NEURAL INFORMATION PROCESSING SYSTEMS

DiffTraj: Generating GPS Trajectory with Diffusion Probabilistic Model

Yuanshao Zhu[1,2], Yongchao Ye[1], Shiyao Zhang[1], Xiangyu Zhao[2,*], James J.Q. Yu[3,*]

[1] Southern University of Science and Technology

[2] City University of Hong Kong

[3]University of York

{zhuys2019, 12032868}@mail.sustech.edu.cn

zhangsy@sustech.edu.cn

xianzhao@cityu.edu.hk

james.yu@york.ac.uk

Motivation & Challenge

➢ Why we need generate GPS trajectories?

- Personal geo-location is sensitive
- Time-consuming and labor-intensive for collection
- Hard for obtaining

➢ The challenge for accomplishing this task

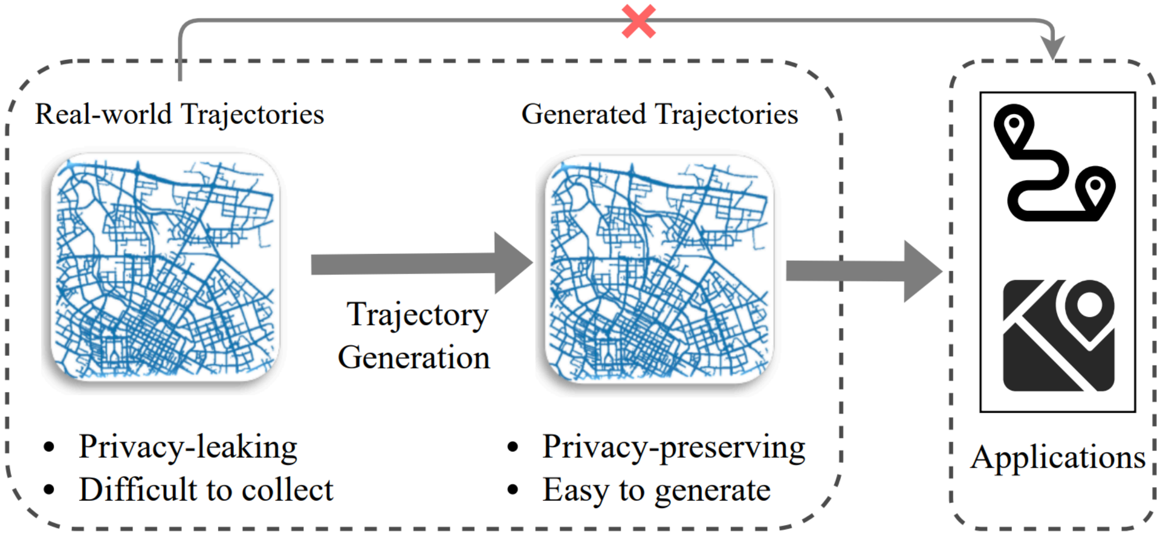
- Non-independent and identically distribution
- Human activities are stochastic
- Extra factors influent the trajectory moving

Objective for GPS Trajectories Generation

- **Similarity:** The generated trajectories can preserve the spatial-temporal characteristics and distribution of the real trajectories.

- **Utility:** The generated trajectories can maintain utility for downstream applications and analysis.

- **Privacy:** The generated trajectories do not reveal sensitive information associated with the individuals.



Diffusion Model-Based GPS Trajectory Generator

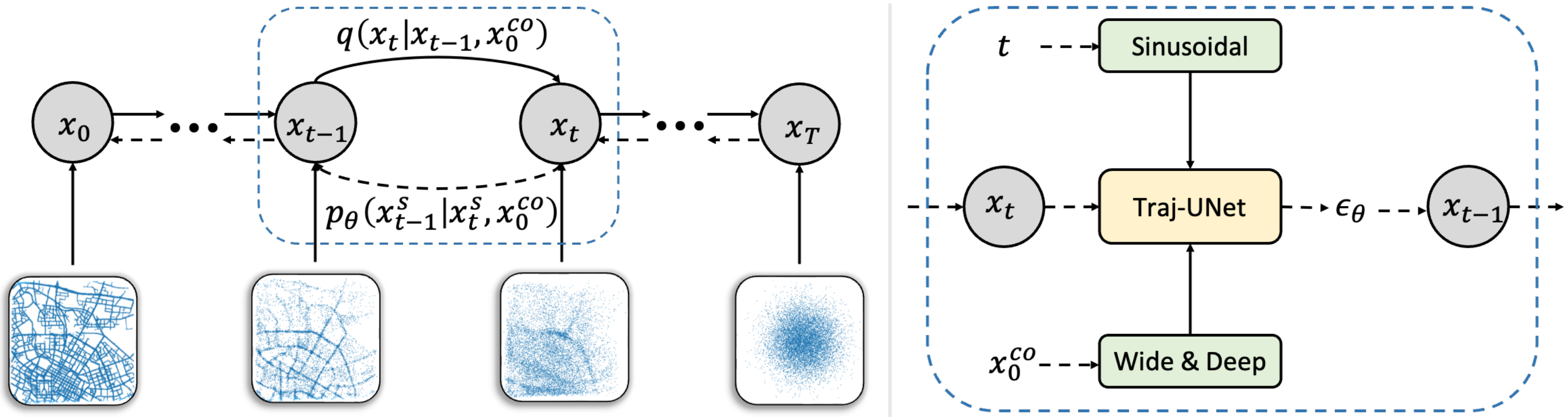


Illustration for trajectory generation with diffusion model

- Forward process:
  - Add Gaussian noise to trajectories

$$q(\boldsymbol{x}_{1:T} \mid \boldsymbol{x}_0) = \prod_{t=1}^{T} q(\boldsymbol{x}_t \mid \boldsymbol{x}_{t-1})$$

$$q(\boldsymbol{x}_t \mid \boldsymbol{x}_{t-1}) = \mathcal{N}\left(\boldsymbol{x}_t; \sqrt{1-\beta_t}\boldsymbol{x}_{t-1}, \beta_t \mathbf{I}\right)$$

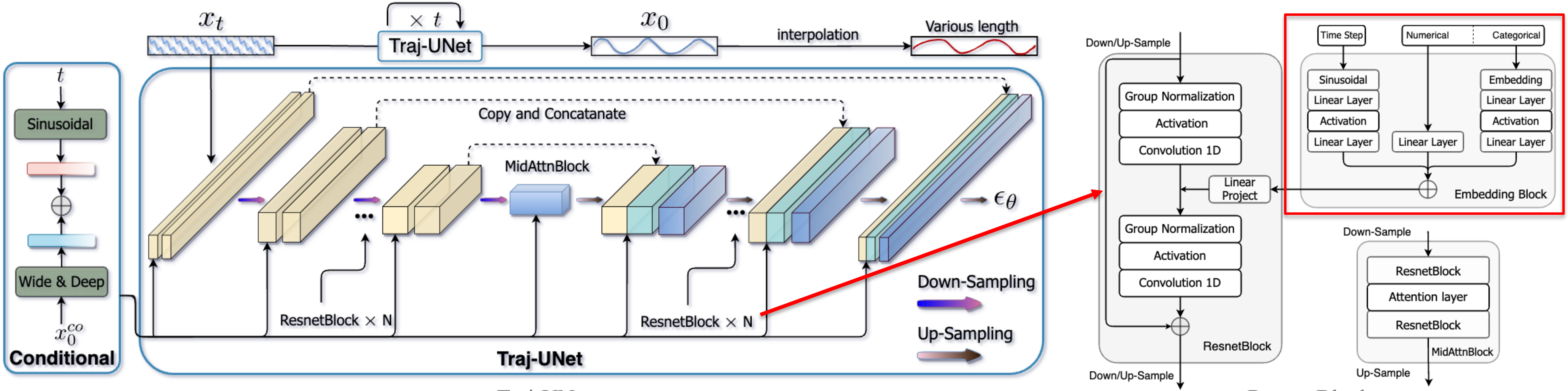
- Reverse process:
  - Recover the trajectories from the noise

$$p_\theta(\boldsymbol{x}_{0:T}) = p(\boldsymbol{x}_T) \prod_{t=1}^{T} p_\theta(\boldsymbol{x}_{t-1} \mid \boldsymbol{x}_t)$$

$$p_\theta(\boldsymbol{x}_{t-1} \mid \boldsymbol{x}_t) = \mathcal{N}\left(\boldsymbol{x}_{t-1}; \boldsymbol{\mu}_\theta(\boldsymbol{x}_t, t), \boldsymbol{\sigma}_\theta(\boldsymbol{x}_t, t)^2 \mathbf{I}\right)$$

$$p_\theta\left(\boldsymbol{x}_{t-1}^{\mathrm{s}} \mid \boldsymbol{x}_t^{\mathrm{s}}, \boldsymbol{x}_0^{\mathrm{co}}\right) := \mathcal{N}\left(\boldsymbol{x}_{t-1}^{\mathrm{s}};\ \boldsymbol{\mu}_\theta(\boldsymbol{x}_t^{\mathrm{s}}, t \mid \boldsymbol{x}_0^{\mathrm{co}}),\ \boldsymbol{\sigma}_\theta(\boldsymbol{x}_t^{\mathrm{s}}, t \mid \boldsymbol{x}_0^{\mathrm{co}})^2 \mathbf{I}\right)$$

Traj-UNet Architecture



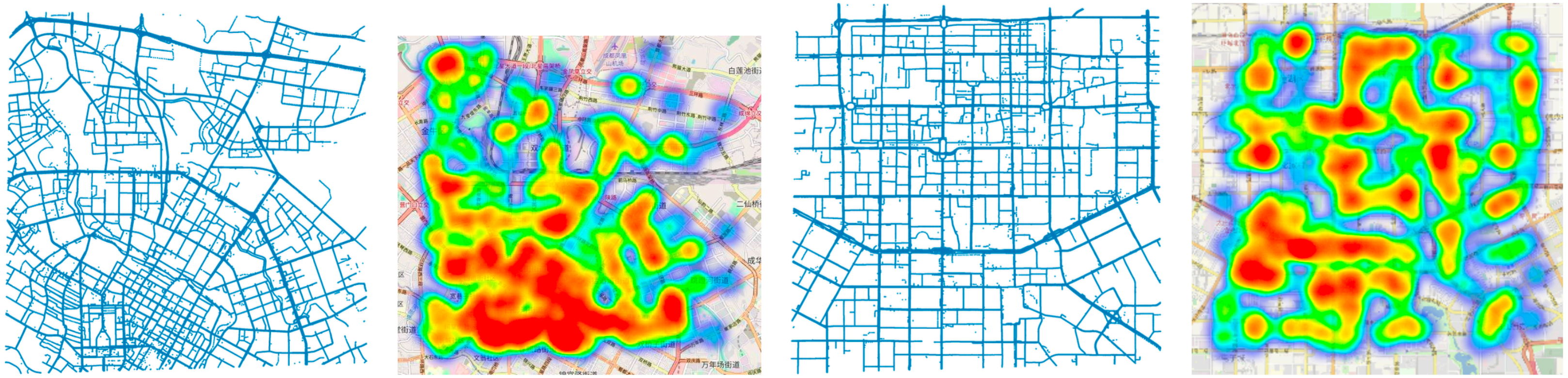
Traj-UNet　　　　Resnet Block

Traj-UNet: Capturing local and global contextual in GPS trajectory by multi-level and enable multi-scale feature fusion.

Wide & Deep: Employed to effectively embeding conditional information, such as departure time, trip distance, trip time.

Experiment Setups

➢ Dataset



(a) Chengdu Trajectory (b) Chengdu Heatmap (c) Xi'an Trajectory (d) Xi'an Heatmap

➢ Metrics

- **Density error**: measures the geo-distribution between the entire generated trajectory and the real one
- **Trip error**: measures the distributed differences between trip origins and endpoints
- **Length error**: focuses on the differences in real and synthetic trajectory lengths
- **Pattern score**: measures the pattern similarity of the generated trajectories

Quantitatively Results

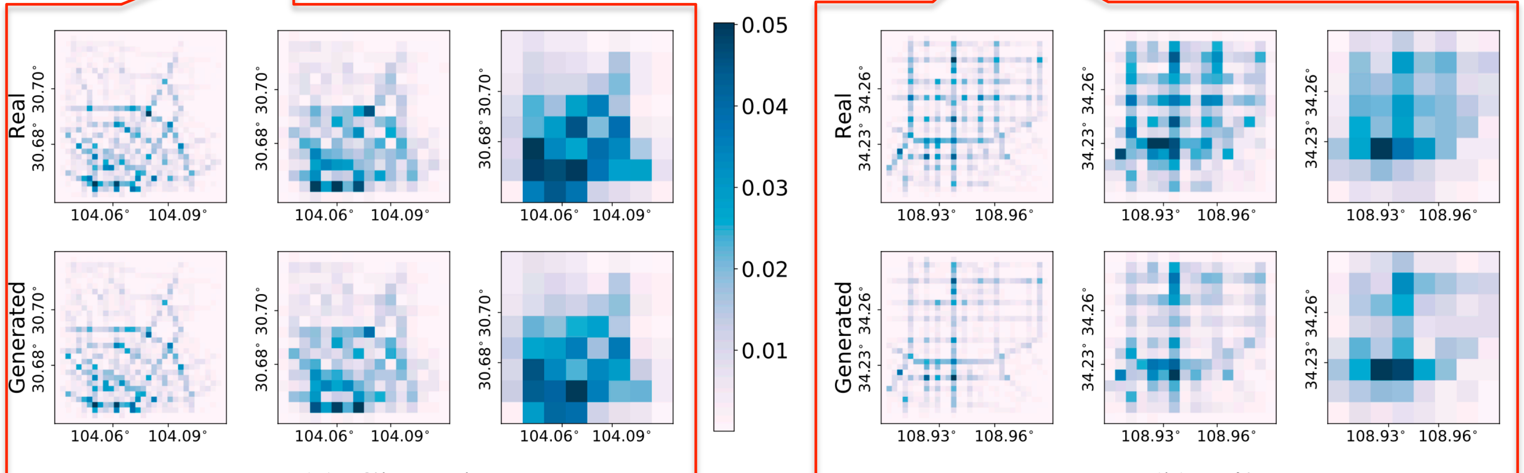
1. Generative models, VAE and TrajGAN, show better performance than RP and GP but are still inferior to DiffTraj (or DiffTraj-wo/Con).

2. Diff-LSTM achieves good results in some metrics compared to the model without UNet, but falls short of DiffTraj due to the differences in the backbone network.

3. The model without the Traj-UNet structure performs unfavorably.

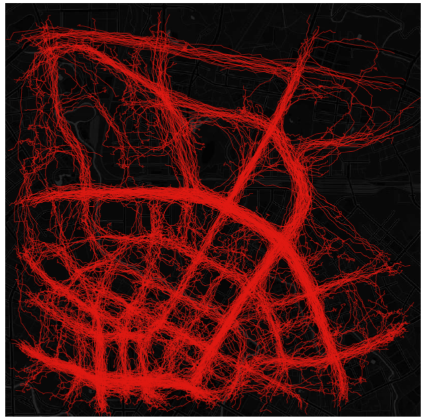
4. DiffTraj can generate high-quality trajectories and retain the original distribution

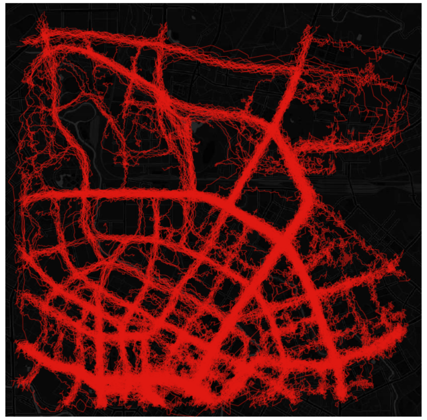
Methods	Chengdu				Xi'an			
	Density (↓)	Trip (↓)	Length (↓)	Pattern (↑)	Density (↓)	Trip (↓)	Length (↓)	Pattern (↑)
RP	0.0698	0.0835	0.2337	0.493	0.0543	0.0744	0.2067	0.381
GP	0.1365	0.1590	0.1423	0.233	0.0928	0.1013	0.2164	0.233
VAE	0.0148	0.0452	0.0383	0.356	0.0237	0.0608	0.0497	0.531
TrajGAN	0.0125	0.0497	0.0388	0.502	0.0220	0.0512	0.0386	0.565
DP-TrajGAN	0.0117	0.0443	0.0221	0.706	0.0207	0.0498	0.0436	0.664
Diffwave	0.0145	0.0253	0.0315	0.741	0.0213	0.0343	0.0321	0.574
Diff-scatter	0.0209	0.0685	–	–	0.0693	0.0762	–	–
Diff-wo/UNet	0.0356	0.0868	0.0378	0.422	0.0364	0.0832	0.0396	0.367
DiffTraj-wo/Con	0.0072	0.0239	0.0376	0.643	0.0138	0.0209	0.0357	0.692
Diff-LSTM	0.0068	0.0199	0.0217	0.737	0.0142	0.0195	0.0259	0.706
DiffTraj	**0.0055**	**0.0154**	**0.0169**	**0.823**	**0.0126**	**0.0165**	**0.0203**	**0.764**

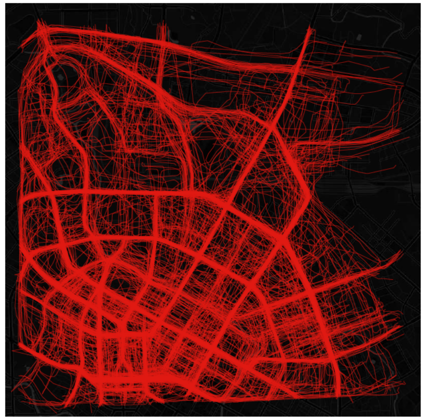


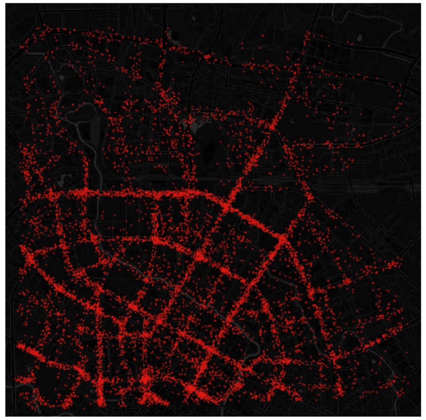
(a) Chengdu. (b) Xi'an.

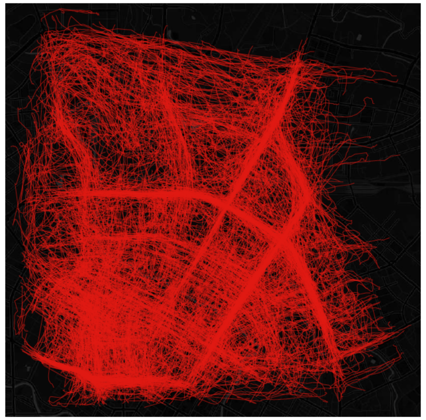
Visualization Results


(a) VAE


(b) TrajGAN


(c) Diffwave


(d) Diff-scatter


(e) Diff-wo/UNet

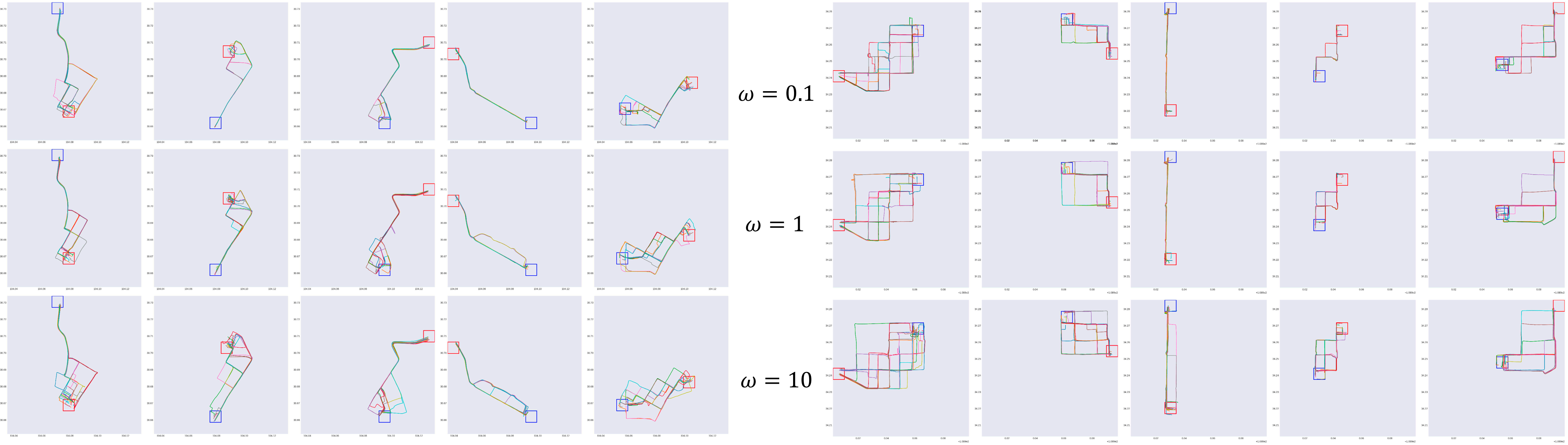

(f) Diff-LSTM


(g) Diff-Traj


(h) Real

The generated trajectories are able to portray city profiles, and also accurately match the real roads.

Conditional Generation & Diversity Control

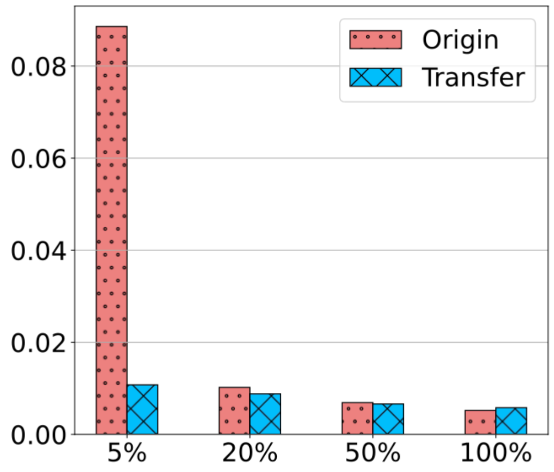


We can control the starting (ending) area and the diversity of generated trajectories.

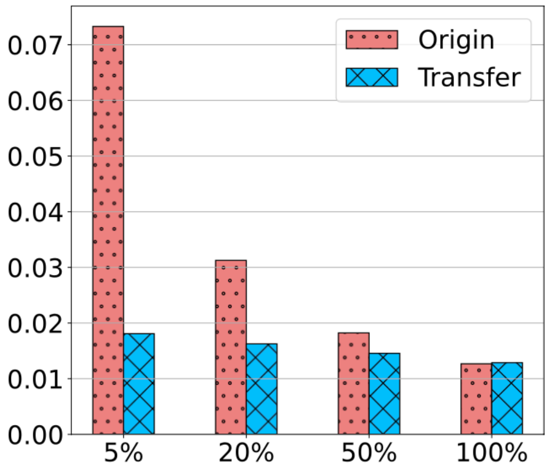
red square: start area

blue square: destination area

Transfer Learning & Speed up Sampling

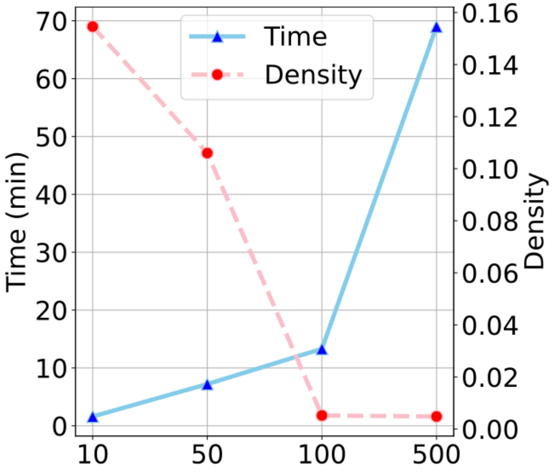


(a) Chengdu

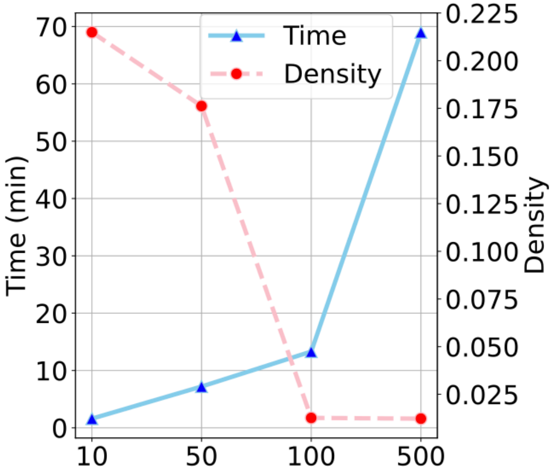


(b) Xi’an

Transfer learning



(c) Chengdu



(d) Xi’an

Speed up sampling

Only using 5% of the data, the transfer learning model achieves a significantly lower error compared to the original one.

The DiffTraj model matches the outcomes of the no skipped steps method at T = 100, saving 81% of the time cost.

Thank You!

Yuanshao Zhu
zhuys2019@mail.sustech.edu.cn
Southern University of Science and Technology
City University of Hong Kong