Modeling Network-level Traffic Flow Transitions on Sparse Data

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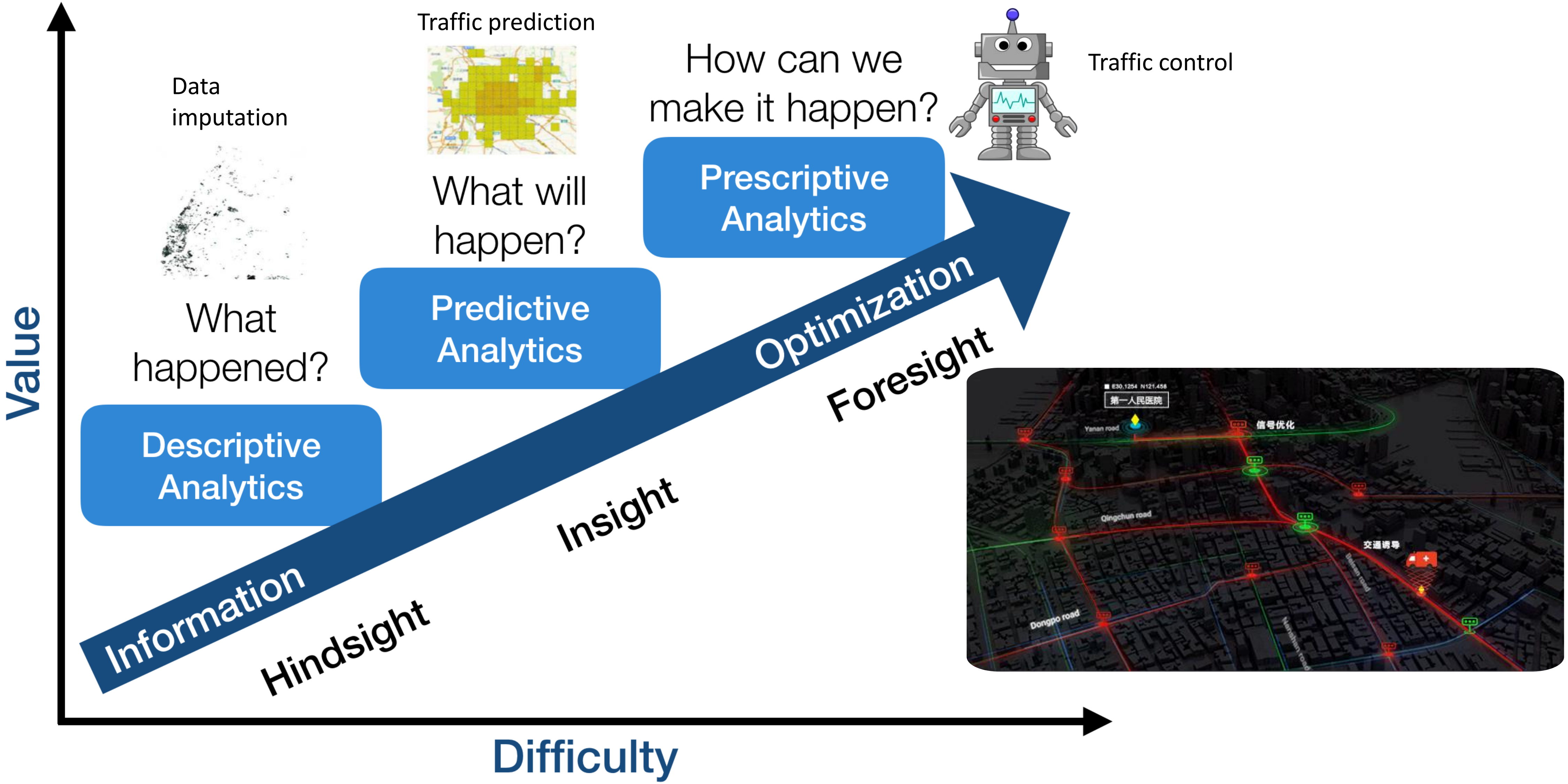
City Intelligence: Descriptive, Predictive, Prescriptive



Prescriptive: Traffic Signal Control

https://traffic-signal-control.github.io/
https://darl-libsignal.github.io/

Tutorial@ITSC'20: Deep Reinforcement Learning for Traffic Signal Control
Survey: SIGKDD Explorations, Arxiv
LibSignal Toolkit - https://darl-libsignal.github.io/

Single Intersection

IntelliLight (KDD'18)
- First step on reinforcement learning based traffic signal control

LIT (SIGSPATIAL'20)
- Theoretical proof on the best reward and state design

FRAP (CIKM'19) , DemoLight(CIKM'19), MetaLight (AAAI'20)
- Learning faster for single intersection

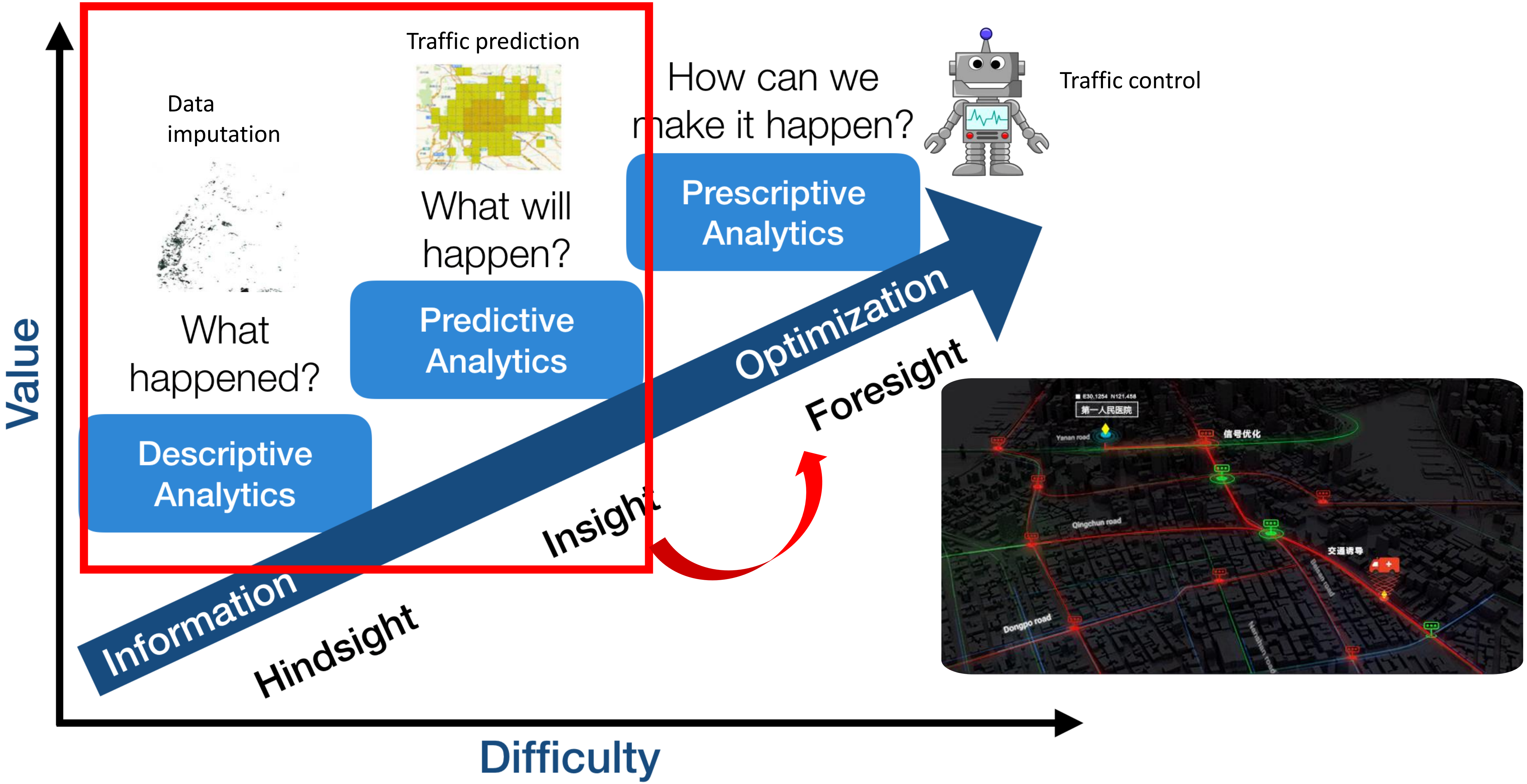
Multiple Intersections

PressLight (KDD'19)
- Theoretical proof on the best reward and state design for coordination

CoLight (CIKM'19)
- Network-level coordination (200 intersections)

ThousandLight (AAAI'20)
- Large-scale, citywide coordination (2000 intersections)

City Intelligence: Descriptive, Predictive, Prescriptive



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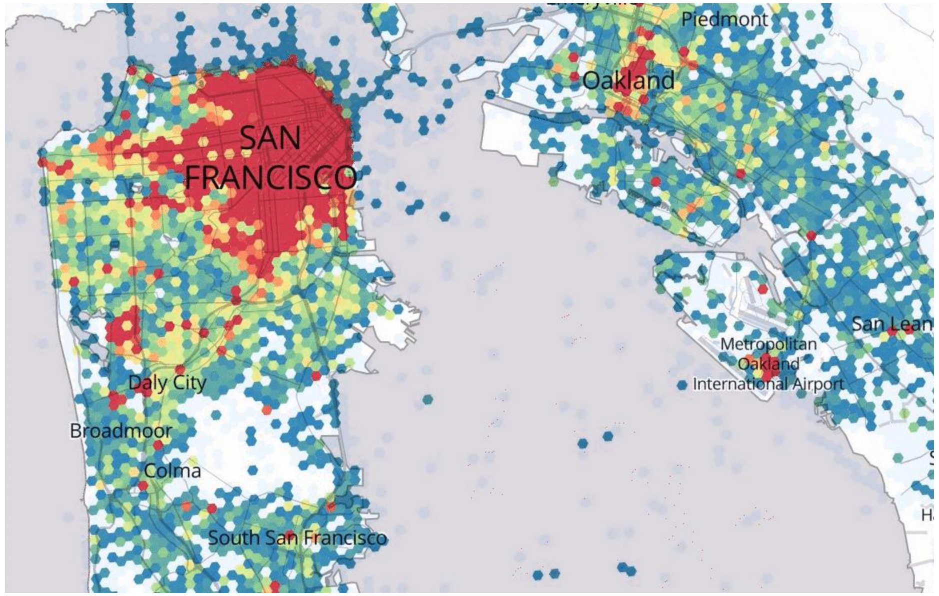
Predictive: Traffic Flow Prediction

- Traffic Flow Prediction

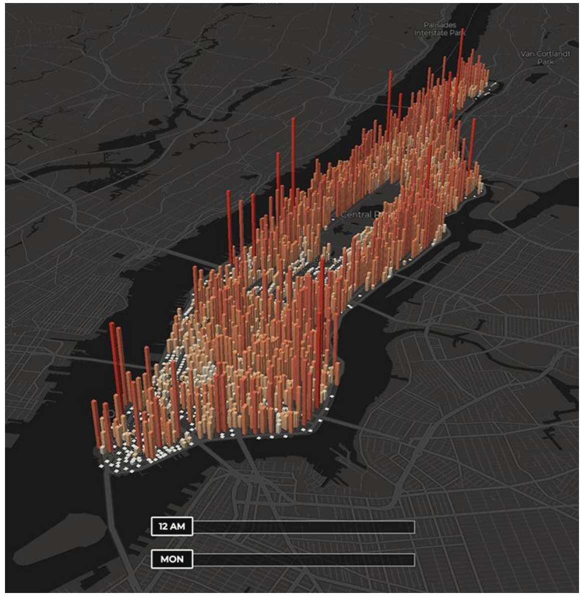
$$[X_{t-T+1}, \dots, X_t] \xrightarrow{f} [X_{t+1}, \dots, X_{t+\tau}]$$

$$s_t \rightarrow P \rightarrow s_{t+1}$$

Src: Yao, et al, 2018



Src: Uber



Src: NYC Open Data

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A bunch of studies here…

Transitional models

- Statistical and machine learning models (ARIMA, kNN, SVR, etc.)

Deep learning model

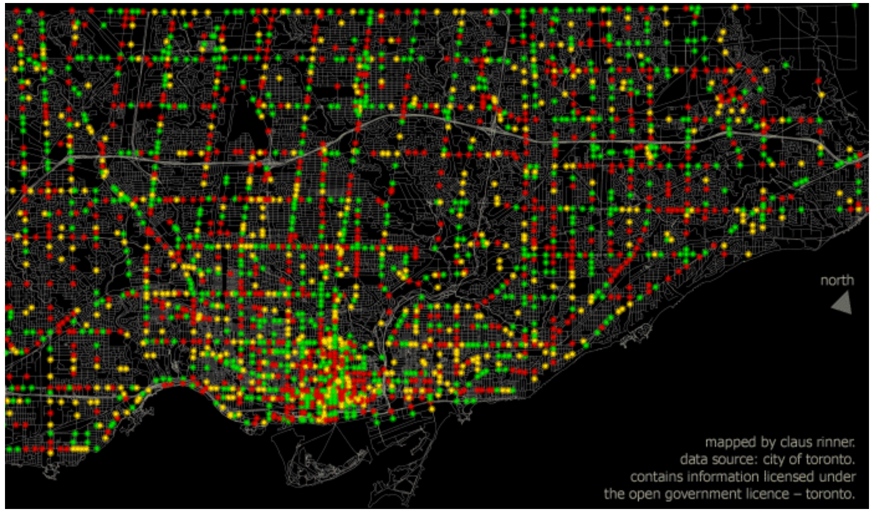
- RNN and CNN model to encode spatial and temporal dependency
- GNN model:
  - Separately model the spatial and temporal dependency: STGCN, GraphWaveNet, DCRNN
  - Transformer models - use attention modules in transformer

Lei, et.al., Modeling Network-level Traffic Flow Transitions on Sparse Data, KDD 2022.

A step back:
Is current prediction enough for making prescriptions?

Question:

Can I use the traffic flow prediction model to help with:
- Controlling traffic signals?
- Routing for social good?



Lei, et.al., Modeling Network-level Traffic Flow Transitions on Sparse Data, KDD 2022.

A step back:
Is current prediction enough for making prescriptions?

Model

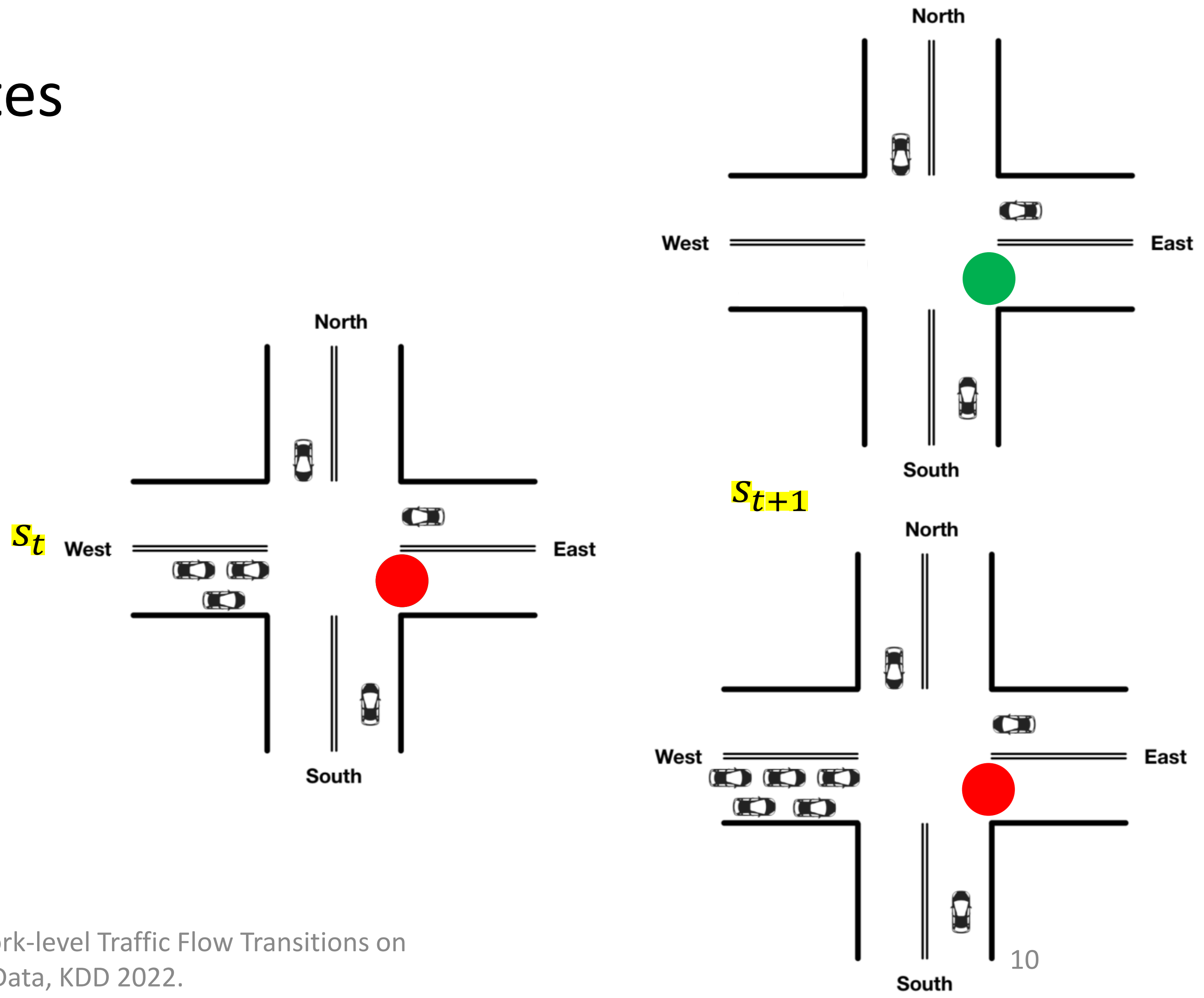
- Modeling actions

Data

- Incomplete, sparse data

Motivation: Modeling actions in state transition

- A single action affects future states



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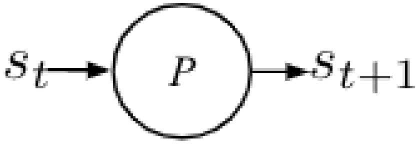
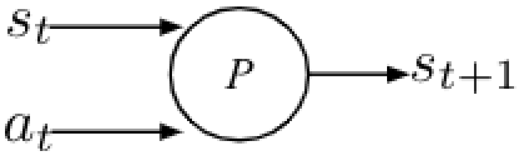
A New Predictive Task:
Modeling state transitions with actions



Transition wo. action



Transition with action

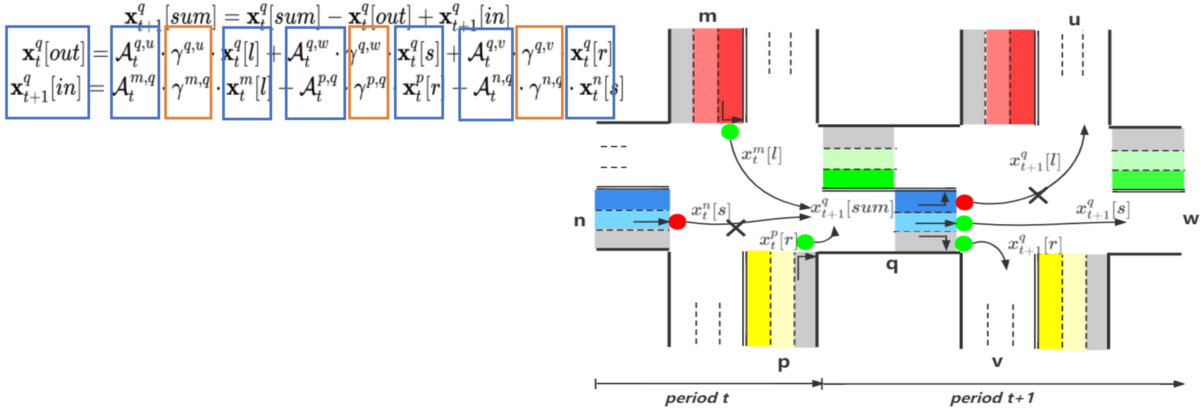
Predictive 1.0

Predictive 1.5

Transition Models: Heuristics-driven vs. Data-driven

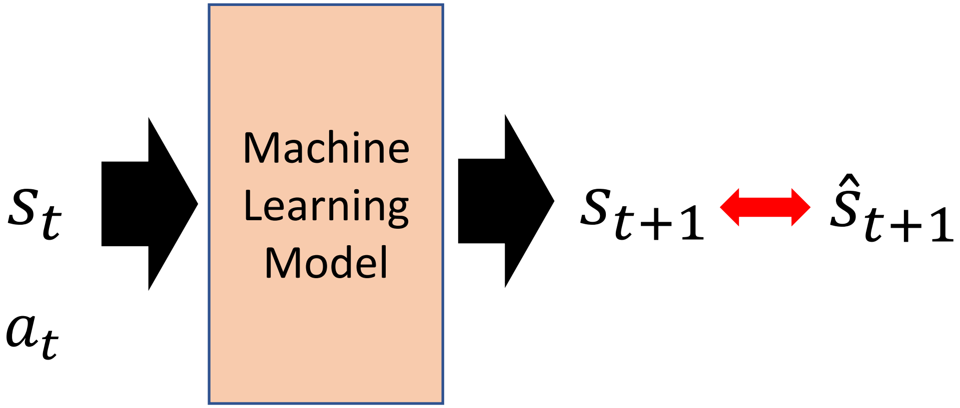
Heuristics-driven Transition model

Parameters Data



- *f(data)* is static
- Strong assumptions on the form
- Rely little on the data

Data-driven model



- f(data) is learned
- Little assumptions
- Rely on big data

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A step back:
Is current prediction enough for making prescriptions?

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Model

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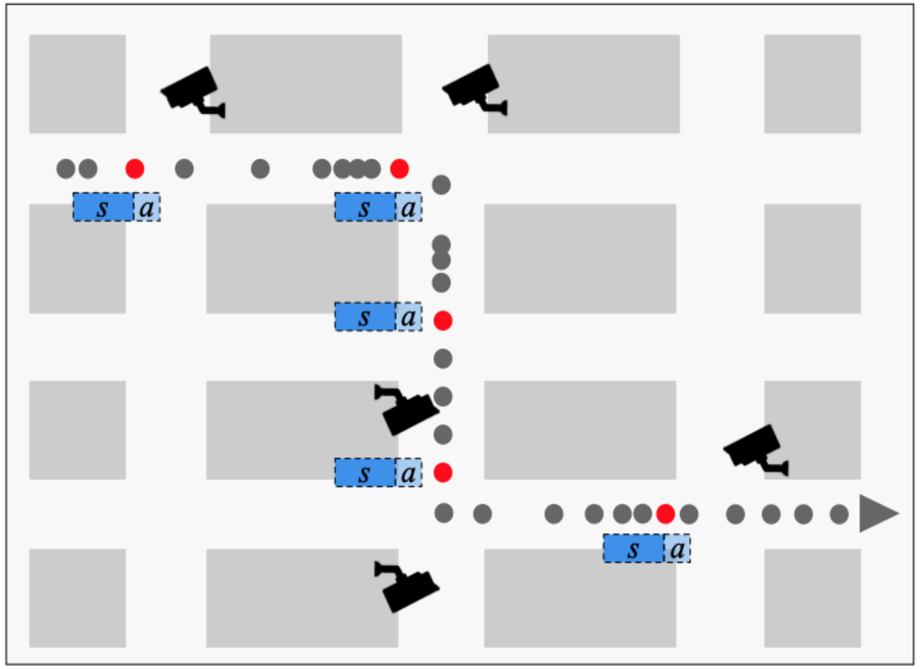
Are we good with data-driven models?

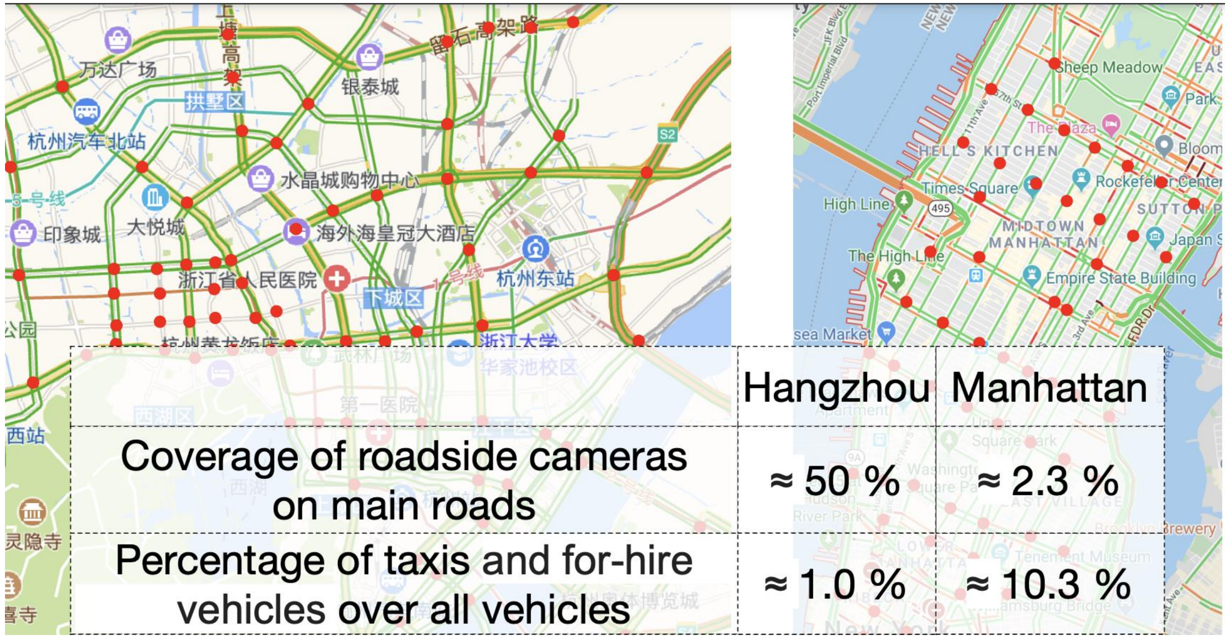
- Ideally, we could have:
  - BIG data
    - As much data as we want
    - As detailed as possible

- In reality, we only have:
  - SMALL data:
    - Do not have direct observations [ICDE'20]
    - Do not have observations for certain timesteps [ECML-PKDD'20]
    - Do not have observations for certain places

Incomplete data in the city



Wei, et.al, Learning to simulate on sparse trajectory data. ECML-PKDD 2020



	Hangzhou	Manhattan
Coverage of roadside cameras on main roads	≈ 50 %	≈ 2.3 %
Percentage of taxis and for-hire vehicles over all vehicles	≈ 1.0 %	≈ 10.3 %

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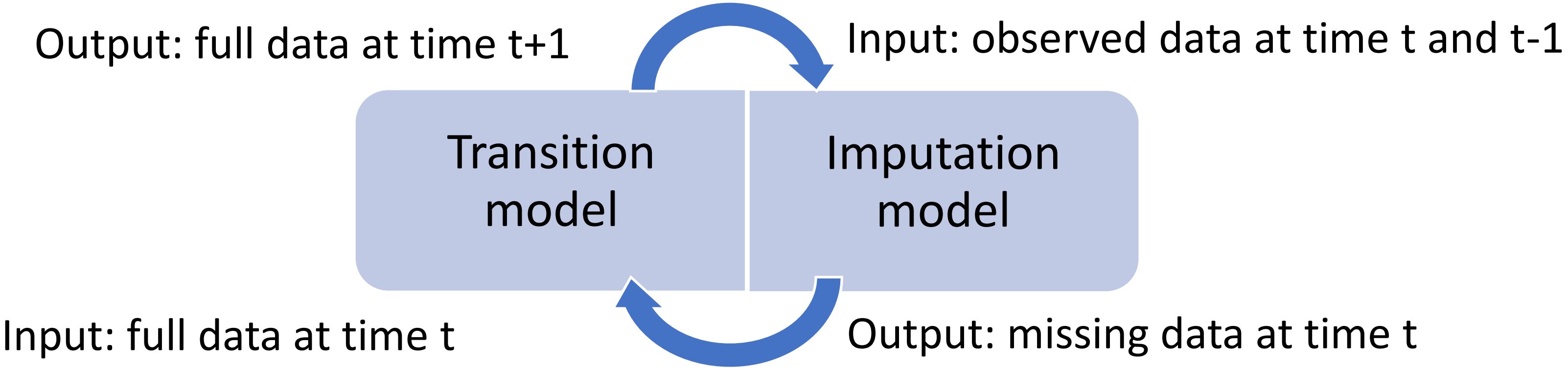
Dealing with incomplete data: Imputation

- Imputation on the missing data:
  - Requires the transition from observed data
  - The transition model is exactly what we what to learn with full data (missing part + observed part)
- Imputation and transition model should be inherently one model



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Transition modeling with incomplete data: Problem formulation

- Traffic Flow Transition Modeling
  - $[\dot{\mathbf{X}}_{t-T+1}, \cdots, \dot{\mathbf{X}}_t; \mathcal{G}_{t-T+1}, \cdots, \mathcal{G}_t] \xrightarrow{f} [\boldsymbol{X}_{t+1}]$

$$\dot{\mathbf{X}}_t = \mathbf{X}_t \odot \mathbf{M}$$

Observability mask $\mathbf{M}$: a static binary matrix $\mathbf{M} \in \{0, 1\}^{N \times F}$
N is the number of road segments
F is the length of state feature

$$\mathcal{G}_t = \{\mathcal{R}, \mathcal{A}_t\}$$

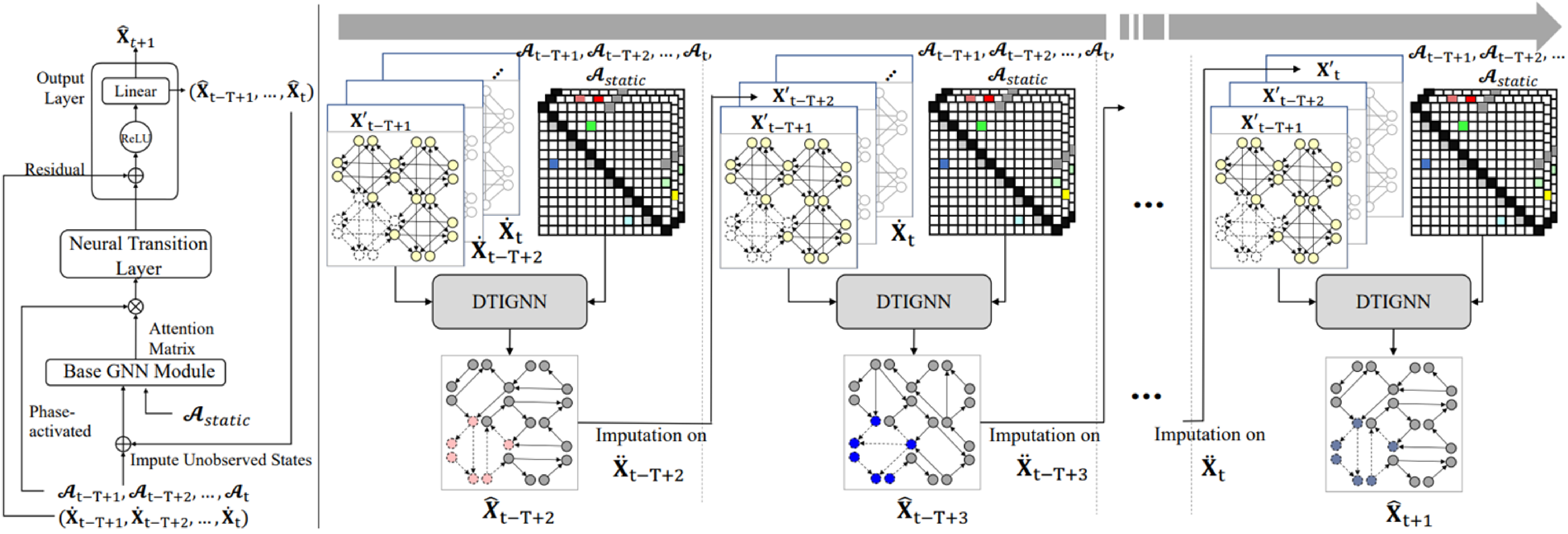
Road network is a directed dynamic graph $\mathcal{G}_t = \{\mathcal{R}, \mathcal{A}_t\}$ at time t, where $\mathcal{R} = \{r^1, \ldots, r^N\}$ is a set of N road segments and $\mathcal{A}_t \in \mathbb{R}^{N \times N}$ is the adjacency matrix indicating the connectivity between road segments at time t.

This is the traffic action (traffic signals)

Summarizing Intuitions

- Modeling action
  - Dynamic graph
- Small data
  - Heuristic transition model from transportation
- Incomplete data
  - Imputation with prediction

DTIGNN: A Flexible Framework with Dynamic graph, Transition function, and Iterative training



(a) Framework (b) Pipeline

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Incorporating heuristics model: Transition-guided Spatial Temporal GNN

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- Neural Transition Layer: Modeling transitions with transportation functions
  - Activated Proportion Matrix

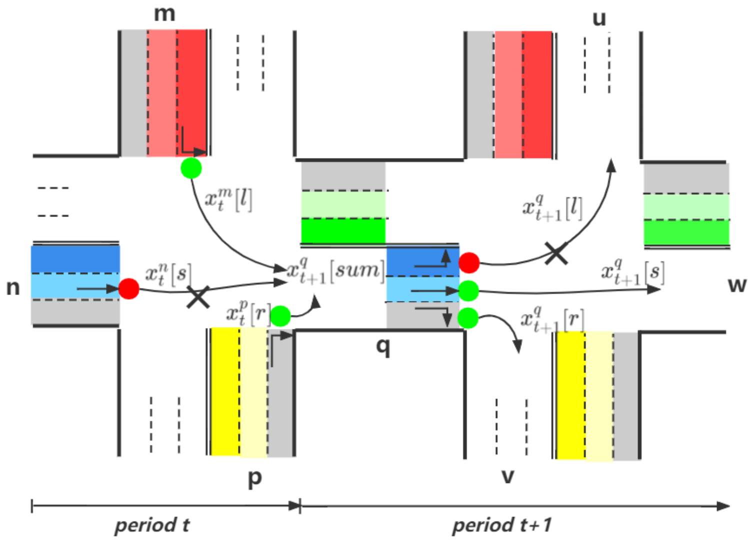
$$\mathbf{\Gamma}_t = \mathcal{A}_t \odot \mathbf{Att}$$

$$\widehat{\mathbf{Z}}_{t+1} = \mathbf{\Gamma}_t^{\intercal} \dot{\mathbf{X}}_t = (\mathcal{A}_t \odot \mathbf{Att})^{\intercal} \dot{\mathbf{X}}_t$$

Theorem 4.1 (Connection with transition equations). The latent traffic volume calculated by above equals to the transition equations below from transportation.

$$\mathbf{x}_t^q[out] = \mathcal{A}_t^{q,u} \cdot \gamma^{q,u} \cdot \mathbf{x}_t^q[l] + \mathcal{A}_t^{q,w} \cdot \gamma^{q,w} \cdot \mathbf{x}_t^q[s] + \mathcal{A}_t^{q,v} \cdot \gamma^{q,v} \cdot \mathbf{x}_t^q[r]$$

$$\mathbf{x}_{t+1}^q[in] = \mathcal{A}_t^{m,q} \cdot \gamma^{m,q} \cdot \mathbf{x}_t^m[l] + \mathcal{A}_t^{p,q} \cdot \gamma^{p,q} \cdot \mathbf{x}_t^p[r] + \mathcal{A}_t^{n,q} \cdot \gamma^{n,q} \cdot \mathbf{x}_t^n[s]$$



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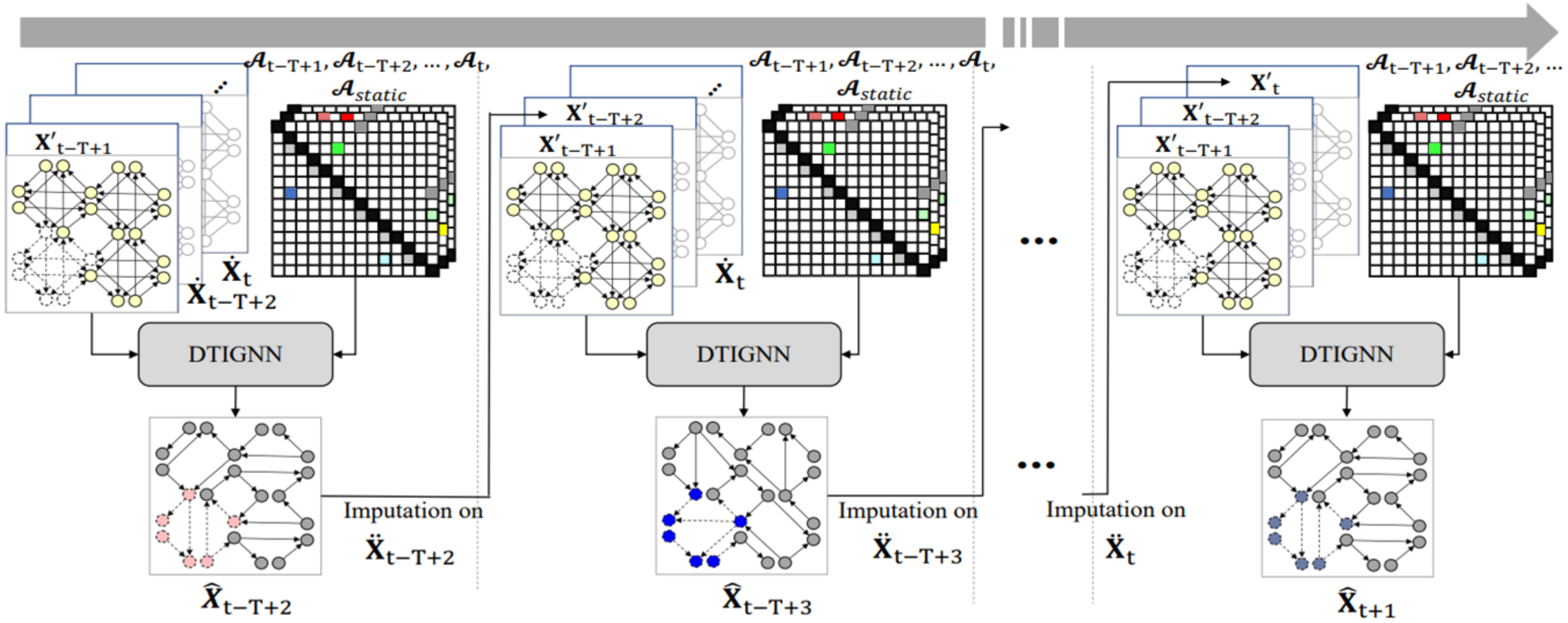
Iterative Imputation for Prediction



$$\mathbf{X}'_{t-\tau+1} = \dot{\mathbf{X}}_{t-\tau+1} + \ddot{\mathbf{X}}_{t-\tau+1} = \mathbf{X}_{t-\tau+1} \odot \mathbf{M} + \widehat{\mathbf{X}}_{t-\tau+1} \odot (1 - \mathbf{M})$$

$$\min_{\theta} \mathcal{L}_p(\theta) = \boxed{\frac{1}{T-1}\frac{1}{N}\sum_{i=1}^{T-1}\sum_{j=1}^{N} \| (\mathbf{x}^j_{T-i} - \widehat{\mathbf{x}}^j_{T-i}) \odot \mathbf{M}^j \|_2} + \boxed{\frac{1}{N}\sum_{j=1}^{N} \| (\mathbf{x}^j_{T+1} - \widehat{\mathbf{x}}^j_{T+1}) \odot \mathbf{M}^j \|_2}$$

Imputation loss

Prediction loss

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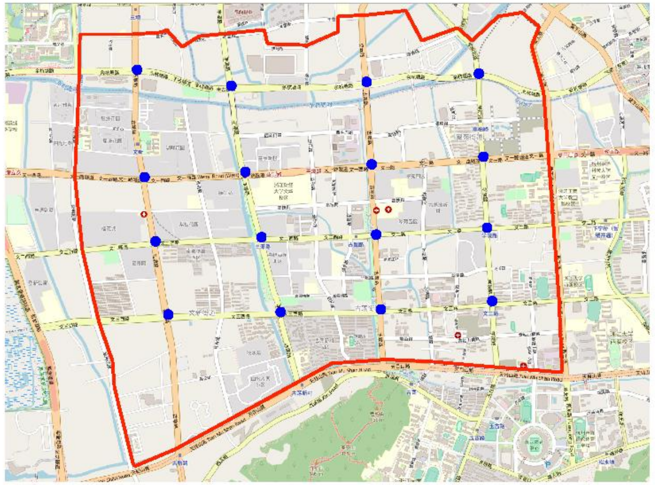
Datasets

- Both synthetic and real-world datasets

Dataset	$D_{4\times4}$	D_{HZ}	D_{NY}
Duration(seconds)	3600	3600	3600
Time steps	360	360	360
# of intersections	16	16	196
# of road segments	80	80	854
# of groundtruth states(full)	23040	23040	282240
% of unobserved intersections	12.5	12.5	10.4



D_{HZ}

D_{NY}

Overall Performance

Datasets	Metrics	SFM	STGCN	STSGCN	ASTGCN	ASTGNN	WaveNet	Ours (ASTGNN)	Ours (WaveNet)
D_{HZ}	MAE	1.2310	0.4909	0.6079	0.4458	0.4020	0.4556	**0.3810**	0.4071
	RMSE	1.5578	0.8756	0.9104	0.7425	0.7408	0.8668	**0.6618**	0.6883
	MAPE	1.1288	0.3135	0.3863	0.2953	0.2527	0.2987	**0.2455**	0.2599
D_{NY}	MAE	1.1385	0.2651	0.4476	0.3136	0.2437	0.2168	0.2437	**0.2060**
	RMSE	1.5227	1.1544	1.1235	1.0625	1.0704	1.1485	**0.9493**	1.1002
	MAPE	0.1638	0.1146	0.2358	0.1620	0.1272	0.0988	0.1283	**0.0978**

- SFM: A heuristic model from transportation for traffic flow transitions.
- STGCN: Utilizes graph convolution and 1D convolution.
- STSGCN: Utilizes multiple localized spatial-temporal graph.
- ASTGCN: Utilizes attention mechanisms to model spatial-temporal dynamics.
- ASTGNN: Based on ASTGCN, ASTGNN further uses a dynamic graph convolution module.
- WaveNet: Combines adaptive graph convolution with dilated casual convolution.

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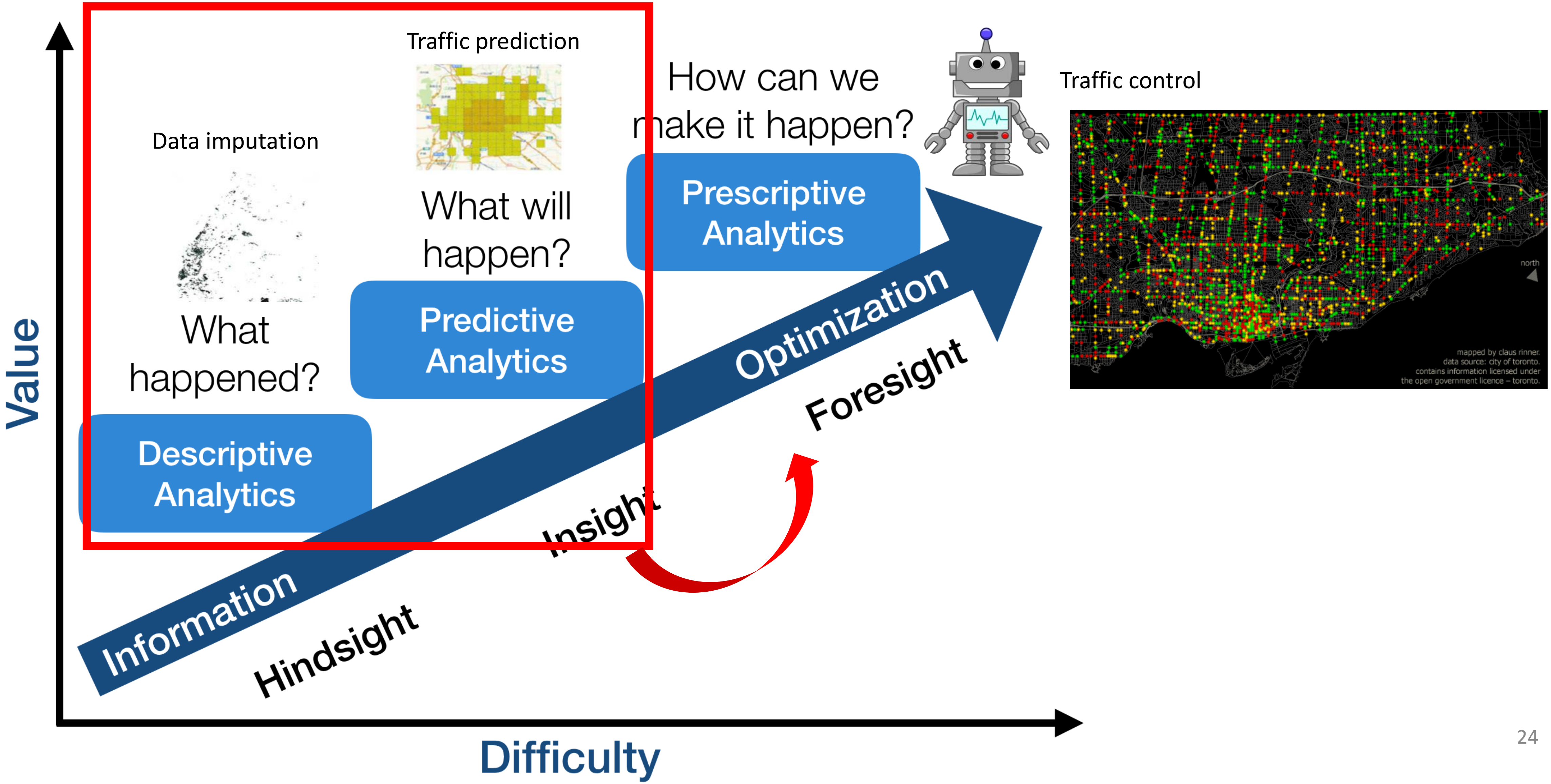
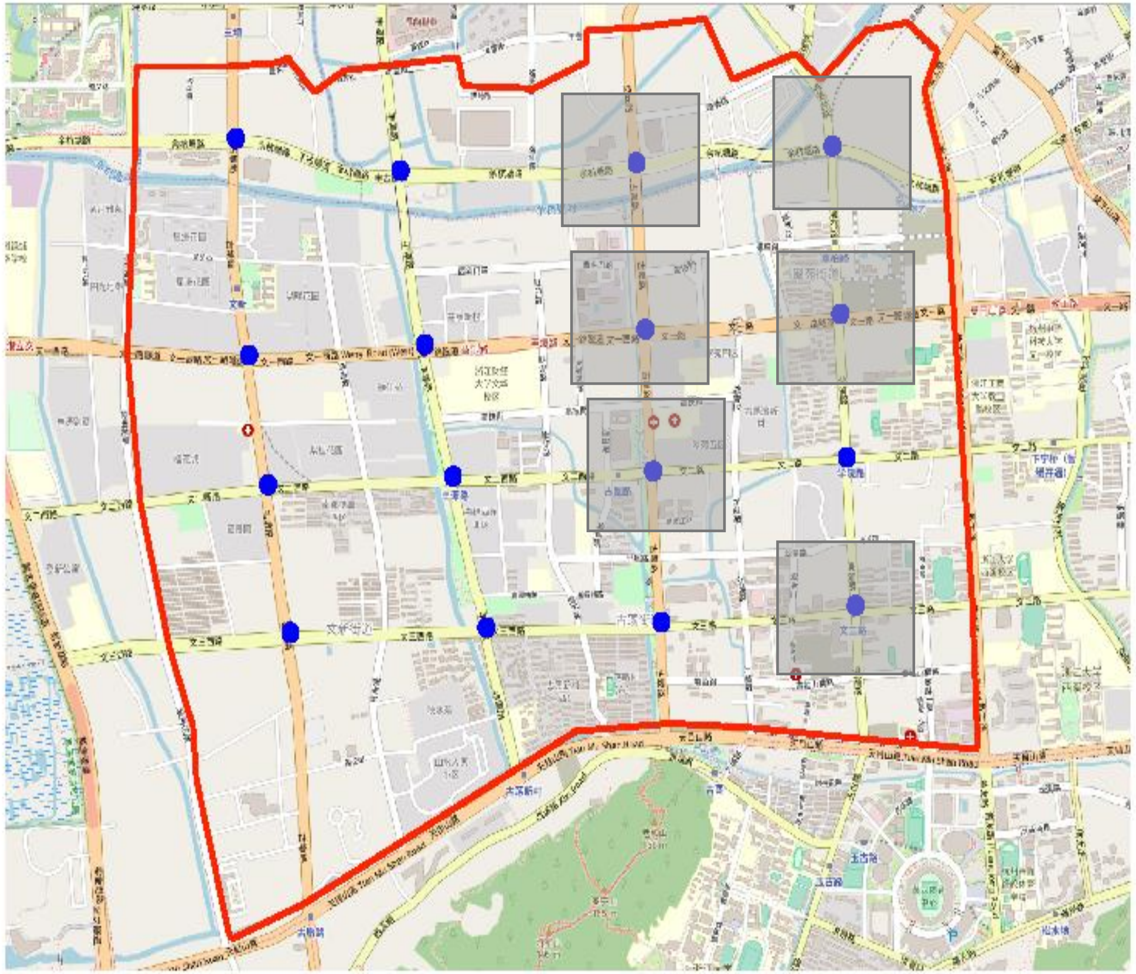
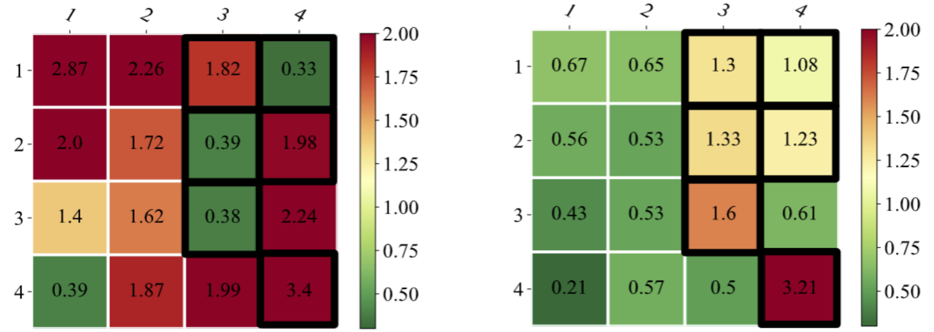


Traffic Signal Control under Sparse Observations

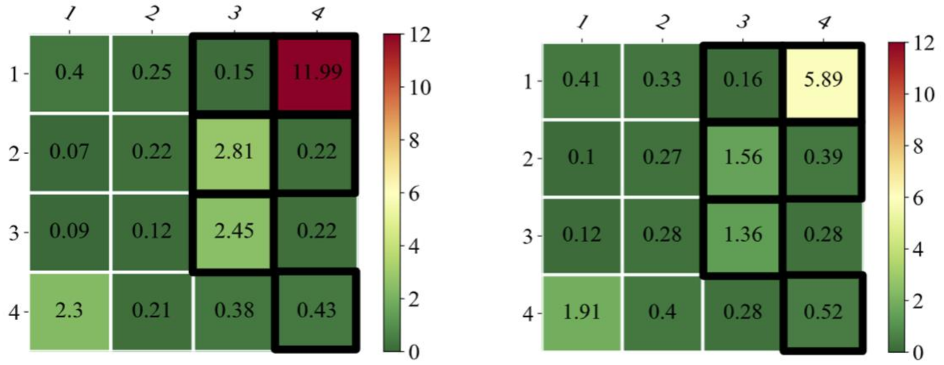


State Transition Modeling



(a) RMSE of baseline (left) and *DTIGNN* (right). The lower, the better.

Traffic signal control based on prediction



(b) Queue length of MaxPressure using predictions from baseline (left) and *DTIGNN* (right). The lower, the better.

Takeaway

- Traffic prediction -> Modeling state transition (with action)
- Sparse data is a challenge for real-world application
- Our model DTIGNN is theoretically supported by transportation equations.
- When dealing with incomplete data, imputation with prediction in one model is better
  - Imputation loss + Prediction loss

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Q & A

Thank you

Poster Position ID: 16
6:00 pm to 7:30 pm tonight

Data & Code:
https://github.com/ShawLen/DTIGNN

Website:
https://web.njit.edu/~hw32/index.html

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