1A3-IOS-3a-4

Proposal of User Modeling Method Employing Reputation Analysis on User Reviews Based on Personal Values

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This paper proposes the user modeling method that reflects user's personal values for recommender systems. Existing methods such as collaborative and content-based approach tend to be less-accurate for new users and items owing to the lack of the relation between items and users' preference. Meanwhile, personal values have been taken notice because of its significant relation to potential preferences of users. While existing recommender systems usually employ user preference of items to make recommendations, proposed method focuses on users' personal values, which mean value judgments that show what attributes users put a high priority on. By analyzing the relation between ratings for an item and attributes, user's priority on each attribute is extracted as a user model that reflects user's value judgment. The proposed method is applied to customer reviews on Kakaku.com, of which results show that the attributes on which users put high priority can be modeled with less reputation information.

1. Introduction

This paper proposes the user modeling method that reflects user's personal values for recommender systems. Recommender systems have been developed as one of solutions against recent information explosion. However, existing methods such as collaborative filtering [Resnick 94] and content-based filtering [Pachet 00] tend to be less-accurate for new users and items owing to the lack of the relation between items and users' preference. This problem is well-known in this field as the cold-start problem [Schein 02].

Meanwhile, personal values have been taken notice because of its significant relation to potential preferences of users. Although personal values are expected to bring a new framework for modeling user's potential preference, modeling method of users' personal values aiming to recommender systems has not yet been established. While existing recommender systems usually employ user preference of items to make recommendations, the proposed method focuses on users' personal values, which mean value judgments that show what attributes users put a high priority on.

By analyzing the relation between ratings for an item and attributes, user's priority on each attribute is extracted as a user model that reflects user's value judgment. The proposed method is applied to customer reviews on Kakaku.com as experiments, and the obtained models support our assumption that different users put high priorities on different attributes. The experimental results also indicate that the attributes on which users put high priority can be modeled with less reputation information.

2. Related Work

2.1 Recommender System

Most recommendation technologies are able to be categorized into two types: content-based approach and collaborative filtering. A content-based recommender system suggests items to a user based on attribute values of items (e.g. author and actor) and information about user interests [Pachet 00]. On the other hand, collaborative filtering approach predicts user interest based on preference information collected from many users [Resnick 94]. Its advantage against content-based approach is that recommendation is possible without information about attributes of items. Collaborative filtering has been the most successful approach so far because of its ease in development.

In general, recommender systems that employ collaborative filtering require vast amount of usage history database because this approach finds recommended items by using the usage history of other users who have similar preference. Therefore collaborative filtering tend to be less-accurate for new users and items owing to the lack of the relation between users' preferences. This problem is well-known in this field as the cold-start problem [Schein 02]. Furthermore the sparsity problem [Lee 04] is also a major limitation. It is known that the relation between items and users' preference tend to be sparse since there is vast amount of targeted items and users in recommender systems. These two problems are known as the common limitations in the field of recommender systems.

Some solutions against cold-start and sparsity problem have been proposed. Model-based approach is a major approach that classify users into groups depending on similarity of preference. Breese et al. have proposed two model-based methods: clustering model and bayes network [Breese 98]. As another approaches, Park et al. have proposed a method employing the robot that automatically filtering content, which is called "naive filterbot", for handling cold-start situations [Park 06]. Lee et al. have attempted to overcome sparsity situations by applying real-life relationships into similarities of users [Lee 04]. Yildirim et al. have proposed the method based on random walk, that first infers transition probabilities between items based on their similarities and models finite length random walks

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on the item space to compute predictions [Yildirim 08].

Meanwhile, content-based filtering method could recommend high accurate items for new users when users' preference of particular attribute values which have relation with recommended items are obtained. Therefore this method is applied to some specific genre such as music recommendation [Pachet 00]. However, the relation between attribute values and users could be sparse when recommender systems target various items such as in online shopping sites owing to the lack of the relation between items and users' preference. Therefore, the cold-start and sparsity problem are considered to be limitation of content-based approaches. The method which can acquire recommended items by using less information is considered to be effective against these problems. While existing recommender systems usually employ user preference of items to make recommendations, proposed method focuses on users' personal values, which mean value judgments that show what attributes users put a high priority on.

2.2 Personal Values

Personal values have been paid attention to in the marketing field because of its strong relation to potential preferences of consumers. Rokeach [Rokeach 73] has defined personal values and proposed the Rokeach Value Survey (RVS) that separates personal values into 18 elements for identifying personal values of people. These values depend on what group and culture people belong to. Vinson et al. [Vinson 77] have surveyed the relation between people's preference and cultures of communities. This study revealed a significant difference of preference between college students belonging to a conservative culture and those belonging to a progressive culture. Holbrook [Holbrook 99] has attempted to define and analyze exactly what consumers want. He has proposed a framework for consumer values that influences their consumption behavior. In these studies, personal values are regarded as a key concept that is related to user preference.

Personal values are also applied in computer science field. Jayawardhena has proposed value-attitude-behavior model to investigate the roles of personal values in e-shopping consumer behavior [Jayawardhena 04]. Hattori et al. have investigated the relation between user preference and personal values in multiple genres [Hattori 12]. Although these works show applicability of personal values for modeling user's potential preference, modeling method of user personal values for recommender systems has not yet been established.

This paper defines personal values as value judgments, which are modeled as influence of item's attributes on item ratings. Therefore, the user modeling method based on personal values has things in common with existing content-based systems in terms of employing evaluation on item's attributes. However, existing systems find items to be recommended based on preference of attribute values such as genre or author. On the other hand, proposed method based on personal values considers the difference of influence on item ratings among different attributes.

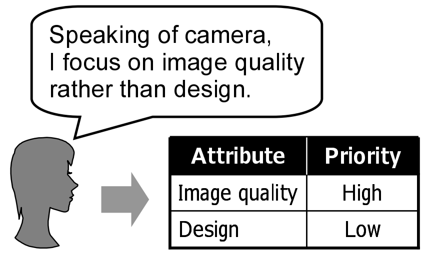

Figure 1: Example of user's value judgment

3. User Modeling Method

3.1 User Model Based on Personal Values

A user modeling method is described in this section. An example of a user's value judgment is shown in Fig. 1. User's value judgment means the criteria for judging what attribute the user focuses on for evaluating items. Proposed method does not analyze user preferences, which means what items or attributes user likes, but the relation between rating for each attribute and that for items. This analysis enables reasoning what attribute mainly contributes to the rating for an item. It is assumed that the attributes on which a user puts high priority have more stable influence for ratings items than the other attributes. Therefore, the proposed method based on personal values is expected to realize user model generation with less information.

As noted above, this paper defines personal values as a judgment which is modeled as the influence of item's attributes on item ratings. Proposed method therefore has things in common with existing content-based filtering method in terms of employing evaluation on item's attributes. The features that set proposed method apart from existing method can be categorized into three topics shown in below:

(1) Use of attribute: Existing method employs attribute values such as the name of author and genres (e.g. action, mystery). Instead of attribute values, proposed method employs attribute such as "author" and "genre", which shows the viewpoint of evaluation. It is difficult for existing method to collect enough ratings to generate user models because there is a large variety of attribute values. By contrast, the proposed method employing attributes is considered to enable acquisition of enough ratings since there is limited number of attributes.

(2) Reasoning influence of attribute: The proposed method models what attribute mainly contributes to the rating for an item. Existing content-based approaches generally collect usage history of recommender system implicitly. Consequently, when a user rate an item as positive, existing methods judge all attribute values as well. This means they ignore the relation between items and attribute values because there might be attribute values the user does not like. On the other hand, proposed method models influence rates of each attribute on evaluation of items. The user modeling method based on personal values, which shows users' priority on each attribute, is expected to enable recommender systems to generate user models with less information.

(3) Easy to rate: The proposed method makes it easy for users to rate each attribute of items because there are fewer variety of attributes than attribute values, as noted in (1). That is, it is difficult for users to rate large amount of attribute values explicitly. For this reason, existing approaches employing attribute values put a burden on users for rating many values when they attempt to collect ratings explicitly.

The proposed method is expected to contribute to model user preference in terms of the content-based filtering. That is, as noted in (3), acquisition of user preference with less information and interaction is expected to be realized by asking users about attributes only in cases on which a user put high priority. In addition, implicit estimation of utility is also expected in utility-based recommender system [Adomavicius 05]. This system provides recommendations based on the computation of the utility function of each item and attribute for users. However, explicit approach for acquiring utility function needs much interaction between users and a recommender system, which raises a burden on users. Implicit approach also has a problem that it needs vast amount of usage history for acquiring utility function. User model based on the proposed method could be alternative of the utility function because the user model shows the influence rate of attribute for evaluating items.

3.2 User Modeling Method by Calculating RMRate

Rating Matching Rate (RMRate) shown in (1) is proposed for the purpose of analyzing user's value judgments for each attribute. Table 1 shows an example of ratings for items and that for each attribute of items. The proposed method employs polarities (positive or negative) of ratings for them. User models are generated based on RMRate, which shows what attribute mainly contributes to the rating for an item. In (1), a polarity $p_{item}(u,i)$ for an item i given by a user u and a polarity $p_{attr}(u,i,j)$ for each attribute j of item i is obtained beforehand from R_u (set of ratings given by a user u). The $O(u,j)$ means the number of ratings in which item $p_{item}(u,i)$ and $p_{attr}(u,i,j)$ are matched. The $Q(u,j)$ means the number of ratings in which $p_{item}(u,i)$ and $p_{attr}(u,i,j)$ are mismatched. A value of RMRate represented as $P(u,j)$ is obtained according to (1) for each attribute.

$$P(u,j) = \frac{O(u,j)}{O(u,j)+Q(u,j)} \tag{1}$$

Proposed user model keeps value of RMRate $P(u,j)$ calculated for ratings by a user in each attribute. When m attributes are employed, a user model is represented as m-dimensional vector. The example of ratings for two digital cameras is shown in Table 1. The result of calculation of RMRate from this example is shown in Table 2. In Table 2, the attributes having high RMRate such as "Operability" and "Battery" are supposed to indicate that the user puts high priority on these attributes for rating items. It might be said that these attributes are important for recommending items in terms of influence on decision making. By contrast, the attribute having low RMRate such as "Design" is supposed to indicate that the user doesn't put high priority on the attribute for rating items. It might be said that this kind of attributes are not important for recommending items because it doesn't have a significant effect on ratings of items.

Table 1: Example of rating on digital cameras

(1) Rating for camera A

Attribute	Polarity
In total	pos.
Design	neg.
Image quality	neg.
Operability	pos.
Battery	pos.

(2) Rating for camera B

Attribute	Polarity
In total	neg.
Design	pos.
Image quality	neg.
Operability	neg.
Battery	neg.

Table 2: Example of calculating RMRate

Attribute	Match	Mismatch	RMRate
Design	0	2	0.00
Image quality	1	1	0.50
Operability	2	0	1.00
Battery	2	0	1.00

4. User Model Generation Using Reputation Information

4.1 Overview

The experiments of generating user models using Kakaku.com*1, online customer review site, are conducted

Table 3: Example of a rating extracted from Kakaku.com

Attribute	Rating
Satisfaction (in total)	★★★★☆
Design	★★★☆☆
Image quality	★★★★★
Operability	★★★☆☆
Battery	★☆☆☆☆
Portability	★★★★★
Functionality	★★★★☆
LCD monitor	★★☆☆☆
Handgrip	★★★★☆

*1 http://kakaku.com/

Table 4: Example of generated user models which have RMRates in each attribute.

User	Attribute							
	Design	Image quality	Operability	Battery	Portability	Functionality	LCD monitor	Handgrip
user8	1.00	0.75	0.67	0.50	0.58	0.42	0.42	0.42
user27	1.00	0.83	0.50	0.33	0.67	0.67	0.33	0.67
user36	0.71	0.71	0.29	0.29	0.43	0.43	0.43	0.71

to show the availability of the proposed method. It is considered that two conditions shown in below are needed to examine the availability of generated user models.

1. Examine that each user model shows different user's value judgment toward attributes of items

2. Examine feasibility of user model generation with less reputation information

These two conditions are respectively examined in Sec. 4.2 and 4.3.

In Kakaku.com, rankings of top 50 users who posted product reviews in each genre are announced. In the rankings, this experiment targets users who have posted five or more reviews within a year in the genre of "single-lens reflex camera" for user modeling. As a result, 382 reviews posted by 37 users meet the conditions as of May 13, 2012.

Kakaku.com employs five-grade rating as shown in Table 3. In such a review site, some users might tend to rate higher grade such as four or five grade, while others might do lower grade such as one or two grade. Implications of three grade by former and latter users are supposed to be different substantially. That is, former users might assume three grade as negative rating, whereas latter users might assume it as positive. Polarities are therefore judged with relative magnitude from average value of a user's ratings. The $\mu_{item}(u)$, which means an average rating value of items given by user u, is obtained by (2). In (2), n is the number of items rated by u. The R_{ui} means a rating value of an item i given by u. A polarity of an item $p_{item}(u,i)$ is judged as positive when R_{ui} is equal to or bigger than $\mu_{item}(u)$. The $p_{item}(u,i)$ is judged as negative when R_{ui} is smaller than $\mu_{item}(u)$.

$$\mu_{item}(u) = \frac{1}{n}\sum_{i=1}^{n} R_{ui} \tag{2}$$

The $\mu_{attr}(u,i)$, which means an average value of ratings for all attributes of an item i given by a user u, is obtained by (3). While $\mu_{item}(u)$ is calculated as the average value of overall ratings for all items, $\mu_{attr}(u,i)$ is calculated as the average value of all attributes' ratings given to item i. The $p_{attr}(u,i,j)$, which means an polarity of an attribute j of item i, is judged as positive when R_{uij} is equal to or bigger than $\mu_{attr}(u,i)$. The $p_{attr}(u,i,j)$ is judged as negative when R_{uij} is smaller than $\mu_{attr}(u,i)$.

$$\mu_{attr}(u,i) = \frac{1}{m}\sum_{j=1}^{m} R_{uij} \tag{3}$$

Table 5: The number of users having high RMRate

Attribute	Over 0.7	Over 0.8
Design	22	17
Image quality	25	16
Operability	10	6
Battery	15	11
Portability	15	12
Functionality	16	15
LCD monitor	11	8
Handgrip	17	13

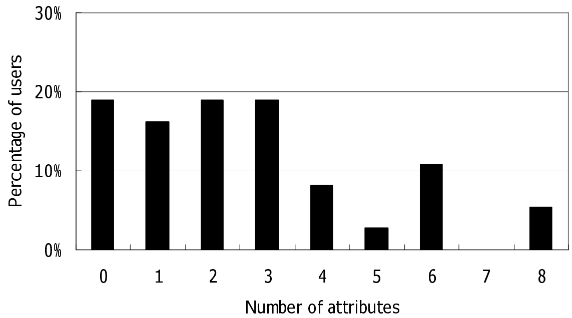

Figure 2: Percentage of users having high RMRate attributes (over 0.8)

4.2 Generated User Model

User models of 37 users in the genre of "single-lens reflex camera" are generated based on the RMRates. Table 4 shows the example of generated user models. The numbers of users having high RMRate (over 0.7 and 0.8) in each attribute is shown in Table 5. The table shows that difference among attributes in terms of the number of such users is small. In addition, Fig. 2 shows the percentage of users who have high RMRate attributes (over 0.8). The average number of attributes having over 0.7 RMRate per user is 3.54 and those over 0.8 is 2.65, respectively. These results indicate that different users put high priorities on different

Attribute	Rating
Design	★★★★★
Image quality	★★★★☆
Operability	★★★☆☆
Battery	★★★☆☆
Portability	★★★★★
Functionality	★★★★☆
LCD monitor	★★★☆☆
Handgrip	★★★★☆

Satisfaction (in total): ★★★★★

User review:

[Design] Excellent! I admired this camera when I touched it.

[Operability] Not good... It is too small for old man such as myself to handle.

[Battery] I'm afraid its battery is at the same level as compact camera.

Figure 3: The example of a translated review comment posted by user 27.

attributes. Therefore, it can be said that proposed method can create user models which reflect users' diversified value judgments.

In Kakaku.com, review comments are also posted by users along with ratings in each attribute. Fig. 3 shows the example of a translated review comment posted by user 27. As shown in Table 4, this user has high RMRate in the attribute of "design." The user mentions this attribute as positive in the review, which coincides with his satisfaction in total. By contrast, the attributes "operability" and "battery" are mentioned as negative, and ratings for these attributes are relatively low as well. Therefore, this review comment also indicates that the user puts a high priority on the attributes "design" for evaluating this camera.

4.3 Consideration about Required Number of Reviews

The proposed method is expected to realize user model generation with less information as noted in the condition (2) shown in Sec. 4.1. The condition means feasibility of reasoning attributes on which users put a high priority with fewer reviews compared to the other attributes. For examining this condition, the relation between RMRate and required number of reviews for reasoning attribute is considered in this section. 4 users who posted more than 20 reviews are selected from 37 users in Sec. 4.2. The delta ΔP_n between RMRate P_{20} and P_n is calculated by (4). P_n shows RMRate at the time nth reviews are posted by a user.

$$\Delta P_n = |P_{20} - P_n| \qquad n = 1, 2, \cdots, 20 \tag{4}$$

As an example, table 6 shows ΔP_n of user 1 in the attribute of "image quality." This example shows the user's RMRate in this attribute is almost exactly reasoned when at least 8 reviews are posted. Thus ratios of attributes whose ΔP_n is less than 0.1 among all attributes are calculated in each number of posted reviews (1 to 20). And then the ratio of $P_{20} \geq 0.8$ in the attributes and the other ratio of $P_{20} < 0.8$ is separately calculated. If the ratios of former attributes become higher in the early stages, it can be said that user modeling with less information is realizable. On the other hand, it is supposed that there is no such tendency in the ratio of latter attributes.

Table 6: ΔP_n of user1 in the attribute of "image quality".

n	*P*	*ΔP*	*n*	*P*	*ΔP*
1	0.00	0.70	11	0.64	**0.06**
2	0.00	0.70	12	0.67	**0.03**
3	0.33	0.37	13	0.69	**0.01**
4	0.25	0.45	14	0.64	**0.06**
5	0.40	0.30	15	0.67	**0.03**
6	0.50	0.20	16	0.63	**0.08**
7	0.57	0.13	17	0.65	**0.05**
8	0.63	**0.08**	18	0.67	**0.03**
9	0.67	**0.03**	19	0.68	**0.02**
10	0.70	**0.00**	20	0.70	**0.00**

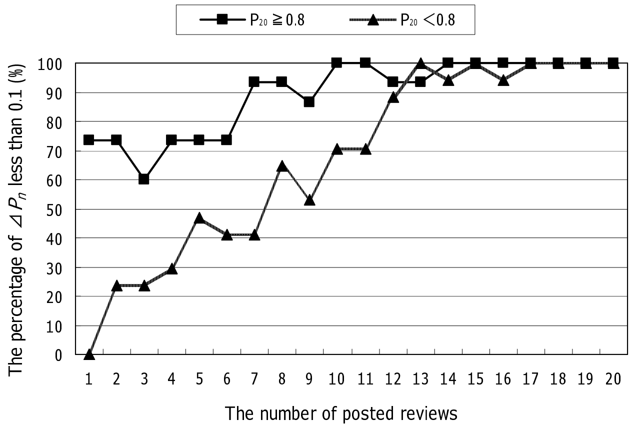

Figure 4: The relation between the ratio of attributes whose ΔP_n is less than 0.1 and the number of posted reviews.

Fig. 4 shows the relation between the ratio of attributes whose ΔP_n is less than 0.1 and the number of posted reviews. In this figure, the ratio of $P_{20} \geq 0.8$ begin exceeding eighty percent when over seven reviews are posted. This result indicates the attributes having high RMRate have more stable influence for ratings items than the other attributes. It is assumed that the attributes on which a user puts high priority have more stable influence for ratings items than the other attributes. Therefore, it can be said the proposed method based on personal values enables to realize user model generation with less information.

5. Conclusions and Future Work

This paper proposed the user modeling method based on user's personal values. The user modeling method analyzes user's tendency of putting priorities on item's attributes when evaluating items. The experimental result using customer review site Kakaku.com showed our assumption that different users put high priorities on different attributes. In addition, the result also indicated users' value judgment can be modeled with less information.

Future work includes the actual development of the recommender system employing proposed modeling methods. Feasibility of analyzing contents of review articles using the state-of-art NLP technologies are currently under consideration. These extracted attributes would contribute to user models which reflect users' wide-ranged value judgment.

Furthermore, categorizing user's tendency of rating into several types could be useful for modeling users. These types can not only be used for selecting recommended items, but also useful for determining recommendation strategy regarding presentation of recommended items, which would contribute to recommendation reflecting user's personal values strongly.

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