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# A Reference-based Recommendation System for Academic Papers on Acemap

Report for Course <Wireless Communication Theory and Mobile Network>

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**Abstract**

Recommendation systems are important and useful to predict items that the user may have an interest in. In the context of academic paper searching, an optimal recommendation system can help increase effectiveness and accuracy when searching for papers in specific or relative fields by suggesting directly related papers. Acemap is an academic paper searching system. However, the current recommendation system based on author name needs to improve. The problem is there are cases where some authors share a same name and papers written by an author do not necessarily relate in the content. Thus to obtain a more reliable recommendation, a reference relationship-based recommendation system is designed.

The recommendation system in this paper is based on reference relationship of academic papers. The results show that it is a considerable improvement in recommendation accuracy comparing to the current system on Acemap. Furthermore, multi-dimensional recommendation is applied to promise rich user experiences. Specifically, an integrated recommendation system for Infocom 2018 is accomplished as a representative feature.

**Keywords**

Recommendation system, Academic search, Acemap, Neighborhood Algorithm

# Catalog

# 1 Background of Academic Recommendation

## 1.1 Overview

Recommendation systems are a useful alternative to search algorithms since they help users discover items they might not have found otherwise. In the context of academic research, a paper recommendation system will provide the most relevant papers to researchers and therefore greatly increase their efficiencies. The rapid development of information technology nowadays made a great number of research papers available online. There are two significant differences between traditional bibliographical search and the modern digital research.

- The incomparable amount of papers that are available in digital research are significantly greater than that of the traditional bibliographical search.
- The increased speed of textual search is enabled by digitalization.

A common practice to building a comprehensive database is to find one related paper and then recursively follow the reference list to construct a network of papers. Although this method is convenient and efficient in some ways, yet the papers being cited are always published beforehand and that the coverage of reference lists are not completed may lead to irrelevant topics. This would severely undermine the efficiency of researchers or even mislead their research.

The downside of digital research is that the search takes place in a strain of keywords. The selection process of the most correlated papers to the topic based on the accuracy of the keywords cost a lot of time. The papers, sometimes, do not have many common words or use different technical terms that mean the same thing. The lack of efficiency in this method is because both the data and digitalization have not been fully exploited.

To tackle the weakness of digital research, scholarly paper recommendation system has already been proposed and advocated in some works. This recommendation system provides perfect complimentary assistance to researchers who execute bibliographical search and has more advanced features than traditional text-based search. It also helps researchers to get familiar with a new field and capture the most important elements of the topic in a short time.

However, the existing recommendation system either requires privileged information or recommends irrelevant papers to the topic concerned. The problem with these existing paper recommendation system is that it requires privileged information such as private document collections and user profiles, etc, a lack of sufficient privileged information does not benefit users that much.

## 1.2 Mainstream Approaches

### 1.2.1 Collaborative Filtering

Collaborative filtering is widely used in recommendation systems. Collaborative filtering methods are based on collecting and analyzing a large amount of information on users' behaviors, activities or preferences and predicting what users will like based on their similarity to other users. A key advantage of the collaborative filtering approach is that it does not rely on machine analyzable content and therefore it is capable of accurately recommending complex items such as movies without requiring an understanding of the item itself. Many algorithms, for example, the k-nearest neighbor (k-NN) approach and the Pearson Correlation have been used in measuring user similarity or item similarity in recommendation systems.

Collaborative filtering is based on the assumption that people who agreed in the past will agree in the future, and that they will like similar kinds of items as they liked in the past. A collaborative filtering algorithm uses matrix factorization, a low-rank matrix approximation technique. Yet the approaches often suffer from three problems: cold start, scalability, and sparsity.

- Cold start: These systems often require a large amount of existing data on a user in order to make accurate recommendations.

- Scalability: In many of the environments in which these systems make recommendations, there are millions of users and products. Thus, a large amount of computation power is often necessary to calculate recommendations.
- Sparsity: The most active users will only have rated a small subset of the overall database. Thus, even the most popular items have very few ratings.

So this is the reason why collaborative filtering can do little when we are trying to build a recommendation system for Acemap since we have scarce collection of user activity.

### 1.2.2 Content-based Filtering

Content-based filtering methods are based on a description of the item and a profile of the user's preferences. In a content-based recommendation system, keywords are used to describe the items and a user profile is built to indicate the type of item this user likes. In other words, these algorithms try to recommend items that are similar to those that a user liked in the past (or is examining in the present). In particular, various candidate items are compared with items previously rated by the user and the best-matching items are recommended.

To create a user profile, the system mostly focuses on two types of information:

1) A model of the user's preference.
2) A history of the user's interaction with the recommendation system.

Basically, these methods use an item profile (i.e., a set of discrete attributes and features) characterizing the item within the system. The system creates a content-based profile of users based on a weighted vector of item features. The weights denote the importance of each feature to the user and can be computed from individually rated content vectors using a variety of techniques.

### 1.2.3 Hybrid Recommendation Systems

Recent research has demonstrated that a hybrid approach, combining collaborative filtering and content-based filtering could be more effective in some cases. Hybrid approaches can be implemented in several ways: by making content-based and collaborative-based predictions separately and then combining them; by adding content-based capabilities to a collaborative-based approach (and vice versa); or by unifying the approaches into one model. Several studies empirically compare the performance of the hybrid with the pure collaborative and content-based methods and demonstrate that the hybrid methods can provide more accurate recommendations than pure approaches. These methods can also be used to overcome some of the common problems in recommendation systems such as cold start and the sparsity problem.

A variety of techniques have been proposed as the basis for recommendation systems: collaborative, content-based, knowledge-based, and demographic techniques. Each of these techniques has known shortcomings, such as the well-known cold-start problem for collaborative and content-based systems and the knowledge engineering bottleneck in knowledge-based approaches. A hybrid recommendation system is one that combines multiple techniques together to achieve some synergy between them.

## 2 Implementation of Recommendation System for Acemap

From the last section, we know that the mainstream approaches described above need user's preference information, thus suffer from the typical cold- start problem. 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. There are only a few users registered in Acemap, and it is hard to obtain users' preference information, which makes it infeasible to use user-to-user method to construct a reliable recommendation system for Acemap.

The current Acemap recommendation system is based on authors' names. It directly correlates papers published by the same authors and treat that set of papers as most related ones. Nevertheless, there are several inherent drawbacks concerning this method.

1) There is no current practice applied to distinguish authors who share a same name, so the recommended papers may not be written by the same author as originally intended to.
2) The same author may have multiple research focuses or collaboration with scholars in another subject, resulting in unrelated recommendation results.
3) The amount of recommendation results depends on how many papers the authors have published, which means if the author has published only a few papers, the recommendation results for his/her papers are very scarse.

In order to overcome all these issues which cause unreliable recommendation results and unsatisfying performance, a novel paper recommendation system is proposed in this paper. Based on citation between papers, we only need reference list provided by the 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 in a more efficient way.

The system is then compared with the existing one on Acemap which is based on authors' names. In three specific scenarios, evaluation is given by the similarity of the recommendation result to the original paper in title, abstract and context. Also three experiments are carried out on papers in different fields to find if the results are satisfying.

In addition, using the proposed algorithm, an integrated recommendation system for Infocom 2018 is constructed. With the multidimensional recommendation results, an affiliation map, as well as a session map, are shown in the Acemap website, which helps users get to know the meeting easily.

### 2.1 Dataset of Acemap

As knowledge graph plays a more and more important role in this artificial intelligence era, many research groups are trying to organize the knowledge in their domain into a machine-readable knowledge graph, which stores knowledge in triple.

Acemap Knowledge Graph (AceKG), supported by Acemap, is now open to everyone for research and non-commercial use. We hope this knowledge graph will benefit the research and development for academic data mining.

AceKG describes 114.30 million academic entities based on a consistent ontology, including 61,704,089 papers, 52,498,428 authors, 50,233 research fields, 19,843 academic institutes, 22,744 journals, 1,278 conferences and 3 special affiliations. In total, AceKG consists of 2.2 billion pieces of relationship information. The schema of AceKG is provided as follows.

Using the references found in research papers, it is possible to create citation webs that reflect academic 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. We investigate 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, 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.

### 2.2 Neighborhood Algorithm

In the citation-based neighborhood method, which is the main algorithm of the new Acemap system, the neighbors are defined as papers and all of they are related by citation.

Citation happens when two papers are researching into similar problems, so it is an indication of related papers so as to make valuable recommendation. What's more, sometimes one paper further study the problem raised in the paper it cited. 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 insufficient user information.

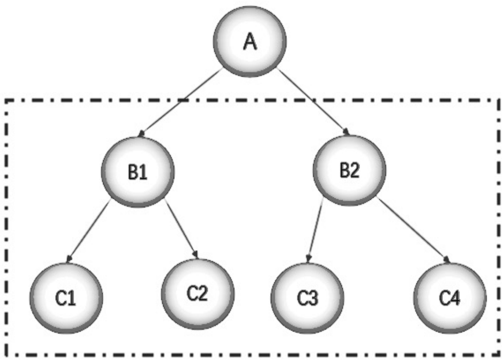


Fig.1. Neighbor set of paper A

As is shown in Figure 1, each node represents a paper and each edge denotes a citation. As A cites B1 and B1 cites C1, we say paper A indirectly cites C1 because there is a two-hop path from A to 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 framed by the dotted line box.

To quantify the recommendation rate, we adopt the recommendation degree of paper p1 to paper p2, which can be denoted as $D_{p1 \rightarrow p2}$. The recommendation degree is measured by the counting of co-citations, which means the most recommended paper has the greatest co-citation amounts with the original paper. The neighbor set of p is denoted as Sp, and the number of papers in Sp as |Sp|. Co-citation amount can be represented by the intersection of p1 's neighbor set and p2 's neighbor set, thus we can calculate $D_{p1 \rightarrow p2}$ by the following equation.

$$D_{p1 \rightarrow \mathrm{p2}} = \frac{|S_{p1} \cap S_{p2}|}{\max\{|S_{p1} \cap S_{p2}|\}}$$

The algorithm is as follows:

1) Firstly, find the neighbor set for each paper.

2) Then for each paper pair, find the number of common neighbors in the neighbor sets of two papers and calculate the recommendation degree from one to another.

3) Finally, normalize and rank the recommendation degree of all other papers to paper p. Papers with greatest recommendation degree are included in the final recommendation list.

### 2.3 To Build a Neighborhood-based System on Acemap

To implement this method, we use a paper dataset from Acemap Website. It totally contains more than 127 million papers in different fields i.e. social network, artificial intelligence, wireless communication.

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.

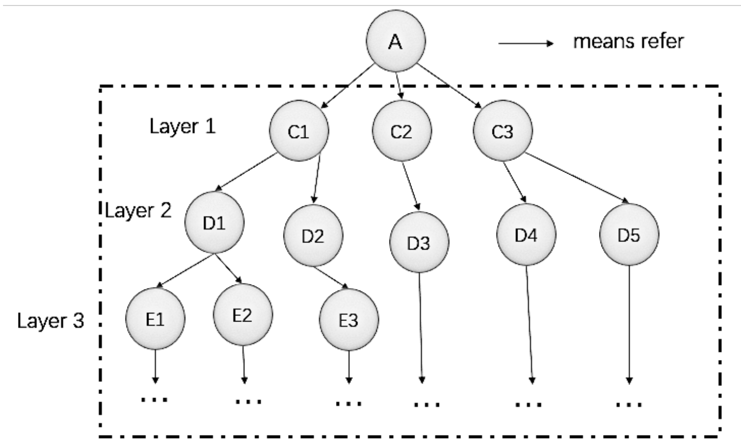


Fig.2. Depth of citation

Function of getting neighbor set:

```
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 recom- mendation 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))
```

### 2.4 Multi-dimensional Recommendation

In many cases, users want to get recommendation papers from different aspects according to their different needs. For example, a newcomer in a certain field may want to search for a survey paper which can quickly get him familiar with the whole topic; or in another case, those who are already familiar with a field, may like to find the latest achievements. Then the previous recommendation systems which only shows one recommendation list containing papers of the closest relationship may not be enough.

To better satisfy different users' need, we implement the idea of multidimensional recommendation matrix. That is to provide paper recommendation in 5 more dimensions:

- Most related papers
- Most cited papers
- Latest papers
- Papers belonging to the same conference
- Surveys for a specific field

Different dimension recommend lists hold different criteria:

1) Most related papers are based on the results of previous neighborhood-based method and they correspond to the greatest recommendation degree.
2) Most cited papers take both recommendation degree and citation count into consideration.
3) Latest papers take both recommendation degree and publish year into consideration.
4) Papers belonging to the same conference restrict the recommend paper network to papers belonging to the same conference and the proposed method is applied.
5) Surveys are extracted using regular expression since they always contains certain words in either title or abstract indicating its type.

## 3 Tests and Analysis

To test and evaluate our new recommendation system, we run the algorithm on the Acemap dataset. The dataset contains more than 127 million papers and more than 500 million citation entries, which is huge enough to suggest highly related results. Also, the new system can reach a speed of up to 100 recommended papers per second.

### 3.1 Author's Name-based vs. Reference-based Recommendation System

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

#### 3.1.1 Author Name Distinguish

In this case, using the previous recommendation system, we get the related paper list offered like below.

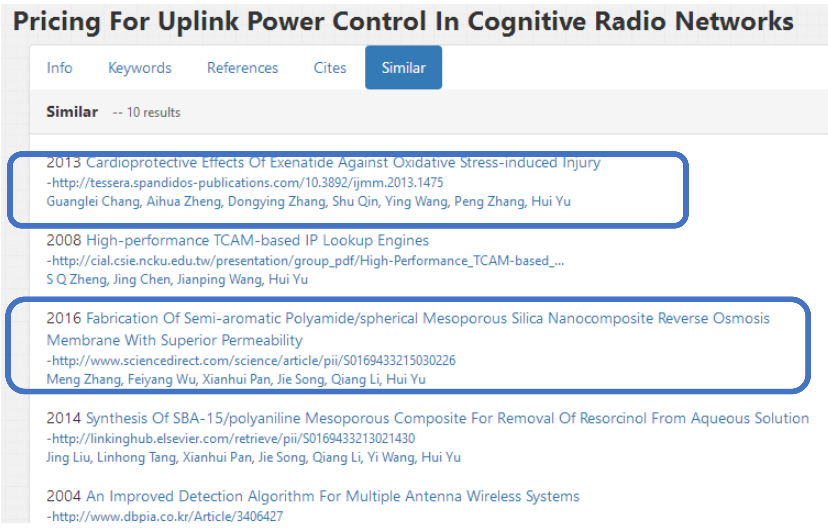

Fig.3. Author name-based recommendation. Irrelevant papers appeared.

Noticed that the first and the third recommendation results seem quite irrelevant to the original paper. One is Cardioprotective Effects Of Exenatide Against Oxidative Stress-induced Injury and the other is Fabrica- tion 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 the misleading information is the failure in distinguishing the same author name. The author of the original paper is called Hui Yu, whose name happens to be the same in Chinese PinYin as another author studying medicine. Due to the immature techniques to distinguish authors with the same name, they are not yet distinguished in the 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.

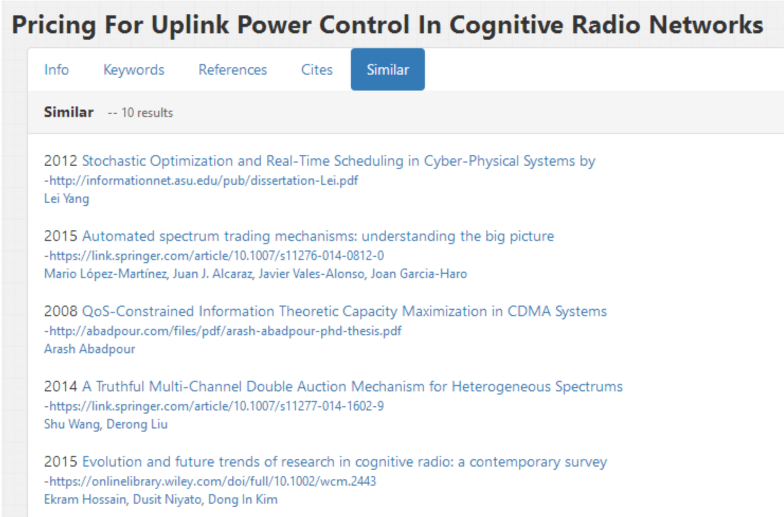


Fig.4. Reference-based recommendation

Now the result in our system is shown in Figure 4. 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 comparing to the existing Acemap recommendation system based on author's name.

#### 3.1.2 Comparison of Effectiveness in 3 Fields

To further evaluate the effectiveness og the new recommendation system, three specific cases including papers in three different fields are tested and the results are exhibited as below.

(A) Wireless Communication

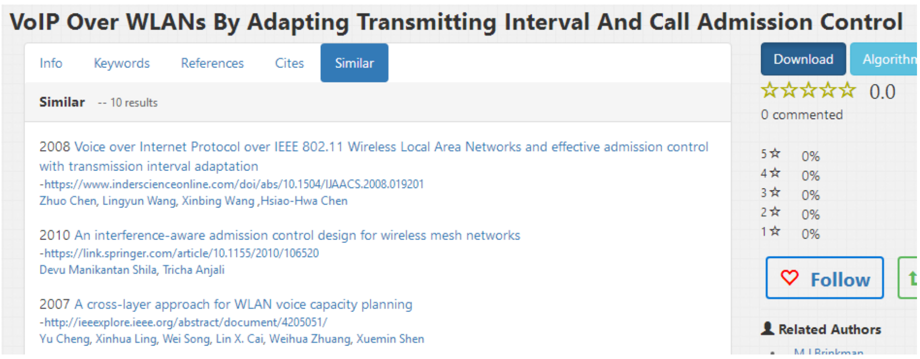


Fig.5. Recommendation in the field of Wireless Communication

In this case we find 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.

Thus the system achieved a great effect, that is, if a user find one version of a paper, it will find other versions which may be more completed. This can save the user's time to find a full version.

(B) Recommendation System

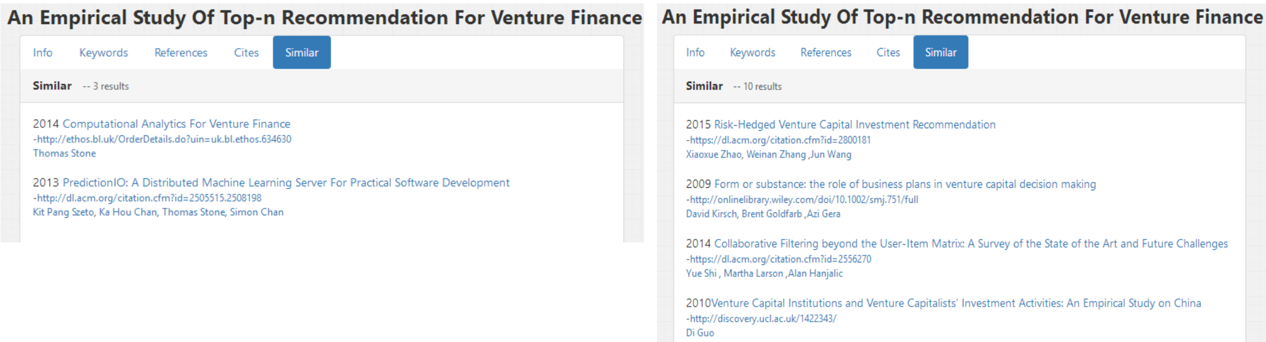


Fig.6. Recommendation in the field of Recommendation System

One obvious problem in the existing recommendation system shown in Figure 6 (left side) is that it only suggests two papers and this amount of data cannot 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 on the right side has two useful features. One is that it recommends 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 Recommendation 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.

(C) Wireless Network

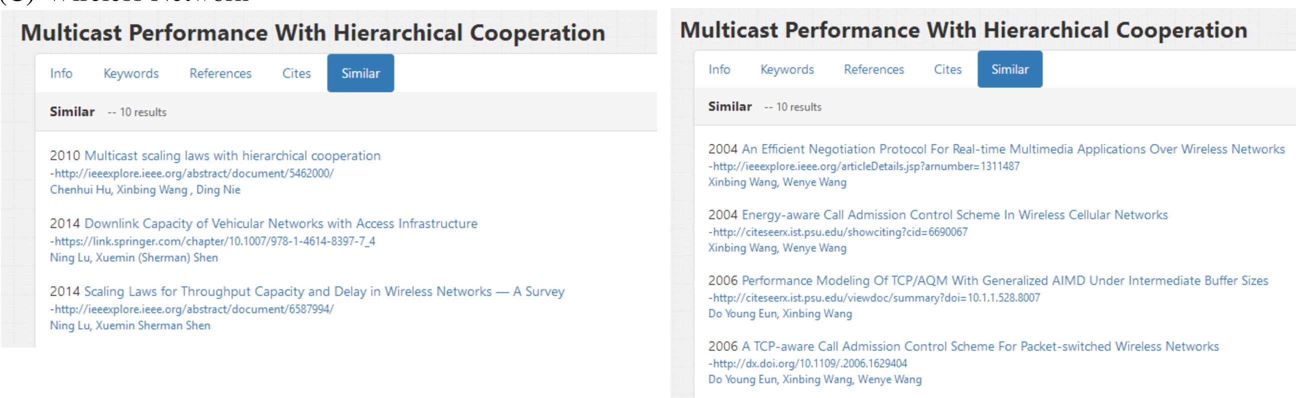


Fig.7. Recommendation in the field of Wireless Network

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 is 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 can suggest papers that look irrelevant but actually have a strong similarity.

The above three cases show that our system is robust 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.

### 3.2 Infocom 2018 Recommendation System

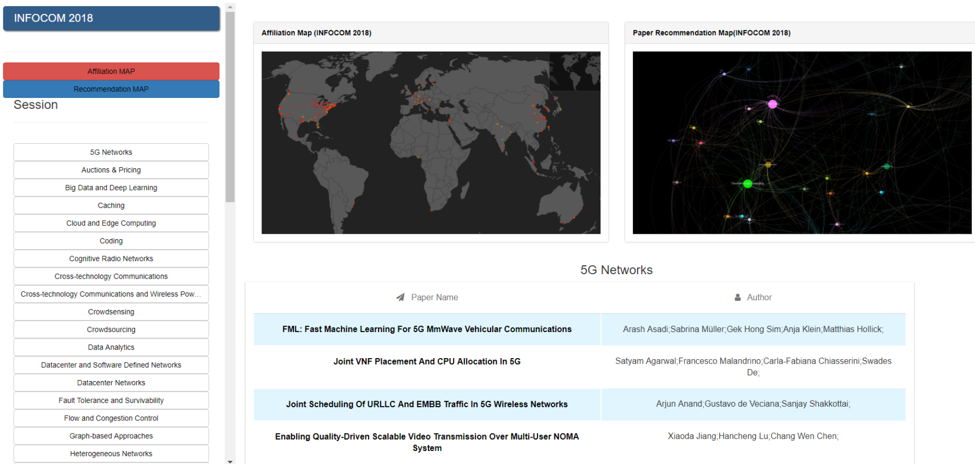


Fig.8. Index page of infocom 2018 paper recommendation system

Infocom 2018 is a specific feature of the work. Applying the new recommendation system to current Acemap website. The function of multidimensional recommendation is added for all the papers published in this year's Infocom. Figure 8 shows the index page of our system on Acemap.

#### 3.2.1 Multi-dimensional Recommendation


Fig.9. Multidimensional recommendation

Figure 9 shows the result of surveys recommendation for paper 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 papers help users who are familiar with this area find the most attractive parts quickly.

#### 3.2.2 Visualization

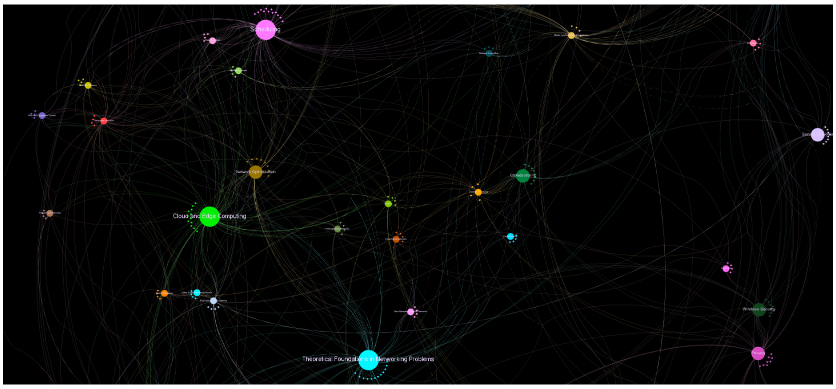

Fig.10. Visualization of recommendation

Visualization is necessary as the slogan of Acemap “Make Academia Visible”, it aims at creating a visual-friendly academic search system. The recommendation result of Infocom 2018 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.

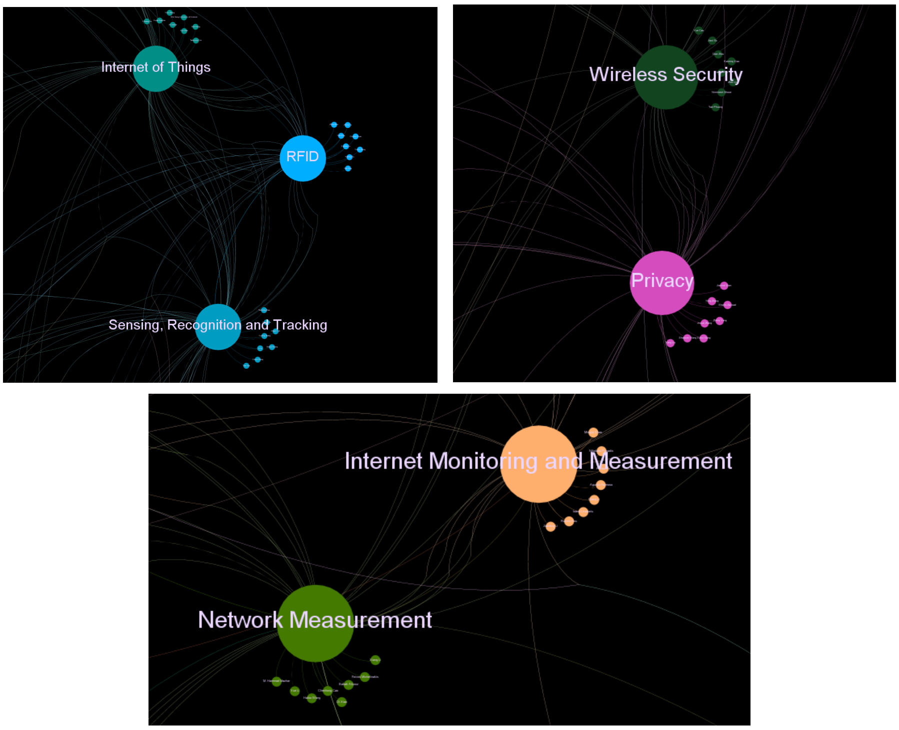


Fig.11. Partial clusters

In Figure 11, we can see session Internet Monitoring and Measurement and Network Measurement are close to each other. Also, Wireless Security and Privacy, Internet of Things, RFID and Sensing, Recognition and Tracking form clustering respectively.

## 4 Conclusion

The new recommendation system on Acemap is based on reference relationship between papers. The common neighborhood method algorithm can accurately provide relative papers and is fast enough to output the results. 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 the similarity of two papers and regard it as the criteria of recommendation degree.

The outcome of the tests and evaluation shows that the new system has obviously improved the effectiveness of recommendation, compared to the current Acemap recommendation 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.

To realize the slogan of Acemap "Make Academia Visible", visualization work of Infocom 2018 is done. From the graph, we can clearly find that the sessions are gathering into clusters due to citations. According to the name of the sessions, we can prove the accuracy of our system. What's more, a multidimensional paper recommendation function is featured to further improve user experience by rearranging the recommendation result from 5 different dimensions.

The work drastically improved the accuracy and effectiveness of the existing Acemap recommendation system and further enhanced the utility and visualization of the Acemap webpage.

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