Using Co-presence Communities to Enhance Social Recommendation

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Abstract— **This paper proposes a social recommendation algorithm for use in a research social network environment. The social recommendation algorithm proposed combines the concepts of a relationship ontology and item-based collaborative filtering (CF). While the network setup in social networking sites can accurately reflect the social landscape of its users, it is much harder to detect the importance or strength of any one link. We therefore propose an extension to our recommendation algorithm which makes use of the idea of co-presence communities to increase the relevance of the recommendations. A co-presence community can be detected from with data collected from Bluetooth-enabled mobiles. Detection of a co-presence community can help determine the nature and importance of the social links between participating members**

Index Terms— **Recommender Systems, social recommendation, item-item recommendation, social networks, relationship ontology, Mobile Social networks and Bluetooth.**

I. Introduction

Over the last few years a variety of Social Network sites have been established to provide their users with the ability to maintain social connections. Some sites, such as Bebo[1] and Facebook[1] are intended to mirror existing friendship relationships online, whereas sites such as LinkedIn[1] are more business networking oriented. Social networks seem to primarily foster existing social connections rather than create new ones. This is reflected in Facebook's slogan "connect and share with the people in your life". Users of a recent application which promoted the formation of new social links have suddenly found themselves banned with the explanation that Facebook "expects accounts to reflect mainly "real-world" contacts rather than mainly "internet-only" contacts"[2]. While some new relationships are formed through the use of Social Networks, the majority of relationships are ones that previously existed. While these sites do not encourage the formation of new relationships they do, however, provide realistic social landscapes. This is because they do not rely on one user's view of the world; rather they aggregate all user's views of the world according to the current user's relationship with the other users. In this manner, social networking can be applied to the research domain to allow for a self-updating, realistic interpretation of state of the art.

In our current research, our primary aim has been to develop a Personalised Research Dashboard[3] that will provide a dynamic self-updating environment in which researchers can retrieve highly-specialised information about the most up-to-date papers/technologies/test-beds. It will explore the possibilities of developing a social networking infrastructure for seamlessly linking researchers at all levels, from both academia and industry, with each other, relevant publications, test-beds and other specialised resources. Most importantly we hope that it will allow users to build up online communities of people who share similar research interests. These communities will allow for near instant dissemination of new information to the people who need it most and facilitate the cross-disciplinary links (especially with people who share similar research interests).

In order to provide our self-updating and realistic interpretation of state of the art, our research dashboard must use collaborative filtering (CF) techniques. CF techniques have become very established in the public realm mostly as a result of successful online retailers such as Amazon[4]. CF in the retail sector is primarily motivated by the potential for increasing revenue. However, CF is well studied ([1][8] and [9]) and many different variants have been suggested.

Recently, a variety of researchers have been investigating adhoc mobile connectivity in terms of providing a basis for sensing both simple and complex social situations. These applications use repeated physical proximity of two or more users to indicate a relationship between the two users. While these systems are complex and difficult to test they provide valuable information about mobility and proximity patterns of users, and also provide the potential of facilitating actual

[1] Bebo: www.bebo.com, Facebook: www.facebook.com, Linkedin: www.linkedin.com
[2] http://www.techcrunch.com/2008/09/15/facebook-isnt-a-social-network-and-dont-try-to-make-new-friends-there/

[3] Research Dashboard is a pilot project for a research Mash-up site for linking researchers across disciplines, funded by the EPSRC under the "Bridging the Gap" initiative.
[4] Amazon: www.amazon.co.uk

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physical social interaction. Another interesting possibility from this data is the potential for using actual physical interaction to lend credibility or strength to the value of the relationship between the users.

In this paper we introduce a novel framework for combining spatio-temporal proximity data along with more traditional recommendation techniques to refine recommendations that take place within a research social network. The framework will combine user profile information from a user's social landscape with spatio-temporal information gathered from the adhoc mobile environment in order to reinforce links between individuals in an intelligent manner.

Section II will discuss some of the relevant advances in recommendation in social networks and the utilization and collection of mobile proximity data. Section III will discuss our proposed CF technique and Section IV will highlight some of the other techniques we wish to consider.

II. Related Work

As previously discussed the focus of most recommendation in social networks is primarily to do with fostering existing connections. Facebook's recommendation system utilizes a user's social graph to recommend them other users which they may know. "May know" is an important condition in this situation. Facebook is not introducing the user to people they may *want to know*, but rather simply aids the user in replicating their already existing real-world social graph in the virtual world.

While social networking sites themselves are only just beginning to harness the power of recommendation systems, they have implicitly added a type of user based collaborative filtering (CF) recommendation. Rather than analysing all the preferences of a large user base and then calculating similarity they use the friend or network relationship to indicate similarity.

CF algorithms help distill the vast collage of information available in such a manner that they attempt to present us with the most relevant information ([1][8]). Essentially, information about the users and their associated preferences are gathered to be used in calculating similarity. Broadly speaking CF is divided into user-based and item-based. User-based CF is done by calculating the similarity between two users. A similar user in user-based CF is one that has shown similar taste. The more items two users have in common, the higher the similarity between the two users. New items are recommended to the original user from the set of dissimilar items from the most similar users. Item-based CF targets items rather than users. It calculates how similar the target item is to the set of items the user has rated.

In order for CF to be successful, accurate and current user profiles must be maintained. However, getting reliable information about the user has always been difficult. Preferences or ratings can be either implicitly or explicitly gather, or both. Implicitly collected information often misses valuable data whereas explicitly gathered information is often incomplete. One way of gather relatively rich information is to harvest Social Network profiles. Liu and Maes present InterestMap [2] which harvests user information from social network profiles. They data mine the profiles for keywords from a variety of different description categories (such as general interests, passions, etc). Once the data has been collect they normalize it and use it to create a map of interests and identities. The map is then used to recommend interests.

Mobile phones have become an integral part of our society; far from just having the capability of receiving phone calls, mobiles devices are capable of a range of activities from checking your email, surfing the web, playing games, etc. While many phones these days have a variety of wireless connections, one of the functions provided by many phones is Bluetooth. Bluetooth provides short range communications and was originally intended for use in personal area networks (PANs). Although the range of Bluetooth is relatively short, the extremely high market penetration among mobile users provides an excellent opportunity in promoting community environments with close to no extra costs to the users.

There have been several recent projects that utilize Bluetooth functionality to collect "reality data" – i.e. data that describes the interactions of everyday life. Eagle and Pentland [3] use a passive running Bluetooth application to collect information about the daily interactions of 100 subjects within a university campus. They do this by recording the Bluetooth ID (BTID) of every device encountered by each of the subjects. Nicolai et Al [4] also use Bluetooth to collect proximity data. Unlike Eagle and Pentland, they collect their data from amongst a set of relative stranger; the attendees of a conference. In [5], a mobile application called Serendipity is introduced. This application uses Bluetooth to detect other mobiles that are nearby. If the mobile encountered uses the Serendipity application it will calculate the similarity between the two users based on the user profile. If this score is above a certain threshold, commonalities between the users are sent back to the two phones.

The reality data collected from the above projects have inspired a variety of different types of usage. Spindler et Al [6] used this idea to introduce a CF approach that was based on spatio-temporal proximity. Spindler et Al used Bluetooth-enabled mobiles to collect the same type of data as location data as Serendipity, however they utilized a user's proximity to another to exchange rating data for recommendation. They use opportunistic information sharing to generate mobile recommendations in a festival setting. In a slightly different direction, Lawrence et al. [7] define the concept of co-presence communities and an algorithm for detecting those communities from mobile data collected by Bluetooth-enabled mobile phones. A co-presence community is defined as a group of individuals who regularly share the same location at the same time. They use this co-presence community detection to initiate content sharing between users. This sharing is based on a variety social context rules.

The recommendation framework proposed in the next section combines social networking, CF techniques and Bluetooth collected mobile proximity data in a research-oriented social network. Our aim is to use repeated co-presence events to strengthen the relationship and thus the importance of that relationship in research resource recommendation.

III. PROPOSED FRAMEWORK

The motivation behind the recommendation framework proposed by this paper is based on improving recommendations within a research social network. The types of recommendations include related people, papers, tools, etc. This section describes the architecture for recommendation currently being implemented within the research dashboard. It then proposes an extension to the framework in order to utilize mobile of co-presence communities to further refine the results.

Research Dashboard Recommendation Architecture

Within the research dashboard we plan to investigate various forms of recommendation and rate them according to how well they recommend people/research resources. Our initial experiment will focus on combining the simplistic style of social recommendation with that of item-based CF recommendation techniques. Since many item-item computations can be done offline we hope to provide a scalable, efficient algorithm which can provide more accurate recommendations by using the social network friend and group relationships to form the neighborhoods of a user-based algorithm.

Social recommendation will be achieved by using a relationship ontology to weight the importance of users of each type relationship to each type of recommendation.

1) Relationships in a Research Social Network

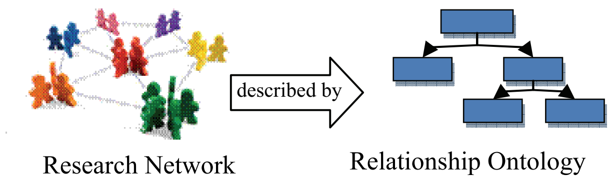

Figure 1: Relationship Ontology

Rather than rely on the traditional one or two tier relationship model of many social networking sites, our research dashboard will provide a relationship ontology. A relationship ontology is required in order to perform recommendation that is contextually sensitive with regards to the types of trust between two people. Modeling this kind of relationship will allow finer nuances of recommendation and implicit referral. The relationship ontology will capture as much detail about the nature of a relationship between two people, without over-complicating and thus annoying/exhausting the user. Where possible, we would like our system to detect the nuances of existing relationships. The use of a relationship ontology, will help fine tune recommendations made. For example, a relationship between two people, A and B, may be that A has cited B. It is logical that A, the cite, is likely to be interested in news, further publications, etc. of B, the person they have cited. However, the reverse is not necessarily true.

Relationship	***Recommendation type***		
	People	Papers	N
ColleagueOf	.2	.3	..
StudentOf	.1	.04	..
CollaboratorOf	.4	.6	..
M	..	..	..

Table 1

2) Item-based Collaborative Filtering

The motivation between choosing an item-based rather than user-based CF algorithm is the fact that we wish to a broader style of recommendation. "Users like you like X" is a difficult measure when faced with a community of broad research interests. With the combination of diverse interests and recommendations, item-based CF will provide better coverage for new or peripheral interests. The predictions will be calculated online for all users that appear in the given user's relationship ontology. An offline version of item-based CF such as the model-based algorithm presented in [1] will be implemented on the existing resources within the dashboard. The results normalized according to the user's relationship/recommendation weights (such as those presented in Table 1) .

While the majority of the preference collection will happen implicitly (i.e. the number of times another friend's profile is looked at, the number of times profiles are looked at for all friends who are members of a specific relationship, the number of times a paper is downloaded or referred to, etc.), we will allow the user an opportunity to influence the ratings through a rating dashboard.

3) Mobile Co-presence Extension

As described in [7], co-presence communities can be detected using reality data collected from Bluetooth enabled phones. A co-presence community is made of users that are regularly are within Bluetooth range. The ability to detect co-presence communities is that they will aid us in distilling the relationships that are important for recommending research resources. Consider three colleagues from research sector in the same institution, see Figure 2. Because they are regular contact with each other, the amount collaboration that is detectable from online sources (such as email or online group participation) is quite limited since they tend to discuss things in person. Previously such interactions were undetectable, however while the content of the conversations can only be conjectured, the fact that a meetings took place, is not. Therefore, the fact that colleague A and B regularly meet to discuss their research and that colleague B and C (who, in reality, have very little research similarity) only meet infrequently and briefly, can be detected and fed back into the recommendation framework.

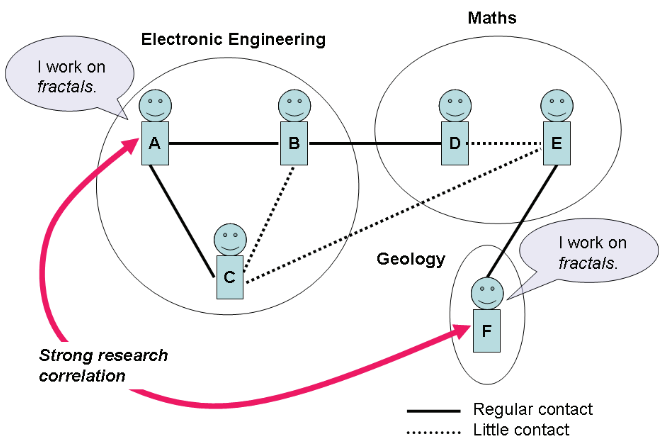

Figure 2 People interaction within an academic community

Our site will therefore allow and encourage users to register their mobile phones. A simple mining application such as BlueAware [3] can then be installed on the user's phone and Bluetooth proximity data can be collected. The phones sync with the server either when they are in proximity to the user's computer or the user uses a data connection to access the personal research dashboard on their phone. A real-time variant of the co-presence community mining algorithm [7] will be implemented and the relationship ontology weightings will be adjusted accordingly.

We can exploit proximity detection to enhance the recommendation functionality in the research dashboard. Referring back to Figure 2, both A and F are working on fractals. Given their social circle and work patterns within the institution, they do not normally have any interaction. Assuming everyone shown has signed up for the mobile research dashboard, since E meets with F regularly and both D and C meet with E regularly; A will find out F's research area through C or B (via D). Without the aid of the mobile research dashboard, it will be more difficult for this type of introduction to occur.

A detailed comparison between the non- mobile CF variant proposed above and the CF variant with mobile extension will be completed.

IV. FURTHER ISSUES

One of the major goals of the personal research dashboard is to facilitate contact between people. To that extent the extension that we see most useful are to:

1. Recommend previously unexplored discussion topics for co-present individuals.
2. Recommend contact between two like-minded strangers, either on the basis of the users' contacts or interests.
3. Calculation and visualizations of Research Fabric. Similar to [2], we hope to use tools to allow users to see where they fit into the overall research fabric. This should allow researchers to be able to see similarity in their research areas with other users from other disciplines.

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