

Power To The People: Exploring Neighbourhood Formations In Social Recommender Systems*

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ABSTRACT

The explosive growth of online social networks in recent times has presented a powerful source of information to be utilised in personalised recommendations. Unsurprisingly there has already been a large body of work completed in the recommender system field to incorporate this social information into the recommendation process. In this paper we examine the practice of leveraging a user's social graph in order to generate recommendations. Using various neighbourhood selection strategies, we examine the user satisfaction and the level of perceived trust in the recommendations received.

Categories and Subject Descriptors

H.3.3 [Information Search and Retrieval]: Information Filtering; J.4 [Computer Applications]: Social and Behavioral Sciences

General Terms

Experimentation, Human Factors

Keywords

Recommender System, Social Network, Collaborative Filtering, Facebook

1. INTRODUCTION

When recommender systems were first proposed, very few people would have imagined the connected world in which we live today. Work on collaborative filtering based recommender systems focussed on algorithmic designs to help build neighbourhoods of similar users to inform the recommendation process. At the time the relationships between the users that make up these neighbourhoods was not easily available. However, with the explosion of social content

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systems whereby users are connected to each other through a social graph means that these relationships cannot be ignored. In this paper, we look at how users go about manually forming neighbourhoods and how these neighbourhoods inform recommendations when compared to other neighbourhood selection strategies. We examine how a user's interpretation of the effectiveness of a neighbourhood is affected when the neighbourhood is revealed to them and also the relationship between the user's satisfaction rating of recommendations compared to that user's perceived trust in the source of those recommendations.

In the next section we will introduce some related work around the area of neighbourhood formations and social graphs. In Section 3, we will introduce our neighbourhood selection strategies and in Section 4 we evaluate the performance of our neighbourhood strategies through a live-user study of Facebook users. We also analyse the user's satisfaction and perceived trust in the received recommendations.

2. BACKGROUND

Collaborative filtering has proved to be a very powerful approach to finding items of interest to users in large scale systems. In collaborative filtering a key step of the recommendation process is the neighbourhood formation stage. The neighbourhood formation stage involves the clustering of similar users together to find possible items which can be recommended to the target user. The neighbourhood formation stage has had a large body of research completed which either revolves around the process of identifying possible users for neighbourhood formation by using different similarity metrics or different ways in which these neighbourhoods are formed such as thresholding or nearest neighbour [2, 11]. However it is not always the case that these approaches make sense when using a recommender system despite their accurate performances in offline evaluations. For instance, previous work has shown that the actual influence neighbours have on the recommendation technique is actually quite minor when considering accuracy during offline evaluations [10]. More recently we've seen services with underlying social networks become more prominent in peoples day to day lives. This has allowed for more meaningful interpretation of relationships between users to be incorporated into the recommendation process. Before social graph information was easily available, a number of alternative ways to forming user neighbourhoods were proposed. One technique used demographic information about the users when trying to generate recommendations [9]. The authors proposed using demographic information to find regularity amongst the

types of users that liked particular items. Overall they found no significant performance increase, but did find it beneficial when used alongside a content based approach. Trust has also been a measure that researchers have used in the recommendation process [6]. Massa found an overall reduction in the rate of incorrect predictions through the use of trust. Additionally work which involved explanations of neighbourhood formations has also been carried out. In one piece of work the authors provided a visual tool to allow a target user to choose their peers when finding recommendations [8]. However the peers in this case were not based on social graph information, therefore it does not allow users to leverage tacit knowledge of their social graph. Another approach explored explaining recommendations from social graph information [1]. The authors demonstrate an approach that uses social recommendations; a familiarity metric was proposed where by a user interacting with the system is shown a potential ‘friends’ score towards the same item they had just rated. The authors conclude that people are likely to prefer recommendations from people they do know, and as such it could prove beneficial to include social data into recommendation systems. Similar conclusions were drawn from the work carried out by Lee [4]. While work carried out in [1] focussed more on an empirical study, the Lee study performed analysis using an online social network. Lee found that users who had a bi-directional relationship had far higher levels of similarity than people with a unidirectional relationship. The authors proposed challenges related to the dissemination of possible recommendations due to the recommendations only being circulated inside their social network. Two other techniques which use social networks in the recommendation approach are proposed in [3, 5]. The authors of both papers use a form of social trust in their recommendation process. In both cases the authors do not have any explicit statement of trustworthiness. Our work specifically asks the user to inform the system how much they trust the different users as well as asking the user which of their friends are ‘experts’ in the specific recommendation objective.

3. NEIGHBOURHOOD FORMATION

In this section, we will describe the neighbourhood formation approaches that we use to inform our recommendation system. We introduce four neighbourhood selection techniques, three of these techniques consider the user’s social graph when deciding neighbourhood formation (a user’s social graph consists of direct friends only), while the final technique calculates a purely algorithmic neighbourhood as per a standard collaborative filtering system.

S1 - Social Graph: User Selected In this technique the target user is provided with a means to manually select users from their own social graph to add to their nearest neighbourhood. In this approach the choice of neighbourhood is fully controlled by the user.

S2 - Social Graph: Communication Frequency In this technique the neighbourhood is formed from a subset of the user’s social graph. However, instead of allowing the user to manually select who to add to the neighbourhood, a simple communication frequency metric is used to automatically select those users who communicate most frequently with the target user. We calculate this based on a simple count of the interactions a user has had with our target user.

S3 - Social Graph: Similarity-Based This technique is similar to *S2* except that users are selected based on the similarity to the target user. In *S3* neighbours are selected from the user’s social network only. Specifically we use the Extended Jaccard similarity metric that compares two users based on their item features (E.g Movie and TV content). The user’s neighbourhood is then composed of people from their social graph who are most similar to them based on their item features.

S4 - Global Similarity Based This final technique corresponds to the neighbourhood formation approach most commonly used in standard collaborative filtering technologies, meaning we use the wider community of system users going far beyond the user’s social graph. Specifically, the target user’s neighbourhood is formed from the k most similar users by comparing users based on their overlapping preferences. The essential point here is that it is unlikely that the target user will have any explicit social relationship with their neighbours, because neighbours are unlikely to be present in the target user’s social graph.

We wish to examine the effects each of these neighbourhood selection strategies has on recommendation satisfaction. In typical systems the neighbourhood is never revealed to the end user - this is because revealing the neighbourhood may not make sense to the user as it most likely will be made up of other users whom they do not recognise or know. However, neighbourhoods formed using our strategies *S1*, *S2* and *S3* will be made up of other users known to our test user, so revealing neighbourhoods may have an impact on recommendation satisfaction. Another hypothesis is that recommendations which are generated using the preferences of close friends in a user’s social graph will benefit from an increase in perceived trust i.e. users will trust recommendations generated using information from their friends over recommendations from strangers. We test the neighbourhood selection strategies, revealing of neighbourhoods and the perceived user trust in recommendations in the following section. This is achieved by using the previously described neighbourhood formations as part of a user based collaborative filtering technique.

4. EVALUATION

To evaluate our work we carried out a live user study. In total, 82 participants took part and the trial ran over April/May 2011. The user study was implemented as a Facebook application which recommended Movie/TV content. We used Facebook because it allowed us access to a user’s social graph which would usually have an extensive list of preferences associated with it for each user. We could also extract the users friends, their profile picture and name. We felt that overall the level of familiarity a user would have with their friends on Facebook is likely to be higher than on other services.

When participants sign into our experimental application we extract the user’s Movie and TV preferences as well as their friends interests which are explicitly stated in their Facebook profiles. From our experiment, the average number of Movie and TV content preferences per profile was 30 and the average size of a user’s social graph was 189 users.

The first step of the experiment asked the user to manually select friends they felt would be a good source from which to generate recommendations. The user then proceeded to select their neighbourhood for use in the S1 neighbourhood selection strategy. The number of friends they selected set the default neighbourhood size for the other neighbourhood selection strategies (a minimum requirement for at least ten friend selections was enforced), we made this decision to reduce the potential number of experimental variables affecting our experiment. Once the neighbourhood selection was complete the application calculated recommendations using the various neighbourhood selection strategies. The preference information extracted from the Facebook profiles is unary in nature. This means that a user will either have an item associated with their user profile (through a “like” preference) or they will not. To produce recommendations, we use the technique proposed by Mild [7]. Mild’s approach uses the Extended Jaccard metric to determine user-to-user similarity, this is used because approaches that use Pearson’s correlation coefficient technique as a similarity metric will have an item rating which is used in the similarity calculations. We only use TV and Movie content when calculating similarities. The prediction algorithm is calculated by the similarity weights between the active user and each of the user’s neighbours who also have the item. Additionally we use inverse user frequency when calculating user similarities to penalise popular items. The focus of this work is not the recommendation algorithm, therefore we chose this simple technique. Recommendations lists were then produced using each of the neighbourhood selection techniques (S1-S4). The recommendation lists were generated by selecting the top recommendation from each of the neighbourhood selection strategies in a random order and interleaving them to produce a final recommendation list. This produced a list of 4 recommendations (If a recommendation item was already assigned to the list the next item on the top N list was inserted). This process was continued until a list of 20 TV/Movie recommendations were complete.

Before displaying the final recommendation list, each participant was randomly assigned to one of two setups. In the first setup the recommendation layout consisted purely of the recommendation and the rating scale. In the second setup the recommendation layout was the same except that the neighbourhood which was utilised in the formation of that recommendation was revealed to the participant. In our evaluation, 43 participants received the default recommendation list (without neighbourhoods shown) where as 39 participants received the recommendation lists with the neighbourhoods revealed.

The recommendations were then displayed to the participant and they were asked to rate each of their 20 TV/Movie items on a typical 5 star rating scale. The final part of the experiment asked each participant to rate each of the neighbourhood selection strategies in terms of how much they would trust recommendations generated using those strategies. The user was shown pictures and names of the neighbours from each neighbourhood. The following statements were made about each neighbourhood formation when informing the user from where they came; **S1**: “Below is a list of your friends that you selected to generate a list of recommended content.” **S2**: “Below is a list of your friends who have left the highest number of messages on your Facebook wall.” **S3**: “Below is a list of your friends that have the most

Table 1: Average Strategy Overlapping Size And Average Similarity

Strategy Type	S1	S2	S3	S4	Avg Sim
S1	N/A	2.21	0.96	0.4	0.0433
S2	2.21	N/A	0.85	0.375	0.0712
S3	0.96	0.85	N/A	2.78	0.211
S4	0.4	0.375	2.78	N/A	0.296

similar interests to you based on their Facebook profiles, and are also your friends.” **S4**: “Below is a list of users that the computer feels are the most similar to you, this is based on all the users that have taken part in this game.”

5. RESULTS

Our experimental results show that on average users would select 14 neighbours, the most popular selection size was 11 and the maximum neighbourhood size was 32. We found that on average users spent three minutes and thirty seven seconds selecting their potential neighbours. Table 1 shows the average size of overlapping users between the different neighbourhood formations. We can see that S3 and S4 which are both algorithmically generated have the highest overlapping size (2.78 users), the only real difference between S3 and S4 is the underlying user base from which neighbours were selected. Whats more interesting is that S1 and S2 have a similar overlapping size (2.21 users), but obviously S1 is not algorithmically generated. This could mean that users who are seen as good sources of information are also more likely to be users who communicate with each other, and that it is less likely a trusted user will have a similar preference profile. Next, we ask the following questions; Did the time investment in manually selecting a neighbourhood produce better quality recommendations? Also, how did the ratings of recommendations differ across the various neighbourhood selection strategies? The results are shown in Figure 1. The bars represent the average rating participants gave to recommendations across the different neighbourhood formations when the neighbourhood was hidden and revealed to the user. We can see that the average rating given to recommendations does not vary significantly across the neighbourhood formation strategies. This holds true for both recommendation list layouts, with participants rating recommendations approximately 3 for the layout without neighbourhoods shown, up to an average rating of approximately 3.5 for the layout with the neighbourhoods revealed. The extra time given over to manual neighbourhood selection does not produce much difference in the actual ratings participants give to recommendations no matter what neighbourhood formation strategy is used. However, the revealing of the neighbourhood to the participant does have an impact. When neighbourhoods were revealed participants rated these recommendations higher than when they had no knowledge of the neighbourhood. Surprisingly, even when participants could see the neighbourhoods, and more importantly, the neighbourhood they manually selected themselves, they still rated recommendations from all neighbourhood strategies in a similar manner.

Participants may not be as good at selecting useful friends for neighbourhoods as they think they are. For instance when we look at the average similarity in Table 1 we can see that the S3 strategy is substantially higher than S1. In ef-

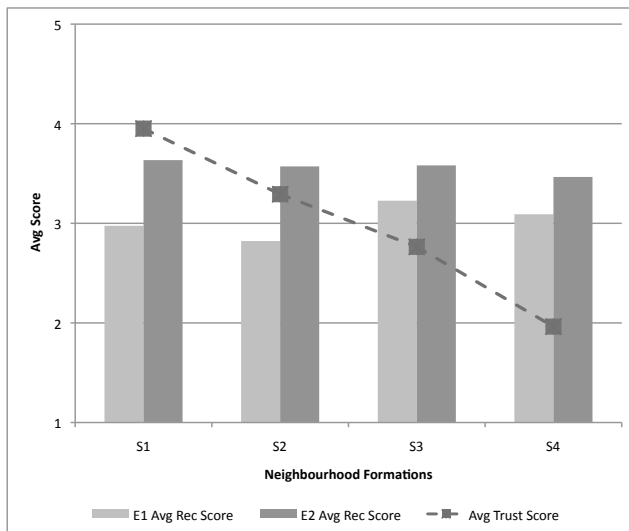


Figure 1: Average participant rating scores with the overall perceived trust overlay.

fect, revealing the neighbourhoods used in the generation of recommendations does have an impact on how users rate recommendations however the formation and makeup of these neighbourhoods has little effect.

Regarding trust, our basic experimental hypothesis is that users will place more trust in recommendations which originate from neighbourhoods that they have a hand in selecting or that are influenced directly by their own social graph. If this hypothesis holds then we expect to see a significant difference in the average trust scores assigned to S1 (user defined neighbourhood) compared to S4 (purely algorithmic neighbourhood). It is not clear, however, the extent to which users will trust S2 and S3 over S4, if at all.

The average trust scores for each of the neighbourhood strategies is shown as the line in Figure 1. We found that throughout the study, users gave high levels of perceived trustworthiness to neighbourhoods which were derived from their own social interactions as opposed to neighbourhoods which were algorithmically generated. The trust ratings remained the same for the groups of users who had the neighbourhoods revealed and those that did not. What is quite interesting is that S3 gets a much lower perceived trust score, despite the recommendations coming from the user's social graph. The user would trust their own pre-selected neighbours to a high regard, and due to familiarity of consistent communication will much prefer the neighbours from S2 over the neighbours from S3. As expected, users did not give high trust scores to S4.

6. CONCLUSION

In this paper we presented a number of different neighbourhood formation strategies and evaluated them in a live user study. The actual neighbourhood selection strategy has little impact on the quality of recommendations. However, end users will trust recommendations more closely if they think that their social ties were involved in the recommendation process. There is not much difference in the actual ratings users give recommendations no matter what neighbourhood selection strategy is used even though the

user perception is that they would trust recommendations powered by their selected neighbourhood/close friends more than they would from the wider community. There are improvements in recommendation ratings when the neighbourhoods are shown, however the trust perceptions remain the same. It is interesting to note that S1 and S2 gain the biggest performance increase when revealing where recommendations come from. Our future work will involve exploration of the social ties when generating recommendations for users, as well as effective ways explaining recommendations from a social point of view.

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