29th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems
Nov. 2 - Nov. 5, 2021, Beijing, China

LibCity: 城市时空预测深度学习开源平台

报告人：王静远

北京航空航天大学

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LibCity: An Open Library for Traffic Prediction

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作者介绍

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先进计算机应用技术教育部工程研究中心，核心成员

研究方向：城市计算、时空数据挖掘

- 出版学术专著2部，发表学术论文50余篇，包括*TKDE*、*TMC*、*TOIS*、*TFS*、*SIGKDD*、*AAAI*、*Ubicomp*、*Infocom*等CCF A类顶级论文近30余篇，最高影响因子12.02，ESI高被引1篇。
- 主持国家自然科学基金重点项目、国家重点研发计划课题等国家级科研项目十余项。
- 担任国务院新冠疫情联防联控机制科研攻关组专班专家、首都公共卫生高端智库理事、中国疾病预防控制中心特聘专家，被授予**“北京市抗击新冠肺炎疫情先进个人”**荣誉称号。
- 获得WGDC全球前沿科技青年科学家,《管理世界》优秀论文奖, *DMKD*最佳论文奖等荣誉。

作者介绍

赵鑫，人大高瓴AI学院，教授、博士生导师

大数据管理与分析方法研究北京市重点实验室，成员

中国中文信息学会社交媒体处理专委会，常务委员

CCF YOCSEF总部AC、CCF NOI科学委员会委员

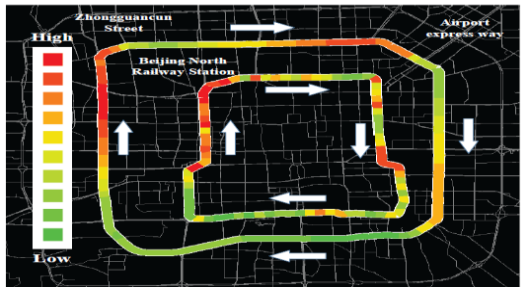
研究方向：信息检索、数据挖掘

- 在ACM SIGIR/KDD, ACL/EMNLP，ACM TOIS，IEEE TKDE等高水平会议和期刊上发表学术论文 50 余篇，长期担任相关国际顶级会议的程序委员会委员。
- 主持和参与国家自然科学基金、北京市自然科学基金、企业横向项目等科研项目十余项。
- 申请国家发明专利10项，其中获批中国专利4项。
- 主持研发了多项开源项目，包括推荐系统“伯乐”、文本生成“妙笔”等。
- 荣获吴文俊人工智能优秀青年奖，入选中国科协青年人才托举工程、北京市智源青年科学家。

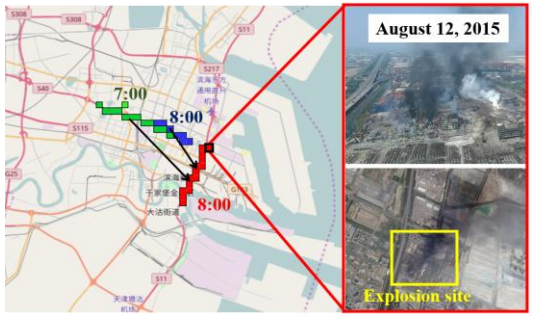
实验室研究方向

现代城市管理重大挑战

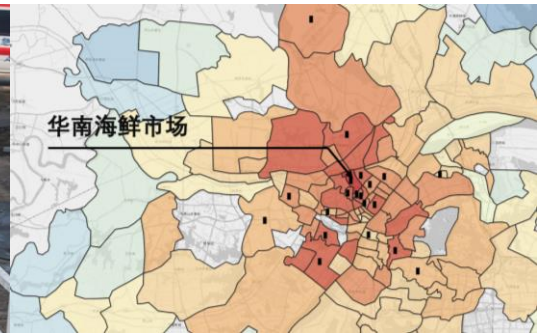
交通拥堵



安全管理



公共卫生



大数据

＋

人工智能

城市智能管理

实验室主页链接：http://www.bigcity.ai

LibCity：阡陌交通、“机”犬相闻

LibCity

LibCity（阡陌）

HomePage|Docs|Datasets|Paper List|中文版

LibCity is a unified, comprehensive, and extensible library, which provides researchers with a credible experimental tool and a convenient development framework in the traffic prediction field. Our library is implemented based on PyTorch and includes all the necessary steps or components related to traffic prediction into a systematic pipeline, allowing researchers to conduct comprehensive experiments. Our library will contribute to the standardization and reproducibility in the field of traffic prediction.

LibCity currently supports the following tasks:

- Time Series Prediction
- Traffic State Prediction
  - Traffic Flow Prediction
  - Traffic Speed Prediction
  - On-Demand Service Prediction
  - OD Matrix Prediction
- Trajectory Next-Location Prediction
- Map Matching
- Road Network Representation Learning

Features

- **Unified**: LibCity builds a systematic pipeline to implement, use and evaluate traffic prediction models in a unified platform. We design basic spatial-temporal data storage, unified model instantiation interfaces, and standardized evaluation procedure.
- **Comprehensive**: 54 models covering 8 traffic prediction tasks have been reproduced to form a comprehensive model warehouse. Meanwhile, LibCity collects 32 commonly used datasets of different sources and implements a series of commonly used evaluation metrics and strategies for performance evaluation.
- **Extensible**: LibCity enables a modular design of different components, allowing users to flexibly insert customized components into the library. Therefore, new researchers can easily develop new models with the support of LibCity.

土地平旷，屋舍俨然，有良田、美池、桑竹之属。**阡陌交通**，鸡犬相闻。

——晋·陶渊明《**桃花源记**》

开源链接：https://www.github.com/LibCity

交通预测问题的介绍

城市场景中的一日生活

7 : 00 出门前
查看路况

百度地图

9 : 00 闪送文件
给合作伙伴

闪送 FlashEx 用善良递送

12 : 00 叫外卖
查看到达时间

饿了么

17 : 00 约朋友
吃饭寻找餐馆

大众点评

18 : 00 驱车前往
定位导航

高德导航

21 : 00 饭后回家
找代驾

滴滴出行 滴滴一下 美好出行

23 : 00 次日出差
预约送机专车

神州专车

现代生活中，时刻与交通预测相关

百度地图　闪送 FlashEx 用善良递送　饿了么　大众点评　高德导航　滴滴出行 滴滴一下美好出行　神州专车

交通预测任务

交通状况预测

POI 推荐

需求预测与调度

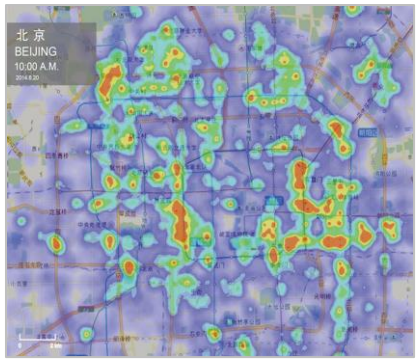
出行时间预测

交通预测的更多应用

交通预测任务

交通状况预测

OD 流量预测



行人流动预测

城市治理应用

拥堵治理

道路规划

重大活动管理

疫情防控

交通预测问题的本质

- **交通预测：带有时空附加属性的时间序列预测**
  - X_t：t 时刻的交通时空数据，$\hat{Y}_t$：预测 t 时刻交通系统的某一状态
  - T：输入因素序列的长度，T'：预测序列的长度

$f(X)$

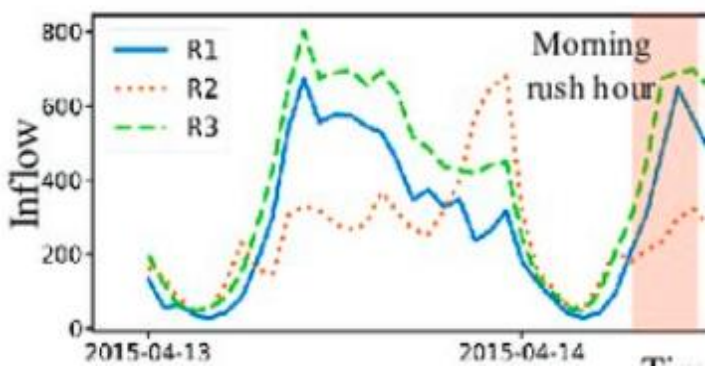
历史交通时空数据 $X_{t-T+1}, X_{t-T+2}, \dots X_t$

未来交通状态 $\hat{Y}_{t+1}, \hat{Y}_{t+2}, \dots \hat{Y}_{t+T'}$

交通预测问题的本质

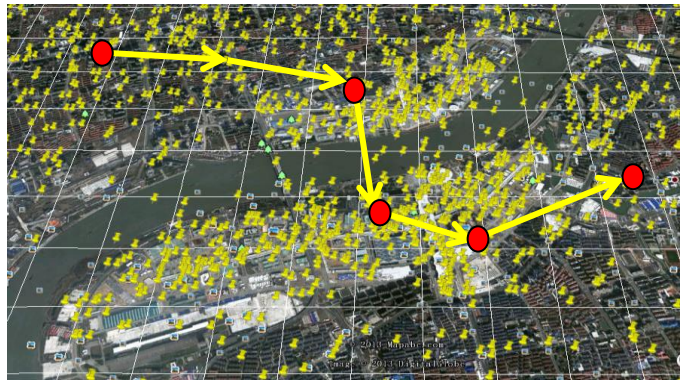
- **交通预测问题：带有时空附加属性的时间序列预测**

面向群体



道路速度预测
行车流量预测
出行需求预测
拥堵时间预测
……

面向个体

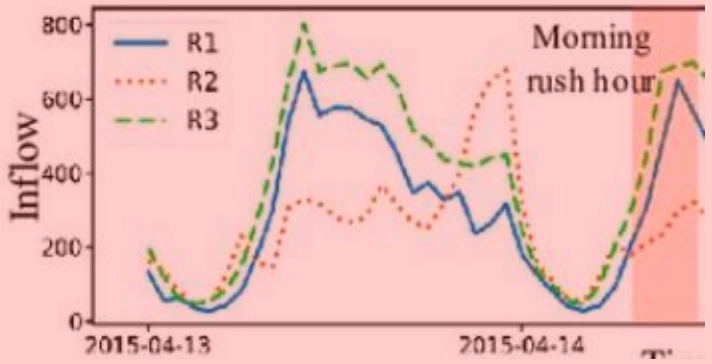


行驶轨迹预测
出行时间预测
到达时间预测
POI服务推荐
……

交通预测问题的本质

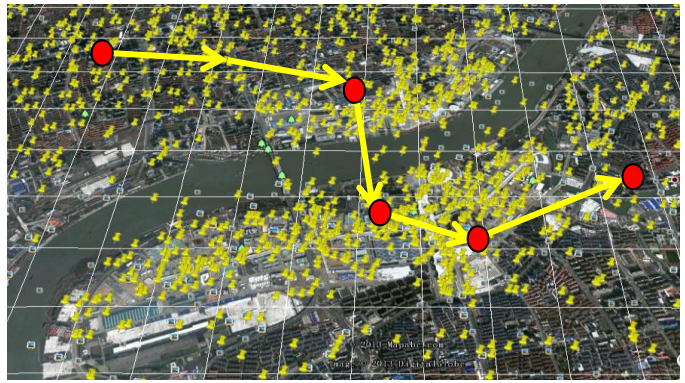
- **交通预测问题：带有时空附加属性的时间序列预测**

面向群体



道路速度预测
行车流量预测
出行需求预测
拥堵时间预测
……

面向个体

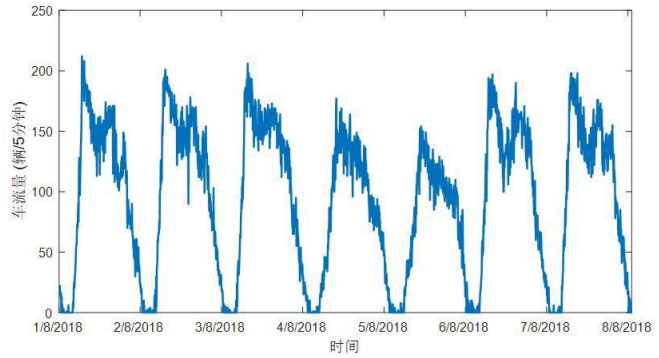


行驶轨迹预测
出行时间预测
到达时间预测
POI服务推荐
……

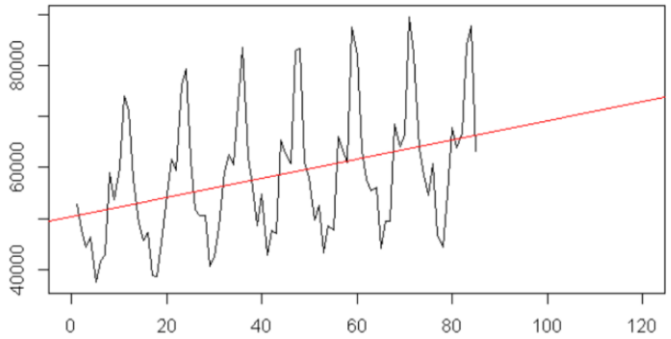
面向群体的交通预测建模

- **时间序列角度的交通特征建模**

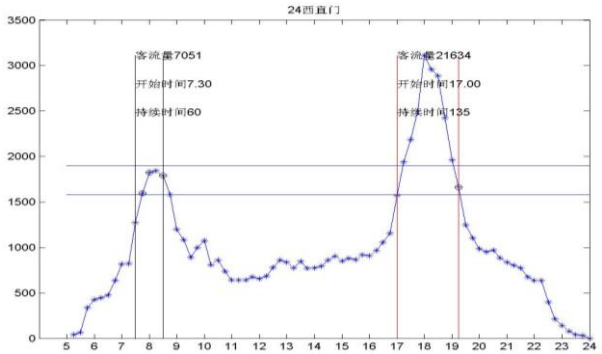
周期性（潮汐性）



趋势性



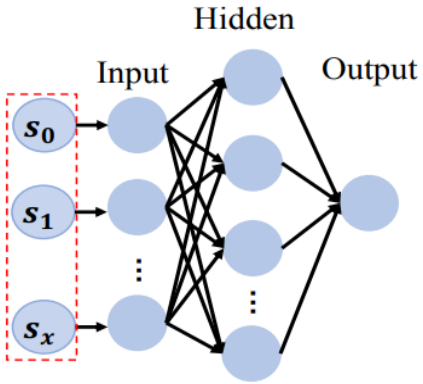
临近性



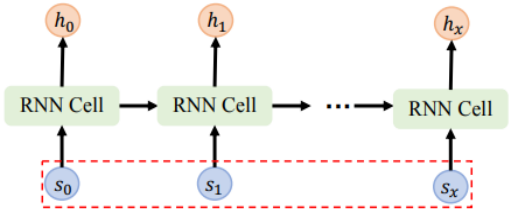
- 早期神经网络：MLP 多层感知机、DBP 深度置信网络、AE 自编码器
- RNN-based：LSTM、BiLSTM、GRU、Seq2Seq
- CNN-based：1D-CNN
- Attention：RNN 与 CNN 的基础上，强化周期性

面向群体的交通预测建模

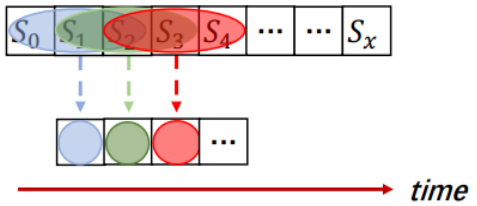
- **时间序列角度的交通特征建模**
  - ➢早期神经网络：MLP 多层感知机、DBP 深度置信网络、AE 自编码器
  - ➢RNN-based：LSTM、BiLSTM、GRU、Seq2Seq
  - ➢CNN-based：1D-CNN
  - ➢Attention：RNN 与 CNN 的基础上，强化周期性



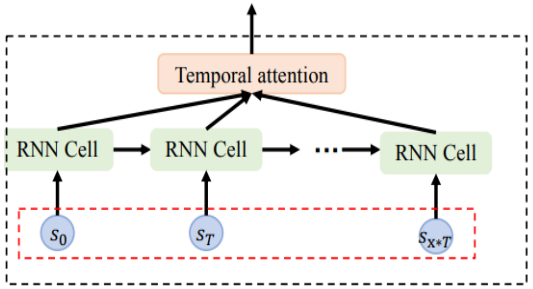
MLP



RNN



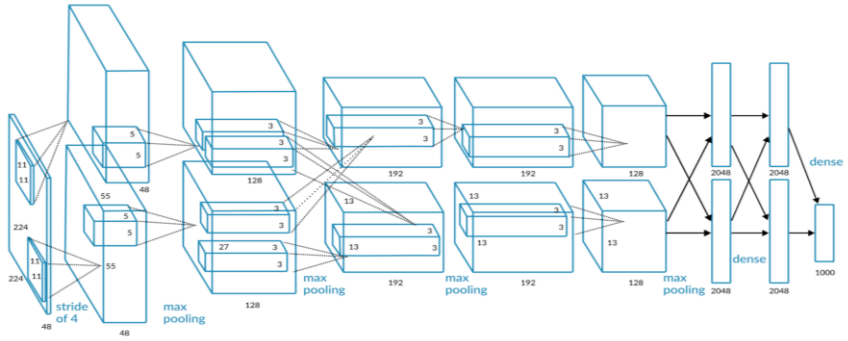
1D-CNN



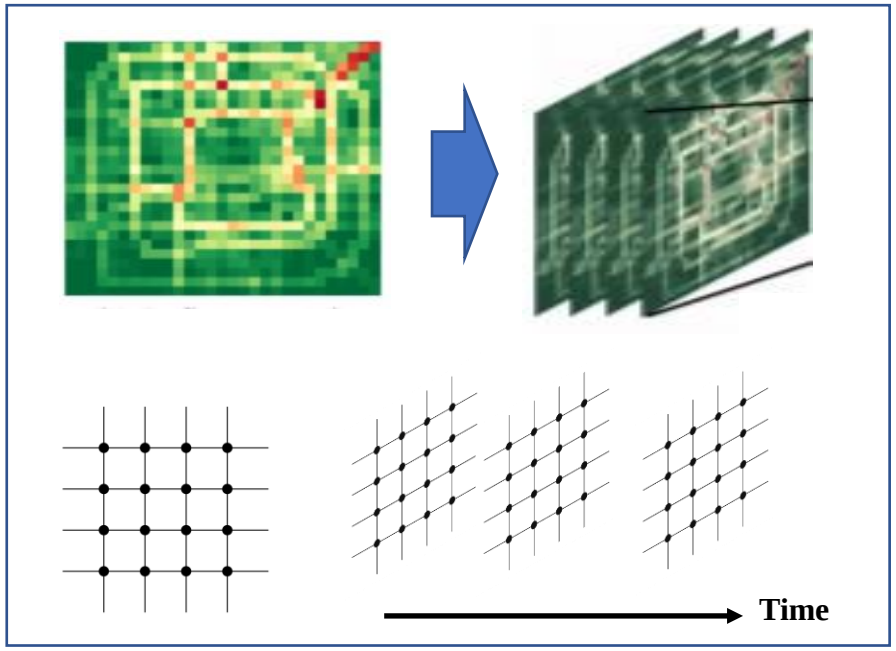
RNN+Attention

面向群体的交通预测建模

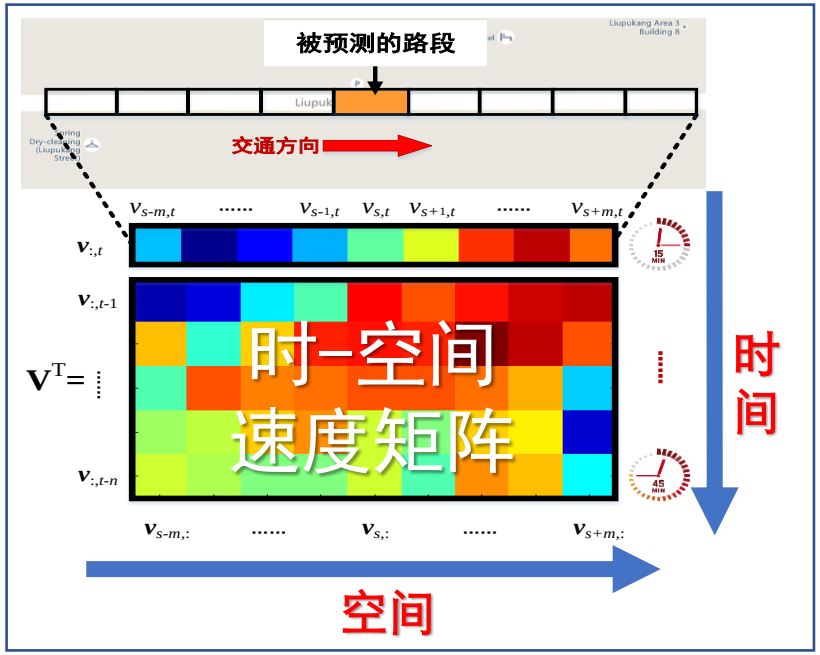
- **空间角度的交通特征建模：栅格结构**
  - ➢CNN-based：2D-CNN、3D-CNN等



空间栅格

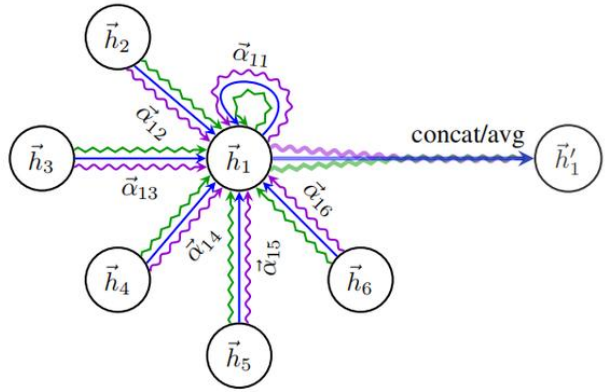


时空栅格

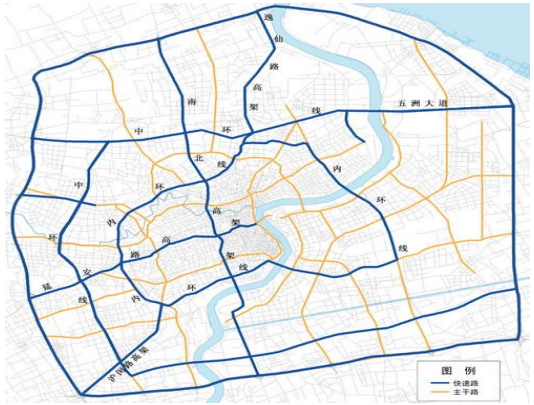


面向群体的交通预测建模

- **空间角度的交通特征建模：网络结构**
  - ➢GNN-based：GCN, GAT等模型

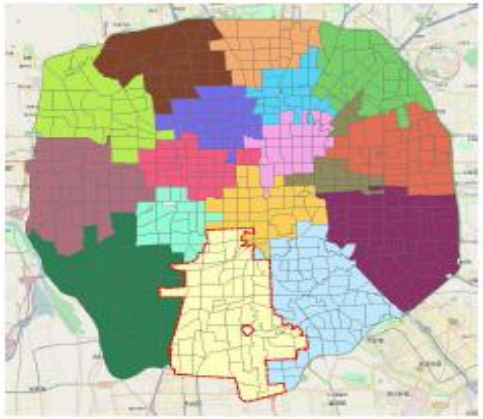


交通路网

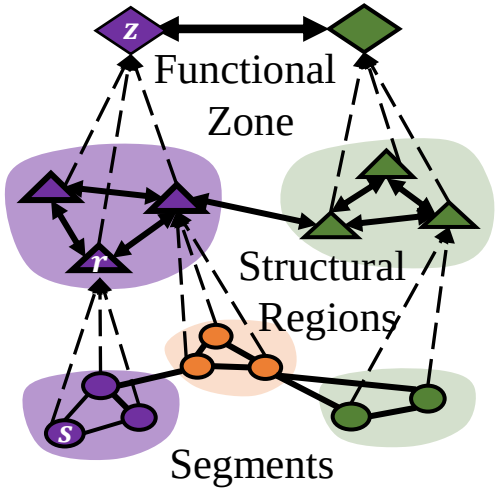


OD网络

地块邻接

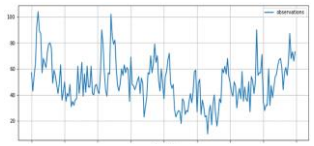


空间聚类

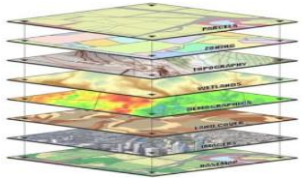


面向群体的交通预测建模

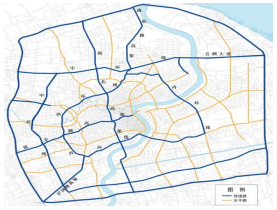
- **时空特征和混合的建模方法**
  - ➢Hybrid Model：CNN+RNN, GCN + RNN, GCN + CNN



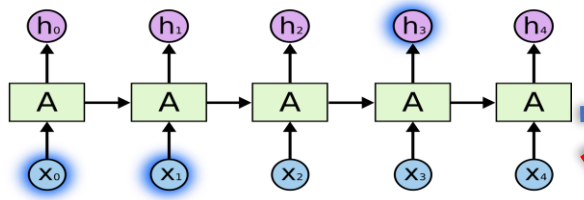
时间序列数据



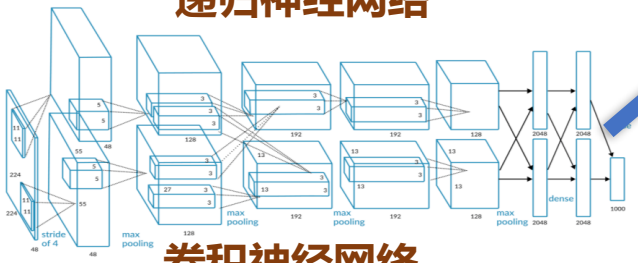
空间网格数据



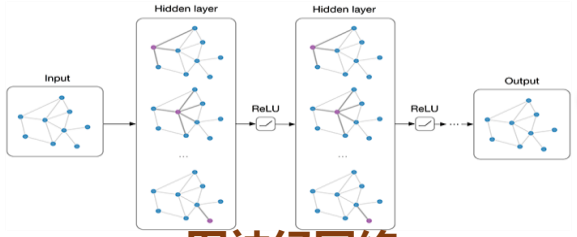
网络结构数据



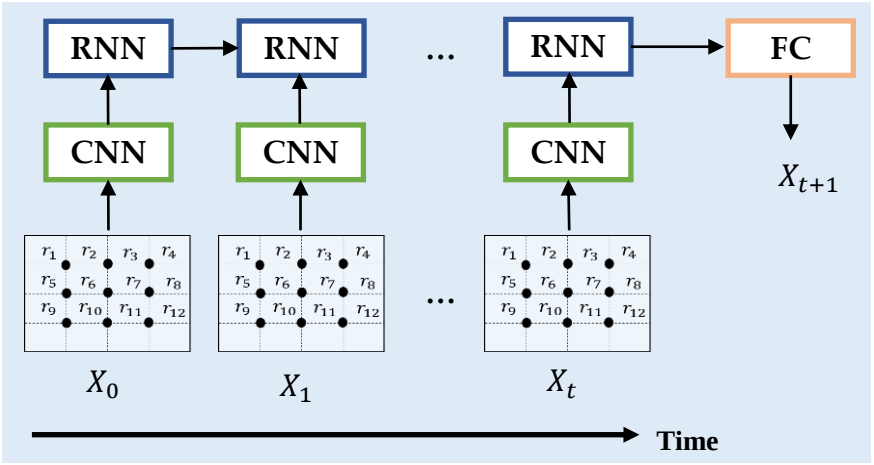
递归神经网络

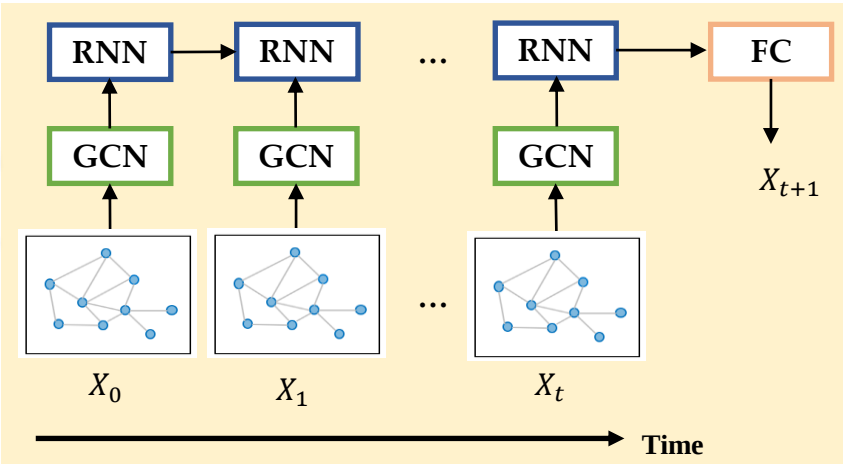


卷积神经网络



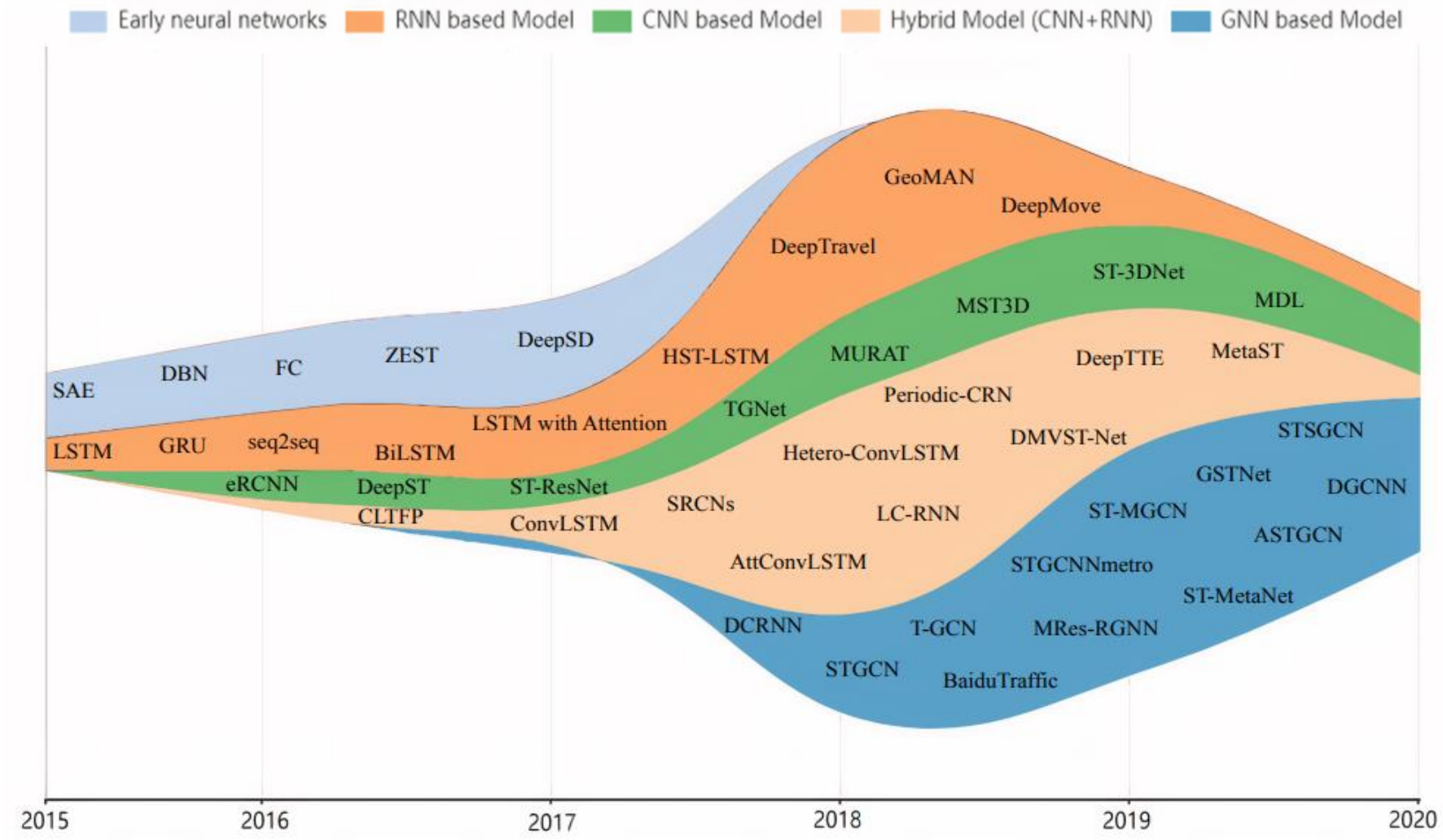
图神经网络





面向群体的交通预测建模

- 深度学习交通预测模型的发展源流



面向群体的交通预测建模

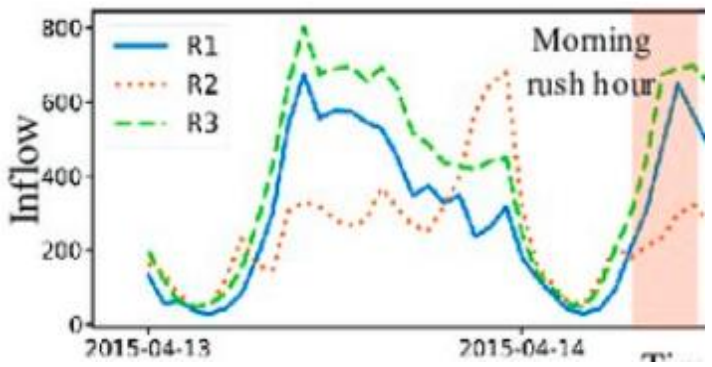
- 从交通任务的角度对模型进行分类

目标交通状态	基于原子单元			基于关系	
	基于点	基于路段	基于区域	基于 OD	基于路网
交通流量	——	DLA, SAE, DBN, Conv-LSTM, ASTGCN ….	Multi-graph, GSTNet, STGCNNmetro, Periodic-CRN, …..	ITRCN, MPGCN, MDL, …..	——
交通速度	LSTM NN, Deep LSTM, Res-RGNN, BDLSTMs, …	DCRNN, eRCNN, SRCNs, Lc-rnn, T-GCN, ….	——	——	——
交通用户需求	——	——	Zest, TGNet, DL-LSTM, LSTM-MDN, ST-MGCN, ……	CSTN, GEML, MultiConvLSTM, ST-ED-RMGC, ……	——
通行时间	——	——	——	ST-NN, MURAT	Deeptravel, DeepTTE, WDR, …..

交通预测问题的本质

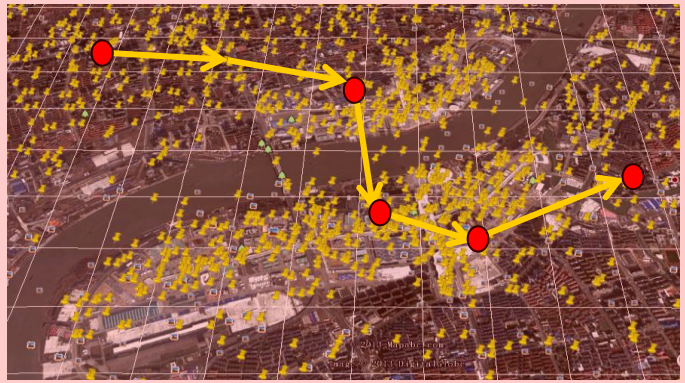
- **交通预测问题：带有时空附加属性的时间序列预测**

面向群体



道路速度预测
行车流量预测
出行需求预测
拥堵时间预测
……

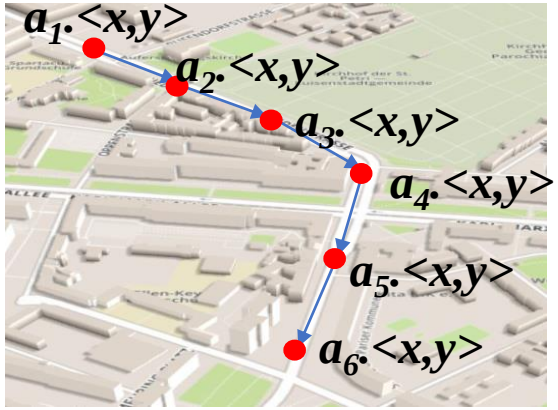
面向个体



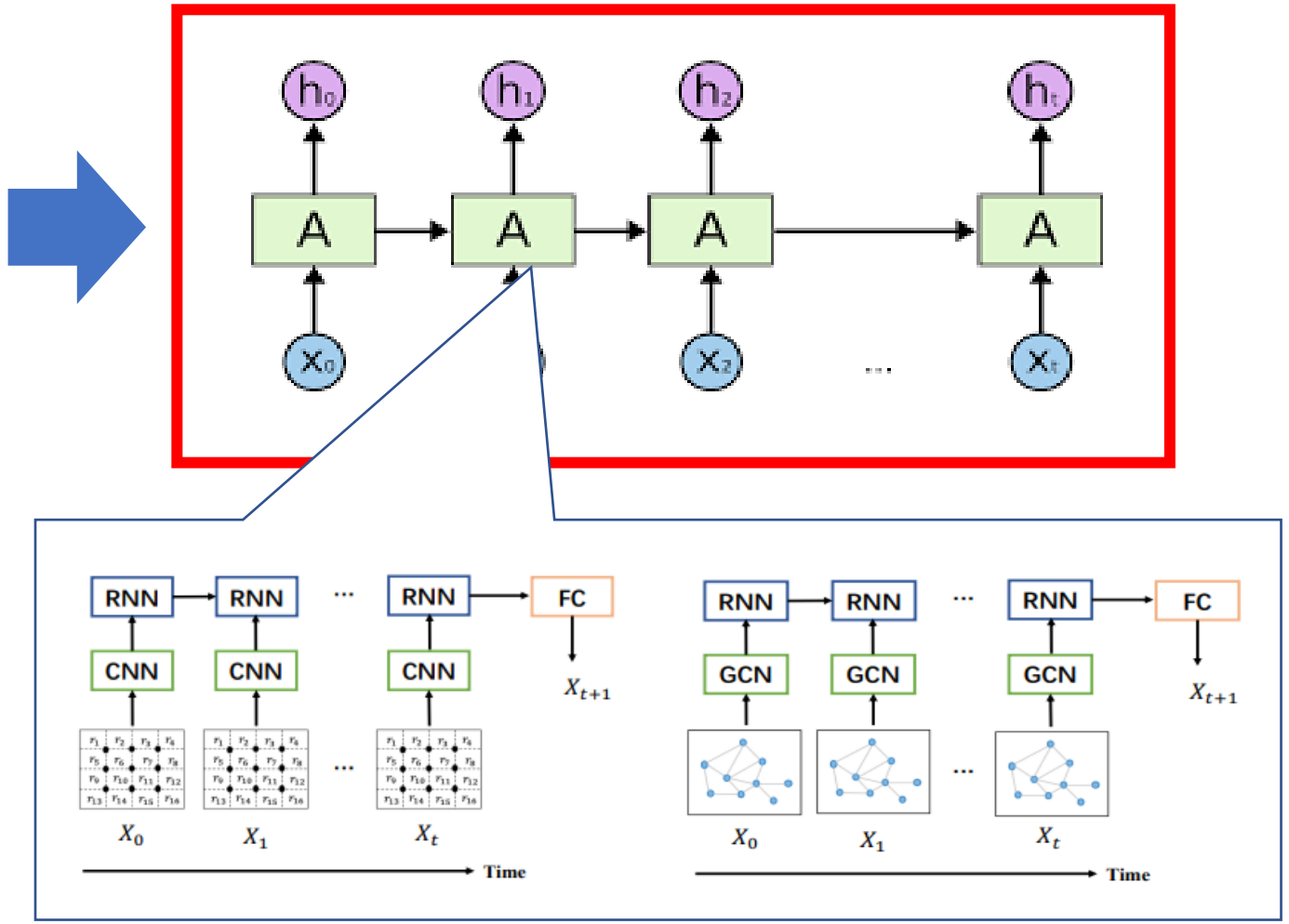
行驶轨迹预测
出行时间预测
到达时间预测
POI服务推荐
……

面向个体的交通预测建模

- 如何将时空上下文信息融入到个体行为建模?



融合入时空上下文信息



面向个体的交通预测建模

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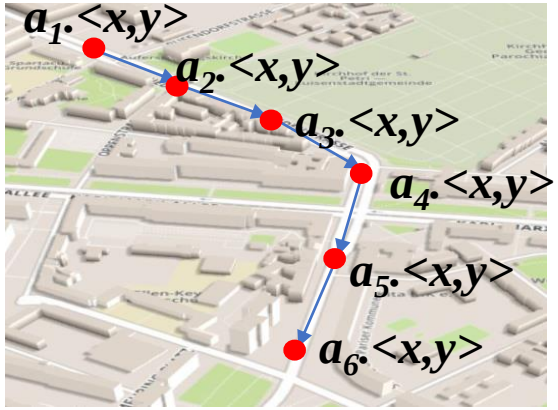
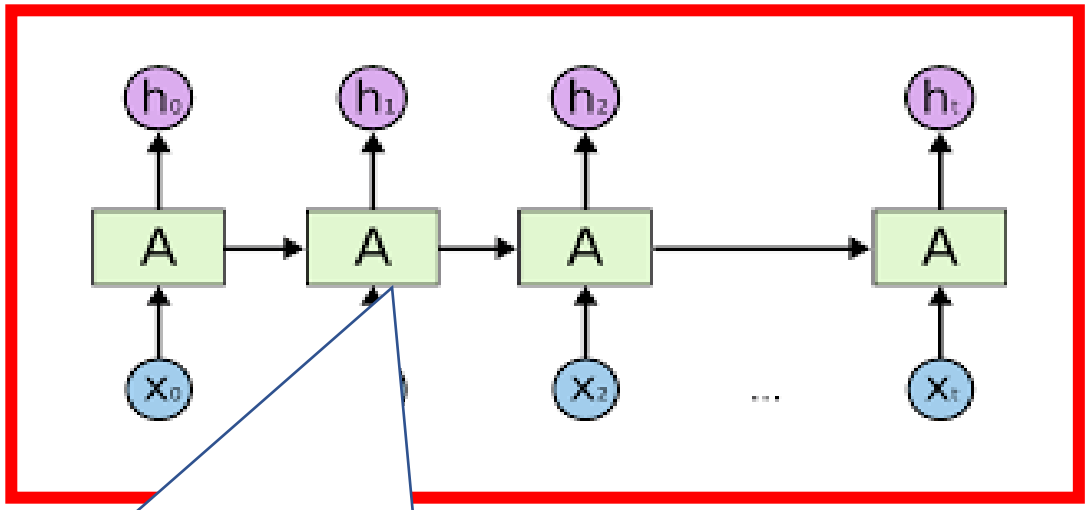
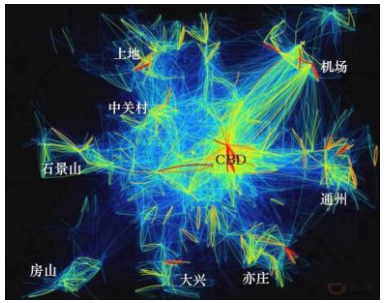




融合入用户偏好信息

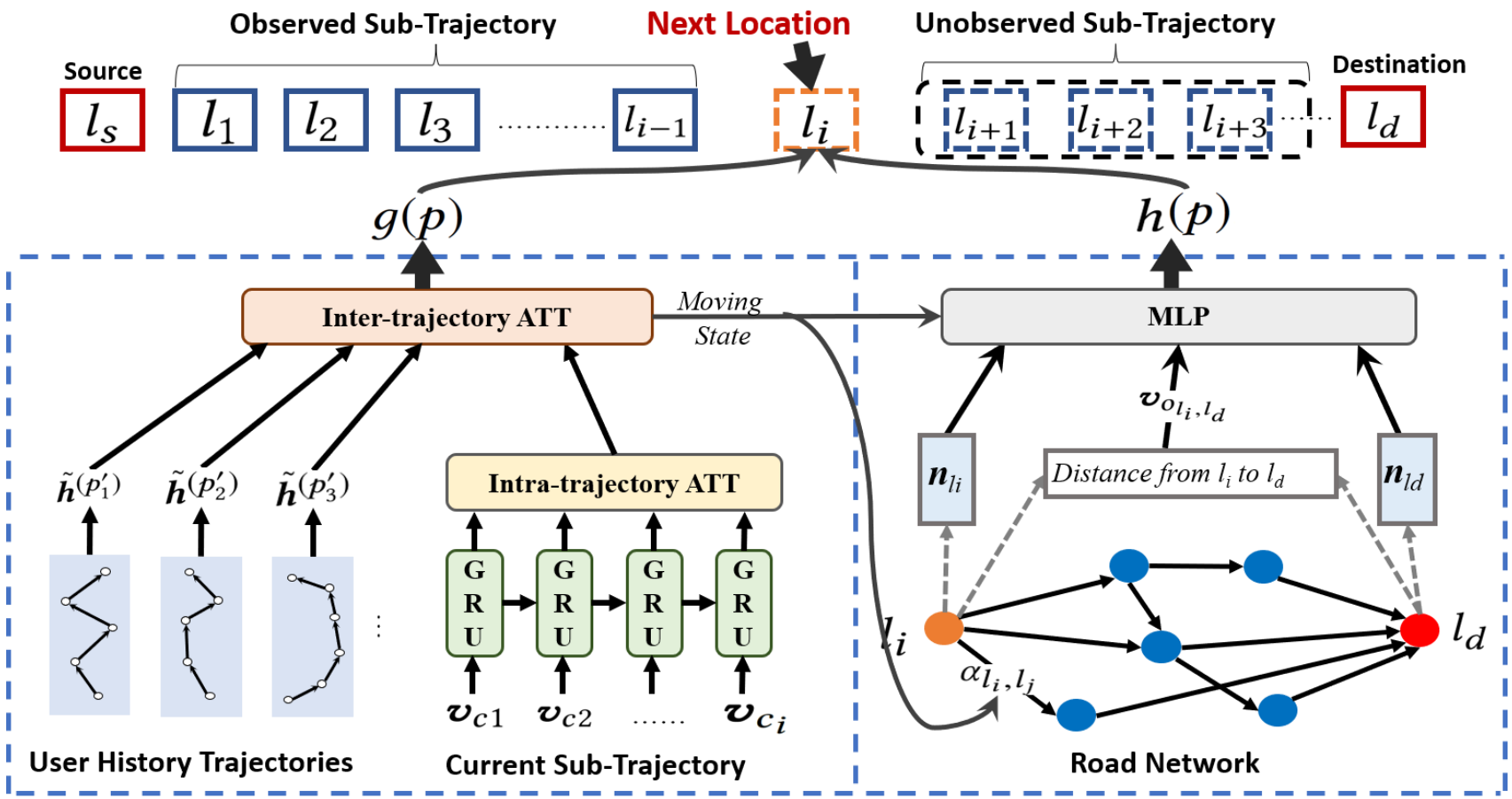
用户画像

出行偏好



面向个体的交通预测建模

基于深度A*算法的个体出行路径推荐[Wang, KDD19]

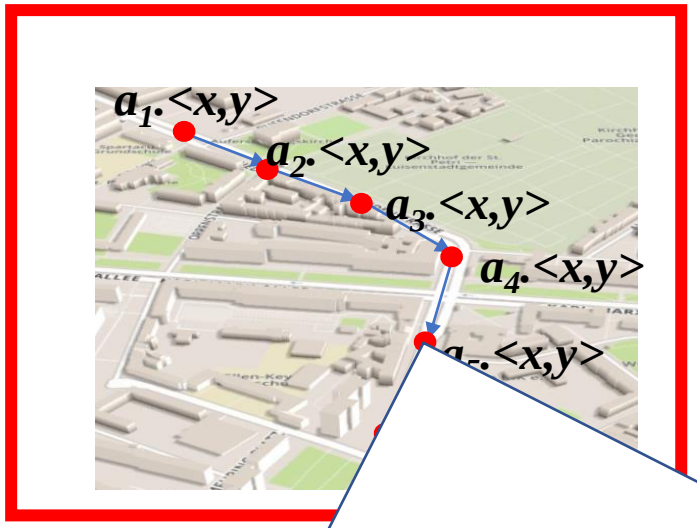


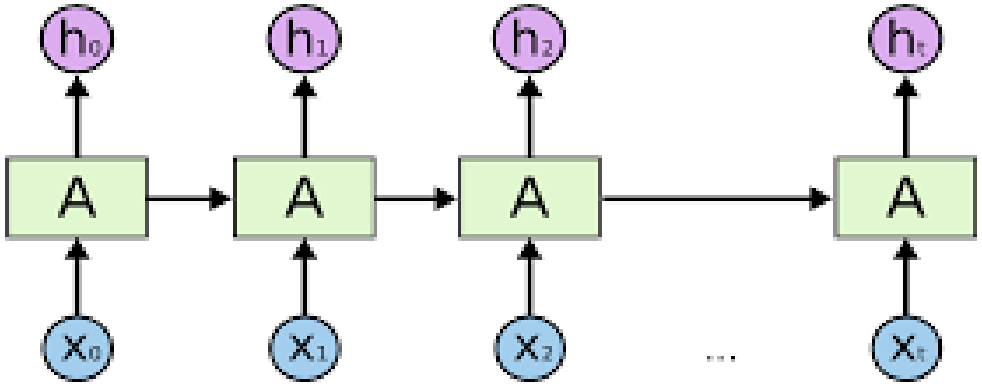
• **J. Wang**, N. Wu, X. Zhao. "Personalized Route Recommendation with Neural Network Enhanced A* Search Algorithm", *IEEE Transactions on Knowledge and Data Engineering (TKDE)*, pages 1-1, 2021.

• **J. Wang**, N. Wu, W. X. Zhao, F. Peng, and X. Lin, "Empowering A* search algorithms with neural networks for personalized route recommendation," *in KDD'19*, pp.539-547

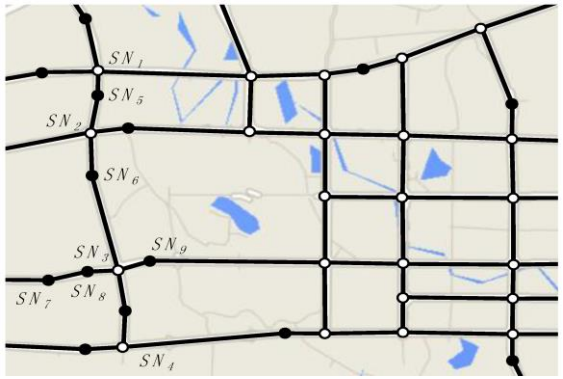
面向个体的交通预测建模

- 如何将时空上下文信息融入到个体行为建模?

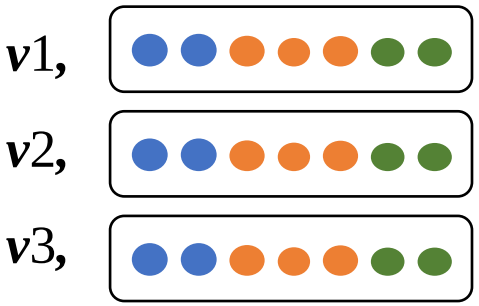




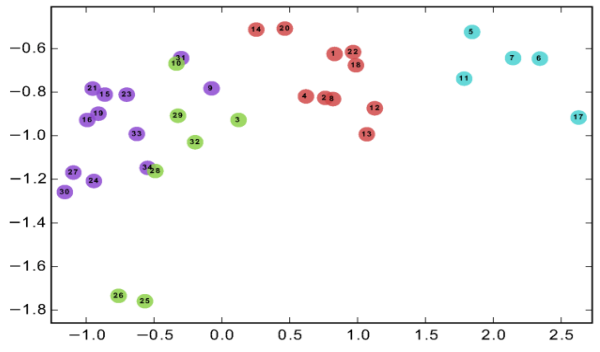
路网节点



向量表征

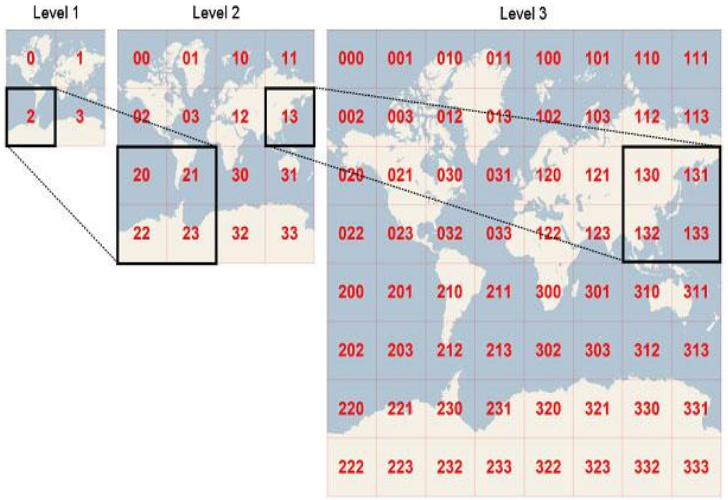


下游任务

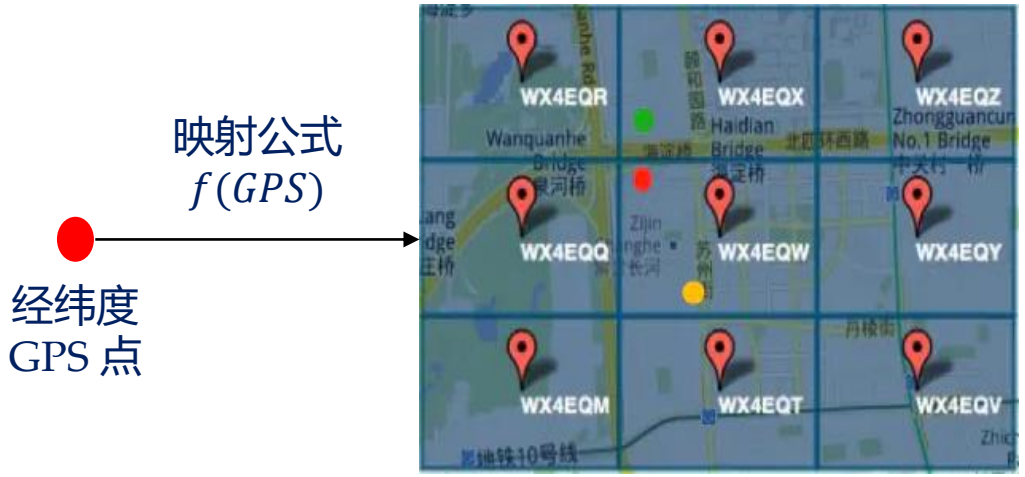


面向个体的交通预测建模

- **个体空间位置的表征方法**
  - **传统经纬度映射嵌入法：**划分区域并进行编码，再将经纬度映射到区域



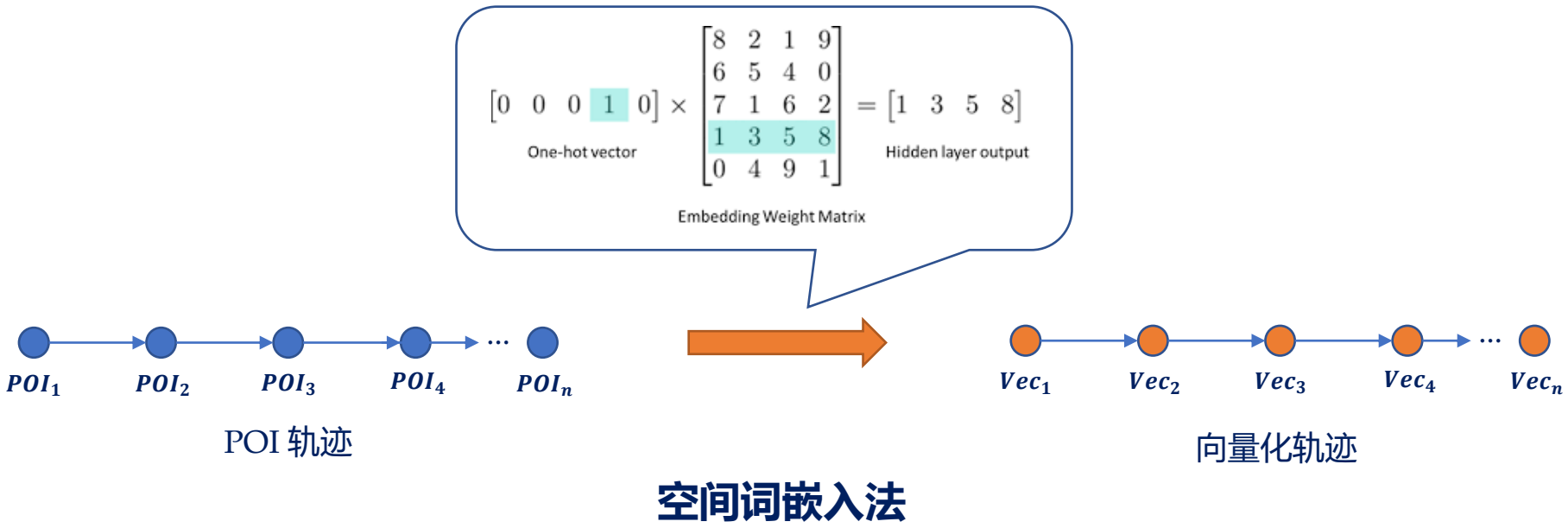
划分区域并对区域编码



将经纬度点映射到区域

面向个体的交通预测建模

- **个体空间位置的表征方法**
  - **传统经纬度映射嵌入法：**划分区域并进行编码，再将经纬度映射到区域
  - **空间词嵌入法：**将空间位置视作单词，轨迹视作句子，使用Embedding矩阵对空间位置进行编码



空间词嵌入法

面向个体的交通预测建模

- **个体空间位置的表征方法**
  - **传统经纬度映射嵌入法：**划分区域并进行编码，再将经纬度映射到区域
  - **空间词嵌入法：**将空间位置视作单词，轨迹视作句子，使用Embedding矩阵对空间位置进行编码
  - **预训练表征嵌入法：**通过预训练获得位置的的表征向量，如 Node2Vec

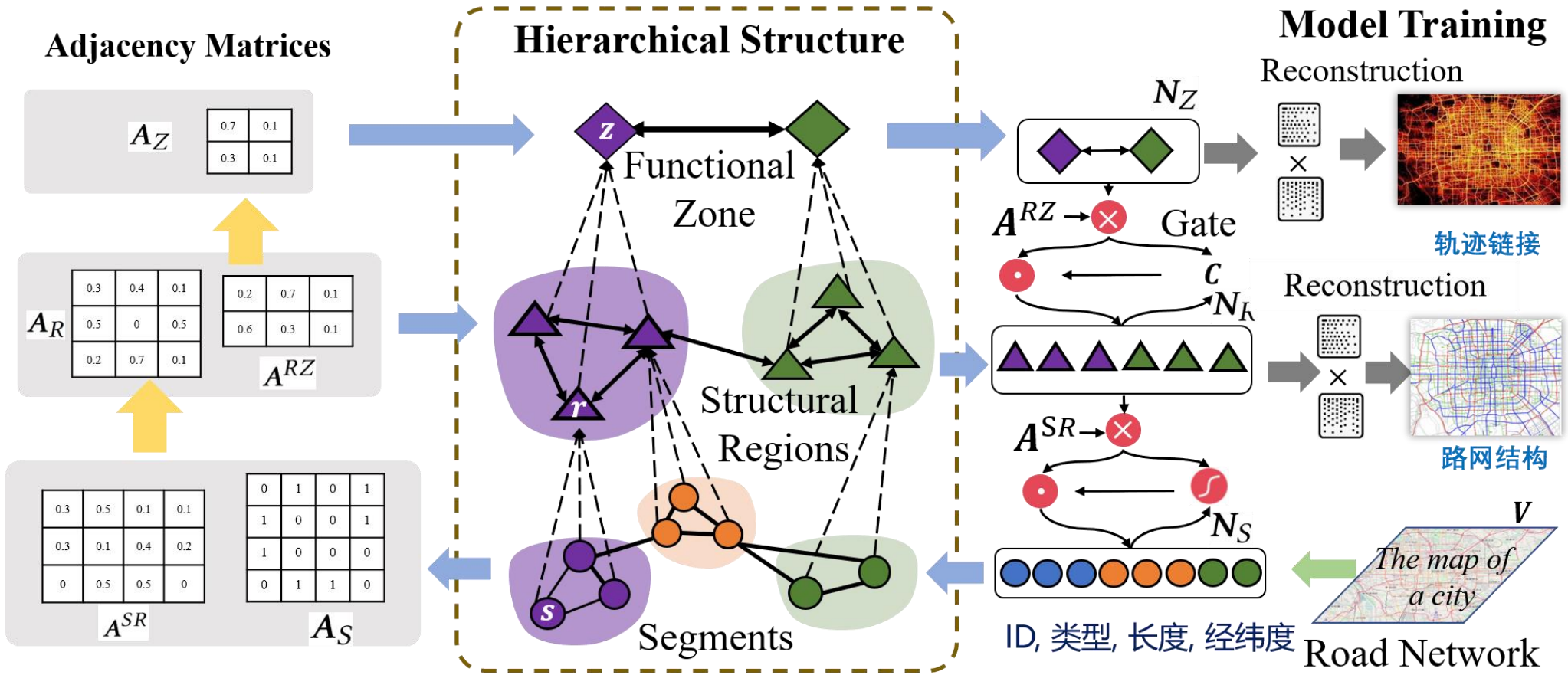
原始路网信息

路段 ID	预训练表征向量
1	(0.1, 0.3, …, -1.2)
2	(7.5, -0.5, …, -1.7)
…	…
n	(2.0, 2.7, …, 5.6)

路段表征 Look-Up 表

面向个体的交通预测建模

城市路网的表征学习[Wang, KDD20]



- N. Wu, X. W. Zhao, **J. Wang**, and D. Pan, "Learning Effective Road Network Representation with Hierarchical Graph Neural Networks," *in KDD'20,* pp.6-14.

现有研究存在的挑战

现有研究成果已经非常丰富

- https://www.github.com/LibCity/Bigscity-LibCity-PaperList

Traffic Prediction Paper Collection

In the paper collection, we collected traffic prediction papers published in the recent years (2016-now) on 11 top conferences and journals, namely, AAAI, IJCAI, KDD, CIKM, ICDM, WWW, NIPS, ICLR, SIGSPATIAL, IEEE TKDE and IEEE TITS. In addition, the surveys since 2016 and representative papers mentioned in the surveys are also included. We will continue to update the collection.

Surveys

- 14篇综述，351篇论文，遍布大数据、人工智能的主流期刊会议

IEEE TKDE

IEEE TITS

现有研究生态存在的问题

- 挑战一：**复现困难**，领域内研究工作的开源程度不足

近 5 年发表在 11 个顶会与期刊共 351 篇论文中，

仅有不到3成开源或部分开源代码与数据……

现有研究生态存在的问题

- 挑战二：**评估困难**，难以对比评价新交通预测模型

实验数据不统一

4 Experiments

4.1 Data set and settings

Our experimental data set are generated from Baidu map[1] log data. We gathered all users' traveling records in city Peking during one week(from Dec. 2, 2015 to Dec. 8, 2015), which contains 311,310 usable point paths and 16,775,817 positioning points. We transform the point paths into AOI paths by

5.1 Experimental Setup

5.1.1 Datasets. We conduct our experiments on the WeChat[3] Moments check-in data. This study was approved by Tencent[4] and the Computer Science and Technology Department University of Cambridge Ethics Committee. Initially, the whole dataset contains all the POI check-in records created by WeChat users living in Beijing for one year spanning from September 2016 to August 2017.

非开源数据集

VS

Evaluation Datasets

We conduct experiments on two widely-used real LSBN datasets, namely Foursquare (Feng et al. 2018) and Gowalla (Yin et al. 2015). The Foursquare check-in dataset is collected from February 2010 to January 2011 in New York while Gowalla contains world-wide check-ins from February 2009 to October 2010. For both of them, we elim-

开源数据集

现有研究生态存在的问题

- 挑战二：**评估困难**，难以对比评价新交通预测模型

缺乏公认的 SOTA 模型

Method	Acc@1				Acc@5			
	20%	40%	60%	80%	20%	40%	60%	80%
Top	0.0106	0.0439	0.0473	0.0506	0.0544	0.0937	0.1130	0.1332
MF	0.0305	0.0487	0.0588	0.0810	0.0629	0.0982	0.1259	0.1653
VOM	0.0299	0.0436	0.0612	0.0833	0.0610	0.0923	0.1387	0.1712
FPMC	0.0473	0.0676	0.0883	0.1077	0.0617	0.0938	0.1407	0.1699
PRME	0.0425	0.0684	0.0950	0.1164	0.0666	0.1042	0.1437	0.1754
ST-RNN	0.0796	0.1072	0.1259	0.1437	0.1869	0.2715	0.3276	0.3639
LSTM	0.0728	0.0964	0.1103	0.1242	0.1875	0.2498	0.2796	0.3039

IJCAI 2018

TABLE II
RESULTS OF DIFFERENT METHODS

Dataset	Method	recall@2	recall@5	recall@10	NDCG@2	NDCG@5	NDCG@10
Gowalla	Popu	0.821%	1.544%	2.812%	0.466%	1.022%	1.427%
	FPMC	8.800%	13.008%	17.217%	7.815%	9.695%	11.053%
	PRME	11.334%	17.479%	22.487%	9.783%	12.548%	14.163%
	RNN	14.623%	20.887%	26.057%	12.981%	15.802%	18.337%
	LSTM	13.979%	19.902%	24.805%	12.440%	15.108%	16.693%
	TMCA	**15.404%**	**21.926%**	**27.725%**	**13.796%**	**16.726%**	**18.597%**
Yelp	Popu	0.115%	0.287%	0.559%	0.057%	0.167%	0.254%
	FPMC	0.548%	1.271%	2.230%	0.451%	0.771%	1.099%
	PRME	0.366%	1.061%	2.101%	0.275%	0.581%	0.915%
	RNN	0.502%	1.099%	2.045%	0.414%	0.676%	0.981%
	LSTM	0.490%	1.097%	1.947%	0.402%	0.669%	0.943%
	TMCA	**1.361%**	**2.870%**	**4.809%**	**1.142%**	**1.809%**	**2.430%**

ICDM 2018

相同领域同年的研究最优秀的 Baseline 不同

现有研究生态存在的问题

- **挑战二：评估困难，难以对比评价新交通预测模型**

不透明的实验设置

tive users and unpopular POIs. In particular, we removed all the users whose check-ins were fewer than twenty and all the POIs where check-ins were fewer than ten from the two datasets.

TABLE 2. STATISTICS OF THE PREPROCESSED DATASETS.

Dataset	#Users	#Check-ins	#Locations	#Sub-trajectories
Gowalla	2,874	445,166	60,534	349,856
Brightkite	3,277	1,062,465	22,789	839,890

We use three publicly available real-world Location-Based Social Network datasets to evaluate our method: Gowalla, Brightkite [4], and Foursquare [35]. We remove users with fewer than 20 check-ins and locations which have been visited fewer than 10 times.

Table 1: Dataset statistics.

	Gowalla	Brightkite	Foursquare
#users	31,708	5,247	12,695
#locations	131,329	48,181	37,344
#check-ins	2,963,373	1,699,579	1,941,959

两篇文章使用相同数据集与相同数据预处理方式

但处理后的结果差别巨大

为什么提出 LibCity?

挑战 一：复现困难，
领域内开源程度不足

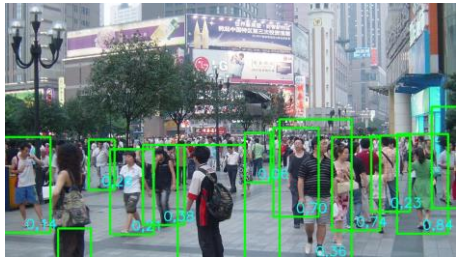
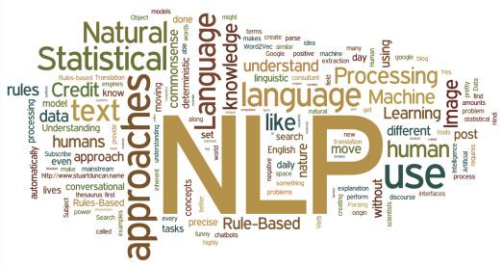
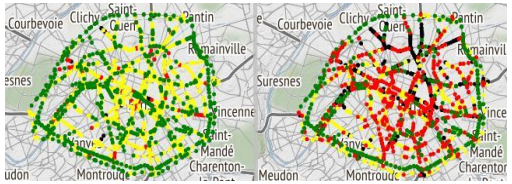
挑战 二：评估困难，
模型间难以对比评价

创新困难

可能我们正在”重复制造轮子”

而不自知！

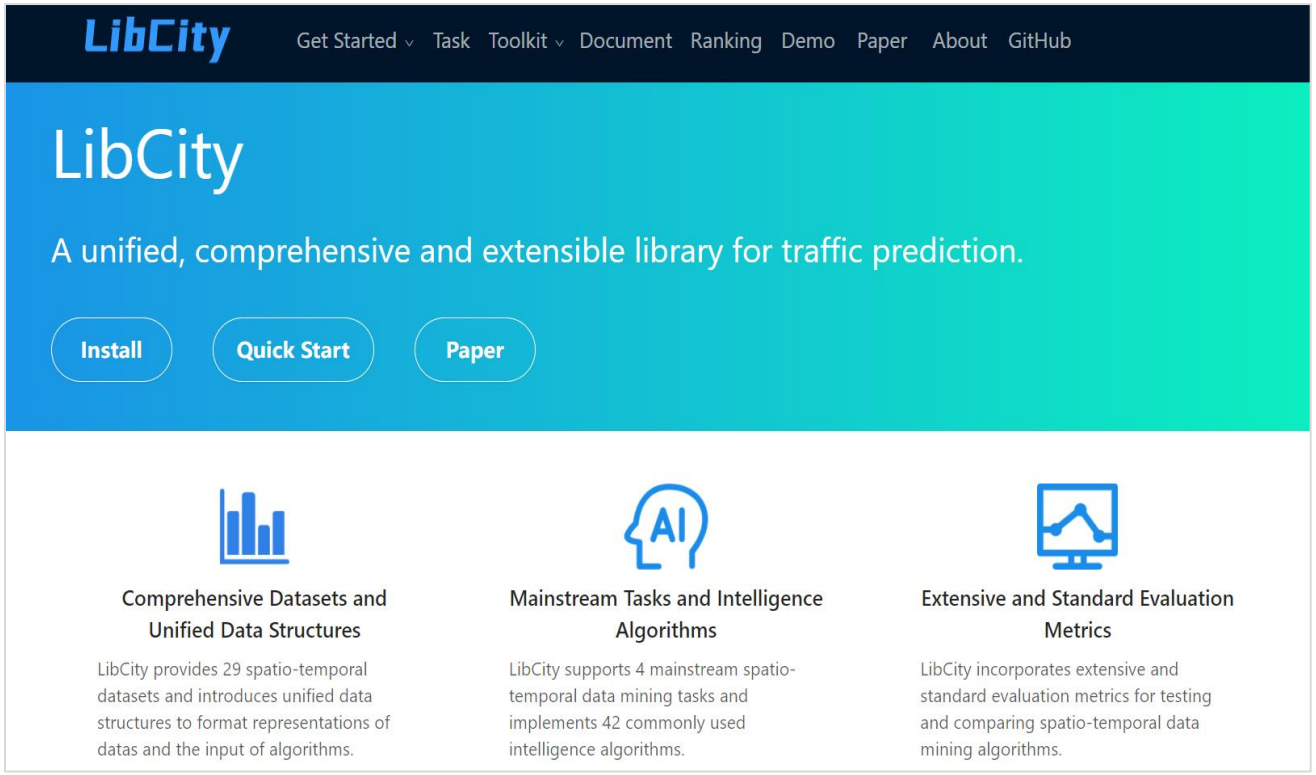
为什么提出 LibCity?

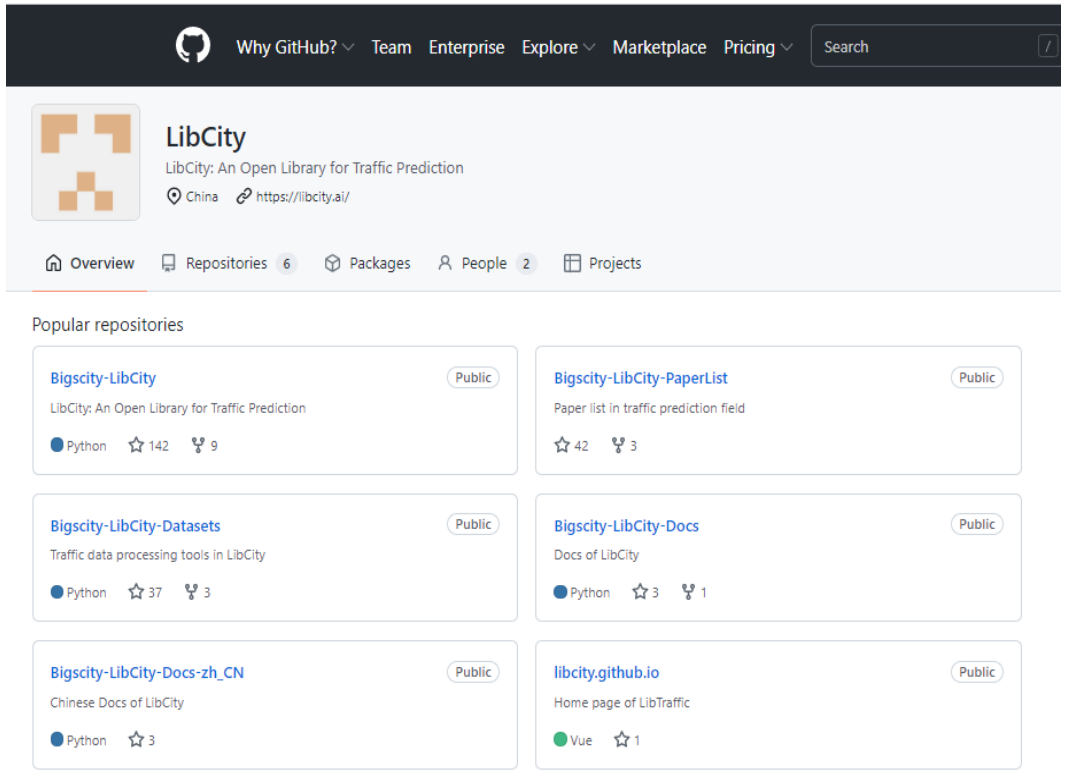
		开源 算法库	标准 数据集
	计算机 视觉	OpenCV	IMAGENET
	自然语言 处理	CoreNLP TextBlob	WordNet
	交通 预测	?	?

LibCity开源平台

LibCity：交通预测的“ImageNet + OpenCV”

- 针对交通预测，构建**统一、全面、可拓展**的全流程**算法库和数据集**



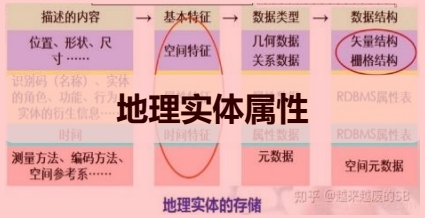


开源链接：https://www.github.com/LibCity

项目主页：https://libcity.ai

LibCity的核心功能

统一的数据输入



5类原子文件
.geo/.usr/.rel/.dyna/.ext

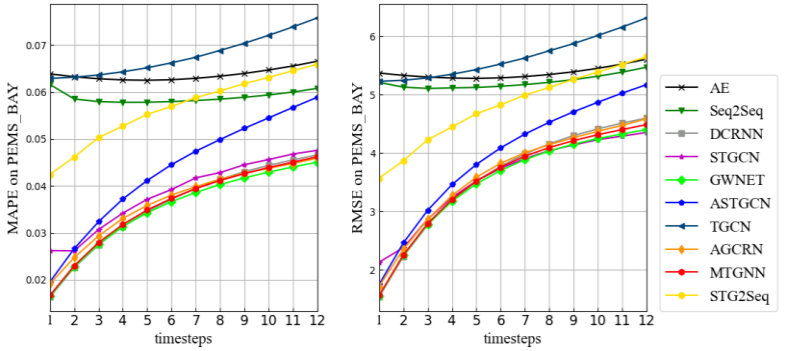
统一的模型接口

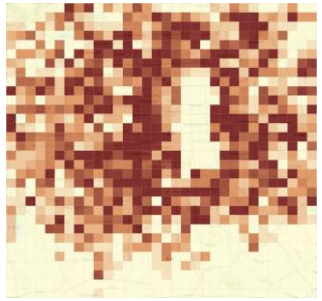
```
<<interface>>
AbstractModel

__init__(self, config, data_feature): void
predict(self, batch): torch.tensor
calculate_loss(self, batch): torch.tensor
```

分类	模型
早期神经网络模型	AutoEncoder
基于 RNN 的模型	FC-RNN/LSTM/GRU、Seq2Seq
基于 CNN 的模型	STResNet
混合模型（RNN+CNN）	ACFM、DMVST-Net
基于 GCN 的模型	STG2Seq、STSGCN、GMAN
混合模型（GCN+RNN）	DCRNN、TGCN、TGC-LSTM、ToGCN、AGCRN
混合模型（GCN+CNN）	STGCN、ASTGCN、GWNET、STAG-GCN、MTGNN、HGCN
涉及注意力机制的模型	ACFM、ASTGCN、STG2Seq、STAG-GCN、GMAN、HGCN

统一的评测标准





truth

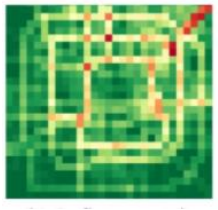
pred

城市时空大数据的特性

特性一：时空动态性

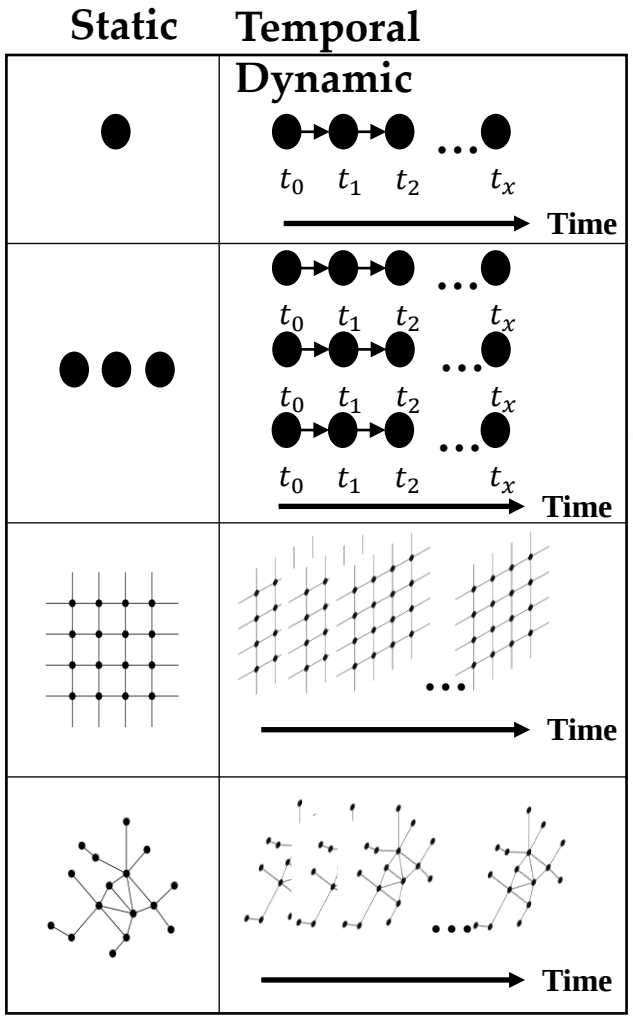
POI

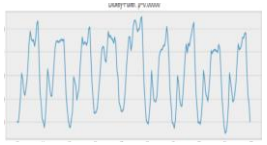
Vehicles



Raster

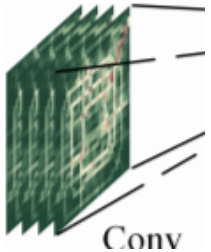
Net





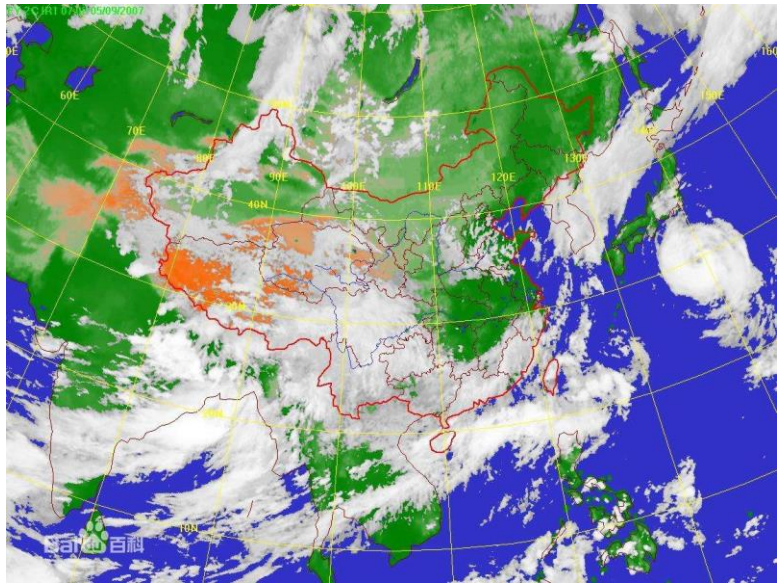
Time Series

Trajectories



Conv

Traffic



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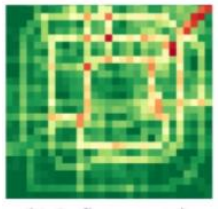
城市时空大数据的特性

特性一：时空动态性

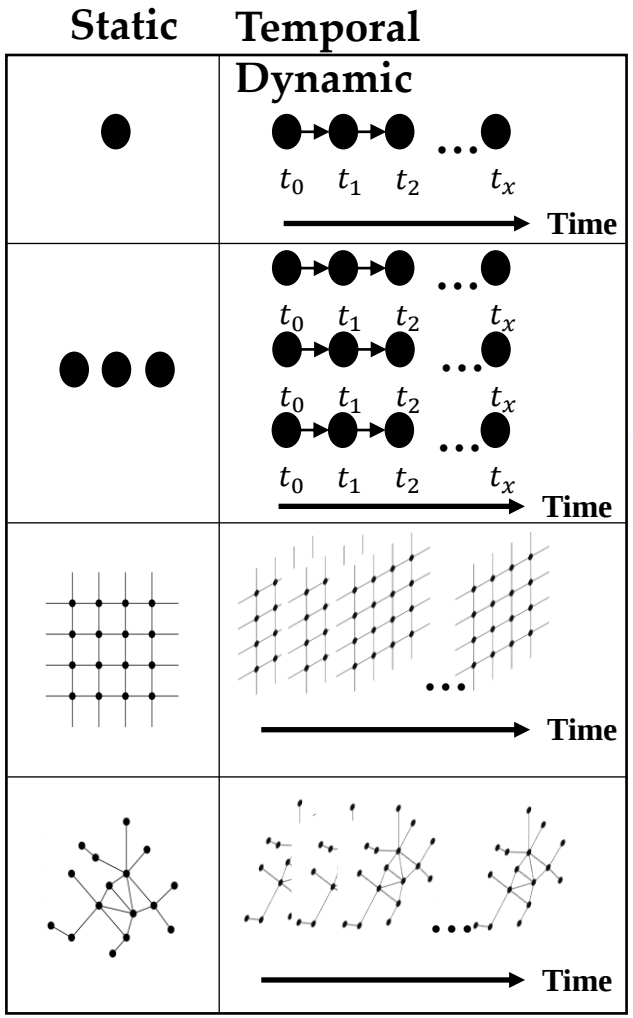
POI

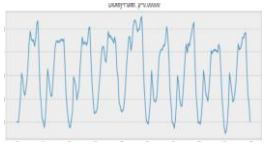
Vehicles



Raster

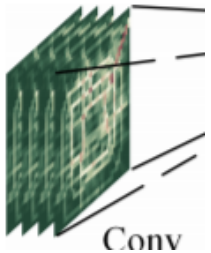
Net





Time Series

Trajectories



Conv

Traffic

特性二：社会感知性

	城市社会感知数据	一般社会感知数据
个体属性	工作地、居住地	性别、年龄
个体行为	出行轨迹	微博留言
个体偏好	POI偏好(餐馆)	社交好友
群体属性	居民区消费	吃瓜群众
群体行为	交通事故	谣言传播
群体偏好	用地性质	热门话题

建立标准的数据输入格式

- 为了统一表示不同种类的交通数据，LibCity定义了五种**原子文件**，即交通数据中的五种**最小信息单元**

文件名	信息	含义
xxx.geo	**地理实体**信息	描述地理空间中点、线、面三类实体的属性信息，如 POI、路段、区域等。
xxx.usr	**用户实体**信息	描述参与交通的人的属性信息，如年龄、性别等。
xxx.rel	**关系实体**信息	描述实体间的关系，如路段间的邻接关系等。
xxx.dyna	**交通状态**信息	描述交通系统在各实体上的状态，如各路口的速度、各路段的流量等。
xxx.ext	**额外辅助**信息	描述有助于交通预测的信息，如天气、温度等。

建立标准的数据输入格式

.geo文件



点　　线　　面

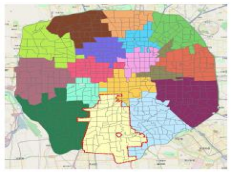
<ID, 类型，坐标，属性>

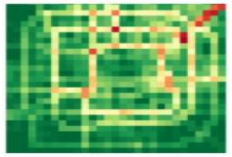
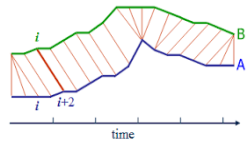
.usr文件




<ID, 用户属性>

.rel 文件

<ID, 源ID，目标ID，关系属性>

.dyna 文件

群体交通动态

人流、路况、出发/到达数量等

个体交通动态

个体出行轨迹

个体OD对等

关系的动态

连接关系的变化

OD人流的变化

.ext 文件

描述有助于交通预测的信息，如天气、温度等。

建立标准的数据输入格式

- 为了统一表示不同种类的交通数据，LibCity定义了五种**原子文件**，即交通数据中的五种**最小信息单元**

文件名	信息
xxx.geo	地理实体信息
xxx.usr	用户实体信息
xxx.rel	实体关系信息
xxx.dyna	交通状态信息
xxx.ext	额外辅助信息

原子文件格式定义

geo_id	type	coordinates
773869	Point	[-118.32,34.15]
767541	Point	[-118.24,34.12]
...	...	...
769373	Point	[-118.32,34.10]

METR-LA.geo

rel_id	type	origin_id	destination_id	cost
0	geo	716328	716328	0.0
1	geo	716328	716331	4123.8
...	...	...	...	...
11752	geo	774207	774207	0.0

METR-LA.rel

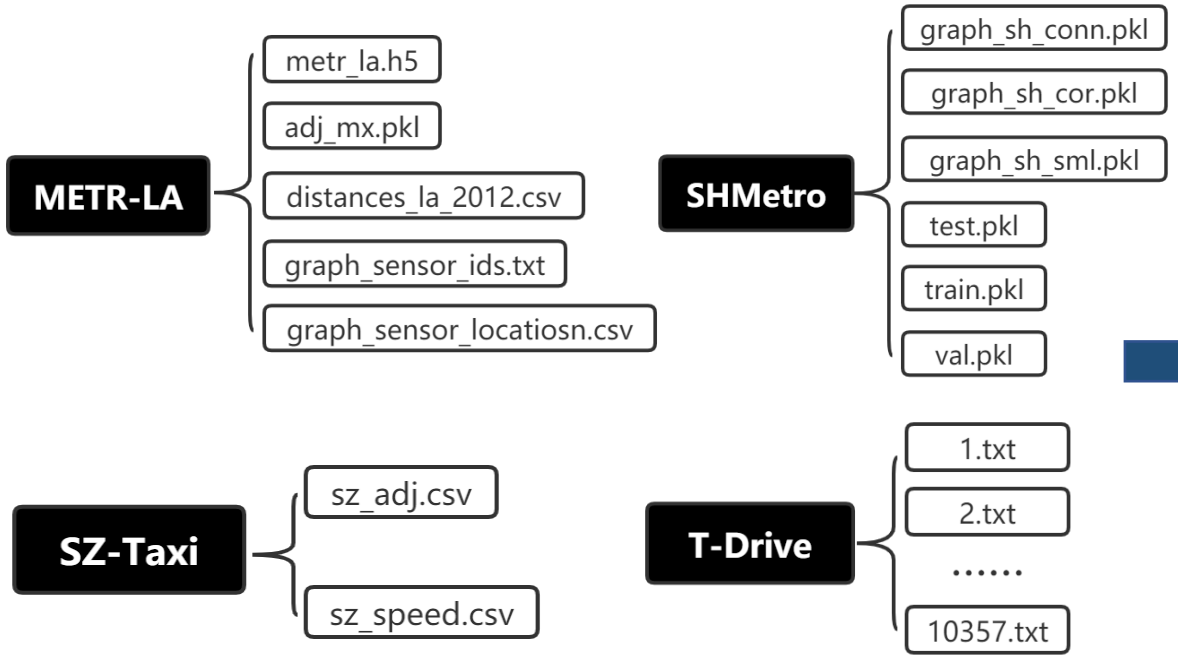
dyna_id	type	time	entity_id	traffic_speed
0	state	2012-03-01T00:00:00Z	773869	64.375
1	state	2012-03-01T00:05:00Z	773869	62.667
...	...	...	...	...
7094303	state	2012-06-27T23:55:00Z	769373	61.778

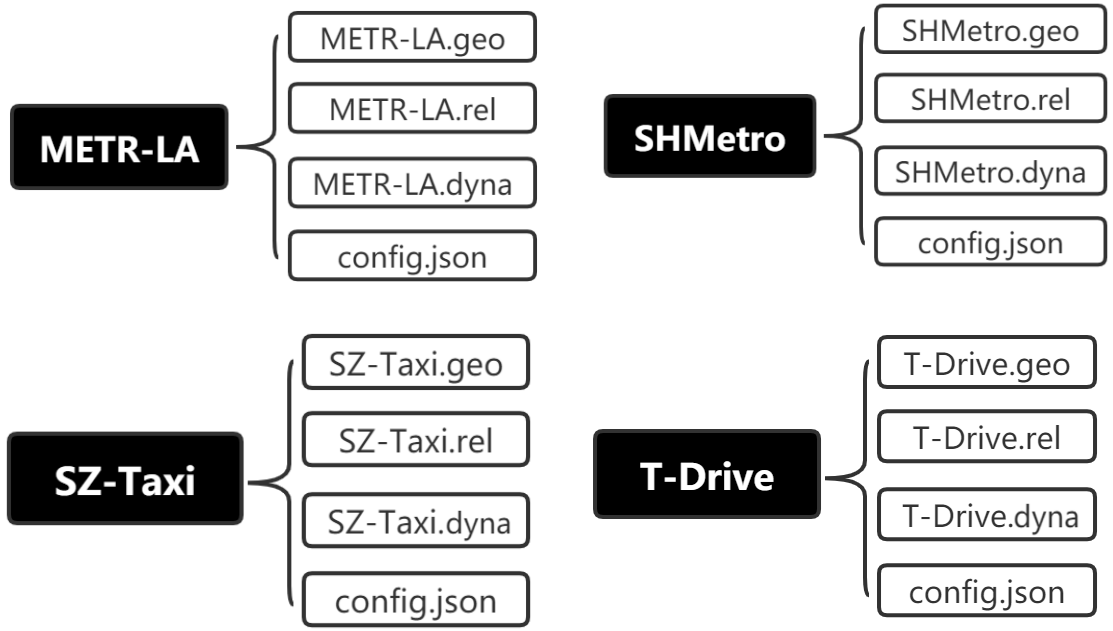
METR-LA.dyna

METR-LA数据集示例

建立标准的数据输入格式

- LibCity已经将32个开源数据集转换为标准的**原子格式数据集**





时空数据集
存储格式不一致

五类标准化
原子文件

建立标准的数据输入格式

- LibCity已经将32个开源数据集转换为标准的原子格式数据集
- 分布于 11 个国家的 22 座城市，覆盖了LibCity中 79% 的模型
- 开源原子数据转换脚本，供用户在转换自有数据集时进行参考

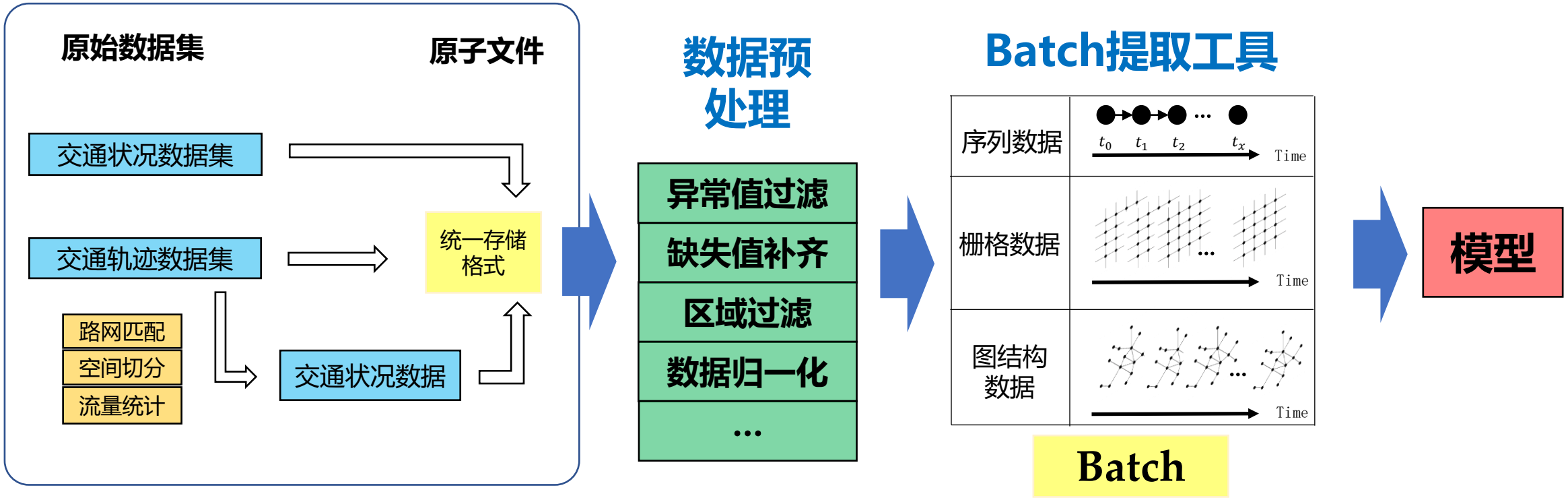
数据集空间分布图

DATASET	#GEO	#REL	#USR	#DYNA	PLACE	DURATION	INTERVAL
METR-LA[19]	207	11,753		7,094,304	Los Angeles, USA	Mar. 1, 2012 - Jun. 27, 2012	5min
Los-loop[43]	207	42,849		7,094,304	Los Angeles, USA	Mar. 1, 2012 - Jun. 27, 2012	5min
SZ-Taxi[43]	156	24,336		464,256	Shenzhen, China	Jan. 1, 2015 - Jan. 31, 2015	15min
Loop Seattle[8, 9]	323	104,329		33,953,760	Greater Seattle Area, USA	over the entirely of 2015	5min
Q-Traffic[21]	45,148	63,422		264,386,688	Beijing, China	Apr. 1, 2017 - May 31, 2017	15min
PeMSD3[31]	358	547		9,382,464	California, USA	Sept. 1, 2018 - Nov. 30, 2018	5min
PeMSD4[13]	307	340		5,216,544	San Francisco Bay Area, USA	Jan. 1, 2018 - Feb. 28, 2018	5min
PEMSD7[31]	883	866		24,921,792	California, USA	Jul. 1, 2016 - Aug. 31, 2016	5min
PEMSD8[13]	170	277		3,035,520	San Bernardino Area, USA	Jul. 1, 2016 - Aug. 31, 2016	5min
PEMSD7(M)[38]	228	51,984		2,889,216	California, USA	weekdays of May and June, 2012	5min
PEMS-BA[19]	325	8,358		16,937,700	San Francisco Bay Area, USA	Jan. 1, 2017 - Jun. 30, 2017	5min
Beijing subway[41]	276	76,176		248,400	Beijing, China	Feb. 29, 2016 - Apr. 3, 2016	30min
M_dense[11]	30			525,600	Madrid, Spain	Jan. 1, 2018 - Dec. 21, 2019	60min
Rotterdam[14]	208			4,813,536	Rotterdam, Holland	135 days of 2018	2min

数据集统计信息表

建立标准的数据输入格式

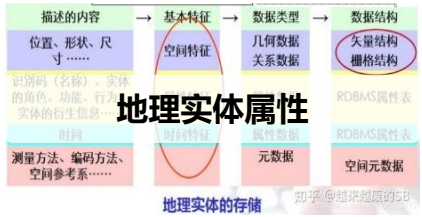
- 基于原子文件，LibCity进一步构建了**数据预处理**和**Batch提取工具**，形成统一的数据处理流程



将原始数据转换为标准化的模型输入

LibCity的核心功能

统一的数据输入



地理实体属性

交通用户

实体关系

交通状态

外部信息

5类原子文件
.geo/.usr/.rel/.dyna/.ext

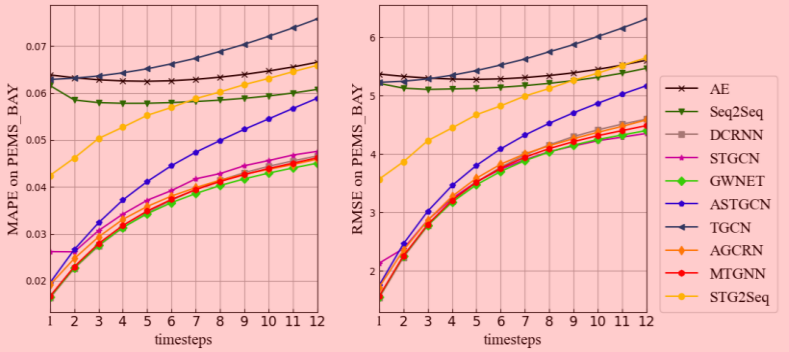
统一的模型接口

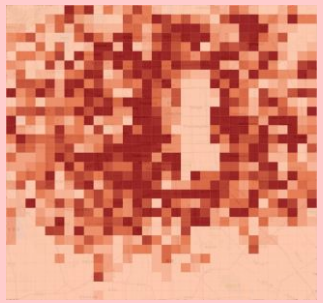
```
<<interface>>
AbstractModel

__init__(self, config, data_feature): void
predict(self, batch): torch.tensor
calculate_loss(self, batch): torch.tensor
```

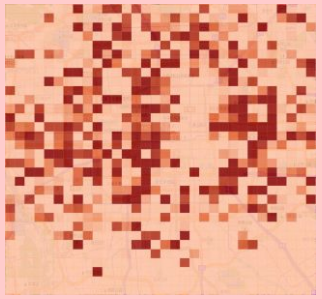
分类	模型
早期神经网络模型	AutoEncoder
基于 RNN 的模型	FC-RNN/LSTM/GRU、Seq2Seq
基于 CNN 的模型	STResNet
混合模型（RNN+CNN）	ACFM、DMVST-Net
基于 GCN 的模型	STG2Seq、STSGCN、GMAN
混合模型（GCN+RNN）	DCRNN、TGCN、TGC-LSTM、ToGCN、AGCRN
混合模型（GCN+CNN）	STGCN、ASTGCN、GWNET、STAG-GCN、MTGNN、HGCN
涉及注意力机制的模型	ACFM、ASTGCN、STG2Seq、STAG-GCN、GMAN、HGCN

统一的评测标准





truth

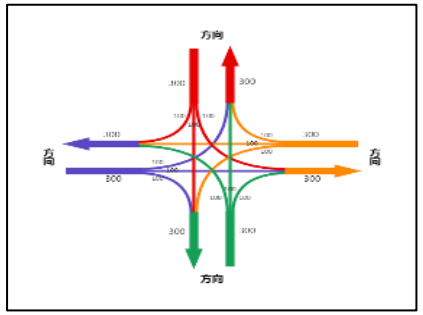


pred

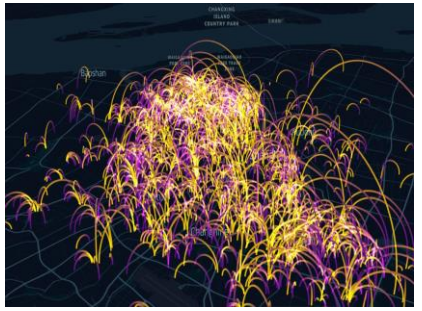
任务导向的测评标准：9类交通预测相关任务

- **交通速度预测（Traffic Speed Prediction）**
  - 预测道路上车辆的平均速度
- **交通流量预测（Traffic Flow Prediction）**
  - 预测流入或流出某道路或区域的车辆数量
- **乘车需求预测（On-demand Service Prediction）**
  - 预测某区域的乘车（出租车、共享单车等）需求
- **OD矩阵预测（Origin-destination Matrix Prediction）**
  - 预测区域之间或者道路之间的车流量或乘车需求
- **交通事故预测（Traffic Accidents Prediction）**
  - 预测道路上出现交通事故的数量或风险

交通速度预测



交通流量预测



OD流量预测

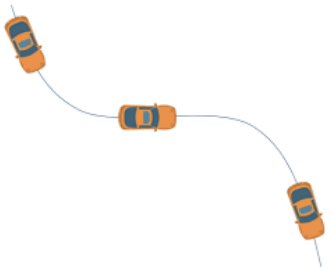
交通需求预测

交通事故预测

任务导向的测评标准：9类交通预测相关任务

➢ 未来位置预测（Future Location Prediction）

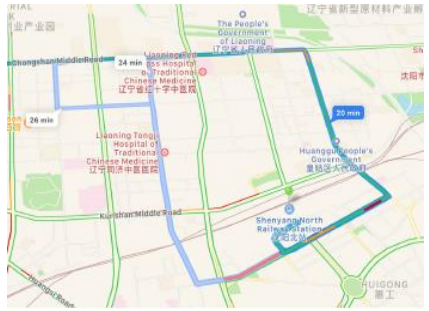
- 预测行人下一步前往的位置，包含进行POI推荐



轨迹下一跳预测

➢到达时间预测（Estimated Time of Arrival）

- 预测两地之间的到达时间

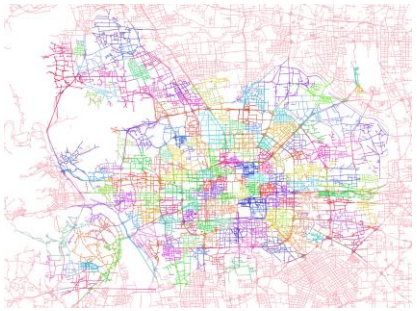


到达时间预测

➢ 路网匹配（Map Matching）

- 匹配GPS轨迹点对应的路段以用于下游任务

路网匹配



路网表征学习

➢ 路网表征学习（Road Network Representation Learning）

- 学习路网结构的低维嵌入表示以用于下游任务

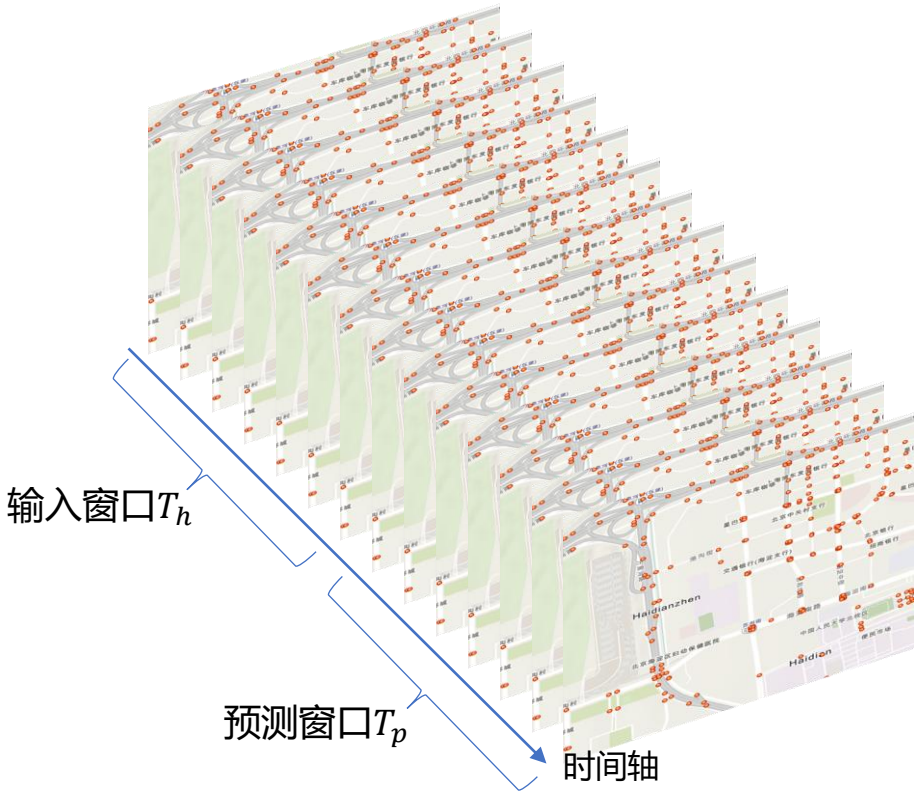
任务导向的测评标准：两大类评估指标

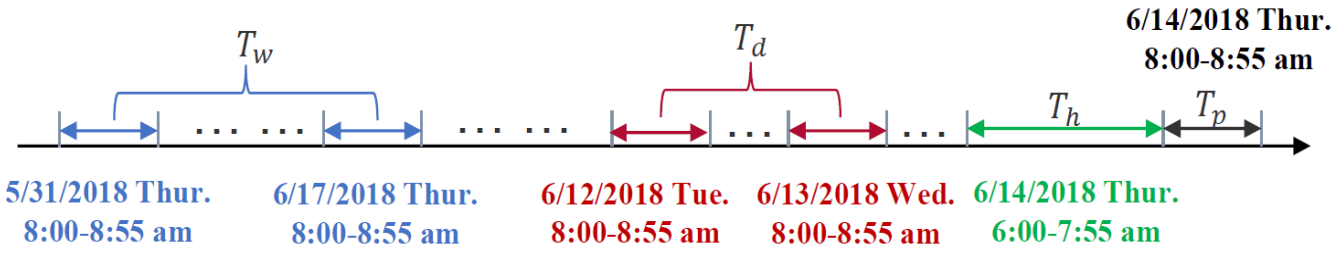
- Value-based 指标：用于回归任务的评估，如交通速度预测等。
- Rank-based 指标：用于分类任务的评估，如轨迹位置预测等。

Value-based 指标		Rank-based 指标	
平均绝对误差	MAE	准确率	Precision@K
均方误差	MSE	召回率	Recall@K
均方根误差	RMSE	F1分数	F1-score@K
平均绝对百分比误差	MAPE	平均排名倒数	MRR@K
决定系数	R^2	平均准确率	MAP@K
可释方差值	EVAR	归一化折损累积增益	NDCG@K
		道路错误匹配指数	RMF
		路网数量匹配率	AN
		路网长度匹配率	AL

任务导向的测评标准：实验环境设置接口

- **输入窗口**：决定模型所基于的历史交通状态序列的长度
- **预测窗口**：决定模型所预测的未来交通状态序列的长度
- **数据集划分**：决定训练集、测试集、验证集的比例等

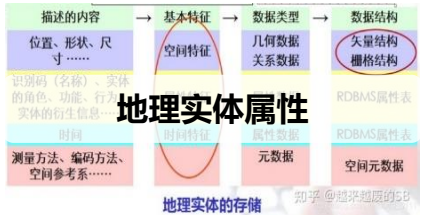




- 左图使用输入窗口T_h的数据预测未来T_p
- 右图考虑时间的周期性，引入一天为周期的数据T_d和以星期为周期的数据T_w

LibCity的核心功能

统一的数据输入



5类原子文件
.geo/.usr/.rel/.dyna/.ext

统一的模型接口

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分类	模型
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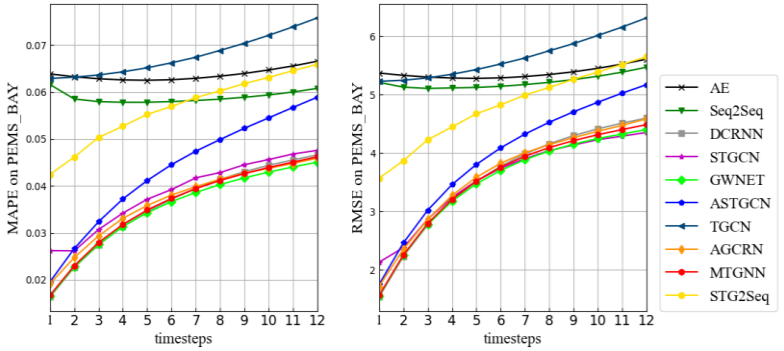
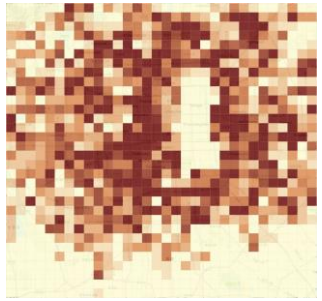
涉及注意力机制的模型	ACFM、ASTGCN、STG2Seq、STAG-GCN、GMAN、HGCN

统一的评测标准





truth

pred

建立开源模型库：充分的模型调研

- 对2016-2020期间在11个会议和期刊上发表的研究论文及综述进行调研
- 共计365篇论文，来自SIGSPATIAL, KDD, ICDM, AAAI, IJCAI, CIKM, WWW, NIPS, ICLR, IEEE TKDE, IEEE TITS等

AAAI

2021

1. **Hierarchical Graph Convolution Networks for Traffic Forecasting.** *Kan Guo, Yongli Hu, Yanfeng Sun, Sean Qian, Junbin Gao, Baocai Yin.* AAAI 2021. link
2. **Traffic Flow Prediction with Vehicle Trajectories.** *Mingqian Li, Panrong Tong, Mo Li, Zhongming Jin, Jianqiang Huang, Xian-Sheng Hua.* AAAI 2021. link
3. **Physics-Informed Deep Learning for Traffic State Estimation: A Hybrid Paradigm Informed By Second-Order Traffic Models.** *Rongye Shi, Zhaobin Mo, Xuan Di.* AAAI 2021. link
4. **GSNet: Learning Spatial-Temporal Correlations from Geographical and Semantic Aspects for Traffic Accident Risk Forecasting.** *Beibei Wang, Youfang Lin, Shengnan Guo, Huaiyu Wan.* AAAI 2021. link
5. **Spatial-Temporal Fusion Graph Neural Networks for Traffic Flow Forecasting.** *Mengzhang Li, Zhanxing Zhu.* AAAI 2021. link
6. **FC-GAGA: Fully Connected Gated Graph Architecture for Spatio-Temporal Traffic Forecasting.** *Boris N. Oreshkin, Arezou Amini, Lucy Coyle, Mark Coates.* AAAI 2021. link
7. **Traffic Flow Forecasting with Spatial-Temporal Graph Diffusion Network.** *Xiyue Zhang, Chao Huang, Yong Xu, Lianghao Xia, Peng Dai, Liefeng Bo, Junbo Zhang, Yu Zheng.* AAAI 2021. link
8. **Pre-Training Context and Time Aware Location Embeddings from Spatial-Temporal Trajectories for User Next Location Prediction.** *Yan Lin, Huaiyu Wan, Shengnan Guo, Youfang Lin.* AAAI 2021. link
9. **Disentangled Multi-Relational Graph Convolutional Network for Pedestrian Trajectory Prediction.** *Inhwan Bae, Hae-Gon Jeon.* AAAI 2021. link
10. **Coupled Layer-Wise Graph Convolution for Transportation Demand Prediction.** *Junchen Ye, Leilei Sun, Bowen Du, Yanjie Fu, Hui Xiong.* AAAI 2021. link
11. **CARPe Posterum: A Convolutional Approach for Real-Time Pedestrian Path Prediction.** *Matias Mendieta, Hamed Tabkhi.* AAAI 2021. link
12. **Temporal Pyramid Network for Pedestrian Trajectory Prediction with Multi-Supervision.** *Rongqin Liang, Yuanman Li, Xia Li, Yi Tang, Jiantao Zhou, Wenbin Zou.* AAAI 2021. link

KDD

2020

1. **Curb-GAN: Conditional Urban Traffic Estimation through Spatio-Temporal Generative Adversarial Networks.** *Yingxue Zhang, Yanhua Li, Xun Zhou, Xiangnan Kong, Jun Luo.* KDD 2020. link
2. **City Metro Network Expansion with Reinforcement Learning.** *Yu Wei, Minjia Mao, Xi Zhao, Jianhua Zou, Ping An.* KDD 2020. link
3. **Delivery Scope: A New Way of Restaurant Retrieval for On-demand Food Delivery Service.** *Xuetao Ding, Runfeng Zhang, Zhen Mao, Ke Xing, Fangxiao Du, Xingyu Liu, Guoxing Wei, Feifan Yin, Renqing He, Zhizhao Sun.* KDD 2020. link
4. **Dynamic Heterogeneous Graph Neural Network for Real-time Event Prediction.** *Wenjuan Luo, Han Zhang, Xiaodi Yang, Lin Bo, Xiaoqing Yang, Zang Li, Xiaohu Qie, Jieping Ye.* KDD 2020. link
5. **Attention based Multi-Modal New Product Sales Time-series Forecasting.** *Vijay Ekambaram, Kushagra Manglik, Sumanta Mukherjee, Surya Shravan Kumar Sajja, Satyam Dwivedi, Vikas Raykar.* KDD 2020. link
6. **Connecting the Dots: Multivariate Time Series Forecasting with Graph Neural Networks.** *Zonghan Wu, Shirui Pan, Guodong Long, Jing Jiang, Xiaojun Chang, Chengqi Zhang.* KDD 2020. link
7. **Competitive Analysis for Points of Interest.** *Shuangli Li, Jingbo Zhou, Tong Xu, Hao Liu, Xinjiang Lu, Hui Xiong.* KDD 2020. link
8. **Calendar Graph Neural Networks for Modeling Time Structures in Spatiotemporal User Behaviors.** *Daheng Wang, Meng Jiang, Munira Syed, Oliver Conway, Vishal Juneja, Sriram Subramanian, Nitesh V. Chawla.* KDD 2020. link
9. **Fast RobustSTL: Efficient and Robust Seasonal-Trend Decomposition for Time Series with Complex Patterns.** *Qingsong Wen, Zhe Zhang, Yan Li, Liang Sun.* KDD 2020. link
10. **Multi-Source Deep Domain Adaptation with Weak Supervision for Time-Series Sensor Data.** *Garrett Wilson, Janardhan Rao Doppa, Diane J. Cook.* KDD 2020. link
11. **Personalized Prefix Embedding for POI Auto-Completion in the Search Engine of Baidu Maps.** *Jizhou Huang, Haifeng Wang, Miao Fan, An Zhuo, Ying Li.* KDD 2020. link

完整论文列表: https://github.com/LibCity/Bigscity-LibCity-PaperList

建立开源模型库：分类复现主流模型

选择了其中56个代表性模型，进行标准化复现，形成开源算法库

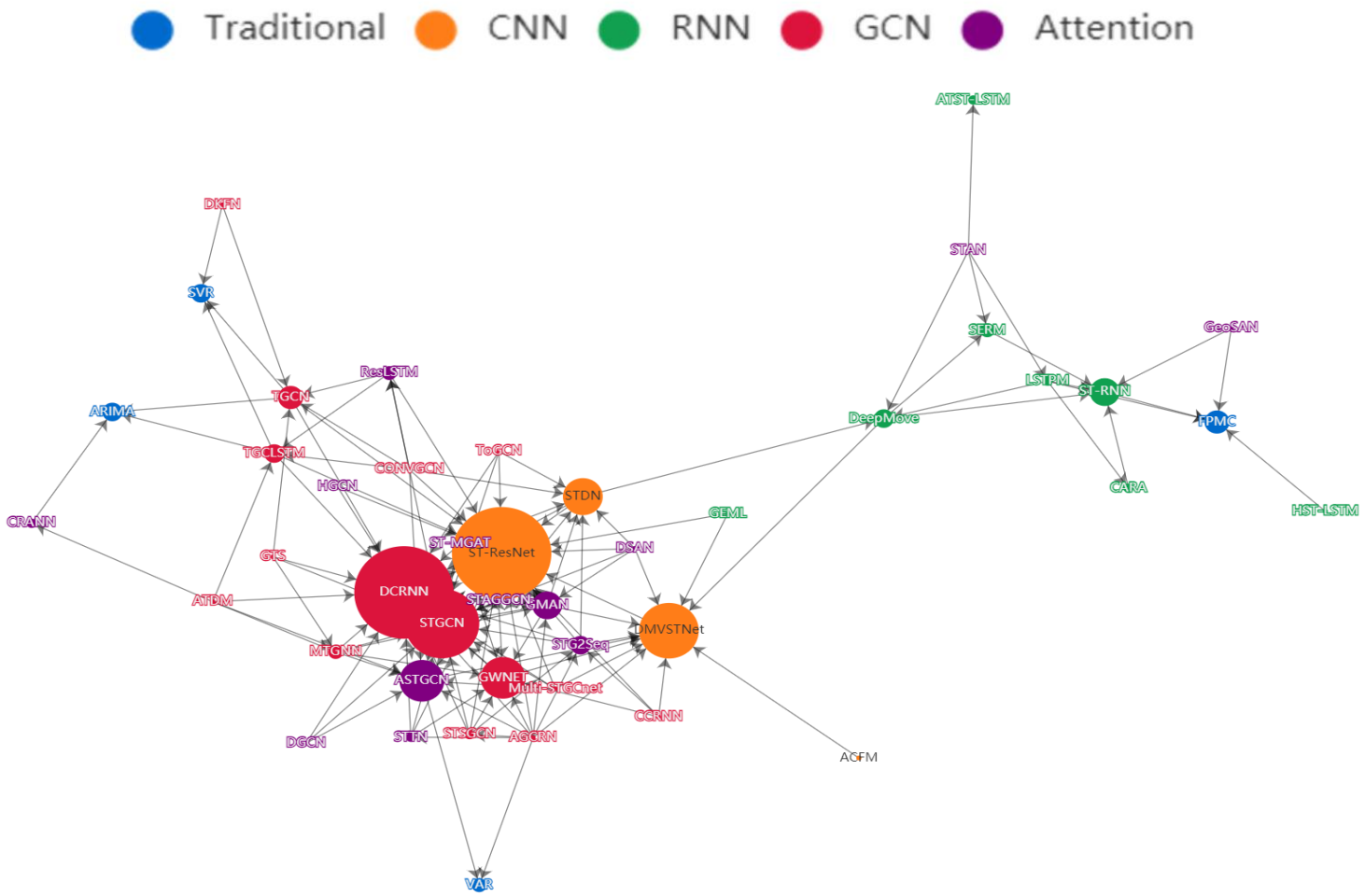
Table 1: The implemented models in LibCity.

Task	Traditional	CNN-based	RNN-based	GCN-based	Attention-based
Traffic flow prediction	AutoEncoder	ST-ResNet, ACFM, STDN	FC-RNN, Seq2Seq	AGCRN, CONVGCN, STSGCN, ToGCN, Multi-STGCnet	ASTGCN, ResLSTM, CRANN, DGCN, DSAN
Traffic speed prediction	AutoEncoder	—	FC-RNN, Seq2Seq	DCRNN, STGCN, GWNET, MTGNN, TGCN, TGCLSTM, ATDM, GTS	GMAN, STAGGCN, HGCN, ST-MGAT
On-Demand service prediction	AutoEncoder	DMVSTNet	FC-RNN, Seq2Seq	CCRNN	STG2Seq
Trajectory next-location prediction	FPMC	—	RNN, ST-RNN, ATST-LSTM, SERM, DeepMove, HST-LSTM, LSTPM, CARA	—	GeoSAN, STAN

建立开源模型库：分类复现主流模型

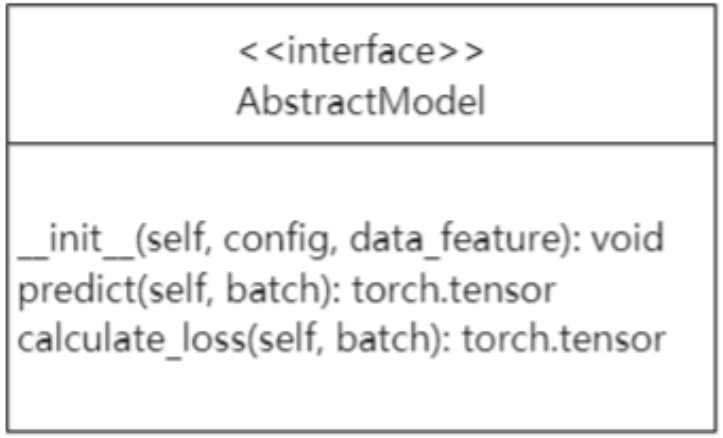
选择了其中56个代表性模型，进行标准化复现，形成开源算法库

模型引用关系图



建立开源模型库：实现统一的模型接口

- **LibCity 为交通预测模型定义了统一的实现接口**
  - *Batch* 结构：面向模型的统一输入数据数据结构
  - *predict()* 接口： 计算模型的预测结果
  - *calculate_loss()* 接口：计算模型训练时的损失Loss值
  - 统一模型的输出接口
  - 简化新模型的实现流程

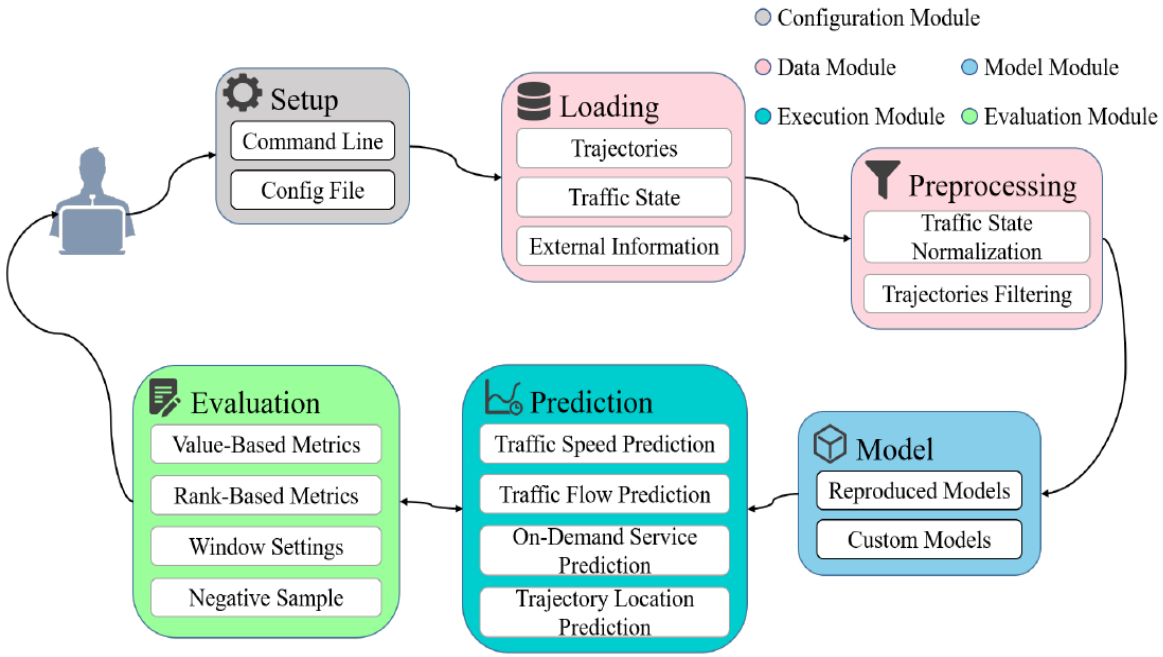


建立开源模型库：支持多样的训练策略

- LibCity 支持多种类型的深度学习模型训练策略
  - **优化器（Optimizer）选择：** SGD / RMSProp / Adam / AdaGrad / SparseAdam
  - **学习率（Learning Rate）调整策略选择：** StepLR / MultiStepLR / ExponentialLR / LambdaLR / ReduceLROnPlateau…
  - **损失函数（Loss Function）选择：** L1失损、L2失损、Huber失损、Log-Cosh失损、Quantile失损
  - **早停机制（Early Stopping）：** 处理过拟合问题
  - **梯度裁剪（Gradient Clipping）：** 处理梯度爆炸、梯度消失问题

建立开源模型库：建立任务流水线机制

- LibCity 将交通预测任务解构为一条模块化的流水线
  - ➢**实验参数配置**
    - 用户命令行设置参数，用户自定义参数配置文件
  - ➢**加载数据集**
    - 轨迹数据, 交通状态数据, 额外信息…
  - ➢**数据预处理**
    - 数据归一化, 数据过滤…
    - 特征提取，生成模型输入
  - ➢**模型选择与训练**
    - 交通速度、交通流量…
  - ➢**模型评估**
    - 根据任务需求建立评估指标和评估策略…



任务流程图

LibCity的应用工具

实验辅助工具

(1) 模型评估实验工具

- 用户仅需在命令行指定相应实验参数，即可完成模型的训练与评估。

```
2021-10-29 17:16:57,288 - INFO - Epoch [2/5] train_loss: 3.5790, val_loss: 3.7031, lr: 0.010000, 9.64s
2021-10-29 17:17:07,440 - INFO - epoch complete!
2021-10-29 17:17:07,440 - INFO - evaluating now!
2021-10-29 17:17:08,045 - INFO - Epoch [3/5] train_loss: 3.5368, val_loss: 3.7144, lr: 0.010000, 10.76s
2021-10-29 17:17:18,414 - INFO - epoch complete!
2021-10-29 17:17:18,415 - INFO - evaluating now!
2021-10-29 17:17:19,022 - INFO - Epoch [4/5] train_loss: 3.5447, val_loss: 3.6842, lr: 0.001000, 10.98s
2021-10-29 17:17:19,026 - INFO - Saved model at 4
2021-10-29 17:17:19,026 - INFO - Val loss decrease from 3.6924 to 3.6842, saving to ./libcity/cache/model_cache/RNN_METR_LA_epoch4.tar
2021-10-29 17:17:19,026 - INFO - Trained totally 5 epochs, average train time is 9.550s, average eval time is 0.559s
2021-10-29 17:17:19,030 - INFO - Loaded model at 4
2021-10-29 17:17:19,030 - INFO - Saved model at ./libcity/cache/model_cache/GRU_METR_LA.m
2021-10-29 17:17:19,033 - INFO - Start evaluating ...
2021-10-29 17:17:28,326 - INFO - Note that you select the single mode to evaluate!
2021-10-29 17:17:28,331 - INFO - Evaluate result is saved at ./libcity/cache/evaluate_cache/2021_10_29_17_17_28_RNN_METR_LA.csv
2021-10-29 17:17:28,344 - INFO -
        MAE  MAPE        MSE       RMSE  masked_MAE  masked_MAPE  masked_MSE  masked_RMSE        R2      EVAR
1   10.449826   inf  466.570465  21.600243    3.988738     0.112915   57.582115     7.588288  0.096302  0.197061
2   10.666377   inf  491.469971  22.169123    3.969328     0.113097   58.237476     7.631348  0.048101  0.156954
3   10.727654   inf  497.926910  22.314276    3.981739     0.113970   59.052402     7.684556  0.035544  0.146701
4   10.754150   inf  500.389252  22.369383    3.995663     0.114886   59.855732     7.736649  0.030906  0.143221
5   10.784980   inf  502.868225  22.424723    4.015014     0.116045   60.834072     7.799620  0.025981  0.139726
6   10.818571   inf  504.286987  22.456335    4.050239     0.117524   62.002796     7.874186  0.022966  0.137987
7   10.836622   inf  505.842468  22.490942    4.062918     0.118501   62.930138     7.932852  0.020235  0.135974
8   10.859600   inf  507.081238  22.518465    4.086273     0.119740   64.014450     8.000903  0.017810  0.134578
9   10.887882   inf  508.681641  22.553972    4.112003     0.121005   65.151192     8.071629  0.014799  0.132539
10  10.910922   inf  510.099335  22.585379    4.134407     0.122306   66.336853     8.144744  0.012169  0.130929
11  10.945717   inf  512.005493  22.627539    4.166443     0.123989   67.725914     8.229575  0.008522  0.128633
12  10.986176   inf  514.222534  22.676476    4.205863     0.126338   69.575996     8.341223  0.004241  0.126475
```

模型训练Log输出

(2)自动超参搜索工具

- 基于 Ray Tune 第三方库扩展实现。
- 用户仅需在命令行指定需搜索的参数名及其搜索算法与范围。

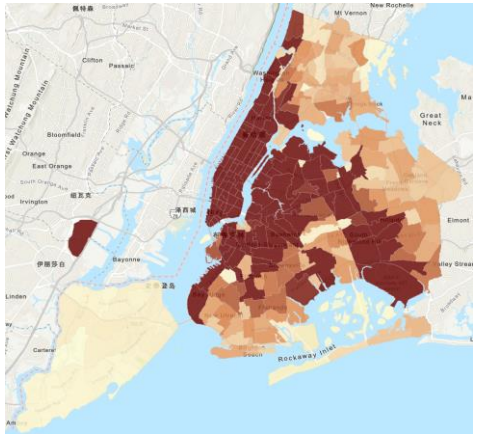
```
== Status ==
Memory usage on this node: 17.1/125.4 GiB
Using FIFO scheduling algorithm.
Resources requested: 0/40 CPUs, 0/4 GPUs, 0.0/71.24 GiB heap, 0.0/23.83 GiB objects (0/1.0 accelerator_type:RTX)
Current best trial: 8e46e_00002 with loss=3.383851404543276 and parameters={'hidden_size': 200, 'max_epoch': 6, 'dropout': 0.19898419823444433, 'learning_rate': 0.005}
Result logdir: /mnt/data/shihonghao/jjw/video/Bigscity-LibTraffic/libtraffic/cache/hyper_tune/inner_2021-07-31_14-00-10
Number of trials: 5/5 (5 TERMINATED)
+-------------------+------------+-------+-----------+-------------+----------------+------------+-------+------------------+---------+
| Trial name        | status     | loc   |   dropout |   hidden_size |   learning_rate |   max_epoch |   iter |   total time (s) |    loss |
|-------------------+------------+-------+-----------+-------------+----------------+------------+-------+------------------+---------|
| inner_8e46e_00000 | TERMINATED |       |  0.485578 |         200 |           0.01 |           2 |      2 |          42.7081 | 3.80721 |
| inner_8e46e_00001 | TERMINATED |       |  0.369783 |          50 |           0.001 |           9 |      9 |         140.862  | 3.6152  |
| inner_8e46e_00002 | TERMINATED |       |  0.198984 |         200 |           0.005 |           6 |      6 |         116.775  | 3.38385 |
| inner_8e46e_00003 | TERMINATED |       |  0.558463 |         500 |           0.005 |           3 |      3 |          56.8903 | 3.52376 |
| inner_8e46e_00004 | TERMINATED |       |  0.58366  |         100 |           0.01  |           2 |      2 |          35.1292 | 3.65274 |
+-------------------+------------+-------+-----------+-------------+----------------+------------+-------+------------------+---------+


2021-07-31 14:02:32,133 INFO tune.py:450 -- Total run time: 145.35 seconds (141.28 seconds for the tuning loop).
INFO - Best trial config: {'hidden_size': 200, 'max_epoch': 6, 'dropout': 0.19898419823444433, 'learning_rate': 0.005}
INFO - Best trial final validation loss: 3.383851404543276
```

自动调参工具Log输出

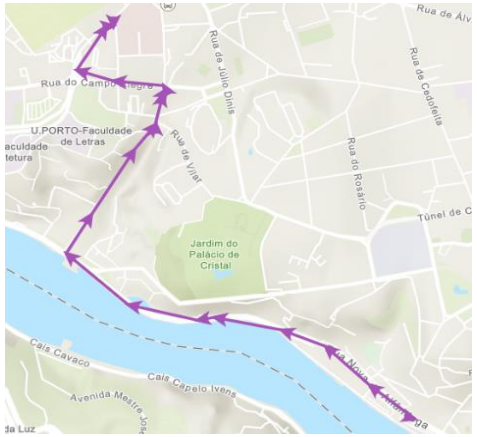
实验辅助工具

(3) 时空数据可视化工具

- 读取数据集原子文件，转为 GeoJSON 格式数据，并在 GIS 上可视化。
- 支持 GIS 点图、线图、区域图。



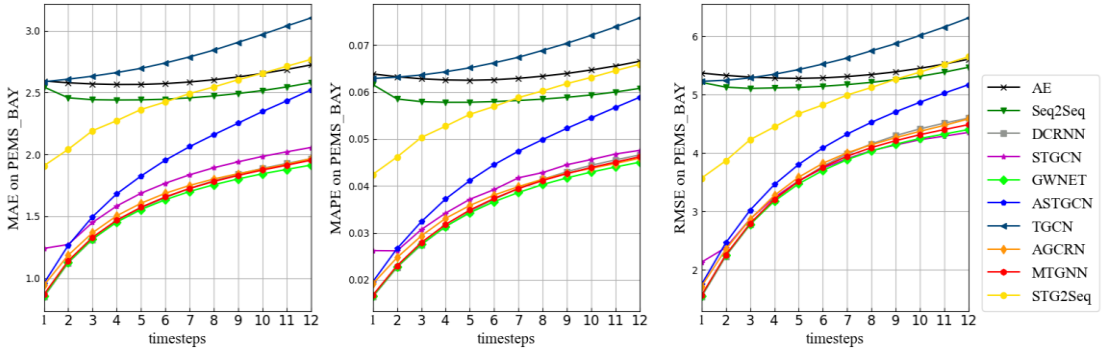
纽约出租车流量数据



葡萄牙单车轨迹

(4) 实验结果可视化工具

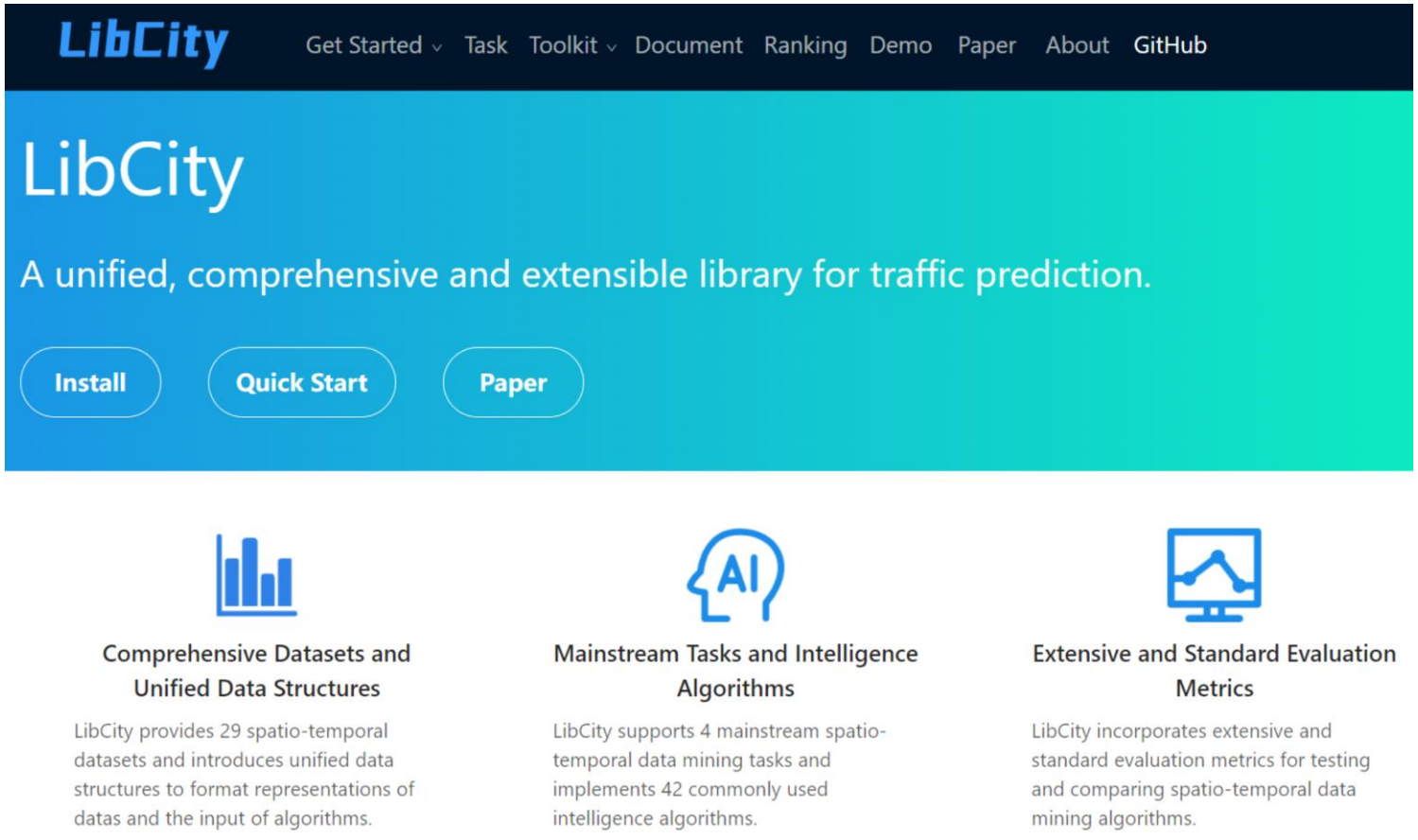
- 基于评估实验评估结果文件，自动绘制实验结果表格与曲线图。



PEMS_BAY数据集模型性能折线图

项目网站建设

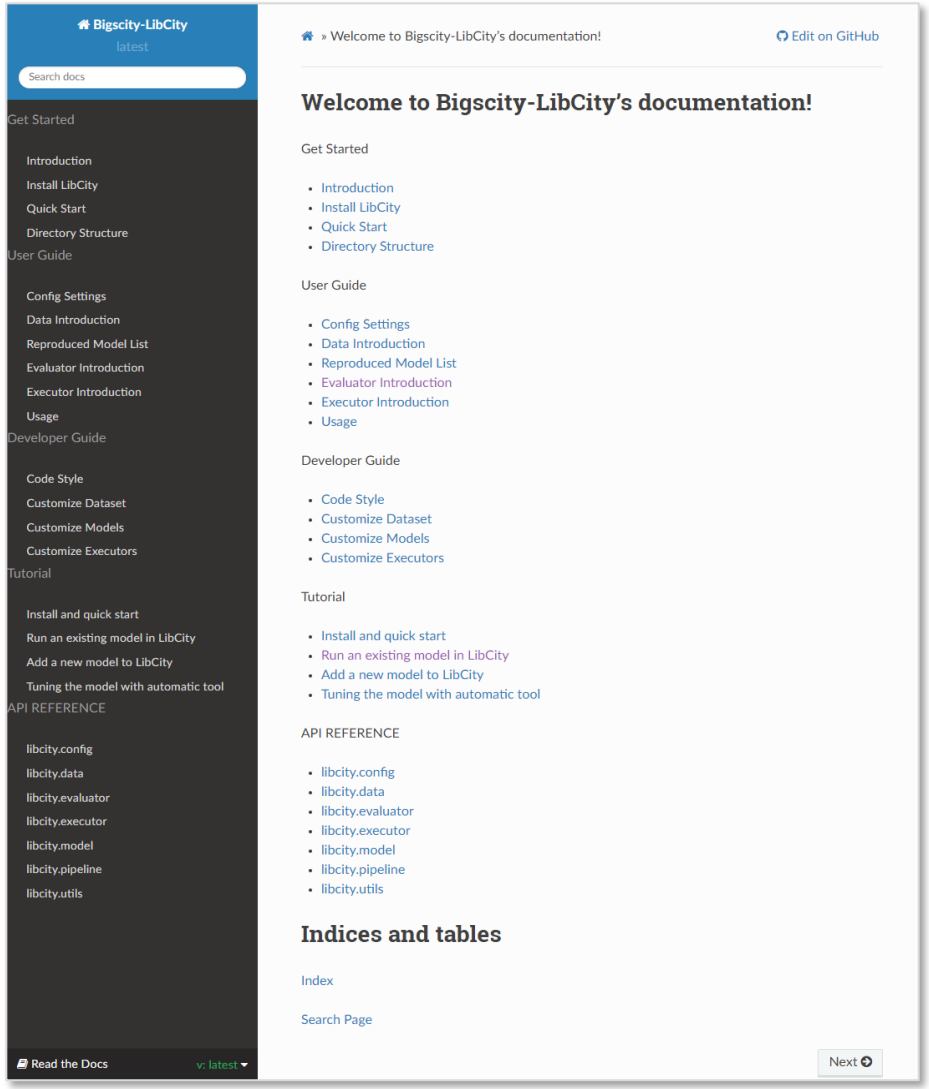
- **项目网站**
  - 安装与环境配置
  - 实验数据
  - 模型列表
  - 评估指标
  - 项目文档
  - 模型排行榜
  - 项目展示视频
  - 项目论文
  - 项目开源地址
  - …



项目网站: https://libcity.ai

项目网站建设

- **项目说明文档（中英文）**
  - 面向全体用户的介绍、安装与配置
  - 面向使用者的使用文档
  - 面向开发者的开发文档
  - 面向初学者的入门教程
  - 项目API接口文档



说明文档: https://bigscity-libcity-docs.readthedocs.io/en/latest/

模型性能排行榜

- 对比不同模型在各数据集上的性能，形成动态排行榜

View MAE @ 12 STEP

模型排行榜——METR_LA数据集

RANK	MODEL	PAPER	YEAR	3 STEP	6 STEP	9 STEP	12 STEP
1	MTGNN	Connecting the Dots: Multivariate Time Series Forecasting with Graph Neural Networks	2020	2.65970	3.03844	3.27913	3.46719
2	STGCN	Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting	2018	2.79312	3.16743	3.38780	3.54005
3	AGCRN	Adaptive Graph Convolutional Recurrent Network for Traffic Forecasting	2018	2.83642	3.20918	3.41369	3.57438
4	GWNET	Graph Wavenet for Deep Spatial-Temporal Graph Modeling	2019	2.80364	3.20603	3.43401	3.58650
5	DCRNN	Diffusion convolutional recurrent neural network: Data-driven traffic forecasting	2018	2.70890	3.12476	3.38887	3.59865
6	GMAN	GMAN: A Graph Multi-Attention Network for Traffic Prediction	2020	2.97876	3.33146	3.56791	3.76438
7	STG2Seq	STG2Seq: Spatial-temporal Graph to Sequence Model for Multi-step Passenger Demand Forecasting	2019	3.20701	3.51383	3.75212	3.98922
8	GRU	Using LSTM and GRU neural network methods for traffic flow prediction	2016	3.87858	3.97065	4.03415	4.10105
9	Seq2Seq	Sequence to Sequence Learning with Neural Networks	2014	3.72423	3.84346	3.96849	4.10702
10	AE	Generalized Autoencoder: A Neural Network Framework for Dimensionality Reduction	2014	4.29603	4.32998	4.38502	4.49087
11	ASTGCN	Attention based spatial-temporal graph convolutional networks for traffic flow forecasting	2019	3.21922	3.84098	4.26184	4.64147
12	RNN	Using LSTM and GRU neural network methods for traffic flow prediction	2016	3.38340	3.89137	4.33444	4.75634
13	TGCN	T-gcn: A temporal graph convolutional network for traffic prediction	2020	4.15217	4.31891	4.53214	4.80658

模型性能排行榜

- 对比不同模型在各数据集上的性能，形成动态排行榜

Traffic State Prediction

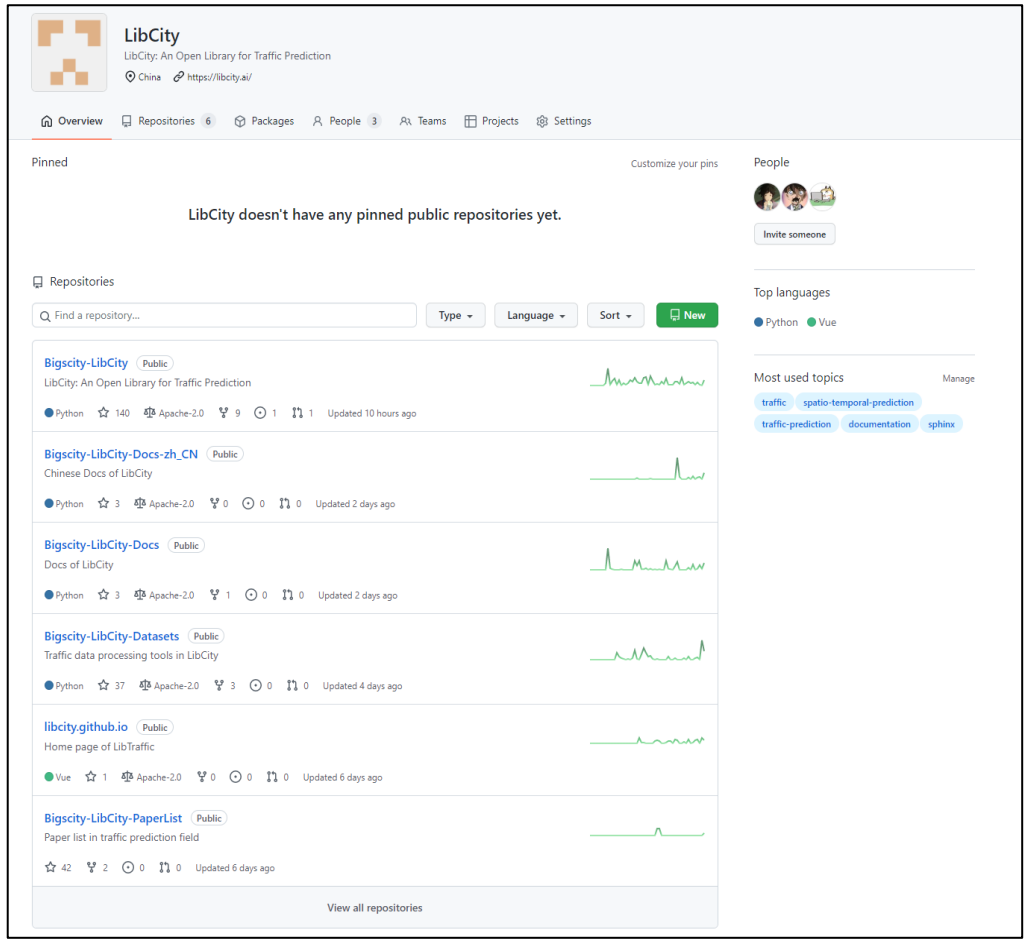
Top模型

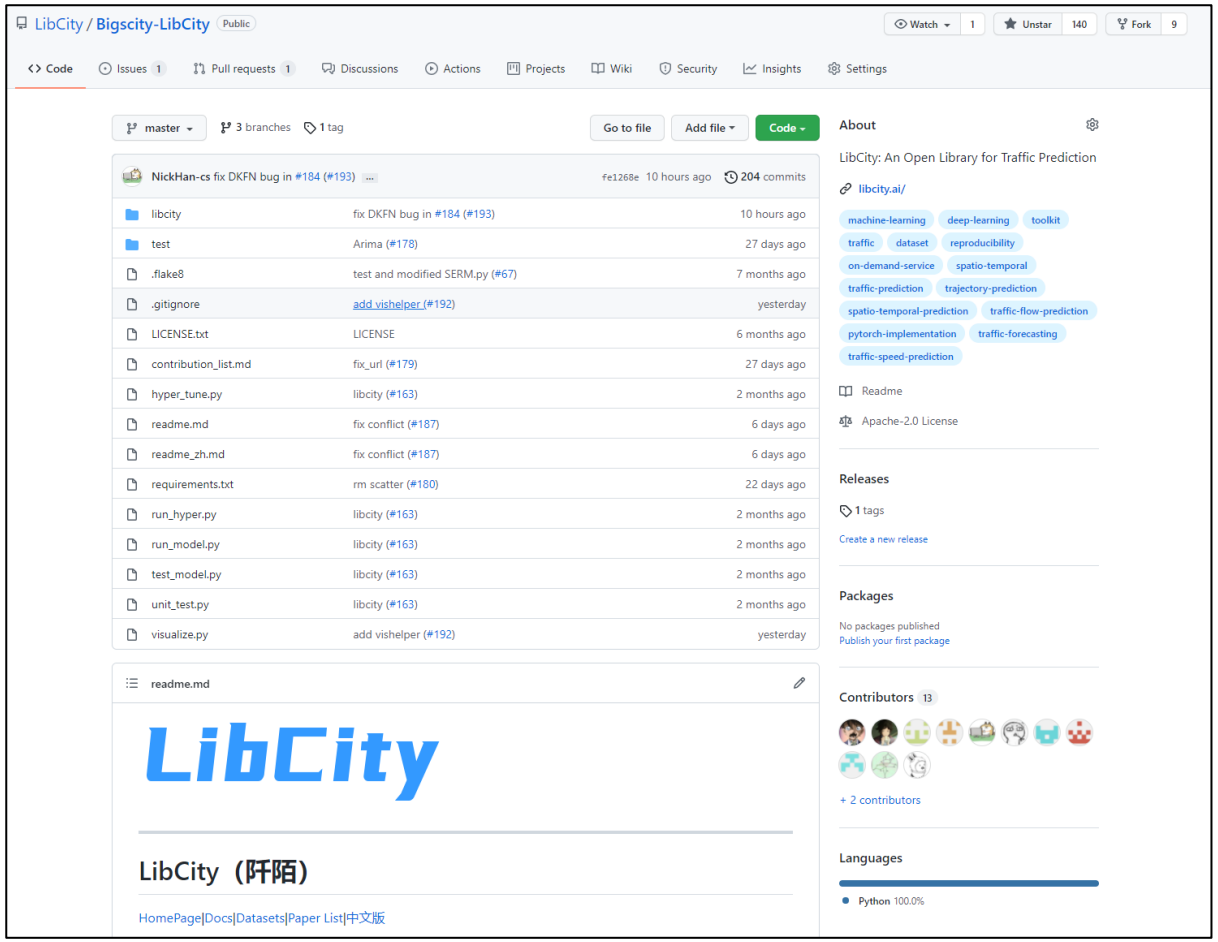
DATASET	BEST METHOD	PAPER	COMAPRE
METR-LA	MTGNN	[KDD2020]Connecting the Dots: Multivariate Time Series Forecasting with Graph Neural Networks	See All
PEMS-BAY	GWNET	[IJCAI2019]Graph Wavenet for Deep Spatial-Temporal Graph Modeling	See All
PEMSD4	GWNET	[IJCAI2019]Graph Wavenet for Deep Spatial-Temporal Graph Modeling	See All
PEMSD8	GWNET	[IJCAI2019]Graph Wavenet for Deep Spatial-Temporal Graph Modeling	See All
T-Drive20150206	MTGNN	[KDD2020]Connecting the Dots: Multivariate Time Series Forecasting with Graph Neural Networks	See All
TAXIBJ2015	AGCRN	[NeurIPS2020]Adaptive Graph Convolutional Recurrent Network for Traffic Forecasting	See All
NYCTAXI202001-202003-3600	DCRNN	[ICLR2018]Diffusion Convolutional Recurrent Neural Network: Data-Driven Traffic Forecasting	See All
NYCBike20140409	MTGNN	[KDD2020]Connecting the Dots: Multivariate Time Series Forecasting with Graph Neural Networks	See All

模型排性能行榜：https://libcity.ai/#/ranking

GitHub开源网站

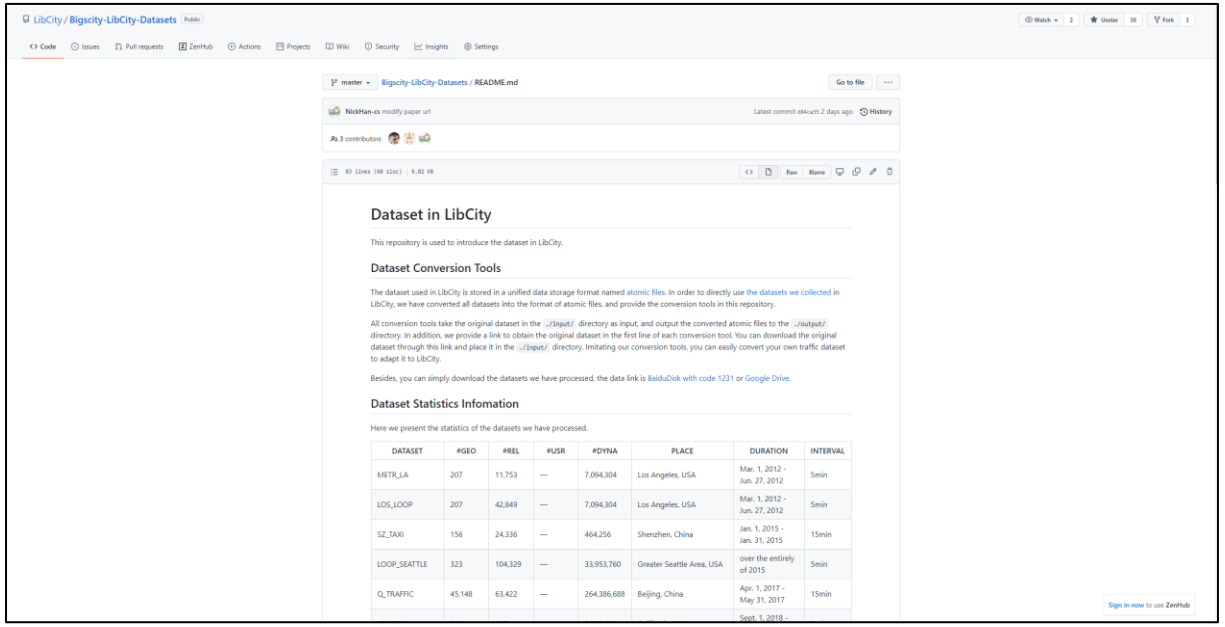
- **项目开源代码主页：** https://github.com/LibCity/Bigscity-LibCity



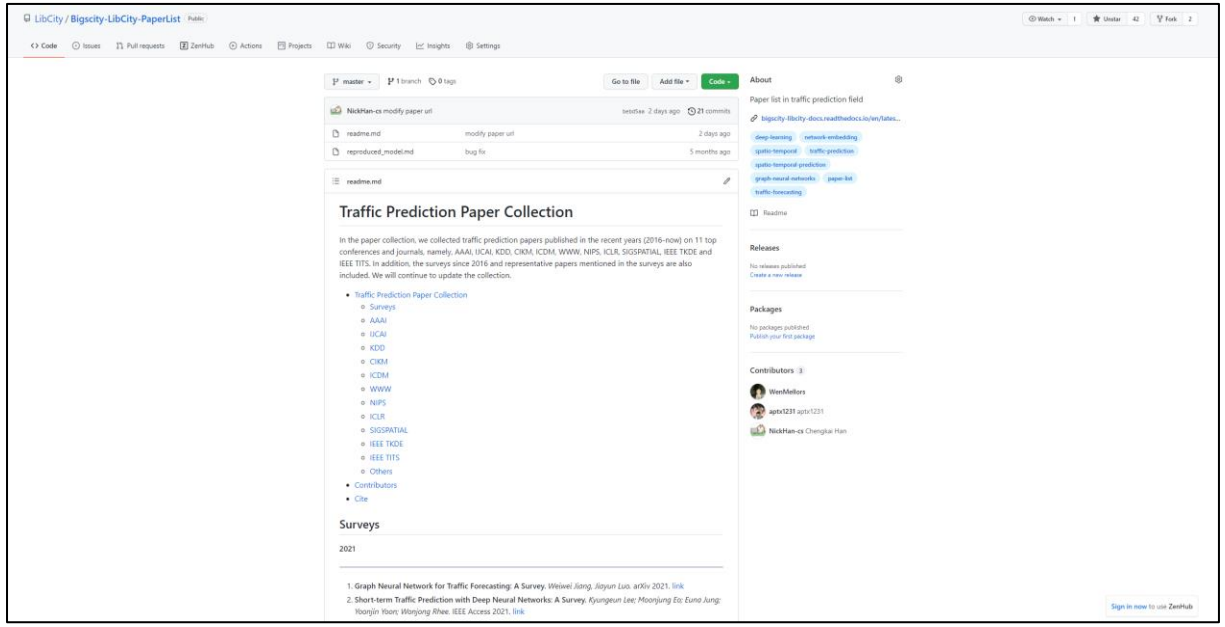


GitHub开源网站

- **除了LibCity代码，还提供了原子数据转换工具、相关论文列表等**
  - https://github.com/LibCity/Bigscity-LibCity-Datasets
  - https://github.com/LibCity/Bigscity-LibCity-PaperList



LibCity 数据集转换工具仓库

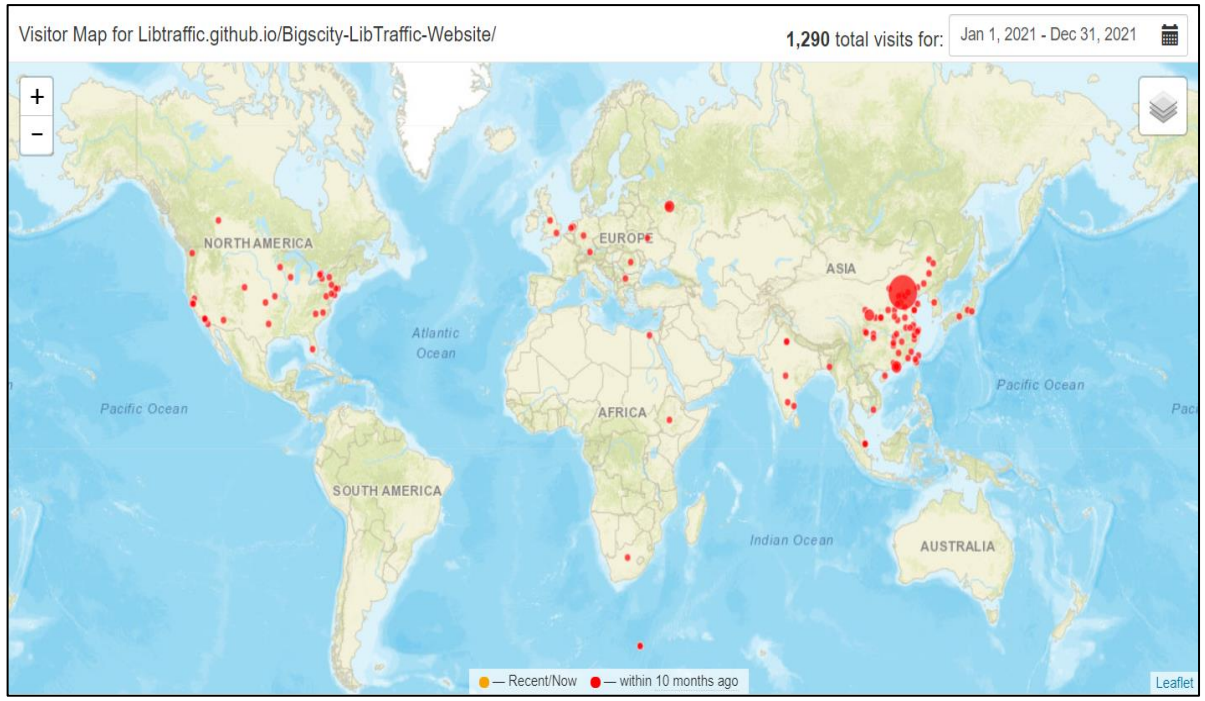


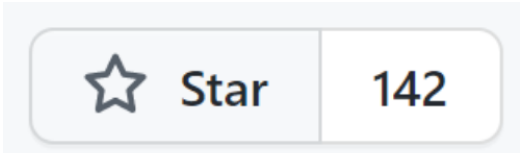
LibCity 论文列表仓库

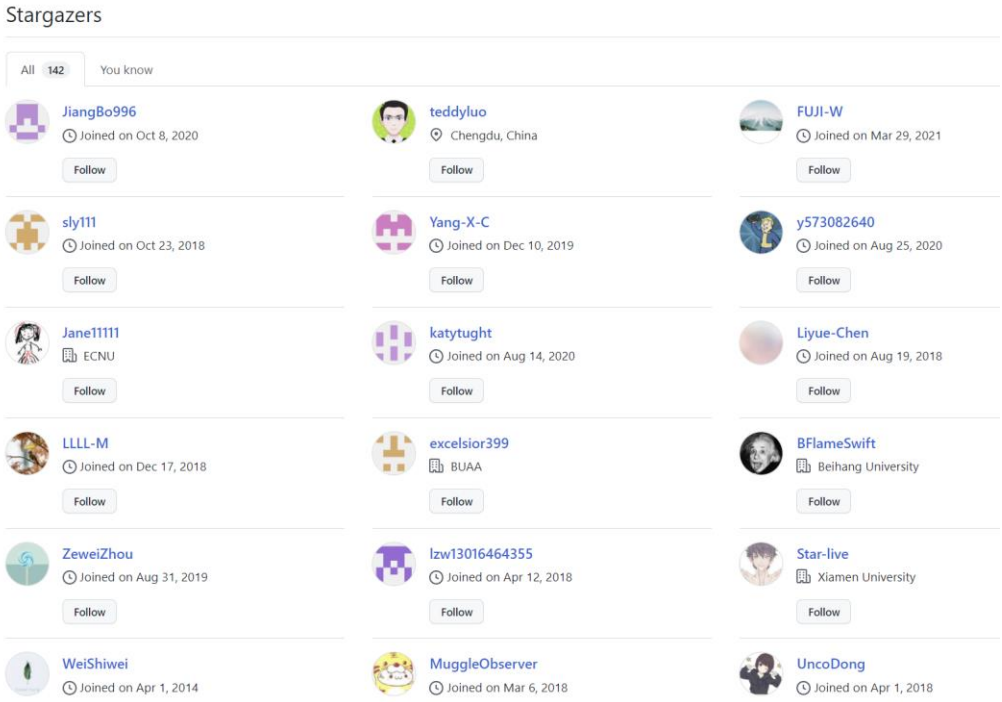
LibCity的影响力

- 受到了来自20个国家的访问，在 GitHub上获得142 星（前 3‰）

LibCity 主页访问分布







LibCity的影响力

被国内外众多

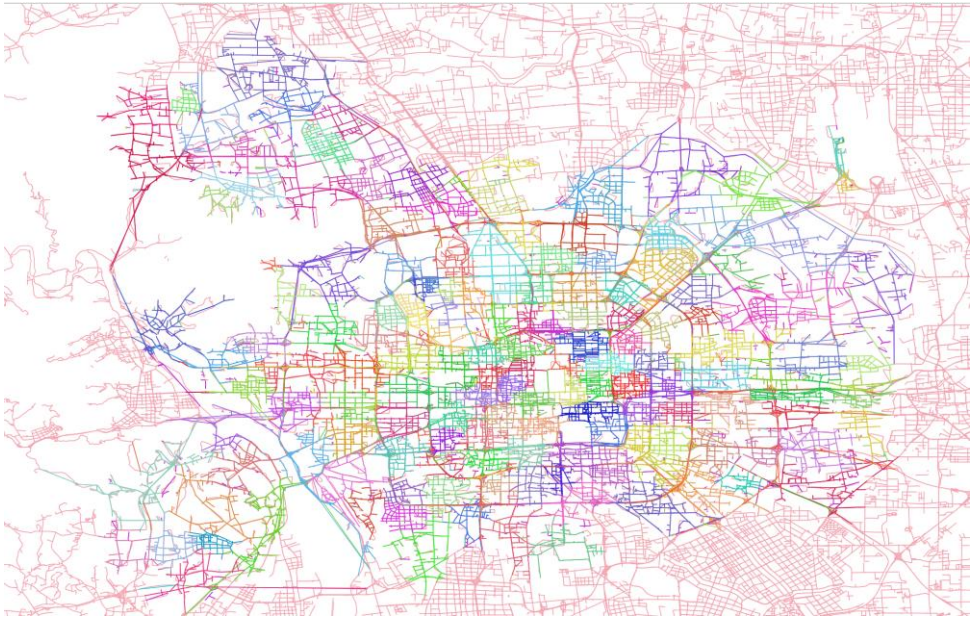
高等院校、科研院

所、科技企业应用

LibCity的影响力

- **LibCity与阿里云开展了深度合作**
  - 标准化评估框架被应用于阿里云城市大脑算法的评测
  - 开源算法库被阿里云城市大脑全量轨迹生成产品应用

城市全量轨迹生成



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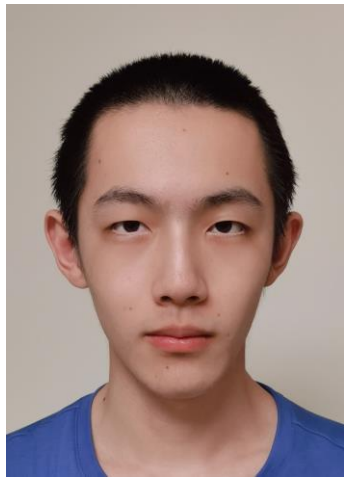

牟钰
北航本科生

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Matty-blu	nan0054	a-l-r
Stevezzy	WANDY666	BugMakerzzz
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敬请批评指正！

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致谢：

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国家自然基金项目“基于深度学习的城市风险时空态势可解释预测研究”(72171013)