ISSN 2229-5518

Group Movie Recommendations via Content Based Feature Preferences

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Abstract—Most research into Recommender systems has focused primarily on delivering recommendations for individuals. However generating recommendations for a group of individuals is becoming increasingly important and recently there have been several forays into the area of group recommender systems. Many of these approaches are based on some adaptation of the basic collaborative filtering strategy to guess the liking of a group. However content information when available may complement the CF techniques in delivering better quality results. This paper, therefore proposes an approach, specifically for movie recommendations, where group interests on various content based features such as genres, actors etc are modeled. Such group content-based feature interest profiles are utilized to match the set of individuals who may have a potential similarity with interests of the group and hence whose ratings can be used for group recommendations. Experimental results comparing to proposed approach with a traditional approach based only on CF reveal that accounting for content based information in the group recommendation process, significantly enhances the quality of recommendations.

Index Terms— Collaborative Filtering, Content based features, Group Recommender Systems , , Preference Aggregation, Recommender Systems.

1 Introduction

WITH the proliferation of online communities facilitated by social networking websites and the like the various scenarios requiring recommendations for a group as a whole has also increased. Though the initial focus of research in the area of recommender systems (RS) was on recommendations for a single user, several group recommendation approaches have been explored in the recent years fuelled by the need of communities of users especially in domains such as books, music, movies etc. Designing group recommender systems involves considering issues unique to them such as: group preference elicitation, designing group RS interface, explanation of recommendations and helping group members to settle on a decision[1].

Approaches offering group recommendations base them on some aggregation mechanism for modeling the interest of the group as a whole. Most approaches however use only the preferences expressed by a user following the Collaborative Filtering approach. However web recommender systems offer millions of items and the user profile and consequently the group profile is very large. The abundance of the number of rate-able items also implies that the profiles are sprase and this may affect the quality of recommendations. This paper proposes an approach to construct a compact group model by leveraging on the user preference and content based information of various items. Such an approach has the advantage on reducing the group profile size considerably thus enhancing the scalability. Such an approach also offers a solution to the sparsity challenge of RS since it gives rise to a denser profile representation thus improving the number of recommendations possible

This paper proposes an approach to group recommender systems by modeling group interest on content based features for computation of similarity between a group and individuals. Such a profile is computed by accounting for individual user interest for various content features and aggregating the user genre preference into a group genre preference. However, a simple strategy of aggregating the genre interest may not suffice since it would not account for variation of interests in the same genre. Thus this paper models group genre interest taking into account the variation of user interests within a group.

The paper is organized as follows. Section 2 reviews related work in literature, Section 3 presents the proposed approach. Experimental results are presented in Section 4 whereas Section 5 presents the conclusions and directions for future work.

2 Literature Review

Collaborative Filtering(CF) is a method of recommendation which is based on the word-of-the-mouth recommendations prevalent in our day to day lives. The CF process relies on identifying a group of users who have similar tastes as the active user (the user for whom the recommendations need to be made). The computation of similarity is usually based on PCC [11] and/or Vector Similarity [10]. The preferences of such similar users are then aggregated to offer suggestions to the active user. Content based techniques on the other hand provide recommendations by matching item profiles with the profiles of items that the user has liked in the past. CF score over their content based counterparts due to their ability to offer out-of-the-box recommendations [12]. However the sparsity in the user expressed preferences weaken the recommendations in CF since for several user pairs its very difficult to estimate the user similarity due to dearth of common preferences. In such situations user profiles may be modeled on their preferences on content based features rather than items themselves. Since the number of such features is generally much smaller than the number of items the user-profile is more compact thus resulting in quicker estimation of similarity. Moreover the content based preferences are more general than item-based ones and thus expected to be denser. This improves the quality and coverage of recommendations.[12]

Group recommender systems offer recommendations to a group of users rather than individuals. The groups may vary in their constitution- from a close-knit group of friends seeking quality movie-watching or book reading activities to a set of people in a gym wishing to hear good music while exercising. One of the earliest group recommender system was Polylens [13] which reported experiments on a relatively small number of groups and presented an analysis of several novel issues to be considered while designing group recommender systems. Approaches to group recommendations have been demonstrated on a wide variety of applications. Ardissono et al. [2] propose a group recommendation approach, INTRIGUE for recommending tourist information to heterogeneous groups by taking into account the conflicts within the groups. Negative preference group profiling as a means to filter out undesirable items for a group is used to implement Adaptive Radio [3], a system that selects music to play in a shared environment. Rather than attempting to play the songs that users *want* to hear, the system avoids playing songs that they do *not* want to hear. A critiquing based group recommender system [4] CATS, a Collaborative Advisory Travel System, allows a group of users to simultaneously collaborate on choosing a skiing holiday. Another application of group recommender system for situations involving groups of people who may not be familiar to each other is explored in Pocket Resturant Finder which suggests restaurants for a group of people that would best meet their needs Such a system is particularly useful in contexts in which people don't know each other very well, and in locations where people don't know the restaurants of the area very well, such as a gathering of researchers at a conference or workshop [5]. Personality aware group recommender system attempts to analyze the personality composition of group members and to leverage on collaborative filtering to offer recommendations.[6]. A similar approach is adopted by [9] which model individual behaviors affecting group suggestions. In addition trust information among users is also used to improve the recommendations Aggregation of group preferences is an important aspect affecting the quality of recommendations. Baskin & Krishnamurthi present a group preference aggregation mechanism aggregates scores by using users' relative preferences to search for a Kemeny-optimal ordering of items, and then uses this ordering to identify good and bad items, as well as those that are the subject of reviewer conflict[7]. In addition to the challenge of group preference elicitation and aggregation evaluation of the effectiveness of group recommendation approaches also pose a challenge. Baltrunas et al. [8] present an approach of estimating the effectiveness of individual and group recommendation lists using normalized discounted cumulative gain. Though there has been several methods for preference aggregation [7,8] which have been explored and some methods which leverage on social interaction information[8], content based profiling of groups has not been investigated in detail. This is the approach being taken in this paper and the proposed technique is outlined in the next section.

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3 Proposed Approach – Content Feature Based Group Profiling (CBGP)

Traditional collaborative filtering systems leverage on user profiles which consist of the set of ratings that the user confers on various items on offer. However most user profiles are sparse since any user experiences only a small subset of items. CF systems rely on user similarity computation which is performed by comparing the set of items which are rated by a pair of users. A sparse user profile thus may imply an insignificant overlap in the profiles on no overlap at all. This in turn implies that the similarity computation may be unreliable or for some pairs it would not be possible to estimate it at all thus affecting the quality and coverage of recommendations. A CF based approach to group recommender system would also suffer from the same drawbacks if the group profiles are expressed in terms of the group interest on various items.

The approach taken in this paper models the group interest on a set of content based features. In the movie domain the contents each movie may be described by the actor, director, genres the movie belongs to, etc. The idea is to build a group profile consisting of the preferences of a group for each feature of the movie. Since the set of such content based features would be limited the group profile would be much more compact than the profiles consisting of preferences of a group for various items. Moreover since the features are more general than specific items, the profiles are expected to be denser. For example, the set of common movies that the user/group have not watched may be large, but if the user/group has watched even a single movie of the genre 'Action' then amount of preference for the genre 'Action' for the user/group may be derived.

Let U be the set of n users where U= {u1, u2, …, un} and I be the set of m items where I = { i1, i2, …, im}. If the number of genres is k then G represents the genre content of each movie such that

$$G_{xy} = \begin{cases} 1, & \text{if movie } i_x \text{ contains the genre } y \\ 0, & \text{if movie } i_x \text{ does not contains the genre } y \end{cases} \quad (1)$$

We denote the ratings matrix by R where R is an nxm matrix and the ratings are in the range [1,r]. The ratings conferred by the different users on various items is subjective, i.e. some users may be strict in their rating while others may be lenient. To build the group profile the ratings matrix R is, therefore, transformed to a normalized ratings matrix R' s.t.

$$R'_{xy} = \frac{R_{xy} - \widehat{R}_x}{var_x} \quad (2)$$

Where $\widehat{R}_x$ is the mean rating for user x and var_x is the variance of ratings of user x. The degree of preference of a user x for the genre g may then be estimated by the formula

$$P_{xg} = \sum_{y=1}^{n} R'_{xy} \times G_{yg} \quad (3)$$

The above formula takes into consideration both the degree of liking of a movie by a particular user as well as the number of movies of the particular genre that the user has liked. Though the discussion here is related to movie genres a parallel approach may be adopted to infer user/group preferences for other content based features, such as actor, director, location etc. The user profile for user x would hence consist of the degree of preference of the user for each of the content features. Consider a group of c users GR_l= {u_{x1}, u_{x2}, …, u_{xc}}, the preference of GR_l for a content based feature *f* may then be computed as a simple average of degree of feature preference for each group member, i.e.

$$P_{GR_l,f} = \frac{\sum_{u \in GR_l} P_{uf}}{|\{u \in GR_l \mid P_{uf} \neq 0\}|} \quad (4)$$

Note the preference of a group for feature *f* is only averaged over the preferences of group members who have some degree of interest/disinterest towards the feature as reflected by the denominator. The above formula, however, doesn't take into account the fact that sometimes even if the average preference for a content feature is high, the member preference for the feature may vary from very high to very low. In such a case the reliability of computation of group feature preference is questionable. To account for this variation the group preference is scaled down by the variance in the preferences of the group. Thus the modified group preference for the feature f may be computed as ;

$$P'_{GR_l,f} = \frac{P_{GR_l,f}}{\underset{u \in GR_l}{mean}(|Puf - P_{GR_l,f}|)} \quad (5)$$

Thus a higher variation in group member preference for a feature would bring down the group preference for the item considerably. Once the group preference profile is built by using Eq. 5, the group profile can be treated as representing a pseudo-user and the normal CF algorithm may be applied to estimate the similarity of the pseudo-user with the other users in the system by comparing the content-based user profiles. The CF framework for the group recommendation is as given below.

Step 1: Convert the rating matrix R to normalized rating matrix R' to remove subjectivity.

Step 2: Compute the user- content feature preference degree by employing Eq. 3 and construct the user profile for all users

Step 3: Compute the group – feature preference degree by employing Eq. 5 and construct the group profile .

Step4: Using vector similarity [10] find the similarity between the group profile computed in Step 3 with all user profiles computed in Step 2.

Step5: Identify the set of neighbors, i.e. the set of users who are most similar to the group profile and use Resnick's formula[12] for prediction of rating for each item not present in the group profile.

4 Experimental Evaluation

To establish the effectiveness of the proposed group recommender framework, it is compared against traditional group recommendation strategy. Traditionally ratings of items by individual users is elicited and the final score for each item by the group is computed as a function of individual member scores. We compare the proposed approach against the policy of assigning average ratings of group members for each item and refer to this scheme as Average Rating based Group profile (ARGP).

Since there is no publicly available dataset consisting of group ratings of items, experiments are performed on the MovieLens dataset, which contains individual ratings by different users on various items, by simulating group via generating them in a manner described shortly. MovieLens [13] is a publicly available and popular movie ratings dataset which consists of 100,000 ratings provided by 943 users on 1682 movies. The ratings scale is in the range 1–5 with 1-''bad" to 5-''excellent". The ratings are discrete. Each user in the dataset has rated at least 20 movies. Since we want to test the performance for various kinds of groups- close-knit ones and ad-hoc groups, we generate these in different ways. To generate close-knit groups, the ratings similarity between different user pairs is computed using cosine similarity [10]. Once this is done, groups are formed by choosing any random user to be the seed member, the next member in the group to be included is the one with maximum similarity with the current group member. The subsequent users are selected for inclusion in such a way that the member has maximum sum of similarities with the members already included in the group. The group sizes are also chosen at random and may be restricted to be within a particular range. Generating ad-hoc groups is simple. It is done by simply adding a random set of users to each group where even the size of the group is chosen at random. The groups are formed in such a way that approximately half the user set is involved in close-knit groups and the other half in ad-hoc groups.

Evaluating group recommendation approaches poses a challenge since the group ratings for various items are unavailable. We, hence, follow the evaluation methodology outlined in [8] which advocates the evaluation of the group recommendations against individual preferences of group members. Unlike [8] however the task in the proposed approach is to offer a group ratings prediction and thus we use the Mean Absolute Error to guage the accuracy of the recommendation approaches, where MAE for the *'l'th* group for the 'y' th item is defined as

$$MAE(GR_l, y) = \frac{\sum_{x \in GR_l} |pr_{ly} - R_{xy}|}{|GR_l|} \quad (6)$$

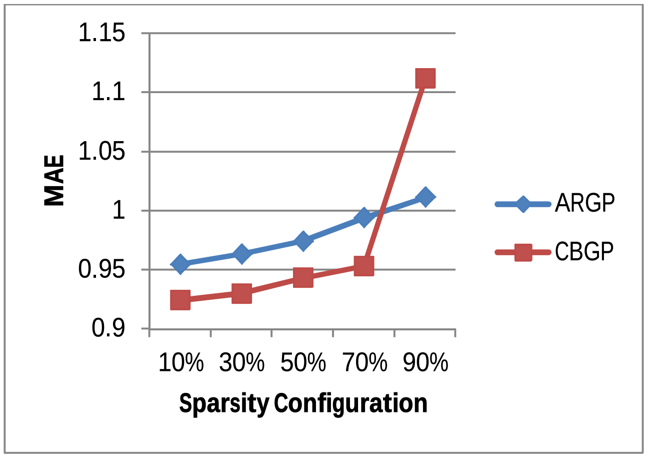

Fig. 1. Comparison of MAE for sparsity 10%-90% for close-knit groups

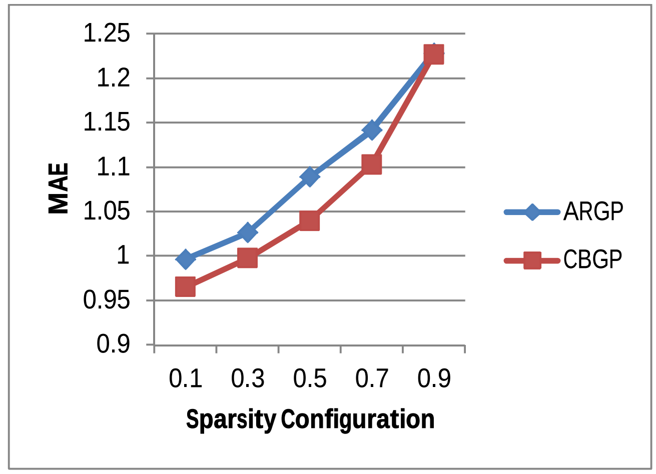

Fig. 2. Comparison of MAE for sparsity 10%-90% for ad-hoc groups

Where pr_{ly} is the predicted rating for item y for the group l. The average error over all items is then computed as the final error.

We evaluate the proposed approach under different sparsity settings. The ratings data is divided into training and test datasets. To obtain various levels of sparsity 10%, 30%,50%, 70%, and 90% of the ratings is retained as training data and the rest are retained for testing. Fig. 1 and 2., compare the performance of the proposed approaches with ARGP. While Fig .1 shows the results for close-knit groups, Fig. 2 shows the results for ad-hoc groups. It is clear from Fig. 1 that under reasonably dense ratings data, the proposed approach outperforms the ARGP in terms of recommendation accuracy. However when the data becomes very sparse the performance of ARGP is better. This may be since the sparsity deters building a reliable feature preference model for the group. Fig. 2 again reiterates the superior performance of the proposed approach against ARGP for ad-hoc groups. Again it is to be noted that as sparsity increases the improvement in performance of the proposed technique as compared to ARGP diminishes. When the accuracy of close-knit vs. ad-hoc groups are compared through any method, the accuracy obtained for the close-knit group is more which is as per our intuition.

5 Conclusions

A major impediment to effective recommendations in a group recommender systems is the large number of items on offer and the sparsity in ratings data. In addition effective group preference aggregation strategy plays a major role in the quality of recommendations offered. To this end, this paper proposes modeling the preferences of a group by building a group profile based on the content features important to group members. This not only helps in reducing the size of the group profiles, but also has the effect of making the profiles denser thus improving both quality and quantity of recommendations. Experimental results comparing the proposed technique with group recommendation strategy based on CF alone, establishes the effectiveness of the proposed approach under reasonably dense ratings data. However at very high sparsity the proposed approach perform no better or even worse(in case of groups which are close-knit). This may be attributed to the lack of enough preference data to model the content level preferences effectively. The future plan is to enhance the group profiles and make it richer by taking into account temporal information too. Application of trust and distrust [9][11] supplementing the ratings data may enhance the quality of recommendations.

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