PITTCULT: A Cultural Event Recommender based on Trust Network

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ABSTRACT

Typical collaborative filtering recommenders (CF) do not provide any chance for users to choose or evaluate the bases for recommendation. Once the system evaluates a group of users as being similar to a target user, her information is tailored by unknown people's taste. As a cultural event recommender, PITTCULT provides a way for users to rate the trustworthiness of other users; then, according to those ratings, a recommendation is generated. This paper explains why trust-based recommendation is necessary, and how studies using PITTCULT cope with the problems of the existing CF.

1. INTRODUCTION

The ever-increasing and -changing range of information on the Web requires the centric area to collect useful information in one place; for the individual user, however, unnecessary information should be filtered out. PITTCULT (http://pittcult.sis.pitt.edu) is designed to share and recommend cultural event information in the Pittsburgh area (Figure 1). This system basically utilizes human psychology to conform to the opinions of friends. When people go to a music concert or exhibition, for example, they commonly ask their friends' opinions, and invite them to go along. Centered on this trusted human network, users can recommend items to their friends and can rate their friends' taste about a certain genre of cultural events.

As a popular recommendation technology, collaborative filtering-based recommendation (CF) works well in domains where contents are not easily comparable, like music, movies, jokes and cultural events (Schafer, et al., 2007). It is designed to find like-minded peers; based on their tastes, the recommender generates recommendations, under the assumption that I may like what they like. It is a way to use the wisdom of crowds beyond the scope of my current human network, and it is known for making diverse and serendipitous recommendations. However, questions about recommendation quality have arisen, since utilizing the taste of unknown users who are calculated by the system to be similar to me has become the standard for tailoring the information I receive.

There could be ad-hoc users. A user having malicious intentions can copy the whole rating of a target user; this would cause the system to calculate the ad-hoc user as being the most similar to the target user and, as a result, items rated by her would be recommended to the target user. If the ad-hoc user desires, this makes it possible to make a profit or distort the system (Lam & Riedl, 2004; Mehta, et al., 2007; O'Donovan & Smyth, 2006; Sandvig, et al., 2007) [1,2,3]. Additionally, a group of ad-hoc users can reinforce their own ratings and shift the prediction for recommendation in the intended direction (O'Donovan & Smyth, 2006). Even a well-intentioned user may have such eccentric tastes that the distributions of ratings will be too different for them to find a peer group (Schafer, et al., 2007). Another problem regarding CF technology is that, if I do not rate a sufficient number of items, I am unable to receive any recommendation because comparisons with other users are not possible. When there are too many items in comparison to the total number of users, it is also hard to generate recommendations, due to too small an overlap of tastes among users (Schafer, et al., 2007; Massa & Avesani, 2007). To cope with these various problems, a recommender system based on trust is proposed. In this proposed system, users will choose those upon whom to base their information filtering.

2. RELATED WORK

Among several sociological theories about social networks, homophily (which is defined as 'people with similar characteristics tend to be connected (Wellman, 2007)') has been investigated by some researchers in the information-science discipline. Singla & Richardson examined the logs of instant messenger and search engines, and determined how information-seeking activities were similar among friends. They found that two people who talk to each other on the messenger shared significantly similar interests. When they compared that with the common interests of random user pairs who were similar in demographics, friend pairs shared significantly similar interests. They found homophily exhibited on the Internet (Singla & Richardson, 2008). Groh and Ehmig showed that users who were connected as friends had similar ratings in the taste-related domain, such as their preferences regarding bars. They also found that the rating similarity within a clique (a group of more than 2 friends) was stronger than that of two friends, because they feared isolation in their group (Groh & Ehmig, 2007). Cultural events can be

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[1] http://www.wired.com/news/ebiz/0,1272,53634,00.html
[2] http://news.com.com/2100-1023-976435.html
[3] http://www.auctionbytes.com/cab/abn/y03/m09/i17/s01

acknowledged as strong group activities. Users know their friends' tastes about cultural events. Additionally, a user may not be interested in a certain event but, if her friends go to the event, she might join them and still have fun.

If friends share similar tastes, how do recommendations by those friends differ from system recommendations made by unknown users who also have similar tastes? Sinha and Swearingen compared the recommendation quality between an online system and friends. They concluded that friends' recommendations were more useful and better than those of the recommender system. The recommendations of friends also generate more trust than those of the system (Sinha & Swearingen, 2001). In addition, Golbeck showed that users prefer recommendations from trusted people (Golbeck, 2008). Bonhard and Sasse explained the reason for that, stating that recommendation is combined with the decision-making process. Advice-seekers decide the value of suggested items according to the identity of the recommender. Therefore, the relationship between the receiver of recommended information and the source of that information is critical. Their study found that, along with rating overlap, such profile similarities as demographics, preference and interests play an important role in trustworthy recommendation (Bonhard & Sesse, 2006). In current CF technology, the process to decide the value of an item is a black-box to users because it is based upon unknown users.

Massa and Avesani investigated CF from a trust perspective. They expanded the existing CF technology by adding local trust metrics, using MoleTrust. In an experiment using trust values in Epinions.com, they concluded that trust-based recommendation was resistant to malicious attacks, and that information propagation was more secure than CF technology. Local trust, which is a personal and subjective trust evaluation, is more effective than a traditional CF in terms of recommendation quality and its ability to cope with both the data sparsity problem and the cold-start problem (Massa & Avesani, 2007). O'Donovan and Smyth proposed a profile- and item-based recommendation that takes into consideration both the similarities among users and the trustworthiness of recommendation histories for CF. In the study, a given user could be adjudged more reliable than others, and a conclusively different peer group for a separate item could be chosen (O'Donovan & Smyth, 2005). However, this recommendation technology was tested solely on an accumulated user history of MovieLens data, and an algorithm would need to be implemented in any real system.

To the best of the author's knowledge, a real recommender application using trust ratings has rarely been explored. Epinions[4] provides mechanisms for evaluating other people's overall opinions, regardless of the categories of the items, but does not provide for any personalized recommendation according to the evaluation. Ebay[5] also lets its users rate trust values about others, but the rating values are only applied to the buying and selling transactions. There are no recommendations, as such.

To date, the trust-based recommenders are Moleskiing and TrustMail. Moleskiing.it is a recommender application for ski mountaineers. It is based on the degree to which a user's review and comments about a ski trip are adjudged to be trustworthy. Even an individual user can specify trustable users, the recommendation could be universal to every user. If the snow condition of a ski resort is described by one user as being reliable, that information would be equally useful to all users who plan to ski there. It is hard to say the recommendation is personal taste-dependent; rather, it chooses editors from among the users (Avesani, et al., 2004). TrustMail implements 'Web-of-Trust' in a mailing application. According to the calculated implicit trust value, the system tells the users which mail is important to them. If users wish, they can also give explicit trust ratings. Specifically, the system uses connected trust paths in a graph, thereby making it easier to propagate trust and, information (Golbeck & Hendler, 2004). There is also a movie system using a web of trust, but the trust value is calculated by the system, and the trust is for the recommendation agents, not for each user s(Bedi & Kaur, 2006).

3. WORK DONE SO FAR

PITTCULT is designed to recommend cultural events. Cultural events constitute a highly taste-dependent domain and group activity. When we go to a music concert, for instance, we ask our friends who have good taste about the music and may thengo to the concert together. Hence, the trustworthiness of a recommender is a critical factor in judging the quality of recommendation in PITTCULT. In the system, trust values can be measured in two ways. First, users can specify their friends' trust level explicitly. Friends are basically trusted people because they know each other well. Secondly, PITTCULT utilizes not only trust ratings among friends but also the evaluation of trust among non-friend users. The system exposes other users' profiles in several ways. Each profile describes brief demographics, her scheduled events and event reviews. Based on the information, users can assess how a user is matched with their own interests. In both evaluations, trust ratings are classified by nine event-kinds: dance, exhibitions, film arts, lectures, literary programs, concerts, musicals, plays and tours (refer to Figure 2). The trust rating has four levels: 'trust strongly,' 'trust,' 'don't know,' and 'block.' By adding a trust rating for other non-friend users, users can expand their online network in a trustable manner. In the aforementioned Sinha & Swearingen study, even the friends' recommendations are useful, better and more trustworthy than system recommendations, but the overall evaluation of recommendation is better for the system than for friends. It is due to serendipity (Sinha & Swearingen, 2001). Hence, my system tries to use the wisdom of crowds in a more secure way.

Figure 1. Front Page of PITTCULT

Figure 2. User Profile Page with Trust Ratings

Figure 3. Recommendation Page

Besides explicit evaluation of trust, PITTCULT also collects and calculates implicit preferences about other users. On a user's profile page, if other users who saw the page find an event interesting, they can save that event in their repository. The system calculates it as the implicit expression of trust in the corresponding event-kind and item. Secondly, users are able to send direct recommendations in the form of an invitation for an interesting event to friend-users. According to ratings that the recipient of the invitations defines, the system calculates how much the receiver implicitly trusts the sender. This idea originated from the

concept of 'active recommendation' by Maltz and Ehrlich (1995). In that study, people preferred to rely on an 'information mediator' for useful information, rather than searching for themselves. An information mediator is a person who has knowledge about information and is active about introducing information to those people within their acquaintance. Anyone can be an information mediator, in PITTCULT; in the future, a reputation-related study will be performed (outlined in Section 4). Another way to imply trust ratings is the other users' assessment for reviews. If a user participated in an event, she is able to create her review with a rating. Then other users vote on the review, to indicate whether it was helpful or not. If a review receives a vote from a user as being helpful, the system assumes that the user trusts the reviewer for the corresponding item.

A relevant study insisted that an item-based trust rating is more accurate than a profile-level trust rating (O'Donovan & Smyth, 2005; 2006). In explicit rating, PITTCULT focuses on the profile-level trust; in implicit rating, it focuses on the item-level trust. This is because users are hardly capable of evaluating others' taste about every item, and implicit rating can reduce human intervention.

Once a user's profile for defining trust ratings is generated, implicitly or explicitly, PITTCULT makes recommendations. Based on the accumulated trustee's ratings, a recommendation is generated, using the similarity and prediction calculation used in CF technology. In addition, every time a trustee saves an event as 'interesting' with her rating, a recommendation is made by the trustee's rating with weight calculation of the trust ratings (Figure 3). Because the recommendation is based on users' trust values, there is no chance that an ad-hoc user can copy others' profiles. In addition, CF based on trust reduces the cold-start problem because it can generate a recommendation, even with only one rating by a single user (Massa & Avesani, 2007). In addition, PITTCULT has more detailed ratings by event kinds than other trust-based recommenders. With a finer level of trust ratings, the PITTCULT system can match the eccentric preferences of users.

3.1 User Study
A user study with eight users was conducted to examine the usability of the system and user requirements for the cultural event domain. Seven of those users were graduate students, and one user was a school employee who organizes school events. Before they responded to the questionnaire, the system's main functions were briefly explained to the participants. The questionnaire consisted of two parts: (1) the usability of the current system and (2) requirements for future implementation.

Deploying five Likert scales (5 = very good, 1 = very bad), overall evaluations of the system were positive, with respondents indicating that the current interface for displaying events was good ($M = 4.88$). They mostly liked the function for saving interesting events to their repository ($M = 4.88$). Direct and indirect recommendations ($M = 4.75$) were also adjudged to be good. All other evaluations, although scoring relatively less well, still exceeded a rating of 'good' ($M = 4.41$). In free-text evaluation, several participants mentioned that assessing their friends' tastes and, especially, negative evaluation was interesting; they liked the idea. In previous research, information about distrust was also an important judgment concerning whether the user was trustworthy and influence onto the web of trust, thereafter (Guha, et al, 2004). For future implementation, users mostly wanted to have event reviews ($M = 4.75$). Therefore, during the mean time between the time of the user study and writing, the event review was implemented. They wanted to have community support such as interest groups ($M = 4.38$), as well as receiving recommendations and event reminders by mail ($M = 4.38$). In addition, some users wanted the ability to add their own event information, and to search by keyword.

4. PLANNED STUDY AND CONCLUSIONS
As for future direction, content-based recommendations will be implemented to minimize the cold-start problem. Context-based recommendation will be studied, as well: the system will ask users to define occasions, time or target audiences for a certain event. Another possible topic concerns how the reputation of a user is propagated. In the near future, users will be able to add their own interesting events to the system. By seeing the popularity of posted events or users' event reviews, some users can be judged as being more knowledgeable than others. Using the web-of-trust approach, it will be possible to study how the reputations of users spread to other users. In addition, personal-level or group-level trust recommendation will be studied. Yet another potential topic concerns recommendation using entered information from users. Search keywords, tags or clicked facets could be defined as their detailed expression of preference. How the accumulated user profile affects recommendation will be the focus of the research question. Recommendations will be made according to the definition. Lastly, integration with existing social web-based system like Facebook will be explored.

This paper discussed the problems of existing collaborative filtering systems, such as data sparsity, ad-hoc users with malicious intentions, and eccentric user preferences. To solve these problems, a cultural event recommender was described, utilizing explicit and implicit trust ratings. In the user study, the overall evaluation of the current system was positive. Several research ideas were also introduced, in anticipation of future studies.

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