Group Recommendation using Feature Space Representing Behavioral Tendency and Power Balance among Members

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ABSTRACT

This paper proposes an algorithm to estimate appropriate or novel content for groups of people who know each other such as friends, couples, and families. To achieve high recommendation accuracy, we focus on "Groupality", the entity or entities that characterize groups such as the tendency of content selection and the relationships among group members. Our algorithm calculates recommendation scores using a feature space that consists of the behavioral tendency of a group and the power balance among group members based on individual preference and the behavioral history of group. After gathering the behavioral history of subject groups when watching TV, we verify that our proposed algorithm can recommend appropriate content, and find novel content. Evaluations show that our proposal achieves higher performance than existing methods.

Categories and Subject Descriptors

H.3.3 [**INFORMATION STORAGE AND RETRIEVAL**]: Information Search and Retrieval

General Terms

Algorithms,Experimentation

Keywords

content recommendation, group recommendation, recommender system, rating estimation, novelty

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1. INTRODUCTION

The rise of the web service such as video hosting service and e-commerce service has increased the number of content accessed all around the world. The increased amount of content has made it difficult for users to find interesting content, and has stimulated the demand for appropriate content recommender systems.

Recommender systems are one of the most popular research fields. Adomavicius classified recommendation methods into three categories: content-based, collaborative, and hybrid recommendation algorithms [1]. Content-based methods extract the appropriate content for the user based on similarity to the contents indicated by user preference. Collaborative methods recommend the content highly rated by other users who share the target user's preferences. Hybrid methods combine content-based and collaborative methods. These recommendation methods attempt to identify what the user is expected to find interesting.

Most recommendation algorithms, including the above mentioned methods, were designed for individuals [2, 3, 4]. However, recommendation systems should also provide content for groups of people. For example, video content is often watched by constant groups of people sitting together in the home, such as friends, couples, and families. Such recommendations are rather more complicated than those for the single user, and appropriate recommendation strategies are needed. For example, in the case of the single user, the recommendation usually tracks the order of content rating. However, in the case of a group, the aggregate preference of the group is diverse and depends on the group's characterizer. To solve such problems, we propose here an algorithm that enables the appropriate or novel content to be recommended to groups of people.

The rest of this paper is organized as follows. Section II describes previous strategies and algorithms relevant to the field of group recommendation. Section III presents our algorithm to estimate appropriate or novel content for groups of people. Section IV provides an evaluation of TV content recommendations. Finally, Section V concludes this paper.

2. RELATED WORKS

Group recommendation strategies fall into two categories.

Strategy 1 Virtual User Strategy

Strategy 2 Merging Strategy

The Virtual User Strategy assumes that a single virtual user can represent the group. For example, this strategy recommends content based on the behavioral history of the virtual user, such as video content watched together. Therefore, this strategy makes it possible to create recommendations by using the same algorithms used for individual recommendations. However, Yu pointed out that the Virtual User Strategy has a long initialization period because it requires the group to store a significant amount of shared history [5].

The Merging Strategy can be implemented in two ways. The first creates the recommendation list from the merged profiles of each group member, such as individual ratings for content or genre. The second generates a recommended content list by merging the results of individual recommendations. Masthoff researched how humans in a group select a sequence of items, and concluded that, in terms of group satisfaction, disagreeable experiences are perceived as outweighing possible pleasurable ones [6]. This conclusion was validated in an experiment by O'Conner in which a method that averaged individual ratings was compared to one that avoided individual misery [7]. Amer-Yahia also asserted that the score reflecting the level at which members disagree with each other impacts the quality and efficiency of group recommendation [8]. Jameson introduced another approach; it selects content with high average scores and low standard deviation to satisfy the group [9]. Goren-Bar [10] applied the weighted average approach to the watching time data to create recommendations for families, and Yu [5] and Shin [11] calculated recommendation scores from the weighted average of common user ratings and merged individual user ratings. Yu [5] and Berkovsky [12] verified that the approach of merging individual profiles is superior to the one that merges recommendation results.

Our basic idea is that the optimum algorithm for group recommendation is dependent on the characteristic of the group. Satelo suggested the idea changing the strategy to reflect the characteristic of the group [13]. Unfortunately, he offered only two classes of groups: Homogeneous Group (members have similar demographic profiles such as friends), and Heterogeneous Group (members have different demographic profiles such as families). We consider that group members have diverse and complex relationships.

To implement our idea, we proposed a method based on the Power Balance Map [14]. The Power Balance Map is the distribution of Shared History (ex. the history of video content watched together) of each member's rating map. Fig.1 shows Power Balance Map examples for a group consisting of user A and user B. The diamond plots in Fig.1 indicate shared video content, i.e. watched together. The horizontal axis denotes the rating score of user A, and the vertical axis denotes that of user B. We assert that the high-density area on the Power Balance Map indicates the characteristic of the group, and that the content near to or within the high-density area is appropriate content for the group. For example, the group characteristic for Map No.1 in Fig.3 reflects user AâĂŹs priority over user B. The characteristic for

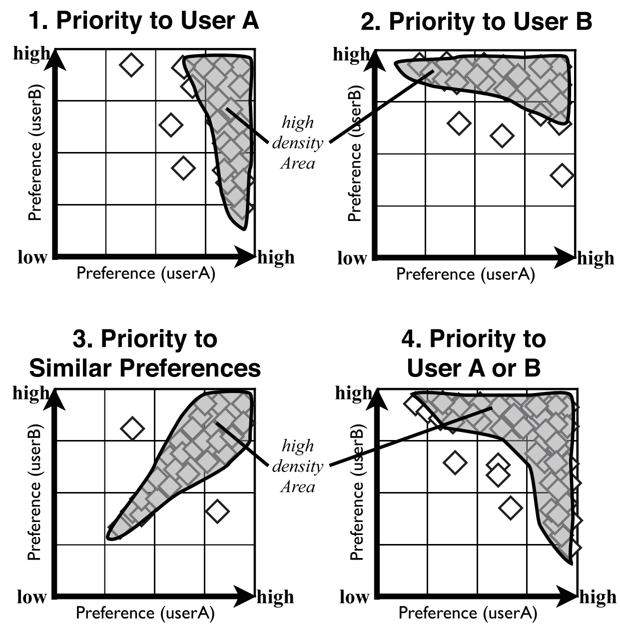

Figure 1: Power Balance Map examples for user A and user B.

Map No.2 in Fig.3 indicates the opposite. Map No.3 indicates that users A and B tend to select the content of similar preferences. The content selection predicated on Map No.4 satisfies the preferences of at least one of the members. Using the Power Balance Map, a recommender system can recommend appropriate content for a group regardless of its characteristic. We have validated the effectiveness of group recommendation, and discovered that our algorithm may help to find novel content.

Our previously proposed method ignores content details when calculating recommendation scores. Therefore, two contents that occupy the same point on the Power Balance Map are given the same recommendation score even if they are dissimilar (ex. different genres). For this reason, our method succeeded in finding novel content for groups, but also picked up inappropriate content. To solve this problem and improve recommendation accuracy, our latest proposal enhances the Power Balance Map with content details. Content details, such as genre frequency, allow the group recommender system to differentiate the two contents in the above case. There is some risk that the group recommender system will become less able to suggest novel content. Therefore, it is necessary to reduce this risk and improve recommendation accuracy.

3. PROPOSED METHOD

Fig.2 shows the flow chart of our recommendation strategy. At first, the proposed strategy calculates each genre frequency based on the behavioral history of the group, and creates a Power Balance Map using ratings lists of the individuals for content genres and the behavioral history. This algorithm uses the ratings lists, genre frequency, and Power Balance Map to calculate a recommendation score for each new content. By adding the genre frequency axis to the Power Balance Map, we assert that the resulting recom-

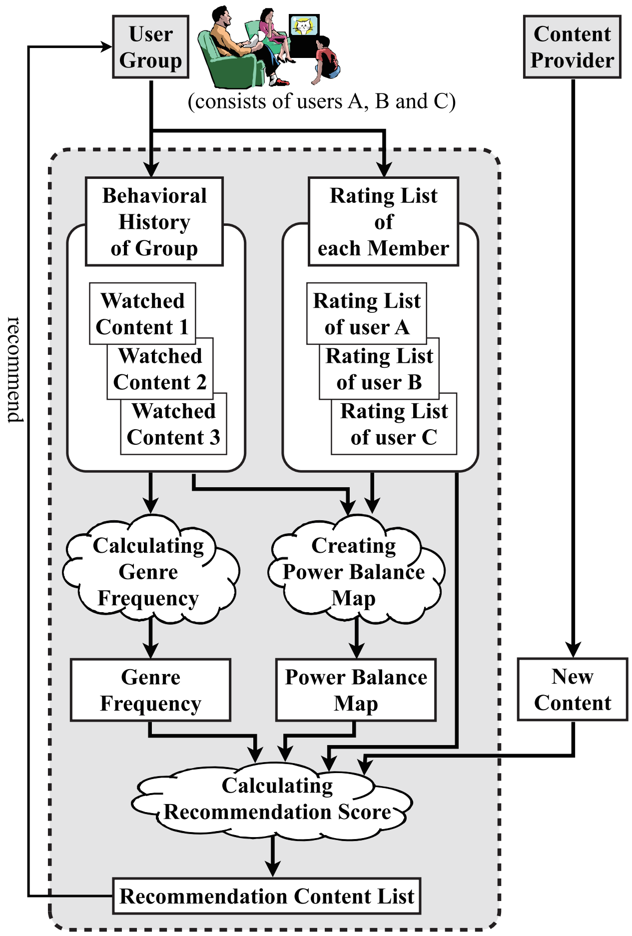

Figure 2: System flow of our new recommendation strategy; merging Power Balance Map with content details.

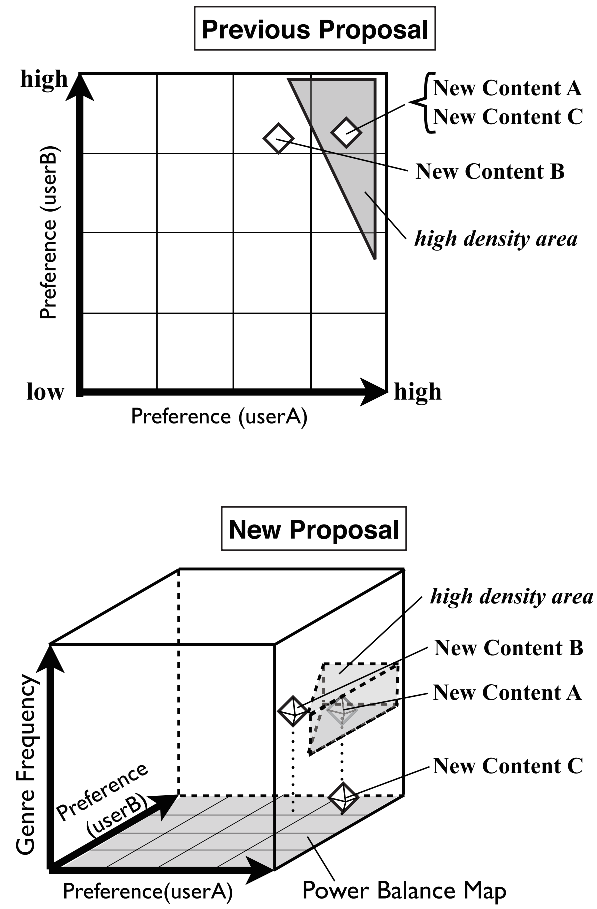

Figure 3: The difference between previous proposal and new one.

mender system achieves the above requirement. Fig.3 shows the difference between our two proposals. Assuming that each new content has a different genre, the previous proposal may plot new contents, A and C, at the same map point, seen Fig.3 . This means that it may recommend inappropriate content. On the other hand, the new proposal can differentiate content A from C by plotting the latter outside the high density area since it is considered inappropriate for the group. Therefore, we assert that this method retains the merits of Power Balance Map while pruning inappropriate content.

In our previous paper [14], we proposed an algorithm for group recommendation based on the Power Balance Map which was generated from the preferences of each member and shared history. However, we only briefly described how to create these maps. Therefore, this section details how to create the Power Balance Map, and then proposes the enhanced Power Balance Map with behavioral tendency of the group based on genre frequency.

3.1 Algorithm to create Power Balance Map

In order to create the Power Balance Map, we use individual preferences for content genre and watched content shared together. At first, our system determines the rating of each watched content using the content genre rating list of each member. Table 1 shows a sample of the content genre rating lists of user A and user B. Our system creates this list by asking each member to rate content genre via a GUI or applying a recommendation algorithm to the individual behavioral histories of the individual users [15, 16]. If the watched content has more than 2 genres, the rating for the watched content is equal to the average value of the ratings for these genres. Assuming that n is the number of genres that cover content c and $r_{i,g}$ is the rating score ascribed to member i for genre g, the rating of member i for content c ($u_{i,c}$) is defined by Equation (1):

$$u_{i,c} = \frac{1}{n}\sum_{k=1}^{n} r_{i,k} \tag{1}$$

Moreover, the system creates the rating vector to plot the watched content on the space which has each member's rating dimension. The rating vector is a multidimensional vector composed of the rating of the content by each member. Assuming that m is the number of group members, the rating vector of content c is given by Equation (2):

$$\boldsymbol{V_c} = \{u_{1,c}, u_{2,c}, \cdots, u_{m,c}\} \tag{2}$$

Table 1: Sample of rating lists for content genres

Genre	User A Rating	User B Rating
News	5	3
Sports	5	1
TalkShow	3	4
Variety	2	4
Baseball	5	1
Comedy	3	3

For instance, assuming that there are 2 users (user A and B), genre ratings are shown in Table 1 ; content c has News and Sports genre. In that case, the rating vector of the group (consisting of user A and B) for content c is:

$$\begin{aligned} \boldsymbol{V_c} &= \{\frac{r_{A,News} + r_{A,Sports}}{2}, \frac{r_{B,News} + r_{B,Sports}}{2}\} \\ &= \{\frac{5+5}{2}, \frac{3+1}{2}\} \\ &= \{5, 2\} \end{aligned}$$

Our system plots the watched content upon the space which has each member's rating dimension based on the rating vector. By repeating this process for all watched content shared together, the system finishes to create the Power Balance Map.

3.2 New recommendation method enhanced Power Balance Map

The system proposed in our previous paper [14] calculated the recommendation score of a new content from the similarity between the rating vector of the new content and the vector of all watched content on the Power Balance Map. In this paper, we propose a new method that uses the behavioral tendency of the group to enhance the Power Balance Map and thus achieve higher recommendation accuracy. Our new proposal adds a dimension axis representing behavioral tendency to the Power Balance Map. We assert that group recommender systems that use the space that holds each member's preference dimension and behavioral tendency dimension will make it possible to recommend appropriate content to a group and to find novel content. The following list describes the process of implementing the new proposal.

In order to add the dimension axis of the group's behavioral tendency to the Power Balance Map, our system estimates the behavioral tendency score. This score is determined from the frequency of meta data, such as genre, present in the group's behavioral history. Assuming that n is the total number of watched content and m is the number of genres present in the watched content, frequency GF_i of genre G_i is defined by Equation (3):

$$GF_i = \sum_{k=1}^{n} \frac{exst(C_k, G_i)}{m} \tag{3}$$

$$exst(C, G) = \begin{cases} 1 & \text{(if content C has genre G)} \\ 0 & \text{(if content C does not have genre G)} \end{cases}$$

Moreover, the system computes the behavioral tendency score for new content. This score is calculated based on the meta data(genres) present in the new content and the genre frequency. Assuming that m is the number of genre present in the new content, the behavioral tendency score, BS_i, of content i is denoted by Equation (4):

$$BS_i = \frac{1}{m} \sum_{k=1}^{m} GF_k \tag{4}$$

Consider the example of 2 watched contents and 4 new contents, where the contents have the genres shown in Table 2 . In that case, each genre frequency (GF_i) and each behavioral tendency score (BS_i) are as follows:

$$\begin{aligned} GF_{News} &= \frac{1}{2} + \frac{1}{3} = \frac{5}{6} \\ GF_{Sports} &= \frac{1}{2} \\ GF_{TalkShow} &= \frac{1}{3} \\ GF_{Variety} &= \frac{1}{3} \\ GF_{Baseball} &= 0 \\ GF_{Comedy} &= 0 \\ GF_{Drama} &= 0 \\ GF_{Mystery} &= 0 \\ GF_{Documentary} &= 0 \\ GF_{Travel} &= 0 \end{aligned}$$

$$\begin{aligned} BS_\alpha &= \frac{1}{2}(GF_{Sports} + GF_{Baseball}) \\ &= \frac{1}{2}(\frac{1}{2} + 0) \\ &= \frac{1}{4} = 0.25 \\ BS_\beta &= \frac{1}{2}(GF_{Comedy} + GF_{TalkShow}) \\ &= \frac{1}{2}(0 + \frac{1}{3}) \\ &= \frac{1}{6} \simeq 0.1667 \\ BS_\gamma &= \frac{1}{2}(GF_{Drama} + GF_{Mystery}) \\ &= \frac{1}{2}(0 + 0) \\ &= 0 \\ BS_\delta &= \frac{1}{3}(GF_{News} + GF_{Documentary} + GF_{Travel}) \\ &= \frac{1}{3}(\frac{5}{6} + 0 + 0) \\ &= \frac{5}{18} \simeq 0.2778 \end{aligned}$$

Second, in order to recommend appropriate or novel content for the group, our system calculates the recommendation score for each new content. Plotting the new content on the space formed by adding the behavioral tendency dimension to the Power Balance Map, the system extends the rating vector of each content to include the behavioral tendency score. For convenience, we call this vector the "Groupality Vector". To calculate the recommendation score of a new

Table 2: Sample of content with genres

	Genre 1	Genre 2	Genre 3
watched content 1	News	Sports	-
watched content 2	News	Talk Show	Variety
new content α	Sports	Baseball	-
new content β	Comedy	Talk Show	-
new content γ	Drama	Mystery	-
new content δ	News	Documentary	Travel

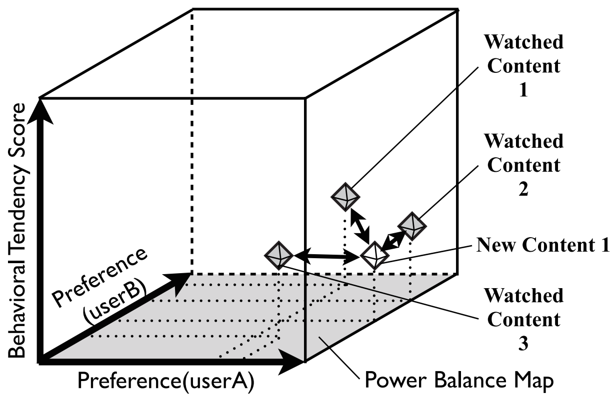

Figure 4: The method used to calculate similarity level between a new content and each watched content in the space.

content, the system computes the Similarity Level between the Groupality Vector of the new content and the Groupality Vector of each watched content in the space. Fig.4 shows the Euclidean Distance-based method used to calculate the Similarity Level between the Groupality Vector of a new content and each watched content. The similarity level $sim(\boldsymbol{V_c},\boldsymbol{V_h})$ between the Groupality Vector of the new content $\boldsymbol{V_c}$ and watched content $\boldsymbol{V_h}$ is given by Equation (5):

$$sim(\boldsymbol{V_c},\boldsymbol{V_h}) = \frac{1}{1+n\|\boldsymbol{V_c}\boldsymbol{V_h}\|^x} \tag{5}$$

$$n, x := \text{parameter for adjustment}$$

Parameters n and x are defined according to applications or services. The larger the parameters are, the smaller the similarity score of distant content becomes. For example, given $n = 3$ and $x = 2$, the similarity score of the Euclidean Distance between content greater than 1 become under 0.1. Therefore, parameters n and x are like the threshold of similarity.

In calculating the recommendation score shown in Equation (5), our proposal system normalizes each axis(user A preference, user B preference and behavioral tendency score) based on Probability Density Function [17] (Equation (6));

$$P(a < X < x) = \int_{-\infty}^{x} f(t)dt \tag{6}$$

In this paper, the system adapts the normal distribution as function f. Hence, Equation (7) replaces $f(t)$ in Equation (6) for normalization.

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{7}$$

$$\mu := \text{average of the preference score unit}$$

$$\sigma := \text{standard deviation of the preference score unit}$$

For instance, given the users' preference scores shown in Table 1 , the normalized value of user A's rating for "Talk-Show" genre ($nr_{A,TalkShow}$) and that of user B ($nr_{B,TalkShow}$) are:

$$\begin{aligned} nr_{A,TalkShow} &= \int_{-\infty}^{3} \frac{1}{\sqrt{2\pi}\sigma_A} \exp\left(-\frac{(x-\mu_A)^2}{2\sigma_A^2}\right) dx \\ &\simeq 0.2461 \\ (\mu_A &\simeq 3.8333, \sigma_A \simeq 1.2134) \end{aligned}$$

$$\begin{aligned} nr_{B,TalkShow} &= \int_{-\infty}^{4} \frac{1}{\sqrt{2\pi}\sigma_B} \exp\left(-\frac{(x-\mu_B)^2}{2\sigma_B^2}\right) dx \\ &\simeq 0.8575 \\ (\mu_B &\simeq 2.6667, \sigma_B \simeq 1.2472) \end{aligned}$$

Therefore, the normalized Rating Vector for "TalkShow" genre is $\{0.2461, 0.8575\}$. In normalizing the Behavioral Tendency Score, our system calculates the normalized value in the same way. The system creates the normalized Groupality Vector ($\boldsymbol{NV}$ by merging the normalized Rating Vector and normalized Behavioral Tendency Score).

Finally, the system sums the similarity levels $sim(\boldsymbol{NV_c},\boldsymbol{NV_h})$ for all watched content to determine the recommendation score. The recommendation score, S_c, of the new content, c, is given by Equation (8).

$$S_c = \sum_{i=1}^{m} sim(\boldsymbol{NV_c},\boldsymbol{NV_{h_i}}) \tag{8}$$

(m is number of watched content.)

By repeating this process for all new contents, the system can rank and thus recommend suitable content. If S_c, the recommendation score of $\boldsymbol{NV_c}$, indicates ranking in the top-K of the new content set, we judge that the new content is suitable for the group. If the group watches different content, the recommendation scores are recalculated. In other words, our system can recommend more appropriate or novel content to the group as they watch more content.

4. EVALUATION

In order to verify the validity of our approach, we analyzed the watching TV program history of three subject groups (Japanese, married couples) for a roughly one month period. The couples live in the same broadcast area and are able to spend similar amounts of time on watching TV programs. One couple has a 2 year old child, the others have no children. In this experiment, the history consisted of just the content watched together. Details of the experiment are omitted in the following subsections.

4.1 Data set

In order to create the feature space consisting of each group's behavioral tendency and power balance map, we gathered three data sets; Individual Rating, Viewing History, and TV Program Data.

Individual Rating: Individual Rating is the preference score of an individual subject for each TV genre. In this experiment, we asked each individual subject to rate 104 genres using a 5 grade scale; grade 1: strongly dislike, grade 2: dislike, grade 3: neutral, grade 4: like and grade 5: strongly like. Considered that recommender systems should be practical, we used the 104 genres which the existing TV program table service site [1] defined.

Viewing History: The Viewing History consisted of the TV programs the group watched together. When watching a TV program together, they recorded the TV program title. The number of Viewing History entries gathered over the term of the experiment was 176, 76, 61 programs for the three groups.

TV Program Data: The TV program data included some meta data about the broadcast TV programs. The data consisted of Program Title, Abstract, Start Time, End Time, Channel Name and at least a Genre Tag. We gathered 12,234 pieces of TV Program Data over a 5 week period. Each TV program was tagged "watched" or "unwatched" for each subject group.

4.2 Evaluation Metrics

We used two evaluation metrics to validate proposal effectiveness in terms of group recommendations. One is the accuracy with which the appropriate TV programs were recommended to the subject groups, called "Appropriate Precision". The other one targets the recommendation of interesting but unknown content, called "Novelty Precision". Precision is one of the most typical evaluation metrics for information retrieval systems [18]. A lot of recommender systems have used this metrics for evaluating recommendation accuracy [19, 20]. We gathered 763 TV programs to verify our recommendation accuracy. Each subject group tagged each of these TV programs as either appropriate or inappropriate. The following list describes the process used to calculate each precision metric.

4.2.1 Appropriate Precision

To evaluate the effectiveness of group recommendations, we measured the accuracy with which the appropriate TV programs were recommended to the subject groups, called Appropriate Precision. Appropriate Precision is the percentage of recommended appropriate TV programs from among all recommended TV programs. Appropriate Programs were annotated by each subject group. In the case of Fig.5 , Appropriate Precision is defined by Equation (9):

$$\text{Appropriate Precision} = \frac{R \cap A}{R} \tag{9}$$

4.2.2 Novelty Precision

Recently, several researchers have asserted that recommendation systems should be able to find appropriate and interesting content for users. Herlocker suggests that recommendation systems should achieve not only high accuracy,

[1]http://tv.so-net.ne.jp/ (in Japanese)

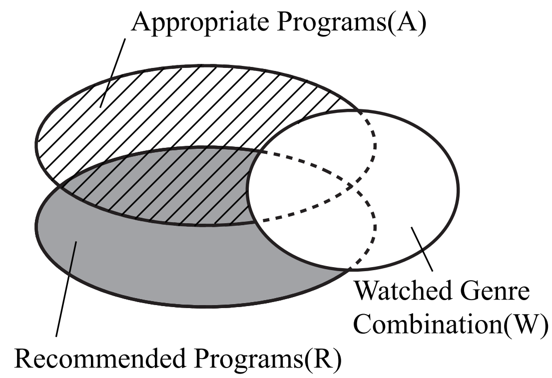

Figure 5: Venn diagram to explain each precision metric

but also usefulness [21]. As usefulness factors, he introduced the terms Novelty and Serendipity. Novelty or Serendipity means interesting but unknown to the user. We think that both are extremely important since known content cannot increase user satisfaction even if the content is appropriate for the user. Thus, we evaluated the proposal's ability to find novel content by calculating "Novelty Precision". In this paper, we define "unknown" as genre combinations that have yet to be watched. Therefore, Novelty Precision is the percentage of Recommended Appropriate Programs in not the Viewing History Genre from among all recommended programs not in the Viewing History Genre. In the case of Fig.5 , Novelty Precision is defined by Equation (10):

$$\text{Novelty Precision} = \frac{R \cap A \cap W^c}{R \cap W^c} \tag{10}$$

4.3 Baseline Methods

To verify the superiority of the proposed algorithm, we compared it against three algorithms for group recommendation.

1. Weighted Average Method
2. Virtual User Method
3. Old Proposed Method

The Weighted Average Method recommends content using the rating scores yielded by merging the individual ratings. This method is a very popular for group recommendations based on Merging Strategy. We implemented the algorithm following Yu's proposal [5]. Yu's algorithm improves recommendation accuracy by adjusting the rating distribution among members by weight normalization. Therefore, this algorithm surpasses simple merging algorithms, such as judging that content with high average rating will most satisfy the group.

The Virtual User Method considers the group to be "a single virtual user" and estimates the content preference of this user. In this experiment, this method estimated the content preference from the frequency with which each TV genre was watched. This algorithm is defined as the above mentioned Equation (4). In other words, this method makes recommendations from only the Behavioral Tendency Score axis of our proposed method.

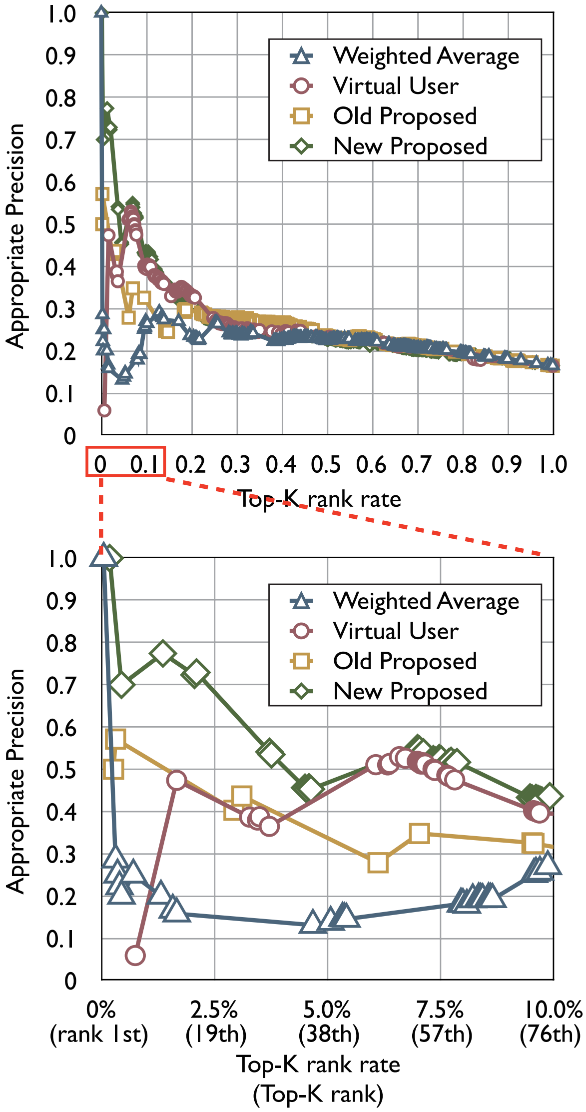

Figure 6: Overall Appropriate Precision.

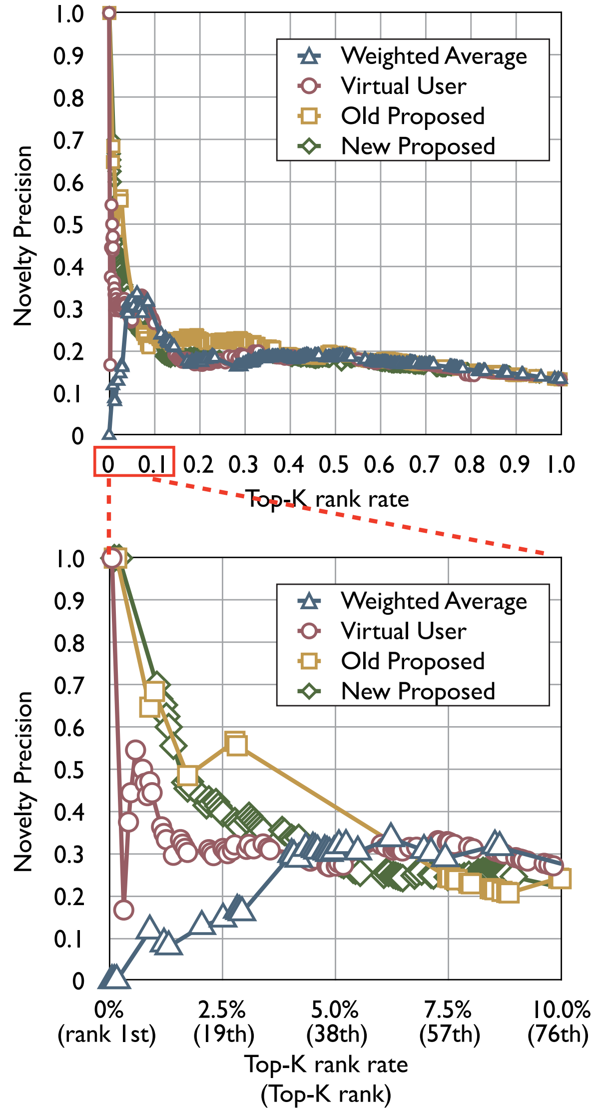

Figure 7: Overall Novelty Precision.

The Old Proposed Method [14] calculates the recommendation score based on the Power Balance Map. That is, this method uses the algorithm described Section 3.1.

4.4 Results and Analysis

Fig.6 plots the overall Appropriate Precision of the Weighted Average method, Virtual User method, Old Proposed Method, and New Proposed method. The upper graph overviews each of the results, and the lower one shows the precision for the top 76 (top 10%) recommendations. The horizontal axis plots the top-K rank, and the vertical axis the Appropriate Precision. This graph shows that the New Proposed method has higher precision than the others. We assert that the New Proposed Method has the merits of both the Weighted Average and the Virtual User Method: one is the feature of assigning the top rank to appropriate TV programs; The other one is achieving high accuracy in the top 20 programs. The Old Proposed Method also has these two merits, but not to the same extent. In other words, enhancing the Power Balance Map with the group's Behavioral Tendency is effective.

Fig.7 shows overall Novelty Precision of the 4 methods. The axes are the same as for the Appropriate Precision graphs (Fig.6). According to this graph, the Old and New Proposed Methods offer, within the top 38 programs (top 5%), high precision compared to the other methods. Comparing the Old Proposed Method to the New Proposed Method, the latter is similar to the former within the top 10 programs. This result indicates that enhancing the Power Balance Map with the group's Behavioral Tendency can also find novel content.

Given the results of Appropriate Precision and Novelty Precision, we assert that the New Proposed Method can recommend more appropriate content than the baseline methods, and has potential for finding novel content similar to the Old Proposed Methods. However, the New Proposed Method can, while retaining the merits of Power Balance Map, prune inappropriate content.

5. CONCLUSION

In this paper, we proposed an algorithm to recommend appropriate and novel content to groups of people; it is based on the Power Balance Map and the Behavioral Tendency of each group. Our algorithm recommends new content in or near high-density areas on the group's feature space which consists of selection tendency with genre frequency and power balance among group members. In order to verify the proposed algorithm, we gathered Individual Ratings for 104 TV genres and Viewing History for one month from three groups (Japanese couples and a family). Using these real data sets, we calculated Appropriate Precision and Novelty Precision to validate the effectiveness of our group recommendation proposal. The results gathered from the three subject groups showed that the Proposed Method offered higher Appropriate Precision than two popular methods and our old proposed method. The results also indicated that the Proposed Method has the potential for finding novel content similar to our old proposed method. Therefore, our algorithm can recommend appropriate and novel content to groups of people.

As future work, we plan to validate the case of groups with over 3 members. Moreover, in order to improve recommendation accuracy and find novel or serendipitous content, we will analyze group recommendations using group spaces based on other features (Actor, Director, Mood etc.).

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