Recommendation System using Graph Neural Networks

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Motivation

- Recommendation systems are a vital tool to:
  - → Streamline user experience.
  - → Mitigate information overload by pinpointing areas of interest.
  - → Enhance customer satisfaction.
- Recommendation systems that have been developed with Graph Neural Networks (GNNs) expedite the aggregation process of macro (e.g., topological structure) and micro (e.g., node information) operations, and therefore enhance the overall information filtering capabilities of the system.
- Interested in extrapolating the knowledge from this study to model relationships found in the Criminal Justice System (CJS) of the U.K.
- 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.

Introduction

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.

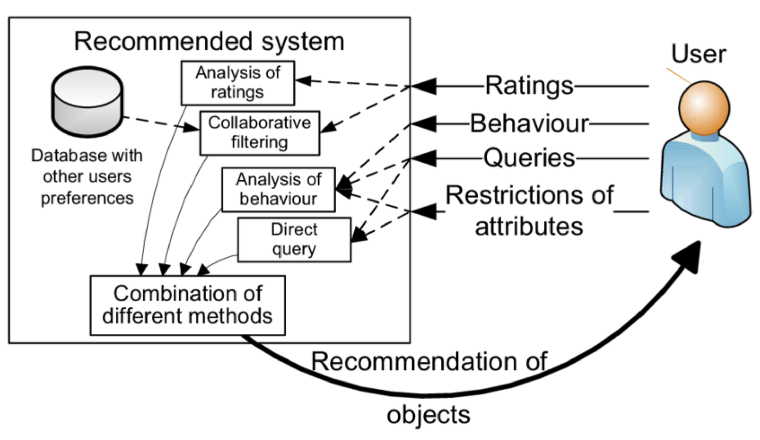

Fig. 1: Overview of a recommendation system

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.

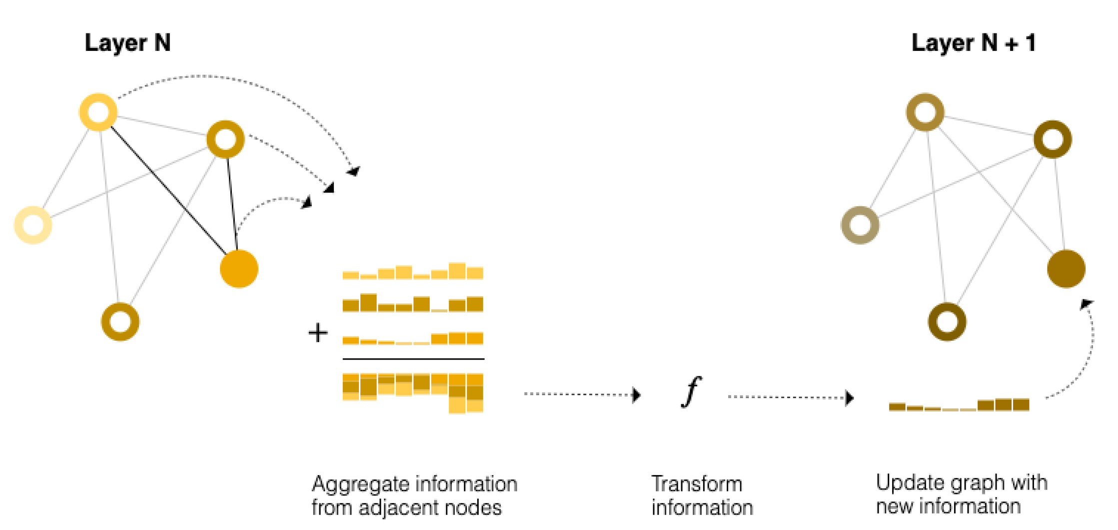

Fig. 2: GNN operations

Problem definition

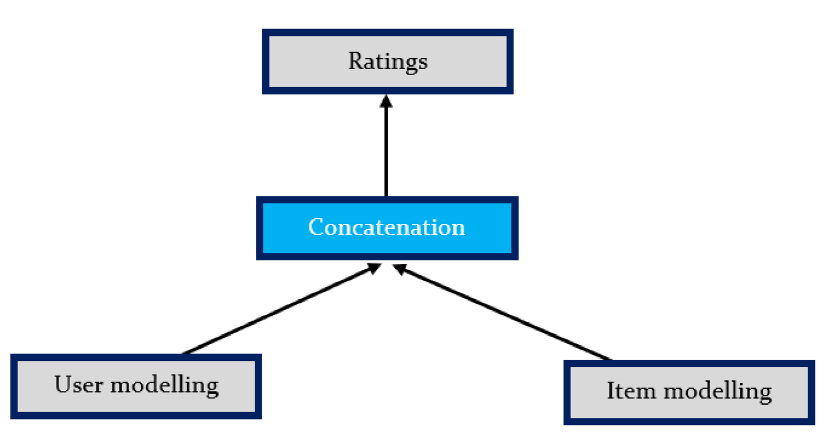

Fig. 3: GNN operations

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 is 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

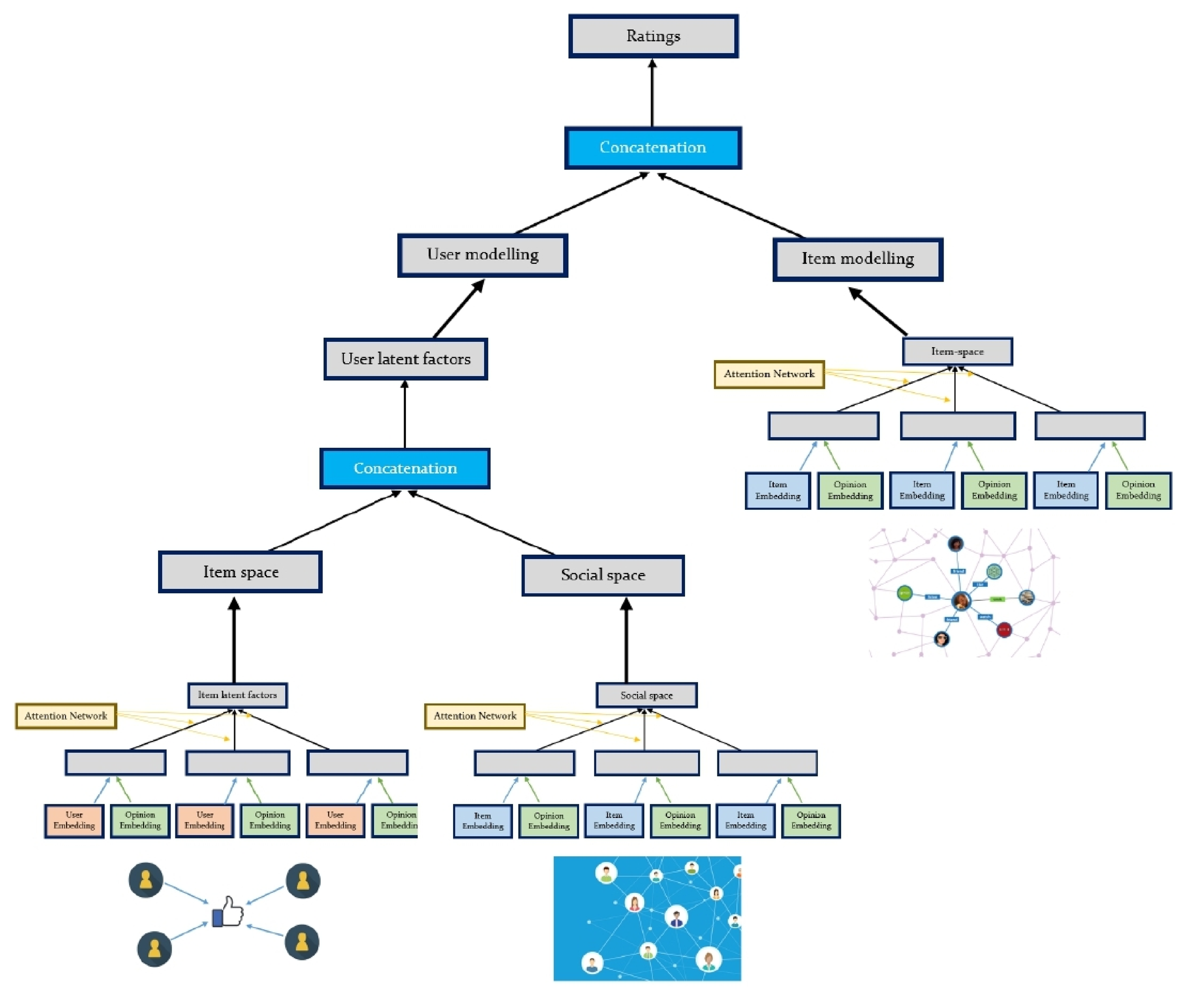

Fig. 4: Overview of the complete network

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:

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

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

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

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:

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

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}.

Results

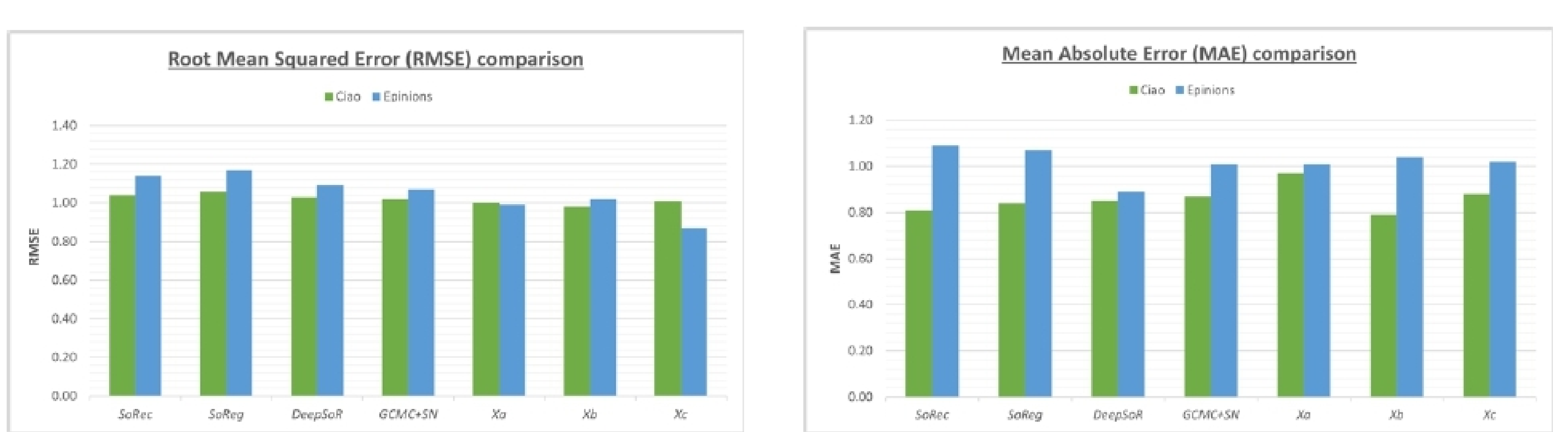

Fig. 5: Evaluation metrics

- Data:
  - → Two datasets from prominent product review websites were used: **Epinions** and **Caio**.
  - → The contents of the datasets contained several data points including *user* and *item ID* and 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.
- Examined two negatively-oriented metrics to analyse the likelihood of a user giving a certain rating for an item.
- Several neural networks connected in a modular framework to map user-to-user relationships and user-to-item interactions.

Conclusion

- Evaluation metrics shows a favourable framework with fluid mapping abilities.
- Clear indicator of the importance of using item interaction information augmented with social network information to develop an accurate recommendation system.