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Toward an accurate mobility trajectory recovery using contrastive learning

Key words: Human mobility; Mobility trajectory recovery; Contrastive learning

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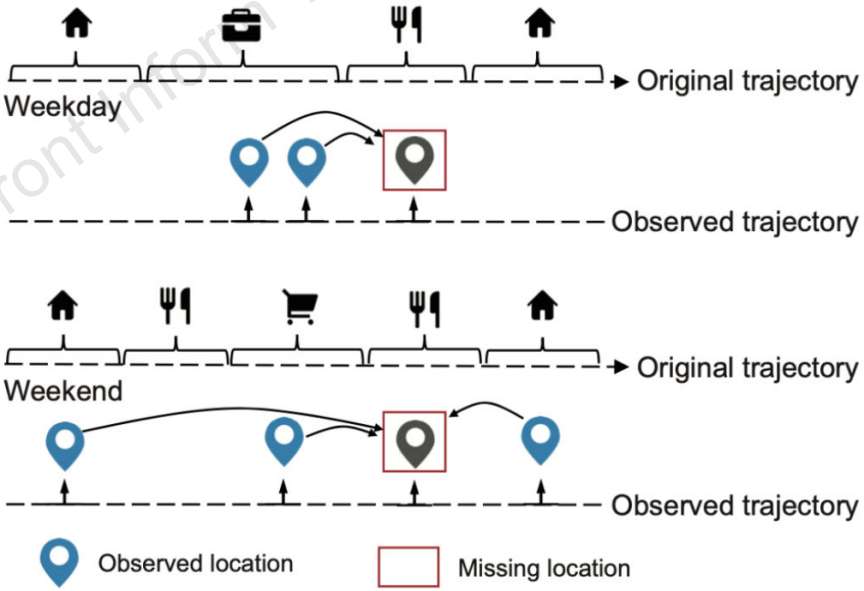
Motivation

- Human mobility trajectories are fundamental resources for analyzing mobile behaviors in urban computing applications. However, these trajectories, typically collected from location-based services, often suffer from sparsity and irregularity. To support the development of mobile applications, there is a need to recover or estimate missing locations of unobserved time slots in these trajectories at a fine-grained spatial–temporal resolution.



Main idea

- To effectively capture the collective and individual spatial patterns, we use a pretrained location encoder module and a novel fine-tuned graph neural network (GNN) based location encoder. To fuse the historical trajectory into the target trajectory, we design an attention-based mobility trajectory recovery module.

- To improve the robustness of the model when encountering unpredictable distribution of missing trajectory points, we design a trajectory-level contrastive learning task.

Method

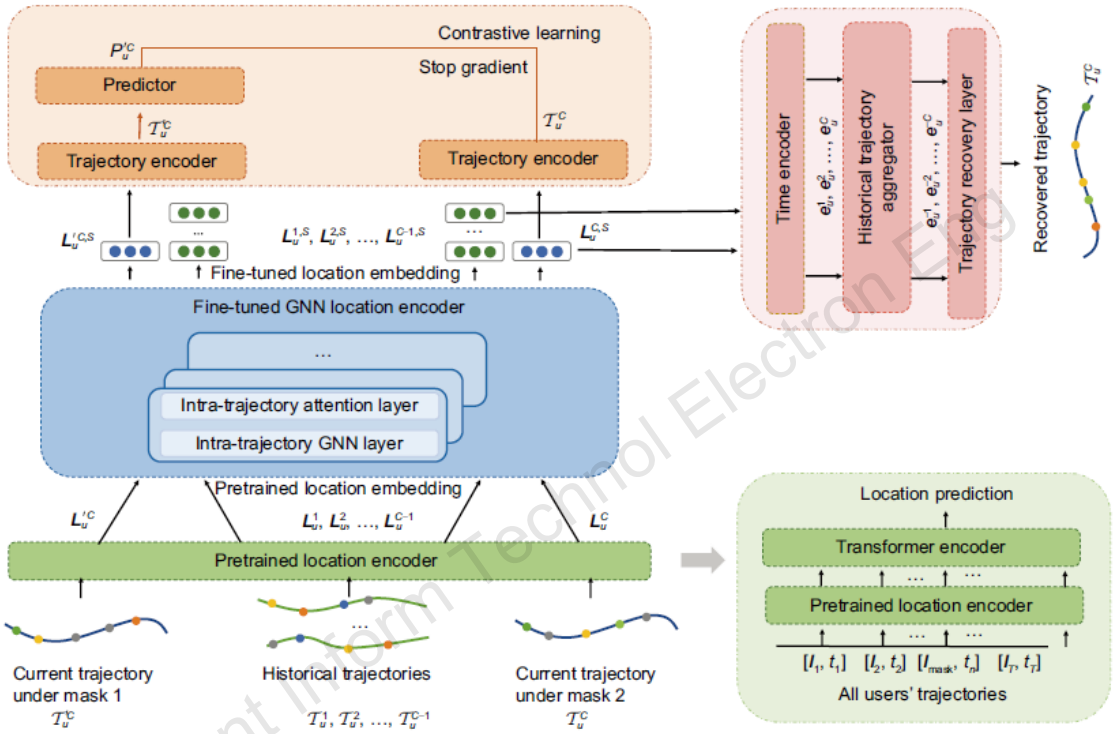


Fig. 2 Main architecture of CLMove

Pretrained location encoder learns the location embeddings through the data from the whole user group in the same city.

Fine-tuned location encoder captures user-specific location transition patterns through simultaneously considering the intra- and inter-trajectory mobility patterns.

Trajectory mobility recovery module fuses the historical spatial–temporal patterns of users into the target recovery trajectory and recovers missing locations.

Contrastive learning task improves the robustness of the model with unpredictable incomplete trajectory contexts.

Results

Table 2 Overall performance comparison

Dataset	Model	Recall@1	Recall@3	Recall@5	Distance@1	Distance@3	Distance@5	MAP
GeoLife	Top	0.016	0.071	0.100	8451	7444	7351	0.069
	Time Top	0.032	0.078	0.116	8628	6908	6158	0.080
	LSTM	0.050	0.105	0.160	8971	6775	5884	0.109
	BiLSTM	0.156	0.242	0.291	8628	5998	5128	0.221
	DeepMove	0.130	0.282	0.351	8037	5852	4982	0.233
	AttnMove	0.130	0.219	0.260	7900	5842	5071	0.191
	PeriodicMove	0.173	0.295	0.359	7860	5063	4146	0.260
	GETNext	0.214	0.300	0.338	11 328	6284	4788	0.271
	TrajBERT	0.217	0.285	0.309	13 613	7706	6025	0.260
	CLMove	**0.224**	**0.362**	**0.421**	**6331**	**4174**	**3434**	**0.318**
Foursquare	Top	0.021	0.051	0.067	9338	8560	7359	0.055
	Time Top	0.018	0.045	0.064	9708	8312	7552	0.048
	LSTM	0.022	0.039	0.045	9209	8037	7059	0.037
	BiLSTM	0.113	0.184	0.221	9321	5946	4924	0.172
	DeepMove	0.253	0.385	0.435	5428	3037	2402	0.340
	AttnMove	0.235	0.317	0.350	6493	4349	3632	0.294
	PeriodicMove	0.259	0.397	0.451	5686	3057	2418	0.349
	GETNext	0.241	0.445	**0.530**	12 201	5462	3739	0.368
	TrajBERT	0.192	0.248	0.269	12 982	7584	5789	0.230
	CLMove	**0.272**	**0.452**	0.510	**5247**	**2581**	**1991**	**0.384**
Porto Taxi	Top	0.093	0.207	0.260	1240	1144	1100	0.189
	Time Top	0.103	0.217	0.286	1236	1114	1047	0.201
	LSTM	0.106	0.217	0.288	1265	1146	1092	0.203
	BiLSTM	0.150	0.262	0.335	1250	990	868	0.247
	DeepMove	0.167	0.281	0.345	1259	951	843	0.261
	AttnMove	0.160	0.275	0.346	1260	**917**	**789**	0.257
	PeriodicMove	0.169	0.281	0.349	1245	925	799	0.264
	GETNext	0.112	0.218	0.283	**1186**	1093	1052	0.197
	TrajBERT	0.154	0.269	0.338	1270	997	886	0.249
	CLMove	**0.172**	**0.289**	**0.359**	1243	920	791	**0.270**

Best results are in bold

Conclusions

In this paper, we propose a novel human mobility trajectory recovery model based on contrastive learning. It encodes individual and collective mobility patterns into location embeddings by the action of a pretrained and fine-tuned location encoder. We further design a trajectory-level contrastive learning task to improve the robustness of model.

Author information

Yang CHEN is a professor within the School of Computer Science at Fudan University, China, and a vice director of the Shanghai Key Lab of Intelligent Information Processing. He leads the Big Data and Networking (DataNET) group since 2014. Before joining Fudan, he was a postdoctoral associate at the Department of Computer Science, Duke University, USA. He received his BSc and Ph.D. degrees from the Department of Electronic Engineering, Tsinghua University in 2004 and 2009, respectively. His research interests include social computing, Internet architecture, and mobile computing. He served as an OC/TPC Member for many international conferences, including SOSP, SIGCOMM, WWW, MobiSys, ICDCS, IJCAI, AAAI, IWQoS, ICCCN, GLOBECOM, and ICC. He is a Senior Member of ACM, IEEE, and CCF.

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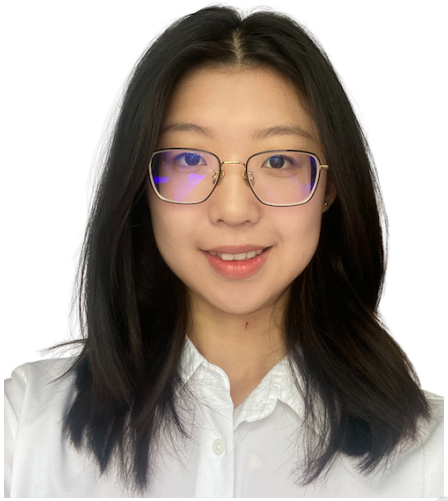

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