Interest-based Recommendation in Academic Networks using Social Network Analysis

Peyman Toreini[1], Mohamed Amine Chatti[2], Hendrik Thüs[3], Ulrik Schroeder[4]

Abstract:

Recommender systems are essential to overcome the information overload problem in professional learning environments. In this paper, we investigate interest-based recommendation in academic networks using social network analytics (SNA) methods. We implemented 21 different recommendation approaches based on traditional Collaborative Filtering (CF), Singular Value Decomposition (SVD)-based RS, Trust-based CF, and SNA-based techniques for recommending new collaborators and research topics to the researchers. The evaluation results show that SNA-based recommendation outperforms traditional CF methods in terms of coverage and thus can provide an effective solution to the sparsity and cold start problems in recommender systems.

Keywords: Recommender Systems, Social Network Analysis, Academic Networks, Collaborative Filtering, Professional Learning

1 Introduction

Academic researchers are lifelong learners who continuously try to stay up to date in their research fields by creating and updating their personal knowledge networks. This is a highly challenging task, given the abundance of information in the new knowledge society characterized by fast-paced change. Recommender systems (RS) provide a potential solution to deal with the information overload problem in academic networks. Effective RS in academic area is a tool to make self-directed learning procedure easier for academic researchers by presenting personalized results to them. RS have become an important research field since the emergence of the first paper on collaborative filtering (CF) in the mid-1990s [AT05] and are used in different domains like bookshops, web pages, movies, music, etc. to support customers finding products in online shops. Amazon's RS and Netflix RS are successful examples of internet-based businesses that focused on RS in their business models. In the academic area, RS help researchers by analyzing their past research activities and identifying information relevant to them. There are four main options suggesting by RS in the academic area: papers, collaborators, research topics and publication venues.

There are different RS techniques, and the most popular one is Collaborative Filtering(CF). Although CF methods have some advantages, they have some challenges such as data

[1] Informatik 9 (Learning Technologies) RWTH Aachen University, peyman.toreini@rwth-aachen.de
[2] Informatik 9 (Learning Technologies) RWTH Aachen University, chatti@cs.rwth-aachen.de
[3] Informatik 9 (Learning Technologies) RWTH Aachen University, thues@cs.rwth-aachen.de
[4] Informatik 9 (Learning Technologies) RWTH Aachen University, schroeder@cs.rwth-aachen.de

sparsity, cold-start problem, and scalability problem [Sa01]. The goal of Social Network Analysis-based Recommender Systems (SNA-based RS) is to improve the performance of traditional recommendation approaches by involving social relationships. There has been much research on social network-based recommendations including trust-based recommendation [MA07], social friends network recommendation [Ma11a], social tag recommendation [Ma11b]. SNA-based SR assumes a social network among users and makes recommendations for a user based on the rating of the users who have direct or indirect social relations with the given user [TD13].

Although there are some efforts to improve the performance of RS algorithm in the field of technology-enhanced learning (TEL) area such as [Ch13] [Ch16], we believe that investigating RS performance in this area needs more attention. Therefore, in this paper, we investigate how SNA-based RS affects the performance of RS in academic networks by implementing and comparing the performance of traditional CF, Singular Value Decomposition (SVD)-based RS, Trust-based CF, and two different SNA-based RS techniques. This comparison is based on collected data that provided by PALM project [Ch14] and are measured through offline and user evaluation methods.

2 Fundamentals and related work

RS will help users to have a better decision by collecting their previous data, analyzing them based on different techniques and providing relevant items close to their interests. In the following, we discuss the background and related works of the RS techniques that are used in this article.

- Traditional CF: Generally, CF techniques are classified into two categories: memory-based and model-based algorithms. Memory-based CF focuses on finding similarity between users or items with techniques like Pearson, Cosine, and Jaccard similarity measurements and then provides a recommendation. In the other hand, Model-based CF learns a model based on the collection of ratings and then make rating predictions. Memory-based CF algorithms are more popular than model-based versions since they are accurate when much past information about the user is recorded and do not have the complexity of the model-based algorithm. On the other hand, there are shortcomings for memory-based CF such as cold-start, sparsity, and scalability problem [Sa01].
- Singular Value Decomposition(SVD) Recommender: There are various types of dimensionality reduction techniques that can reduce the amount of data in the rating matrix and capture better model[KBV09]. The singular value decomposition (SVD) is a well-known method for matrix factorization and a solution for sparsity problem for recommendation systems. It is used to reduce the dimensionality of the sparse user-item matrix. These low-dimensional matrixes have features of the original data, and the neighborhoods and recommendation are computed using the less dimensional data. It is proved that SVD-based RS achieves better performance than traditional CF[BP98].

- Trust-based RS: In this types of RS, the recommendation provided by assuming a trust network among users and focusing on the ratings of the users that are directly or indirectly trusted by the active user (cf. [MA07],[Ma08]). One of the conventional approaches of trust-based RS is using trust over CF approach [KCP09]. In contrast with traditional user-based CF, by involving social relationships to the CF, the neighbors of the active user can be selected by trust relations instead of similarity [KCP09]. The recommendation results of these methods show that the performance of traditional RS can be improved by utilizing trust relations [Ph11]. Moreover, using trust-based CF will solve the problem of scalability in memory-based CF using clustering. However, the cold start and sparsity problems are not addressed using this method. In fact, it is still hard to recommend items to users without or with fewer ratings.
- SNA-based RS: SNA explores relationships among entities of networks and analyzes their features. There are several metrics available for SNA. These metrics help to identify the important node in a given social graph such as Degree, Betweenness, Closeness, Eigenvector. SNA-based RS algorithms apply the social influence of the users on the procedure of recommendation to improve its accuracy. This technique can provide the recommendation for cold start users as long as they are connected to the social network. Several SNA-based RS approaches have been proposed in the literature (cf. [Ma11b], [Lo10],[Hu12],[Pa04], [DAK12], [CALdI12], [YSZ10]). In general, these approaches use social networks as the source of information to generate recommendations. However, none of these approaches build social networks based on the user's interests.

3 Study

In this paper, we focus on leveraging SNA techniques and interest information to provide the recommendation of collaborators and research topics as new interests to the researchers. We used SNA-based recommendation methods and compared their performance with user-based CF, SVD recommendation and Trust-based CF based on a dataset generated within the PALM environment [Ch14]. For this investigation, the 754 researchers, 14.208 individual interests, and 40.674 publications, 169 cold-start researchers that are stored in PALM dataset are used. In this study, the co-authorship information of cold-start users is provided while the interest of them was not listed in the dataset.

21 algorithms are categorized into eight groups and are proposed in this paper. The list of proposed algorithms can be seen in Figure1. All these 21 algorithms support interest recommendation though 18 of them handle collaboration suggestion. In the following, we discuss the implementation of the proposed algorithms.

- User-based CF: This group consists of two algorithms that both support collaborators and interests recommendation. The idea behind algorithms of this group is to consider users with similar tendencies and choose interests from them to recommend. They use the entire user-item matrix of PALM dataset to find similar users by

Techniques	Cat. No.	Category Name	Alg. No	Strategies	Collaboration Rec.	Interests Rec.
User-based CF	1	Classic user-based CF	1	CF (Pearson)	✓	✓
			2	CF (Cosine)	✓	✓
SVD Recommender	2	SVD Recommender	3	SVD (ALSWRFactorizer)	×	✓
Trust-based CF	3	Trust-based CF with 1-depth Co-authorship Network	4	CF (Pearson)	×	✓
			5	CF (Cosine)	×	✓
	4	Trust-based CF with 2-depth Co-authorship Network	6	CF (Pearson)	✓	✓
			7	CF (Cosine)	✓	✓
	5	Trust-based CF with 3-depth Co-authorship Network	8	CF (Pearson)	✓	✓
			9	CF (Cosine)	✓	✓
SNA – based RS on Co-authorship Network	6	SNA-based RS based 2-depth Co-authorship Network (Centrality + Vertex similarity)	10	SNA (Degree) - Jaccard	✓	✓
			11	SNA (Closeness) - Jaccard	✓	✓
			12	SNA (Betweenness) - Jaccard	✓	✓
			13	SNA (Eigenvector) - Jaccard	✓	✓
	7	SNA-based RS based 3-depth Co-authorship Network (Centrality + Vertex similarity)	14	SNA (Degree) - Jaccard	✓	✓
			15	SNA (Closeness) - Jaccard	✓	✓
			16	SNA (Betweenness) - Jaccard	✓	✓
			17	SNA (Eigenvector) - Jaccard	✓	✓
SNA – based RS on Interest Network	8	SNA-based RS based Interest Network (Centrality)	18	SNA (Degree)	✓	✓
			19	SNA (Closeness)	✓	✓
			20	SNA (Betweenness)	✓	✓
			21	SNA (Eigenvector)	✓	✓

Abb. 1: List of proposed algorithms

Pearson or Cosine, and the implementation of these algorithms is done by applying Mahout. To apply collaboration recommendation for a researcher, ten new scientists who have similar taste with the active researcher are recommended. Additionally, to apply interest recommendation, the entire user-item matrix is used to find neighbors who are similar to the active researcher. Based on the conducted evaluation, ten neighbors for Pearson based version and 30 neighbors for Cosine based version are selected as the fittest parameter for implementing these algorithms in PALM. After that, the recommender is asked to provide ten new interests from the interest lists of neighbors.

- SVD-based recommendation: This group has one algorithm that supports only interest recommendation. The idea behind this algorithm is to build a recommender based on matrix factorization and a lower dimensional representation of the underlying user-item matrix data. Neighborhoods and recommendations are then computed using the lower dimensional data. The ALSWRFactorizer is used to do factorization and creation of the lower dimensional matrix and the number of features in this factorization is decided as 50 based on evaluated parameters. In the end, ten interests are recommended as the result.

- Trust-based CF: This group consists of six algorithms that all support interest recommendation but only four supports collaboration recommendation. The idea behind algorithms of this group is to use trust information provided by 1-depth, 2-depth and 3-depth co-authorship networks of an active researcher and use it to identify the neighbors. To provide interest recommendation, the similarity between the active researcher and co-authors are computed based on Pearson and Cosine. Furthermore, the number of direct co-authors is picked as the neighborhood number. In the end, a list of 10 interests is recommended based on all direct co-authors instead of the entire data of PALM. The implementation of these algorithms is done by utilizing Mahout. The collaboration proposal for an active researcher is collected from the indirect list of researchers who are in the second or third depth of co-authorship network and known as indirect nodes for the active researcher. The collaboration recommendation is not provided in 1-depth co-authorship network based algorithm since there are no indirect co-authors in this type of algorithms.
- SNA-based RS on Co-authorship Network: This group consists of eight algorithms, and all algorithms recommend collaborators and interests by utilizing 2-depth or 3-depth co-authorship network of the active researcher. Beside these networks, network centrality measures such as Degree, Betweenness, Closeness and Eigenvector in addition to Jaccard similarity is used to provide a recommendation. The procedure of recommendation for these algorithms starts by creating 2-depth or 3-depth co-authorship network and computing centrality metrics. In the next step, the Jaccard similarity between the active researcher and all the other nodes in the graph is computed. Those researchers who are known as cold-start users have the Jaccard similarity of zero or very low with all the other users. Each node in the graph has centrality and Jaccard similarity values and in the fourth step, these two elements are added together and compute an individual value for each node in the graph. In the end, top ten researchers in this graph are listed for collaborator recommendation. This list is unique and new for the active researcher. After finding the list of top ten new collaborators, all their interests are detected and sorted based on their scores by recommended researchers. As the result, top ten interests that are new to the active researcher is recommended.
- SNA-based RS on Interest Network: This group has four algorithms that are responsible to provide new collaborators and interest recommendation. The primary component of all four algorithms is interest network. This network is created based on two aspects, co-authorship relationship and the correlation between interests. To create an interest network; first, the 3-depth co-authorship network of the active researcher is built. After that, the five top interests of each node are picked, and the completed graph of these five interests is created. In the complete graph, every pair of distinct vertices is connected by a unique edge. In the next step, these complete graphs are connected to each other based on their intersections and the final interest

graph is achieved. The recommendation in this group is made by using SNA centrality metrics degree, closeness, betweenness and eigenvector values computed by Gephi toolkit.
After creating interest network, the first ten interests that have the highest centrality values in the interest network and are new for the active researcher are selected as recommended interest list. The collaborator recommendation list is then chosen from the combination of indirect co-authors in the 3-depth co-authorship network and the interest list. For each interest in the list, the indirect co-author who has the top score for the selected interest is recommended to the active researcher.

4 Evaluation Results

The assessment scheme of this project is done in two main phases, offline and user evaluation. Offline evaluation is done on all provided algorithms and it covers only interest recommendation results. Therefore, 8 best-performed algorithms in offline evaluation are selected. After this selection, user evaluation phase investigates the performance of the algorithms based on the comments of the users. User evaluation phase is done for both collaboration and interest recommendation.

4.1 Offline Evaluation

In the offline evaluation, eight algorithms are selected as the best-performed algorithm of each category. The name and detailed information about their execution can be seen in Table 1. In this section, the chosen algorithms of each group are compared with each other. This comparison is based on F-measure and coverage results. F-measure is important since both precision and recall is used in the computation of it. Coverage is also necessary to notice the outcome of recommendation for cold-start users.

As it can be seen, among the first five algorithms, CF based on 1-depth co-authorship network and Cosine similarity has the best performance result. The result can be explained as highest similarity rate of a researcher and direct co-authors. From the coverage point of view, SVD-based RS has the best-performed outcome in these five algorithms. Among last three algorithms, SNA-based RS on interest network has the best performance, and the algorithms number 6 and 8 covers most researchers in PALM with the percentage of 92%. Those who missed recommendation on these two algorithms can be from two distinct groups. First, researchers that the system could not build their 2 or 3-depth co-authorship network while there is no information about them except direct co-authors. Second, researchers whom their 2 or 3-depth co-authors are cold-start users. It also can be seen that the coverage is improved a lot through SNA based algorithms. It shows that the performance of interest network based recommendations had significant difference than other implemented algorithms and known as the best algorithm among all. Moreover, it can be seen that the performance of CF algorithm improved by using social relationships as the source of trust information. Selecting neighbors based on co-authorship network in trust-based CF algorithms could improve the result of recommendations compared with

Alg.No	Strategies	Precision	Recall	F-Measure	Coverage
1	CF (Pearson)	4.76%	6.67%	0.0555	65%
2	SVD-based RS	0.80%	1.82%	0.0111	78%
3	CF (Cosine) - 1d Co-authorship Network	10.32%	6.38%	0.1914	13%
4	CF (Cosine) - 2d Co-authorship Network	3.92%	3.99%	0.1197	13%
5	CF (Cosine) - 3d Co-authorship Network	2.37%	3.18%	0.0954	19%
6	SNA 2-depth Co-Authorship Network (Degree)	8.47%	7.89%	0.2345	92%
7	SNA 3-depth Co-Authorship Network (Betweenness)	6.77%	6.44%	0.1934	83%
8	SNA Interest Network (Degree)	14.59%	19.77%	0.5933	92%

Tab. 1: Selected algorithms for user evaluation

classic CF. This situation happens while it can be explained that using SNA centrality metrics based on different social networks can improve the quality of recommendation even better than trust-based CF recommendations.

4.2 User Evaluation

According to [PCH11] the quality of user experience often does not correlate with high recommendation accuracy measured by offline evaluation metrics. For this reason, a user evaluation phase is conducted for well-performed algorithms in the offline evaluation.

4.2.1 Evaluation Methodology

For the user evaluation, a user-centric questionnaire is prepared based on the ResQue (Recommender systems Quality of user experience) framework [PCH11]. To answer the survey, researchers are asked to respond to the questions based on 1-5 Likert scale in which 'Strong Disagree' means number 1 and 'Strong Agree' means number 5. To conduct user evaluation, eight researchers who had a profile on PALM are participated in the assessment and answered following questions:

- Ability to recommend: The system can provide a recommendation for me. (Y/N)
- Accuracy: In my opinion, the system can recommend to me 1-3 / 4-6 / 7-10 relevant Interests/Collaborators.

- Relative accuracy: The recommendation I received better fits me than what I may receive from a colleague
- Novelty: The interest/collaborators recommended to me are novel and interesting
- Diversity: The interest/collaborators recommended to me are diverse
- Context Compatibility: The interest/collaborators recommended to me considered my personal interests.
- Perceived usefulness: I feel supporting to find proper new interests/collaborators with the help of recommender.
- Attitudes: Overall, I am satisfied with the recommender.

4.2.2 Discussion of The Results

The discussion is divided into two sections. First, the results for the interest recommendations are illustrated and in the second section, the outcomes for collaboration recommendation are addressed. A summary of the average scores per question and per algorithm are given in Figure 2 and 3. As it can be seen in these diagrams, the performance of the algorithms fluctuates based on different aspects. In the end, attitude question focused on the overall satisfaction of the user about the fulfillment of each RS algorithm. Before answering this question, users needed to consider all the previous aspects of RS performance. Therefore, besides, to provide the result of all points, here we discuss the result of attitude in detail for both types of recommendation.

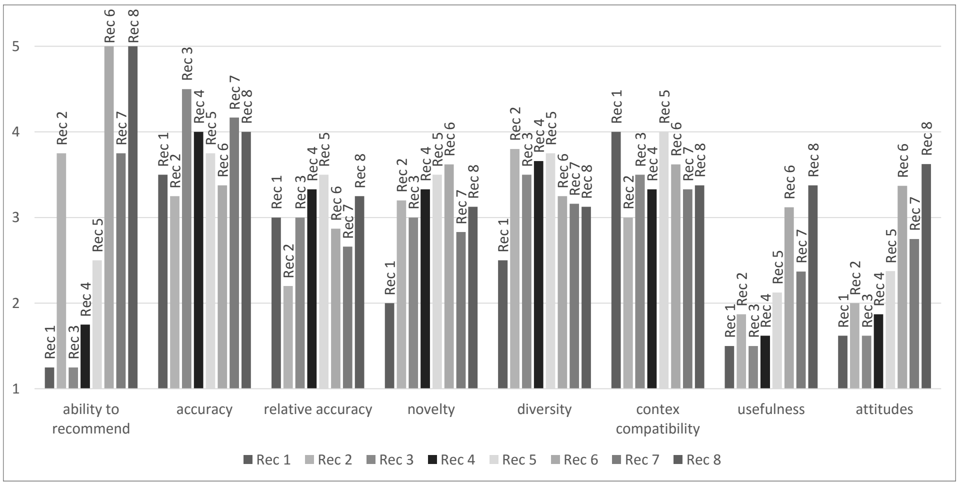

Abb. 2: User evaluation average results for interest recommendation

As it can be seen in Figure 2, the algorithm number eight, which relies on interest network, has the best-performed value in interest recommendation compared with the other algorithms. This happened while the second best-performed algorithm is SNA-based (Degree) based on 2-depth co-authorship network. The overall satisfaction has a significantly higher value based on these two algorithms compared with the other algorithms. Comparison of SNA-based algorithms with other algorithms shows that all three SNA-based algorithms satisfy users more than the other ones while the performance of the other algorithms has only a slight difference with each other.

Six algorithms of best-performed algorithms that are also providing collaborator recommendation are listed in the table 2.

Alg. No	Strategies
1	CF (Pearson)
2	CF (Cosine) - 2d Co-authorship Network
3	CF (Cosine) - 3d Co-authorship Network
4	SNA 2-depth Co-authorship Network (Degree)
5	SNA 3-depth Co-authorship Network (Betweenness)
6	SNA Interest Network (Degree)

Tab. 2: Selected algorithms of collaboration recommendation for user evaluation

The same questions for interest recommendation evaluation are used for collaboration recommendation evaluation. A summary of the average scores per question and per algorithm are given in Figure 3 and detailed discussion of the attitude factor are discussed in this section.

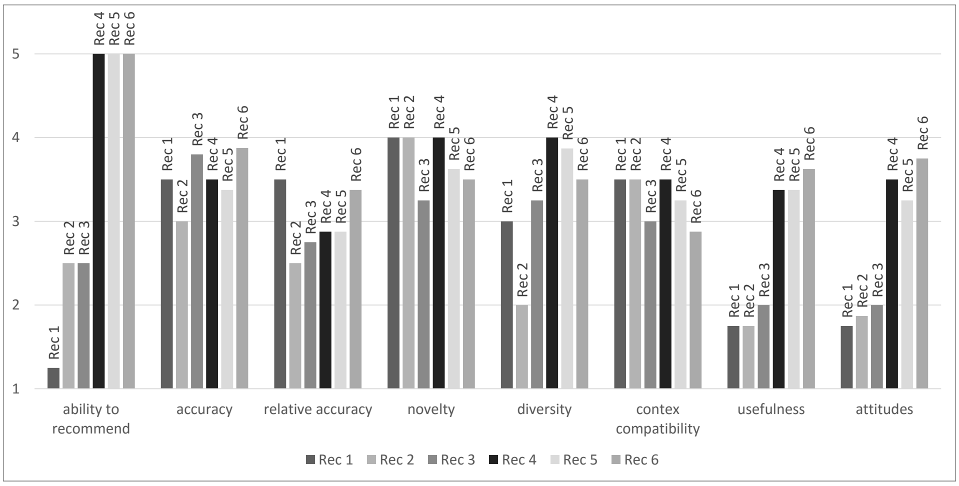

Abb. 3: User evaluation average results for collaboration recommendation

Overall, It can be seen that the level of satisfaction is provided with SNA-based algorithms significantly better result than other types of algorithms. As this diagram shows, all 3 provided algorithms based on SNA are identified as first three top algorithms while the algorithm SNA-based interest network, satisfied participated users more than the other algorithms. By analyzing it more, we can conclude that SNA-based 2-depth co-authorship is satisfying users a little more than the same algorithm based on 3-depth co-authorship. It can be found that users prefer to have a recommendation based on closer indirect co-authors than those who are in more depth. On the other hand, by evaluating trust-based CF results, we conclude that making a co-authorship network bigger in trust-based CF algorithms, the satisfaction slightly improves. All these results happened while the traditional CF performed worst than all the other algorithms.

4.3 Offline versus User Evaluation

In this article, only interest recommendation performance is examined in both offline and user evaluation. Figure 4 shows the comparison of these two evaluations in interest recommendation. As it can be seen, the result of the user evaluation and offline evaluation has a little difference. The order of trust-based recommendations that work with 1, 2, 3-depth co-authorship networks is changed in user evaluation. Additionally, SVD-based RS has the lowest performance result in offline evaluation while it moved to the fifth position in the evaluation result. The SVD-based algorithm could satisfy users more than trust-based RS of one and two depth co-authorship networks. This difference confirmed the claim in [PCH11] that says the quality of user evaluation experience with RS does not meet the high accuracy performance measured by metrics such as F-measure. In the other way, as it can be seen, the first three top algorithms in both types of evaluations have remained stable. These are algorithms that are implemented based on SNA centrality metrics while the SNA-base algorithm that deals with interest network has the topped rank in both evaluation results.

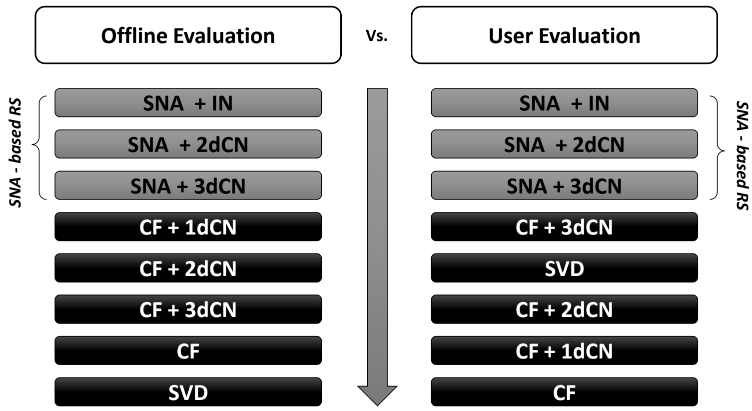

Abb. 4: Comparison of best performed algorithms in online and offline evaluation

The result of coverage performance in offline evaluation is reliable enough as it only checks the possibility of providing a recommendation list for all the users in PALM, not the quality of recommended items. Additionally, the participated users in user evaluation are not enough to have an accurate result for this factor. Therefore, to compare the results of coverage the user evaluation results are not included. As it can be seen in 1, SNA-based interest network, and SNA-based 2-depth co-authorship network have the highest coverage value with 92% while the third well-performed algorithm from this evaluation metric is SNA-based 2-depth co-authorship network. These results show that all the SNA-based algorithms could provide the recommendation for more users than the other recommendation algorithms. In the other hand, classic CF and SVD-based RS provided recommendation lists for significantly more users than all trust-based CF algorithms. Moreover, it can be seen that the coverage is improved by increasing the size of co-authorship networks in trust-based CF algorithms.

5 CONCLUSION AND FUTURE WORK

In this paper, we investigated how SNA-based RS can improve the performance of traditional CF RS algorithms in the academic area. Combination of interest and social information of researchers are used to study this question and check if using this information solve the sparsity and cold start problems of traditional CF RS. The offline evaluation based on Pearson, recall and F-measure in addition to the user evaluation results based on the ResQue framework confirmed that SNA-based CF can provide an effective solution to these problems. Furthermore, it is proven that SNA-based RS has better performance than SVD-based and Trust-based RS.

Even though two proposed SNA-based algorithms provide impressive results in both interest and collaboration recommendation, there can be several improvements. First, this paper is covering interest and collaboration recommendation while the paper recommendation is another possible important type of recommendation in the academic area. Moreover, in addition to co-authorship networks and interest networks, other types of networks such as weighted co-authorship networks or citation networks can be investigated in the future.

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