Explainable Mobility Predictions and POI Recommendations

[POI – Points of Interests]

Shiveswarran R

- Transportation Engineering [CIVIL]

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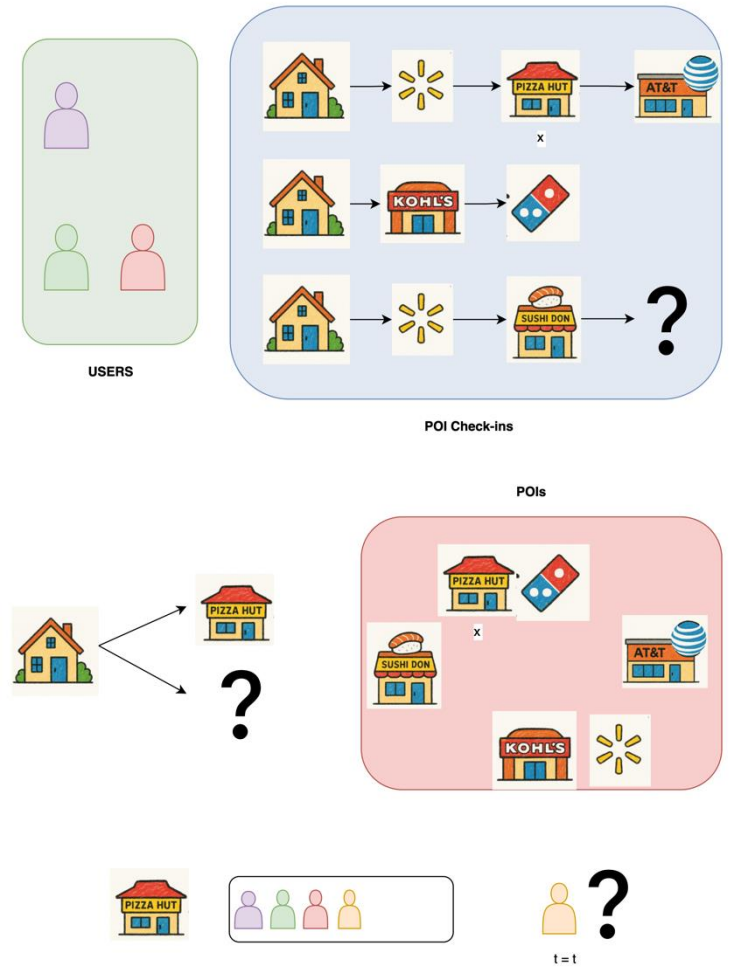
Introduction

Points of Interests (POIs) Recommendations

- There are multiple kinds of recommendation cases associated with Points of Interests (POIs) in the area of urban mobility, in perspectives of users, business, urban planners.
    1. Personalized Next POI recommendations
    2. Alternative Destination recommendations [ride service providers with incentives
    3. Cold-start recommendations [New users, New POIs] → Sub Problem of Next POI
    4. Conditional recommendations [e.g. Spatio-temporal and Visitor count prediction to specific POIs]
- **Why POI Recommendation matters?**
    - Personalized trip planning
    - Targeted advertisements (coupons, offers etc.)
    - Tourism [Visiting new unknown city]
    - Pandemic spread prediction



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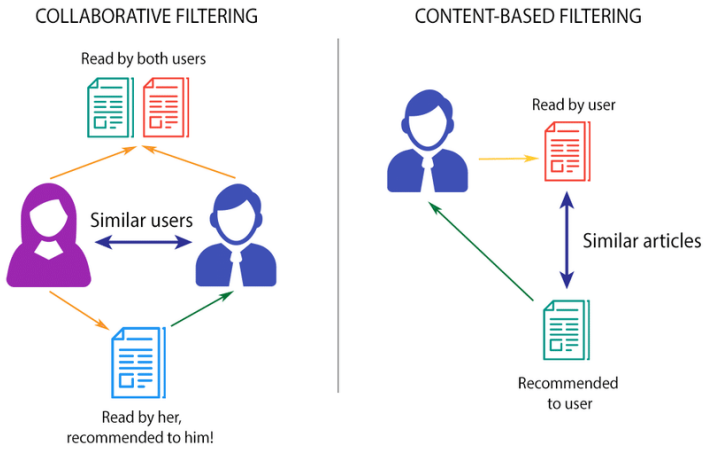
IN SUCH CASES, EXPLAINABLE RECOMMENDATIONS SUPPORTS DECISION MAKING

Previous Works

Points of Interests (POIs) Recommendations

1. Matrix Factorization methods → Collaborative Filtering
2. Content Based recommendations
3. Sequential Recommendations → Feature engineering



Previous works on Representation learning of RecSys

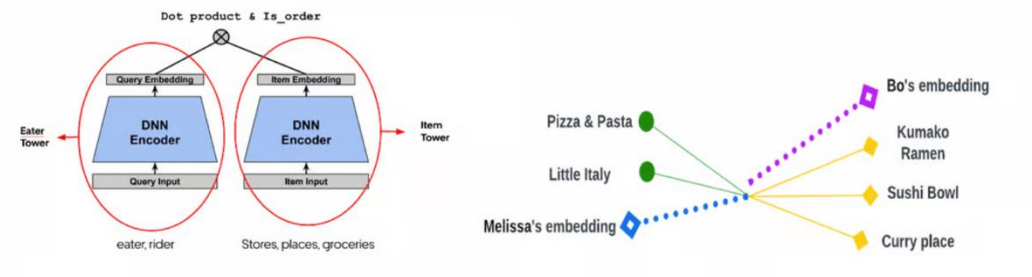


Figure 2: Left image shows the architecture of eater-item two tower embedding model; Right images shows how we can use the two tower embeddings to find the most relevant restaurants for eaters.

Query tower encodes search query and user profile to query embeddings (precomputed)

Item tower encodes restaurant, dishes, location
Probability of engagement is by dot-product [1]

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1. https://www.uber.com/blog/innovative-recommendation-applications-using-two-tower-embeddings

Motivation

The main Challenges:

- User–POI interaction matrices are extremely sparse because users typically visit only a small subset of available POIs. [e.g. NYC POIs list has over 1 Million POI IDs], With thousands of restaurants, a single user check in to less than 1% of them. The density in the NYC Foursquare next-POI transition tensor is on the order of 2.81×10^{-9} [1] .

- Failed to tackle cold start problem [3]: New Users, New POIs [Recently opened POIs have no check-in history, making them invisible to CF models]

- Inefficient to handle spatio-temporal dynamics with the sequential modelling of user check-ins, location proximity → temporal dynamics handled by sequential models like RNNs, transformers [4]

- POI choices depend in context (e.g. location, time of day, POI category, reviews, etc.] CF methods hard to detect if any changes in POI with similar check in sequence [2].

- Lack of Explainability with advanced methods of recommendations

[1] Li, Ranzhen, Yanyan Shen, and Yanmin Zhu. "Next point-of-interest recommendation with temporal and multi-level context attention." 2018 IEEE International Conference on Data Mining (ICDM). IEEE, 2018.
[2] Q. Zhang *et al.*, "A Survey on Point-of-Interest Recommendation: Models, Architectures, and Security," in *IEEE Transactions on Knowledge and Data Engineering*, vol. 37, no. 6, pp. 3153-3172, June 2025, doi: 10.1109/TKDE.2025.3551292.
[3] Natarajan, Senthilselvan, et al. "Resolving data sparsity and cold start problem in collaborative filtering recommender system using linked open data." Expert Systems with Applications 149 (2020): 113248.
[4] Yin, Feiyu, et al. "Next POI recommendation with dynamic graph and explicit dependency." Proceedings of the AAAI conference on artificial intelligence. Vol. 37. No. 4. 2023.

Datasets

- LOCATION BASED SOCIAL NETWORKS (LBSN): Generate vast amount of Spatio-temporal data through user check-ins

1. **FourSquare dataset** → NYC, Tokyo
2. **Gowalla dataset** → by Stanford → California
3. **Massive-STEPS** → hugging face → recent and massive collection from around world cities

+ META DATA from Yelp Reviews, SafeGraphs (POIs)
+ Pre-trained encoders

[1] FOURSQUARE [NYC, Tokyo] https://sites.google.com/site/yangdingqi/home/foursquare-dataset?pli=1

[2] GOWALLA https://snap.stanford.edu/data/loc-gowalla.html

[3] Massive-STEPS - https://huggingface.co/collections/CRUISEResearchGroup/massive-steps-point-of-interest-check-in-dataset

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Proposed Methodology

Inputs

- Check-in History
- Trajectories
- POI info
- Pretrained encoder of POI names

Representation Learning

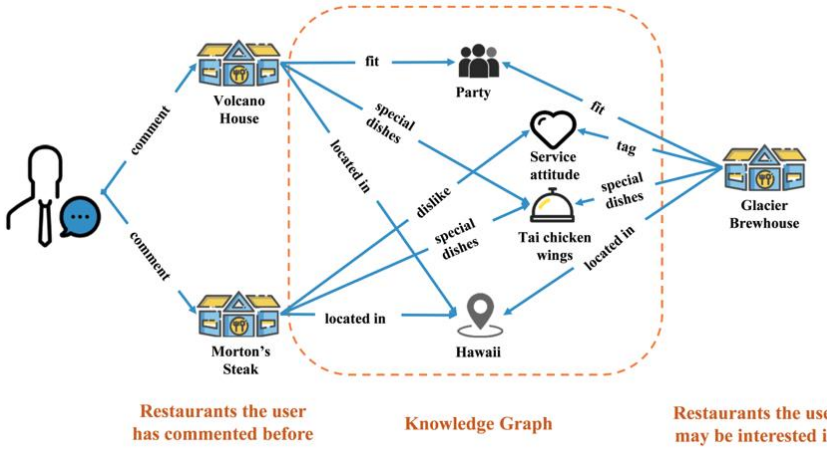
- Knowledge graphs
- Self-supervised learning
- Collaborative filtering

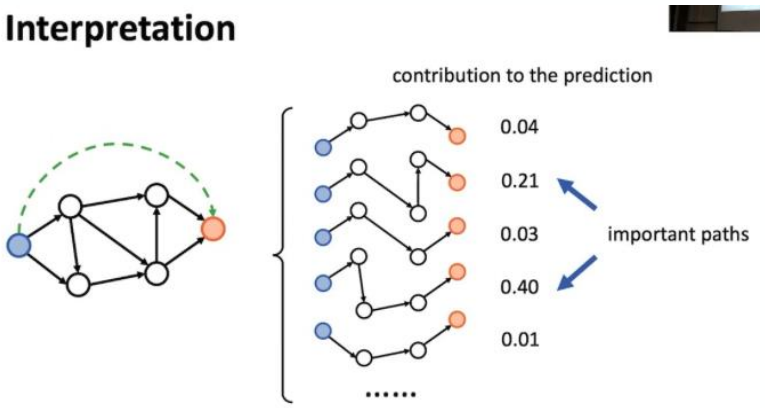
Recommendations

- Next POI prediction
- Spatio-temporal Rec
- [Ranking metrics]

Interpretation

- Hop reasoning path of KGs
- Probabilistic modelling of CF





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