★ ICML 2026 | Spotlight

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Learning Coupled Continuous-Time Latent Dynamics from Irregular Events

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Background & Problem

➢ **Challenge 1:** Real-world event sequences (user behavior, mobility, logs) are **irregularly sampled & extremely sparse** with long gaps.

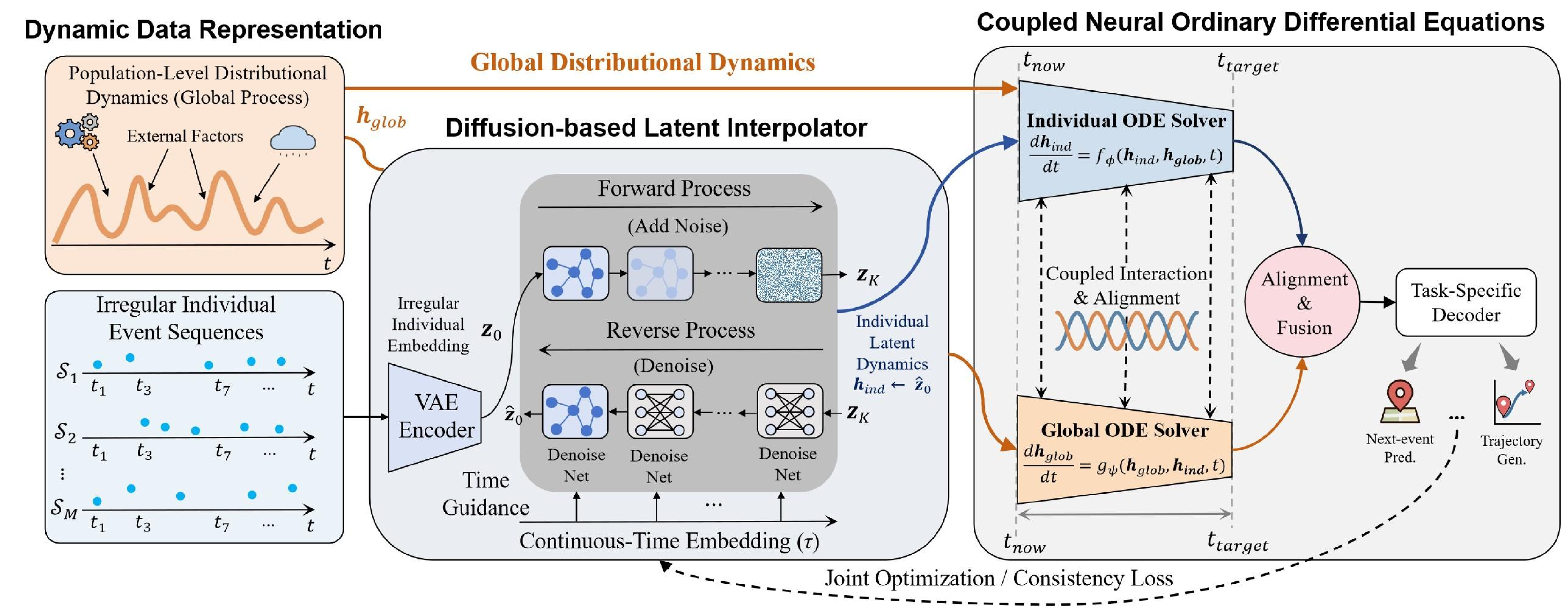
➢ **Challenge 2:** Individual states evolve **continuously** but are strongly influenced by **population-level global dynamics** (season, trend, crowd flow).

➢ **Limitation of existing methods:**

- Discrete models blur long-range temporal structure.
- Vanilla Neural ODEs fail under severe sparsity.
- Diffusion models treat time as static condition.
- Most ignore individual–global asynchronous coupling.

Core Idea & Key Innovation

We propose **CoCLD** (Coupled Continuous-Time Latent Dynamics): A unified framework that **jointly models individual & global continuous dynamics** in a shared latent space, using **diffusion for interpolation** and **coupled Neural ODE** for evolution.



Key Contributions

a) Novel **coupled continuous-time framework** for irregular event sequences.

b) Synergy of **time-guided diffusion** and **coupled Neural ODE** for sparse data.

c) Rigorous theoretical proof & state-of-the-art empirical performance.

d) Wide applicability: urban planning, intelligent transportation, recommendation system.

- CoCLD effectively models **coupled individual-global continuous dynamics** from irregular & sparse events.
- CoCLD provides a principled "***Interpolate-then-Evolve***" paradigm and sets a new baseline for irregular sequence modeling.

Experiments & Results (Task 1: POI Prediction; Task 2: Trajectory Generation; Task 3: Sequential Recommendation)

Table 1. Performance comparison on next-event prediction. The best results are highlighted in **bold**, and the second best are underlined.

Dataset	Metrics	SASRec	LightGCN	GNG-ODE	SGODE	DiffRec	DreamRec	DDRM	PreferDiff	**CoCLD**
IST	Acc@5	0.2141	0.2417	0.2400	0.2714	0.2854	0.2887	0.3125	<u>0.3285</u>	**0.3486**
	Acc@10	0.2796	0.2824	0.2899	0.3605	0.3604	0.3530	0.3830	<u>0.3981</u>	**0.4255**
	NDCG@5	0.1774	0.1911	0.1922	0.2356	0.2301	0.2314	0.2504	<u>0.2587</u>	**0.2706**
	NDCG@10	0.1848	0.2044	0.2088	0.2557	0.2544	0.2528	0.2739	<u>0.2817</u>	**0.2964**
NYC	Acc@5	0.2443	0.3016	0.3302	0.3645	0.3533	0.3196	0.3205	<u>0.3838</u>	**0.3937**
	Acc@10	0.2907	0.3620	0.4023	0.4334	0.4225	0.4020	0.4088	<u>0.4755</u>	**0.5083**
	NDCG@5	0.1935	0.2011	0.2232	<u>0.2762</u>	0.2419	0.2417	0.2691	0.2705	**0.2801**
	NDCG@10	0.2163	0.2364	0.2571	<u>0.3024</u>	0.2846	0.2840	0.2978	0.3008	**0.3179**
DC	Acc@5	0.2048	0.2024	0.2680	0.2517	0.2843	0.2896	0.2901	<u>0.2963</u>	**0.3090**
	Acc@10	0.2963	0.3090	0.3210	0.3037	0.3448	0.3420	<u>0.3685</u>	0.3655	**0.3827**
	NDCG@5	0.1869	0.1859	0.2131	0.1995	0.2226	0.2250	0.2307	<u>0.2309</u>	**0.2368**
	NDCG@10	0.2109	0.2168	0.2356	0.2169	0.2439	0.2492	0.2540	<u>0.2545</u>	**0.2620**
Gowalla	Acc@5	0.1675	0.1943	0.2019	0.2354	0.2604	0.2806	0.2764	<u>0.2857</u>	**0.3003**
	Acc@10	0.2578	0.2737	0.2758	0.3001	0.3385	<u>0.3710</u>	0.3632	0.3700	**0.3775**
	NDCG@5	0.2880	0.3587	0.3585	0.3646	0.3812	0.4215	0.4159	<u>0.4221</u>	**0.4313**
	NDCG@10	0.3271	0.3664	0.3622	0.3860	0.4254	0.4659	0.4627	<u>0.4688</u>	**0.4725**
Brightkite	Acc@5	0.1738	0.2448	0.2721	0.2878	0.2943	0.2753	0.2989	<u>0.3058</u>	**0.3158**
	Acc@10	0.2220	0.2918	0.3216	0.3335	0.3404	0.3248	0.3478	<u>0.3584</u>	**0.3649**
	NDCG@5	0.1630	0.2328	0.2602	0.2750	0.2824	0.2635	0.2863	<u>0.2935</u>	**0.3025**
	NDCG@10	0.1847	0.2539	0.2825	0.2955	0.3030	0.2857	0.3083	<u>0.3171</u>	**0.3245**

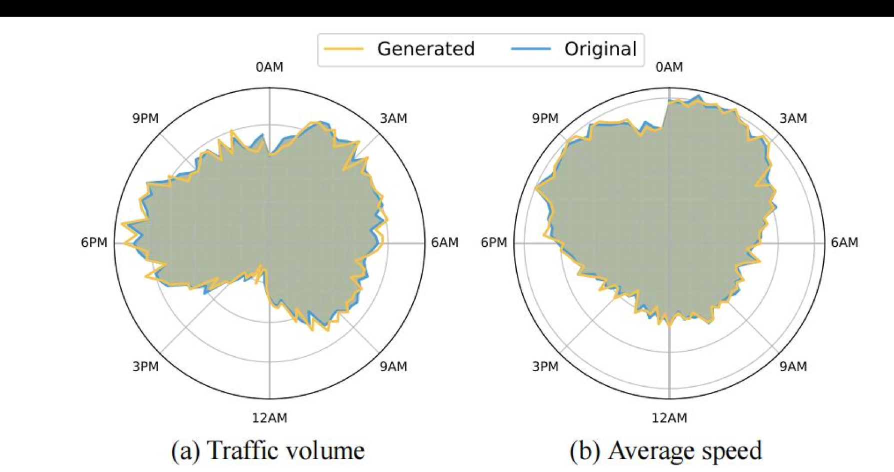


Figure 2. Comparison between generated trajectories and original.

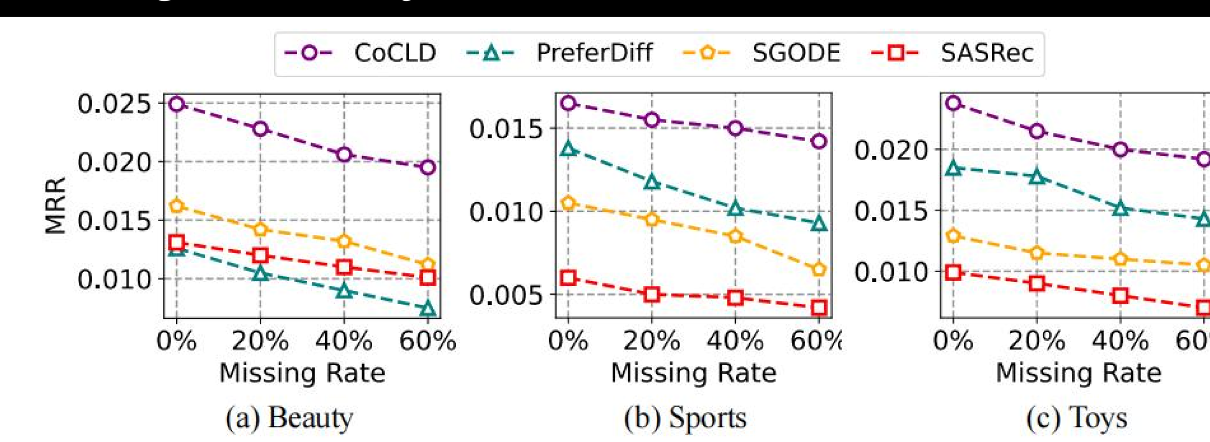


Figure 5. Robustness under increasing data sparsity ratios.

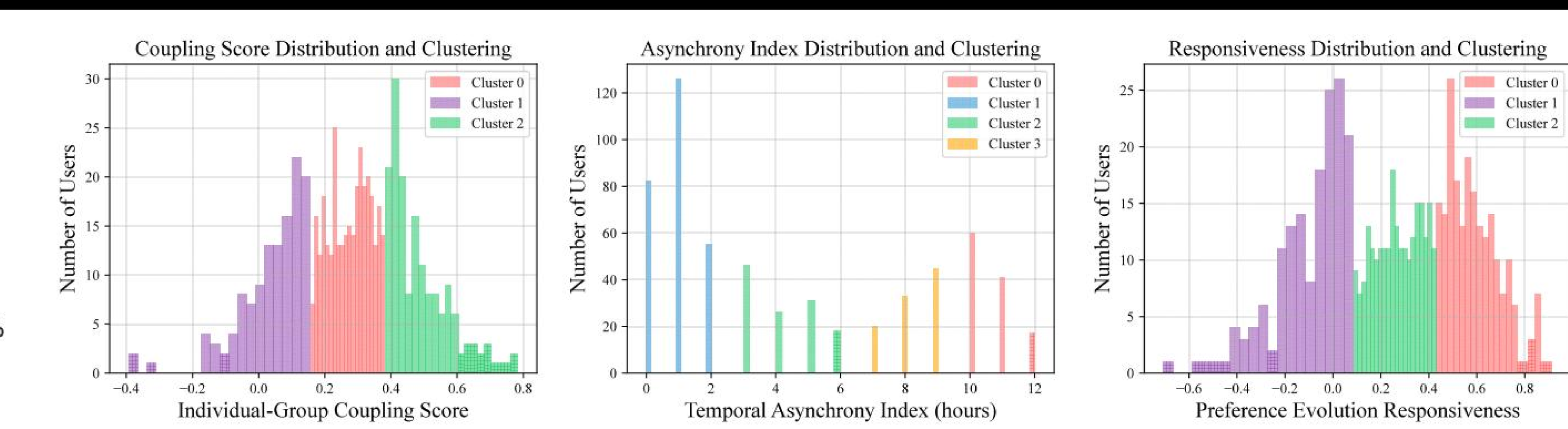


Figure 15. Interpretability of feature distribution learned by the CoCLD model (**NYC dataset**) from three perspectives: (a) coupling score distribution; (b) asynchrony index distribution; (c) responsiveness distribution.

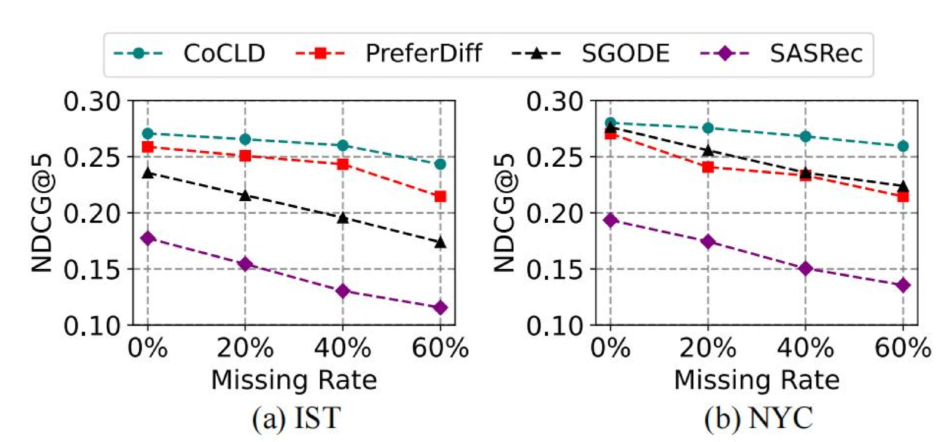


Figure 4. Performance degradation under increasing data sparsity

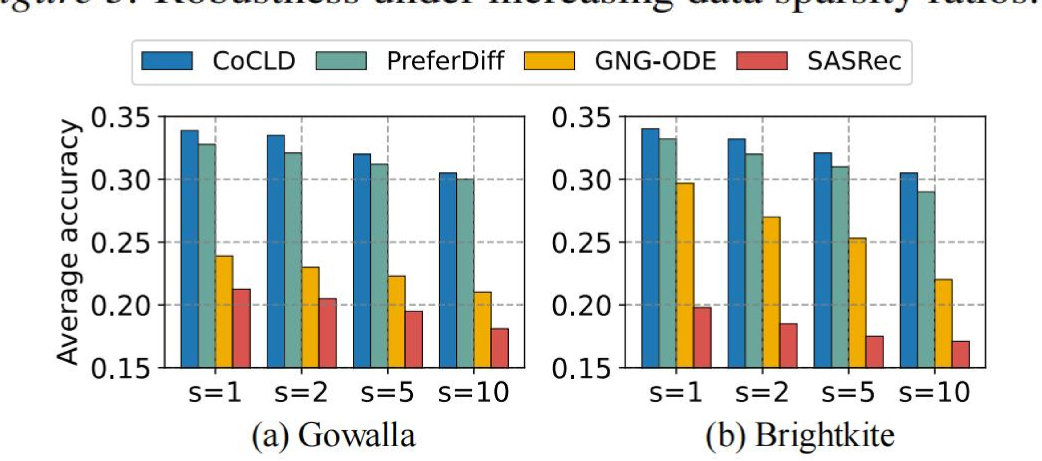


Figure 6. Performance of long-term dynamics.

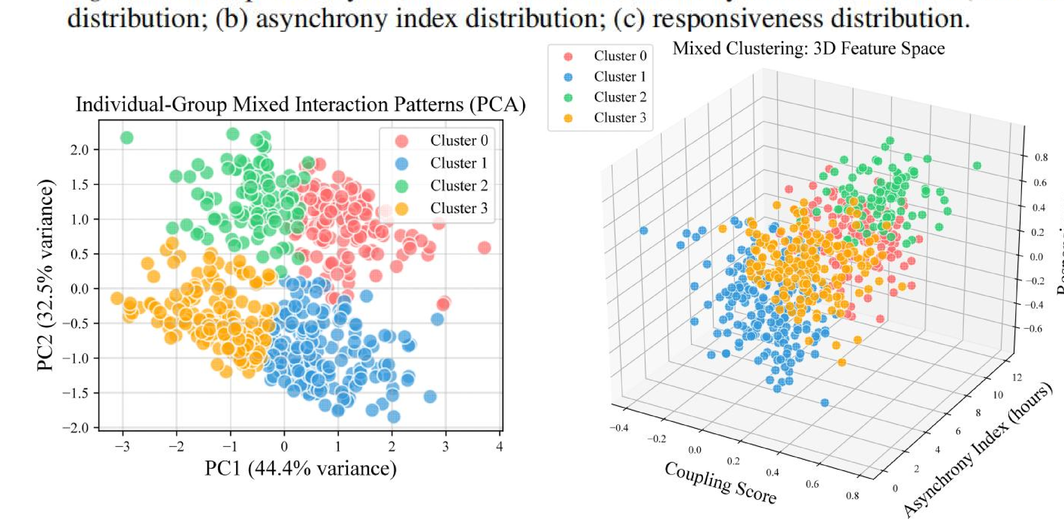


Figure 16. Interpretability of feature distribution learned by the CoCLD model. PCA 2D scatter and 3D scatter plots (**NYC dataset**).

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