Adaptive Graph Co-Attention Networks for Traffic Forecasting

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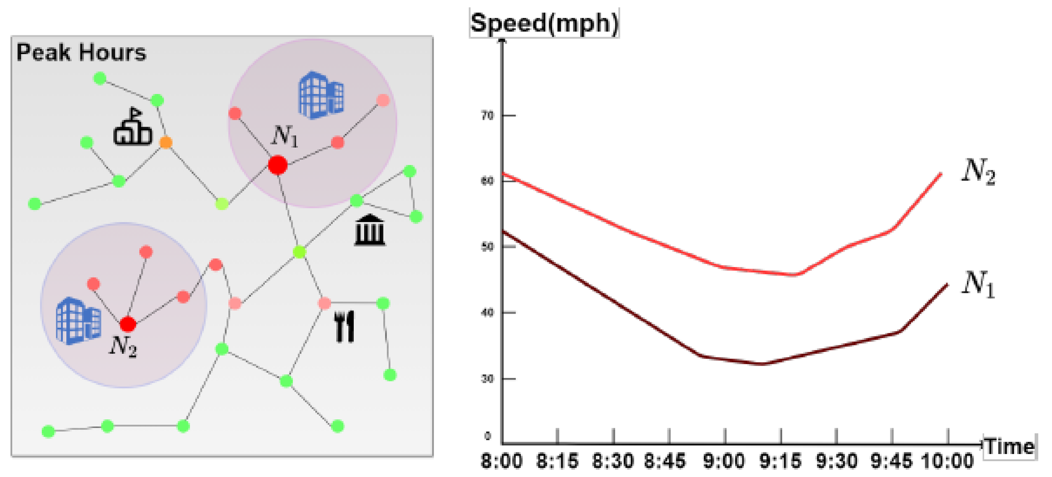
INTRODUCTION

Traffic forecasting has remained a challenging topic in the field of transportation, due to the time-varying traffic patterns and complicated spatial dependencies on road networks. To address such challenges, we propose an adaptive graph co-attention network (AGCAN) to predict traffic conditions on a road network graph.



AIM

Traffic forecasting is a typical time-series prediction problem, i.e., predicting the most likely traffic measurements (e.g., speed and traffic volume) in the subsequent time steps given the previous traffic observations.

METHODS

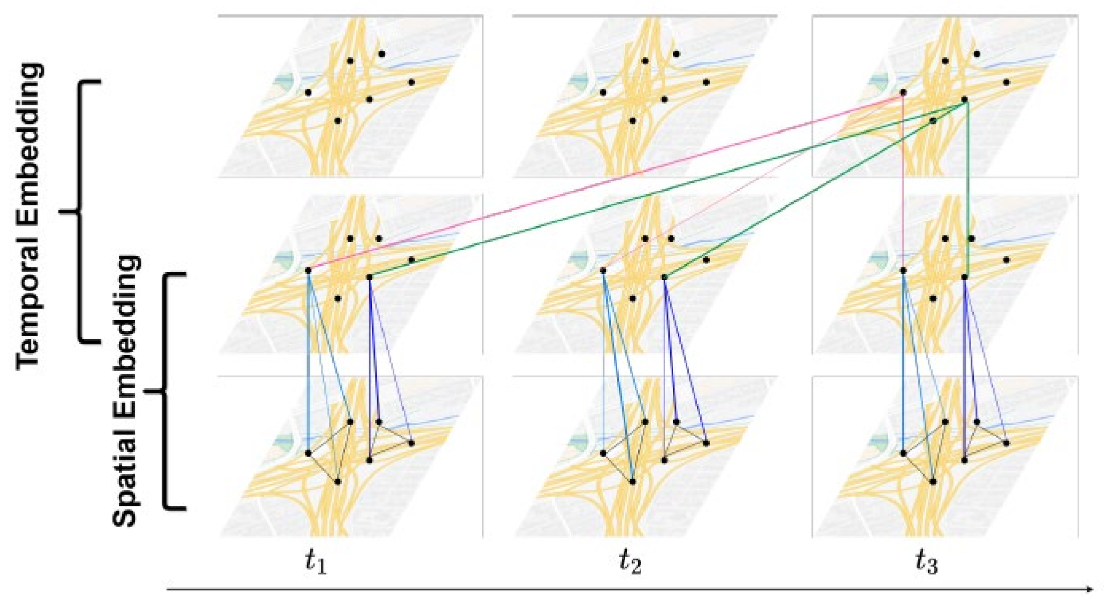
A. Adaptive Graph Construction

1. Physical Graph (By physical distance):

$$[\mathcal{A}_\mathcal{P}]_{ij} = \begin{cases} \exp\left(-\frac{\mathrm{d}(\mathcal{V}_i,\mathcal{V}_j)^2}{\sigma^2}\right), & \mathrm{d}(\mathcal{V}_i,\mathcal{V}_j) \geq \rho; \\ 0, & \text{otherwise}. \end{cases}$$

2. Adaptive Graph Learning (By functional area):

$$\alpha_{ij}^t = \frac{\exp(\langle \mathscr{F}_\alpha([X_t]_{i\cdot}), \mathscr{F}_\alpha([X_t]_{j\cdot})\rangle/\sqrt{C})}{\sum_{m\in\{m|\mathcal{M}_{ij}=1\}} \exp(\langle \mathscr{F}_\alpha([X_t]_{i\cdot}), \mathscr{F}_\alpha([X_t]_{m\cdot})\rangle/\sqrt{C})}$$



B. Spatial-Temporal Attention

1. Spatial Attention

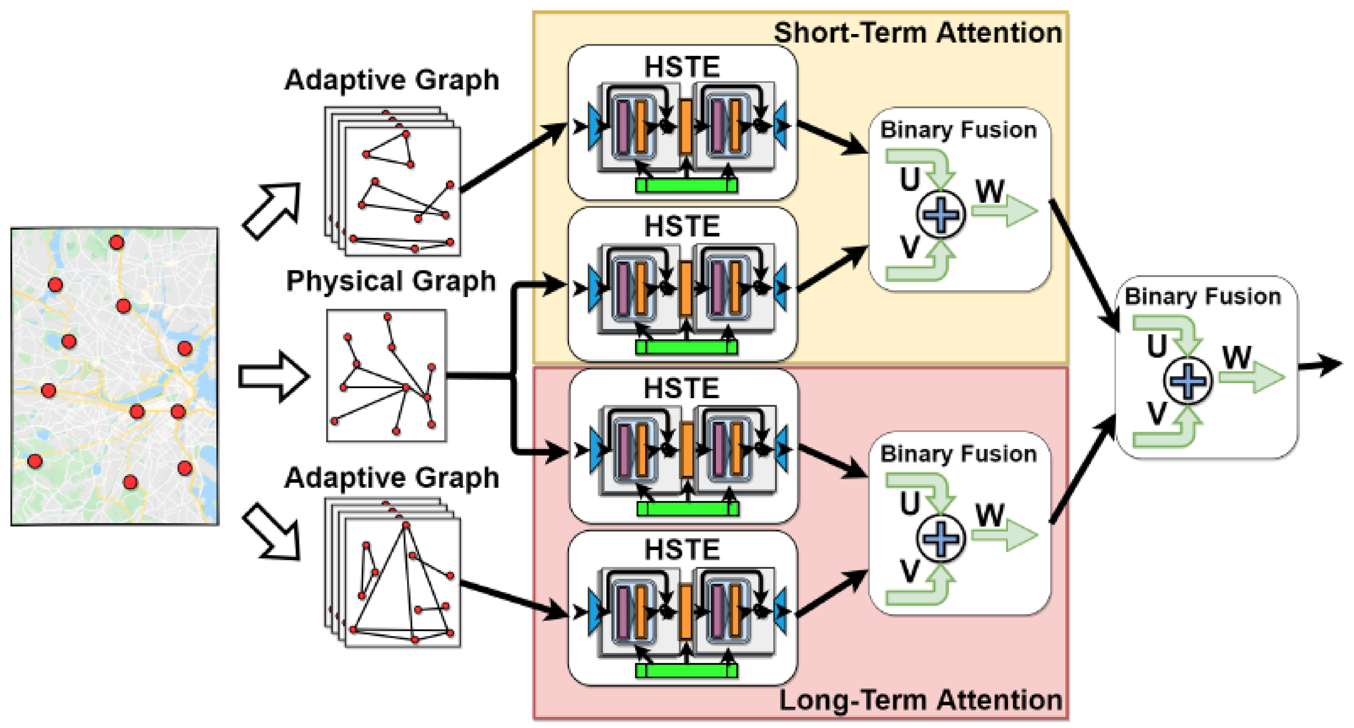
$$\gamma_{ij}^{(k)v} = \frac{\exp(\langle \mathscr{F}_{\gamma_1}^{(k)}([H_i^{(l-1)}]_{v\cdot}), \mathscr{F}_{\gamma_1}^{(k)}([H_j^{(l-1)}]_{v\cdot})\rangle/\sqrt{D})}{\sum_{a\in\mathcal{N}_i} \exp(\langle \mathscr{F}_{\gamma_1}^{(k)}([H_i^{(l-1)}]_{v\cdot}), \mathscr{F}_{\gamma_1}^{(k)}([H_a^{(l-1)}]_{v\cdot})\rangle/\sqrt{D})}$$

$$[H_i^{(l)}]_{v\cdot} = \|_{k=1}^K \left\{ \sum_{j\in\mathcal{N}_i} \gamma_{ij}^{(k)v} \cdot \mathscr{F}_{\gamma_2}^{(k)}\left([H_j^{(l-1)}]_{v\cdot}\right) \right\}$$

2. Temporal Attention

$$\beta_{ij}^{(k)t} = \frac{\exp(\langle \mathscr{F}_{\beta_1}^{(k)}([H_t^{(l-1)}]_{i\cdot}), \mathscr{F}_{\beta_1}^{(k)}([H_t^{(l-1)}]_{j\cdot})\rangle/\sqrt{D}) \cdot \mathcal{A}_{ij}}{\sum_{a\in\{a|\mathcal{A}_{ia}\neq 1\}} \exp(\langle \mathscr{F}_{\beta_1}^{(k)}([H_t^{(l-1)}]_{i\cdot}), \mathscr{F}_{\beta_1}^{(k)}([H_t^{(l-1)}]_{a\cdot})\rangle/\sqrt{D}) \cdot \mathcal{A}_{ia}}$$

$$[H_t^{(l)}]_{i\cdot} = \|_{k=1}^K \left\{ \sum_{j\in\{j|\mathcal{A}_{ij}\neq 1\}} \beta_{ij}^{(k)t} \cdot \mathscr{F}_{\beta_2}^{(k)}\left([H_t^{(l-1)}]_{j\cdot}\right) \right\}$$



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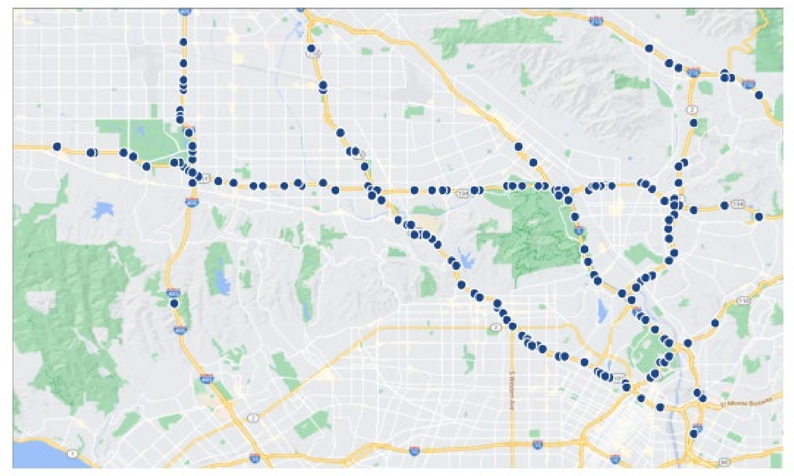
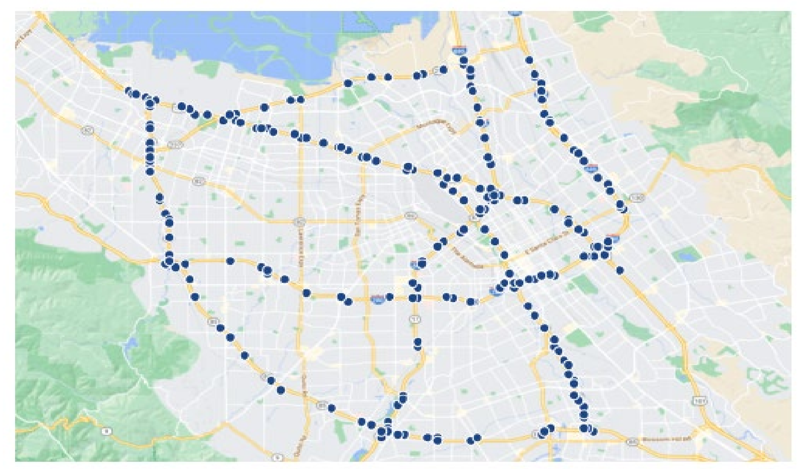
RESULTS

To validate the performance of AGCAN in real-world applications, we choose two benchmark traffic datasets, **PEMS-BAY** and **METR-LA**.



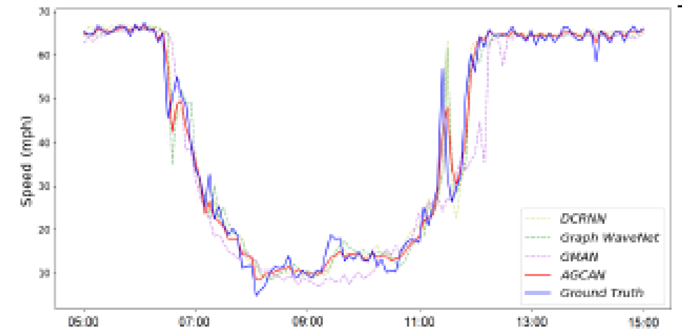
(a) METR-LA



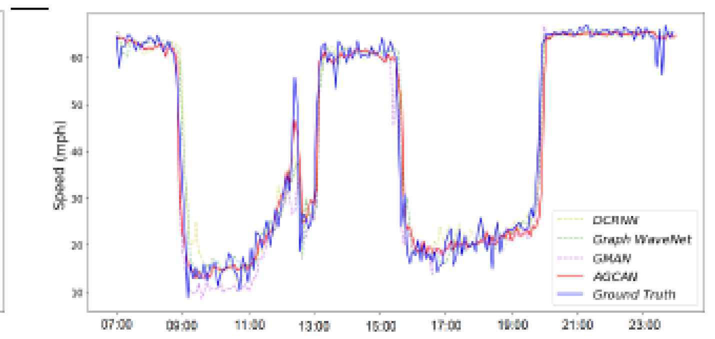
(b) PEMS-BAY

Table 2. Performance of ASGAN and Other Models

Data	Model	15 min			30 min			60 min		
		MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE
METR-LA	ARIMA	3.99	8.21	9.60%	5.15	10.45	12.70%	6.90	13.23	17.40%
	FC-LSTM	3.44	6.30	9.60%	3.77	7.23	10.90%	4.37	8.69	13.20%
	WaveNet	2.99	5.89	8.04%	3.59	7.28	10.25%	4.45	8.93	13.62%
	STGCN	2.88	5.74	7.62%	3.47	7.24	9.57%	4.59	9.4	12.70%
	DCRNN	2.77	5.38	7.30%	3.15	6.45	8.80%	4.59	9.40	12.70%
	Graph WaveNet	2.69	5.15	6.90%	3.07	6.22	8.37%	3.53	7.37	10.01%
	GMAN	2.77	5.44	7.26%	3.10	6.34	8.53%	3.44	7.21	9.99%
	AGCAN	**2.63**	**5.08**	**6.72%**	**3.02**	**6.23**	**8.17%**	**3.39**	**7.19**	**9.72%**
PEMS-BAY	ARIMA	1.62	3.30	3.50%	2.33	4.76	5.40%	3.38	6.50	8.30%
	FC-LSTM	2.05	4.19	4.80%	2.20	4.55	5.20%	2.37	4.96	5.70%
	WaveNet	1.39	3.01	2.91%	1.83	4.21	4.16%	2.35	5.43	5.87%
	STGCN	1.36	2.96	2.90%	1.81	4.27	4.17%	2.49	5.69	5.79%
	DCRNN	1.38	2.95	2.90%	1.74	3.97	3.90%	2.07	4.74	4.90%
	Graph WaveNet	**1.30**	2.74	2.73%	1.63	3.70	3.67%	1.95	4.52	4.63%
	GMAN	1.34	2.82	2.81%	1.62	3.72	**3.63%**	1.86	4.32	**4.31%**
	AGCAN	**1.30**	**2.73**	**2.68%**	**1.60**	**3.66**	3.65%	**1.82**	**4.30**	**4.31%**



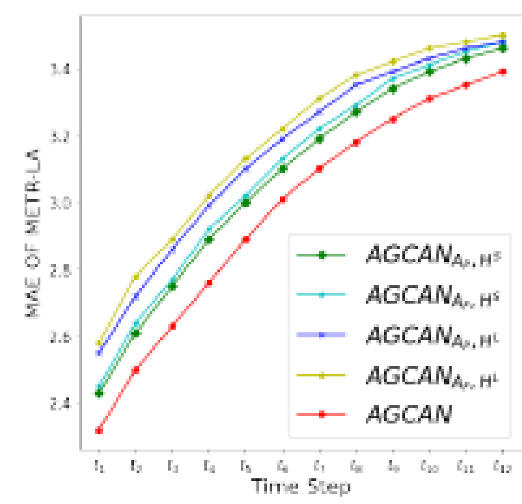
(a) Morning Peak.



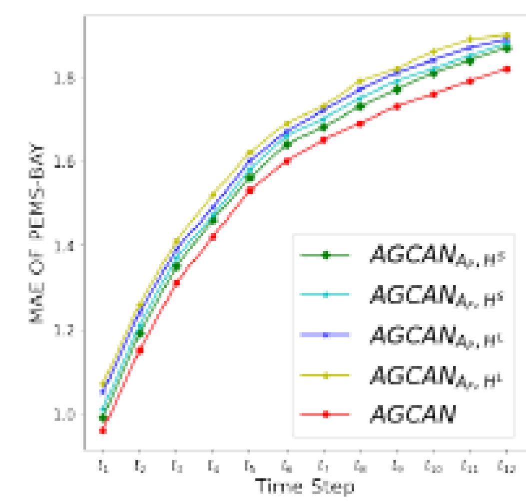
(b) Morning & Evening Peak.

DISCUSSION

To better understand the contribution of each component in our model, we test the performance of four variants by separating the different components separately. We observe that AGCAN consistently outperforms its variants, indicating the usefulness of the combinations of cross-region and cross-time information in modeling the complicated spatiotemporal correlations.



(a) METR-LA.



(b) PEMS-BAY.

CONCLUSIONS

1. We propose an adaptive graph co-attention networks (AGCAN) to predict the traffic conditions on a given road network over time steps ahead.
2. We introduce an adaptive graph modelling method to capture the cross-region spatial dependencies with the dynamic trend.
3. We design a long- and short-term co-attention network with novel hierarchical spatio-temporal embedding blocks to learn both daily periodic and near real-time traffic patterns.

https://link.springer.com/chapter/10.1007/978-3-030-75762-5_22