You Never Walk Alone: Recommending Academic Events Based on Social Network Analysis

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Abstract. International conferences, symposiums, and workshops etc. provide researchers a discussion forum to present advanced research work and results, and also bring them together to have academic communities. Young researchers often encounter the problem to find the “right” academic events or the “right” communities, for instance, when they started with their PhD research. The numerous existing conference management systems or digital library Web sites have not supported the “newbie” in this way. We combine the Social Network Analysis (SNA) approach and recommender systems to help researchers get involved in diverse academic events. Based on a comprehensive academic event model, SNA is applied to analyze the development of academic events as well as communities, and certain recommendation algorithms are put into practice. As a proof of concept, the prototype AERCS has been realized through analyzing a great amount of data from the DBLP and EventSeer Web sites. The system evaluation result shows great interest from researchers and the academic event recommendation does help.

Key words: Recommender systems, Social Network Analysis, community analysis, community of practice, information visualization

1 Introduction

Academic events play an important role as the major publication and dissemination outlet in scientific communities. In computer science, the number of academic events has increased dramatically in recent years, which is shown in emails from DBWorld[1] collected by Zhuang, Z. [6] and data from DBLP[2] and EventSeer.net[3] (see Figure 1). Especially young researchers encounter problems how to find the suitable academic events for paper submission or which research communities to join in. It is also interesting to identify the research community of a particular researcher.

[1] `http://www.cs.wisc.edu/dbworld/`
[2] `http://www.informatik.uni-trier.de/~ley/db/`
[3] `http://eventseer.net/`

Till now, there are still problems in the existing tools and methodologies developed for academic events management and recommendation. Event management systems consider event managing process including event announcement, paper submission, paper review and paper acceptance notification. Digital libraries like ACM[4], DBLP[5] or CiteSeer[6] mainly focus on research publications and provide tools for papers search. Some other systems like EventSeer.net[7] make a step forwards in the area of academic event and community analysis. None of the aforementioned systems recommends academic events to researchers. To solve

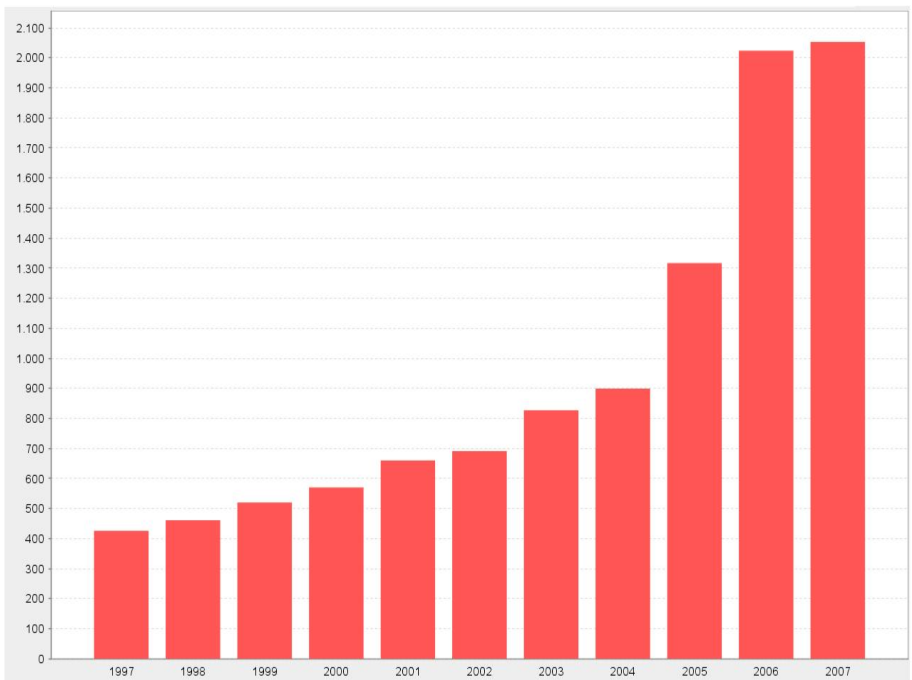

Fig. 1. Number of events collected in DBLP (by distinct proceedings)

the aforementioned problem, a model for academic events is required. Currently, event and community data exists in an unstructured way. Past events and their communities are documented by conference proceedings in digital libraries. Upcoming events are announced by Call for Papers and detail information can be obtained from their Websites. So there is no structural data for academic events. Moreover, with the recent advantages in technical communication as well as the increasing use of digital cooperation mechanism, there is also a requirement to

[4] `http://portal.acm.org/dl.cfm`
[5] `http://www.informatik.uni-trier.de/~ley/db/`
[6] `http://citeseerx.ist.psu.edu/`
[7] `http://eventseer.net/`

integrate new digital media such as blogs, wikis, mailing-lists, images, etc. into one model for event documentation. The model must reflect all aspects of events and their communities as well as be capable of connecting and collecting data from heterogeneous data sources such as digital libraries and diverse conference Websites etc.

In this paper, we propose a model for events and scientific communities. Based on this model, we realize a SNA based approach to recommend events to researchers. We study how research communities support individual members in events finding by applying Collaborative Filtering techniques for event recommendation.

The rest of the paper is organized as follows. In the next section, we briefly survey the related work on Collaborative Filtering, Actor Network Theory and Social Network Analysis. In Section 3, we present a conceptual model for academic events and communities. In Section 4, the design of recommendation algorithm is discussed. In Section 5, we evaluate our experimental results on the real dataset from DBLP and EventSeer.net. In Section 6, we conclude our paper with a discussion and an outlook at our future work.

2 Related Work

Recommender systems have been studied and applied in different application domains. In digital libraries, many approaches have been proposed to provide useful tools to researchers, e.g. citation recommendation [19], book recommendation [20], paper recommendation [21] etc. Generally, recommendation techniques can be categorized into three classes: Collaborative Filtering (CF), content-based and hybrid approaches. CF is based on the user community, while content-based approach uses features of items to generate recommendations. Hybrid approaches combine CF and the content-based approach with some other techniques such as demography, utility-based, knowledge-based recommendation to improve the quality of recommendation results. In this paper, we investigate how CF could be applied to solve the event recommendation problem. We leave out hybrid approaches for the future work.

Collaborative Filtering (CF)

CF is widely used in commercial applications. CF provides recommendations based on user's previous preferences and the opinion of other users who have similar preferences [4]. Users' preferences can be expressed explicitly by rating for an item or implicitly by interpreting user behavior like purchase history, browsing data and other types of information access pattern. Collaborative filtering algorithms can be divided into two categories: memory-based algorithms operate on the entire user-item database to generate recommendations; model-based algorithms use the user database to learn a model which is used in recommendation processes. In general, a recommender system has three components: background data, input data and an algorithm. Background data is the information that system has before the recommendation process begins. Input data is the information that user must communicate to the system in order to generate a recommendation. Finally, an algorithm combines background and input data to arrive at its suggestions [2]. In Collaborative Filtering, background data is the rating history of users on a set of items, input data is rating history of the target user. Collaborative Filtering works by viewing the previous dataset as a rating matrix. Ratings may be binary or real values indicate user's preference on the item. Columns in this matrix are items (called item vectors) and rows represent users (called user vectors). Each entry in the matrix is the user's rating for a particular item.

Actor Network Theory (ANT)

Actor Network Theory (ANT) was developed by two French scholars, Michel Callon and Bruno Latour [7]. Digital networks are a meeting point for the socialogy and technology. In the ANT model, we have a network formulated by actors and relationships [8]. A person or an object is observed as an actor in the same way. Any set of actors involved in a certain activity formulates a network. There are three special kinds of actors. The member stands for a person or a community. The medium enables members to perform the activities, for example, establishing communication links and exchanging information. Artifacts are objects created by members using some media.

The conceptual model for academic event proposed in this paper is based on ANT. As mentioned earlier, digital media need to be integrated into the model for events and communities documentation. ANT tries to explain social order not through the notion of "the social" but through the networks of connections between human agents, technologies and objects [9]. Communities of academic events have been seen as communities of practice in which members share the information and communicate among themselves using the combination of various communication methods such as face-to-face meeting and technology-enhanced methods, e.g. discussion forums, Websites, mailing-lists, blogs, wikis etc. Technology-enhanced communication techniques have become more and more important, especially when the number of international conferences has increased. Members of the community can live in different countries and continents. Recently it is hard to organize a face-to-face meeting and discussion. Therefore, technology-enhanced communication methods are one of important mechanism contributing to the success of a scientific community. All these aspects need to be modeled for scientific communities with regard to the cross-media aspect.

Social Network Analysis

In digital libraries, it is possible to create networks that reflect the collaboration between researchers by using the reference data in research papers. In particular, much research work has studied the creation of these networks and applied Social Network Analysis for scientific communities to understand the structure and pattern of research collaboration [10, 11, 12]. In the domain of publication and venue ranking, several approaches have been proposed to measure the impact of scientific collection (journals, proceedings) and scholar authors [15, 16, 17, 18]. This work regards on citation and co-authorship networks as the professional network between researchers. Studies have also been done to apply Social Network Analysis to evaluate the quality of academic events [6]. We investigate the role of research communities in helping researchers to find academic events and to identify the communities.

3 A Model for Academic Events and Scientific Communities

Based on ANT, we propose a model for academic events and communities depicted in Figure 2. In this model, we consider the network of researchers in the relation with academic events. For each event (and event series), we have a network representing research collaboration between members. There are three kinds of networks under consideration, including the co-authorship network, the citation network and the co-participation network. *Scientist* entity describes the node of network, *Link* entity represents the connection between nodes and *Subnetwork* entity models the subnetwork extracted from *global network* which is composed of *Scientist* and *Link* entities. *Link* entity has an attribute *type* to differentiate three kinds of networks.

Each *Event* belongs to an *Event series*, e.g. ACM SIGMOD, VLDB series etc. We consider all kinds of academic events, including conferences, workshops, international symposiums, doctoral consortiums as well as winter/summer schools. In general, workshops can be held as independent events (therefore, they have their own series) or in combination with conferences, symposiums or consortiums. Each *Event* has a set of *Topics* which present the research domains and objectives. In fact, research topics tracking as well as topics classification are two complicated problems. Research topics can be categorized in hierarchical structure in which a common topic (e.g. Database, Information Systems) can be divided into subclasses. To keep it simple, in our model we use a “flat” list of topics to specify research interests of an event. In the mediabase, we integrate all types of digital media, e.g wikis, blogs, Websites, videos, images etc. This model intends to be the basic on which a recommendation tool is designed and implemented.

4 Collaborative Filtering and Academic Event Recommendation

Standard Collaborative Filtering needs to be mapped to event recommending problem. We present a model and algorithm based on research communities of academic events. Formally, the problem can be stated as the following:

Given a set of academic events E, a set of researchers U and a set of participation history vectors V in which $v_u = (e_1, e_2, ..., e_n)$ represents the

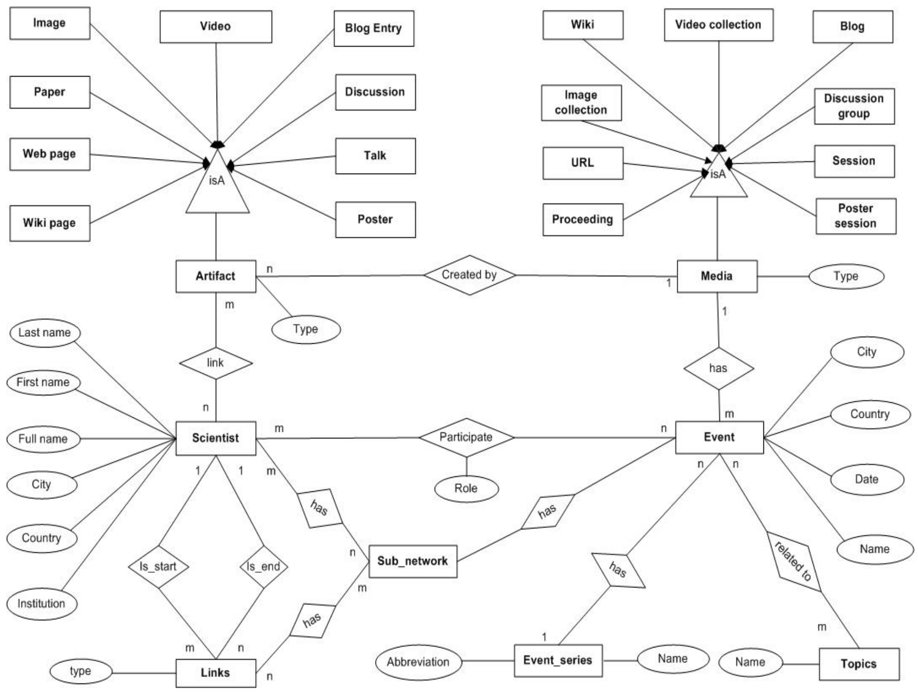

Fig. 2. Model for events and communities

participation history of researcher u. Recommend top K upcoming events for a target researcher u_t.

General Algorithm

Standard collaborative filtering processes in three steps: building the model, computing similarity and generating recommendation. Our algorithm follows these steps and can be presented as following:

Input: a set of events $E = (e_1, e_2, ..., e_N)$, a set of researchers $U = (u_1, u_2, ..., u_M)$.

Output: top K most recommended events to a target researcher u_t.

1. Building the model: construct the participating matrix $R(M \times N)$.
2. Computing the similarity between target researcher u_t and others.
3. Generating recommendations: Select L most similar researchers and rank unknown events by aggregating the rating of L most similar researchers. Return most K ranked unknown events.

Building the Model

As presented in Section 2, collaborative filtering operates on a rating matrix in which each entry is user rating on an item. To map this model to our problem, we use the following approach. We consider academic events as "items" and researchers are users who are going to get recommendations. The rating value of a researcher on an event is binary (i.e. 1 and 0), which means he participated or he is going to take part in this event, or not. We use event participation history of researchers as background data. Input data is the participation history and preferences of a particular researcher. The rating matrix then can be built using the background data. Formally, given a set of academic events E, set of researchers U then $R(M, N)$ is the rating matrix in which entry $R_{u,e} = 1$ if user u participated in event e and $R_{u,e} = 0$ if user u did not participated in event e. We use U_p to denote the p^{th} row of R which is called the researcher vector of researcher u_p and E_q to denote q^{th} column of R which is called event vector of event e_q.

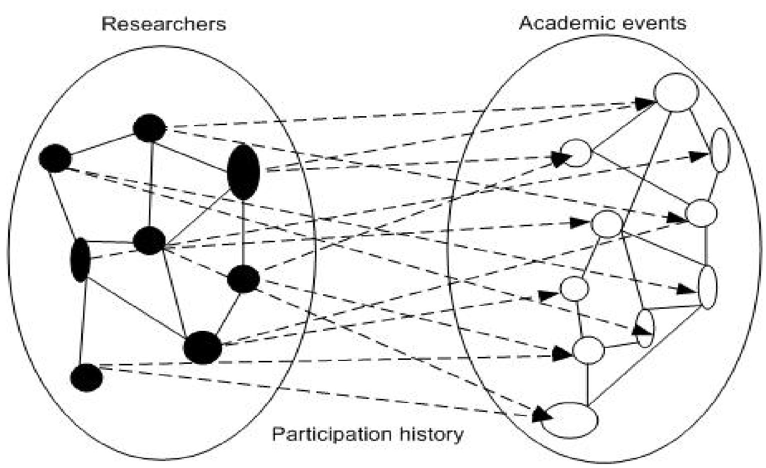

Fig. 3. Collaborative Filtering model mapping

This approach suffers from *start-up* and *generality* problems. Newbie researchers who did not attend any events before nor ever published any papers with other researchers will not get recommendations since the system has no information about them. To overcome this problem, we use the profile building mechanism as in the other recommender systems. Users have to rate a sufficient number of items before they can get recommendations. Under the assumption that normally a newbie researcher starts his research work with the help of his professors, advisors, as well as his colleagues. They build up an implicit research community around him. He could also join communities of events in which he is interested, in order to keep track of what these communities are doing. Overall, by explicitly declaring his own "implicit" community, a newbie researcher can involve himself into a scientific community and let that community help him to find events.

Generality problem emerges from the fact that researchers may change their fields as well as work on different fields. For example, a researcher may work on database systems and distributed systems as well. Therefore, he attends conferences on database technologies and distributed systems. The target researcher attended many conferences with him on database technologies and then he may be recommended conferences on distributed systems. With many researchers like that, it is difficult to find a set of recommended events which satisfy the target researcher's preferences. We solve this problem by a subjective classification via profile building mechanism. User's preferences on topics are used to filter out events which are not relevant before performing the recommendation process. This preprocessing procedure guarantees that recommendation algorithm will work on a set of events which satisfies user's needs in general.

Computing Similarity

In this step we compute the similarity between researchers to find the set of closest researchers to the target researcher. According to [5], various approaches can be applied to compute similarity. The two most popular approaches are *correlation* and *cosine-based* method. In our work, we use the *cosine-based* approach. To present them, let $E_{x,y}$ be the set of events which researcher x or researcher y, or both attended, i.e. $E_{x,y} = \{e \in E \mid R_{x,e} = 1 \| R_{y,e} = 1\}$. $E_{x,y}$ is the union of events which researcher x and y attended (E_x and E_y relatively). In correlation approach, similarity function $sim(x, y)$ is computed by the Pearson correlation coefficient:

$$sim(x,y) = \frac{\sum_{e \in E_{x,y}} (R_{x,e} - \overline{R_x})(R_{y,e} - \overline{R_y})}{\sqrt{\sum_{e \in E_{x,y}} (R_{x,e} - \overline{R_x})^2 \sum_{e \in E_{x,y}} (R_{y,e} - \overline{R_y})^2}} \tag{1}$$

in which the average rating of researcher x, $\overline{R_x}$ is:

$$\overline{R_x} = \frac{1}{\mid E_x \mid} \sum_{e \in E_x} R_{x,e} \tag{2}$$

which is equals to 1 in our case.

In the cosine-based approach, two researchers x and y are treated as two vectors $\overrightarrow{x}$ and $\overrightarrow{y}$ in m-dimensional space, where $m = \mid E_{x,y} \mid$. Similarity between two vectors can be measured by computing the cosine of the angle between them:

$$sim(x,y) = cos(\overrightarrow{x}, \overrightarrow{y}) = \frac{\overrightarrow{x} \cdot \overrightarrow{y}}{\parallel \overrightarrow{x} \parallel \times \parallel \overrightarrow{y} \parallel} = \frac{\sum_{e \in E_{x,y}} R_{x,e} R_{y,e}}{\sqrt{\sum_{e \in E_{x,y}} R_{x,e}^2} \sqrt{\sum_{e \in E_{x,y}} R_{y,e}^2}} \tag{3}$$

where $\overrightarrow{x} \cdot \overrightarrow{y}$ denotes the dot-product between the vectors $\overrightarrow{x}$ and $\overrightarrow{y}$.

Generating Recommendations

Recommendation generation is a ranking process in which we compute a ranked values for unknown events. According to [5], a ranked value is usually computed as an aggregate of the ratings of L most similar researchers for the same event:

$$R_{c,e} = aggr_{d \in C} R_{d,e} \tag{4}$$

where C denotes the set of L researchers who are most similar to researcher c and have participated in (or will attend) event e. Some of the aggregate functions are:

$$R_{c,e} = \frac{1}{L} \sum_{d \in C} R_{d,e} \tag{5}$$

$$R_{c,e} = k \sum_{d \in C} sim(c,d) \times R_{d,e} \tag{6}$$

$$R_{c,e} = \overline{R_c} + k \sum_{d \in C} sim(c,d) \times (R_{d,e} - \overline{R_d}) \tag{7}$$

where $\overline{R_c}$ is the result of the similarity computation. The multiplier k serves as a normalizing factor and is usually selected as:

$$k = \frac{1}{\sum_{d \in C} sim(c,d)} \tag{8}$$

We use aggregate as an average (defined in the first case). However, in more complicated cases, the aggregate could be a weighted sum in which the similarity between c and d is used as a weight, i.e. the more similar c and d are, the more weight $R_{d,e}$ will carry in the ranked value $R_{c,e}$.

5 Prototype Evaluation

Datasets

As a proof-of-concept, a prototype called AERCS is implemented based on the data from DBLP XML record and EventSeer.net[8]. First, DBLP XML record is parsed to get the list of past events and co-authorship network of each event. Event series are taken by parsing the DBLP Website. Events then are bound into series by the unique URL prefixes of event and event series. Location information of events is also taken from DBLP Website. Upcoming events are extracted from EventSeer.net Website. EventSeer.net contains most of Call for Papers for conferences in Computer Science. From EventSeer.net, we got a list of upcoming (and past) conferences with the information about time, locations, topics, persons and organizations. The parsing process is described in Figure 4. Overall, we have a large dataset as summarized in Table 1.

Data from DBLP and EventSeer.net is enough for the evaluation, though it is not complete. Ideally, we should have the list of all participants, authors and programm committee members (PC members) of each event. DBLP contains only the authors, while EventSeer.net indexes persons who are mentioned in

[8] `http://bosch.informatik.rwth-aachen.de:5080/AERCS/`

Table 1. Dataset summary

Data	Quantity
Events	16821
Series	2099
Authors	522938
Topics	4910
Co-authorship of events	1282796 links

Call for Papers, so they are mostly PC members. However, using authors and PC members as background data for recommendation algorithm is reasonable. Authors and PC members of each event have a closed relation via papers review process. Authors also have knowledge about the others since they have worked on the same problems.

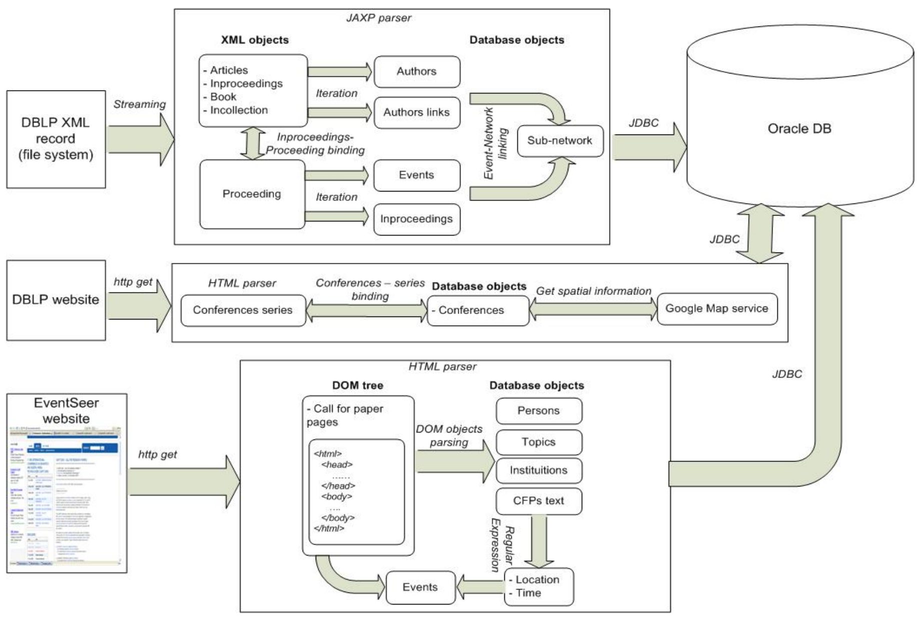

Fig. 4. Data preparation process

Online Experiment

We conducted an online survey on a set of users to collect the opinion about recommendation result and community analysis provided by the system. Users are selected from colleagues and students working and studying at Information Systems, RWTH Aachen University, Germany. A short tutorial is given to users. The tutorial guides users through several tasks to let users get to know the concepts of the system, e.g. profile building, recommendations, finding events and event series as well as community analysis and visualization. The system gains over 20 survey result as feedback in which most of the questions are answered. First, we analyze the feedback to see users' experiences in academic events as well as their roles in the events they attended. Most of users have participated in 6 to 20 events, others have attended 1 to 5 events. Among them, about 11 users took part in the events as participants, 6 users as presenters and a small number of users (about 4 users) as PC members. This result shows that our user community are young researchers.

In the second step, we assess the feedbacks to know users opinion about recommendation result. Users are asked to build their profiles in which they have to declare preferences on topics, locations, persons and events. System then generates a list of upcoming events recommended to them. Users can compare the list with events they are interested in as well as discover new events which they do not know. Users express their opinion by answering a question about their satisfaction with recommendations. As shown in Figure 5, most of users satisfy with recommended events.

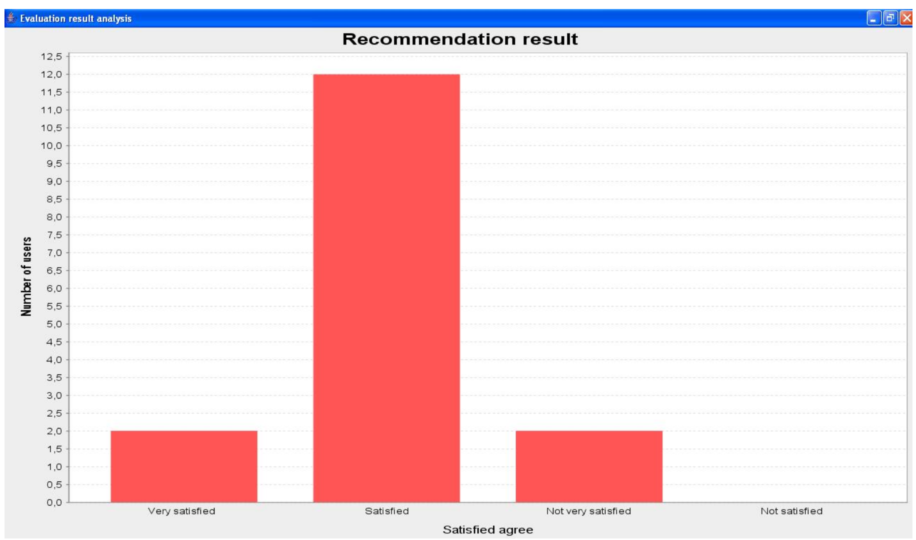

Fig. 5. Users satisfaction with the recommendation results

Besides recommending events to users, we perform the analysis on event series communities. This aims to provide to users an insight into community of an event as well as event series. With our dataset, we are able to measure and present some parameters about communities as proposed by Wenger at al. (2002) [14] and Kienle [13]. We analyze the development and continuity of communities by measuring the number of participants over years and number of participants according to the number of events they attended. Within an academic event series, key members of the communities are also identified according to the number of events they attended in the series.

One of the most interesting features of the prototype is community visualization. We provide co-authorship network visualization of an event and event series as well as local network of a particular researcher. Community visualization is implemented based on yFile AJAX - a commercial network visualization tool. From the visualization, users can see the development of community of an event series over years as well as the community of event series as a whole (6).

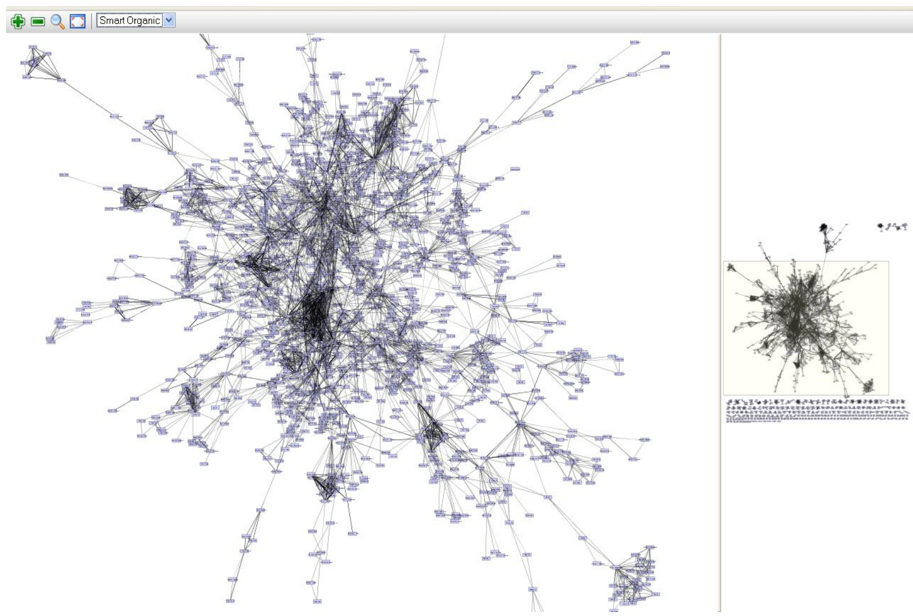

Fig. 6. ACM SIGMOD community visualization

6 Conclusions and Future Work

Recommender systems for digital libraries and scientific communities is an emerging research domain. A recommender system could be a great tool for young researchers to find academic events to which they can submit papers. Our experiments show that applying a community based recommendation algorithm supports researchers in event finding. By using event participation history as background data for a Collaborative Filtering based algorithm, we are able to recommend the most relevant academic events to researchers. The algorithm is applied on the dataset which can be easily extracted from references in papers documented in digital libraries like DBLP, ACM or EventSeer.net.

The dataset of our system should be enhanced with some other data sources. Currently, data from DBLP and EventSeer.net is imported into our database. To have better recommendation results and analysis, we need also data from other digital libraries such as ACM, CiteSeer. The problem is to connect these data sources to provide a unique repository for academic events. We are working on this issue by investigating and applying different data mining and Web mining techniques in order to create a mash-up data source network. Based on this, useful services could be further designed and implemented.

In the future, it would be interest to investigate other recommendation techniques as well as algorithms for event recommendation problem. Content-based recommendation and the combination of content-based with CF and other recommendation techniques could be a promising direction. It would also be interesting to see these recommendation approaches in other domains. Currently, we are performing Social Network Analysis of cooperations among 45.000 schools in Europe.

Another idea is to follow the dynamic behaviour of researchers. The movement of researchers between communities could be captured. The question is that what are important factors affecting this movement and the role of spanners in the communities. By tracking and analyzing the dynamic movement of members, we are able to recommend future directions in research as well as career paths for researchers.

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