DREANRec: Deep Relation Enhanced Attention Networks for Social Recommendation

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I. Introduction

Nowadays, Recommender System (RS) has become increasingly popular and essential in daily life. Classic methods for Recommendation System include Collaborative Filtering(CF) and context-based approaches. However, existing approaches consider only the user's interests and the attributes of items, ignoring the user's social connections and the fact that social connections could influence the user's choices. This can cause the recommended results to have problems called filter bubbles.

In this paper, we propose **DREANRec**(Deep Relation Enhanced Attention Networks for Social Recommendation), a novel graph neural network, which effectively incorporates social information among users and considers the heterogeneous strength of social relations and latent item-item relations through the attention mechanism. Extensive experiments were implemented to prove the effectiveness of our approach.

II. The proposed model DREANRec

In this section, we briefly introduce our proposed model: Deep Relation Enhanced Graph Attention Networks for Social Recommendation Systems(DREANRec). In our model, we handle the two main parts in parallel, one of which is user modeling including business aggregation and social aggregation while the other one including user aggregation and relation aggregation.

We followed the main idea of the GraphRec [1], which used the GNN together with the masked-attention mechanism to model the user embedding and item embedding. However, it is not sufficient to consider social relations between users without the necessary information aggregation of items. Our model is a location-aware recommendation system model, which exploits the location relationships between items to model item representations. The architecture of our proposed model is shown in Figure 1. This model mainly has two parts: User Modeling and Item Modeling. User Modeling exploits item aggregation and social relation aggregation to model user embedding. Item Modeling leverages user aggregation information and item-item relations to model item embedding.

A. User Modeling

Mean operator is a very common and popular aggregation method, which considers the contribution of each node equal to each other. However, the importance of these nodes is not quite the same. In order to analyse the weight difference of the nodes, we used the masked attention mechanism introduced by [2].

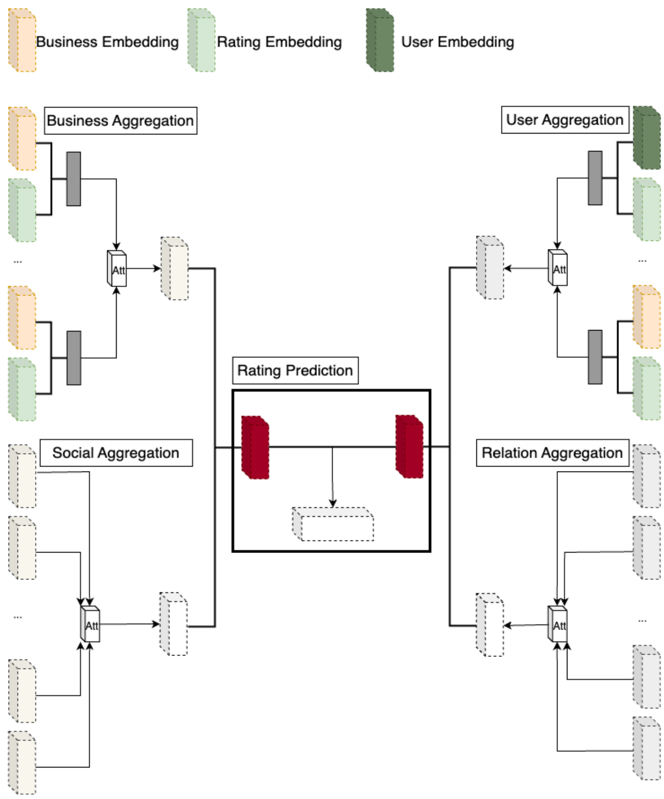

Fig. 1. Architecture of our proposed model

First, we concatenate the converted business embedding with their associated opinion embedding and then use an attention network to take this concatenation as the input to get the output latent user embedding.

Second, we feed the generated user embeddings into another attention network that aggregates the social relations of these users to get the latent social embedding.

Finally, we concatenate the latent user embedding with the latent social embedding to get the user vector as output.

The whole process can be presented as the following math equations:

$$Emb\ B_{i,j} = b_i \oplus r_{b_i,u_j} \tag{1}$$

$$s_j = Att(Emb\ B_{i,j}) \quad for\ all\ embeddings\ of\ user_j \tag{2}$$

$$S_j = Att(s_k) \quad for\ all\ users \tag{3}$$

where b_i denotes the converted embedding of the i^{th} business, r_{b_i,u_j} denotes the rating of i^{th} business given by $user_j$,$\oplus$ denotes the concatenation operation, s_j denotes the latent vector of $user_j$ after aggregating his/her rating towards each business, $S_j$denotes the latent user embedding after concatenating the user vector s_j and the social aggregated vector, $Att()$ denotes the masked-attention network.

B. Business modeling

We use a similar method in learning the user latent vector in user modeling to aggregate the item-to-item relation with its associated rating, which can be shown as the following equations:

$$Emb\ U_{i,j} = u_j \oplus r_{b_i,u_j} \tag{4}$$

$$t_r = Att(Emb\ U_{i,j}) \quad for\ all\ embeddings\ of\ business_i \tag{5}$$

$$T_r = Att(t_q) \quad for\ all\ businesses \tag{6}$$

where u_i denotes the converted embedding of the j^{th} user, r_{b_i,u_j} denotes the rating of i^{th} business given by $user_j$,$\oplus$ denotes the concatenation operation, t_r denotes the latent vector of $business_j$ after aggregating its rating from all users, $T_r$denotes the latent user embedding after concatenating the user vector s_j and the business aggregated vector.$Att()$ denotes the masked-attention network.

C. Rate Predicting

After getting the above aggregated latent vectors, we use a fully-connected feed-forward neural network with Softmax to get the final rating prediction:

$$\alpha_i = \frac{\exp(\alpha_i)}{\sum \exp(\alpha_i)} \tag{7}$$

III. Experiment

Dataset and Evaluation Metrics: In our experiments, we choose a representative real-life dataset of Yelp, which is a well-known location-based restaurant recommendation website. On Yelp, users also could make friends and comment on restaurants. The rating scale is from 1 to 5 and restaurants have the location attribute. In this paper, we use Yelp-CA which means all of the items' location is based in California. The statistics of the Yelp-CA dataset are shown in Table I. In order to evaluate the performance of our model, we use two widely used metrics, Mean Absolute Error(MAE) and Root Mean Square Error(RMSE). Smaller values of MAE and RMSE indicate better performance.

TABLE I
Statistic of the dataset

Dataset	Yelp-CA
Users	5945
Items	2491
Ratings	13980
Social Relation	37510
Rating Density	0.0943
Social Relation Density	0.1061

Effect of Attention Mechanisms: As a key component of our proposed model DREANRec, there are different attention mechanisms during user-item aggregation, item-user aggregation, user-user aggregation, and item-item aggregation. We show the result of an ablation experiment on attention mechanisms in Table II. We launched experiments with and without the attention mechanism, the result can be seen in table 2.

TABLE II
Result of the ablation experiment

Model	RMSE	MAE
DREANRec	0.5550	0.2961
DREANRec **w/o** $B2B\ Graph$	0.5702	0.3210
DREANRec **w/o** Attention	0.5732	0.4116

From the aforementioned tables, we can see that our method has reached a fairly low error. Compared with the model without the location information(the B2B Graph), the original model has a better performance, which shows the effectiveness of businesses' location information. Besides, the attention mechanism showed a strong positive influence on the whole model. Further study of the attention mechanism of our model can be seen in another paper [3].

IV. Conclusion and Future Work

We have presented a Graph Neural Network based model(DREANRec) for rating prediction. In our model, we proposed a method that considers both the social network of users and the latent relation between businesses. Besides, our experiment also shows a strong improvement with the attention mechanism in the aggregation step. Currently, we only consider simple information of the users and the businesses, in real-world recommendation, the user-user relations and the business-business relations can be much more complicated. Besides, users' opinions toward businesses are usually time-related, thus, constructing a dynamic graph will be a better approach to take users' changing opinions into consideration for better recommendation performance.

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References

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