Graph Enhanced Attention Network for Explainable POI Recommendation

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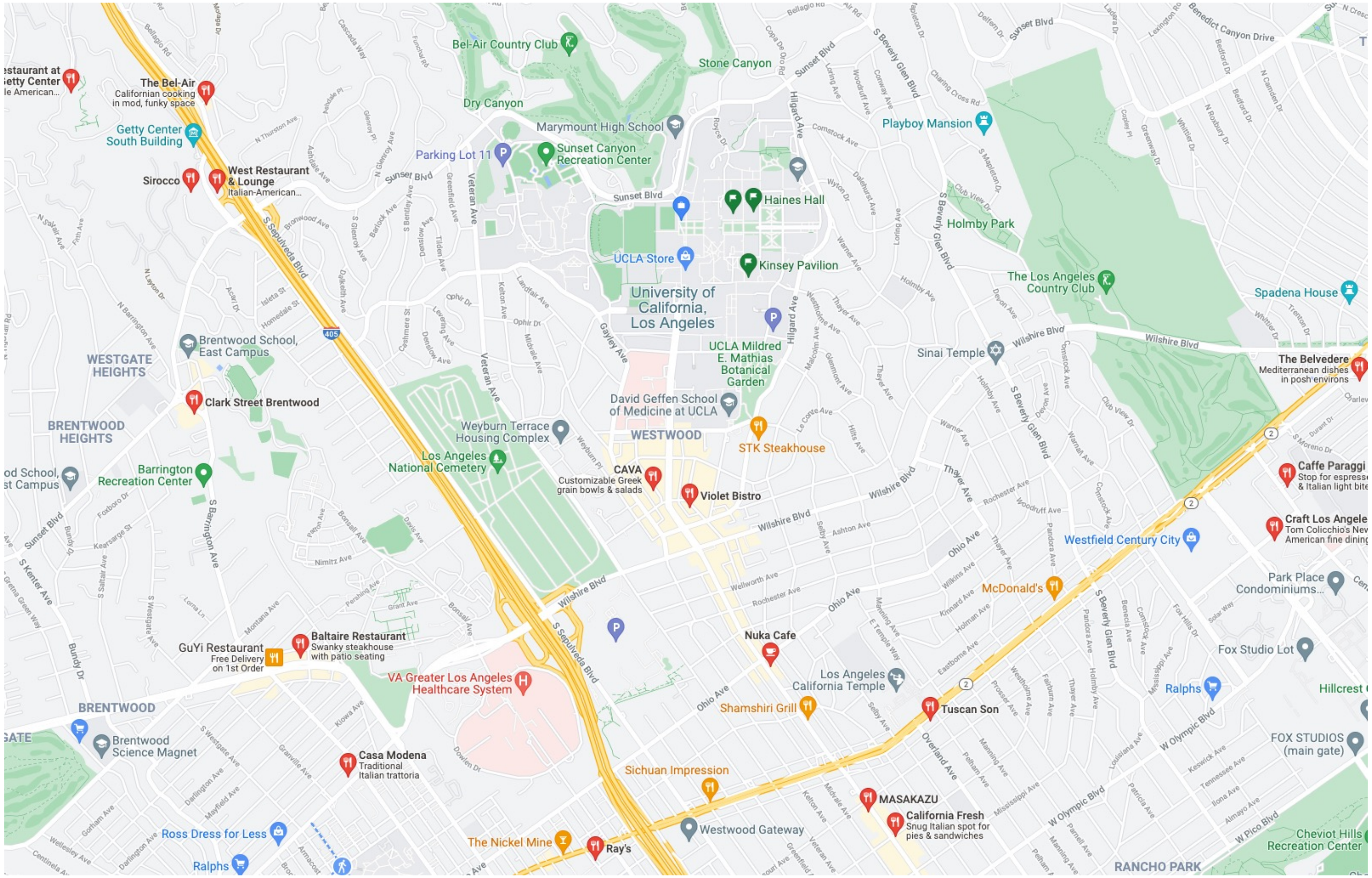
Point-of-interest (POI)



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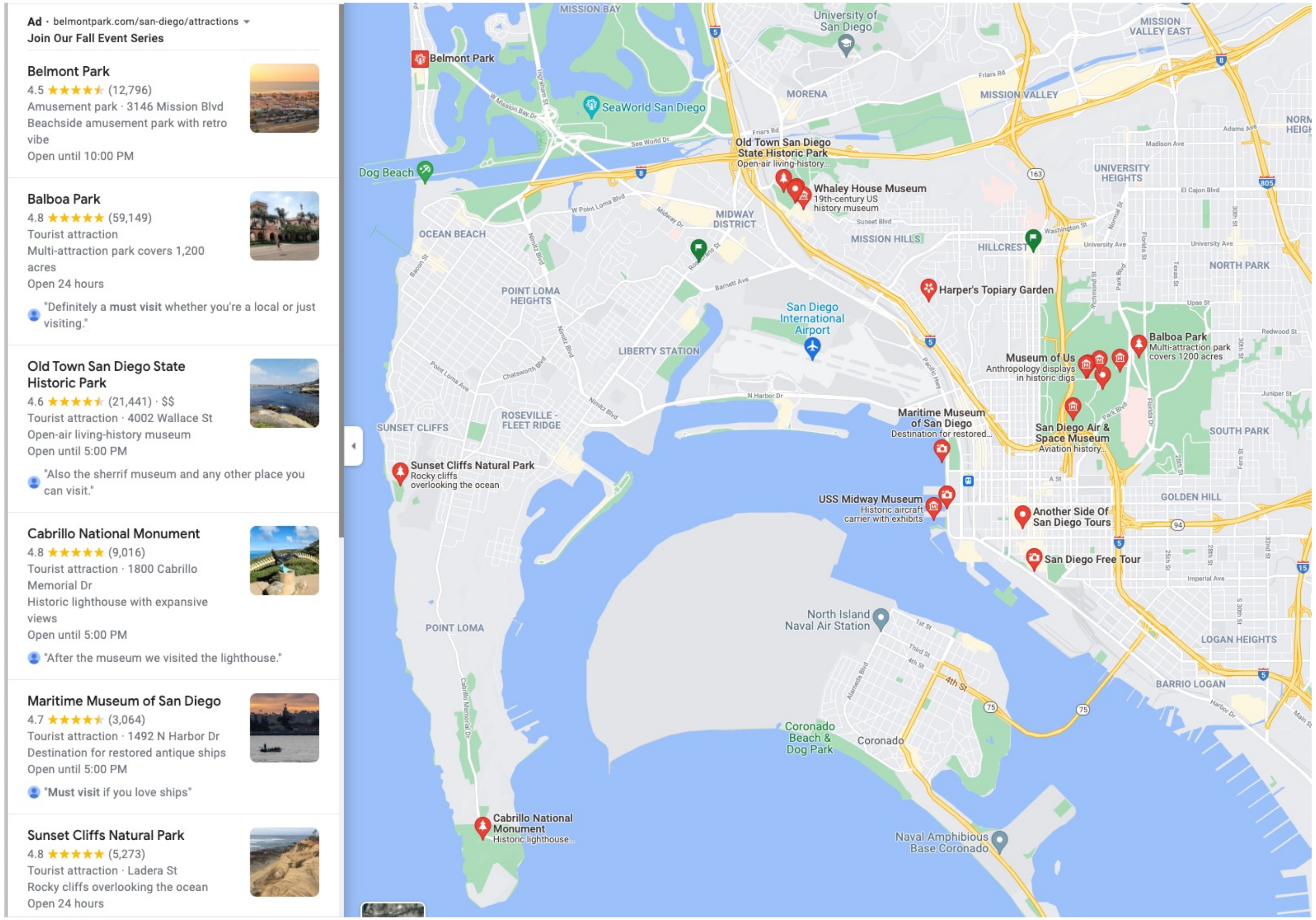


Point-of-interest (POI)

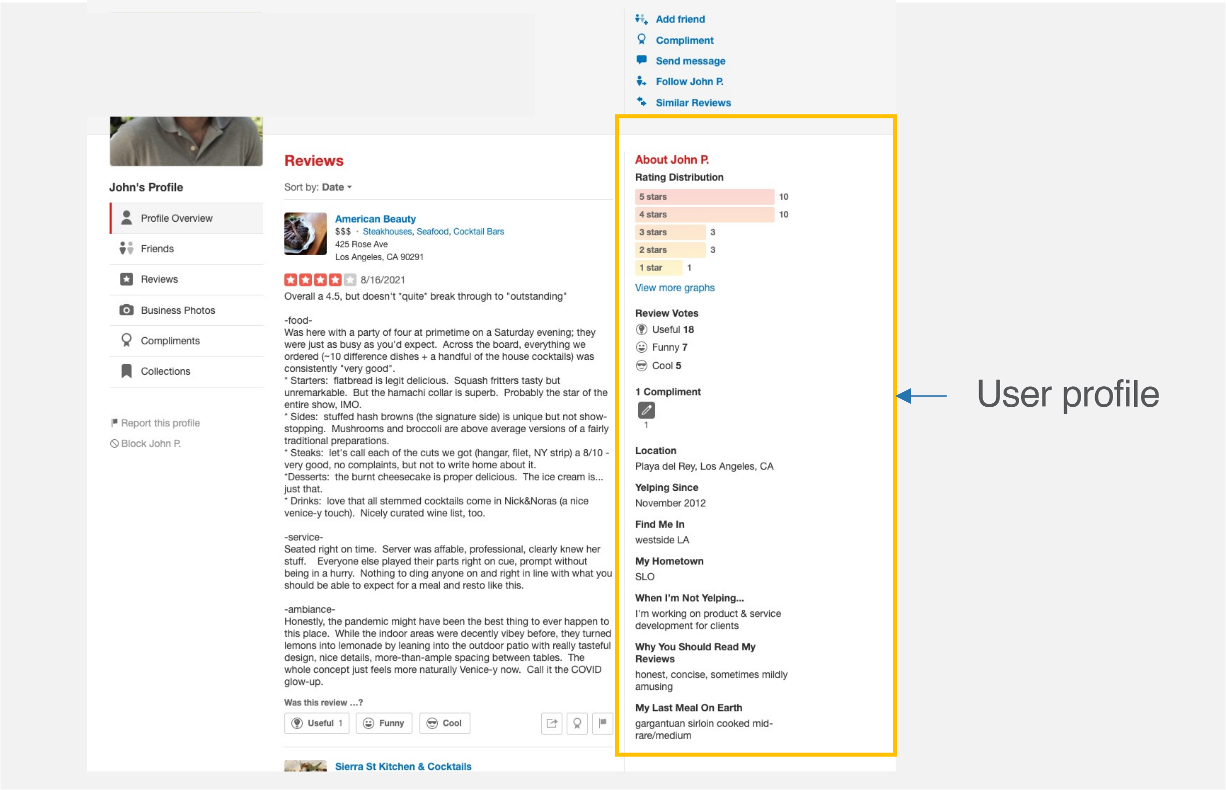
POI: POINT OF INTEREST

1. POI: locations that customers of online business directories or review forums are interested in.
2. LBSN: location-based social network
3. E.g.: Yelp, Foursquare, etc.

Point-of-interest (POI)

DRAWBACKS OF EXISTING POI ALGORITHMS

1. Attributes of individual have been largely ignored.



User profile

Point-of-interest (POI)

DRAWBACKS OF EXISTING POI ALGORITHMS

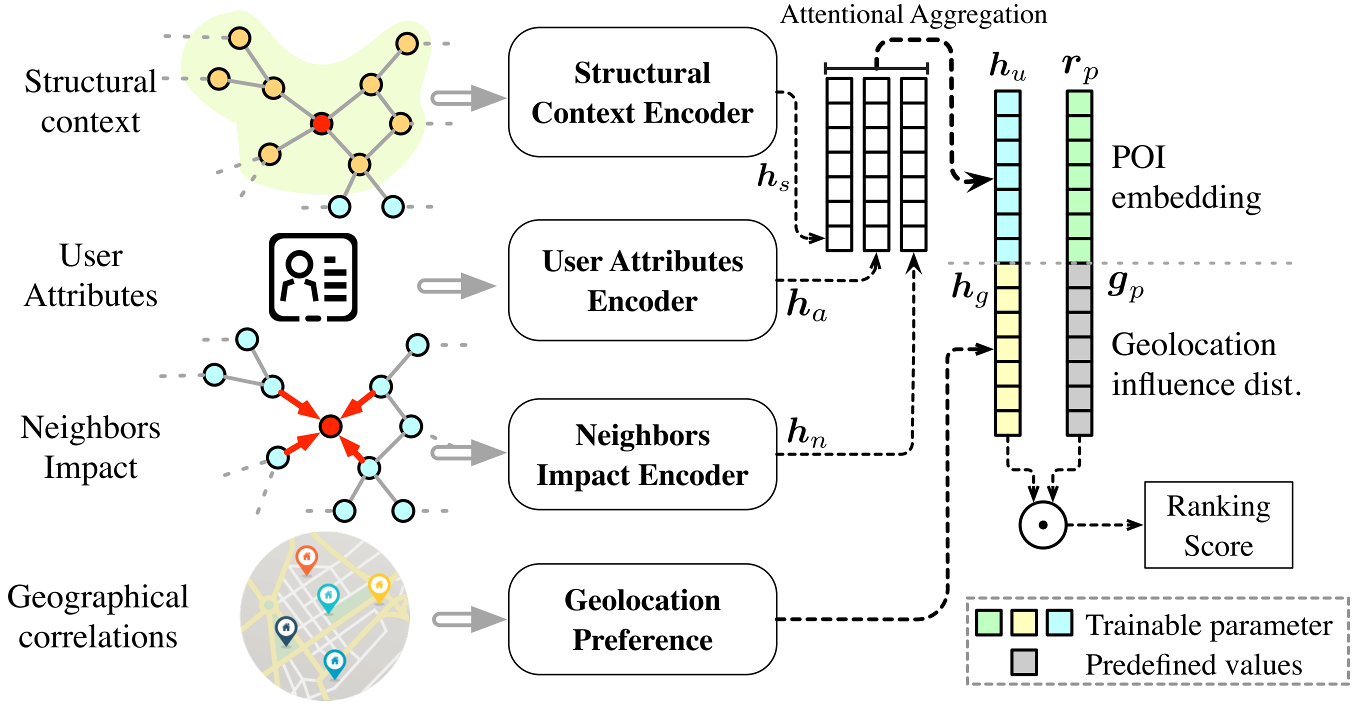
1. Attributes of individual have been largely ignored.
2. Existing models preserve the information of users or POIs by latent presentation without explicitly highlighting salient factors or signals.

GEAPR

GRAPH ENHANCED ATTENTION NETWORK FOR EXPLAINABLE POI RECOMMENDATION

Four factors:

1. Structural Context
2. Neighbor Impact
3. User Attributes
4. Geolocation Influence



Structural Context

- **Motivation:** Check-in can be motivated by neighboring users with high structural proximity in the social network since they have a similar social context.
- The structural context tries to model the commonality of the close neighbors of a certain user.
- **How to:**
  - Random Walk with Restarts (RWR) (M_a is adjacency matrix, $p^{(0)}$ is the col of M_a)

$$\boldsymbol{p}^{(r)} = \gamma \boldsymbol{p}^{(0)} + (1-\gamma)\boldsymbol{p}^{(r-1)}[\mathbf{D}^{-1}\mathbf{M}_a],$$

$$\mathbf{D}_{ii} = \sum_{j=1}^{n_u} \mathbf{M}_{a,ij}.$$

$$\boldsymbol{h}_s' = \sum_{r=1}^{R} \boldsymbol{p}^{(r)}$$

$$\boldsymbol{h}_s = \mathrm{ReLU}(\mathbf{W}_2^T(\mathrm{ReLU}(\mathbf{W}_1^T \boldsymbol{h}_s' + \boldsymbol{b}_1)) + \boldsymbol{b}_2),$$

Neighborhood Impact Factor

- **Motivation**: one may naturally check in the POIs suggested by friends
- **How to**:
  - GAT: graph attention network
  - Aggregate information from direct neighbors and compute the attention to pinpoint significant neighbors

$$\boldsymbol{h}_n = \underbrace{\sigma}_{\text{Non-linear function}}\left(\sum_{j \in \underbrace{\mathcal{N}_G(u)}_{\text{The friends of u}}} \alpha_{uj} \underbrace{\mathbf{W}_n}_{\text{Learnable parameter}} \boldsymbol{v}_j\right)$$

Neighborhood Impact Factor

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$$\boldsymbol{h}_n = \sigma\left(\sum_{j \in \mathcal{N}_G(u)} \alpha_{uj} \mathbf{W}_n \boldsymbol{v}_j\right)$$

$$\alpha_{uj} = \frac{\exp\left(\text{LeakyReLU}\left(\boldsymbol{a}^T\left[\mathbf{W}\boldsymbol{v}_u || \mathbf{W}\boldsymbol{v}_j\right]\right)\right)}{\sum_{i \in \mathcal{N}_G(u)} \exp\left(\text{LeakyReLU}\left(\boldsymbol{a}^T\left[\mathbf{W}\boldsymbol{v}_u || \mathbf{W}\boldsymbol{v}_i\right]\right)\right)}$$

Attribute Interactive Factor

- **Motivation**: The combinatorial possibilities of feature interactions create diverse influences on the users' preference towards POIs, which has been thoroughly studied in feature-based recommender systems.
- **How to**: We combine feature-based FM method with attention mechanism to analyze feature interaction while maintaining the interpretability.

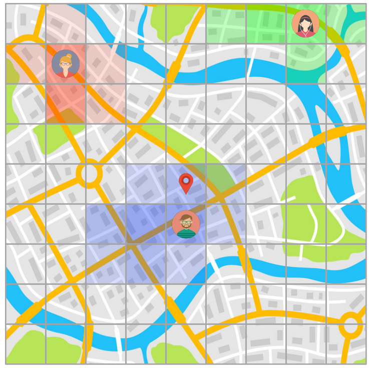
$$\boldsymbol{h}_a = \boldsymbol{w}_0 + \sum_{i=1}^{m} \beta_i \boldsymbol{f}_i + \sum_{i=1}^{m} \sum_{i=j+1}^{m} \lambda_{ij} \boldsymbol{f}_i \odot \boldsymbol{f}_j,$$

First- and second- order attention weights

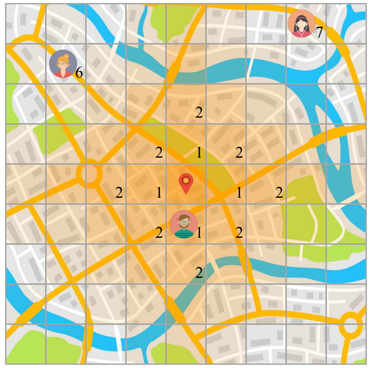
Feature representation

POI Geographical Influence

- Two aspects:
  - Learnable user geolocational interest
  - Predefined POI area influence
- Geo-preference: $\boldsymbol{h}_g \in \mathbb{R}^{(n_{\text{long}} \cdot n_{\text{lat}})}$
- POI influence: $$g_{p,t} = K\left(\frac{d_{\text{man}}(p,t)}{\sigma_g}\right)$$



User geo-preference



POI influence area

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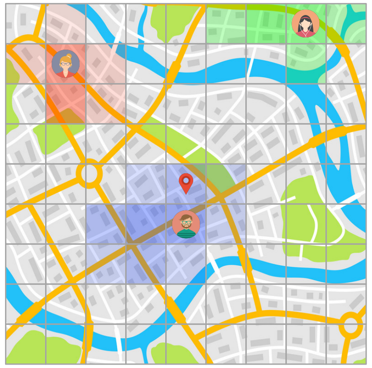
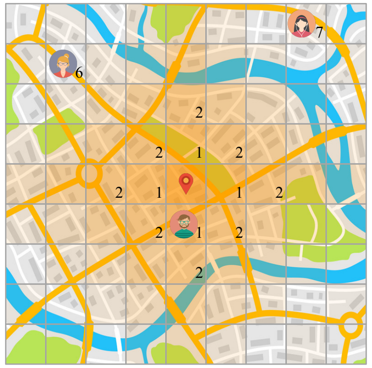


User geo-preference



POI influence area

GEAPR can be **painlessly transplanted** to geolocation-irrelevant recommendation scenarios by simply detaching the geolocation module.

Objective and Optimization

- Attention-based aggregation:

$$\boldsymbol{h}_u = \pi_s \cdot \mathrm{ReLU}(\boldsymbol{h}_s) + \pi_n \cdot \mathrm{ReLU}(\boldsymbol{h}_n) + \pi_a \cdot \mathrm{ReLU}(\boldsymbol{h}_a)$$

$$\pi_{x \in \{s,n,a\}} = \frac{\exp(\boldsymbol{w}^T \mathrm{ReLU}(\boldsymbol{h}_x))}{\sum_{x' \in \{s,n,a\}} \exp(\boldsymbol{w}^T \mathrm{ReLU}(\boldsymbol{h}_{x'}))}$$

$$s_{u,p} = [\boldsymbol{h}_u || \boldsymbol{h}_g] \cdot [\boldsymbol{r}_p || \boldsymbol{g}_p] = \boldsymbol{h}_u^T \boldsymbol{r}_p + \boldsymbol{h}_g^T \boldsymbol{g}_p.$$

POI personalization
representation

Objective and Optimization

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$$s_{u,p} = [\boldsymbol{h}_u || \boldsymbol{h}_g] \cdot [\boldsymbol{r}_p || \boldsymbol{g}_p] = \boldsymbol{h}_u^T \boldsymbol{r}_p + \boldsymbol{h}_g^T \boldsymbol{g}_p.$$

- L2 Regularization and Loss Function (Point-wise and Pair-wise)

$$L = L_{\mathrm{rank}}(\mathcal{D}, \mathcal{D}') + cL_{\mathrm{reg}}$$

$$L_{\text{rank-po}} = -\sum_{\mathcal{D},\mathcal{D}'} \left(y \log(\sigma(s_{u,p})) + (1-y)\log(1-\sigma(s_{u,p})) \right).$$

$$L_{\text{rank-pa}} = \sum_{\mathcal{D},\mathcal{D}'} -\Delta_{u,p,p'} + \log(1 + \exp(\Delta_{u,p,p'})). \quad \Delta_{u,p,p'} = s_{u,p} - s_{u,p'}.$$

Experiments

DATASET

- Yelp Challenge Round 13
- Subsets of **Toronto** and **Phoenix**

Table 2: Statistics of the datasets for evaluation.[3]

Dataset	#.User	#.POI	#.Reviews	#.U-Cxn	%.Reviews	%.U-Cxn
Toronto	9582	9102	234388	104402	2.687×10^{-3}	1.139×10^{-3}
Phoenix	11289	9633	249029	163900	2.290×10^{-3}	1.286×10^{-3}

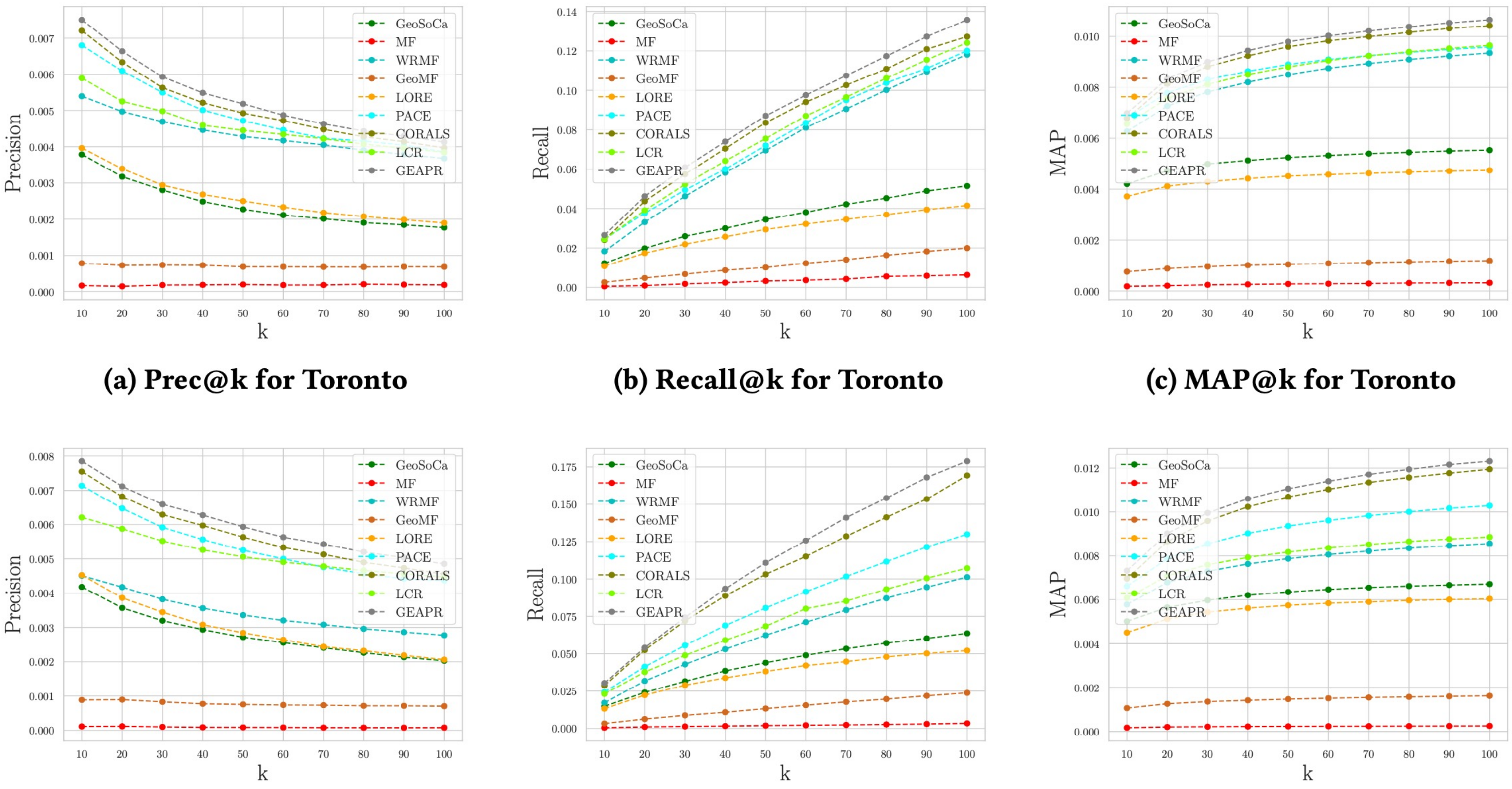
Experiments

METRIC AND BASELINE MODELS

- Mean Average Precision@k
- Precision@k and Recall@k
- Eight baseline models
  - Matrix factorization based
  - Deep learning based

Experiments

RESULTS



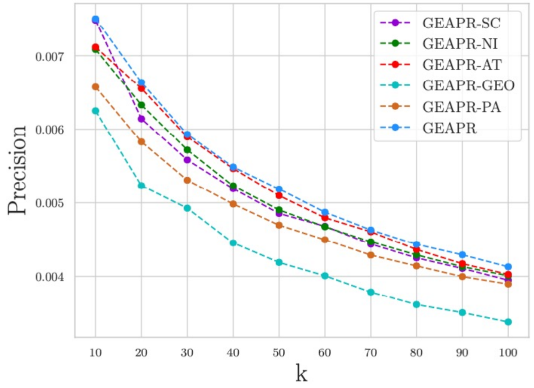
(a) Prec@k for Toronto (b) Recall@k for Toronto (c) MAP@k for Toronto

(d) Prec@k for Phoenix (e) Recall@k for Phoenix (f) MAP@k for Phoenix

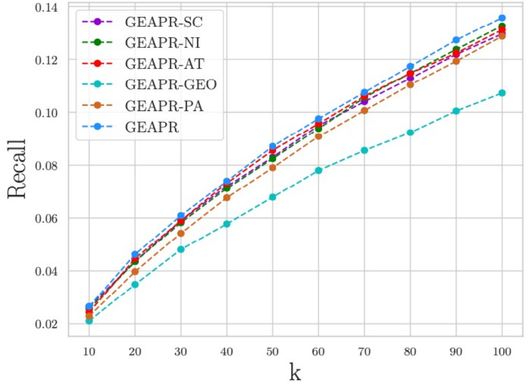
Figure 3: Performance evaluation of GEAPR compared with baseline models.

Experiments

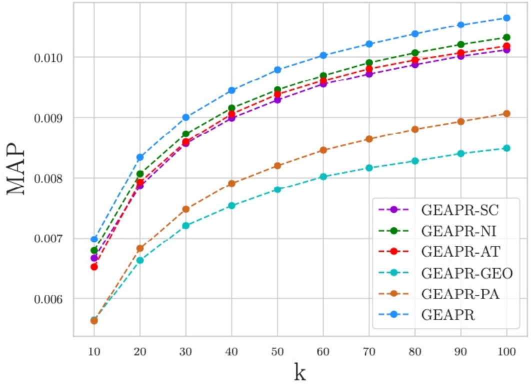
ABLATION STUDY



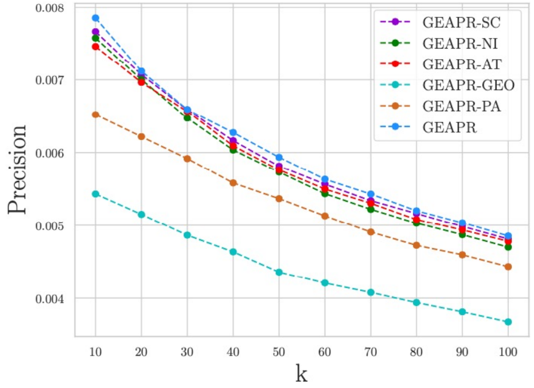
(a) Prec@k for Toronto



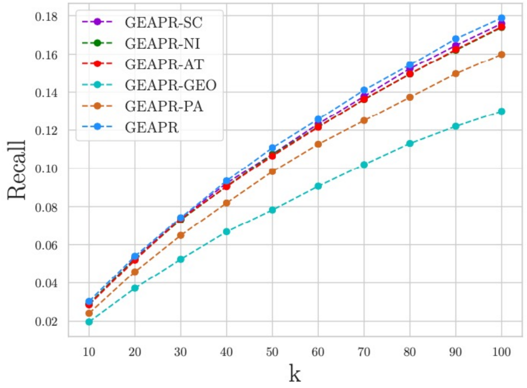
(b) Recall@k for Toronto



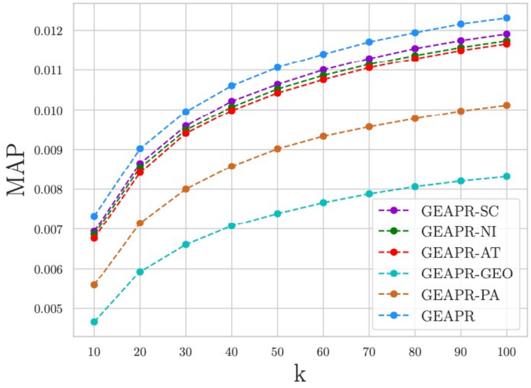
(c) MAP@k for Toronto



(d) Prec@k for Phoenix



(e) Recall@k for Phoenix



(f) MAP@k for Phoenix

Figure 4: Ablation study of GEAPR compared with its variants.

Experiments

CASE STUDY

- Significant neighbor impact
  - Single strong neighbor
- Structural context
  - Context composed of 422/8838/4153
- Attribute
  - "YelpYrs"
  - Neighbor 1269

Figure 5: Example with significant neighbor impact. User neighbor ID are omitted for better visualization.

Figure 6: Example with significant structural context.

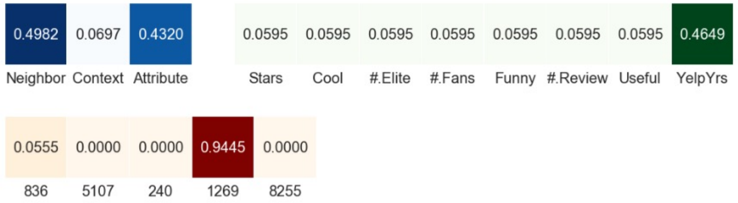


Figure 7: Example with significant user attribute.

Conclusion

- We proposed GEAPR: a graph-enhanced POI recommendation algorithm that incorporates
    - User friendship network information
    - User attributes
    - Geolocation features.
- GEAPR decomposes the motivation of user check-ins into four different aspects.
- GEAPR employs the attention mechanism to generate interpretations that reveal the salient motivating factors, influential neighbors, informative attribute interactions, and heated geographical areas, etc.

Other materials

- Code: https://github.com/zyli93/GEAPR
- Reproducibility details: Please refer to the paper
- Paper ID: **afp1813**
- See you in the poster session!

Thanks for listening!

- We would like to thank the reviewers for the feedback.
- See you in the poster session.

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