Hybrid Spatio-Temporal Graph Convolutional Network: Improving Traffic Prediction with Navigation Data

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Contribution:

- intended traffic flow from Navigation planning data in Gaode map
- design the domain transformer to integrate the heterogeneous modality of traffic flow
- compound adjacency matrix
- H-STGCN

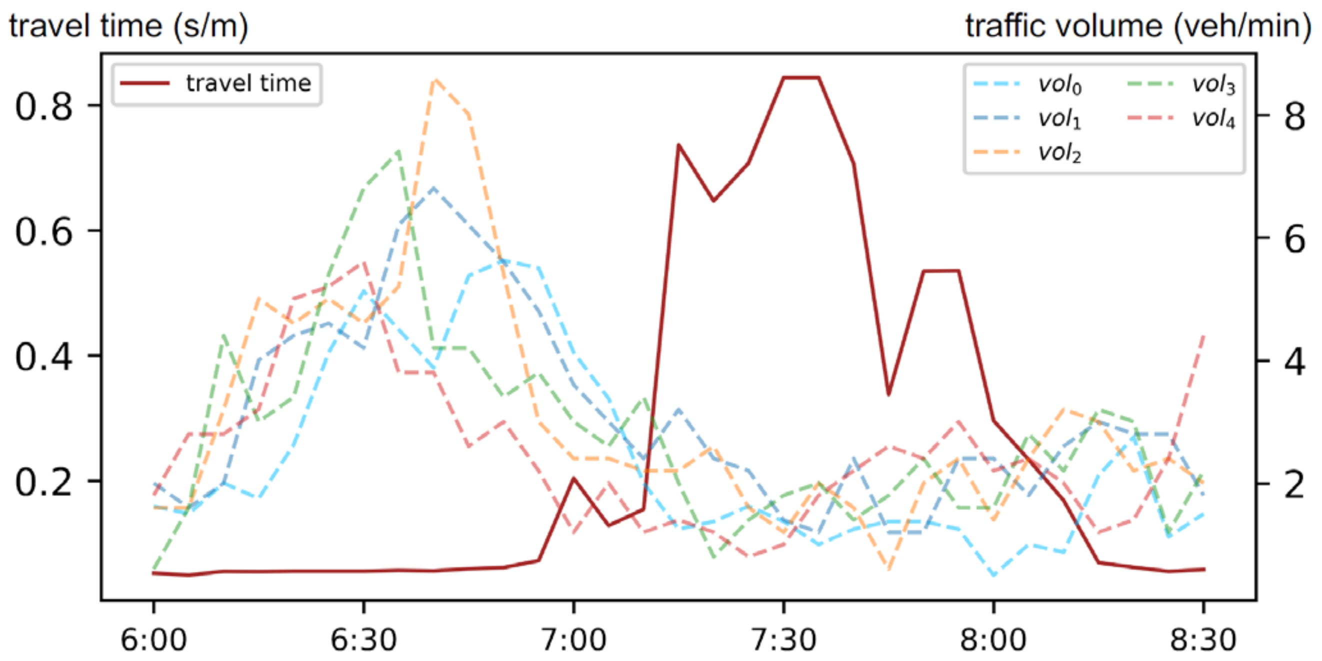


Figure 1:

- intended traffic flow from Navigation planning data in Gaode map

How to integrate this heterogeneous modality into a travel time forecasting model?

- design the domain transformer to integrate the heterogeneous modality of traffic flow

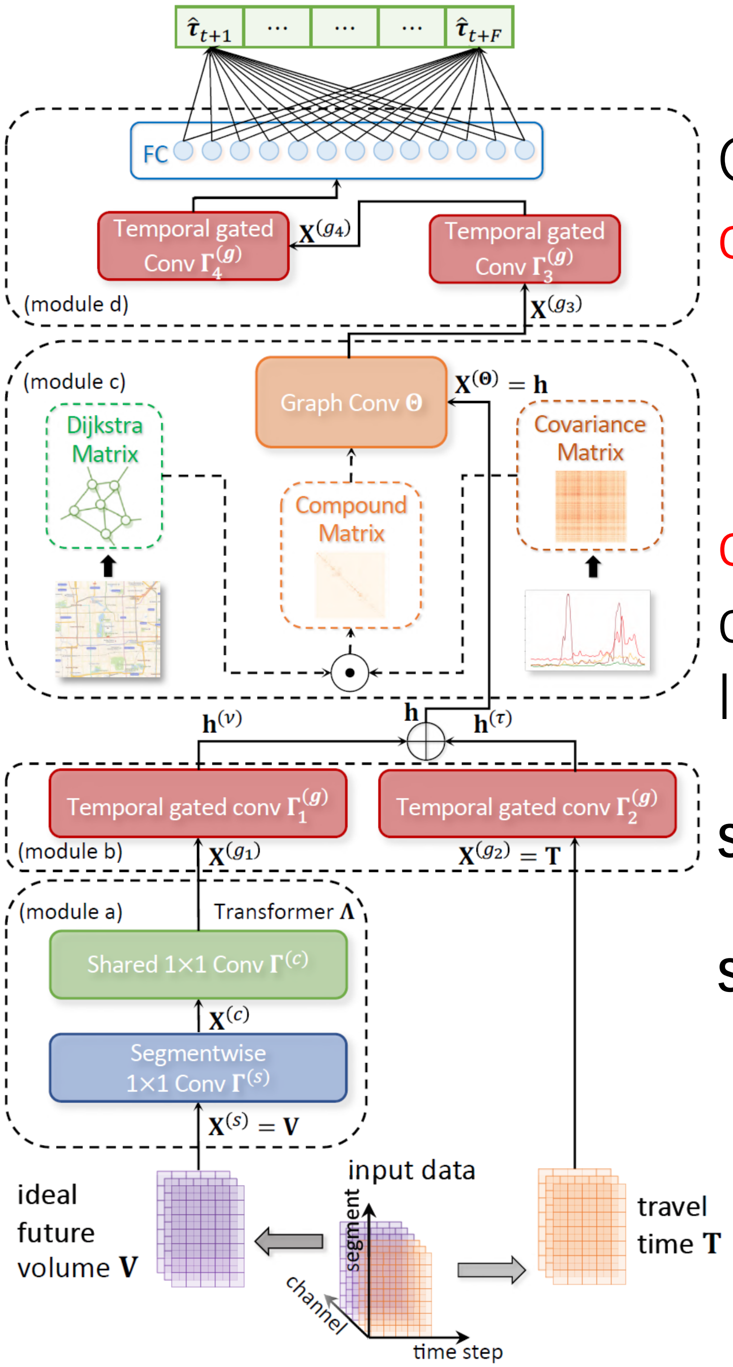


Figure 2:

Overall Architecture and domain transformer

domain transformer consists of two cascaded layers:

Shared 1 × 1 Convolution.

Segmentwise 1 × 1 Convolution.

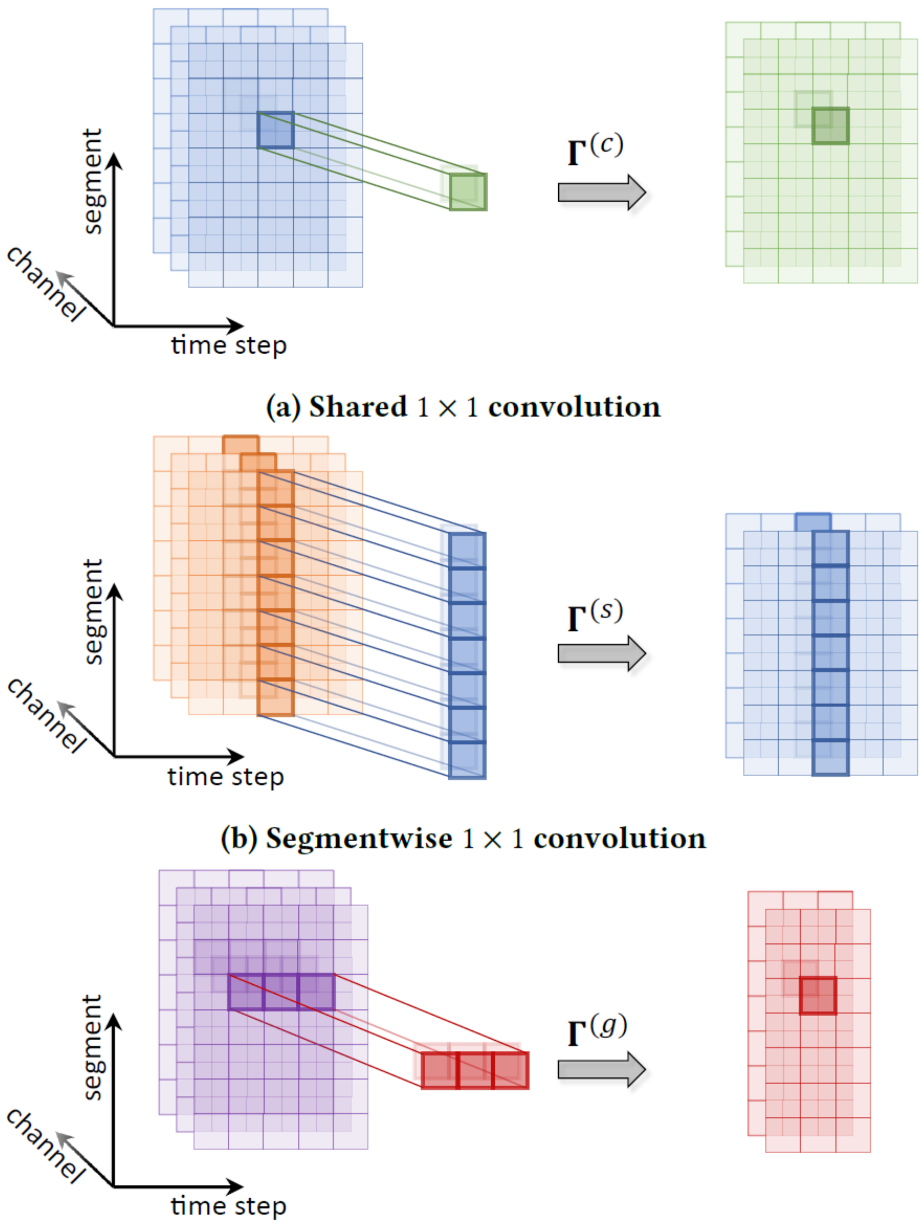


Figure 3:

compound adjacency matrix

simple exponential distancedecay:

$$w_{ij}^{(d)} = \begin{cases} \exp\left(-\frac{d_{ij}^2}{\sigma^2}\right) & , \exp\left(-\frac{d_{ij}^2}{\sigma^2}\right) \geq \epsilon \\ 0 & , \text{otherwise} \end{cases},$$

compound adjacency matrix

$$w_{ij}^{(c)} = \sigma_{ij} \cdot w_{ij}^{(d)}, 1 \leq i \leq n, 1 \leq j \leq n,$$

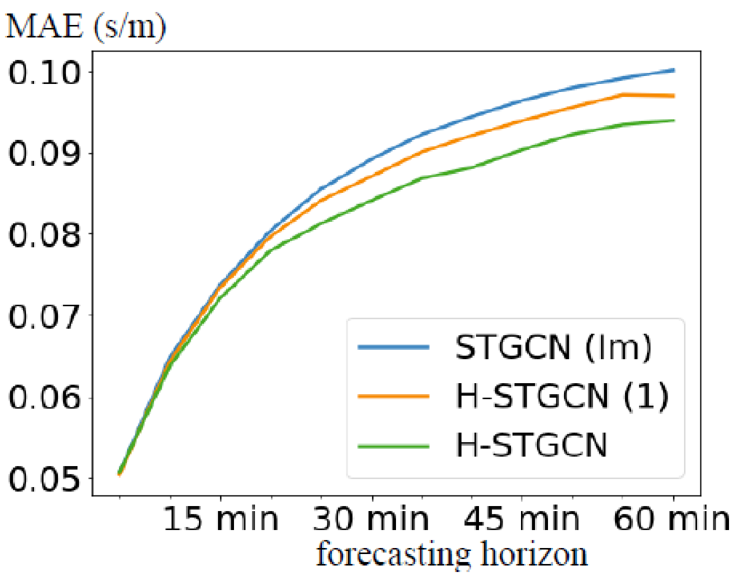
$$\sigma_{ij} = \sum_{t \in [0, S_{\text{train}})} \left(\tau_{i,t} - \bar{\tau}_i\right)_+ \left(\tau_{j,t} - \bar{\tau}_j\right)_+,$$

Graph Convolution with Compound Adjacency Matrix

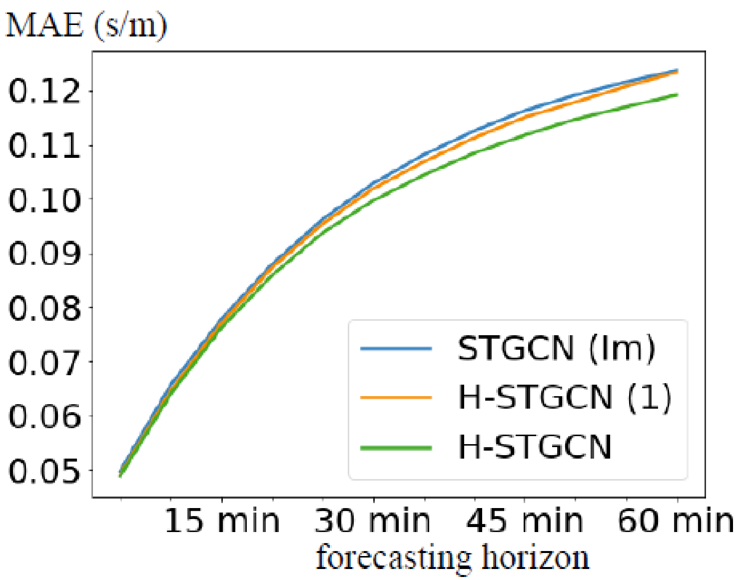
$$\mathbf{L} = \mathbf{I}_n - \mathbf{D}^{-\frac{1}{2}} \mathbf{W}^{(c)} \mathbf{D}^{-\frac{1}{2}},$$

$$\tilde{\mathbf{L}} = 2\mathbf{L}/\lambda_{\max} - \mathbf{I}_n,$$

$$\mathbf{Y}_{:,t,j}^{(\Theta)} = \sigma\left(\sum_{m=1}^{C^{(\Theta_{\text{in}})}} \sum_{k=0}^{K-1} \mathbf{\Theta}_{k,m,j} T_k(\tilde{\mathbf{L}}) \mathbf{X}_{:,t,m}^{(\Theta)} + \mathbf{b}_j^{(\Theta)}\right) \in \mathbb{R}^n,$$



(a) Dataset W3-715



(b) Dateset E5-2907

Figure 4:

- STGCN (Im): Improved STGCN uses a compound adjacency matrix as opposed to the Dijkstra matrix.
- H-STGCN (1): H-STGCN (1) uses an input volume tensor V with all elements set to one (1). (no future traffic volume)

Dataset	Model	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE
		Test set (Full)			Test set (C)			Test set (NRC)		
W3-715	HA	0.03886	20.73	0.09285	0.07040	34.36	0.10479	0.10303	39.39	0.16486
	LR	0.03334	16.58	0.08467	0.06469	33.52	0.10582	0.09080	39.57	0.14768
	GBRT	0.03264	16.10	0.08409	0.06236	32.08	0.10479	0.09085	39.35	0.14945
	MLP	0.03272	16.57	0.08269	0.06096	31.84	0.10190	0.08733	38.71	0.14427
	Seq2Seq	0.03231	15.81	0.08252	0.06033	28.79	0.10174	0.08599	34.04	0.14467
	STGCN	0.03219	16.01	0.08182	0.05975	30.48	0.09901	0.08599	38.72	0.14004
	STGCN (Im)	0.03200	15.83	0.08196	0.05965	29.96	0.09995	0.08539	36.71	0.14197
	H-STGCN (1)	0.03138	15.52	0.08099	0.05804	29.14	0.09806	0.08373	34.71	0.14012
	H-STGCN	**0.03114**	**15.36**	**0.08045**	**0.05711**	**28.34**	**0.09644**	**0.08124**	**33.22**	**0.13711**
E5-2907	HA	0.04615	21.22	0.11405	0.09786	44.95	0.16729	0.13161	46.96	0.21769
	LR	0.04096	17.03	0.10732	0.08229	41.69	0.14270	0.10747	47.01	0.18192
	GBRT	0.04032	16.61	0.10680	0.07997	39.51	0.14465	0.10657	44.68	0.18593
	MLP	0.04031	17.16	0.10547	0.08025	41.26	0.14229	0.10580	45.84	0.18236
	Seq2Seq	0.04087	17.52	0.10631	0.08413	41.72	0.14703	0.10981	44.81	0.18722
	STGCN	0.03984	16.95	0.10296	0.07561	38.13	0.13677	0.09966	43.28	0.17563
	STGCN (Im)	0.03957	16.85	0.10221	0.07498	37.80	0.13579	0.09843	42.74	0.17399
	H-STGCN (1)	0.03870	16.31	0.10095	0.07380	37.07	0.13455	0.09750	42.32	0.17257
	H-STGCN	**0.03861**	**16.28**	**0.10067**	**0.07254**	**36.31**	**0.13308**	**0.09528**	**40.82**	**0.17030**

Figure 5: