韓國經營科學會誌
第32권 第4號
2007年 12月

Group Recommender System을 위한 구성원 합의 도출 함수에 관한 연구

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Toward Socially Agreeable Aggregate Functions for Group Recommender Systems

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■ Abstract ■

In ubiquitous computing, shared environments are required to adapt to people intelligently. Based on information about user preferences, the shared environments should be adjusted so that all users in a group are satisfied as possible. Although many group recommender systems have been proposed to obtain this purpose, they only consider average and misery. However, a broad range of philosophical approaches suggest that high inequality reduces social agreeability, and consequently causes users' dissatisfactions. In this paper, we propose social welfare functions, which consider inequalities in users' preferences, as alternative aggregation functions to achieve a social agreeability. Using an example in a previous work[7], we demonstrate the effectiveness of proposed welfare functions as socially agreeable aggregate functions in group recommender systems.

Keyword : Group Recommender, Recommender Systems, Ubiquitous, Social Welfare Function

논문접수일 : 2007년 02월 07일 논문게재확정일 : 2007년 11월 06일
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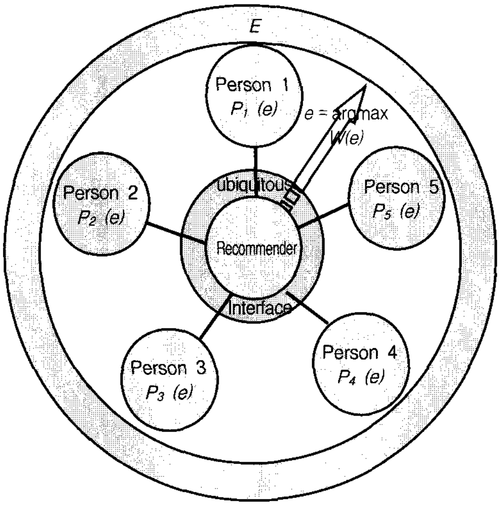
1. Introduction

Ubiquitous computing is a vision that our natural surroundings will adapt to people by autonomous interactions between invisible embedded computers[19]. Such intelligent environments are being realized as a result of the miniaturization of electronic devices, the increase of connectivity, and the decrease of cost. One important application area of the ubiquitous computing technologies is the recommender systems which attempt to predict items that a user or a group of users may be interested in, based on some information collected from users. The tedious and time-consuming preference elicitation process of current recommender systems can be mediated by the ubiquitous computers. A user's preference model would be available at current time without any significant effort by the user. When a user is approaching to access points of a particular system, his/her preference model can be transferred to and managed by a recommender system [17].

In ubiquitous computing environments, many of the items are often used by groups rather than by individuals. For example, in MusicFX [9], people in a fitness center at any given time listen the same music while working out. Based on individual music preferences MusicFX selects a music genre to maximize the satisfaction of the people as a group. Similarly, in many ubiquitous computing applications such as Interactive Workspaces at Stanford University (iROOM) and BlueBoards at IBM [14, 17], a need for adjusting the preferences of people currently participating in those applications arises. One possible solution for the accommodation of individual preferences is group recommender system. During the past few years several group recommender systems have been designed for diverse items such as movie, music, and travel course. These research efforts can be classified into the two following approaches[21] : merging recommendations and merging user profiles. In the first approach[1, 12], firstly individual recommendation lists are generated for each user and these recommendation lists are aggregated as a common recommendation list for the group. While, the merging user profile approach[7, 21] merges all users profile to create a common user profile. Then, a common recommendation list is generated based on the common profile. Regardless of the approaches, one obvious functionality of group recommender systems is to find a compromise acceptable to all the group members. For this functionality, appropriate aggregation functions should be defined to transform individual preference models to a group preference model. The aggregation function is an essential component of any group recommender systems and is an area of research we have investigated in this article.

The notion of the aggregate function is shown in [Figure 1]. A set $K = \{a : a \in K\}$ of individuals exist and an agent represents each individual with the knowledge of the individual's preferences $P_a(e)$ for the alternative items. The recommender system is responsible to choose one of a set $E = \{e : e \in E\}$ of items such that the value of a certain aggregate function $W(e) = f[P(e)]$, where $P(e) = \{P_a(e) : a \in K\}$, is maximized.

One can imagine diverse forms of the aggregate function. However, in spite of the diversity, there has been no thorough research to clearly define the goodness of possible aggregate functions, though many functions have been already deployed in group recommender systems. Our argument here is that the aggregate functions should be consistent with the opinions of the people. Since the basic objective of group recommender systems is to suggest a solution that is agreed by all the individuals, if a system uses an aggregate function that reflects social opinions, the resultant solution would be agreed also. Therefore, the goodness of an aggregation function can be evaluated via social agreeability.



[Figure 1] Group recommender system architecture. A recommender system coordinates the ubiquitous computers of individuals in order to determine a compromise based on individuals' preferences $P(e)=\{P_a(e): a \in K\}$.

However, the existing aggregate functions in literature are not capable of representing the social opinions. They do not take into account the inequality which is generally considered by people. Therefore, we apply so called social welfare functions designed in social sciences which explicitly take into account the inequality. Based on the experimental results found in literature, we prove their superiority to the existing functions with respect to the social agreeability and hence suggest considering the inequality in the group recommender systems. However, note that there is no function that is good independently of the context where the system is used. The culture of a society affects the penalty for inequality and hence the penalty varies from society to society. Moreover, the penalty depends on the nature of recommended items. For example, the recommended items can be used for short-term or long-term, and related to health or just pleasure. Researchers may want to move towards standardizing the context-dependent functions with richer and more effective functional forms provided in this article.

2. Aggregation Functions

Due to the lack of common consensus, the designers of group recommender systems have offered diverse alternative aggregation functions. <Table 1> shows a brief summary of representative strategies found in literature [7]. First, in Plurality voting strategy, each user votes for his or her most preferred alternative and the alternative with the most votes wins. To build a sequence of alternatives this method can be applied repetitively. Additive utilitarian strategy is based on the sum of preferences of each item. This strategy is used by Flytrap [3] which tries to satisfy musical tastes of the users in a room. Multiplicative utilitarian strategy is similar to the previous one except that the preferences are multiplied. In the case of Borda count strategy, each alternative earns points based on its rank in the user's preference list. The last ranked alternative gets zero point, the next one up one point, and so on. To build a group preference order, the points determined by users are added up and an alternative having the highest point is the best. This strategy is used by Movies2Go [11] which is a online movie recommender system. Next, Copeland rule strategy orders the alternatives according to the Copeland index that is the number of wins minus the number of losses in pairwise comparisons. For every pair of alternatives, one alternative that more half of users like wins and the other loses. Least misery strategy is based on the minimal of the preferences of each item. This strategy is used by PolyLens [12] for movie and Adaptive Radio [2] for music. Most pleasure strategy is a reverse version of the previous one. It is based on the maximal of the preferences. Average without misery strategy averages only the preferences over a predefined threshold. This strategy is used by MusicFx [10] which is a system for choosing music in fitness centers. Lastly, in Fairness strategy, each user chooses one item for group in turn. One user chooses first, then another, till everybody has made one choice. Next, everybody chooses a second item and this procedure continues till all alternatives have been chosen [18]. This strategy considers the fairness of rather choice opportunity than user satisfaction.

<Table 1> Aggregate functions in literature

Aggregate function	Recommender systems
Plurality voting strategy	--
Additive utilitarian strategy	Flytrap
Multiplicative utilitarian strategy	--
Borda count strategy	Movies2Go
Copeland rule strategy	--
Least misery strategy	Polylens, Adaptive Radio
Most pleasure strategy	--
Average without misery strategy	MusicFX
Fairness strategy	Market-based recommendations

3. Masthoff's Experiment

Though these recommender systems are adopting some strategies, there has been no investigation of the effectiveness of the different strategies. For the first time, Masthoff presented an interesting experiment to explore how real people make decisions for groups based on preference information of the group. In her experiment, 18 subjects participated and each subject was given the same individual preferences of three people, John, Adam, and Mary, for 10 video clips A~J as shown in <Table 2>. The subjects were asked to rank top 7 clips. The scenario presented was: "*John, Adam, and Mary are going to watch video clips together. We know how interested they are in the topics of the clips. Each clip is rated from 1 (really hate this topic) to 10 (really like this topic).*" Given <Table 2>, subjects were asked to rank the top 7 video clips which John, Adam, and Mary should watch as a group. <Table 3> lists the preference orders of 18 subjects. Note that this list gives 18 video

<Table 2> Experimental preference set(from [7])

	A	B	C	D	E	F	G	H	I	J
John	10	4	3	6	10	9	6	8	10	8
Adam	1	9	8	9	7	9	6	9	3	8
Mary	10	5	2	7	9	8	5	6	7	6

〈Table 3〉 The preference orders of 18 subjects (from [7])

	1	2	3	4	5	6	7	Unplaced
sub1	F	E	D	H	J	A	B	C or G or I
sub2	F	E	H	J	D	I	B	A or C or G
sub3	F	E	J	H	D	G	I	A or B or C
sub4	F	E	H	J	D	G	I	A or B or C
sub5	F	E	D	H	J	G	B	A or C or I
sub6	F	E	A	H	J	D	I	B or C or G
sub7	F	E	H	J	D	G	A	B or C or I
sub8	F	G	E	A	B	D	H	C or I or J
sub9	F	E	H	J or D		A	I	B or C or G
sub10	F	E	H	J	D	G	B	A or C or I
sub11	F	E	H	J	D	G	B	A or C or I
sub12	F	H	J	D	E	G	B	A or C or I
sub13	F	E	A	H	J	D	I	B or C or G
sub14	E	F	H	J	D	A	I	B or C or G
sub15	F	G	J	E	D	H	B	A or C or I
sub16	F	E	J	G	H	D	A	B or C or I
sub17	F	E	H	D	J	B	G	A or C or I
sub18	F	E	J	H	G	D	B	A or C or I

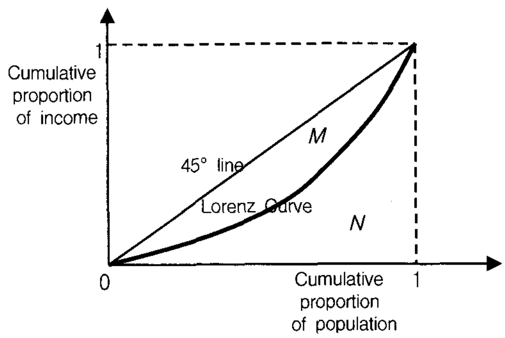
sequences, the subjects thought, John, Adam, and Mary should watch.

By comparing with 18 preference orders from subjects, this experiment accessed preference orders from several alternative strategies. The conclusion of the experiment was that there is no clearly dominant strategy, but Average, Average without Misery, and Least Misery are all plausible candidates. This conclusion explains why current recommender systems are adopting these three strategies. The designers are using some plausible strategies which are agreeable by themselves as well as users.

Another important observation was that there are many instances that subjects do not follow the Pareto rule. Five subjects broke the Pareto rule because, as some of them explained, a group is happy if everybody were equally happy or miserable. That is, people consider inequality in addition to average and misery, as an important consideration when they make decisions for groups. However, none of the strategies mentioned in section 2 consider this important property. The question is whether there exist some functions that take into account all the important properties simultaneously : average, misery, and inequality. If there exist such functions it would be possible to better represent social opinions and hence to provide designers with the effective way of aggregating.

4. Social Welfare Functions

In the social sciences such as economics or politics, there have been considerable efforts to define so called social welfare functions to compare the welfare between space and time. Average is still the most widely used welfare function despite its well-known shortcomings. However, a broad range of philosophical approaches suggest that high inequality reduces aggregate welfare. We describe several welfare functions



[Figure 2] Lorenz curve. It plots the cumulative proportion of income earned by the people ranked from bottom to top. As the degree of inequality increases, the area M between Lorenz curve and 45° line becomes larger that jointly consider average and inequality to arrive at better measures of welfare than average alone.

Sen welfare function [15], $\overline{P}(e)(1-I_G(e))$, has a simple form of weighting the average $\overline{P}(e)$ by Gini index $I_G(e)$. The Gini index is one of the most commonly used indicators of income inequality. It is derived from Lorenz curve, which plots the cumulative proportion of income earned by the people ranked from bottom to top as shown in [Figure 2]. In perfect equality the Lorenz curve follows 45° line. As the degree of inequality increases, the area between the curve and 45° line becomes larger. If the area between the curve and 45° line is M, and the whole area below 45° line is N, then the Gini index is computed as $M/(M+N)$. Dagum welfare function [4], $\overline{p}(e)(1-I_G(e))/((1+I_G(e))$, imposes more penalty for inequality on the Sen welfare function by the denominator.

Replacing Gini index with Atkinson index in Sen welfare function gives Atkinson welfare function [16]. The general form of Atkinson index is $I_{A(\varepsilon)}(e)=1-\left[\frac{1}{n}\sum_{a\in K}\left(\frac{P_a(e)}{\overline{P(e)}}\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}$, where ε is the so-called inequality aversion parameter and n number of people. The parameter ε reflects the strength of society's penalty for inequality, and can take values ranging from zero to infinity. When ε equals to zero, there is no penalty for inequality. As ε rises, society has more penalties for inequality. Note that when $\varepsilon = 1$, the general form of the Atkinson welfare function is not defined and the function is transformed into $e^{\frac{1}{n}\sum_{a\in K}\ln P_a(e)}$. Typically used values of ε include 1.5 and 2.5 [20]. Thus, we will evaluate the Atkinson welfare functions with ε = 1, 1.5, 2, and 2.5 in the experiment section.

The social welfare functions described above take into account all the three considerations: average, inequality, and misery, based on which people make decision for groups. Note that misery is implicitly considered in inequality indices. The inequality indices tend to assign more penalties to lower preferences. Since the welfare functions integrate all the considerations, they can be used as alternative aggregate functions that better represent social opinions compared to the current aggregate functions.

Here is an example to show how the social welfare functions can be used as aggregation function. In this example, we apply the Atkinson welfare function with $\varepsilon=2$ as an aggregate function. First, we calculate social welfares of John, Adam, and Mary for each item or alternative. In the case of the video clip A, we have the set of individuals' preferences, $P(A)$ = {10, 1, 10}, and the average of the preferences, $\overline{P}(A)$ = 7. Using these values, the Atkinson index is given by $I_{A(\varepsilon)}(A)=1-\left[\frac{1}{3}\times\left\{\left(\frac{10}{7}\right)^{-1}+\left(\frac{1}{7}\right)^{-1}+\left(\frac{10}{7}\right)^{-1}\right\}\right]^{-1}$ = 0.64. Accordingly, the social welfare of the group by the clip A is 7 × (1-0.643)

〈Table 4〉 The preference order by the Atkinson welfare function

	A	B	C	D	E	F	G	H	I	J
Social Welfare	2.50	5.35	3.13	7.13	8.48	8.64	5.63	7.45	5.21	7.20
Ranking	10	7	9	5	2	1	6	3	8	4

= 2.499. Similarly, we calculate social welfares of three users for other items and rank all the items as shown in <Table 4>. Finally, we have a preference order with 7 items, "FEHJDGB", by the Atkinson welfare function with $\varepsilon=2$.

5. Evaluation of Aggregate Functions

To evaluate aggregate functions, two metrics, satisfaction function and social agreeability, can be used. The satisfaction function is a direct measurement for how satisfied users are in a shared environment, while the social agreeability is devised to quantify the satisfaction of users with selected items in an indirect manner. The social agreeability assesses how satisfied, people outside think, users would be.

To measure individual's satisfaction, obviously it is more effective to use the satisfaction function. However, in evaluation of users' satisfactions as a group, little evidence exists for the effectiveness of the satisfaction function with respect to evaluation satisfactions of individuals as a group. In [7, 8], to evaluate the aggregate functions mentioned in Section 2, Masthoff performed an indirect experiment asking subjects pick what they thought actual users should watch instead of having an actual group sit down to decide what to watch. This previous work argues that this indirectness prevents experiment results from being biased to a specific individual and reduces effects of different individual tastes on experiment results. Thus, to discuss the effectiveness of our approach, we choose two satisfaction functions from [7] and propose a heuristic metric, called social agreeability, to capture the features of the indirect experiment.

5.1 Satisfaction Function

To measure how happy actual users are with preference orders by aggregate functions, we introduce the two simplest satisfaction functions from [7].[1)]

- Linear Addition without Normalization : summation of users' ratings for selected items. For example, John's satisfaction with a preference order FEHJD is 41 (10+9+8+8+6), while Adam and Mary's are 39 (9+7+9+8+9) and 36 (8+9+6+6+7). Thus, the satisfaction of John, Adam, and Mary with the preference order FEHJD is 116 (41+39+36).
- Linear Addition with Normalization : summation of users' normalized rating for selected items. A user's normalized rating is calculated by dividing the sum of ratings of selected items by the maximal 'possible' sum for the user. For instance, without considering Adam and Mary, John's maximum satisfaction with 5 items is 47 (10+10+10+9+8). The John's normalized satisfaction with FEHJD is 0.87 (41/47). Similarly, Adam and Mary's maximum satisfactions are 44 and 41. Their normalized satisfaction with FEHJD are 0.88 (39/44) and 0.87 (36/41). Finally, the normalized satisfaction of three users is 2.62 (0.87+0.88 +0.87).

5.2 Social Agreeability

As discussed earlier, an aggregate function

1) Even though other satisfaction functions are also available in the previous work, these functions do not make any different results in Section 6. Therefore, we do not consider the other satisfaction function in this presentation.

should be consistent with social opinions to be effectively used to group recommender systems. When the aggregate function corresponds to the human decision patterns, it is socially agreeable. To quantify the social agreeability of each alternative aggregate function, distance measures on preference orders can be used. We denote m as the number of alternative environments E and p as the number of subjects S. The rank of environment e from subject s and aggregate function w are denoted as $R_s(e)$ and $R_w(e)$. Note that unranked items are assigned the worst ranking, say 10, in this work. Lastly, $\delta_s(E)$ and $\delta_w(E)$ represent preference orders on the finite set E from subject s and aggregate function w respectively. Now, we introduce four well-known distance measures between two preference orders; Spearman's Footrule, Euclidean Distance, Spearman's Rank Correlation Coefficient (Spearman's rho), and Probabilistic Distance. According to the distance measures, the distance between two preference orders from each aggregate function w and subject s, called $D(\delta_s(E),\ \delta_w(E))$, is defined as :

- Spearman's Footrule [5] :

$$D(\delta_s(E),\ \delta_w(E)) = \frac{1}{2}\sum_{i \in E}|R_s(i) - R_w(i)|.$$

- Euclidean distance :

$$D(\delta_s(E),\ \delta_w(E)) = \sqrt{\sum_{i \in E}(R_s(i) - R_w(i))^2}$$

- Spearman's rho [13] :

$$D(\delta_s(E),\ \delta_w(E)) = 1 - \rho$$

$$where \qquad \rho = 1 \frac{6 \cdot \sum_{i \in E}}{m(m^2 - 1)}$$

- Probabilistic distance [6] :

$$D(\delta_s(E),\ \delta_w(E)) = \frac{2}{m(m-1)}$$

$$\sum_{1 \le i < j \le m} c_{\delta_s(E),\ \delta_w(E)}(i,\ j)$$

$$where\ c_{\delta_s(E),\ \delta_w(E)}(i,\ j) = \begin{cases} 1 \text{ if } R_s(i) \ne R_w(i) \\ 0\ otherwise \end{cases}.$$

In case of spearman's rho, since ρ is an indicator of how two orders are similar, the distance between the orders become $1-\rho$. The probabilistic distance is a probability that a uniformly and randomly chosen pair $(i,\ j)$ of E will cause a conflict between w and s. The social agreeability of an aggregate function w is represented in terms of average $AD(w)$ of the distance measure over the subjects as in (1). If an aggregate function gives a low average distance, the function can be considered socially agreeable.

$$AD(w) = \frac{\sum_{s \in S} D(\delta_s(E),\ \delta_w(E))}{p} \tag{1}$$

6. Numerical Results

This section gives numerical results to validate the effectiveness of social welfare function as aggregate function.

<Table 5> Alternative aggregate functions

	Aggregate function
w_1	Average
w_2	Least Misery Strategy
w_3	Average without Misery(threshold = 3)
w_4	Sen Welfare Function
w_5	Atkinson Welfare Function(ε = 1)
w_6	Atkinson Welfare Function(ε = 1.5)
w_7	Atkinson Welfare Function(ε = 2)
w_8	Atkinson Welfare Function(ε = 2.5)
w_9	Dagum Welfare Function

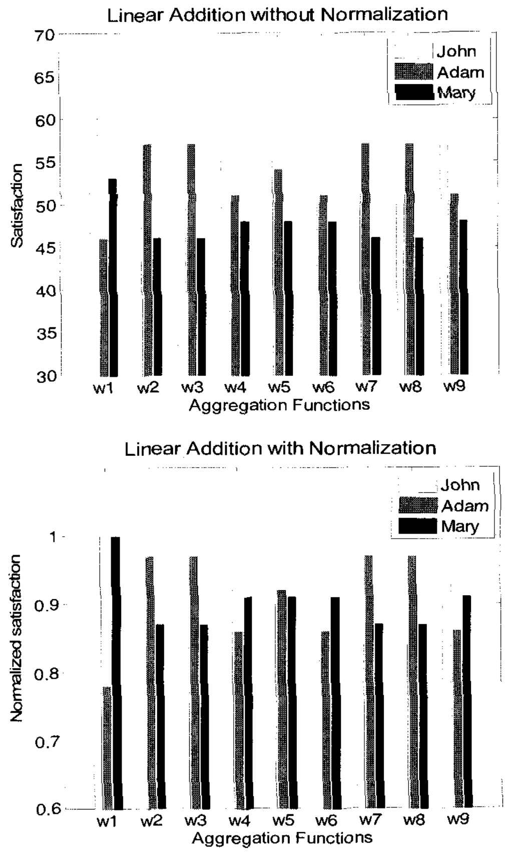
<Table 5> lists aggregate functions used in this experiment. In [7], Masthoff recommended Average, Average without Misery, and Least Misery as plausible candidates for implementation of aggregate function. Thus, the first three aggregate functions are extracted directly from [7] and others are social welfare functions mentioned earlier. <Table 6> summarizes preference orders generated by 9 aggregate functions in <Table 5>. While three existing aggregate functions fail to differentiate items with many ties, social welfare functions are able to distinguish the items certainly. This is an additional strong point of social welfare functions as aggregate functions. In many group recommender systems, indifference among alternatives requires a tie-breaking rule and makes the systems more complex [6].

〈Table 6〉 The preference orders by 9 aggregate functions

	1	2	3	4	5	6	7	Unplaced
w_1	F or E		H	D or J		A	I	B or C or G
w_2	F	E	D or H or J			G	B	A or C or I
w_3	F or E		H	D or J		B	G	A or C or I
w_4	F	E	H	J	D	G	I	A or B or C
w_5	F	E	H	J	D	I	B	A or C or G
w_6	F	E	H	J	D	G	I	A or B or C
w_7	F	E	H	J	D	G	B	A or C or I
w_8	F	E	H	J	D	G	B	A or C or I
w_9	F	E	J	H	D	G	I	A or B or C

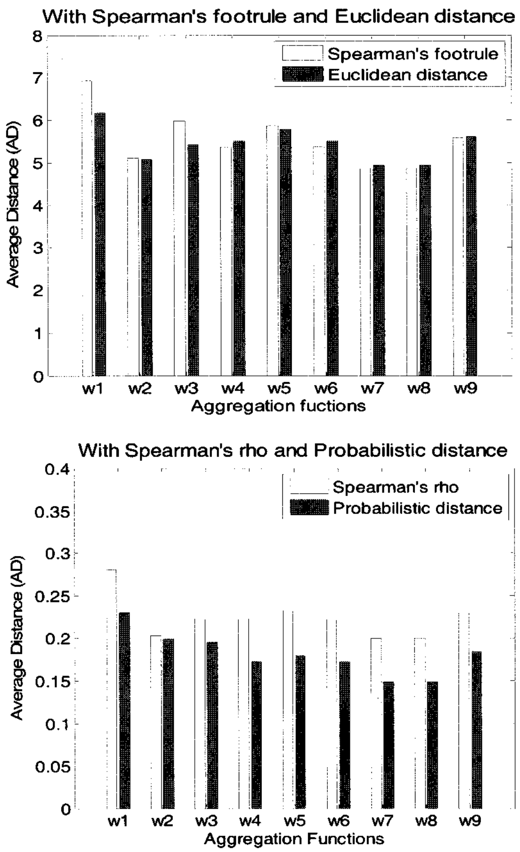
6.1 User Satisfaction of Aggregate Functions

[Figure 3] shows how satisfied actual users (John, Adam, and Mary) are with 9 preferences orders in <Table 6>. To calculate the satisfactions of users, we use the two satisfaction functions explained in Subsection 5.1. Since the satisfaction function are devised so that a high average gives a high satisfaction, it is natural that w_1 leads the highest satisfaction of users. However, note that the differences among users' satisfactions of w_1 are relatively high than other aggregate functions in [Figure 3]. The reason is that the Average strategy considers neither how terrible users feel about selected items nor how different satisfaction users have. Other aggregate functions reduce the differences among the satisfactions of users by minimizing misery or inequality.



[Figure 3] Satisfactions of users with preference orders from aggregate functions

In fact, w_7, and w_8 are designed to consider relatively higher penalties for inequality than other aggregation functions. Ironically, these aggregate functions provoke a reverse discrimination that Adam has much higher satisfaction than John and Mary. This discrimination is caused by that Adam has a different taste on video clips from John and Mary's. To avoid Adam's misery, these aggregate functions sacrifice John and Mary's satisfactions. Even though some of our social welfare functions(w_7, w_8) produce the undesirable results in this experiment, it is obvious that the proposed aggregate functions pursue not only maximization of average but also minimization of inequality simultaneously.



[Figure 4] Average Distance(AD)s of aggregate functions from subjects

6.2 Social Agreeability of Aggregate Functions

[Figure 4] shows the Average Distance(AD)s of the aggregate functions from subjects with Spearman's footrule(SF), Euclidean distance (ED), Spearman's rho(SR), and Probabilistic distance(PD). As shown in the figure, the w_7 and w_8 have the lowest AD regardless of distance measure. To examine a statistical significance among the distance values of the aggregate functions from subjects, we performed the Mann-Whitney test which is commonly considered as a test of populations in medians. For every pair of aggregation functions and distance measures 144 tests are implemented and the <Table 7> summarizes the results. Basically, we failed to conclude that our aggregation functions (w_4, w_5, w_6, w_7, w_8, and w_9) are dominant over the existing aggregation functions (w_1, w_2, and w_3). However, for the majority of the distance measures, w_7 and w_8 have statistically significant lower AD values compared with the Average aggregate function (w_1) which is one of typical aggregate functions ($p < 0.05$ or $p < 0.1$). In addition, it is possible to say that other social welfare functions have lower distance values than w_1 with one or two distance measures. Based on these results, we can conjecture that people are considering inequality in addition to average and misery when making decisions, and hence it is necessary to utilize the aggregate functions which integrate these three properties altogether. In fact, this is not an unexpected result because this welfare function is capable of flexibly adjusting its inequality aversion parameter. On the contrary, other welfare functions such as Sen and Dagum welfare functions are lacking in the flexibility. Therefore, the Atkinson welfare function is the

〈Table 7〉 P-values from the Mann-Whitney tests for every pair of aggregation functions

		w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9
w_1	SF	**0.0868**	0.2238	**0.0750**	0.1753	**0.0750**	**0.0453**	**0.0453**	0.1341
	ED	0.1341	0.1673	0.2145	0.2099	0.2145	**0.0894**	**0.0894**	0.2238
	SR	0.1177	0.1794	0.2286	0.2145	**0.0750**	0.1028	0.1028	0.2383
	PD	0.2054	0.1794	**0.0357**	**0.0409**	0.1557	**0.0249**	**0.0249**	**0.0796**
w_2	SF		(0.1673)	(0.3639)	(0.2099)	(0.3639)	0.4185	0.4185	(0.2482)
	ED		(0.3639)	(0.3119)	(0.2191)	(0.3119)	0.4372	0.4372	(0.2432)
	SR		(0.3175)	(0.3119)	(0.2383)	(0.4062)	0.4434	0.4434	(0.2432)
	PD		(0.4874)	(0.2334)	(0.2845)	(0.4247)	0.0844	0.0844	(0.3699)
w_3	SF			0.2583	0.4811	0.2583	0.1341	0.1341	0.3289
	ED			0.5000	(0.3462)	0.5000	0.3346	0.3346	(0.4811)
	SR			0.5000	(0.3879)	0.3462	0.3119	0.3119	(0.4685)
	PD			0.2191	0.2686	0.4247	0.0973	0.0973	0.3699
w_4	SF				(0.2845)	0.5000	0.2792	0.2792	(0.3580)
	ED				(0.4124)	0.5000	0.2845	0.2845	(0.3699)
	SR				(0.4748)	0.3819	0.2845	0.2845	(0.3699)
	PD				0.5000	(0.3819)	0.2634	0.2634	0.2899
w_5	SF					0.2845	0.1595	0.1595	0.4247
	ED					0.4124	0.1794	0.1794	0.4559
	SR					0.2899	0.2009	0.2009	(0.4309)
	PD					(0.3580)	0.1921	0.1921	(0.3064)
w_6	SF						0.2792	0.2792	(0.3580)
	ED						0.2845	0.2845	(0.3699)
	SR						0.4309	0.4309	(0.2686)
	PD						0.1341	0.1341	0.4748
w_7	SF							0.5000	(0.1965)
	ED							0.5000	(0.2145)
	SR							0.5000	(0.2145)
	PD							0.5000	(0.1633)
w_8	SF								(0.1965)
	ED								(0.2145)
	SR								(0.2145)
	PD								(0.1633)

주) $H_0 : \eta_1 = \eta_2$ vs $H_1 : \eta_1 > \eta_2$ (or $\eta_1 < \eta_2$) where η_1 and η_2 denote population medians of distances of aggregation functions.

most plausible aggregate function of the alternative functions under consideration. However, there need some standardization efforts of defining the parameters as a function of contexts. Though $\varepsilon = 2$ and 2.5 in the Atkinson welfare function are the best in this context of the experiment, other parameter values will fit better to different contexts.

<Table 8~10> and <Table 11> in Appendix enumerate distances of all pairs of subjects and aggregate functions in terms of Spearman's footrule, Euclidean distance, Spearman's rho, and Probabilistic distance respectively.

7. Discussions

The way of managing group recommender systems will make considerable impacts on not only quality of life but also business competitiveness. One of the most important functionalities of group recommender systems is the aggregate function. It is essential for the systems to be equipped with socially agreeable aggregate functions since then the solution of the system would be also acceptable by most of the group members. The social agreeability can be achieved successfully when an aggregate function considers three properties of average, misery, and inequality, in conjunction with the social powers of the group members. These properties are the considerations that people take into account when they make decision for groups. The social welfare functions we have introduced are integrating all the three properties and hence compatible to social opinions.

However, the social agreeability depends on the context. It is hard to say there exists a universal aggregate function that can represent social opinions in all different contexts. Therefore, these should be some efforts to standardize them upon some categorized contexts. The categories may lie on two-dimensional space of culture of society and nature of items. Since the standardization task requires considerable efforts, appropriate methodologies should be explored beforehand. It would be also necessary to consider that social opinions change with the times.

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Appendix

〈Table 8〉 Spearman's footrule

Subjects	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9
1	5	5	6	9	7.5	9	6	6	9
2	5	5	5	4	1.5	4	4	4	5
3	5	4	5	0	2.5	0	3	3	1
4	6	4	6	1	3.5	1	4	4	0
5	9	1	3	5	5	5	2	2	5
6	3.5	10	10.5	7	8	7	10	10	7
7	5	4	5	3	5.5	3	3	3	4
8	15.5	12	12.5	15	15	15	12	12	15
9	0.5	8	7.5	4.5	5.5	4.5	7.5	7.5	5.5
10	8	1	2	3	3	3	0	0	4
11	8	1	2	3	3	3	0	0	4
12	10.5	3	4.5	6	6	6	3	3	6
13	3.5	10	10.5	7	8	7	10	10	7
14	1	9	8	5	6	5	8	8	6
15	13	5	7	8	8	8	5	5	7
16	8	6	8	6	8.5	6	6	6	5
17	8	2	1	5	4	5	2	2	6
18	10	2	4	5	5	5	2	2	4

〈Table 9〉 Euclidean Distances

Subjects	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9
1	4.69	5.83	5.48	7.48	6.67	7.48	6.16	6.16	7.62
2	5.2	5.83	5.2	5.1	2.55	5.1	5.66	5.66	5.29
3	5.74	4.47	5.2	0	3.08	0	4.24	4.24	1.41
4	6	4.47	5.48	1.41	3.39	1.41	4.47	4.47	0
5	7.35	1.41	2.45	4.9	4.95	4.9	2.45	2.45	5.1
6	3.61	9.38	9.33	8.25	8.09	8.25	9.27	9.27	8.37
7	5.2	4.47	5.2	4.24	5.79	4.24	4.24	4.24	4.47
8	12.37	10.3	10.63	11.83	11.94	11.83	10.49	10.49	12.08
9	0.71	7.18	7.11	5.7	5.48	5.7	7.11	7.11	5.96
10	7.14	1.41	1.73	4.24	4.3	4.24	0	0	4.47
11	7.14	1.41	1.73	4.24	4.3	4.24	0	0	4.47
12	8.12	3.74	4.24	5.48	5.52	5.48	3.46	3.46	5.66
13	3.61	9.38	9.33	8.25	8.09	8.25	9.27	9.27	8.37
14	1	7.35	7.14	5.83	5.61	5.83	7.21	7.21	6
15	10.77	5.1	6.63	6.93	7.78	6.93	5.48	5.48	6.48
16	7.42	5.29	6.56	5.29	7.04	5.29	5.29	5.29	4.9
17	7.14	2	1	5.29	4.53	5.29	2	2	5.66
18	8.06	2.45	3.32	4.69	5.05	4.69	2	2	4.47

〈Table 10〉 Spearman's rho

Subjects	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9
1	0.13	0.21	0.18	0.34	0.27	0.27	0.23	0.23	0.35
2	0.16	0.21	0.16	0.16	0.04	0.13	0.19	0.19	0.17
3	0.2	0.12	0.16	0	0.06	0	0.11	0.11	0.01
4	0.22	0.12	0.18	0.01	0.07	0.02	0.12	0.12	0
5	0.33	0.01	0.04	0.15	0.15	0.16	0.04	0.04	0.16
6	0.08	0.53	0.53	0.41	0.4	0.22	0.52	0.52	0.42
7	0.16	0.12	0.16	0.11	0.2	0.11	0.11	0.11	0.12
8	0.93	0.64	0.68	0.85	0.86	0.44	0.67	0.67	0.88
9	0	0.31	0.31	0.2	0.18	0.18	0.31	0.31	0.22
10	0.31	0.01	0.02	0.11	0.11	0.11	0	0	0.12
11	0.31	0.01	0.02	0.11	0.11	0.11	0	0	0.12
12	0.4	0.08	0.11	0.18	0.18	0.18	0.07	0.07	0.19
13	0.08	0.53	0.53	0.41	0.4	0.22	0.52	0.52	0.42
14	0.01	0.33	0.31	0.21	0.19	0.18	0.32	0.32	0.22
15	0.7	0.16	0.27	0.29	0.37	0.27	0.18	0.18	0.25
16	0.33	0.17	0.26	0.17	0.3	0.18	0.17	0.17	0.15
17	0.31	0.02	0.01	0.17	0.12	0.16	0.02	0.02	0.19
18	0.39	0.04	0.07	0.13	0.15	0.16	0.02	0.02	0.12

〈Table 11〉 Probabilistic distances

Subjects	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9
1	0.18	0.22	0.2	0.27	0.24	0.34	0.2	0.2	0.29
2	0.18	0.22	0.18	0.13	0.07	0.16	0.16	0.16	0.16
3	0.2	0.18	0.18	0	0.09	0	0.11	0.11	0.02
4	0.22	0.18	0.2	0.02	0.11	0.01	0.13	0.13	0
5	0.29	0.07	0.09	0.16	0.16	0.15	0.04	0.04	0.18
6	0.11	0.36	0.33	0.22	0.2	0.41	0.29	0.29	0.24
7	0.18	0.18	0.18	0.11	0.18	0.11	0.11	0.11	0.13
8	0.49	0.4	0.42	0.44	0.47	0.85	0.38	0.38	0.47
9	0.02	0.27	0.24	0.18	0.16	0.2	0.24	0.24	0.2
10	0.27	0.07	0.07	0.11	0.11	0.11	0	0	0.13
11	0.27	0.07	0.07	0.11	0.11	0.11	0	0	0.13
12	0.33	0.13	0.13	0.18	0.18	0.18	0.07	0.07	0.2
13	0.11	0.36	0.33	0.22	0.2	0.41	0.29	0.29	0.24
14	0.04	0.31	0.27	0.18	0.16	0.21	0.24	0.24	0.2
15	0.42	0.18	0.22	0.27	0.27	0.29	0.16	0.16	0.24
16	0.24	0.22	0.24	0.18	0.24	0.17	0.18	0.18	0.16
17	0.27	0.09	0.04	0.16	0.13	0.17	0.04	0.04	0.18
18	0.31	0.09	0.11	0.16	0.16	0.13	0.04	0.04	0.13