

GROUP RECOMMENDATIONS: SURVEY AND PERSPECTIVES

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Abstract. The popularity of group recommender systems has increased in the last years. More and more social activity is generated by users over the Web and thus not only domains as TV, music or holiday resorts are used and researched anymore 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 in order to overcome some single-user recommendation shortcomings, such as a cold start problem. Numerous group recommenders have been proposed, they differ in application domains (which are in the group recommender context specific in different 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

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 the every human life routines. These changes result into the huge information explosion. The

amount of information over the Web is increasing dramatically, which brings several serious problems in the connection to the 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, moreover, 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 respectively. 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 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, learning, articles recommendation or graphical interface personalization. Depending on the domain, the recommendation can be immediately experienced by the group members on the one place (music in the gym), or only the suggestion 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 art of group recommendation approaches. The paper is organized as follows. Section 2 describes approaches for the user and the group modeling respectively. 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 considers 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 nowadays 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 connection to the recommendation approach success. The user modeling process can be divided into three basics 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.

The user's interest can be in general represented as a set of pairs (item, relevance). Let the C be the concept in the domain and V the value from interval $< 0, 1 >$ (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 degree of intensity of the satisfaction level for the specific semantic concept (Article - normalized time spent during reading / scrolling).
- *Quantity of Interest* characterizes 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 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 do 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 of 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 is this approach used for example in restaurant recommendation [29], where user has to specify his/her preferences for several attributes (e.g. "Definitely want", Price, Distance). When recommending TV shows or movies, the remote control is often used in order to obtain explicit feedback. The whole group preference can be obtained also, but the inter group discussion have to be accomplished before (the consensus problem reach).

Negative feedback. Some researchers argue that the negative preferences should be discussed in the recommendations rather than the positive. 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 express usually negative feelings more likely than positive, so we can group people by their dislikes sometimes better than 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 save the user's effort. 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 respectively 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 respectively. 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 [4,44].

Implicit feedback acquisition is, in the context of group recommendation, more complex task as the feedback is 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. 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 the Figure 1.

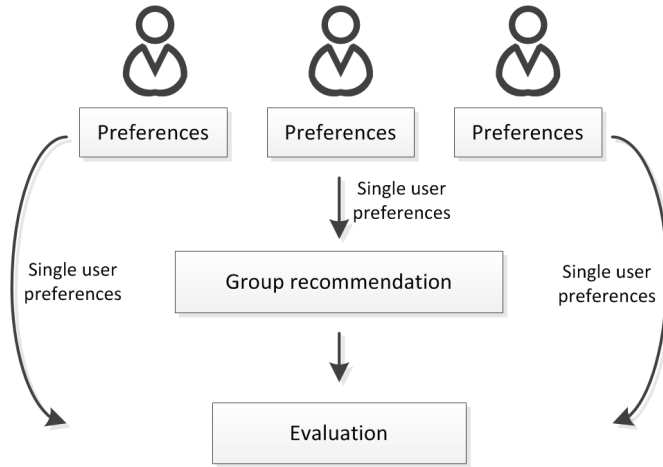


Fig. 1. Example of the single-user oriented evaluation. Single-user preferences are used for the recommendation generation. In the evaluation phase the recommendation accuracy is compared to the every user single preference (the single and group rating prediction difference).

3 GENERATING RECOMMENDATIONS

Generating of recommendations for a group of users highly depends on the aggregating strategy involved into the approach. From the historic point of view the group recommendations are generated based on the 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

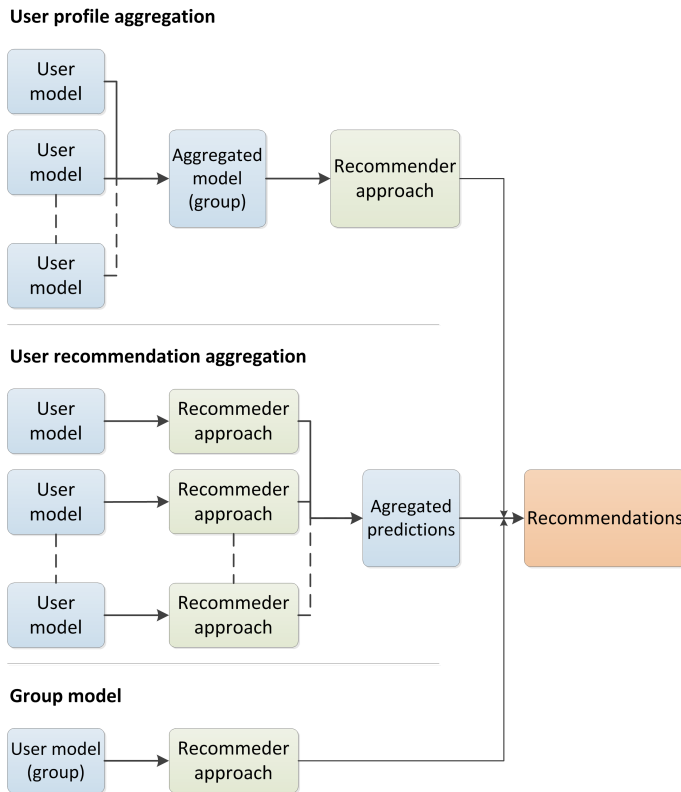


Fig. 2. General approaches for the group recommendation. Single-user ratings and recommendations are aggregated or one group model is constructed and no aggregation is performed [5].

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 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. More and 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 more realistic.

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 plenty of strategies used for specific domains such as the label aggregation, recipe recommendation, searching and many others, where these general strategies are modified or mixed for various groups' settings [5] to obtain better results [55]. Some methods instead of simple aggregation use probabilities prediction [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).

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

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	

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 - methods differ only in 3-6% from each other [2].

Voting strategies seems 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 as a web-based application MovieRec 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 the 11 groups and 93 events. During the experiment we observed users' behavior based on the sharing preferences (even events - preferences were visible), users consistency and the performance of used aggregation strategy. After the event deadline, three lists of the generated recommendation were presented to the every user of the group (additive, multiplicative or the 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, thus 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.

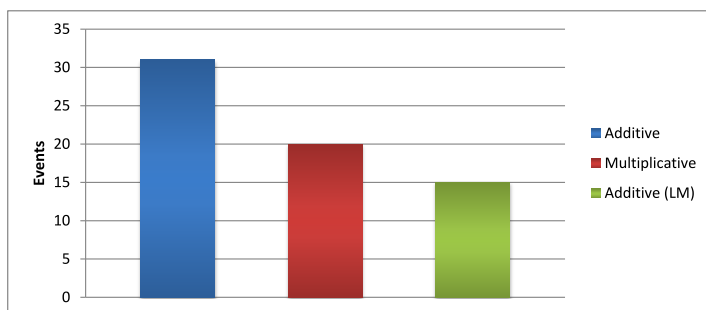


Fig. 3. Absolute count of winning strategies.

Obtained results clearly show, that when a large group is requesting for the rec-

¹ <http://www.facebook.com>

² <http://www.imdb.com>

ommendation (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.

Table 2. Voting strategies comparison.

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

There is one of the standard methods 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 as Cosine similarity, Euclidean distance are used to find the "nearest" ratings [49,56].

Sometime 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 respectively. 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, thus 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 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 strategies are the most used strategies 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 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 proposed strategies. To put it simply merging strategy should be chosen dynamically in order to 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).

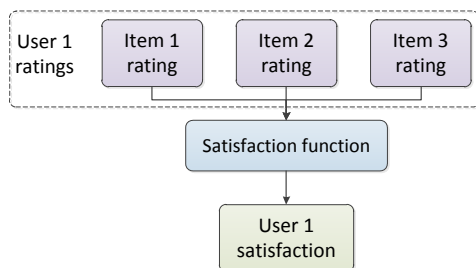


Fig. 4. General satisfaction modeling process, which helps to predict real user satisfaction within the group or after sequence of recommended items.

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:

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

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]:

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

Proposed satisfaction function Masthoff evaluated 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 of approaches model the real life condition in the group recommendation, the need for personality detection is in case of the group extremely important [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 the 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 is based and computed so-called "Conflict Mode Weight" [41]. Prada proposed a model based on the Five Factor Model [39]. The basic model considers only two factors of Five Factor Model which was extended to use all of five factors respectively (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 most preferred method 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 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 function 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 top score selected.

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

Extraversion	Introversion
Sensing	Intuition
Thinking	Feeling
Judgment	Perception

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, the 60 questions were selected for each of five dimensions (12 per dimension), while the validity of several questions is still researched [32].

In the contrary to previous approaches, NEO-FFI recognizes 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 the increased stress or pressure.
- **Extraversion** can be understood as the psychical energy directed outside - to the surroundings. Typical characteristics are the openness to new people, assertiveness, communicativeness or optimism.
- **Openness** is connected to the sensibility, intellect and culture. Higher score obtained in this dimension, ensures that person is opened to new experiences, has an aesthetic feelings or is interested in the new ideas.
- **Agreeableness** refers to the ability to accommodate in social situations. Typical characteristics are the altruism, the positiveness to others or the tenderheartedness.
- **Conscientiousness** characterizes painstaking and self -controlled people, which can be described as people which prefer active planning, organizing of tasks, are purposefulness 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

The 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 the single-user's satisfaction. The strength of this influence depends on the type of the relationship. Four basic relationships were proposed [28, 42]:

- Communal sharing (somebody you share everything with - best friend)
- Authority ranking (somebody you respects 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 as Equality matching or Market pricing.

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

The second type of impact is the conformity. It was shown that users are influenced by the group in 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 first picture. All group members answered before the tested user and all of them picked the same wrong answer. The tested persons in the most of cases picked the same wrong answer in order to adapt to the group opinion.

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

- Normative influence, when user inside believes that he/she is true, but outwards he/she expresses the same opinion as the group.
- Informational influence, when user changes his/her opinion, based on 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).

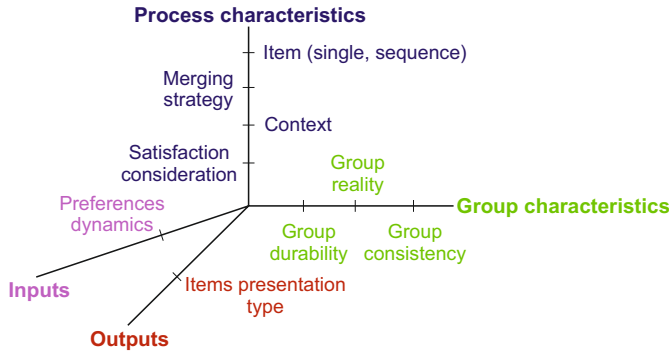


Fig. 5. Various dimensions of group recommender characteristics.

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 - if 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 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 already proposed. Thanks to the various possibilities of group recommender construction considering above discussed dimensions, existing recommenders present diverse approaches often dependent on the particular domain (For the list of most relevant group recommender system see Appendix).

Thanks to the recommendation systems history (the evolution of online sources), the group recommendation is typical for several multimedia domains. The TV or movie recommendation is thanks to the variety and accessibility one of the most popular domains for the personalized recommendation. Group recommendation can be used everywhere, where 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 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 of nowadays systems the aggregation of user’s preferences instead of

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

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

individual recommendations (gRecs [22], Happy Movie [40]) is used. The preference aggregation brings in the general better results, while various aspects of the group can be considered. In the opposite the 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 there is need for the implicit detection) and often some kind of estimation is used (e.g. Intrigue [1]). These virtual groups are most interesting when the 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" 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, the minimal satisfaction is not guaranteed even. Clearly, group recommendations can overcome some of the single recommender system problems (the 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 the single-users and groups. The 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).

The group recommender system should take an advantage from the fact that human relationships change the way how we process the social information. On the one hand, we tend to idealize our close others, 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.

The actual research focuses on the role of individuality within the 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 the 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, the malevolence can be observed in some cultures - the sadness of other member brings us satisfaction. This type of the emotional contagion is present also with a type of relationship, e.g. market pricing.

So-called groupthink can be observed - the tendency to attend more to the members which 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 mean of social group identification) is present and the group recommendation is constructed.

Correspondingly, "black sheep effect" can be observed within the group [38]. On one hand, anyone who is disliked, incompetent or non-normative is judged more strictly and considered as 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 to the group self-improvement.

The social interaction or influence is present not only when the other (people, audience, group) is 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 the modeling of the affective state closer to the reality. There are several activities contributing to the social knowledge building as social rules, shared language, past experience, goals and expectations or exchange of argumentation [48].

When making a decision and more alternatives are available, the 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 to the group decay, while someone's preferences are permanently ignored. On the other hand, when all possibilities are more less satisfying, voting is fast and effective approach. The situation when all possibilities are good enough to correspond the group consensus [8].

The 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 will 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 the fairness and avoiding the misery [27, 42], while sometimes the minimal satisfaction can decrease the overall group satisfaction. This should be considered when designing adaptive (dynamically changing) aggregation functions. Users prefer some special situations and group structure respectively. 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 the single recommendation with taking to the 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. The consideration of the Social Theory Choice when recommending to group is a straightforward step as the group increases the social interaction. It is clear that the user's personality plays a critical role in the process of the social interaction. People inside the group have a great impact on other users' satisfaction and feelings. This can be in a positive but on the other hand in a negative way respectively. 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.

The typical problem when including a personality type to the recommendation is to obtain such information. Usually this is done by questionnaires what 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 and some weaker influence. Social networks can also help us in detecting user's personality [54]. Moreover, social networks are ideal as the group recommender systems interface. Many of activities are negotiated and planned here, thus giving a tool for movie or pub's recommendation seems to be a logical step.

The personality type is not only the interesting source for additional information [51]. The 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 on the end of the recommendation process, even if the previous items were a 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 it's incorporating to the aggregation strategy seems to be promising research area, while it can significantly increase the recommendation accuracy. When recommending a sequence it is clearly important to know which effect will have 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 as the cold start problem or the 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 the known groups should ensure that such a recommendation will be good for the new user respectively.

The 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 actually should be used, 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 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 possibilities of the group recommendation in domains as learning or digital libraries (recommending a book to buy for the research group etc.). The principle of the group recommendation can be used in the educational systems, where the online collaborative cooperation or collaborative learning (learning within the group) can be strengthened. This can be done as the standard single-user recommender system extension, while the single-user recommenders are often well established in such a 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 an 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 the 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 of users tend to prefer the user with special occasion (birthdays) or horizontal and vertical social stats is considered. The personality type can be detected based on various questionnaires or can be extracted partially from social networks, where we can also extract the user's social status.

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

The group recommendation can be also used for solving problems of the single-user 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 recommenders suffer from cold start problem. The state when 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 new user and all or several representative 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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REFERENCES

- [1] Liliana Ardissono, Anna Goy, Giovanna Petrone, Mario Segnan, and Pietro Torasso. Intrigue: personalized recommendation of tourist attractions for desktop and hand held devices. In *Applied Artificial Intelligence*, number 8, pages 687–714. Taylor & Francis, 2003.
- [2] Linas Baltrunas and Francesco Ricci. Group Recommendations with Rank Aggregation and Collaborative Filtering. In *Proceedings of the fourth ACM conference on Recommender systems (RecSys '10)*, pages 119–126. ACM, 2010.
- [3] Michal Barla, Michal Tvarožek and Maria Bielikova. Rule-Based User Characteristics Acquisition from Logs with Semantics for Personalized Web-Based Systems. In *Computing and Informatics*, volume 28, pages 399-427, 2009.
- [4] David Ben-Arieh and Zhifeng Chen. Linguistic-labels aggregation and consensus measure for autocratic decision making using group recommendations. In *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, volume 36, pages 558–568. IEEE, May 2006.
- [5] Shlomo Berkovsky and Jill Freyne. Group-based recipe recommendations: analysis of data aggregation strategies. In *Proceedings of the 4th ACM conference on Recommender systems*, pages 111–118. ACM, 2010.
- [6] Reagan D. Brown and Robert J. Harvey. Detecting personality test faking with appropriateness measurement: Fact or fantasy. In *Proceedings of the Annual Conference of*

- the Society for Industrial and Organizational Psychology, Orlando, Western Kentucky University, 2003.*
- [7] Peter Brusilovsky. Methods and techniques of adaptive hypermedia. In *User Modeling and User-Adapted Interaction*, volume 6, pages 87–129. Springer Netherlands, July 1996.
 - [8] C.T. Lawrence Butler and Amy Rothstein. *On conflict and consensus: A handbook on formal consensus decisionmaking*. Food Not Bombs Publishing, 3rd edition, 2007.
 - [9] Dennis L. Chao, Justin Balthrop, and Stephanie Forrest. Adaptive radio: achieving consensus using negative preferences. In *Proceedings of the 2005 international ACM SIGGROUP conference on Supporting group work*, pages 120–123. ACM, 2005.
 - [10] Andrew Crossen, Jay Budzik, and Kristian J. Hammond. Flytrap: intelligent group music recommendation. In *Proceedings of the 7th international conference on Intelligent user interfaces*, pages 184–185. ACM, 2002.
 - [11] Oskar Van Deventer, Joost De Wit, Jeroen Vanattenhoven and Mark Gualbahar. Group Recommendation in a Hybrid Broadcast Broadband Television Context. In *Proc. of the Workshop on Group Recommender Systems: Concepts, Technology, Evaluation (GroupRS)*, pages 12–18, CEUR-WS, 2013.
 - [12] Greg Dunn, Jurgen Wiersema, Jaap Ham, and Lora Aroyo. Evaluating interface variants on personality acquisition for recommender systems. In *User Modeling, Adaptation, and Personalization*, volume 5535, pages 259–270. Springer, 2009.
 - [13] Rosta Farzan and Peter Brusilovsky. Community-based conference navigator. In *Proceedings of SociUM Workshop (1st Workshop on "Adaptation and Personalisation in Social Systems: Groups, Teams, Communities") at UM2007*, 2007.
 - [14] Yolanda Blanco Fernández, José J. Arias, Martin Lopez-Nores, Alberto Gil-Solla, and Manuel Ramos Cabrer. TV program recommendation for groups based on multidimensional TV-anytime classifications. In *IEEE Transactions on Consumer Electronics*, volume 52, pages 223–231. IEEE, 2006.
 - [15] Mike Gartrell, Xinyu Xing, Qin Lv, Aaron Beach, Richard Han, S. Mishra, and Karim Seada. Enhancing group recommendation by incorporating social relationship interactions. In *Proceedings of the 16th ACM international conference on Supporting group work*, pages 97–106. ACM, 2010.
 - [16] Dina Goren-Bar and Oded Glinansky. FIT-recommend ing TV programs to family members. In *Computers and Graphics*, volume 28, pages 149–156. Elsevier, 2004.
 - [17] Tom Gross, Christoph Beckmann, and Maximilian Schirmer. GroupRecoPF: Innovative Group Recommendations in a Distributed Platform. In Yiannis Cotronis, Marco Danelutto, and George Angelos Papadopoulos, editors, *2011 19th International Euromicro Conference on Parallel, Distributed and Network-Based Processing*, Ayia Napa, Cyprus, pages 293–300. IEEE Computer Society, February 2011
 - [18] Tomáš Horváth. A Model of User Preference Learning for Content-Based Recommender Systems. In *Computing and Informatics*, volume 28, number 4, pages 453-481, 2009.
 - [19] Anthony Jameson. More than the sum of its members: challenges for group recommender systems. In *Proceedings of the working conference on Advanced visual interfaces*, pages 48–54. ACM, 2004.

- [20] Anthony Jameson and Barry Smyth. Recommendation to groups. In Peter Brusilovsky, Alfred Kobsa, and Wolfgang Nejdl, editors, *The adaptive web - Lecture notes in computer science*, volume 4321, pages 596–627. Springer-Verlag, 2007.
- [21] Judy Kay and William Niu. Adapting Information Delivery to Groups of People. In Peter Brusilovsky, Charles Callaway, and Andreas Nurnberger, editors, *1st International Workshop on New Technologies for Personalized Information Access (PIA 2005) in conjunction with 10th International Conference on User Modeling (UM'05)*, pages 34–43, Magdeburg. University of Magdeburg, 2005.
- [22] Jae Kyeong Kim, Hyea Kyeong Kim, Hee Young Oh, and Young U. Ryu. A group recommendation system for online communities. In *International Journal of Information Management*, volume 30, pages 212–219. Elsevier, June 2010.
- [23] Michal Kompan. Personalized recommendation with social aspects consideration. In *Workshop on Intelligent and Knowledge oriented Technologies*, pages 155–160. TU Kosice, 2011.
- [24] Michal Kompan and Maria Bielikova. Context-based Satisfaction Modelling for Personalized Recommendations. In *Proc. of the Semantic Social Media Adaptation and Personalization, SMAP 2013*, pages 33–38. IEEE, 2013.
- [25] Henry Lieberman, Neil Van Dyke, and S. Adriana Vivacqua. Let's browse: a collaborative browsing agent. In *Proceedings of the 4th international conference on Intelligent user interfaces*, volume 12, pages 65–68, Los Angeles, California, United States. ACM, 1999.
- [26] Kuei-Hong Lin, Yu-Shian Chiu, and Jia-Sin Chen. An adaptive correlation-based group recommendation system. In *Intelligent Signal Processing and Communications Systems*, pages 1–5. IEEE Computer Society, 2011.
- [27] Judith Masthoff. Group Modeling: Selecting a Sequence of Television Items to Suit a Group of Viewers. In *User Modeling and User-Adapted Interaction*, volume 14, number 1, pages 37–85. Kluwer Academic Publishers, 2004.
- [28] Judith Masthoff and Albert Gatt. In pursuit of satisfaction and the prevention of embarrassment: affective state in group recommender systems. In *User Modeling and User-Adapted Interaction*, volume 16, number 3-4, pages 281–319. Kluwer Academic Publishers, August 2006.
- [29] Joseph F. McCarthy. Pocket RestaurantFinder: A situated recommender system for groups. In *Proceedings of the Workshop on Mobile Ad-Hoc Communication at the 2002 ACM Conference on Human Factors in Computer Systems*, pages 1–10. ACM, 2002.
- [30] Joseph F. McCarthy and Theodore D. Anagnost. MUSIC FX : An Arbiter of Group Preferences for Computer Supported Collaborative Workouts. In *Proceedings of the 1998 ACM conference on Computer supported cooperative work*, pages 363–372. ACM, 1998.
- [31] Kevin McCarthy, Maria Salamó, Lorcan Coyle, Lorraine McGinty, Barry Smyth, and Paddy Nixon. CATS: A synchronous approach to collaborative group recommendation. In Geoff Sutcliffe and Randy Goebel, editors, *Proceedings of the Nineteenth International Florida Artificial Intelligence Research Society Conference, Melbourne Beach, FL*, pages 86–91. AAAI Press, 2006.

- [32] Robert R. McCrae, and Paul T. Costa. A contemplated revision of the NEO Five-Factor Inventory. In *Personality and Individual Differences*, volume 36, pages 587–596. Elsevier, 2004.
- [33] Lihl Naamani Dery, Meir Kalech, Lior Rokach, and Bracha Shapira. Iterative voting under uncertainty for group recommender systems. In *Proceedings of the fourth ACM conference on Recommender systems*, pages 265–268. ACM, 2010.
- [34] Irene Ntoutsi and Kostas Stefanidis. gRecs: A group recommendation system based on user clustering. In *Database Systems for Advanced Applications*, pages 299–303. Springer Berlin Heidelberg, 2012.
- [35] Mark O’Connor, Dan Cosley, Joseph A. Konstan, and John Riedl. PolyLens: A recommender system for groups of users. In *Proceedings of the seventh conference on European Conference on Computer Supported Cooperative Work*, pages 199–218. Kluwer Academic Publishers, 2001.
- [36] Sebastiano Pizzutilo, Bernardina De Carolis, Giovanni Cozzolongo, and Francesco Ambruoso. Group modeling in a public space: methods, techniques, experiences. In *Proceedings of the 5th WSEAS International Conference on Applied Informatics and Communications*, volume 2005, pages 175–180. World Scientific and Engineering Academy and Society (WSEAS), 2005.
- [37] George Popescu. What is the Best Music You Have? Designing Music Recommendation for Group Enjoyment in GroupFun. In *ACM SIGCHI Conference on Human Factors in Computing Systems*, pages 1–6. ACM, 2012.
- [38] Tom Postmes and Jolanda Jetten. *Individuality and the Group: Advances in Social Identity*. pages 296. Sage Publications Ltd, 2006.
- [39] Rui Prada, Samuel Ma, and Maria Augusta Nunes. Personality in Social Group Dynamics. In *Proceedings of the Computational Science and Engineering* pages 607–612. IEEE, 2009.
- [40] Lara Quijano-Sanchez, Juan A. Recio-Garcia, and Belen Diaz-Agudo. Personality and Social Trust in Group Recommendations. In *Proceedings of the 2010 22nd IEEE International Conference on Tools with Artificial Intelligence*, volume 2, pages 121–126. IEEE, October 2010.
- [41] Juan A. Recio-Garcia, Guillermo Jimenez-Diaz, Antonio A. Sanchez-Ruiz, and Belen Diaz-Agudo. Personality aware recommendations to groups. In *In Proceedings of the third ACM conference on Recommender systems*, pages 325–328. ACM Press, 2009.
- [42] Francesco Ricci, Paul B. Kantor, Lior Rokach, and Bracha Shapira. *Recommender systems handbook*. Springer, 2011.
- [43] Philip Robbins and Murat Aydede. *The Cambridge Handbook of Situated Cognition*. Cambridge University Press, New York, NY, USA, 2008.
- [44] R Sauri, P. Duaygues, S. Soler, and N. Agell. A recommender system based on group consensus. In *Proceedings of the International Workshop on Qualitative Reasoning*, pages 66–71, 2010.
- [45] Christophe Senot, David Kostadinov, Makram Bouzid, Jerome Picault, Armen Aghasaryan, and Cedric Bernier. Analysis of Strategies for Building Group Profiles. In *User Modeling, Adaptation, and Personalization*, volume 6075, pages 40–51. Springer, 2010.

- [46] Barry Smyth, Evelyn Balfe, Jill Freyne, Peter Briggs, Maurice Coyle, and Oisín Boydell. Exploiting Query Repetition and Regularity in an Adaptive Community-Based Web Search Engine. In *User Modeling and User-Adapted Interaction*, volume 14, pages 383–423. Kluwer Academic Publishers, 2005.
- [47] David Sprague, Fugu Wu, and Melanie Tory. Music selection using the PartyVote democratic jukebox. In *Proceedings of the working conference on Advanced visual interfaces*, pages 433–436. ACM, 2008.
- [48] Gerry Stahl. *Group Cognition: Computer Support for Building Collaborative Knowledge (Acting with Technology)*. MIT University Press, 2006.
- [49] Xiaoyuan Su and Taghi M. Khoshgoftaar. A Survey of Collaborative Filtering Techniques. In *Advances in Artificial Intelligence*, volume 2009, pages 1–20. Hindawi Publishing Corp., 2009.
- [50] Marián Šimko. Automated Acquisition of Domain Model for Adaptive Collaborative Web-Based Learning. *Information Sciences and Technologies Bulletin of the ACM Slovakia*, volume 4, number 2, pages 1–10, 2012.
- [51] Lei Tang and Huan Liu. Graph Mining Applications to Social Network Analysis. In Charu C. Aggarwal and Haixun Wang, editors, *Managing and Mining Graph Data*, Vol. 40 of *Advances in Database Systems*, pages 487–513. Springer, 2010.
- [52] Kenneth W. Thomas and Ralph H. Kilmann. *Thomas-Kilmann Conflict Mode Instrument*. Xicom, 1974.
- [53] Boban Vesin, Aleksandra Klačnja-Milićević, Mirjana Ivanović and Zoran Budimac. Applying Recommender Systems and Adaptive Hypermedia for E-learning Personalization. *Computing and Informatics*, volume 32, number 3, pages 629–659, 2013.
- [54] Stefan Wehrli. Personality on Social Network Sites: An Application of the Five Factor Model Personality on Social Network Sites: An Application of the Five Factor Model. In *ETH Zurich Sociology Working Papers*, volume 1, pages 1–16. ETH Zurich, 2008.
- [55] Zhiwen Yu, Xingshe Zhou, Yanbin Hao, and Jianhua Gu. TV Program Recommendation for Multiple Viewers Based on user Profile Merging. In *Journal User Modeling and User-Adapted Interaction*, volume 16, number 1, pages 63–82, March 2006.
- [56] Yu Zhiwen, Zhou Xingshe, and Zhang Daqing. An Adaptive In-Vehicle Multimedia Recommender for Group Users. In *Proceedings of Vehicular Technology Conference*, volume 5, pages 2800–2084. IEEE, 2005.

APPENDIX – 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 article 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 treating equally, which do 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. System CATS is designed to provide assistance in skiing vacation planning. System generates individual collaborative recommendations based on critiquing. 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. System aggregates explicitly obtained users' preferences in order to create recommendations. The aggregation strategy is nonmanipulatable in two ways - strategy is difficult to understand by human and strategy integrates various attitudes and behavior of other members.

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

Group Modeler. Interesting domain, which is not typical for the group recommendation is the domain of museums. Group Modeler provides recommendations for museum visitors. System constructs group model based on single-users models and combines three basic approaches - adhoc 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 tee.).

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. System was designed in order to allow members of a gym to influence not to control 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. Music recommender Flytrap for music recommendation, 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. Firstly, one artist cannot be played in a row more than one time. Secondly, genre coherence has to be maintained.

The user interface allow users to control and easily see the reason of recommendation provided, while every user agent is represent 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 representing 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 satisfy the majority of the group usually. The least misery is not considered and taking 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). Remaining songs are chosen based on standard voting - better wins. Clearly, system have to be used in small groups or highly homogeneous groups, while in some circumstances number of users may be greater than possible number of songs to be played.

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

Adaptive radio. Adaptive radio group recommender system is based on the negative explicit feedback. System recommends songs which are streamed over the web. User specifies his/her not preferred songs, and these are excluded from the recommendation. System provides recommendations through client-side (single-user) application and users have to be logged in which is in the contradiction with 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 the probability. To put it simply, user has to explicitly define gender, age and occupation and the time he/she usually watch 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. Speaking generally the sum of correlated genres ratings multiplied by probability of users' presence is used as the aggregation function. It is clear that 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 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 respectively.

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. Platform provides three types of aggregation functions - weighted maximum average, weighted maximum minimum and maximum minimum.

Several resources are available for developers, whose 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. System is implemented as a Facebook application, which recommends movies to the group of users.

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

The recommendation is some 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. 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. 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.

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

Groupfun. Is a web application, which is designed to help group of people attending event to agree on a music playlist. Firstly users have to create their playlists based on the 10000 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. 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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