Group and Single-user Influence Modeling for Personalized Recommendation

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Abstract
There are plenty of activities performed in the group instead of the single user. This can be observed in the digital world respectively. Various "social" activities are performed over the Web or at least are discussed and agreed within the Web, e.g., social networks. For such scenarios the group recommendation is needed. Our work is focused on the improvement of recommendation approaches for group of users by introducing the inter group processes and members characteristics. Next, we proposed improvements in single-user recommendations by enhancing it with user context or virtual communities, which we treat similarly as groups in group recommenders. Proposed approaches are evaluated in several offline experiments, where the standard datasets are used. In order to investigate group-based features of proposed approaches, we performed user studies experiments as well.

Categories and Subject Descriptors
H.1.1 [Information technology and systems]: Models and Principles - Human factors, Human information processing, Software psychology; H.3.3 [Information technology and systems]: Information Storage and Retrieval - Information filtering

Keywords
recommendation, groups, social interaction, satisfaction modeling, influence modeling, adaptive social web, virtual groups

1. Introduction
Personalized recommendations are integral part of nowadays Web-based applications. The amount of information available to the Web users is tremendous and increasing day by day as a result of the information accessibility and tendency to transform Web users from the passive role of content consumers to the active content producers.

The problem of information overload is studied and researched from nearly beginning of the "information revolution". Personalized recommendations are generally used to overcome some of the problems connected to information overload by reducing irrelevant or recommending relevant information. From the historic point of view recommender systems are connected to the single-user an his/her preferences. On the contrary, we are facing up the tremendous social activity over the Web increase. The popularity of social oriented services is increasing continuously. Thanks to these trends the need for group recommendations - recommendations suitable for the group members is increasing.

Today's group recommenders were applied in various domains. In some approaches the relationship type is considered (e.g. the dictatorship). There are several other characteristics which are not or minimally considered as the group structure, social connections or users personalities in order to generate recommendations. Consideration of such extra information can significantly improve recommendations and increase users' satisfaction as it is clear that similar intergroup processes as in the real life can be observed.

1.1 Personalized recommendations
When discussing personalized recommendation, it is necessary to understand the difference between recommendations and personalized recommendation. As the first one refers to the general suggestions for most users (e.g., most watched movies, highest rated books), the second refers to the specific user, based on the knowledge about his/her preferences and tastes. As we are interested in construction personalized recommendations, the personal aspect will be implicitly considered to be present. For the single-user recommendations there are two basic widely used recommenders approaches:

- collaborative recommendation
- content-based recommendation

These approaches are often mixed in order to produce so-called "hybrid methods". Various enhancements as the knowledge-based or context-aware approaches have been
proposed in order to improve the performance and thus users’ satisfaction.

Content-based recommendation is often used in well-structured domains, where the relevant information can be extracted from the analyzed and recommended content easily (Equation 1).

$$\forall u \in Users; \ i \in Items = \max(similarity(RecentItems, Items)) \ \setminus \ RecentItems(u)$$  \hspace{1cm} (1)

The idea of the content-based recommenders is based on the assumption that users usually like similar items and thus the advanced content analysis (in order to find similarities between items), e.g., similar articles (Sport), books (History), movies (Drama). The typical representative of such a well-structured domain is news portal. For every article various metadata can be extracted (title, authors, category etc.) and used for the similarity search and finally in recommendation respectively [6]. Not only explicit metadata about some item are important, the advanced content analysis is often performed and distinctive features extracted [7].

In the collaborative recommendation user to user connections (based on the preference similarity) are analyzed (Equation 2). The basic idea of collaborative recommendation is that similar users (based on the preferences extracted from the previous activity) like similar items [4]. In the contrast to the content-based recommendation no content analysis have to be performed.

$$\forall u \in Users; \ i \in Items = \max(similarity(User, User)) \ \setminus \ RecentItems(u)$$  \hspace{1cm} (2)

Various approaches within the collaborative recommendation have been proposed. The matrix factorization models as SVD, SVD++, PLSA or neural networks are comparable to the state-of-art approaches, while they often offer memory efficient model [8]. On the other hand, neighborhood based models are used more often, thanks to their simplicity and possibility to easily understand the reason for providing specific recommendations (ability to explain recommendations is one of the recommender system important characteristics), while this is often crucial from the user’s satisfaction point of view.

One of the proposed enhancements to recommenders approaches is the consideration of additional information, e.g., the user’s context. In this case, the final predicted rating is not based only on the user and the item, but his/her context is considered additionally. Three basic paradigms for the context integration to the recommenders have been proposed in the literature [1]:

- The contextual pre-filtering uses the context information in order to filter the dataset used for the recommendation.
- The contextual post-filtering generates the recommendations without the context information and in the final phase is the context used to adjust these recommendations.
- The contextual modelling uses the context as the part of the rating computation process.

In our work we will use the contextual modelling, as the rating prediction can be easily used in various approaches in the group or single-user recommendation.

### 1.2 Group recommendation

Often we have to act socially. The activity is performed in the group instead of as a single-user. These activities can be natural, e.g., watching movies with friends or we are forced to be participant of various groups, e.g., listen to the music in the gym or in the bus. In all these situation the group recommendation can be beneficial, when the single-user satisfaction is taken as an optimization function.

The group recommendation task can be formulated as follows: let the $G$ be the set of groups and $I$ all the possible items available to the recommendation, $u$ the usefulness function (usefulness of an item for the specific group), then the group recommendations task is defined as:

$$\forall g \in G, \ i \in I = argmax_{i \in I} u(g, i)$$  \hspace{1cm} (3)

Generally, the group recommendation systems are based on the standard single-user recommendation approaches, the group structure, members relationship or personalities are considered minimally. Often the difference between collaborative and group recommendations is overlooked. While the collaborative recommendation creates sets of similar users as an part of the computation step, the group recommenders take group as an input for the recommendation process, while the group similarity may vary.

In order to model group and users’ preferences two basic approaches are used in today’s group recommenders [5]:

- group preferences are modelled as preferences of one user, while the inconsistent preferences from various users have to be solved
- for every user single-user model is maintained, while aggregation of group members profiles is performed in the time of recommendation

It is clear that if single user profiles are maintained for every user, the aggregation of users preferences can be performed on two levels - the users preferences can be aggregated or personalized recommendations of group members are aggregated (Figure 1).

Modeling whole group preferences as s single-user model is not so widely used as it is suitable for the stable groups. It can be quite difficult to extract single-user preferences when the group structure changes. On the other hand this can be an advantage is specific domains, where users preferences have to be stored anonymously.

The user’s interest can be in the general represented as a set of pairs (item, relevance). Let the $I$ be the item and $V$ the value from interval $<0,1>$, then

$$M_u = \bigcup(I_u, V_u)$$  \hspace{1cm} (4)

$M_u$ represents user model of the user $u$. Three types of preferences are usually stored in this way (Equation 4) [14]:
Today's group recommenders vary in the domain, aggregation function or context consideration, minimal satisfaction guarantee, or social aspects and cover only the "fair" aggregation (instead the dictatorship strategy).

1.3 Aims

We target at improving recommendation approaches based on identified problems described above. We propose novel methods for the personalized recommendation for group and single-users according the following aims:

- Improving group recommendation performance with respect to the user satisfaction, focusing on considering various aspects of recommendation and users and specific domain optimization.
- Improving single-user personalized recommendation by enhancing it with group recommendation principles focusing on improving the performance of recommendation for new users and/or specific domains and improving the accuracy of standard recommendation approaches.

Our contributions covers three areas:

- **Low quality of recommendations in various domains and special situations.** Nowadays recommenders fail in many special domains and common situations (e.g., low number of similar users, cold-start problem, rating sparsity). This is crucial from the user’s satisfaction point of view, because user attitudes to the system are formed rapidly. Thus the sufficient recommendations are required as soon as possible. Moreover, the performance of recommender systems can be increased from various points of view (rating prediction, precision etc.).

- **No or minimal consideration of social aspects within the group of users.** When the group decides which activity will be performed, users consider the group structure and special users’ preferences respectively. This is notably not considered in aggregation functions or satisfaction modeling nowadays. In general, in order to model real life conditions (intergroup processes) we need to include social aspects into the process of group recommendation.

- **Limited context modeling as the source for user satisfaction influence.** The context of a user can be understood similarly as the social influence in the group recommendation. One context type is able to
2. Proposed group recommendation approaches

We proposed several approaches for the group recommendation. We considered various domains as the multimedia or educational domain. Moreover, specific group characteristics are taken into account is particular approaches, which allows us to increase the performance of such recommendations.

2.1 Group recommendation based on voting

Sometimes there is not possible to obtain group structure and user’s social characteristics. When the group is constructed adhoc - from the "random" users, there is almost impossible to collect information about the group structure or users characteristics.

On the other hand, even when the members preferences or the group structure are known, the group activeness can indicate that group members desire to be actively involved into the recommendation (consensus obtaining) process.

One of the best performing approaches for the group recommendation, which is suitable for the active groups, is the recommendation based on voting of users (group members). Group members suggest their recommendation and then the voting is performed. It is clear that the voting process, especially when performed online and when the goal is to reach consensus can be influenced and enhanced by various aspects (e.g., sharing preferences, aggregation strategies, group size, users’ consistency). In order to investigate the influence of these specific aspects we propose a voting mechanism in the domain of movies.

Proposed approach consist of the construction of users’ ratings matrix, which is created based on users’ votes (Items x Votes). Every user can vote for the items already voted by other users, or the new item can be added as the suggestion to the group. Next, the matrix of normalized ratings is constructed (Min-max normalization) in order to minimize low or high ratings influence to aggregation strategy. Finally, the total of three representative aggregation strategies (additive, multiplicative and additive with minimal satisfaction) are used in order to construct the group recommendation, which is presented to users (Figure 3).

Not only the lack of users’s preferences knowledge or active group indicate to use the voting based recommendation. Often there is no information about the recommended content available (e.g., movie genre, director), which are used for the similarity search. In the voting based approach, these information is processed by the users thus no content analysis or the lack of new items is required or present.

2.2 Group recommendation for learning domain

One of the domains where the group recommendations have not been researched and applied is the education. The learning groups are natural part of learning process, thus offers ideal environment for the group recommender implementation.

Recommendations generated with the respect of the group members can increase the users satisfaction and to reduce the effort needed to obtain some knowledge level. Positive aspects of the group learning have been reported in the literature [16]. Moreover, the specific characteristics of the educational domain can be harnessed, e.g., the user’s learning style, in order to maximize user’s satisfaction.

The typical problem in the educational system is the lack of users’ activity (except “before exam” time). Thus, the group recommendation seems to be an optimal solution to satisfy users by providing resources and exercises suitable for “online users” (actual group in our context).

The basic source of influence in the context of education is the learning style preference. Partially, learning style can be considered as the one of the personality characteristics. Every user can be from the learning style point of view characterized based on the 4 dimensions [3]:

- Perception - sensory vs. intuitive
- Input - visual vs. auditory
- Processing - active vs. reflective
- Understanding - sequential vs. global

It was shown that these learning styles and their corresponding teaching styles improve standard learning process (successfully used in the pedagogy) from the quality and quantity respectively [3]. To our best knowledge, no recommender system in the educational domain (single or group) considers these styles in the recommendation approach nowadays.

In order to improve the group recommendations in the learning process (aiming to optimize the knowledge increase and time need for learning), we proposed novel approach for group recommendation considering users’ learning styles.

Proposed approach consist of three basic steps - learning groups construction, generating of single-user recommendations for the group members and finally aggregation of
These recommendation and providing group recommendation (Figure 4).

First, the learning groups from the actual present users (online users) in the system are created. As the amount of users within the educational system varies, thus we use standard $K$-means algorithm based on the users’ learning style dimensions in order to create group of users of similar learning styles. These dimensions are previously obtained by the questionnaire proposed by Ortigosa [10].

After the groups are constructed, second part - generating of the personalized recommendations is performed. For this purpose, we involved standard the single-user recommendation. The single-user recommendation for the every group member is constructed based on the adjusted recommendation proposed in [9]. For every item predicted rating is computed as the minimum of the item relevances - thematic, difficulty and repetition relevance. The set of objects and their predicted relevance (ratings) are next ordered and Top-N relevant objects are recommended to the user.

Finally, the single-user (every group member) recommendation aggregation is performed, in order to obtain one list of recommended items for the learning group. We propose to use the hybrid aggregation strategy because various homogeneity levels of groups can occur in the system (various knowledge levels or various learning styles).

In this manner, we obtain a list of recommended items for the particular group, based on the single-user recommendations enhanced by users’ learning styles.

3. **Single-user recommendation approaches**

The ideas of the group recommendations can be used in order to improve single-user recommendations and specific problems as the cold-start, recommendation diversity etc. We propose three single-user recommenders, which improves the recommendation performance for new users and regular users (user preferences are known).

3.1 **Recommendations for new users**

The problem of the new user well known as the cold start problem is present in almost every recommender system. When a new user desires for recommendations (or interacts with the system) usually there are no or minimal information about his/her preferences. Unfortunately, users form their attitudes to the system in very first interactions, thus the success of the system is often dependent functionality and services which are available for new users.

The standard collaborative recommendation is based on the assumption that system users can be clustered (similar users can be found across the system). If we are able to find similar users, we are able to generate recommendations. Based on these assumptions we can reformulate the problem of the new user as the problem of assigning a cluster of most similar users (group of similar users). Thus, if we generate recommendations suitable for every group some of them should be suitable for the new user respectively.

Based on this hypothesis we propose a novel group inspired recommendation approach for new users, which consists of these steps:

1. create similar users clusters
2. generate group recommendation for every cluster
3. aggregate these group recommendations into one list

The clusters of similar users represents some "stereotypes" of all possible preferences across the system. Because there is need to generate recommendations for every cluster (group of users) we use group recommendation for every cluster ("virtual group"). Finally, as there are numerous groups, the final aggregation of recommendations for all groups have to be performed (to obtain Top-N items to recommend). As the result, one list of recommendations is obtained (Figure 5), while the recommended items should be suitable for all similar users group, and thus all users in the system (some of the list for some groups).

3.2 **Single-user recommendation improvement**

Based on the assumption that including the virtual users as a part of virtual groups can bring improvement of the single-user recommendations by introducing more diverse recommendations, we proposed novel method for the single-user recommendation. Proposed approach consists of three basic steps:

- virtual groups construction
- similarity computation between virtual users and real users outside the group
- generation of recommendation for specific user

The main difference between the classic single-user collaborative recommendation process and our proposed method (Figure 6) is that our proposed recommendation process is not based on the user to user similarity, but based on the similarity between users and a virtual users.

Every user is assigned to a virtual group. These groups are generated pseudo-randomly based on the inter-group similarity (average of members similarities). Real-life groups derived from the social networks or the other web activity
may be used. Primary, we construct virtual user preferences by using average strategy. Various strategies may be used with or without minimal satisfaction guarantee. In this manner we obtain preferences of a virtual user-which represent preferences of the whole group. Likewise, various group sizes can be constructed, larger groups should increase the variety of recommended items and vice versa.

Final step consists of generating recommendation for the specific user of the group, whose preferences are represented as the average of the group (by the virtual user) instead of concrete user preferences. The recommendation approach is similar as the single-user collaborative approach.

In this manner we obtain a list of recommendations for every user in the group. The group itself do not obtains the same recommendations, but every group member receives own, personalized list. In our experiments we use random group construction, while the inner-group similarity is considered. In the real life users belongs to various groups - natural or virtual. These groups can be used similarly as virtual groups, we generated.

3.3 Influence-based recommendation

In the group various intergroup processes can be observed, while the horizontal and social status, users’ personalities and other factors play important role in this process [11, 15, 13]. In the single-user recommendation, the user context is the source for the (preferences) influence. Various context types as weather or mood influence users behaviour and preferences. In the recommender systems domain the context is often understood (from the representational view) as the predefined set of observable attributes [2]. It is a set of information connected to the specific user and item in the time of the recommendation, e.g., mood, location, time, weather. Adjusted rating function $R$ for the context-aware recommendations is defined as [12]:

$$R : User \times Item \times Context \rightarrow Rating \quad (5)$$

As there are various context types and sources, it is clear that a specific combination of contexts can influence user’s behaviour and preferences in various manner. In other words, one context type can influence the strength of other context types (e.g., bad mood can be strengthen by the bad weather).

In order to include context influence modeling to the rating prediction process, we proposed a novel method for rating prediction considering context influence model. Proposed approach is based on the assumption that one context type can influence other context types and that user is influenced by the previous experienced content as well. Proposed approach consists of three basic steps:

1. predict ratings for unrated items.
2. spread activation through user’s item specific influence graph.
3. combine the user’s ratings history and the final stable state of influence graph.

Based on the actual user available context, we construct context influence graph and spread activation (predicted item rating) within this graph (Figure 7). One vertex represents item, while other the available context. Edges refers to the influence presence between contexts and items.
The previous experienced items influence user’s preferences as well. This influence is considered as the ratings of previous items (if user experienced two items which he/she rates as top items, we believe that small amount of this positive feeling is propagated to actual rating as well). This rating history we consider with time decay factor - more recent items influence user’s rating more.

4. Evaluation of proposed recommendation approaches

We evaluated proposed approaches in order to investigate and to optimize several parameters which are used in our approaches. Similarly, we focused on the recommendation approaches improvement in the mean of the precision or the rating prediction error.

As the methodology of performed experiments was similar we will deeply describe one of experiments we performed to evaluate the idea and the performance of the single-user recommendation based on the group principles (Section 3.2).

We experimented with various settings of proposed approach as the group sizes, intergroup similarities or aggregation strategies used for aggregations.

Hypothesis. By introducing more diverse items (some level of user similarity is guaranteed) we expect to improve generated recommendations - proposed approach based on the virtual groups and virtual users outperforms standard collaborative recommendation.

Data. For the experiments, we used the MovieLens 100k, which consists of users’ rating on movie items - 100,000 ratings (scale 1-5) from 943 users on 1682 items (minimal 20 ratings per user). The dataset was split into train (80%) and test data (20%). In addition, 5 fold cross validation was performed.

Process. We developed single-user recommender system, which is based on the proposed group recommendation approach. Similarly, we developed standard single-user collaborative recommender in order to compare expected improvements. The standard single-user collaborative approach was designed as follows: for a user find most similar users across the system, next recommend best rated items from these users (which were not visited by user to whom recommendation is computed).

Results. We compared proposed approach (the top 3 and top 10) to standard collaborative approach. While the precision of proposed approach is decreasing with the size of the group used for recommendation, MAE and RMSE is improving with the group size (Table 1). From the other hand, the difference between predicted ratings over various group sizes is very small and in the average it is almost identical to the standard collaborative approach. When compared the best performer (group size 3 and 91 similar users, ratings considered as positive feedback >=3) to the standard approach, our proposed approach brings the improvement more than 11.5% for the P@3 and 10.4% for the top P@10 recommendation respectively. This is a huge improvement for the recommender approach and thus indicates that proposed approach can be used for the task of single-user recommendation.

The groups used for the recommendation not necessarily have to be virtual, while the real groups with specific preferences can be used. Moreover based on various similarities levels within the groups we can control the level of diversity obtained in the recommendation lists candidates.

Based on strategy used for the group construction another application for proposed approach raised. When combining not active users with some active one, more recent results can be expected. Similarly, sometimes some kind of influence may be desired - teacher of specific class, girlfriend and her birthday etc. In such a situation proposed approach consider the preferences of another person and thus recommendations are moved from the single-user preferences.

5. Contributions

In our work we focused on designing and evaluating such approaches of personalized recommendation, which help users in everyday life situation to overcome information overloading problems.

Thanks to the users’ social activity increase over the Web, the group recommendations became important part of the recommender systems area. In this thesis we focused on the exploration various influence sources within the personalized recommendation, focusing on the group recommendation. We experimented with the social aspects of users in the process of recommendation.

Moreover, we proposed approaches for the single-user recommendation approaches based on the group principles by considering virtual users or users’ context influence and the group recommendation itself.

- Improvement of the group recommendation in the movie domain by proposing voting-based recommender based for active groups. One of the most used approaches for the group recommendation is the voting (suitable for the highly active groups). We proposed a method for the voting-based recommendation, which provides recommendations based on the three aggregation strategies, considering sharing preferences and the users’ rating consistency. We have shown that groups and users themselves ignore the sharing preferences, moreover including sharing preferences brings higher voting deviations in our experiments (movie recommendation domain). The voting seems to be an ideal group recommendation approach when the group is active and small in general. When the large groups are involved, the voting strategy destroys the minority. Moreover, the minimal satisfaction is not desirable although (when a large group of users requesting recommendations).

- Improvement of the group recommendation by proposing novel influence based recommendation method, considering users’ personalities and intergroup relationships.

Usually there is not only one item recommended when recommending but the whole sequence of items. As we have shown, user prefers specific order of items in the sequence (based on the rating). The sequence recommendation obtains a new dimension in the group recommendation. It is important to consider the order of the sequence for the single-user and its influence on other group members. This
Table 1: Results of proposed single-user group approach for 3 and 10 top recommended items compared to the standard collaborative approach (Std.).

<table>
<thead>
<tr>
<th>Gr. size</th>
<th>Top 3</th>
<th>Top 10</th>
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<tbody>
<tr>
<td></td>
<td>P@10</td>
<td>MAE</td>
</tr>
<tr>
<td>3</td>
<td>0.4272</td>
<td>0.41</td>
</tr>
<tr>
<td>4</td>
<td>0.3948</td>
<td>0.48</td>
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<tr>
<td>5</td>
<td>0.3929</td>
<td>0.48</td>
</tr>
<tr>
<td>7</td>
<td>0.3891</td>
<td>0.49</td>
</tr>
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</table>

Optimization task is enhanced to the all group members. For this purpose we propose satisfaction function, which models the satisfaction level and influence over the group in specific time of the sequence.

The satisfaction modeling in the group context have to face up several dimensions. The process of emotional or social contagion is usually bi-directional and thus the all possible combination of interaction within the group have to be considered. As we have shown users consider social relationships within the group, moreover, some special occasions are considered by users (e.g., birthdays). For this purpose, we proposed an activation-spreading based approach, which models the complicated inter-group relations (based on the users’ personalities and horizontal or vertical social interactions). Thanks to proposed approach, we can model the inter-group processes, discover real users’ ratings (preferences) and thus improve the recommendation process from the users satisfaction and recommendation precision point of view.

- **Group recommendation improvement by proposing novel group recommendations method for the learning task recommendation with users’ learning styles consideration.**

We have shown that the group recommendation can be used in various (not usually used) domains as educational systems. We proposed enhanced approach for the single-user recommendation including the users’ learning styles as the source for the user influence and context. In the next step, we used these single-user recommendations to construct group based recommendation for the small learning groups (created from online users with similar learning styles) in order to support the learning process. Proposed approach brings statistically significant improvement from the knowledge increase point of view. Obtained results support our hypothesis that the group recommendation as the one of the learning support tools can improve the learning process not only in the quantity but as the students’ interview reveals in the quality of such a learning as well.

- **Improvement of the context-aware recommendation by proposing single-user context-aware recommender which, is based on the context to context influence assumption.**

Not only real users within the group are the source for the influence. The context of user influences the user’s preference or stereotypes (similarly as the group members in the group recommendation). Moreover, various context types influence other specific contexts (e.g., weather, mood or day). Such an influence can be compared to the users influence within the group. Based on this assumption we proposed a single-user recommender system considering users’ actual context. This context is adjusting predicted weights of items to recommend for each user. Moreover, the context strength is spread over the context model. The statistically significant results, we obtained, show that our approach considering the user’s context and rating history outperforms standard approaches for the collaborative recommendation as the Matrix factorization or Bi-polar slope (without and with the context consideration respectively).

From the computation cost point of view, proposed approach does not notably decrease the recommendation performance, as the context types considering in the recommendation process are highly limited. As the group recommendation is often based on the single-user recommendation (or preferences), using proposed context boosted rating prediction can be used for the group recommendations respectively. Thanks to the smart mobile devices increase the availability of the contextual information allows us to design new context-aware recommenders in new domains.

- **Improvement of the single-user recommendation for new users by proposing novel approach for recommendation based on the virtual group construction.**

One of the basic problems of recommendation approaches is providing worthy recommendations for new users (no user preferences are known). As we have shown, aggregation strategies help us to reduce such a problem. Users can be clustered in the means of the similar users (user to user similarity), which provides natural user clusters (based on their preferences). The new user will be a part of such a group after his/her preferences are known. Our proposed approach generates virtual groups (similar user groups) and then the group recommendations are generated for every group. In this manner we obtain a list of recommendations suitable for all group members (for every group). Finally, these group recommendations are aggregated into the one list - which covers recommendations for all virtual groups and thus all users. As we have shown, proposed approach outperforms standard most visited items approach. Similar pattern can be observed when the diversity of items is desired.

- **Improvement of the single-user recommendation by proposing novel recommendation approach enhanced by virtual groups construction and aggregation of the group preferences.**
As we have shown by introducing the virtual groups and enhancing the idea of the group recommenders, the performance of single-user recommendation can be increased. We propose a new approach which creates virtual groups, which preferences are represented by virtual users (aggregation strategy used). Next, the similar user search is performed, while virtual user to real user similarity is computed. Finally, the interesting items from most similar users are recommended. As the statistically significant results show, our proposed method outperforms standard collaborative filtering approaches (by introducing more diverse items). Moreover, our experiments proved the domain independency of proposed approach.

We have shown that our proposed approach can be used in domains, where there is low users' activity - there is not enough similar users for the standard collaborative recommendation. Virtual group based recommender can be used for various tasks. If there are inactive (minimal activity) users in the system, the virtual group with more active users can be constructed. Thanks to this, the influence of active users will result in more diverse and actual recommendation. Similarly, when a new user desires recommendations, proposed approach brings qualitatively better recommendations.

6. Conclusions

Group recommendation is an interesting research area nowadays. There are several activities, which we perform in a social rather than an individual manner. In this situation, individual recommender systems cannot be applied. TV watching, going to the cinema, restaurant, pub are only few examples, moreover new domains of application educational systems, games with purpose or digital libraries becomes more popular and important. These activities are usually attended after some agreement over the group. We also distinguish situation, when we cannot choose, e.g., music played in the gym or in the vehicle etc.

For the purpose of ratings merging, 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, but as we shown this is highly dependable on the group size.

Today’s group recommenders do not consider the social aspects of their users. As we model real life group characteristics, it is important to incorporate user’s personality or relationships. 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 extravert is unsatisfied, other members will probably share his/her feelings, even if their were partially satisfied. Moreover, not only the personality but also the social status of every group member or their relationships have a great impact to the satisfaction. Some of users tend to prefer the user with special occasion (birthdays). 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. In order to reflect these aspects new recommender approaches are desirable.

The consideration of social aspects influence and person-ality types during the preference aggregation process (adjusting the ratings) can bring qualitatively better recommendation for individuals and for the group as a whole respectively. In connection to the satisfaction modeling, various real-life scenarios can be modelled. Not only the horizontal influence but also the vertical influence modelling can be beneficial in some domains (e.g., considering teachers preferences within the group).

One of the important characteristics is also the size and the group homogeneity. The researchers usually consider these characteristics, while the proposed methods fall when the group is large and heterogeneous.

We can expect increasing trend in the group recommenders usage. The trend of integrating new platforms as the TV, internet or mobile devices brings new domains where the need for group recommenders arises. Similarly, content or usage history analysis in order to fill create user models are not sufficient anymore. The tendency to use the content generated by the users is visible, while the most powerful sources seems to be social networks.

While the standard single-user recommender approaches suffer from several problems, new extensions, e.g., the application of group recommendations to the single-user recommendation by introducing the virtual communities and representing their preferences by virtual users are desirable. These virtual users are in this context understood as another source for influence. As we have shown such approaches bring better results in some specific situations and problems of single-user recommendations.

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**Selected Papers by the Author**


