

GROUP RECOMMENDATIONS: SURVEY AND PERSPECTIVES

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Abstract. The popularity of group recommender systems has increased in the last years. Ever more social activity is generated by users over the web and thus not only domains such as TV, music or holiday resorts are used and researched for group recommendations, but also collaborative learning support, digital libraries and other domains seem to be promising for group recommendations. Moreover, principles of group recommenders can be used to overcome some single-user recommendation shortcomings, such as cold start problem. Numerous group recommenders have been proposed; they differ in application domains (which in the group recommender context are specific in various group characteristics). Today’s group recommenders do not include and use the power of social aspects (a group structure, social status etc.), which can be extracted and derived from the group. We provide a survey of group recommendation principles for the Web domain and discuss trends and perspectives for further research.

Keywords: Group recommendation, satisfaction modeling, social aspects, state-of-the-art

1 INTRODUCTION

Nowadays we are experiencing stunning changes. The phenomenon from the last 50 years has changed into “on-line revolution”, which has a great impact on every human life routines. These changes result in huge information explosion. The

amount of information over the web is increasing dramatically, which brings several serious problems in relation to information accessibility.

Web and information technologies should make our everyday life easier and more comfortable, or in other words, they should relieve us from routine actions and strengthen social interactions. Recommender systems try to help us in everyday life by reducing the information overload problem. Standard recommendation approaches used in various domains focus mostly on a single-user. However, there are plenty of situations when the user interacts socially, with or without restraint. In some situation we want to interact socially (e.g. dinner with friends), but in other situations we are forced to participate in groups (e.g. mass transit). We are also a part of much larger social groups, which form our behavior and are adjusting norms [8]. It is clear that in the context of the group, recommendation obtains new dimensions – the single-user preferences and needs are important, as well as the others preferences and thus the group’s needs to become more visible.

For such scenarios, the group recommendation is the optimal solution. The user is considered as a group member and actually generated recommendations should consider other group’s members. Nowadays there is only little attention paid to consider social aspects of individuals and the group as a unit. Incorporating users’ social links based on social networks and users’ personalities and other contexts seems to be interesting research topic these days, while it can bring reality to the recommendation process and to the group modeling. From the view of group recommendation and social background, the social interaction, groupthink or the distance of opinions are interesting attributes [43, 48] to research, while they can be partially extracted directly from the social networks structure [51].

The group recommendation is currently used in several domains such as TV, movie, music, or holidays. The increase of social networking and mobile devices reveals new domains where the group recommenders can be applied as collaborative cooperation support, game scenario recommendation for group of users, e-learning, articles recommendation or graphical interface personalization. Depending on domain, the recommendation can be immediately experienced by the group members on one place (music in the gym), or only some suggestions can be recommended (holiday trips). Moreover, group members do not have to experience the recommended items at the same place and time (online educational system). Introducing virtual instead of real groups dramatically increases the amount of domains where group recommenders or group principles can be used and the advantage of such approach can be profitable.

In this paper we present the state of the art of group recommendation approaches. The paper is organized as follows. Section 2 describes approaches for the user and the group modeling. The process of generating group recommendation based on various approaches is described in Section 3. In Section 4 we present overview of group recommender systems. Social aspects that can be used in the group modeling and recommendation are described in Section 5. Proposed areas for further research are presented in Section 6.

2 USER AND GROUP MODELING FOR RECOMMENDATION TASK

There is a strong connection between a user and a group model. Broadly speaking, the user or group model represents users' preferences (depending on the domain, e.g. knowledge level in an educational system). While the user model is focused on the single-user preferences [18], the group model reflects the whole group preferences. Various group recommendation techniques consider preferences of the single-user, thus the group model is often only a union of group's members' models.

2.1 User and Group Models Basics

In order to provide a recommendation for a user or a group of users, preferences for the subject of the recommendation have to be known and (usually) stored. For this purpose several approaches to user modeling have been proposed, while two basic approaches are widely used in current systems [7]:

Stereotype model that maps individual user into one of the predefined groups.

Overlay user model that reflects user characteristics by adding a layer with the user related information to the domain model for each user.

The process of user or group modeling is crucial in relation to the recommendation approach success. The user modeling process can be divided into three basic steps [7]:

1. Data collection from various sources such as questionnaires, implicit or explicit feedback, social networks etc.
2. User model inference, when the system processes collected user's data into higher level such as interests and preferences.
3. Adaptation and personalization, which represents the use of the constructed model in order to provide personalized content to the user.

Similarly as the single-user model, the group model can be defined as the set of information (which describes characteristics or preferences) connected with the specific group, based on which recommendations are generated. There are several approaches how to represent and store the whole group's preferences, while in general the conflict situations have to be solved. Two approaches for group modeling have been studied and used (merging of the single-user profiles is often performed in the time of recommendation generation and thus the group model consists of single-user models): merging single-user profiles and group profile construction [55].

Modeling of the group as the one static unit (group profile construction) is not so widely used, because such an approach brings several significant shortcomings. Firstly, this approach is unsuitable when groups are changing over the time, because it is hard to extract single-user's characteristics and preferences from the group preference model in order to replace members. Equally, it is almost impossible to compute satisfaction or aggregation functions including social relationships,

social status or personality type, if we do not know preferences for every member separately. On the other hand this is the most visible feature of such approach, while it clearly brings the privacy advantage. Merging of single-user preferences or profiles is thus the most used approach in today's systems. This is suitable when the users are stored and modeled in the existing system, while minimal changes have to be implemented.

In general, the user's interest can be represented as a set of pairs (item, relevance). Let the C be the concept in the domain and V the value from interval $\langle 0, 1 \rangle$ (intensity of item's preference), then

$$M_u = \bigcup (C_u, V_u) \quad (1)$$

M_u represents user model of the user u .

Three types of preferences are usually stored in this way (Equation (1)) [45]:

Quantity of affiliation characterizes the affiliation of the content to specific semantic concept (Article – World = 0.7, Business = 0.1).

Quantity of consumption describes the degree of intensity of the satisfaction level for the specific semantic concept (Article – normalized time spent during reading/scrolling).

Quantity of interest characterizes the degree of interest for specific semantic concept (Article – interest rate).

Such a representation allows us to represent user's or group's preferences in various levels of granularity, e.g. (article ID, interest rate) or (Business, normalized time spent during reading). It is clear that the second example (topic preference) gives us more possibilities to use stored information in other domains which brings us to the "domain independency" which is usually a desired feature of a recommender system.

2.2 Acquiring Information for User and Group Models

The quality of the user or group model is highly dependable on the quality of data used for its construction. The process of obtaining suitable data for user (group) can be divided into [3]:

- acquisition of data for initializing the user or group model (new user),
- acquisition of data for maintaining and updating existing user or group model.

Usually, acquiring methods for the group models does not differ from the single-user modeling nowadays [20]. Some methods despite consider and focus on the group modeling, e.g. sharing preferences (group influence is used to obtain minimal level of satisfaction by explicit sharing of the preferences of other users within the group). There are several types of feedback, which are generally based on the way how the user expresses his/her preferences.

Implicit preferences acquisition. The standard approach, when there is no or a minimal need for a user to specify his/her preferences. This is usually done by monitoring the user's behavior over the web – time spent on web site, scrolling, eye activity etc. This can be also done in the field of the group modeling. It is clear that in general the group preference acquisition involves single-user preference acquisition.

Several systems use implicit feedback (preference acquisition) in order to maintain the user (group) model. The system recommending music played on a public area acquires information about users from their mp3 players [20]. In this way users implicitly show their preferences without any other additional activities required.

Explicit preference acquisition. The explicit feedback (preference acquisition) is based on a direct preference specification. This is usually done by various questionnaires or rating scales. In the context of the group modeling this approach is used for example in restaurant recommendation [29], where the user has to specify his/her preferences for several attributes (e.g. "Definitely want", Price, Distance). When recommending TV shows or movies, remote control is often used to obtain explicit feedback. The whole group preference can also be obtained, but inter-group discussion has to be accomplished before (the consensus problem).

Negative feedback. Some researchers argue that the negative preferences should be discussed in the recommendations rather than the positive ones. The group recommendation is designed mainly to avoid recommending items disliked by other members [20]. However, the power of negative aspects is interesting, while users tend to usually express negative feelings more likely than positive, so sometimes we can group people by their dislikes better than by their likes.

The negative feedback can be effective in situations, when a user dislikes only some of the recommended items (content), while it can significantly reduce the user's effort needed. Unfortunately, this is not so often; moreover, the opposite is usually true, i.e. the user likes only some items from the domain (e.g. World news on the news portal or music artist). In such case positive feedback is more effective. On the other hand, even when the recommender approach focuses on the positive feedback, it is useful to consider the negative feedback in order to help the user avoid unnecessary items (especially in the training phase of approach).

Sharing preferences. Presenting other users' preferences can bring a positive effect in the context of the group recommendation. This is partially the effect of the group suggestibility, user's personality and the social status. On the one hand, users can learn from others' preferences (lack of knowledge about specific item etc.), on the other hand users may "cheat" and copy some preferences from other users [20]. This is useful especially when voting strategy is applied on an active group. In these settings, the process of recommendation is generally moved to users and their ability to reach the group consensus [44, 4].

Implicit feedback acquisition is, in the context of group recommendation, more complex task as the feedback collected for the whole group. Various video and audio analyzing systems have been proposed, while they do not outperform the standard feedback acquisition based on single user approaches. This is useful when the evaluation of group recommender is performed and information of every user satisfaction is important. The example of the evaluation process is shown in Figure 1.

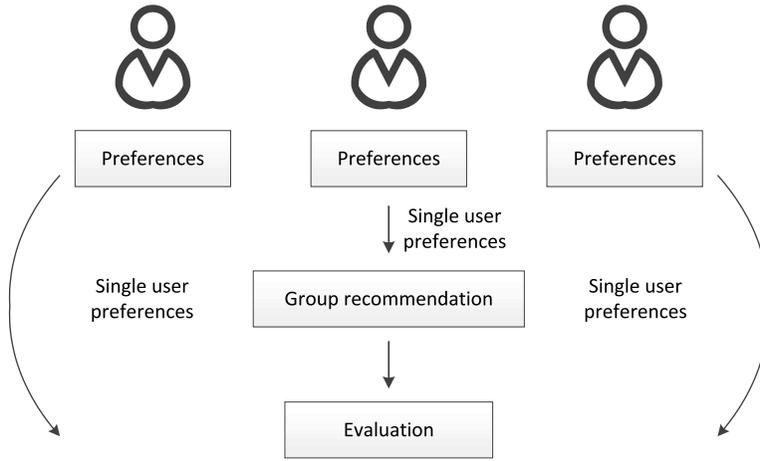


Figure 1. Example of single-user oriented evaluation. Single-user preferences are used for the recommendation generation. In the evaluation phase the recommendation accuracy is compared to every user's single preference (the single and group rating prediction difference).

3 GENERATING RECOMMENDATIONS

Generating of recommendations for a group of users highly depends on the aggregation strategy involved into the approach. From the historical point of view the group recommendations are generated based on merging of users' profiles, users' personal recommendations or simply by representing the whole group as a single-user and by applying single-user recommendations [5]. The comparison of the recommendation processes is presented in Figure 2.

In the group recommendation based on single-user recommendations instead of aggregating user preferences the personalized recommendations are aggregated. This is useful when such an approach is applied to the existing recommender system as the extension. In such a situation minimal changes to existing recommender are needed to be performed [35]. Such an approach guarantees that even the worst recommendation for single-user will be good enough, which is not true for the whole group. It is clear that single-user recommendation maximizes the satisfaction of the

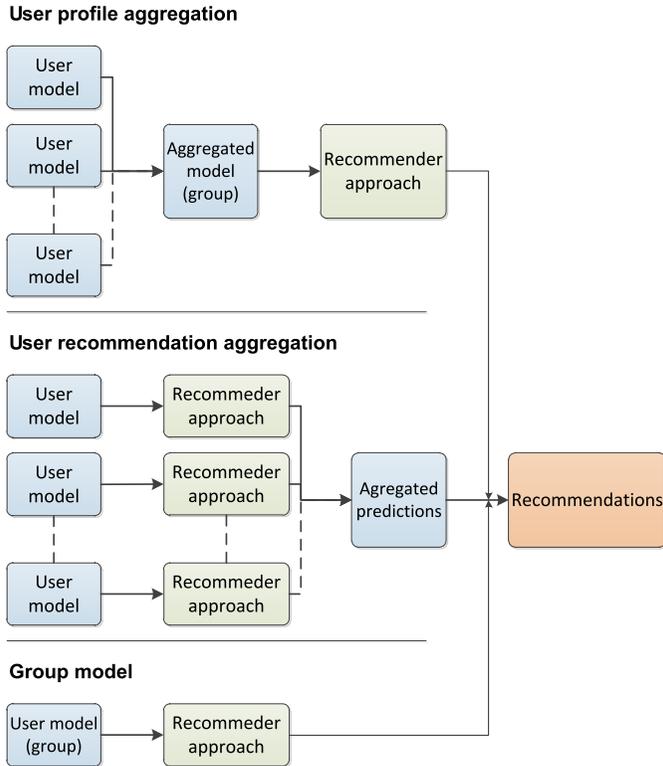


Figure 2. General approaches for the group recommendation. Single-user ratings and recommendations are aggregated or one group model is constructed and no aggregation is performed [5].

concrete user; on the other hand, when such an input is used for the group recommendation, the chance of obtaining unsatisfactory recommendation for the group is highly probable. The merging of individual's recommendations brings the worst results in general. Some improvements have been proposed as the dissatisfaction minimization [22]. The problem of optimal solution search is the reason why individual recommendation aggregation for the task of group recommendations is not used and further researched nowadays [20].

The group recommendation based on the single group profile is thus not so widely used while except the privacy it does not bring any advantage or efficiency improvement. Instead, the most used approach is the recommendation based on aggregated individual user models. On the whole, after the single-user preferences aggregation, the standard recommendation approach (collaborative or content-based recommendation) can be applied.

On the other hand, if we want to include other group characteristics, some extensions as the satisfaction function, personality types or the group suggestibility have to be considered. Ever more attention is paid to including social relations or personality types to the group recommendation, in order to model the group and its internal connections in a more realistic manner.

3.1 Aggregation Strategies

The preference aggregation is the most used and studied approach for the user/group modeling when recommending to groups nowadays. The main problem of the group recommendation task is how to adapt to the group based on single-user's preferences knowledge [42]. This is usually solved by using various aggregation strategies, thus choosing appropriate strategy seems to be a critical step when a group recommender is designed.

As the merging of recommendations or ratings is the most used approach in the group recommendation, several merging strategies have been proposed. There are numerous strategies used for specific domains such as label aggregation, recipe recommendation, personalized search and many others, where these general strategies are modified or mixed for various groups' settings [5] to obtain better results [55]. Some methods use probabilities prediction instead of simple aggregation [5] or they estimate the dynamic information gain [33].

Based on two basic principles, aggregation strategies can be divided into strategies which consider minimal satisfaction during recommendation (aggregation) and strategies where minimal satisfaction is omitted (Table 1).

Basic strategies	Minimal satisfaction
Plurality voting	Approval voting
Average strategy	Average without misery
Multiplicative strategy	Least misery
Adding strategy	Fairness strategy
Borda count	
Copeland rule	
Most pleasure	
Dictatorship	
Spearman footrule	

Table 1. Aggregation strategies with minimal satisfaction guarantee and basic strategies

Most of the aggregation strategies bring similar results (when considering several equal choices). Baltrunas compared Least misery, Borda count, Average aggregation and Spearman footrule with surprising results – the methods differ only in 3–6% from each other [2].

Voting strategies seem to be fair but it is necessary to mention that these strategies can be highly affected by the way how the voting process is presented to users

(preferences sharing). Moreover, if there is a majority of users preferring some content, then voting strategies does not consider fairness and misery. Such a behavior (fairness) can be ensured by the presentation technique (e.g., users see everyone's preferences).

In order to investigate users' behavior in the voting based group recommendation, we implemented the MovieRec web-based application available for the free usage within the social network Facebook¹. The total of 73 users within 10 days voted for 902 movies (obtained from the IMDB² database), which were divided into 11 groups and 93 events. During the experiment we observed the users' behavior based on sharing preferences (even events – preferences were visible), user's consistency and the performance of used aggregation strategy. After the event deadline, three lists of the generated recommendations were presented to every user of the group (additive, multiplicative or additive with minimal satisfaction strategy). Users rated for the best recommendation of these three.

When comparing the winning strategy depending on the group size we discovered that larger groups (based on single users preferences opinion) prefer additive strategy, while the decreasing trend can be observed when multiplicative strategy is used. Finally, the additive strategy with least misery performs the worst (Figure 3). This can be explained by the fact that least misery prefers votes from the minority, thus when only one user dislikes an item, this will not be recommended. With the group size number of such users (preferences diversity) is increasing, the quality of recommendation is decreasing. Moreover, when standard single-user feedback evaluation is used in the group recommendation, results are biased by the majority (least misery protects one user satisfaction, while others' satisfaction is decreasing). Thus the least misery can be understood as the extreme preference (negative) prevention based on the assumption that overall lower satisfaction is better than one extremely disappointed user.

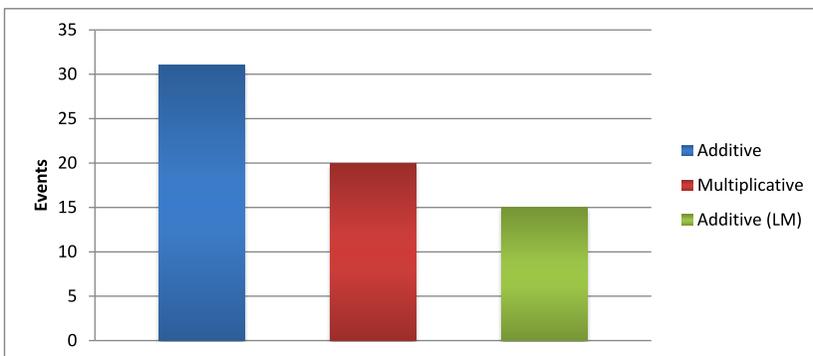


Figure 3. Absolute count of winning strategies

¹ <http://www.facebook.com>

² <http://www.imdb.com>

The obtained results clearly show that when a large group is requesting for the recommendation (voting based), the minimal satisfaction from the group point of view decreases the quality of the recommendation. This is supported by the standard deviation of obtained votes for particular strategies (Table 2). From the average score point of view, the additive strategy with least misery outperforms the multiplicative, thus the preference diversity was probably small within the group members.

Strategy	Total winning events	Standard deviation	Average vote
Additive	184	0.90	4.14
Multiplicative	147	0.83	4.08
Additive(LM)	138	0.95	4.12

Table 2. Voting strategies comparison

One of the standard methods is often chosen and enhanced by weights or by the maximal or minimal rating for specific user [17]. Similarly, as the most used representation of user's ratings are vectors, standard distance metrics such as cosine similarity, Euclidean distance are used to find the "nearest" ratings [49, 56].

Sometimes avoiding the misery and the fairness brings us to an average recommendation for the whole group. Every group member should be satisfied at some minimal level for the one recommendation session. On the other hand, when ignoring these aspects, the recommendation will be better for one user, but there will be highly unsatisfied users as well. When only single recommendation is generated instead of regularly repeating recommendations, the fairness principle is desirable.

Standard strategies used today are quite simple approaches and do not consider social environment at higher level and for all group members. Also, no group suggestibility or personality type is considered.

As users use various rating stereotypes, several issues have to be considered. User's ratings should be normalized in order to avoid extreme cases and the manipulation. Research also shows [28] that the issue of linearity should be considered. The rating in the middle of the scale (e.g. 5 and 6) should have lower importance as that in the top or down of the scale (e.g. 9 and 10). The question is how real users deal with the aggregation task. Average, Average without misery and Least misery strategy are the strategies most used by real users [27].

Several additional properties for merging strategies in group recommendation were proposed [20]:

- Treating group members differently if appropriate will allow the recommender system (merging strategy) to react on the situation such as user's birthday or when planning a trip etc. Dictatorship strategy seems to be reflecting this goal, but the preferences of other users should be considered too.
- Discouraging manipulation of recommendation process is the goal not only in group recommendations, but it can also has a significant influence on other group members.

- Ensuring comprehensibility and acceptability to allow users to understand the recommendation, which can have impact on user's next interaction and attitude to the system and recommendations.

The group cannot be understood as the set of isolated individuals with their separated content ratings, but the individuals' characteristics and thus, the group characteristics have to be considered in the aggregation strategy in order to reflect user behavior – when we add some special occasions or vertical social status to the group, users tend to use Approval voting or they prioritize some users and do not follow any of the proposed strategies. To put it simply, merging strategy should be chosen dynamically for the actual group structure and circumstances.

3.2 Satisfaction Modeling

The single-user preferences stored in individual user models do not exactly match to the final rating after experiencing in the group or after sequence of recommended items. Even when we consider the user A and we know his/her rating for some content $C1$ is 5, the rating after experience within the group will differ (Figure 4).

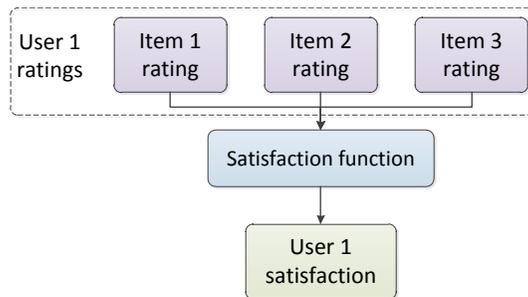


Figure 4. General satisfaction modeling process, which helps to predict real user satisfaction within the group or after sequence of recommended items

Masthoff proposed three variants of the satisfaction function which are taking into account users' ratings, impact decrease over the time or the members' mood influence. The best performer in empirical evaluation is computed as follows:

$$Sat(items + \langle i \rangle) = \frac{\delta + Sat(items) + Impact(i, \delta \times Sat(items))}{1 + \delta} \quad (2)$$

where δ represents the decrease factor over the time ($\delta = 1$ no decrease) and the mood impact ($\varepsilon = 0$ no mood influence) is defined as [28]:

$$Impact(i, s) = Impact(i) + (s - Impact(i) \times \varepsilon). \quad (3)$$

Masthoff evaluated the proposed satisfaction function not in the group recommender system domain but in the domain of learning while users deal with the lexical decision task. Users were asked to answer two questions:

- “How satisfied are you with your performance on the last task?”
- “How satisfied are you with your performance so far?”

The need for further evaluation was pointed out. As we can see both decrease factors are highly user dependent. This can be a serious problem, when recommending to large user groups. Moreover, such satisfaction function does not consider the group suggestibility.

The problem of satisfaction modeling is not dependent only on the actual group structure, but the sequence of recommended items has to be considered. Moreover, the inner-group influence is bi-directional and this process should be considered. Activation spreading considering the sequence has been proposed [24] in order to reflect these aspects of various influence sources.

3.3 Personality Type Inclusion

As most approaches do not model the real life conditions in the group recommendation, the need for personality detection is extremely important in case of the group [15, 27]. The group recommendation tries to maximize the group satisfaction function, which is in general based on the partial satisfaction function after the sequence of items, or in the respect to periodically repeating recommendations. For the purpose of personality inclusion various types have been proposed. Quijano-Sánchez used Thomas-Kilmann Conflict Mode Instrument to discover several personality modes [40]. Users are categorized by the questionnaire on which so-called “Conflict Mode Weight” is based and computed [41]. Prada proposed a model based on the Five Factor Model [39]. The basic model considers only two factors of the Five Factor Model which was extended to use all the five factors (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism).

Even when the recommendation method is designed to handle the user’s personality, problem is how to obtain the user’s type with minimal effort. Three types of personality identification (question based questionnaire, game, implicit measurement based on reaction time to visual stimuli) have been studied in [12], where the interesting results were pointed out. Broadly speaking, the standard questionnaire was the method most preferred by users, though it takes the longest time. In the case of the personality type acquisition the test faking should be also considered [6].

Thomas – Kilmann Conflict mode Instrument. The approach is designated to describe user’s behavior in conflict situations based on two dimensions: assertiveness (the extent to satisfy own concerns) and cooperativeness (the extent to satisfy others concerns). Based on these two dimensions then five personality modes were derived in total – competing, collaborating, compromising, avoiding and accommodating [52]. Thomas and Kilmann proposed 30 questions based

questionnaire. As a result we obtain a value between 0 to 100% for every mode which together represents the respondent's conflict mode.

Mayers Briggs Type Indicator (MBTI). MBTI was developed to describe people type based on C.G. Jung theory of psychological types and to make it understandable. Four pairs of cognitive functions are distinguished (Table 3). The total count of 16 possible combinations of these characteristics represents 16 personality types. There are several MBTI tests used in order to discover these characteristics. Then the score is computed for every type and characteristic (one from each pair) with the top score selected.

Extraversion	Introversion
Sensing	Intuition
Thinking	Feeling
Judgment	Perception

Table 3. Basic types distinguished by Mayers-Briggs Type Indicator

Neuroticism-Extroversion-Openness Five Factor Inventory. This model is based on the NEO-I measurement published in 1989 by Costa and McCrae. From the basic pool of 180 questions, 60 questions were selected for each of the five dimensions (12 per dimension), while the validity of several questions is still researched [32].

Unlike the previous approaches, NEO-FFI recognizes the following personality dimensions:

Neuroticism refers to the tendency to experience negative emotions such as fear, sadness or anger. People with high score are sensible to increased stress or pressure.

Extraversion can be understood as psychical energy directed outside – to the surroundings. Typical characteristics are the openness to new people, assertiveness, communicativeness or optimism.

Openness is related to sensibility, intellect and culture. Higher score obtained in this dimension ensures that a person is open to new experiences, has aesthetic feelings or is interested in new ideas.

Agreeableness refers to the ability to accommodate in social situations. Typical characteristics are altruism, positiveness to others or tenderheartedness.

Conscientiousness characterizes painstaking and self-controlled people, which can be described as people who prefer active planning, organizing of tasks, are purposeful or accurate.

Based on scores obtained in every dimension, various personality types with desirable characteristics can be discovered and used for the recommendations.

3.4 Group Suggestibility

Group can have a great impact on the individual user behavior. The first type of the impact is the emotional contagion [42]. Other users in the group which are satisfied can significantly increase the user's actual satisfaction.

This can be done inversely likewise, in other words if the group is unsatisfied, it can decrease a single user's satisfaction. Strength of this influence depends on the type of the relationship. Four basic relationships were proposed [42, 28]:

- Communal sharing (somebody you share everything with – best friend)
- Authority ranking (somebody you respect highly – boss)
- Equality matching (somebody you are on equal foot with – classmate)
- Market pricing (somebody you deal with/compete with).

It is clear that the person with Communal sharing or Authority ranking relationship will have higher influence than Equality matching or Market pricing.

In order to investigate other emotional contagion aspects we provided an experiment [23]. The results show clearly that users in our experiment were influenced more by a special occasion (birthday) than by a relationship. Also vertical social status plays an important role. It is interesting that while Masthoff pointed out that positive contagion dominates, our results show the opposite. This can be explained by cultural differences and various relationship types included in questionnaires.

The second type of impact is conformity. It was shown that users are influenced by the group most of the time [42]. A simple question was given to the group in the experiment. They were asked to decide, which line has the same orientation as in the picture presented to the group. All group members answered before the tested user and all of them picked the same wrong answer. The tested persons picked the same wrong answer in most cases in order to adapt to the group opinion.

Similarly, Brusilovsky proposed conference navigation system [13], which displays to users the most preferred presentations of whole conference – users are influenced by the group of other participants. There are two types of conformity:

- Normative influence, when user believes that he/she is true, but expresses the same opinion as the group.
- Informational influence, when user changes his/her opinion, based on the assumption that the group has to be right.

The normative influence can change the satisfaction to others by emotional contagion, while the informational influence can change user's own satisfaction.

4 GROUP RECOMMENDERS IN PRACTICE

Several group recommender systems have been proposed. In general, they vary in the domain, aggregation function or in the way of users' presence detection. Based

on this, we proposed a set of disjoint attributes of recommender characteristics, which serve for classification of existing approaches (Figure 5).

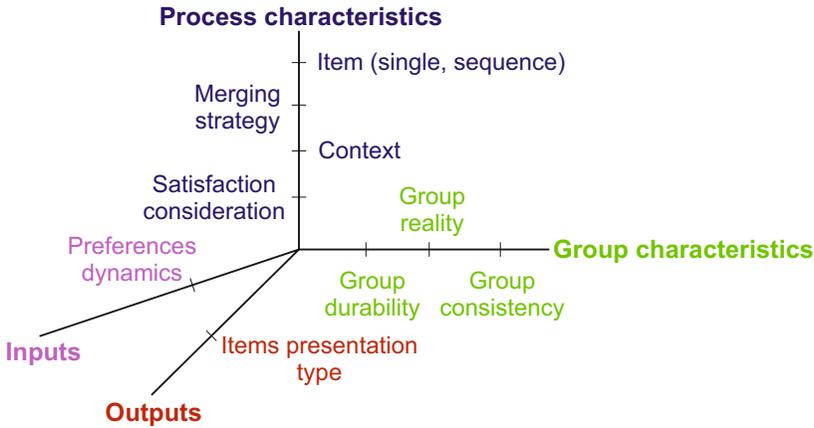


Figure 5. Various dimensions of group recommender characteristics

As we can see, there are several characteristics, which can describe every group recommender. Firstly, we recognize real and virtual groups – in some situations there is no need for the real groups, as in educational systems etc. Next, we focus on the group dynamics – whether the group is stable or temporal. This aspect has a great impact on the recommenders as the group change between or during recommendation can bring serious complications for recommendation approaches. Finally, from the recommender realization point of view, recommenders differ in the aggregation applied directly on the user profiles or in recommendations generated before the aggregation process (several aggregation strategies are discussed in Section 3.1.).

Even though the group recommendation methods and techniques have appeared only recently, many recommenders have been proposed already. Thanks to the various possibilities of group recommender construction considering the dimensions discussed above, existing recommenders present diverse approaches often dependent on the particular domain (for the list of most relevant group recommender system, see the Appendix).

Thanks to the recommendation systems history (the evolution of online sources), the group recommendation is typical for several multimedia domains. Thanks to the variety and accessibility, the TV or movie recommendation is one of the most popular domains for personalized recommendation. Group recommendation can be used everywhere, where the resource providing a content is shared by several people (TV, music) or one activity is performed by several users (museum visit, holiday). Today, new domains such as educational systems or digital libraries can benefit by incorporating group recommenders, but these domains have not been studied as exercises or learning materials recommendation. Similarly, group recommendation

can be used in order to generate predefined stereotypes for specific roles within offices, companies etc.

In most current systems the aggregation of user's preferences instead of individual recommendations (gRecs [22], Happy Movie [40]) is used. The preference aggregation brings better results in general, while various aspects of the group can be considered. Conversely, recommendation aggregation solves some privacy issues, while the single-user's preferences are not visible.

Often the presence detection of group members is missing, thus the virtual group is constructed in order to generate recommendations. The presence detection is one of the most challenging tasks in group recommenders (if implicit detection is needed) and often some kind of estimation is used (e.g. Intrigue [1]). These virtual groups are most interesting when group size increases. In such a situation group preference can be represented by some approximation. Another example of virtual groups usage is the construction of virtual groups in order to "influence" the generated recommendation (e.g. learning groups). Sometimes the combination in repeated recommendation can be used, in order to maximize group satisfaction and to fulfill second goals (e.g. task completion, education).

Today's group recommender systems differ in aggregation functions or presence detection (Table 4). Most of them ignore the social structure of the group and individual user's characteristics. Often, even minimal satisfaction is not guaranteed. Clearly, group recommendations can overcome some of the single recommender system problems (cold start or the multiple criteria problem), whereas there are scenarios when the group recommendation is used as a single one. For example, when several people share one computer, or in other words, when there is more than one user model available and we do not know which one should be used for actual recommendation (family computer etc.).

5 SOCIAL ASPECTS OF GROUP RECOMMENDATION

In order to model the group interaction and the influence of each member, we have to consider the social context of single users and groups. Social psychology focuses on the human behavior or how are people's thoughts, feelings and actions influenced or implied by other people [43]. Three areas of research are important in the context of group recommendation:

- Social perception studies how people perceive others, explain their behavior and intentions.
- Social influence is the other side of social perception. It is clear that human opinions are influenced by other people and groups.
- Social relationship confronts perception and influence in the context of relationship type (friendships, authority ranking).

Group recommender system should take an advantage from the fact that human relationships change the way how we process social information. On the one hand,

Year	Name	Domain	Group type	Group duration	Aggregation
1998	MusicFX [30]	music	real	temporary	profiles
1999	Let's Browse [25]	browsing	real	temporary	profiles
2001	PolyLens [35]	movie	real	stable	profiles
2002	FlyTrap [10]	music	virtual	temporary	profiles
2002	Pocket RestaurantFinder [29]	restaurant	real	temporary	profiles
2003	Intrigue [1]	tours	virtual	stable	profiles
2004	Travel Decision Forum [19]	tours	real	stable	profiles
2004	FIT-Family [16]	TV	virtual	temporary	profiles
2005	I-Spy [46]	search	virtual	temporary	profiles
2005	G.A.I.N [36]	news	virtual	temporary	profiles
2005	Adaptive radio [9]	music	real	temporary	profiles
2005	In-vehicle multimedia recommender [56]	music	real	stable	profiles
2005	Group modeler [21]	museum	real	stable	profiles
2006	CATS [31]	holiday	real	stable	recomm.
2006	Avatar [14]	TV	real	stable	profiles
2008	PartyVote [47]	music	real	stable	profiles
2010	GRrc_OC [22]	books	real	stable	profiles
2011	GroupRecoPF [17]	generic	real	temporary	profiles
2011	Happy Movie [40]	movie	real	stable	recomm.
2011	Addaptive correlation based RS [26]	movie	real	temporary	profiles
2012	gRecs [34]	movie	virtual	temporary	recomm.
2012	Groupfun [37]	music	real	stable	profiles
2013	HbbTV [11]	TV	real	stable	profiles

Table 4. List of most relevant group recommender systems. The stable group refers to the group which do not change during the recommendation process. Two types of multiple preferences aggregation are used – merging of user profiles and merging of single-user recommendations.

we tend to idealize our close people, but on the other hand, we are more influenced by people we like, than by people we dislike [43]. In other words all the people we interact with, affect our decisions and feelings in some ways.

Current research focuses on the role of individuality within a group. Usually the group to single member influence and intergroup relations were supported [38]. This brings us to the assumption that study of individual personalities should bring us to better intergroup process understanding. Two basic types of respect can be observed [38]. The competence-based respect is derived from vertical society

hierarchy (e.g. boss). The liking-based respect is mainly based on horizontal social interaction (e.g. experts) while the most powerful is the combination of these types.

When we consider social groups everyone identifies with, these also influence our behavior all the time. Moreover, they influence our behavior even though no group members are present. Similar effect as relationship can be observed within the group social identity. We treat group members better – more fairly and altruistically [43]. In-group members are able to persuade us more easily while emotion and attitude sharing can be observed. This is useful when the recommender system deals with homogeneous group. Here we can assume that the group will be able to forgive more in some user's preferences. Similarly, malevolence can be observed in some cultures – sadness of other member brings us satisfaction. This type of emotional contagion is present also with a type of relationship, e.g. market pricing.

So-called groupthink can be observed – the tendency to tend more to the members whose opinion is consistent to the group. To put it simply, the impact of member's opinion decreases with the distance of group consensus [43]. However, the other side of social group identification can be observed. People outside the group are also seen as competitors and they are likely to become targets of some discrimination [43]. This should be carefully considered when heterogeneous group (in the sense of social group identification) is present and the group recommendation is constructed.

Correspondingly, “black sheep effect” can be observed within the group [38]. On the one hand, anyone who is disliked, incompetent or non-normative is judged more strictly and considered as a threat to the integrity of the group. On the other hand, we have to note that in some circumstances internal criticism can be seen as productive and desirable as a tool for the group self-improvement.

The social interaction or influence is present not only when the others (people, audience, group) are present, but for example when communicating electronically. When analyzing the group members' relationships and influence, cultural aspects should be considered [48]. In addition the interaction is bi-directional, what can be understood as the process of negotiation and feedback providing. The direction of social influence (emotional contagion) can bring modeling of the affective state closer to the reality. There are several activities contributing to the social knowledge building such as social rules, shared language, past experience, goals and expectations or exchange of argumentation [48].

When making a decision and more alternatives are available, simple elimination is often used [43]. The process of discussion and voting should be visible and real-time. This is important from the view of self-preferences adaptation, while single user is adjusting his/her preferences based on other user's preferences [48].

The voting and group consensus can be understood as an opposite. When the process of voting is applied, some kind of competitive dynamics is created [8]. In some group types this results in the group decay, while someone's preferences are permanently ignored. On the other hand, when all possibilities are more or less

satisfying, voting is fast and effective approach. This is the situation when all possibilities are good enough to correspond to the group consensus [8].

Formal consensus is based on the group principles while it is not necessarily time consuming and it is suitable for large groups. It is clear that some principles have to be fulfilled in order to obtain group consensus. The trust, respect or cooperation are required from group members. Similarly, active participation and commitment to group are also desired [8]. Without these rules the consensus would be found quite hardly.

6 CONCLUSIONS AND DIRECTIONS FOR FURTHER RESEARCH

Several aggregating strategies for the group recommendation have been proposed recently. Studies have shown that users tend to prefer fairness and avoiding misery [42, 27], while sometimes minimal satisfaction can decrease overall group satisfaction. This should be considered when designing adaptive (dynamically changing) aggregation functions. Users prefer some special situations and group structure. This is notably not considered in aggregation functions nowadays. There is a need to design new aggregation strategies for various domains, also when applying to single recommendation taking into account various activity and homogeneity types of groups (e.g. it is useless to produce recommendations based on the voting strategy for a passive group).

Personality type inclusion. Consideration of the Social Theory Choice when recommending to group is a straightforward step as the group increases social interaction. It is clear that user's personality plays a critical role in the process of social interaction. People inside the group have a great impact on other users' satisfaction and feelings, both in a positive and in a negative way. Someone who is typical extrovert and is the leader of the group and he/she is not satisfied with the recommended item (TV program) can discourage others, and whole recommendation will be unsuccessful.

A typical problem when including a personality type to the recommendation is to obtain such information. Usually this is done by questionnaires; this is not an ideal approach, because of the effort needed. Some image or video-based personality tests have been proposed, but their accuracy is highly discussable.

Social aspects. Nowadays we live the age of social networks. Social networks can help us by incorporating a social structure into the group modeling process. It is clear that when the group is not socially equal, some of the members have stronger influence and some have weaker. Social networks can also help us in detecting user's personality [54]. Moreover, social networks are ideal as the group recommender systems interface. Many activities are negotiated and planned here, thus giving a tool for movie or pub recommendation seems to be a logical step.

Personality type is not only the interesting source for additional information [51]. Vertical or horizontal social status influences users in some situations. For example the negative or positive emotional contagion can be observed. Generally, in order to model real life conditions (intergroup processes) we need to include social aspects into the process of the recommendation. This can bring the recommendation improvement (group satisfaction).

Sequence recommendation and satisfaction modeling. The sequence or repeating recommendations research is one of the actual topics nowadays. The impact of the sequence is important in connection to measuring satisfaction for every user. Users are strongly influenced by actual experienced item; in other words, if the last recommended item in the sequence is a bad one, most of the users will be unsatisfied in the end of the recommendation process, even if the previous items were good ones. The recommendation in sequences allows us to introduce a level of non-fairness, when some items can be less satisfying for some users in one recommendation, but in the next they will be prioritized.

On the other hand, the sequence recommendation brings us to the problem of the satisfaction functions and to the prediction of user satisfaction after several recommended items. The satisfaction function is extremely important when the sequence recommendation is provided, for example. Designing the satisfaction function and its incorporating to the aggregation strategy seems to be a promising research area, while it can significantly increase the recommendation accuracy. When recommending a sequence it is clearly important to know which will be the effect of such a sequence for every member and in the next step for the whole group as well. Based on this knowledge, the optimal sequence might be chosen.

In general, while the aggregation function gives a group rating of specific item, the satisfaction function gives the real satisfaction of user for specific item with reference to the actual group structure after specific sequence of items.

Group to individual recommendation application. Group recommendations can be applied for single-user recommendations to overcome their standard shortcomings, such as the cold start problem or multiple criteria aggregation. It is clear that the new user will be a part of some virtual or real group in the portal. The problem is that we do not know which one. Thus applying group recommendation on known groups should ensure that such a recommendation will be good for the new user.

Group recommendation can be used as the single-user recommendation accordingly; for example a family sharing one computer, or a recommender system, which carries more micro-profiles for one user. In all of these situations, when the single recommender system cannot distinguish, which user profile should be used actually, the group recommendations approach can be applied.

In some situations, group recommendation can be applied to construct some “stereotypes” which can be applied to a single user, for example, automatic generation of user interfaces for some roles within the system (economist, manager, tester etc.), while these are dynamically adjusting to the actual needs of particular group of users. In total, when there is a group of people (virtual or real) and general role can be assigned for every user, stereotypes or some templates (recommendations) can be derived.

Application domains. As we have mentioned, several domains are suitable for the group recommendation based on their social character. Domains such as multimedia, holidays, restaurants and many others are such examples. There are also domains which have not been widely studied in connection to the group recommendation. It is interesting to investigate the group recommendation possibilities in domains such as learning or digital libraries (recommending a book to buy for a research group etc.). The group recommendation principle can be used in educational systems, where online collaborative cooperation or collaborative learning (learning within the group) can be strengthened. This can be done as standard single-user recommender system extension, while the single-user recommenders are often well established in such domains [53, 50].

Group recommendation is an interesting research area nowadays. There are several activities, which we are usually performing in a social rather than individual manner. In this situation individual recommender systems cannot be applied. Watching TV, going to the cinema, restaurants, pubs or collaborative cooperation support are only few examples. These activities are usually attended after an agreement over the group. We also distinguish a situation, when we cannot choose, e.g. music played in the gym or in the vehicle etc. There are two basic group recommendation approaches:

- aggregation of individuals preferences
- aggregation of individuals recommendation.

For the purpose of aggregating ratings, several aggregating strategies have been proposed. It seems that some of them, which consider fairness and avoiding misery perform better (real people consider these two aspects) in some domains.

Usually there is not only one item recommended when recommending. The sequence recommendation is an interesting task, especially in group recommendation. We have to consider the order of the sequence for single-user and also its influence on other group members. This is strongly connected to designing satisfaction functions, while they model the satisfaction level over the group in specific time of the sequence. As we model real life group characteristics, it is important to incorporate user’s personality. It was shown that user’s mood and personality could have a significant influence to other group member’s feeling. In other words, when a respected extrovert is unsatisfied, other members will probably share his/her feelings, even if

they were partially satisfied. Moreover, not only the personality but also the social statuses of every group member or their relationships have a great impact on the satisfaction. Some users tend to prefer the user with special occasion (birthdays) or horizontal and vertical social status is considered. The personality type can be detected based on various questionnaires or can be partially extracted from social networks, where the user's social status can also be extracted.

The important characteristics also include the group size and homogeneity. These characteristics are usually considered by the researchers, while today's methods fail when the group is large and heterogeneous.

Group recommendation can also be used for solving problems of single user's recommendation. The multiple criteria are the usual complication, where a recommended item consists of several attributes. Merging strategies can be used to overcome the multiple criteria, while only some modifications are needed (not considering fairness etc.). Many of today's recommenders suffer from the cold start problem, i.e. the state when a new user comes and wants to interact with the system and there is not enough information about his/her preferences. In this case, we can apply the group recommender (group consisting of the new user and all or several representatives of the old system users) to solve this problem. More research and evaluation is needed in order to investigate the influence of every proposed approach not only in the context of new domains, but also from the view of the reality and group modeling.

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A GROUP RECOMMENDERS OVERVIEW

Let's Browse. The system Let's Browse provides support to collaborative group browsing. This scenario is not used generally nowadays. The similarity between user profiles and actually browsed web pages is computed based on TFIDF and standard distance metrics. The system uses a linear combination of user profiles, and provides recommendations with explanations.

G.A.I.N. The main purpose of G.A.I.N is to filter news articles in public areas, e.g. kiosks. News articles are filtered based on the standard additive aggregation strategy. Two groups of users are considered – “sure set” users are present in front of the kiosk and “probabilistic set” users are probably present. Several additional interfaces as RSS or mobile device are included into the solution.

The group structure plays critical role, while it highly influences the accuracy of recommender system. Thus, the probabilistic method seems to not be an optimal solution. On the other hand, the problem of group structure detection is a difficult task, mainly in domains as multimedia recommendation to groups.

GRec_OC. The system consists of two phases – typical collaborative filtering provides set of recommendation for the group, then removing of irrelevant items for single-users is performed.

Group preferences are computed based on summation of single-user preferences. The collaborative filtering is applied on the aggregated ratings. Finally, items below satisfaction threshold for every user are removed from the recommendation.

I-Spy. The I-Spy is a collaborative search framework, which adapts search queries and re-ranks obtained results. This is done in respect to community choices. Every member of the search community is treated equally, which does not reflect the real life condition.

Intrigue. The system recommends tourist information around Torino city. Intrigue provides interactive tool for scheduling through desktop or mobile device interface.

The group is modeled as the set partitioned into homogeneous subgroups. Each subgroup consists of preference information, socio-demographic characteristics and the importance of the subgroup preference.

The aggregation function sums multiplication of weights (importance) and preferences. The system also provides an explanation of provided recommendations.

CATS. The CATS system is designed to provide assistance in skiing vacation planning. The system generates individual collaborative recommendations based on criticizing. The group preference is computed based on simple aggregation.

Recommendations are not provided for the group as a whole, but when users view some hotel details, group critiques are displayed or the hotels sequence is reordered.

Travel Decision Forum. The system aggregates explicitly obtained users’ preferences in order to create recommendations. The aggregation strategy is non-manipulable in two ways – strategy is difficult to understand by human and strategy integrates various attitudes and behavior of other members.

The system tries to help group members to arrive at final decision by including animated agents and explanations of single-users’ preferences.

Group Modeler. An interesting domain, which is not typical for the group recommendation, is the domain of museums. Group Modeler provides recommendations for museum visitors. The system constructs group model based on single-users models and combines three basic approaches – ad hoc rules, ontological reasoning (Person 1 likes all cheese, and person 2 likes the Edam cheese. Hence it is likely that person 1 will like Edam cheese.) and stereotypical reasoning (People who like coffee also like tea.).

Pocket RestaurantFinder. The system recommends restaurants to a group of people going to eat together. User preferences are obtained explicitly by rating predefined restaurant characteristics (distance, cost, cuisine). The recommendation is generated based on the summation of individual preferences (user score, feature importance).

MusicFX. The system was designed in order to allow members of a gym to influence but not to control the music played. Users joining the gym specify their preferences to specific genres (5 level scale). The actual group structure is detected by logging in by members badges.

The recommendation process is based on the rating, which is computed as the summation over the genres (square). Next the top n genres are selected to play with some probability. This probability is computed from the gap between final ratings. No group structure is considered. Moreover, only genres instead of songs are considered.

Flytrap. The music recommender Flytrap detects users presence based on their RFID identification. Next a voting agent represents each user in the room. Standard voting is performed, in order to obtain final recommendations.

The special user – “DJ” is added to each group. This user ensures several rules to be adhered to. Firstly, one artist cannot be played in a row more than one time. Secondly, genre coherence has to be maintained.

The user interface allows users to control and easily see the reason of recommendation provided, while every user agent is represented by distinct color.

In-vehicle Multimedia Recommender. In-vehicle recommender is designed to recommend music for small groups generally. Users’ presence and logging into the system is detected through mobile devices. Every user model is represented as a vector of ratings (1 rating above threshold, -1 rating below threshold, 0 rating is missing.)

For the aggregation the sum of each user’s vector is used, which satisfies the majority of the group usually. The least misery is not considered and taken into account.

PartyVote. Sprague proposed a “democratic jukebox”, which should replace the standard DJs during small house parties. The voting is performed by several users, while at least one choice from each user’s choice is guaranteed to be played.

The standard voting strategy is enhanced by including some kind of least misery (one song from every user selection is played). The remaining songs are chosen based on standard voting – the better wins. Clearly, the system has to be used in small groups or highly homogeneous groups, while in some circumstances the number of users may be greater than possible number of songs to be played.

The system tries to minimize users' interactions and is based on local users' music stores.

Adaptive radio. Adaptive radio group recommender system is based on negative explicit feedback. The system recommends songs which are streamed over the web. The user specifies his/her not preferred songs, and these are excluded from the recommendation. The system provides recommendations through client-side (single-user) application and users have to be logged in which contradicts standard group recommender systems.

The union of negative explicit feedback from every user within the group represents the group preference. Because it is not possible to filter every song, the similarity between songs is included (songs from one album are similar). In general, when at least one song from one album is disliked, no song from this album will be played. No group structure or other aspects are considered.

FIT-Family. Interactive TV System FIT is designed to recommend TV programs within the family. As the system tries to minimize user interaction and there is no presence detection, group structure is detected based on probability. To put it simply, the user has to explicitly define gender, age and occupation and the time he/she usually watches TV. Secondly, preferences are derived based on usual genres and gender, age and occupation correlations.

Actual group structure is only an estimation, based on specified times of watching. This is included in the prediction phase, when users' preferences are multiplied by the probability of their presence. Generally speaking, the sum of correlated genres ratings multiplied by probability of users' presence is used as the aggregation function. It is clear that the system suffers from the absence of real and trusted data about users.

PolyLens. PolyLens is designed as a small group extension for well-established single-user recommender MovieLens. The system uses the least misery strategy: while there is a rating for movie to be recommended from at least one group member, this movie is eliminated from the recommendation process. Some kind of explanation is included, while users see their and whole group ratings.

AVATAR. The system uses hybrid recommendation – content based and collaborative to provide recommendation of TV programs. The knowledge about the TV domain is represented by ontology.

The content based approach recommends similar TV programs as seen previously, while hierarchical and inferential semantic search is considered.

The Pearson correlation is used to obtain group preferences, and then the hybrid recommender approach, which reduces the sparsity problem, is applied.

GroupRecoPF. GroupRecoPF is a platform providing support for building user-friendly and scalable recommender systems. The platform provides three types of aggregation functions – weighted maximum average, weighted maximum minimum and maximum minimum.

Several resources are available for developers, who can edit and adjust properties of the recommendation process through graphical front-end. Recommendations are presented via a client side desktop application.

Happy Movie (Gruppito). The system provides recommendations based on personality social trust and memory of past recommendations. The system is implemented as a Facebook application, which recommends movies to a group of users.

Personality of every user is identified based on standard questionnaire. Next, initialization is performed – the user rates several movies. The social trust is derived based on information stored in social network.

The recommendation is a kind of filtering, while probably interesting movies are chosen and users have to vote for the final decision.

gRecs. Group recommender framework is designed to provide recommendation over the MovieLens dataset. The proposed approach consists of two steps: standard collaborative filtering, while similar users and recommendation for single-user are generated; group recommendation, while results of collaborative filtering results are merged based on standard merging strategies.

In order to reduce the computation complexity of similar users search, agglomerative hierarchical clustering is used and computed offline.

Adaptive correlation-based RS. The system estimates (predicts) the group preferences – ratings based on the applying correlations between group and its members. Members' weights in the group are estimated and finally the group recommendation is generated based on the merging of members' weights and ratings.

The system was evaluated over the MovieLens dataset and proves that it can provide help in deciding when multimedia content is experienced and recommended.

Groupfun. This is a web application, designed to help group of people attending an event to agree on a music playlist. Firstly users have to create their playlists based on the 10 000 music dataset. Moreover, the Last.fm profile for every user is available. Next the process of invitation and the group construction is initialized. Finally, the songs for specific event have to be chosen by

every user and based on the probabilistic voting scheme the recommendation is generated.

HbbTV. This is an application designed for HbbTV browser. Users presence is detected based on the QR-code mobile application principle, while similarly the voice recognition user identification was implemented. The recommendation part of the system is based on the PREF framework, which combines automated metadata enrichment, user preferences collection and several filtering algorithms.

Recommendations are provided based on three steps: firstly the prediction for the group members is performed, next the filtering of all not relevant items for the user and group removes these not relevant candidates. Finally, the list of candidates is turned into recommendations.



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