



Spatiotemporal Activity Modeling via Hierarchical Cross-Modal Embedding





Yang Liu^{1,2}, Xiang Ao^{1,2}, Linfeng Dong³, Chao Zhang⁴, Jin Wang⁵, and Qing He^{1,2}

¹Key Lab of Intelligent Information Processing of Chinese Academy of Sciences (CAS), Institute of Computing Technology, CAS, Beijing, China ²University of Chinese Academy of Sciences, Beijing, China ³Zhejiang University, Hangzhou, China ⁴College of Computing, Georgia Tech, United States ⁵Megagon Labs, Mountain View, United States (6) Megagon Labs

Email: {liuyang17z,aoxiang,heqing}@ict.ac.cn; linfengdong22@zju.edu.cn; chaozhang@gatech.edu; jin@megagon.ai

Contribution

- We propose a novel hierarchical cross-modal representation learning method for spatiotemporal activity modeling, which can preserve high-order proximities in mobile data.
- We propose a flexible meta-graph based embedding framework named ACTOR, which can perform hierarchical embedding on graphs. We evaluate the effectiveness and efficiency of ACTOR on three realworld datasets.

Paper, Code and Author Contact

Scan the QR code to get the paper and the code. Any questions and suggestions are welcomed.

Repo:







U

 M_2

U

W

U



Dataset Description

- Let $\mathcal{R} = \{r_1, ..., r_N\}$ be a corpus of mobile data records. Each record $r_i \in \mathcal{R}$ is defined by a tuple $\langle t_i, l_i, W_i \rangle$ where
- 1. t_i is the creating timestamp of r_i ;
- 2. l_i is a two-dimensional vector that represents the user's location when r_i is created ;
- 3. W_i is a bag of keywords denoting the text message of r_i .

Problem Definition

The problem of spatiotemporal activity modeling can be decomposed into three sub-tasks:

- 1. Activity prediction. Given the time, location and a text candidate set, find the most possible activity keyword.
- Location prediction. Given the time and keywords, find the location.

U

Time prediction. Given the location and keywords, find the most possible time from a time candidate set.

U

 \mathbf{M}_1



Main Frameworks

 $p_e(v_j|v_i) = \frac{\exp(\boldsymbol{x}_j^{\prime \mathrm{T}} \boldsymbol{x}_i)}{\sum \exp(\boldsymbol{x}_k^{\prime \mathrm{T}} \boldsymbol{x}_i)}$ $f_e(v_i, v_k) = \epsilon$



Performance: Cross-Modal Retrieval

-												
I I	Data	UTGEO2011			TWEET			4SQ				
I I	Task	Text	Location	Time	Text	Location	Time	Text	Location	Time		
I	LGTA	0.3571	0.3440	/	0.4615	0.4439	/	0.5739	0.5409	/		
ł	MGTM	0.2993	0.3022	/	0.3615	0.3619	/	0.4538	0.4191	/		
i.	metapath2vec	0.5062	0.5267	0.3169	0.5083	0.5369	0.2986	0.8475	0.8673	0.3262		
L	LINE	0.5433	0.5442	0.3427	0.6246	0.5997	0.3235	0.9076	0.8954	0.3637		
!	LINE(U)	0.5830	0.5798	0.3578	0.6315	0.6066	0.3297	0.9078	0.8972	0.3719		
i	CrossMap	0.5778	0.6015	0.3852	0.6701	0.6561	0.3439	0.9393	0.9138	0.3690		
L	CrossMap(U)	0.5808	0.6070	0.3712	0.6894	0.6632	0.3469	0.9441	0.9137	0.3735		
1	ACTOR	0.6207	0.6275	0.3885	0.6991	0.6805	0.3509	0.9519	0.9211	0.3758		
-												

Case Study

1 Los Angeles	ACT	OR	CrossMap			
Santa Monica	Text	Time	Text	Time		
	portofla	10:57:39	today	10:57:39		
Torrance Anaheim	dock	14:34:54	day	17:42:27		
Ling Beach Santa A	groovecruise	17:42:27	time	14:34:54		
Huntington Irvi Beach	departure	18:53:55	get	18:53:55		
	mex	10:13:51	camera	10:13:51		
	passport	10:38:16	work	13:33:17		
Two Harbors Catalina Island Essential	berth	6:06:47	another	16:49:07		
Fish Habitat Avalon	ship	16:49:07	segundo	15:51:17		
	segundo	14:59:13	got	10:38:16		
	evo	5:47:58	hit	14:59:13		

- ACTOR consistently outperform all the other methods on the three datasets, with at most 85.9 percent improvements compared with LGTA and 16.0 percent
- When we query the location of the port of Los Angeles, the results of ACTOR are closely related to the port, like "dock", "departure" or the place "port of LA". However, CrossMap

improvements with CrossMap.

prefers some general words like "today", "time", etc.

