Modeling Network-level Traffic Flow Transitions on Sparse Data

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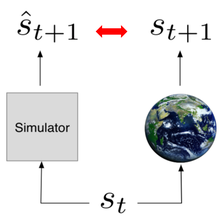
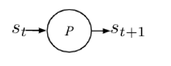
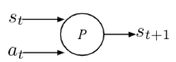
1 What's the problem? Modeling traffic state transitions





Predictive 1.0



Predictive 1.5

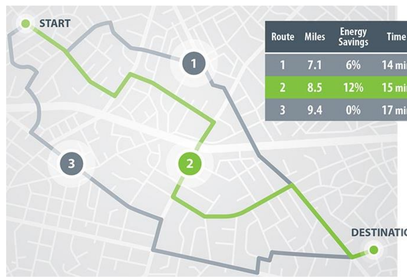
Prediction

- Using current state and previous states
- Heuristic models
- ML models
  - ARIMA, kNN, SVR
  - RNN/CNN
  - GNN: STGCN/ASTGCN/ASTGNN/DCRNN

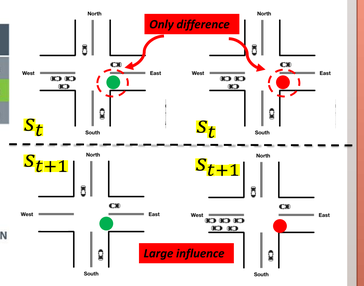
2 Why do we need predictive 1.5?

Your predictions affect future states.

Predictions made by a traffic prediction system, might affect the route people take, or the traffic signal control actions, which changes the traffic in return



Route	Miles	Energy Savings	Time
1	7.1	6%	14 min
2	8.5	12%	15 min
3	9.4	0%	17 min

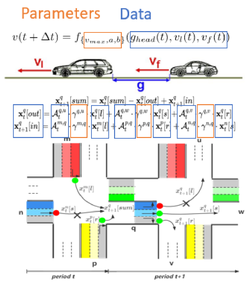


3 Transition Models and Sparse Data

Heuristics-driven

Parameters Data

$$v(t+\Delta t) = f(v_{max}, a, b)(g_{head}(t), v_l(t), v_f(t))$$



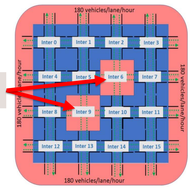
- *f(data)* is static
- Strong assumptions on the form

Data-driven model

- f(data) is learned
- Little assumptions

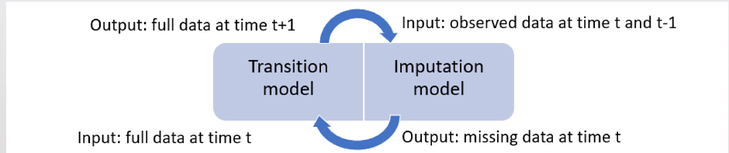
Full observations are not easy to access.

Unobservable Intersections

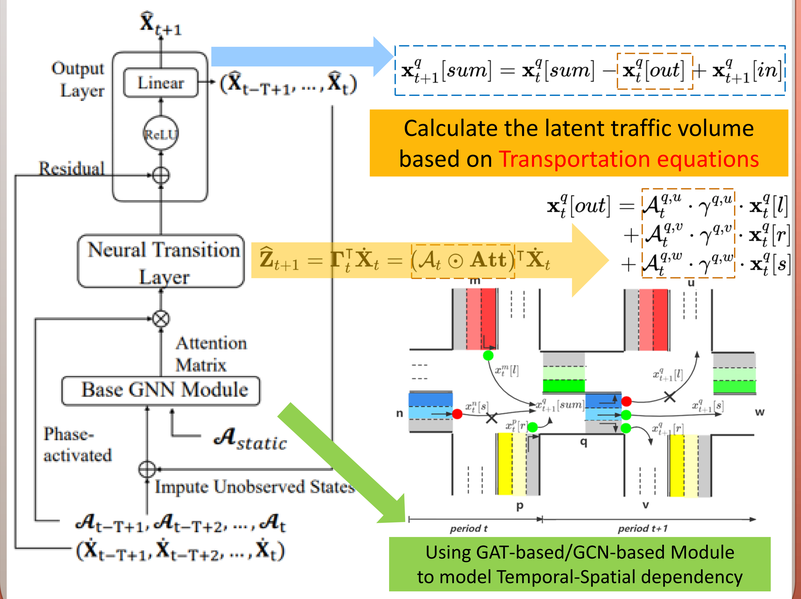


3 Method: Dynamic graph, Transition function, and Iterative training (DTIGNN)

Imputation and transition model should be inherently one model



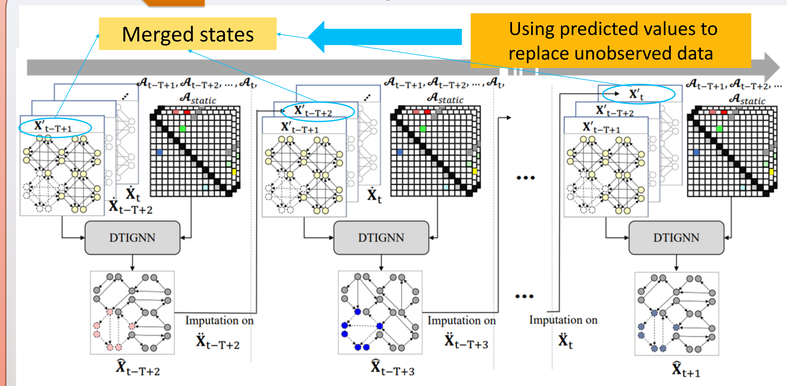
3.1 Transition-based Spatial Temporal GNN



Calculate the latent traffic volume based on Transportation equations

Using GAT-based/GCN-based Module to model Temporal-Spatial dependency

3.2 Iterative Imputation for Prediction

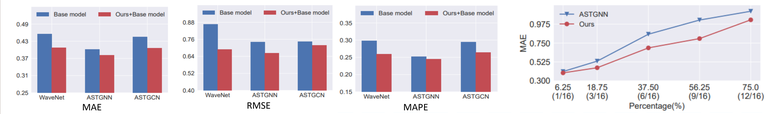


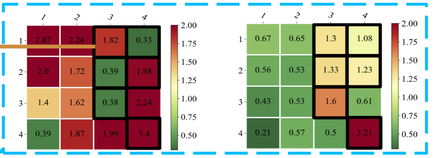
$$\min_\theta \mathcal{L}_p(\theta) = \frac{1}{T-1}\frac{1}{N}\sum_{i=1}^{T-1}\sum_{j=1}^{N} \| (\mathbf{x}^j_{T-i} - \hat{\mathbf{x}}^j_{T-i}) \odot \mathbf{M}^j \|_2 + \frac{1}{N}\sum_{j=1}^{N} \| (\mathbf{x}^j_{T+1} - \hat{\mathbf{x}}^j_{T+1}) \odot \mathbf{M}^j \|_2$$

Imputation loss *Prediction loss*

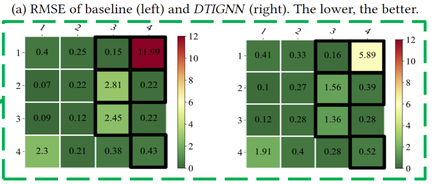
4 Experiments

Datasets	Metrics	STGCN [38]	STSGCN [22]	ASTGCN[8]	ASTGNN[7]	WaveNet [32]	Ours (ASTGNN)	Ours (WaveNet)
$D_{4\times4}$	MAE	0.0563	0.1244	0.0605	0.0562	0.0427	0.0484	**0.0378**
	RMSE	0.1885	0.2993	0.2092	0.2124	0.1981	0.1920	**0.1825**
	MAPE	0.0216	0.0460	0.0302	0.0256	0.0165	0.0215	**0.0145**
D_{HZ}	MAE	0.4909	0.6079	0.4458	0.4020	0.4556	**0.3810**	0.4071
	RMSE	0.8756	0.9104	0.7425	0.7408	0.8668	**0.6618**	0.6883
	MAPE	0.3135	0.3863	0.2953	0.2527	0.2987	**0.2455**	0.2599
D_{NY}	MAE	0.2651	0.4476	0.3136	0.2437	**0.2168**	0.2437	0.2306
	RMSE	1.1544	1.1235	1.0625	1.0704	1.1485	**0.9493**	1.1002
	MAPE	0.1146	0.2358	0.1620	0.1272	0.0988	0.1283	**0.1207**





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



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

Black boxes: Intersections without any observation

Performance of state transition task (Prediction task)

Performance of traffic signal control task (Downstream task)

Open Discussion

- More traffic operations can be considered
- More exterior data like weather conditions can be considered
- Sometimes actions are not known and need to be inferred.

Code and data can be found at:

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