Social-Aware Video Recommendation for Online Social Groups

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***Abstract*—Group recommendation plays a significant role in today's social media systems, where users form social groups to receive multimedia content together and interact with each other, instead of consuming the online content individually. Limitations of traditional group recommendation approaches are as follows. First, they usually infer group members' preferences by their historical behaviors, failing to capture *inactive* users' preferences from the sparse historical data. Second, relationships between group members are not studied by these approaches, which fail to capture the inherent personality of members in a group. To address these issues, we propose a social-aware group recommendation framework that jointly utilizes both social relationships and social behaviors to not only infer a group's preference, but also model the *tolerance* and *altruism* characteristics of group members. Based on the observation that the *following* relationship in the online social network reflects common interests of users, we propose a group preference model based on external experts of group members. Furthermore, we model users' tolerance (willingness to receive content not preferred) and altruism (willingness to receive content preferred by friends). Finally, based on the group preference model, we design recommendation algorithms for users under different social contexts. Experimental results demonstrate the effectiveness of our approach, which significantly improves the recommendation accuracy against traditional approaches, especially in the cases of inactive group members.**

***Index Terms*—Experiment, group recommendation, measurement, social media.**

I. Introduction

THE rapid emergence of user generated content (UGC) and online social networks (OSNs) results in a large number of social media contents. Such social media contents are different from traditional ones in a sense that social relationship, user behavior, and user preference jointly affect which contents may interest a user. Chen *et al.* [1] investigated the recommendation for *individuals* in Twitter using collaborative social and contextual information.

A new trend in online social networks is to recommend for groups instead of individuals [2]. Social TV brings a new trend of combining video streaming service with social network service, which has deeply influenced the way people produce and consume video content [3]. Some examples include the integration of Twitter updates during live video streaming [4] and the Facebook applications that allow commenting while watching video content. Users tend to watch videos in groups instead of being alone. As a result, the concept of group interactions in such systems emerges. Such group viewing provides great potential for users to find videos that interest all members in the group, namely, group recommendation.

The composition of a group in such Social TV systems varies from relatives, friends, classmates and colleagues. Recommending content for a group consisting of people with different preferences has been addressed by two types of solutions: 1) Combining group members into a "pseudo-user," which represents the overall preference of the group, and 2) Merging recommendation results of individuals in the group [5], [6].

Social relationship between group members and social behaviors are also important factors in group recommender systems. Some previous studies measured user status within a group by evaluating the strength of the social connections. Some users are even named "experts" and their characteristics can largely influence the preference of the whole group [6]. As a group generally has more than one user, group recommendation is expected to balance diverse interest of different users [7]–[9].

Existing approaches for group recommendation are facing the following challenges: 1) They usually infer group members' preferences by their historical behaviors, failing to capture *inactive* users' preferences from the sparse historical data. 2) Relationship between group members is not studied by these approaches, which fail to capture the inherent personality of members in a group.

To address the above problems, in this work, we study social group recommendation using a data-driven approach [10], by considering influence of external experts, aiming at performing group recommendation under situations of high dynamic and diversity of group membership, sparse data of group member viewing behavior in history, and loose relationship among group members. More specifically, we tackle the following problems: 1) Can group recommendation benefit from external experts, and in what kind of groups do external experts perform the best? 2) Can individuals with different personality and different

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opinions reach consensus or agreement in group recommendation? The answers to these are a set of recommendation strategies designed in this paper, whose contributions can be summarized as follows.

First, we propose a group preference model based on external experts' social profiles, which can overcome the problem of sparse historical data of internal group members. We determine the set of external experts by measuring their preference importance. We also take into consideration of external experts' relationship with group members. We cluster the selected external experts and model group preference using external experts' social behaviors, such as microblogs they posted.

Second, we propose a joint tolerance and altruism model with social sensed user information to describe user personality. We conduct TKI conflict tests and obtain group members' personality as ground truth. Then, we collect various types of user social behavior features from a microblogging system, and observe a mapping between users' personality (including the preference tolerance and altruism) and their social behaviors. The group preference model is then enhanced by the tolerance and altruism model.

Third, we carry out subjective experiments with different group size to evaluate the effectiveness of our design. Several interesting observations are presented and the results show that our approach significantly improves the recommendation accuracy against traditional approaches.

The rest of the paper is organized as follows. We survey related papers in Section II. We present our framework in Section III. In Section IV, we present a tolerance and altruism based group preference model, using external experts as collaborative references. We implement a prototype of our group recommendation framework in Section V. In Section VI, we conduct comprehensive experiments to evaluate the effectiveness and performance of our design. Finally, we conclude the paper in Section VII.

II. Related Work

In this section, we survey related work on conventional content recommendation, social-aware content recommendation, and recommendation techniques for groups.

A. Conventional Content Recommendation

For general video recommendation, content collaboration and collaborative filtering (CF) have been widely used in the existing recommender systems [11], with the idea to performance recommendation based on the similarity of contents. Such similar contents can be identified by content analysis and/or user behaviors. However, such CF-based approaches usually suffer from the sparsity of users' preference database.

Due to the above drawbacks of pure content-based and collaborative filtering approaches, there have been some studies using multi-domain information. Basilico *et al.* [12] have designed a kernel function between user-item pairs that allows simultaneous generalization across the user and item dimensions. There are also other recommendation frameworks for user-generated video recommendation. Baluja *et al.* [13] have proposed to use a random walk through a co-view graph in YouTube to recommend the videos. Pan *et al.* [14] proposed a generic mixed factorization transfer-learning framework to exploit different types of explicit feedbacks for content recommendation. There are also proposals that considered content recommendation as optmization problems to learn personal preferences of users and provide tailored suggestions, and designed practical solutions [15], [16].

In this paper, we are focused on a different type of content recommendation, i.e., recommendation in the online social networks.

B. Recommendation in the Context of OSN

Online social network has become a popular research topic in recent years. Krishnamurthy *et al.* [17] investigate Twitter and identify the distinct classes of users and their behaviors, as well as geographic growth patterns of the social network. Information in a online social network spreads among users in a "word-of-mouth" manner. Due to the massive number of user-generated videos available in the online social network, recommendation is essential to realize the potential of social media in the online social network [18]. In order to keep users entertained and engaged, it is imperative that these recommendations are updated regularly and reflect a user's recent activity on the site [19].

Social connections and users' social activities are important records that can be used in video recommendation. Debnath *et al.* [20] have proposed to improve the recommendation performance using online social network, where attributes used for content based recommendations are assigned weights depending on their importance to users. Walter *et al.* [21] have proposed a trust-based model to perform recommendation, where users leverage their social connections to reach interesting information and make use of the trust relationship to filter unwanted information. Since recommendation generally relies on users' private information (e.g., video ratings), it is challenging to perform content suggestion when users will not contribute their rating information. Isaacman *et al.* [22] have proposed to use matrix factorization for recommendation for user-generated contents when the rating information is only shared between content producer and consumer pairs, which is a common privacy demand by users.

Chen *et al.* [1] investigated the recommendation for *individuals* in Twitter using collaborative social and contextual information. Wang *et al.* [23] have proposed a joint social and content recommendation framework for user-generated contents that propagate across social connections. Mao *et al.* [24] studied how to performance recommendation using users' "capability" (e.g., being able to sing a particular song) in the recommender systems. Today, such social recommendation is not only important to content services and applications, but also important to content systems and networks [25].

Different from previous studies, in this paper, we investigate how the social relationship and social behaviors are jointly utilized. In particular, in this paper, we infer group preference from social relationship, and model the personality of users from their behaviors.

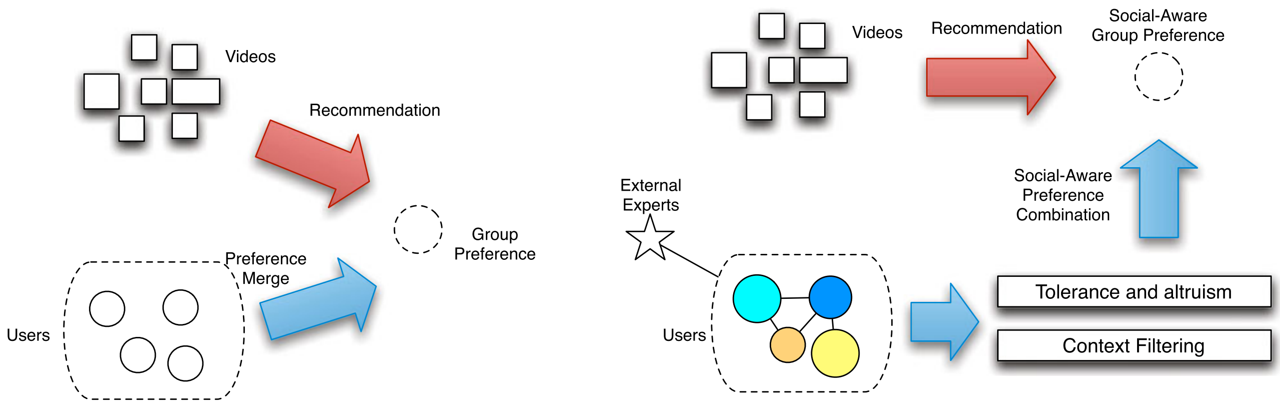

Fig. 1. Comparison between our tolerance- and context-aware group recommendation and traditional approach. (a) Traditional group recommendation. (b) Our context, trust, and tolerance-aware group recommendation.

C. Recommendation for Social Groups

A new trend in online social networks is to recommend for groups instead of individuals. Users tend to watch videos in groups instead of being alone. Such group recommendation plays an important role in today's social-aware content services and socialized content distribution [26]. As a result, the concept of group interactions in such systems emerges. Such group viewing provides great potential for users to find videos that interest all members in the group, namely, group recommendation. Recommending content for a group consisting of people with different preferences has been addressed by two types of solutions: 1) Combining group members into a "pseudo-user," which represents the overall preference of the group [5]; and 2) Merging recommendation results of individuals in the group [27]. The these approaches, the recommendation results are generated according to principles including "average satisfaction," "least misery" and "most pleasure" [6].

Previous studies measured user status within a group by evaluating the strength of the social connections. Some users are even named "experts" and their characteristics can largely influence the preference of the whole group [6]. Others study the dissimilarity among group members [7]. There are also studies on how each member contributes to the group consensus [28].

As a group generally has more than one user, group recommendation is expected to balance diverse interest of different users. Some research made a more precise description of user preferences to better understand their common interests on different content categories [9]. In [29], group members are aware of the opposite views from others. A system was built to help users obtain the consist agreement with group discussions [8]. Influence of members on each other and the influential people in the group were identified for creating the preference of a whole group [7]. Amirali *et al.* [30] studied how group preferences are filled when preferences of some individuals are not observed.

In our previous study [31], we have investigated recommendation for social groups based on the preference inferred from social relationship. Different from the previous efforts, in this paper, we study the tolerance and altruism characteristics of group members using the social information, for better group recommendation.

III. Framework

Traditional group recommendation is illustrated in Fig. 1(a). In traditional group recommendation, users in the same group are treated equally, i.e., their preferences are merged together with the same priority, and videos are suggested to the merged preferences of the users. In real scenario, such assumption is however not true: (1) Users in the same group have different preference "weights," e.g., some users' preferences are more important to the group; (2) Users also have different tolerance levels, meaning how much user would like to accept contents of others' interests; (3) Recommendation is context-aware, i.e., users are likely to enjoy videos which are similar to the ones they have already watched or the one they are watching right now.

We propose a new group recommendation framework, as illustrated in Fig. 1(b). It consists of a group preference model, a personal tolerance modeling and a contextual filter.

A. Followee-Based Preference Model

First, we introduce the preference model. As users are interested in social media content generated by their followees (i.e., people a user is following in the online social network), such followees' characteristics can reflect users' preferences. In our study, these followees are referred to as "external experts," who are usually more active than ordinary users. We will design a model to "aggregate" the followees' characteristics, to reflect the preference of a user. Such social relationship based preference model captures the preferences of users even if they only have little historical interaction records.

B. Preference Model for Social Groups

Preference of a social group and preference of an individual is different: First, the preference of a group is affected by the preferences of members in the group; Second, the preference of a group is affected by not only the preferences of group members,

TABLE I
IMPORTANT NOTATIONS

Symbol	Description
$\mathbf{G}$	A group which is a set of members
$\mathbf{F}_u$	Set of friends of a user u in the online social network
$\mathbf{I}_u$	Set of followees of a user u in the online social network
$\mathcal{Q}_u$	A vector representing a user u's preference
$\mathcal{R}_e$	A vector representing an external expert e's preference
$\mathcal{P}_{\mathbf{G}}$	A vector representing a group $\mathbf{G}$'s preference
$\mathcal{V}_c$	A content vector representing a video c's characteristics
S	A similarity function to measure the relevance between a content vector and a preference vector
Υ	A normalization function to normalize a vector

TABLE II
CBR FOR ONE-WAY EXTERNAL EXPERTS

Group	A (size: 3)	B (size: 5)	C (size: 5)	D (size: 8)	E (size: 8)
CBR (%)	50.67	37.60	42.37	56.86	53.16

but also the relationship between them, because users behave differently when they are in different types of social groups. In this paper, we try to understand how the social relationship in a group affects the preference of the group.

C. Personal Tolerance Model

We investigate the inherent tolerance of users in a group recommend, when they have to accept contents that do not satisfy their preference but are interested by other members in the same group. Traditional group recommendation only considers internal group members' preferences. In our study, we design a tolerance model to capture the group preference practically.

D. Contextual Filter

Finally, we design a contextual filter that enhances the recommendation results using the context information. Existed algorithms are generally conducted by analyzing historical data from users, which seldom concerns about influence of current context, especially in group recommender systems. We also use current context as a "filter" of recommended videos to improve the relevance of recommendation.

Next, we will present the detailed design of each part.

IV. SOCIAL-AWARE GROUP PREFERENCE

In this section, we study a group's preference based on the social relationship and user behaviors. Important notations are listed in Table I.

A. Preference Model Based on Social Relationship

In previous efforts, preference is generally inferred from users' demographics, which can then be inferred from other sources [32]. However, such approaches may suffer from the low availability of data for a large fraction of users. Thus, we study whether there exist external experts who can reflect the interests of members in a group, and then we study how the external experts can be selected for the recommendation.

1) External Experts for Preference Inference: We first study the friend relationship between a group member and another user outside the group. Using the traces provided by Tencent microblog service, we observe that a major fraction of two-way relationship is usually based on real-life social connections, e.g., friends, colleagues, etc. Though the two-way social relationship between users indicates close social tie, it is not suitable for preference inference, since the social connections are created not according to preference but real-world social relationship [33].

On the other hand, the one-way relationship (e.g., following) usually created according to interests, can reflect a user's preference. For example, a user usually follows celebrities on Twitter if she likes them, but she does not necessarily have to know the ones she follows. In our design, we thus use the one-way relationship to infer the preferences of users. At the same time, in online social networks like Twitter, there are much more two-way social connections between group members and other users.

The one-way social connections can be roughly classified into two categories: 1) celebrities, who usually have millions of followers in the online social network and are generally famous to the public in the real world; and 2) specialists, who are usually popular in a specific area.

2) Common Behavior Measurement on External Experts: We use a common behavior rate (CBR), to measure the preference similarity between a group member and an external expert. CBR is defined as the fraction of the number of microblogs involved (e.g., reposted or commented) by both the group member and the external expert, over the sum of the microblogs they involved individually. A larger CBR thus indicates that the two users behaves more similarly.

To verify that the external experts can actually help infer the preference of a group, we recruited 80 users in universities in Beijing. We have 50 males and 30 females in our subjective experiments, aging from 20 to 35 (average age 25), which covers majority of social network users' age range. They are typical mobile users and they all frequently use online services including both online social network services and online video services. The diversity of the subjects can generalize the results, though our methodology is general for different types of social groups.

We let them form groups with different size (in $\{3, 5, 8\}$). We then measure the CBRs of groups with different size. In Table II, we calculate the average CBR of members in groups with different sizes. Note that these group members also share a large fraction of followees (e.g., celebrities). As illustrated in the table, the CBR is relatively large when we use the one-way external expert for preference inference, e.g., when the group size is 8, the CBR is as large as 56%.

3) Group Preference Modeling With External Experts: We use a clustering algorithm based on topic modeling [34] to calculate the eigenvectors of videos to be recommended to users.

Topic modeling project contents into a topic space which facilitates effective document clustering.

In our experiments, we crawl titles and tags of 45,470 videos from the top 10 famous video sharing sites in China, e.g., Youku. After keyword segmentation by Latent Dirichlet allocation (LDA) and data training, we obtain 10 topics using the topic model clustering, e.g., the keyword "UGC" (in Chinese) is one of the top-weighted words. Each video has a 10-dim vector measuring its relevance to the 10 topics, i.e., each entry in the vector represents a likelihood level that the video can be categorized into the corresponding topic.

We use $\mathbf{G}$ to denote the set of group members content is to be recommended for. For a user $u \in \mathbf{G}$ in the group, we use $\mathcal{Q}_u$ to denote a normalized preference vector of a group member, which is a 10-dim vector, measuring her interests in the 10 topics above.

Next, we study the preferences of external expert users that are followed by the group members. For an external expert e, we use $\mathcal{R}_e$ to denote her 10-dim normalized preference vector. In our design, $\mathcal{R}_e$ for an external expert is calculated according to her social behaviors: we collect the contents (e.g., microblogs) posted and re-shared by external expert e, and perform the same LDA and clustering algorithm to these contents, and derive a 10-dim preference vector $\mathcal{R}_e$ for the external expert e.

Using external experts preferences, we will be able to infer the preference of users in the group, as follows:

$$\mathcal{Q}_u = \Upsilon\left(\frac{\sum_{e\in\mathbf{I}_u} \eta_{eu}\mathcal{R}_e}{\sum_{e\in\mathbf{I}_u} \eta_{eu}}\right) \tag{1}$$

where $\mathbf{I}_u$ is the set of external experts followed by the group member u, and η_{eu} is a weighting parameter. $\Upsilon(\mathcal{R}_M)$ is a normalization function: $\Upsilon(\mathcal{R}_M) = \{\frac{\mathcal{R}_1}{\sum_i \mathcal{R}_i}, \frac{\mathcal{R}_2}{\sum_i \mathcal{R}_i}, \ldots, \frac{\mathcal{R}_M}{\sum_i \mathcal{R}_i}\}$. The rationale of this calculation is that we average the entries in the preference vectors of the external experts to form the preference vector of a group member.

The weighting parameter η_{eu} reflects the importance of a particular external expert e to represent the group member u's preference. In practical implementation, the weighting parameter can be set according to user behaviors, e.g., a larger η_{eu} is set if group member u has more social interactions with the external expert e. In our experiments, η_{eu} is calculated using the number of reshares as follows:

$$\eta_{eu} = \frac{Y_{eu}}{\sum_{e'\in\mathbf{I}_u} Y_{e'u}}$$

In particular, Y_{eu} represents the number of reshares by user u of content items originally posted by an expert e.

B. *Tolerance and Altruism Model Based on Social Behaviors*

In the group recommendation, some members may have to receive contents that are not their preferred contents. We investigate the tolerance of group users to receive such contents.

1) Tolerance Modeling Based on TKI Conflict Test: To balance individual preferences conflict in a group, we introduce a conflict dealing model called Thomas-Kilmann Conflict Mode Instrument (TKI), proposed by Thomas and Kilmann [35].

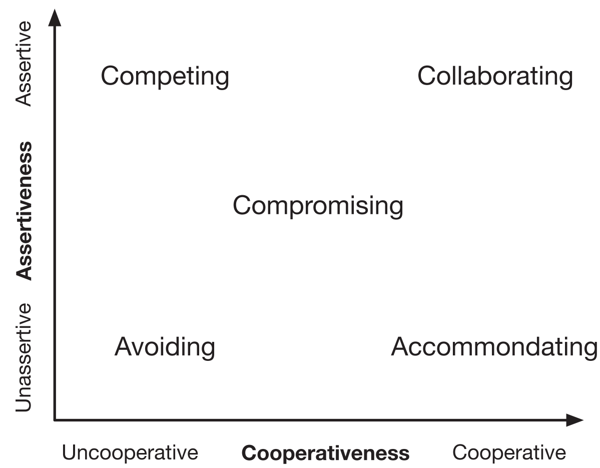

Fig. 2. Thomas-Kilmann Conflict Mode [35].

TKI conflict test can determine one's personality mode along two basic dimensions: *assertiveness* and *cooperativeness* to show whether users tend to fulfill themselves or to meet others' benefits in conflict situations. 5 specific personality modes can be defined and mapped to the two dimensions of behavior, namely *competing*, *collaborating*, *compromising*, *avoiding* and *accommodating*, as illustrated in Fig. 2. We choose the behaviors competing and accommodating which are the most relevant properties to preference tolerance in our model.

Using the subject TKI conflict test, we record the number of users choosing to competing ($C \in [0, 1]$, where larger C indicates more assertive personality), and the number of users choosing to accommodate ($A \in [0, 1]$, where larger A indicates more cooperative personality). We define a user's tolerance compensation $\mathcal{T}_{\mathrm{TKI}} \in [0, 1]$ index as follows:

$$\mathcal{T}_{\mathrm{TKI}} = 1 - \tfrac{C - A + 1}{2}. \tag{2}$$

The rationale is that larger C and smaller A lead to smaller $\mathcal{T}_{\mathrm{TKI}}$, indicating a user is more likely to be willing to receive content not preferred.

We use a subjective experiment to investigate the distribution of tolerance compensation values of different users. In our experiment, we calculate the tolerance compensation values for 80 individuals. We plot the statistics of the tolerance compensation values in different ranges, as illustrated in Fig. 3.

Because the original TKI conflict test requires subjective experiments, it is in-scalable inherently: the information needed in the general TKI model is hard to be collected all from the online social network. Thus, we use a simplified model—a tolerance-altruism model—that can be supported by the social network information, to estimate the results. Next, we present our design of a social-aware tolerance model.

2) Social-Aware Tolerance: Since social behaviors reflect personality [36], we propose to model user tolerance with features collected from the online social networks. The features we choose include 1) the social activeness of users, and 2) the social importance of users.

To this end, we collect 1) the microblogs posted by a user, including the original microblogs, reposted microblogs, and liked

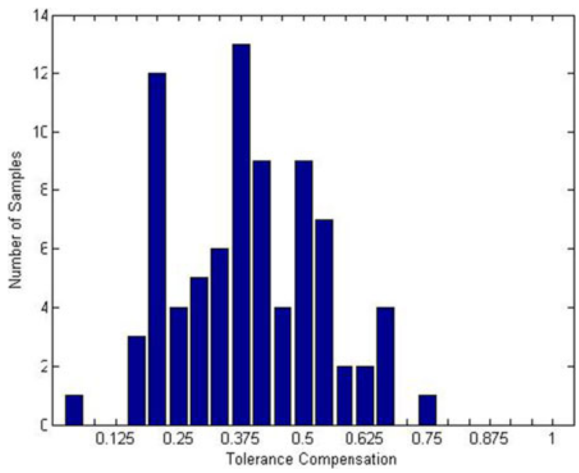

Fig. 3. Tolerance compensation distribution of 80 users in our subjective experiments.

TABLE III
CORRELATION BETWEEN SOCIAL FEATURES AND TOLERANCE

Features	Correlation coefficients	p-value
Number of followees	0.000303043	**0.01214493**
Registration time	1.13236E-09	**0.0650444**
Number of two-way social connections	−0.00059593	**0.08075964**
Number of followers	1.35039E-05	0.368399403
Number of all microblog	−0.00015953	0.38770815
Number of original microblogs	0.000135953	0.506542677
Number of forwarded microblogs	9.1578E-05	0.589259486

microblogs; 2) the followers and followees of a user; 3) the profile of users, e.g., the registration time.

We carry out subjective experiments to investigate the users' tolerance using the TKI conflict tests. In particular, we have recruited over 80 users let them answer the questions in the TKI tests. Then, we study the correlation between users' tolerance index $\mathcal{T}_{\mathrm{TKI}}$ and the social behaviors. Our results are presented in Table III: we give the Pearson correlation coefficient and p-value between the tolerance index and social behaviors. We mark social features with the p-value smaller than 0.1: the number of followees, the number of two-way social connections, and the registration time have relative strong correlation with user tolerance.

Based on the statistical analysis, we use two independent variables X_1, X_2 to describe users' preference tolerance, as follows:

$$X_1 = \frac{\text{number of followees}}{\text{registration time length}} \tag{3}$$

$$X_2 = \frac{\text{number of two-way social connections}}{\text{registration time length}}. \tag{4}$$

Using the social behaviors, we design a tolerance compensation index ($\mathcal{W}_u$) for group member u as follows:

$$\mathcal{W}_u = 1 - (\alpha X_1 + \beta X_2 + \gamma) \tag{5}$$

where α, β and γ are implementation parameters to combine the tolerance variables, such that a larger $\mathcal{W}_u$ indicates that user u is more likely to receive contents preferred by others. In a practical implementation, these parameters can be learnt from subjective tests.

TABLE IV
CORRELATION BETWEEN SOCIAL BEHAVIOR VELOCITY FEATURES AND PERSONALITY

	Coefficients	RMSE	p-value
Intercept	0.37068	0.024343	3.26E-25
X_1	0.031876	0.009938	0.001935
X_2	−0.06832	0.023334	0.004454

1) Some users (e.g., 80 users in our experiments) are allocated to perform the TKI tests, and their tolerance values are collected as ground-truth.
2) The historical social information of these users are collected to calculate X_1 and X_2. Using the previous model, regression analysis yields the estimations of X_1 and X_2, as shown in Table IV.
3) We also use the regression method to find the parameters α, β and γ that best fit the collected tolerance values. In our experiments, $\alpha = 0.03$, $\beta = -0.07$ and $\gamma = 0.37$.

3) Altruism Between Group Members: Tolerance model captures the inherent characteristics of individuals, to receive contents that are not preferred. Tole rance usually affect when group members are strangers. On the other hand, friends may be willing to altruistically receive contents that are preferred by their friends. We capture such *altruism* (trust) between group members by an altruism index ($\mathcal{E}_{u,v}$), which is based on the fraction of common social ties between 2 individuals u and v, as below

$$\mathcal{E}_{u,v} = \frac{|\mathbf{F}_u \bigcap \mathbf{F}_v|}{|\mathbf{F}_u \bigcup \mathbf{F}_v|} \tag{6}$$

where $\mathbf{F}_u$ is the set of friends of user u in the online social network. A larger altruism index $\mathcal{E}_{u,v}$ indicates it is more likely that the two users would like each other to receive contents of their preference. The rationale is that the social tie is likely to be closer if two users share more common social connections.

C. Joint Tolerance- and Altruism-Aware Group Preference

Using the previous building blocks, we are now able to present the joint tolerance- and altruism-aware group preference model. First, we have the original preference of group members, based on the preference combination of external experts; Then, we use the tolerance and altruism indices as controlling parameters to adjust the impact of members in the group, as follows:

$$\mathcal{P}_{\mathbf{G}} = \Upsilon\left(\left(1 - \sum_{u\in\mathbf{G}} \frac{\mathcal{W}_u}{|\mathbf{G}|-1} \sum_{v\in\mathbf{G}-\{u\}} \mathcal{E}_{u,v}\right) \mathcal{Q}_u\right). \tag{7}$$

The rationale is that we first give weights to preferences of group members according to their tolerance index and altruism index, both of which reflect the willingness of a user to accept contents preferred by others—large $\sum_{u\in\mathbf{G}} \frac{\mathcal{W}_u}{|\mathbf{G}|-1} \sum_{v\in\mathbf{G}-\{u\}} \mathcal{E}_{u,v}$ indicates that u is willing to sacrifice her own preference; then we combine the weighed preferences of group members to generate the preference of the group.

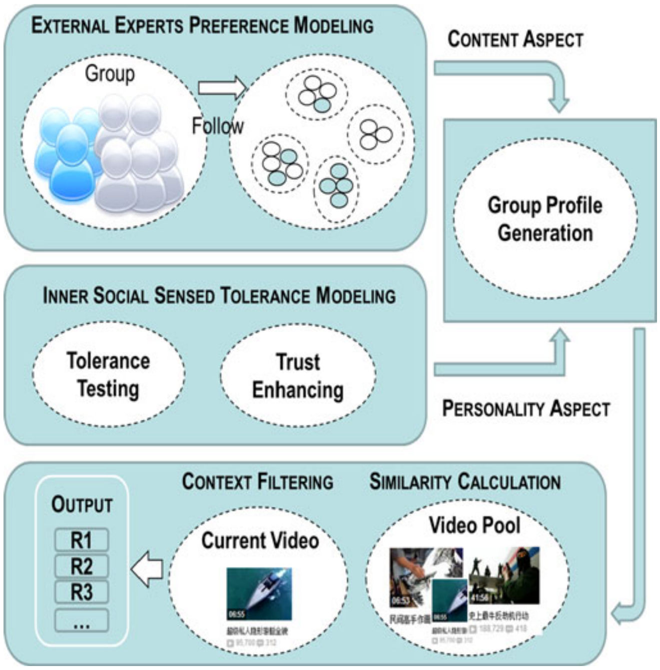

Fig. 4. Framework of the video recommendation for the group.

Fig. 5. iOS App based on our group recommendation framework.

TABLE V
AVERAGE MICROBLOGGING AND FOLLOW NUMBER

Group Size	3	5	8
Avg. # of microblogs posted	32.42	21.51	86.88
Avg. # of followers	90.00	54.24	50.83

V. IMPLEMENTATION OF OUR GROUP RECOMMENDATION

Based on the techniques above, the implementation of our group recommendation includes the following components as illustrated in Fig. 4. 1) Group preference modeling based on external experts: in our design, we use Sina Weibo as the online social network service. 2) Tolerance and altruism (trust) model. 3) Context filtering, which also takes the videos group members are currently watching into consideration. In this paper, we will omit the details of context filtering in the implementation.

A. Group Recommendation

Next, we present how the recommendation is performed. Given a candidate content c, which can be one of the newly published contents. Using content information (e.g., title and description of the video), we are able to use the same 10-dim vector based on the *topic modeling*, to capture the characteristics of video c. We denote the vector of video c as $\mathcal{V}_c$.

We then use a Cosine distance between the preference vector of a group and the vector of a video $S(\mathcal{P}_{\mathbf{G}}, \mathcal{V}_c)$, to capture the "similarity" between a content and the preference of a group. In the recommendation, candidate videos with largest similarity level $S(\mathcal{P}_{\mathbf{G}}, \mathcal{V}_c)$ are then recommended to the group members.

In our experiments based on a prototype implementation, members in a group are provided videos are interested by the group members; meanwhile, the rank of videos are automatically adjusted when social relationship between group members and their social behaviors change. For example, videos are prioritized for a member whose tolerance index is small.

B. iOS App Implementation

We developed a concept-of-proof App on iPad, to integrate the proposed group recommendation modules, as illustrated in Fig. 5. In our implementation, users can browse the users and existing groups, as well as look into others' viewing history. Once joint a group to watch videos together, the user will receive videos recommended by the system, which monitors users' social behaviors and social relationship online.

C. Real-World Implementation

Our recommendation relies on both social graph and social behavior information. The data processing mainly involves social graph retrieval and parameters regression, which can be implemented using large-scale graph engines. In the real-world implementation, a large fraction of the parameters can also be pre-calculated, including the social-aware tolerance for fast group recommendation.

VI. PERFORMANCE EVALUATION

In this section, we conduct experiments based on real-world groups to evaluate our group recommendation solution.

A. Experiment Setup

1) Experiment Subjects and Contents: We let the invited subjectives randomly form several groups, including 8 groups of size 3, 6 groups of size 5 and 2 groups of size 8. The statistics of social behaviors of these groups are illustrated in Table V. We retrieve the social relationship and behaviors of these users from Sina Weibo, for our group recommendation algorithm.

In our experiments, we test 2,000 videos collected from Youku: an online video sharing service in China. These videos are in the categories of movies, TV shows, music and cartoon. For each test members of a group will be shown that they are watching videos together with other members. They will be provided with a list of videos recommended by the group recommendation algorithms, and will independently give a rating score in $[1, 5]$ to each of the recommended videos. Based on the scores, we are able to evaluate the performance of different group recommendation algorithms.

2) Baselines: We compare our design with three state-of-the-art group recommendation algorithms. Recommendation algorithms including our design evaluated in the experiments are as follows:

1) Group recommendation that considers user tolerance and altruism, including 1) Our social-aware group recommendation algorithm (TC-SF), based on social preference inference, and the joint tolerance and altruism model. 2) The conventional TKI-based tolerance compensation (TC-TKI): recommendation based on TKI conflict tests.
2) Group recommendation without consideration of user tolerance and altruism, including 1) Average satisfaction (AS), in which videos are recommended according to the average preference of users, based on the historical behaviors (i.e., microblogs posted by group members are used for preference inference). 2) Most pleasure (MP) [28], which is similar to AS, but recommends videos that can satisfy most of the members. 3) Least misery (LM) [7], which is similar to AS, but recommends videos that have the smallest number of members who do not like it.

3) Metrics: Hit Rate (HR). In the experiment, for each group, we have 7 tests. Except for the first one, the remaining 6 need participants to watch 8 videos and then give scores for the recommended videos. For each recommended video, a group member should mark a score from 1 to 5. We require users to give unique scores to the videos.

We then calculate the average score for each video in one group. We define the hit rate (HR) as a measure of the performance of the recommendation algorithms. The hit rate is calculated as follows: After we sort the average scores for the 8 videos in one test, we pick out the top 3 ones with the highest scores, and calculate the fraction of videos in the 3 videos recommended by different algorithms. A larger hit rate indicates a better recommendation algorithm.

Adjusted-Score (AD-Score): Adjusted-score is an evaluation to the recommended video list against a perfect video list. It captures the distance between the recommended video list and the perfect video list requested by users. We rank all the 2000 videos in our experiments using the proposed method (TC-SF), TC-TKI and the three algorithms (AV, LM and MP), and calculate the mean of similarity distance between user groups and videos, as illustrated in Fig. 6.

A smaller AD-score indicates the two lists are more similar, and the performance is better. This is an example to show how we evaluate the recommended videos in later experiments: we measure the similarity distance between a group and the video recommended to it, and the recommended videos are ranked by this similarity distance. Later in our evaluation, we calculate the same similarity distance between groups and videos recommended by different algorithms, and use it to compare the performance of these algorithms.

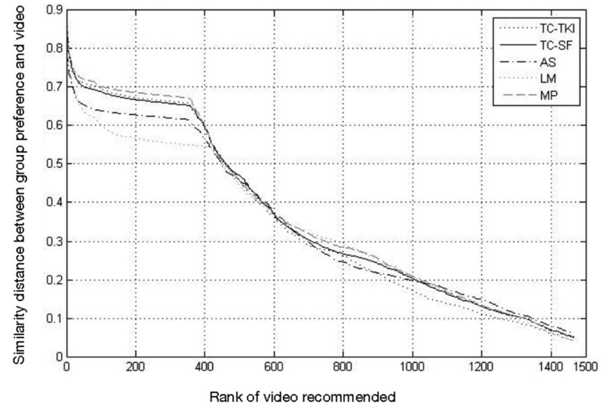

Fig. 6. Distribution of mean similarity distance between groups and videos recommended.

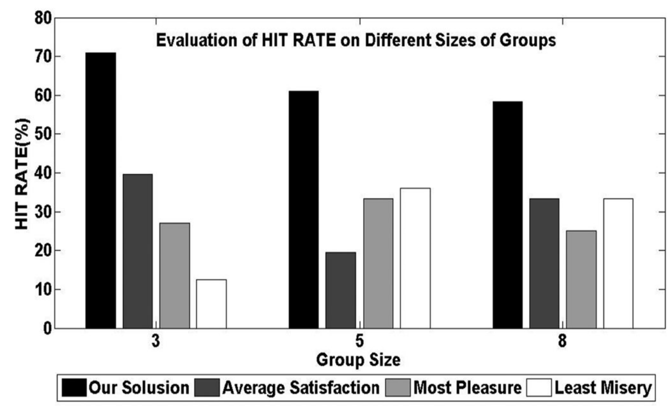

Fig. 7. Hit rates under different group size.

B. Experiment Results

1) Impact of Group Size: We first study the impact of the group size. The results are shown in Fig. 7: the bars are the hit rates versus the group size for different algorithms. Our observations are as follows: (1) Our proposal outperform the conventional average satisfaction, the most pleasure and the least misery approaches. (2) There is a trend that the hit rate degrades when the number of group members increases, but our algorithm outperforms other algorithm even more when the group size is larger. The reason is that our design takes into consideration of the social relationship (altruism) between group members.

2) Impact of Social Activeness of Group Members: We evaluate the impact of social activeness of group members, in terms of the average number of microblogs posted by them. We divide the number into three ranges: (0, 50), (50, 100), and $(100, \infty)$. The results are shown in Fig. 8: in all the three ranges, our solution outperforms the other three group recommendation strategies. The reason is that in our design, preferences of group members not are inferred according to users' historical behaviors, which is used in the other approaches, but are learnt from the preferences of the external experts; while external experts are generally active users in the online social networks.

3) Effectiveness of the Tolerance and Altruism Model: Next, we study the effectiveness of the tolerance and altruism models. To evaluate the effect of tolerance compensation, users are asked

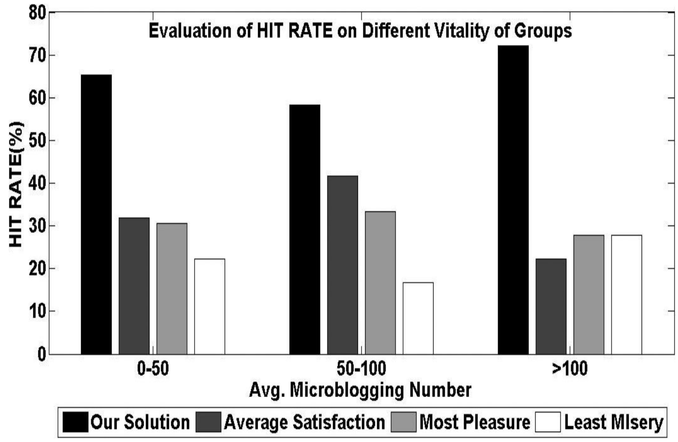

Fig. 8. Hit rates under different social activity of external experts.

TABLE VI
AD-SCORE FOR DIFFERENT GROUP RECOMMENDATION ALGORITHMS

Groups	Our algorithm	TC-TKI	AV	LM	MP
$[0, 0.15)$	21.36	18.36	24.42	27.75	27.39
$[0.15, 0.3)$	16.24	16.67	20.54	29.67	25.63
$[0.3, 0.5]$	27.45	29.29	42.88	48.71	49.55

TABLE VII
HIT RATE OF DIFFERENT GROUP RECOMMENDATION ALGORITHMS

Group	Our algorithm	TC-TKI	AV	LM	MP
$[0, 0.15)$	55.91%	65.05%	58.60%	54.30%	55.38%
$[0.15, 0.3)$	61.90%	67.65%	60.00%	45.71%	52.38%
$[0.3, 0.5]$	58.33%	63.89%	38.89%	36.11%	36.11%

to choose one or two friends who know each other, to form a group and choose the top-3 videos they are willing to watch together from the ones recommended to the group. We calculate tolerance differences between each pair of group members, and they all fall into the interval of [0, 0.5]. We divide the interval into 3 ranges [0, 0.15], [0.15, 0.3], and [0.3, 0.5], and calculate the AD-score using the previous calculation for groups who fall into each range.

Results shown in Table VI indicate that our method outperforms the other three approaches. For groups in the range [0, 0.15] in which users have relatively similar tolerance degrees, our method can still improve recommendation satisfaction. With the increase of tolerance difference, advantage of our methods becomes more obvious. The tolerance model in our design actually works for group recommendation.

To compare absolute accuracy among different methods which users concern the most, we calculate the hit rate of top-10 videos recommended by each method. Result shown in Table VII indicates that our methods have a higher hit rate overall and the performance improvement is higher with tolerance differences, which further verifies that our method can provide a high overall satisfaction as well as provide better preference balance.

VII. CONCLUSION

In this paper, we propose a social-aware group recommendation approach that jointly considers group-level interest and individual personality. We propose the group preference model based on external experts, and a social-aware tolerance and altruism model to capture the personality of group members, based on social behaviors. Subjective experiments show that our design achieves significantly better performance in situations of high group dynamics and inactive group members than traditional methods under different group sizes. In particular, the social-aware tolerance and altruism model for group recommendation is effective when social relationship exists between group members. In our design, though we only use information that can be collected from public services (e.g., Weibo, Twitter), such information can be sensitive when being used in a collaborative manner. In our future work, we are willing to investigate whether our approach still works if only partial information is used in our algorithms.

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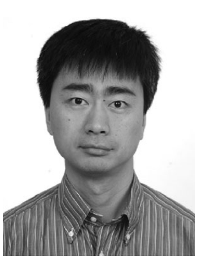

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