Graph-Flashback Network for Next Location Recommendation

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Code: https://github.com/kevin-xuan/Graph-Flashback .

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1.Introduction

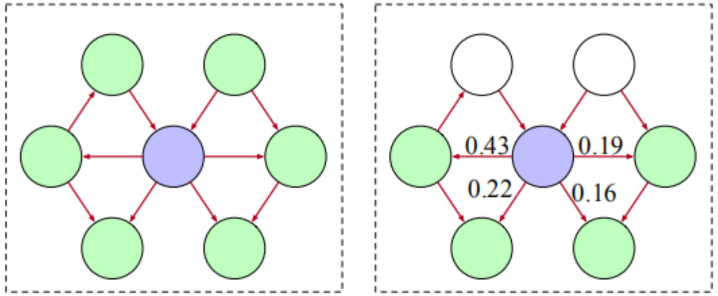
2.Method

3.Experiments

Introduction

1. Existing methods usually use rich side information, or customized POI graphs to capture the sequential patterns among POIs. However, the graphs only focus on connectivity between POIs.

2. Author define a similarity function to consider both spatiotemporal information and user preference in modelling sequential regularity.



(a) Customized POI graph (b) Learned POI graph

Figure 1: A simple example that illustrates the difference between customized POI graph and our learned POI transition graph. We use purple circle and green circle to indicate current POI and neighbor POI, respectively.

Method

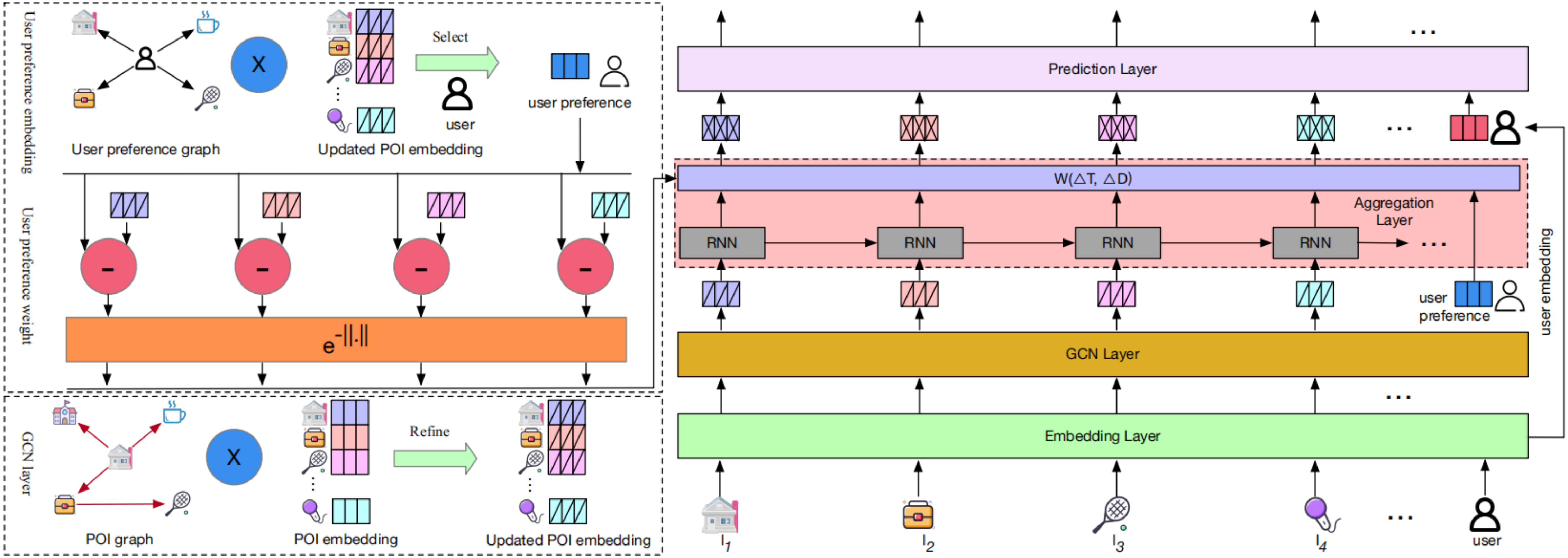


Figure 3: The overview of Graph-Flashback.

PROBLEM STATEMENT

set of users $\mathcal{U} = \{u_1, u_2, \ldots u_{|\mathcal{U}|}\}$

set of locations (POIs) $\mathcal{L} = \{l_1, l_2, \ldots, l_{|\mathcal{L}|}\}$

Check-in $c = (u, l, t)$

User trajectory $T_{u_i} = \{c_1, c_2, \ldots, c_m\}$

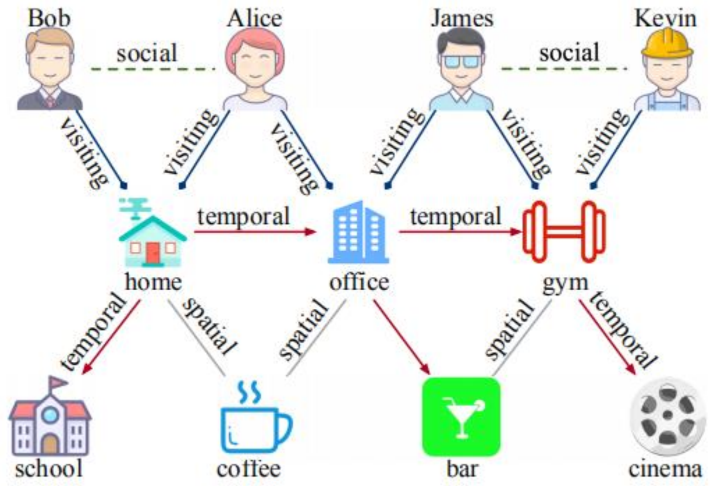


Figure 2: A simple illustration of our Spatial-Temporal Knowledge Graph.

A knowledge graph $\mathcal{G} = (V, E, \mathcal{A}, \mathcal{B}, \phi, \psi, \mathcal{R})$

$\phi(v) \in \mathcal{A}$ $\psi(e) \in \mathcal{B}$

$r = (h, p, l)$ (Bob, visit, aquarium)

visiting (u, r_v, l)

temporal (l_1, r_t, l_2)

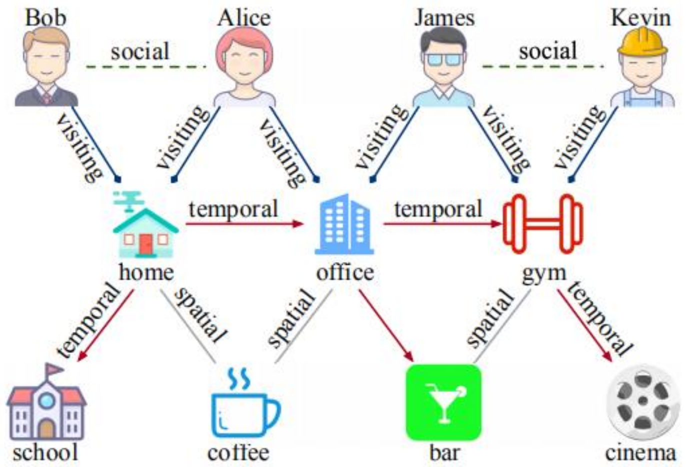
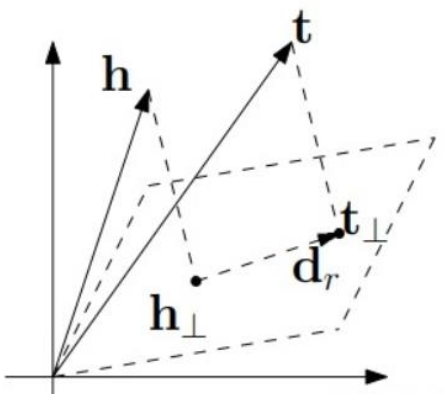


Figure 2: A simple illustration of our Spatial-Temporal Knowledge Graph.



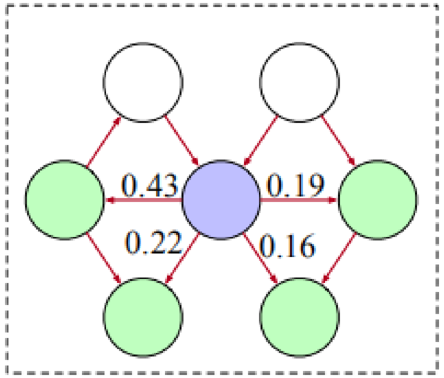
$$h_\perp = h - w_r^T h w_r, \quad t_\perp = t - w_r^T t w_r, \quad ||w_r||_2 = 1, \tag{1}$$

$$g_r(h,t) = ||h_\perp + d_r - t_\perp||_2^2, \tag{2}$$

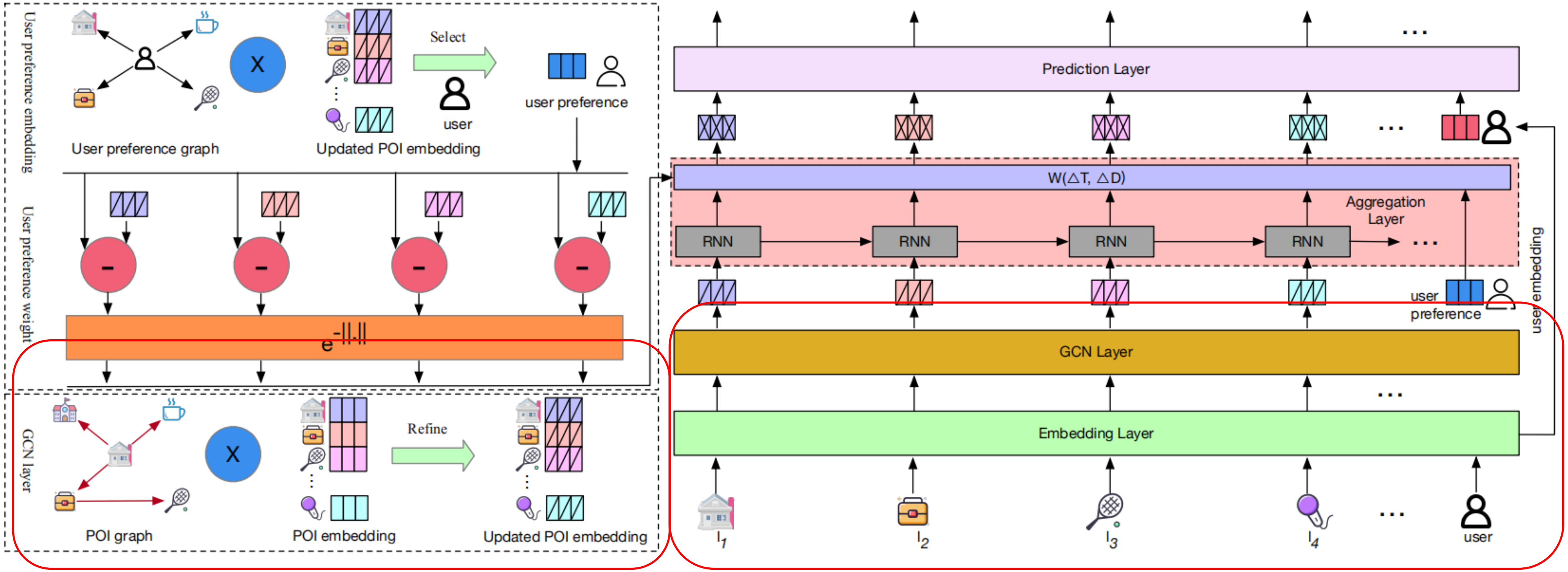
$$s(l_1, l_2) = e^{-d(l_1,l_2)}, \quad d(l_1,l_2) = ||l_1 + r_t - l_2||, \tag{3}$$

$$G(i,j) = \begin{cases} M(i,j), & \text{if POI } l_j \in \mathcal{N}_k(l_i), \\ 0, & \text{otherwise,} \end{cases} \tag{4}$$

$$A = D^{-1}G. \tag{5}$$



(b) Learned POI graph



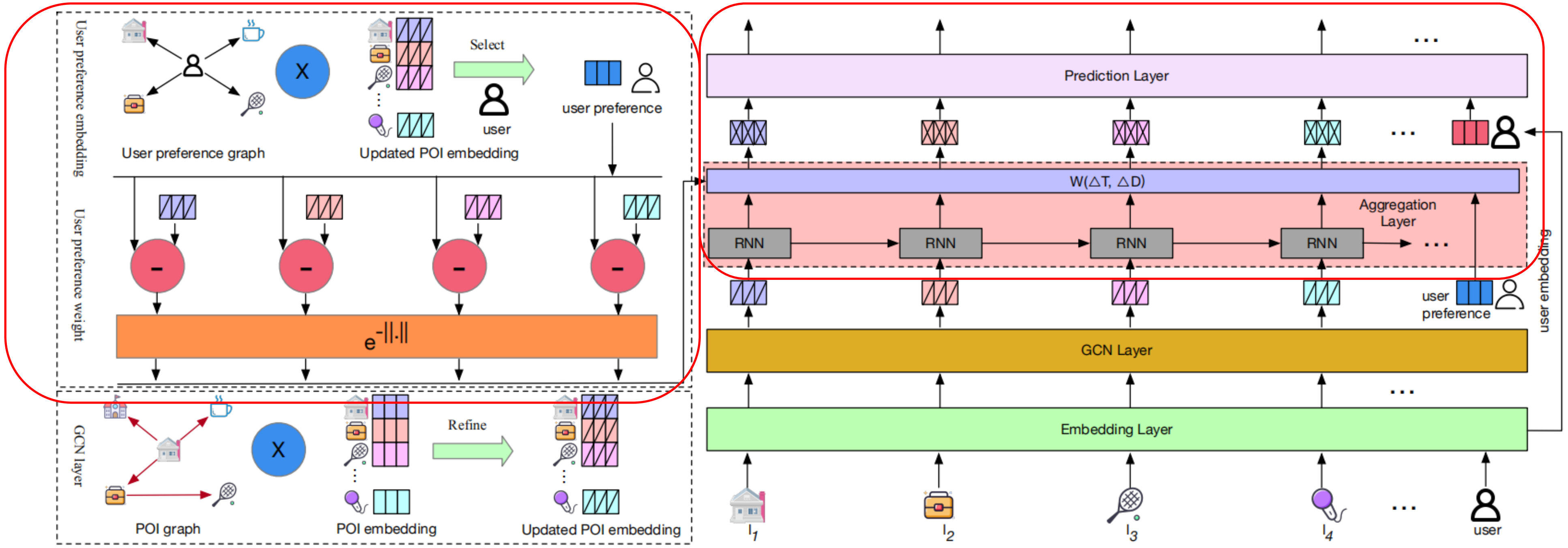
$$e^{u} \in \mathbb{R}^{d} \text{ and } e^{l} \in \mathbb{R}^{d}$$

$$\hat{A} = A + I. \tag{6}$$

$$\hat{A} = \hat{D}^{-1}\hat{A}, \tag{7}$$

$$\hat{X} = \hat{A}X, \tag{8}$$

$$X \in \mathbb{R}^{|\mathcal{L}|\times d} \qquad \hat{X} \in \mathbb{R}^{|\mathcal{L}|\times d}$$



historical hidden state $\boldsymbol{h}_j$ and current one $\boldsymbol{h}_i$, $j < i$.

$$\boldsymbol{w}(\Delta T_{i,j}, \Delta D_{i,j}) = hvc(2\pi \Delta T_{i,j}) e^{-\alpha \Delta T_{i,j}} e^{-\beta \Delta D_{i,j}}, \tag{9}$$

$$hvc(x) = \frac{1+\cos x}{2}$$

$$\boldsymbol{P} = \mathcal{G}_p \hat{X}, \tag{10}$$

$$\boldsymbol{P} \in \mathbb{R}^{|\mathcal{U}| \times d} \qquad \mathcal{G}_p \in \mathbb{R}^{|\mathcal{U}| \times |\mathcal{L}|}$$

$$\hat{\boldsymbol{w}}(\Delta T_{i,j}, \Delta D_{i,j}) = \boldsymbol{w}(\Delta T_{i,j}, \Delta D_{i,j}) e^{-||\boldsymbol{P_u} - \boldsymbol{e}^{l_j}||}, \tag{11}$$

$$\hat{\boldsymbol{h}}_i = \frac{\sum_{j=0}^{i} \hat{w}_j * \boldsymbol{h}_j}{\sum_{j=0}^{i} \hat{w}_j}, \tag{12}$$

where $\hat{w}_j$ denotes the similarity $\hat{\boldsymbol{w}}(\Delta T_{i,j}, \Delta D_{i,j})$.

$$\hat{\boldsymbol{y}}_t^u = \boldsymbol{W_f}[\hat{\boldsymbol{h}}_t || \boldsymbol{e}^u], \tag{13}$$

$$-\sum_{u=1}^{|\mathcal{U}|} \sum_{i=1}^{m} \left(\log \sigma(\boldsymbol{y}_k^u) + \sum_{j=1, j \neq k}^{|\mathcal{L}|} \log(1 - \sigma(\hat{\boldsymbol{y}}_j^u)) \right), \tag{14}$$

Experiments

Table 1: Datasets Statistics

Dataset	Gowalla	Foursquare
#Users	7,768	45,343
#POIs	106,994	68,879
#Check-ins	1,823,598	9,361,228
#Entities	114,762	114,222
#Relations	4	4
#Triplets	6,420,914	7,200,989

Experiments

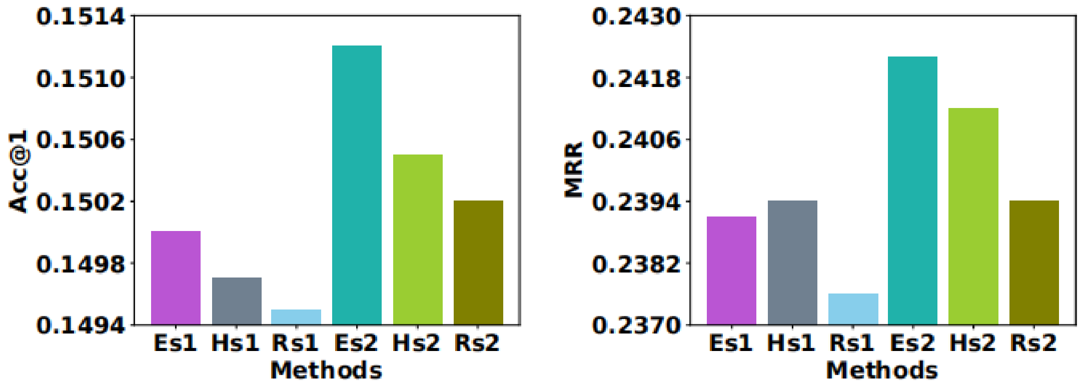
Table 2: Performance comparison against baselines on Gowalla and Foursquare datasets. In each column, we use boldface and underline to indicate the best and second-best results, respectively. (*STAN use a part of users (100) to train model at a time and test performance on these users. Therefore, it requires running many experiments to test model performance on all users and regards the average performance of these experiments as the final performance. In this light, we use all users and first 2000 users to test model performance on Gowalla and Foursquare datasets due to the large number of users on Foursquare dataset.)

Methods	Gowalla				Foursquare			
	Acc@1	Acc@5	Acc@10	MRR	Acc@1	Acc@5	Acc@10	MRR
PRME	0.0740	0.2146	0.2899	0.1503	0.0982	0.3167	0.4064	0.2040
STRNN	0.0900	0.2120	0.2730	0.1508	0.2290	0.4310	0.5050	0.3248
DeepMove	0.0625	0.1304	0.1594	0.0982	0.2400	0.4319	0.4742	0.3270
LBSN2Vec	0.0864	0.1186	0.1390	0.1032	0.2190	0.3955	0.4621	0.2781
STGN	0.0624	0.1586	0.2104	0.1125	0.2094	0.4734	0.5470	0.3283
LightGCN	0.0428	0.1439	0.2115	0.1224	0.0540	0.1790	0.2710	0.1574
Flashback	<u>0.1158</u>	<u>0.2754</u>	<u>0.3479</u>	<u>0.1925</u>	<u>0.2496</u>	<u>0.5399</u>	<u>0.6236</u>	<u>0.3805</u>
STAN*	0.0891	0.2096	0.2763	0.1523	0.2265	0.4515	0.5310	0.3420
Graph-Flashback	**0.1512**	**0.3425**	**0.4256**	**0.2422**	**0.2805**	**0.5757**	**0.6514**	**0.4136**
Improvement (%)	30.57%	24.36%	22.33%	25.82%	12.38%	6.63%	4.46%	8.70%

Experiments

Table 3: Ablation experiments on Gowalla dataset. Graph-Flashback *w/o* GCN denotes disabling the GCN layer, and Graph-Flashback *w/o* Preference represents disabling the User-POI preference graph.

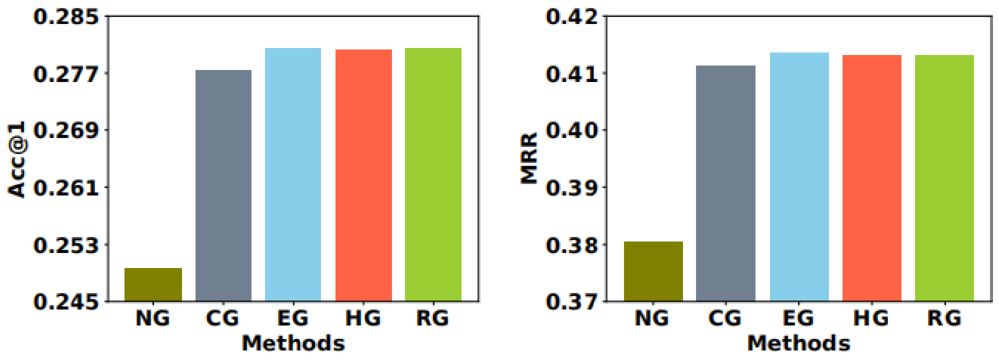
Methods	Gowalla			
	Acc@1	Acc@5	Acc@10	MRR
Flashback	0.1158	0.2754	0.3479	0.1925
Graph-Flashback *w/o* GCN	0.1356	0.3055	0.3762	0.2163
Graph-Flashback *w/o* Preference	0.1506	0.3419	0.4253	0.2419
Graph-Flashback	**0.1512**	**0.3425**	**0.4256**	**0.2422**



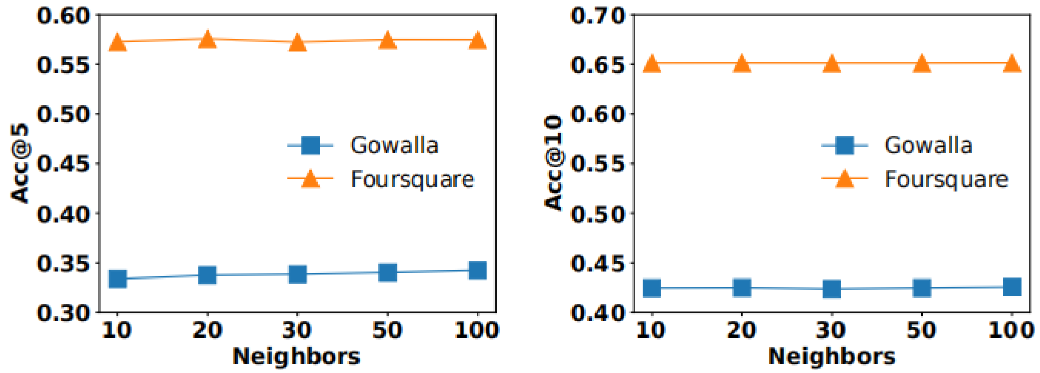
(a) Acc@1 comparison on Gowalla (b) MRR comparison on Gowalla

Figure 4: The performance comparison among different KGE algorithms used in different knowledge graphs constructed by different schemes on Gowalla dataset. *E* is TransE, *s*1 denotes that knowledge graph is constructed by first scheme.

Experiments



(a) Acc@1 comparison on Foursquare (b) MRR comparison on Foursquare



(a) The impact of neighbor number k_t (b) The impact of neighbor number k_p

Figure 5: The performance comparison among learned POI graphs and customized POI graph. NG denotes not using any graph, CG represents the customized graph, and EG denotes the POI graph learned by TransE algorithm.

Figure 6: The performance comparison about the number of nearest neighbors k_t and k_p .

Thanks !