STformer: A Noise-Aware Efficient Spatio-Temporal Transformer Architecture for Traffic Forecasting

Yanjun Qin
Beijing University of Posts and Telecommunications
qinyanjun@bupt.edu.cn

Yuchen Fang†
Beijing University of Posts and Telecommunications
fangyuchen@bupt.edu.cn

Haiyong Luo†
Institute of Computing Technology, Chinese Academy of Sciences
yhluo@ict.ac.cn

Liang Zeng
Tsinghua University
zengl18@mails.tsinghua.edu.cn

Fang Zhao†
Beijing University of Posts and Telecommunications
zfsse@bupt.edu.cn

Chenxing Wang
Beijing University of Posts and Telecommunications
wangchenxing@bupt.edu.cn

ABSTRACT
Traffic forecasting plays an indispensable role in the intelligent transportation system, which makes daily travel more convenient and safer. However, the dynamic evolution of spatio-temporal correlations makes accurate traffic forecasting very difficult. Existing work mainly employs graph neural networks (GNNs) and deep time series models (e.g., recurrent neural networks) to capture complex spatio-temporal patterns in the dynamic traffic system. For the spatial patterns, it is difficult for GNNs to extract the global spatial information, i.e., remote sensors information in road networks. Although we can use the self-attention to extract global spatial information as in the previous work, it is also accompanied by huge resource consumption. For the temporal patterns, traffic data have not only easy-to-recognize daily and weekly trends but also difficult-to-recognize short-term noise caused by accidents (e.g., car accidents and thunderstorms). Prior traffic models are difficult to distinguish intricate temporal patterns in time series and thus hard to get accurate temporal dependence. To address above issues, we propose a novel noise-aware efficient spatio-temporal Transformer architecture for accurate traffic forecasting, named STformer. STformer consists of two components, which are the noise-aware temporal self-attention (NATSA) and the graph-based sparse spatial self-attention (GBS3A). NATSA separates the high-frequency component and the low-frequency component from the time series to remove noise and capture stable temporal dependence by the learnable filter and the temporal self-attention, respectively. GBS3A replaces the full query in vanilla self-attention with the graph-based sparse query to decrease the time and memory usage. Experiments on four real-world traffic datasets show that STformer outperforms state-of-the-art baselines with lower computational cost.

CCS CONCEPTS
• Information systems → Spatial-temporal systems; • Computing methodologies → Neural networks.

KEYWORDS
traffic forecasting, spatio-temporal data, transformer, self-attention

1 INTRODUCTION
The traffic forecasting task aims to predict future traffic information (e.g., speed and volume) based on historical traffic conditions. Accurate forecasting assists traffic management departments in diverting traffic to avoid congestion and is beneficial for daily travel.

Traffic forecasting is very challenging because of its complex spatio-temporal dependencies. The early statistical methods, e.g., ARIMA [30] and VAR [16], are difficult to capture the non-linear temporal dependence in real-world traffic time series. The standard machine learning methods, e.g., SVR [31] and KNN [25], can capture the non-linear temporal dependence and the spatial dependence. However, they mostly rely on the hand-craft features, resulting in weak generalization performance.

With the success of deep learning [8] used in computer vision [7], natural language processing [15], and speech recognition [9] in recent years, [12, 26, 32] use deep time series models such as Temporal Convolution Networks (TCNs), Self-Attention Networks (SANs), and Recurrent Neural Networks (RNNs) to extract non-linear temporal dependence of each sensor individually for traffic forecasting. However, these methods ignore the impact of complex spatial dependence on traffic data. Subsequently, [14, 19, 33, 34] combine deep models that can capture spatial dependence (e.g., graph neural networks (GNNs) and SANs) with deep time series models mentioned above and achieve significant results.

Nevertheless, prior methods neglect some issues in the spatial and temporal dimensions. For the spatial dimension, the global spatial receptive field brings more useful information than the local does. However, whether we use GNNs or SANs to extract the global spatial information, they take a lot of time and memory to train. Concretely, most GNN-based models receive information of neighboring nodes, and they capture distant information by stacking GNN layers. But the more GNN layers are stacked, the more difficult to optimize it. Moreover, the SAN-based models have a quadratic issue, i.e., the time complexity and memory usage is $O(N^2)$ on a graph with $N$ vertexes. Although GMAN [35] proposes an algorithm for grouping nodes to optimize SAN, the time complexity in GMAN is still exponential. For the temporal dimension, as shown in Figure 1a and 1c, traffic time series contains not only stable daily periodic patterns but also short-term fluctuations caused by accidents. Moreover, the fluctuations in the black circle in Figure 1c...
are deviate from the long-term trend of low-frequency component in Figure 1b, thus these fluctuations cannot bring positive effects for traffic forecasting and are noise for the future. We consider the existing of noise will decrease prediction accuracy. However, prior traffic forecasting models ignore to remove noise in time series.

To capture the global spatial dependence efficiently and remove the noise in the traffic time series, we propose a novel noise-aware efficient Transformer architecture, named STformer. Inspired by the state-of-the-art self-attention optimization method ProbSparse Self-Attention (PBSA) [36], we design a Graph-Based Sparse Spatial Self-Attention (GBS3A) to extract global spatial information efficiently. Concretely, GBS3A utilizes the sparse query to replace the full query in the vanilla self-attention, and the sparse query consists of sensors with max flow from other sensors on the road network based graph. On the other hand, different from directly using discrete wavelet transform (DWT) [22] to remove the noise in time series. We propose a Noise-Aware Temporal Self-Attention (NATSA) in STformer, which uses the learnable filter and the self-attention for the high and low frequency component of time series after DWT to determine whether the high-frequency component are noise and extract the stable temporal dependence from the low-frequency component.

The main contributions of this paper are summarized as:

- We propose GBS3A to efficiently extract global spatial information, which significantly reduces memory and time consumption compared with vanilla self-attention.
- We propose NATSA to identify noise from high-frequency component and extract stable temporal information from low-frequency component.
- We propose STformer, which is a noise-aware efficient Transformer architecture, and we evaluate it on four real-world traffic datasets. Experimental results demonstrate that STformer outperforms all baselines.

2 RELATED WORK

Traffic Forecasting. Early researches [16, 30] use the traditional statistical methods which are based on linear assumptions to predict traffic. Later, [25, 31] apply machine learning in traffic forecasting (e.g. SVR and KNN). The limitation of machine learning models is they require hand-craft features and are hard to generalize. With the success of deep learning in many fields, [28, 29] apply RNNs in traffic forecasting tasks. However, because of they neglect the spatial correlations in road networks and the noise in time series, the performance of them is not significantly improved. In spatial dimension, researchers utilize GNNs to extract the spatial information from non-Euclidean road networks, such as DCRNN and STGCN [14, 34]. Subsequent work considers building a dynamic graph for traffic forecasting. Graph WaveNet [33] uses learnable parameters to learn posterior node vectors to calculate the adjacency matrix through a data-driven manner. STGNN [27] uses dot products for hidden states in GRU to calculate the dynamic adjacency matrix. STSFGCN and STFGNN [18, 23] design a learnable parameter matrix to multiply the adjacency matrix and adjust the weights of the adjacency matrix through backpropagation. GMAN and ST-GRAT [19, 35] apply SAN in spatial dimension to capture the global spatial dependence, which avoid over-smoothing of stacking GNN. However, the SAN-based methods are inefficient in large-scale traffic data.

Attention Model. Attention firstly appear in the translation task, [1] propose the addictive attention to improve the word alignment of the encoder-decoder architecture. Then, the widely used dot-product attention proposed by [17]. The addictive attention and dot-product attention are mostly used in RNN-based encoder-decoder frameworks. Subsequently, [26] propose the Transformer, which is a pure attention model, and the Transformer achieves brilliant success in NLP [15] and CV [7]. However, the quadratic issue of self-attention hinders the application of Transformer to large-scale datasets. The Image Transformer [20] and Sparse Transformer [5] restrict the receptive field of the self-attention to a fixed local neighbor. Reformer and Routing Transformer [11, 21] use the dynamic pattern to replace the static fixed pattern. Set Transformer [13] proposes a novel global memory which access the entire sequence and Longformer [3] combines the global memory with a fixed pattern. Finally, Informer [36] takes query-key pairs in self-attention that away from the uniform distribution as dominate pairs to get the global memory. Besides, the proposed ProbSparse Self-Attention in Informer is the state-of-the-art method of efficient self-attention.

3 PRELIMINARY

Problem Definition. We use the three-dimensional tensor \( X \in \mathbb{R}^{T \times N \times F} \) for traffic forecasting, which records \( F \) features by \( N \) sensors of \( T \) timeslices. We set \( F = 1 \) to represent traffic volume. The data at time \( t \) is \( X_t \in \mathbb{R}^{N \times F} \), and \( X^i \in \mathbb{R}^{T \times F} \) denotes the \( i \)-th sensor features of all timesteps. To represent the topological connection of road network, the graph of road network is defined as \( G = (\mathcal{V}, \mathcal{E}, \mathcal{A}) \), where \( \mathcal{V} \in \mathbb{R}^N \) denotes a finite node set, i.e., we record \( N \) sensors’ data on the road network. \( \mathcal{E} \) is the edge set, and \( \mathcal{A} \in \mathbb{R}^{N \times N} \) denotes the adjacency matrix based on \( \mathcal{E} \), e.g., if sensors \( i \) and \( j \) are adjacency on the road network, there will be an edge between them and \( \mathcal{A}_{ij} = 1 \). The aim of traffic forecasting is learning a function \( F \), which learn from historical data \( X = \{X_1, X_2, ..., X_T\} \in \mathbb{R}^{T_0 \times N \times F} \) to predict next \( T_p \) traffic data.
\[ d = \text{where FC and STE denote the fully connected layer and the spatio-temporal embedding.} \]

\[
\hat{Y} = \{\hat{Y}_1, \hat{Y}_2, ..., \hat{Y}_p\} \in \mathbb{R}^{T_p \times N \times F}.
\]

\[
\{\hat{Y}_1, \hat{Y}_2, ..., \hat{Y}_p\} = \mathcal{F}(X_1, X_2, ..., X_T, \mathcal{G}). \tag{1}
\]

**Self-Attention.** The self-attention is the mostly used attention mechanism. The key idea behind the mechanism is each element in a sequence learns to gather information from other tokens. The input of self-attention consists of queries, keys, and values of dimension \( d \). Then compute the dot products of the query with all keys, divide each by \( \sqrt{d} \), and apply a softmax function to obtain the weights on the values:

\[
\text{Attention} = \text{softmax}(\frac{QK^T}{\sqrt{d}})V. \tag{2}
\]

4 **METHODOLOGY**

At the beginning, historical inputs are transformed to a high dimension space \( \mathbb{R}^D \) through a fully connected layer to enhance the representation power of STFormer. As shown in Figure 2, STFormer adopts a Transformer-like encoder-decoder architecture. The encoder and decoder consist of \( L \) identical layers, and each layer of encoder and decoder contains two and three sub-layers, respectively. Each layer of encoder and decoder firstly utilizes NATSA to remove noise and capture the temporal dependence, then uses GBS3A to extract global spatial information efficiently. Besides, decoder utilizes the encoder-decoder self-attention to absorb the historical spatio-temporal information from encoder outputs. We will describe each component in details. Finally, we use a fully connected layer at the bottom of STFormer to transform outputs of decoder to predicted values.

4.1 **Noise-Aware Temporal Self-Attention**

For the multivariate time series forecasting, it is very important to extract the temporal information from historical. However, because of various accidental factors (e.g., car accidents and thunderstorms) in road networks, there is a lot of noise in traffic time series. The existence of noise makes the temporal information intricate. Prior models are not aware of the negative impact of noise and hard to get accurate patterns from time series with noise. Therefore, we propose NATSA to adaptively denoise time series and capture the stable temporal dependence by combining DWT and neural networks.

DWT decomposes time series into high-frequency component and low-frequency component through a low-pass filter \( l \) and a high-pass filter \( h \) with 1-level decomposition:

\[
X_l, X_h = \text{DWT}(X, l, h), \tag{3}
\]

where \( X_l \in \mathbb{R}^{T \times N \times d} \) and \( X_h \in \mathbb{R}^{T \times N \times d} \) are the low-frequency component and the high-frequency component of \( X \in \mathbb{R}^{T \times N \times d} \) after decomposing and down-sampling in DWT. Figure 1 shows that the low-frequency component is stable and represents the trend of time series, while the high-frequency component is covered by noise. Therefore, the traditional noise-aware methods [6] usually remove noise by setting the part of the high-frequency component that is lower than threshold to zero.

Different from traditional methods, we use a learnable filter \( W^p \in \mathbb{R}^{T \times N \times d} \) to multiply the high-frequency component \( X_h \in \mathbb{R}^{T \times N \times d} \) to adjust the weight of each frequency in \( X_h \). The weight of the noise frequency will be reduced by back-propagation. Then we remove the noise in \( X_h \) through a non-linear activation function \( \text{ReLU} \). Formally:

\[
\text{DE}(X) = \prod_{n=1}^{N} \text{ReLU}(W^{p} \odot X^n_h), \tag{4}
\]

where \( \odot \) and \( \prod \) indicate the hadamard product and the concatenate operation along with the spatial dimension \( N \).

Moreover, because of the low-frequency component \( X_l \in \mathbb{R}^{T \times N \times d} \) is stable. We consider it is easier to capture long-term temporal dependence than high-frequency component \( X_h \). Similar to recent work such as GMAN and ST-GRAT, we choose the self-attention to capture the global temporal dependence in \( X_l \). However, using the vanilla temporal self-attention for pure time series is over-fitting and inefficient. Therefore, we use a random coefficient matrix [24] to replace the coefficient matrix obtained by the multiplication of query and key to reduce complexity. Concretely, a learnable parameter matrix \( W^c \in \mathbb{R}^{T \times T} \) is used as the coefficient matrix to update value. Besides, all sensors share the \( W^c \) to avoid over-fitting:

\[
\text{TA}(X) = \prod_{n=1}^{N} (W^c X^n_l), \tag{5}
\]

At the end of NATSA, we use the high-frequency component after denoising and the low-frequency component after global interaction to perform inverse discrete wavelet transform (IDWT) to reconstruct a more stable and temporal interacted time series, formulated as follows:

\[
\text{NATSA}(X) = \text{IDWT}(\text{TA}(X), \text{DE}(X)), \tag{6}
\]

where \( X \in \mathbb{R}^{T \times N \times d} \) is the input of NATSA.
The actual shortest path distance (red line) between A and B is larger than the spherical distance (black line).

4.2 Graph-Based Sparse Spatial Self-Attention

Most of the existing efficient Transformer methods use local patterns and lose global information. Informer [36] proves that selecting ‘active’ tokens to be a sparse query to store global information can achieve outstanding performance under the long-tail distribution of coefficient correlations of self-attention. As shown in Figure 3a, the long-tail distribution phenomenon also exists in spatial self-attention. Similar to Informer, we propose the GBS3A to reduce complexity of spatial self-attention by finding most active sensors in the road network and selecting their hidden states from input \( X \in \mathbb{R}^{T \times N \times d} \) to be the sparse query \( S \in \mathbb{R}^{T \times U \times d} \). The sparse query \( S \) can learn global spatial information at all time steps, and \( U \) denotes the number of active sensors in the road network. Formulated as:

\[
\text{GBS3A}(X) = \prod_{t=1}^{T} (\text{softmax}(\frac{S_{t}K_{t}^{T}}{\sqrt{d}})V_{t})_{T}
\]

(7)

where \( \prod (\cdot)_{T} \) is the concatenate operation along with the temporal dimension \( T \) and \( W^{Q}, W^{K}, W^{V} \in \mathbb{R}^{d \times d} \) are the learnable parameters of projections. The \( idx \in \mathbb{R}^{T \times U} \) indicates the index of selected active sensors. Next we will introduce how to get the \( idx \). Besides, sensors are not selected as the sparse query in GBS3A will be updated with the average of all sensors of the input \( X \) in each timestep.

Informer [36] utilizes the ProbSparse Self-Attention (PBSA) to replace the vanilla self-attention, which assumes sensors with correlation coefficients in the query-key coefficients matrix of self-attention away from the uniform distribution are active from the perspective of probability distribution. However, each sensor only samples a few sensors (wrt only \( \log N \) sensors) to calculate the distribution of its correlation coefficients to keep efficiency, it is difficult to reflect the true distribution. Different from PBSA, we spare the query from the perspective of message passing. We select active sensors that receives max flow from other sensors. To this end, we employ a trainable scalar projection vector \( P \in \mathbb{R}^{N \times 1} \) to project the 2-D coefficient matrix \( QK^{T} \in \mathbb{R}^{N \times N} \) in self-attention to 1-D to evaluate how much flow from other sensors can be retained in query when projected onto the direction of \( P \). Formally:

\[
M = \prod_{t=1}^{T} \left( \frac{(X_{t}W^{K})(X_{t}W^{K})^{T}P}{||P||} \right)_{T},
\]

(8)

where \( M \in \mathbb{R}^{T \times N} \) denotes the activity of each sensor and \( || \cdot || \) indicates the Frobenius norm.

Then we select \( U \) sensors with the largest scalar projection values on the direction of \( p \) as the sparse query \( S \) and the time complexity of our GBS3A is \( O(NU) \). The formula of getting the top-\( U \) index from \( M \) is:

\[
\text{idx} = \text{rank}(M,U),
\]

(9)

where \( \text{rank}(\cdot) \) returns the index of the top-U largest values.

Further, the time complexity of eq. 8 is \( O(N^{2}) \). Informer samples a subset of key in all sensors for each sensor to reduce the time complexity of eq. 8. However, as shown in Figure 3a, correlation coefficients of the subset of key which sampled in all sensors (i.e. All in Figure 3a) show a more obvious long-tail trend than the subset of key which sampled in sensors with shortest distance (i.e. SPD and SD in Figure 3a). Therefore, we argue that the subset of key sampled in all sensors is not enough to reflect the real flow of sensors. Here we select \( O \) sensors with the shortest path distance in the road network based graph as a subset of key for each sensor to calculate \( M \), as follows:

\[
M = \prod_{t=1}^{T} \left( \frac{\prod_{k=1}^{N}((X_{t}^{idx_{k}}W^{Q})(X_{t}^{idx_{k}}W^{K})^{T})_{N}P}{||P||} \right)_{T},
\]

(10)

where \( p \in \mathbb{R}^{O \times 1} \) and the time complexity of eq. 10 is \( O(NO) \). The \( idx_{k} \in \mathbb{R}^{N \times O} \) denotes the index of the subset of key for each sensor. As for the choice of the shortest path distance, because of the spherical distance may be misleading, e.g., the spherical distance between sensor A and sensor B is close but the actual distance between them in the road network is very far in Figure 3b.

Finally, we analyze why choose the sparse query instead of the sparse key to optimize self-attention. The spatial receptive field of the sparse key is limited. Even if the sampled subset of key contains most of the information, a small part is missing. We choose sparse query to optimize vanilla self-attention because the use of the sparse query ensures we can get the global spatial information through active sensors.

4.3 Other Components

4.3.1 Encoder-Decoder Self-Attention. Similar to the vanilla Transformer, we use the Encoder-Decoder Self-Attention (EDA) at the end of each layer of the decoder to extract historical spatio-temporal information, formulated as:

\[
\text{EDA}(X_{en}, X_{de}) = \prod_{n=1}^{N} (\text{softmax}((Q^{n}K^{nT})V^{n})_{N})_{T}
\]

(11)

\[
Q^{n} = X_{de}^{n}W^{Q}, \quad K^{n} = X_{en}^{n}W^{K}, \quad V^{n} = X_{en}^{n}W^{V},
\]

where \( X_{en} \in \mathbb{R}^{T_{en} \times N \times d} \) and \( X_{de} \in \mathbb{R}^{T_{de} \times N \times d} \) denote the output of encoder and the output of previous layer of EDA.

Specifically, at the top of the decoder, we use the future spatio-temporal embedding and the historical spatio-temporal embedding...
as the query and key in EDA to perform generative style inference instead of step-by-step decoding, which reduces the cumulative error and time consumption of long-term prediction. We put the details of spatio-temporal embedding (STE) in Appendix A.

Multi-Head Mechanism. At present, researchers use multi-head self-attention to get more information from different sub-spaces, and all the self-attention operations in our STformer adopt the multi-head mechanism, as shown below:

$$\text{MultiHead}(X) = W^H \prod_{h=1}^{H} (\text{head}_h)_H$$

where $\text{head}_h = \text{Attention}(X)$.

where $H$ denotes the number of head. $\prod (\cdot)_H$ is a concatenate operation along with feature dimension $H$. Each head has three linear projections to project the input to query, key and value. The $W^Q_h$, $W^K_h$, $W^V_h \in \mathbb{R}^{d \times d}$ are learnable parameters of linear projections in each head and $W^H \in \mathbb{R}^{d \times d}$ is the learnable parameter of output projection.

4.4 Loss Function.

STformer can be trained end-to-end via back-propagation by minimizing the L1 Loss between the predicted values and ground truths:

$$L(\Theta) = \frac{1}{T \times N} \sum_{t=1}^{T} \sum_{i=1}^{N} |\hat{y}_{t,i} - y_{t,i}|,$$

where $\Theta$ denotes all learnable parameters in STformer.

4.5 Complexity Analysis

In the following analysis we compute the complexity involved in a single layer of the encoder and the decoder with $T$ timesteps. The complexity of GBS3A is $O(TN \log Nd)$ because of $U \approx \log N$ and $O \approx \log N$. NATSA has dominant complexity $O(\frac{1}{4} NT^2 d)$, as is evident from eq. (4) and eq. (5). Besides, the complexity of EDA follows the vanilla temporal self-attention and is $O(NT^2 d)$. Therefore, the complexity of the single layer in encoder and decoder is $O(TN(\frac{1}{4} + \log N)d)$ and $O(TN(\frac{1}{4} + \log N)d)$.

5 EXPERIMENTS

5.1 Datasets

We use four large-scale datasets in traffic forecasting to evaluate the performance of our model, which are PEMSD3, PEMSD4, PEMSD7, and PEMSD8 [23]. They are all collected by California Transportation Agencies (CalTrans) Performance Measurement System (PeMS) [4]. The detailed information is shown in Table 1.

| Dataset | #Nodes | #Edges | #Samples | Sample Rate | #MissingRatio |
|---------|--------|--------|----------|-------------|---------------|
| PEMSD3  | 358    | 547    | 26208    | 5 mins      | 0.672%        |
| PEMSD4  | 307    | 340    | 16992    | 5 mins      | 3.182%        |
| PEMSD7  | 883    | 866    | 28224    | 5 mins      | 0.452%        |
| PEMSD8  | 170    | 295    | 17856    | 5 mins      | 0.696%        |

Table 1: Dataset statistics

5.2 Experimental Settings

Baselines. We compare STformer with widely used baselines and state-of-the-art models to evaluate the overall performance of our work, including 1) DCRNN [14]: a diffusion convolutional recurrent neural network, which utilizes the diffusion convolution in GRU to extract spatial information; 2) STGNN [34]: a spatial-temporal graph convolutional network, which combines GCN with GLU to capture spatio-temporal dependencies; 3) STSGCN [23]: a spatial-temporal synchronous graph convolutional network, which designs the spatial-temporal synchronous modeling mechanism; 4) STFGNN [18]: an advanced version of STGNN, which uses FastDTW to create the temporal graph; 5) GNN WaveNet [33]: a spatial-temporal graph convolutional network, which combines the self-adaptive adjacency matrix based GCN with TCN; 6) AGCRN [2]: an adaptive graph convolutional recurrent network, which integrates the GRU with the self-adaptive adjacency matrix based GCN; 7) GMAN [35]: a variant of the Transformer network that uses the self-attention mechanism for temporal and spatial dimensions; 8) ST-GRAT [19]: a variant of the Transformer network that takes the external graph structure information (e.g. distance between roads) in spatial self-attention. The details of baselines in Appendix C.

Metrics. We use the Mean Absolute Errors (MAE), Mean Absolute Percentage Errors (MAPE), and Root Mean Squared Errors (RMSE) to measure the performance of models. The detailed information of evaluation metrics MAE, RMSE, ans MAPE in Appendix D.

Experimental Environment. All models are implemented in Pytorch 1.7.1 and executed on a server with the Tesla V100S-PCIe 32GB GPU. We repeat all experiments 5 times and report the average of evaluation metrics.

Parameter Settings. In STformer, we set the layer $L = 3$, the feature size $d = 128$, and the head number $H = 8$ according to the previous work [19]. The batchsize is 16 except 8 on the PEMSD7 dataset. Besides, we adopt the Adam [10] optimizer with the initial learning rate of 0.001 in STformer. The optimal setting of $O$ and $U$ are $\log N$ according to the Appendix E.

5.3 Main Results

Due to space limit, Table 2 summarizes prediction performances of two larger datasets PEMSD3 and PEMSD7, which are the MAE, RMSE, and MAPE over next one, two, and three hours of our
| Dataset  | Method            | 1 Hour MAE (RMSE MAPE (%)) | 2 Hour MAE (RMSE MAPE (%)) | 3 Hour MAE (RMSE MAPE (%)) |
|----------|-------------------|-----------------------------|-----------------------------|-----------------------------|
| PEMSD3   | DCRNN             | 18.97 (32.99, 18.34)       | 23.35 (40.31, 21.58)       | 28.25 (47.72, 25.59)      |
|          | STGCN             | 18.75 (32.79, 17.82)       | 27.21 (46.99, 25.58)       | 21.15 (37.60, 20.86)      |
|          | STSGCN            | 19.60 (32.69, 18.49)       | 28.35 (46.61, 24.22)       | 22.35 (37.52, 23.15)      |
|          | Graph WaveNet     | 17.20 (30.71, 16.93)       | 19.72 (34.10, 19.28)       | 21.72 (35.87, 20.86)      |
|          | AGCRN             | 18.04 (31.22, 17.84)       | 18.49 (33.56, 19.19)       | 20.22 (34.47, 19.95)      |
|          | STGFNN            | 18.57 (31.19, 17.15)       | 19.47 (32.66, 18.92)       | 21.17 (35.47, 20.73)      |
|          | Graph WaveNet     | 19.60 (32.69, 18.49)       | 28.35 (46.61, 24.22)       | 22.35 (37.52, 23.15)      |
|          | GMAN              | 18.64 (31.22, 17.84)       | 16.84 (30.24, 16.84)       | 18.91 (33.98, 18.95)      |
|          | ST-GRAT           | 20.79 (36.02, 8.68)        | 17.22 (30.35, 18.92)       | 20.22 (34.47, 19.95)      |
|          | STformer (ours)   | 16.07 (28.77, 16.18)       | 17.82 (31.03, 17.81)       | 19.29 (32.87, 19.16)      |

**Table 2:** Performance comparison of STformer and baselines on PEMSD3 and PEMSD7. The bold font indicates the optimal results. The Improvement column denotes the reduction of optimal results compared with the sub-optimal result. GMAN and ST-GRAT ran out of GPU memory (OOM) on the PEMSD7 dataset.

| Variant | MAE | RMSE | MAPE | Improvement |
|---------|-----|------|------|-------------|
| Basic   | 18.70 | 32.32 | 19.07 | -           |
| + NATSA | 17.91 | 31.86 | 18.50 | +4.22%      |
| + GBS3A (ours) | 16.87 | 29.83 | 16.97 | +9.79%      |

**Table 3:** Results for ablation study on the PEMSD3 dataset. The Improvement denotes the reduction of MAE.

| Variant | Memory Usage | MAE | RMSE | MAPE | Improvement |
|---------|--------------|-----|------|------|-------------|
| VTSA    | 34818 M      | 17.47 | 30.35 | 18.92 | -           |
| NAVTSA  | 28541 M      | 17.38 | 30.25 | 18.63 | +0.52%      |
| NATSA (ours) | 24701 M | 16.87 | 29.83 | 16.97 | +3.43%      |
| VSSA    | 56814 M      | 17.85 | 31.27 | 17.52 | -           |
| PBSA (Informer) | 25749 M | 17.43 | 31.21 | 17.26 | +2.35%      |
| GBS3A-SD| 24701 M      | 16.87 | 29.83 | 16.97 | +5.49%      |
| GBS3A (ours) | 24701 M | 16.87 | 29.83 | 16.97 | +5.49%      |

**Table 4:** Comparison of different self-attention methods on the temporal view and spatial view. The Improvement denotes the reduction of MAE.

We draw the following conclusions from the experimental results: 1) STGCN and DCRNN first combine graph convolutional network (GCN) with deep time series models (e.g., RNN and 1D-CNN) to extract spatio-temporal dependencies, their performance is improved compared with traditional methods. 2) Based on the above two models, Graph WaveNet and AGCRN use the self-adaptive adjacency matrix based GCN and achieve better results than the road network based DCRNN and STGCN. 3) STSGCN and STFGNN design the spatio-temporal synchronous mechanism and the spatio-temporal fusion graph to increase receptive filed of GCN to improve performance, respectively. 4) GMAN and ST-GRAT are the Transformer-like models, they apply vanilla self-attention to two dimensions of temporal and spatial in traffic forecasting tasks and achieve better results than GCN-based methods because of the global receptive filed of self-attention. However, the existing Transformer-based models are limited by the quadratic issue and difficult to handle large-scale datasets.

STformer adopts a Transformer-like architecture, which uses not only GBS3A to efficiently extract global spatial information, but also combines DWT with neural networks to propose NATSA to adaptively denoise the input and hidden states. Therefore, it is natural that STFormer shows much better performances against above baselines and improves a maximum of 13.4% on MAE, 9.46% on RMSE, and 14.95% on MAPE. Besides, results of STformer on PEMSD7 is better than the simple dataset PEMSD3.
As shown in Figure 4, STformer reduces the training and inference time compared with other Transformer-based models. Moreover, the inference time of ST-GRAT and STGCN that utilizes step-by-step dynamic decoding is higher than other generative models in Figure 4b. Besides, using RNN will increase the training and inference time consumption, such as AGCRN, because RNN cannot be paralleled.

### 5.5 Spatio-Temporal Study

**Temporal Study.** To further estimate the effect of NATSA, we replace NATSA with the vanilla temporal self-attention (i.e. VTSA in Table 4) and the noise-aware vanilla temporal self-attention (i.e. NAVTSA in Table 4). By comparing results of VTSA and NAVTSA, we found that removing noise and extracting temporal patterns on the high and low-frequency component of time series after DWT can reduce the memory usage and improve model performance. We further found that using VTSA on the low-frequency component does not significantly improve the prediction accuracy. We speculate that the pure time series does not require a complicated deep time series model. Therefore, STformer utilizes the random coefficient matrix shared by sensors and improves the forecasting performance.

**Spatial Study.** To further estimate the effect of GBSSA, we replace GBSSA with the vanilla spatial self-attention (i.e. VSSA in Table 4), the ProbSparse Self-Attention in Informer (i.e. PBSA in Table 4), and GBSSA with the subset of key based on the spherical distance (i.e. GBSSA-SD in Table 4). As shown in Table 4, methods use sparse query reduce the memory usage and improve the performance of STformer compared with VSSA, because of the full self-attention is low-rank and has useless information. Besides, our graph-based sparse methods avoids to get the wrong distribution of correlation coefficients compared with PBSA and further improves the prediction accuracy. Moreover, the shortest path distance can better reflect spatial correlations between sensors than directly using the spherical distance.

### 5.6 Computation Cost

As shown in Figure 4, STformer reduces the training and inference time compared with other Transformer-based models. Moreover, the inference time of ST-GRAT and STGCN that utilizes step-by-step dynamic decoding is higher than other generative models in Figure 4b. Besides, using RNN will increase the training and inference time consumption, such as AGCRN, because RNN cannot be paralleled.

### 5.7 Visualization

Figure 5 visualizes the learnt sparse query of using GBSSA and PBSA in STformer on the PEMSD3 dataset. We found that active sensors in the sparse query obtained by GBSSA and PBSA are distributed on different road segments, so that different active sensors will extract global and diverse spatial information that is more focused on their distributed road segments. The difference of them is that active sensors obtained by GBSSA are distributed in the middle of the road segment and active sensors obtained by PBSA are distributed at the ends of the road segment. When the active sensor at one end of the road segment, it is easy to ignore information at the other end, resulting in lower performance.

## 6 CONCLUSION

In this paper, we propose a novel noise-aware efficient Transformer architecture for traffic forecasting, named STformer. STformer uses NATSA to capture more stable temporal properties in denoised time series and uses GBSSA to capture the global spatial dependence more efficiently. Extensive experiments on multi-step traffic forecasting tasks demonstrate the effectiveness of both STformer and the proposed modules. In the future, we will look for applying STformer to other multivariate time-series forecasting applications, such as travel demand, stock price prediction, and electricity used forecasting.

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