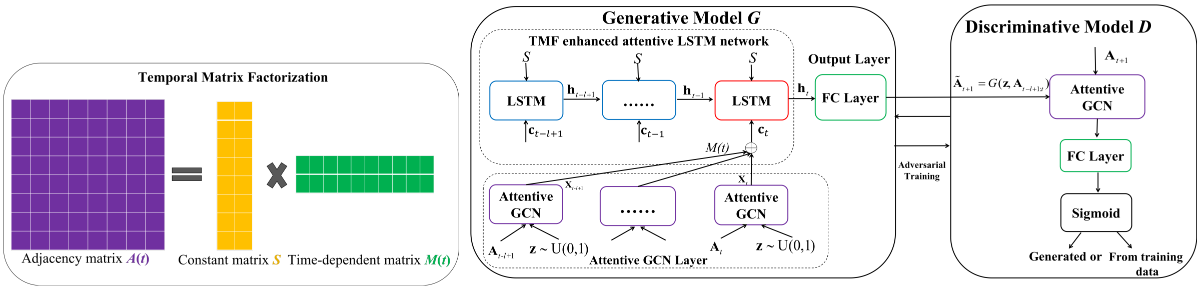
Appendix for Paper 6441

1 The Overall Architecture of TrafficGAN

Figure 1 illustrates the overview architecture of TrafficGAN, which consists of three primary modules: the attentive GCN, the TMF-LSTM module, and the generative adversarial network (GAN). First, to capture the spatial features from the traffic network snapshot at each timestamp, we leverage the attentive graph convolutional network (GCN), which has shown to be a powerful technique of characterizing deep complex non-linear features of nodes in traffic network, to encode the structural characteristics of the traffic network at each timestamp. Second, we employ the TMF-LSTM, which takes in a sequence of network representations learned by attentive GCN and predicts the traffic network snapshot in the next timestamp, to capture the temporal characteristics and evolving patterns of time-varying traffic networks with multiple successive time intervals. Third, due to the difficulty of leveraging the benefits of linear units in the generative process, generative adversarial network (GAN) is applied to refine the performance of traffic flow prediction by using a discriminative model to guide the training of the deep generative model (i.e., LSTM) in an adversarial process. In the adversarial process, we train a generative model G to predict the network snapshot in the next timestamp based on the previously observed sequential network snapshots via the LSTM network. We also train a discriminative model D which attempts to distinguish the generated snapshots from the real ones in the training data. The generative model and the discriminative model are trained by performing a minimax two-player game. Thus, this adversarial process can eventually adjust G to generate high-quality traffic network snapshot.



(a) (b)

Figure 1: (a) The illustration of temporal matrix factorization model. (b) The overall architecture of the TrafficGAN model, consisting of a generative network G and a discriminative network D. The generative model G is composed of (i) an attentive GCN model and (ii) a TMF-LSTM network followed by a fully-connected output layer. The discriminative network D is a binary classifier which consists of an attentive GCN network followed by a fully-connected output layer.

2 Qualitative Analysis: A Case Study

To better understand the proposed model, we use an exemplary case chosen from PEMS-BAY dataset to demonstrate the adaptive ability of GAN for traffic flow prediction. We visualize forecasting results in Figure 2. From the results, we can observe that TrafficGAN can generate more accurate prediction than the model without GAN when small oscillation exists in the traffic network. In addition, TrafficGAN is more likely to accurately predict the abrupt changes in the traffic forecasting than the model without GAN. This reflects the robustness of TrafficGAN.

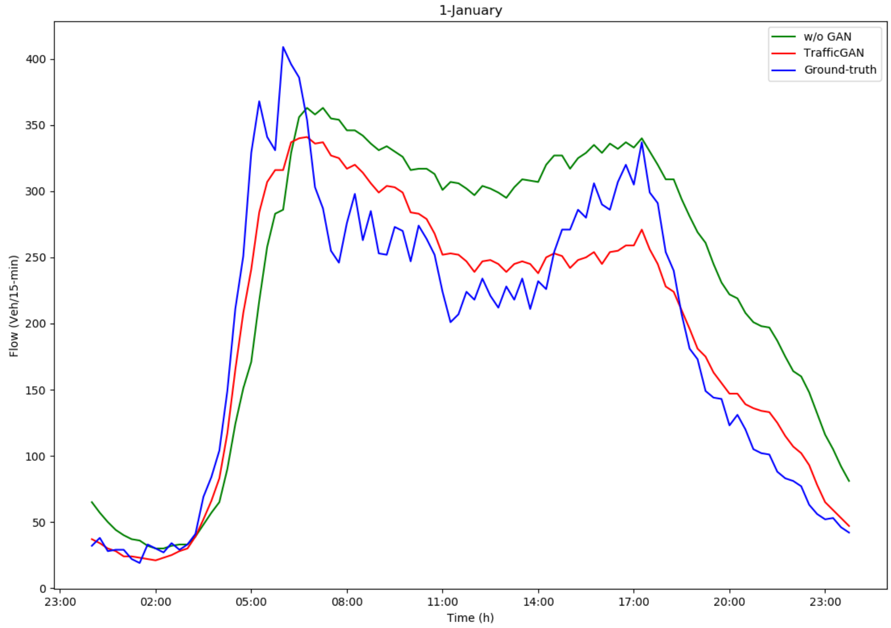


Figure 2: Traffic time series forecasting visualization.

3 Experimental Results on METR-LA Dataset

In the experiments, we utilize the proposed model to predict 15-min traffic flow on METR-LA dataset. We report the automatic evaluation results in Table A.1. SAE and SRCN stably exceed the conventional statistical and machine learning methods because they explore both the complex non-linear features of the traffic network snapshot. In practice, the non-linear transformations over time are commonly seen in the transportation networks. The proposed TrafficGAN takes a further step towards emphasizing the temporal and spatial information in the traffic data with deep generative networks. It substantially and consistently outperforms the compared methods by a noticeable margin on both datasets. This demonstrates the advantages of leveraging deep generative models in predicting traffic flow.

Method	MAPE	MAE	RMSE
HA	13.0%	4.16	7.80
ARIMA	9.6%	3.99	8.21
KNN	9.2%	3.65	7.93
BM	9.0%	3.78	8.04
MNR	8.8%	3.43	7.76
VAR	10.2%	4.42	7.89
SVR	9.3%	3.99	8.45
FNN	9.9%	3.99	7.94
SAE	8.5%	3.58	7.33
SRCN	8.2%	3.23	6.46
DCRNN	7.3%	2.77	5.38
TrafficGAN	**6.4%**	**2.56**	**5.27**
w/o GAN	7.0%	2.68	5.39
w/o GCN	6.9%	2.74	5.41
w/o recons.	6.6%	2.62	5.34

Table A.1: Experimental results on METR-LA dataset in terms of MAPE, MAE, RMSE.

4 Experimental Results on Rush-hours and Non-rush-hours

To evaluate the effectiveness of TrafficGAN in rush-hour, we split the PEMS-BAY dataset into two parts: rush-hour data (6:00-10:00 am and 16:00-20:00 pm) and non-rush-hour data. We conduct experiments on these two datasets separately. The MAPE, MAE, and RMSE scores are summarized in Table A.2.

We can observe that the results on non-rush-hour data is significantly better the results on the rush-hour dataset. This may be because that rush-hour data has more complex non-linear temporal-spatial characteristics than non-rush-hour data, which are difficult to explore. On the other hand, the results on the rush-hour data is slightly better than the results on the standard PEMS-BAY dataset. The reason may be that segmenting the PEMS-BAY traffic data into rush-hour and non-rush-hour can reduce the non-linear temporal dynamics of the data distribution with changing road conditions. We may further improve the performance of TrafficGAN on rush-hour data by using more training data.

Dataset	MAPE	MAE	RMSE
Standard PEMS-BAY	2.2%	1.20	2.52
Rush-hour data	2.3%	1.18	2.49
Non-rush-hour data	1.9%	1.15	2.43

Table A.2: Experimental results of TrafficGAN on rush-hour and non-rush hour datasets from METR-LA data in terms of MAPE, MAE, RMSE.