Heterogeneous Network-based Group Recommendation Method for Scientific Social Network

Research-in-Progress

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Abstract

The overwhelming number of groups in Scientific Social Network (SSN) makes it a great burden for researchers to find their desirable groups. Therefore, it's critical to automatically recommend groups to researchers according to their preferences. Moreover, recommending groups to researchers in SSN naturally belongs to a One-Class Collaborative Filtering (OCCF) problem. Therefore, in this paper, a Heterogeneous Network-based (HN) Group Recommendation (HNGR) method is proposed to recommend groups to researchers in SSN. Specifically, to consider both the direct and indirect relations between entities in SSN, HN is employed to conduct similarity calculation to support further negative instances extraction and Probabilistic Matrix Factorization (PMF) recommendation processes. Experiments were conducted on the real world CiteULike dataset. The experimental results demonstrate the effectiveness of the proposed HNGR method, and the superiority of HN for similarity calculation which indicates the necessity of considering the indirect connections between researchers and groups.

Keywords: Scientific Social Network, Group Recommendation, Heterogeneous Network

Introduction

With the rapid development of Web 2.0 technology, Scientific Social Network (SSN) has become one of the most prevalent ways for researchers to establish contacts with each other. Popular SSN includes ResearchGate, CiteULike, Academic, and ScholarMate (Zhao et al. 2018). SSN enables researchers to browse, collect, label, and share research papers. Besides, it also allows researchers to establish their own groups or participate in the existed ones according to their research interests. This makes it more convenient for researchers to find research papers, share academic achievements, and communicate with each other. However, the number of groups in SSN grows at an explosive rate, making it increasingly difficult for researchers to find groups they are really interested in. Therefore, it's critical to automatically recommend groups to researchers according to their preferences.

With regard to group recommendation, several studies have been conducted to recommend groups in Flickr, or other social networks (Bok et al. 2016; Zha et al. 2013). However, few of these studies have concerned recommending groups in the SSN scenario. In addition, the techniques they employed can mainly be classified into two categories: One is the Content-Based Filtering (CBF) methods, e.g., Yu et al. suggested to integrate both content and relationship information of images to recommend groups to images (Yu et al. 2010). Nevertheless, the recommendations of the CBF methods are inclined to lack diversity due to their content-based nature. Hence the Collaborative Filtering (CF) methods are more frequently used in practice, e.g., Guo suggested to take advantage of the trust-aware CF and the user-based CF to recommend groups to users (Guo et al. 2016). However, when recommending groups to researchers in SSN, there is only information about which groups researchers have joined, indicating researchers' positive preferences for groups, whereas the negative preferences of researchers are unavailable. Therefore, it naturally belongs to a One-Class Collaborative Filtering (OCCF) problem. However, this has rarely been explored in previous studies.

The sampling scheme is one of the frequently used schemes to address the OCCF problem. The central idea is to introduce negative instances from the unlabeled examples. Three commonly used strategies include All Missing data As Negative (AMAN), All Missing data As Unknown (AMAU), and Random Missing data As Negative (RMAN) (Pan et al. 2008). However, when adopting these strategies, only static statistical information of users' historical behaviors are used, making it no difference in the probability of each unlabeled item being a negative instance for each user. It is obviously unreasonable in practice. Hence the similarity-based sampling methods have been proposed to take full advantage of other useful information. For example, Wang et al. proposed a social information-aware method integrating textual information with social tag information to extract negative instances (Wang et al. 2017). However, the aforementioned sampling strategies can only capture the direct relations between users and items. Whereas in SSN, there are multiple types of objects with multiple types of connections, i.e., SSN is a typical Heterogeneous Network (HN). In the heterogeneous SSN, any two objects can connect through many indirect ways, for example, researcher-researcher-group, and researcher-paper-group. It is unreasonable to introduce negative instances by considering only the direct relations. Therefore, a HN-suitable similarity calculation method is urgent to take the indirect interactions into account. To the best of our knowledge, we are the first to employ HN to handle the OCCF problem in SSN.

In this paper, a Heterogeneous Network-based Group Recommendation method (HNGR) is proposed to solve the OCCF problem encountered when recommending groups to researchers in SSN. Firstly, HN is employed to describe the complex relations between entities in SSN. Afterwards, the adaptive HeteSim method is applied to calculate researcher-group similarity and researcher-researcher similarity. Secondly, based on the researcher-group similarity calculated in the first step, negative instances are extracted and filled into the original researcher-group rating matrix. Thirdly, based on the supplemented researcher-group rating matrix, the researcher-researcher similarity is embedded into the Probabilistic Matrix Factorization (PMF) approach to generate final group recommendations. Experiments have been conducted on the real world CiteULike dataset. The experimental results indicate that compared with the baselines, the proposed method achieves the best performance in terms of all evaluation metrics, hence demonstrate the effectiveness of the proposed method. In addition, the results also demonstrates the superiority of HN for similarity calculation which indicates the necessity of considering the indirect connections between researchers and groups.

Our contributions can be summarized as follows. (1) In the proposed HNGR method, recommending groups to researchers in SSN is formalized as an OCCF problem to alleviate the extreme data imbalance and data sparsity problems. (2) HN is applied to conduct similarity calculation to take both the direct and indirect relations between entities into account. To the best of our knowledge, investigation of employing HN to handle the OCCF problem in SSN has not been explored. (3) Experiments have been conducted on the real world CiteULike dataset and the experimental results demonstrate the effectiveness of the proposed HNGR method.

The rest of the paper is organized as follows: In section Methodology, we introduce the framework and details of the proposed HNGR method. We outline the experimental settings in section

Experiments Setup. The experimental results and discussions are presented in section Results and Discussions followed by the conclusions and future work in section Conclusions and Future Work.

Methodology

SSN is a research-centered virtual community where researchers can annotate research papers with personal tags and join interest groups to communicate with others. However, the overwhelming number of groups makes it a great burden for researchers to find their desirable groups. Moreover, only researchers' positive preferences for groups can be acquired, whereas the negative preferences of researchers are unavailable. Considering these characteristics of SSN, the HNGR method is proposed to solve the aforementioned problems. Figure 1 shows the overview of the proposed HNGR method. It contains 4 primary steps: heterogeneous SSN construction, similarity calculation, negative instances extraction with researcher-group similarity, and PMF prediction with researcher-researcher similarity. In the heterogeneous SSN construction step, HN is employed to describe the complex relations between entities in SSN. In the similarity calculation step, the researcher-group similarity and researcher-researcher similarity are calculated by the adaptive HeteSim method. In the negative instances extraction step, the groups owing high dissimilarity with researchers are extracted as negative instances and filled into the original researcher-group rating matrix. In the prediction generation step, to conform similar researchers have similar latent vectors, the researcher-researcher similarity information is embedded into the PMF model to generate final group recommendations.

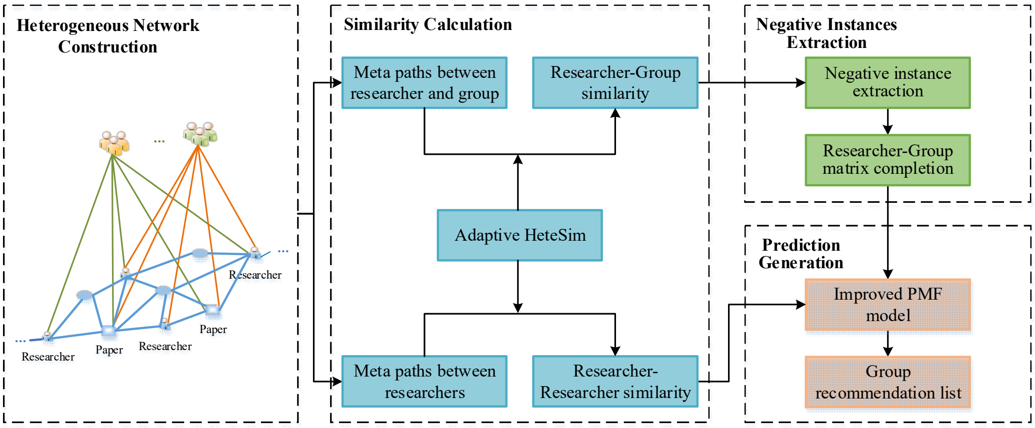

Figure 1. Overview of the HNGR Method

Heterogeneous SSN Construction

In this section, we introduce some terms and the construction details of the heterogeneous SSN.

Definition 1 Heterogeneous SSN. Heterogeneous SSN contains four types of entities: researchers (u), groups (g), papers (p), and tags (t). And five types of relations exist among these entity types: ug (researcher u_i joins group g_j), up (researcher u_i collects paper p_k), ut (researcher u_i assigns tag t_s), pg (group g_j uploads paper p_k), and pt (paper p_k possesses tag t_s).

Definition 2 Meta path. A meta path ρ is a path from entity type a_1 to entity type a_{l+1} : $a_1 \xrightarrow{r_1} a_2 \xrightarrow{r_2} \cdots \xrightarrow{r_l} a_{l+1}$. We denote the connection between a_1 and a_{l+1} as $\rho = r_1 \circ r_2 \circ \cdots \circ r_l$ where $\circ$ denotes the composition operator on relations. The length of a meta path is the number of relations which is l here.

HN comprises multi-typed entities, and different paths between them denote different semantic meanings. As a result, the similarity calculated may be totally different based on different paths. Therefore, it is necessary to predefine meta path for subsequent similarity calculation. Here we define two types of meta paths between researchers and groups: upg (individual researcher reads paper in group), and $utpg$ (individual researcher assigns tag which is possessed by paper in group). We also define three types of meta paths between researchers: upu (researchers read the same paper), utu (researchers assign the same tag), and ugu (researchers join the same group).

Similarity Calculation

In this section, we describe how to apply the adaptive HeteSim method to calculate similarity in heterogeneous SSN. Traditional feature-based methods (e.g., Cosine similarity) and link-based methods (e.g., PageRank) are not applicable in computing similarity between two nodes of HN. To solve this problem, the HeteSim method was proposed which can measure the similarity of objects with the same or different types in a uniform framework (Shi et al. 2014). Therefore, we employ the adaptive HeteSim method to calculate the researcher-group similarity and researcher-researcher similarity in heterogeneous SSN.

HeteSim is a path-based method, it calculates the probability that two objects encounter each other at the same node as they walk randomly in opposite directions. Given a meta path $\rho = r_1{\circ}r_2{\circ}\cdots{\circ}r_l$, the HeteSim score between researcher u_i and group g_j can be computed according to formula (1):

$$HeteSim(u_i, g_j \mid r_1 \circ r_2 \circ \cdots \circ r_l) = \frac{1}{|O(u_i \mid r_1)| * |I(g_j \mid r_l)|} \sum_{i=1}^{|O(u_i|r_1)|} \sum_{j=1}^{|I(g_j|r_l)|} HeteSim(O_i(u_i \mid r_1), I_j(g_j \mid r_l) \mid r_2 \circ r_3 \circ \cdots \circ r_{l-1}) \quad (1)$$

where $O(u_i|r_1)$ is the out neighbors of u_i based on relation r_1, and $I(g_j|r_l)$ is the in-neighbors of g_j based on relation r_l.

Formula (1) indicates that the calculation of $HeteSim(u_i, g_j|r_1{\circ}r_2{\circ}\cdots{\circ}r_l)$ is a recursive process. It needs to iterate over all subsequent node pairs $(O_i(u_i|r_1), I_j(g_j|r_l))$ of (u_i, g_j) along the path $r_1{\circ}r_2{\circ}\cdots{\circ}r_l$ until u_i and g_j meets. When $|O(u_i|r_1)| = 0$ or $|I(g_j|r_l)| = 0$, i.e. u_i has no out-neighbors along r_1, or g_j has no in-neighbors along r_l, the HeteSim score between u_i and g_j is 0. Specially, the HeteSim method denotes the relation between objects of the same entity type as self-relation, and the HeteSim score of two objects with a self-relation is 1 if and only if they are the same node, 0 otherwise.

However, researcher u_i and group g_j may not meet along path $utpg$ for its path length is an odd. Therefore, to ensure these two entity types will encounter each other, the HeteSim method suggests to add an entity type e in the middle of the path, hence transforms $utpg$ to $utepg$. Then the similarity along the meta path upg and $utpg$ can be computed as formula (1).

After computing the similarities between researcher u_i and group g_j along different meta paths, we just take their average as the final similarity between researcher u_i and group g_j. The similarity between researchers is calculated in the same way as the researcher-group similarity is calculated. Due to the space constraints, we will not repeat the process here.

Negative Instances Extraction with Researcher-group Similarity

In this section, we describe the details of negative instances extraction process. To begin with, we specify a proper scale of negative instances extraction regarding each researcher. Afterwards, we extract negative instances based on the researcher-group similarity calculated in section Similarity Calculation.

We assume that the scale of negative instances, which shall be extracted for each researcher, has a positive correlation with the activeness of the researcher. Specifically speaking, the more active a researcher is, the more groups s/he has joined previously, hence the groups s/he does not join are more likely to be seen but not appealing to him/her, rather than not to be seen. Therefore, it is of great necessity to extract more negative instances for researchers with high activeness. The scale of negative instances for researcher u_i is computed as formula (2):

$$NI_i = \beta * \sum ng_i \quad (2)$$

where NI_i is the scale of negative instances for researcher u_i. β is a negative rate parameter to control the balance between positive and negative instances. Here we set $\beta = 0.2$ according to Wang's study (Wang et al. 2017). $\sum ng_i$ is the total number of groups researcher u_i has joined.

Now that the scale of negative instances and similarity between researchers and groups are specified, the top NI_i groups with the highest dissimilarity is chosen as negatives instances for researcher u_i.

PMF Prediction with Researcher-researcher Similarity

Supposing there are M researchers with u_i indicating the i-th researcher, and N groups with g_j indicating the j-th group. The original researcher-group rating matrix $R_{M*N} = \{r_{ij}\}$ is generated based on the heterogeneous SSN. Specifically, if there is a ug relation between researcher u_i and group g_j, then$r_{ij} = 1$, 0 otherwise. Then the researcher-group similarity calculated before is filled into the original researcher-group rating matrix to introduce negative instances. Subsequently, based on the supplemented researcher-group rating matrix, the PMF progress is conducted as follows and the corresponding probability graph model is showed as Figure 2.

Under the probabilistic view, the observed researcher-group rating matrix R is subject to $U_i^T G_j$ mean Gaussian priors. To avoid over-fitting, the researcher latent feature matrix U and the group latent feature matrix G are assumed to subject to zero-mean spherical Gaussian priors. In addition, we assume that the researcher latent feature vector U_i is also affected by his/her similar researchers' latent vectors at the same time. Therefore, the overall posterior to be optimized is

$$\begin{aligned} &\arg\max_{U,G} P(U,G \mid R,S,\sigma_U^2,\sigma_G^2,\sigma_R^2,\sigma_S^2) \propto P(R \mid U,G,\sigma_R^2)P(U \mid S,\sigma_U^2,\sigma_S^2)P(G \mid \sigma_G^2) \\ &= \prod_{i=1}^{M}\prod_{j=1}^{N}[N(R_{ij} \mid g(U_i^T G_j),\sigma_R^2)]^{I_{ij}} \prod_{i=1}^{M} N(U_i \mid 0,\sigma_U^2 I)\prod_{i=1}^{M} N(U_i \mid \sum_{k\in N(i)} S_{ik}U_k,\sigma_S^2 I)\prod_{j=1}^{N} N(G_j \mid 0,\sigma_G^2 I) \end{aligned} \tag{3}$$

where S is the similarity matrix of researchers, and S_{ik} is the similarity between researcher u_i and researcher u_k calculated in section Similarity Calculation. $N(i)$ is the similar researcher set of researcher u_i. $N(x|\mu,\sigma^2)$ is the probability density function of the Gaussian distribution with mean μ and variance σ^2. I is the identity matrix. I_{ij} is an indicator function which is equal to 1 when researcher u_i joins group g_j, 0 otherwise. $g(x) = 1/(1+\exp(-x))$ is the logistic function to bound the range of $U_i^T G_j$ within the interval [0,1].

To maximize the posterior can be equivalent to minimize the following objective functions:

$$\begin{aligned} &E(U,G,R,S) \\ &= \frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{N} I_{ij}(R_{ij}-g(U_i^T G_j))^2 + \frac{\lambda_G}{2}\sum_{j=1}^{N} G_j^T G_j + \frac{\lambda_U}{2}\sum_{i=1}^{M} U_i^T U_i + \frac{\lambda_S}{2}\sum_{i=1}^{M}(U_i - \sum_{k\in N(i)} S_{ik}U_k)^T(U_i - \sum_{k\in N(i)} S_{ik}U_k) \end{aligned} \tag{4}$$

where $\lambda_G = \sigma_R^2/\sigma_G^2, \lambda_U = \sigma_R^2/\sigma_U^2, \lambda_S = \sigma_R^2/\sigma_S^2$ reflects the influence of each matrix on the objective function.

Afterwards, the Stochastic Gradient Descent (SGD) method is used to learn the researcher latent feature vector U_i and the group latent feature vector G_j:

$$\partial E/\partial U_i = \sum_{j=1}^{N} I_{ij}(g(U_i^T G_j)-R_{ij})g'_{U_i}(U_i^T G_j)G_j + \lambda_U U_i + \lambda_S(U_i - \sum_{k\in N(i)} S_{ik}U_k) - \lambda_S\sum_{k=1}^{N} S_{ik}(U_k - \sum_{h\in N(k)} S_{kh}U_h) \tag{5}$$

$$\partial E/\partial G_j = \sum_{i=1}^{M} I_{ij}(g(U_i^T G_j)-R_{ij})g'_{G_j}(U_i^T G_j)U_i + \lambda_G G_j \tag{6}$$

Finally, the preference of researcher u_i on group g_j is predicted as the value $\widehat{r_{ij}} = U_i^T G_j$, and for each researcher, the top-K groups are selected to form his/her recommendation list.

To sum up, the proposed HNGR method contains 4 primary steps: heterogeneous SSN construction, similarity calculation, negative instances extraction with researcher-group similarity, and PMF prediction with researcher-researcher similarity. Figure 3 shows the overall procedures of the proposed HNGR method.

Experiments Setup

Comprehensive experiments were conducted to evaluate the performance of the proposed HNGR method. The dataset was collected from CiteULike (http://www.citeulike.org/), a commonly used SSN. In the CiteULike, researchers can establish their own libraries consisting of scholar papers, and bookmark those papers with their personal tags. In addition, it provides researchers rights to create groups or choose interesting groups to join. Therefore, the website CiteULike appropriately fits the experiment requirements of our research. The original data of researcher's participating in groups, researcher's collecting papers, researcher's assigning tags to papers, researcher-in-group's uploading papers, and paper's all tags were obtained by crawler. To improve the reliability of the experimental results, some insufficient data were eliminated from the original data. For instance, researchers participating in only one group or collecting less than 15 papers, and groups with less than 3 members were removed. Finally, the pre-processed dataset comprises 3024 researchers, 987 groups, 120821 papers, and 203475 tags. To measure the recommendation quality, the precision, the recall, the Mean Average Precision (MAP), and the Mean Reciprocal Rank (MRR) are adopted, which are standard metrics in recommendation systems and have been widely used (Shi et al. 2012; Symeonidis et al. 2010; Torkestani 2012). The 10 trails hold-out verification method was used to verify the effectiveness of the proposed method. In the experiment, 80% of the original dataset was selected as the training set randomly, while the remaining 20% was used as the testing set. We set parameters $\lambda_G = \lambda_U = 0.05, \lambda_S = 0.01, \mathrm{Iter} = 1000$, in the experiments. We selected the recommendation number K=10 because we have tried different number of K from 10 to 50 and find that the best performance was achieved when K=10. We selected the latent feature dimension D=15 because we have tried different number of D from 5 to 30 and find that the best performance was achieved when D=15.

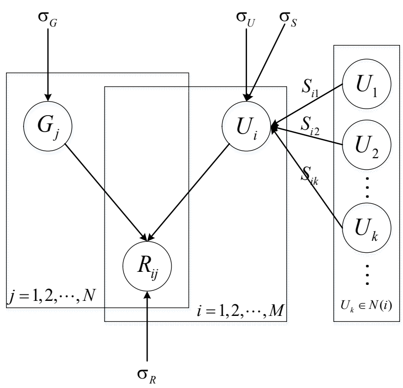

Figure 2. Improved PMF Prediction Model

Input: the relation types ug, up, ut, pg, pt, the meta paths upg, utpg, upu, utu, ugu, number of iteration Iter.
Output: the recommendation list.

1. Construct heterogeneous SSN based on relation types ug, up, ut, pg, and pt
2. For each $<u_i, g_j>$
3. if u_i does not join g_j
4. Calculate the researcher-group similarity by HeteSim using equation (1) based on upg and utpg
5. End for
6. Extract negative instances based on the researcher-group similarity
7. Generate researcher-group rating matrix R according to the relation type ug and the negative instances
8. For each $<u_i, u_k>$
9. Calculate the researcher-researcher similarity by HeteSim using equation (1) based on upu, utu, and ugu
10. End for
11. Initialize researcher latent feature matrix U and group latent feature matrix G
12. For iteration =1,2,…,Iter
13. Update U_i by equation (5)
14. Update G_j by equation (6)
15. End for
16. Obtain the fulfilled researcher-group matrix $\tilde{R}_{M \times N}$ $(\tilde{R} = \{\tilde{r}_{ij} = U_i^T G_j\}_{M \times N})$
17. For $u_i \in u$
18. Select top-K groups to u_i's recommendation list
19. End for
20. Return recommendation list

Figure 3. The Algorithm of the HNGR Method

Results and Discussions

Experimental Results

In this section, we investigate the performance of the proposed HNGR method by comparing with the baselines including HN, PMF, AMAN, RMAN, CBSamp_PMF, HNSamp_PMF, PMF_CBSim, PMF_HNSim, and CBGR. HN is the method directly applies heterogeneous network to recommend groups. CBSamp_PMF is the method adopting CBF to extract negative instances before conducting PMF recommendation. HNSamp_PMF is the method adopting HN to extract negative instances before conducting PMF recommendation. PMF_CBSim is the method integrating user similarity information calculated by CBF with the PMF model. PMF_HNSim is the method integrating user similarity information calculated by HN with the PMF model. CBGR is the combination of the CBSamp_PMF method and the PMF_CBSim method.

Table 1 shows the overall performances of different methods. Apparently, the proposed HNGR method achieves the best performance among all compared approaches. Specifically, the HNGR method achieves the highest precision of 0.0265, the highest recall of 0.0153, the highest MAP of 0.0506, and the highest MRR of 0.0527, which demonstrates the superiority of the proposed HNGR method. On the contrary, HN returns the worst performance as we expected, which indicates that considering only connections between researchers and groups without taking their latent characteristics into account will result in poor recommendations.

Table 1. The Experimental Results (K = 10, D = 15)

Methods	Precision (%)	Recall (%)	MAP (%)	MRR (%)
HN	1.03	0.65	3.53	4.17
PMF	1.56	0.73	3.96	4.34
AMAN	1.77	0.91	4.21	4.41
RMAN	2.14	1.17	4.61	4.79
CBSamp_PMF	2.31	1.25	4.72	4.95
HNSamp_PMF	2.43	1.39	4.80	5.14
PMF_CBSim	1.94	1.05	4.41	4.67
PMF_HNSim	2.05	1.21	4.53	4.86
CBGR	2.54	1.45	4.82	5.19
HNGR	2.65	1.53	5.06	5.27

Discussions

Effect of Parameters

The recommendation number K and the latent feature dimension D are two influential factors for the recommendation results. Therefore, the recommendation performance under different settings of these two parameters is further explored. From Figure 4 (a) we can learn that with increased K, the precision, MAP, and MRR are reduced while the recall is increased, which is consistent with previous studies. Figure 4 (b) depicts that as D increases, the performance first increases and reaches the peak when D=15, then decreases gradually as D increases further. Moreover, it can be seen that the proposed HNGR method consistently outperform other baselines in spite of K and D, which also reveals the superiority of the proposed HNGR method.

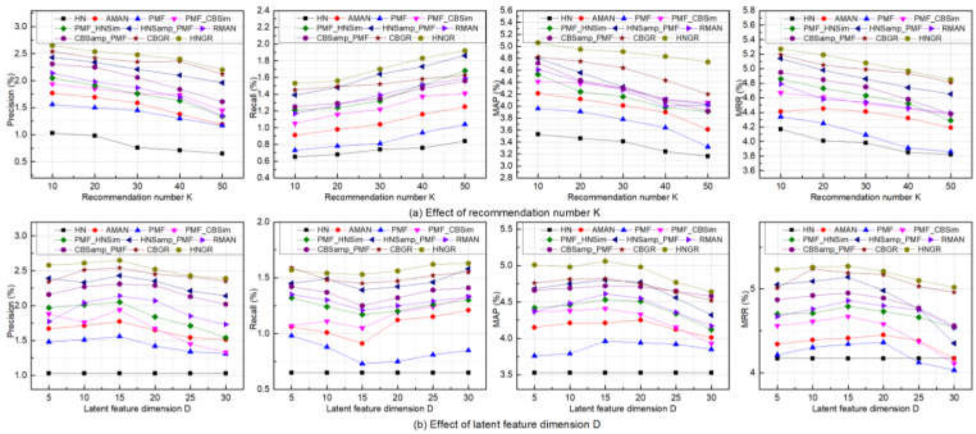

Figure 4. The comparison results under different K and different D

Effect of Sampling and Regularization Strategy

Here we explore the effects of the sampling and regularization strategy for alleviating the data sparsity problem. From Table 1 we can observe that all methods adopting a sampling strategy in advance outperform the standard PMF method, which demonstrates the necessity of negative instances introduction for recommendations with positive-only data. We can also observe that PMF methods adding regularization also achieve a performance improvement against the baseline PMF. It is interesting that the performance improvement of regularization is a weak improvement compared with sampling, which indicates that the sampling strategy is more effective than the regularization strategy when handling extreme sparse dataset.

Effect of HN for Similarity Calculation

Here we explore the performance of HN for similarity calculation. As shown in Table 1, on one hand, among all the compared sampling strategies, the HN-based sampling strategy achieves the best performance which demonstrates the efficiency of HN for similarity calculation. On the other hand, it is evident that the PMF method adding HN regularization outperforms the PMF method adding CB regularization, which verify the validity of HN once again. Generally, this indicates that indirect connections between researchers and groups does make a difference and should be considered in group recommendation for researchers.

Conclusions and Future Work

In this paper, a heterogeneous network-based group recommendation method is proposed to solve the OCCF problem encountered when recommending groups to researchers in SSN. HN is employed in the negative instances extraction and the PMF prediction process to derive a better recommendation performance. Experiments have been conducted on the real world CiteULike dataset and the experimental results demonstrate the effectiveness of the proposed HNGR method. Actually, when handling the OCCF problem, there is another solution called the weighting scheme which can solve the OCCF problem alternatively. Therefore, in the future, this work will be extended to integrate HN with the weighting scheme to solve the OCCF problem encountered in recommendations in SSN. In addition, network embedding techniques which convert a network into a low dimensional space while preserving the network information at the same time, provide an efficient and effective way to represent HN, and hence attract increasing attention from both research communities and industries recently. Therefore, the future work will employ the network embedding techniques to make better use of the rich information hidden in HN.

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