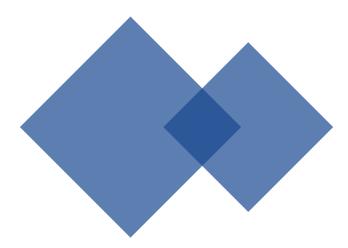
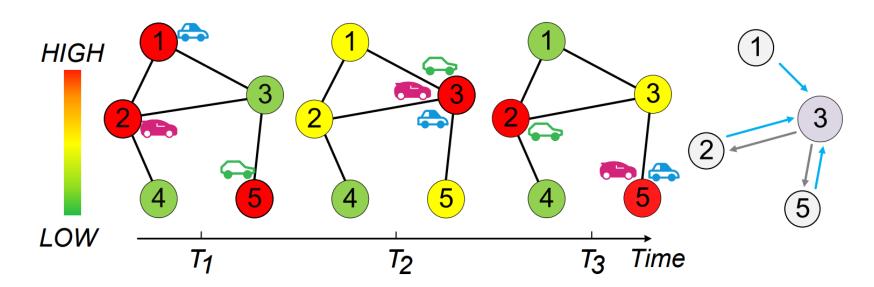
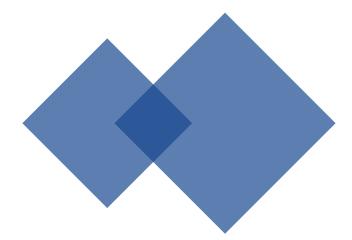


STPGNN

Spatio-Temporal Pivotal Graph Neural Networks for Traffic Flow Forecasting

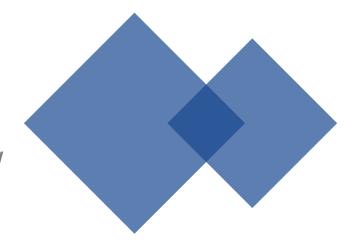






STPGNN

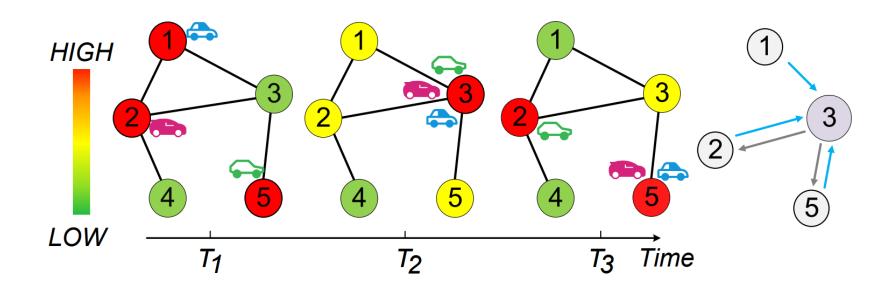
Spatio-Temporal Pivotal Graph Neural Networks for Traffic Flow Forecasting



24.4.9

Pivotal Nodes 路网中的关键节点

- ▶ 地理位置(在城中心)或特征(靠近大交通枢纽)与多个其他节点表现出广泛的联系
- > 在汇聚和分配交通流方面表现出更强的能力

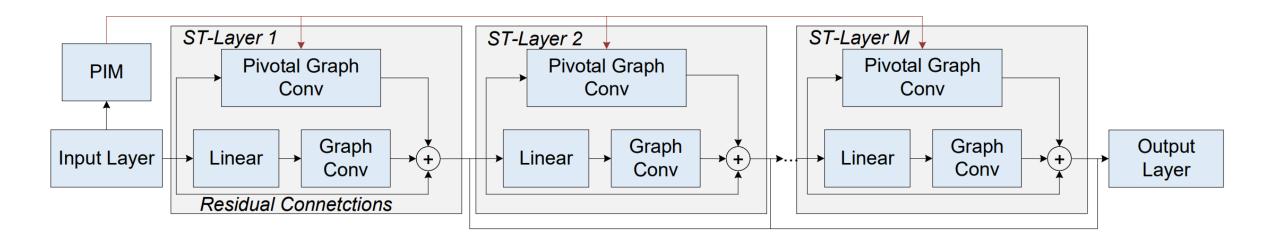


- ▶ 怎么识别关键节点?
- ▶ 怎么精确提取关键节点的时空特征?
- > 非关键节点的时空特征补充

- → 评分函数识别关键节点
- → 关键图卷积模块
- 图卷积+线性单元



算法实现:整体结构





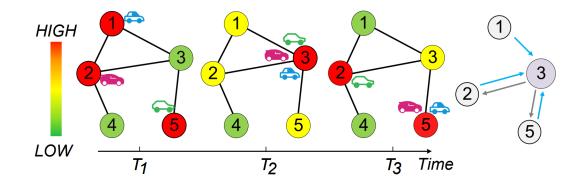


算法实现: 关键节点识别 PIM

> 量化节点的流量聚合和分发能力

计算余弦相似度

$$e_{i,j} = \frac{\sum_{k=1+d}^{S} (H_{i,k} H_{j,k-d}^{\top}) w_{i,j}}{\sqrt{\sum_{k=1+d}^{S} (H_{i,k}^{2})} \cdot \sqrt{\sum_{k=1}^{S-d} (H_{j,k}^{2})}},$$
 { 矩阵E中,行的总和:节点的聚合能力

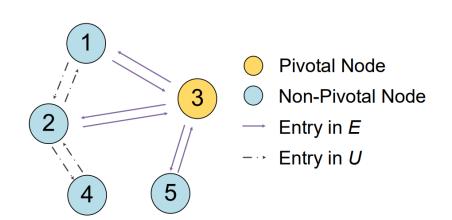


• 评分函数

$$Score(i) = \sum_{j=1}^{N} (e_{i,j} + e_{j,i}).$$
 $C = \{i | Score(i) \in TopK(Score)\},$

关键节点邻接矩阵

$$a_{i,j} = \begin{cases} sigmoid(e_{i,j}), & \text{if } i \in C \lor j \in C \\ u_{i,j}, & \text{others} \end{cases},$$





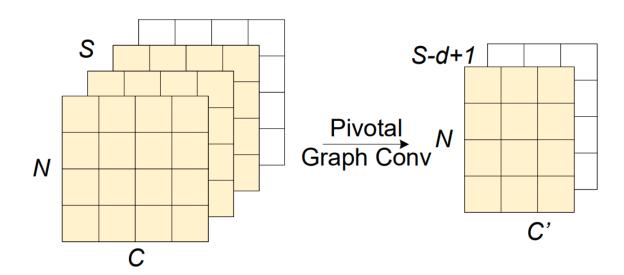
算法实现: 关键图卷积 PGCM

> 关注关键节点的时空依赖性

• 在时域上对每个节点做卷积

• 复杂度: $T_d^2 N^2 \rightarrow T_d KN$

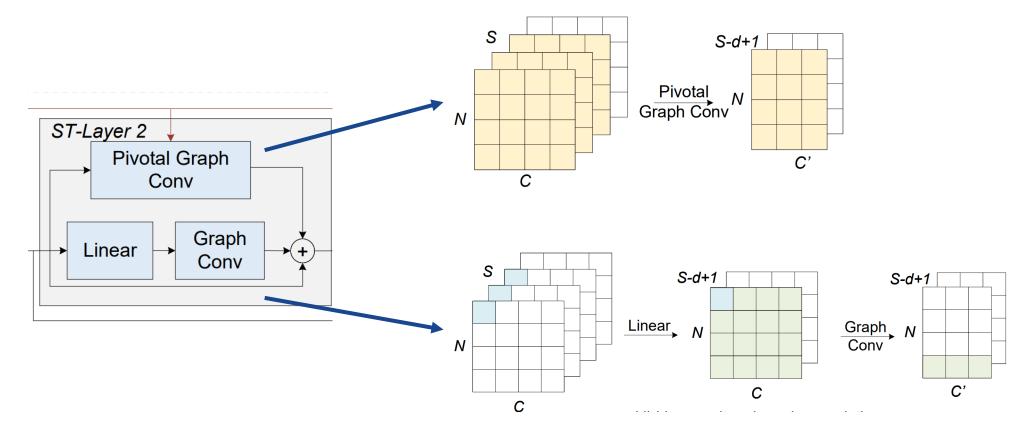
{输入: N个节点, S个时间步, C个通道输出: N个节点, S-d+1个时间步, C'个通道(d是时间维度上的kernel size)



03

算法实现: 时空层

- ▶ 针对关键节点: 关键图卷积
- ▶ 针对非关键节点: 图卷积(空间信息)+线性单元(长程的时间信息)



04 🔷 实验: 数据集

Dataset	Node	Samples	Sample Rate	Data Type
PEMS-03	358	26208	5min	Traffic Flow
PEMS-04	307	16992	5min	Traffic Flow
PEMS-07	883	28224	5min	Traffic Flow
PEMS-08	170	17856	5min	Traffic Flow
England	314	17353	15min	Traffic Flow
TaxiBJ	1024	5596	30min	Taxi GPS
PEMS-BAY	325	52116	5min	Traffic Speed





实验1: 预测效果对比

12个时间步预测未来12个时间步:

Datasets	Metric	ARIMA	DCRNN	GWNet	STSGCN	MTGNN	DMSTGCN	DSTAGNN	TPGNN	SGP	STPGNN	Improve(%)
PEMS03	MAE	26.33	18.18	19.85	17.48	17.23	16.82	15.67	16.88	15.82	14.37	9.05
	MAPE(%)	22.90	18.18	19.85	16.78	17.35	16.71	14.74	16.53	15.74	14.23	3.58
	RMSE	33.05	30.31	32.94	29.21	25.89	25.81	27.21	<u>25.78</u>	25.92	24.62	4.71
PEMS04	MAE	28.55	24.70	25.45	21.19	19.98	19.75	19.53	19.63	19.57	18.34	6.49
	MAPE(%)	19.55	17.12	17.29	13.90	14.13	13.91	12.97	13.04	13.13	12.49	3.84
	RMSE	40.36	38.12	39.70	33.65	31.92	<u>31.43</u>	31.46	31.44	31.52	29.64	6.03
PEMS07	MAE	33.89	25.30	26.85	24.26	23.92	23.73	<u>21.42</u>	23.52	23.66		4.39
	MAPE(%)	17.60	11.66	12.12	10.21	12.43	12.21	<u>9.08</u>	11.20	9.92	8.75	3.77
	RMSE	46.38	38.58	42.78	29.03	35.86	36.01	<u>34.51</u>	35.20	34.97	33.38	3.39
PEMS08	MAE	31.23	17.86	19.13	17.13	15.03	14.87	15.67	14.92	14.96		6.98
	MAPE(%)	19.25	11.45	12.68	10.96	10.23	10.11	<u>9.94</u>	10.11	10.27	1	10.32
	RMSE	33.47	27.83	31.05	26.80	23.89	23.86	24.77	<u>23.76</u>	24.03		3.08
England	MAE	4.23	3.59	3.12	3.02	3.03	2.98	<u>2.97</u>	3.07	3.05	2.87	3.48
	MAPE(%)	5.72	4.90	4.53	4.48	4.42	<u>4.37</u>	4.39	4.41	4.52	4.19	4.30
	RMSE	7.68	7.42	7.17	7.03	7.05	<u>6.99</u>	7.02	7.11	7.25	6.81	2.64
TaxiBJ	MAE	25.32	19.81	18.77	17.69	18.07	17.59	<u>16.85</u>	17.23	17.03	15.66	7.60
	MAPE(%)	l .	34.19	33.52	31.04	31.98	31.79	<u> 29.76</u>	30.89	30.12	1	14.15
	RMSE	51.54	31.68	30.66	28.30	29.97	27.71	<u>27.53</u>	28.19	27.86	25.84	6.54
	MAE	2.33	1.74	1.64	1.67	1.68	1.78	1.71	1.65	1.54	1.45	6.21
PEMS-BAY			3.90	3.85	3.75	3.69	4.10	3.60	3.47	3.44	3.57	*
	RMSE	4.76	3.97	3.75	3.82	3.74	3.97	3.71	3.65	<u>3.52</u>	3.46	1.73
					·	·					·	

04



实验2: 关键参数K

TOPK: 最优K值出现在大约五分之一处

Dataset	PEMS07(with 883 sensors)								
K	100	125	150	175	200	225			
MAE	21.32	21.13	20.85	20.52	20.56	20.63			
MAPE(%)	9.32	9.13	8.86	8.75	<u>8.79</u>	8.91			
RMSE	34.25	33.96	33.51	33.38	<u>33.42</u>	33.63			
Dataset	PEMS08(with 170 sensors)								
K	5	15	25	35	45	55			
MAE	15.21	14.63	14.02	13.77	13.96	14.38			
MAPE(%)	10.17	9.53	<u>9.22</u>	8.96	9.31	9.74			
RMSE	23.97	23.25	<u>23.03</u>	22.90	23.11	23.68			

•RemPG: 随机选择节点作为关键节点

•RemPGCN: 去除关键图卷积,不使用关键图邻接矩阵

•RemGCN: 仅使用关键图卷积, 删除全局图卷积

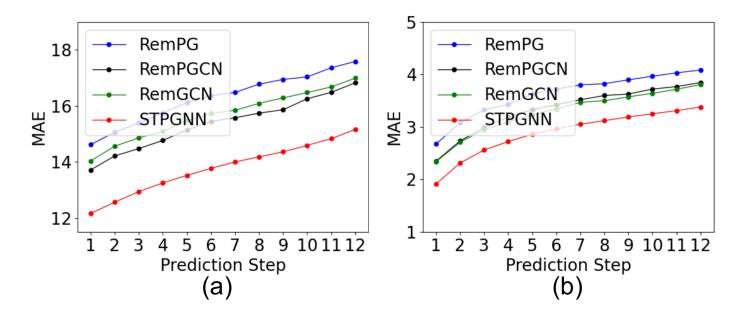


Figure 3: Performance comparison of different variant on PEMS08 and England datasets.



04 实验4: 关键节点的影响

节点90: 评分最高

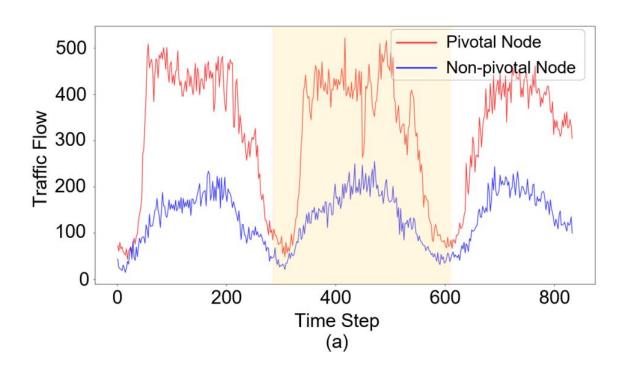


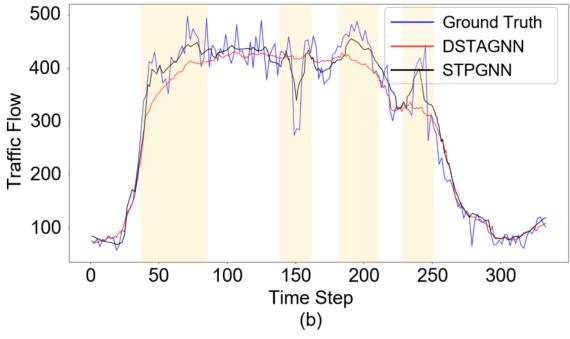


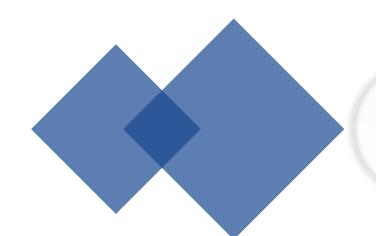
实验4: 关键节点的影响

关键节点: 节点0

非关键节点: 节点113







谢谢观看

MANY THANKS!

24.4.9

