STCGAT: Spatial-temporal causal networks for complex urban road traffic flow prediction
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Abstract—Traffic forecasting is an essential component of intelligent transportation systems. However, traffic data are highly nonlinear and have complex spatial correlations between road nodes. Therefore, it is incredibly challenging to dig deeper into the underlying spatial-temporal relationships from the complex traffic data. Existing approaches usually use fixed traffic network topology maps and independent time series modules to capture spatial-temporal correlations, ignoring the dynamic changes of traffic road networks and the inherent temporal causal relationships between traffic events. Therefore, a new prediction model is proposed in this study. The model dynamically captures the spatial dependence of the traffic network through a Graph Attention Network (GAT) and then analyzes the causal relationship of the traffic data using our proposed Causal Temporal Convolutional Network (CTCN). STCGAT adaptively models the traffic road network topology maps and independent time series modules with other traffic prediction methods on two real traffic datasets to evaluate the model’s prediction performance. Compared with the best experimental results of different prediction methods, the prediction performance of our approach is improved by more than 50%. You can get our source code and data through https://github.com/zhangshqii/STCGAT.

Index Terms—Spatial-temporal forecasting, Causal Temporal Convolutional Network, Graph Attention Network.

I. INTRODUCTION

WITH the demands of economic development and urbanization, the rapid expansion of urban areas has led to a rapid increase in urban residents and car ownership, posing a significant challenge for urban road traffic facilities. Along with the development of artificial intelligence technology, the construction blueprint of a new type of smart city is being gradually realized in the actual city construction. Intelligent Transportation System (ITS) [1], as a crucial intelligent traffic management system in a smart city, can contribute a new solution to the urban road traffic problem. Traffic forecasting is an essential part of ITS, which helps traffic managers sense road traffic conditions in advance, manage and control traffic flow scheduling, select good travel routes for travelers, avoid possible future road congestion, and improve travel efficiency [2]–[4]. Although researchers have achieved remarkable results in traffic flow prediction, it is still difficult to accurately predict future road traffic conditions due to the variability of road network topology and the highly nonlinear correlation of traffic data.

For traffic prediction models, information on future traffic conditions at a road node is not only predicted based on historical traffic data at that node but also requires consideration of historical traffic information at its neighboring nodes. Early traffic flow prediction methods usually use queuing theory [5], traffic behavior theory [6], and machine learning methods [7]. Still, these methods only consider the dependence in the time dimension and ignore the reliance on the spatial dimension. In recent years, as deep learning has been widely used in artificial intelligence. The spatial dependence of traffic networks is captured using Convolutional Neural Networks (CNN) [8] in some studies [9]–[11], and then the temporal dependence is captured using Recurrent Neural Networks (RNN) [12]. Although this approach captures the underlying Spatial-temporal patterns in the traffic network, CNN applies to Euclidean data with regular grids, and modeling irregular road networks inevitably loses the topological information of the traffic network. To address this issue, Graph Convolutional Network (GCN) [13] are used instead of CNNs to handle non-Euclidean data in traffic road networks better.

Although the existing hybrid models based on GCN and RNN have greatly improved the prediction performance, these models still have some drawbacks. On the one hand, since GCN uses the Laplacian feature matrix [14] of the graph to compute and update the feature information of all nodes in the chart [15], the GCN approach to capture the traffic road network’s spatial dependence is poor flexible and scalable. On the other hand, the chain structure design of RNNs, which strictly follow the chronological development, makes RNN models unable to predict the future and thus cannot capture the potential causal relationships [16] between traffic events. In addition, the signal of RNN must propagate along the longest path in the network [17], [18], which leads to the more extended the way in the network, the more likely it is to lose some vital information.

To address some of the above existing problems, we propose the Spatial-temporal Causal Graph Attention Network (STCGAT), which consists of a Graph Attention Network (GAT) [19] and our proposed Causal Temporal Convolutional Network (CTCN). STCGAT adaptively models the traffic road network spatially and dynamically captures the spatial dependencies of the traffic network. The causal relationships of traffic events in time series data are then analyzed while capturing the long-time dependence of traffic data. The contributions of this paper are mainly the following three points.
1) We propose a new spatial-temporal network model for modeling spatial-temporal data with complex topology and dynamic time dependence.
2) We use GAT to model the spatial information of the traffic road network and adaptively capture the spatial dependence of the traffic network.
3) We propose a CTCN for modeling time-series data, which captures the overall temporal dependence by performing contextual analysis of traffic events in a time series to uncover potential causal associations.

This paper is organized as follows. Section 2 briefly describes some related work on spatial-temporal prediction studies. Section III provides a detailed description of the structure, methodological details, and some optimization schemes of STCGAT. Section IV analyzes the performance of STCGAT through a large number of comparative experimental results. Finally, Section V summarizes our shortcomings and the subsequent work.

II. RELATED WORKS

A. Time Correlation

The task of traffic volume forecasting is typically a multi-variate time series analysis problem with some early modeling approaches such as History Average Model (HA) [20], Vector Autoregression (VAR) [21], Support Vector Regressor (SVR) [22] and other machine learning models. However, these simple time series models focus only on the time dependence of the traffic network, ignoring the spatial correlation of the traffic road network, and they rely too much on the ideal smoothness assumption, which contradicts the nonlinear correlation of the traffic data. Deep learning has gradually dominated time series prediction tasks with sophisticated data modeling capabilities and autonomous learning abilities in recent years. Most of such studies rely on models such as Long-short Term Memory (LSTM) [23] or Gated Recurrent Unit (GRU) [24] to capture the dynamic temporal correlation of time series data. Still, due to the chained structure of RNNs, they consume a lot of resources when dealing with long time series. Therefore some studies have employed a Temporal Convolutional Network (TCN) [25, 26] to enable the models to process more comprehensive time-series information in less time. Recently some researchers have focused on the powerful modeling capability of Transform [27] for time series data and proposed many models using Transform and its variants [28–30] for relevant time series prediction. Although these deep learning-based time series prediction models have significantly improved prediction accuracy compared with some earlier research methods, these models still cannot model the spatial information of traffic road networks, resulting in significant errors in prediction accuracy when dealing with traffic flow prediction tasks.

B. Spatial-temporal Correlations

Some studies [9–11] model traffic road networks as regular two-dimensional grids to capture the spatial and temporal dependencies of the traffic networks. These two-dimensional data are then given to CNN for processing to capture the spatial dependence of the traffic network and finally integrated into RNNs to capture the spatial and temporal dependence of the traffic network. Considering the non-Euclidean nature of irregular traffic road networks, researchers have turned to study GCN-based spatial-temporal prediction models. For example, the DCRNN [31] model treats the spatial dependence of traffic networks as a diffusion process and captures spatial dependence by moving randomly over the graph; the SRCNs [32] model fuses GCN and 1D convolutional networks into deep convolutional networks (DCNNs) and captures temporal dependence using LSTM. The T-GCN [33] model uses GCN and GRU to capture spatial and temporal dependence. AGCRN [34] and STGCN [35] and STSGCN [36] are proposed successively to capture the spatial-temporal dependencies of the traffic network simultaneously. To dynamically capture the spatial-temporal dependencies of traffic networks, ASTGCN [37] and GMAN [38] further incorporate attention mechanisms. In recent work, STGGN [39] provides a learnable location attention tool and a sequence component to model traffic flow dynamics to capture spatial dependence and traffic networks’ overall (local and global) temporal dependence. STFGNN [40] combines a parallel fusion of gated CNN and spatial-temporal fusion graph network (STFGN) models to capture local and international spatial-temporal correlations. However, these methods rely on predefined traffic road network connectivity graphs, which impose high demands on the quality of the graphs and require substantial domain knowledge.

Inspired by these studies, we propose a new Spatial-temporal forecasting method that does not rely on a fixed spatial connectivity map but captures spatial and temporal dependencies dynamically from the traffic road network.

III. METHODS

A. Problem formulation

Traffic flow forecasting uses historical traffic information of a road to predict the traffic information of a future period. Traffic information here is an abstract concept: traffic flow, traffic density and traffic speed, etc. In our method, traffic speed is used to represent traffic information.

Definition 1: In a realistic traffic road network, the closer the road nodes are in the spatial distance, the more similar the road conditions are. Based on this property, a weighted graph \( G = (V, E, L) \) is defined to describe the topological structure information of the traffic road network. \( E \) denotes the set of edge connection relations between road nodes, all road nodes on the road network topology graph are denoted by \( V = \{v_1, v_2, \cdots, v_N\} \), \( N \) is the total number of road nodes. For any node \( v_i \), the relationship with neighboring nodes is expressed as follows.

\[
v_{i,j} = \begin{cases} \frac{1}{d_{i,j}}, & \text{if } v_i \text{ and } v_j \text{ are connected,} \\ 0, & \text{otherwise.} \end{cases}
\]
Fig. 1. Spatial-temporal Causal Graph Attention Network framework.

$d_{i,j}$ denotes the distance between $v_i$ and $v_j$. The adjacency matrix $A$ of the graph is constructed using the computed connectivity relationships between the nodes. $L$ denotes the connectivity matrix between road nodes after processing using the Laplace operator, and the calculation procedure is shown in Equation 1.

$$L = D^{-\frac{1}{2}}AD^{-\frac{1}{2}}$$

where $D$ is the degree matrix of the adjacency matrix $A$.

Definition 2: Construct the feature matrix $M = \{X_{t-n}, X_{t-(n-1)}, \cdots, X_{t}\}$ as the feature matrix of the traffic network. The traffic flow prediction task learns a mapping function $f(\cdot)$ through the traffic network topology graph $G$ and the feature matrix $M$ of historical traffic information to complete the prediction of the future $T$ time length, and the calculation process is shown in Equation 2.

$$[X_{t+1}, \cdots, X_{t+T}] = f(G; (X_{t-n}, X_{t-(n-1)}, \cdots, X_{t}))$$

where $M \in R^{N \times n}$, $n$ denotes the number of node feature attributes (length of historical time series), and $X_t \in R^{N \times 1}$ represents the set of traffic speed information of $N$ road nodes in the traffic network at time $t$.

B. The Model Architecture

We will present how the proposed STCGAT model implements the road traffic prediction task. As shown in Figure 1, STCGAT consists of three main components: 1) GAT layer: the traffic network is modeled to capture the spatial correlation between road nodes; 2) CTCN layer: the causal temporal convolutional network is mainly composed of a combination of Bi-directional Long-short Term Memory (BiLSTM) and TCN; 3) Prediction layer: Prediction results are output using a fully connected neural network. Next, we will first introduce modeling the traffic network space with GAT and capturing spatial dependencies and then discuss the use of causal, temporal convolutional layers to capture temporal correlations. After submitting these components, we will briefly summarize the entire framework.

C. Spatial Dependence Modeling

Dynamically capturing complex spatial correlations is a critical issue in traffic flow prediction. The GCN-based traffic

Fig. 2. Graph attention mechanism.
flow prediction method relies on a predefined traffic network connectivity map, which cannot be applied when the road topology changes. To get rid of the limitation of the fixed graph structure, we use the attention mechanism of GAT to calculate the attention coefficients [27] between road nodes and their neighboring nodes to capture the spatial dependence of the traffic road network dynamically. As shown in Figure 1, the set of feature vectors \( X = \{x_1, x_2, \ldots, x_N\} \) (\( x_i \in R^{N \times F} \), \( F \) is the number of node features) of our traffic time series and the defined traffic road network topology graph \( G \) are used as inputs to the graph attention layer. As shown in Figure 2 (a), GAT Layer first acts as a weight matrix of inputs to the graph attention layer. As shown in Figure 2 (b), the defined traffic road network topology graph \( G \) are used in the graph and then calculates the attention coefficients between the vertex and each neighbor node. Specifically, for a vertex \( v_i \) and any neighbor node \( v_j \), the calculation process is shown in Equation 3.

\[
e_{ij} = \text{LeakReLU}(a^T [W x_i \parallel W x_j])
\]

where \( e_{ij} \) is the number of attention interrelationships, \( \parallel \) is the vector splicing operation, \( \text{LeakReLU} \) is the nonlinear activation function, and the parameter is a single-layer feedforward neural network with \( a \in R^{2F} \). Then all neighboring nodes of the central node are normalized using softmax, as shown in Equation 4.

\[
\alpha_{ij} = \text{softmax}(e_{ij}) = \frac{\exp(e_{ij})}{\sum_{k \in N_i} \exp(e_{ik})}
\]

\( N_i \) represents the set of first-order neighbors of \( v_i \), and \( \alpha_{ij} \) is the final attention coefficient between \( v_i \) and \( v_j \). Note that both \( e_{ij} \) and \( \alpha_{ij} \) are called attention coefficients, except that \( \alpha_{ij} \) is the result of the normalization of \( e_{ij} \). Combining Eqs. 3 and 4, the complete formula for calculating the attention factor between adjacent nodes is given in Eq. 5.

\[
\alpha_{ij} = \frac{\exp(\text{LeakReLU}(a^T [W x_i \parallel W x_j]))}{\sum_{k \in N_i} \exp(\text{LeakReLU}(a^T [W x_i \parallel W x_k]))}
\]

To further improve the generalization ability of the attention mechanism, the multi-head attention [27] mechanism is additionally adopted, as shown in Figure 2 (b). Precisely, \( P \) groups of mutually independent attention mechanisms are executed, and then the output results of these \( P \) groups are averaged to obtain the final output results. The calculation process is shown in Equation 6.

\[
\hat{h}_i = \sigma\left(\frac{1}{P} \sum_{p=1}^{P} \sum_{j \in N_i} \alpha_{ij}^p W^p x_j\right)
\]

According to the above computational procedure, all vertices on the graph are cyclically traversed, and a new set of node feature vectors \( H = \{\hat{h}_1, \hat{h}_2, \ldots, \hat{h}_N\}, \hat{x}_i \in R^{F'} \) are output to capture the spatial dependence of the traffic network dynamically.

**D. Temporal Dependence Modeling**

After obtaining the spatial dependence, we need to address another critical problem in traffic prediction: capturing time-dependent information from complex traffic data. Existing approaches typically use models such as LSTM or GRU to capture the temporal dependence of traffic timing data. However, the chained sequential structure of the RNN model is designed such that the output of the current moment in the RNN network is only related to the information before the present moment. But there is often a hidden causal relationship between traffic events in some real traffic scenarios. For example, a sudden traffic accident on the current road may cause traffic congestion on adjacent roads afterward. Moreover, traffic data are not always sequentially correlated, such as unscheduled traffic road maintenance, unexpected traffic accidents, etc. Therefore, we propose CTCN capture the time series’ potential causality and temporal dependence. The CTCN layer mainly consists of two parts, BiLSTM and TCN, and its structure is shown in Figure 3. CTCN first uses BiLSTM to analyze the contextual information of timing data to mine the potential causal relationships of traffic events from traffic data. Then, we use TCN to parallelize the temporal data output from BiLSTM to obtain global temporal correlation and long-term dependence from it. Specifically, to fuse the Spatial-temporal relationships in the traffic data, we use the node space feature set output from GAT as the input of the BiLSTM layer. After the BiLSTM processing, we initially obtained the spatial-temporal dependence of the traffic network. For the convenience of description, we will take a single rightward LSTM as an example to introduce the LSTM process.

As shown in the general framework of the LSTM in Figure 4, the LSTM is composed of several memory cells sequentially connected with the same structure. The module is divided into three central gate units: 1) forgetting gate: controls the degree of forgetting of historical information; 2) input gate: controls the information added in the current storage unit; 3) output gate: controls which information in the storage unit is used as output. The specific calculation process is shown in Equation 7.

\[
\begin{align*}
    f_i &= \sigma(W_f \cdot [S^R_{i-1}, H_i] + b_f) \\
    i_i &= \sigma(W_i \cdot [S^R_{i-1}, H_i] + b_i) \\
    \tilde{C}_i &= \tanh(W_c \cdot [S^R_{i-1}, H_i] + b_c) \\
    C_i &= C_{i-1} \ast f_i + \tilde{C}_i \ast i_i \\
    o_i &= \sigma(W_o \cdot [S^R_{i-1}, H_i] + b_o) \\
    S^R_i &= o_i \ast \tanh(C_i)
\end{align*}
\]

where \( \sigma(\cdot) \) is the nonlinear activation function; \( S^R_{i-1} \in R^d \) is the hidden state of the output at time i-1 (d is the feature dimension of the LSTM layer output); \( C_{i-1} \) is the memory cell at time i-1; \( W_f, W_i, W_c, W_o, U_f, U_i, U_c \) and \( U_o \) are the weight vectors to be learned; \( b_f, b_i, b_c, b_o \) is the bias term; \( \ast \) represents the corresponding elements in the matrix multiplied; \( \parallel \) denotes the matrix addition; \( \ast \) denotes the final output of the BiLSTM by stitching together the rightward and leftward outputs, as shown in Equation 8.

\[
S = (S^R \parallel S^L), S \in R^{N \times 2d}
\]
time and cannot process the whole time series holistically, lacking the ability to capture the global time dependence. Therefore, we combine BiLSTM with TCN, i.e., we input the sequence of BiLSTM output into TCN at one time and use the parallelism of TCN and the prediction mechanism (we can predict the most likely situation at future t time points based on the sequence of a known sequence) to obtain the global time dependence and capture longer time correlation. The figure shows that TCN uses a one-dimensional Fully Convolutional Network architecture [41] with the same length of the input, hidden, and output layers. At the same time, TCN uses Causal Convolution [25], so that the output of the current moment relates only to the input information before that moment, while, to capture longer-term temporal dependencies and avoid linearly stacking too many convolutional layers, TCN proposes Dilated Convolution [42] so that the effective window size grows exponentially with the number of layers, so that the convolutional network can use fewer convolutional layers and obtain a larger receptive field [42]. Specifically, for a BiLSTM output time series $S \in R^{N \times 2d}$ with feature vector $s^t \in R^{2d}$ and filter $f : \{0, 1, \cdots, k - 1\} \rightarrow R$ at any i time, the procedure for calculating the extended convolution of sequence element x is shown in Equation 9.

$$F(x) = (s^t *_d f)(x) = \sum_{j=0}^{k-1} f(j) \cdot s^{t-d-j} \quad (9)$$

where $d$ is the dilation factor, $x - d \cdot j$ represents the past direction and $k$ is the filter size.

In addition, TCN uses residual connectivity [43] to address problems such as gradient disappearance and overfitting caused by deep networks. As shown in Fig. 5 each residual module contains two layers of inflated convolution with non-linear activation, and Weight Norm and Dropout regularization networks are also added. The i-th residual module is calculated as shown in Equation 10.

$$S^i = S^{i-1} + \phi(S^{i-1}) \quad (10)$$

where $S^i \in R^{N \times 2d}$ is the output result of the i-th residual module, $S^{i-1} \in R^{N \times 2d}$ is the output result of the previous residual module, and $\phi(\cdot)$ is the mapping function of the residual module. After the last residual module, we get the final output result: $\tilde{S} \in R^{N \times 2d}$.

**E. Traffic Flow Forecasting Layer**

Finally, we use the fully connected neural network to process the CTCN output $\tilde{S} \in R^{N \times 2d}$ to obtain the final prediction result. That is, the time length we need to predict is obtained. The specific calculation process is shown in Equation 11.

$$Y' = [X_{t+1}, X_{t+2}, \cdots, X_{t+T}] = \delta(W_f \cdot \tilde{S} + b_f) \quad (11)$$
where $Y_i' \in \mathbb{R}^{N \times T}$, T is the predicted time duration, $\delta(\cdot)$ denotes the activation function of the linear neural network, $W_f \in \mathbb{R}^{2d \times T}$ is the weight matrix of the fully connected neural network, and $b_f$ is the bias term.

To further optimize our model, as shown in Fig. 6 on the predicted velocity profile B and the actual velocity profile A, we observe that $A(t_i)$ and $B(t_j)$ on 1 have waveforms with high similarity but are not aligned on the time axis, and the traditional loss function, which cannot compute this similarity error. To solve this problem, we use the Soft Dynamic Time Warping (soft-DTW) algorithm to replace the traditional loss function. The similarity error of the two series is calculated by finding a suitable match based on the characteristics of the two-time series. Then, the model is continuously corrected by backpropagation to achieve the optimal prediction result finally. For the predicted value $Y_i' \in \mathbb{R}^T$ and the true label value $Y_i \in \mathbb{R}^T$ of any node $v_i$, the loss function is calculated as shown in Equation 12.

$$loss = dtw_\gamma(Y_i', Y_i) = \min \gamma \{ <A, \Delta(Y_i', Y_i) >, A \in \mathcal{A}_{T,T} \} = -\gamma \log(\sum_{A \in \mathcal{A}_{T,T}} e^{-<A, \Delta(Y_i', Y_i) > } / \gamma)$$

(12)

where $\gamma \subset (0, 1]$ denotes the range of values of Euclidean loss values, $\mathcal{A}_{T,T} \subset \{0, 1\}^{T \times T}$ is the set of calibration matrices on a sequence of lengths all T, and $A \in \mathcal{A}_{T,T}$ represents a path.

IV. EXPERIMENT

A. Datasets

To evaluate the prediction performance of STCGAT, we conducted extensive experiments on two real public traffic datasets, PEMS04 and PEMS08 [35, 36]. These two datasets are from Caltrans’ Performance Measurement System (PeMS), aggregating the collected traffic information every 5 minutes. Meanwhile, the spatial network of each dataset is constructed based on a real road network, containing information such as the distance of road nodes. Table I summarizes some critical statistics for these two datasets.

| TABLE I | DATASET STATISTICS |
|---------|-------------------|
| Dataset | Sensors | Edges | Unit | Length |
| PEMS04  | 307     | 340   | 5 min| 2 month|
| PEMS08  | 179     | 293   | 5 min| 2 month|

B. Baseline Methods

We compared STCGAT with several traditional baseline methods and graphical neural network-based Spatial-temporal prediction models.

- HA [20]: The weighted average of the historical traffic data is used as the forecast result for the future period.
- VAR [21]: Vector Auto-Regression autoregression is a traditional time series model that captures the pairwise relationships between time series.
- GAT [19]: The spatial feature information of road nodes is aggregated using the multi-headed attention mechanism, and the prediction results are output through the fully connected layer.
- FC-LSTM [23]: Prediction of traffic data using a Long short-term memory network with fully connected layers.
- TCN [25]: Temporal Convolutional Network uses inflated convolution to obtain a larger perceptual field with less cost.
- DCRNN [31]: Spatial correlation is captured using a bidirectional random walk on the graph, and temporal correlation is captured using an encoder-decoder architecture with predetermined sampling.
- T-GCN [33]: The spatial dependence is first captured using GCN and then further processed using GRU to capture the temporal dependence.
TABLE II
EXPERIMENTAL RESULTS

| Model    | Dataset PEMS04 | Metrics | MAE  | RMSE | MAPE   | Model    | Dataset PEMS08 | Metrics | MAE  | RMSE | MAPE   |
|----------|----------------|---------|------|------|--------|----------|----------------|---------|------|------|--------|
| HA       |                |         | 37.87| 55.44| 26.13% | 33.77    |                |         | 52.24| 24.42%|
| VAR      |                |         | 24.15| 37.68| 17.88% | 22.42    |                |         | 34.36| 15.53%|
| SVR      |                |         | 27.14| 40.55| 19.43% | 22.35    |                |         | 34.18| 14.85%|
| GAT      |                |         | 35.50| 51.40| 29.20% | 32.65    |                |         | 49.23| 28.12%|
| FC-LSTM  |                |         | 25.10| 38.44| 18.19% | 20.02    |                |         | 30.69| 13.77%|
| TCN      |                |         | 20.94| 32.36| 14.54% | 17.21    |                |         | 26.12| 10.85%|
| DCRNN    |                |         | 20.27| 31.77| 13.78% | 17.02    |                |         | 26.73| 10.89%|
| T-GCN    |                |         | 21.26| 32.90| 14.43% | 17.98    |                |         | 28.64| 11.54%|
| ASTGCN   |                |         | 21.26| 32.35| 14.42% | 17.86    |                |         | 26.12| 10.76%|
| STGNN    |                |         | 20.43| 33.84| 14.72% | 18.12    |                |         | 28.64| 11.54%|
| STSGCN   |                |         | 20.27| 31.77| 13.78% | 17.02    |                |         | 26.73| 10.89%|
| AGCRN    |                |         | 19.35| 30.87| 12.69% | 15.74    |                |         | 25.18| 9.74% |        |
| STFGNN   |                |         | 19.17| 31.02| 12.21% | 16.71    |                |         | 26.22| 10.36%|

STCGAT (Ours) | 5.05 | 14.34 | 5.14% | 4.76 | 11.54 | 4.75% |

Improvements | +73.66% | +53.55% | +57.90% | +69.76% | +54.17% | +51.23% |

- STGCN [35]: The model uses ChebNet and a two-dimensional convolutional network to capture the spatial and temporal correlation of the traffic network.
- ASTGCN [37]: Spatial and temporal attention mechanisms are designed to dynamically model space and time.
- STGNN [39]: The S-GNN is used to model the spatial relationships between nodes. The GRU and Transformer layers capture local and global dependencies in the time dimension.
- STSGCN [36]: It uses local Spatial-temporal subgraph modules to model local correlations independently.
- AGCRN [34]: The model captures the fine-grained spatial-temporal correlation of specific nodes in a traffic sequence.
- STFGNN [40]: Spatial and temporal maps are fused to capture the Spatio-temporal correlation in the traffic network.

C. Experimental Settings and Evaluation Metrics

We divided the dataset into a training set, validation set, and test set in the ratio of 6:2:2 in that order. Then a window of size $T + T'$ is slid over the partitioned dataset to generate time-series data. Expressly, both $T$ and $T'$ are set equal to 12, the first $T$ time steps are our input data, and the last $T'$ time steps are considered to be our actual label values. Using 12 consecutive time steps from the past was used to predict 12 successive time steps in the future. In each dataset, all experiments were repeated ten times.

STCGAT is written in Pytorch 1.10.0, using the same hyperparameters in both datasets. In GAT, the number of hidden layers was set to 6 using the 4-head attention mechanism. The size of the BiLSTM hidden layers was set to 64; the size of the TCN kernel was set to 2; a total of 9 hidden layers were set to 64 for the residual module. The initial value of the expansion factor was set to 2; the batch size was set to 64; the learning rate size was 0.001, and the model was optimized using the Adam optimizer with a maximum number of iterations of 500. All experiments were performed on a server with NVIDIA GeForce RTX 2080Ti graphics cards.

To measure the model’s predictive performance, we evaluated between the labeled value $Y_i$ and the predicted value $Y'_i$ using the following three metrics.

- **Mean absolute error(MAE):**

  $$MAE = \frac{1}{N} \sum_{i=1}^{N} |Y_i - Y'_i|$$  (13)

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

  $$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (Y_i - Y'_i)^2}$$  (14)

- **Mean absolute percentage error(MAPE):**

  $$MAPE = \frac{100}{N} \sum_{i=1}^{N} \frac{|Y_i - Y'_i|}{Y_i}$$  (15)

where $N$ denotes the total number of samples, and $Y_i$ and $Y'_i$ denote the actual and predicted values of the $i$th sample. The smaller the value of the above indicators, the better the prediction performance of the model.
D. Experiment Results and Analysis

Table II shows the results of different models on the PEMS04 and PEMS08 datasets using 60 minutes of historical data to predict the future 60 minutes of the experiment. The results show that our STCGAT has an overwhelming advantage over all baseline models on each dataset.

From Table II we can observe that the model using historical mean HA as traffic flow prediction does not perform as well as the other techniques on all three metrics. In addition, traditional machine models using VAR and SVR, while slightly better than HA, still compare favorably with other deep learning-based methods other than those using GAT. All predictions are better than HA among the deep learning methods because GAT only captures spatial dependence and ignores temporal dependence. Both FC-LSTM and TCN only consider temporal correlation; the difference is that LSTM only captures local temporal features and TCN captures global temporal features. Experiments prove that the TCN model outperforms not only LSTM in three metrics but also DCRNN, T-GCN, STGNN, and ASTGCN in some metrics. STGNN combines RNN and Transformer based on capturing spatial dependence, capturing both local and global temporal support. STGCN stacks multiple spatial-temporal synchronous graph convolution layers, which can also learn long-range material relationships and heterogeneity. STFGNN, by processing various Spatial-temporal graphs in parallel for different periods, performing new fusion operations, can effectively learn the hidden Spatial-temporal dependencies. The best results of our proposed STCGAT bring more than 50% improvement in MAE, RMSE, and MAPE comparison experiments for both PEMS04 and PEMS08 datasets. In particular, on the PEMS04 dataset, the MAE of STCGAT was improved by more than 70% compared with other methods. Figure 7 and Figure 8 show the visualization results of the traffic speed prediction for the first road node of PEMS04 and PEMS08 at consecutive 12*24 (24-hour) time steps in the future, respectively, and the STCGAT prediction results fit the actual labeled values almost perfectly. These experimental results show that our model can effectively capture spatial dependencies dynamically from complex traffic road networks and accurately capture temporal causality by analyzing the cause of traffic events in the temporal dimension to prepare predictions of traffic flows.

E. Ablation Study on Model Architecture

To further investigate the impact of different modules of STCGAT, we designed five variants of the STCGAT model. We compared these four variants with the STCGAT model on the PEMS04 dataset. The differences between these five variant models are described below.

1. Baseline: The model does not preprocess spatial information using Laplace matrices, captures spatial depen-
Laplace: The model preprocesses the spatial data using the Laplace operator based on model 1.

BiLSTM: This model replaces the LSTM with a single-layer LSTM. And uses MSE loss as the loss function.

TCN: This model adds a TCN layer on top of model 3 to process the data output from the LSTM.

3. Baseline (L-S): This model is based on model 2, using soft-DTW instead of MSE loss as the loss function.

4. Add_TCN: This model adds a TCN layer on top of model 3 to process the data output from the LSTM.

5. Replace_BiLSTM: This model replaces the LSTM with BiLSTM based on model 3.

As shown in Table III, the experimental results for Horizon 3 (15Min), Horizon 6 (30 Min), Horizon 12 (60 Min) are presented. The results show that the model using the Laplace operator to preprocess the nodes has better performance than the one without it because the Laplace operator introduces both the adjacency matrix and the degree matrix of the graph, thus describing the difference information between the vertices and the neighboring nodes in more detail. Meanwhile, using soft-DTW as the loss function is significantly better than MSE loss. Model 4, with the addition of TCN layers, has little difference in short-term prediction from model 3 using only LSTM. Still, as the prediction time interval increases, we can see that TCN can better capture long-time dependence. Model 5 using BiLSTM has excellent Spatial-temporal prediction ability. As shown in the histogram of the average performance metrics in Fig. 9, the RMSE even outperforms our STCGAT. However, there are still some gaps in the overall performance compared to our STCGAT model using causal convolution. These experiments demonstrate the effectiveness of our model components, and STCGAT combines the advantages of these components, which makes STCGAT have excellent Spatial-temporal prediction ability.

V. CONCLUSION

In this paper, we propose a new model for Spatial-temporal traffic data prediction. The model uses graph attention neural networks to model spatial information and adaptively learn spatial feature information of traffic networks. Based on capturing spatial dependencies, the causal relationships between events and overall temporal dependencies of the latent traffic data are mined using our proposed CTCN. The excellent Spatial-temporal prediction capability of the STCGAT model is demonstrated by extensive comparison experiments on two datasets, PEMS04 and PEMS08. The effectiveness of our proposed CTCN is shown in the ablation experiments. However, traffic prediction is also influenced by external factors such as weather and road regulation constraints in real traffic scenarios. We can consider this external information to improve prediction accuracy in future work. Besides, as a data-driven neural network framework, our model is limited by the amount and quality of data in the dataset. How to efficiently utilize the limited amount of data in the dataset for learning from small samples is also a problem to be solved in our future work.

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