Reseach paper recommendation based on citation

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***Abstract*—A well-designed recommender system for papers reduces the time researchers spend on bibliographical search and helps a newcomer in a field quickly get familiar with the topic and find the most attractive part by suggesting directly related papers. However, performance of the current recommender system on Acemap website is quite unsatisfying and requires improvement urgently. The main problem with the current system is that it is based on the name of the authors and simply recommend papers written by the same authors. Since an author may work on different areas and there exists multiple authors with the same name, this method would output unreliable recommendation results.**

In this paper, we first propose a neighborhood-based paper recommender system, using the citation network between papers to create the ratings matrix. Then, we evaluate our proposed framework by performing an extensive experimentation and comparing it with the existing system. The results indicate that our system generally has a considerable advantage over the existing one in terms of accuracy and robustness. To improve performance, we also implement the idea of multidimensional recommendation, which is to recommend most related papers, most cited papers, latest papers, papers belonging to the same conference, surveys respectively. In addition, by using the proposed method, we design and implement an integrated recommender system for Infocom2018 which is accessible through Acemap website.

***Keywords*—Recommender System, Common Neighborhood-based Method**

I. Introduction

Millions of researchers around the world are doing researches and bibliographical search is one essential part of the job, where they have to look for loads of scientific papers related to their work in order to build a set of papers on which they can develop their new research. A paper recommender system will benefit them in finding the most relevant papers and saving their precious time. A typical method to find the set of papers is to first find one related paper and then recursively follow the reference list to construct a network of papers [14]. Although this method is convenient and efficient in some way, the fact that papers being cited are always published beforehand and that the coverage of reference lists are not complete may lead to other topics. That will waste researchers' time and even mislead them sometimes.

Nowadays, with the rapid development of information technology, massive amount of research papers are available online. There are two notable differences between traditional bibliographical search work and modern digital one. The first difference is the considerable amount of papers in digital environment which machine learning and statistics can be applied to and the second difference is the fast textual search ability enabled by digitalization. Despite the advantages of digital environment, researchers have to manually type in the best keywords they can think of and select the most suitable papers from the result which is time-consuming. Sometimes, the paper they actually need may not have many common words. The lack of efficiency in this method is because both the data and digitalization have not been fully exploited.

As a potentially more advanced way to do bibliographical search than textual search, scholarly paper recommender system has already been proposed and advocated in [3], [5], [8], [10], [11], [19], where [5] includes a list of papers authored by an author, [19] inputs a single paper and so on. These recommender system can be a great helper for researchers when executing bibliographical search and has more advanced features than traditional textual based search. It also helps researchers quickly get familiar with a new field and the interesting point in it. However, existing recommender system either requires privileged information or recommends some irrelevant paper.

However,the problem with these existing paper recommendation system is that it requires "privileged" information such as private document collections and user profiles, etc, which perform bad when lacking sufficient "privileged" information and do not support cross-system in some way [14].

One example is the existing Acemap paper recommendation system which is based on authors' name. It directly finds papers published by the same authors and considers them as most related ones. Nevertheless, there are several inherent drawbacks concerning this method. Firstly, with immature technique to distinguish authors having the same name, sometimes the system recommends papers written by another author. What's more, even the same author may works on different areas, result in totally unrelated recommendation results. Also, amount of recommendation results depends on how many papers the authors have published. That means if the author have published only a few papers, the recommendation results for his/her papers are very sparse. All this issues cause unreliable recommendation results and unsatisfying performance.

In this paper, we propose a novel paper recommender system based on citation between papers which only needs reference list provided by paper itself other than information from users. In this way, the framework does not suffer from sparse information due to lack of users and can do recommendation on latest papers as soon as it's published. Our system also helps researchers explore unfamiliar fields and find what interests them most quickly.

Then we compare our system with the existing paper recommendation on Acemap which is based on authors' name in three specific scenarios and evaluate the result by looking at the similarity of the recommendation result to the original paper in title, abstract and body. We also carry out three experiments on papers in different fields and find the results satisfying.

In addition, using our proposed algorithm, an integrated recommender system for Infocom2018 is built. With the multidimensional recommendation results, an affiliation map as well as a session map are shown in the Acemap website, users can get familiar with Infocom2018 conveniently.

The rest of this paper is organized as follows. We start by discussing related work in Section 2. In Section 3, we describe the method we use in this system algorithmically. In Section 4, we test our system in four different scenarios and prove the accuracy and robustness. In Section 5, we introduce the integrated recommender system for Infocom2018 which is accessible through Acemap website. In Section 6, we conclude the paper. In Section 7, we show contributions of both authors.

II. Related Work

Collaborative Filtering (CF) is a widely used technique in recommender systems. CF works by matching users in a system based on the similarity of each user's past preferences. Each user has a 'neighborhood' of other users with similar opinions about items in the system. This neighborhood can be used to generate recommendations by suggesting items to the user that he has not viewed but that his neighbors have viewed and rated highly. Many algorithms beyond the original k-nearest neighbor algorithm [17] have been proposed and used for collaborative filtering. These include item-based algorithms [18] and model-based algorithms such as Bayesian networks [4] and clustering [4]. Researchers have experimented with CF systems in a wide variety of domains, including news [17], jokes [7], movies [21] and music [21]. Collaborative filtering has succeeded in helping users in all of these domains.

Most CF domains have independent items with relatively thin relationships to each other and little pre-existing ratings data. Specially, papers start with the rich web of citation relationships among papers. Applying CF to this domain successfully requires that the algorithms be modified to interpret the citation network effectively. Following [1], collaborative filtering methods can be grouped in the two general classes of neighborhood and model-based methods.

Commonly, neighborhood-based recommendation methods are divided into two classes [15]. One is user-based approach which predicts the rating that a user will assign to an unrated item by referring to other users who are similar to this user. The other is item-based approach which estimates a user's preference to an unrated item based on other items that are similar to this unrated item. The two approaches follow the same principle.

The user-to-user method is also known as the collaborative filtering approach. In such an approach a user profile is created using information that reflects user preferences and then the profile is compared to other user profiles. Based on the preferences of similar profiles, new items are suggested to a user. As examples of the use of the collaborative filtering approach for research paper recommendation we have [2], [16].

The item-to-item method is also known as the content-based approach. In this approach, a user profile is created using features of a user's preferred items, while an item profile is also created for each item using its own features. After that, user and item profiles are compared using some similarity function and the most similar items are recommended.

The content-based and the collaborative filtering approaches are not mutually exclusive to each other, and there have been many efforts to integrate them in order to obtain more accurate recommendations. These systems can be loosely categorized into several classes. Hybrid system try to combine user-to-user and item-to-item methods. For instance, in [20], a content-based strategy that uses the cosine metric is applied to find similar papers, and then a collaborative filtering algorithm that exploits the k-nearest neighbors is used to suggest citations. And in [9], a bipartite-graph is built using information on users, books and transactions, and the recommendation problem is seen as a graph searching. These methods fully utilize the user, item and access information available.

The approaches described above need user's preference information, thus suffer from a typical problem called cold-start [13]. That means, in the beginning, there are many items in the system, very few users in the system and no user preference information, implying in poor performance due to the lack of information. Obtaining a significant amount of direct user ratings and access information might take a long time. This is the reason why we can not use user-to-user method when constructing Acemap recommendation system. There are only a few users registered in Acemap, and it is hard to obtain users' preference information.

Using the references found in research papers, it is possible to create citation webs that reflect professional social networks between researchers. Many people have studied the connections between research papers and authors of research papers [**?**]. In particular, information professionals have studied the creation of these webs and ways to index them for years [6]. We investigat how research papers directly relate to each other as opposed to the relationships that exist between papers and authors, and how these paper-to paper relationships can be exploited to create a system to recommend papers to authors. We draw a subtle but important distinction between the idea of a citation and that of a paper. A citation represents a research paper for which we only have a reference. A paper is a citation for which we have access to the full text, including the paper's citation list. Thus, for a paper we have a listing of all the citations that it references, some of which may also be papers in dataset but all of which must be citations in our dataset.

In order to overcome the cold-start problem raised in the previous approaches, we refer to the co-citation matching method [12], and propose a neighborhood method based on citation. Using the references found in papers, it is possible to create citation networks that reflect professional social networks between researchers. Our method is done by calculating intersection of different neighbor sets. For each paper in the basket, the algorithm counts the number of times other papers were co-cited with it. We are investigating how papers directly relate to each other as opposed to the relationships that exist between papers and authors, and exploit these paper-to-paper relationships to create a system to recommend papers to authors.

III. Methodology

A. Neighborhood-based Method

We define our problem as follows:

Definition 1: Given an input paper p, find a set of papers P that are the most related to p considering a given criterion c.

We use citation-based neighborhood method as our main algorithm for the system where the neighbours defined in the system are papers and they are related by citation.

The rationale behind using citation as the indicator of neighbors is that citation is a nice basis for recommendation. As a general principle, citation happens because two papers are researching similar problems. What's more, sometimes, one paper further study the problem raised in the paper it cited. Suffice it to say that, if two papers have cited more papers in common, they are more related. Also using this method, we could avoid the cold-start problem resulted from having only a few users' information.

Before illustrating this method, some terms used are defined as follows.

The neiborhood set of a paper p is defined in a recursive way. Initially, there is only p in its neiborhood set. Then papers cited by those in p's neiborhood set are included iteratively. We use L to represent the maximum iterations, which greately affects the algorithm's performance.

As is shown in Figure 1, each node represents a paper and each edge denotes a citation. We say paper A indirectly cites C1 because there is a two-hop path from A to C1 which, more specifically, is A cites B1 and B1 cites C1. Then we consider all these directly and indirectly cited papers of A as the neighbors of A and call the set of these neighbors the neighbor set of A. A's neighbor set is marked by a red box.

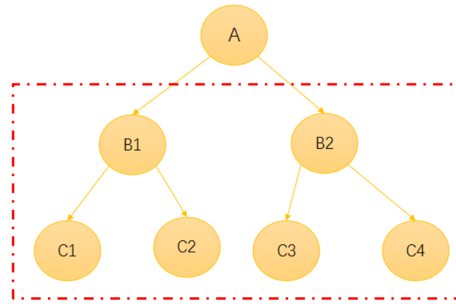

Fig. 1. Neighbor set of paper A

Denote the neighbor set of p as S_p, the number of papers in S_p as $|S_p|$, the recommendation degree of paper p_1 to paper p_2 as $D_{p_1 \to p_2}$. Our method is done by counting co-citations and recommend papers having the greatest co-citation amounts. Co-citation amount can be represented by the intersection of p_1's neighbor set and p_2's neighbor set, thus we can calculate $D_{p_1 \to p_2}$ using the following equation.

$$D_{p_1 \to p_2} = \frac{|S_{p_1} \cap S_{p_2}|}{max\{|S_{p_1} \cap S_{p_2}|\}}$$

Our algorithm is as follows:

1) Firstly, we find the neighbor set for each paper.
2) Then for each paper pair, we find the number of common neighbors in the neighbor sets of two papers and calculate the recommendation degree from one to another.
3) Finally, we normalize and rank the recommendation degree of all other papers to paper p. The papers with greatest recommendation degree are included in the final recommendation list.

B. Multidimensional Recommendation

In the previous recommender systems, it only shows one recommendation list containing papers related in some way. However, users may want to know specialized recommendation results according to their different needs.

In order to better satisfy different users' need, we implement the idea of multidimensional recommendation matrix. That is to provide the most related papers, most cited papers, latest papers, papers belonging to the same conference, surveys for a specific paper recommdation. This idea is shown in Figure 2. In this way, for example, when a newcomer in a field search a paper and read the survey list, he can quickly get familiar with the whole topic. On the other hand, those who are familiar with this field, can find the most attractive part in the latest paper list.

Fig. 2. Multidimensional Recommendation

Different criterion are used when calculating different lists:

1) The most related papers are results of our neighborhood-based method and they correspond to the greatest recommendation degree.
2) When calculating the most cited papers, both recommendation degree and citation count are taken into consideration.
3) When calculating the latest papers, both recommendation degree and publish year are considered.
4) When calculating the related papers belonging to the same conference, we narrow the total paper network to papers belonging to the same conference and run our proposed method.
5) Surveys are extracted using regular expression since they always contains certain words in either title or abstract indicating its type.

C. Implementation

When implementing this method, we use a paper dataset from Acemap Website. It contains totally more than 127 million papers from different fields like social network, artificial intelligence.

First, we need to get the neighbor set of each paper. Define layer L as the deepest layer when considering the neighbor set. L determines the recommendation accuracy and needs to be adjusted elaborately. With greater L, the final recommendation list may contains papers about different topic but somehow related. With smaller L, the recommendation list contains papers that are apparently related. Thus by setting an appropriate L, we could achieve satisfying recommendation accuracy as well as a great breadth.

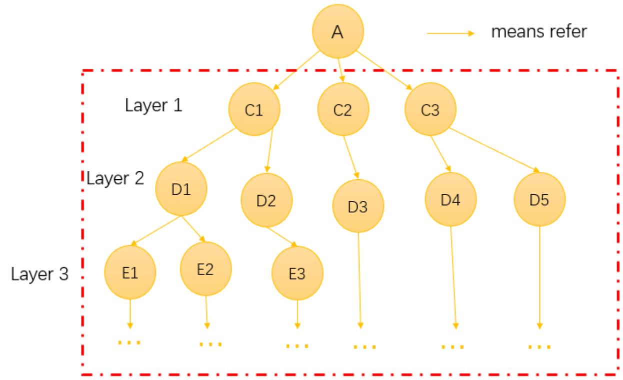

Fig. 3. Depth of citation

Here is the function that returns the neighbor set of A:

```
def getNeighborSet(A, layers):
    NeighborSet=set()
    for paper in referencelist of A:
        NeighborSet.add(paper)
    CurrentLayer=NeighborSet.copy()
    NextLayer=set()
    for i in range(layers-1):
        for ref in CurrentLayer:
            for refref in referencelist of ref:
                NextLayer.add(refref)
        NeighborSet=NeighborSet|NextLayer
        CurrentLayer=NextLayer.copy()
    return NeighborSet
```

Next, for each paper pair, we find the number of common neighbors in the neighbor sets of two papers

Finally, we normalize the recommendation degree we get and rank the results.

In implementation, we put the two functions above into one single function which returns a list as the recommendation result and the format is [[Recommend paper 1,rate1],[Recommend paper 2,rate2],...]:

```
def recommendMain(A):
    recdict={}
    maxrate=0
    NeighborSetA=getNeighborSet(A)
    for paper in NeighborSetA:
        recpapers=sql:select recpapers where paper
    is recpapers' neighbor
        for recpaper in recpapers:
            if recpaper!=paper:
                if recpaper in recdict.keys():
                    recdict[recpaper]+=1
                else:
                    recdict[recpaper]=1
                if recdict[recpaper]>maxrate:
                    maxrate=recdict[recpaper]
    if maxrate>0:
    for rate in tempdict.values():
            rate/=maxrate
         return(sorted(tempdict.items(),key = lambda
     x:x[1],reverse = True))
```

By far, we get the recommend result through detailed algorithm and it's the core of our system.

IV. Experiments

We run the proposed algorithm on a dataset containing more than 127 million papers and more than 500 million citation entries, which is hugh enough to suggest highly related results. Also, our system finishes sixty to a hundred papers' recommendation per second which ensures the speed.

In this section, we describe the experiments we performed to evaluate our proposed framework for research paper recommendation. The goals of our experiments are to verify:

1) Our method based on citation achieves greater recommendation accuracy compared with the existing Acemap recommender system based on authors' names.
2) Our method is more robust that can always recommend multiple related papers with high quality in different fields.

We compare our system with the existing Acemap research paper recommender system based on authors' names and find ours outperforms the existing one in some ways.

A. *Case 1:*

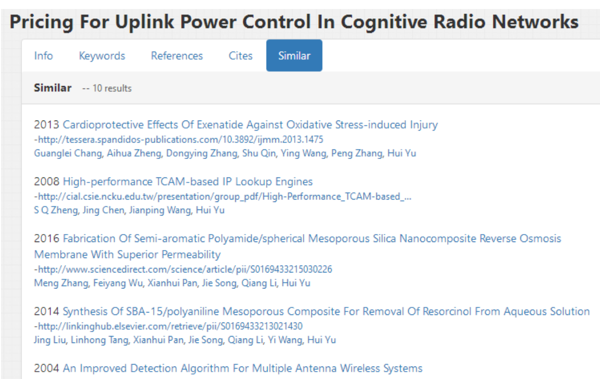

Fig. 4. Recommender system based on authors' names

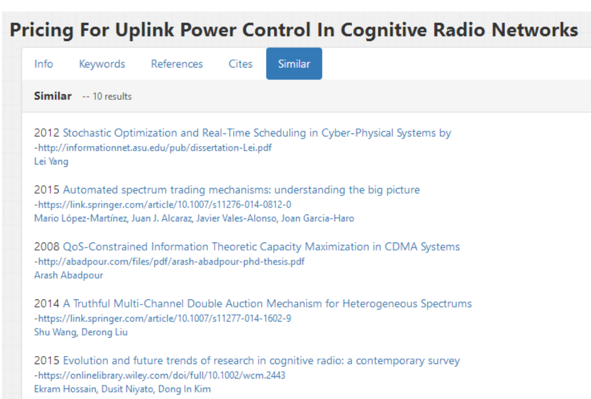

Fig. 5. Recommender system based on citation

The first thing we notice is that the first and the third recommendation results of the former recommender system shown in Figure 4 seem quite irrelevant to the original paper. One is *Cardioprotective Effects Of Exenatide Against Oxidative Stress-induced Injury* and the other is *Fabrication Of Semi-aromatic Polyamide/spherical Mesoporous Silica Nanocomposite Reverse Osmosis Membrane With Superior Permeability*. Both of them belong to the field of medicine. After throughout analysis, we find that the reason for this lies in the author list of the paper. One author called Hui Yu who studies medicine happens to have the same name in Chinese PinYin as the first author of the original paper. And due to the immature techniques to distinguish authors with the same name, they are not yet distinguished in database. Since the system is based on authors' names, the papers published by Hui Yu in medicine field are naturally listed in the recommendation papers, which is not what we expect.

Now the result in our system is shown in Figure 5. All the papers recommended are at least in the same field as the original paper so that there won't be absurd result such as recommending papers are in different fields. By sampling from the total dataset, we execute multiple comparison evaluation experiments. All of them indicate that our method achieves greater recommendation accuracy compared with the existing Acemap recommender system based on authors' names.

Next, we are going to look at three cases that include papers in three different fields and evaluate our method's performance in various domains.

B. *Case 2: Wireless Communication*

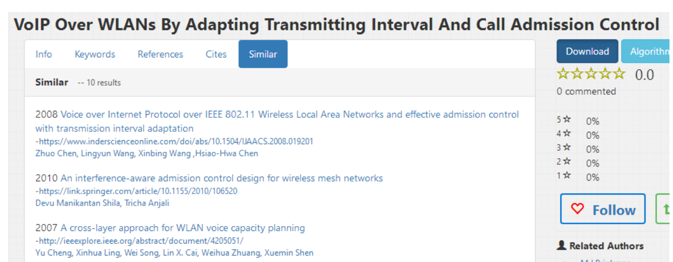

Fig. 6. Recommender system based on citation

The first paper in the recommendation list has very similar name to the original paper. After we scrutinize the abstract and content of both papers, we find that the result is the full version published on a journal and the original paper is a brief version published on ICC 2008.

That is to say, if a user find one version of a paper, our system will find other versions which may be more complete. It can save the user's time to find a full version.

C. *Case 3: Recommender System*

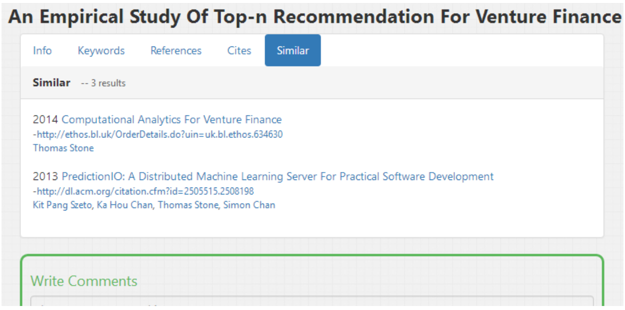

Fig. 7. Recommender system based on authors' names

Fig. 8. Recommender system based on citation

One obvious problem in the existing recommender system shown in Figure 7 is that it only suggests two papers and this amount of data can not satisfy most users' demand. It's probably because the authors don't have many publications so there is a limited number of papers in the recommendation pool.

In contrast, our system shown in Figure 8 have two useful features. One is that it recommend a sufficient set of papers that meets the recommendation requirement. In addition, the publication dates of the results are distributed evenly, containing papers published both before and after the publication date of the original paper. Although papers can only cite papers predating them, the results in this case demonstrate the recommendation result can also include papers published later.

Speaking of the similarity between these two papers, let's first look at the first entry of the result. The keywords analysis tags both paper *Portfolio Theory* and *Recommender System*. That is to say, both papers are researching exactly the same thing using similar method. It can readily be added to the users' reference lists who find the original paper.

D. *Case 4: Wireless Network*

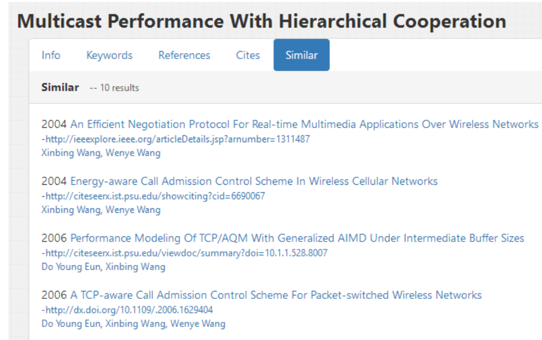

Fig. 9. Recommender system based on authors' names

Fig. 10. Recommender system based on citation

Firstly, the title of the first paper recommended is *Multicast Scaling Laws With Hierarchical Cooperation*. Notice that the original paper is titled *Multicast Performance With Hierarchical Cooperation* , and there are only one difference in their titles, which is *Performance* and *Scaling Laws*, and the authors are similar, so these two papers are in a series of study and this information can be useful to many researchers in this particular field. The keywords analysis shows that they have four keywords in common: *Unicast, Scheduling, Mimo and Throughput*, which make up 80% of the total keywords of the second paper.

The title of the third result is seemingly irrelevant to the original paper and looks like it's doing some research related to vehicle, which is *Downlink Capacity of Vehicular Networks with Access Infrastructure*. But when we look closer at its abstract and content, they both carry out research on the capacity of wireless network. This shows that our system is able to suggest papers that look irelevant but actually have a strong similarity.

The above three cases show that our system is robost enough in different fields and yields related papers and some of them even look irrelevant at first glance. The year and author distribution and similarity of the recommendation results are acceptable.

V. RESULT

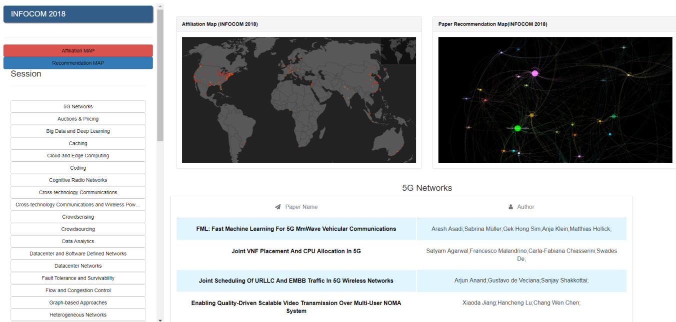

Fig. 11. Index page of infocom 2018 paper recommendation system

We apply our system to current Acemap website and finish the multidimensional recommendation for all the papers published in this year's infocom and Figure 11 shows the index page of our system on Acemap.

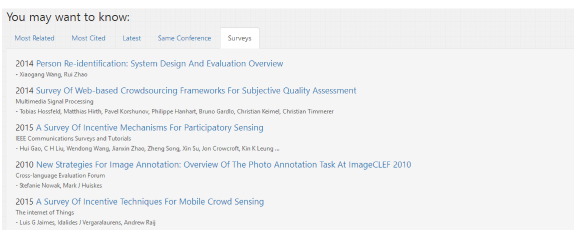

Fig. 12. Multidimensional recommendation for one paper

Figure 12 shows the result of surveys recommendation for paper *CrowdBuy: Privacy-friendly Image Dataset Purchasing Via Crowdsourcing*. This helps users quickly get familiar to that field. On the other hand, most cited and most related help users who are familiar with this area find most attractive parts quickly.

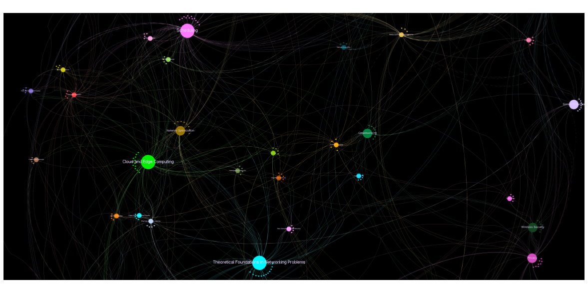

Fig. 13. Visualization of recommendation result

In order to analyze different affiliations in this conference, we visualize the paper distribution in a world map shown in Figure 14. Each affiliation is represented with a red node and these nodes could also link to the corresponding affiliation page.

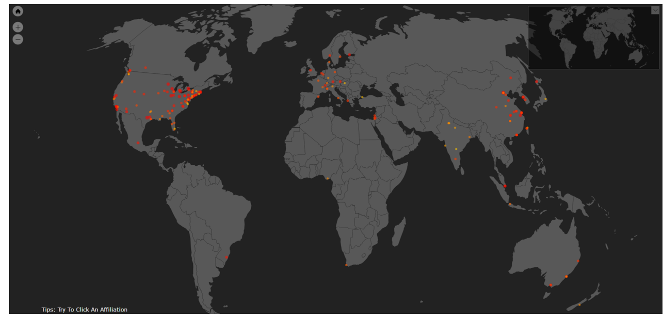

Fig. 14. Affiliation Map

We visualize the recommendation result of this year's infocom papers by drawing a map that shows the relevance of different sessions in the conference where each big node represents a session and each small node around it represents the paper in that session. There are also some almost invisible tiny nodes in the map that represents papers being cited. These different papers are connected by citation. we can clearly see some clustering in this map.

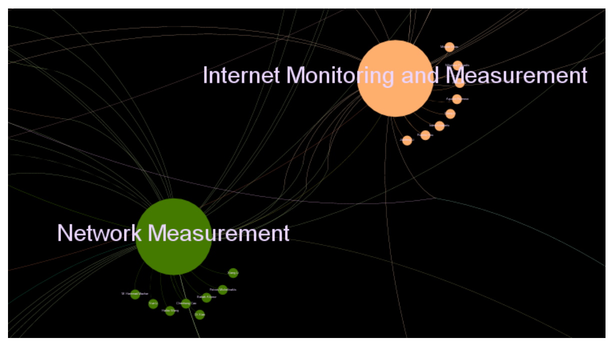

Fig. 15. Clustering in session map1

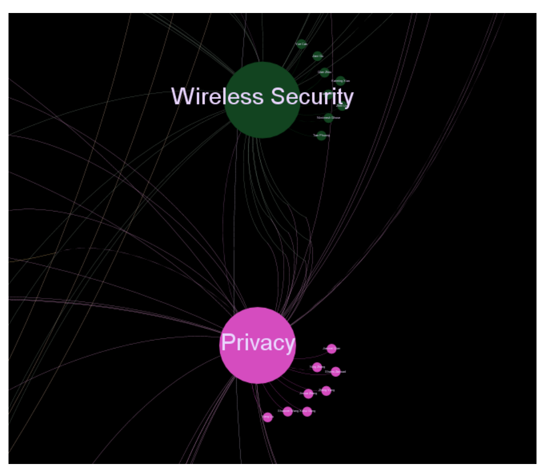

Fig. 16. Clustering in session map2

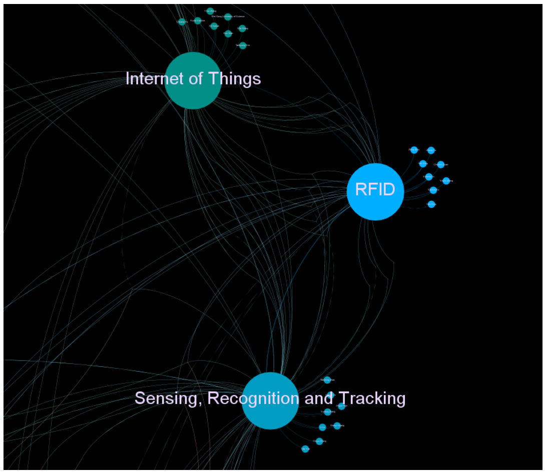

Fig. 17. Clustering in session map3

In Figure 15, we can see session *Internet Monitoring and Measurement* and *Network Measurement* are close to each other. Similarly, in Figure 16 and Figure 17, we can see *Wireless Security* and Privacy, Internet of Things, RFID and Sensing, Recognition and Tracking form clustering respectively.

VI. Conclusion

We propose a research paper recommender system based on citation and common neighborhood method that does not need those privileged information. And the algorithm is fast enough to output results that are accurate as well as robust. It takes one paper and get the reference lists of related papers to form the neighbor set of the paper. Then it finds out all the papers whose neighbor set includes each paper in the neighbor set of the original paper. And the size of the intersection of these two neighbor sets indicates how similar these two papers are and use it as the basis for recommendation. Also, we propose multidimensional paper recommendation to further improve user experience by rearranging the recommendation result, for instance, ranking the result by most cited, latest etc.

Then, we evaluate our work by comparing our system with the existing Acemap scholarly paper recommender system. We observe that ours outperform the existing one in multiple ways. We also test our system in three different fields and confirm that our system works well for papers in different fields, indicating its robustness.

Finally, we apply our system to a real-life application. We finish the recommendation of this year's infocom papers by making designing several webpages and visualize the result by showing a map consisting of papers and sessions. The sessions on that map cluster naturally by the force of citation. And based on the name of the session so that we can prove the accuracy of our system. We also draw an affiliation map which shows the information of different organizations in this conference.

VII. Contribution

This project is done by Jiasheng Zhou and Xinzhu Cai. Jiasheng Zhou finished the following parts:

1) Prepared total paper dataset used in this project.
2) Designed and implemented the common neighborhood method.
3) Implemented the idea of recommending papers with greater breadth.
4) Did comparison experiments to evaluate proposed method.
5) Participated in designing Infocom index page.
6) Drawed Infocom 2018 session map and affiliation map.

Xinzhu Cai finished the following parts:

1) Prepared total paper dataset used in this project.
2) Designed and implemented the common neighborhood method.
3) Implemented the idea of multidimensional recommendation matrix.
4) Optimized Infocom 2018 dataset.
5) Designed Infocom recommendation result display page.
6) Participated in drawing Infocom 2018 affiliation map.

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