

深度出行感知:从区域出行需求预测到出行目的地预测

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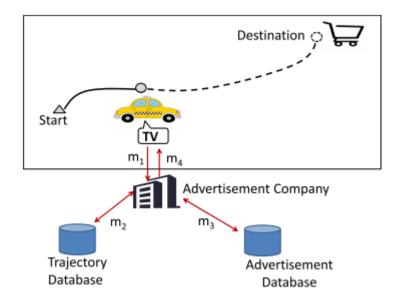
2021/01



出行需求预测

$R^{T imes V} o R^V$

出行目的地预测



Spatiotemporal Multi-Graph Convolution Network for Ride-hailing Demand Forecasting, AAAI 2019.

Multi-Scale and Multi-Scope Convolutional Neural Networks for Destination Prediction of Trajectories, TITS 2019

将深度学习方法应用于某种交通问题,分析特定的交通现象。

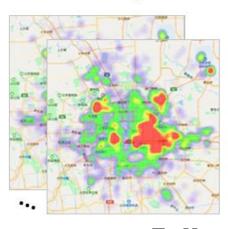
Multi-community passenger demand prediction at region level based on spatiotemporal graph convolutional network

Published in Transportation Research Part C

研究问题

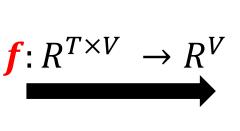


- **出行需求**:在一个时间片段内,一个区域内所有人/车的出行次数
- \blacksquare 出行需求预测:学习从输入到输出之间的映射函数f



输入 $R^{T \times V}$

所有V个区域在过去T个 时间片段内的出行需求



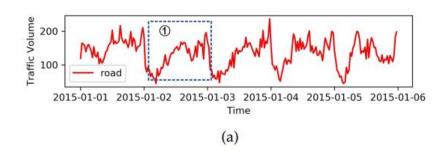
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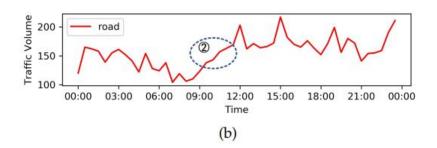
輸出 *R^V* 下一个时间片段内所有 V个区域的出行需求



■ 时间依赖

- 趋势性
- 周期性
- 季节性





T-gcn: A temporal graph convolutional network for traffic prediction. TITS 2019.

■ 空间依赖

- 邻近(地理学第一定律)
- 遥远 (功能相似、交通可达)



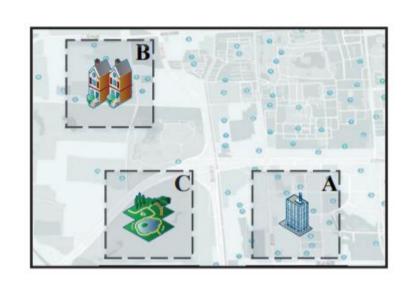
Spatiotemporal multi-graph convolution network for ride-hailing demand forecasting. AAAI 2019.

研究动机



- 现有的多数方法都是在网格划分的基础上进行需求预测
 - 网格划分会破坏城市路网结构,一个学校或医院会被划分到两个网格单元中
 - 区域级别的出行需求预测相关研究较少

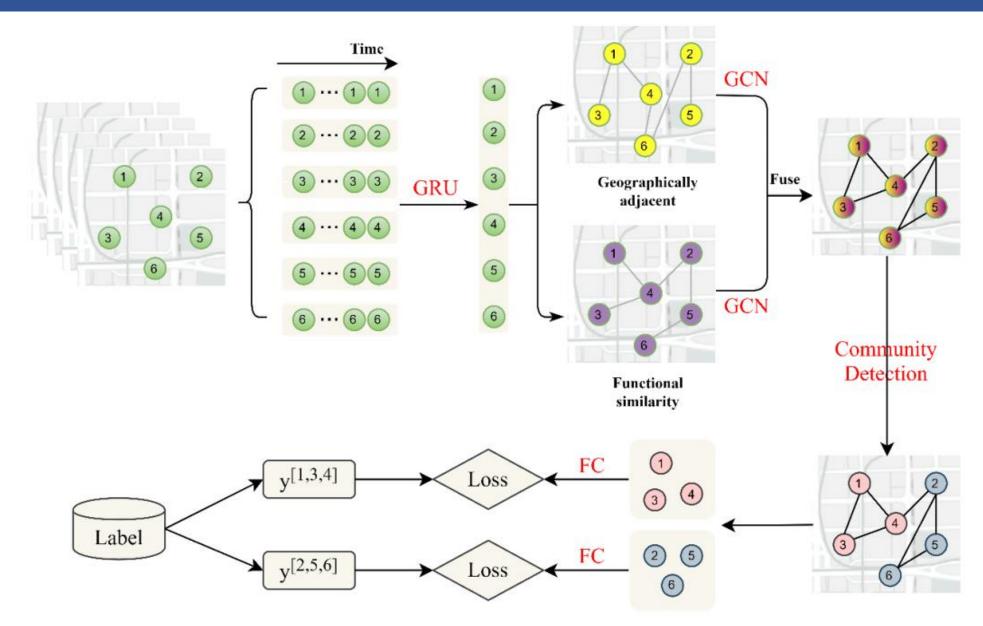
- 区域间复杂的空间关联没有被充分考虑
 - 区域具有语义信息,使得区域间的空间关联更加复杂
 - 区域特性互不相同,不同区域特性导致不同的出行需求分布



Matrix Factorization for Spatio-Temporal Neural Networks with Applications to Urban Flow Prediction. CIKM 2019.

研究方法





实验结果: 模型比较



Mathada		TaxiSZ	Z	TaxiNY			
Methods	MAE RMSE M		MAPE ₁₀ (%)	MAE	RMSE	MAPE ₁₀ (%)	
HA	10.894	18.257	36.149	7.968	17.996	43.553	
ARIMA	12.576	20.634	113.569	5.328	11.620	101.042	
XGBoost	7.552	11.898	26.074	4.464	8.904	23.435	
MLP	10.224	17.405	29.266	6.150	10.554	24.249	
GRU	7.711	12.851	27.780	4.585	9.345	26.375	
LSTM	8.369	13.623	30.128	5.328	10.435	29.118	
GCN	14.263	23.164	44.704	11.662	25.418	56.455	
STGCN	10.180	15.334	32.655	5.241	9.778	23.489	
T-GCN	7.737	11.740	24.290	5.585	9.155	21.370	
Graph WaveNet	9.735	13.920	23.610	4.641	9.229	21.617	
MC_STGCN ^{daily}	8.078	13.699	25.675	5.690	13.190	25.470	
MC_STGCN ^{hourly}	7.200	12.054	23.383	4.035	8.638	19.817	
MC_STGCN ^{GA}	6.764	11.279	21.944	4.609	10.345	21.944	
MC_STGCNFS	N ^{FS} 6.753 11.365 22.		22.136	4.133	9.235	20.310	
MC_STGCN	MC_STGCN 6.555 11.005 21.312		21.312	3.727	7.863	19.241	

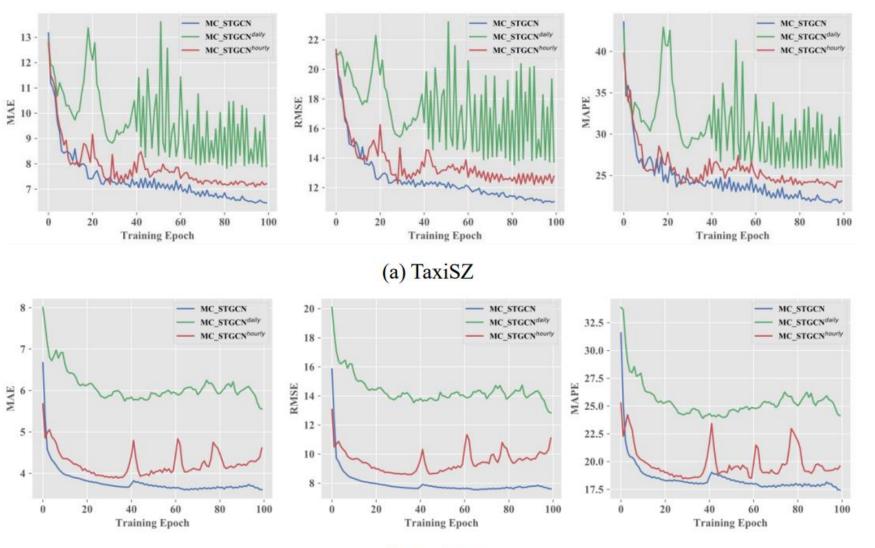
消融实验: 时间相关性



MC_STGCN

趋势性

周期性



(b) TaxiNY

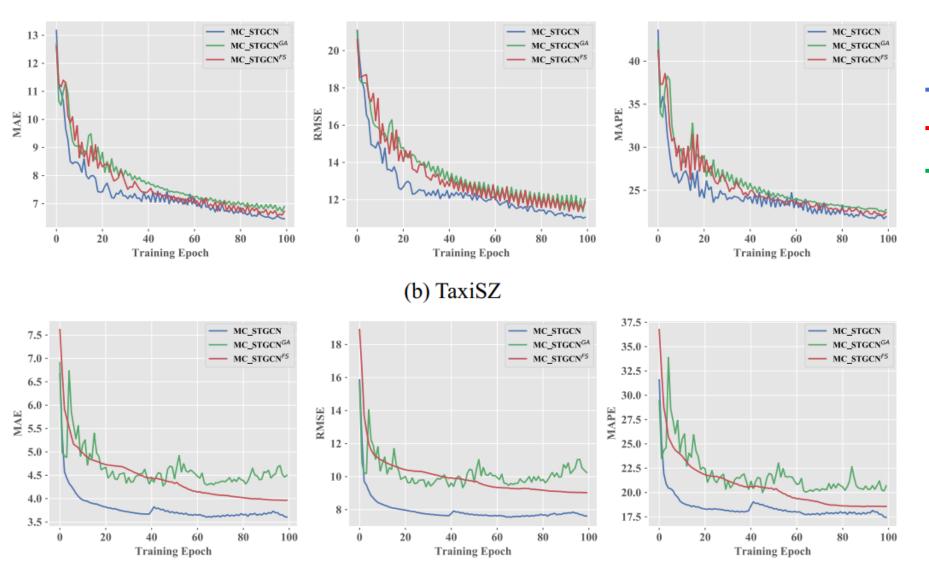
消融实验: 空间相关性



MC_STGCN

无地理相邻图

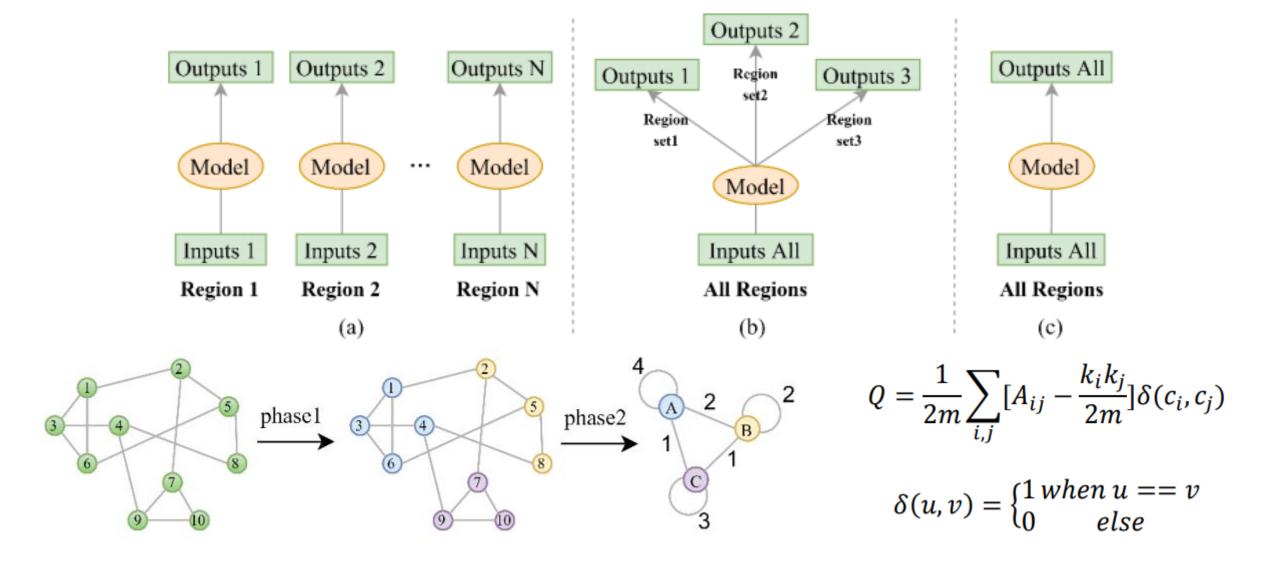
无功能相似图



(b) TaxiNY

消融实验: 社团检测算法





消融实验: 社团检测算法



Division strategies			TaxiSZ		TaxiNY			
		MAE	RMSE	$MAPE_{10}(\%)$	MAE	RMSE	MAPE ₁₀ (%)	
4	First sampling	9.309	15.922	29.460	4.593	9.938	22.800	
	Second sampling	8.530	14.687	26.763	4.920	10.556	24.060	
	Third sampling	8.232	14.059	25.803	4.655	10.007	22.225	
6	First sampling	13.229	26.589	39.301	9.431	30.384	36.908	
	Second sampling	13.569	24.949	43.733	5.241	15.818	23.143	
	Third sampling	14.505	31.211	39.801	5.815	14.426	31.937	
	First sampling	8.802	15.181	27.614	12.444	29.398	58.742	
8	Second sampling	8.948	15.272	27.806	12.225	33.733	55.275	
	Third sampling	8.912	15.180	27.798	8.551	21.851	44.459	
10	First sampling	19.631	37.538	61.095	11.029	28.104	52.226	
	Second sampling	20.906	37.988	64.667	14.837	36.523	70.436	
	Third sampling	21.699	41.477	60.899	15.738	40.386	65.841	
Lo	ouvain method	6.555	11.005	21.312	21.312 3.727 7.863 19.241			

出行需求预测中的可塑性面积单元问题讨论



(i) ConvLSTM, 0.5km gride

可塑性面积单元问题 (MAUP)

分析结果随基本面积单元定义的不同而变化,包括两个方面:

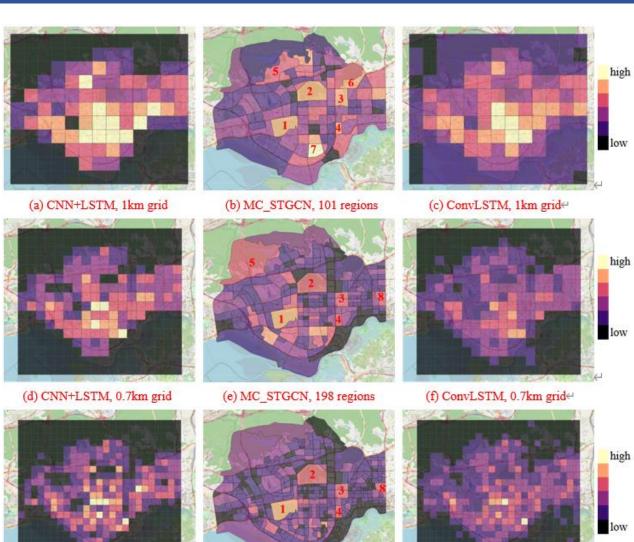
● 区划效应: 规则网格 & 不规则区域

• 尺度效应: 101 regions, 104 valid grids (1 km)

198 regions, 194 valid grids (0.7 km)

370 regions, 379 valid grids (0.5 km)

Methods	101 region & 1 km grid			198 region & 0.7 km grid			370 region & 0.5 km grid		
	MAE	RMSE	MAPE (%)	MAE	RMSE	MAPE (%)	MAE	RMSE	MAPE (%)
CNN+LSTM	6.727	16.291	29.583	3.949	9.328	30.466	3.289	8.762	40.952
ConvLSTM	7.115	12.460	28.208	3.184	6.285	21.396	3.185	6.391	34.650
MC_STGCN	6.555	11.005	21.312	3.971	5.546	28.758	2.727	3.822	36.829



(h) MC_STGCN, 370 regions

(g) CNN+LSTM, 0.5km grid



Thank You!

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