TrajFlow: Nationwide Pseudo GPS Trajectory Generation with Flow Matching Models

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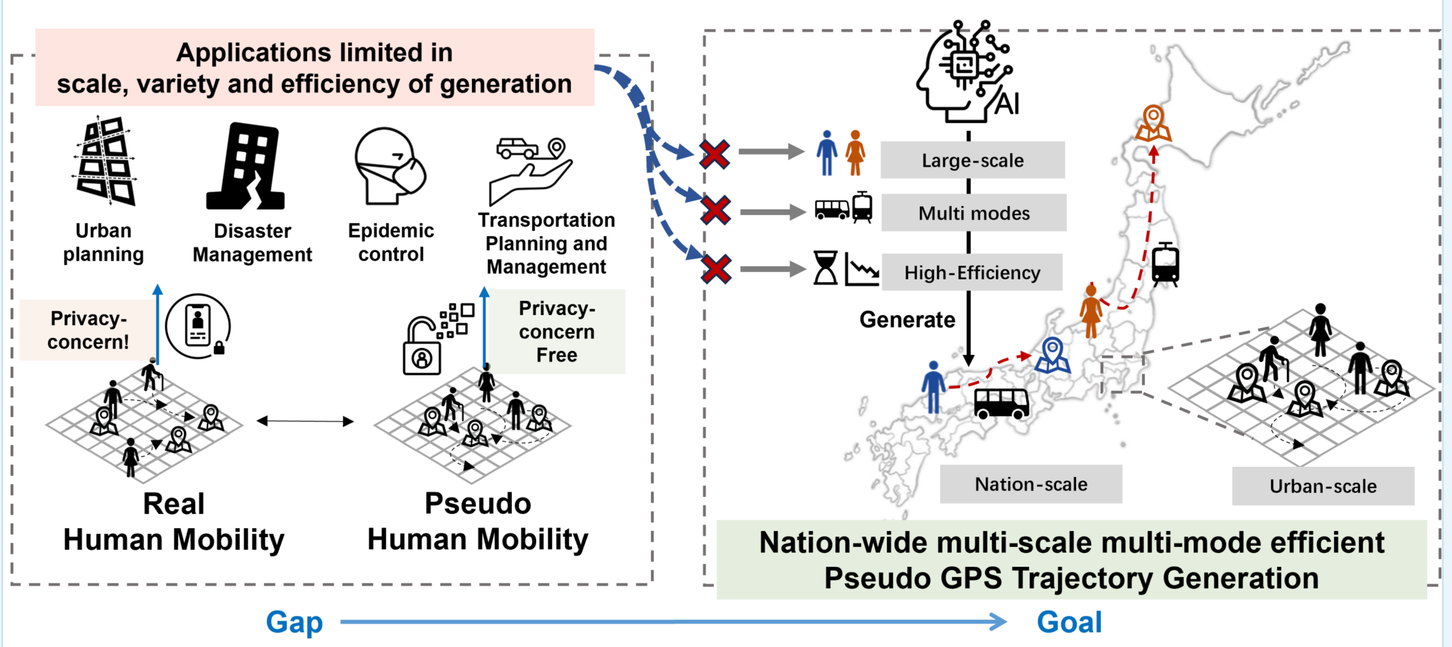
Introduction

GPS trajectory data is vital for urban planning, epidemiology, and transportation. Privacy concerns, limited accessibility, and high cost make real data hard to obtain. Generating synthetic (pseudo-GPS) trajectories is the key enabling solution.

Existing pseudo-GPS generation models have THREE critical gaps:

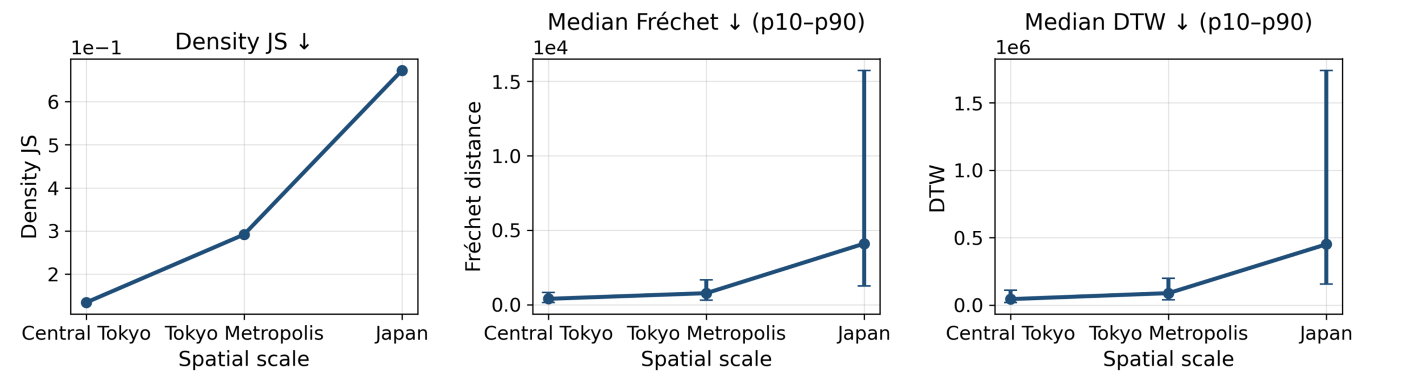
Multi-scale	Mode Diversity	Efficiency
Restricted to urban areas; fails at metro/nationwide scale	Taxi-only; walk, bike, and train not represented	Diffusion needs 200+ denoising steps to converge

Gap → Goal: *nationwide, multi-scale, multi-mode, efficient generation*

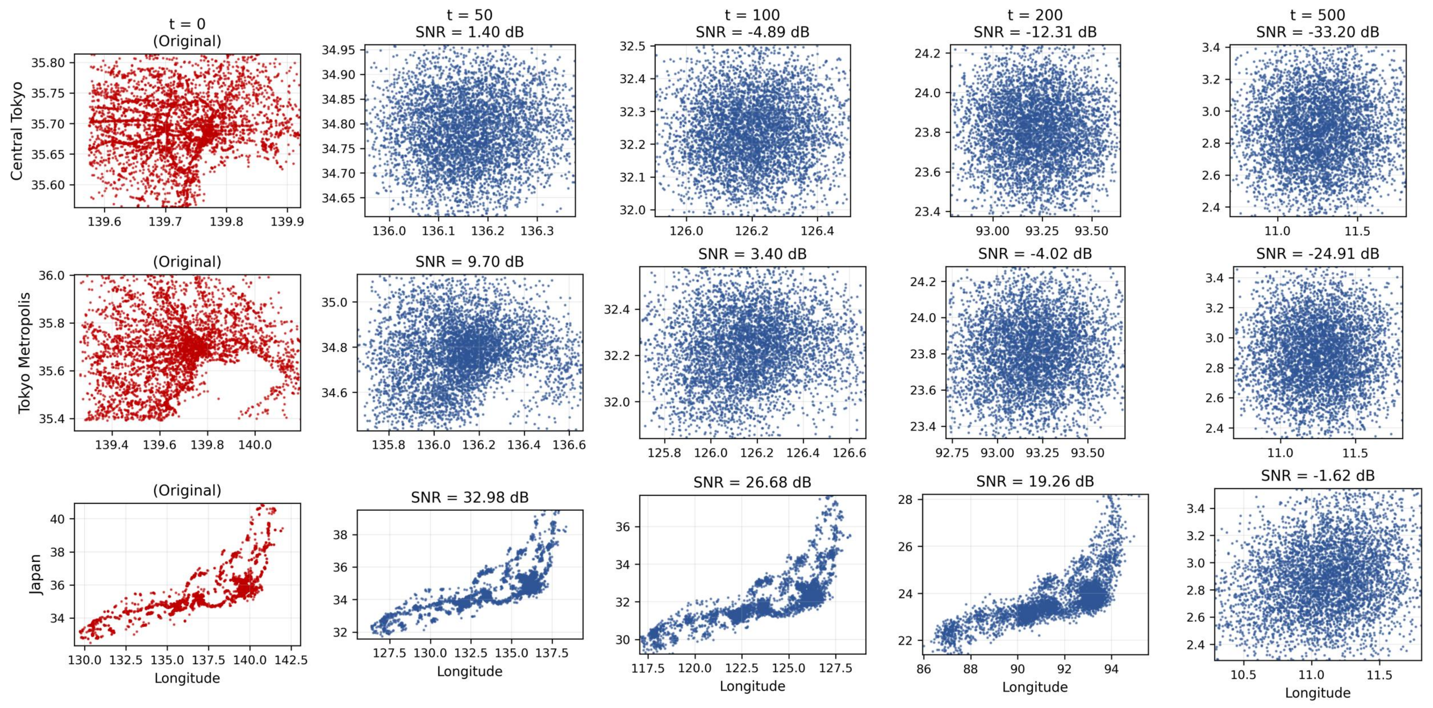


Root Cause: SNR Collapse in Diffusion

DDPM's fixed-magnitude noise injection drowns out fine-grained local trajectories when mixed with long-distance trips, causing SNR collapse at larger scales. *TrajFlow* addresses this from both sides: trajectory harmonization normalizes all trips into a shared bounded space to restore SNR, while flow matching replaces iterative denoising with a deterministic ODE transport, avoiding step-count sensitivity and enabling robust multi-scale generation.

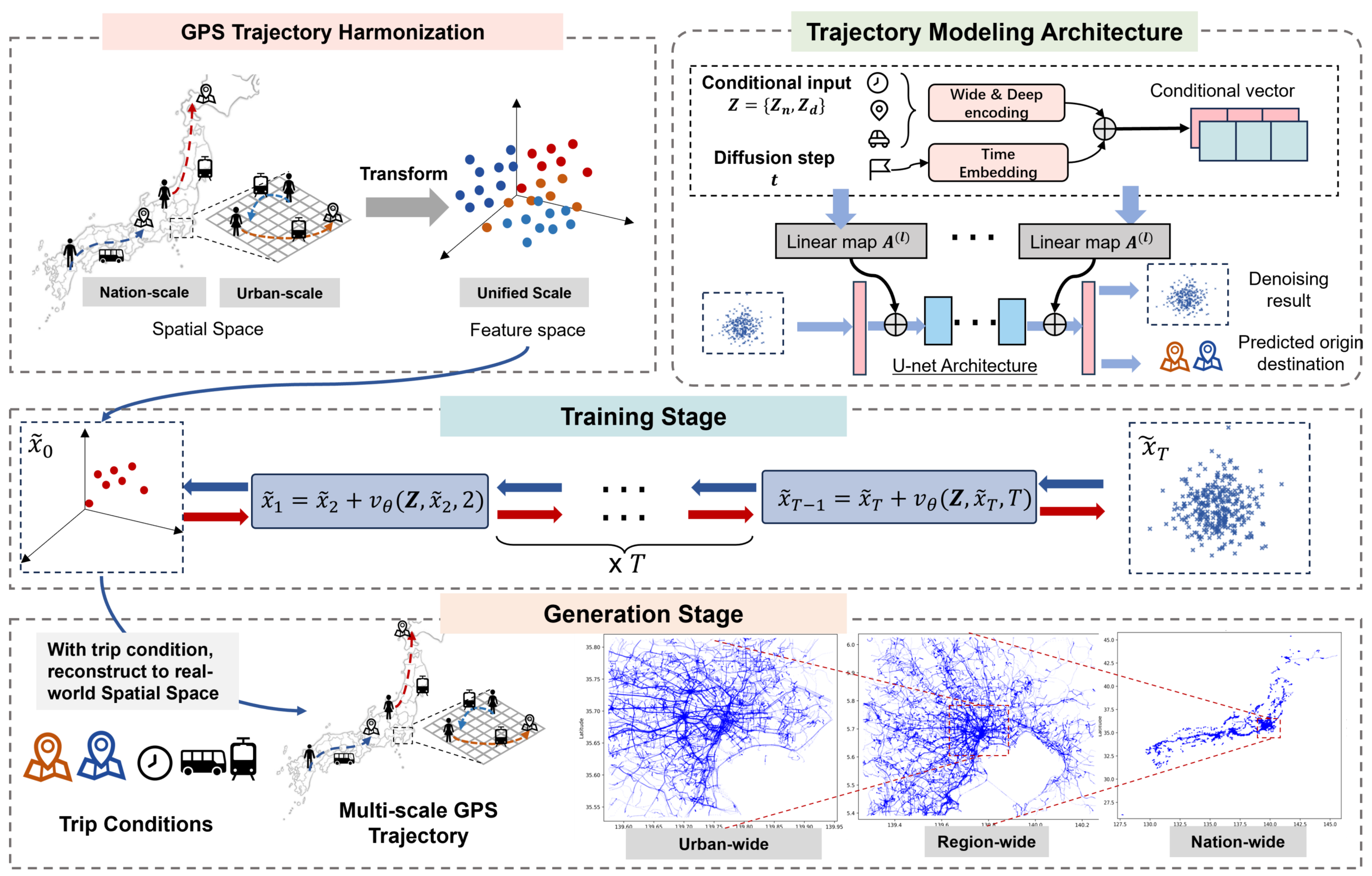


DiffTraj performance collapse: Central Tokyo → Tokyo Metro → Nationwide



Fixed noise β suits nation-scale but overwhelms smaller regions (SNR collapse)

TrajFlow Framework



GPS Harmonization → Conditioning → CFM Training → ODE-based Generation

Three Key Components

Trajectory Harmonization

GPS trajectories span orders of magnitude across scales. We compress each to its geometric skeleton via the Ramer-Douglas-Peucker algorithm (D ≪ L points) and normalize coordinates into a shared bounded space. This equalizes SNR, suppresses micro-jitter, and stabilizes gradient magnitudes during training.

Conditioned Flow Matching

We train vector field $v_\theta(x_t, t, e_c)$ using the CFM objective, regressing straight-line paths $x_0 \rightarrow x_1$. An OD prediction head anchors origin-destination pairs for accurate per-trajectory denormalization back to geographic coordinates — essential for nationwide-scale generation.

Mode-aware Conditioning

Departure time, OD zone, and transport mode are fused via a Wide & Deep encoder into e_c, injected into every flow block as additive bias: $\bar{h} \leftarrow f(\bar{h}) + \bar{A}\tilde{e}$. Provides rich multi-modal context while keeping the ODE parameterization clean and lightweight.

Flow Matching Training Objective

CFM Training Loss:

$$\mathcal{L}_{FM} = E_{t,p(x_1),p(x_0)}\left[\left\| v_\theta\big((1-t)x_0 + t x_1, t\big) - (x_1 - x_0)\right\|^2\right]$$

$t \sim \mathrm{Uniform}[0,1]$ · $x_1 \sim$ real trajectory · $x_0 \sim$ Gaussian prior

Inference: Sample $x_0 \sim N(0,I)$, then numerically integrate $dx/dt = v_\theta(x,t)$ from $t=0$ to $t=1$ using only 10 steps. Condition-control at every step via e_c. Final state x_1 is post-processed to geographic coordinates.

Dataset & Setup

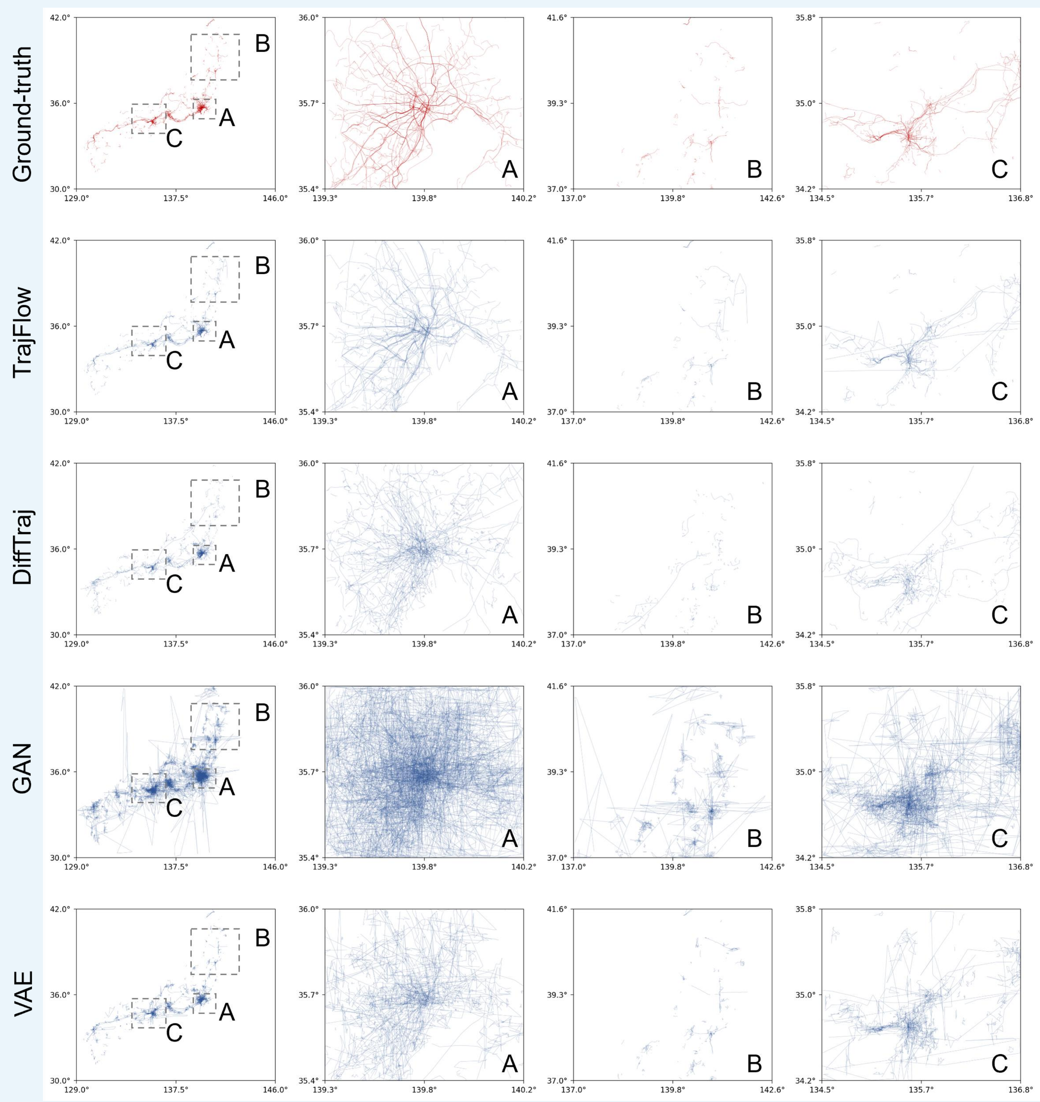
Dataset: Japan nationwide Blogwatcher GPS (2023), ~3M anonymized trajectories with lat/lon, timestamps, and transport modes across 140+ mobile apps. **Scales:** Central Tokyo (urban) · Tokyo Metropolis (metro) · Japan (nationwide) **Metrics:** Density JS (population-level) · DTW & Fréchet distance (trajectory-level, median + P10/P90)

10× Faster	#1 Nationwide	3 Spatial Scales
inference vs. DDPM 10 ODE steps vs. 200+	ALL metrics beat DiffTraj / GAN / VAE /Abolition	Urban · Metro · Nationwide With multi modes: bus, car, bike, walk

Quantitative Results — Japan Nationwide (km, ↓ lower is better)

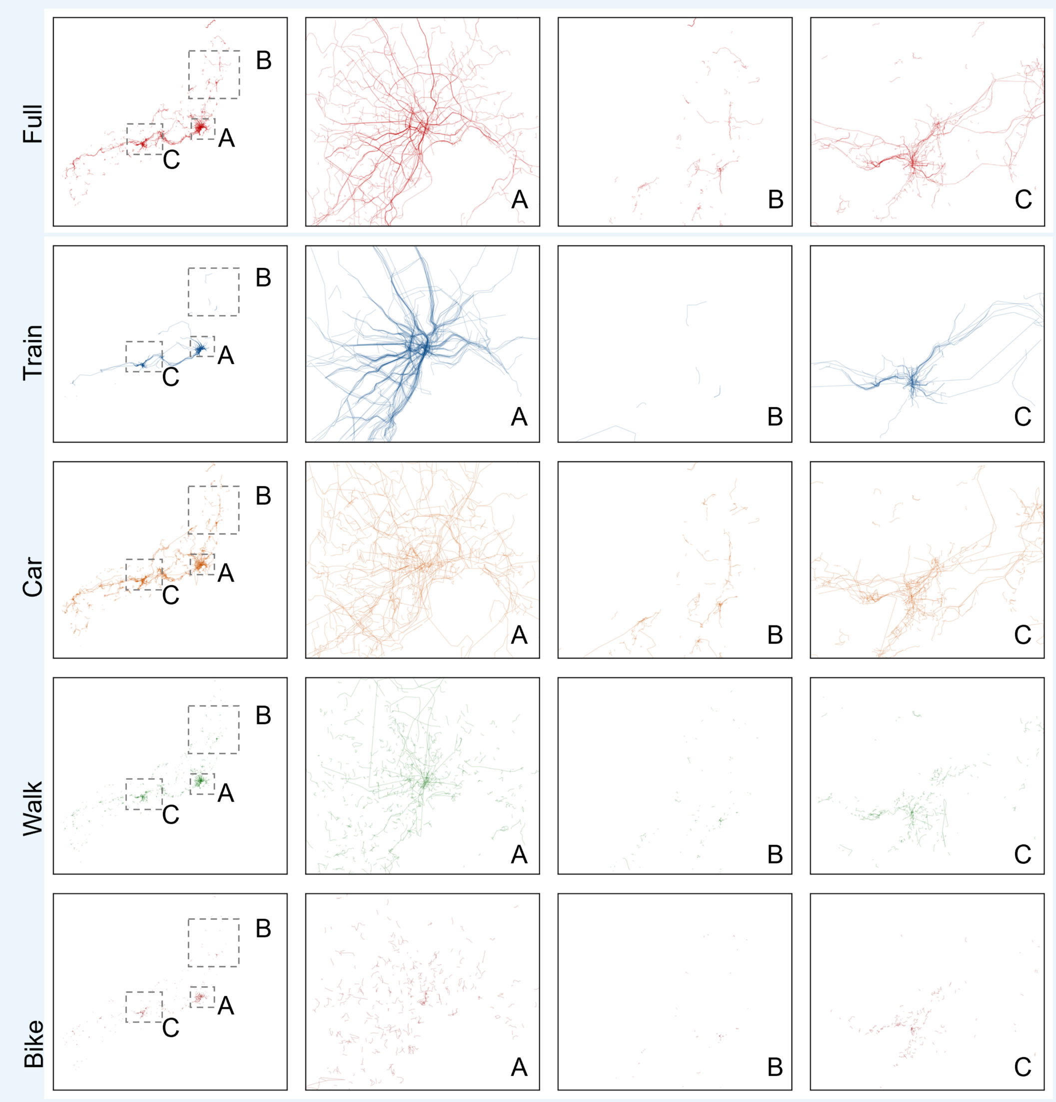
Method	Density JS ↓	DTW_med ↓	Fr_med ↓	DTW_IQR ↓	DTW_P10 ↓	DTW_P90 ↓	Fr_IQR ↓	Fr_P10 ↓	Fr_P90 ↓
Central Tokyo									
TrajFlow (ours)	0.067	20.350	0.304	13.392	10.574	39.119	0.174	0.200	0.674
TrajFlow-w/o-OD	0.356	916.436	13.862	708.183	432.567	1740.890	7.313	7.064	20.858
TrajFlow-w/o-RDP	0.064	22.088	0.340	16.491	11.149	47.959	0.238	0.209	0.873
TrajFlow-w/o RDP & OD	**0.032**	**8.179**	**0.184**	**4.586**	**4.994**	**14.159**	**0.118**	**0.110**	**0.363**
DiffTraj	0.134	44.321	0.651	40.713	19.399	109.349	0.544	0.341	1.774
TrajGAN	0.309	292.430	4.442	448.839	119.230	1288.929	7.660	1.606	21.477
TrajVAE	0.104	32.874	0.469	36.387	14.000	103.232	0.679	0.258	1.842
Tokyo Metropolis									
TrajFlow (ours)	0.124	18.167	0.335	16.892	7.678	44.316	0.333	0.130	0.933
TrajFlow-w/o-OD	0.106	16.466	0.307	10.189	9.307	32.126	0.192	0.180	0.683
TrajFlow-w/o-RDP	0.120	18.417	**0.298**	24.152	**6.637**	67.674	0.473	**0.121**	1.339
TrajFlow-w/o RDP & OD	**0.080**	**14.416**	0.303	**7.684**	8.659	**23.978**	**0.188**	0.176	**0.592**
DiffTraj	0.292	88.559	1.220	78.339	38.663	199.501	0.982	0.586	3.035
TrajGAN	0.382	604.399	10.224	1184.077	155.401	2854.060	20.627	2.290	51.389
TrajVAE	0.193	46.363	0.765	54.484	16.234	122.556	1.006	0.250	2.299
Japan nationwide									
TrajFlow (ours)	**0.227**	**10.977**	**0.192**	**18.221**	**3.984**	**55.964**	**0.361**	**0.072**	**1.119**
TrajFlow-w/o-OD	0.489	100.271	1.522	75.774	50.877	216.168	1.177	0.774	3.145
TrajFlow-w/o-RDP	0.273	24.690	0.400	27.928	9.047	92.641	0.511	0.156	1.699
TrajFlow-w/o RDP & OD	0.487	105.011	1.662	89.509	53.549	280.092	1.380	0.870	3.802
DiffTraj	0.673	451.042	5.329	635.120	157.379	1741.025	6.973	1.915	18.924
TrajGAN	0.528	403.282	6.653	999.210	79.556	2853.557	17.703	1.134	48.838
TrajVAE	0.523	135.377	2.216	236.143	28.394	577.139	3.884	0.435	9.919

Generated Trajectories — Japan



Rows: GT / TrajFlow / DiffTraj / TrajGAN / TrajVAE · Zoomed: (A) Tokyo Metro, (B) Tohoku, (C) Kansai

Transportation Mode Diversity



Per-mode trip distance (Japan): Zoomed: (A) Tokyo Metro, (B) Tohoku, (C) Kansai

Conclusion

TrajFlow is the first flow-matching GPS trajectory generation model. By coupling RDP trajectory harmonization with OD-conditioned normalization, it conquers the multi-scale SNR challenge that defeats diffusion baselines. It supports diverse transport modes (walk / bike / car / train), achieves state-of-the-art accuracy on a Japan-wide dataset of millions of trajectories, and requires only 10 ODE steps — a 10× speedup over DDPM with better fidelity.

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Open-sourced in GitHub

Now, it's open sourced in https://github.com/ZeroCSIS/TrajFlow