RATING PREDICTIONS USING GNN

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ABSTRACT

Graph Neural Networks, which can naturally integrate node information and topological structure, provide to be a great potential for social recommendation. Data in social recommender systems can be represented as user-user social graph and user-item graph. The aim is to provide ratings score from a user to an item with missing rating score. Working with graphs has few challenges, like combining user-user and user-item graph, capturing interactions and opinions between users and items jointly and considering heterogeneous strengths of social relations. The architecture tries to deal with these challenges. Have implement the code of the referenced paper from scratch, comparing results among using both attention (GAT) and without attention networks using Author's implementation. Will be using CIAO dataset that contains around 280k ratings of around 104k items by 7317 users.

***Index Terms*—** Social Recommendation, Graph Attention Networks, user-user social graph, user-item graph

1. INTRODUCTION

A graph data structure is proposed to work on social recommendations. Modelled both social and user-item data coherently, using different weight for different type of social relation and captured opinion as well as relation data between users and items. Few of the previous works on rating prediction on Social recommendataion include **SoRec**: here the authors performed co-factorization on the user-item rating matrix and user-user social relations matrix, **NeuMF**: matrix factorization model with neural network architecture and **DeepSoR**: employs a deep neural network to learn representations of each user from social relations and integrates them into probabilistic matrix factorization for rating prediction.

2. TECHNICAL DETAILS

The architecture is divided into 3 parts - User modelling, Item modelling and Rating prediction.

2.1. User Modelling

This is done to obtain latent vector representation of the user in context. Is divided into two sub graphs, the embeddings obtained through both graphs ${h_i}^I$ and ${h_i}^S$ are concatenated and fed into a MLP to obtain user latent vector h_i

2.1.1. *Item-Space*

Here item aggregation is done to capture the relation between the user of interest and all items that are related to this user. We first obtain an opinion-aware representation of the interaction between u_i (i^{th} user) and v_a (item) by by concatenating and sending them to a MLP to get x_{ia} x_{ia} is calculated for all a (items) that i^{th} user interacted with. Now GAT is applied on all such x_{ia} since different interactions will have different influences. Now we have obtained user-item embedding, h_i^I

$$\mathbf{h}_i^I = \sigma(\mathbf{W} \cdot \left\{ \sum_{a \in C(i)} \alpha_{ia} \mathbf{x}_{ia} \right\} + \mathbf{b})$$

$$\alpha_{ia} = \frac{exp(\alpha_{ia}^*)}{\sum_{a \in C(i)} exp(\alpha_{ia}^*)} \qquad \alpha_{ia}^* = \mathbf{w}_2^T \cdot \sigma(\mathbf{W}_1 \cdot [\mathbf{x}_{ia} \oplus \mathbf{p}_i] + \mathbf{b}_1) + b_2$$

Fig. 1. One of the possible configurations of Kuka robot corresponding to given (x,y) coordinates

2.1.2. *Social-Space*

Here Social aggregations are done. Item-space embeddings of all the users related to the i^{th} user are taken and GAT is applied, the same way as applied in section 2.1.1 to obtain h_i^S

2.2. Item Modelling

User Modelling is done to obtain latent vector representation of the item in context, to obtain z_j. Here we do user aggretions, to aggregate information from the set of users who have interacted with the item in context. Here also we obtain the opinion information by sensing item embedding and opinion embedding to the MLP. Again GAT is applied on opinion information by all users for v_j, the item of context to obtain z_j, item latent vector

2.3. Rating prediction

After obtaining user and item latent vectors from section 2.1 and 2.2, they are contatenated and fed into a MLP to obtain the predicted rating of j^{th} item by ith user

3. RESULTS

Have used RMSE loss and Adam optimizer for training. Ran the model for both GCN and GAT variant of the algorithm and observed the effects of using attention networks in the architecture. Obtained RMSE score of 5.209 without attention layer (GCN variant) and RMSE score of 4.934 with an attention layer on 20 epochs. Authors got RMSE score of 1.0093 using GATs in 100 epochs. Initialized random embeddings of 64 dimension size in the Embedding layer, with 60% of the data for training.

4. CONTRIBUTIONS

Implemented the architecture from scratch, moreover studied the effect of attention layer by obtaining the predictions with and without them in all graph networks.

5. REFERENCES

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