

# Urban Computing

## Building Intelligent Cities with Big Data and AI

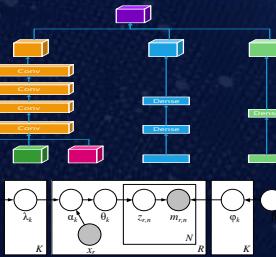
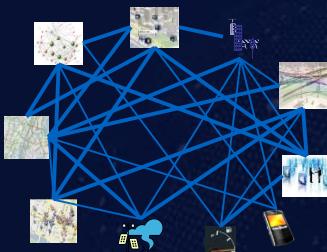
Prof. Dr. Yu Zheng

Vice President of JD.COM, Director of JD Intelligent City Research  
Editor-in-Chief of ACM Transactions on Intelligent Systems and Technology (TIST)

<http://icity.jd.com>

# Urban Computing

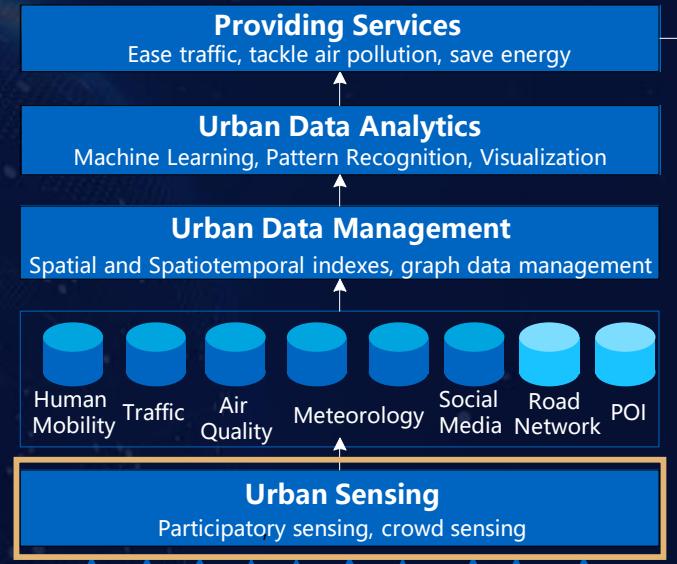
Zheng, Y., et al. Urban Computing: concepts, methodologies, and applications. *ACM TIST*.



Cloud Computing + Big Data + AI

+

Cities



# Urban Sensing

Learning about urban challenges

Supporting intelligent cities

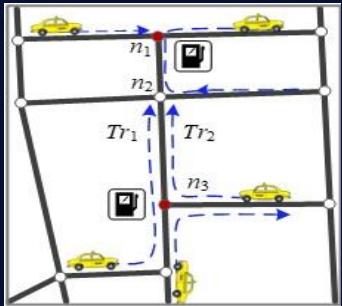
Building the Urban Computing Platform

Urban Resources

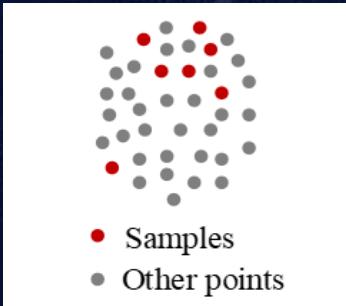
with Big Data and Artificial Intelligence

# Urban Sensing

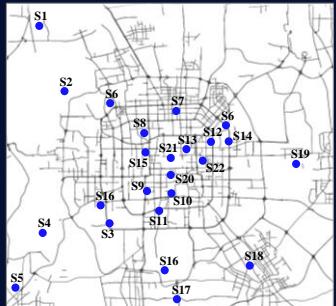
- Challenges & Research Topics



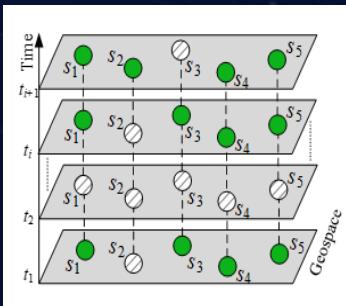
Resource deployment



Sampled data → Biased distribution



Data sparsity



Data missing

Providing Services

Urban Data Analytics

Urban Data Management

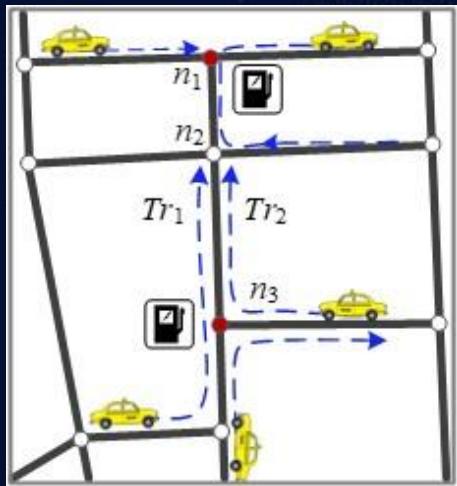


Urban Sensing

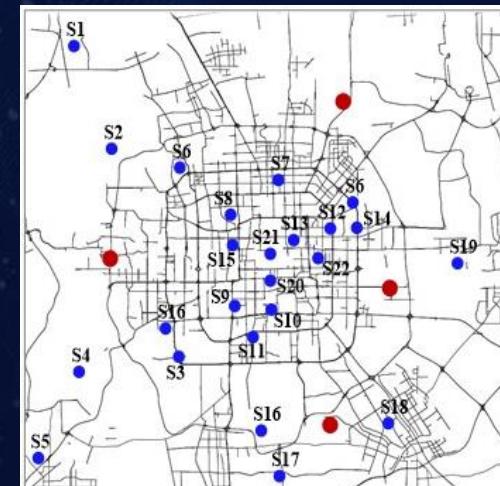


## Urban Sensing Challenges- Resource deployment

Candidate selection is could be a NP-hard Problem



Hard to define a measurement for evaluating the deployment



Y. Li, et al. Mining the Most Influential k-Location Set From Massive Trajectories. IEEE Transactions on Big Data. 2017

Hsieh H.P, S.D. Lin & Yu Zheng  
[KDD2015]

## Urban Sensing Challenges- Biased Samples

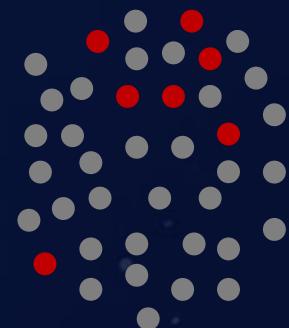
Sampled Data → Biased Distribution



Taxi Flow

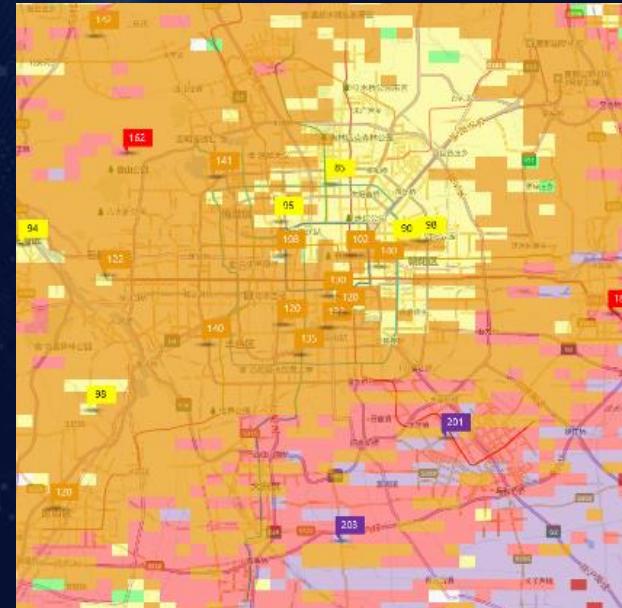
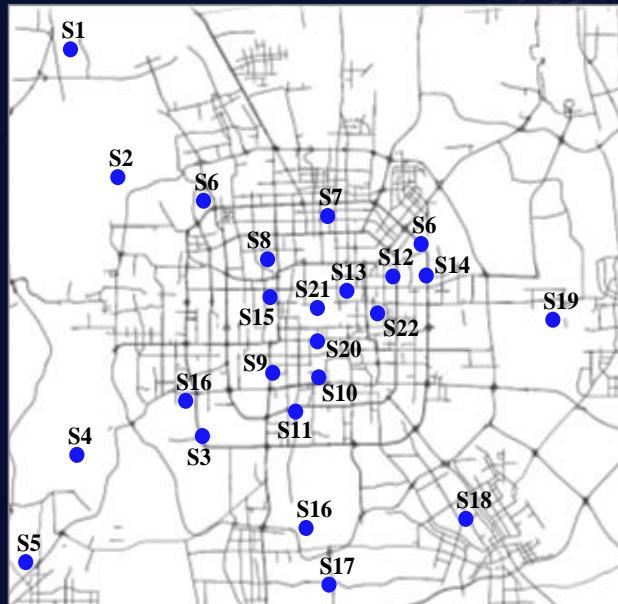


Entire Traffic Flow



- Samples
- Others

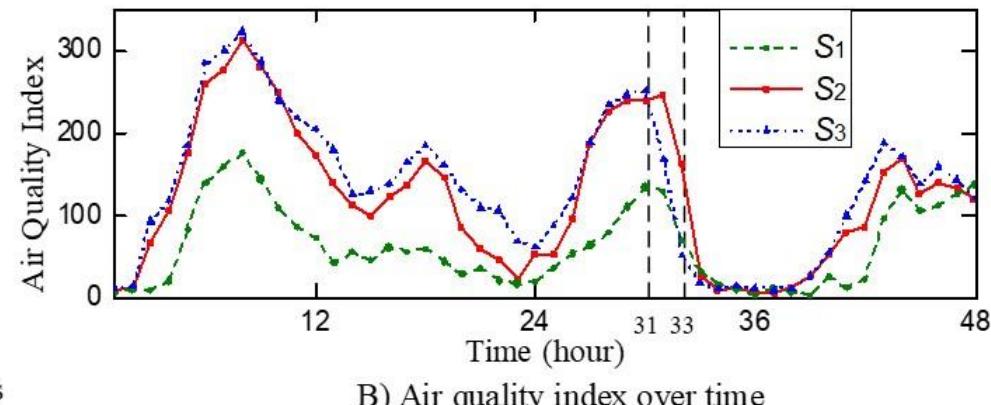
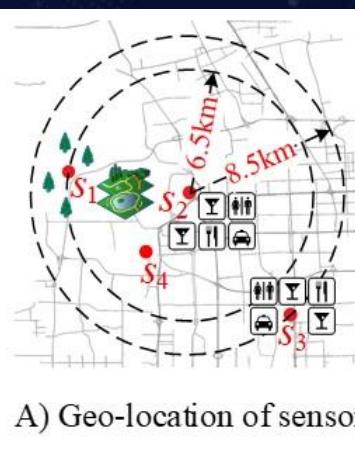
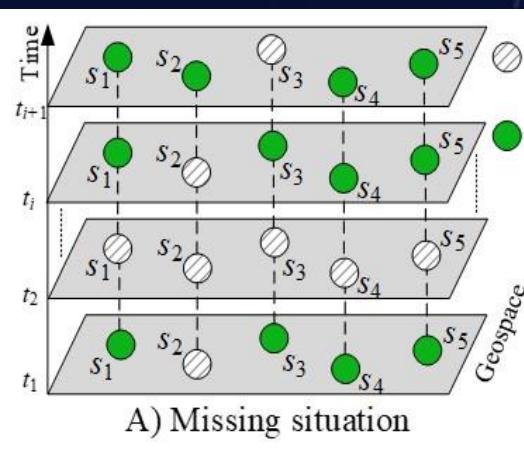
## Urban Sensing Challenges - Data Sparsity



Zheng, Y., et al. U-Air: When Urban Air Quality Inference Meets Big Data. KDD 2013

# Urban Sensing Challenges - Data Missing

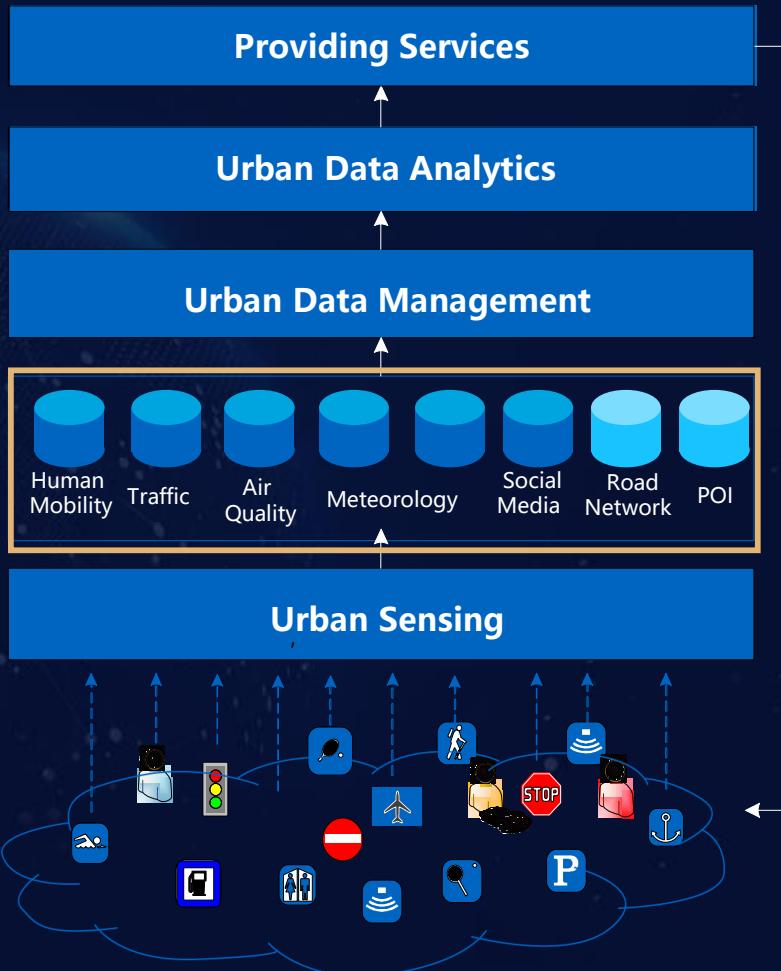
- Lost data that is supposed to receive because of communication or device errors
- Difficult to fill
  - Randomly missing and block missing
  - Readings changing over time and location non-linearly

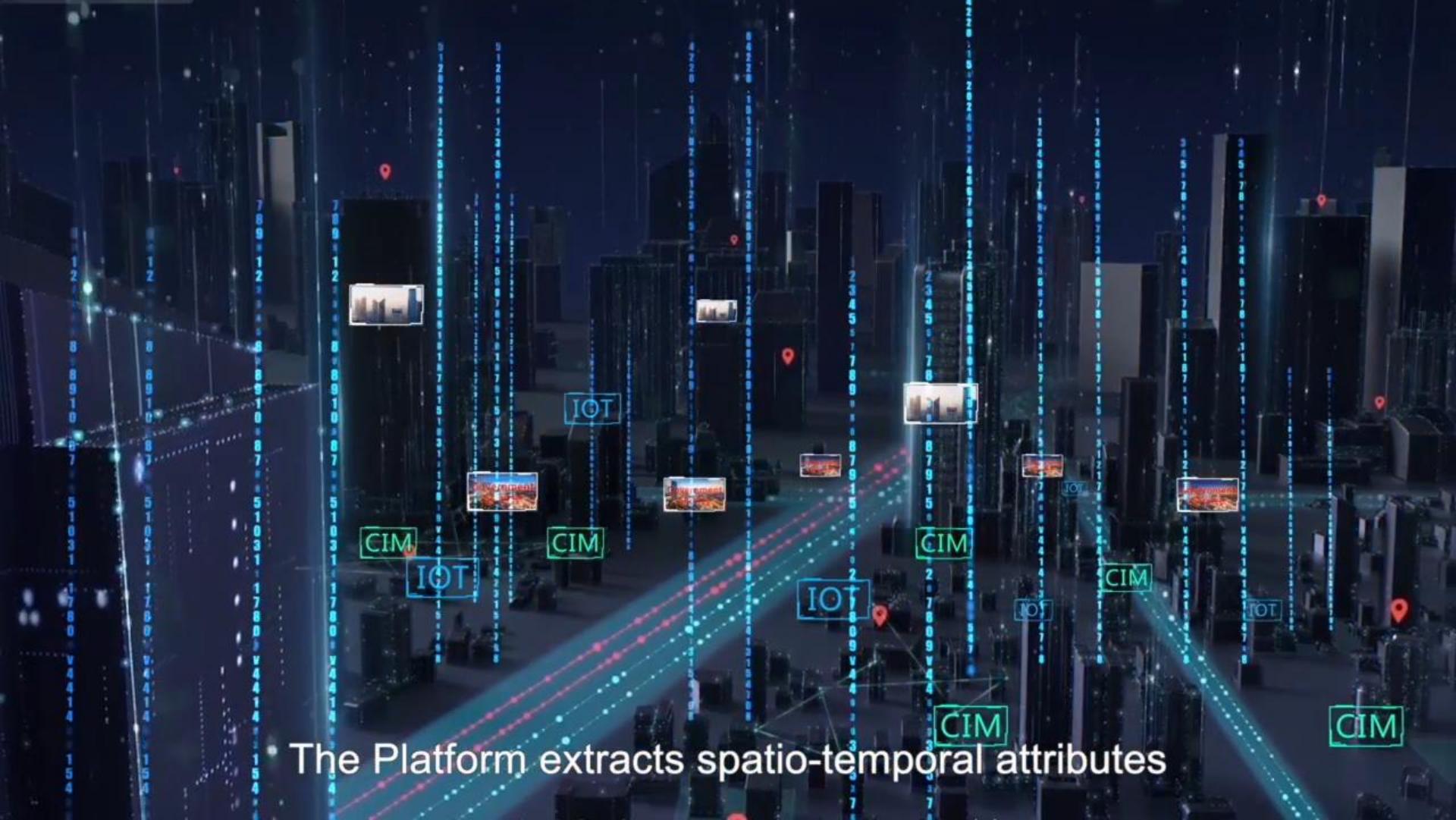


# Urban Big Data

- Urban Data: Why unique
  - Data structures
  - Spatio-Temporal dynamics

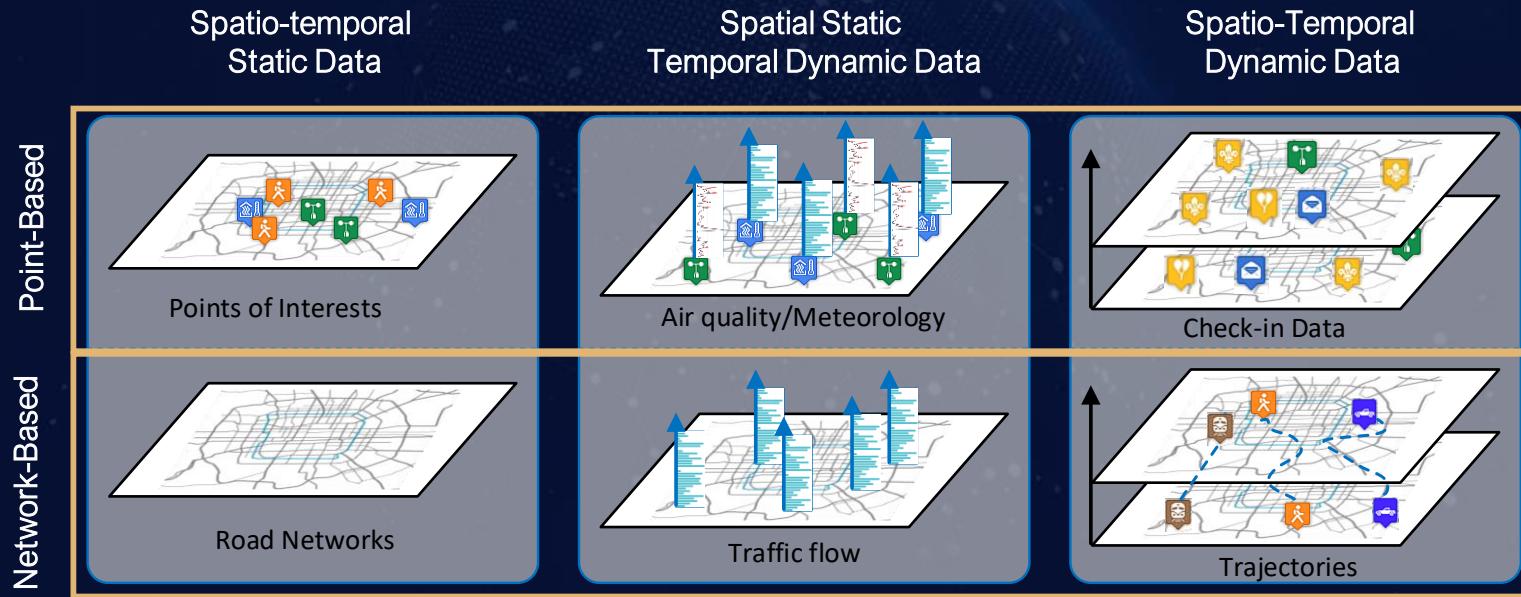
## Spatio-temporal Data





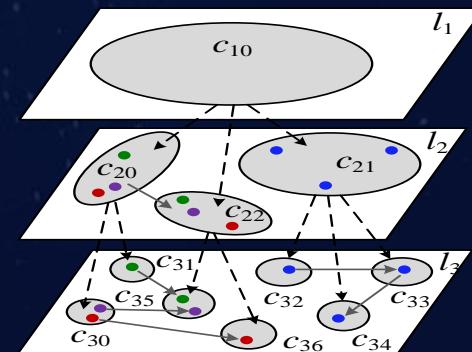
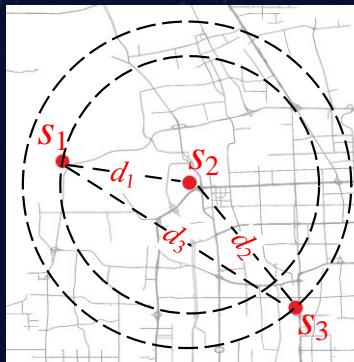
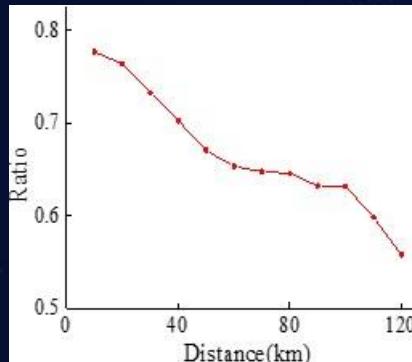
The Platform extracts spatio-temporal attributes

# Spatiotemporal Data in Cities



# Why Spatiotemporal Data is unique

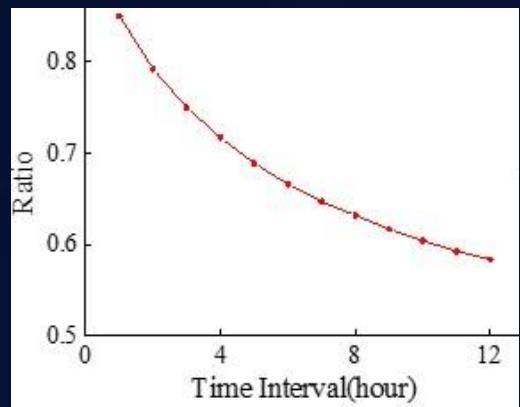
- Spatial Properties
- Spatial Distance
  - Spatial correlation
  - Triangle inequality:  $|d_1 - d_2| \leq d_3 \leq |d_1 + d_2|$
- Spatial hierarchy
  - Different spatial granularities
  - City structures



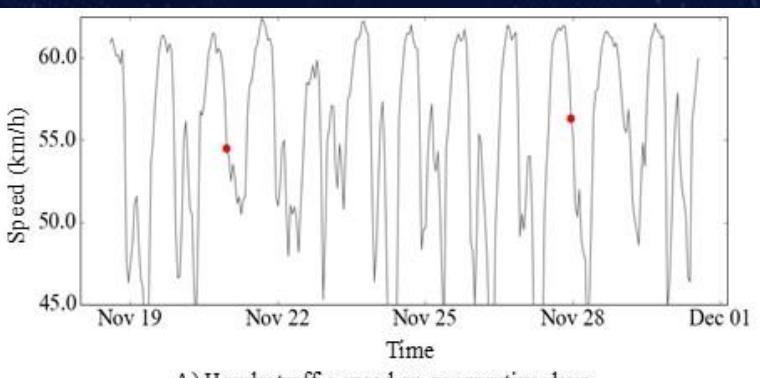
# Why Spatiotemporal Data is unique

## Temporal Properties

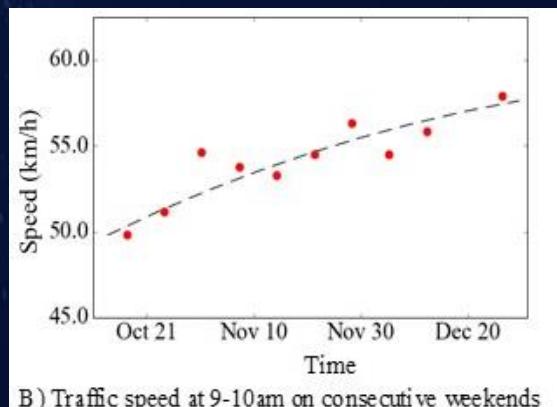
Temporal closeness



Period

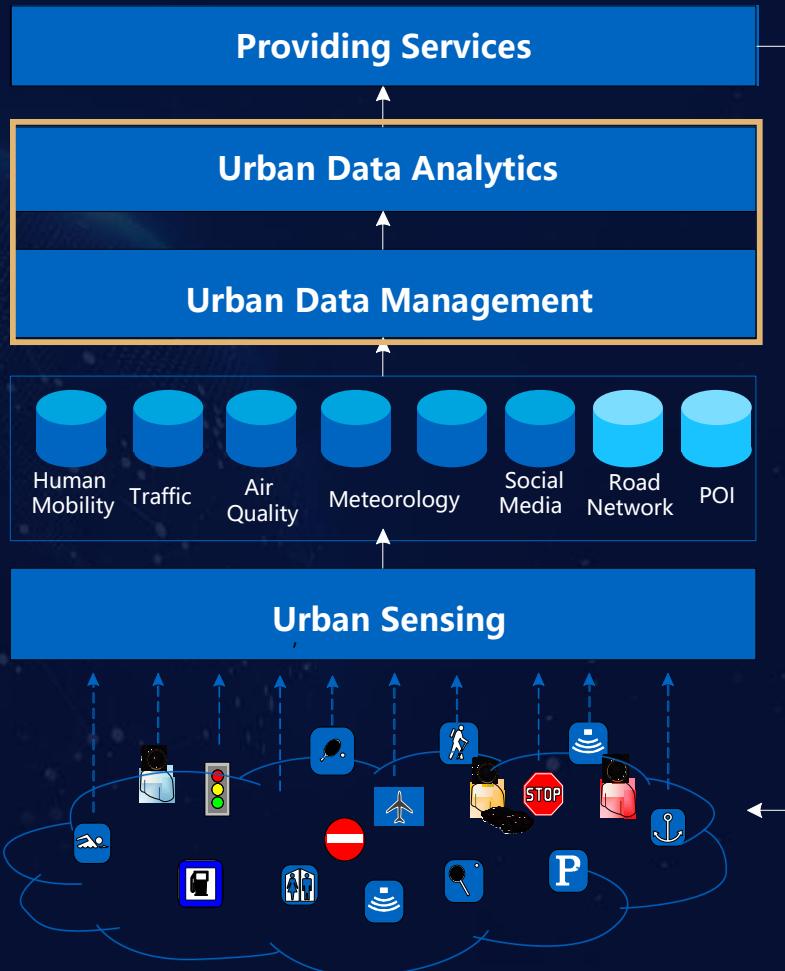


Trend



# Urban Data Mining

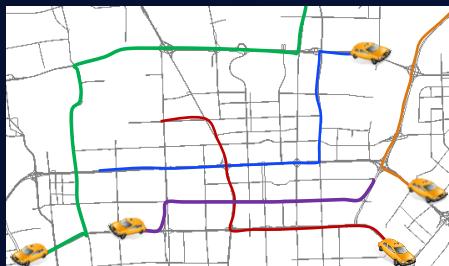
- Challenges to Data Management
- Challenges to Data Analytics



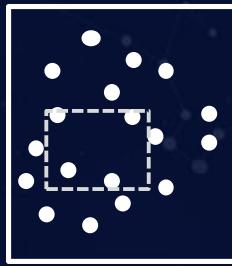
# Challenges Posed to Urban Data Management

- Large-scale and highly dynamic → cloud computing
- Cloud computing platforms do not support ST Data well
  - Unique ST data structures: trajectories (the most complex ST Data)
  - Unique queries: ST-Range queries and KNN queries rather than key words
  - Data across different domains: Hybrid indexing for managing multi-modality data

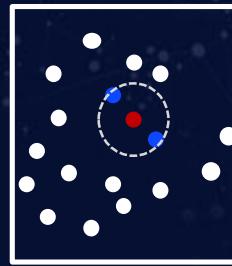
Trajectories



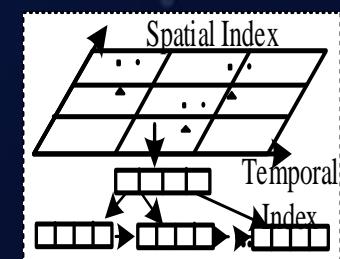
Range Queries



KNN Queries



Hybrid indexing



## Example 1

Detecting Vehicle Illegal Parking Using  
Sharing Bikes' Trajectories

# Detecting Vehicle Illegal Parking Using Sharing Bikes' Trajectories



城市中违章停车随时随地可见

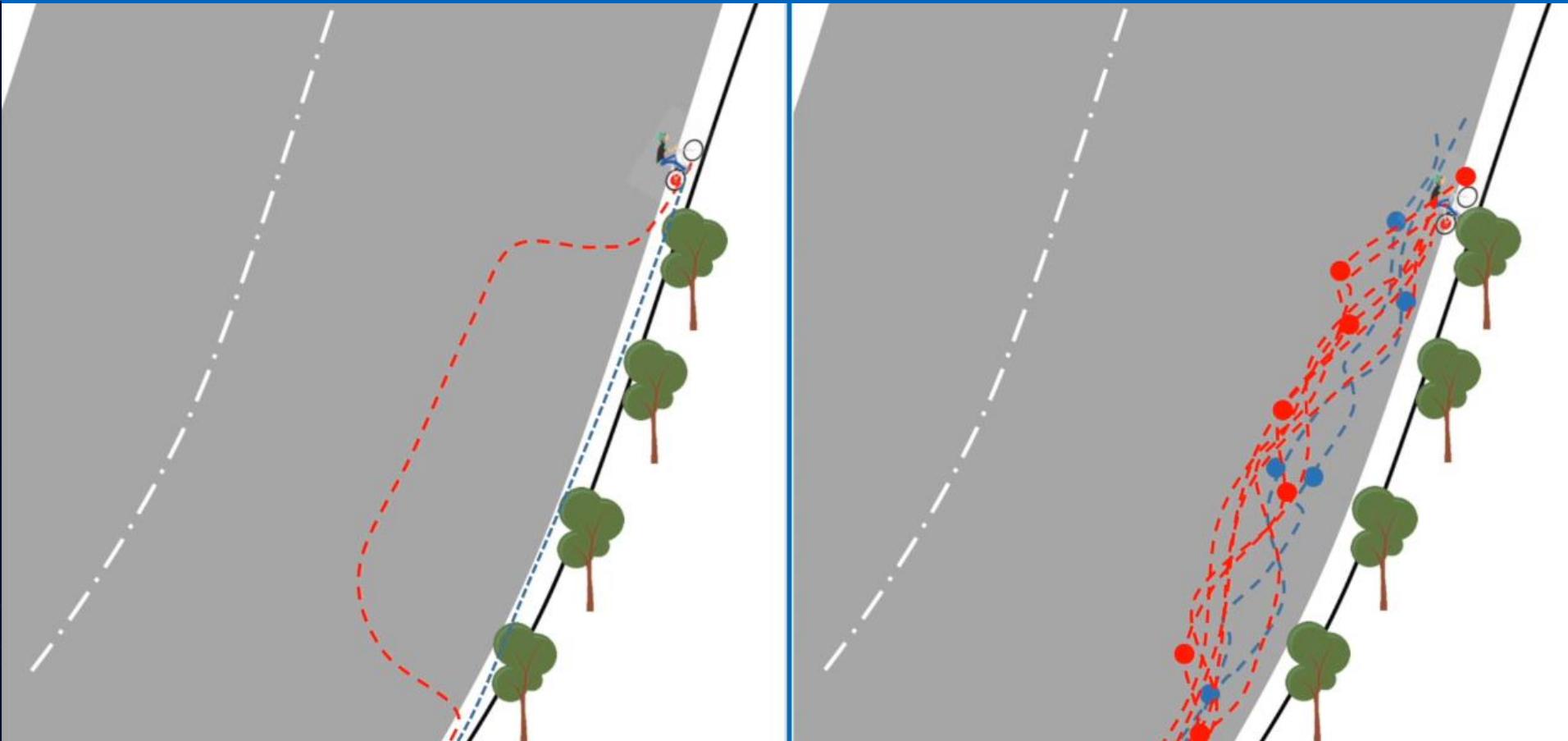
# Detecting Vehicle Illegal Parking Using Sharing Bikes' Trajectories



# Detecting Vehicle Illegal Parking Using Sharing Bikes' Trajectories



# Detecting Vehicle Illegal Parking Using Sharing Bikes' Trajectories



# Detecting Vehicle Illegal Parking Using Sharing Bikes' Trajectories



# Challenges Posed to Urban Data Analytics

- Urban Data Analytics
  - Texts and images → spatial and spatiotemporal data; (encoding spatiotemporal properties)
  - Mining a single data source → Mining data across different domains
  - Pure machine learning → Visual and interactive data analytics

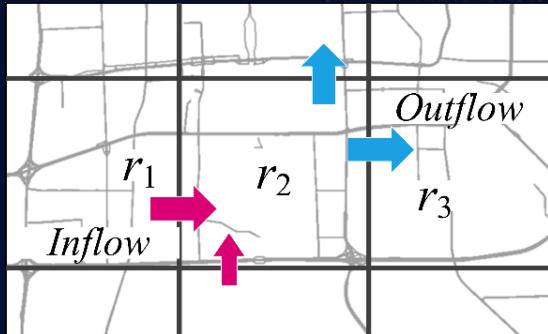
## Challenge 1: Encoding spatiotemporal properties in machine learning models

Example

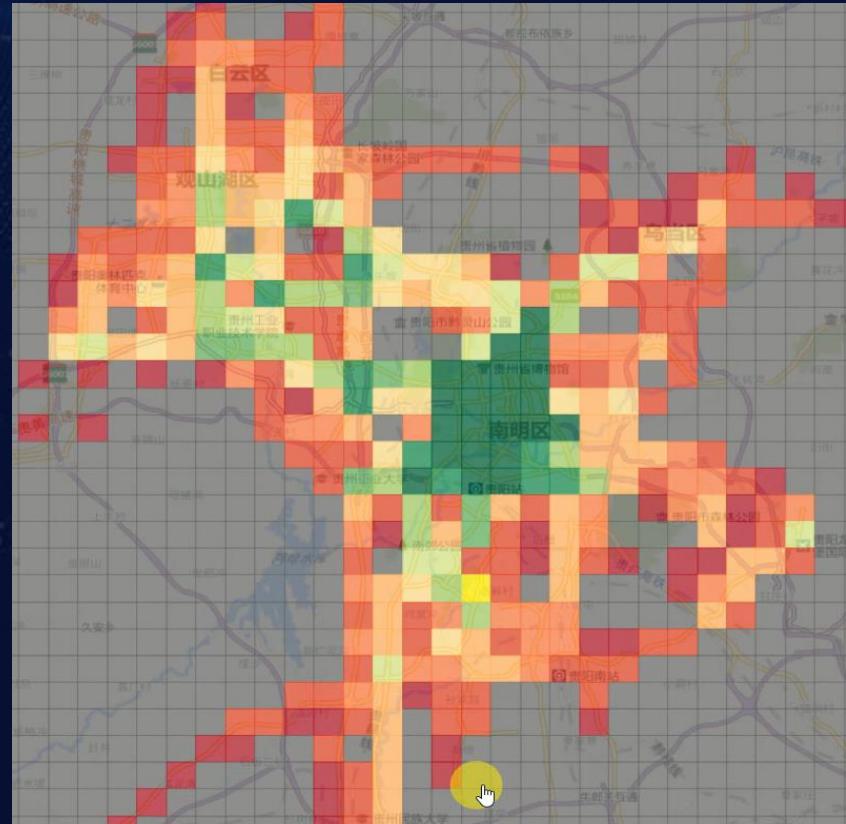
Crowd Flow Prediction

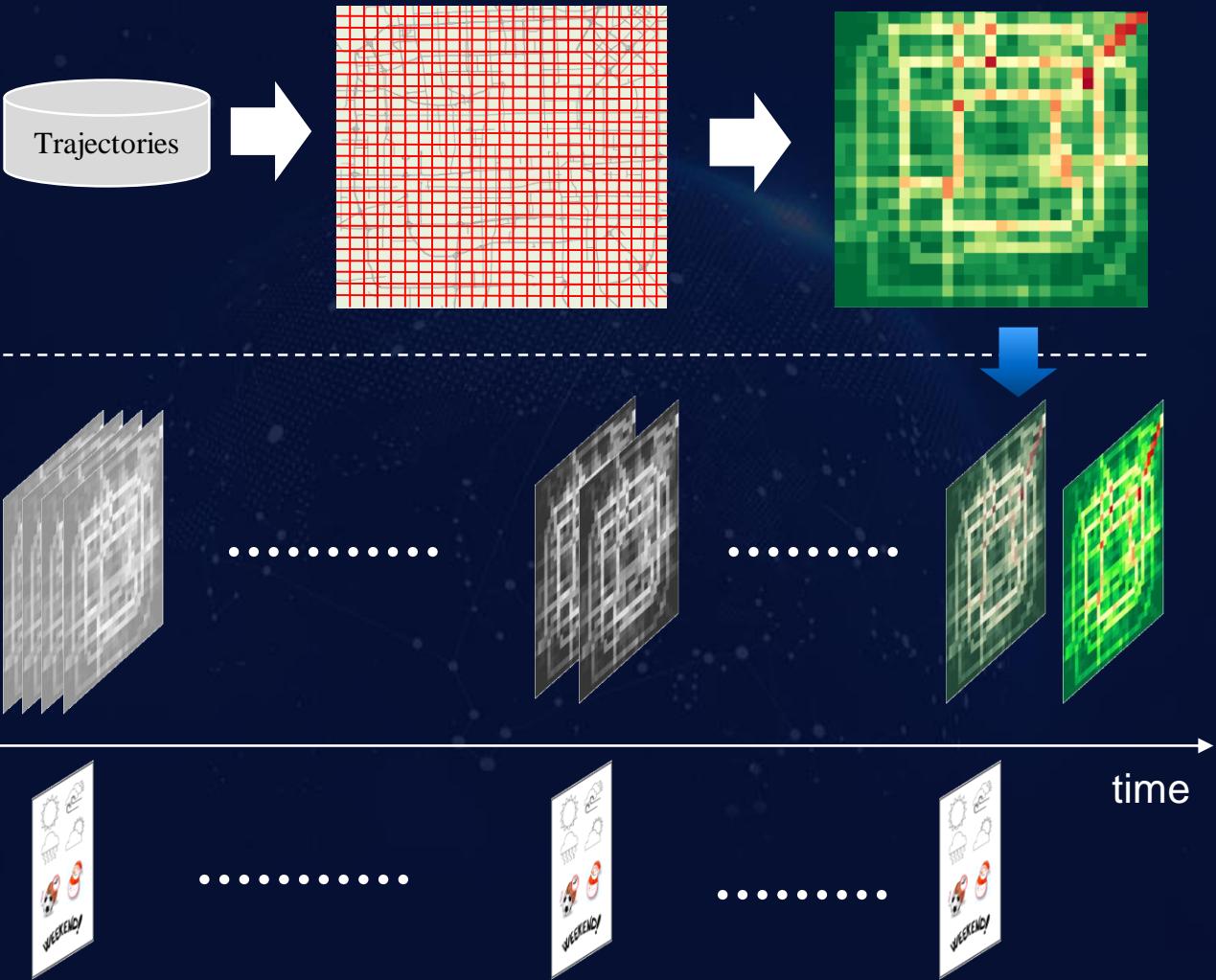
# Predicting Crowd Flows throughout a City

- Predict in and out flow of crowds
  - In each grid
  - Over the next few hours



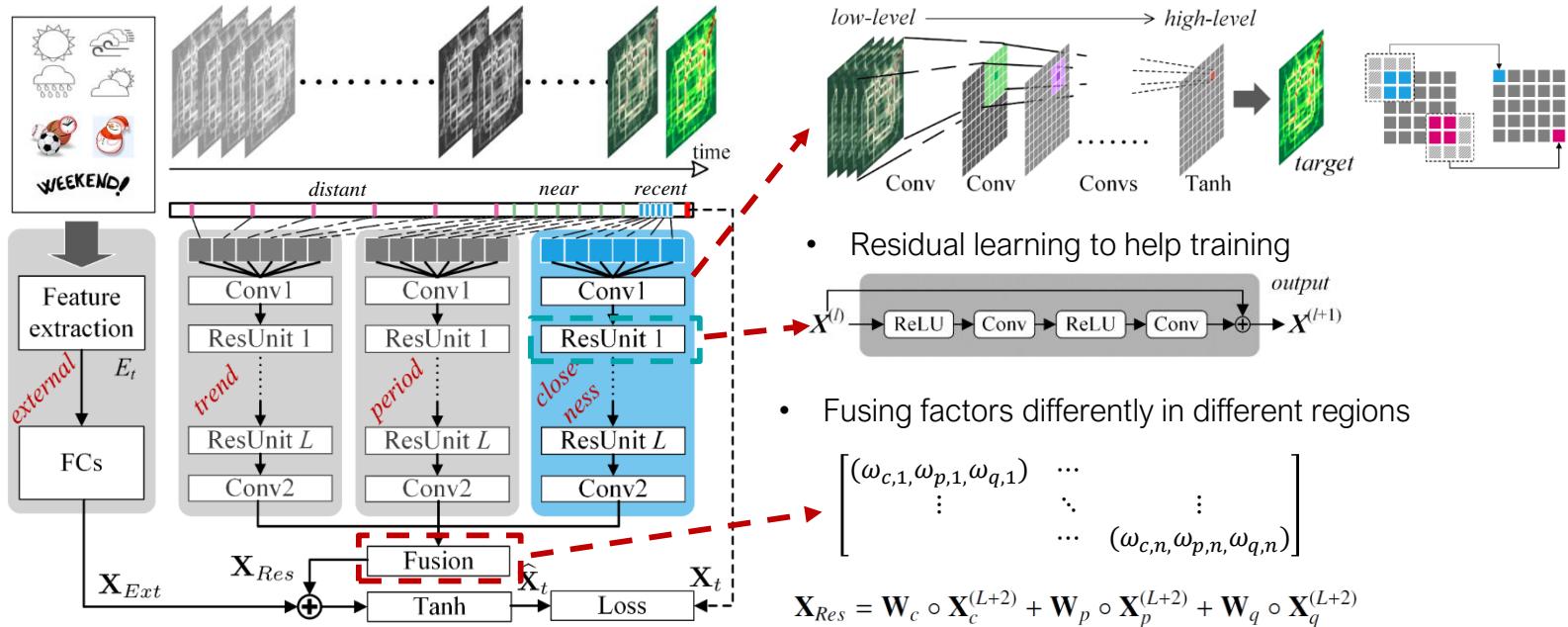
- Challenges
  - Complex and dynamic factors
  - Encoding spatiotemporal properties



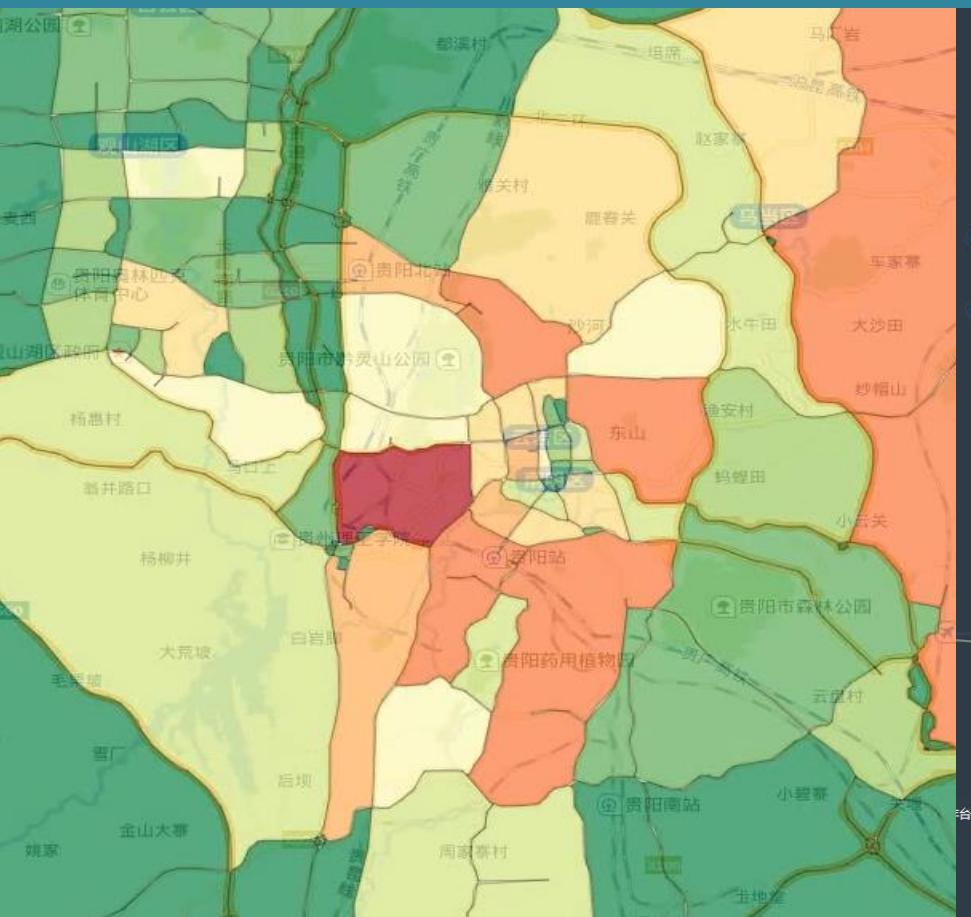


# ST-ResNet Architecture: A Collective Prediction

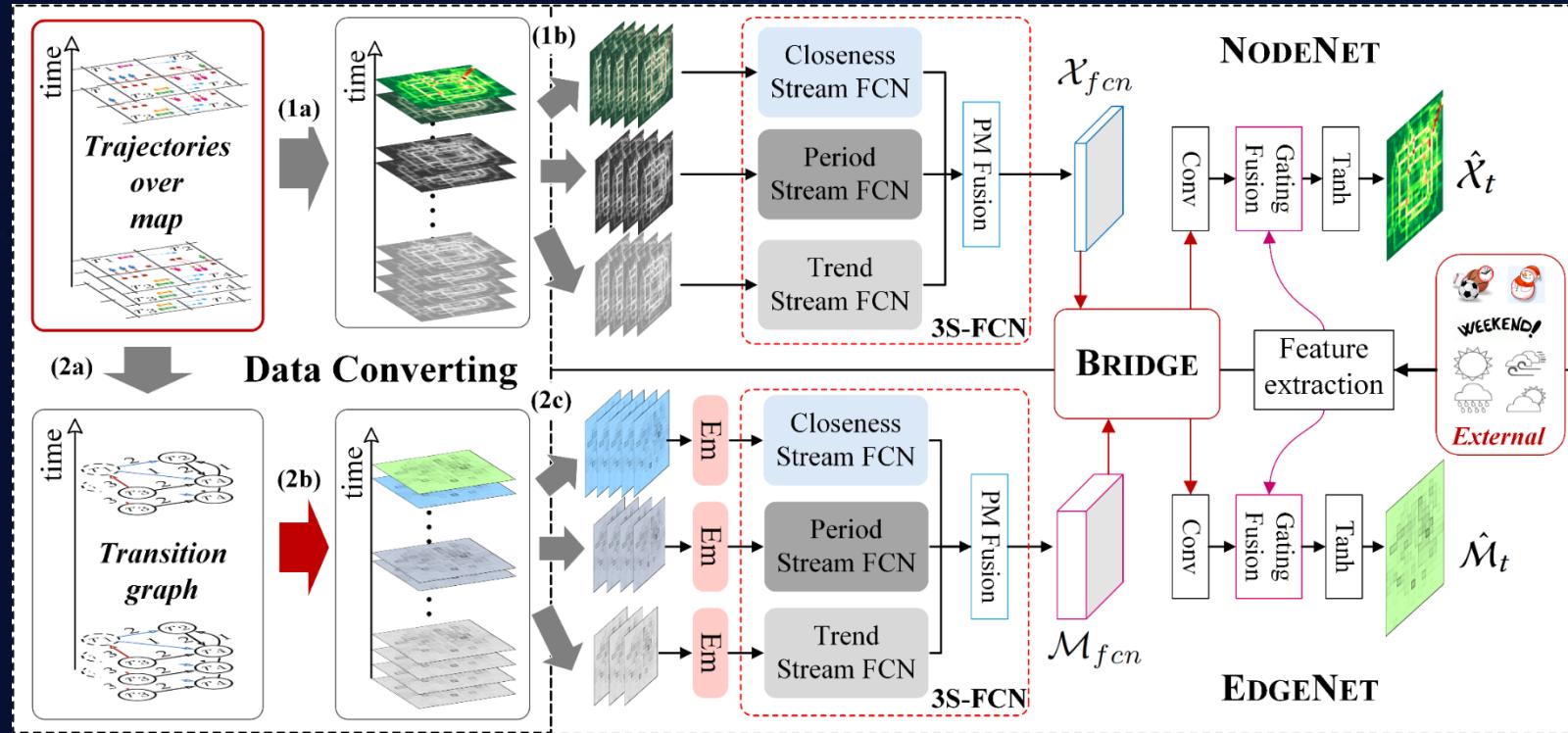
- Capture temporal closeness, period, and trend
- Capture external factors
- Capture spatial correlation of both near and far distances



# Predicting Crowd Flow Using AI



# Multitask Deep Learning Framework



Challenge 2: Mining data across different domains

### Example

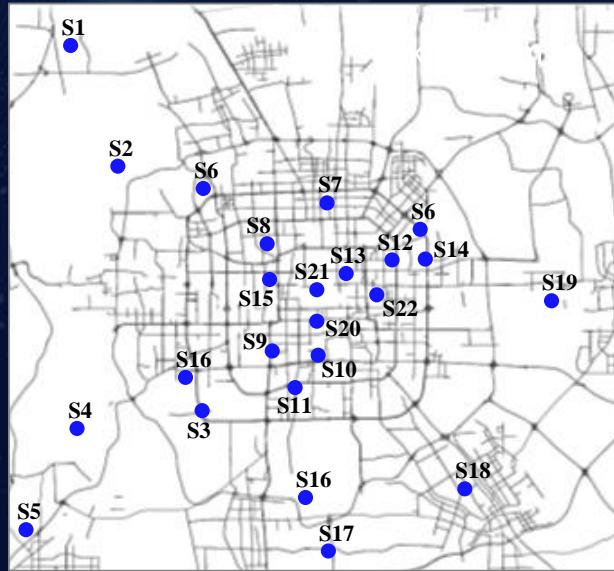
Air Quality Inference and Forecasting

# Air Pollution: A Global Concern !

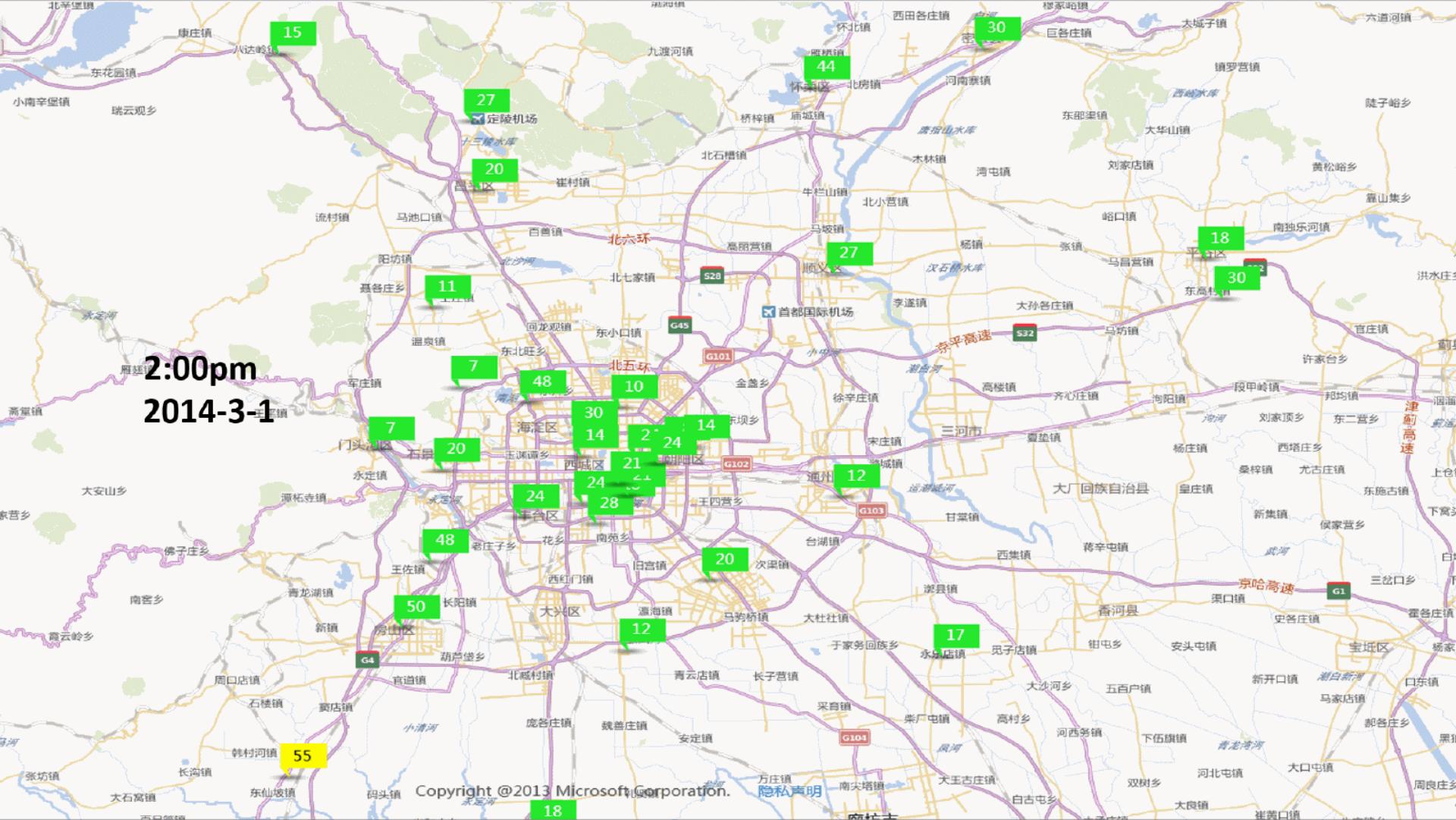
PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>2</sub>, SO<sub>2</sub>, CO, O<sub>3</sub>



- Air quality monitor station



**2:00pm  
2014-3-1**



# Infering **Real-Time** and **Fine-Grained** air quality throughout a city



Meteorology



Traffic



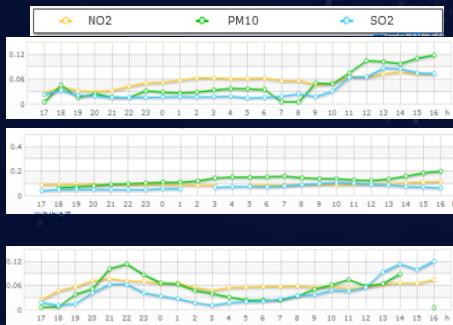
Human Mobility



POIs



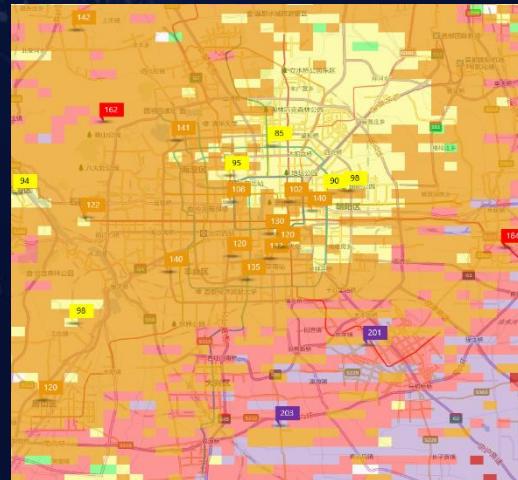
Road networks



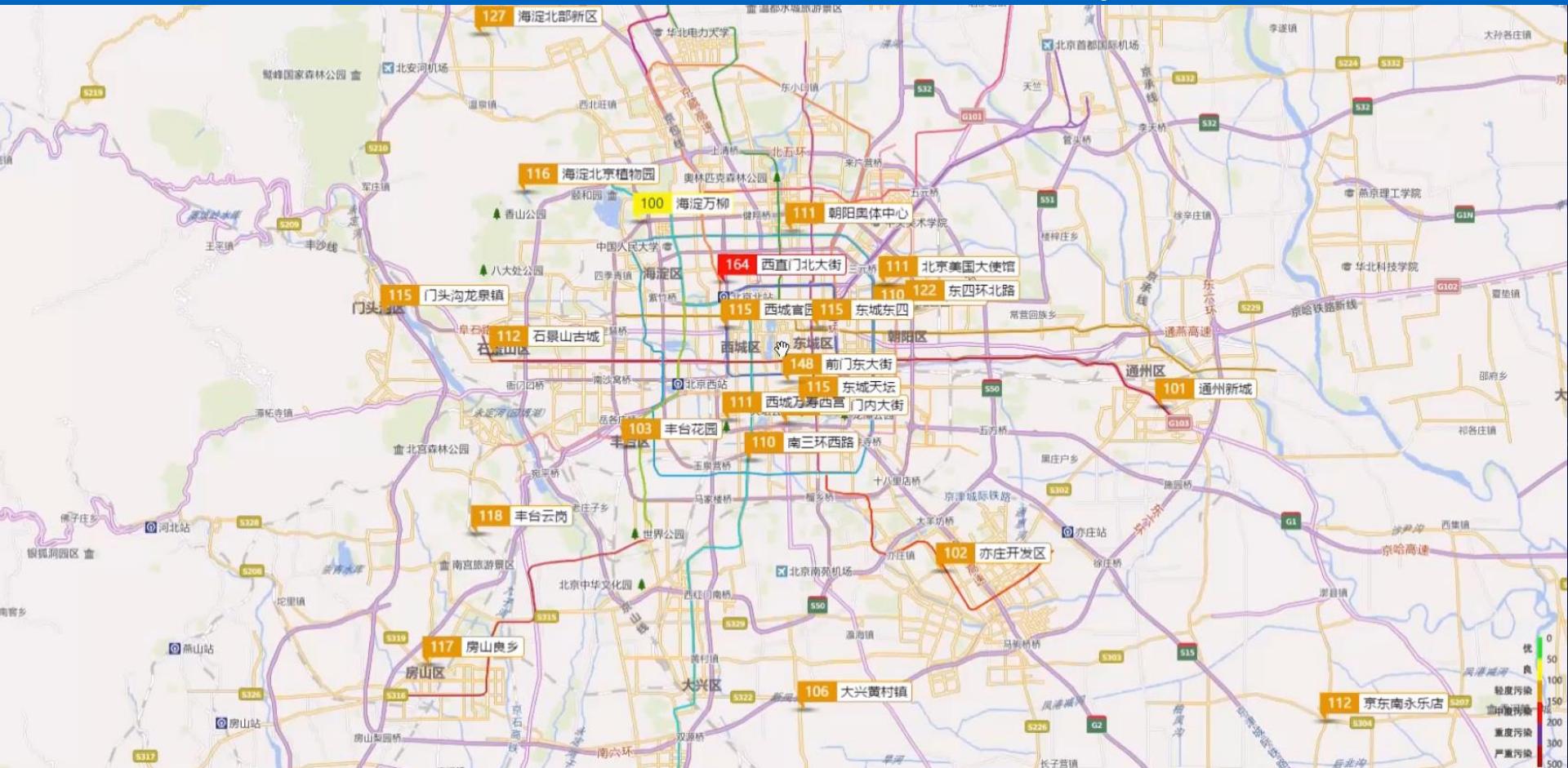
Historical air quality data



Real-time air quality reports



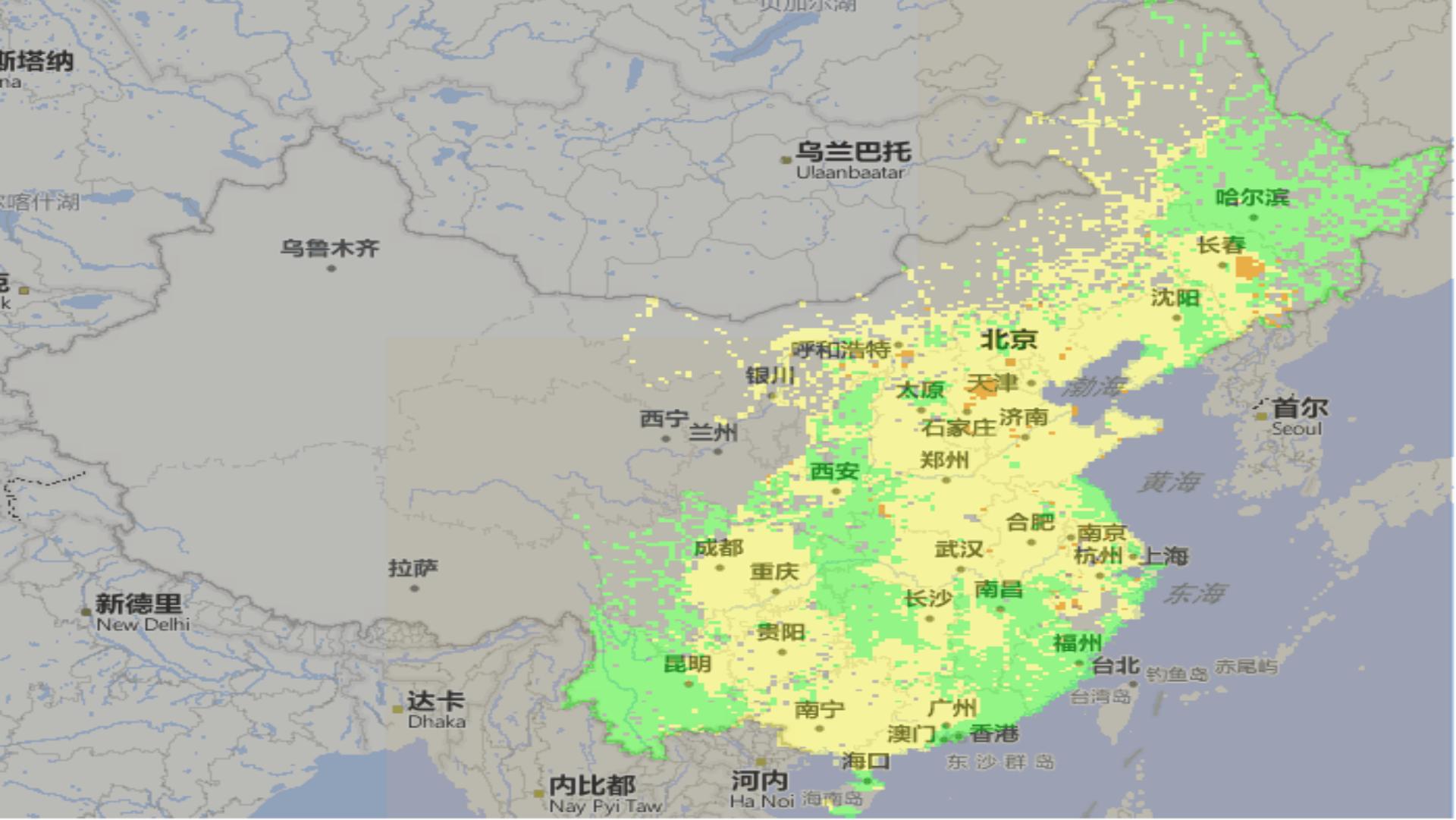
# Fine-Grained and Real-time Air Quality Inference



## Intelligent Environment

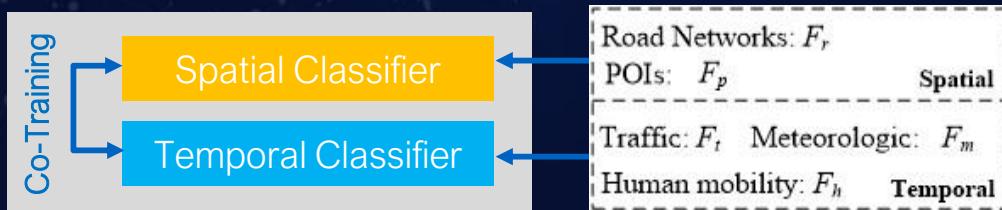
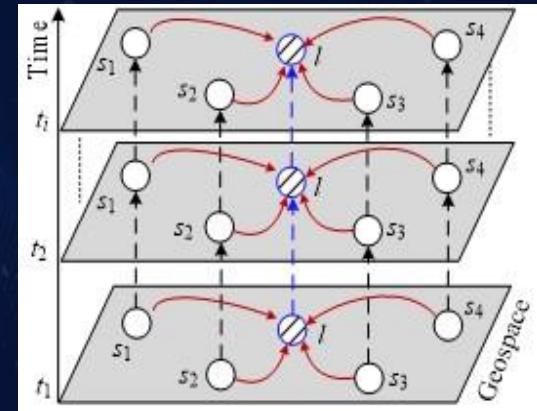
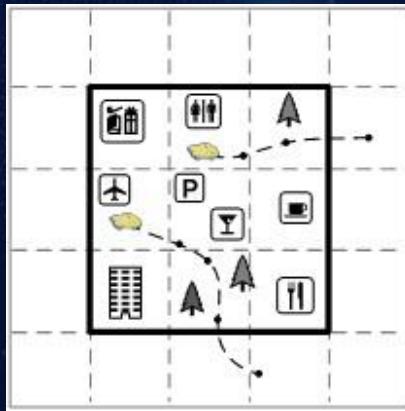


and every local area despite incomplete air quality data

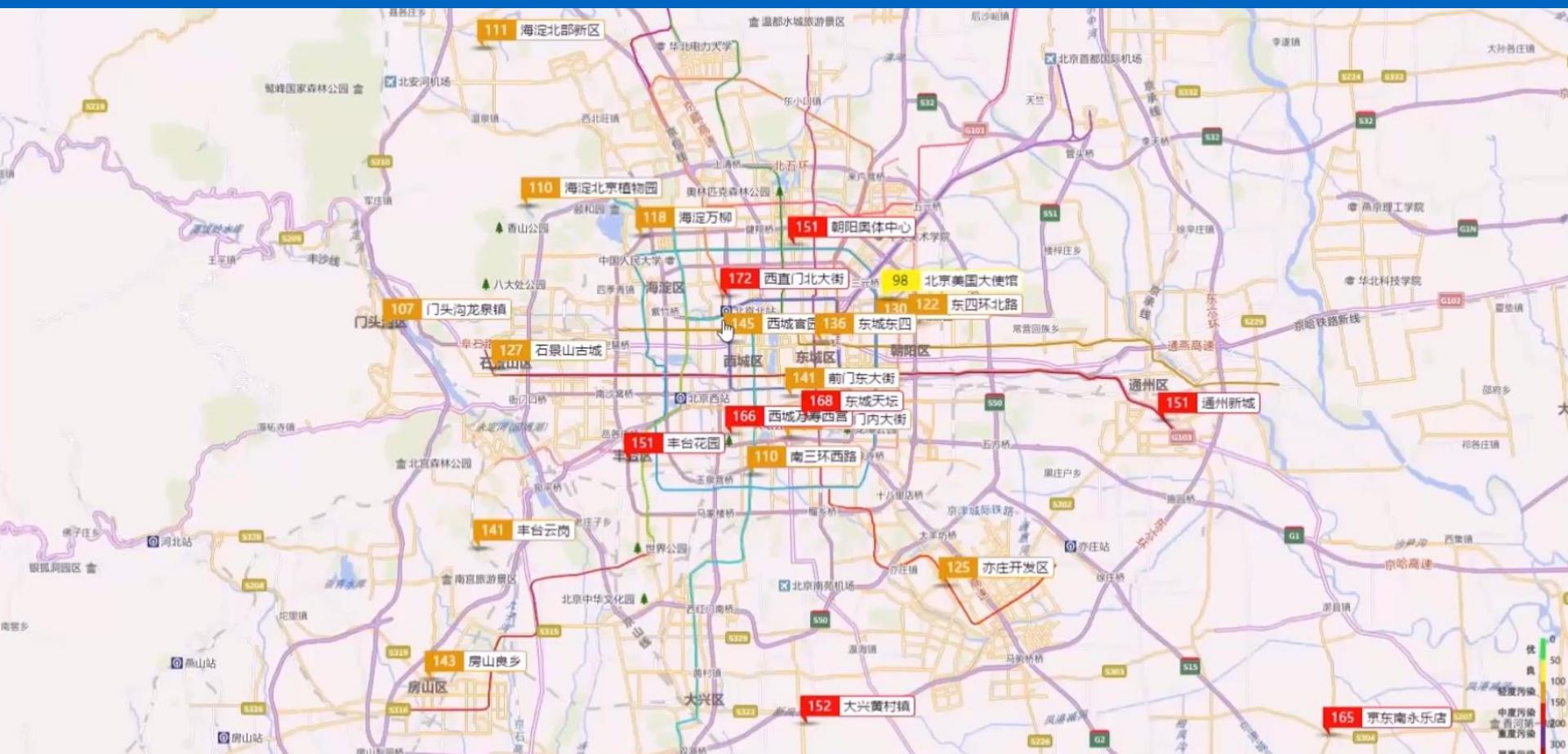


# Semi-Supervised Learning Model

- Partition a city into disjoint grids
- Features from different datasets
- Encoding spatiotemporal properties
  - Temporal dependency in a location
  - Geo-correlation between locations
- Domain knowledge
  - Emission from a location
  - Propagation among locations
- Co-training-based inference model

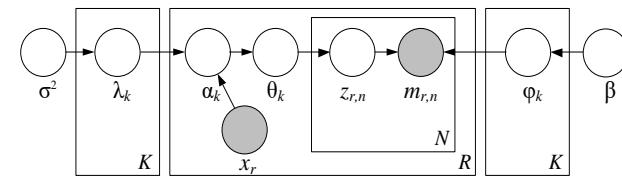
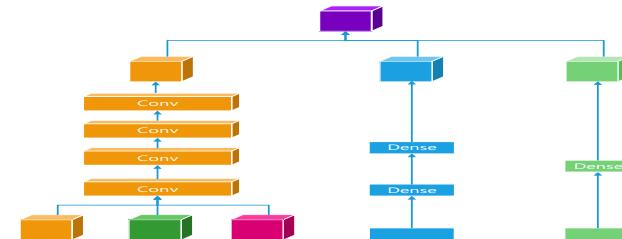
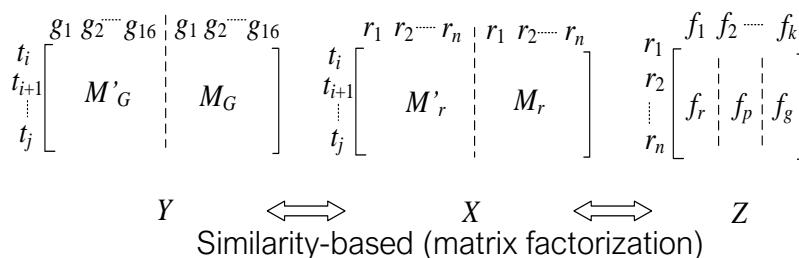
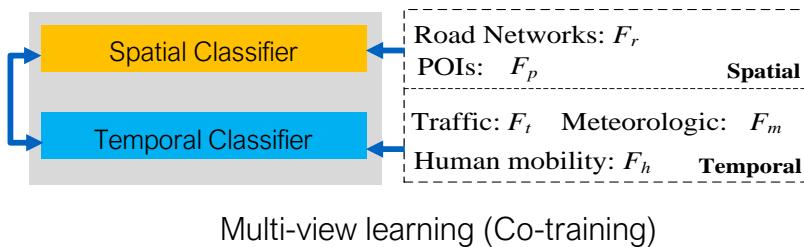


# Forecast Air Quality over the next 48 hours

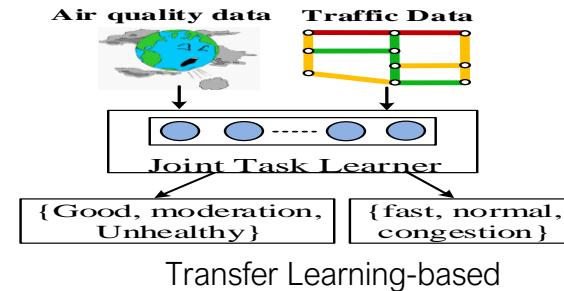


# Methodologies for Cross-Domain Knowledge Fusion

- Stage-based data fusion
- Feature-level-based data fusion
  - Feature concatenation + regularization
  - DNN-based
- Semantic meaning-based fusion



Pro. dependency-based (Topic Models)

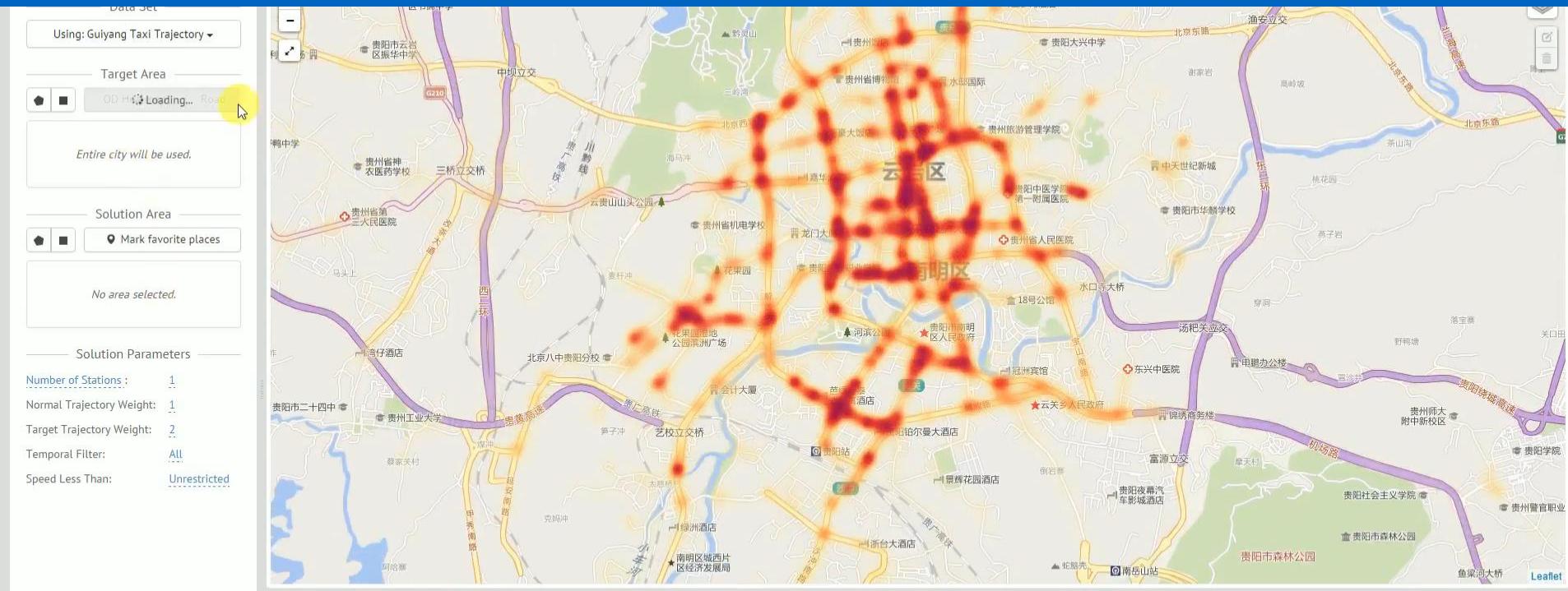


## Challenge 3: Visual and interactive data analytics

**Example**

Selecting locations for charging stations

# Finding Top-k Most Influential Location Set



Interactive Visual Data Analytics

No available solution.

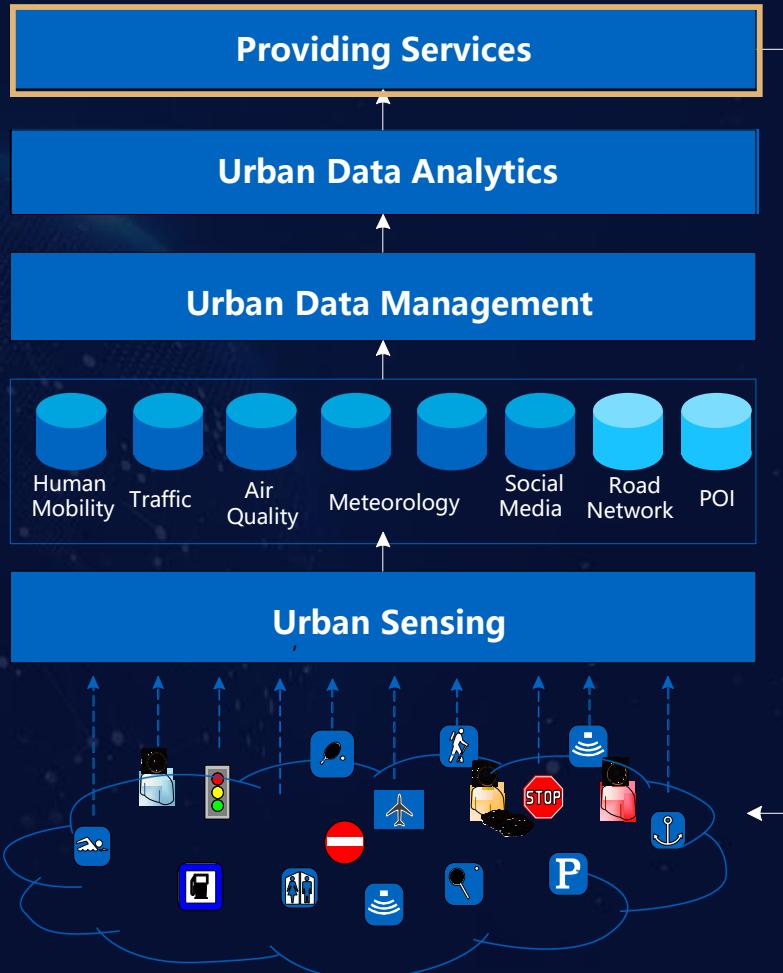
Generate Solution

A submodular maximization problem, NP-hard

“SmartAdP: Visual Analytics of Large-scale Taxi Trajectories for Selecting Billboard Locations”, VAST 2016

# Providing Services

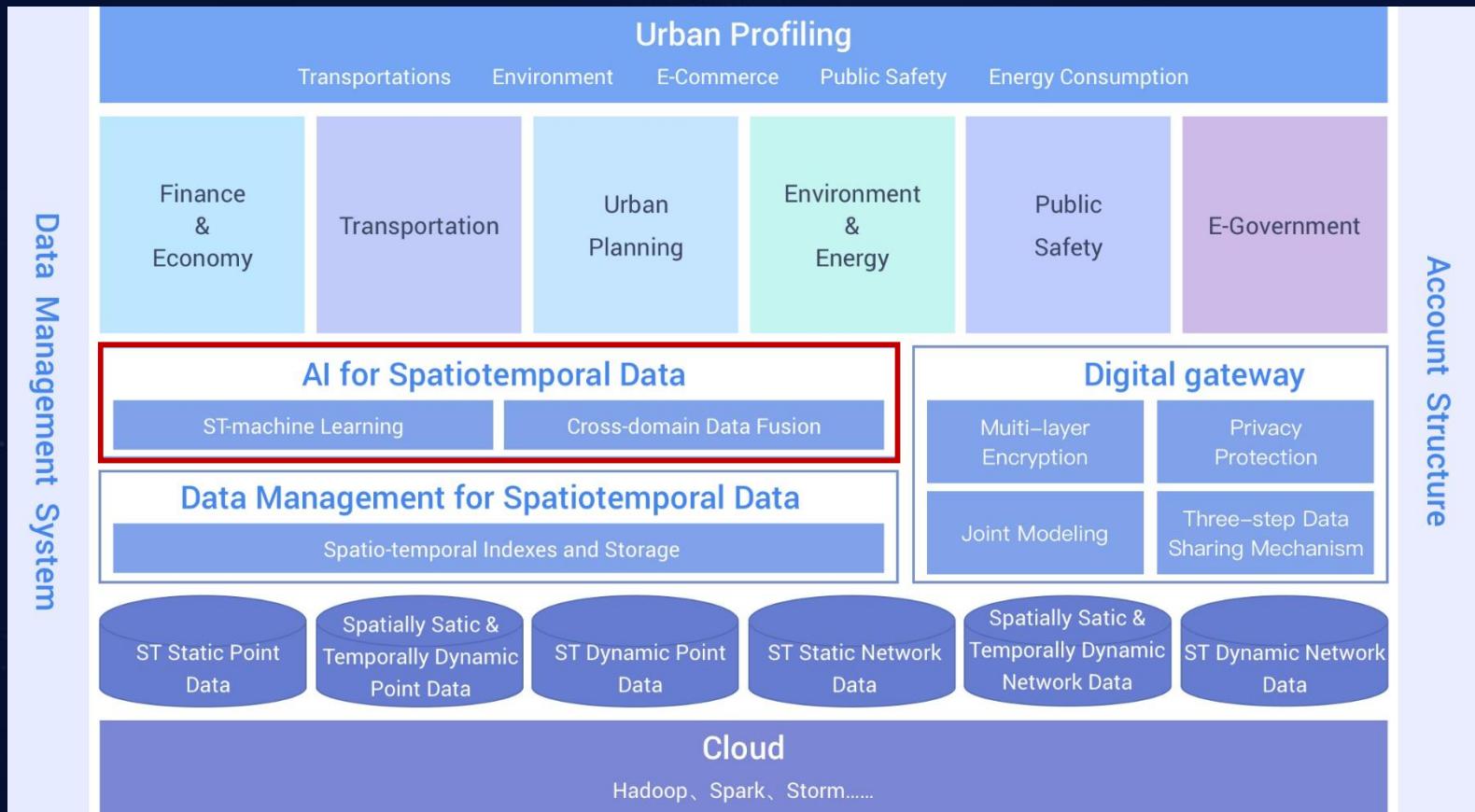
- Urban computing platforms
  - Six Spatio-temporal (ST) data models
  - ST data management
  - ST machine learning
  - Cross-domain machine learning
- Building City OS → an ecosystem



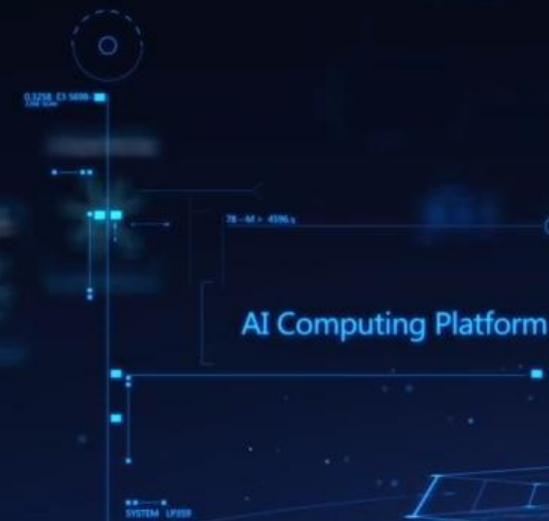
<http://ucp.jd.com/>

# Urban Computing Platform

<http://ucp.jd.com>



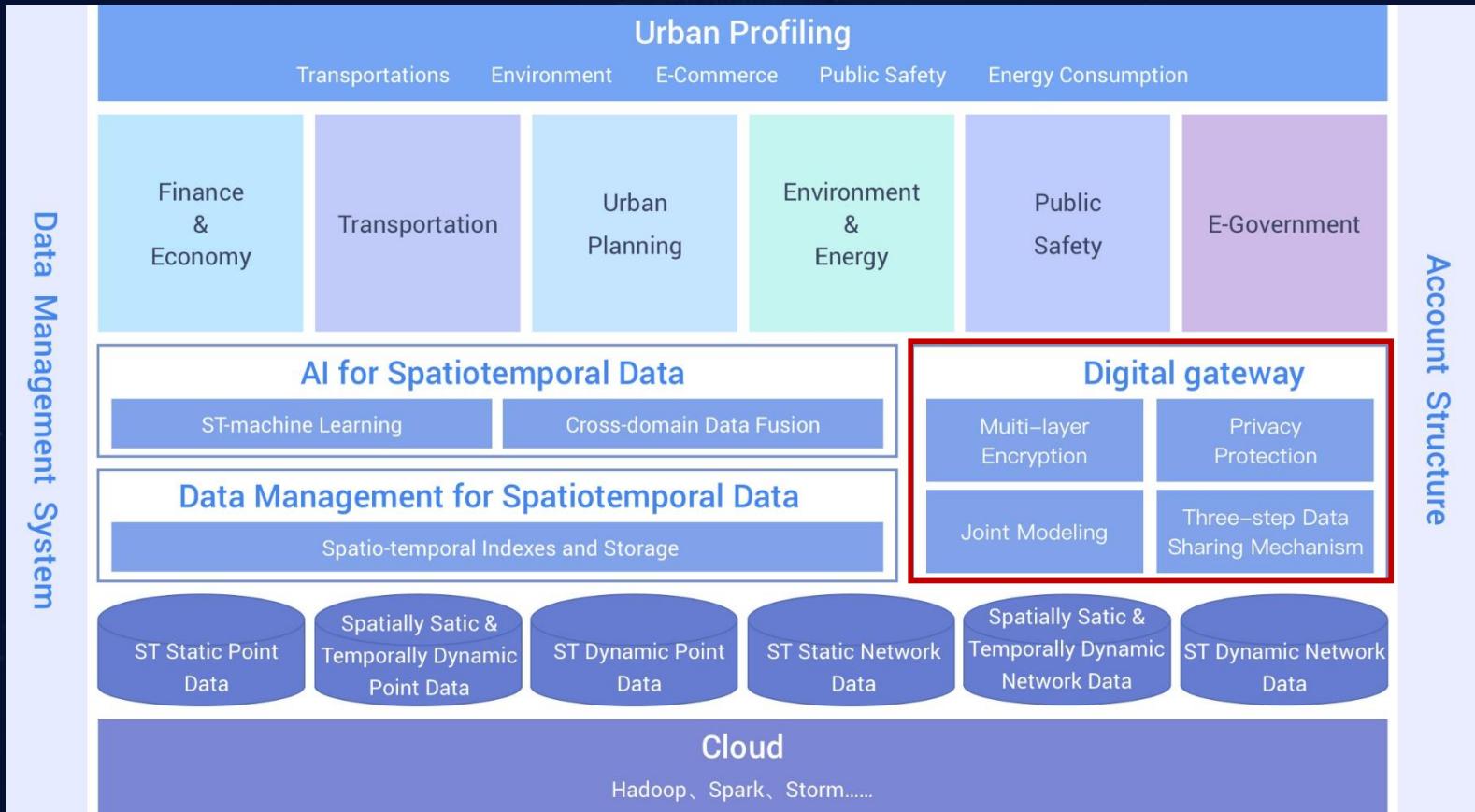
<http://ucp.jd.com>



for more dynamic data management and efficient query

# Urban Computing Platform

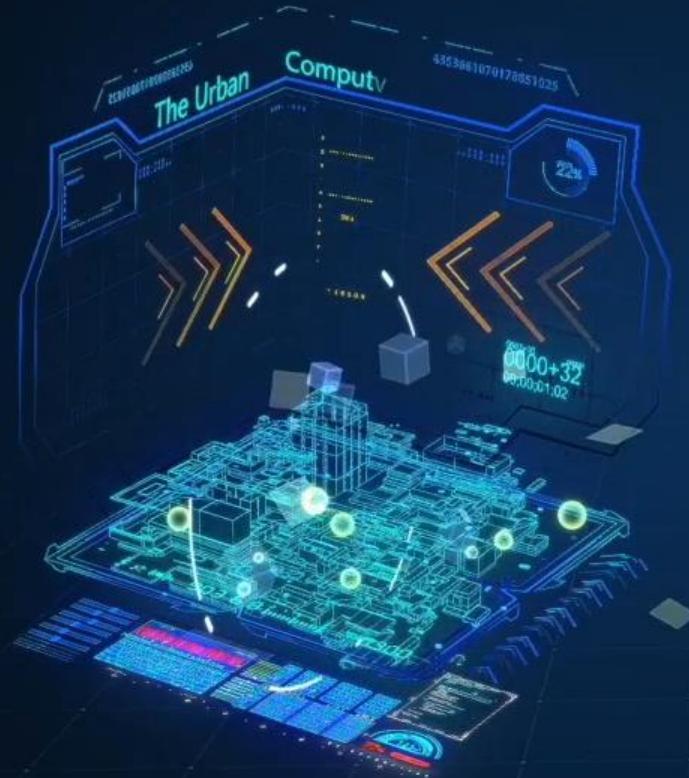
<http://ucp.jd.com>



<http://ucp.jd.com>

The Digital Gateway on this platform ensures data security

<http://ucp.jd.com>



The Platform adopts an open structure providing enterprise users



新建

组件

- 标签区间缩放标准化
- 异常检测
- 特征工程
  - 特征分析
  - 特征选择
    - 随机森林特征选择
    - GBDT特征选择
    - 单变量特征选择
  - 特征编码
  - 特征降维
- 机器学习
  - 聚类
  - 分类
  - 回归
    - 线性回归训练
    - 线性回归预测**
    - 自回归训练
    - 自回归测试
    - 回归树训练
    - 回归树测试
- 自定义脚本
- 数据源
  - breast\_cancer

典型应用

- 智能选址
- 空气质量监测
- 区域流量预测

ai\_flow X

```

graph TD
    A[breast_cancer] --> B[MinMaxNormaliz...]
    B --> C[TrainTestSplit]
    C --> D[RandomForestSe...]
    D --> E[LinearRegressi...]
    E --> F[LinearRegressi...]
  
```

作业参数设置

学习器种类

- 回归器
- 分类器

topK特征 5

topK特征值不要超过样本数

回归标准: 均方误差

弱学习器个数 90

Bootstrap

- True
- False

http://ucp.jd.com

<http://ucp.jd.com>

创建应用

模型训练中...

X



基本信息



配置数



配置字段



训练模型

完成72轮模型训练

均方误差**6.5475**

返回

生成网页应用

上一步

训练模型

# Summary

- Framework of urban computing
- Research challenges, topics and techniques
- Unique spatio-temporal data
- Urban computing platform → City OS
- Many more challenges beyond technology...



# A text book

MIT Press

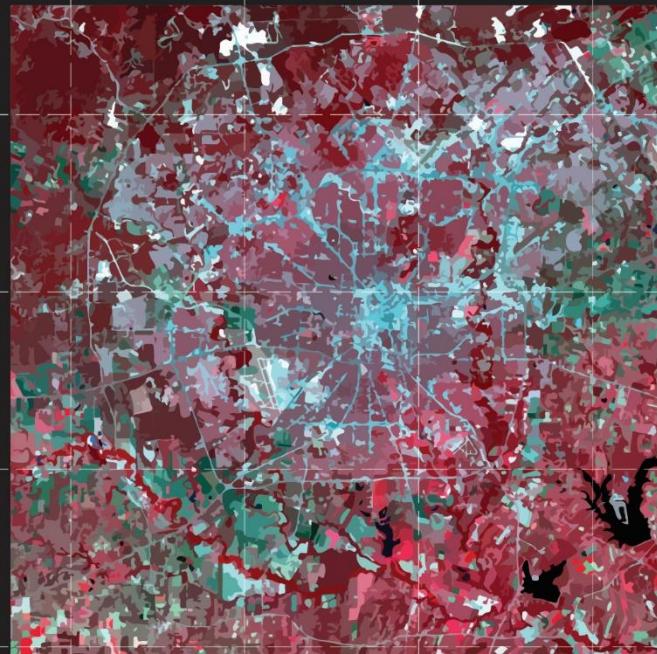
Thanks!

Dr. Yu Zheng, JD Digits

msyuzheng@outlook.com

<http://urban-computing.com/yuzheng>

# Urban Computing



Yu Zheng

Urban Computing

Urban Computing

Yu Zheng

Yu Zheng

# A text book

MIT Press

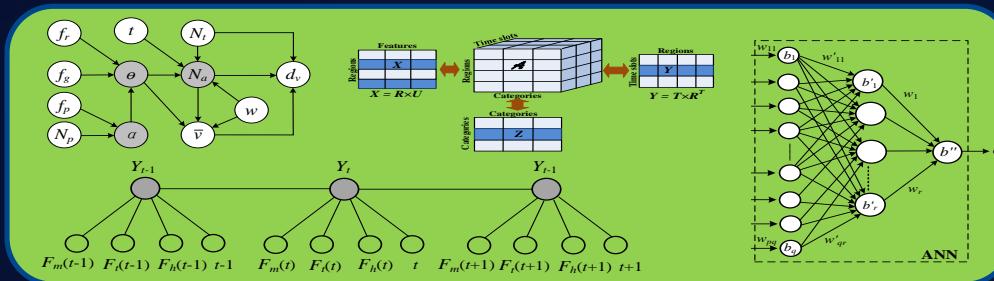


# Data Scientist

## Models and Algorithms

京东城市  
JD iCity

### Problems



### Data

