Recommendation System using Graph Neural Networks

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Introduction

- Recommendation systems are a vital tool to:
  - → Streamline user experience.
  - → Mitigate information overload by pinpointing areas of interest.
  - → Enhance customer satisfaction.
- Recommendation systems that leverage Graph Neural Networks (GNNs) expedite the aggregation process of macro (e.g., topological structure) and micro (e.g., node information) operations on graph-like data structures, therefore enhancing the overall information filtering capabilities.

Aims and objectives

Primary

- This research project aimed to develop, explore, and test a GNN framework for recommendation tasks by incorporating social information and item interactions.

Secondary

- Explore how relationships between the users and items can be mapped onto the Criminal Justice System (CJS). For example, the representation of the users as nodes in the social graph can be perceived as the defendant and lawyers, while the vertices connecting two nodes can be considered as the underlying relationship between the sentencing of another defendant accused of a similar act by the same judicial process. The objective is to develop a framework that highlights the bias of sentencing for different people from various socioeconomic backgrounds.

Background

Recommendation System

- A subclass of information filtering systems that provide suggestions for items that are most pertinent to a particular user.
- Capable of integrating multiple sources of attributes to increase precision of the recommendation such as user-to-user social network information and user-to-item interactions.

Graph Neural Networks (GNNs)

- Graphs are all around us; real world objects are often defined in terms of their connections to other things.
- Two main operations within a GNN:
  - → **Aggregation**: Enables the equal treatment of each neighbouring node with a mean-pooling operation or via an attention mechanism.
  - → **Update**: The aggregated neighbourhood is integrated into an updated representation of the current node.

Problem definition

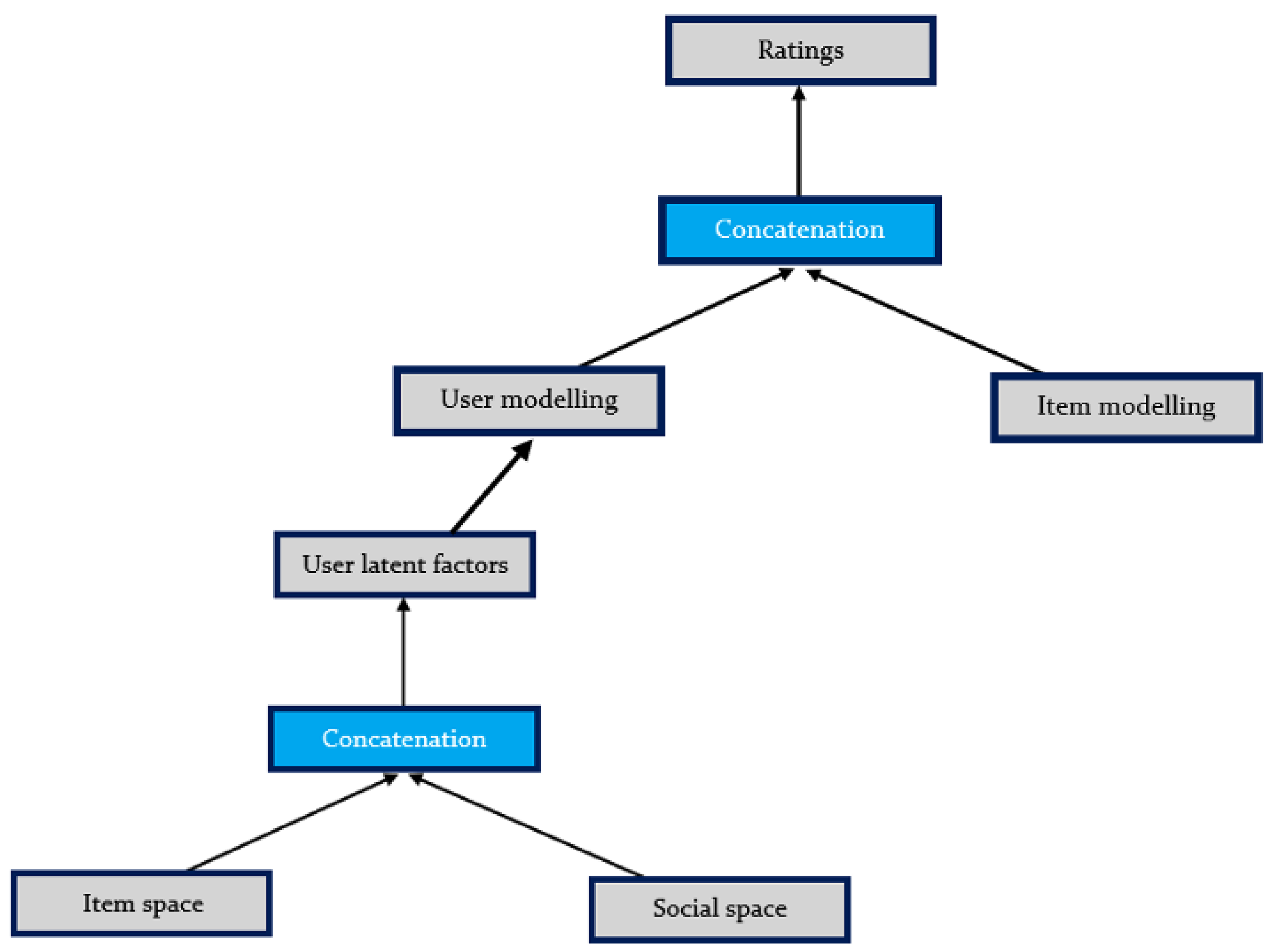

Fig. 1: Overview of the complete network

Consider a system comprised of sets of users $U = \{u_1, u_2, \ldots, u_n\}$ and items $V = \{v_1, v_2, \ldots, v_m\}$, where $\mathbf{R} \in \mathbb{R}^{n\times m}$ is the user-item graph represented as a rating matrix. Users can create social relations, where $\mathbf{T} \in \mathbb{R}^{n\times n}$ highlights the user-user social graph and is given a value of 0 or 1 dependent on if u_j has a relation to u_i. Therefore, in combination with a user-item graph $\mathbf{R}$ and $\mathbf{T}$, the aim of the project was to predict the missing value in $\mathbf{R}$.

Fan, W., Ma, Y., Li, Q., He, Y., Zhao, E., Tang, J. and Yin, D., 2019, May. Graph Neural Networks for Social Recommendation. *In The World Wide Web conference* (pp. 417-426).

Methodology

User modelling

Item space operation $\mathbf{h}_i^I$: Utilises the interactions between the users and items $C(i)$, and also the users preferences $\mathbf{x}_{ia}$ regarding an item:

$$\mathbf{h}_i^I = \sigma\left(\mathbf{W}\cdot A_{\text{item}}\left(\mathbf{x}_{ia}, \forall a \in C(i)\right) + \boldsymbol{b}\right) \quad (1)$$

Social space operation $\mathbf{h}_i^S$: To encode heterogeneous strengths of social relations $N(i)$, an attention mechanism is introduced:

$$\mathbf{h}_i^S = \sigma\left(\mathbf{W}\cdot A_{\text{neighbours}}\left(\mathbf{h}_o^I, \forall o \in N(i)\right) + \boldsymbol{b}\right) \quad (2)$$

Item modelling

For each item, the user's preferences are aggregated i.e., the mean of the ratings for all items ($R = r \in 1, 2, 3, 4, 5$), and using a Multi-Layer Perceptron (MLP), the two vectors holding information regarding plain user embedding and opinion embedding are concatenated:

$$\mathbf{z}_j = \sigma\left(\mathbf{W}\cdot A_{\text{users}}\left(\mathbf{f}_{jt}, \forall t \in B(j)\right) + \boldsymbol{b}\right) \quad (3)$$

Ratings

The rating predictions are gained by concatenating the latent factors from the user and item modelling, $\mathbf{h}_i \oplus \mathbf{z}_j$, and propagated forward to get the final rating predictions r'_{ij}.

Data and evaluation metrics

The data was sourced from prominent product review websites with the contents containing numerical information regarding the user and item ID with the rating given to a specific item by a user. Multiple users had given ratings for a specific item, thereby establishing the social relationship aspect that could be modelled.
The evaluation criteria included examining two negatively-oriented metrics to analyse the model's precision in measuring the likelihood of a user giving a certain rating for an item, where the lowest numerical value is taken as the most accurate.

Results

TABLE V
WEIGHTED AVERAGE OF MAE AND RMSE

Algorithm	Dataset	
	Ciao	Epinions
SoRec	0.925	1.115
SoReg	0.950	1.120
DeepSoR	0.940	0.990
GC-MC	0.945	1.040
X_a	0.985	1.000
X_b	0.885	1.000
X_c	0.945	0.945

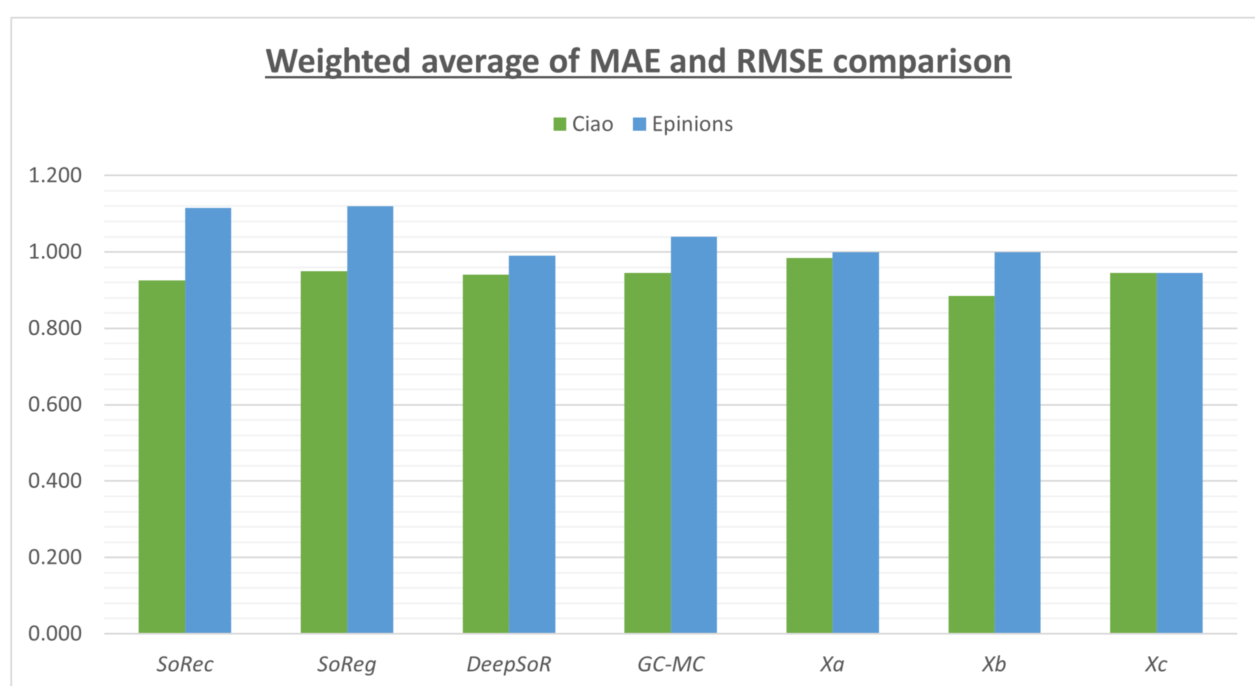

Fig. 3: Weighted averages of MAE and RMSE

Conclusion and further work

- Evaluation metrics shows a favourable framework with fluid mapping abilities.
- The results for model X_a serve as a clear indication of the importance of using item interaction information augmented with social network information to develop an accurate recommendation system.
- The study can be improved by introducing nodes that are representative of the judge, and vertices connecting to the lawyer and defendant node to analyse the bias in sentencing accurately.
- The modelling in this research serves as a simplification of a complex system with innumerable variables that are currently out of scope for autonomous frameworks. However, as a baseline study the research serves the purpose of bridging the gap between social justice and Artificial Intelligence.