R}^{3F_{ST}}$ is the fused features of traffic node $i$ at $t$. $\text{XST}_t = [\text{XST}_t^1, \ldots, \text{XST}_t^N] \in \mathbb{R}^{N \times 3F_{ST}}$ is the fused matrix for the whole traffic network. $\rho$ is the activation function (e.g. ReLu). $W_x \in \mathbb{R}^{F_{ST} \times F_I}, W_i \in \mathbb{R}^{F_{ST} \times F_T}, W_t \in \mathbb{R}^{F_{ST} \times F_S}$ are trainable parameters shared by all the traffic nodes.

C. Multi-view Spatial Graph Convolutions

The fused features contain rich spatiotemporal information for each traffic node. However, the future traffic condition of a target traffic node is influenced not only by its own historical information but also by historical observations of other traffic nodes. The fact that traffic objects (e.g. passengers, vehicles) keep moving from one traffic node to another traffic node results in the spatial correlations between traffic nodes and such correlations are complex. Different from most previous works only capturing one kind of spatial correlation, we model the complex spatial dependency in the traffic network comprehensively from multiple perspectives, i.e. adjacency correlation, semantic correlation and reachability correlation. Following previous works \cite{5, 8, 11, 12, 21}, we leverage

Fig. 2. Figure (a) is the spatial graph of the traffic network where a node represents a traffic region. Figure (b) is a temporal graph of a week where a node represents a time slot. Each day is divided equally into $T$ time slots, denoted as $[1, \ldots, T]$. All time slots are connected sequentially as a line.

Fig. 3. The visualization of three spatial attention scores. $[1, \ldots, p, \ldots, P]$ are the input steps and $q$ is an output step. $a^{ij}$ describes the spatial correlation between traffic node $i$ and traffic node $j$ based on geographical proximity and feature trend similarity. $a^{ij}$ is static and local. $a^{ij}_{pq}$ represents the semantic correlation of node pair $ij$ based on their flow patterns on time slot $p$. $a^{ij}_p$ is dynamic and global. $a^{ij}_p$ extracts the reachability based spatial correlation determining by the travel time $m_{ij}$ of node pair and their time slot gap. $a^{ij}_{pq}$ is cross space and time.

Fig. 1. The architecture of our model MSEG-Seq2Seq. The circles represent regions in the traffic network and the various shapes in the circles refer to various features. GRU refers to Gated Recurrent Unit.
graph convolutional network to extract each spatial correlation respectively.

1) Graph Convolution Network: Graph Convolution generalizes convolution operation from regular grid data to graph data. It models influence from related nodes on the target node through aggregating the features of related nodes [31]–[33]. Such aggregation is usually achieved by the matrix multiplication of feature matrix and spatial matrix. The aggregated features are fed into fully connected layers to produce high-level features. The graph convolution layer adopted in this paper can be denoted as follows:

\[ Y^i = \rho(WLX^{i-1}) = \text{GCN}(A, X^{i-1}) \]  

where \( X^{i-1} \) is the input and \( Y^i \) is the output of \( l_{th} \) graph convolution layer. \( \rho \) is activation function and \( W \) is trainable parameter. \( L = I_N - D^{-\frac{1}{2}}AD^{-\frac{1}{2}} \) is the normalized version of spatial matrix \( A \) which represents spatial correlation in the traffic network. Different spatial correlation is represented by different spatial matrix. Next, we introduce the construction of spatial matrix for each kind of spatial correlation in this paper.

2) Semantic Spatial Correlation: If two traffic nodes share similar flow patterns, they might have similar traffic conditions, such as traffic congestion, functional similarity and owning similar POIs. Therefore, they can learn from each other. Such spatial correlation based on current flow patterns of traffic nodes is defined as semantic correlation.

**Dynamic Semantic Score.** Inspired by the transformer [28], a state-of-the-art method to learn correlations between objects, we assign two latent semantic spaces to each traffic node as follows:

\[
K_i^t = W_{k2}(	ext{ReLU}(W_{k1}XST_i^t)) \in \mathbb{R}^F \\
Q_i^t = W_{q2}(	ext{ReLU}(W_{q1}XST_i^t)) \in \mathbb{R}^F
\]

where \( K_i^t \) and \( Q_i^t \) are the embeddings in key space and query space respectively for traffic node \( t \) at time slot \( t \). \( \{W_{k1}, W_{k2}, W_{q1}, W_{q2}\} \) are trainable parameters shared by all traffic nodes. Further, we can calculate the influence from traffic node \( j \) on traffic node \( i \) at time slot \( t \) as \( a_{ij}^t = (K_i^t)^T \cdot Q_j^t \in \mathbb{R} \). The corresponding dynamic attention matrix is as follows:

\[
A_i^t = \text{Softmax}\left( \begin{bmatrix} a_{i1}^1 & \cdots & a_{i1}^N \\ \vdots & \ddots & \vdots \\ a_{iN}^1 & \cdots & a_{iN}^N \end{bmatrix} \right)
\]

Note that the Softmax function is operated on each row.

**Semantic Correlation Extraction.** The dynamic attention matrix contains dynamic correlations between any two traffic nodes based on their flow patterns. We capture such spatial dependency through GCN at each input step \( p \) as follows:

\[
XF_p = \text{GCN}(A_i^p, XST_p)
\]

where \( XF_p \in \mathbb{R}^{N \times F_F} \) is the high-level output matrix of the traffic network.

3) Adjacent Trend Spatial Correlation: Many previous works focus on capturing the influence between geographically adjacent traffic nodes and assign different weights to different neighbors of the target traffic node to model their different influence strength [18], [23], [34], [35]. It is argued in [36] that the correlation of two adjacent roads depends on their historical traffic speed trends. The larger the proportion that the speeds of two traffic nodes both rise or fall is, the higher the correlation between two adjacent traffic node is.

**Adjacent Trend Score.** Following [36]'s works, we define the adjacent trend score to present the weight between adjacent traffic nodes based on their historical traffic states trends as follows:

\[
a_{ij} = \sum_{f=1}^{F_t}[a(v_{t,f}^i \geq \bar{v}_f^i, v_{t,f}^j \geq \bar{v}_f^j) + a(v_{t,f}^i < \bar{v}_f^i, v_{t,f}^j < \bar{v}_f^j)] \in \mathbb{R}^N \times \mathbb{R}^N
\]

where \( v_{t,f}^i \) and \( v_{t,f}^j \) are the \( f_{th} \) traffic feature of traffic node \( i \) and traffic node \( j \) at time \( t \). \( \bar{v}_f^i \) and \( \bar{v}_f^j \) are their average values respectively. \( a(v_{t,f}^i \geq \bar{v}_f^i, v_{t,f}^j \geq \bar{v}_f^j) \) and \( a(v_{t,f}^i < \bar{v}_f^i, v_{t,f}^j < \bar{v}_f^j) \) are the numbers of time slots that the \( f_{th} \) traffic feature of adjacent traffic nodes both rise or fall. \( F_t \) is the number of features and \( \text{Total} \) is the total number of time slots in historical data. For any two traffic nodes, if they are adjacent geographically, we calculate the adjacent trend score as their edge weight. Otherwise, their edge weight is set as zero. Based on the adjacent trend score, we obtain the adjacent trend matrix \( A^a = (a_{ij})_{N \times N} \). Then we capture the spatial locality based on historical adjacent trend through GCN as follows:

\[
X_{A_p} = \text{GCN}(A^a, XST_p)
\]

where \( X_{A_p} \in \mathbb{R}^{N \times F_F} \) contains local spatial dependency based on historical trends of traffic features.

4) Reachability Spatial Correlation Across Steps: The reachability correlation intends to model the spatial correlation based on reachability knowledge between any traffic nodes from input steps to output steps.

**Reachability Knowledge.** Suppose that we want to predict the traffic states \( v_j \) of the target traffic node \( j \) during interval \([t_3, t_4]\) with the traffic states \( v_i \) of the context traffic node \( i \) during previous interval \([t_1, t_2]\). We denote the average travel time from node \( i \) to node \( j \) as \( M_{ij} \). For simplicity, we assume
that all the passengers spend almost the same time from \(i\) to \(j\). For all passengers departing from context traffic node \(i\) during \([t_1, t_2]\) to target traffic node \(j\), we can observe that (as shown in Figure 4):

1. If \(t_3 > t_2 + M_i\), nearly all passengers can’t reach traffic node \(j\) during \([t_3, t_4]\). Therefore, there is little correlation between traffic condition \(v_j\) and \(v_i\) from reachability perspective.
2. If \(t_4 > t_2 + M_i\) or \(t_4 > t_1 + M_i\) \(\geq t_3\), we can infer that part of passengers can reach traffic node \(j\) during \([t_3, t_4]\). For simplicity, we assume that all passengers enter a traffic node evenly during the given time slot, therefore the influence strength between these two traffic nodes depends on the overlap of \([t_1 + M_i, t_2 + M_i]\) and \([t_3, t_4]\).
3. If \(t_1 + M_i > t_4\), passenger might have already arrived at traffic node \(j\) before \(t_4\). If passengers don’t stay, they might leave \(j\) for a long time. Therefore, we can infer that the impact from \(v_i\) on \(v_j\) is critically little.

**Reachability Score.** To calculate the correlation between traffic nodes across different time slots based on reachability knowledge, we novelly define the reachability score as follows:

\[
a_{ij}^{\delta} = \begin{cases} 
1 & i = j \\
0 & p^\delta + M_i < (q - 1)^\delta, i \neq j \\
0 & M_i + p^\delta - (q - 1)^\delta > q^\delta, i \neq j \\
(q - 1)^\delta < p^\delta + M_i, i \neq j \\
\frac{q^\delta - M_i - (p - 1)^\delta}{s} & q^\delta \geq p(\delta - 1) + M_i, i \neq j 
\end{cases} 
\]  

where \([t_1, t_2] = [(p - 1)^\delta, p^\delta]\), \([t_3, t_4] = [(q - 1)^\delta, q^\delta]\). Here \(\delta\) is time granularity, \(p\) is the input step and \(q\) is the output step. \(a_{ij}^{\delta}\) in \([0, 1]\) is the attention score based on reachability indicating the importance of context traffic node \(i\) at step \(p\) to target traffic node \(j\) at step \(q\). If there is little correlation between traffic condition \(i\) and \(j\), \(a_{ij}^{\delta} = 0\) and the importance of a traffic node to itself is defined as \(a_{ii}^{\delta} = 1\).

With the attention score \(a_{ij}^{\delta}\), we can construct the reachability matrix which represents the influence from the whole network at input step \(p\) on the whole network at output step \(q\), denoted as \(A_{qp}^\delta \in \mathbb{R}^{N \times N}\) as follows:

\[
A_{qp}^\delta = \begin{bmatrix} 
a_{11}^{\delta} & \ldots & a_{1N}^{\delta} \\
\vdots & \ddots & \vdots \\
a_{N1}^{\delta} & \ldots & a_{NN}^{\delta} 
\end{bmatrix} 
\]  

**Reachability Correlation Extraction.** Based on the reachability attention matrix, we can extract the spatial dependency from input step \(p\) on output step \(q\) with graph convolution network as follows:

\[
XR_{qp} = GCN(A_{qp}^\delta, XST_p) 
\]  

where \(XR_{qp} \in \mathbb{R}^{N \times F_S}\) is the high-level features containing influence from step \(p\) on step \(q\). To measure the impact from all input steps on the output step \(q\), we concatenate them together: \(XR_q = [XR_{q1}, \ldots, XR_{qp}] \in \mathbb{R}^{N \times PF_S}\).

We have extracted the spatial correlations by graph convolution network from three perspectives above. In the next section, we will extract the temporal dependency from the high-level features produced by GCN.

### D. Multi-Head Temporal Attention Based Seq2Seq

In this paper, we aim to predict the traffic status of the traffic network over multiple future steps. This is a typical multi-step time series prediction problem. We employ the Sequence to Sequence (Seq2Seq) model with an encoder and a decoder to extract the temporal dependency [37]. Seq2Seq takes an input sequence to generate an output sequence with different length as follows:

\[
[X_1, \ldots, X_p, \ldots, X_P] \xrightarrow{Seq2Seq} [\hat{Y}_1, \ldots, \hat{Y}_q, \ldots, \hat{Y}_Q] 
\]  

We leverage GRU (Gated Recurrent Units) [38] as the encoder and decoder to learn the long-term temporal dependency in traffic data, for that GRU is a simple yet powerful and efficient variant of RNNs.

1. **Multi-Spatial Seq2Seq:** We have captured three kinds of spatial dependencies through graph convolution networks respectively. Semantic matrix and adjacent matrix both contain the spatial correlations among traffic nodes at the same time slot while reachability matrix contains spatial dependency among traffic nodes at different time slots. In other words, high-level features based on semantic correlation and adjacent correlation only contain spatial dependency extracted at each input step and we feed them into the encoder to learn the temporal dependency from all the input steps. However, the reachability correlation has already extracted the spatiotemporal dependency from all the previous input steps. Therefore, we directly feed the high-level features based on reachability into the decoder at each output step. The Seq2Seq taking multi-spatial correlations as inputs is stated as follows:

\[
H_p = GRU_{\text{Encoder}}(W_1(xf_p|xap), H_{p-1}) \\
C = H_p \\
S_q = GRU_{\text{Decoder}}(W_2(C||xr_q||Y_{q-1}), S_{q-1}) \\
\hat{Y}_q = \text{ReLU}(W_3S_q) 
\]  

where \(H_p \in \mathbb{R}^{F_u}\) is the hidden state of encoder at input step \(p\) and \(C \in \mathbb{R}^{F_u}\) is the context vector, \(S_q \in \mathbb{R}^{F_s}\) is the decoder hidden state at output step \(q\), \(Y_{q-1} \in \mathbb{R}^{F_o}\) is the ground truth at step \(q - 1\) and \(\hat{Y}_q \in \mathbb{R}^{F_o}\) is the prediction output at step \(q\). \(\{W_1, W_2, W_3\}\) are the trainable parameters. \(xf_p \in \mathbb{R}^{F_v}, xa_p \in \mathbb{R}^{F_a}, xr_q \in \mathbb{R}^{F_p}\) are vectors from XFp, XAp, XRq, representing high-level features of a traffic node based on semantic similarity, adjacent trend and reachability respectively.

Following [6], we integrate scheduled sampling into Seq2Seq to ease the prediction error accumulation problem, which feeds \(Y_{q-1}\) into the model with \(\epsilon_t\) probability and \(\hat{Y}_{q-1}\) with \(1 - \epsilon_t\) at \(t_{th}\) iteration during training process.

2. **Multi-Temporal Attention:** The previous traffic conditions at different steps of the encoder can impact each future step of the decoder differently [6]. To model such relationship, a temporal attention allows the decoder to focus on relevant historical observations for any given future step by assigning different attention weights to every encoder hidden state \([H_1, \ldots, H_P]\). Inspired by [39], we calculate the attention
score between historical step \( p \) and future step \( q \) and normalize it through a Softmax layer:

\[
e_{qp} = (v)^T \tanh(W[H_p][S_q])
\]

\[
\alpha_{qp} = \frac{\exp(e_{qp})}{\sum_{i=1}^{P} \exp(e_{qi})}
\]

where \( W \in \mathbb{R}^{F_v \times (F_h+F_k)} \) and \( v \in \mathbb{R}^{F_v} \). With the temporal attention scores, the decoder hidden state \( S_q \) can be updated as follows:

\[
C_q = \sum_{p=1}^{P} \alpha_{qp} H_p
\]

\[
S_q = \text{GRU}_\text{Decoder}(W_2(C_q||x_q||Y_{q-1}), S_{q-1})
\]

To learn more complicated time dependency in different perspectives, we also extend the temporal attention to \( H \) heads as follows:

\[
e_{qp}^h = (v_h)^T \tanh(W_k[H_p][S_q])
\]

\[
\alpha_{qp}^h = \frac{\exp(e_{qp}^h)}{\sum_{i=1}^{H} \exp(e_{qi}^h)}
\]

\[
C_q^h = \sum_{p=1}^{P} W_C^h (\|h=1 \alpha_{qp}^h H_p)
\]

where \( W_h \in \mathbb{R}^{F_v \times (F_h+F_k)} \) and \( v_h \in \mathbb{R}^{F_v} \), \( W_h^C \in \mathbb{R}^{F_h \times HF_h} \).

IV. Experiments

This paper focuses on the research questions as follows:

1. How does our model MSGC-Seq2Seq perform at prediction accuracy and efficiency compared with other benchmarks on different datasets?

2. Does each component in our model make contributions for prediction?

3. What’s the performance of our model when the traffic data is insufficient and noisy?

4. How does our model react to parameter sensitivity test?

To answer the research questions above, we conduct extensive experiments on two real-world highway traffic datasets.

A. Datasets

We compare our model with baselines on the following highway traffic datasets.

METR collects traffic speed by sensors on the highway of Los Angeles County. We utilize 207 sensors in the highway and the time period observed is from Mar 1st to Jun 30th in 2012, i.e. four months.

PEMS datasets are from California Transportation Agencies’ (CalTrans) Performance Measurement System (PeMS). There are more than 39,000 sensors deployed on the highway in the major metropolitan areas in California [5]. The Geographic information about each sensor is recorded in the datasets. The traffic measurement chosen in this experiment is the average traffic speed, which is collected in real time every 30 seconds and aggregated in 5 minutes. The dataset in this paper contains 6 months data ranging from Jan to May in 2017 in the San Francisco Bay Area and 325 sensors are selected.

For all the datasets, 70% data is utilized for training, 10% for validation and the rest 10% for testing, and Z-Score normalization [6] is applied to normalize the datasets. We follow the way in [6] to build the adjacent matrix. The details of the datasets are shown in Table I.

B. Experimental Settings

1) Evaluation Metrics: MAE (Mean Absolute Error), RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error) are the most widely utilized evaluation metrics in traffic state prediction tasks. Following previous works [5], [6], [19], we utilize them to evaluate the model performance.

2) Baselines: We compare our approach with the following baselines, which can be categorized as traditional statistic methods (i.e. HA, VAR, ARIMA, SVR) and simple deep learning methods (i.e. FNN, FC-LSTM), graph-based deep learning methods (STGCN, DCRNN, GMAN).

HA: Historical Average, which predicts the future traffic conditions by averaging the traffic conditions at historical time.

VAR: Vector Auto-Regression is extensively leveraged in time series prediction task. It is a simple multivariate model where each variable is explained by its own past values and the past values of all the other variables in the system.

ARIMA [40]: Auto-regressive integrated moving average, a well known model for predicting time series data.

SVR: Support Vector Regression is a regression method utilizing linear support vector machine in prediction.

FNN: Feed Foward Neural Network can extract the nonlinearity in traffic data.

FC-LSTM [37]: A variant of Long Short Term Memory Network with fully connected layer as the output layer.

STGCN [17]: Spatio-temporal graph convolutional network which consists of graph convolutional layers and 1D convolution layers and can capture both spatial and temporal dependencies in traffic prediction.

DCRNN [6]: Diffusion Convolutional Recurrent Neural Network, which integrates diffusion convolution with recurrent neural network to capture the spatial and temporal properties in traffic data.

GAMAN [19]: Graph Multi-Attention Network, which designs an encoder-decoder architecture with multiple spatio-temporal attention mechanisms to predict traffic conditions.

3) Parameter Settings: For baselines STGCN, DCRNN, GMAN, we utilize the parameter settings as suggested by the original papers as much as possible. Following previous works [6], the number of input steps is set the same as output steps. For instance, we use \( P = 3 \) steps (15 minutes) to predict the next \( Q = 3 \) steps (15 minutes). In terms of training, Adam optimizer [41] is utilized to optimize all the deep learning.
methods. The maximum number of epochs is set as 1000 and the batch size is set as 16. The initial learning rate is 0.001 with a learning rate decay strategy. Our model is developed using Python and TensorFlow 1.x. Most of the experiments are run on a GPU (32GB) machine with TESLA V100.

The hyper-parameters in our model include the spatiotemporal embedding dimension $F_S$, the number of hidden units of GRU in encoder $F_H$ and decoder $F_S$, the number of heads in temporal attention $H$, the numbers of hidden units in adjacency $S$, the output of GRU in encoder $F$, and decoder $F$. For simplicity, both encoder and decoder have two layers and each layer shares the same number of hidden units. All GCN in this paper have two layers and each layer shares the same number of hidden units. All parameters are tuned on the validation set and we get the best model performance on the setting $F_A = F_F = F_R = 64$, $F_ST = 256$, $F_H = F_S = 64$, $H = 5$.

### C. Experimental Analysis

To reduce the randomness of deep learning based methods in Table II, we repeat the related experiments five times to get more stable and convincing results. We present their model performances with the means and standard errors of all metrics. In addition, the experiment results of traditional methods (i.e. HA, ARMA, VAR, SVR) are from previous work [6]. The best performance on each dataset is highlighted in bold font.

1) Approaches Comparison: In this subsection, we compare our model with other benchmarks in the overall model performance, efficiency, and visualization.

**Model Performance.** As shown in Table II, the graph-based deep learning methods (STGCN, DCRNN, GMAN, MSGC-Seq2Seq) perform significantly better than the simple deep learning methods (i.e. FNN, FC-LSTM) and statistic methods. It proves the effectiveness of extracting spatial correlation based on a traffic graph. When the predicted time period is short (i.e. 3 steps), some statistic method even has a better performance than the simple deep learning methods. For example, ARIMA performs better than FNN and FC-LSTM at PEMS dataset on 3 steps. However, as the output steps become longer, the deep learning methods show their superiority over statistic methods, probably because the spatiotemporal correlation become more complex in a long time prediction. Among the graph-based deep learning approaches, our model has the best performance on two datasets at all the metrics. On METR dataset, compared with STGCN, it has increased nearly 1% in MAPE on 3 steps. When the predicted period become longer, the MAPE gap between these two models becomes larger, i.e. 2% on 6 steps, 3% on 12 steps. On PEMS dataset, the differences on MAPE between MSGC-Seq2Seq and STGCN become more obvious, i.e. 0.5%, 1%, 2.3% on 3, 6, 12 steps respectively. It proves that our model can handle long outsteps better than STGCN, perhaps due to...
all models achieve the best performance at the first output step. As the time gap between input steps and output steps increases, the model performance become worse and worse. The deterioration rates of different models are different. The deterioration rate of DCRNN is the fastest while that of GMAN is the slowest. As to our model, it has a suboptimal deterioration rate.

**Efficiency.** Table III shows the average time per epoch of all the deep learning based models on METR dataset for 3 steps prediction. FNN and FC-LSTM require the least time to finish an epoch, around 20 seconds for that they have the simplest structures and the fewest trainable parameters. Both STGCN and DCRNN need less than 60 seconds to finish training. GMAN has the longest time per epoch, nearly 400 seconds probably because it has the largest number of trainable parameters. Our model MSGC-Seq2Seq takes less than half of the time required by GMAN while it has the best performance on both datasets. Note that the reachability attention matrix in our model is calculated during the data preprocess.

**Visualization.** In order to visualize the prediction results of all the deep learning models, we randomly choose a node in the traffic network (i.e. a sensor) of METR dataset to observe the prediction values of its traffic speed on one day of weekday and weekend (also chosen randomly). Note that we choose the first output step prediction as the observed prediction values because the prediction at the first output step is the most accurate. As shown in Figure 8 our model seems to have a better prediction at the peak hour in afternoon.

2) **Model Ablation:** We integrate spatial attribute embedding, temporal attribute embedding, three kinds of spatial correlations and multi-head temporal attention mechanism into our model MSGC-Seq2Seq. To evaluate the effect of these mechanisms, we remove them from the original model to observe the performance of the corresponding degraded models. We conduct the experiments on METR dataset for 3 steps prediction. The results in Table IV show that the
prediction performance decreases no matter which mechanism to remove, indicating that all mechanisms make contributions to improve the model performance. However, as we can see in Table IV their contributions are different. When the Spatiotemporal Embedding or the Semantic Correlation are removed, the model performance becomes worst, referring that they play more important roles than other mechanisms.

3) Fault-tolerance Test: In real world traffic scenarios, we might collect the low-quality data with missing or wrong values due to the limited data collection methods and tools. In addition, mistakes brought by some data processing methods also decrease the data reliability. Therefore, the robustness of an approach to process noisy data is important for real world application. In this subsection, we want to test the effectiveness of our model and compare it with other benchmarks. We choose a set of fault-ratio from 10% to 90% to replace the traffic data values with noise of zero values. As we can see from Figure 6 the performances of all models on all metrics deteriorate quickly as the proportion of noise increases, however, in different speed. Among the graph deep learning methods, performance of STGCN becomes worse more quickly than others which refers that its robustness is the worst. Surprisingly, FC-LSTM has the lowest rate of deterioration among all the deep learning methods. When the fault-ratio is 90%, FC-LSTM has the suboptimal performance while STGCN has the worst performance. The relative performance of ANN also becomes better as the data becomes noiser. This implicates that simple deep learning models have better capacity to combat noise. However, our model also has a slower deteriorated rate and its performance evaluated by MAE and MAPE are the best on all the fault-ratio settings. This proves that MSGC-Seq2Seq is effective and robust in the cases where the data is noisy. The mechanisms we design to enhance the spatiotemporal information in the model might play a key role against noisy data.

4) Data Sparsity Test: We want to test the effectiveness of graph deep learning models in sparse data scene. We randomly sample several subdatasets from METR at a proportion ranging from 10% to 100% and conduct experiments for 3 steps prediction. As shown in Figure 7 as the data scale decreases, most models generally have worse performances but in different speeds. The performance of our model decreases steadily while GMAN performance has a slight fluctuation. Note that our model performs better than other methods in all data scale, proving the effectiveness of our model and such effectiveness is more obvious when data size is smaller.

5) Parameter Sensitivity Analysis: In this section, we choose several important hyper-parameters to analyze the parameter sensitivity of our model on METR dataset for 3 steps prediction as follows:

Spatiotemporal Embedding Dimension. We conduct experiments on different embedding dimensions, i.e. [16, 32, 64, 128, 256, 512]. As shown in Figure 9 when the number of dimension units increases, the MAE decreases. When the dimension is 256, our model has the best performance at MAE. When it keeps increasing, the model performance decreases, perhaps due to overfitting problem.

GCN Units. We choose [8, 16, 32, 64, 128] GCN units to conduct the experiments. The smallest MAE is achieved at 64 units.

GRU Units. [16, 32, 64, 128, 256] GRU units are chosen to conduct the experiments. The smallest MAE is also achieved at 64 units.

The Multiple Heads. The head list test in the experiment is [1, 2, 3, 4, 5]. Figure 9 shows that the best performance achieves at 5 heads. If there are only 1 or 2 heads, the model might be unable to capture more complex correlation in traffic data. However, more heads might lead to more parameters, resulting in overfitting.

V. RELATED WORK

Traffic prediction has been extensively researched for many years. Compared with statistic methods in early stage (e.g.
ARIMA [42], VAR [43], Kalman filtering [44]), which can only capture linear correlation in traffic data, and traditional machine learning (e.g., Support Vector Machine [45], K-Nearest Neighbors [46]), which requires handcrafted feature engineering, deep learning based methods provide an end-to-end learning and have the superior capacity to capture the complex traffic pattern. The main ideas of most deep learning frameworks in traffic tasks can be summarized as: first aggregate the spatial dependencies between nodes at the same input step, then treat the aggregated traffic features over multiple input steps as a high-dimensional time series and extract the temporal dependency in the time series.

To capture the spatial dependency, CNNs [47] decompose the network into grids while many traffic networks are graph based naturally. Recently, GNNs [5, 12] are used to aggregate features from neighbors based on the adjacent matrix or data-driven matrix [5, 12]. These models have extracted the spatial information of the network in each input step and achieved better performance than previous works. However, they can not work well to extract complex spatio-temporal dependencies in multi-step forecasting for that the spatial correlation between nodes across different time steps is not well considered.

To extract the temporal dependency, LSTM and GRU are often adopted for one step prediction [14, 48, 49]. For multi-step forecasting, Seq2Seq model with an encoder and a decoder is commonly utilized [6, 50]. To distinguish the different impact of each input step on a given future step, a temporal attention mechanism, which can help a model make decisions by focusing on the important parts of input data [51–53], is added to the decoder [5, 12, 20, 55]. However, few works pay attention to differentiate the contribution of different feature dimensions for prediction, which is important to help a model focus on the important input features.

VI. CONCLUSION

In this paper, we focus on traffic network level multi-step traffic prediction. Compared with one-step traffic prediction, multi-step traffic prediction is more challenging because it requires to fully model the dynamic correlations among traffic nodes across time and space in a longer period. To address this problem, we design a novel deep learning model called MSGC-Seq2Seq. We first use the traffic features and their spatiotemporal attributes via graph embedding methods to enrich the spatiotemporal information of model input. Afterward, we extract spatial correlations based on both data-driven knowledge (i.e. semantic similarity) and prior knowledge (geographical proximity and feature similarity). The former can dig out hidden traffic patterns while the latter can provide more valuable spatial information, especially in insufficient or noisy data cases. Then we extract the temporal dependency by utilizing a GRU-based Seq2Seq model. We novelly develop a cross-step attention mechanism based on reachability to ease the dilution problem in Seq2Seq. In addition, we employ a multi-head temporal attention to distinguish the impact from different historical steps on each future step. We conduct experiments on two real-world traffic datasets. The experiments demonstrate that our model outperforms other baselines.

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