Learning Social Influence from Network Structure for Recommender Systems

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Abstract. The purchase decision of users is influenced by their basic preference of items, as well as the social influence of peers. Most social recommendation methods focus on incorporating the semantic collaborative information of social friends. In this paper, we argue that the semantic strength of their friends is also influenced by the subnetwork structure of friendship groups, which had not been well addressed in social recommendation literature. We propose a deep adversarial social model (SoGAN) that can automatically integrate the subnetwork structure of social groups and their semantic information into a unified recommendation framework. Specifically, we first align users in two different views, i.e., the "social-friend" view and "co-purchase" view. Then a generative adversarial network is used to learn the structure information of social groups to enhance the performance of recommender systems. We utilize the structural similarity between two views to produce true samples in SoGAN, and generate the mimic data based on the similarity between the semantic representations of users in two views. By discriminating the true instances based on structure similarity, we naturally inject the structure information into semantic learning of users. Extensive experiments on three real-world datasets, show the superiority of incorporating the social structure impact in recommender systems.

Keywords: Social recommendation · Generative adversarial networks · Multi-view graph · Network structure

1 Introduction

The social activities among friends in recommender systems enhance the activeness and retention of users [6], and had attracted increasing attention in the research area [12,28]. The social recommendation aims to incorporate the collaborative influence from social friends, which had been proved to be effective

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in modeling users' preference of items, as well as improving the performance of recommendation systems. Most existing social recommendation methods mainly focus on incorporating the different semantic collaborative information of social friends in different ways. For example, SocialMF [15] integrates the influences of users' friends into the matrix factorization model, based on trust relationships between users. SocialReg [16] incorporates social information into recommender systems by regularizing users' latent factors with latent factors of their connected users, and they assume that similar users would share similar latent preferences. Recently, some deep neural networks based methods [8,12,27,28] mainly focus on learning the strength of social ties by assigning different attention weights or finding more reliable social friends by using generative adversarial neural networks. For example, the hand-craft structure properties, like motifs, had been used to select the reliable neighborhood information of a user to enhance social recommendation [27]. But few of them had addressed the structural collaborative information of social groups, as well as its impact on the social influence of users.

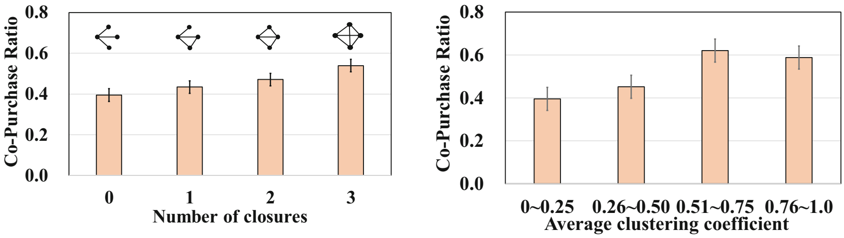

Fig. 1. The correlation between structure properties of social groups, i.e., triadic closure pattern and clustering coefficient, and their influence on user behavior, i.e., co-purchase of items.

In this paper, we argue that the semantic strength of their friends is also influenced by the subnetwork structure of friendship groups, which had not been well addressed in social recommendation literature. As shown in Fig. 1, we explore the subnetwork structure of social groups and their influence on a user's purchase behavior. We use two representative structure properties to characterize the structure of subnetwork, i.e., triadic closure pattern: the most basic unit of social network structure for studying group phenomena [14] and clustering coefficient: measuring how connected a vertex's neighbors are to one another, and use co-purchase ratio of items to represent the social influence of the friends on a user, that means the higher co-purchase ratio of items, the more influence of his friends. We can see that, there are some correlations between subnetwork structure and user's purchase behavior, for example, as the number of closures increases, the social influence will be higher, so is the clustering coefficient that is grouped by different threshold values (from 0–0.75).

However, the correlations are not consistent when measured by different structure properties, and the correlations within certain structure properties are also nonlinear, making it very difficult to find out the relevance between subnetwork structure of social groups and their social impact on users' interests. What's more, it is also impossible to enumerate all the hand-craft features to characterize subnetwork structure of friendship groups. In order to automatically learn the structure information of social groups, in this paper, we propose a deep adversarial social model (SoGAN) that can automatically integrate the subnetwork structure of social groups and their semantic collaborative information into a unified recommendation framework. As shown in Fig. 2, we decouple the different relationships into three views, "user-item" view (user-item relation), "co-purchase" view (user-user relation) and "social-friend" view (user-user relation). Different from other generative adversarial social recommendation models [25,27], we firstly select the useful social information in homogeneous "co-purchase" and "social-friend" views then integrate it into "user-item" view for the final prediction of user interests, which avoids the negative transfer of information across the heterogeneous views.

To make full use of the structure information, we align the users in "social-friend" view and "co-purchase" view. The more similar the subnetwork structures of the two views are, the more reasonable to believe that the different user groups in two views share the same purchase interests. We utilize the structural similarity between two user-user views to produce true instances in SoGAN, and generate the mimic data based on the similarity between the semantic representations of the two user groups. By forcing the semantic similarity of user representations to approach the inherent structure similarity, our model naturally injects the structure information into semantic representation learning of users. Finally, we update the representation of users in "user-item" view by incorporating the semantic information from both social-friends view and co-purchase view for the final prediction. Our contributions of this paper are summarized as follows:

- We propose a novel generative adversarial model SoGAN. By forcing the semantic similarity of user representation to approach the inherent structure similarity, SoGAN has the ability to take full use of the structure information of social groups and can automatically incorporate its impact into the collaborative social influence learning from other users.
- We decouple two types of relationships, user-item and user-user relations, into three different views. The useful social information of users is only selected in homogeneous "co-purchase" and "social-friend" views with user-user relation, and it is further integrated into heterogeneous "user-item" view for the final prediction of user interests, which avoids the negative transfer of information across the heterogeneous view.
- We conduct extensive experiments on three real-world datasets, showing the effectiveness of incorporating the social structure impact in social recommender systems.

2 Related Works

Our work is mostly related to social recommendation and adversarial learning. The related work is summarized as follows.

2.1 Social Recommendation

Traditional recommendation methods [17,18] use the basic interaction information of users and items, which suffer from the data sparsity problem. Leveraging social network information provides an effective approach to alleviate data sparsity and improve the model performance. The social information has been used in several studies [7,16]. For example, SocialMF [15] integrates the influences of users' friends into the matrix factorization model, based on trust relationships between users. SocialReg [16] incorporates social information into recommender systems by regularizing users' latent factors with latent factors of their connected users, and it assumes that similar users would share similar latent preferences. SBPR [29] assumes that users tend to assign higher ratings to the items which their friends prefer and incorporates this assumption into the pair-wise ranking loss. As friends at different degrees of closeness have different social influences, many methods also measure the strength of social ties. The attention mechanism is widely adopted in assigning different weights on the users' friends when modeling users' preferences in social recommendations [5,8].

Some graph-based recommendation models are proposed to capture the high order neighborhood relations [1,8,20,20,22,23]. For example, GraphRec [8] is a graph neural network based model for rating prediction in a social recommendation setting, and it aggregates representations for items and users from their connected neighbors. Diffnet [22] designs a layer-wise influence propagation structure to model how users' preferences evolve as the social influence propagates recursively. MHCN [28] is a social recommendation system based on hypergraph convolution to capture users' high-level information to improve recommendation performance. SEPT [26] argues that the supervision signals from other nodes are also likely to be beneficial to the representation learning, and proposes a general social perception self-supervision framework. Few of them had addressed the structural collaborative information of social groups, as well as its impact on the social influence of users.

2.2 Generative Adversarial Learning in RS

As the successful usages of generative adversarial networks (GAN) in many areas. Some GAN-based recommendation models have been proposed [2–4,19,21,30]. CFGAN [4] is a GAN-based collaborative filtering framework, in which the generator generates realistic purchase vectors instead of discrete item indexes for a given user. Instead of relying on a static and fixed rating score prediction function, an adversarial framework for collaborative ranking is proposed in [21] to approximate a continuous score function with pairwise comparisons. Some GAN-based models are proposed for social recommendation [9,13,25]. RSGAN [25] utilizes adversarial training to generate implicit friends, which are further used to generate social feedbacks to improve recommendation performance. DASO [9] proposes a deep adversarial social recommendation framework composed of two adversarial learning components in the social domain and item domain respectively, which adopts a bidirectional mapping method to transfer users' information between two domains. APR [13] adds perturbations to the latent factors of recommendation models as adversarial attacks, which enhances the performance and robustness of Bayesian personalized ranking.

3 Preliminary

3.1 Problem Statement

Assume we have a set of users and items, denoted by U and I respectively. $\mathbf{R} \in \mathbb{R}^{|U| \times |I|}$ is a binary adjacent matrix that records user-item interactions. If a user u consumed/clicked an item i, $r_{ui} = 1$, otherwise $r_{ui} = 0$. In social recommendation scenario, the behavior of a user is also influenced by their friends. We define the users who produce social influence on a user u as S_u and use $\mathbf{R}_S \in \mathbb{R}^{|U| \times |U|}$ to denote the social adjacency matrix, which is binary and symmetric because we work on undirected social networks.

Given the purchase history I^u of a user u and his/her social connected peers S_u, the recommender system aims to predict the interests of user u in the next purchase, defined as:

$$P(i^u_{next}) = \mathcal{F}(i \in I | u, I^u, S_u), \tag{1}$$

where $P(i^u_{next})$ is the probability of item $i \in I$ being purchased by user u at the next time, and $\mathcal{F}$ is the prediction function. The prediction problem can also be formulated as a ranking problem so that the top K items to user u are recommended.

3.2 Construction of Multi-views

To avoid the negative transfer of information across the heterogeneous views, we decoupling the different relationships into three views, "user-item" view (user-item relation), "co-purchase" view (user-user relation) and "social-friend" view (user-user relation). Different views are aligned by the users that appear in the views at the same time. We firstly select the useful social information in homogeneous "co-purchase" and "social-friend" views, then integrate it into "user-item" view for the final prediction of user interests. The details are as follows:

- User-item view: consists of the interacted user and item nodes, as well as the edges of their interaction relations.
- Co-purchase view: the edge in co-purchase view is built between two users if they had purchased the same items. It intuitively reflects the same purchasing habit between users [6]. Considering the strength of co-purchase relation is

low and may introduce noise to the social impact learning, we filter the edges between two users by adding the restriction of social-friend relations. The adjacency matrix in co-purchase view is $\mathbf{M}_C = (\mathbf{R} \cdot \mathbf{R}^T) \odot \mathbf{R}_S$, where $\mathbf{R}$ and $\mathbf{R}_S$ are the adjacency matrix of user-item interaction and user-user social relationship, $\odot$ is the Hadamard product.

– Social-friend view: the edge in social-friend view is constructed according to the social friendship relations. Considering some friends may establish relationships occasionally [24,27], and it will not play a positive role in the modeling of users' social information. According to the stability of relationship mentioned in [14,26]: the structure of friendships in ternary closures is stable, we keep the edges with ternary closure social structure in social-friend view. The adjacency matrix of social-friend view $\mathbf{M}_S$ is computed as $\mathbf{M}_S = (\mathbf{R}_S \cdot \mathbf{R}_S) \odot \mathbf{R}_S$.

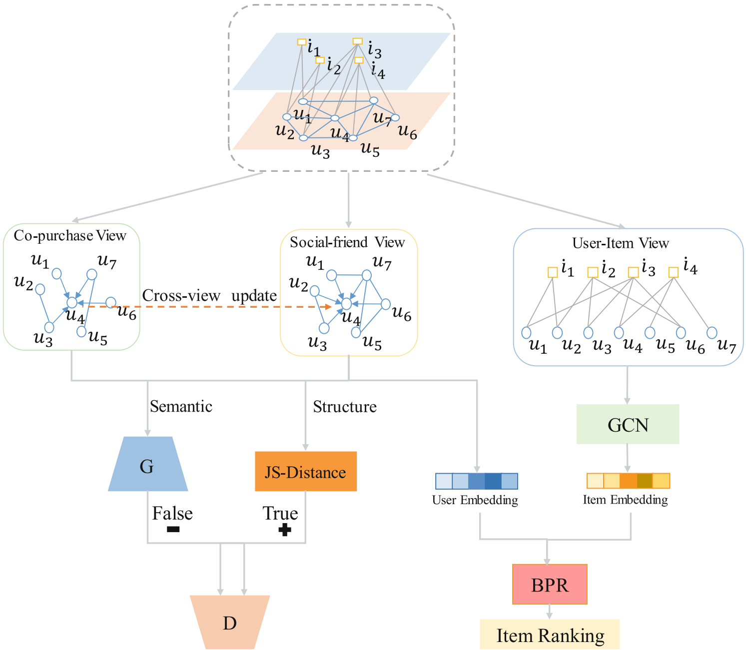

Fig. 2. The architecture of SoGAN model, including network structure learning component and item prediction component. The network structure is learned by generative adversarial networks, in which the mimic data is generated by computing the similarity between semantic representations of user in different views, while the true instance is computed based on the structure similarity of social groups. We update the representation of u_4 in "user-item" view by incorporating the semantic information from both "social-friend" views and "co-purchase" view for the final item prediction.

4 Our Proposed Model

The overview of our proposed model SoGAN is illustrated in Fig. 2. SoGAN is consist of two components, the subnetwork structure learning component by generative adversarial networks (GAN) and the prediction component for item ranking.

4.1 Network Structure Learning Component

The more similar the subnetwork structures of the two views are, the more reasonable to believe that the different user groups in two views share the similar user representations. We utilize the structural similarity between two user-user views to produce true instances and generate the mimic data based on the similarity between the semantic representations. By forcing the semantic similarity of user representation to approach the inherent structure similarity, our model naturally injects the structure information into semantic representation learning of the user.

True Instances from Structure Similarity. We generate the true training instances by computing the structure similarity of social groups in co-purchase and social-friend views. Given co-purchase view C and social-friend view S, for a user u_a, we calculate the normalized probability of his neighbors u_b according to the adjacency matrix $\mathbf{M}_C$ in co-purchase view.

$$p(u_b|u_a, \mathbf{M}_C) = \frac{\mathbf{M}_C(u_a, u_b)}{\sum_{u_k \in U} \mathbf{M}_C(u_a, u_k)}. \tag{2}$$

We formula the topological structure of user u_a as a vector $\mathbf{t}(u_a, C)$ by concatenating the normalized probability of all other users in view C, as follows:

$$\mathbf{t}(u_a, C) = p(u_1|u_a, \mathbf{M}_C) \oplus p(u_2|u_a, \mathbf{M}_C), ..., \oplus p(u_{|U|}|u_a, \mathbf{M}_C). \tag{3}$$

For the social-friend view S, we can obtain the topological structure $\mathbf{t}(u_a, S)$ of user u_a by the same way as in view C.

Then the locally topological structural similarity of user u_a between views C and S can be calculated by the Jensen-Shannon distance between $\mathbf{t}(u_a, C)$ and $\mathbf{t}(u_a, S)$ as:

$$D_{JS}(\mathbf{t}(u_a, C)||\mathbf{t}(u_a, S)) = \frac{1}{2}[D_{KL}(\mathbf{t}(u_a, C)||M) + D_{KL}(\mathbf{t}(u_a, S)||M)], \tag{4}$$

where $M = \frac{\mathbf{t}(u_a,C)+\mathbf{t}(u_a,S)}{2}$, and D_{KL} denotes the Kullback-Leibler divergence:

$$D_{KL}(P||Q) = \sum_x P(x) log \frac{P(x)}{Q(x)}. \tag{5}$$

Given a user u_a, we get the structure similarity of two views C and S by :

$$S_{structure}(C, S|u_a) = 1 - D_{JS}(\mathbf{t}(u_a, C)||\mathbf{t}(u_a, S)). \tag{6}$$

Finally, given a user u_a and a specific view C, we can estimate the true instance $P_{true}(S|C, u_a)$ for discriminator according to:

$$P_{true}(S|C, u_a) = \frac{S_{structure}(S, C|u_a)}{\sum_{r\in\{C,S\}} S_{structure}(r, C, u_a)}. \tag{7}$$

Mimic Instances Based on Semantic Similarity. The mimic data is generated based on the similarity between the semantic representations of a user in two views. Given a specific view C, we use graph neural networks [11] to capture the semantic information of user u_a by aggregating the neighborhood information in the view, termed as "inner-view aggregation", formulated as:

$$\mathbf{v}^k_{u_a,C} = \text{aggregation}(\mathbf{v}^{k-1}_{u_b,C}|u_b \in \mathcal{N}_{u_a,C}), \tag{8}$$

where $N_{u_a,C}$ is the set of neighbors (include user u_a, i.e., self-loop) associated with user u_a in view C, and k is a hyper parameter to represent the depth for inner-view aggregation.

Following GraphSAGE [11], the aggregation operation can have many forms, we use mean aggregator, formulated as:

$$\mathbf{v}^k_{u_a,C} = \sigma(\mathbf{W}^k_C \cdot \text{mean}(\mathbf{v}^{k-1}_{u_b,C}|u_b \in \mathcal{N}_{u_a,C})), \tag{9}$$

where $\sigma(x) = \frac{1}{1+exp(-x)}$ is the sigmoid activation function.

The semantic representation of user u_a in the social-friend view can be computed by the same way. Given the semantic vectors $\mathbf{v}^k_{u_a,C}$ and $\mathbf{v}^k_{u_a,S}$ in co-purchase view and social-friend view respectively, we compute the semantic similarity of u_a in two views as:

$$S_{semantic}(C, S|u_a) = \cos\left\langle \mathbf{v}^k_{u_a,C}, \mathbf{v}^k_{u_a,S} \right\rangle. \tag{10}$$

The mimic data generated based on the semantic similarity of user in two views is:

$$\mathcal{G}(S|C, u_a) = \frac{\exp(S_{semantic}(S, C|u_a))}{\sum_{r\in\{C,S\}} \exp(S_{semantic}(r, C, u_a))}, \tag{11}$$

where exp is the exponential function to make the similarity value be positive.

Based on the semantic similarity of two views, we update the representation of user u_a in co-purchase view C (same for u_a in social-friend view S) by incorporating the information from other view, termed as "cross-view aggregation", defined as:

$$\mathbf{v}^k_{u_a,C} = \mathbf{v}^k_{u_a,C} + \mathcal{G}(S|C, u_a) \cdot \mathbf{v}^k_{u_a,S}. \tag{12}$$

4.2 The Generative and Adversarial Process

We have generated the true and mimic data based on the structure and semantic similarity respectively. By discriminating the true and mimic data, our model will force the semantic similarity of user representations to approach the inherent structure similarity, so as to inject the structure information into semantic representation learning of users. The discriminator is defined as:

$$\mathcal{D}(u;\theta_{\mathcal{D}}) = \sigma(\mathbf{W}_{\mathcal{D}} \cdot \mathbf{e}_u + \mathbf{b}), \tag{13}$$

where $\theta_{\mathcal{D}}$ is the parameters optimized in discriminator, $\mathbf{e}_u$ is the input data from structure similarity or semantic similarity, and $\mathbf{W}_{\mathcal{D}}$ and $\mathbf{b}$ are the translation matrix and bias vector.

Following the optimization of GAN [10], we maximize the output log-probability when the similarity is computed by sub-structure of social group (see Eq. 7), and minimize the output log-probability when the similarity is computed based on the semantic representations of user in two views (see Eq. 11). The parameters are optimized by:

$$\begin{aligned}\min_{\mathcal{G}} \max_{\mathcal{D}} V(\mathcal{G},\mathcal{D}) = \sum_{u_a \in U} \{ & \mathbb{E}_{X \sim P_{true}(S|C,u_a)}[log\mathcal{D}(X;\theta_{\mathcal{D}})] \\ & + \mathbb{E}_{Z \sim \mathcal{G}(S|C,u_a)}[log(1-\mathcal{D}(Z;\theta_{\mathcal{D}}))]\} .\end{aligned} \tag{14}$$

4.3 The Optimized Loss Function

We update the representation of users in user-item view by incorporating the semantic information from both social-friend view and co-purchase view for the final prediction, formulated as:

$$\mathbf{v}_{u_a,P} = \mathbf{v}_{u_a}^{P} + \mathbf{W}_C \cdot \mathbf{v}_{u_a,C} + \mathbf{W}_S \cdot \mathbf{v}_{u_a,S}, \tag{15}$$

where $\mathbf{v}_{u_a}^{P}$ is the user representation generated by GCN in user-item view. $\mathbf{v}_{u_a,C}$ and $\mathbf{v}_{u_a,S}$ are the user representations in the generator of GAN in co-purchase view and social-friend view.

The generator of GAN is optimized by:

$$\mathcal{L}_1 = \mathbb{E}_{Z \sim \mathcal{G}(S|C,u_a)}[log(1-\mathcal{D}(Z;\theta_{\mathcal{D}}))]]. \tag{16}$$

Given a user u and item i, the predicted interaction value r_{ui} is defined as:

$$\hat{r}_{ui} = \mathbf{v}_{u_a,P} \cdot \mathbf{v}_i, \tag{17}$$

where $\mathbf{v}_i$ is the learned vector of item i.

We use Bayesian Personalized Ranking (BPR) loss [17] to optimize our model, defined as:

$$\mathcal{L}_2 = \sum_{i,j \in I^a, u \in U} -log\sigma(\hat{r}_{ui} - \hat{r}_{uj}). \tag{18}$$

Finally, we integrate the GAN training loss function Eq. (16) and BPR loss Eq. (18) by weight β as the final optimization function:

$$\mathcal{L} = \beta\mathcal{L}_1 + \mathcal{L}_2. \tag{19}$$

The training process of our model is summarized in Algorithm 1.

Algorithm 1: SoGAN Algorithm

Input: User-Item interactions $(U, I, \mathbf{R})$, Social relations $\mathbf{S}$.

```
Initialize all parameters for 𝒢 and 𝒟
Sample true training instances by Eq. (7)
while not converge do
    for Generator_steps do
        Generate the similarity of views for each user a in view C by Eq. (11)
        Incorporate the information from generated view by Eq. (12)
        Update 𝒢 by minimizing Eq. (19)
    for Discriminator_steps do
        Sample true similarity based on structure for each user a in view C by Eq. (7)
        Generate the mimic similarity for each user a in view C by Eq. (11)
        Update 𝒟 by maximizing the discriminator in Eq. (14)
return the representations of user and item in Eq.(15)
```

5 Experiments

5.1 Experimental Settings

Datasets. We experiment with three representative real-world datasets Ciao,[1] Douban Book[2] and Yelp.[3] Ciao is a review website where users give ratings and opinions on various products, and have trust relationships with other users. Douban is a popular site on which users can review movies, music, and books. Yelp comes from the Yelp challenge 2019. It contains users' reviews and check-in information of restaurants, businesses and so on. All the datasets contain both the user-item interactions and the user-user social relations, such as trust and following. Table 1 summarizes the statistics of the datasets.

Baseline Methods. The primary goal of our work is to employ the user's local structure information in different views to improve the accuracy of recommendation. We compare our model with the state-of-the-art baseline methods including MF-based, GAN-based, and GCN-based methods. The detailed introduction of the baselines are as follows:

[1] https://www.librec.net/datasets.html.
[2] https://www.dropbox.com/s/u2ejjezjk08lz1o/Douban.tar.gz?dl=0.
[3] https://www.yelp.com/dataset/challenge.

Table 1. Statistics of the datasets.

Datasets	Ciao	Douban Book	Yelp
# Users	3,787	23,585	84,528
# Items	16,121	23,386	44,691
# Interactions	35,310	809,697	1,018,438
# Social Links	9,215	22,863	7,766

- **BPR** [17]: It only uses the user-item interaction information. It optimizes the matrix factorization model with a pairwise ranking loss. This is a state-of-the-art model for traditional item recommendation.
- **SBPR** [29]: It's a social Bayesian ranking model that considers social relationships in the learning process. It assumes that users tend to assign higher ranks to items that their friends prefer.
- **SocialReg** [16]: It's a typical social-based model that regularizes and weighs friends' latent factors with social network information.
- **SoicalMF** [15]: It's a social-based model by reformulating the contributions of trusted users to the information of activating user's user-specific vector.
- **IRGAN** [19]: It's a GAN-based framework that unifies the generative and discriminative information retrieval models. It's a pioneering method that demonstrates the potential of GAN in information matching.
- **CFGAN** [4]: It's a GAN-based collaborative filtering framework, in which the generator generates realistic purchase vectors instead of discrete item indexes for a given user.
- **RSGAN** [25]: It's a state-of-the-art GAN-based social recommendation framework, where the generator generates reliable implicit friends for each user and the discriminator ranks items according to each user's own preference and her generated friends' preference.
- **Diffnet** [22]: It models the recursive dynamic social diffusion in social recommendation with a layer-wise propagation structure.
- **LightGCN** [12]: It is a graph-based model, consisted of two basic components: light graph convolution and layer combination for recommendation.
- **MHCN** [28]: It proposes a multi-channel hypergraph convolutional network, which works on multiple motif-induced hypergraphs integrating self-supervised learning into the training to improve social recommendation.
- **SEPT** [26]: It's a socially-aware self-supervised tri-training framework to improve recommendation by discovering self-supervision signals from two complementary views of the raw data.

Evaluation Metrics. Given a user, we infer the item that the user will interact with. Each candidate method will produce an ordered list of items for the recommendation. We adopt two widely used ranking-based metrics to evaluate the performance: Hit ratio at rank k (Hit Ratio@k) and Normalized Discounted Cumulative Gain at rank k (NDCG@k). We report the top K ($K = 5$ and $K = 10$) items in the ranking list as the recommended set.

Parameter Settings. We use different settings on validation data to obtain the best results. For the embedding size, we test the values of $[8, 16, 32, 64, 128, 256]$. The batch size and learning rate are searched in $[32, 64, 128, 256, 512]$ and $[0.001, 0.005, 0.01, 0.05, 0.1]$, respectively. The parameters for the baselines algorithms are carefully tuned to achieve optimal performance. We use Adam for optimization. The depth k for inner-view aggregation in set to 1 for model efficiency. The embedding size is set to $\{32, 64, 128, 256\}$ for the three datasets, respectively. The learning rate is set to $\{0.0001, 0.0005, 0.0005, 0.001\}$. We stop training if the evaluation metrics on the validation set decreased for 10 successive epochs. The dropout is set to 0.5 to avoid overfitting. The weight β is set to 0.5 in Eq. (19).

Table 2. Performance comparison of SoGAN and other methods.

Dataset	Ciao				Douban Book				Yelp			
Metric	H@5	H@10	N@5	N@10	H@5	H@10	N@5	N@10	H@5	H@10	N@5	N@10
BPR	0.219	0.329	0.145	0.180	0.418	0.541	0.306	0.346	0.572	0.741	0.405	0.460
SBPR	0.241	0.359	0.157	0.192	0.443	0.562	0.332	0.370	0.609	0.772	0.437	0.491
SocialReg	0.240	0.356	0.157	0.195	0.431	0.561	0.336	0.374	0.604	0.772	0.438	0.492
SocialMF	0.241	0.356	0.157	0.194	0.431	0.562	0.335	0.374	0.601	0.771	0.435	0.490
IRGAN	0.245	0.363	0.161	0.196	0.459	0.565	0.337	0.375	0.615	0.774	0.445	0.503
CFGAN	0.247	0.368	0.167	0.203	0.464	0.579	0.345	0.380	0.629	0.778	0.451	0.516
RSGAN	0.252	0.372	0.169	0.208	0.478	0.588	0.359	0.395	0.638	0.791	0.463	0.522
Diffnet	0.255	0.373	0.163	0.201	0.460	0.583	0.343	0.382	0.642	0.791	0.472	0.521
LightGCN	0.247	0.373	0.167	0.207	0.480	0.596	0.360	0.398	0.634	0.780	0.468	0.516
MHCN	0.242	0.360	0.163	0.201	0.482	<u>0.604</u>	0.361	0.400	<u>0.674</u>	<u>0.818</u>	<u>0.502</u>	<u>0.549</u>
SEPT	<u>0.251</u>	<u>0.381</u>	<u>0.170</u>	<u>0.212</u>	<u>0.486</u>	0.603	<u>0.367</u>	<u>0.405</u>	0.671	0.816	0.497	0.544
SoGAN	**0.294**	**0.432**	**0.199**	**0.244**	**0.665**	**0.781**	**0.517**	**0.554**	**0.717**	**0.853**	**0.544**	**0.597**
Gain[%]	16.83↑	13.38↑	17.06↑	15.09↑	36.81↑	29.49↑	40.58 ↑	36.74↑	6.87↑	4.52↑	9.41↑	9.59↑

5.2 Main Results

The performance of different models is shown in Table 2. We can see that:

(1) Our proposed model SoGAN outperforms all the baselines, including MF-based, GAN-based, or GCN-based models. This indicates that the local structure information of social groups plays an important role in improving the accuracy of the recommender systems, and our model can effectively learn the network structure information of social groups.
(2) GCN-based and GAN-based models perform better than MF-Based methods. The collaborative social information can be well captured by aggregating the information from neighbors in graph neural networks. SEPT and MHCN achieve the best performance in all the GCN-based baselines. The self-supervised signals in SEPT and MHCN are used to learn information from different views of the original data, which improves the model performance.
(3) GAN-based models perform better than MF-Based models, i.e., the GAN-based social method RSGAN achieves better performance than SocialReg and SBPR. IRGAN and CFGAN have comparable results and outperform

the classical method BPR. This indicates the usefulness of using generative adversarial training process in social recommender systems.

(4) The models that leverage social relations perform much better than the general models, i.e., SocialReg and SBPR outperform BPR, RSGAN outperforms IRGAN and CFGAN, SEPT and MHCN outperform LightGCN. This shows that the social information can be well utilized to improve the model performance.

5.3 Experimental Analysis

The Effectiveness of Generative Adversarial Learning. We verify the effectiveness of generative adversarial learning and evaluate its ability to distinguish the complementary information from social structure. We remove the GAN training process, and the variant model is termed as "SoGAN(-GAN)", in which the semantic information of users in two views is obtained by simply aggregating their neighborhood information and optimized by Eq. (18). The comparisons of SoGAN and its variant model SoGAN(-GAN) are shown in Fig. 3. We can see that: by using generative adversarial training process, our model can learn from the local structure information of social groups. Such structure information is useful to enhance the performance of social recommender systems.

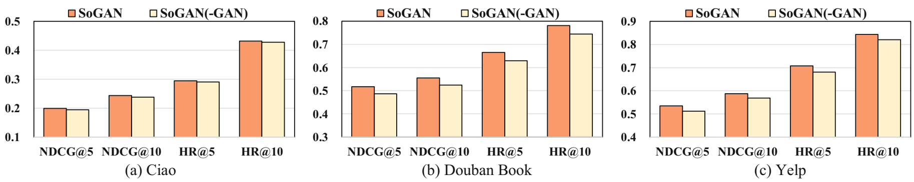

Fig. 3. The effectiveness of generative adversarial learning.

The Effectiveness of Inner-view and Cross-view Aggregation. Two aggregation methods are used in SoGAN: inner-view aggregation (see Eq. 8) and cross-view aggregation (see Eq. 12). To better understand and verify the effect of each aggregation operation, we make ablation analysises by removing one of the aggregation operation from our model. The comparisons of SoGAN with two degenerated variants: SoGAN(-Inner) and SoGAN(-Cross), by removing inner-view aggregation and cross-view updating respectively, are shown in Fig. 4. We can see that: SoGAN(-Inner) and SoGAN(-Cross) perform worse than SoGAN, indicating that the collaborative neighborhood information in the view itself (captured by inner-view aggregation) and complementary collaborative information from another view (learned by cross-view updating) are both critical for learning a better user representation. The complementary information from other view is incorporated based on the structural similarity of two views, showing the usefulness of using the network structure information of social groups.

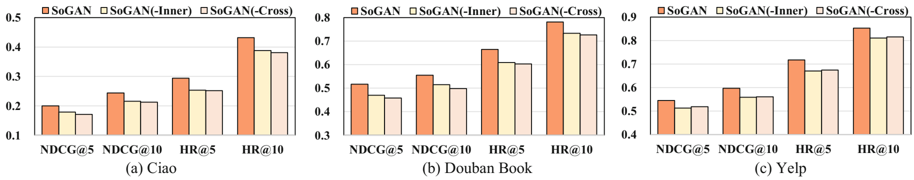

Fig. 4. The usefulness of inner-view and cross-view aggregations.

Model Convergence. The GAN framework encounters the problem of slow model convergence and long training time during the training process, especially when it is applied to the model with discrete data sampling. We show the learning curves of NDCG@10 and HR@10 about each GAN-based model and our model on datasets Ciao in Fig. 5, from which we can see that our model converges faster than other GAN-based models, and can gain superior experimental results. The results are consistent in other datasets with larger data amount, showing that our model can achieve better recommendation performance, and require less time for model training.

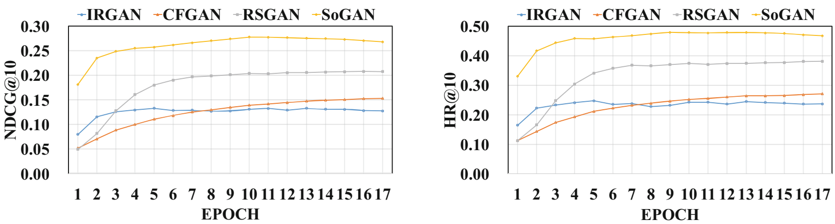

Fig. 5. The convergence curve of the GAN-based models on Ciao.

6 Conclusion

In this paper, we verify that the influence of social friends for a user is also influenced by the subnetwork structure of friendship groups. We propose a deep generative adversarial model SoGAN to learn the structural information of users from different views, and integrate the subnetwork structure of social groups and their semantic collaborative information into a unified recommendation framework. By learning the social influence from the network structure, our model achieves a better performance in social recommendation task.

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