Personal Values-based User Modeling from Browsing History of Reviews

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ABSTRACT
This paper proposes a user modeling method from user's browsing history of reviews. Personal values-based recommendation method has been proposed, which models users' personal values as the effect of item's attribute on their decision making. While existing method obtains a user model from reviews posted by a user, this paper proposes to obtain it from reviews a user consulted for decision making. In order to identify an attribute that affects on user's decision making efficiently, the proposed method dynamically selects reviews mentioning attributes on which a user might put priority and presented to the user. A method for selecting items to recommend based on the obtained user models is also proposed. An experimental result with test participants shows the effectiveness of the proposed method.

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

Author Keywords
Recommender system; personal values; user modeling; online reviews.

INTRODUCTION
This paper proposes to obtain user models reflecting their personal values by analyzing their record of browsing online reviews. The obtained models are used for recommendation.

In recent years, users have made huge numbers of reviews and ratings online. Such social big data[5] can be utilized for enriching our lives in various ways, including recommendation. In order to promote products, it is necessary to establish a method for predicting users' preferences and recommending suitable items to them. As ratings are supposed to reflect users' opinions about items, they can be used to estimate their preferences. Collaborative filtering (CF)[14] and its related algorithms are based on this idea.

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The CF is one of common and successful approaches of recommendation, and those variations and extensions have been studied by many researchers. Variations include item-based[10], matrix factorization-based[8, 9, 16], and graph-based approaches[2]. Extensions include introduction of additional information for calculating inter-user similarity[1, 13, 11]. This paper focuses on one of those extensions: introduction of personal values[4]. Personal values and personalities are supposed to be important factors in decision making, and they have recently received attention by those studying recommendation[4, 12]. In particular, the Rating Matching Rate (RMRate), which estimates the effect of an item's attributes on a user's rating[4], has been proposed for modeling users' personal values. Its effectiveness for recommendation has been shown in terms of content-based approach[4], CF[17, 18], and item modeling[19].

Existing studies obtain user models based on RMRate (called PV model hereinafter) from reviews posted by target users, which limits its applicable situations. That is, it can be only applied to online review sites with attribute-level evaluations. Even though attribute-level evaluations are available, majority of users on online review sites seldom post reviews. The PV model cannot be obtained for such users.

This paper focuses on the latter problem. In order to calculate PV model for users posting no review, this paper proposes a method to obtain it from users' histories of browsing reviews posted by others. A method for recommending items based on the obtained PV models is also proposed, and those effectiveness are shown by experiments with test participants.

RELATED WORKS
This section briefly introduces studies utilizing personality and personal values for recommender systems. Personal values and personality determine the characteristics of a user's decision making, and they have been used in marketing. Jayawardhena modeled a hierarchical relationship among personal values, attitudes, and behaviors in e-shopping[6]. Wu et al. proposed a method for recommending diversified items in terms of the most important attributes[20]. In their study, the degree of diversity is determined from the relationship between the user's personality and his/her needs for diversity.

These studies have shown that personal values are one of the main factors affecting consumption habits. However, they model users' personal values and personality with abstract factors such as the Rokeach Value Survey[15] and Big Five[7], which have no intuitive relationship with the items to be recommended[12].

As a more direct approach, Hattori et al.[4] have proposed a personal values-based user modeling using Rate Matching Rate (RMRate). A user's personal values are modeled as the effect each attribute an item has on his/her decisions. Given data including users' item-level evaluation (i.e. rating) and attribute-level evaluation, the RMRate of u_i relative to an attribute a_k is calculated as

$$RMR_{ik} = \frac{\sum_{x_j \in I_i} \delta(p_{ij}, p_{ij}^k)}{|I_i|}, \qquad (1)$$

where I_i is a set of items rated by u_i, p_{ij} is the polarity of item-level evaluation (positive or negative) of u_i on item x_j, p_{ij}^k is the porality of attribute-level evaluation of u_i on a_k of x_j. The function $\delta(x,y)$ returns 1 if x is equal to y, 0 otherwise.

The personal values-based CF[18] calculates inter-user similarity on the basis of PV models. Given a set of attributes of an item (A), a PV model of u_i is represented as $|A|$-th dimensional vector, which consists of $RMR_{ik}(a_k \in A)$. Pearson correlation between PV models is calculated among users, which is used to find neighborhood users.

One of advantages of the personal values-based CF is that a matrix used for calculating inter-user similarity tends to be dense compared with user-item matrix, because the number of attributes of an item is usually much smaller than that of items. Therefore, the number of users to which the similarity to a target user can be calculated is expected to be large.

PV MODELING FROM BROWSING HISTORY

Outline of proposed approach

In order to obtain PV model, not only item-level evaluation of a target user on items, but also attribute-level evaluations are necessary. Instead of analyzing reviews posted by target users, as done by existing studies, this paper tries to estimate users' personal values from their history of browsing reviews.

Note that this section uses a term 'user' as a person for which a user model is obtained; 'reviewer' is used as a person who posted reviews. Let us consider the case that a user is going to make a decision on whether or not to buy a certain camera by reference to the following 3 reviews.

1. The image quality of this camera is good.
2. It is easy to operate this camera with a single touch of buttons.
3. This camera is lightweight and suitable for bringing it anywhere.

If this user decides to buy this camera following the first review, s/he is supposed to put priority on image quality when s/he evaluates cameras. Therefore, RMRate can be calculated by identifying attributes mentioned as positive / negative in reviews.

Actually, extracting mentioned attributes with sentiment from reviews accurately is difficult even with the state-of-the art text mining techniques[21]. Instead of applying text mining techniques, this paper utilizes attribute-level evaluations attached to reviews. That is, this paper supposes online review sites which have attribute-level evaluations. As a review explains its reviewer's opinion about a target item, it is assumed that a reviewer makes positive comment on an attribute if s/he positively evaluates it.

This paper considers that reviews to be presented to users for obtaining their feedback should satisfy the following conditions.

1. Polarity of an opinion about an attribute mentioned in a review is the same as the polarity of attribute-level evaluation explicitly given by a user.
2. A review mentions some attributes as evidence of evaluation.
3. Polarity of evaluations of all attributes are not be the same.

The first condition is required to guarantee the above-mentioned assumption. The proposed method supposes that users make a decision by reading reviews. Therefore, if the second condition is not satisfied, a user reading a review cannot understand the reason why a reviewer made such an evaluation for attributes. The third condition is considered to identify attributes focused by a user.

As it is difficult to automatically collect reviews satisfying these conditions with high accuracy, we manually examined collected reviews and constructed a database.

Modeling with dynamic review presentation

The proposed modeling process is shown in Fig. 1. From the constructed database, a set of reviews is selected and presented to users to obtain their feedback. In this paper, 3 reviews are presented to users at the same time. A user feedback includes the user's rating to the item (5-point scale, binary, etc.) and one review that s/he think is the most helpful to determine the rating. Based on these feedback, RMRate of attributes are updated. That is, polarity of user's rating corresponds to p_{ij} in Eq. (1), and that of attribute-level evaluation attached to a review corresponds to p_{ij}^k.

An important thing to consider in this algorithm is how to determine reviews which are presented to users. It is inconvenient for users if they have to interact with recommender systems many times before receiving recommended items. Therefore, this paper aims to identify at least one attribute on which a user would put priority for his/her decision making as soon as possible. Even though complete PV model is not obtained, recommender systems could start recommendation based on a single attribute on which a user put priority.

For the first loop, reviews are randomly selected from the database so that every attribute can be mentioned in at least one of those reviews. In the subsequent loops, reviews are selected so as to satisfy the following conditions. Here, target attribute means an attribute of which RMRate at this time is the highest among all attributes.

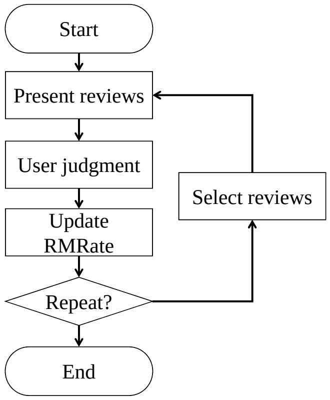

Figure 1. Procedure of modeling process.

1. Present at least one review that positively evaluates target attribute.
2. Present at least one review that negatively evaluates target attribute.
3. Reviews should have the highest score calculated as Eq. (2) while satisfying conditions 1 and 2.

$$Score_r(r,u_i) = \frac{\sum_k |e_r^k - e_r| \cdot RMR_{ik}^2}{K_r} \log N_r, \qquad (2)$$

where u_i is a user, r is a review, e_r^k is evaluation of r to an attribute k, and e_r is r's average evaluation over all attributes. The N_r and K_r are the number of characters and mentioned attributes in r, respectively. This equation gives high score for a review when evaluation to the attribute, of which current RMRate is high, is higher / lower than other attributes. The K_r in denominator plays a role to give priority on reviews focusing on specific attributes. Equation (2) also considers the length (number of characters) of reviews, because we found in the preliminary experiment that users tended to consult longer reviews than shorter ones.

The RMRate is calculated based on the correspondence of polarity between item-level evaluation (rating) and attribute-level evaluation. Therefore, presenting reviews satisfying conditions 1 and 2 aims to obtain a feedback regarding whether or not polarity of attribute-level evaluation is the same as that of his / her rating to target item. As a termination condition, we decide to repeat presenting reviews 20 times.

Recommender system based on PV models

This subsection describes a recommender system based on PV models obtained as described in the previous subsection. A straightforward approach is to recommend items to which predicted rating for a user is higher than others. Instead of predicting ratings, this paper proposes to estimate a degree of recommendation for an item based on user's PV model.

Given a set of RMRate of a user u_i ($\{RMR_{ik} | a_k \in A\}$), a score of an item x_j is defined as follows.

$$Score_i(x_j,u_i,c_j) = \sum_{a_k \in A_i} \{e_j^k - e_{c_j}^k\} \cdot RMR_{ik}^2, \qquad (3)$$

$$A_i = \left\{ a_k | RMR_{ik} \geq \frac{\sum_{a_l \in A} RMR_{il}}{|A|} \right\}, \qquad (4)$$

where c_j is an item category to which x_j belongs, e_j^k is average evaluation for a_k of x_j, $e_{c_j}^k$ is average evaluation for a_k of items belonging to c_j. As these average evaluations, we used the values released on the online review site.

The score is calculated based on only the attributes of which target user's RMRate is higher than average of his / her RMRate for all attributes (Eq. (4)). We employ it in order to focus on attributes which strongly affect user's decision making. For the same reason, we use RMRate squared for the calculation.

EXPERIMENTS

Settings

An experiment with test participants is conducted. The experiment is divided into two phases: user modeling and recommendation phases. We asked 20 graduate / undergraduate students in engineering field to take part in the experiment.

In user modeling phase, proposed dynamic review presentation method is compared with random presentation method. In both methods, 3 reviews about different hotels are combined into one set. Test participants were asked to evaluate different 20 sets as if they were going to book a hotel for the specified purpose.

Reviews and hotel information were collected from online hotel review site 4travel[1]. The number of collected reviews is 592. Regarding polarity of attribute-level evaluation, which is required for calculating RMRate, average evaluation over all attributes is calculated for each review. If evaluation of an attribute is equal to or more than the average, it is regarded as positive evaluation, and vice versa. The 4travel employs 7 attributes: access, cost performance (CP), service, room, bath, meal, and barrier-free. As it is supposed that whether a hotels is barrier-free or not would not affect decision making of test participants in this experiment, we removed it.

We supposed two purpose of booking hotels, i.e. for business and sightseeing, and prepared two datasets for each purpose. The test participants were divided into 4 groups (5 persons each) as shown in Table 1. We designed the experiment so that hotels in different area are presented in different presentation method. As the purpose of booking hotels is supposed to affect participants' decision making, datasets used for a participant belong to the same purpose for keeping consistency of his/her evaluation. The order of presentation methods was rotated so as to remove the order effect.

In recommendation phase, 10 hotels are selected based on a user model obtained by each presentation method. For the comparison purpose, additional 10 hotels are also selected

[1] http://4travel.jp/

Group	Dynamic	Random
SightseeingA	Tokyo, Kanagawa	Hokkaido
SightseeingB	Hokkaido	Tokyo, Kanagawa
BusinessA	Osaka, Kyoto	Tokyo, Aichi, Fukuoka
BusinessB	Tokyo, Aichi, Fukuoka	Osaka, Kyoto

Table 1. Used dataset for modeling.

Group	Dynamic	Random
SightseeingA	Osaka, Hyogo, Kyoto	Okinawa
SightseeingB	Okinawa	Osaka, Hyogo, Kyoto
BusinessA	Kanagawa	Hyogo, Kyoto
BusinessB	Hyogo, Kyoto	Kanagawa

Table 2. Used dataset for recommendation.

based on review site's satisfaction ranking. Therefore, each participant was asked to evaluate at most 30 hotels; if different methods select the same hotels, the number of presented hotels is less than 30. The order of presenting items was shuffled so that the participants could not know by which method (model) a hotel was selected. We prepared different datasets from modeling phase as shown in Table 2. In the dataset, we removed hotels which were evaluated as 4 or more for all attributes, as such hotels are preferred by almost everyone regardless of their personal values. For each of presented hotels, test participants were asked to evaluate it as either positive or negative.

Result of User modeling

After the experiment, test participants were asked to answer attributes which they concerned. Table 3 shows average RMRate over attributes they concerned. The table shows that average RMRate by random presentation method is higher than that of dynamic presentation method for all groups. It is because dynamic presentation method focuses on specific attributes, and estimation for other attributes is not enough compared with random presentation method.

Table 4 compares the number of reviews selected by test participants. The number of selected reviews is counted for each attribute of which RMRates is relatively high: 0.7 or more (≥ 0.7) / 0.8 or more (≥ 0.8). Each cell shows the number of attributes, for which 10 or more (≥ 10) / less than 10 (< 10) reviews were respectively selected. The table shows that dynamic presentation method estimates RMRate from much reviews than random presentation method. It means that when an attribute has high RMRate, dynamic presentation method estimates it based on enough information compared with random presentation method.

Group	Dynamic	Random
SightseeingA	0.536	0.547
SightseeingB	0.567	0.675
BusinessA	0.483	0.636
BusinessB	0.538	0.744

Table 3. Average RMRate for concerned attributes.

Presentation method	RMRate	≥ 10	<10
Dynamic presentation	≥ 0.7	28	2
	≥ 0.8	17	0
Random presentation	≥ 0.7	13	21
	≥ 0.8	9	12

Table 4. Number of selected reviews.

Purpose	Dynamic	Random	Satisfaction
Sightseeing	0.720	0.800	0.670
Business	0.630	0.710	0.580
Total	0.675	0.755	0.625

Table 5. Comparison of precision

Result of Recommendation

Table 5 shows average precision: the ratio of items test participants judged as positive to all recommended items. Both of dynamic and random presentation methods achieved higher precision than satisfaction ranking regardless of purpose of booking hotels. This result shows the effectiveness of modeling users' personal values from browsing histories of reviews.

It is also shown that precision by dynamic presentation method is lower than that by random method. This result corresponds to the fact that dynamic presentation method puts priority on fast estimation rather than exhaustive estimation. That is, identifying attributes with high RMRate as many as possible is expected to be effective in terms of accuracy.

CONCLUSION

This paper proposed a method for obtaining personal values-based user models from user's browsing history of reviews. The proposed method dynamically selects and presents reviews mentioning attributes on which a user might put priority. A method for selecting items to recommend based on the obtained user models was also proposed. An experimental result with test participants shows user models obtained from browsing history achieved higher recommendation accuracy than recommendation based on a review site's satisfaction ranking. It is also shown that proposed dynamic presentation method is effective for identifying specific attributes of high RMRate from relatively many reviews.

As the number of read-only users is much larger than those posting reviews, the proposed method will contribute to extend the applicability of personal values-based recommender systems. Future work includes application to other kinds of items, as well as automatic collection of reviews to be used for user modeling.

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