

Enhance Social Recommendation with Adversarial Graph Convolutional Networks

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Abstract—Recent reports from industry show that social recommender systems consistently fail in practice. According to the negative findings, the failure is attributed to: (1) a majority of users only have a very limited number of neighbors in social networks and can hardly benefit from relations; (2) social relations are noisy but they are often indiscriminately used; (3) social relations are assumed to be universally applicable to multiple scenarios while they are actually multi-faceted and show heterogeneous strengths in different scenarios. Most existing social recommendation models only consider the homophily in social networks and neglect these drawbacks. In this paper we propose a deep adversarial framework based on graph convolutional networks (GCN) to address these problems. Concretely, for the relation sparsity and noises problems, a GCN-based autoencoder is developed to augment the relation data by encoding high-order and complex connectivity patterns, and meanwhile is optimized subject to the constraint of reconstructing the original social profile to guarantee the validity of new identified neighborhood. After obtaining enough purified social relations for each user, a GCN-based attentive social recommendation module is designed to capture the heterogeneous strengths of social relations. These designs deal with the three problems faced by social recommender systems respectively. Finally, we adopt adversarial training to unify and intensify all components by playing a minimax game and ensure a coordinated effort to enhance social recommendation. Experimental results on multiple open datasets demonstrate the superiority of our framework and the ablation study confirms the importance and effectiveness of each component.

Index Terms—recommender systems, social recommendation, adversarial training, graph neural networks.

1 INTRODUCTION

RECOMMENDER systems are often compromised by the sparsity of data as users can only consume a tiny fraction of items, which leads to a frustrating result that in many cases recommender systems fail to fulfill their intrinsic capacity. With the popularity of social platforms, social relations become effective in mitigating the problem of data sparsity since people's decisions are often influenced by their friends according to the principle of social homophily [1]. Based on this fact, a large number of social recommendation models which focus on integrating explicit social information into traditional recommender systems [2], [3], [4], [5], [6], [7] were developed, showing decent improvement under the ideal circumstances. However, the real situations are rather complex and follow-up investigations [8] from the industry revealed that the effectiveness of applying explicit social information into recommender systems had been overestimated.

Briefly, the failure of social recommendation can be attributed to: (1) The observed social relations are extremely sparse, and users with few ratings/purchase records are also likely to have few social relationships [9]. Therefore it is questionable to claim that the majority of users who have limited purchase data can benefit from limited social relations. (2) The low cost of social connection formation and the openness nature of social networks enable malicious accounts to easily build connections with normal users, making social networks noisy [10]. However, social relations are often indiscriminately used in most social recommendation models. (3) Social relations have multi-facets and show heterogeneous strength in different situations [11]. They are not universally applicable to any contexts but it is often as-

sumed that users can reach a consensus with their friends in all the aspects of preferences. In view of these findings, it is less controversial that researchers should change their way of leveraging social relations and develop new approaches to better exploit these imperfect information.

Having been aware of the adverse factors of social recommendation, a few studies had made attempts to overcome these drawbacks. For example, to alleviate the influence of relation noises, a series of work [12], [13] aiming to distill the observable social networks was proposed in quick succession. Instead of using all the relations, they propose to extract useful explicit social links or divide social connections into fine-grained classes and only make use of the filtered information. However, in consideration of the high sparsity of original social networks, the extracted relations are too sparse to effectively improve recommendation performance. Meanwhile, an opposite way focusing on augmenting available relations was also explored. Researchers who follow this way paid attention to discovering potential but reliable relations for each user and identify those users who are not directly connected to the current user but share the similar interests with her as the *implicit* friends [14], [15], [16]. Following their ways, the sparsity of explicit social relations can be alleviated but on the other hand the augmentation also inevitably introduces noises. Specifically, in these methods, the friend-searching strategies are not coupled with the recommendation process, which questions the validity of the implicit friends for recommendation. Besides, none of these augmentation-based methods pay attention to the multi-facets problem of social relations. Therefore, approaches which can fully cover the challenges and work in a coherent way should be developed.

In this paper, we propose a deep adversarial framework

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based on graph convolutional networks (GCN) [17], whose architecture is shown in Fig. 1, to tackle the aforementioned issues and enhance social recommender systems. The key idea of GCN is to stack multiple convolutional operations to simulate the message passing among nodes, which is well aligned with modeling social influence diffusion. Technically, by treating the social network and the user-item interactions as graph structures, we are able to borrow the strength of GCNs to capture the social influence and perform social recommendation. To help gain a deep understanding of our work, here we first briefly introduce our framework from a problem-driven perspective:

(1) How does our model address the problem of relation sparsity? The studies focusing on the identification of implicit relations have set a good example for us that searching for unobserved but helpful connections upon the known social networks/bipartite networks is practicable [9], [15], [18]. However, we claim that such models struggle to capture higher-order and complex connectivity patterns among nodes, because they only draw on information from immediate neighborhood or linear contexts (e.g. random walk based neighbors). Actually, in social networks, it has been shown to be beneficial to consider the higher-order structure [19]. In light of this, we follow their ideas and further design some *network motifs* [20] which are local structures involving multiple nodes to help uncover the high-order social information. To fully exploit the motifs, a tailored GCN is employed to aggregate information from motif-induced neighborhood and output a certain number of new relations, which are called the alternative neighborhood in this paper. By doing so, each user, especially those who have a very small number of relations, can benefit from the social network.

(2) How can our model guarantee the validity of the alternative neighborhood? The identification process of the new neighbors is unsupervised and hence it is hard to assess the validity of the alternative neighborhood before used for recommendation. Thus we adopt the idea of autoencoder and investigate if we can use these new neighbors to reconstruct the original input. As shown in Fig. 1, we concatenate the motif-based GCN with a multilayer perceptron (MLP) and make them act as a concrete autoencoder [21] for denoising. Technically, GCN works as an encoder while the MLP acts as the decoder. By mapping the alternative neighborhood to the original input, we believe that the informative and important information of the social network has been encoded into these new neighbors. Intuitively, this design allows users to filter irrelevant relations or noises and guarantees the validity of the alternative neighborhood.

(3) How does our model cope with the multi-facets problem of social relations? After obtaining a certain number of helpful alternative neighbors for each user, we can replace the original explicit relations with the new neighborhood. Then the multi-facets problem is the next to be handled. As the social relation may show heterogeneous strengths in different contexts [11], it is necessary to develop a recommendation module that can selectively exploit the social information. To this end, we introduce an attentive social embedding propagation layer to our GCN based recommendation module in which a social attention mechanism is employed to weigh the contribution of the new neigh-

bors and selectively aggregate information. Specifically, the attention mechanism is coupled with the context and then the importance of the social relations varies from context to context, enabling our model to capture the heterogeneous strengths of trust to improve recommendation performance.

Overall, our proposed framework includes three main stages: alternative neighborhood generation, neighborhood denoising, and attention-aware social recommendation. Due to the great capacity of GCNs to model the social influence among users, the framework can tackle the three key problems of social recommendation mentioned above. However, before enjoying the benefits of GCNs, there is still something to be considered. That, although the framework can be trained end-to-end, each component in the framework mainly focuses on its own task and fails to closely cooperate with each other. To unify all the components and ensures a coordinated effort against all the challenges, we finally adopt adversarial training [22] to enhance our framework. In our adversarial framework, the motif-based GCN acts as a generator that produces the alternative neighborhood, while the attentive social recommendation module, works as the discriminator to recognize the informative connections and enforce the generator to learn the real distribution of the relations that can improve recommendation performance. With the competition between the generator and the discriminator, they mutually enhance each other and all the components in our framework work more collaboratively. As a result, the whole framework will show better recommendation performance. The major contributions of this paper are summarized as follows:

- We design three different components to fully and effectively deal with the three tough problems in social recommender systems.
- We unify and intensify these three components by integrating them into a deep adversarial framework based on GCNs. To our best knowledge, we are the first to combine adversarial learning and graph neural networks for social recommendation.
- We conduct extensive experiments on multiple real-world datasets to demonstrate the superiority of the proposed framework and show the effectiveness of each component.

The remainder of this paper is organized as follows. In Section II the related work is presented. Section III illustrates the proposed adversarial social recommendation framework. The experimental studies are presented in Section IV. Finally, Section V concludes the paper.

2 RELATED LITERATURE

2.1 Social Recommendation

The principle of homophily [1] lays the theoretical basis for the majority of social recommendation models which assume that socially connected users share similar preferences. Among the early attempts, the leading ideas can be categorized into three groups including co-factorization methods, ensemble methods, and regularization methods [8]. As the representative work of co-factorization methods, SoRec [23] and TrustMF [24] jointly co-factorize the rating and social matrices and project rating and social contexts

into the same latent space. STE [25] and mTrust [11], as the typical ensemble methods, regard user's primary preference as the linear combination of ratings from the user and her social network. Another line of work, social regularization model [4], proposes to narrow the preference gap between users and their friends by using weighted social regularization terms. Besides, the subsequent studies also explore social impact on users' preferences from other perspectives. the models of [26], [27] use social connections to capture users' exposure instead of preference based on the finding that user exposure to items also impacts recommendation. Wu *et al.* [7] developed a deep influence propagation model to integrate the recursive social diffusion process into recommendation. In the work of [6], [28], the graph convolutional operation is used to model the social influence.

After the frustrating experience of applying social recommender systems in industry has been noticed [8], a few research efforts shift attention to addressing the practical problems of social recommendation. Based on the weak tie theory, Wang *et al.* [12], [13] proposed fine-grained models to distinguish strong ties and weak ties. Inspired by the wide use of network embedding techniques, CUNE [9] and IF-BPR [15] adopted homogeneous and heterogeneous network embeddings to capture reliable implicit social relations, respectively. InSRMF [29] takes advantage of the indirect social relations detection and collaborative filtering on social network and rating behavior information to mitigate the relation sparsity. However, most of these studies only partially overcome the challenges of social recommendation and achieve suboptimal results.

2.2 Adversarial Training in Recommender Systems

Generative adversarial networks (GANs) [22] have led a revolution in many fields including recommender systems. The most popular paradigm of applying adversarial learning to recommender systems is that, by playing a minimax game, the discriminator guides the generator towards fitting the underlying relevance distribution over items given the user, while the generator generates difficult examples to confuse and then improve the discriminator [30], [31], [32], [33], [34]. IRGAN [30] is the first GAN-based recommendation model which unifies the discriminative models and generative models. GraphGAN [31] designs graph softmax function to accelerate training and improve computing efficiency. Wang *et al.* [32] employed an adaptive negative sampling framework to optimize the proposed streaming recommendation model. Besides, instead of generating samples, Chae *et al.* [33] proposed to learn user profiles with GAN. He *et al.* [35] made the first attempt to add adversarial perturbations to the latent factor to avoid overfitting. Additionally, [36], [37] explore a new application of GAN by augmenting user-item interactions to improve collaborative filtering.

There are also a few studies combining adversarial learning and social recommendation [38], [39], [18]. Krishnan *et al.* [38] proposed a modular adversarial framework to disentangle the architectural choices for the recommender and social representation models. Fan *et al.* [39] adopt a bidirectional mapping method to transfer users' information between social domain and item domain using adversarial learning. Among these work, RSGAN [18] is the most similar to our

proposed model in terms of the motivation. This work also focuses on identifying reliable relations with adversarial training to improve social recommendation. However, it only covers the relation sparsity problem and the scarcity of labeled reliable friends for supervised learning is its bottleneck which lowers the model's capacity.

3 PROPOSED FRAMEWORK

In this paper we present our GCNs-based deep adversarial social recommendation framework. Figure 1 shows the schematic overview of our framework. We firstly present how each component in our framework deals with the aforementioned problems of social recommendation and then show how adversarial learning unifies and intensifies all the components by playing a minimax game.

3.1 Notations and definitions

Let $U = \{u_1, u_2, \dots, u_m\}$ and $I = \{i_1, i_2, \dots, i_n\}$ respectively be the sets of users and items in recommender systems, where m is the number of users, and n is the number of items. $\mathcal{N}(u)$ is the set of items which were clicked/consumed by user u and $\mathcal{N}(i)$ is the user set including the users who clicked/purchased item i . $\mathbf{Y} \in \mathbb{R}^{m \times n}$ is the feedback matrix. For each pair (u, i) , y_{ui} denotes the user's feedback on the item and \hat{y}_{ui} denotes the predicted score. In this paper, we focus on Top-N recommendation, following the convention, y_{ui} is either 1 (positive) or 0 (negative or unknown). For each user pair (u_1, u_2) , $s_{u_1, u_2} = 1$ indicates that u_1 follows u_2 in the social network. It should be noted that we work on directed graph and the relation matrix $\mathbf{S} \in \mathbb{R}^{m \times m}$ is asymmetric. As the GCNs [17] are the basic building blocks of our framework, we use $\{\mathbf{W}^1, \mathbf{W}^2, \dots, \mathbf{W}^l\}$ to denote the parameters of the networks. The low dimensional vector $\mathbf{e}_{u_1}^{(l)}$ represents the node embedding where the superscript l denotes the l -th layer and the subscript denotes the node. In this paper, we use bold capital letters to denote matrices and bold lowercase letters to denote vectors.

3.2 Alternative Neighborhood Generation

As explicit social networks are sparse and noisy. for enhanced social recommendation, we firstly need to identify the alternative neighborhood for each user. In this paper, alternative neighborhood refers to a group of users who share similar preferences with the specified user. Conceptually, it is literally like the *implicit friends* proposed by [14], [15], but actually a superset of them. For users with few social connections, the alternative neighborhood may be totally new neighbors, while partially overlaps with the neighbors of the users with a large number of social relations. Technically, prior studies [14], [15] identify implicit friends by means of rating similarity computation and network embedding techniques. But they struggle to capture the high-order and complex connectivity pattern among users because they only explore linear contexts (e.g. random walk based neighbors). In light of this, in our framework, we exploit the *motifs* for alternative neighborhood identification.

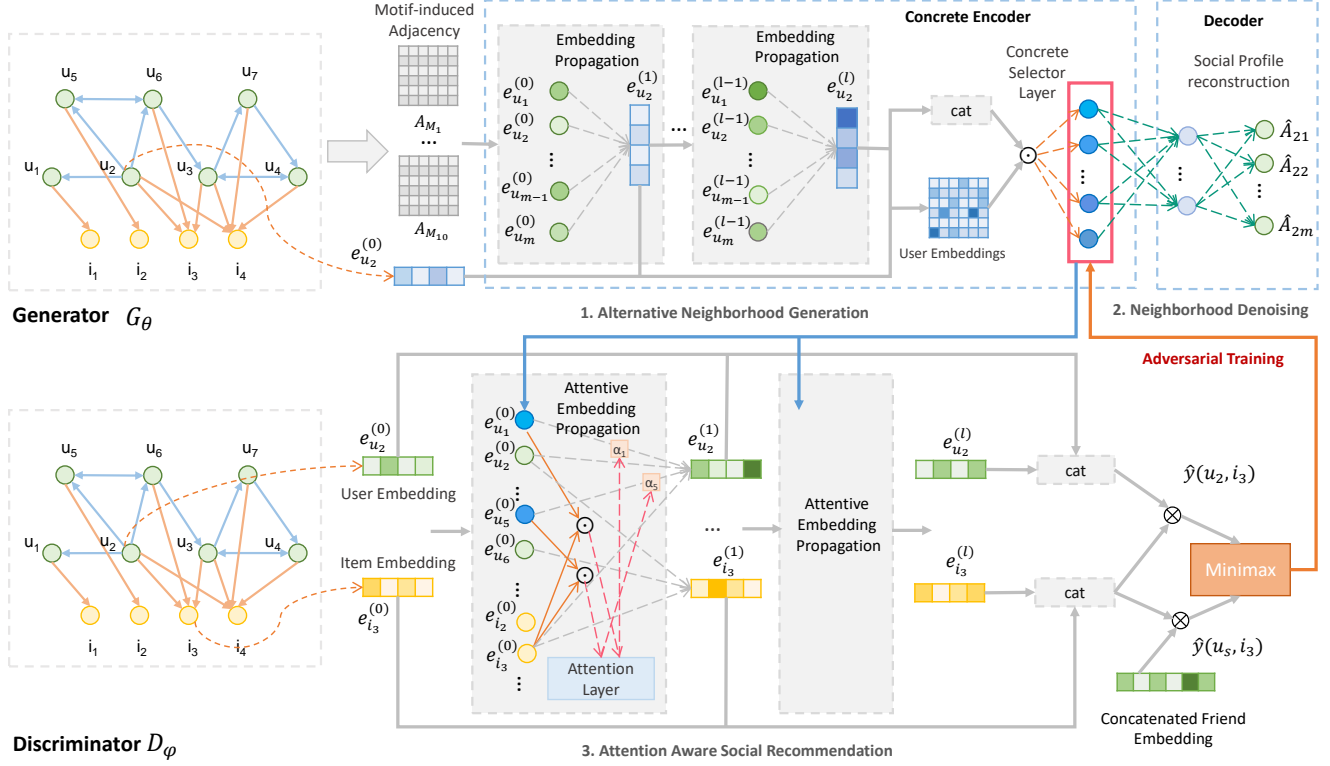


Fig. 1. The schematic overview of our framework. The upper part is the generator in charge of identifying the alternative neighborhood and the lower part is the discriminator which is responsible for recognizing generated neighborhood and generating recommendations. The arrows with solid line indicate the flow of information and the arrows with dashed line represent the computational operations of neural networks.

3.2.1 High-order Social Information Exploitation

Motif, which was first introduced in [20], is the specific local structure involving multiple nodes [19]. It has been shown to be useful in many applications such as social networks [20]. In this paper, we only focus on triangular motifs because of triadic closure in social networks. Fig. 2 shows the used triangular motifs in which $\mathcal{M}_1 - \mathcal{M}_7$ are homogeneous and $\mathcal{M}_8 - \mathcal{M}_{10}$ are heterogeneous. According to [19], $\mathcal{M}_1 - \mathcal{M}_7$ are crucial for social computing and in our work they can help weigh the importance of explicit relations. To leverage the common purchase information, we further design $\mathcal{M}_8 - \mathcal{M}_{10}$ for our application. Specifically, the common purchase in \mathcal{M}_8 and \mathcal{M}_9 is used to strengthen the established relations, and in \mathcal{M}_{10} helps link users who are not directly connected via social relations. Obviously, introducing purchase information to social domain enables similarity measuring when social relations are very sparse.

The motif-induced adjacency matrix $\mathbf{A}_{\mathcal{M}_k}$ represents the frequency of two nodes appearing in a given motif \mathcal{M}_k , which is computed by:

$$(\mathbf{A}_{\mathcal{M}_k})_{i,j} = \sum_{i \in U, j \in U} 1(i, j \text{ occur in } \mathcal{M}_k). \quad (1)$$

For example, given the motif \mathcal{M}_8 , we can observe that, in the graph in Fig. 1, (u_3, u_4, i_4) forms one instance of \mathcal{M}_8 , thus $(\mathbf{A}_{\mathcal{M}_8})_{u_3, u_4} = 1$. Counting motifs in a network may be time-consuming. But as we only exploit triangular motifs, following [40], we show that motif-induced adjacency matrix can be computed based on simple matrix computation. Let $\mathbf{B} = \mathbf{S} \odot \mathbf{S}^T$ and $\mathbf{U} = \mathbf{S} - \mathbf{B}$ be the adjacency matrix

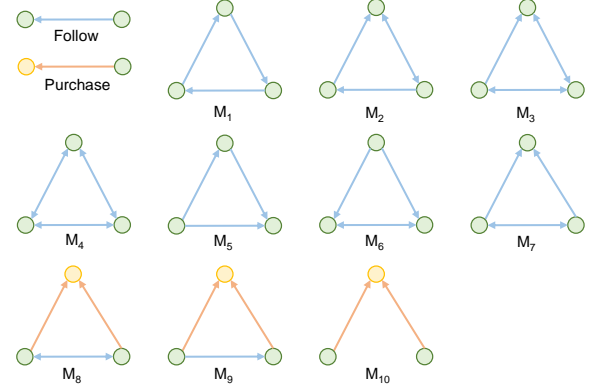


Fig. 2. Motifs used in our work. The green circles denote users and the yellow circles denote items.

of the bidirectional and unidirectional links of the explicit social network respectively, where \odot denotes element-wise product. The computation of all the motif-induced adjacency matrices is summarized in Table 1.

As can be seen, all the formulations are almost based on the operation $(\mathbf{XY}) \odot \mathbf{Z}$ which can be efficiently calculated since all the involved matrices are very sparse. For symmetric motifs, $\mathbf{A}_{\mathcal{M}} = \mathbf{C}$ and for the asymmetric ones, $\mathbf{A}_{\mathcal{M}} = \mathbf{C} + \mathbf{C}^T$. It is easy to understand these formulations as the operation \mathbf{XY} denotes a path connecting the three vertices in a triangular motif and the operation $\odot \mathbf{Z}$ complements the motif with the missing edge and closes the triangle. With the motif-induced adjacency matrices, we

TABLE 1
Computation of motif-induced adjacency matrices.

Motif	Matrix Computation
\mathcal{M}_1	$\mathbf{C} = (\mathbf{U}\mathbf{U}) \odot \mathbf{U}^T$
\mathcal{M}_2	$\mathbf{C} = (\mathbf{B}\mathbf{U}) \odot \mathbf{U}^T + (\mathbf{U}\mathbf{B}) \odot \mathbf{U}^T + (\mathbf{U}\mathbf{U}) \odot \mathbf{B}$
\mathcal{M}_3	$\mathbf{C} = (\mathbf{B}\mathbf{B}) \odot \mathbf{U} + (\mathbf{B}\mathbf{U}) \odot \mathbf{B} + (\mathbf{U} \cdot \mathbf{B}) \odot \mathbf{B}$
\mathcal{M}_4	$\mathbf{C} = (\mathbf{B}\mathbf{B}) \odot \mathbf{B}$
\mathcal{M}_5	$\mathbf{C} = (\mathbf{U}\mathbf{U}) \odot \mathbf{U} + (\mathbf{U}\mathbf{U}^T) \odot \mathbf{U} + (\mathbf{U}^T \mathbf{U}) \odot \mathbf{U}$
\mathcal{M}_6	$\mathbf{C} = (\mathbf{U}\mathbf{B}) \odot \mathbf{U} + (\mathbf{B}\mathbf{U}^T) \odot \mathbf{U}^T + (\mathbf{U}^T \mathbf{U}) \odot \mathbf{B}$
\mathcal{M}_7	$\mathbf{C} = (\mathbf{U}^T \mathbf{B}) \odot \mathbf{U}^T + (\mathbf{B}\mathbf{U}) \odot \mathbf{U} + (\mathbf{U}\mathbf{U}^T) \odot \mathbf{B}$
\mathcal{M}_8	$\mathbf{C} = (\mathbf{Y}\mathbf{Y}^T) \odot \mathbf{B}$
\mathcal{M}_9	$\mathbf{C} = (\mathbf{Y}\mathbf{Y}^T) \odot \mathbf{U}$
\mathcal{M}_{10}	$\mathbf{C} = (\mathbf{Y}\mathbf{Y}^T)$

are able to leverage the high-order connectivity patterns in the social network and the user-item relations. Particularly, $\mathbf{A}_{\mathcal{M}_{10}}$ is a complement that uses common purchase to establish implicit relations when users have few relations. It should be noted that we only preserve elements that are larger than 3 in $\mathbf{A}_{\mathcal{M}_{10}}$ to avoid noises.

3.2.2 Neighborhood Generation with Motif-based GCN

Due to the great capacity to capture the dependence of nodes via message passing, we employ a tailored GCN [17] to aggregate information from the explicit and motif-induced neighborhoods for the generation of alternative neighborhood. Formally, a general GCN is constructed using the following layer-wise propagation:

$$\mathbf{E}^{(l+1)} = \sigma \left(\mathbf{Z}\mathbf{E}^{(l)}\mathbf{W}^{(l)} \right), \quad \mathbf{Z} = \mathbf{D}^{-\frac{1}{2}}\tilde{\mathbf{A}}\mathbf{D}^{-\frac{1}{2}}, \quad (2)$$

where $\tilde{\mathbf{A}} = \mathbf{A} + \mathbf{I}$ (\mathbf{I} represents an identity matrix with size M) with added self-loop, \mathbf{D} is the diagonal degree matrix of $\tilde{\mathbf{A}}$, and σ is the nonlinear activation function. In our framework, to capture the high-order connectivity, we define:

$$\mathbf{A} = \mathbf{D}_S^{-\frac{1}{2}}\mathbf{S}\mathbf{D}_S^{-\frac{1}{2}} + \mathbf{D}_{\mathcal{M}_1}^{-\frac{1}{2}}\mathbf{A}_{\mathcal{M}_1}\mathbf{D}_{\mathcal{M}_1}^{-\frac{1}{2}} + \dots + \mathbf{D}_{\mathcal{M}_{10}}^{-\frac{1}{2}}\mathbf{A}_{\mathcal{M}_{10}}\mathbf{D}_{\mathcal{M}_{10}}^{-\frac{1}{2}}. \quad (3)$$

At each layer, each user's node representation is updated via a weighted sum of the features of its motif-induced neighborhood and itself. Formally, the node-wise message construction and aggregation are defined as:

$$\begin{aligned} \mathbf{m}_{u_i \leftarrow u_j} &= z_{ij} \mathbf{W}^{(l)} \mathbf{e}_{u_j}^{(l-1)}, \\ \mathbf{e}_{u_i}^{(l)} &= \sigma(\mathbf{m}_{u_i \leftarrow u_i} + \sum_{j \in \mathcal{N}(u_i)} \mathbf{m}_{u_i \leftarrow u_j}). \end{aligned} \quad (4)$$

A more flexible solution may be allowing each node to choose the most beneficial motif-induced neighborhood to integrate information [41]. However, considering that our design has shown decent performance in the experiments, we leave the adaptive selection of motif-induced neighborhood as our future work.

After propagating through multiple layers, we obtain multiple representations for each user, namely $\{\mathbf{e}_u^{(0)}, \mathbf{e}_u^{(1)}, \dots, \mathbf{e}_u^{(l)}\}$. Each representation in this set captures different node interactions at different layers. To fully exploit the obtained user embeddings, we concatenate these

embeddings as a final embedding \mathbf{e}_u to predict the alternative neighborhood. As our goal is to ensure the framework can be trained end-to-end, the process of neighborhood generation must be differentiable rather than using non-differentiable probability-based sampling. In other words, the output of the prediction should be discrete indexes, i.e., integers, that can represent user ID. To this end, a concrete selector layer [21] is employed for discrete user selection. By using the concrete distribution [42] and the reparametrization trick [43], our framework is able to produce a relaxation of the one-hot vector to represent the selected new neighbor. The extent to which the one-hot vector is relaxed is controlled by a temperature parameter $\tau \in (0, \infty)$. In detail, the concrete selector layer contains k neurons, each with a $\sum_{t=0}^l d^t$ dimension parameter \mathbf{h}_i , where d_t denotes the dimension of corresponding representation and the subscript i denotes the index of the neuron. For each user, we conduct element-wise product between its final embedding and all users' final embeddings and then feed the intermediate result to the concrete selector layer. The operation of the neuron inside first performs an inner product $(\mathbf{e}_u \odot \mathbf{E}_\theta) \cdot \mathbf{h}_i = \alpha_i$ and then outputs a relaxation of one-hot vector, which is computed as:

$$\mathbf{v}_i = \frac{\exp((\log \alpha_i + \mathbf{g}) / \tau)}{\sum_{j=1}^m \exp((\log \alpha_{ij} + \mathbf{g}_j) / \tau)}, \quad (5)$$

where \mathbf{g} is an m -dimensional vector of i.i.d. samples from $\text{Gumbel}(0, 1)^1$ [44], which is used to simulate the probability-based relation sampling. When $\tau \rightarrow 0$, the concrete random variable \mathbf{v}_i smoothly approaches the discrete distribution, and v_{ij} would be 1 with the probability $\alpha_{ij} / \sum_{p=1}^m \alpha_{ip}$. The j^{th} user would then be chosen as one of the new neighbors. As there are k neurons in the concrete selector layer, we can total up all the output and then get a vector \mathbf{v} with k (e.g., 20) positions being 1 that denote the alternative neighborhood.

3.3 Neighborhood Denosing

Although a majority of users in social recommender systems have only a few friends, there are also a portion of users that have built a lot of connections with others. For the majority, generating alternative neighborhood is the augmentation of relations, and for the rest, it is like relation denosing, namely, filtering the irrelevant and malicious relations out. The problem is therefore analogous to feature selection or dimensionality reduction [45]. With this in mind, the finally identified alternative neighborhood should be those users which contribute most to our prediction task in the user preference domain. However, in the social domain, we can also further exploit the beneficial information from explicit connections. It is reasonable to think that, for users with a large number of social relations, if we can use the alternative neighborhood to reconstruct their motif-induced social profiles, we may have successfully encoded the essential pattern of connectivity into the new neighborhood. To impose this constraint, we concatenate the motif-based GCN with a fully-connected multi-layer perception (MLP) and make them work as a concrete autoencoder [21]. Structurally, the

1. $\text{Gumbel}(0, 1)$ can be sampled with $g = -\log(-\log(\mu))$, where $\mu \sim \text{Uniform}(0, 1)$.

GCN is the encoder while the MLP is the decoder. From the perspective of data flow, the initial input is the motif-induced adjacency matrix, the learned representation is the output of the concrete selector layer, and the ground truth is the original social profile. Let $\tilde{\mathbf{A}} = f_g(\mathbf{A}, \Theta)$ be the reconstructed social profiles, where \mathbf{A} is defined in Eq. 3 and Θ denotes the parameters of both the motif-based GCN and the MLP. We can formally define the objective function of the concrete autoencoder as:

$$\mathcal{L}_s = \arg \min \|\mathbf{A} - \tilde{\mathbf{A}}\|^2. \quad (6)$$

By minimizing the above loss, the learned new neighborhood becomes less noisy even in the user preference domain due to the homophily across social and user-item networks. But it should be noted that, for the users who not only have few social relations but also few purchase records, the effect of reconstruction constraint is limited as the supervision of a small number of ground truths is relatively trivial. In Section 3.5, we will continue discussing how to directly improve the validity of the alternative neighborhood in the user preference domain.

3.4 Attention Aware Social Recommendation

With the alternative neighborhood, we next replace the explicit neighborhood for boosted performance. Due to the successful experience of GCN in practice [6], [46], we are motivated to develop an attentive GCN-based recommendation model to perform social recommendation.

3.4.1 Attentive Social Embedding Propagation Layer

As social relations often show heterogeneous strengths in different situations, it is crucial to model the importance of social relations when propagating social embeddings. Wang *et al.* [46] set up a good example to capture the node interactions between users and items in recommender systems by using GCN, but they did not consider the interactions among users. Following their work, we propose an attentive social embedding propagation layer to make GCNs applicable to social recommendation. We perform embedding propagation between both user pairs and user-item pairs, formulating the process with two major operations: attentive message construction and message aggregation.

Attentive Message Construction. For each user in the graph consisting of user and item nodes, during message propagation, it draws on information from both the purchased/clicked items and the alternative neighborhood. Given a user-item pair (u, i) , following [46], we define the message passing from item i to user u at layer l as:

$$\mathbf{m}_{u \leftarrow i}^{(l)} = \frac{1}{\sqrt{|\mathcal{N}_u|} \sqrt{|\mathcal{N}_i|}} \left(\mathbf{W}_1^{(l)} \mathbf{e}_i + \mathbf{W}_2^{(l)} (\mathbf{e}_i \odot \mathbf{e}_u) \right), \quad (7)$$

where $\mathbf{W}_1^{(l)}$ and $\mathbf{W}_2^{(l)} \in \mathbb{R}^{d \times d}$ are the trainable weight matrices to distill useful information for propagation. For the sake of simplicity, in this section we omit the superscript $(l-1)$ for the node representation \mathbf{e} . Unlike the embedding propagation in conventional GCNs, not only the contribution of \mathbf{e}_i but also the additional interaction between \mathbf{e}_i and \mathbf{e}_u are encoded into the message via $\mathbf{e}_i \odot \mathbf{e}_u$. The effectiveness of the additional interaction has been confirmed in [46].

The above part is what we inherit from [46] for modeling user-item interactions. To capture the information from the alternative neighborhood when propagating, we propose a novel attentive social embedding propagation. Specifically, given a user pair (u, u') , the user-to-user message is constructed as follows:

$$\mathbf{m}_{u \leftarrow u'}^{(l)} = \alpha_{u, u'}^{(l)} \left(\mathbf{W}_1^{(l)} \mathbf{e}_{u'} + \mathbf{W}_2^{(l)} (\mathbf{e}_{u'} \odot \mathbf{e}_u) \right). \quad (8)$$

The difference is that we do not use the node centrality, e.g., degree, to measure the neighbor importance or how much information the alternative neighbor u' contributes. Instead, we use the trainable parameter $\alpha_{u, u'}^{(l)}$ to selectively acquire information from the neighbors which are the most relevant to the current context. To calculate $\alpha_{u, u'}^{(l)}$, a social attention mechanism is employed and it formally operates in this way:

$$\alpha_{u, u'}^{(l)} = \frac{\exp \left(\sigma \left(\mathbf{a}^{(l)} \left[\mathbf{W}_1^{(l)} \mathbf{e}_u \| \mathbf{W}_2^{(l)} (\mathbf{e}_{u'} \odot \mathbf{e}_i) \right] \right) \right)}{\sum_{v \in \mathcal{A}_u} \exp \left(\sigma \left(\mathbf{a}^{(l)} \left[\mathbf{W}_1^{(l)} \mathbf{e}_u \| \mathbf{W}_2^{(l)} (\mathbf{e}_v \odot \mathbf{e}_i) \right] \right) \right)}, \quad (9)$$

where i is the item in the current instance (u, i) sampled from the historical data (i_3 in Fig.1), \mathcal{A}_u is user u ' alternative neighborhood, $\|$ is the concatenation operation, and \mathbf{a} denotes the parameter of the attention layer. As can be seen, in our social attention mechanism, the attention coefficient $\alpha_{u, u'}$ is closely coupled with the current item which denotes the context in this paper. When the current user u acquires information from one of its social neighbors u' , the interaction between u' and the current item i is considered. By doing so, the contribution received from u' varies from items to items, giving the recommendation model the ability to capture the different strengths of social relations in different situations. Although we are not the pioneer to apply graph attention mechanism to social recommendation, we are the first to couple attention with contexts to deal with the multi-facets problem of social relations. Additionally, it should be noted that, as this work focuses on social recommendation, we only apply attentive embedding propagation to user-user connections for clear evaluation in the experimental part.

Message Aggregation. In this stage, we aggregate the messages propagated from u 's vicinity to refine its representation. Specifically, the aggregation function is defined as:

$$\mathbf{e}_u^{(l)} = \sigma \left(\mathbf{m}_{u \leftarrow u}^{(l)} + \sum_{i \in \mathcal{N}_u} \mathbf{m}_{u \leftarrow i}^{(l)} + \sum_{v \in \mathcal{A}_u} \mathbf{m}_{u \leftarrow v}^{(l)} \right). \quad (10)$$

Three parts contribute information to the next-layer user embedding: the user itself, the items purchased, and the identified alternative neighborhood. Analogously, the representation $\mathbf{e}_i^{(l)}$ for item i is obtained by propagating information from users who purchased it.

3.4.2 Model Prediction and Optimization

By stacking L attentive social embedding propagation layers, users and items are capable of receiving the messages propagated from their l -hop neighbors. As the embeddings obtained in different layers characterize user preferences at different levels, i.e. the first-layer embeddings are only refined by its immediate neighborhood while the last-layer

embeddings also receive messages from distant nodes, we concatenate these embeddings to constitute the final embeddings \mathbf{e}_u^* and \mathbf{e}_i^* for model prediction. Given an instance (u, i) , the predicted score $\hat{y}(u, i)$ is computed by $\mathbf{e}_u^{*T} \mathbf{e}_i^*$.

As this paper focuses on Top-N social recommendation, we adopt the pairwise ranking to model the order of items for each user. Following the Bayesian Personalized Ranking loss [47], we define our optimization function as follows:

$$\mathcal{L}_r = \sum_{(u,i,j) \in \mathcal{O}} -\log \sigma(\hat{y}_{u,i}(\Phi) - \hat{y}_{u,j}(\Phi)) + \lambda \|\Phi\|_2^2, \quad (11)$$

where Φ denotes the parameters of the attentive recommendation module, $\sigma(\cdot)$ here is the sigmoid function. Each time a triple including the current user u , the positive item i purchased by u , and the negative item j which is disliked by u or unknown to u , is fed to the model. The model is optimized towards ranking i higher than j in the recommendation list for u . In addition, message dropout with probability $p = 0.1$ and an L_2 regularization are imposed on to reduce generalized errors.

3.5 Enhance Framework with Adversarial Training

So far, we have built an end-to-end framework that can deal with the three tough problems in social recommender systems respectively. However, we notice that there is no distinct reward to stimulate the motif-based GCN to generate better alternative neighborhood that can further enhance recommendation performance. The neighborhood generation model and the recommendation model mainly focus on their own task and there are few interactions between them to make them work cooperatively.

The principle of homophily refers to the tendency for people to have ties with others who are similar to themselves in socially significant ways. According to this principle, a good neighbor in social recommender systems may be very likely to share the same preference with the current user. But for a given item only purchased by the current user, a reasonable assumption is that the neighbor would not show a higher level of interest on this item, which is analogous to the assumption of the social ranking model [48] that a user tends to rank the items purchased by her higher than the ones purchased by her friends. Hence, we came up with such an idea that we should on one hand generate alternative neighbors who are interested in what the current user has purchased, but on the other hand make their opinions to the items a little restrained. These two demands of our aim seem to be at cross-purposes. However, our goal is consistent with the key idea of generative adversarial networks (GANs) [22]. Inspired by the success of GANs in IR applications [30], [18], we are able to make the two demands of our aim compatible.

The key idea of GANs is to let two neural networks contest with each other by playing a minimax game. In our scene, we need to select new neighbors that can minimize the gap between the scores of the neighbors and the current user on the items purchased by the current user, which is explained to find neighbors who have the similar preferences with the current user. Meanwhile, we also have to maximize this gap because the user herself should show more affection to the purchased item. Let G denote the

motif-based GCN, which plays the role of the generator, and D denote the attentive recommendation module, which acts as the discriminator. The minimax game under our framework can be formulated as:

$$\mathcal{L}_{adv} = \arg \min_{D_\Phi} \max_{G_\Theta} -\log \sigma(\hat{y}_{u,i}(\Phi) - \hat{y}_{u',i}(\Phi)), \quad (12)$$

$$i \in \mathcal{N}_u, u' \in \mathcal{A}_u \sim P_G(\Theta|u, \mathbf{A}).$$

By fixing the parameters of G and minimizing the above loss, D is optimized towards recognizing the generated neighbor u' and giving higher score to $\hat{y}_{u,i}$. On the contrary, by fixing the parameters of D and maximizing the loss, G evolves towards generating neighbors that can get comparable score $\hat{y}_{u',i}$. With the competition between G and D , the optimization for \mathcal{L}_{adv} will eventually reach an equilibrium where the framework shows the best performance.

The use of adversarial training gives our framework a distinct objective that forces G to generate new neighborhood which provides valuable information to D , and also empowers D to capture fine-grained use preferences. Additionally, the neighbors who get lower score $\hat{y}_{u',i}$ would have less probability to be selected again, which can also be regarded as a way to denoise selected relations in the preference domain. With adversarial training, the interactions between two GCNs increase, making all the components in our framework couple closely and ensuring a coordinated effort to improve social recommendation. Finally, we unify all the objective functions:

$$\begin{aligned} \mathcal{L} &= \mathcal{L}_r + \mathcal{L}_s + \mathcal{L}_{adv} \\ &= \sum_{(u,i,j) \in \mathcal{O}} -\log \sigma(\hat{y}_{u,i}(\Phi) - \hat{y}_{u,j}(\Phi)) + \lambda(\|\Phi\|_2^2 + \|\Theta\|_2^2) \\ &\quad - \beta \arg \min_{D_\Phi} \max_{G_\Theta} \log \sigma(\hat{y}_{u,i}(\Phi) - \hat{y}_{u',i}(\Phi)) + \|\mathbf{A} - \tilde{\mathbf{A}}\|^2 \end{aligned} \quad (13)$$

where β is the coefficient to control the magnitude of the minimax game. The integrated objective function is optimized by stochastic gradient descent and all the parameters are jointly learned for better recommendation performance.

3.6 Discussion

Our framework integrates multiple components to cope with different issues. However, it is still lightweight in terms of space and time complexity. Here we discuss the running cost of our framework.

Model size. For the generator G , the weight matrix of size $d^{(l-1)} \times d^{(l)}$ is used for convolutional operation and another two matrices of size $m \times k$ and $k \times m$ are required for neighborhood denosing (m is the number of users and k is the number of identified alternative neighbors). Besides, the concrete select layers has the parameter of size $\sum_{t=0}^l d^t$. For the discriminator D , the convolutional weight matrices \mathbf{W}_1 and \mathbf{W}_2 are of the same size $d^{(l-1)} \times d^{(l)}$, and the parameter of attention layer is of size $d^{(l)}$. By adding up all the numbers, the total model size approximates $2mk + (2L+1)\hat{d} + 3L\hat{d}^2$ (Here \hat{d} denotes the average dimension of embeddings for the sake of simplicity). Considering that \hat{d} and k are small numbers generally less than 100 and the number of layers L is not greater than 3, the model size is still a small number.

Time complexity. The computation cost is mainly from three parts: layer-wise propagation, motif counting, and prediction. For the two GCNs, the layer propagation consumptions are $O(|\mathcal{A}^+|\hat{d}^2)$ and $O(|\mathcal{Y}^+|\hat{d}^2)$, respectively, where $|\mathcal{A}^+|$ is the number of non-zero elements in \mathbf{A} , and $|\mathcal{Y}^+|$ is the number of non-zero elements in \mathbf{Y} . The time complexity for computation through fully connected layer is $O(m^2k)$. The time consumption for counting motifs is at least as good as $O(\max(|\mathcal{S}^+|, |\mathcal{Y}^+|)|m|)$ and is one-off. For the prediction layer, only the inner product is involved, resulting in a time complexity of $O(|\mathcal{Y}^+|(l+1)\hat{d})$. As can be seen, in contrast to other GCN-based social recommendation models which directly use explicit social relations, our framework has two extra time expenses in searching for reliable neighbors. Considering the sparsity of the relation and feedback matrices, the compromise is acceptable. After witnessing the significant improvement presented in Section 4, we insist that the small sacrifice in time complexity is worthwhile.

TABLE 2
Dataset Statistics

Dataset	#Users	#Items	#Feedbacks	#Relations
LastFM	1,892	17,632	92,834	25,434
Douban	2,848	39,586	894,887	35,770
Gowalla	18,737	32,510	1,278,274	86,985

4 EXPERIMENTAL RESULTS

4.1 Experimental settings

Datasets. We evaluate our proposed model over three real-world datasets: LastFM², Douban³, and Gowalla⁴. For the dataset of Douban, we only preserve the ratings larger than 3 as the user feedback because our aim is to generate Top-N recommendation. The details of the datasets are summarized in Table 2. We divide each dataset into two partitions in portion of 80% to 20% in which 80% of the datasets is for training and the rest is for testing. Ten times of 5-fold cross validation is adopted in the experiments and the presented result is the average of them.

Baselines. We name our framework **ESRF** (Enhanced Social Recommendation Framework) in the experiments. To evaluate the performance of ESRF, we compare it with the following methods: BPR [47], SBPR [48], IF-BPR [15], RSGAN [18], NGCF [46] and SocialGCN [28]. Among them, BPR and NGCF are general recommendation models based on implicit feedback while the rest are social recommendation models. As SBPR and SocialGCN directly leverages explicit social relations for item ranking, comparing ESRF with them can prove the effectiveness of the alternative neighborhood. IF-BPR and RSGAN are implicit relation-aware models which are highly relevant to ESRF, but they only partially overcome the intrinsic problems of social recommender systems. Choosing these two models as baselines can highlight the integrality of ESRF with regard to fully

addressing the social recommendation issues. Specifically, NGCF and SocialGCN are GCN-based models as well. In the experiments, we can observe the performance improvement with the evolution of the use of social information.

Metrics. To evaluate the performance of all algorithms, two relevancy-based metrics *Precision@10* and *Recall@10* and one ranking-based metric *NDCG@10* are used.

Settings. In our experiments, we use grid search to tune all the specific parameters of baselines and ESRF to ensure the best performance of the baselines for fair comparison. For ESRF, the numbers of the alternative neighbors k on LastFM, Douban, and Yelp are set to 40, 30, and 40, respectively. The coefficients for controlling the magnitude of adversarial training β are 0.3, 0.6, and 0.5, respectively. The temperature τ that controls the degree of relaxation for neighborhood generation is set to 0.2. LeakyReLU with slope coefficient 0.2 is used as the activation function. For the general settings of all the models, we empirically set the dimension of latent factor vectors to 50, the regularization coefficient λ to 0.005, and the batch size to 512. For all the GCN-based models, we uniformly construct a three-layer structure with embedding sizes $\{50, 100, 50\}$ for message propagation.

4.2 Recommendation Performance

In this part, we validate if ESRF is as effective as expected and outperforms the recent baselines. We respectively conducted experiments on the whole training set and the selected training set in which only the data of the cold-start users with less than 20 historic purchase records are included. The results are shown in Table 3 and Table 4.

As can be observed, ESRF outperforms the baselines in both the general and cold-start cases on all the datasets. Particularly, the performance improvement in the cold-start case is remarkable, more than 9% on average over all the datasets. As for the performance of baselines, we notice that GCN-based recommendation models: NGCF and SocialGCN, outperform the corresponding shallow models: BPR and SBPR, which shows the great capacity of GCNs. Social recommendation models using explicit social relations by and large outperform (at least are comparable to) the general recommendation models on two denser datasets: LastFM and Douban. But when it comes to the dataset of Gowalla which is much sparser in both the social and preference domains, these social recommendation models are less competitive. This situation deteriorates in the cold-start case with SBPR and SocialGCN even failing to beat BPR. But meanwhile, the implicit relation aware models: IF-BPR and RSGAN show good performance on three datasets, It is in line with the motivation of this paper that explicit social relations sometimes may mislead the social recommendation models and it is necessary to explore and exploit implicit but helpful relations. Besides, RSGAN which is also based on adversarial training shows the second best performance in most cases. The success of RSGAN and ESRF confirms the effectiveness of applying adversarial training to social recommendation. Finally, to verify that the the performance improvement of ESRF is brought by the generated alternative neighborhood, we randomly built the same number of relations for each user and replace the alternative neighborhood with them in the recommendation

2. <http://files.grouplens.org/datasets/hetrec2011/>

3. http://smiles.xjtu.edu.cn/Download/download_Douban.html

4. <https://www.dropbox.com/sh/qy3s8rs66nirhl9/AAClmTnFO-rR4ecEYO-jU4ba?dl=0>

TABLE 3
General recommendation performance comparison.

Dataset	Metric	Random	BPR	SBPR	NGCF	IF-BPR	SocialGCN	RSGAN	ESRF	Improv.
LastFM	Precision@10	7.874%	7.585%	8.276%	9.735%	9.102%	9.628%	9.475%	10.283%	5.629%
	Recall@10	11.231%	11.306%	12.764%	14.658%	13.625%	14.273%	14.128%	15.173%	3.513%
	NDCG@10	0.10693	0.10763	0.12188	0.14002	0.13043	0.13934	0.13509	0.14836	5.963%
Douban	Precision@10	14.627%	14.892%	15.497%	17.178%	16.433%	17.075%	17.263%	18.145%	5.109%
	Recall@10	4.994%	5.023%	5.422%	5.965%	5.542%	5.878%	6.032%	6.507%	7.874%
	NDCG@10	0.14511	0.15855	0.17245	0.19206	0.18551	0.18859	0.19469	0.20391	4.735%
Gowalla	Precision@10	4.615%	4.521%	3.972%	5.046%	5.245%	4.872%	5.360%	5.637%	5.168%
	Recall@10	5.533%	5.484%	4.807%	5.935%	6.287%	5.739%	6.327%	6.722%	6.243%
	NDCG@10	0.06470	0.06311	0.05459	0.07033	0.07279	0.06889	0.07450	0.07882	5.799%

TABLE 4
Cold-start recommendation performance comparison.

Dataset	Metric	Random	BPR	SBPR	NGCF	IF-BPR	SocialGCN	RSGAN	ESRF	Improv.
LastFM	Precision@10	5.863%	5.903%	6.129%	6.229%	6.857%	6.571%	7.142%	7.695%	7.742%
	Recall@10	12.904%	13.924%	15.478%	14.605%	16.736%	15.854%	16.667%	18.207%	9.239%
	NDCG@10	0.10218	0.11577	0.12128	0.12885	0.13855	0.13309	0.14017	0.15011	7.091%
Douban	Precision@10	1.576%	1.722%	1.935%	1.891%	2.152%	2.031%	2.178%	2.379%	9.228%
	Recall@10	6.576%	7.178%	8.084%	7.890%	8.441%	8.223%	8.583%	9.355%	8.994%
	NDCG@10	0.04433	0.04784	0.05716	0.05152	0.06246	0.06133	0.06447	0.07106	10.221%
Gowalla	Precision@10	2.245%	3.017%	2.776%	3.213%	3.431%	3.002%	3.560%	3.977%	11.713%
	Recall@10	4.983%	6.693%	5.855%	6.924%	7.285%	6.433%	7.427%	8.121%	9.344%
	NDCG@10	0.04278	0.05782	0.05276	0.05938	0.06262	0.05683	0.06487	0.07082	9.172%

TABLE 5
Performance of ESRF when any module is decoupled.

DS	Metric	Motif \times	Denosing \times	Attention \times	AT \times
L	P@10	10.021%	10.089%	9.870%	9.842%
	R@10	14.833%	14.920%	14.536%	14.491%
	N@10	0.14508	0.14738	0.14127	0.14105
D	P@10	17.724%	17.522%	17.354%	17.158%
	R@10	6.300%	6.225%	6.189%	6.013%
	N@10	0.19856	0.19630	0.19395	0.19211
G	P@10	5.256%	5.440%	5.348%	5.315%
	R@10	6.264%	6.514%	6.329%	6.301%
	N@10	0.07198	0.07661	0.07407	0.07362

module of ESRF. We name the modified ESRF Random in Table 3 and Table 4 and find that the performance of Random is much worse than that of other models in all the cases. Then we can draw a conclusion that the alternative neighborhood contributes a lot to the performance of ESRF.

4.3 Ablation Study

In this section, we perform an ablation study to analyze how different components in ESRF contribute to the overall performance and justify some of our architectural decisions. In ESRF, we design three components to address three problems in social recommender systems, and then use adversarial training to unify and intensify them. Here we respectively decouple the three components and adversarial training from ESRF to verify the validity of each module.

In Table 5, we present the results of modified ESRFs in different cases. In each case, one of the four modules of

ESRF is decoupled from ESRF for general recommendation. Due to the limited space, we abbreviate the names of datasets, metrics and adversarial Training (AT). Each column represents a case and \times means the corresponding module is decoupled. It should be noted that we directly perform convolutional operation on explicit social relations to generate the alternative neighborhood when motifs are not exploited. As can be seen, each module contributes to the overall performance and the importance of modules varies from dataset to dataset. For the performance on two denser datasets, adversarial Training and social attention mechanism play more important roles, while motif-induced high-order information contributes more on the sparser dataset, Gowalla. Besides, the contribution of the denosing mechanism can not be overlooked although the contribution is not as significant as those of other modules. We think because the useless relations would be less likely to be generated and exploited with adversarial training and social attention mechanism. Since these two modules partially undertake the job of the denosing mechanism, the missing of the denosing mechanism would not heavily degenerate ESRF. Overall, according to the results, we can infer that capturing high-order social information is more essential when the social network is sparse while adversarial training and social attention mechanism are always effective because they determine how the alternative neighborhood is generated and used.

4.4 Comparison of Explicit Social neighbors and Alternative Neighborhood

As the focus of our paper, the alternative neighborhood is conceptually a superset of the implicit friends proposed

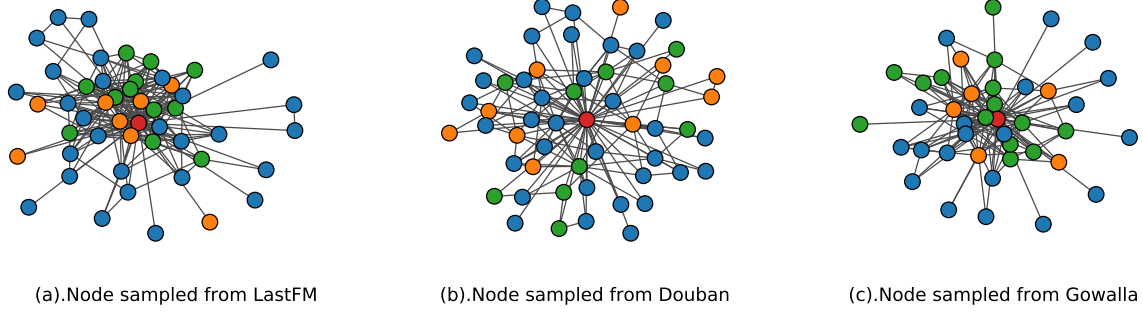


Fig. 3. Three nodes with their ego social networks sampled from three datasets. The red node denotes the user herself, the blue nodes denote the explicit social relations, and the orange and green nodes denote the alternative neighbors. The overlapped part of explicit social relations and alternative neighbors is denoted by green nodes.

by [14]. Prior studies [15], [18] compared implicit friends with explicit friends and found that the numbers of followers of implicit friends are more evenly distributed. Following these studies, we conducted experiments with regard to the follower distribution as well. In the explicit social network, a small number of users receive a large portion of following links, which is subject to the power-law distribution. This uneven distribution may degrade the diversity of recommendations because users' preferences would be constrained by these users who have huge social influence. When we replaced the explicit social relations with the alternative neighbors, we had the same finding with [15], [18] that the follower distribution becomes even and an increased number of users share the incoming links which belonged to a small number of users. This may help increase the diversity of recommendations and explain the performance improvement of ESRF from a nontechnical perspective.

Besides, we further explore the connectivity patterns of explicit social neighbors and the alternative neighborhood. For each center user, we identify 20 alternative neighbors for her. Three ego social networks with both explicit and alternative neighbors are randomly sampled from three datasets, shown in Fig. 3. We can observe that: (1). More than half of alternative neighbors are also explicit neighbors when the center user has a large number of explicit social relations. (2). Compared with explicit neighbors, alternative neighbors are less isolated. Most of them are socially connected with other alternative neighbors or explicit neighbors. The second finding is very crucial. Intuitively, the strength of a tie becomes strong if the tie builders have common friends. According to the theory of homophily [1], they will also become similar in preferences. By contrast, the isolated explicit neighbors may have tenuous relationships with the center user and are less likely to share common interests with her. This can be another reason that explains why ESRF beats the social recommendation models using explicit social relations.

4.5 Parameter Sensitivity

We introduce two hyper-parameters k and β to ESRF. k denotes the number of identified alternative neighbors for each user and β controls the magnitude of adversarial

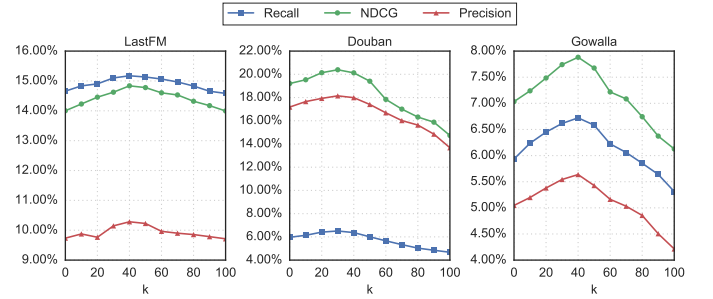


Fig. 4. The influence of the number of alternative neighbors.

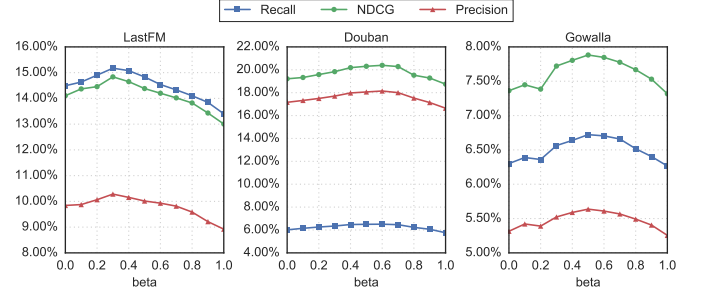


Fig. 5. The influence of the magnitude of adversarial training.

training. In this part, we show how these two parameters impact the performance of ESRF.

When social information is not available, ESRF degenerates to NCCF. As can be seen from Fig. 4, with the increase of the number of alternative neighbors, the performance of ESRF on all the datasets becomes better. After reaching its peak when k are 40, 30, 40 on LastFM, Douban, and Gowalla, respectively, it steadily declines on LastFM, and sharply decreases on Douban and Gowalla. Overall, the performance curve on Gowalla changes more dramatically. These trends can be explained as that, augmenting the social information helps when data are sparse, but excessive augmentation may introduce noises, which would mislead the model. From Fig. 5, we can observe similar trends that adversarial training improves ESRF, but a large magnitude of adversarial training will lower the performance of ESRF. Intuitively, we think it happens because maximizing the ad-

versarial loss is opposite to our optimization goal. Excessive maximization would emphasize the goal of generating useful neighborhood while deprioritizes the recommendation task.

5 CONCLUSION

Social recommender systems have received attention these years due to the potential value of social relations to improve traditional recommendation. However, the practice of social recommendation is not as successful as expected. It often suffers from some problems including relation sparsity, noises, and multi-facets. Existing social recommender systems only pay attention to the homophily in social networks and neglect these drawbacks. In this paper, we develop a deep adversarial framework based on GCNs to address the challenges of social recommendation. Our framework mainly includes three stages: the alternative neighborhood identification, the neighborhood denosing, and the attention aware social recommendation. For each problem, our framework provides a corresponding component to tackle the related challenge. Finally, adversarial training unifies all the components and ensures a coordinated effort to enhance social recommendation by playing a minimax game. To the best of our knowledge, this is the first work that combines adversarial training and GCNs to overcome the drawbacks of social recommender systems. Experimental results on three real-world datasets show that our recommendation model significantly outperforms other state-of-the-art social recommendation models.

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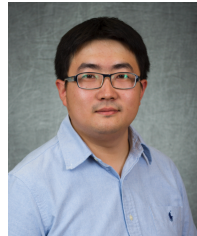
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