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Attention Based Spatial-Temporal GCN with Kalman filter for Traffic Flow Prediction

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Abstract. Intelligent Transportation Systems (ITS) are becoming increasingly important as traditional traffic management systems struggle to handle the rapid growth of vehicles on the road. Accurate traffic prediction is a critical component of ITS, as it can help improve traffic management, avoid congested roads, and allocate resources more efficiently for connected vehicles. However, modeling traffic in a large and interconnected road network is challenging because of its complex spatio-temporal data. While classical statistics and machine learning methods have been used for traffic prediction, they have limited ability to handle complex traffic data, leading to unsatisfactory accuracy. In recent years, deep learning methods, such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), have shown superior capabilities for traffic prediction. However, most CNN-based models are built for Euclidean grid-structured data, while traffic road network data are irregular and better formatted as graph-structured data. Graph Convolutional Neural Networks (GCNs) have emerged to extend convolution operations to more general graph-structured data. This paper reviews recent developments in traffic prediction using deep learning, focusing on GCNs as a promising technique for handling irregular, graph-structured traffic data. We also propose a novel GCN-based method that leverages attention mechanisms to capture both local and long-range dependencies in traffic data with Kalman Filter, and we demonstrate its effectiveness through experiments on real-world datasets where the model achieved around 5% higher accuracy compared to the original model.

Keywords: Deep leaning; Graph; Machine learning; Traffic prediction

1. Introduction

In recent years, with the rapid increase in the number of vehicles on the street, traditional traffic management systems cannot keep up leading to many problems related to congestion and the reliability of road networks. Researchers have been working on integrating technologies from different domains such as connected devices and sensors to improve transportation systems and build Intelligent transportation systems (ITS) (Zhang *et al.*, 2021; Wu *et al.*, 2020).

In intelligent transportation systems, traffic prediction is an integral part that helps

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make traffic management systems more efficient. In road networks, a congestion problem in a single road could impact other roads in the network. Hence, accurate traffic prediction is essential to traffic management systems. Moreover, traffic prediction can help people avoid busy roads, but more notably, it can help achieve more efficient resource allocation for connected vehicles. For several years, researchers have used many time series analysis methods for traffic prediction such as historical average (HA), auto-regressive integrated moving average (ARIMA) and machine learning methods to model large traffic data such as k-nearest neighbors (KNN) and support vector machines (SVM) (Williams *et al.*, 2014; Mingheng *et al.*, 2013) . However, the large and interconnected road networks make it difficult to model road network traffic using traditional prediction models as these models require domain-specific features engineering. To address these issues several studies focused on utilizing deep learning methods to develop models that can handle larger-scale and complex spatio-temporal data of road networks.

Recurrent neural network (RNN) and its variants, Gated Recurrent Unit (GRU) and long short-term memory networks (LSTM), were mainly for natural language processing and due to their capabilities to learn from long range temporal data, they were utilized to build traffic predictions models(Hussain *et al.*, 2021; Zhao *et al.*, 2017).

Although traffic data is collected as temporal data, traffic in one location is impacted by traffic in neighboring and connected roads making it a challenge to capture spatial correlation. Convolutional neural networks (CNN) were developed to capture the spatial features and their correlation to grid-structured images (Lopez Pinaya *et al.*, 2020). Several studies used CNN in integration with LSTM to be able to capture both spatial and temporal traffic data (Zhao *et al.*, 2021). However, CNN-based models are limited to processing regular Euclidean grid-structured data such as 2D images or 1D sequences.

Traffic road network data, on the other hand, are irregular, more complex, and better represented as graph-structured data. Although, many researchers applied CNN-based models to graph-structured data, it requires transforming the graph into the grid-like structure, which may not fully capture the inherent relationships within the graph. The need to extend deep neural networks to non-Euclidean domains motivated the work on geometric deep learning, leading to the emergence of variants of graph neural networks (GNNs) (Zhou *et al.*, 2020). Inspired by the success and computational efficiency of convolutional neural networks (CNNs) in grid-structured data, Graph Convolutional Neural networks (GCNs) extend the concept of convolution to graphs (Zhao *et al.*, 2015).

However, GCN requires their entire graph structure for training, which consumes a large amount of memory resources and fails to handle the dynamic spatial correlations of traffic conditions. To tackle the above challenges, Guo *et al.* (2019) propose a novel deep learning model: Attention-based Spatial Temporal Graph Convolution Network (ASTGCN) models to predict traffic data more accurately at different locations while considering many internal and external factors.

In this paper, we proposed a new model that integrates Kalman Filter with ASTGCN to improve its accuracy. The main contributions of this paper are summarized as follows:

We improved the accuracy of the ASTGCN model by using Kalman Filter to fuse the data coming from different blocks. Specifically, the spatial attention block and temporal attention block to capture the correlations between them. We tested the proposed model on real-world high-way traffic datasets to verify that our improved model archives better results compared to the original model and existing baselines.

The remainder of this paper is organized as follows. Section 2 presents a literature review on traffic flow prediction. Section 3 gives details about the problem definition and the model architecture. Section 4 presents and discusses the experimental results. Finally, we conclude with Section 5.

2. Related Work

Traffic flow prediction is an integral part of ITS applications and enables traffic management systems to efficiently control traffic by making more informed decisions. Traffic prediction methods have been through several stages of evolution. We can divide them into three main categories: statistical analysis methods, traditional machine learning methods, and deep learning methods. In statistical methods, the historical average (HA) is the simplest model to predict future values using historical data typically based on the average or mean of all or subsets of past observations.

HA offers a simple and fast way to predict future values, but when dealing with complex data that has many irregularities and trends it starts to lose accuracy (Smith and Demetsky, 1997). To overcome the challenges the HA model faced, around 1976 Box and Jenkins (Park *et al.,* 2011) proposed the Autoregressive Integrated Moving Average model (ARIMA). In (Yao *et al.,* 2019), the authors proposed the use of the ARIMA model for traffic volume prediction in urban roads. Though ARIMA models show better accuracy and can handle more complex patterns and trends in the data, the nature of traffic data imposed some challenges affecting the prediction accuracy, such as seasonal fluctuations, non-linearity dependencies, and high-dimensional data.

To tackle these issues, different variants were introduced. Kohonen ARIMA was proposed to handle the non-linear dependencies and high-dimensional data using the Kohonen Self-Organizing Map with ARIMA (Connor, Martin, and Atlas, 1994). In a work by Williams *et al.,* (2014), Williams, Durvasula, and Brown (1998), they developed and tested seasonal ARIMA models and Winters exponential smoothing models on two different datasets. In their work, both of their models achieved promising results compared to HA models and generic ARIMA models. In another work by (Cho *et al.,* 2014), the authors proposed seasonal ARIMA to handle the seasonality patterns in traffic data by incorporating additional seasonal components to capture the seasonal fluctuations. As we are dealing with traffic data, we can expect to have all kinds of distinct patterns and trends.

In order to take these patterns and behavior into account, the researchers needed to divide traffic data into subsets or segments and fit ARIMA models to each subset. Lee and Fambro (1999) investigated the use of subset ARIMA for short-term traffic volume prediction, and their results showed that the subset ARIMA model gives more stable and accurate results.

Kalman Filter has been widely used in various applications such as sensor fusion and target tracking, given its ability in prediction and measurements. Kalman Filter has been applied to traffic prediction to estimate and predict future traffic values based on available data(Ojeda, Kibangou, and De-Wit, 2013; Van-Hinsbergen *et al.,* 2012; Okutani and Stephanedes, 1984).

Statistical methods often assume that the traffic data is linear and stationary, which limits the model's ability to capture complex and non-linear relationships in traffic data. To tackle these challenges, machine learning-based traffic prediction models have emerged and received a lot of attention from researchers. Among the first machine learning models used for traffic prediction is the K-Nearest Neighbor algorithm (KNN) (Davis and Nihan, 1991). In (Davis and Nihan, 1991) the authors conclude that linear time-series methods performed better than k-NN, but further research was needed to better understand which scenarios k-NN is better than conventional methods.

In recent years, some researchers utilized k-NN models for traffic predictions and were able to achieve promising results. Zhang *et al.* (2013) proposed a k-NN model for short-term traffic flow prediction in urban expressways that achieved a 90% accuracy. In another work by Yang *et al.* (2019), they proposed a k-NN model for traffic flow prediction in road ports and used k-Dimension Tree (KD Tree) to reduce the time complexity of neighbor searching. Other machine learning includes support vector regression (SVR), and Bayesian model. In a study by Wu, Ho, and Lee (2004), the authors applied SVR for travel-time prediction using real highway traffic data.

The SVR model has been applied to traffic prediction in several studies due to its generalization ability (Nidhi and Lobiyal, 2022). The Bayesian networks model can take into account the causal probabilistic relationship between random variables, which enables the modeling of complex systems and capturing dependencies. Sun, Zhang, and Yu (2006) proposed a traffic flows prediction model based on a Bayesian network, and traffic flows among adjacent road links are modeled as a Bayesian network (Sun, Zhang, and Yu, 2006).

In recent years, with the rapid development of sensors and road networks, more and more data traffic data are generated with increasing complexity. The use of traditional traffic prediction models becomes inefficient and limiting, considering the complexity of data. It becomes clear that more powerful computing and data processing technologies are required. Furthermore, computers become more powerful with highly advanced computing capabilities. This enabled the advancement of prediction models, specifically deep learning-based models.

These deep learning models showed very good performance in many fields. Therefore, several researchers focused on developing predictive models that used a variety of deep learning methods. Recurrent Neural Networks (RNN) and its variants were introduced into traffic flow prediction. Since RNN-based models were built to model and capture sequences of data, they became the first choice for time-series prediction and classification. In (Xiangxue, Lunhui, and Kaixun, 2019), the authors proposed a short-term traffic flow prediction framework based on the LSTM-RNN model that was trained and tested using an urban road network traffic dataset. The model can correctly capture the time trends and temporal correlations of the traffic flow in multiple time steps into the future. In another work by Du *et al.* (2017), the authors proposed an LSTM-based prediction model to predict 24-hour traffic count data. The prediction results of the model are then used for resource allocation in Vehicle-to-Vehicle (V2V) communication.

Other works used LSTM with other algorithms, such as Principal Component Analysis (PCA), where PCA was applied to extract the main trend data and then LSTM was applied to the residual data, which shows that subtracting the main trend data gives better results compared to directly using LSTM (Zhao and Zhang, 2018). Though LSTM shows good results, it still cannot fully capture the characteristics of traffic data, where the traffic in one location can impact the traffic of several locations. This is referred to as the spatial information or spatial dependencies that the generic LSTM models cannot capture. By incorporating spatial correlations, it is possible to capture both the temporal and spatial correlations and dependencies between data points.

Due to their ability to learn the spatial features effectively, many research works incorporated CNNs with LSTM. This enabled CNN-LSTM models to learn the spatial information by applying conventions over the input data before feeding it to LSTM to learn the temporal information and the correlations between them in an automatic and hierarchical manner. Zhao *et al.* (2021). proposed a CNN-LSTM-based prediction model using spatial-temporal trajectory topology, which achieved 1%~2% accuracy compared to normal LSTM. As discussed above, CNN is built to handle grid-structured data, which is not fully compatible with road network data, which are irregular and better represented as graph data. (Lu *et al.,* 2020) proposed a graph LSTM (GLSTM) model to capture spatial-temporal representations in road traffic flow prediction, which can model complex traffic flow and outperform LSTM and GRU models.

LSTM and its variants give promising results, but the accuracy degrades with long sequences. In order to solve this problem, graph convolution is used to handle traffic data more efficiently. There are two methods of graph convolution spatial methods and spectral methods, where spatial methods apply convolution filters on a graph's nodes and their neighbors (Guo *et al.,* 2019). Guo *et al.* (2021) proposed an optimized graph network with RNN for traffic prediction, where the spatial characteristic of the road network is represented as a graph. In their paper, Guo *et al.* (2021) evaluated the models on three real-world datasets, and the results show that the proposed method outperforms methods such as GRU, SVR, and GRU.

In their work, Yu, Yin, and Zhu (2018) proposed a graph complete convolutional structure that effectively captures the spatio-temporal correlations in traffic data. The proposed model was able to outperform LSTM-based models as well as the GCGRU model proposed by (Guo *et al.,* 2021). However, these models do not consider the dynamic spatial-temporal correlations of traffic data. To address the shortcomings of graph convolutions or other models based on graph convolutions, a graph attention networks (GATs) architecture that leverages masked self-attentional layers was introduced (Veličković *et al.,* 2018). *Liang et al.* (2018) proposed a multi-level attention network that leverages graph attention over data from traffic sensors. The authors used a multi-level attention-based recurrent neural network to predict the readings of geo-sensor over several future hours where a graph multi-level attention model can capture the dynamic spatio-temporal dependencies. The proposed model outperformed LSTM, Seq2seq, and stDNN (Zhang *et al.,* 2016; Sutskever, Vinyals, and Le, 2014). However, it is time-consuming in practice since a separate model needs to be trained for each traffic prediction model.

To address the issues addressed above, Guo *et al.* (2019) proposed an attention-based spatial-temporal graph convolutional networks (ASTGCN) based on the graph structure of the traffic network and the dynamic spatio-temporal information of the traffic data. Based on the promising results of the ASTGCN model, we were motivated to improve the performance of the models by changing the model's architecture and adding a Kalman Filter layer.

3. Attention Based Spatial-Temporal Graph Convolutional Networks

3.1. Problem Definition

A traffic network is defined as an undirected graph $G = (V, E, A)$, where V is a finite set of N nodes and E is a set of edges and the connectivity between the nodes is indicated as $A \in R^{N \times N}$ which denotes the adjacency matrix of the graph G. Where each node is a traffic detection sensor that generates the traffic flow in a certain road network, the measurements detected is denotated as F where they have the same sampling frequency.
Based on the graph road network definition above, the traffic flow prediction problem can be defined as follows:

- Each node detects and records f where $f \in (1, \dots, F)$.
- x_t^i donates the values of all the features of node i at time t.
- c donates a feature of node i.
- $x_t^{c,i}$ donates the value of the c-th feature of node i at time t.

Based on the above definitions, we will have $X_t = (x_t^1, x_t^2, \dots, x_t^N)^T \in R^{N\times F}$ which donates the values of all the features of all nodes at time t. Then $X = (X_1, X_2, \dots, X_\tau)^T \in R^{N\times F\times\tau}$ denotes the value of all the features of all the nodes over τ time slices. Finally, $y_t^i = x_t^{f,i} \in R$ is set to represent the traffic flow of node i at time t in the future.

Then, the problem the model needs to solve is given x, which donates the historical measurements of all the nodes on the traffic network over past τ time slices. The prediction problem is defined as $\boldsymbol{Y} = (\boldsymbol{y}^1, \boldsymbol{y}^2, \dots, \boldsymbol{y}^N)^T \in R^{N\times T_p}$ of all the nodes on the whole traffic network over the next T_p time slices, where $\boldsymbol{y}^i = \left(y_{\tau+1}^i, y_{\tau+2}^i, \dots, y_{\tau+T_p}^i\right) \in R^{T_p}$ denotes the future traffic flow of node i from $\tau + 1$.

3.2. Model Architecture

Figure 1 displays the overall framework of the proposed model. It comprises three independent components, all designed with the same structure to model the recent, daily, periodic, and weekly-periodic dependencies of the historical data.

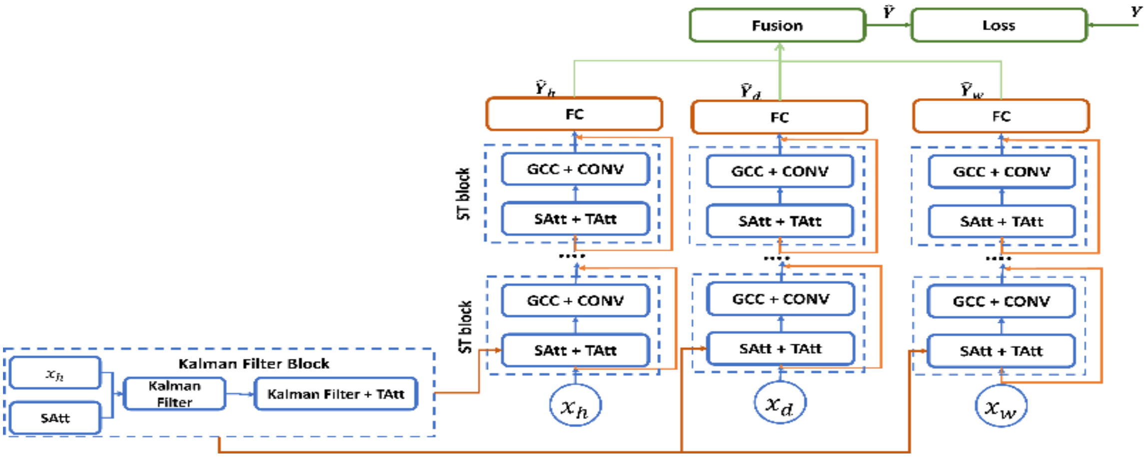

Figure 1 The framework of ASTGCN. SAtt: Spatial Attention; TAtt: Temporal Attention GCN: Graph Convolution; Conv: Convolution; FC: Fully connected; ST block: Spatial-Temporal block

Figure 2 shows how the Kalman Filter is integrated into the original model, where we fuse the spatial attention output with the original time-series which ensures we have more information preserved throughout the training process.

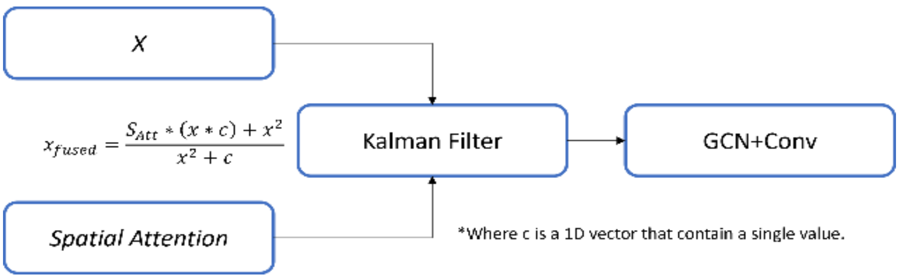

Figure 2 The integration of Kalman Filter with the model.

4. Results and Discussion

Figure 3 shows the traffic sensors distribution from the PEMS dataset; the sensors data are collected from the PEMS dataset. The map is created using the adjacency matrix for the graph data, which also shows the connections between the sensors based on the road network.

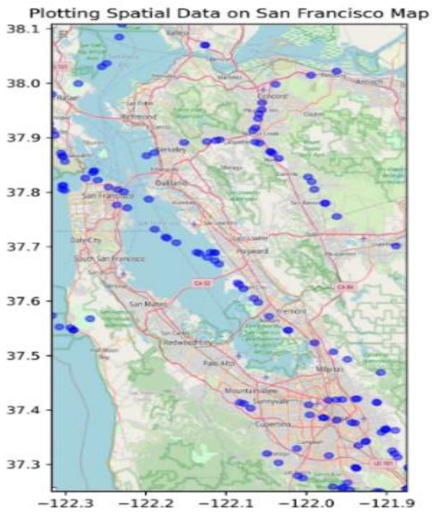

Figure 3 Traffic sensors distribution map in the PEMS04 dataset.

Figure 4 shows the graph representation of the sensor data with its nodes and edge connections. The graph shows how dense is the connection between all of the nodes. These connections represent the possible impact of the nodes on each other.

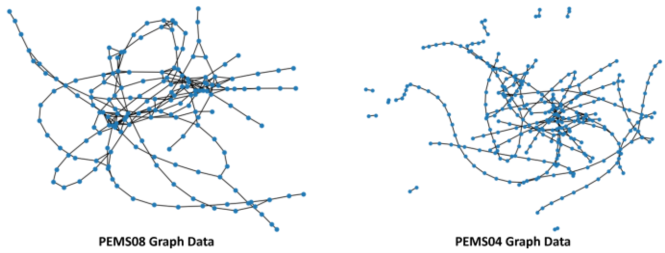

Figure 4 Traffic sensors distribution over a graph for both datasets.

Figure 5 shows the error matrix values for the original model and the improved model. We can notice that the proposed model with Kalman Filter shows smaller error values compared to the original model. Which indicates an improvement when using Kalman Filter with ASTGCN model.

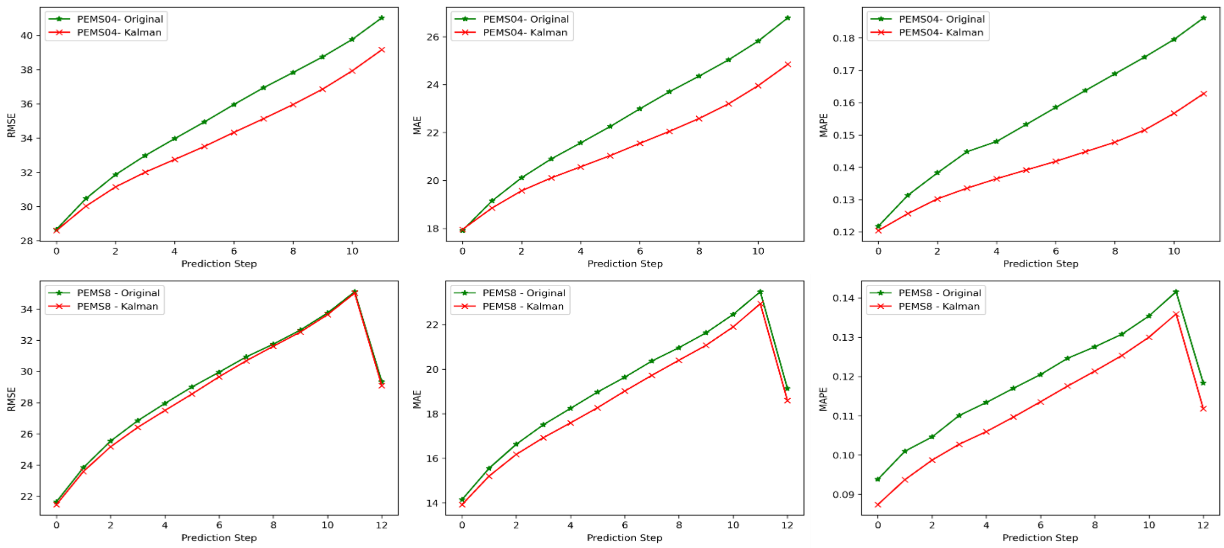

Figure 5 Model prediction accuracy with and without Kalman Filter.

Table 1 displays the average performance of traffic prediction for various models. It is evident that the original ASTGCN model outperforms the other models, we can notice that the ASTGCN original model shows better performance compared to the other models. Moreover, we can see that our proposed model shows better performance results compared to the other models and the original model. We trained the original model and our proposed model using PeMSD4 and PeMSD8 datasets for 40 Epoch.

Table 1 Average performance comparison of different approaches on PeMSD4

	PeMSD4		*PeMSD8*	
Model	RMSE	MAE	RMSE	MAE
HA	54.14	36.76	44.03	29.52
ARIMA	68.13	32.11	43.30	24.04
VAR	51.73	33.76	31.21	21.41
LSTM	45.82	29.45	36.96	23.18
GRU	45.11	28.65	35.95	22.20
STGCN	38.29	25.15	27.87	18.88
GLU-STGCN	38.41	27.28	30.78	20.99
GeoMAN	37.84	23.64	28.91	17.84
ASTGCN	35.45	22.55	29.34	19.13
Our Model	**33.56**	**21.14**	**29.09**	**18.59**

4. Conclusions

In this paper, we addressed the challenge of accurate traffic flow prediction in large and interconnected road networks by proposing an attention-based spatial-temporal graph convolutional network (ASTGCN) with a Kalman filter. Traditional statistical and machine learning methods have limitations in handling the complex spatio-temporal data of traffic networks, leading to unsatisfactory accuracy. To overcome these limitations, we leveraged graph convolutional neural networks (GCNs), which extend the concept of convolution to graph-structured data. Our proposed ASTGCN model integrates attention mechanisms to capture both local and long-range dependencies in traffic data with a Kalman filter to fuse data from different blocks and improve the model's accuracy. Finally, our research demonstrates the potential of attention-based spatial-temporal graph convolutional networks with a Kalman filter for traffic flow forecasting. Further research can explore additional enhancements and applications of this model, such as real-time traffic prediction, adaptive traffic management, and integration with emerging technologies like connected and autonomous vehicles.

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