Personalized POI Recommendation: Spatio-Temporal Representation Learning with Social Tie

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Outline

- Background
- Motivation
- Framework
- Experiment
- Conclusion

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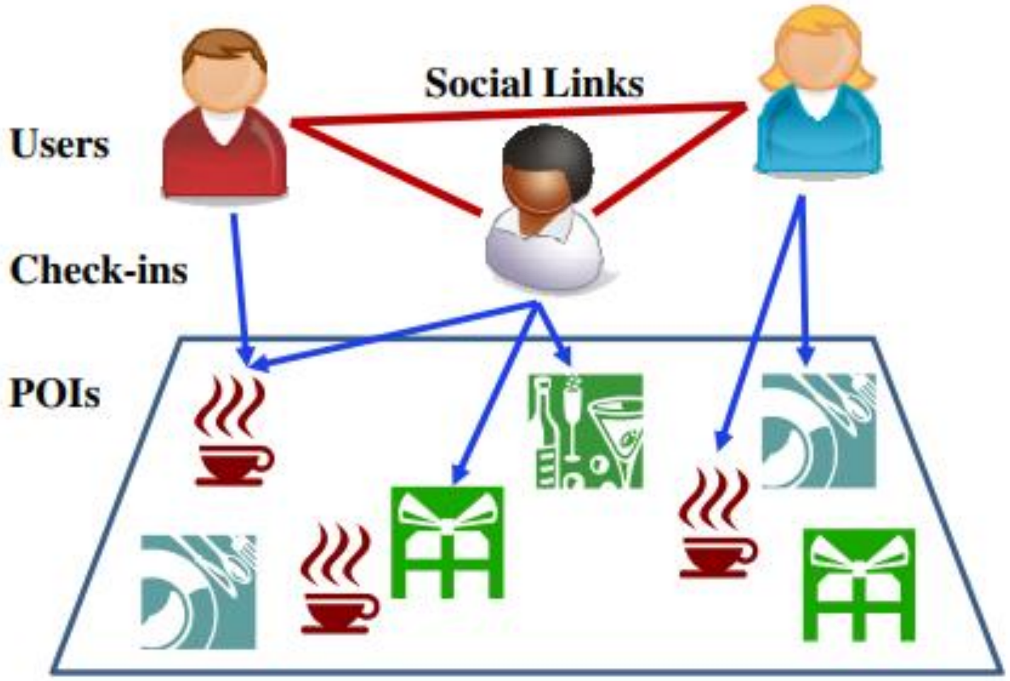
Background

Location Based Social Network

- ✓Share their experience
- ✓Bridge the gap
- ✓And so on…

POI Recommendation

- ✓Explore attractive and interesting places
- ✓Guidance to location-based service providers
- ✓And so on…



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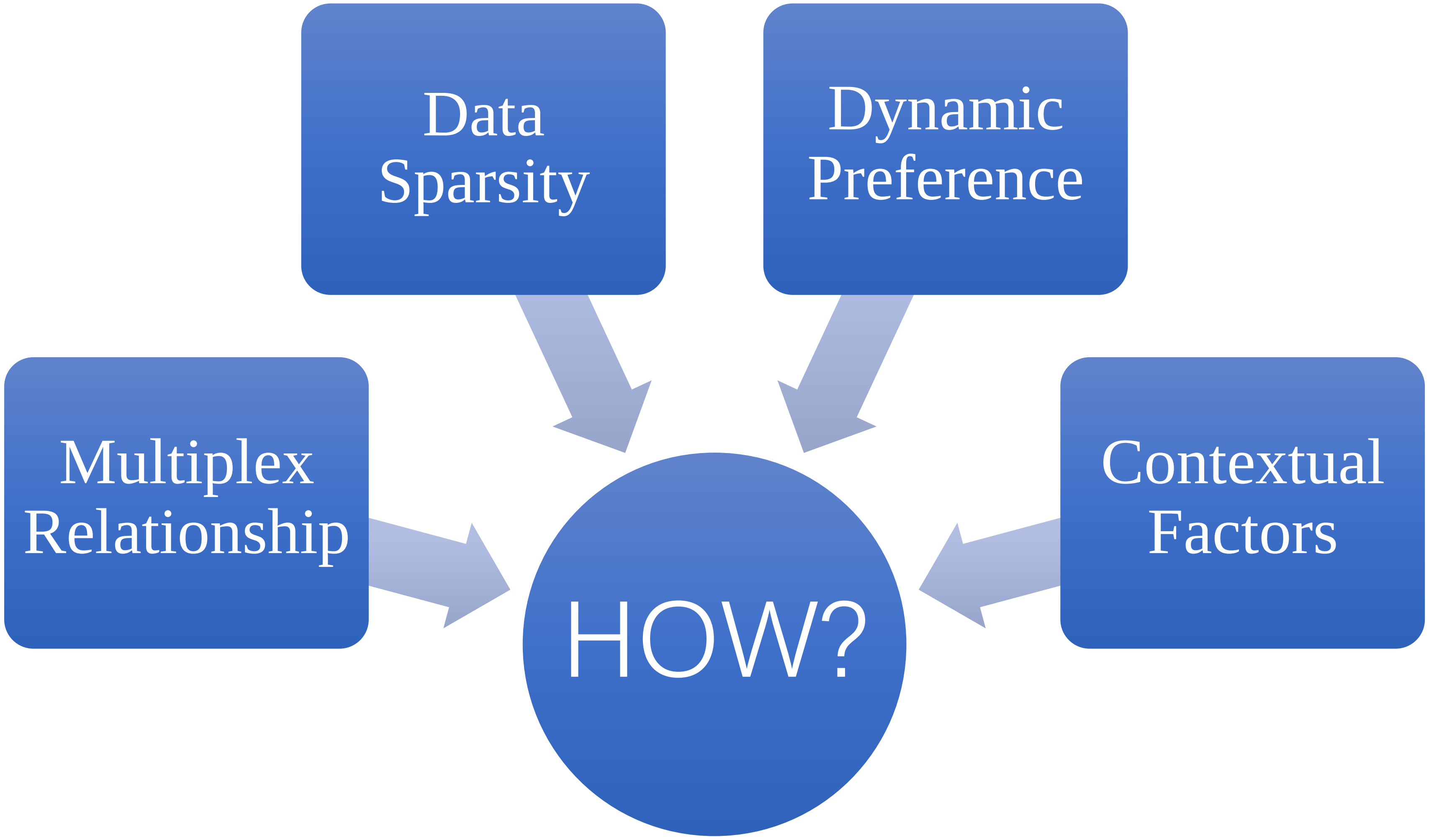
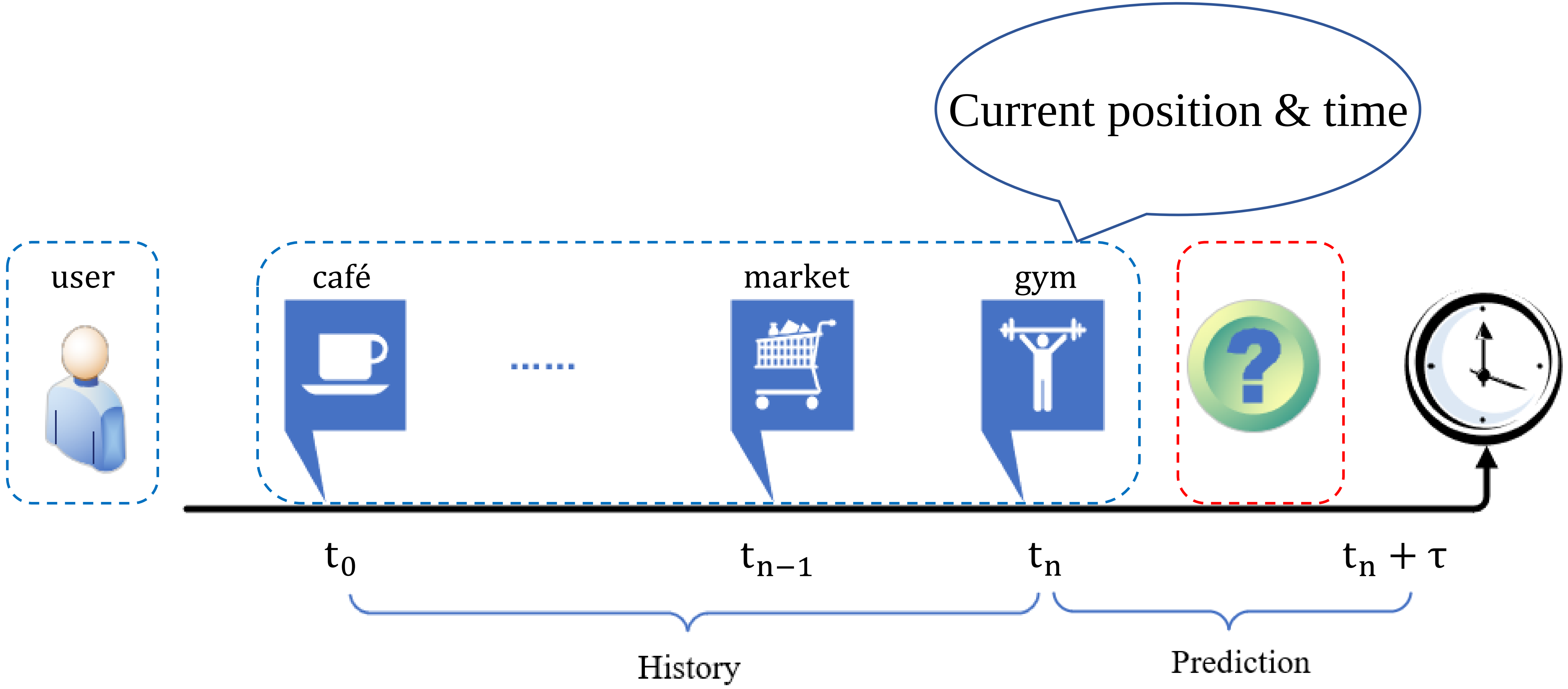
Motivation


Data Sparsity
Dynamic Preference
Multiplex Relationship
Contextual Factors
HOW?

Next POI Recommendation



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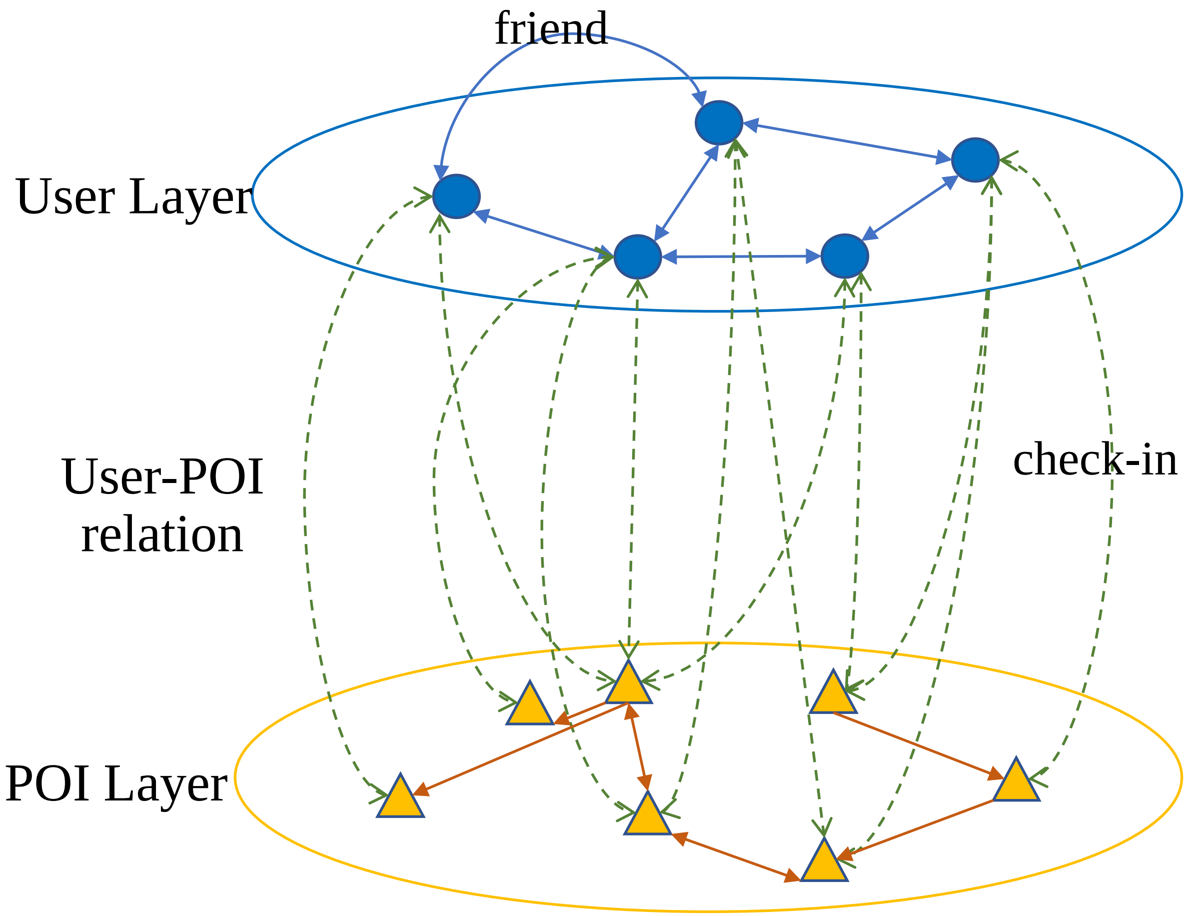
Framework

PPR - Personalized POI Recommendation: Spatio-Temporal Representation Learning with Social Tie.

The framework consists of five parts:

1st Heterogeneous Graph Construction
2nd Densifying Graph
3rd Learning Latent Representation
4th Modeling Dynamic and Personalized Preference
5th POI Recommendation

Heterogeneous Graph Construction



$\varepsilon_{u,v}$ User-POI Relation:

$$w_{i,j} = freq(u_i, v_j)$$

ε_v POI-POI Relation:

$$w_{i,j} = w_{i,j}^{(seq)} \cdot w_{i,j}^{(geo)}$$

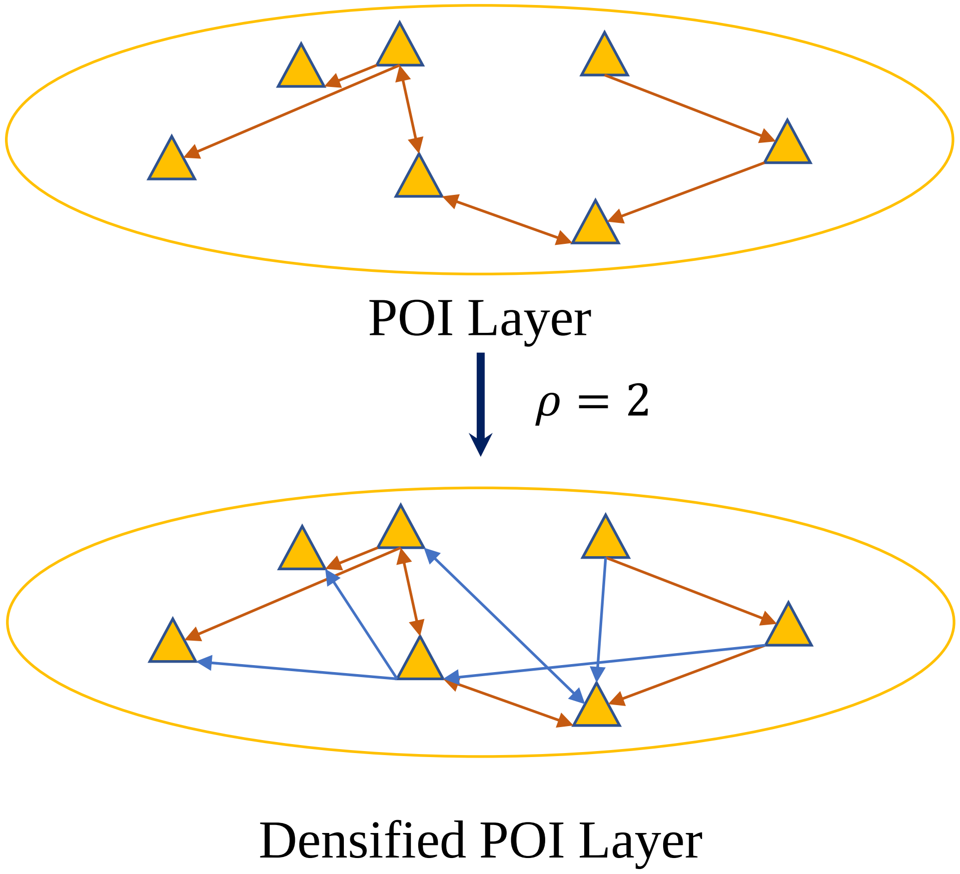
ε_u User-User Relation:

$$w_{i,j} = \frac{\varepsilon + \sum_{v \in V} min(f_{u_i,v}, f_{u_j,v})}{\left|T_{u_i} \cap T_{u_j}\right| + 1}$$

And $w_{i,j}^{(seq)}$ is the total number of times that all users visit v_i first and then v_j (time interval less than θ).

$$w_{i,j}^{(geo)} = \frac{d_{i,j}^{\kappa}}{\sum_{v_{k \in N(v_i)}} d_{i,k}^{\kappa}} (\kappa < 0)$$

Densifying Graph



Most recommendation models need to take the data sparsity into consideration.

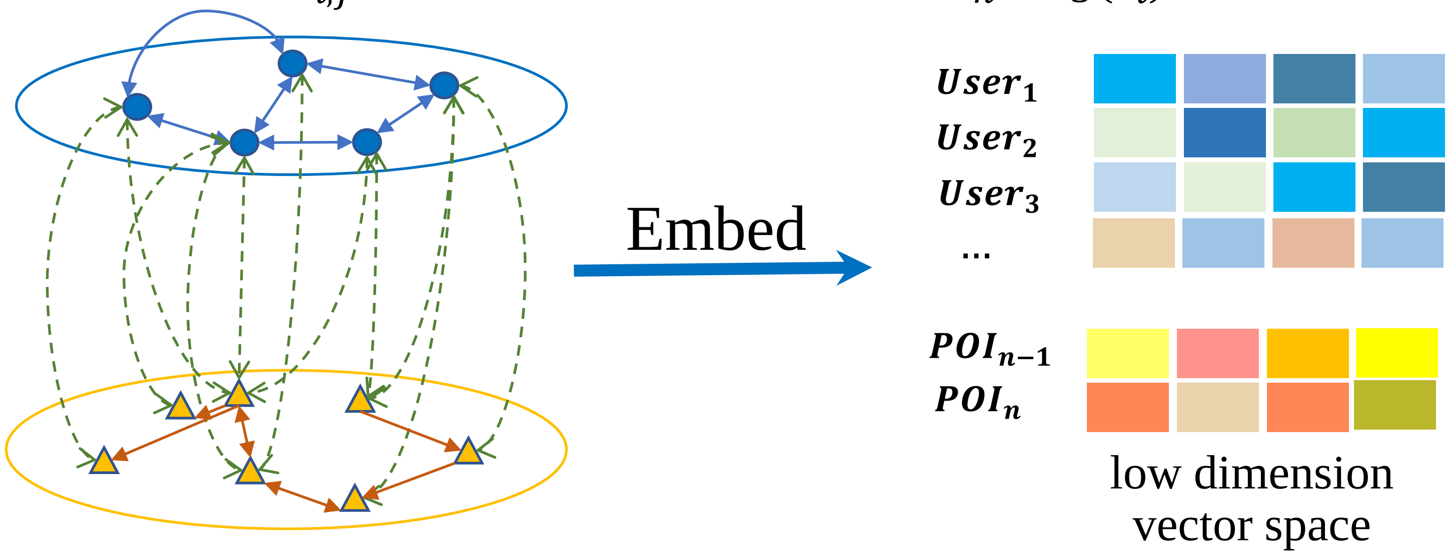
We propose to construct a dense graph based on the check-in graph.

$$w_{i,j} = \sum_{v_k \in N(v_i)} w_{i,k} \frac{w_{k,j}}{d_k^{(o)}} (d_k^{(o)} < \rho)$$

Learning Latent Representation

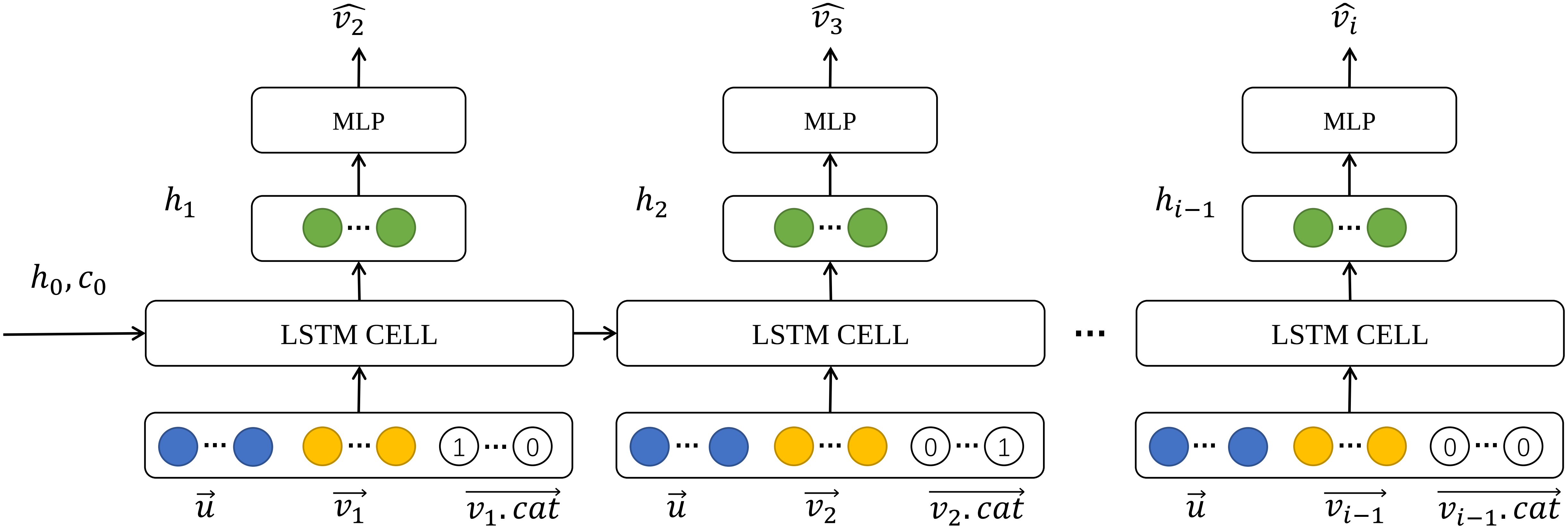
Inspired by LINE[1], which learns the first and second-order relations representations of homogeneous networks.

$$O = -\sum_{e_{i,j}\in\varepsilon}\left(\log\left(\sigma\left(\vec{v_j}'^{T}\cdot\vec{v_i}\right)\right) + w_n \sum_{v_n\in Neg(v_i)} \log\left(1-\sigma\left(\vec{v_n}'^{T}\cdot\vec{v_i}\right)\right)\right)$$



[1] Tang, J., et al.: Line: Large-scale information network embedding. In: WWW. 2015

Dynamic and Personalized Preference



$$O_{lstm} = \sum_{t=1}^{i-1} MSE(MLP(h_t), \overrightarrow{v_{t+1}})$$

POI Recommendation

Given a user u and his/her trajectory sequence T_u, for each POI v, we calculate its recommendation score as follows:

$$Score = (v|\widehat{v_{i+1}}, u, T_u) = 1 - MSE(\overrightarrow{v_{i+1}}, \vec{v})$$

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Dataset

Table 1. Basic statistics of three datasets

Dataset	Foursquare[1]	Gowalla[2]	Brightkite[3]
# of users	4,163	6,846	5,677
# of POIs	121,142	74,856	128,799
# of check-ins	483,813	251,378	572,739
# of categories	35	/	/
Time span	Dec. 2009-Jul. 2013	Feb. 2009-Oct. 2010	Apr. 2008 - Oct. 2010

1 https://sites.google.com/site/dbhongzhi/
2 http://snap.stanford.edu/data/loc-Gowalla.html
3 http://snap.stanford.edu/data/loc-Brightkite.html

Baseline

Table 2. Baseline Methods

Baseline	From
Rank-GeoFM [2]	SIGIR 2015
ST-RNN [3]	AAAI 2016
GE [4]	CIKM 2016
PEU-RNN [5]	WWW 2019
SAE-NAD [6]	CIKM 2018

[2] Li, X, et al.: Rank-geofm: A ranking based geographical factorization method for point of interest recommendation. In: SIGIR. 2015.
[3] Liu, Q, et al.: Predicting the next location: A recurrent model with spatial and temporal contexts. In: AAAI. 2016.
[4] Xie, M , et al.: Learning graph-based poi embedding for location-based recommendation. In: CIKM. 2016.
[5] Lu, Y.S., et al.: On successive point-of-interest recommendation. In: WWW. 2019.
[6] Ma, C., et al.: Point-of-interest recommendation: Exploiting self-attentive autoencoders with neighbor-aware inuence. In: CIKM. 2018.

Performance Study: Foursquare

Table 3. Performance comparison on **Foursquare** dataset

Methods	Acc@5	Acc@10	Pre@5	Pre@10	Rec@5	Rec@10	NDCG@5	NDCG@10
Rank-GeoFM	0.2456	0.2983	0.0618	0.0413	0.0509	0.0669	0.0683	0.0468
ST-RNN	0.1642	0.2150	0.0167	0.0118	0.1207	0.1790	0.0175	0.0152
GE	0.1357	0.3100	0.0378	0.0342	0.1579	0.1919	0.0431	0.0362
PEU-RNN	0.2021	0.2775	0.0495	0.0276	0.1888	0.2848	0.0494	0.0375
SAD-NAE	0.2429	0.3221	0.0588	0.0442	0.0333	0.0505	0.0672	0.0542
PPR	**0.3008**	**0.3935**	**0.0698**	**0.0501**	**0.2471**	**0.3387**	**0.0802**	**0.0628**

Performance Study: Gowalla

Table 4. Performance comparison on **Gowalla** dataset

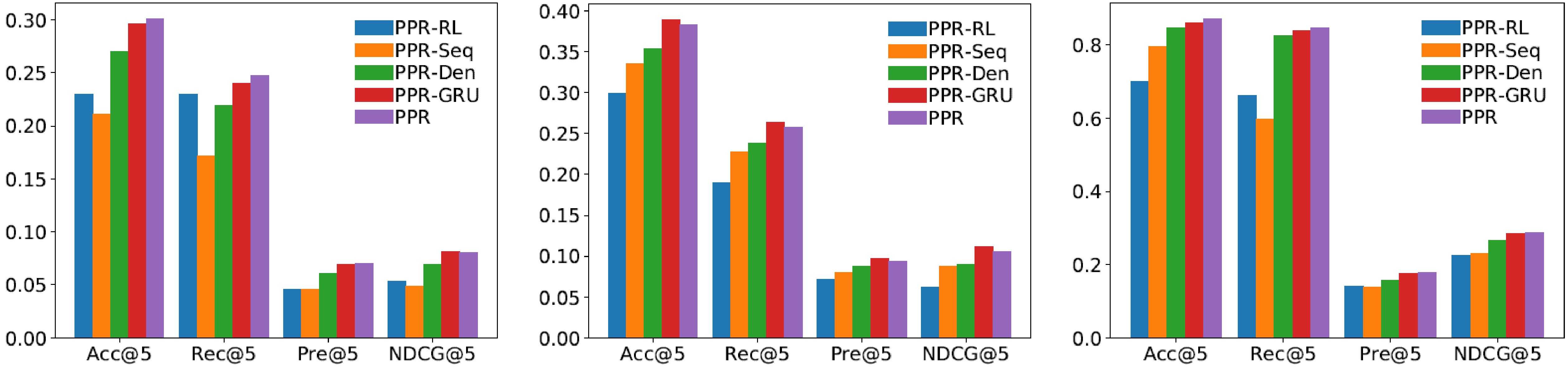
Methods	Acc@5	Acc@10	Pre@5	Pre@10	Rec@5	Rec@10	NDCG@5	NDCG@10
Rank-GeoFM	0.2162	0.2643	0.0647	0.0453	0.0887	0.1180	0.0696	0.1865
ST-RNN	0.1642	0.2246	0.0278	0.0217	0.0817	0.1075	0.0606	0.0574
GE	0.1763	0.4060	0.0391	0.0203	0.1363	0.3135	0.0813	0.0157
PEU-RNN	0.3329	0.3766	0.0663	0.0390	0.2504	**0.3613**	0.0919	0.0627
SAD-NAE	0.3273	0.4300	0.0849	0.0645	0.1102	0.1600	0.0956	0.0777
PPR	**0.3835**	**0.4905**	**0.0936**	**0.0687**	**0.2573**	0.3430	**0.1055**	**0.0840**

Performance Study: Brightkite

Table 5. Performance comparison on **Brightkite** dataset

Methods	Acc@5	Acc@10	Pre@5	Pre@10	Rec@5	Rec@10	NDCG@5	NDCG@10
Rank-GeoFM	0.3681	0.4270	0.0968	0.0618	0.2497	0.2983	0.1058	0.0700
ST-RNN	0.2396	0.3540	0.0389	0.0394	0.2279	0.3400	0.1166	0.1074
GE	0.1903	0.4259	0.0869	0.0483	0.1303	0.4119	0.1313	0.1217
PEU-RNN	0.7187	0.7383	0.1437	0.0720	0.6944	0.7204	0.2348	0.1538
SAD-NAE	0.2578	0.3383	0.0645	0.0499	0.0703	0.1047	0.0708	0.0584
PPR	**0.8717**	**0.8966**	**0.1788**	**0.0927**	**0.8485**	**0.8741**	**0.2875**	**0.1889**

Ablation Study



(a) Foursquare (b) Gowalla (c) Brightkite

Fig. 1. Performance comparison of variations

Parameter Sensitivity: Foursquare

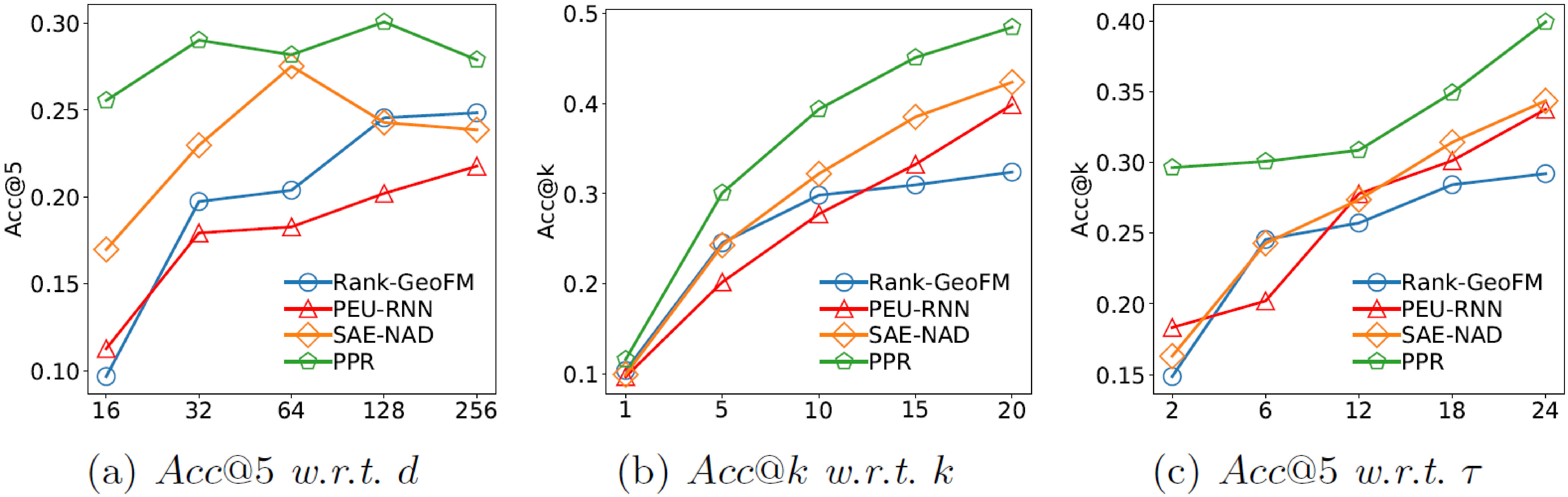
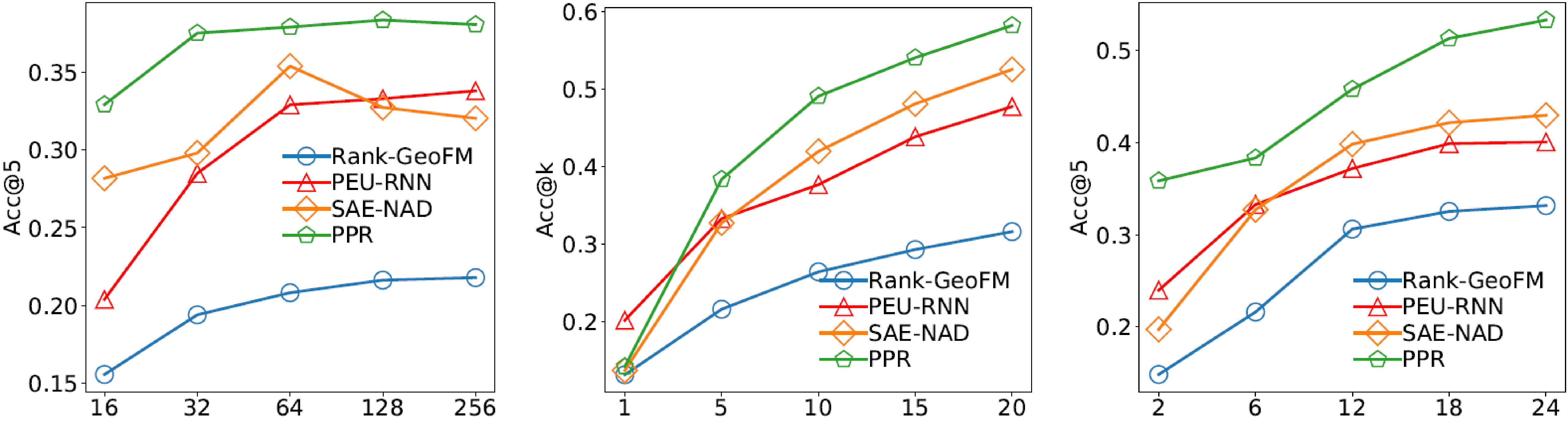


Fig. 2. Parameter sensitivity $w.r.t.$ parameter d, k and τ on Foursquare

Parameter Sensitivity: Gowalla



(a) $Acc@5$ $w.r.t.$ d (b) $Acc@k$ $w.r.t.$ k (c) $Acc@5$ $w.r.t.$ τ

Fig. 3. Parameter sensitivity $w.r.t.$ parameter d, k and τ on Gowalla

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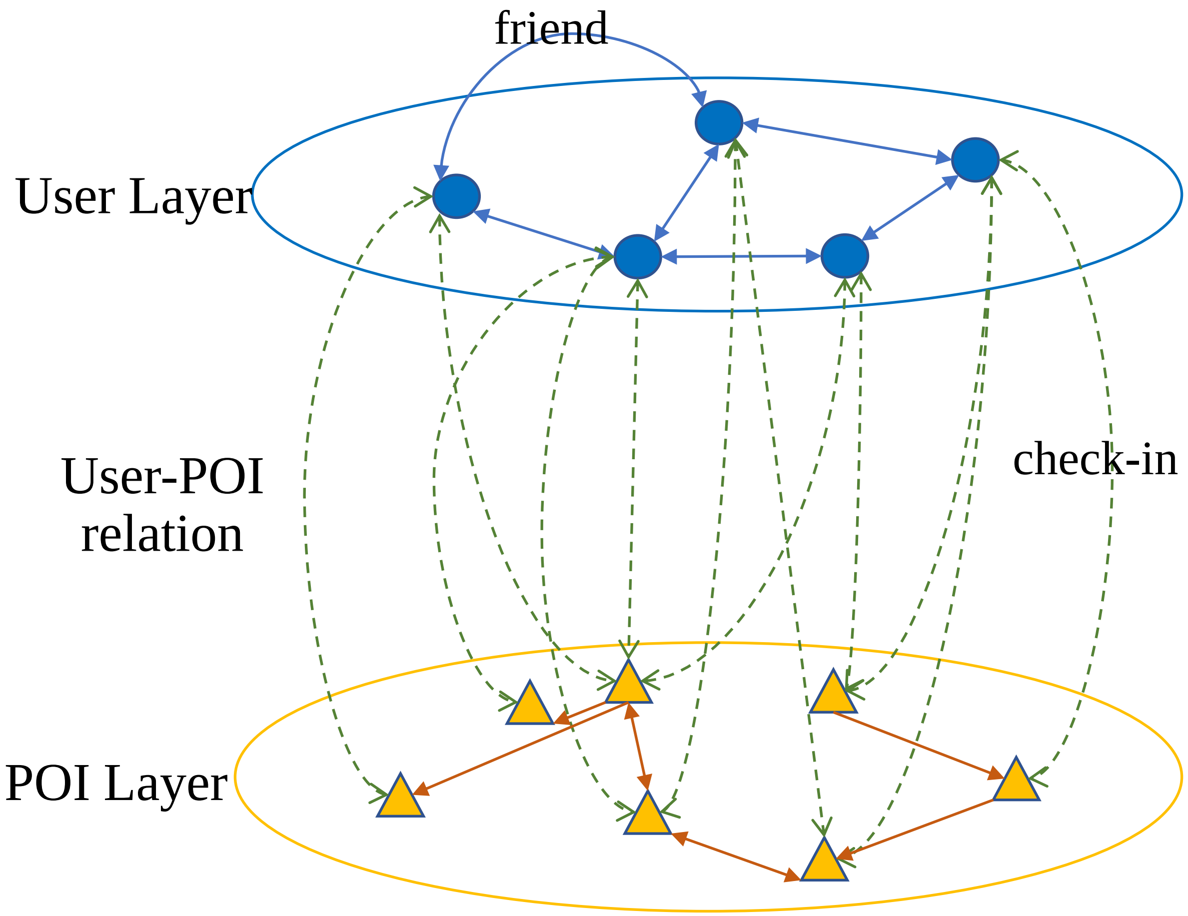
- We construct a heterogeneous graph by jointly taking **user-POI relation**, **sequential pattern**, **geographical effect** and **social ties** into consideration to learn the representations of users and POIs.
- We propose a spatio-temporal neural network to model users' **dynamic and personalized preference**.
- We conduct extensive experiments, and **explore the importance** of various factors in improving POI recommendation performance.

Q&A

Thanks!

Code: https://github.com/dsj96/PPR-master

Heterogeneous Graph Construction



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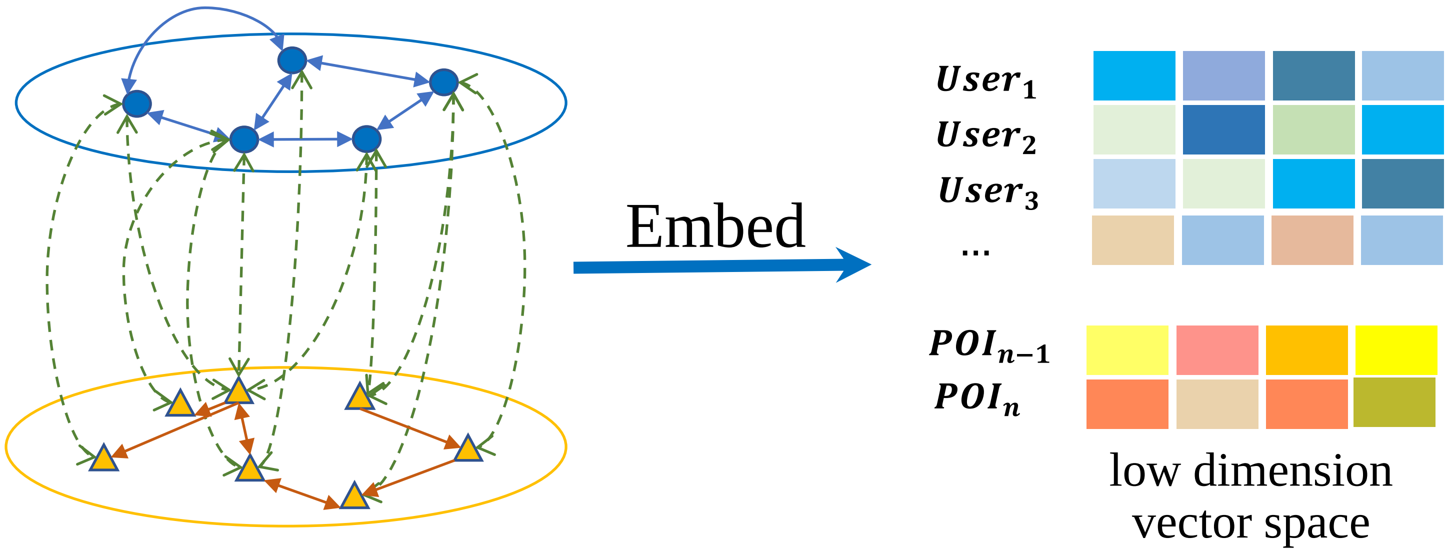
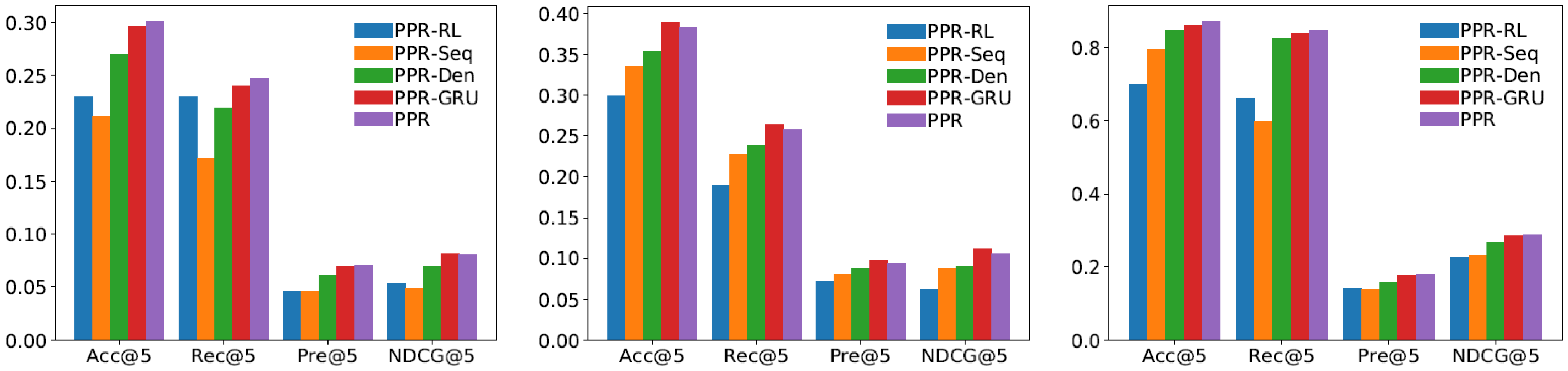


Ablation Study



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