Origin-Destination Travel Time Oracle for Map-based Services

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Outline

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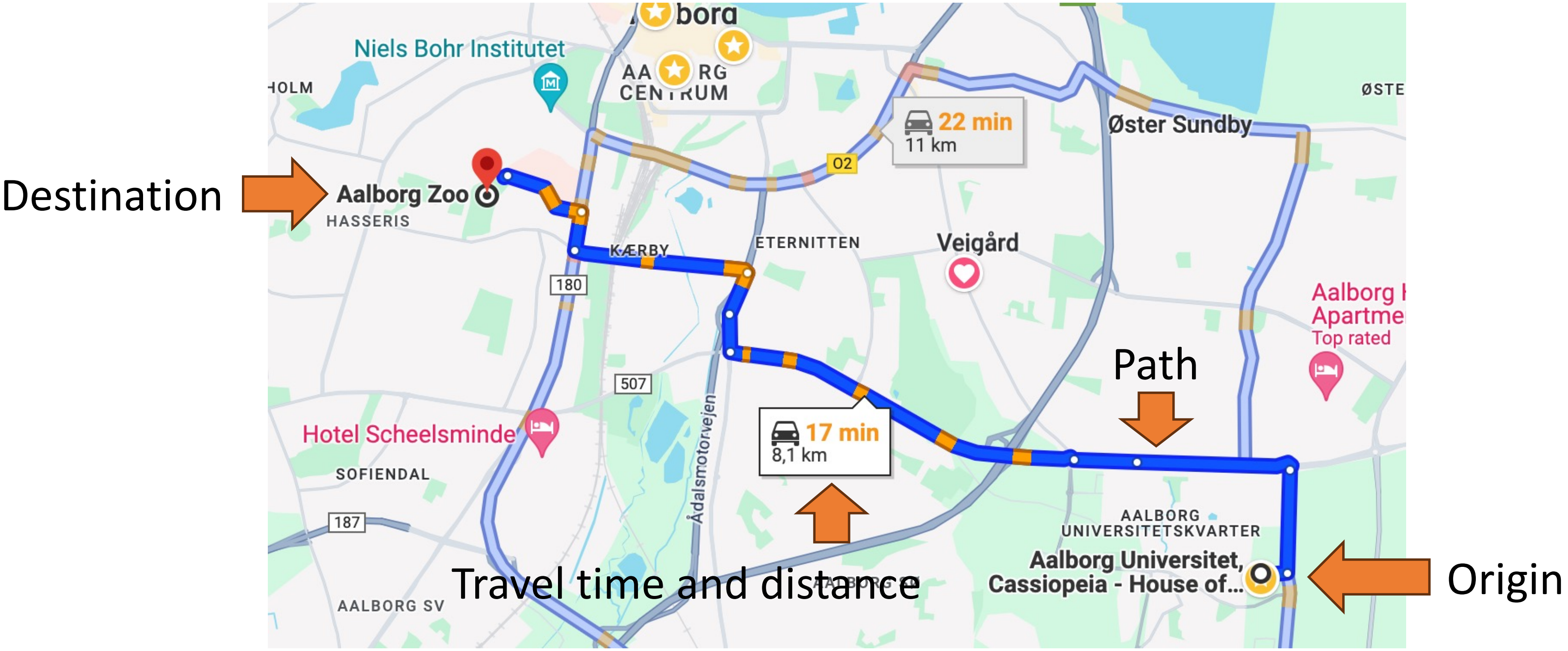
OD Oracle

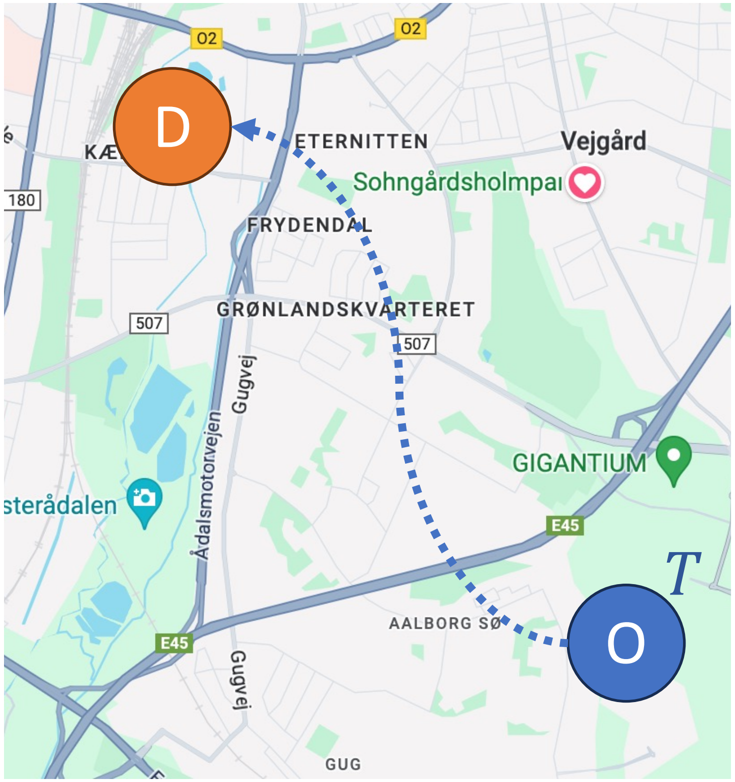
- Provide estimates of the travel times, distances, and paths between origin (O) and destination (D) locations.



- Sankaranarayanan, Jagan, and Hanan Samet. "Distance oracles for spatial networks." 2009 IEEE 25th International Conference on Data Engineering. IEEE, 2009.
- Sankaranarayanan, Jagan, Hanan Samet, and Houman Alborzi. "Path oracles for spatial networks." Proceedings of the VLDB Endowment 2.1 (2009): 1210-1221.

OD Travel Time Oracle

- Takes an OD pair and a departure time T as input
- Returns a travel time needed to travel from O to D when departure at time T.

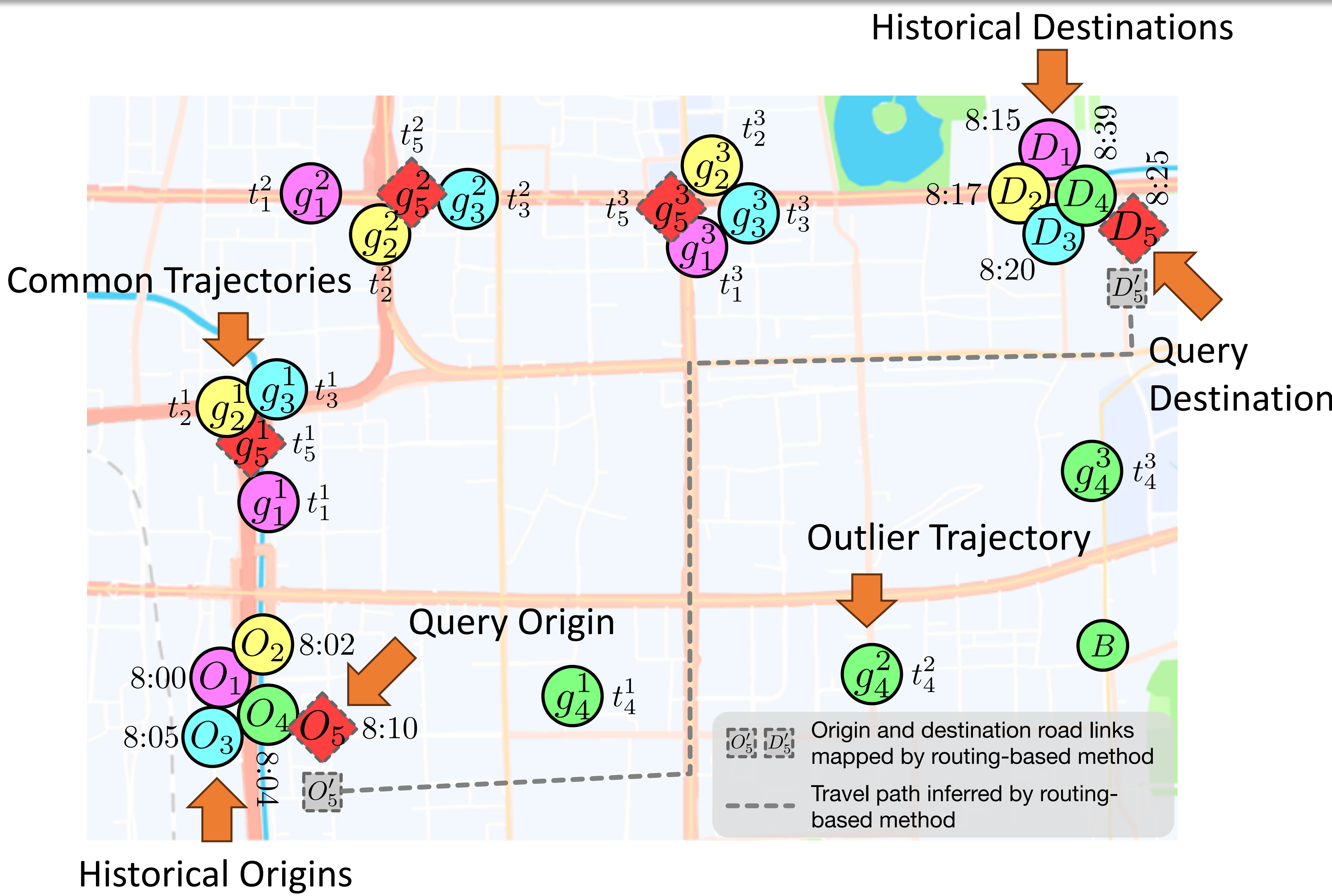


ODT-Input

Δt

Estimated Travel Time

Example



Historical Destinations
Common Trajectories
Query Destination
Outlier Trajectory
Query Origin
Historical Origins
8:15
8:17
8:20
8:39
8:25
8:00
8:02
8:04
8:05
8:10
Origin and destination road links mapped by routing-based method
Travel path inferred by routing-based method

Outline

Motivation

- Build the connections between ODT-Input, travel trajectory, and travel time
- Learn common patterns of trajectories corresponding to similar ODT-Inputs
- Effectively detect outliers and remove their impact on the prediction accuracy

Outline

1 Background

2 Motivation

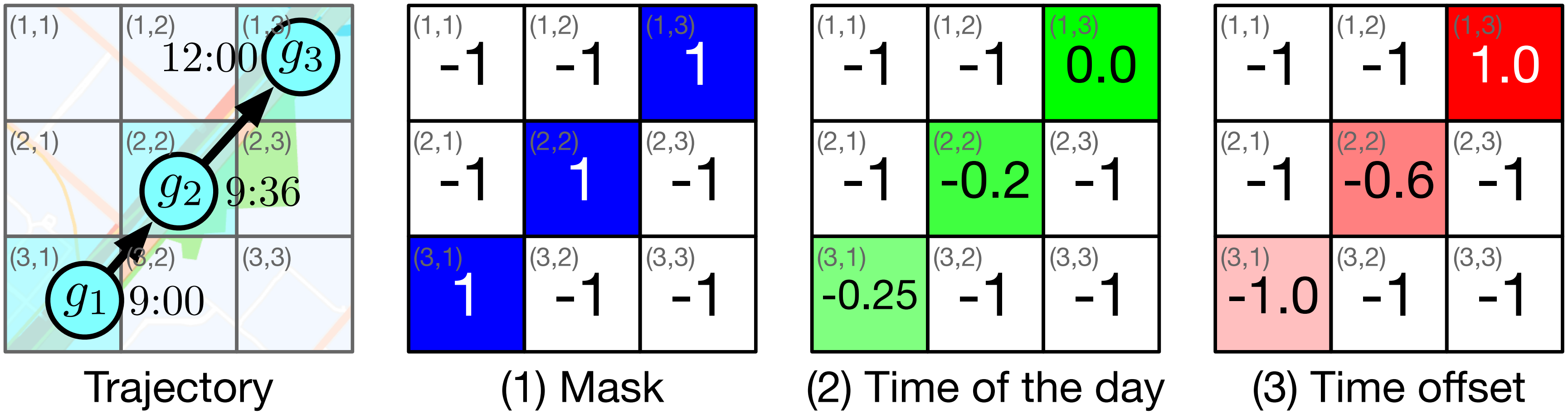
3 Methodology

4 Experiments

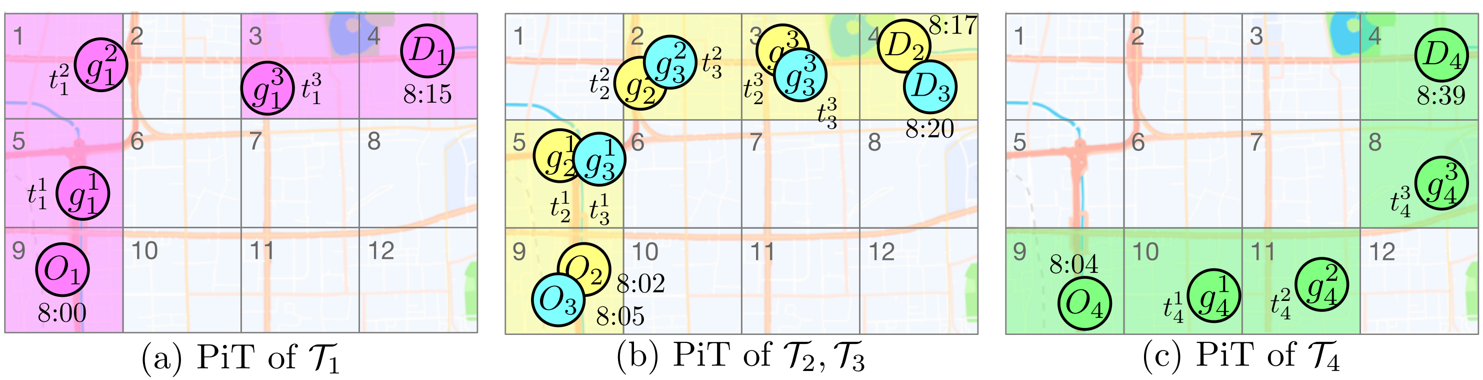
5 Future Works

Pixelated Trajectory (PiT)

- An image representation of a trajectory



Constructing the channels of PiT from GPS points

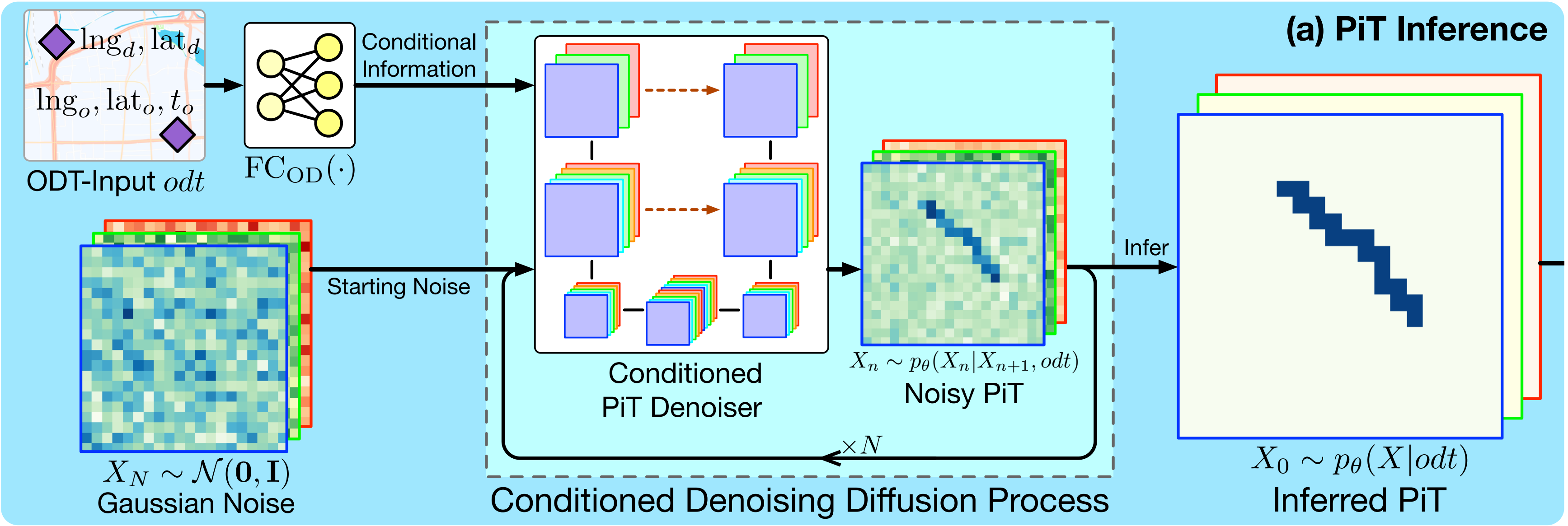


PiTs corresponds to example trajectories

➢Diffusion-based probabilistic model

- Build the connections between ODT-Inputs and trajectories.

$$p_\theta(\boldsymbol{X}|odt)$$



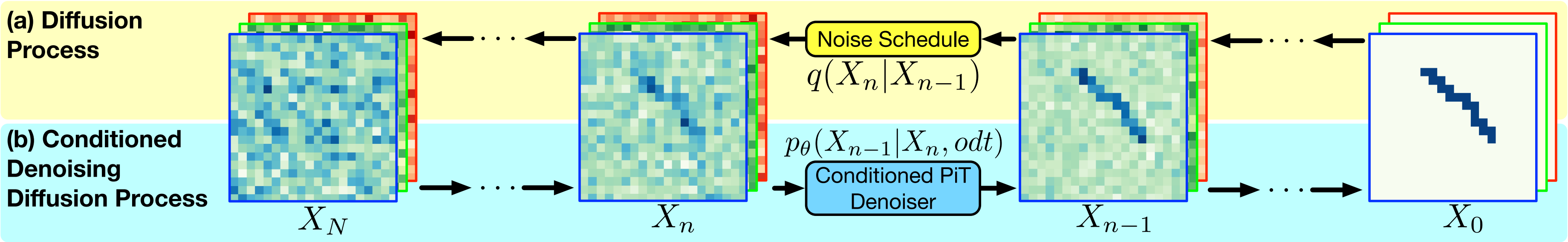
Framework of the conditioned PiT inference.

➢Conditioned denoising diffusion process

- Parameterize the posterior probability $p_\theta(\boldsymbol{X}|odt)$

$$q(X_n|X_{n-1}) = \mathcal{N}(X_n; \sqrt{1-\beta_n}X_{n-1}, \beta_n\mathbf{I})$$

$$p_\theta(X_{n-1}|X_n, odt) = \mathcal{N}(X_{n-1}; \boldsymbol{\mu}_\theta(X_n, n, odt), \Sigma_\theta(X_n, n, odt))$$

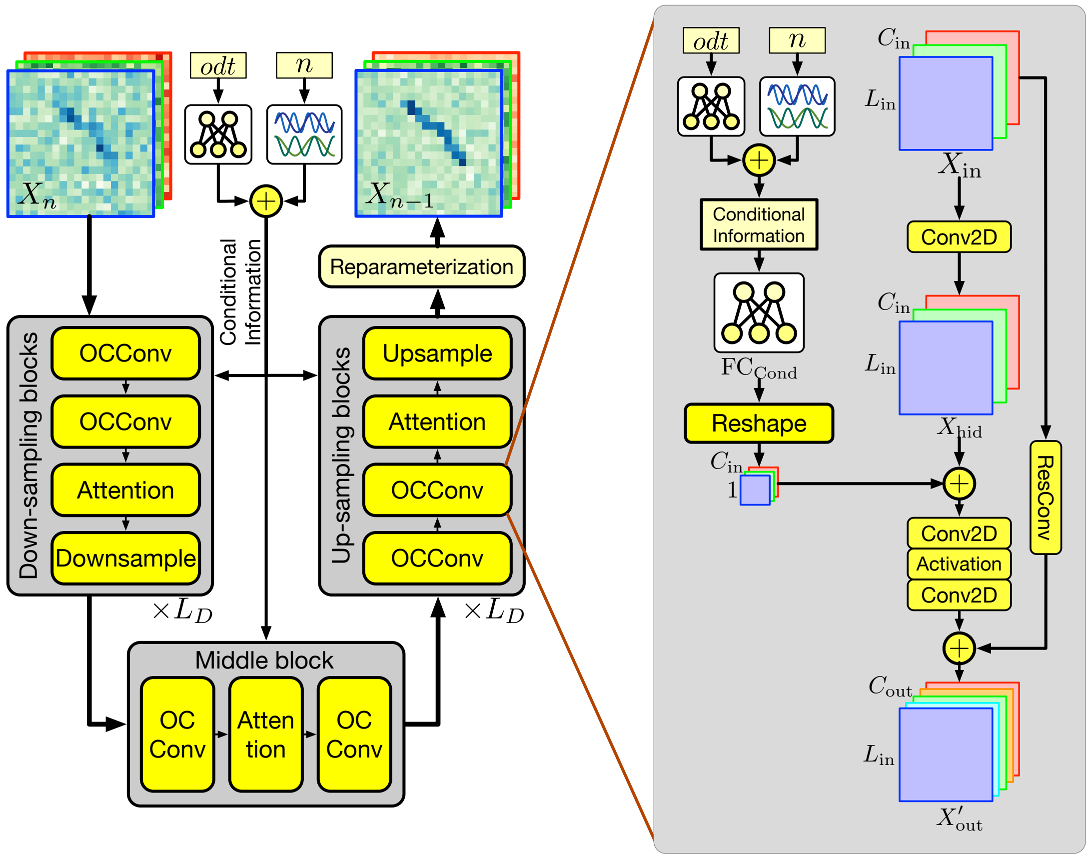


Two Markov processes in the conditioned PiT inference.

- Ho, Jonathan, Ajay Jain, and Pieter Abbeel. "Denoising diffusion probabilistic models." Advances in neural information processing systems 33 (2020): 6840-6851.

➢Conditioned PiT Denoiser

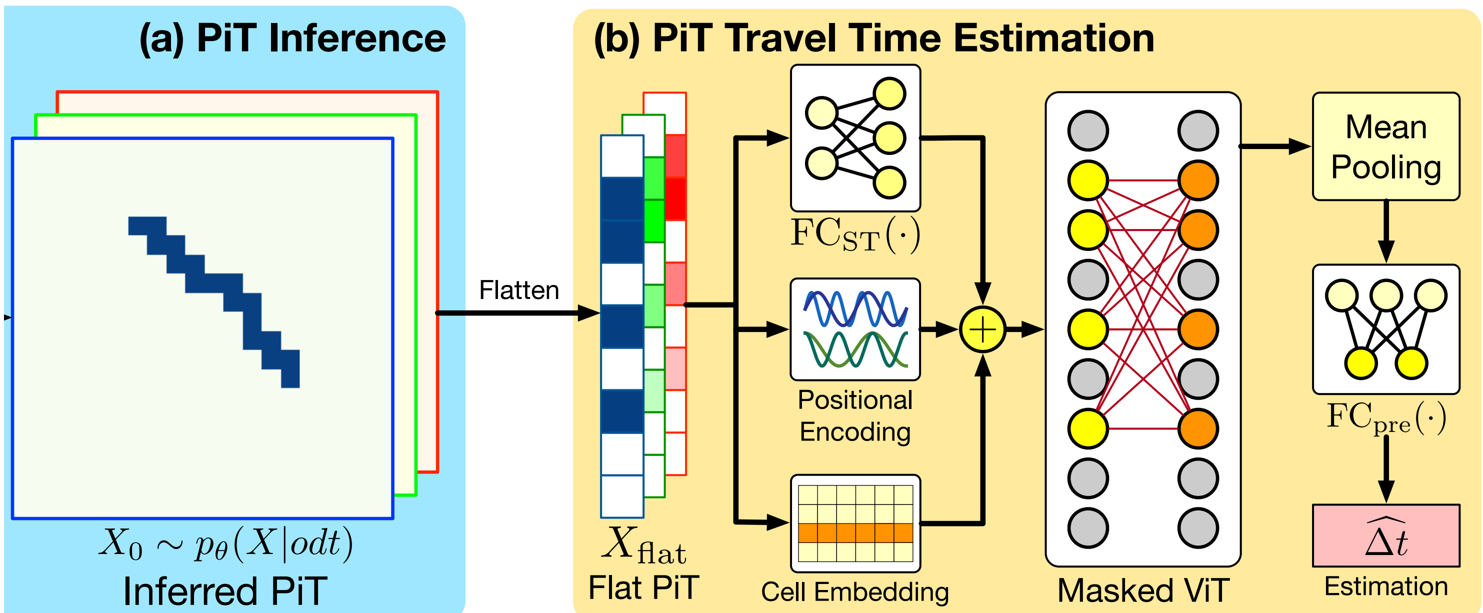
- Guide the conditioned denoising diffusion process



Structure of the conditioned PiT denoiser

Travel Time Estimation

- Flatten an inferred PiT to a sequence
- Masked Vision Transformer for more efficient sequential modeling



Framework of the PiT-based travel time estimation

Outline

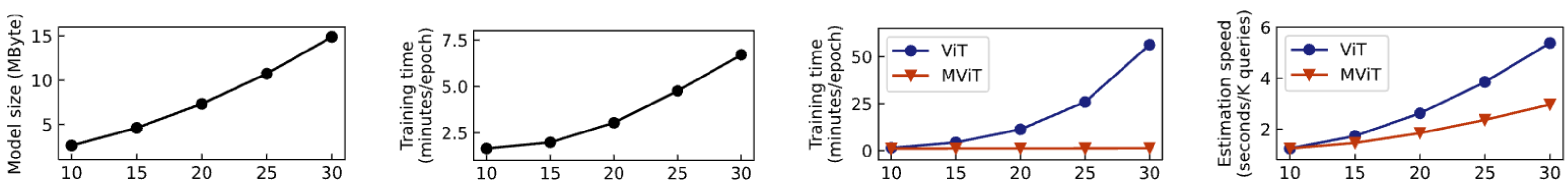
Quantitative Results

Datasets	Chengdu/Harbin		
Metric	RMSE (minutes)	MAE (minutes)	MAPE (%)
Dijkstra	9.677/11.865	7.618/8.447	48.618/55.261
DeepST	4.717/8.926	3.452/5.849	27.503/37.772
WDDRA	4.581/8.836	3.210/5.705	24.553/35.617
STDGCN	4.469/8.679	3.104/5.564	23.187/33.771
TEMP	5.578/10.150	4.267/7.891	36.611/66.781
LR	6.475/10.290	5.036/8.006	44.514/67.669
GBM	4.999/9.069	3.655/6.748	29.636/54.413
RNE	4.624/8.571	3.416/6.245	27.660/47.956
ST-NN	3.961/8.492	2.803/6.114	21.532/45.891
MURAT	3.646/7.937	2.384/5.360	18.345/41.128
DeepOD	3.764/7.859	1.789/4.533	14.997/36.974
DOT (Ours)	**3.177/7.462**	**1.272/3.213**	**11.343/26.698**

Overall performance comparison

Datasets	Chengdu/Harbin		
Metric	RMSE (minutes)	MAE (minutes)	MAPE (%)
Dijkstra+DeepTEA	9.641/11.862	7.582/8.396	48.337/53.949
DeepST+DeepTEA	4.692/8.901	3.416/5.821	26.959/37.063
WDDRA+DeepTEA	4.497/8.584	3.140/5.545	23.537/34.723
STDGCN+DeepTEA	4.393/8.569	3.056/5.501	22.812/33.688
RNE+DeepTEA	4.627/8.403	3.447/6.061	28.239/45.345
ST-NN+DeepTEA	3.912/8.427	2.740/5.994	20.818/43.664
MURAT+DeepTEA	3.644/7.899	2.367/5.181	17.986/37.728
DeepOD+DeepTEA	3.763/7.817	1.783/4.345	14.835/33.127
DOT (Ours)	**3.177/7.462**	**1.272/3.213**	**11.343/26.698**

Performance comparison of baselines with outlier detection



(a) Model size

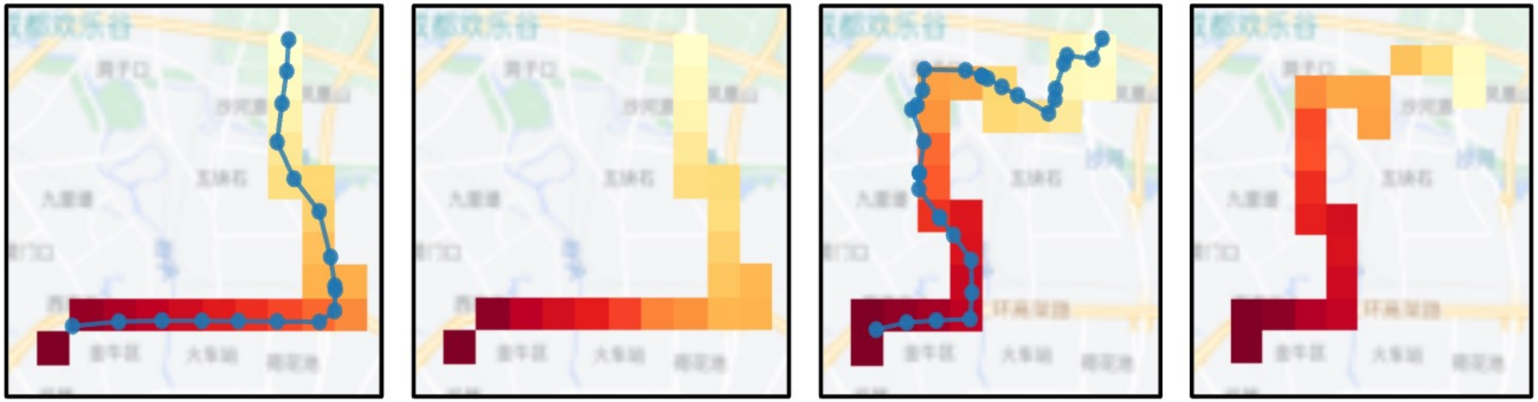
(b) Training time of the first stage

(c) Training time of the second stage

(d) Estimation speed

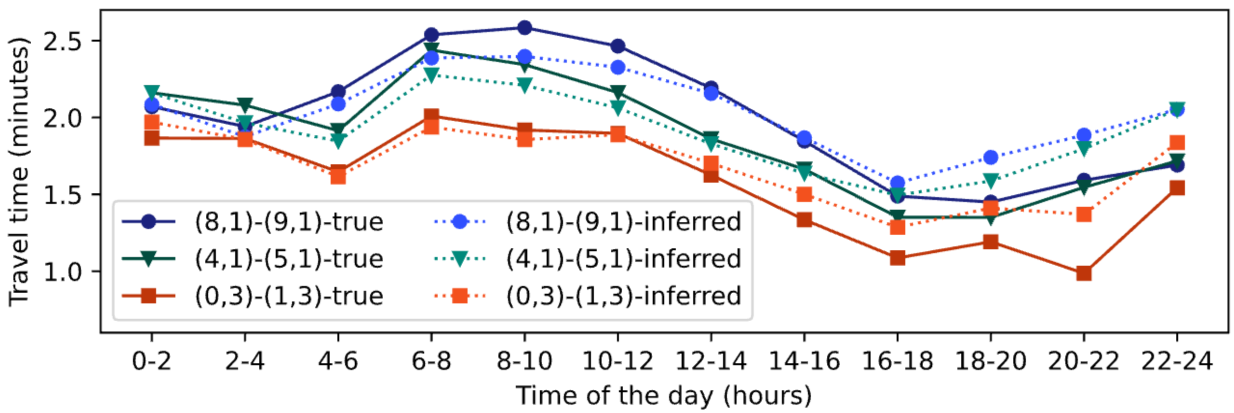
Efficiency impact of PiT's size

Case Studies



(a) GT PiT at 9:00 (b) Inferred PiT at 9:00 (c) GT PiT at 17:00 (d) Inferred PiT at 17:00

Trajectories or the same OD pair that depart at different times of the day



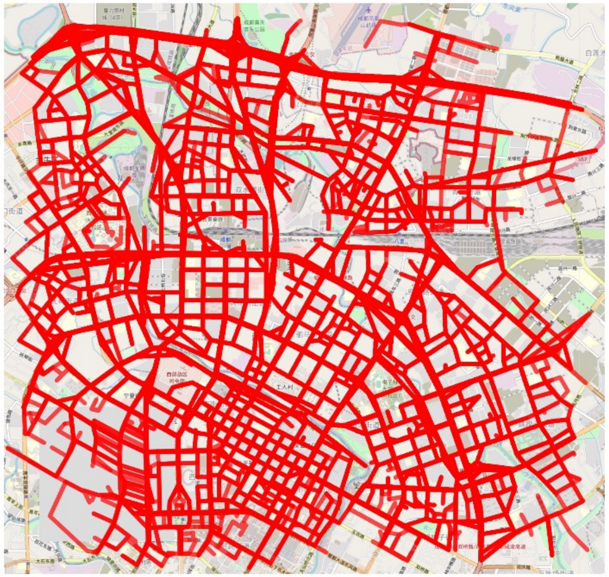
Average travel time between spatial cells during a day

Outline

Road-constrained Trajectory Inference

- Vehicle trajectories happen on road networks
- Challenge: Diffusion-based inference road networks (discrete space)

(a) Real paths



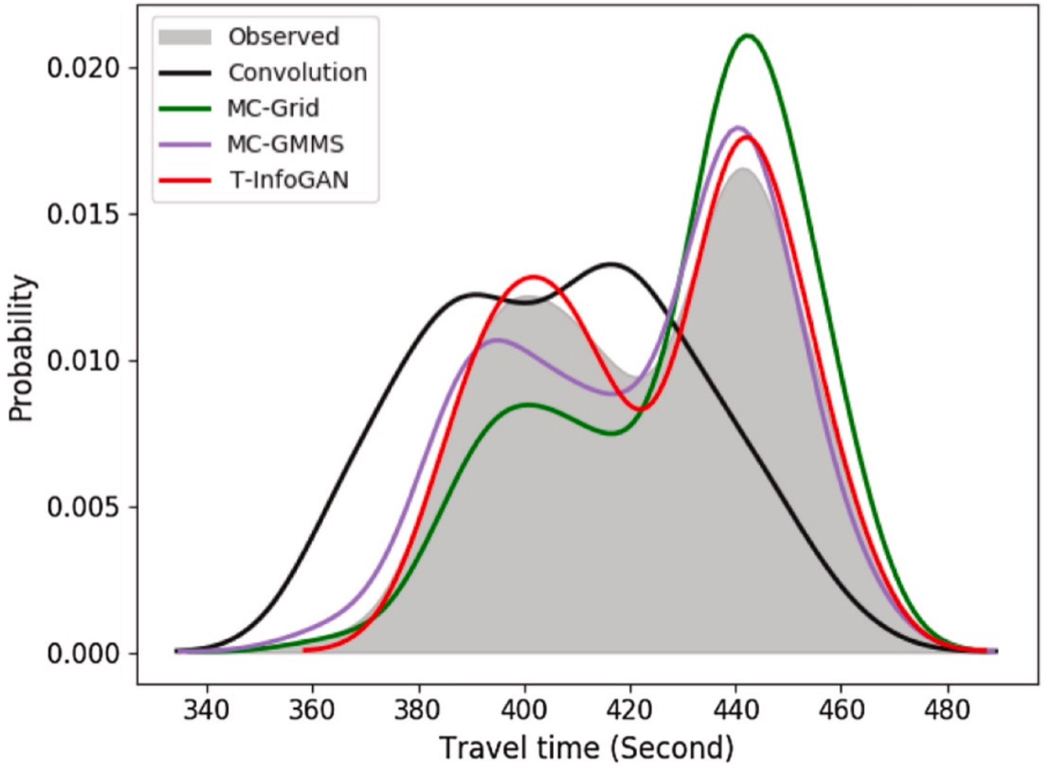
(b) Generated paths

Real and generated paths from GDP*

- Austin, Jacob, et al. "Structured denoising diffusion models in discrete state-spaces." Advances in Neural Information Processing Systems 34 (2021): 17981-17993.
- Shi, Dingyuan, et al. "GRAPH-CONSTRAINED DIFFUSION FOR END-TO-END PATH PLANNING." ICLR 2024 Accepted.

Uncertainty Quantification

- Uncertainty in travel time due to the diversity in traffic conditions
- Challenge: Efficient quantification of diffusion model's uncertainty

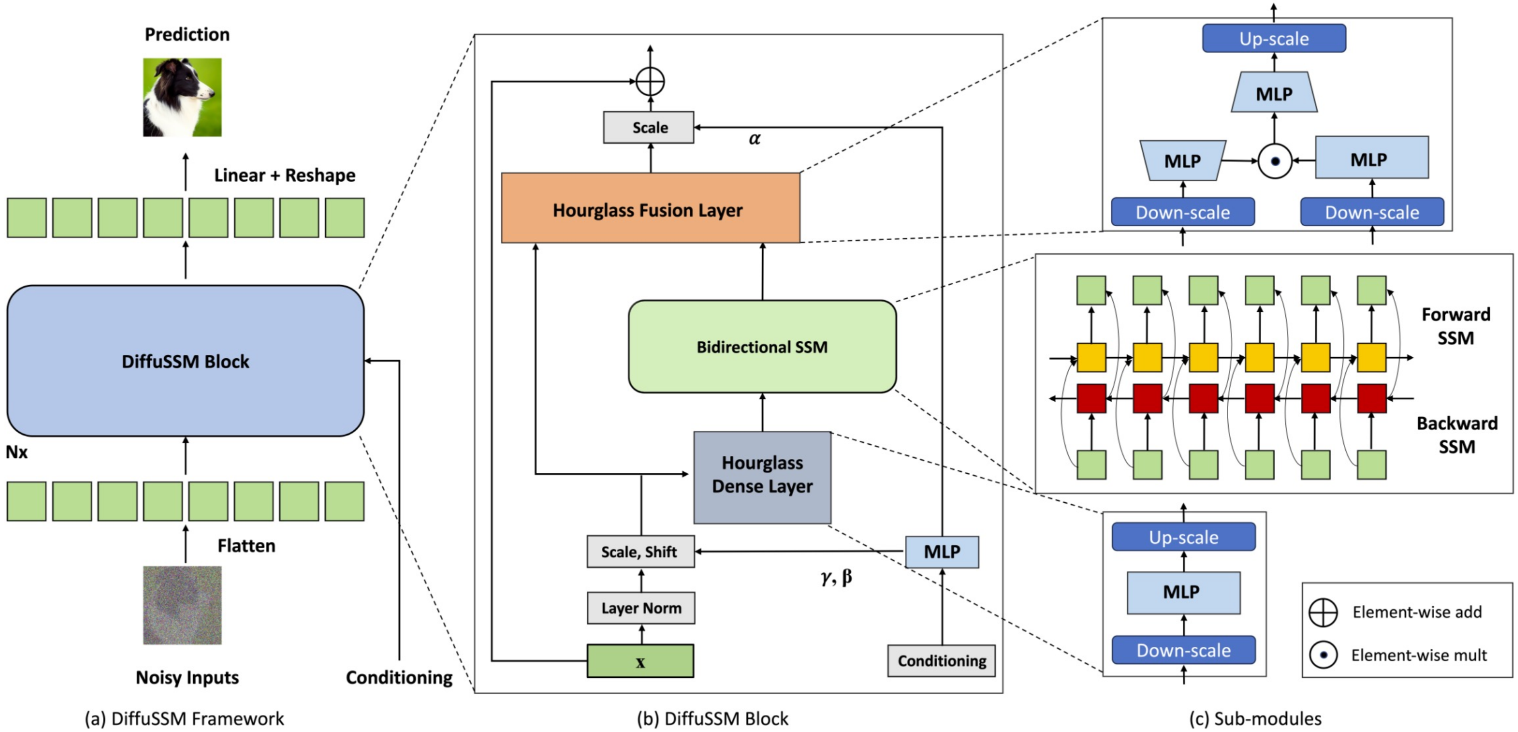


Distribution of travel time

- Zhang, Kunpeng, et al. "A novel generative adversarial network for estimation of trip travel time distribution with trajectory data." Transportation Research Part C: Emerging Technologies 108 (2019): 223-244.

Efficiency Improvements

- Faster oracle for swifter response in map services
- Challenge: Efficient diffusion process without sacrificing accuracy



Architecture of DiffuSSM*

- Song, Jiaming, Chenlin Meng, and Stefano Ermon. "Denoising diffusion implicit models." ICLR 2021 Accepted.
- Jing Nathan Yan, Jiatao Gu, Alexander M. Rush. "Diffusion Models Without Attention. " CoRR abs/2311.18257 (2023).

Thank You!