Self-Supervised Cross Domain Social Recommendation

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ABSTRACT

Social recommendation focuses on leveraging social information to enhance recommendation quality for social users. It requires that rating histories of these social users are available, which presents a great challenge for recommendation on cold-start social users who have no rating records. In fact, cold-start social recommendation can also be regarded as a cross domain recommendation(CDR) task, where user-item interactions form information domain and user-user links form social domain. Mainstream CDR approaches map or share bridge users representations between domains to enhance performance on non-bridge users in target domain. However, the performance of CDR methods heavily relies on the bridge users scale, which leads the system very vulnerable. In order to eliminate above mentioned problem, in this paper, we propose a novel Self-supervised Cross Domain Social Recommendation(SCDSR), aiming at cold-start social users. By innovatively integrating information domain and social domain into a heterogeneous graph, SCDSR builds higher-order connections between cold-start social users and items via very limited bridge users. Meanwhile, SCDSR employs mutual information maximization on heterogeneous graph with self-supervised signals to optimize node representation learning. Finally, extensive experiments on two real-world datasets (i.e., Epinions and Dianping) clearly demonstrate the effectiveness of our proposed method.

CCS CONCEPTS

• **Information systems** → Information systems applications; Data mining; Collaborative filtering.

KEYWORDS

Social recommendation, Cross domain, Self-supervised learning

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1 INTRODUCTION

With the rapid development of E-commerce platforms, the data sparsity problem becomes much severer, which presents a great challenge for recommender systems. Luckily, the social connections of users can be used to alleviate this problem, which is defined as social recommendation [8], [17], [25] and has gained much attention.

Traditionally, social recommendation requires that social users should have rating histories, so that their preference can be measured. For example, TrustSVD introduced social influence as additional terms for users' embedding learning based on SVD++ [6]. However, this requirement limits the capability of social recommendation, making it incapable of dealing with cold-start social users, who have no user-item interactions. A promising way is to regard this problem as a cross domain recommendation, where information domain contains user-item interactions and social domain provides user-user social connections. By transferring auxiliary knowledge from source information domain to target information domain, the recommendation of cold-start users can be handled properly. For example, Man et.al [18] designed a mapping function from source domain to target domain based on bridge users in order to alleviate cold-start users problem in target domain. Wang et.al [21] utilized pre-trained bridge user embeddings from information domain as ground truth for the label propagation from bridge users to non-bridge users in social domain.

Though great progress has been made, one important issue still remains unresolved. Specifically, most existing CDR methods heavily rely on the bridge users scale, which determines the transfer capability of models from source domain to target domain [18], [12]. Thus, the quality(e.g., numbers, representations) of bridge users will dominate the model performance. However, a large number of bridge users are not always available. A common situation in true world is that only few bridge users are in both domains. In other words, how to capture signals in both domains as more as possible with very limited bridge users is the main challenge that we must tackle in cross domain social recommendation.

In this paper, we propose a novel Self-supervised Cross Domain Social Recommendation (SCDSR) to tackle the bridge users scale dependency problem in CDR. In particular, we first integrate social domain and information domain into a heterogeneous graph, so that non-bridge users in social domain can capture latent item preference via bridge users by graph propagation. Based on the heterogeneous graph, high-order correlations between non-bridge users in social domain and items in information domain via limited bridge users should be considered, which is in favor of generating better user (item) representations. Furthermore, considering the uniqueness of different domains on the heterogeneous graph, we introduce self-supervised learning for optimization by performing multiple mutual information maximization, which aims to learn better node embeddings by capturing the global heterogeneous graph properties from two domains perspectives. Extensive experiments on two real-world datasets demonstrate the effectiveness of our proposed methods. Moreover, additional experiments on the size of bridge users prove that SCDSR can better deal with CDR situations with small size of bridge users.

2 RELATED WORK

2.1 Social Recommendation

Social recommendation utilizes social connections as auxiliary information to alleviate data sparsity problem in recommender systems [15], [6]. Several researchers treated social connections as regularization terms [16], [8], [17]. Recently, several works deal with social recommendation in a graph perspective [24], [25], [4]. MHCN exploits the mutual information maximization technique between the user, user-centered sub-hypergraph and hypergraph representations to learn users representations distinguishably in social recommendation [9]. However, these models are not suitable for cold-start social recommendation. To address such issue, Wang et.al [21] proposed NSCR to learn the preference of the cold-start social users via sharing bridge users embeddings. While most existing models heavily rely on the bridge user scale and perform worse when the bridge users are very few.

2.2 Cross Domain Recommendation

Cross domain recommendation leverages richer source information domain to handle the data sparsity problem in target information domain. EMCDR [18] is proposed to learn a MLP mapping function between bridge users to align both domains. Hu et.al [7] introduced deep transfer learning method into CDR to learn latent user-item interactions between domains. PPGN [12] expanded the adjacency matrix to capture high order user-item relationships among both domains. However, most existing methods can only be applied in the fully user overlapped scenario. In real world, the common phenomenon is that only partial users are shown in both or multiple domains simultaneously, which presents a greater challenge for recommendation in CDR. Several works have been proposed to address such issue [12], [13], [22]. Liu et.al [14] transferred bridge users embeddings to alternative domain during graph convolution learning in both domains. Generally, the performance of the embedding-based transfer approaches are also relied on the scale of bridge users. Thus, their performances are heavily limited when the bridge users are very few.

2.3 Self-supervised Graph Learning

Self-Supervised Learning(SSL) is a common paradigm which aims to learn representative characteristics for the downstream tasks from the raw data. SSL has been paid much attention due to its excellent performance in CV [5], [9], [10] and NLP [2], [3], [11]. Recently, SSL is also extended to the area of graph representation learning by fully exploiting the graph structure [1], [20]. Similarly in recommender systems, several works have been proposed by mutual information maximization technique to learn better graph representations with self-supervised signals [26], [23], [27]. EGLN exploited mutual information maximization to constrain the local-global consistency in the enhanced graph learning process [27]. SGL was proposed to optimize graph learning via mutual information maximization among multi-views of graph structure [23]. Naturally, in cross domain social recommendation task, when the bridge users are very few, it is very promising to employ mutual information maximization to help models learn better user representations from the constructed heterogeneous graph.

3 PROBLEM DEFINITION

Given the user-item graph of information domain $\mathcal{G}^{\mathcal{I}} = (U^I \cup V, R)$, where $U^I(|U^I| = M)$ and $V(|V| = L)$ are the user set and item set in $\mathcal{D}^{\mathcal{I}}$, respectively, and $\mathcal{R}$ is the user-item rating matrix, as well as the undirected user-user social graph of social domain $\mathcal{G}^{\mathcal{S}} = (U^S, S)$, where $U^S(|U^S| = N)$ is the users set in $\mathcal{D}^{\mathcal{S}}$ and S is the user-user social matrix. $U^B = U^I \cap U^S(|U^B| = T)$ is employed to represent the bridge users set and T is a small value. We integrate $\mathcal{G}^{\mathcal{I}}$ and $\mathcal{G}^{\mathcal{S}}$ into a heterogeneous graph $\mathcal{G} = \mathcal{G}^{\mathcal{I}} \cup \mathcal{G}^{\mathcal{S}} = \mathcal{G}\langle U^I \cup U^S \cup V, R, S\rangle$ via limited bridge users. The goal is to learn a recommender system $f(\cdot)$ to predict social domain non-bridge users' preference to items as: $\hat{R} = f(\mathcal{G}) = f(U^I \cup U^S \cup V, R, S)$, where $\hat{R} \in R^{(N-T)\times L}$ denotes the predicted preference of non-bridge users in social domain to the items in information domain.

4 METHODOLOGY

The overall framework of SCDSR consists of two parts: ***Heterogeneous Graph Embedding Learning*** and ***Model Optimization with Self-supervised Learning***, where the former part introduces how we construct heterogeneous graph and the later explains how we use self-supervised learning for graph optimization.

4.1 Heterogeneous Graph Embedding Learning

Since bridge users exist in both information domain and social domain, it is natural to leverage bridge users to integrate two domains into a heterogeneous graph, as shown in first step in Figure 1. Even bridge users are very few, we can also build higher-order connections between non-bridge users in social domain and items in information domain based on graph convolution. Similar as other embedding based graph models [24], [25], we transform the IDs of all users and items into embedding vectors with one-hot encoding, where $\boldsymbol{P} \in R^{(M+N-T)*d}$ and $\boldsymbol{Q} \in R^{L*d}$ denote the user and item embedding matrices, respectively. d is the embedding dimension.

For each node (i.e., user or item) in heterogeneous graph, we update their embeddings by various neighbors aggregation methods. Generally, the aggregation processes for users and items are formulated as follows:

$$p_u^{k+1} = p_u^k + \epsilon \sum\nolimits_{i\in R_u} \frac{1}{|R_u|} q_i^k + \tau \sum\nolimits_{a\in S_u} \frac{1}{|S_u|} p_a^k, \qquad (1)$$

$$q_i^{k+1} = q_i^k + \sum\nolimits_{a\in R_i^T} \frac{1}{\left|R_i^T\right|} p_a^k \qquad (2)$$

where p_u^k and q_i^k denote the user and item embeddings respectively in the k-th layer. R_u and S_u represent interacted items and connected users for user u. R_i represents the set of users who had rated the item i. If users belong to bridge users, $\epsilon = 1$ and $\tau = 1$; if users are non-bridge users in information domain, $\epsilon = 1$ and $\tau = 0$; and if users are non-bridge users in social domain, $\epsilon = 0$ and $\tau = 1$. As shown in Eq.(1), bridge user embeddings can capture both user-item and user-user correlations via graph aggregation. Next, we adopt a readout function to generate final representations for prediction, which is formulated as follows:

$$p_u = f_{readout}\left(p_u^k | k = [0, \dots K]\right),\ q_i = f_{readout}\left(p_i^k | k = [0, \dots K]\right) \tag{3}$$

where $f_{readout}$ denotes a readout function (average pooling) for generating representation from each layer.

After obtaining the final embeddings of users and items, inner product is employed to denote the preference of users to items. The preference of non-bridge users a in social domain to each item i can be calculated as:

$$\hat{r}_{ai} = \langle p_a, q_i \rangle \tag{4}$$

where $\langle , \rangle$ denotes inner product operation.

Since we focus on implicit feedbacks, we employ Bayesian Personalized Ranking (BPR) [19] loss to optimize our SCDSR, which is a pairwise loss supposing that the observed positive samples have higher scores than the unobserved negative samples. The objective function can be formulated as follows:

$$\mathcal{L}_{\mathcal{R}} = -\sum\nolimits_{(u,i,j \in D^I)} ln\sigma\left(\hat{r}_{ui} - \hat{r}_{uj}\right) + \psi\theta^2 \tag{5}$$

where user u and item i, item j are the user and items in information domain $\mathcal{D}^{\mathcal{I}}$, respectively. σ denotes the sigmoid activation function. User u has interaction behavior with item i, dubbed as the positive sample. Those items which are not interacted by user u are treated as negative samples, such as item j. $\theta = [\boldsymbol{P}, \boldsymbol{Q}]$ is user and item latent matrices and ψ is a regularization coefficient.

4.2 Model Optimization with Self-supervised Learning

As we focus on recommending items to non-bridge users in social domain who have no interaction records, it brings a great challenge that how to learn their preferences on lacking of supervised signals. Recently, SSL based models have achieved great success in CV and NLP, and also successfully applied in graph learning based recommendation tasks [23], [27]. To this end, we present our optimization solution with self-supervised signals from contrastive learning within heterogeneous graph data.

Given node embeddings learned from above heterogeneous graph, we aim to capture the global heterogeneous graph properties through maximizing the mutual information about local-global representation. Next, we firstly describe the calculation process of local and global representation of the graph $\mathcal{G}$ then we present local-global infomax for self-supervised learning.

4.2.1 Local Representation. The above heterogeneous graph learning module has provided each node's embedding for rating prediction. To better represent the graph properties, we perform local-global infomax for node embedding learning. For each node in heterogeneous graph, we first introduce how to represent local formulation.

Considering the edge uniqueness, we formulate the node's local representation from different perspectives. In social domain $\mathcal{D}^{\mathcal{S}}$, for the nodes with social connections, similar as other homogeneous graph works with MI [20], we directly use the learned embeddings p_a from heterogeneous graph as user a's local representation h_a. Due to two prototype nodes included in information domain $\mathcal{D}^{\mathcal{I}}$, we summarize the sub-graph of each user-item pair (u_a, v_i) as the local representation h_{ai}. Specifically, the local representations are depicted as follows:

$$\mathbf{h_a} = \sigma\left(p_a\right) \tag{6}$$

where σ is an activation function(sigmoid), and we use concatenation function to combine node pair's embeddings as the local representation for users in information domain.

4.2.2 Global Representation. As we have two kinds of local representation from domain perspectives, we then summarize two graph-level global representations to capture the domain properties. Refer to other graph based representation learning works [1], [20], [27], we also adopt a readout function to formulate the global representation $\mathbf{g}$. Considering the difference between both domains, we define two modified local-level filter based readout function, $\mathcal{FR}_{\mathcal{S}}$ and $\mathcal{FR}_{\mathcal{I}}$ to obtain global representations:

$$\mathbf{g^S} = \mathcal{FR}_{\mathcal{S}}\left(\mathcal{G}\right) = \frac{1}{\left|U^S\right|}\sum\nolimits_{a \in U^S} \mathbf{h}_{\boldsymbol{a}}, \tag{7}$$

$$\mathbf{g^I} = \mathcal{FR}_{\mathcal{I}}\left(\mathcal{G}\right) = \frac{1}{R_1}\sum\nolimits_{a=0}^{M-1}\sum\nolimits_{i=0}^{L-1} r_{ai}\mathbf{h}_{\boldsymbol{ai}} \tag{8}$$

4.2.3 Local-Global Infomax. In order to capture the whole heterogeneous graph properties on the node representation, we utilize mutual information maximization on each $\langle local, global \rangle$ pair of users. Generally, we use two discriminators to assign the score to all $\langle local, global \rangle$ pairs in both domains. To be specific, for social domain, we employ a discriminator $\mathcal{D}_{\mathcal{S}}$, formulated as follows:

$$\mathcal{D}_S\left(\mathbf{h_S}, \mathbf{g^S}\right) = \sigma\left(\mathbf{h_S^T W_S g^S}\right) \tag{9}$$

where h_S and g^S denote the local representation and global representation in social domain, respectively. $W_S \in R^{d \times d}$ is a trainable weight matrix. Similarly, we also employ a discriminator $\mathcal{D}_{\mathcal{I}}$ for information domain, which is formulated as follows:

$$\mathcal{D}_I\left(\mathbf{h_I}, \mathbf{g^I}\right) = \sigma\left(\mathbf{h_I^T W_I g^I}\right) \tag{10}$$

where $\mathbf{h_I}$ and $\mathbf{g^I}$ denote the local representation and global representation in information domain, respectively. $W_I \in R^{2d \times 2d}$ is a trainable weight matrix. For both discriminators, we combine the corresponding local representation $\mathbf{h_S}(\mathbf{h_I})$ and global representation $\mathbf{g^S}(\mathbf{g^I})$ as the positive samples $[\mathbf{h_S}, \mathbf{g^S}]([\mathbf{h_I}, \mathbf{g^I}])$.

In order to perform contrastive learning for discriminators $\mathcal{D}_S$ and $\mathcal{D}_I$, we devise three data augmentation for the corrupted graph $\hat{\mathcal{G}}$. Specifically, the corrupted strategies we used conclude: (1) **Edge Modification(EM)** randomly drops a certain proportion of edges and adds the same number edges in each domain for the heterogeneous graph, similar as [2]. (2) **Node Dropout(ND)** randomly drops a certain proportion of nodes and their edges in the heterogeneous graph. (3) **Node Feature Shuffling(NFS)** randomly selects a certain proportion of nodes in the heterogeneous graph and shuffles their embeddings.

After the above procedure, we can obtain the corrupted heterogeneous graph $\hat{\mathcal{G}}$. Then, we summarize the local representation $\tilde{\mathrm{h}}_S$ and $\tilde{\mathrm{h}}_I$ in social and information domain. The local representation

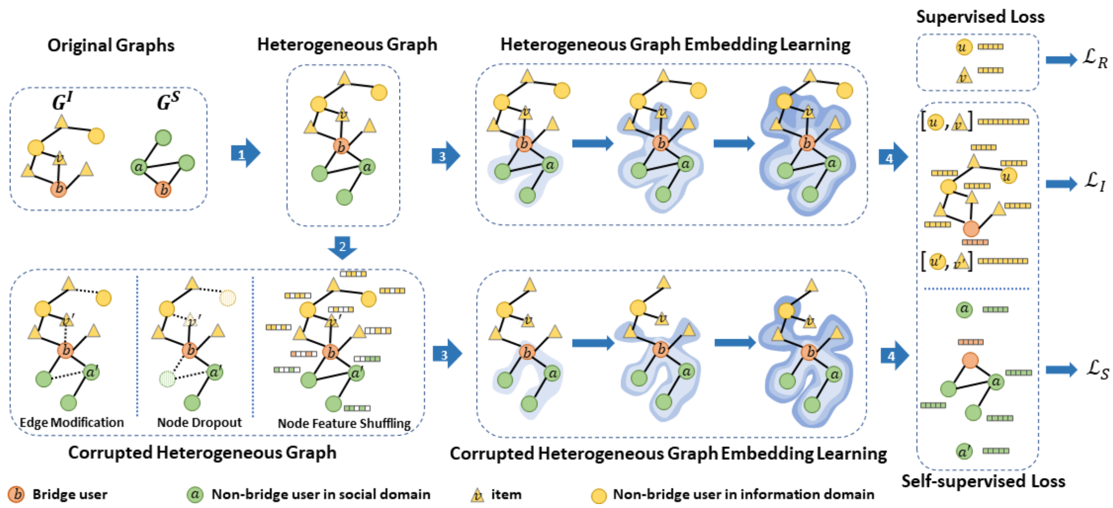

Figure 1: The overall architecture of our proposed model.

from the corrupted graph combine the global representation from the original graph as negative samples $[\tilde{\mathbf{h}}_S, \mathbf{g}^{\mathrm{S}}]([\tilde{\mathbf{h}}_I, \mathbf{g}^{\mathrm{I}}])$ for discriminators. Same as DGI [20], we use InfoNCE as our local-global mutual objective for optimization:

$$argmin_{\Theta_{D^S}} \ \mathcal{L}_S = -\frac{1}{|U^S|}\sum\nolimits_{a\in U^S}\left(\log D_S\left(\mathbf{h}_{\boldsymbol{a}}, \mathbf{g}^{\mathrm{S}}\right)\right) + \left(1 - logD_S\left(\tilde{\mathbf{h}}_{\boldsymbol{a}}, \mathbf{g}^{\mathrm{S}}\right)\right), \tag{11}$$

$$argmin_{\Theta_{D^I}} \ \mathcal{L}_I = -\frac{1}{R_1}\sum_{a=0}^{M-1}\sum_{i=0}^{L-1} r_{ai}\left(\log D_I\left(\mathbf{h}_{\boldsymbol{ai}}, \mathbf{g}^{\mathrm{I}}\right)\right) + \left(1 - logD_I\left(\tilde{\mathbf{h}}_{\boldsymbol{ai}}, \mathbf{g}^{\mathrm{I}}\right)\right) \tag{12}$$

where $\Theta_{D^S} = \mathbf{W}_{\mathrm{S}}$ and $\Theta_{D^I} = \mathbf{W}_{\mathrm{I}}$ are discriminator parameters in social and information domain. Note that bridge users are constrained with both mutual information modules simultaneously.

By maximizing the mutual information between local and global representation, we introduce self-supervised signals for graph embedding learning which contributes to capture the global graph properties. Last, we joint the supervised signals and self-supervised signals in a multi-task form as follows:

$$\mathcal{L} = \mathcal{L}_{\mathcal{R}} + \alpha\mathcal{L}_S + \lambda\mathcal{L}_I \tag{13}$$

where α and λ are weights to balance each part.

5 EXPERIMENTS

5.1 Dataset Description

We process two public datasets: Epinions[1] and Dianping[2] to meet our task. Given information domain and social domain are composed of rating data and social links respectively, firstly, we filter the candidate users who exist in both domains.Then, we randomly select 10% candidate users as bridge users. Later, we treat up to 4-order social neighbors of bridge users as non-bridge users in social domain. The rest of candidate users are treated as non-bridge users in information domain. 20% ratings of bridge users and all the ratings of non-bridge uses in social domain are treated as test set. And the train set consists of the remained rating data in information domain and social links data in social domain. The specific data statistics are shown as Table 1.

5.2 Baselines and Evaluation Metrics

We select several state-of-the-art recommendation methods containing social recommendation (TrustSVD and DiffNet) and cross domain recommendation(EMCDR, NSCR and BiTGCF) methods as our baselines:

- **TrustSVD** [6] treats the social trust as additional terms when learning bridge users' preference.
- **DiffNet** [25] utilizes GNN to model bridge users' high-order social relations for better preference learning.
- **EMCDR** [18] utilizes MLP to learn the mapping function between both embeddings for bridge users.
- **NSCR** [21] leverages bridge users' preference embedding for feature propagation in the social domain.
- **BiTGCF** [14] transfers bridge users' embeddings to alternative domains during graph learning.

Note that only cross domain approaches can be evaluated for the non-bridge social users, as no rating data is available to learn their preference embedding directly. As we focus on recommending *Top-N* items, we adopt Hit Ratio (HR) and Normalized Discounted Cumulative Gain (NDCG) as metrics. For both metrics, the higher results we get, the greater performance the model achieves. Last, for fair comparisons, we repeat the evaluation process 10 times and report the average results as final results.

5.3 Overall Performance

After comparing the performance of all the models on two datasets in Table 2, we have the following findings:

[1] http://www.trustlet.org/downloaded_epinions.html
[2] https://lihui.info/data/dianping/

Table 1: The statistics of datasets

Domains		Dianping	Epinions
Information	Users	10,182	8,725
	Items	8,627	23,115
	Ratings	199,407	206,612
Social	Users	5,296	3,261
	Links	13,282	11,544
Bridge	Users	1,303	1,107
	Ratings	23,892	16,351
	Links	3,934	2,625

- TrustSVD and DiffNet show better performance than EMCDR and NSCR on bridge users. It may because EMCDR and NSCR only consider the bridge users' collaborative filtering information in the information domain, while TrustSVD and DiffNet fuse social information with collaborative filtering knowledge in information domain.
- As EMCDR and NSCR mainly depend on the scale of bridge users, thus, when the bridge users are very few, they have poor performance on the non-bridge users in social domain. As for BiTGCF, it leverages GNN to capture the high-order social relations in social domain, and obtain the high-order collaborative information transferred from information domain, which can alleviate the few bridge users issue to some extent.
- Except slightly worse performance on NDCG results of bridge users on Dianping, our proposed SCDSR consistently shows the best performance than other models on both bridge users and non-bridge users in social domain. The reason is that constructing heterogeneous graph via bridge users can capture the high-order correlations across domains, then non-bridge users can capture the potential item preferences by propagating from bridge users. Moreover, we introduce self-supervised signals for graph embedding learning by maximizing the mutual information between local and global representations in both domains, which is beneficial to capture the whole heterogeneous graph properties in final node representation. It needs declare that the overall low values are understandable because there are no available user-item interactions for non-bridge social users.

5.4 Influence of Bridge Users

Bridge users build connections between items and non-bridge social users. Thus, we conduct experiments to explore the influence of bridge users. Specifically, we select 5%, 10%, 30% and 50% of all the users in both domains as bridge users in Epinions and compare the recommendation performance on non-bridge users. As shown in Figure 2, we observe that SCDSR consistently achieves the best performance under four bridge user proportions. Besides, SCDSR shows a larger improvement than the strongest baseline on the smaller proportion of bridge users. It indicates that SCDSR has strong ability to dig more signals in both domains with very limited bridge users for learning non-bridge users' preferences through high-order neighbors aggregation. Besides, the performance on bridge users also outperforms in each proportions, proving the effectiveness of our SCDSR.

5.5 Ablation Study

5.5.1 Effect of Mutual Information Modules. To investigate the effect of two mutual infomax modules, we conduct experiments on SCDSR with different MI settings. Limited to the space issue, we only report the HR@10 and NDCG@10 values on Dianping dataset. As shown in Table 3, we compare SCDSR with different variants, where SCDSR+noMI is an original heterogeneous graph with no MI modules, SCDSR+inforMI and SCDSR+socMI represent the models with MI in information domain and MI in social domain respectively based on a heterogeneous graph. SCDSR is our proposed model with both MI modules constrain. According to the results, it is apparent that each single MI module (SCDSR+inforMI, SCDSR+socMI) has positive effect on our model. Moreover, both MI modules encourage better node learning and non-bridge users can learn better item preference via bridge users.

5.5.2 Comparisons of Negative Sampling Methods. For investigate the influence of negative sampling, we conduct experiments on SCDSR with three negative sampling methods: Edge Modification(EM), Node Dropout(ND) and Node Feature Shuffling(NFS). Due to the space, we only report our results on Dianping. We construct corrupted heterogeneous graph $\hat{\mathcal{G}}$ randomly in every epoch process. In such dynamic way, we can obtain more comprehensive structure information and learn more precise representation for each non-bridge user. As shown in Table 4, we observe that SCDSR with edge modification outperforms significantly compared to another two methods. A possible reason is that node dropout and node feature shuffling cause corrupted graph to lose most of the important graph structure information.

5.5.3 Parameter Sensitivities. We study the performance of SCDSR with different parameters α and λ, where α and λ are utilized to weight the importance of mutual infomax in social domain and information domain, as illustrated in Formula 13. Limited to the space, we only show the results on Dianping as shown in Figure 3. We search α and λ in [0,1,1e2,1e3,1e4] and observe that when α =1e2 and λ =1e3, SCDSR achieves the best performance. Moreover, we observe that the performance of SCDSR decreases quickly when α is larger than 1e2, and the performance of SCDSR enhances with increasing λ from 0 to 1e3, then drops significantly after 1e3. It indicates that suitable parameters of each MI module are beneficial for overall objective optimization.

6 CONCLUSION

In this paper, we propose a novel self-supervised cross domain model SCDSR for social cold-start recommendation, which integrates information domain and social domain into a heterogeneous graph with very limited bridge users. By multiple layer graph propagation, SCDSR can build the high-order correlations between non-bridge users in social domain and items in information domain. Furthermore, self-supervised learning is introduced for optimizing node representations learning by mutual information maximization on both domains. Finally, the experimental results obviously verify the effectiveness of our proposed model.

Table 2: The performance of HR@N and NDCG@N on the Dianping and Epinions datasets.

Target User	Model	Dianping						Epinions					
		HR@N			NDCG@N			HR@N			NDCG@N		
		10	20	30	10	20	30	10	20	30	10	20	30
Bridge Users	TrustSVD	0.0509	0.0796	0.1027	0.0370	0.0475	0.0551	0.0324	0.0473	0.0632	0.0233	0.0291	0.0341
	DiffNet	0.0592	0.0877	0.1139	**0.0440**	**0.0545**	**0.0626**	0.0357	0.0588	0.0756	0.0258	0.0343	0.0407
	EMCDR	0.0503	0.0715	0.0926	0.0371	0.0451	0.0520	0.0309	0.0405	0.0502	0.0201	0.0223	0.0262
	NSCR	0.0158	0.0253	0.0345	0.0126	0.0163	0.0193	0.0208	0.0341	0.0461	0.0148	0.0199	0.0237
	BiTGCF	0.0505	0.0795	0.1042	0.0372	0.0473	0.0552	0.0359	0.0579	0.0733	0.0247	0.0329	0.0379
	SCDSR	**0.0599**	**0.0911**	**0.1156**	0.0435	0.0543	0.0619	**0.0368**	**0.0590**	**0.0762**	**0.0276**	**0.0356**	**0.0411**
Non-bridge Users in Social Domain	EMCDR	0.0071	0.0083	0.0105	0.0067	0.0071	0.0079	0.0084	0.0134	0.0186	0.0072	0.0091	0.0110
	NSCR	0.0140	0.0176	0.0222	0.0135	0.0148	0.0165	0.0102	0.0135	0.0177	0.0092	0.0104	0.0119
	BiTGCF	0.0217	0.0299	0.0378	0.0185	0.0213	0.0241	0.0287	0.0429	0.0552	0.0243	0.0296	0.0340
	SCDSR	**0.0263**	**0.0359**	**0.0445**	**0.0221**	**0.0255**	**0.0284**	**0.0303**	**0.0443**	**0.0593**	**0.0257**	**0.0311**	**0.0365**

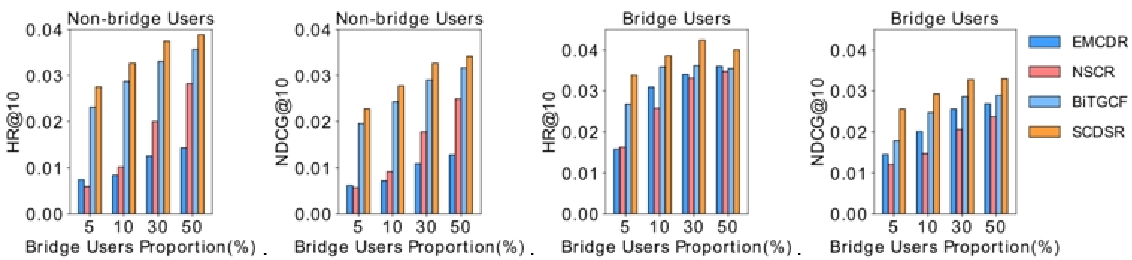

Figure 2: HR@10 and NDCG@10 comparisons on bridge users and non-bridge users in social domain under various proportions of bridge users on Epinions.

Table 3: HR@10 and NDCG@10 of different variants on bridge users and non-bridge users in social domain on Dianping.

Model	Non-bridge Users		Bridge Users	
	HR@10	NDCG@10	HR@10	NDCG@10
SCDSR+noMI	0.0203(-)	0.0204(-)	0.0534(-)	0.0409(-)
SCDSR+inforMI	0.0244(+6.09%)	0.0207(+1.47%)	0.0565(+5.8%)	0.0415(+1.47%)
SCDSR+socMI	0.0255(+10.87%)	0.0215(+5.39%)	**0.0614(+14.98%)**	**0.0449(+9.78%)**
SCDSR	**0.0263(+14.35%)**	**0.0221(+8.33%)**	0.0599(+12.17%)	0.0435(+6.35%)

Table 4: The results with different negative sampling methods on Dianping.

Model	HR@N			NDCG@N		
	N=10	N=20	N=30	N=10	N=20	N=30
SCDSR+EM	**0.0263**	**0.0359**	**0.0445**	**0.0226**	**0.0257**	**0.0286**
SCDSR+ND	0.0255	0.0340	0.0437	0.0222	0.0252	0.0285
SCDSR+NFS	0.0262	0.0351	0.0438	0.0224	0.0255	0.0284

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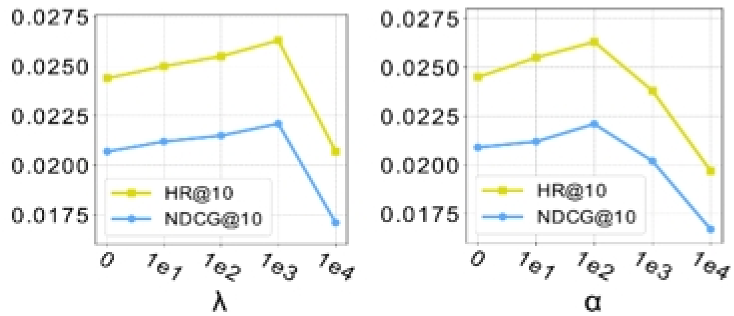

Figure 3: HR@10 and NDCG@10 comparisons under various weights for inforMI and socMI.

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