ECSE 552 Project Proposal
A Deep Learning Recommendation System for Sequential Data

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1 Background

A recommendation system is to analyze a user's prior history and interests and then predict items that may be interesting to him/her in the future. Sequential patterns in data play a significant role in how well a recommendation system performs. However, the struggle to uncover complex relationships in a user's history is still common.

[Yan et al., 2019] developed a sequential recommendation system for heterogeneous data. They use pair-wise encodings between items which are then fed to a 2D convolutional neural network to learn a representation. However, a strong limitation for this method is that even though they are using graph-based data, they do not fully utilize the graph's long-range interactions with their network.

Our aim is to work on the above-mentioned idea and fully utilize the graph-based data available. In terms of precision and recall, their highest reported results are 0.3308 and 0.1438, respectively. Therefore, we aim to develop a deep learning architecture that can outperform this method. We plan to use accuracy and F_1 Score among other metrics for this method for a better evaluation of the model.

2 Aim/Goals

- To develop a sequential recommendation system for heterogeneous graph-based data to recommend new items for users based on user attributes and interaction history.
- Consider the task as an edge-prediction task where nodes represent users and items and edges represent interaction with the addition of the items having a sequential order.
- Incorporate user, item and edge specific features such as ratings.

3 Methodology

To capture the graphical nature of the data, the main idea is to use a graph convolutional neural network (GCNN) [Defferrard et al., 2017]. The GCNN will learn a representation from the nodes and edges of the graph.

Alongside this, to capture the sequential nature of the items, an LSTM model [Yu et al., 2019] will be used. These two representations will then be concatenated together and passed to a feed-forward neural network for the final classification.

4 Datasets

We plan to use the same datasets as Yan et al. [2019] for the initial training and validation. The Movielens dataset [Harper and Konstan, 2015] comprises of data of users who have watched certain types of movies at specific times and leave ratings. The Gowalla dataset [Cho et al., 2011] is a location-based social networking dataset where users share their locations by checking in. After a thorough evaluation, we will incorporate different sequential datasets (temporal point dataset as an example) to further evaluate the performance of the model.

5 Potential pitfalls and risks

Some of the potential pitfalls/risks that we might face are simply the matters of over- and under-fitting. Cross-validation, regularization and hyper-parameter tuning are some of the techniques we plan to implement.

6 Group member roles

All the group members are expected to contribute to all the tasks. However, each member has been assigned a role that is his/her responsibility. Table 1 highlights the roles of each member.

Group Member	**Role**
Sohaib Jalali	Literature review
Yazdan Zinati	Data processing and deep learning architecture
Safyan Memon	Data processing and deep learning architecture
Mai Zeng	Data processing and deep learning architecture
William Ma	Model evaluation and report writing
Yuxiao Liu	Model evaluation and report writing

Table 1: The roles of each group member

References

An Yan, Shuo Cheng, Wang-Cheng Kang, Mengting Wan, and Julian McAuley. Cosrec: 2d convolutional neural networks for sequential recommendation, 2019.

Michaël Defferrard, Xavier Bresson, and Pierre Vandergheynst. Convolutional neural networks on graphs with fast localized spectral filtering, 2017.

Yong Yu, Xiaosheng Si, Changhua Hu, and Jianxun Zhang. A review of recurrent neural networks: Lstm cells and network architectures. *Neural computation*, 31(7):1235–1270, 2019.

F Maxwell Harper and Joseph A Konstan. The movielens datasets: History and context. *Acm transactions on interactive intelligent systems (tiis)*, 5(4):1–19, 2015.

Eunjoon Cho, Seth A Myers, and Jure Leskovec. Friendship and mobility: user movement in location-based social networks. In *Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1082–1090, 2011.