Urban Computing

–Using Big Data to Solve Urban Challenges

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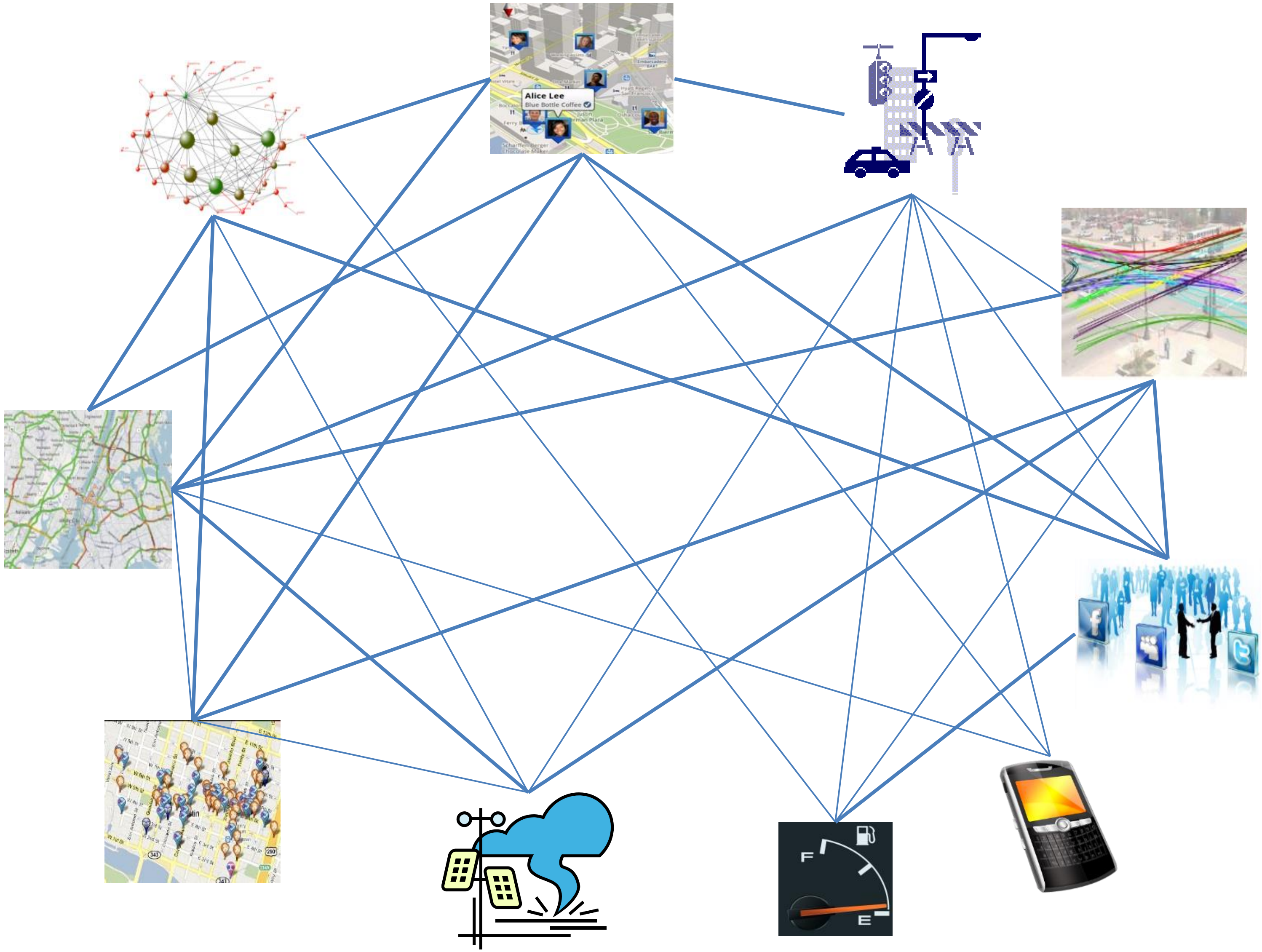
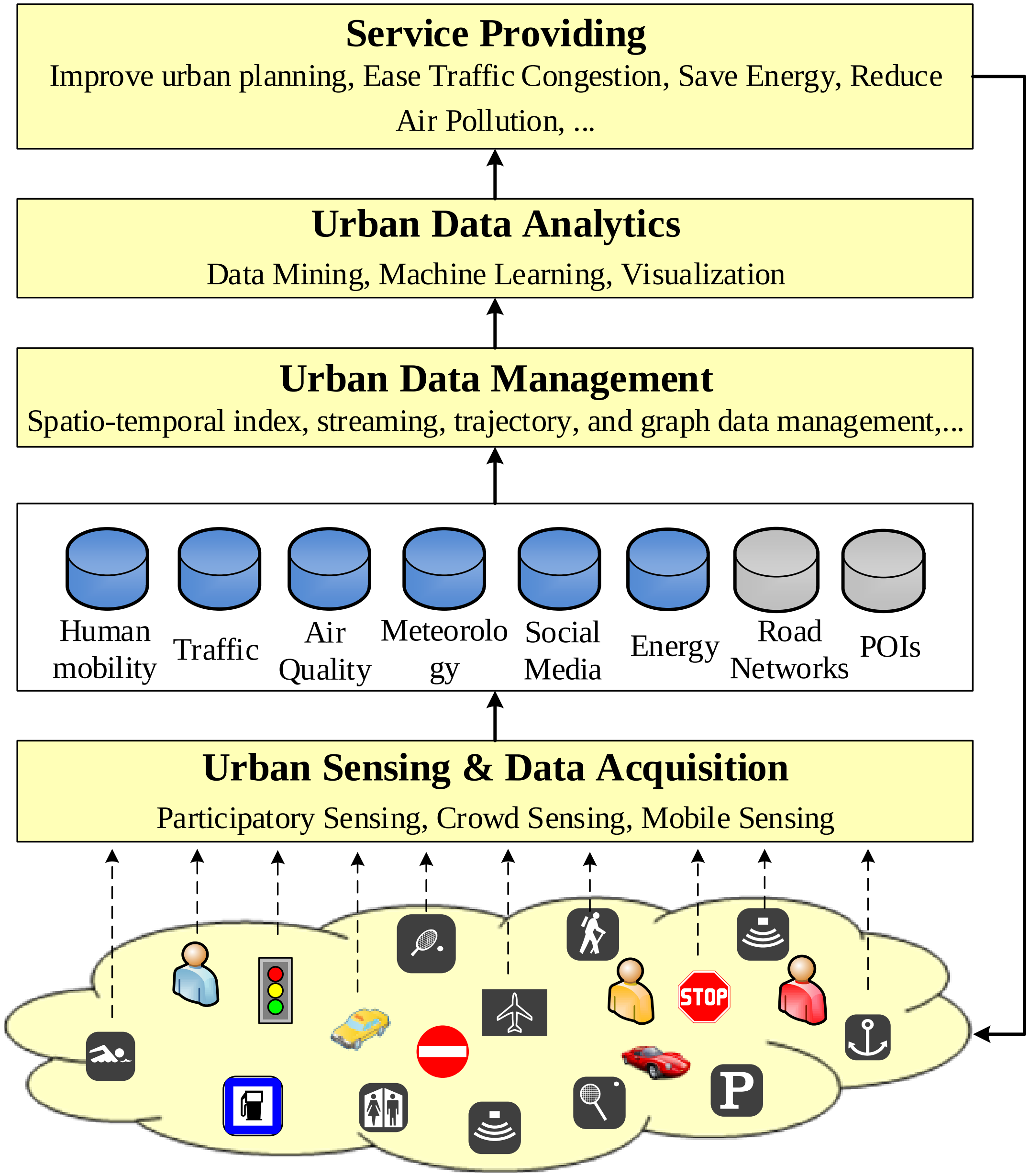
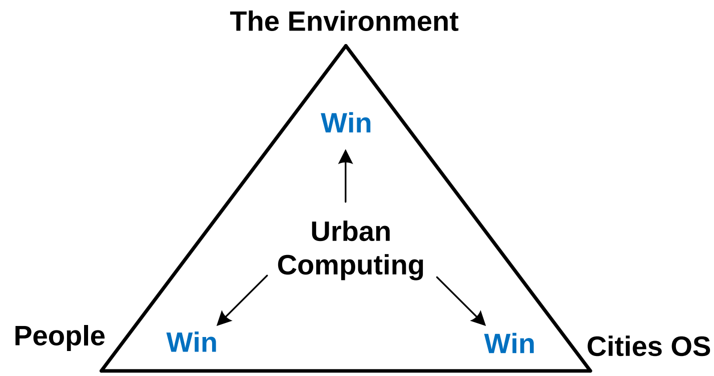
http://research.microsoft.com/en-us/projects/urbancomputing/default.aspx

Big Challenges in Big Cities

Big Data in Cities







Tackle the Big challenges

in Big cities

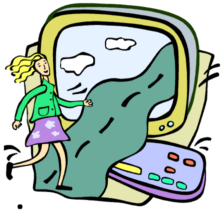
using Big data!

Zheng, Y., et al. Urban Computing: concepts, methodologies, and applications. *ACM transactions on Intelligent Systems and Technology*.

Key Focuses and Challenges

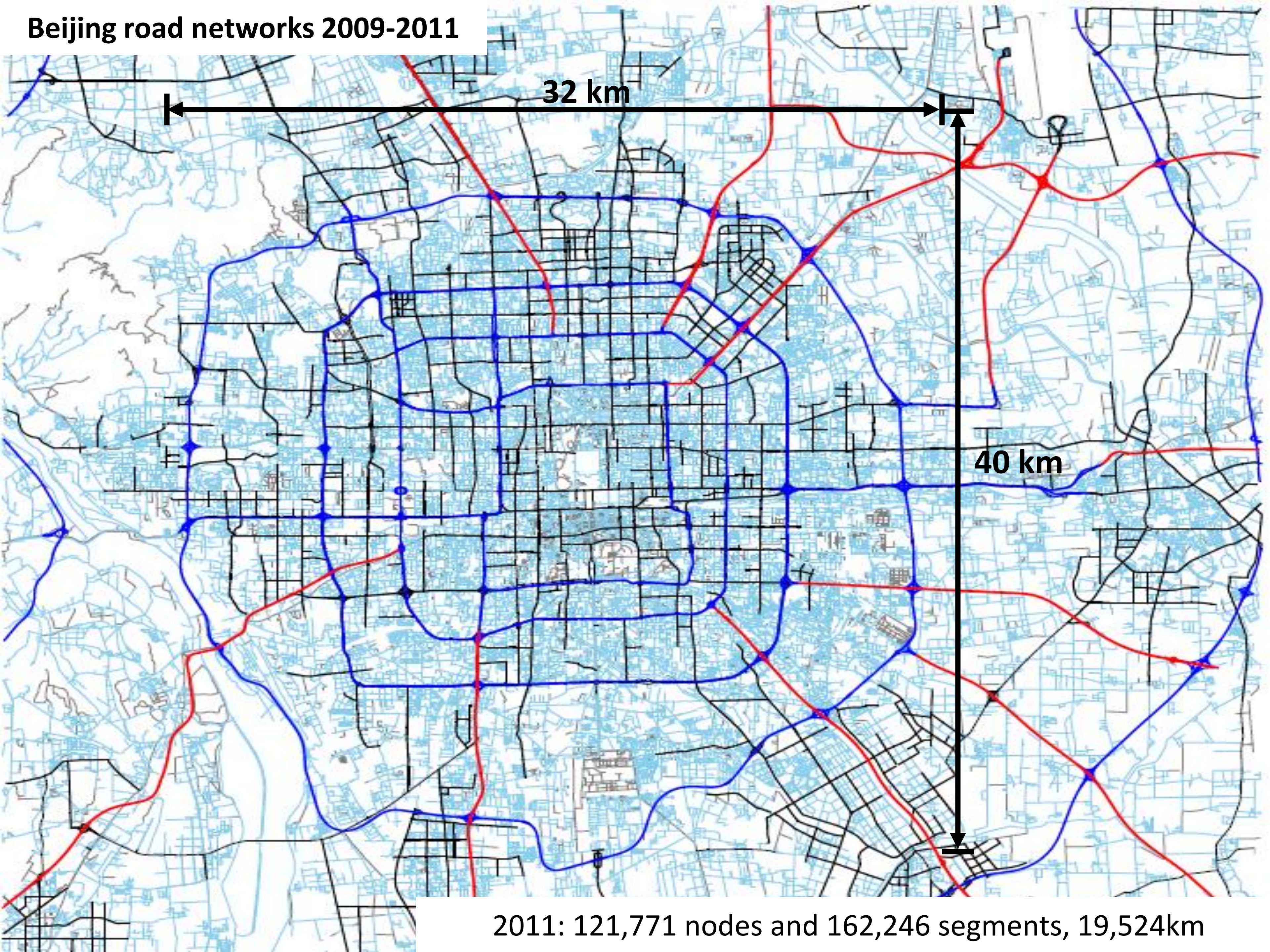
- Sensing city dynamics
  - Unobtrusively, automatically, and constantly
  - A variety of sensors: Mobile phones, vehicles, cameras, loops,…
  - **Human as a sensor:** User generated content (check in, photos, tweets)
    - Loose control and unreliable → data missing and skewed distribution
    - Unstructured, implicit, and noisy data
    - Trade off among energy, privacy and the utility of the data

- Computing with heterogeneous data sources
  - Geospatial, temporal, social, text, images, economic, environmental,…
  - Learn mutually reinforced knowledge across a diversity of data
  - Efficiency + Effectiveness: Data Management + Mining + Machine Learning

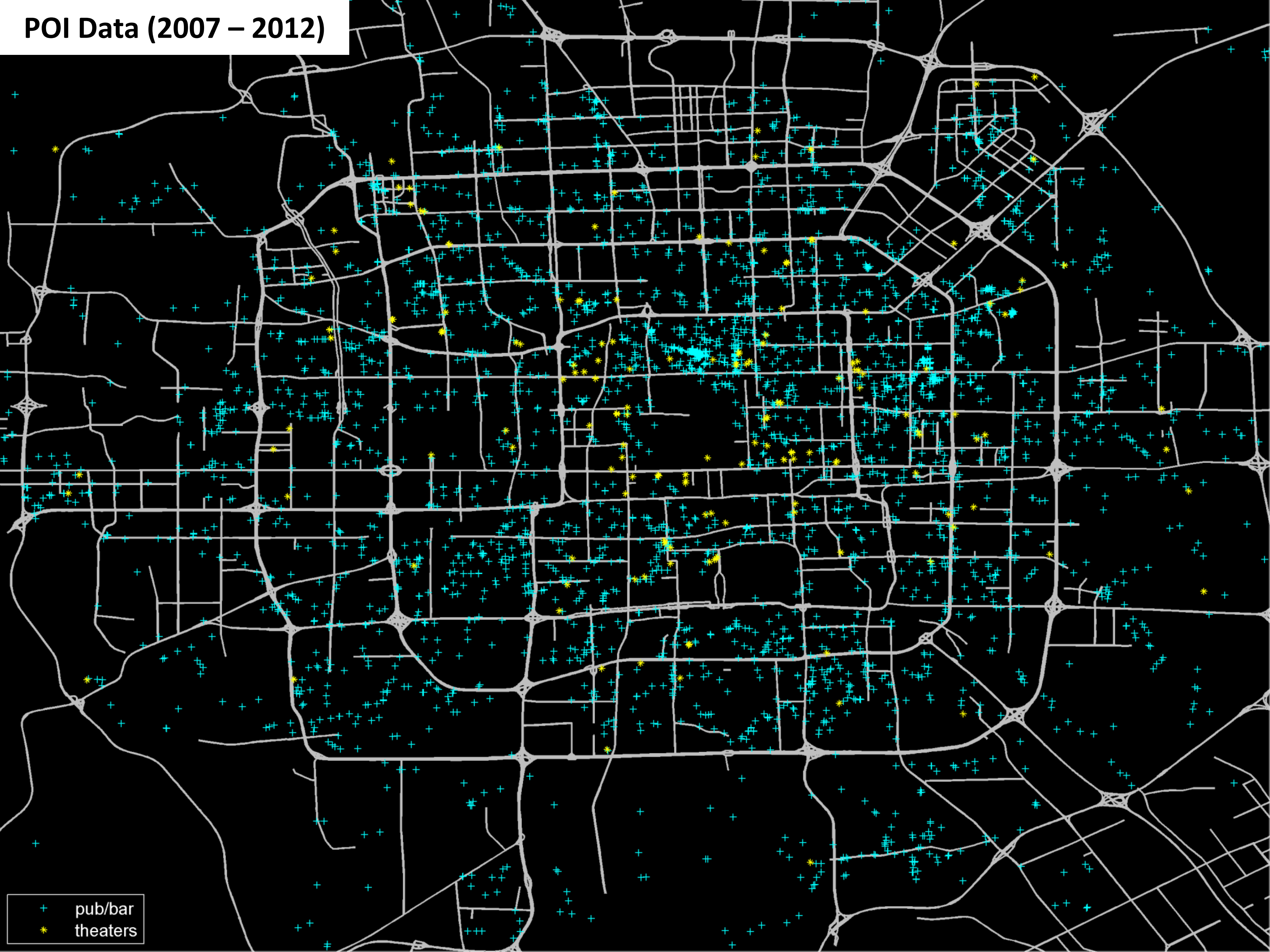


- Blending the physical and virtual worlds
  - Serving both people and cities (virtually and physically)
  - **Hybrid systems**: Mobile + Cloud, crowd sourcing, participatory sensing…

Yu Zheng, et al. Urban Computing: concepts, methodologies, and applications. ACM Trans. on Intelligent Systems and Technology. 2014


Beijing road networks 2009-2011
32 km
40 km
2011: 121,771 nodes and 162,246 segments, 19,524km

POI Data (2007 – 2012)




260
240
220
200
180
160
140
120
2007
2007.5
2008
2008.5
2009
2009.5
2010
2010.5
2011
2011.5
2012
theater

Air Quality Data

Forecast | Current AQI | More Maps

National Parks/Monuments   Tribal Boundaries

The tribal boundaries shown here are provided by the Bureau of Indian Affairs and are intended to be used as a general spatial reference only. They are not a formal determination of tribal boundaries by the EPA.

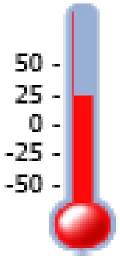
Click on the city name for more detailed information. printable summary	FORECAST Tue Aug 20	FORECAST Wed Aug 21	CURRENT AQI
Ann Arbor	! USG	n/a	69
Benton Harbor	Mod	n/a	67
Detroit	! USG	n/a	84
Eastern U.P.	Mod	n/a	62
Flint	Mod	n/a	66
Grand Rapids	! USG	n/a	74
Houghton Lake	Mod	n/a	63
Kalamazoo	Mod	n/a	67
Lansing	Mod	n/a	72
Ludington	! USG	n/a	63
Saginaw	Mod	n/a	73
Traverse City	Mod	n/a	63

Good | Moderate | USG | Unhealthy | Very Unhealthy | Hazardous | ! Action Day

Meteorological data

Weather Observation

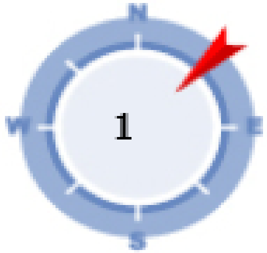
Temp



26℃

Humidity: 73%

Wind direction



NE

Monthly Climate History

Accumulated Rainfall
159.7mm

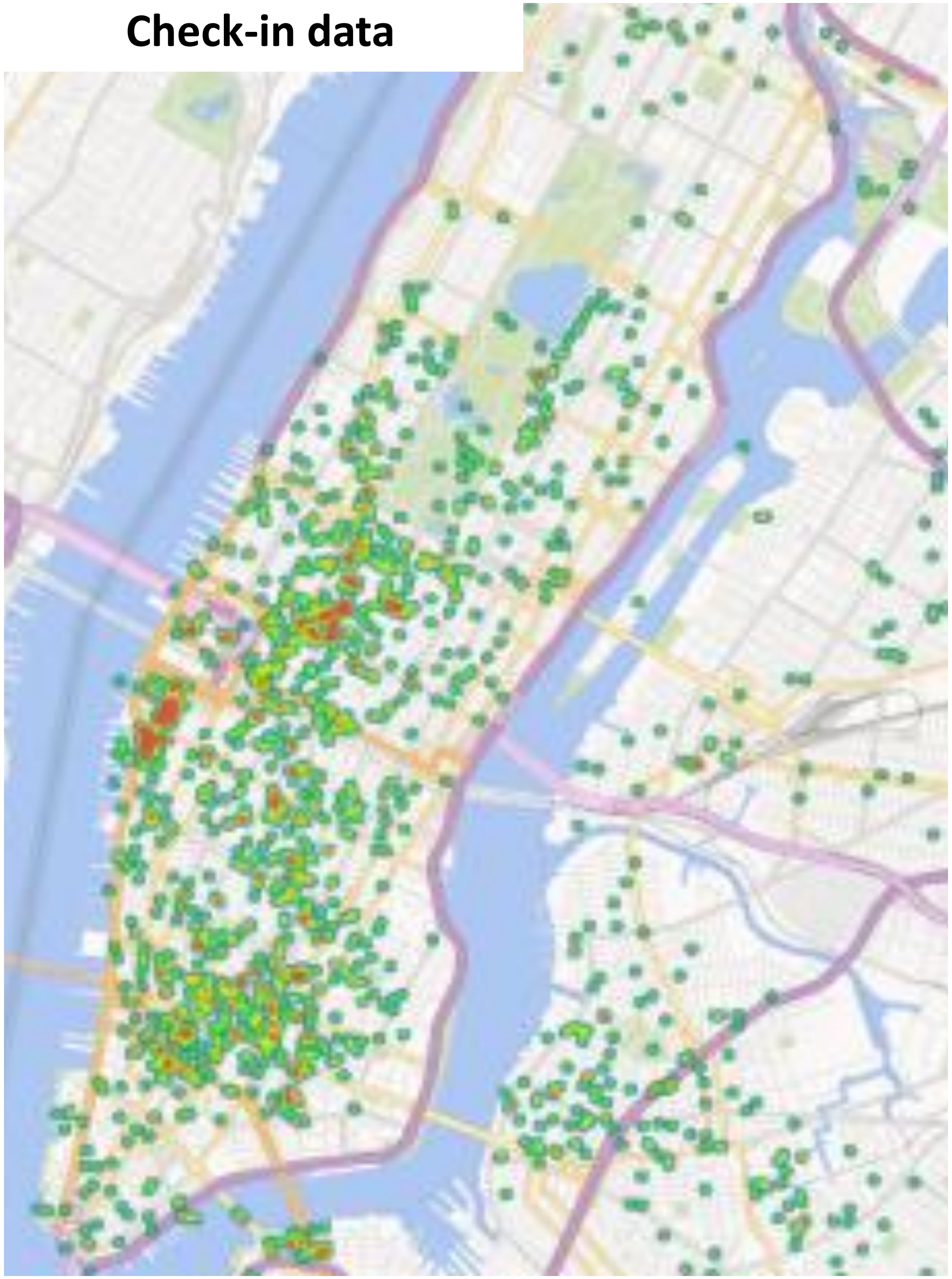
Average Temperature
24.9℃

High Temperature
36.1℃

BeijingWeather Forecast (2013-08-20 18:00)

4-7 Days Forecast

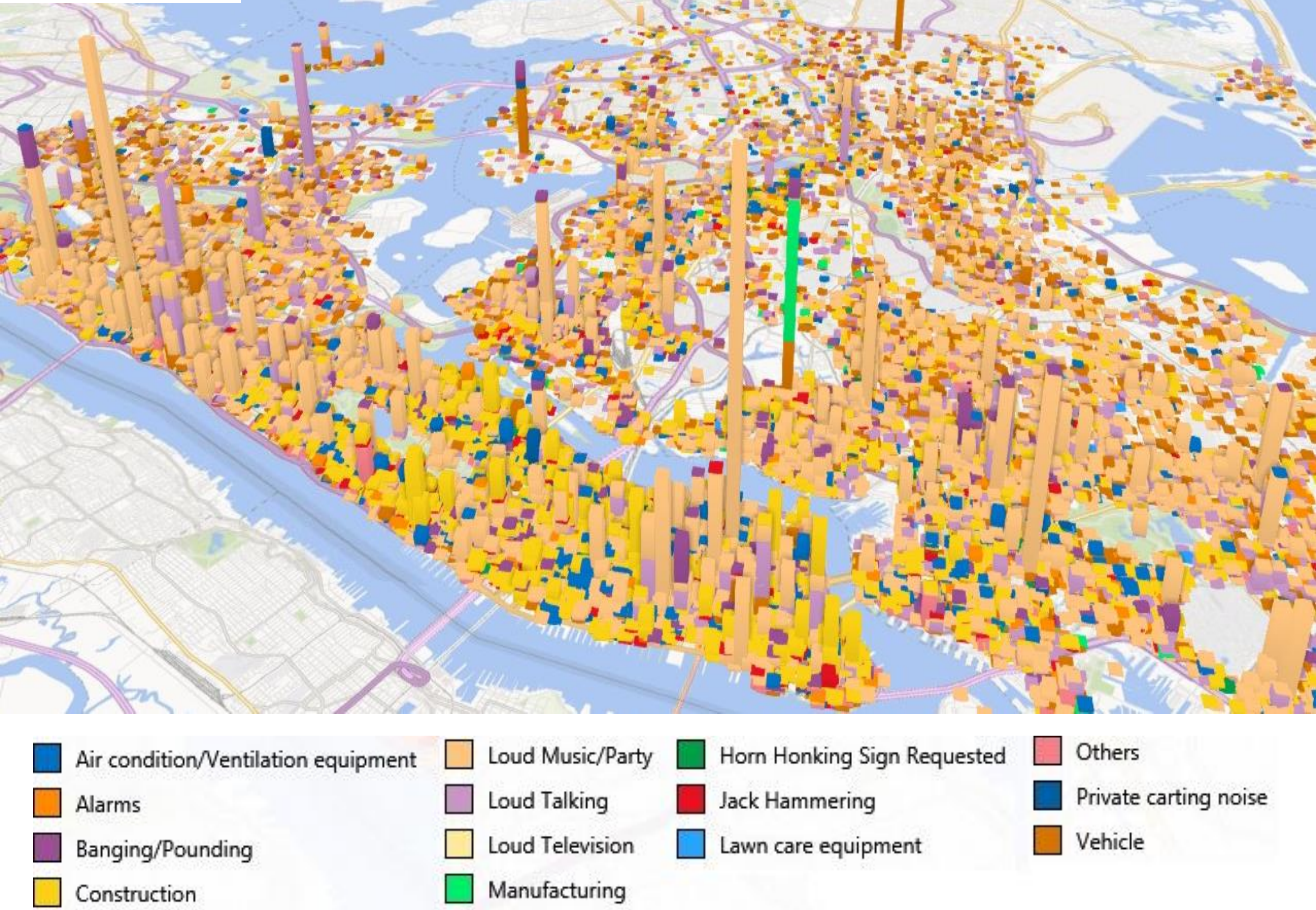
Date		weatherForecast		Temperature	wind
Tuesday Aug 20	night		Shower	Low: 23℃ (73℉)	<12km/h
Wednesday Aug 21	day		Cloudy	High: 30℃ (86℉)	<12km/h
	night		Cloudy	Low: 22℃ (72℉)	<12km/h
Thursday Aug 22	day		Sunny	High: 29℃ (84℉)	<12km/h
	night		Sunny	Low: 22℃ (72℉)	<12km/h
Friday Aug 23	day		Sunny	High: 32℃ (90℉)	<12km/h
	night		Sunny	Low: 22℃ (72℉)	<12km/h



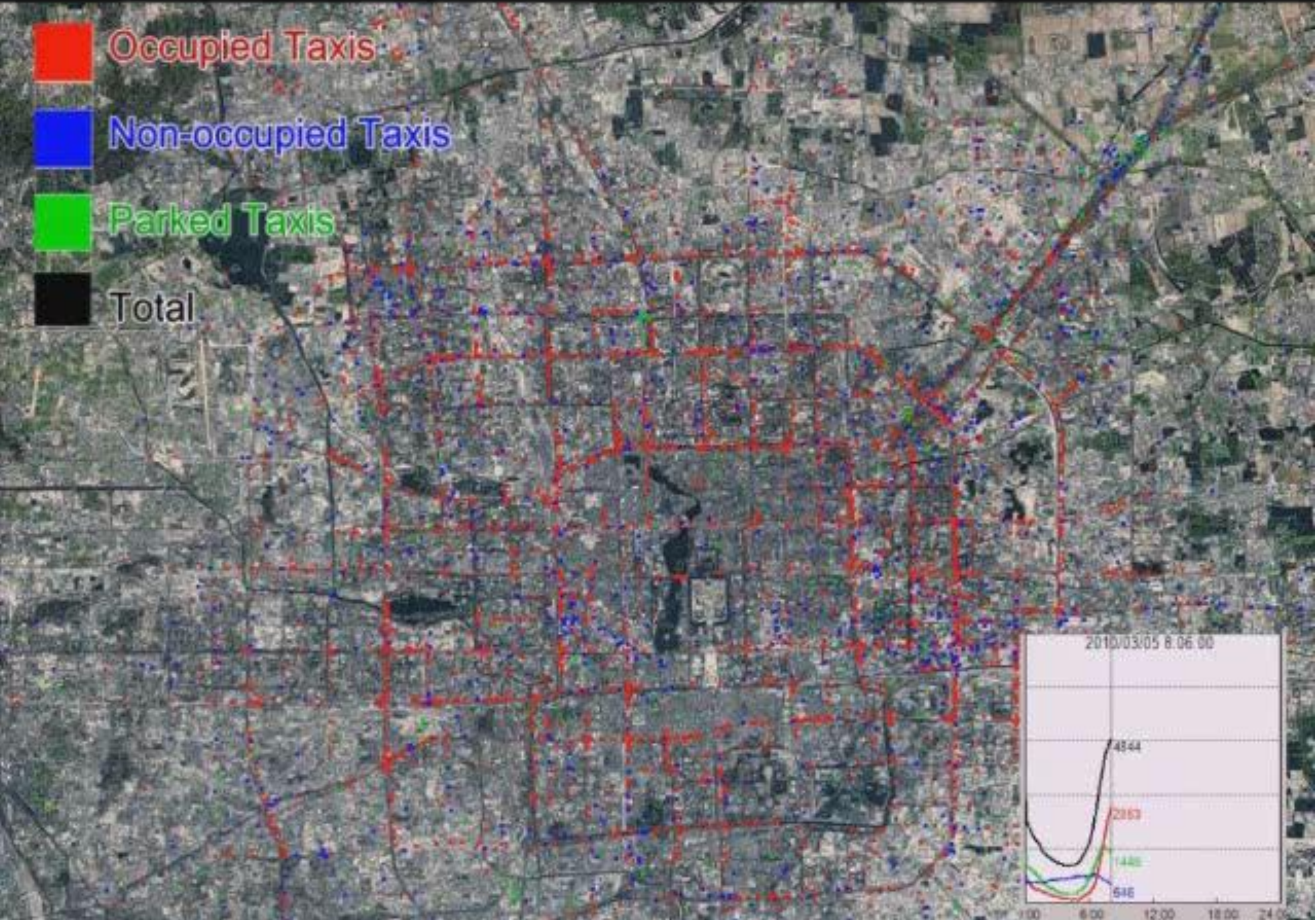
Check-in: Entertainment

Check-ins: Nightlife Spot

Urban Noises

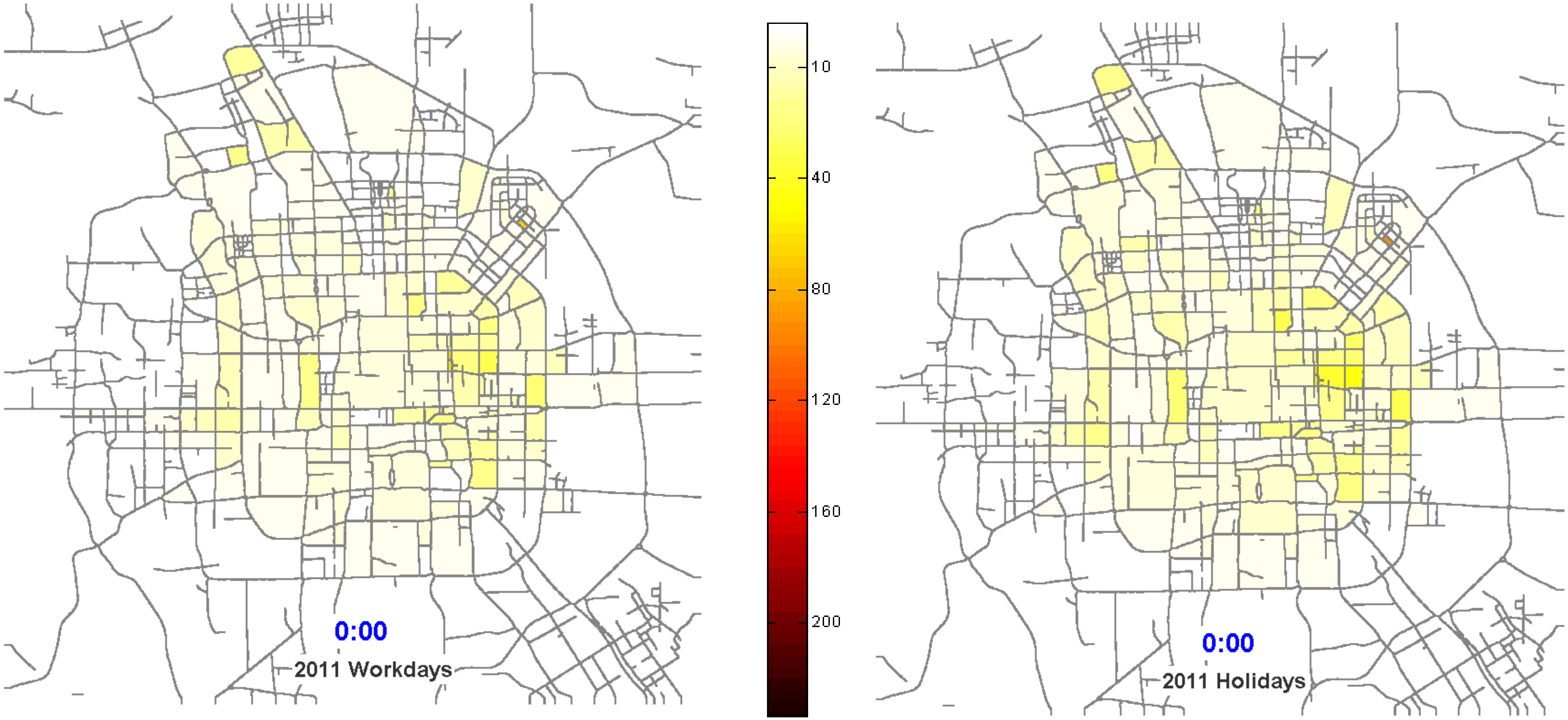


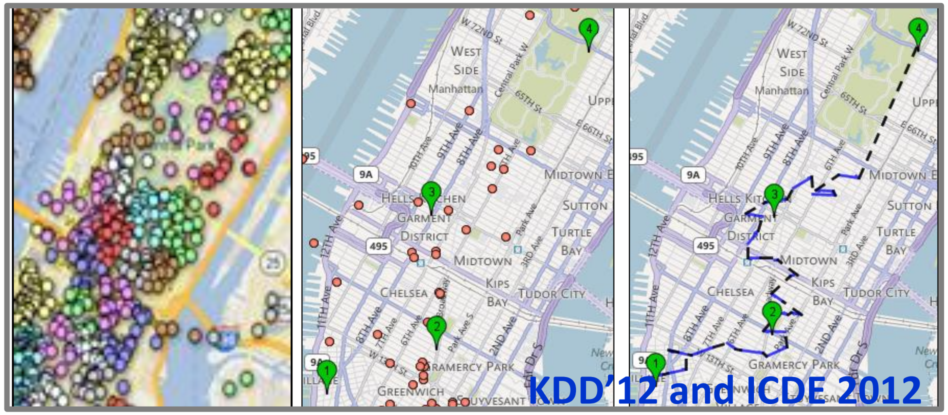
GPS trajectories of 33,000 taxis from 2009 to 2013



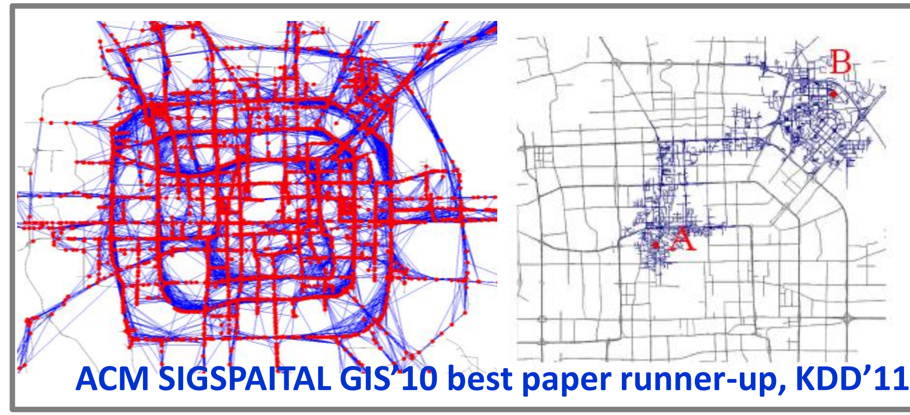
Occupied Taxis
Non-occupied Taxis
Parked Taxis
Total
2010/03/05 8:06:00
4844
646
6:00
12:00
18:00

Heat Maps of Beijing (2011)

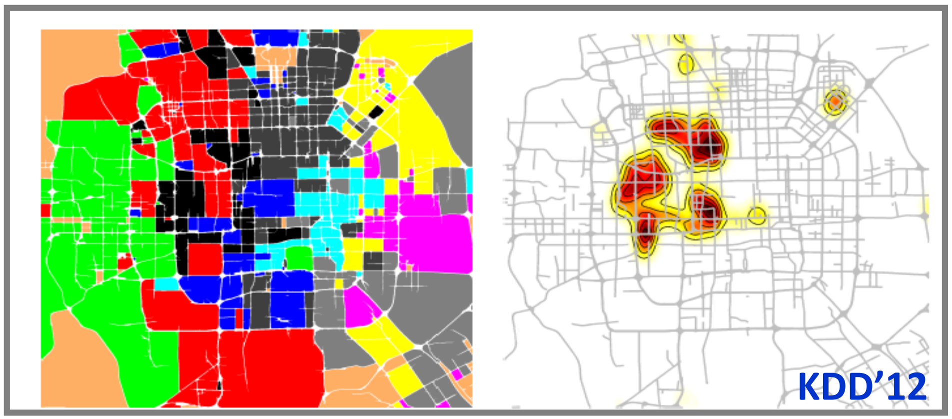




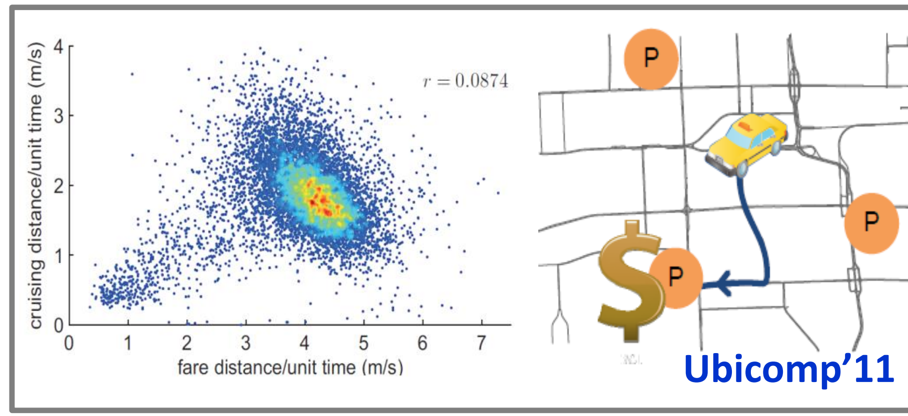
Route Construction from Uncertain Trajectories



Finding Smart Driving Directions

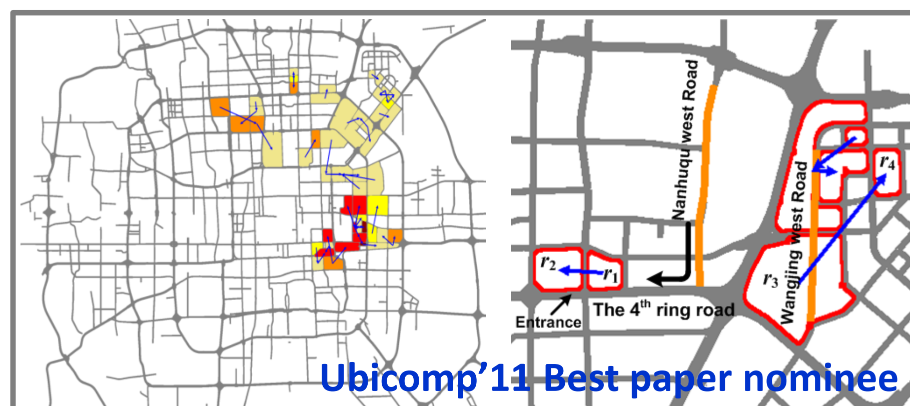


Discovery of Functional Regions

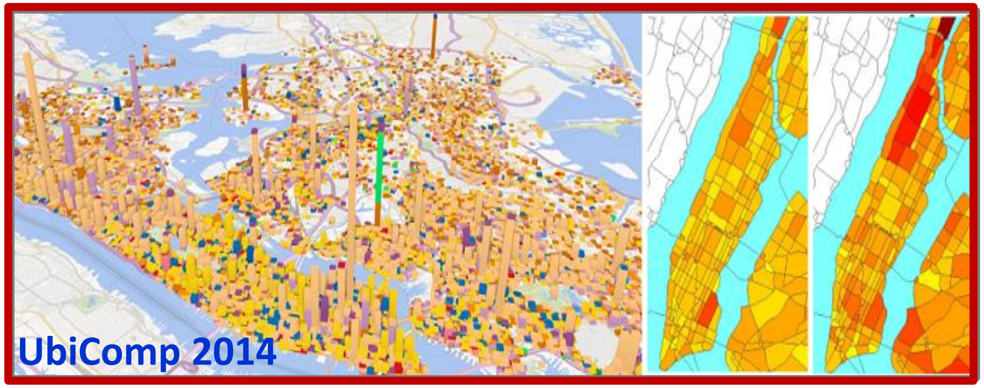


Passengers-Cabbie Recommender system

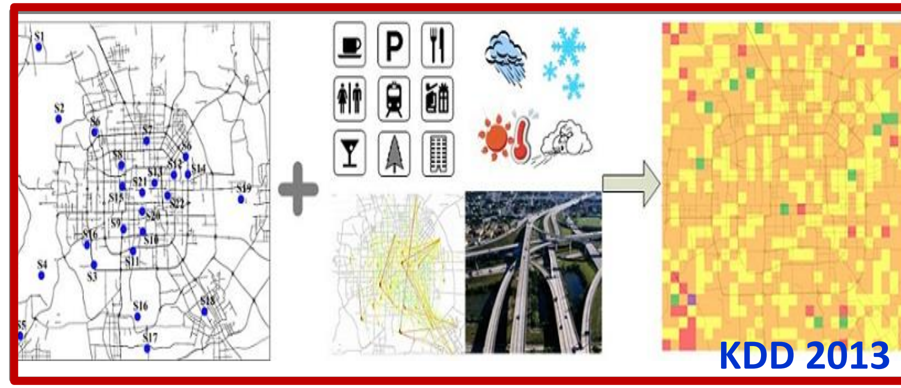
Anomalous Events Detection KDD'11 and ICDM 2012



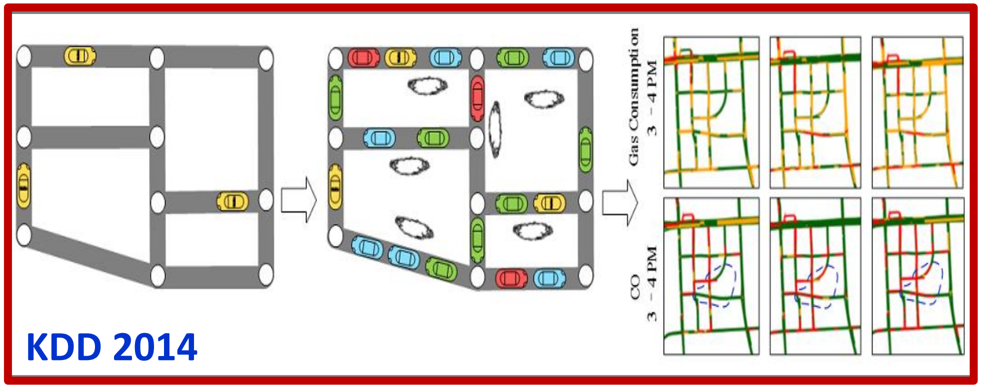
Urban Computing for Urban Planning



Diagnose urban noises using big data

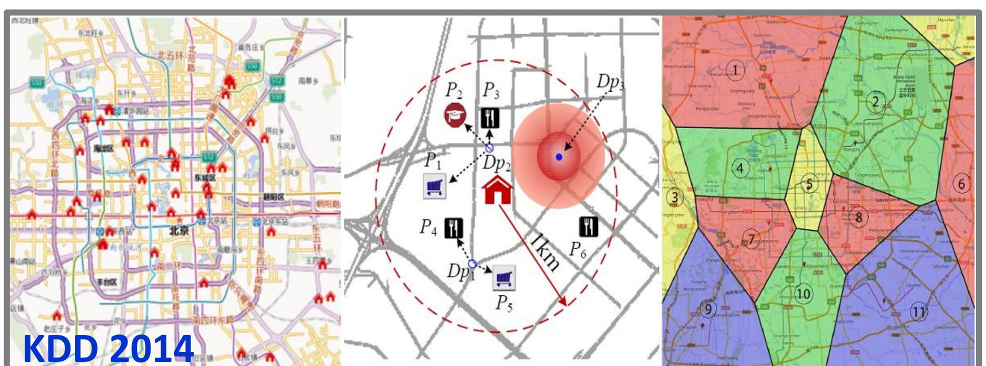


Infer air quality using big data

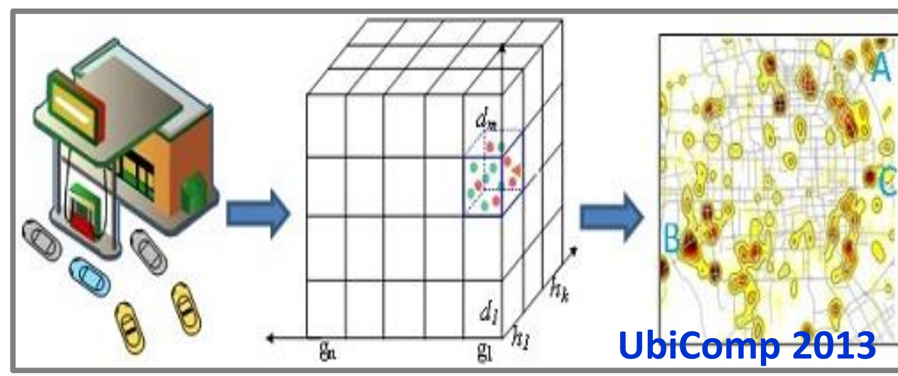


Real-time gas consumption and pollution emission

Real-time and large-scale dynamic ridesharing



Residential Real estate ranking and clustering

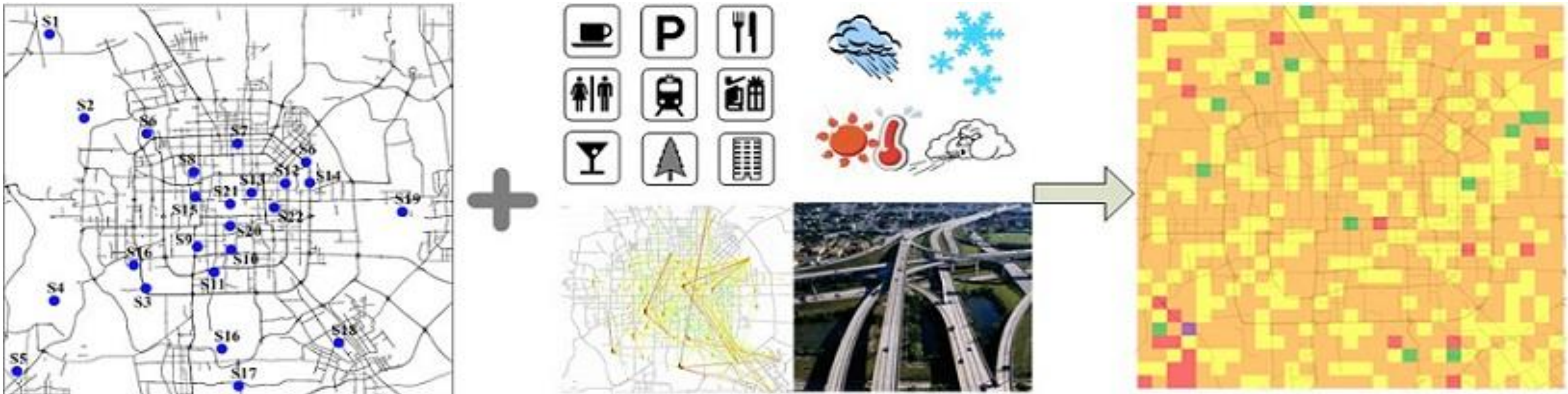


Real-time city-scale gas consumption sensing

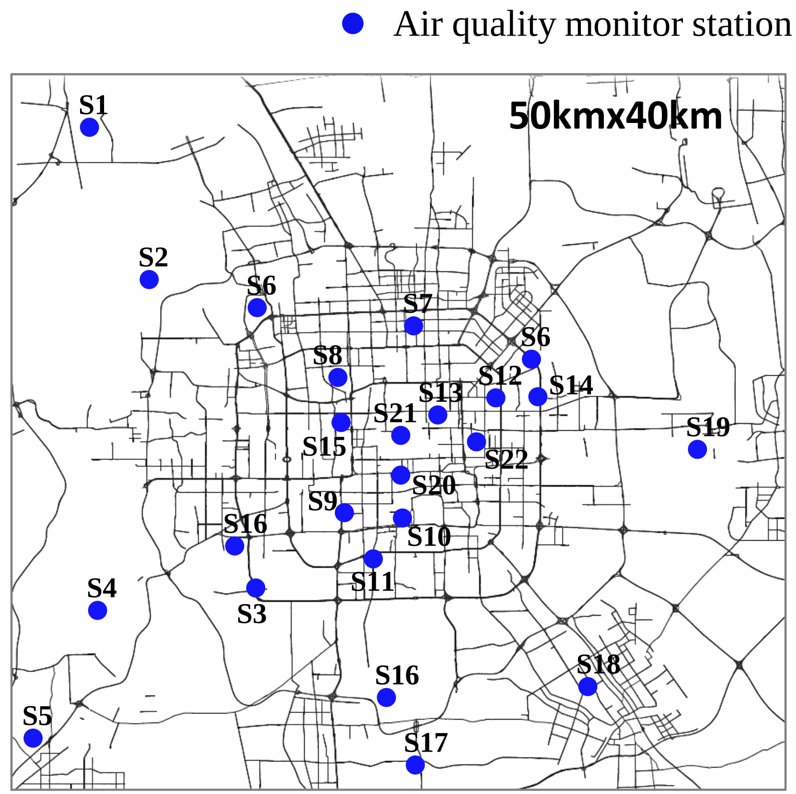
When Urban Air Meets Big Data

KDD 2013

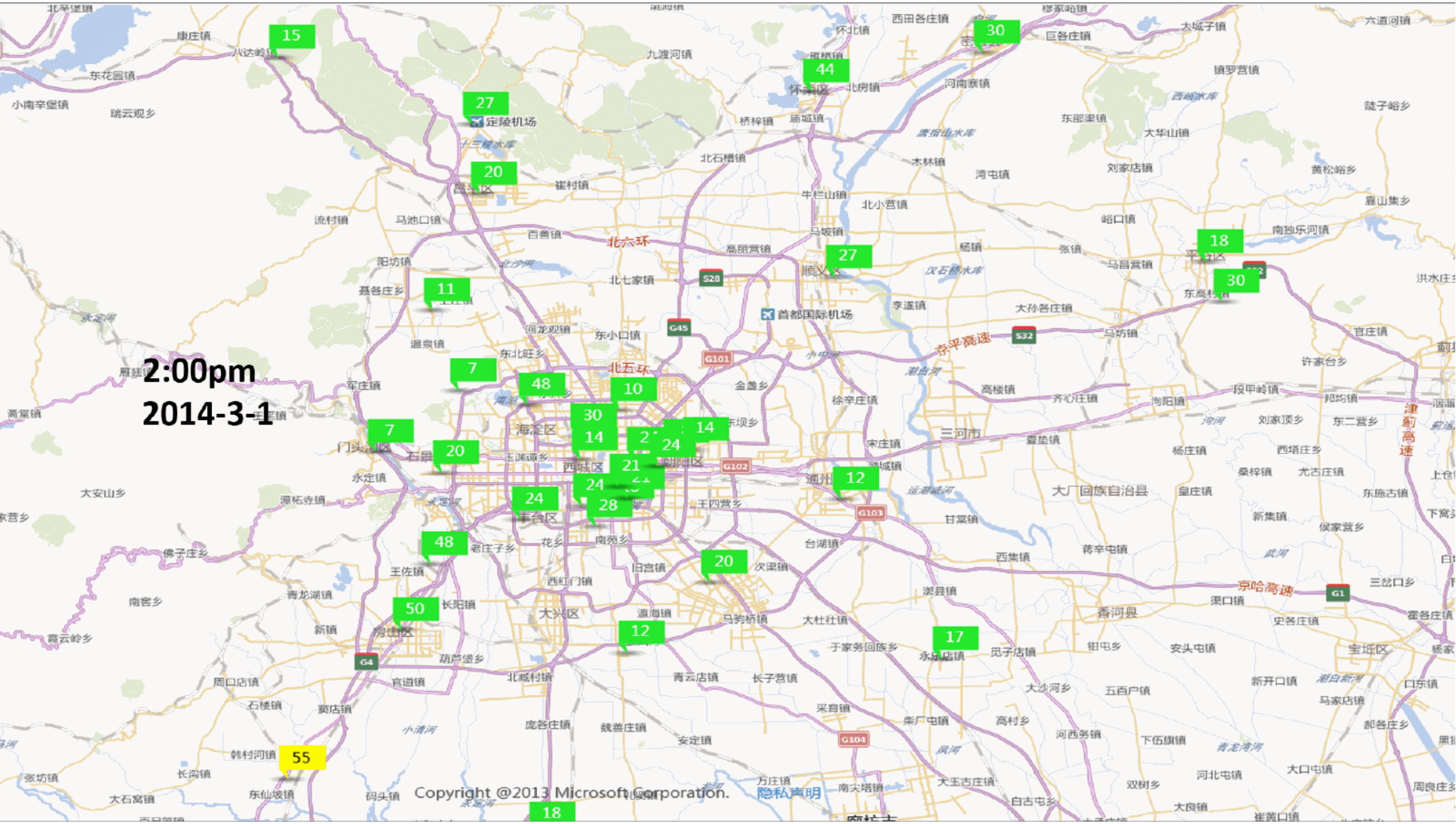
http://urbanair.msra.cn/



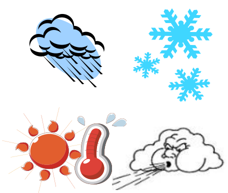
Background


Air quality monitor station
50kmx40km
S1
S2
S6
S7
S6
S8
S12
S14
S13
S21
S15
S22
S19
S20
S9
S16
S10
S11
S4
S3
S16
S18
S5
S17

We do not really know the air quality of a location without a monitoring station!



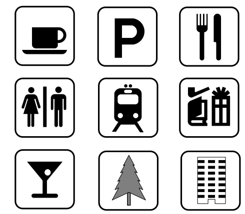
Inferring **Real-Time** and **Fine-Grained** air quality throughout a city using **Big Data**



Meteorology

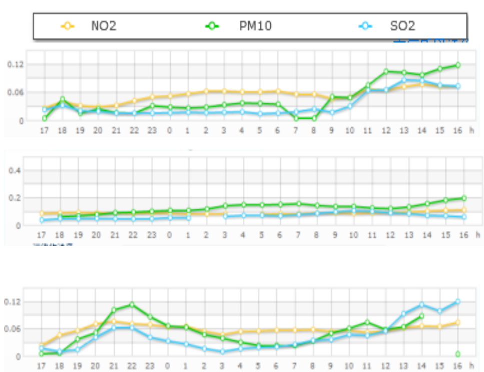
Traffic

Human Mobility

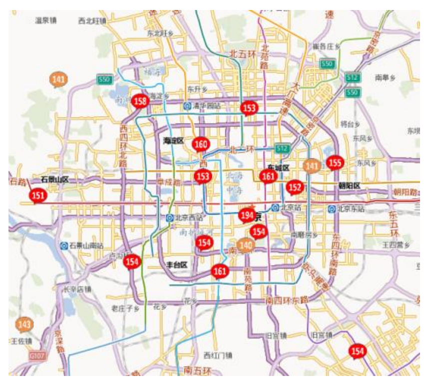


POIs

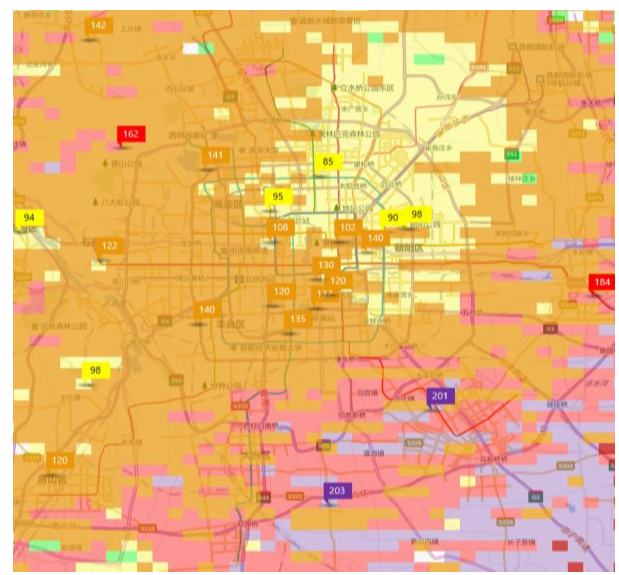
Road networks



Historical air quality data



Real-time air quality reports



Zheng, Y., et al. U-Air: when urban air quality inference meets big data. KDD 2013

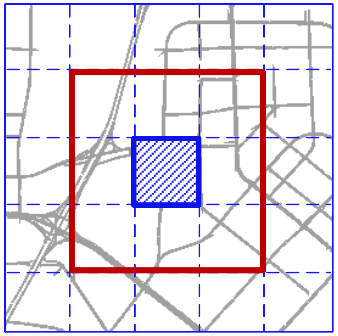
Difficulties

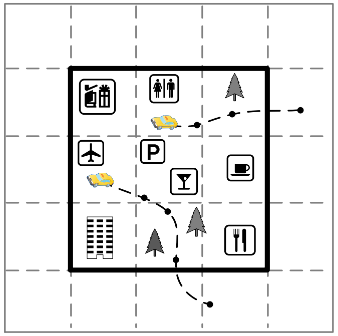
- Incorporate multiple heterogeneous data sources into a learning model
  - Spatially-related data: POIs, road networks
  - Temporally-related data: traffic, meteorology, human mobility
- Data sparseness (little training data)
  - Limited number of stations
  - Many places to infer
- Efficiency request
  - Massive data
  - Answer instant queries

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

Methodology Overview

- Partition a city into disjoint grids
- Extract features for each grid from its impacting region
  - Meteorological features
  - Traffic features
  - Human mobility features
  - POI features
  - Road network features





- Co-training-based semi-supervised learning model for each pollutant
  - Predict the AQI labels
  - Data sparsity
  - Two classifiers

AQI	Values Levels of Health Concern	Colors
0-50	Good (G)	Green
51-100	Moderate (M)	Yellow
101-150	Unhealthy for sensitive groups (U-S)	Orange
151-200	Unhealthy (U)	Red
201-300	Very unhealthy (VU)	Purple
301-500	Hazardous (H)	Maroon

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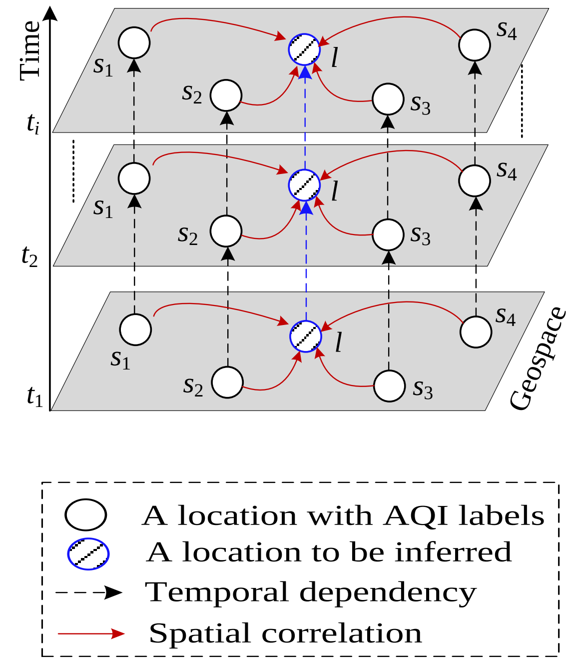
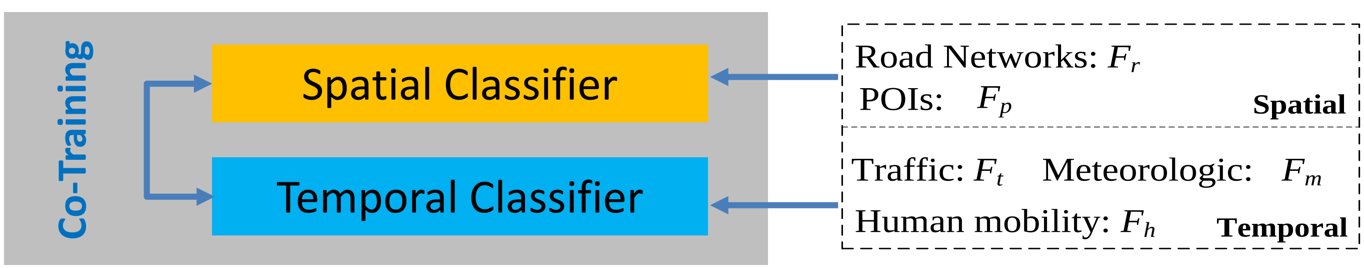
Semi-Supervised Learning Model

- Philosophy of the model
  - States of air quality
    - Temporal dependency in a location
    - Geo-correlation between locations
  - Generation of air pollutants
    - Emission from a location
    - Propagation among locations
  - Two sets of features
    - Spatially-related
    - Temporally-related





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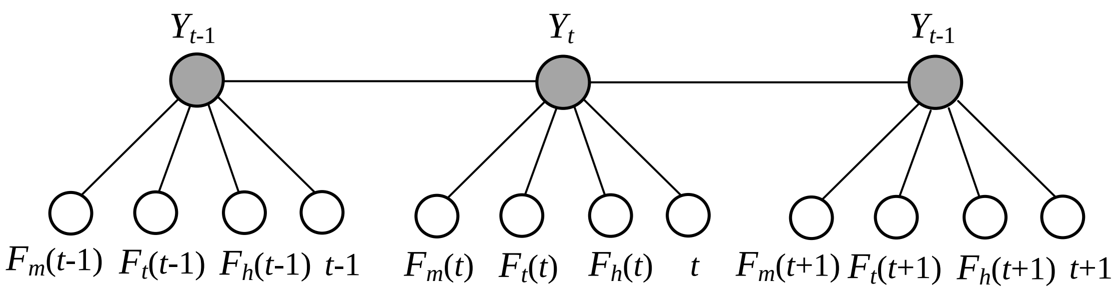
Semi-Supervised Learning Model

- Temporal classifier (TC)
  - Model the temporal dependency of the air quality in a location
  - Using temporally related features
  - Based on a Linear-Chain Conditional Random Field (CRF)



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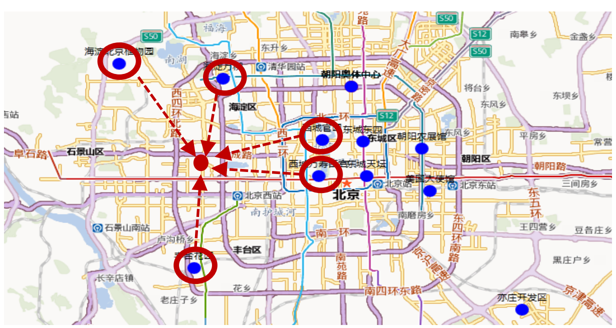
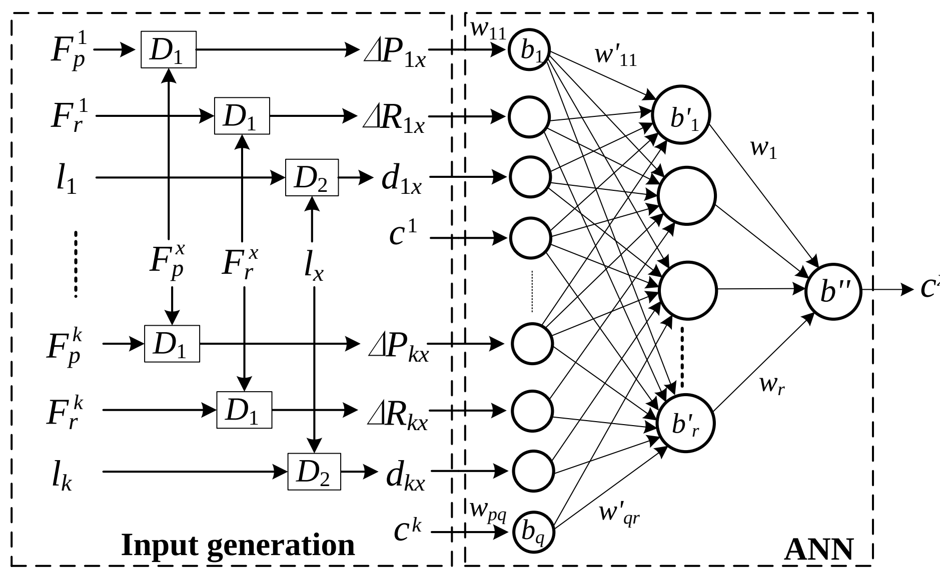
Semi-Supervised Learning Model

- Spatial classifier (SC)
  - Model the spatial correlation between AQI of different locations
  - Using spatially-related features
  - Based on a BP neural network
- Input generation
  - Select *n* stations to pair with
  - Perform *m* rounds





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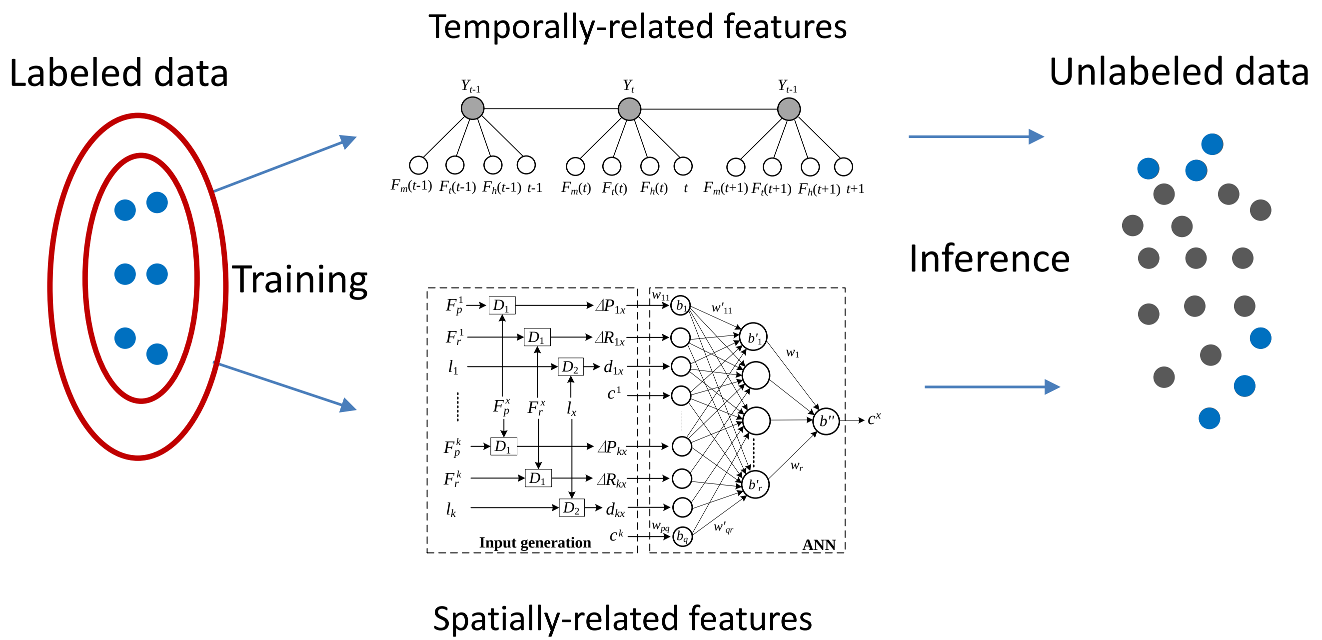
Learning Process of Our Model



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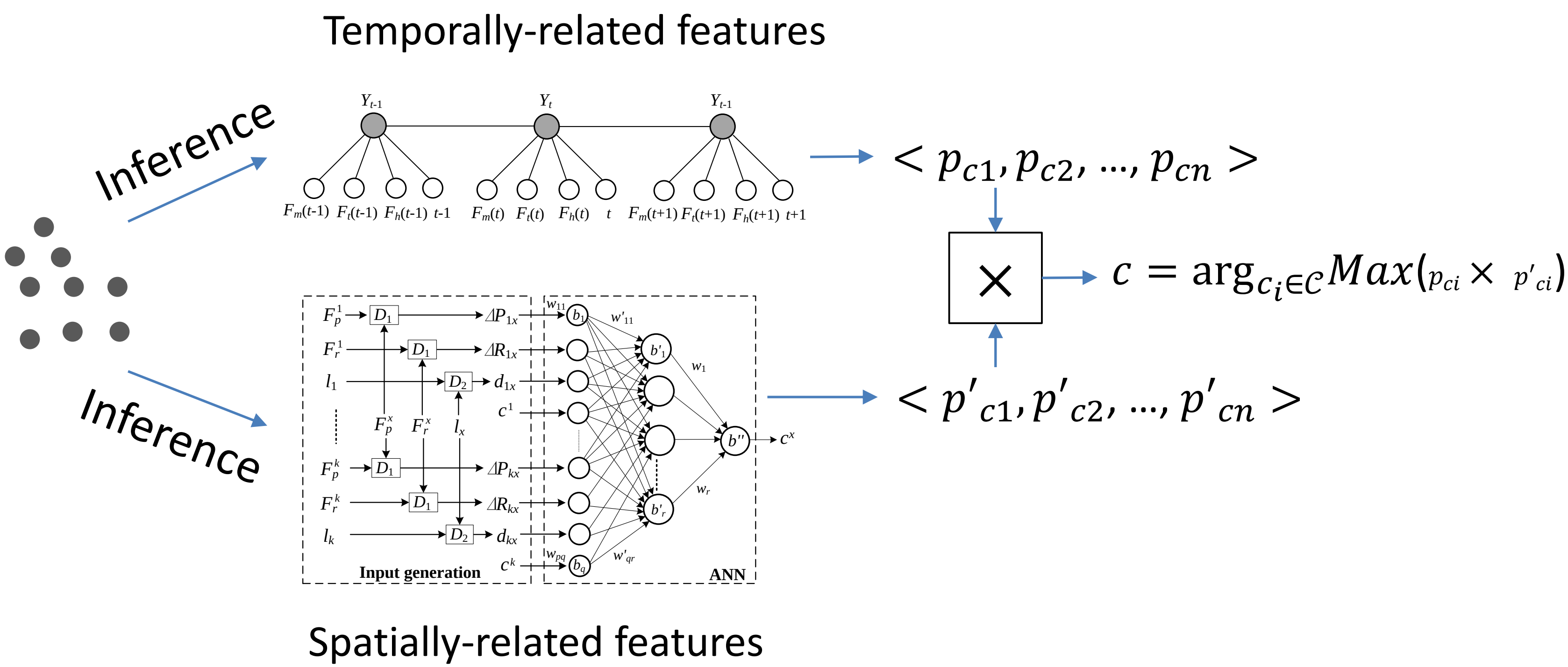
Inference Process



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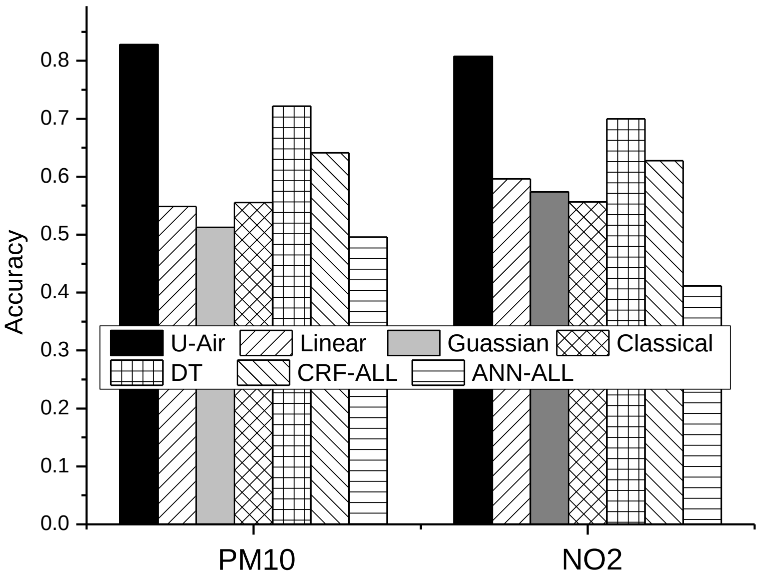
Evaluation

- Overall performance



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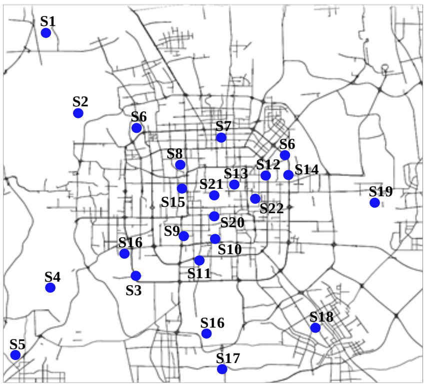
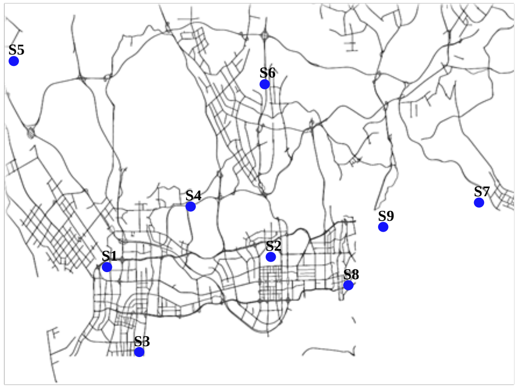
KDD 2013



A) Beijing

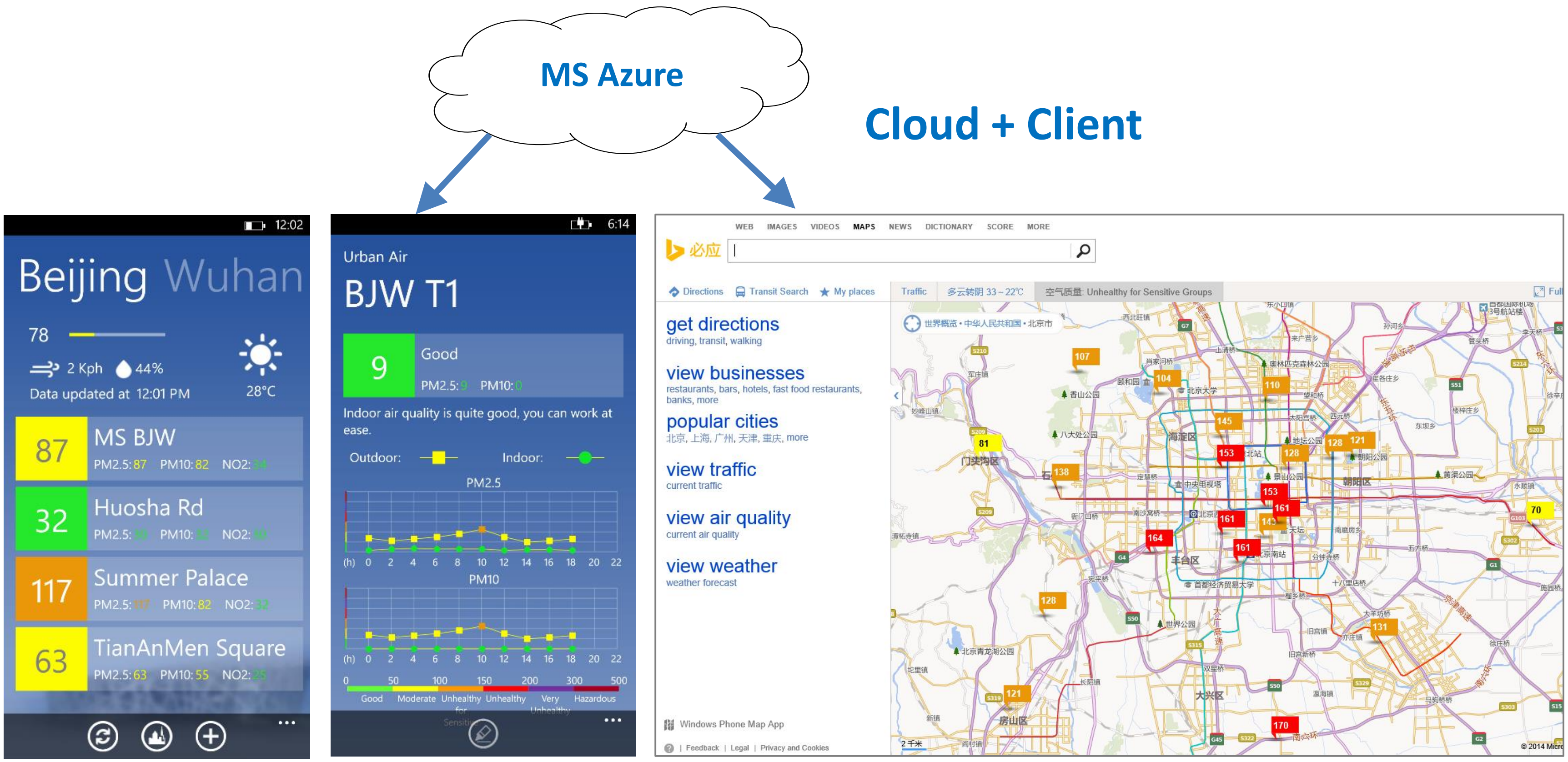
B) Shanghai



C) Shenzhen

D) Wuhan

Cloud + Client

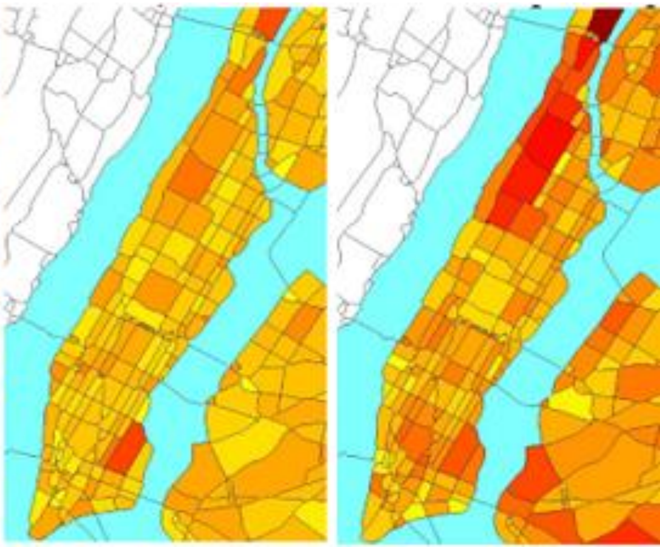


Urban Air **Bing Map**

- Transferred to CityNext and Bing Map China
- Working with Chinese Ministry of Environmental Protection
- Forecasting air quality in the near future
- To identify the root cause of the air pollution

Diagnosing Urban Noises using Big Data

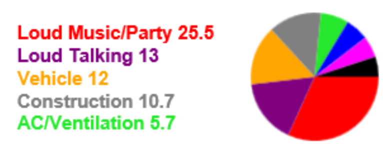
UbiComp 2014



Background

- Many cities suffer from noise pollutions
  - Traffic, loud music, construction, AC…
  - Compromise working efficiency
  - Reduce sleep quality
  - Impair both physical and mental health
  - …

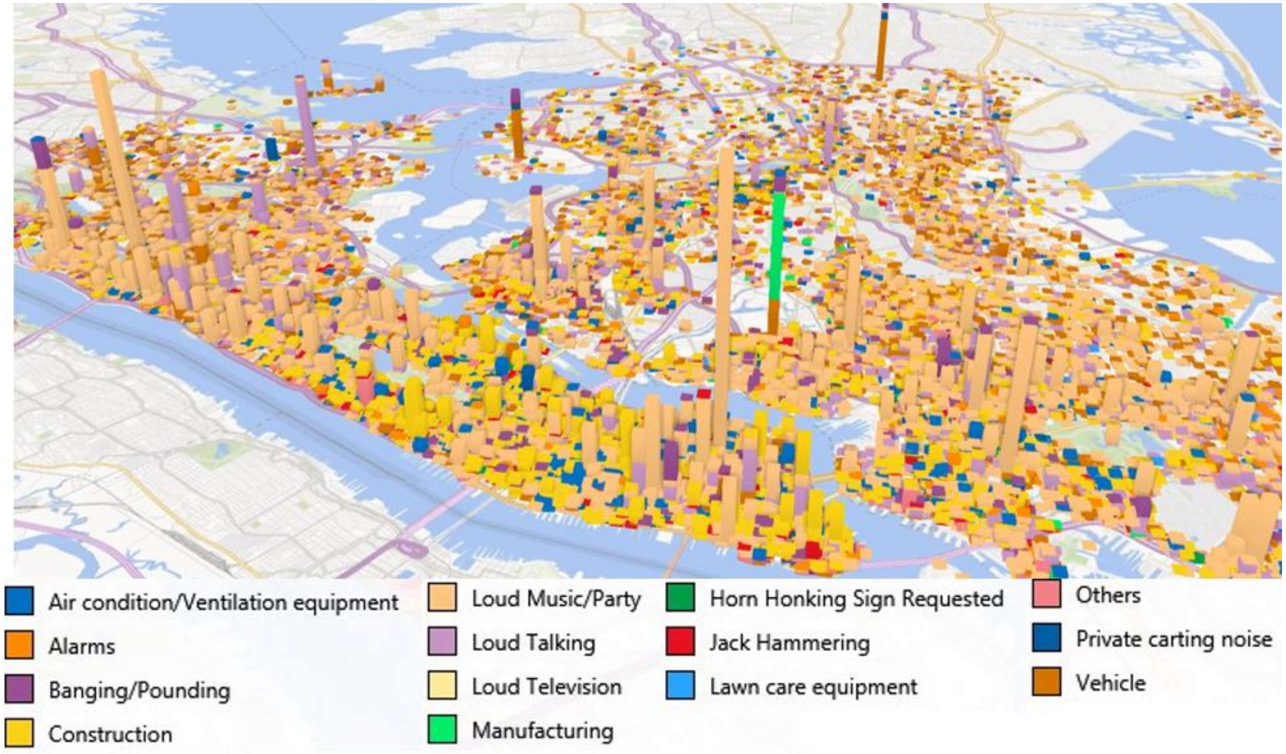
- Urban noise is difficult to model
  - Change over time very quickly
  - Vary by location significantly
  - Depends on sound levels and people's tolerance
  - The composition of noises is hard to analyze



Yu Zheng, et al. [Diagnosing New York City's Noises with Ubiquitous Data](). UbiComp 2014.

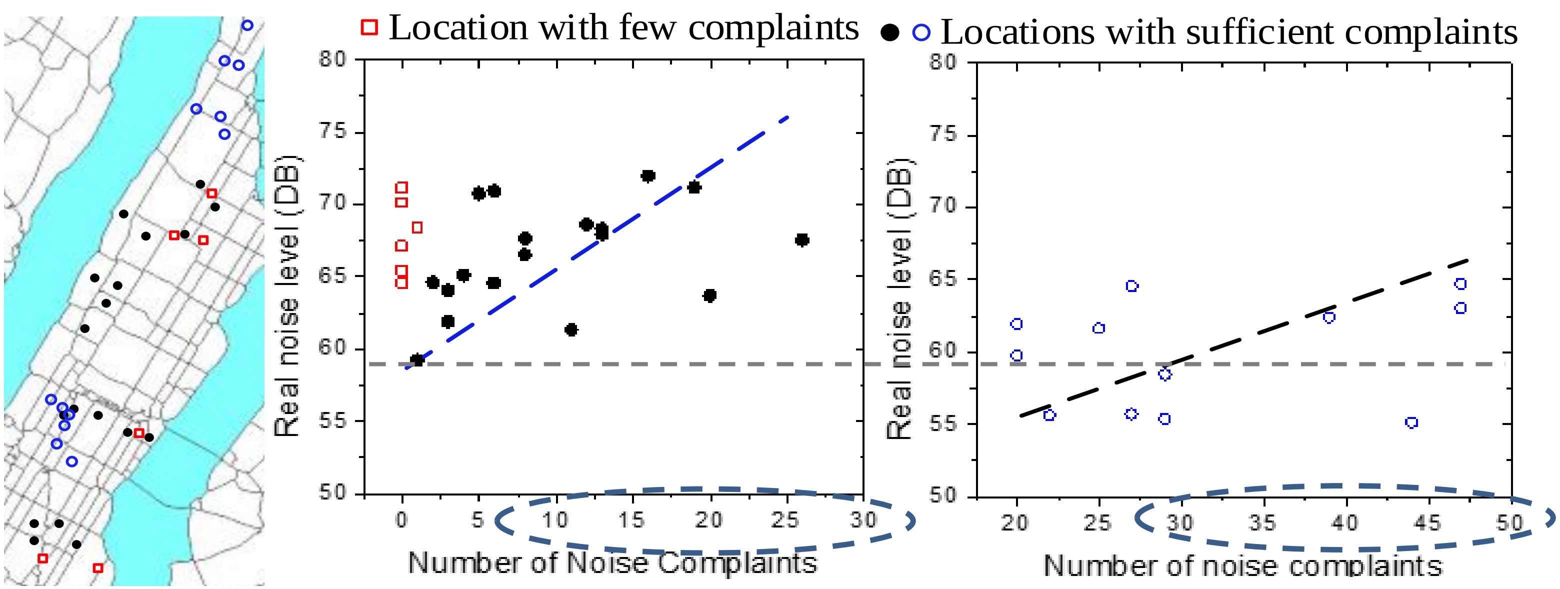
311 in NYC

- 311 Data
  - A platform for citizen’s non-emergent complaints
  - Associated with a location, timestamp, and a category
  - Human as a sensor → crowd sensing
  - Implies people’s reaction and tolerance to noises



311 in NYC

- Correlation between 311 complaints and real noise levels
  - Measured the real noise levels of 36 locations in Manhattan
  - People's tolerances vary in time of day



A) Locations

B) Correlation in 6am-6pm

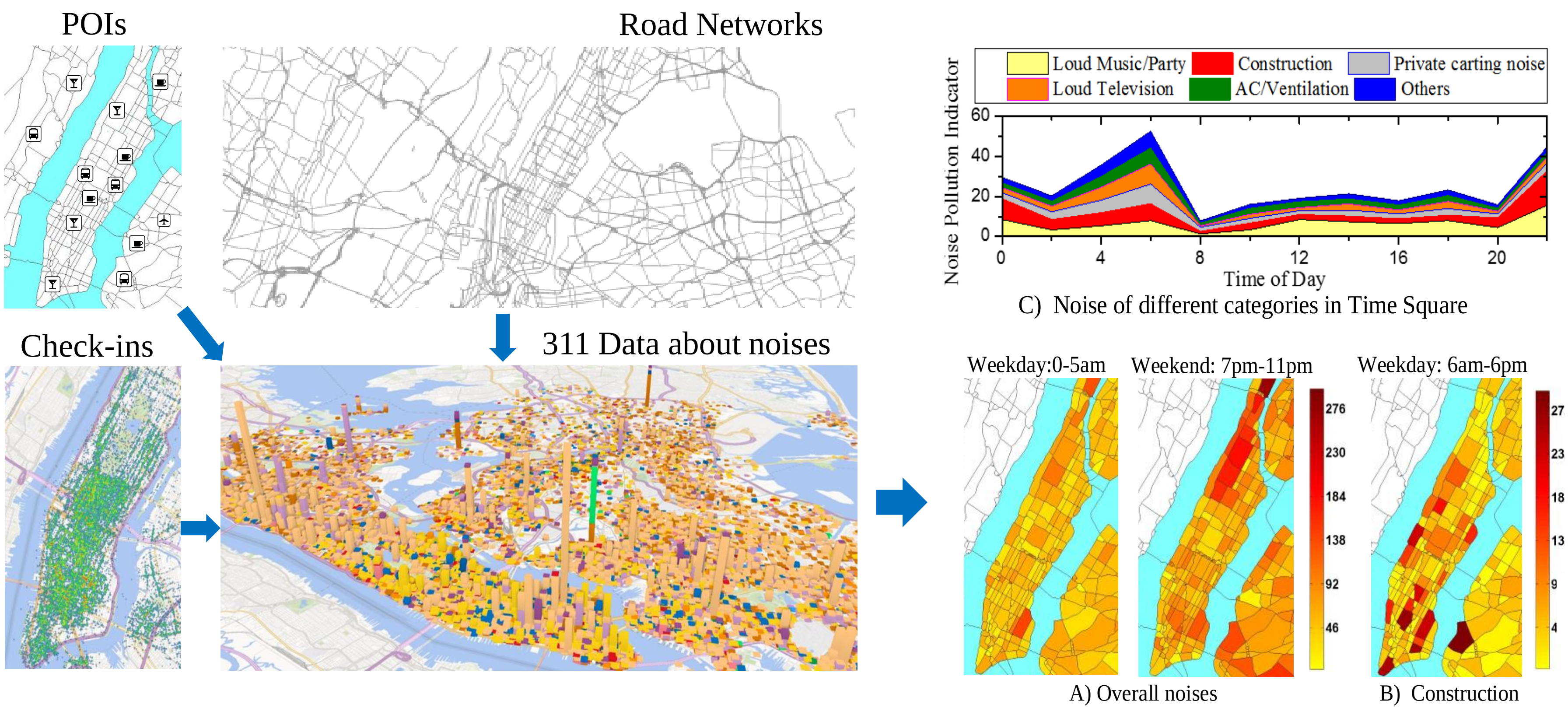
C) Correlation in 7pm-11pm

24 locations

12 locations

Goal

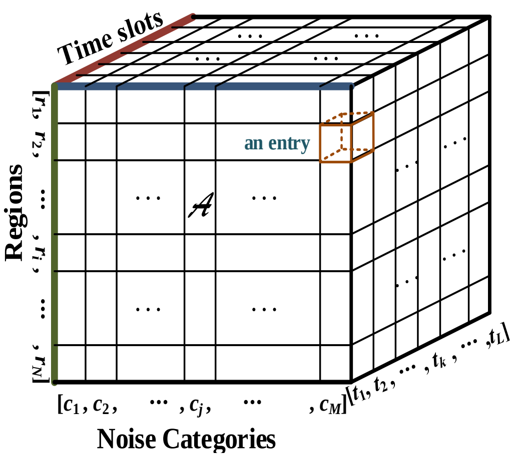
- Reveal the noise situation of each region in each hour
  - A noise indicator denoting the noisy level
  - Composition of noises in each location



Methodology

- Partition NYC into regions by major roads

- Build a 3D tensor to model the noises
  - Region
  - Time slot
  - Noise categories
- Supplement the missing entries through
  - A context-aware tensor decomposition
  - In collaborative filtering



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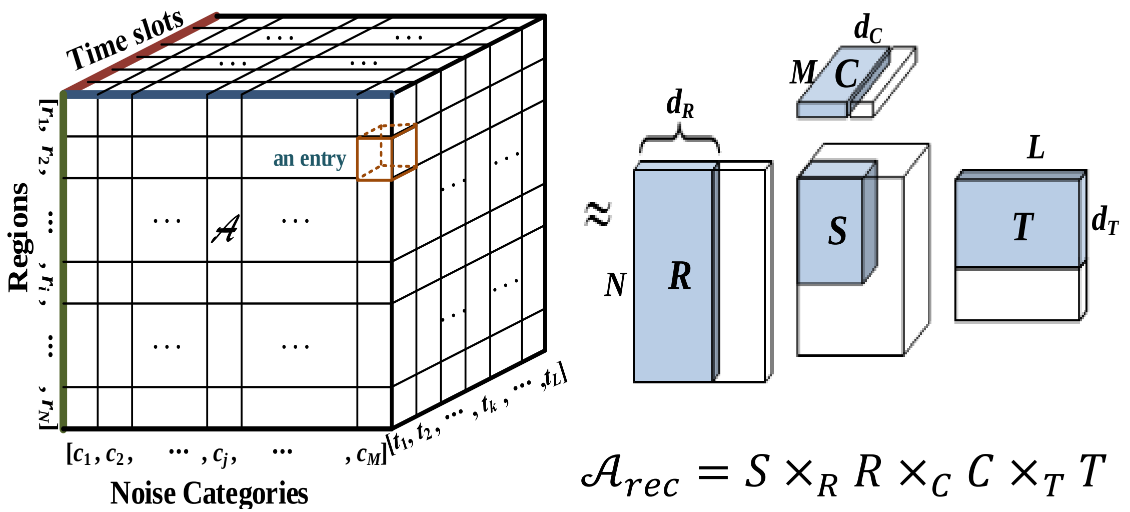
Methodology

- Simple idea: Tensor Decomposition
- Not very accurate
- Need more inputs from other sources



$$\mathcal{A}_{rec} = S \times_R R \times_C C \times_T T$$

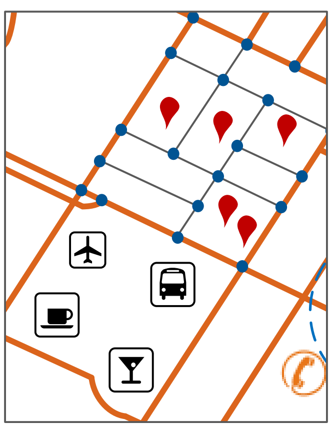
$$\mathcal{L}(S, R, C, T) = \frac{1}{2}\|\mathcal{A} - S \times_R R \times_C C \times_T T\|^2 + \frac{\lambda}{2}(\|S\|^2 + \|R\|^2 + \|C\|^2 + \|T\|^2)$$

Yu Zheng, et al. Diagnosing New York City's Noises with Ubiquitous Data. UbiComp 2014.

Methodology

- Geographical Features
  - Road networks
    - Number of intersections f_s
    - Length of road segments in different levels f_r
  - POIs
    - Total number of POIs f_n and density of POIs f_d
    - Distribution over different categories f_c

$$X = \begin{array}{cc} & \begin{matrix} f_s & f_r & f_n & f_d & f_c \end{matrix} \\ \begin{matrix} r_1 \\ r_2 \\ \vdots \\ r_i \\ \vdots \\ r_N \end{matrix} & \left[\begin{array}{c|c} \boldsymbol{F_r} & \boldsymbol{F_p} \end{array}\right] \end{array}$$



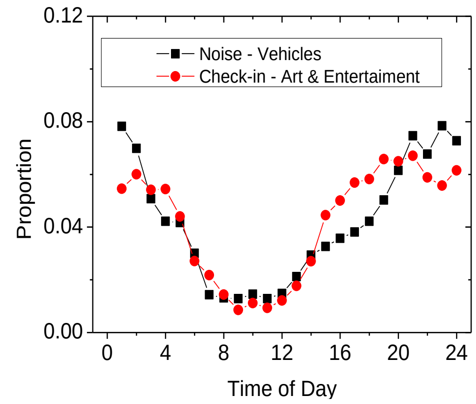
A) Loud talking B) POI: Food C) Loud Music D) POI: Entertainment

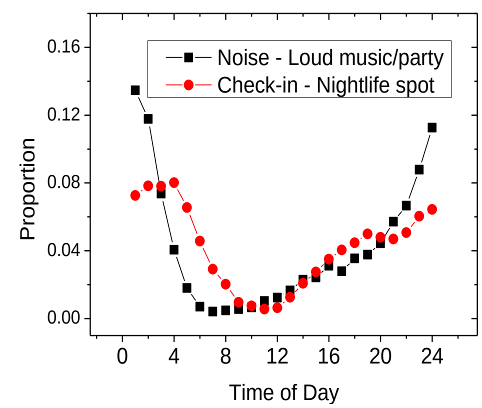
Yu Zheng, et al. Diagnosing New York City's Noises with Ubiquitous Data. UbiComp 2014.

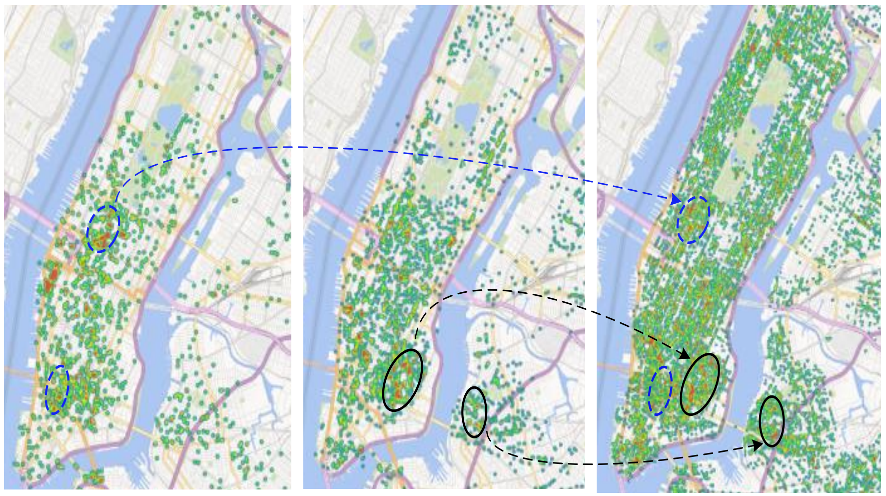
Methodology

- Check in data in NYC
  - Gowalla: 127,558 check-ins (4/24/2009 to 10/13/2013)
  - Foursquare: 173,275 check-ins (5/5/2008 to 7/23/2011)
- Correlation with noises
- Y implies
  - correlation between different time slots
  - correlation between different regions

$$Y = \begin{array}{c} \\ t_1 \\ t_2 \\ \vdots \\ t_k \\ \vdots \\ t_L \end{array} \begin{array}{c} \begin{array}{ccccc} r_1 & r_2 \cdots & r_i & \cdots & r_N \end{array} \\ \left[\begin{array}{ccc} d_{11} & \cdots & \\ \vdots & \ddots & \\ & d_{ki} & \\ & & \ddots \\ & \cdots & d_{LN} \end{array} \right] \end{array}$$





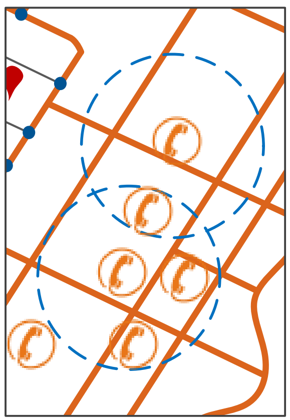


Check-in: Entertainment   Check-ins: Nightlife Spot   Noise: Loud Music/Party

Yu Zheng, et al. Diagnosing New York City's Noises with Ubiquitous Data. UbiComp 2014.

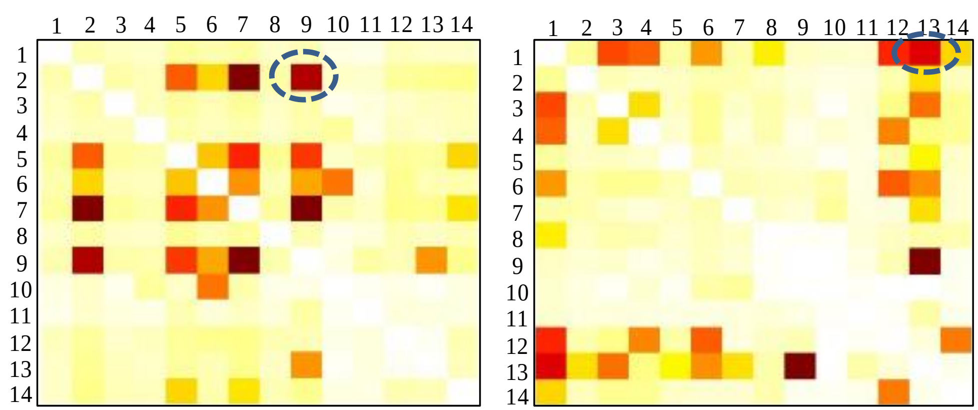
Methodology

- Correlation between different noise categories



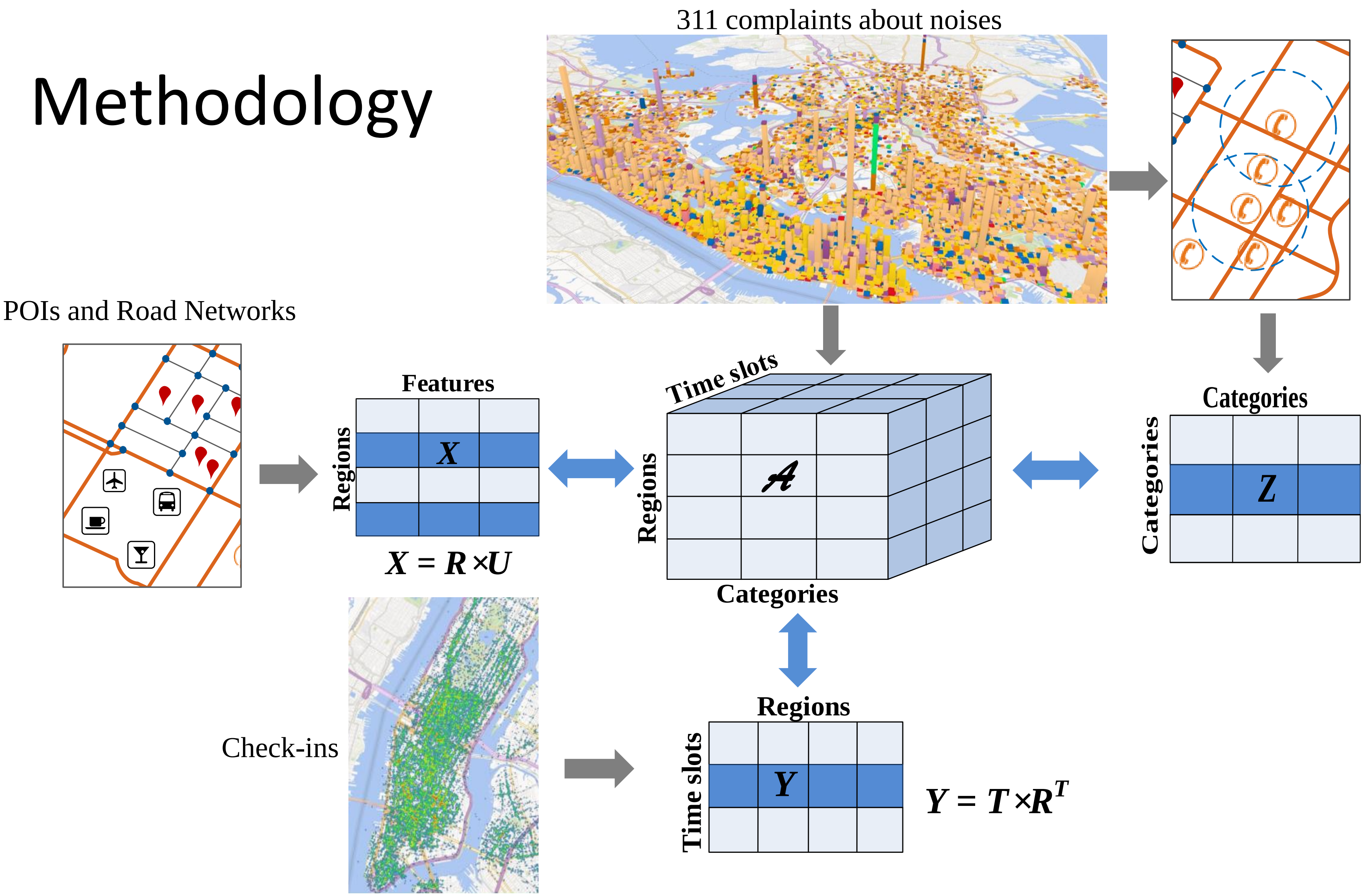
Categories	%	Categories	%
c_1. Loud Music/Party	42.2	c_8. Alarms	1.7
c_2. Construction	17.2	c_9. Private carting noise	0.8
c_3. Loud Talking	14.6	c_{10}. Manufacturing	0.3
c_4. Vehicle	13.7	c_{11}. Lawn care equipment	0.3
c_5. AC/Ventilation	3.9	c_{12}. Horn Honking	0.2
c_6.Banging/Pounding	2.1	c_{13}. Loud Television	0.1
c_7. Jack Hammering	2.1	c_{14}. Others	0.8

$$Z = \begin{array}{cc} & \begin{array}{ccccc} c_1 & c_2 \cdots & c_j & \cdots & c_M \end{array} \\ \begin{array}{c} c_1 \\ c_2 \\ \vdots \\ c_j \\ \vdots \\ c_M \end{array} & \begin{bmatrix} c_{11} & \cdots & & \\ \vdots & \ddots & & \\ & & c_{jj} & \\ & & & \ddots \\ & \cdots & & c_{MM} \end{bmatrix} \end{array}$$



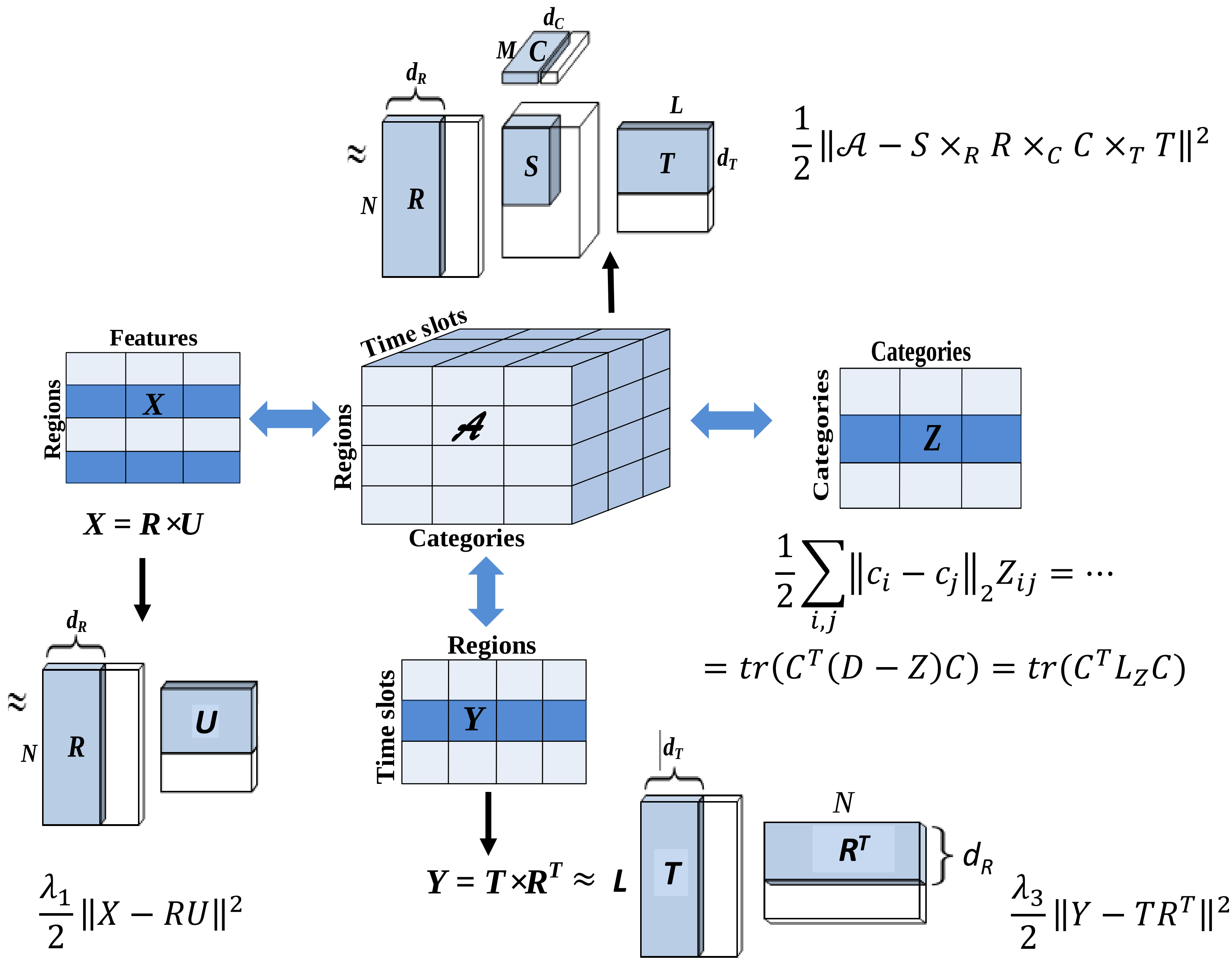
A) weekday B) weekend

Methodology

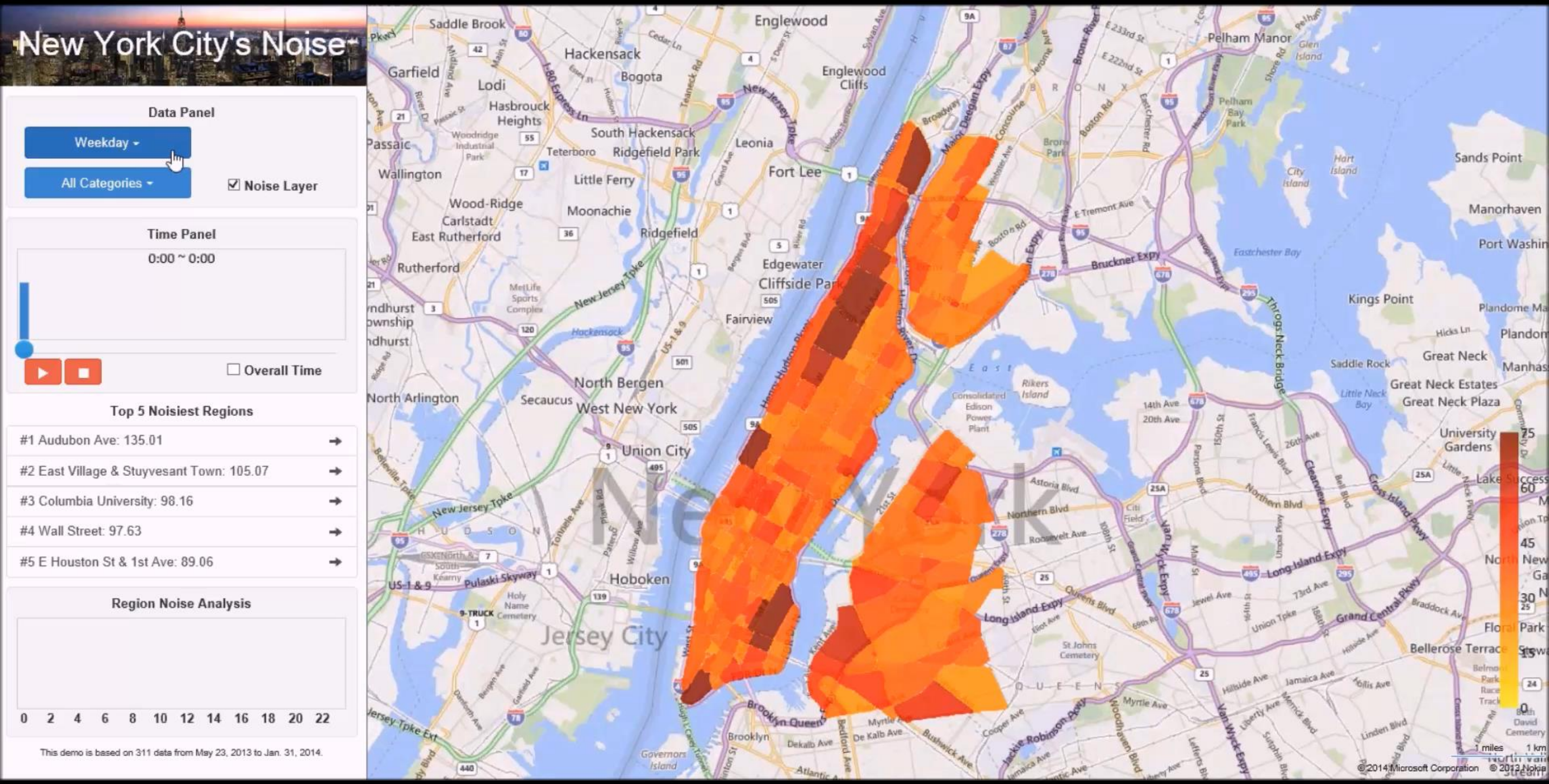


$$\mathcal{L}(S,R,C,T,U) = \frac{1}{2}\|\mathcal{A} - S \times_R R \times_C C \times_T T\|^2 + \frac{\lambda_1}{2}\|X - RU\|^2 + \frac{\lambda_2}{2}\mathrm{tr}(C^T L_Z C) + \frac{\lambda_3}{2}\|Y - TR^T\|^2 + \frac{\lambda_4}{2}(\|S\|^2 + \|R\|^2 + \|C\|^2 + \|T\|^2 + \|U\|^2)$$

$$\mathcal{L}(S,R,C,T,U) = \frac{1}{2}\|\mathcal{A} - S \times_R R \times_C C \times_T T\|^2 + \frac{\lambda_1}{2}\|X - RU\|^2 + \frac{\lambda_2}{2}\mathrm{tr}(C^T L_Z C) + \frac{\lambda_3}{2}\|Y - TR^T\|^2 + \frac{\lambda_4}{2}(\|S\|^2 + \|R\|^2 + \|C\|^2 + \|T\|^2 + \|U\|^2)$$



http://citynoise.azurewebsites.net/



Experiments

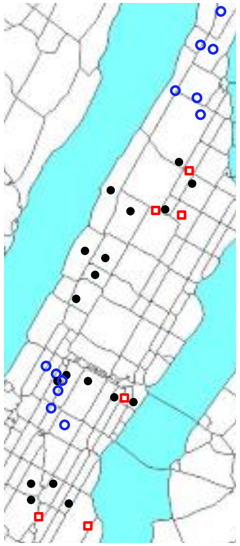
- Accuracy of the inferences
  - Remove 30% non-zero entries
  - Metrics: RMSE & MAE
  - Compared with six Baseline methods

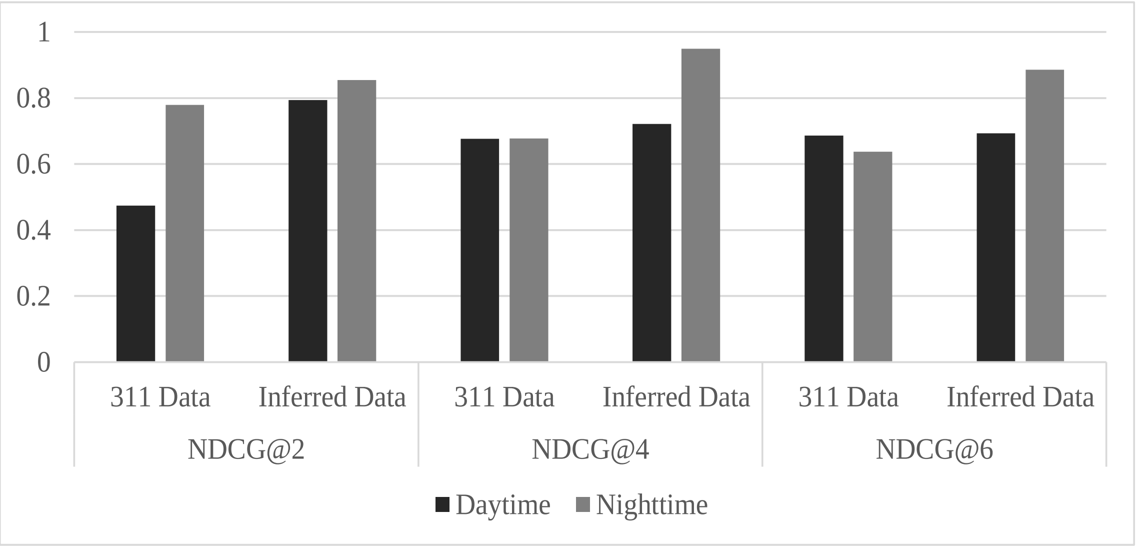
Methods	Weekdays		Weekends	
	RMSE	MAE	RMSE	MAE
AWR	4.736	2.582	4.446	2.599
AWH	4.631	2.461	4.42	2.522
MF	4.600	2.474	4.393	2.516
Kriging	4.59	2.424	4.253	2.495
TD	4.391	2.381	4.141	2.393
TD+ X	4.285	2.279	4.155	2.326
TD+ $X+Y$	4.160	2.110	4.003	2.198
TD+ $\boldsymbol{X+Y+Z}$	4.010	2.013	3.930	2.072

Yu Zheng, et al. Diagnosing New York City's Noises with Ubiquitous Data. UbiComp 2014.

Experiments

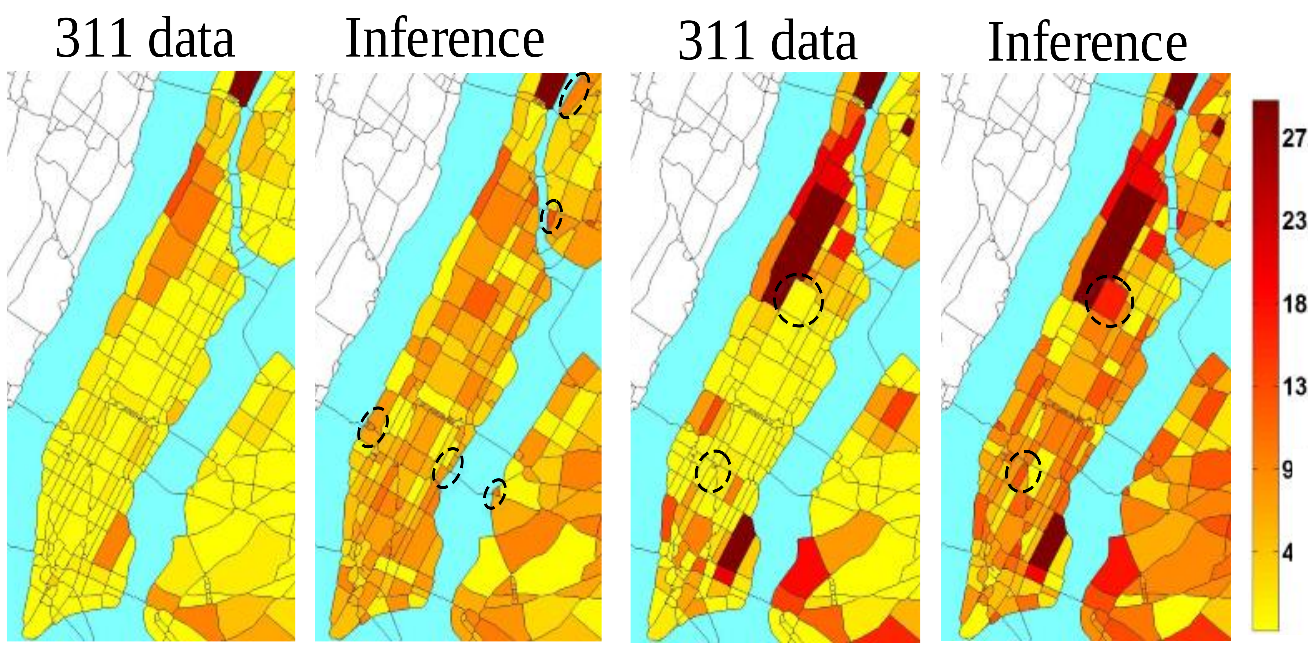
- Relative ranking performance
  - Ranked by the inferred noise indicators
  - Ground truth: measured by a mobile phone running a client program
  - Metric: NDCG





Experiments

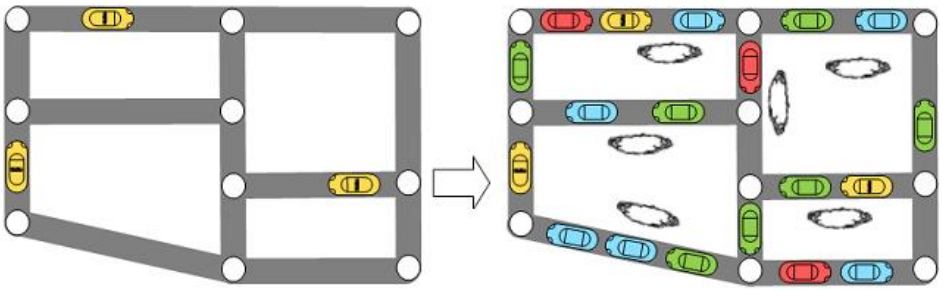
- 311 vs. Inferences
  - 2.75% of entries on weekdays are from 311 data (97.25% by inference)
  - 1.83% of entries on weekends are from 311 data (98.17% by inference)



A) Vehicles (6am-6pm) B) Loud Talking (0-5am)

Inferring Gas Consumption and Pollution Emission of Vehicles throughout a City

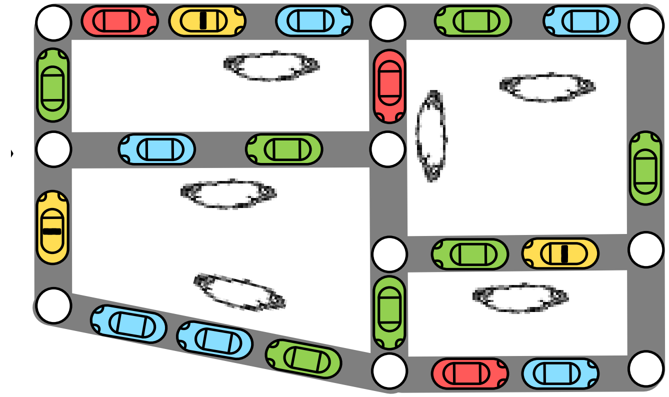
KDD 2014



Questions

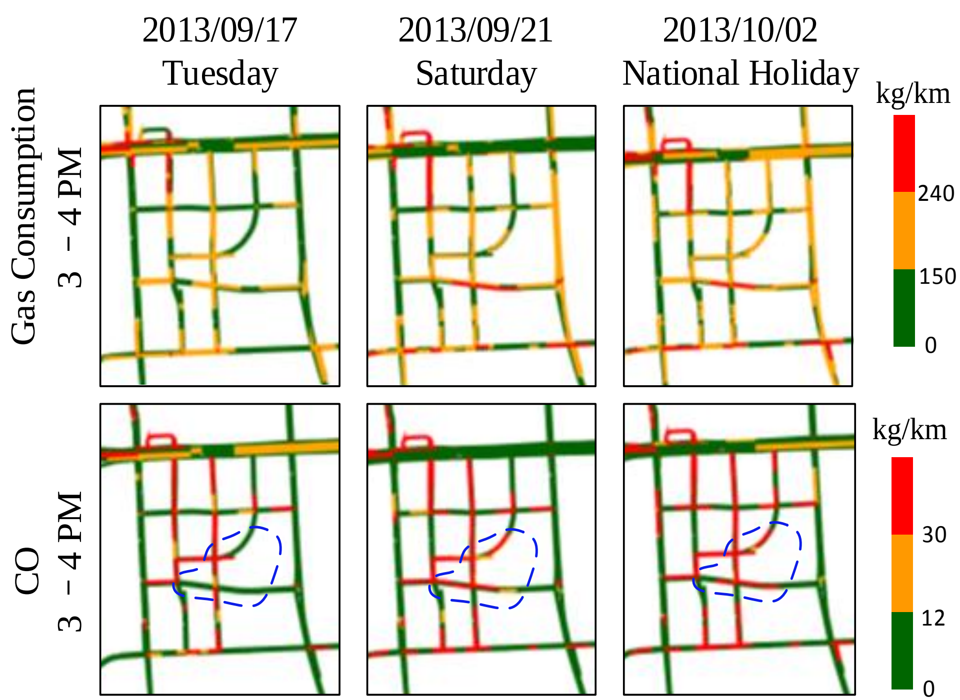
How many liters of gas have been consumed by the vehicles, in the entire city, in the past one hour?

What is the volume of PM2.5 that has been generated accordingly?



Goals

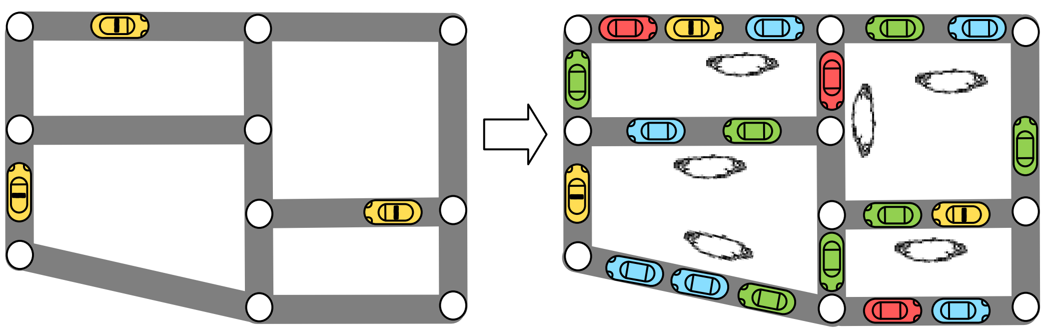
- Estimate the gas consumption and vehicle emissions
  - on arbitrary road segment
  - at any time intervals
  - using GPS trajectories of a sample of vehicles



Jingbo Shang, **Yu Zheng,** et al. Inferring Gas Consumption and Pollution Emission of Vehicles throughout a City. **KDD 2014**.

Our Approach

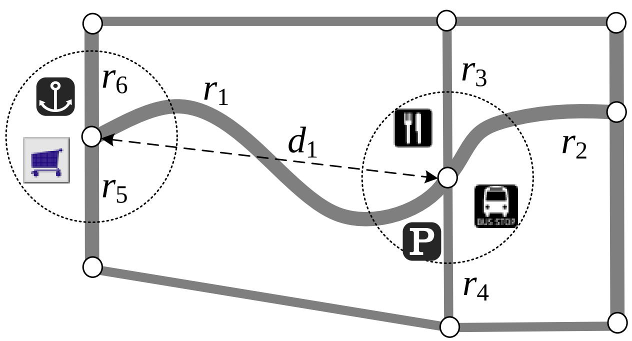
- Using the GPS trajectories of a sample of vehicles
  - Estimate travel speed on each road segment
  - Infer the traffic volume of each road segment
  - Calculate the gas consumption and emission of vehicles



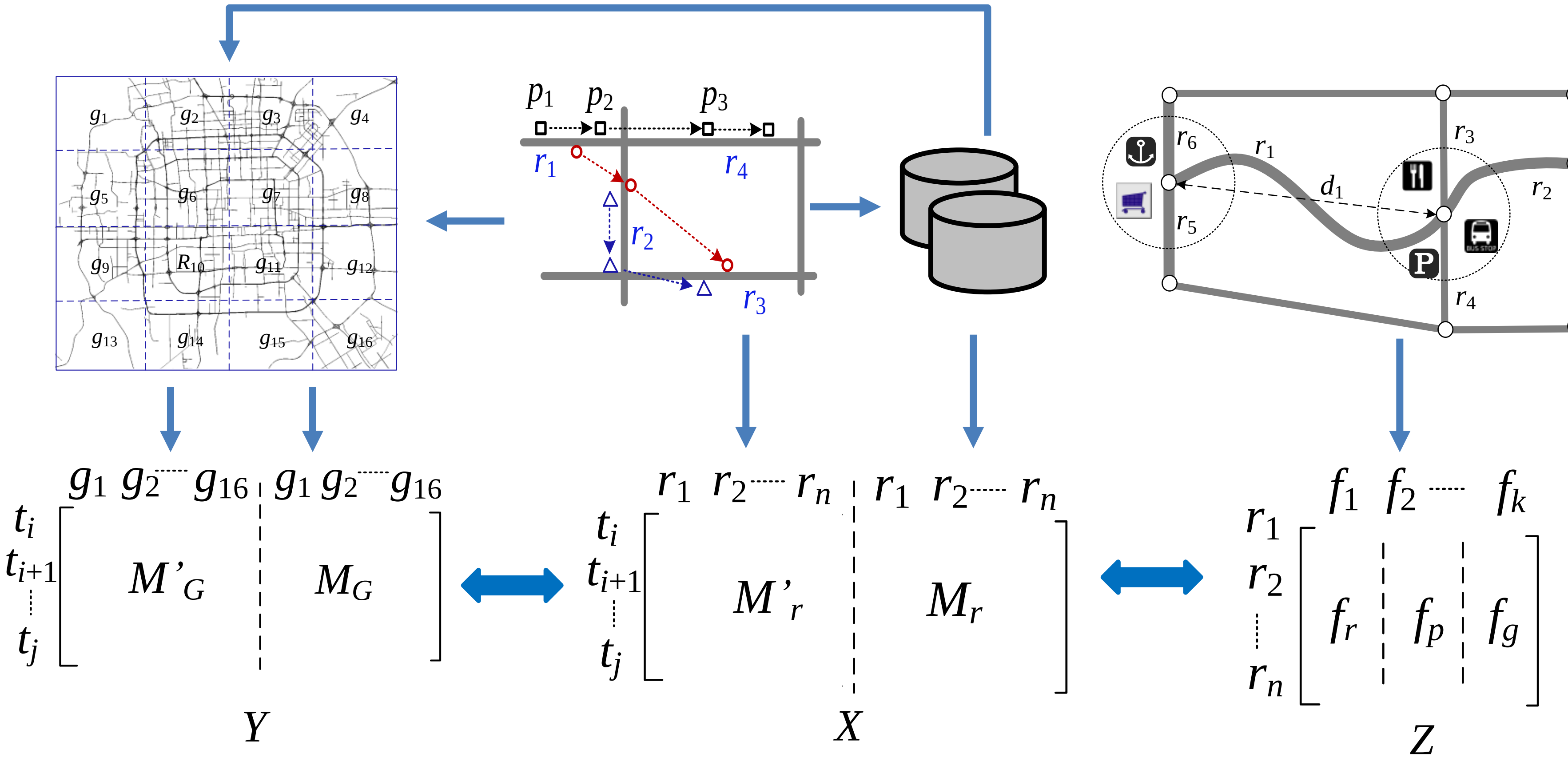
Jingbo Shang, **Yu Zheng,** et al. [Inferring Gas Consumption and Pollution Emission of Vehicles throughout a City](). **KDD 2014**.

Difficulties

- Data sparsity
- From speed to volume
  - Depends on multiple factors, such as
    - the current travel speeds and density of vehicles
    - the length, shape, and capacity of a road
    - weather conditions
  - Insufficient training data
  - Biased distribution of the samples
- Real-time and citywide
  - Over 100,000 road segments to infer
  - Need to finish it in a few minutes



Jingbo Shang, **Yu Zheng,** et al. [Inferring Gas Consumption and Pollution Emission of Vehicles throughout a City]. **KDD 2014**.



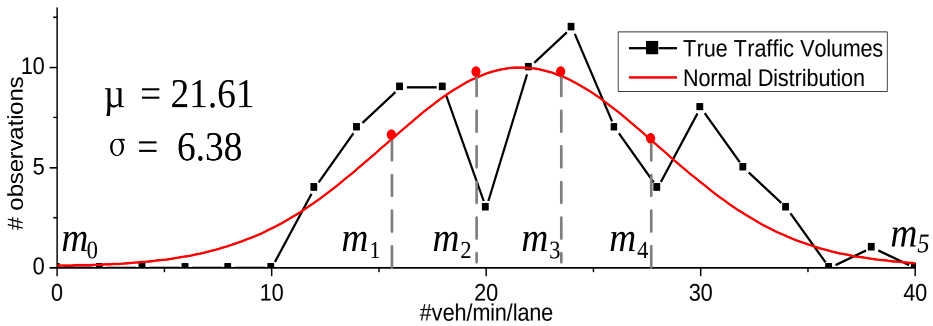
$$Y \approx T \times (G;G)^T;\ \ X \approx T \times (R;R)^T;\ \ Z \approx R \times F^T$$

- X: denotes fine-grained traffic conditions
- Y: denotes coarse-grained traffic conditions
- Z: geographical contexts of road segments

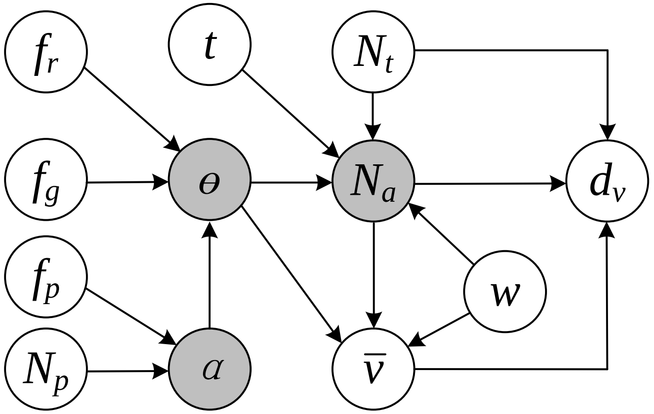
$$L(T,R,G,F) = \frac{1}{2}||Y - T(G;G)^T||^2 + \frac{\lambda_1}{2}||X - T(R;R)^T||^2 + \frac{\lambda_2}{2}||Z - RF^T||^2 + \frac{\lambda_3}{2}(||T||^2 + ||R||^2 + ||G||^2 + ||F||^2),$$

Traffic Volume Inference (TVI)

- Objective: From travel speed to traffic volume
- Traffic volume depends on
  - the current travel speeds and density of vehicles
  - the length, shape, capacity of a road, and weather conditions
- Biased distribution between taxis and other vehicles
- Unsupervised learning approach



A) Level 0-1 (highways)



Jingbo Shang, **Yu Zheng,** et al. [Inferring Gas Consumption and Pollution Emission of Vehicles throughout a City](). **KDD 2014**.

Energy and Emission Calculation

$$EF = (a + cv + ev^2)/(1 + bv + dv^2).$$

	a	b	c	d	e
CO	71.7	35.4	11.4	-0.248	0
Hydrocarbon	5.57×10^{-2}	3.65×10^{-2}	-1.1×10^{-3}	-1.88×10^{-4}	1.25×10^{-5}
Nox	9.29×10^{-2}	-1.22×10^{-2}	-1.49×10^{-3}	3.97×10^{-5}	6.53×10^{-6}
Fuel Consumption	217	9.6×10^{-2}	0.253	-4.21×10^{-4}	9.65×10^{-3}

$$E = EF \times r.N_a \times r.n \times r.len$$

Jingbo Shang, **Yu Zheng,** et al. [Inferring Gas Consumption and Pollution Emission of Vehicles throughout a City](). **KDD 2014**.

Experiments

- Evaluation on TSE

Methods	RMSE of $\overline{v}$	RMSE of dv	Time (sec)
MF(M'_r)	2.172	1.833	2.2
MF($M'_r + Z$)	1.939	1.385	18.2
MF($M'_r + M'_g + Z$)	1.908	1.314	20.2
TSE	**1.369**	**1.035**	**22.2**
Kriging	2.340	1.300	1,000
KNN	3.360	1.590	0.14

RMSE	level 0-1	level 2	level 3	level >=4
Speed	2.575	1.189	0.977	1.612
Variance	1.526	1.128	0.628	1.234

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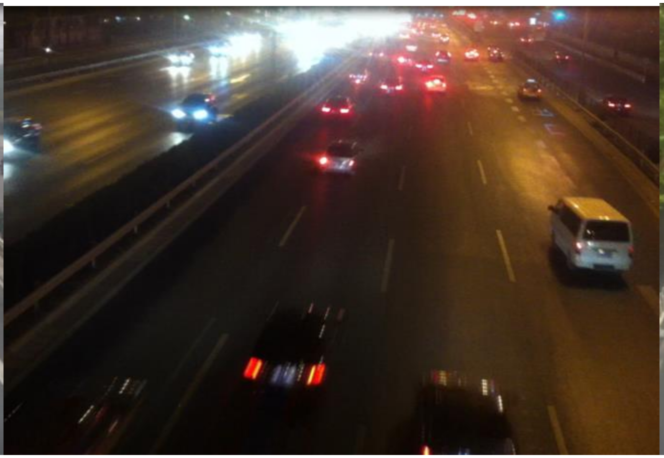
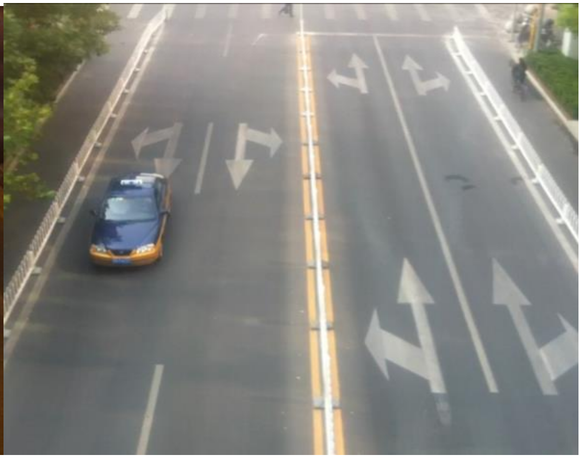
Experiments

- Evaluation on TVI

Methods	MAE	MRE	Inference time (us/road)
TVI	3.01	29%	7.27
TVI w/o dv	3.19	31%	7.18
TVI w/o w	3.15	29%	7.10
LR	3.06	27%	0.15
FD	2.66	16%	0.13
FD-SC	3.9	42%	0.13
FD-DC	6.7	137%	0.13

	level 0-1	level 2	Weekday	Weekend
MAE	5.55	2.23	2.97	3.28
MRE	22%	41%	29%	30%

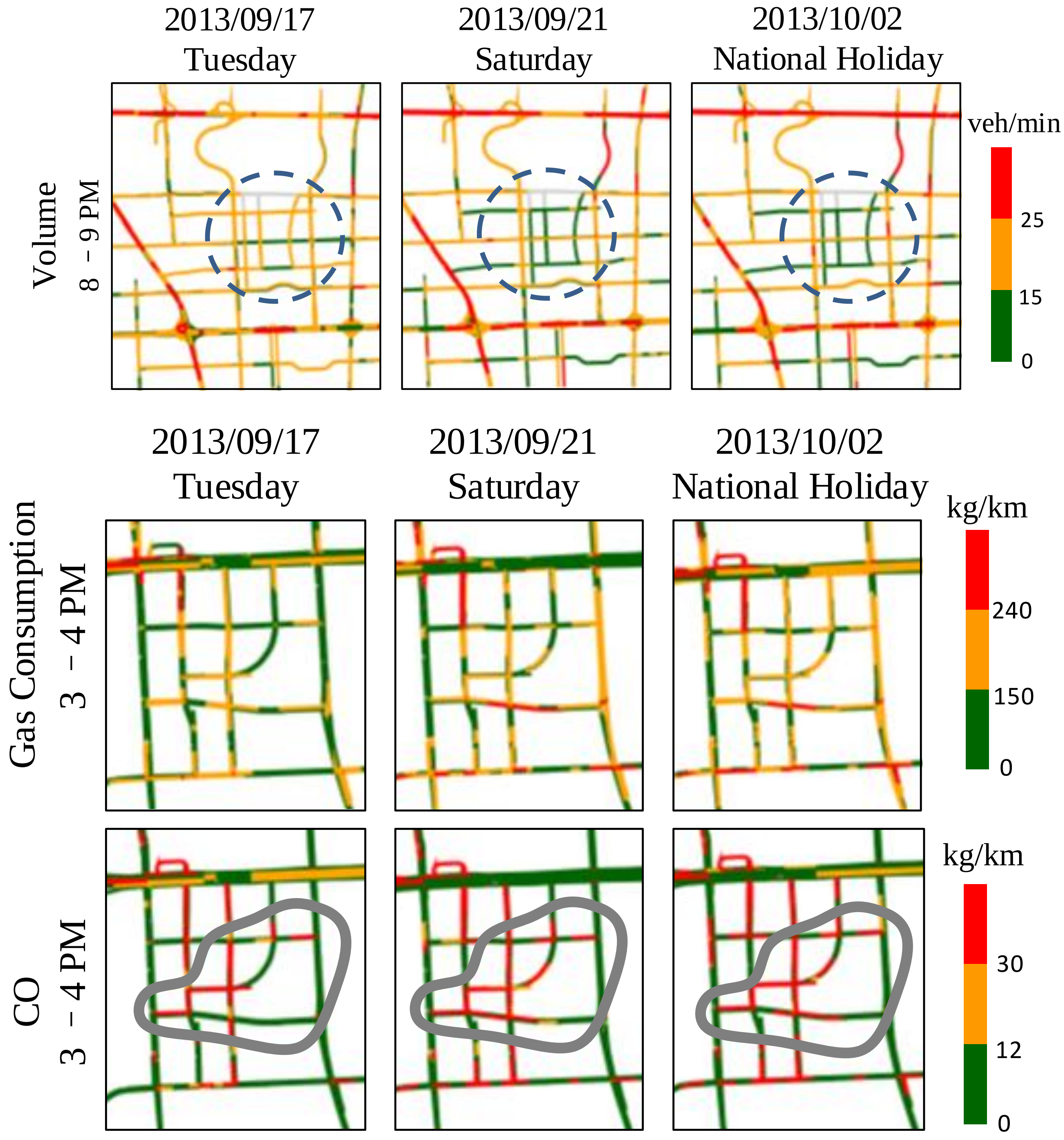
Jingbo Shang, **Yu Zheng,** et al. [Inferring Gas Consumption and Pollution Emission of Vehicles throughout a City](). **KDD 2014**.

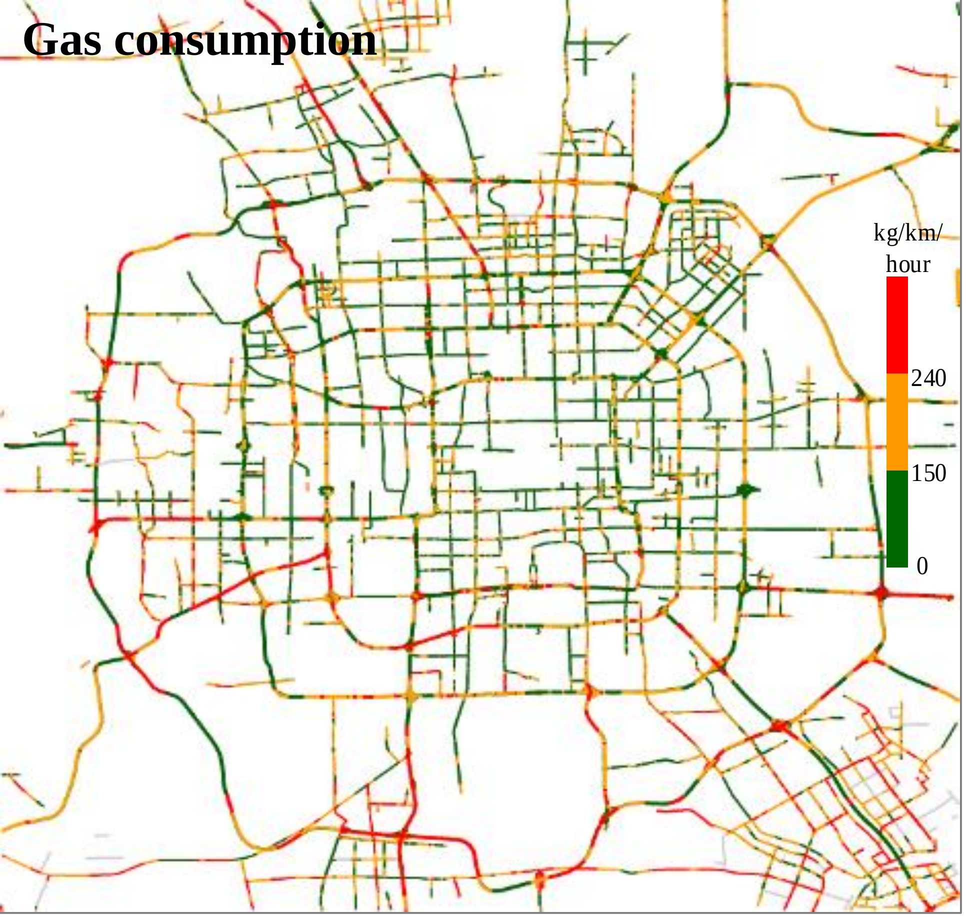
Time	7:00 ~ 10:00			10:00~16:00			16:00~20:00			after 20:00			total
Level	0,1	2	3	0,1	2	3	0,1	2	3	0,1	2	3	
Holiday	0	0	0	6	14	4	6	8	1	4	6	0	49
Workday	7	28	8	29	74	9	28	92	7	6	17	4	309
Total	43			136			142			37			358

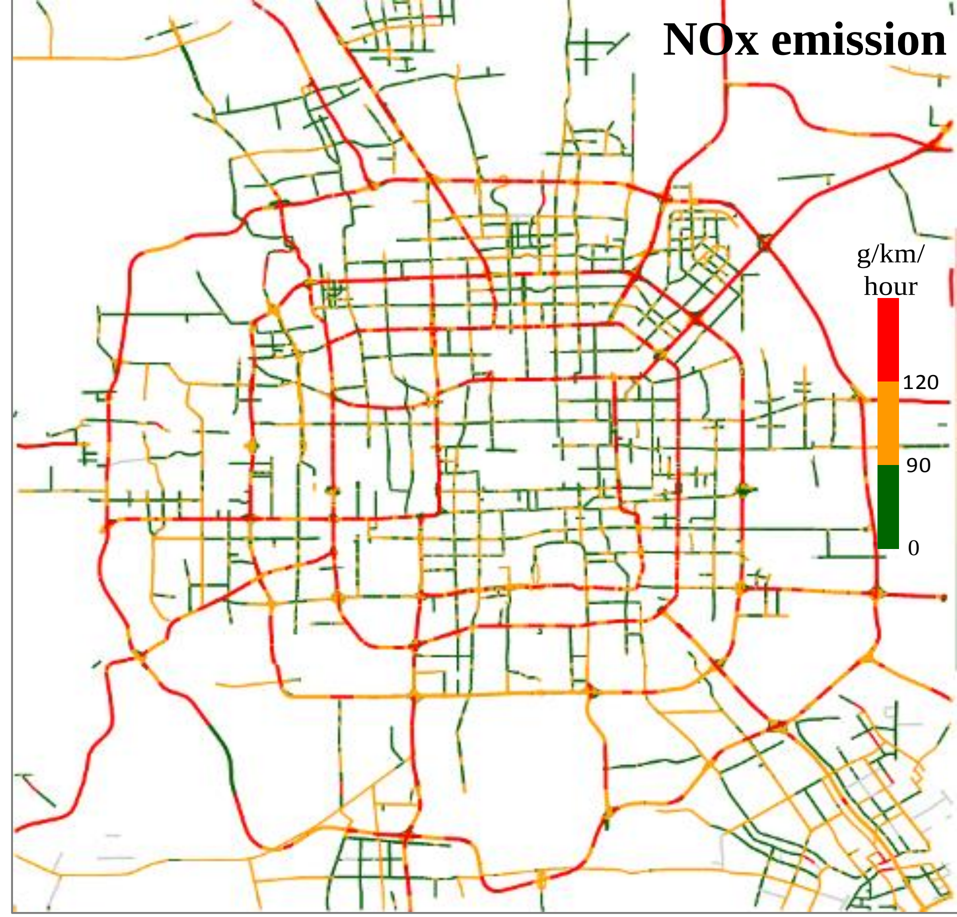
- Efficiency

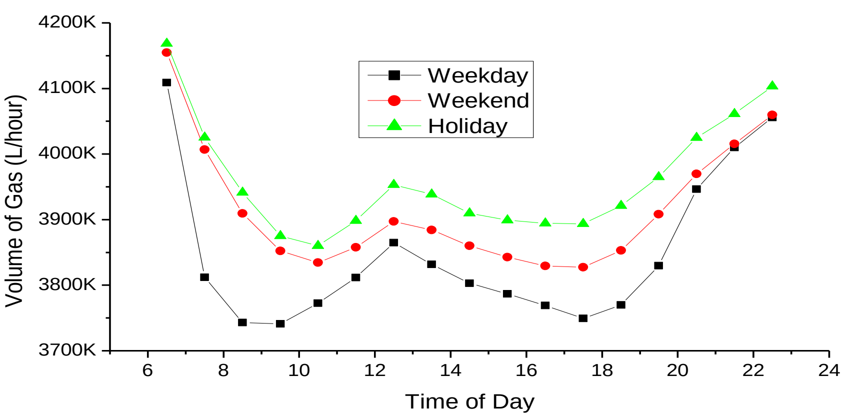
Online components	Time	Offline components	Time
Map-matching	4.94min	Geo-feature extraction	149s
TSE	22.2s	Historical pattern extraction	240s
TVI (inference)	0.84s	TVI learning	89s
Total	5.32min	Total	478s

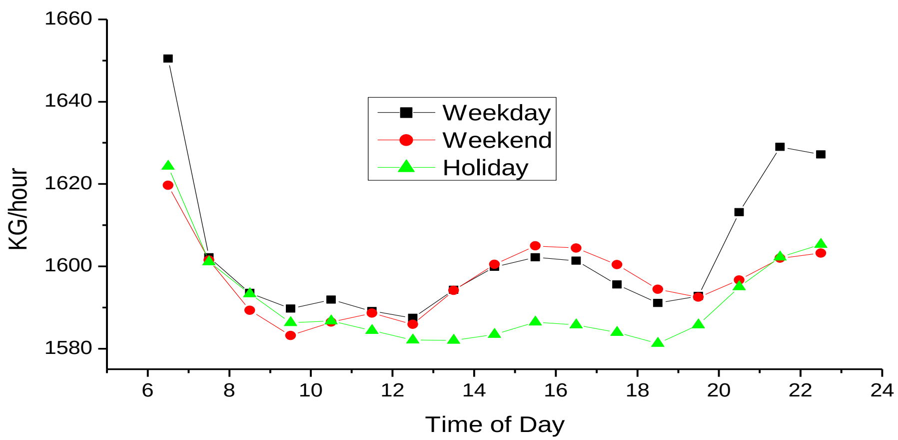


2013/09/17
Tuesday
2013/09/21
Saturday
2013/10/02
National Holiday
Volume
8 – 9 PM
veh/min
25
15
0
2013/09/17
Tuesday
2013/09/21
Saturday
2013/10/02
National Holiday
Gas Consumption
3 – 4 PM
kg/km
240
150
0
CO
3 – 4 PM
kg/km
30
12
0

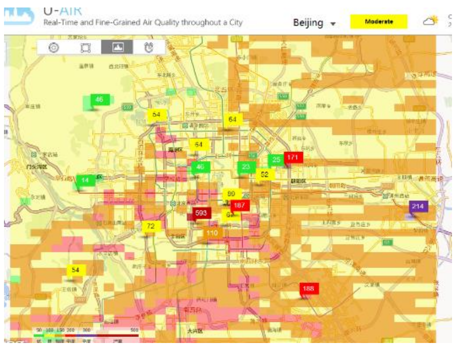

Gas consumption
kg/km/
hour
240
150
0

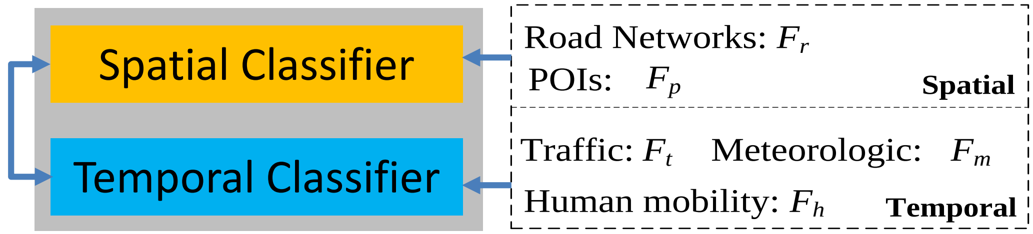

NOx emission
g/km/
hour
120
90
0


4200K
4100K
4000K
3900K
3800K
3700K
Volume of Gas (L/hour)
6
8
10
12
14
16
18
20
22
24
Time of Day
Weekday
Weekend
Holiday

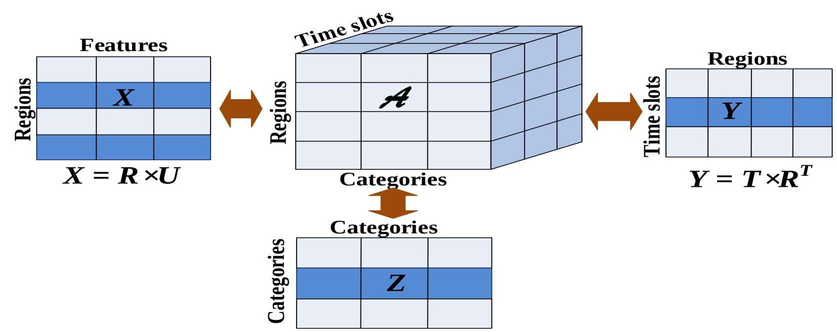

1660
1640
1620
1600
1580
KG/hour
6
8
10
12
14
16
18
20
22
24
Time of Day
Weekday
Weekend
Holiday

Computing with Multiple Heterogeneous Data Sources

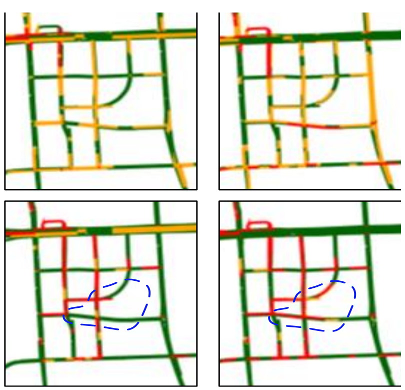


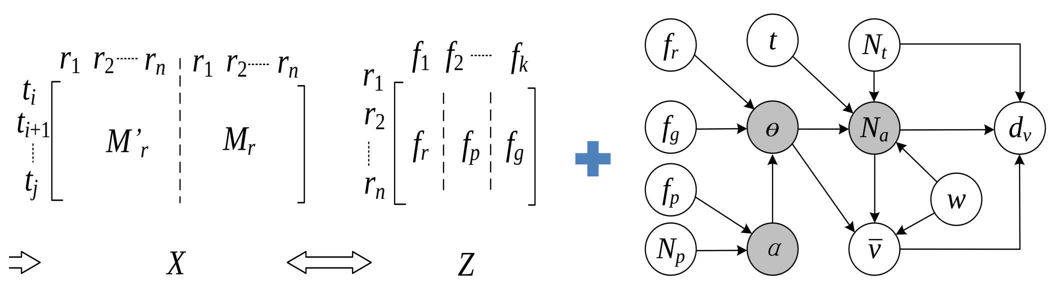


Co-Training-based Semi-supervised learning



Context-aware Tensor Decomposition





Matrix Factorization + Graphical Models

Take Away Messages

- 3**B**: *B*ig city, *B*ig challenges, *B*ig data
- 3**M**: Data *M*anagement, *M*ining and *M*achine learning
- 3**W**: *W*in-*W*in-*W*in: people, city, and the environment

3·BMW

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