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# Identifying and comparing features and facilities of scientific social networks for recommending collaborators

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**Abstract.** Social networks are now an inseparable part of our life, each of us use social network for a special purposes from social interaction to marketing. One of the flourishing aspects of social networks is scientific social networks; users of these networks try to make public profiles, attach publications there, ask their questions and find new collaborators for future work. Having been considered for the last several decades in the data management field, recommending systems has also attracted a great deal of attention in computer science, and after the emergence of on-line social networks collaboration, suggestions for its use became an inseparable dimension of these young networks. In this paper some of the most popular and creative social networks have been considered, all of the useful features have been identified and compared, and finally the limitations of considered systems in providing direct collaborator recommendation has been discussed.

**Keywords:** Social networks · Recommending systems · Collaborator recommendation · Expertise finding

## 1 Introduction

Now intersected subjects, data management and social networks have become trends in academic communities with less than one decade after introduction. After the emergence of the data management field of computer science from the early years of 90s, the study of information systems for finding expertise has attracted much attention. The main aim of these systems, also known as expertise retrieval systems, is finding experts or extracting the members' expertise level in a specialist field. In the early years of the new century, social networks proliferated and availability of massive amount of data produced by billions of users have made old expert finding systems extremely inefficient. In the later era, huge amounts of information, produced by on-line users, can be collected automatically, unlike traditional systems in which data are collected manually. Furthermore, on-line platforms provide opportunities to evaluate self-expressed expertise levels with existing classifications of expertise level in on-line data. In other words, social networks have changed nature of management systems from manual to automatic.

A Social network's main purpose is removing the distance factor from human relations as a deterrent in social life. Although eliminating distances in human life is useful, its usage in academic communities can be even more productive. For example, with new computer and communication technologies a researcher from middle-east is a potential collaborator with a researcher in South America and the distance between them is not a preventing element anymore. The growth on the number of published international researches is the most important evidence which has been reported recently (see Figure. 1 and Ref. [1] and [2]. One of the most important reasons for this increase is advent of state-of-the-art platforms known as academic social networks. In these networks researchers are able to make new connections and improve their communications.

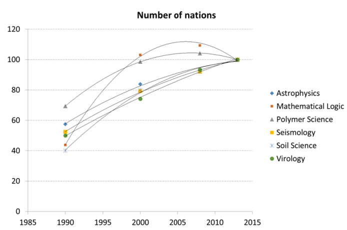


**Fig. 1.** International collaboration growth from 1995 to 2005 [1]

In [3], Bullinger et. al. presented a taxonomy for social research networks, based on social network definition in [4]. First of all, a specific definition for social research networks has been provided: Social research network sites (SRNS) are a web-based service that allows individual researchers to 1) construct a public or semi-public profile within a bounded system (identity), 2) articulate a list of other researchers with whom they share a connection and communicate (communication), 3) share information with other researchers within the system (information) and 4) collaborate with other researchers within the system (collaboration).

An increasing number of scientific social networks pushes participants toward increasing members' loyalty by providing new facilities. Accordingly, one of the most useful facilities that is able to present a unique opportunity for the researcher to broaden their scientific network is the collaborator recommender, that is, a system for recommending the best choice to someone for starting new project or continuing the established one. Recommending new collaborator has approached computer science to data management field.

Collaboration is a general concept, literally it means working together or participating in an activity. Here we specifically concentrate on what is known as *scientific collaboration* or *Scholary Collaboration* of which *Co-authorship* is an example. Co-authorship is an indistinguishable concept with scientific collaboration and has frequently been used as a measure for it. Collaborator recommending is a special kind of expertise suggestion in scientific contexts.

Generally, expertise recommendation is categorized in two levels. The first one originate from document retrieving, these systems recommend experts based on expert knowledge-base content, in addition to the user requirements and in these systems data and text mining methods are called to help [5,6], as a result, the most similar experts to the user requirements are suggested. The main assumption in this system is considering experts as documents, moreover, having used keyword matching techniques, semantic analysis is neglected in existing systems [7, 8]. Systems existing in the next level recommend experts based on analyzing the social relations of the experts. In these systems only relations are taken into accounts and no room has been dedicated to semantic information in systems [9].

Knowledge recommender systems are a special type of recommenders in which the system, by comprehending user's needs, provides the required knowledge in a short time much more efficiently. Expert finding systems, a subgroup of recommender systems, are trying to suggests experts as a source of knowledge [10]. Collaborator finding systems are subgroups of expert finding systems also [9].

The questions in this work are: Whether or not the existing social networks provide adequate facilities for finding the most suitable collaborator? And if the answer is positive, how does it work?

Among the huge number of academic and scientific social networks, for this work, a number of networks are chosen for different reasons, some have gained striking popularity and reputation, others have significant generality and a few have new ideas and promising future. Academia has been chosen for its popularity, over 61 million academics have signed up to Academia, adding 20 million papers. Academia attracts over 28 million unique visitors a month [11]. Although not specifically designed for academic usage, LinkedIn's popularity and reputation among the academic communities convinced us to choose it. Mendeley is supported by Elsevier, one of the most famous academic databases, moreover, as it will be described it provides new facilities and ideas which have granted its sufficient worth to be considered. Aminer is the most progressed system among the existing ones to look for new collaborators. Even though it did not have generic uses initially, Aminer has been extended to cover almost all research fields. Finally, ResearchGate is investigated, the most popular systems for the scientists. Not only it is a classic social network based on definitions but also is specifically developed for researchers and scientists.

The organization of this paper is in this order: we are going to review related works in Section 2, social networks will be introduced and considered in depth in Section 3, in addition, we compare networks regarding their collaborator recommendation abilities, and finally we conclude the paper in Section 4.

## 2 Related works

The literature on the collaborator recommendation can be categorized into three groups. The first group of methods classifies researchers based on published papers, co-workers, research interests and so on in different clusters and these clusters are used to recommend new collaborators. The second group uses behaviors and features for predicting some of the most possible collaborations in the future. Finally, social network analysis is utilized for suggesting new collaborator in third group of algorithms.

Heck et al. [12] suggest K-means method which uses researcher's profile information for learning and predicting. Text mining and clustering are used in [13] by Rany et al. for finding experts in scientific collaborator networks. These methods make up the first group of methods.

Machine learning is the base of the second group of methods. Adaji et al. [14] have considered predicting a chain of experts in stackflow.com websites based on classification and data mining methods. In this research logistic regression, neural network, and support vector machine (SVM) are utilized for classification tasks. Gollapalli et al. [15] proposed a model in which by searching a researcher name the system returns a list of similar researchers.

In the third group, social networks play the most important role. Xu et al. [9] have developed a customized scientific collaborator recommending systems based on the Harpfield algorithm. Their method includes two layers: semantic and network data. Experimental evaluations have shown that this method is able to satisfy users better than all other methods. Huynh et al. [16] to suggest the best collaborator for new researchers, have proposed a new method relying on social network and link data.

## 3 Scientific social networks

Although a great number of social networks has been considered before and in [3] many of them could not increase their popularity in recent years. In this research we try to consider the most popular and useful and unique networks, and confine ourselves to Academia, Aminer, LinkedIn, Mendeley and ResearchGate.net. Although some of these services are not completely social network based on [4] definition, the existence of other types of relations like collaboration or citation networks in these services convinces us to put them in social networks category.

In the next subsections we will talk about scientific social networks, particularly, their ability in collaborator recommendation will be discussed much in depth.

### 3.1 Academia

Academia is a platform for sharing research papers, and its main purpose is enabling timely research regardless of collaborator distance. Users, in addition to sharing research results, use Academia for monitoring and tracing the latest developments in their research interests. More than 55 million university members have joined to Academia and more than 20 million papers have loaded in this service and it has 28 million monthly unique visitors [11].

Academia's system has a limited recommender facility for recommending scientific collaborator based on real world collaboration. Moreover, Academia utilizes users other social networks profiles to find related users for recommending, based on their relations in other social networks. In addition to direct collaborator recommending by simulating real world relations in social networks, Academia tries to recommend collaborator indirectly:

- Recommending a user who has been followed by another user who has similar following list with you.
- Recommending friend of friend or a user who has been followed by a person who has been followed by you.
- Recommending a user who has been followed by a person whose research works has been marked as favorite by you.
- Recommending a person who has read your research works more than others.

– Recommending a user who has visited your profile more than others.

Among the five items, items 1, 2, and 5 are free but for getting recommends based on items 3 and 4, you should pay money.
*Session* is another helpful opportunity provided by Academia which looks like social network communities. Academia analyzes users' tags and suggests related sessions which could be used for finding potential collaborators.

To the best of our knowledge there is no published paper about recommending system in Academia.

### 3.2 LinkedIn

LinkedIn[9] is the biggest profession/occupation based social network with more than half of a billion users, and is used primarily for connecting job seekers and employers. LinkedIn was created in 2002 by Reid Hoffman's house and in 2003 was introduced publicly [17].

LinkedIn developers have provided a variety of methods for collaborator and friend recommendation which use recommender systems directly and indirectly. *My network* is a link in LinkedIn in which different suggestions are available and these suggestions are recommended using the following methods.

Based on available information about each user, LinkedIn surveys features like work field, school, university and communities, and recommends users to each other using their similarities in these features. Part of utilized methods for recommendation are:

– People who might know each other. In this method relations are proposed based on:
  - Similarity between two users, such as same university, same corporation.
  - A user's friends based on email contacts (private massage addresses are not considered in this method [18])
– People who have visited a user's profile. Five best choices are suggested in this method. Also this method is not active if the user has not used LinkedIn in last 90 days [19].
– Users whose profile has been visited by your friends in the network. In this method, which is updated several times monthly, profiles of ten users who have been visited by your friends are shown [20].
– Users who are known in advance. This method is the most basic method for creating personal network in LinkedIn, and usually utilizes users' email or phone contact lists.
– Organizations users are interested in. Corporations and other employers which are looking for employee are being matched with user's profile and suggested for contact purposes.

[9] https://www.linkedin.com/

- Users who have visited the same job profile. This is a useful method for expanding a social network with people who have similar interests.

In addition to aforementioned methods LinkedIn includes a tree level relation architecture Fiureg **??**, If one of your co-workers works with another person you can have promising collaboration with him or her with high probability, and LinkedIn collaborator suggestion is based on this idea. Users will be introduced to three level of users to find new collaborator. If a user's collaborator works with user $u$ in the network $u$ will have higher probability in suggestion list. In other words, the more shared the collaborator, the higher the score in recommendation list. By doing so, introducing two or more direct collaborators to each other will increase a user's own network in the system. [21].

A number of research projects have been undertaken on colleagues and collaborator recommender systems using LinkedIn data. Hence, we are going to introduce them here.

Wang et. al [1] use life style in order to recommend new friends and collaborators to a special user. After collecting data utilizing new technologies and after processing collected data the method, proposed in this paper, finds similar users to the special user based on the life style. Based on their experiments on LinkedIn and facebook, the authors believe that this method can be utilized successfully in LinkedIn and facebook.

The research undertaken by Sharma and Yan [22], has used pairwise learning in its proposed recommender system. This system also takes users feedback into account, as a result, a subtle improvement has been reported using LinkedIn data. In the next part of their work, Sharma and Yan changed their system to include users variety in their preference, and by doing so, when using LinkedIn data, the outcome shows a significant improvement.

### 3.3 Mendeley

Mendeley is a mapping and publishing system useful for finding papers as well as collaborators. This system follows social networks structures. Mendeley belongs to Elsevier and has different versions for use in Mac OS X, Windows, Linux, Android, and iOS platforms. The most important aspect of Mendeley is holding seminars in the recommender system field and gathering useful information and methods in this regard.

Two methods for recommending collaborators are used by Mendeley.

1. Content based recommendation: In this method, a users' paper reading record in addition to searching history is collected then using term frequency–inverse document frequency (TF-IDF) algorithm [23] similar papers are suggested. This methods is fast but main shortcoming is its cold start,

that is, some data should be available for the system to start its prediction. However, in Mendeley one just needs to load only one paper and waits for the system recommendations.
2. Similarity based recommendation: In this methods other similar users items are recommended to the user and there is no need for collecting data about searched or read papers. The only needed factor for recommending is similarity.

Mendeley developers claim that their recommender systems are the best and rely on the huge amount of information gathered from user behavior in the network. They also assert that 80 percent of users are satisfied and based on their feedbacks, 43 percent believe recommender is **very good** and 37 percent believe it is just **good** [24].

A separate recommendation page is available for Mendeley users including four algorithms for recommending.

- Popular in the user field: Most famous research works done in user's research interests.
- Trending in the user field: Research works which are conducting in user's interests.
- Based on the last document in the user's library: Similar works to the last researches done by user.
- Based on all documents in the user's library: Similar researches to all the works done by user.

In addition, Mendeley has a recommender for collaborator suggestion: (i) Users who have been followed by other users who the specified user, for recommending collaborator, has followed them. (ii) Users who followed some users who specified user for recommending collaborator, also followed them. (iii) The most famous researcher in user's research interests.

As mentioned above, Mendeley mainly relies on the following concept for recommending a collaborator. The algorithm used by Mendeley is available for developing as a python package. Some of the features of this package are: (i) Efficient implementation of similarity calculation SLIM [25]. (ii) Implementing weighted matrix for collecting users feedback from using a link [26]. (iii) Providing and preparing tools for data collection and qualitative criteria computing.

### 3.4 Aminer

Aminer was created at the Tsinghua University by Jie Tang in 2006 and its initial name was Arnetminer. Tang has published a paper about distributed research search which was initially implemented at the Tsinghua university and the results were promising. This system looks for researcher names in different sources and after collecting data and disambiguating collected data as well categorization makes recommendations; users will be able to change searching features in the system and by getting users' feedbacks the system will be capable of improving itself [27].

In 2006 the second generation of Aminer-mini, **Aminer** was introduced. Unlike the past version, introduced in 2014, this system tries to adapt a systematic point of view to researchers, by which the system is able to have a broader perspective of the networks created among researchers. The new system extracts researcher profiles from the web and after disambiguation makes a profile for each researcher consisting of all papers found for each researcher. This system has collected the information of 130 million researchers and contains 100 million papers. Aminer uses a new method for collecting data from LinkedIn and VideoLecture known as Cosnet [28] and these meta data sources have made Aminer magnificently enriched. Moreover, Aminer by integrating data gathered from different sources and based on sorted data recommends the best potential collaborators to its users [29].

Some of the main used methods for analyzing data in Aminer are:

- Profile searching: Considering a special researcher name, the system with data extracting technique creates a profile for the researcher. Available data in this profile page include: connecting information, picture of the researcher, citation statistics, scientific improvement evaluation, research interests, educational experiences, personal social graph of the user and published papers in different websites.

- expert recommendation: This method gets a research field (like "social network") as input and returns expert names in this subject. Furthermore, the method is able to return some of the best papers in this way. In addition to some ranking algorithms users feedback is utilized to improve returned results too.

Figure 2 shows four levels architecture of Aminer:

1. Extracting: Users profile information is extracted in this order:
   - Identifying homepages of users on the web.
   - Extracting information from identified pages.
2. Integration: Extracted data after being disambiguated are saved in a database known as RNKB (Researcher network knowledge base)
3. Storage and availability: This stage provides a storing and indexing facility for integrated data using an *inverted-file* indexing format.
4. Searching: There are tree searching methods: person, publication and conferences.
5. Mining: Five mining methods are provided in Aminer (Figure 2): expert finding, association finding (between two searched researchers), hot-topic finding, sub-topic finding and survey paper finding.

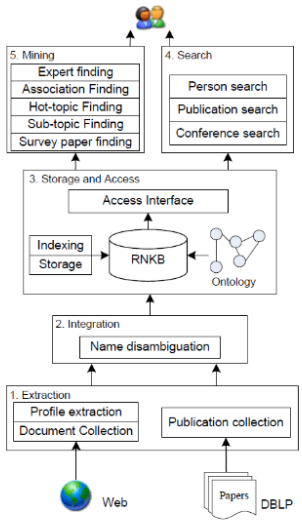


**Fig. 2.** Aminer four level architecture

Like other expert finding systems, in Aminer, the *expert finding* services try to find the most expert member in a special research field. A special method in Aminer is proposed for finding experts in which two aspects of user profile and users relation are taken into account, and includes candidates scoring and expertise diffusion.

In the *scoring* stage, each member gets a score for each field based on the amount of work in the field in which he or she participated. In the *diffusion* stage, the scores are spread out in the network to increase the results' precision, the intuition behind this is: the more relation with experts in a research field, the more knowledge a user can have in it [30]. In Aminer, users can find researchers and features in a special field. Results, also, can be filtered out using h-index, gender, language, and location.

### 3.5 ResearchGate

ResearchGate was founded in 2008 by physicians Dr. Ijad Madisch and Dr. Soren Hofmayer, and the computer scientist Horst Fickenscher, ResearchGate today has more than 14 million members [31], and based on this number [32] has the most active users among all academic social networks.

The main purposes of ResearchGate are exploring different fields, making new relations and finding new collaborators [33]. Researchers can make desired networks based on introduced or suggested users by ResearchGate and base efficient collaborations relying on features provided by ResearchGate.

Facilities presented in ResearchGate can be used for making personal and professional profiles. In addition, by following subjects, researchers, and contributions, users can keep themselves up-to-date, and be aware of the new accomplishments in the subjects the researchers follow.

ResearchGate has been categorized differently from different perspectives. It has been considered as research awareness network [3, 34], as research oriented collaborative Social Networking Services (SNSs) [35], as collaborative Social Networking Services [36] and finally as a researcher social network. Nocera et al. [37] has introduced ResearchGate as a system which "allows researchers to interact with each other, to share their results."

Free sign up has made easy access to ResearchGate for all researchers, but this is not the only distinctive feature provided by it. This social network is intrinsically generic and is not confined to a specific research field. After making a free personal profile, users are able to load all contributions. ResearchGate has defined contribution as published works, failed experiments and raw data. There is no limitation on loaded contributions, and by uploading all contributions a personal and self-made archive is available for each user.

In ResearchGate members can make their own groups which can be public or private [38]. The groups' restrictions are mentioned as: (i) Only administrators can invite new members to the group, (ii) Only group members can access data such as discussions, files, appointments, (iii) The group name is not displayed in each member's group list.

There is a job suggestion button on top of the homepage of users in ResearchGate for recommending similar jobs based on activities and profile information. Moreover, by ResearchGate search ability, members can search for other researcher, institutes, topics, publication and questions which will be discussed more specifically.

Another facility provided by ResearchGate is **RG** measure. RG is a measure for ranking active researcher in ResearchGate based on three factors [39]:

- Contribution (A contribution is anything you share on ResearchGate or add to your profile).
- Interaction (Not only does our algorithm look at how your peers receive and evaluate your contributions, it also looks at who these peers are. This means that the higher the scores of those who interact with your research, the more your own score will increase. Your published research is then factored in to reflect your current standing within the scientific community).

– Reputation (With the RG Score, reputation is passed from researcher to researcher, allowing you to build and leverage your reputation based on anything you choose to contribute).

Considering ResearchGate as a scientists social network and considering relations as the most important part of every networks, ResearchGate suggests some users for following. By doing so, it tries to expand the user's networks in the system. Several features have been presented by the ystem to provide suggestions such as: (i) Institution (ii) Department (iii) Co-authors (iv) Citation (v) Interests similarity (vi) Network (follower lists).

Not directly suggested for finding a collaborator, these recommendations can also be used in this regard. Another provided method in ResearchGate for collaborator finding is based on the created projects in the system. There are two types of projects: private and public. After creating a project, some potential collaborator will be recommended by ResearchGate for assessment.

There is also "Research Interests" link in the ResearchGate user profile in which and relying on **research items**, **projects** and **asked questions**, some recommendation for reading and following are provided for users. Contributions and following list play an important role in filtering out the results and preparing the most helpful recommendations.

Although there is no direct link for suggesting collaborator or expertise locating, recommending new users for following and suggesting new papers for reading is presented by ResearchGate for expanding social networks and users' knowledge in their interested fields.

### 3.6 Evaluation

We have introduced and described different social networks with their ability for recommending collaborators separately, now we are going to integrate all information provided in this section, and compare the networks' ability in recommending collaborators.

Data management scientists consider different factor for a scientific collaboration such as having same nationality and language, political obstacles, and international relations, trustworthy, confidence, and so on.

Also from a computer science perspective, the most important features by which a good suggestion can be provided and is available and extractable from Academic social networks include:

– Node features: (1) number of papers, (2) educational information, (3) number of paper provided by co-authoring with authors from other universities, (4) novelty of researchers, (5) scientific level of researcher, (6) number of question

and answer (in platforms which contain this ability), (7) level of activity in network
- Network features: (1) ethnicity , (2) language, (3) nationality, (4) academic major (5) university, (6) participating in same conference, (7) follower and following lists

Taking all this into account, Table 1 shows different platforms' ability in using these features for providing collaborator suggestion:

**Table 1.** Features and their usage in different social networks

| Social networks / Features | Academia | Mendely | LinkedIn | Aminer | ResearchGate |
|---|---|---|---|---|---|
| Following | ✓ | ✓ | ✓ | ✓ | ✓ |
| University | | | ✓ | | ✓ |
| Ethnicity and nationality | | | ✓ | | ✓ |
| Collaboration | | ✓ | ✓ | ✓ | ✓ |
| Major | | ✓ | ✓ | ✓ | ✓ |
| Number of publication | ✓ | | | ✓ | ✓ |
| Question and answering relation | ✓ | private | private | private | ✓ |
| Tendency to accept collaboration suggestion | | | ✓ | | |
| Activity in social network | | | | | ✓ |
| Scientific level | | ✓ | ✓ | ✓ | ✓ |
| Participating in same conferences | | ✓ | ✓ | ✓ | |
| Co-citing by published paper | | | | ✓ | ✓ |
| Number of publication reader | ✓ | ✓ | | | ✓ |
| Number of profile visitors | ✓ | | ✓ | | ✓ |
| Number of users who have visited both candidates profile | | | ✓ | | ✓ |
| Relation in other social networks | ✓ | ✓ | ✓ | | |
| Following other collaborator's collaborators | ✓ | ✓ | ✓ | | ✓ |
| Research interests | ✓ | ✓ | | ✓ | ✓ |
| Direct collaborator suggestion ability | **limited** | **limited** | **limited** | **limited** | **limited** |

## 4 Conclusion

In this work, different features and facilities for on-line collaborator recommending systems have been studied. For this purpose, some of the academic and scientific social networks based on popularity and creativity have been selected including ResearchGate, Academia, Mendely, LinkedIn, and Aminer. Finally all useful features and facilities in social networks for suggesting collaborators are collected, determined and presented in Table 1. Considering and comparing all the features and facilities shows ResearchGate has better and more useful facilities and features, however, not only ResearchGate but also all the other networks do not have any direct and user-specific option for collaborator recommendation. The authors in their future works will try to provide a theoretical framework for implementing collaborator detection system in on-line social networks.

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