SpecSTG: A Fast Spectral Diffusion Framework for Probabilistic Spatio-Temporal Traffic Forecasting

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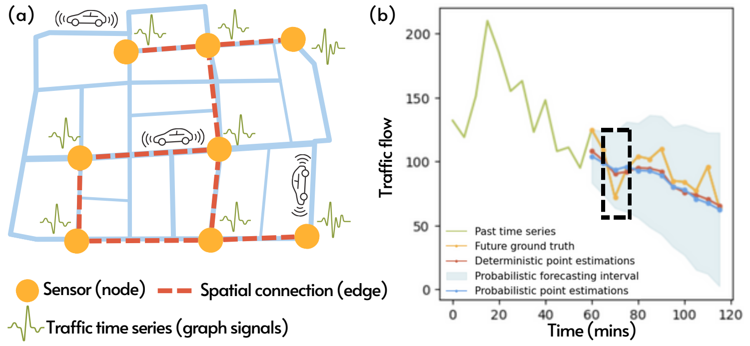
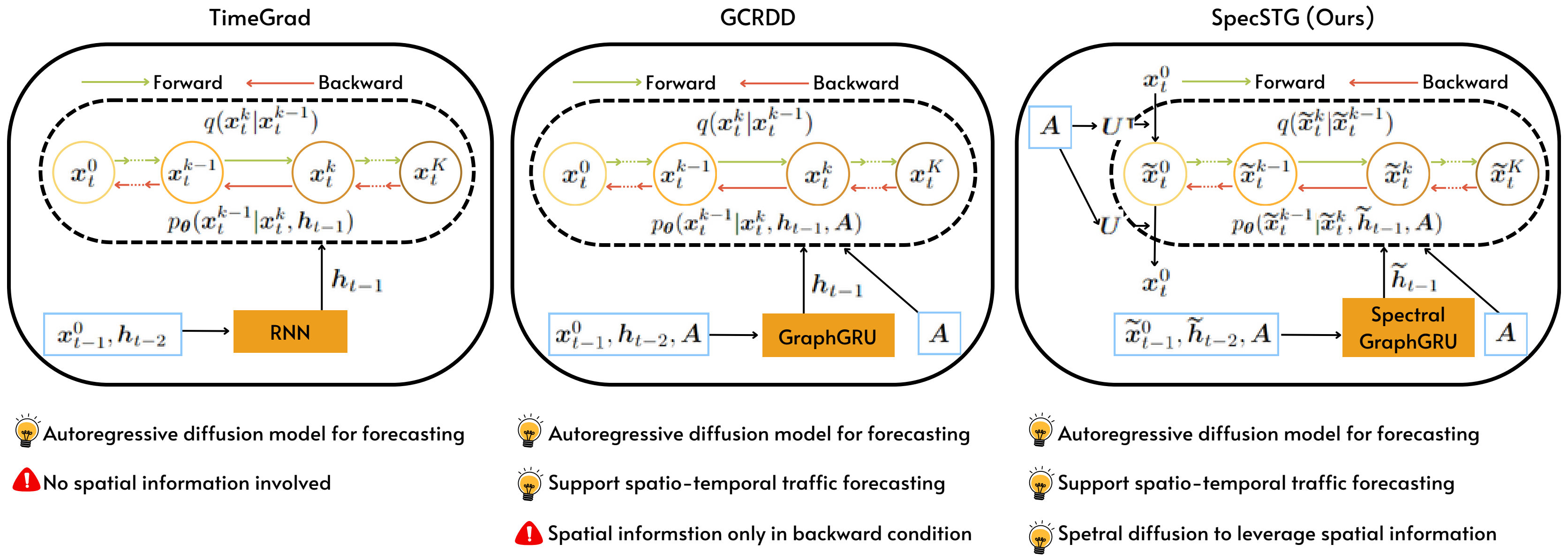
Background

Traffic data such as vehicle are collected from sensors in the continuous space of road networks, thus they present strong spatio-temporal dependencies. This naturally leads to their representation as Spatial-Temporal Graphs (STGs): the traffic network is modelled as a graph, in which nodes are sensors and edges are decided with some criteria such as geographic distances. STG traffic forecasting aims at predicting future values at all sensors based on past time series and spatial connections in the traffic network



Motivation

Our work considers a critical limitation of existing diffusion methods for STG forecasting. Although these methods emphasize on the importance of spatial information, they only use it in the backward kernel condition. Consequently, the involvement of spatial information in the overall forward-backward diffusion learning process is limited.



Contributions

1. To our best knowledge, this is the first work that explores probabilistic STG forecasting on the graph spectral domain.
2. SpecSTG achieves up to 8% improvements on point estimations and up to 0.78% improvements on generating compatible forecasting intervals.
3. SpecSTG's training and validation speed is 3.33× of the most efficient existing diffusion method for STG forecasting. Additionally, SpecSTG significantly accelerates the sampling process, particularly for large sample sizes.

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Experiment Results

(1) Comparison with SOTA Methods

The results of traffic forecasting experiments in a future window of 60 minutes. Average RMSE, MAE, CRPS, and their point values at 15/30/60 minutes are reported. Lower values indicate better forecasting performance. The best results are marked in bold and the second best results are underlined. Improvements of SpecSTG on existing methods are shown in percentage.

Models	RMSE				MAE				CRPS			
	Avg.	15min	30min	60min	Avg.	15min	30min	60min	Avg.	15min	30min	60min
PEMS04F												
DeepVAR	50.59	43.90	48.76	60.46	37.74	32.97	36.72	45.87	0.2094	0.1997	0.2108	0.2209
TransNVP	82.74	68.26	81.70	99.81	61.85	53.06	62.25	73.49	0.2359	0.2008	0.2377	0.2819
TimeGrad	35.58	33.22	35.24	38.95	21.70	20.26	21.56	24.04	0.0801	0.0747	0.0795	0.0887
GCRDD	36.28	31.94	45.31	41.99	22.16	19.48	21.87	26.18	0.0779	0.0689	0.0768	0.0982
DiffSTG	37.62	34.99	36.68	43.04	24.90	22.53	24.65	29.24	0.0904	0.0815	0.0894	0.1077
PriSTI	33.74	33.56	33.71	37.31	22.46	21.65	22.32	25.19	0.0772	0.0751	0.0764	0.0870
SpecSTG	**33.15**	**30.07**	**32.81**	**37.29**	**21.53**	**19.29**	**21.39**	**23.29**	**0.0766**	**0.0683**	**0.0761**	**0.0866**
Improve.	1.75%	5.86%	2.67%	0.54%	0.78%	0.98%	0.79%	3.12%	0.78%	0.87%	0.39%	0.46%
PEMS04S												
DeepVAR	6.23	5.72	6.11	6.93	2.76	2.52	2.72	3.13	0.0490	0.0450	0.0488	0.0549
TransNVP	6.25	5.73	6.27	6.98	3.36	3.12	3.39	3.74	0.0408	0.0382	0.0412	0.0446
TimeGrad	5.92	5.62	5.91	6.35	2.38	2.19	2.37	2.66	0.0307	0.0282	0.0308	0.0345
GCRDD	4.33	3.10	4.30	5.63	1.94	1.51	**1.97**	2.58	**0.0245**	**0.0189**	**0.0248**	0.0329
DiffSTG	4.46	3.24	4.46	5.72	2.15	1.66	2.20	2.83	0.0264	0.0206	0.0267	0.0340
PriSTI	4.42	3.31	4.67	5.60	1.96	1.54	1.99	2.62	0.0252	0.0198	0.0258	0.0329
SpecSTG	**4.06**	**3.01**	**4.09**	**5.15**	**1.93**	**1.50**	**1.97**	**2.51**	**0.0245**	0.0192	0.0253	**0.0319**
Improve.	6.24%	2.90%	4.88%	8.04%	0.52%	0.66%	0.00%	2.71%	0.00%	-	-	3.04%

(2) Visualized Analysis:

In traffic speed forecasting, SpecSTG's mean estimation is closer to future time series, but the intervals generated by TimeGrad and GCRDD sometimes better fit the variations in future values. Upon closer examination of the data patterns, we observe that this impact is particularly pronounced in windows with very small variations. Our hypothesis is that **STG forecasting with larger variations benefits more from the spectral diffusion process**. Because more systematic fluctuations exist in such data, and thus more information can be captured by the Fourier representation, and eventually learned by the diffusion process.