Spatial-Temporal Synchronous Graph Convolutional Networks: A New Framework for Spatial-Temporal Network Data Forecasting

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Introduction

Existing methods usually use separate components to capture spatial and temporal correlations and ignore the heterogeneities in spatial-temporal data. We propose a novel model, named Spatial-Temporal Synchronous Graph Convolutional Networks (STSGCN), for spatial-temporal network data forecasting. The model can effectively capture the complex localized spatial-temporal correlations through an elaborately designed spatial-temporal synchronous modeling mechanism. Meanwhile, multiple modules for different time periods are designed to effectively capture the heterogeneities in localized spatial-temporal graphs.

Methods

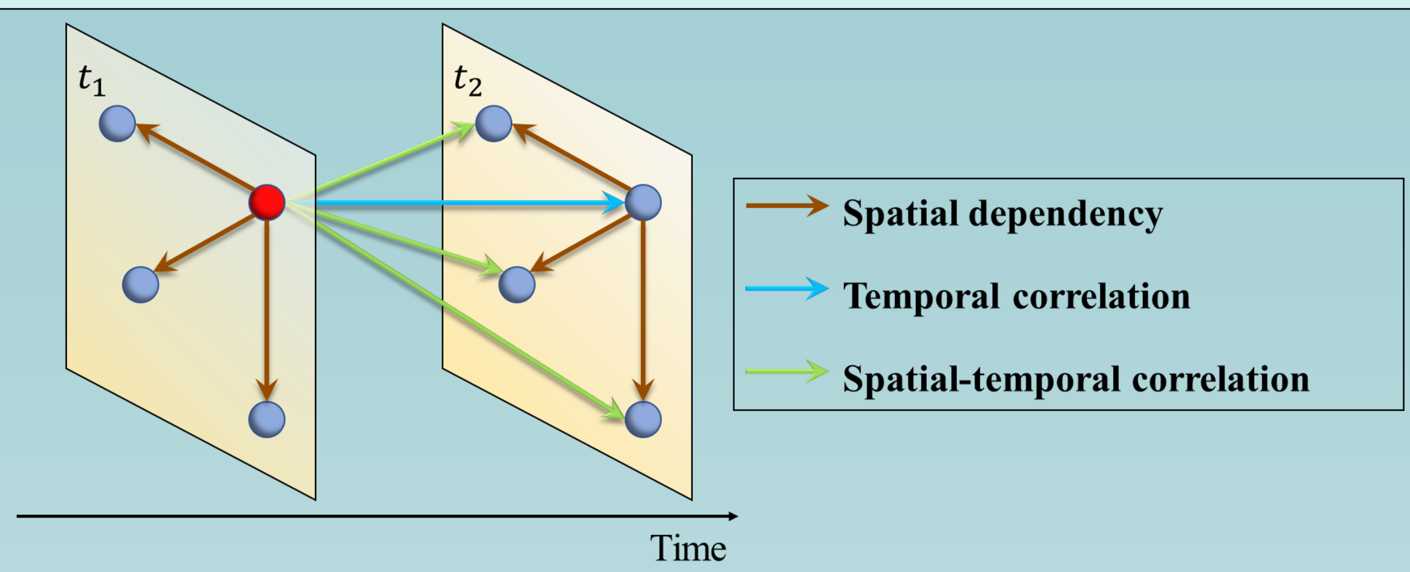
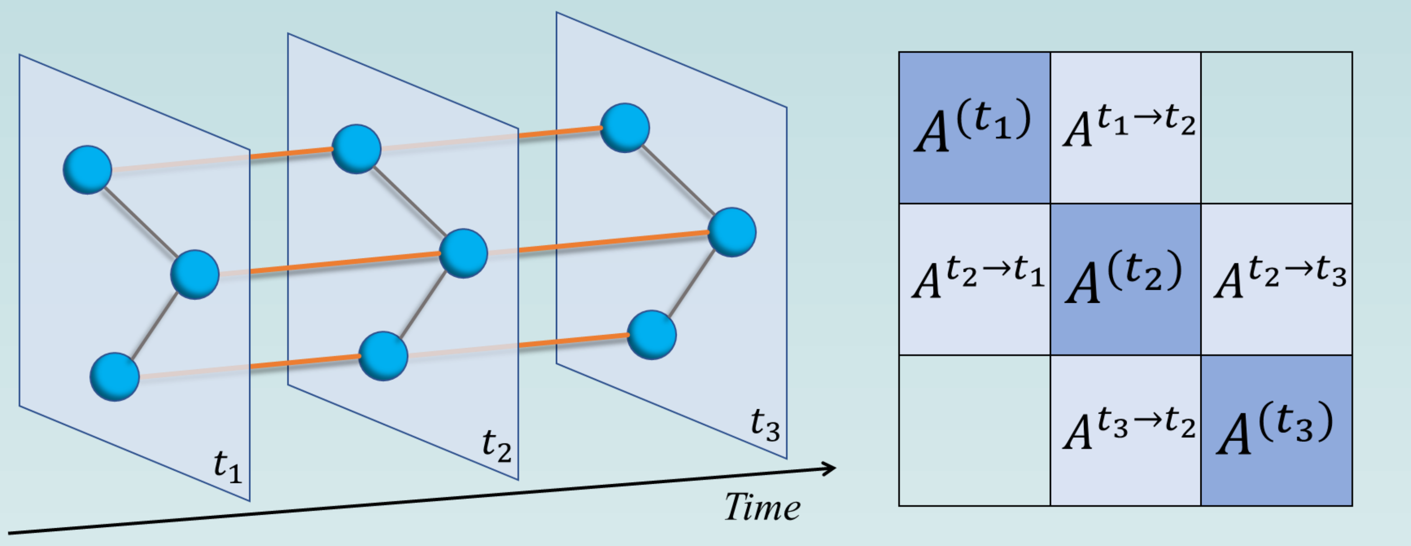


Fig 1. Spatial-temporal correlations

There are three different types of correlations in a spatial-temporal network (Fig 1), i.e. spatial dependencies, temporal correlations and spatial-temporal correlations.



(a) Localized Spatial-Temporal Graph (b) Adjacency matrix of Localized Spatial-Temporal Graph

Fig 2. Localized Spatial-temporal Graph

We proposed a concept called localized spatial-temporal graph (Fig 2). It can reveal the three different types of correlations in the spatial-temporal networks. We design a spatial-temporal synchronous graph convolutional module (STSGCM) based on JK-net to capture the complex spatial-temporal correlations.

To filter useless information in the network, we design a cropping operation in aggregation layer, which only retains the nodes in the middle time step (Fig 3c).

A sliding window is used to generate different localized spatial-temporal graphs, and multiple STSGCMs are deployed on these graphs to capture the heterogeneity in ST-network series.

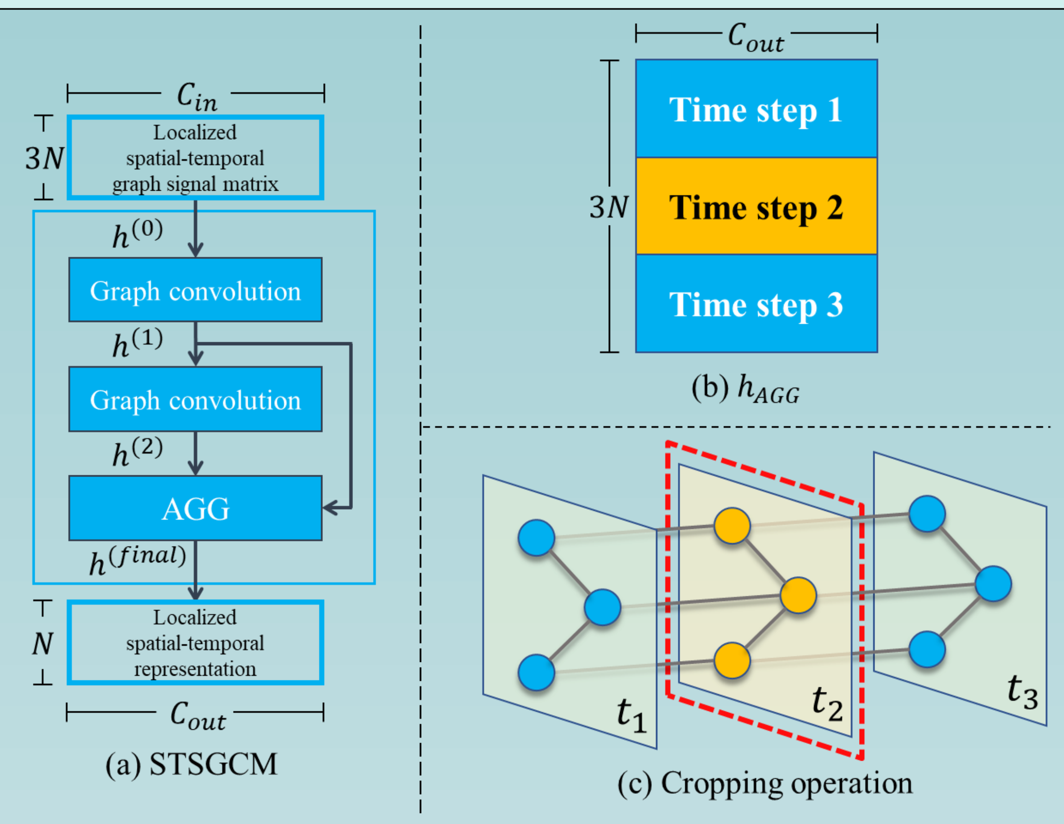


Fig 3. Spatial-temporal synchronous graph convolutional module (STSGCM)

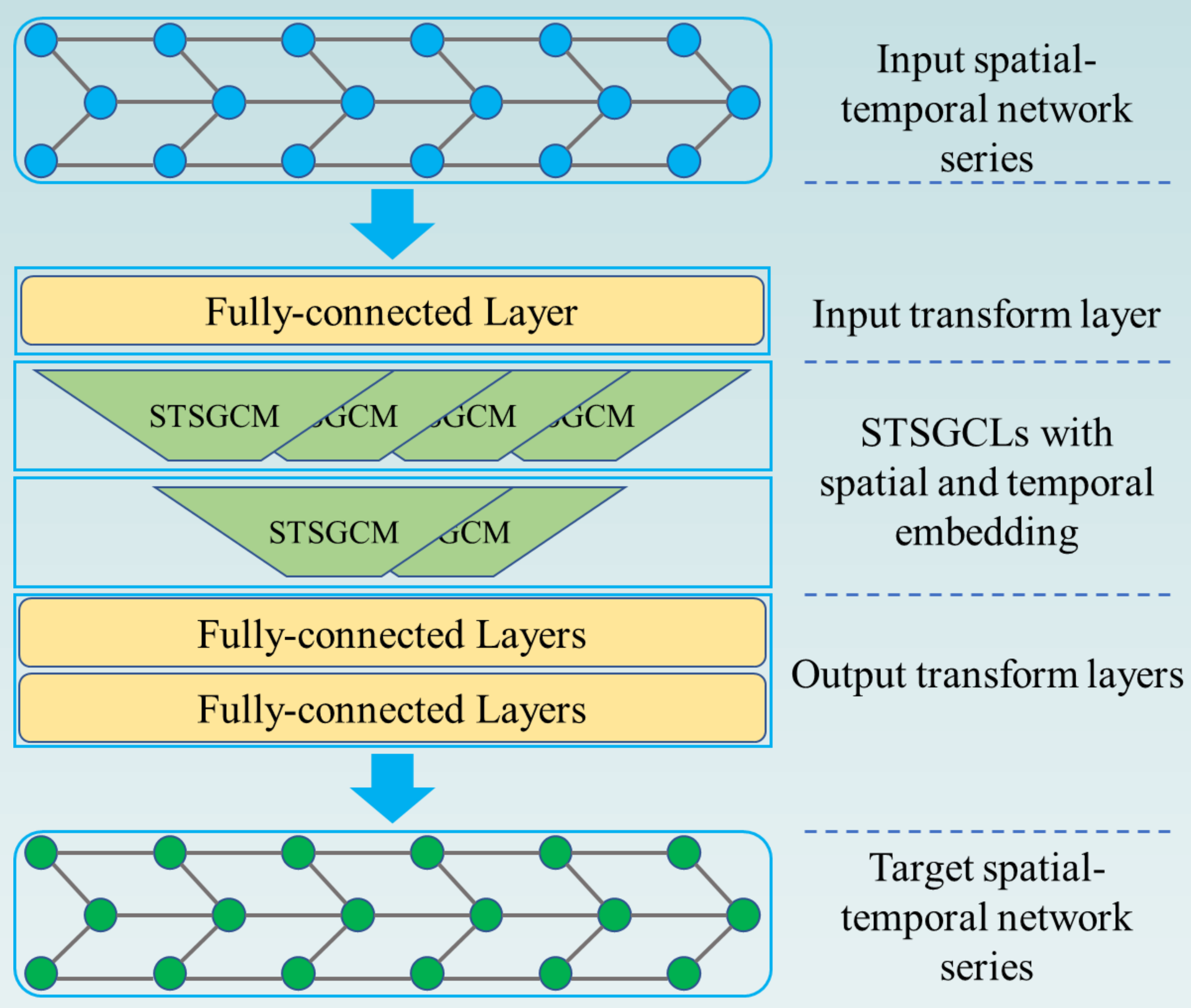


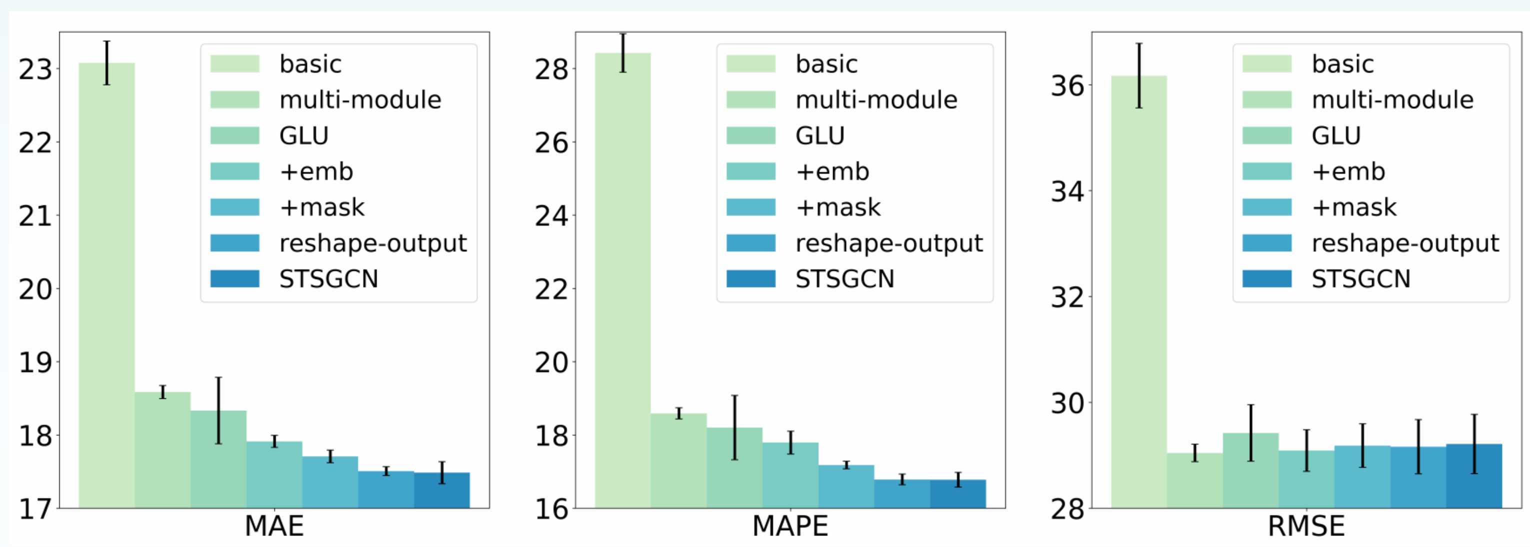
Fig 4. Architecture of spatial-temporal synchronous graph convolutional network (STSGCN)

Multiple individual STSGCMs allow each one to focus on modeling the localized spatial-temporal correlations in the localized graph. STSGCN (Fig 4) consists of multiple stacked STSGCMs.

Results

Table 2: Performance comparison of different approaches for traffic flow forecasting.

Datasets	Metrics	VAR	SVR	LSTM	DCRNN	STGCN	ASTGCN(r)	STG2Seq	Graph WaveNet	**STSGCN**
PEMS03	MAE	23.65	21.97 ± 0.00	21.33 ± 0.24	18.18 ± 0.15	17.49 ± 0.46	17.69 ± 1.43	19.03 ± 0.51	19.85 ± 0.03	**17.48 ± 0.15**
	MAPE (%)	24.51	21.51 ± 0.46	23.33 ± 4.23	18.91 ± 0.82	17.15 ± 0.45	19.40 ± 2.24	21.55 ± 1.68	19.31 ± 0.49	**16.78 ± 0.20**
	RMSE	38.26	35.29 ± 0.02	35.11 ± 0.50	30.31 ± 0.25	30.12 ± 0.70	29.66 ± 1.68	29.73 ± 0.52	32.94 ± 0.18	**29.21 ± 0.56**
PEMS04	MAE	23.75	28.70 ± 0.01	27.14 ± 0.20	24.70 ± 0.22	22.70 ± 0.64	22.93 ± 1.29	25.20 ± 0.45	25.45 ± 0.03	**21.19 ± 0.10**
	MAPE (%)	18.09	19.20 ± 0.01	18.20 ± 0.40	17.12 ± 0.37	14.59 ± 0.21	16.56 ± 1.36	18.77 ± 0.85	17.29 ± 0.24	**13.90 ± 0.05**
	RMSE	36.66	44.56 ± 0.01	41.59 ± 0.21	38.12 ± 0.26	35.55 ± 0.75	35.22 ± 1.90	38.48 ± 0.50	39.70 ± 0.04	**33.65 ± 0.20**
PEMS07	MAE	75.63	32.49 ± 0.00	29.98 ± 0.42	25.30 ± 0.52	25.38 ± 0.49	28.05 ± 2.34	32.77 ± 3.21	26.85 ± 0.05	**24.26 ± 0.14**
	MAPE (%)	32.22	14.26 ± 0.03	13.20 ± 0.53	11.66 ± 0.33	11.08 ± 0.18	13.92 ± 1.65	20.16 ± 4.36	12.12 ± 0.41	**10.21 ± 0.05**
	RMSE	115.24	50.22 ± 0.01	45.84 ± 0.57	**38.58 ± 0.70**	38.78 ± 0.58	42.57 ± 3.31	47.16 ± 3.66	42.78 ± 0.07	39.03 ± 0.27
PEMS08	MAE	23.46	23.25 ± 0.01	22.20 ± 0.18	17.86 ± 0.03	18.02 ± 0.14	18.61 ± 0.40	20.17 ± 0.49	19.13 ± 0.08	**17.13 ± 0.09**
	MAPE (%)	15.42	14.64 ± 0.11	14.20 ± 0.59	11.45 ± 0.03	11.40 ± 0.10	13.08 ± 1.00	17.32 ± 1.14	12.68 ± 0.57	**10.96 ± 0.07**
	RMSE	36.33	36.16 ± 0.02	34.06 ± 0.32	27.83 ± 0.05	27.83 ± 0.20	28.16 ± 0.48	30.71 ± 0.61	31.05 ± 0.07	**26.80 ± 0.18**



Conclusion

We propose STSGCN which can not only capture the localized spatial-temporal correlations effectively but also take the heterogeneities in spatial-temporal data into considerations. STSGCN can use one component to capture the complex spatial-temporal correlations simultaneously. The code and datasets have been released at: https://github.com/Davidham3/STSGCN.