Predicting Points of Interest in Dynamic Semantic Contexts Using Proximity Priors
Emily Li, Information Lab
Westridge School, Class of 2025
USC Viterbi Department of Computer Science, SHINE 2024

Introduction

The prediction results become suboptimal as semantic context changes, combining all contexts with a Transformer model. However, as semantic context changes, the prediction results become suboptimal.

Objective & Impacts

To counter the limitation, we proposed a mechanism to better account for changes in semantic information. Example: If a store closes, the model should reduce the times it predicts that store, and vice versa for when it first opens.

This enhanced POI prediction model can contribute to the following:
- smart and sustainable urban planning
- improved emergency responses with up-to-date information on active locations
- business growth with better-targeted marketing and operational strategies

Next Steps

Currently, the POI predictions are made from semantic context combined with a distance histogram to counter the changes in semantic information. However, human trajectories depend on more complex scenarios, like:
1. social change (i.e. befriending and unfriending)
2. transportation changes (i.e. ways of commute, which affect the distance the user would likely travel)

While continuing to improve the current model for semantic information changes, we plan to incorporate other dynamic features into the model, perhaps by implementing a graph neural network structure to model the social context.

Acknowledgements

I am very honored to be selected to work under Professor Cyrus Shahabi, and I am beyond grateful for my mentor Kate, who offered me so much help and guidelines for the research work!

Methods & Results

1. Review literature, including MobTCast [1], the SOTA:

2. Reproduce the MobTCast results on all POIs:

3. Identify changed semantic contexts, i.e. unseen POIs:

4. Design and implement an improved model:

5. Compare and analyze using a widely-used Foursquare NYC POI dataset [2] and the Top-k accuracy metric:

<table>
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<th>POIs</th>
<th>Method</th>
<th>Acc@1</th>
<th>Acc@5</th>
<th>Acc@10</th>
<th>Acc@20</th>
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<td>0.0964</td>
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</table>

Glossary

**Point of Interest (POI):** a specific, named location (e.g. USC bookstore)

**Semantic context:** the category of a POI (e.g. shop, school, restaurant, …)

References

