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Individual and group behavior-based customer profile model for personalized product recommendation

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Abstract

The development of efficient customer profile models is crucial for improving the recommendation quality of the recommendation system. In this paper, we propose a new customer profile model based on individual and group behavior information such as clicks, basket insertions, purchases, and interest fields. We also implement a recommendation system using the proposed model, and evaluate the recommendation performance of the proposed model in terms of several well known evaluation metrics. Experimental results show that the proposed model has a better recommendation performance than existing models.

Keywords: Recommendation system; Customer profile; Collaborative filtering; Content-based filtering

1. Introduction

The rapid spread of the Internet has offered e-commerce companies easy and effective acquisition of customer information. The information collected from customers is converted into high quality products and services through managing a personalized web experience and retaining communication with customers. However, the increase in available information afforded by the Internet has resulted in information overload. And Web users have difficulty finding the information they need.

A recommendation system has emerged as an important response to this problem. The recommendation system uses information filtering by applying data analysis techniques to the problem of helping customers find the products they would like to purchase, producing a predicted likeness score or list of recommended products for a given customer (Min & Han, 2005). Thus far, the recommendation system has been implemented by many web sites such as Amazon.com, Yahoo, and Movie Critic (Ansari, Essegaier, & Kohli, 2000).

The underlying techniques used in today's recommendation systems fall into two distinct categories, content-based filtering and collaborative filtering. In the content-based filtering, it provides items that are similar to what the user has favored in the past. On the other hand, in the collaborative filtering, it identifies other users that have showed similar preference to the given users and provides what they would like (Changchien, Lee, & Hsu, 2004). However, each of the two methods has strengths and weaknesses, so some researchers combine content-based filtering and collaborative filtering to improve the accuracy of recommendation (Balabanovic & Shoham, 1997; Cunningham et al., 2001).

It seems that some shortcomings in recommendation techniques are caused by the methods defining the customer profiles that describe customer interests. In content-based filtering, unique or different products cannot be recommended to customers, because the method uses the customer profile created from individual behavior information, and then recommends products using the similarity between the profile and products. On the other hand, in collaborative filtering, product nature cannot be analyzed, because the method uses the customer profile created from customer purchase transaction records, and then

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recommends products using the similarity between the profile and preferences of a similar customer group.

Many customer profile models have been suggested in the literature to more accurately reflect customer preferences (Cho & Kim, 2004; Weng & Liu, 2004; Cho, Cho, & Kim, 2005; Fan, Gordon, & Pathak, 2005). However, the models do not comprehensively consider customer interest. In this paper, we propose a new customer profile model based on individual and group behavior information such as clicks, basket insertions, purchases, and interest fields which can be good indicators of customer preferences. The proposed model analyzes the product features and reflects not only the individual behavior information of the corresponding customer, but also the behavior data of other customers having similar characteristics. Experimental results show that the proposed model has a better recommendation performance than existing models.

The remaining document is organized as follows: Section 2 describes the research background, Section 3 proposes a new customer profile model, Section 4 suggests experimental results to evaluate the performance of the proposed model, and Section 5 presents conclusions and future works.

2. Research background

In this paper, we propose a new customer profile model to improve the performance of recommendation methods, and a recommendation system using the proposed model. Thus, in this section, we first review previous recommendation methods and customer profile models.

2.1. Recommendation method

In the literature, two types of recommendation methods, content-based filtering and collaborative filtering, have been suggested (Resnick & Varian, 1997; Wang, Chuang, Hsu, & Keh, 2004). Content-based filtering is based on a comparison between items and a user profile (Wang & Shao, 2004). Content-based filtering systems analyze the content of items and create customer profiles that are a representation of a user's interest in terms of keywords, phrases, and features. Then, the systems analyze the content of items unknown to the user, compare them with the profile, and estimate which of those items could be interesting to the user (Min & Han, 2005). For instance, a content-based movie recommendation system will typically rely on information such as genre, actors, director, and producer and will match these against the learned preferences of the user in order to select a set of promising movie recommendations (O'Donova & Smythe, 2005). Generally, this method is most effective in text-intensive domains. Examples of such systems are News Weeder (Lang, 1995), Infofinder (Krulwich & Burkey, 1996), and News Dude (Billsus & Pazzani, 1999).

However, the method has several shortcomings and critical issues. Multimedia information, such as images, pictures, and sounds, cannot be analyzed by the method (Weng & Liu, 2004). Moreover, a user is restricted to seeing items similar to those already rated, since the system can recommend only items scoring highly against the user profile (Lee, Kim, & Rhee, 2001). In other words, unique or different products cannot be recommended, because the method ignores data from other users.

Collaborative filtering has been successfully used in information retrieval and e-commerce applications. This method is very different from content-based filtering. Content-based filtering computes similarities between data items and user profiles, but collaborative filtering computes similarities between user profiles. In collaborative filtering a user's profile consists simply of the data the user has specified. This data is compared to those of other users to find overlaps in interests among users. These are then used to recommend new item. Typically, for each user a set of "nearest neighbors" is defined using the correlation between past ratings. Scores for unseen items are predicted using a combination of the scores from the nearest neighbor (Montaner, Lopez, & De La Rosa, 2003). Collaborative filtering systems, such as GroupLens, WebWatcher, and Let's Browse, utilize the similarity among user profiles to recommend interesting materials (Zeng, Xing, Zhou, & Zheng, 2004).

However, this method also has several shortcomings and critical issues. The first problem is the early-rater problem. A collaborative filtering system provides little or no value when a user is the first one in his neighborhood to enter a rating for an item (Sarwar et al., 1998). The second problem results from a lack of users. If the number of users is small relative to the volume of information in the system, then there is a danger of the rating coverage becoming very sparse, thus reducing the collection of recommendable items (Balabanovic & Shoham, 1997). The third problem deals with scalability. Recommendation systems usually handle very high-dimensional profiles to form the neighborhood; hence the nearest neighbor algorithm is often very time-consuming and scales poorly in practice (Cho & Kim, 2004).

To improve the quality of recommendation, many efforts have been made to combine content-based filtering and collaborative filtering (Huang, Chung, & Chen, 2004). The approaches exploit features of content-based and collaborative filtering, since they almost always prove to be complementary. Thus, both recommendation methods contribute to the other's effectiveness by avoiding the limitations mentioned for each system allowing an integrated system to achieve both reliability and serendipity (Montaner et al., 2003).

2.2. Customer profile model

One way to solve the information overload problem is to provide a customized web site for each individual visitor. The most important aspect of personalization is knowing user preferences. Lee and Yang (2003) pointed out that the most important issue in personalization research is to construct a computational model for each individual user to predict his preferences for incoming information. Balabanovic and Shoham (1997) noted that constructing accurate profiles is a key task since the system's success will depend, to a large extent, on the ability to represent the user's current interests. Accurate user profiles are vital for both content-based filtering (to insure that recommendations are appropriate) and collaborative filtering (to insure that users with similar profiles are indeed similar). Therefore, it is important to define customer profiles correctly.

Thanks to advances in Web technology we can collect valuable information from users implicitly or explicitly. By analyzing this information, we can construct user profiles to help serve users (Yen & Kong, 2002). A historical approach is most commonly used in e-commerce, where systems keep a list of purchased products and user ratings, as a user profile.

A variety of customer information such as purchase information, membership information, and navigational and behavioral patterns has been used for user profile construction. Fan et al. (2005) noted that user profiles can be created through a consumer's purchase history, such as the categories of products that consumers have purchased recently. User profiles can also be created through consumer information explicitly specified when they initially register or subscribe to service. Cho et al. (2005) used purchase information represented by binary data to create customer profiles. However, besides purchase information, there is lots of information showing customer preferences. And binary data does not represent the actual number of behaviors, but the presence of certain behaviors only.

Lee et al. (2001) suggested four general shopping steps in online stores: product impression, click-through patterns, basket placement, and purchase. Subsequently, Cho and Kim (2004) used three general shopping steps modified from the work of Lee et al. (2001) to construct a customer profile. They created a customer profile using the frequency of click-through, basket placement, and purchase. Though the research reflects various customer behavior data in creating the customer profile, product attributes are ignored. Weng and Liu (2004) proposed a technique based on customer behaviors and product features. They attempted to analyze customer purchasing behaviors based on product features from transaction records and product feature databases. Even though this research reflects product attributes, it ignores data from other users. Thus, existing customer profile models do not comprehensively consider customer preferences.

3. Customer profile model and product recommendation

In this section, we propose a new customer profile model reflecting product features, individual behavior information, and the behavior information of other users; then we suggest a product recommendation technique using product profiles and the proposed customer profiles.

3.1. Product profile

A product profile is a description of product features. We recommend products by computing the similarities between the product and customer profiles defined in Section 3.2. The product profile for a product group m containing more than one product is defined by formula (1) (Weng & Liu, 2004).

$$PP_m = (f_m^{ij}, i = 1, \ldots, I,\ j = 1, \ldots, K_i) \quad m = 1, \ldots, M, \tag{1}$$

where I is the total number of product features, K_i is the total number of feature values in the ith product feature, and M stands for the total number of product groups. If the product group m has the jth feature value in the ith product feature, f_m^{ij} is 1, otherwise, f_m^{ij} is 0.

For example, using the library classification described in Table 1, we define product profiles as follows. The items contained in the first and second classifications of the table correspond to the product features and feature values of each product feature, respectively. That is, the product features are defined as Fiction and Literature ($i = 1$),..., and Study Guides ($i = 10$). In the case of Fiction and Literature, the feature values are defined as Korean Literature ($j = 1$),..., and Fiction Subjects ($j = 4$).

The product profile of the group of books contained in the "Foreign Literature" classification is defined by formula (2).

$$\begin{aligned} PP_m &= (f_m^{11}, f_m^{12}, f_m^{13}, f_m^{14}, f_m^{21}, \ldots, f_m^{10,4}) \\ &= (0, 1, 0, 0, 0, \ldots, 0). \end{aligned} \tag{2}$$

The product profile of the group of books simultaneously contained in the "Foreign Literature" and "All Children's Books" classifications is defined by formula (3).

Table 1
Library classification

First classification	Second classification
Fiction and Literature	Korean Literature, Foreign Literature, Literary Criticism, Fiction Subjects
Foreign Language	English, Japanese, Chinese, French
Religion	Christianity, Buddhism, Hinduism, Islam
Home and Garden	Gardening, Home Design, Crafts & Hobbies, Animal Care & Pets
Computers and Internet	Operating Systems, Programming, WWW and Internet, Graphic Design
Science and Nature	Astronomy, Earth Science, Mathematics, Chemistry
Art	Painting, Fashion, Architecture, Photography
Teens	Health, Mind & Body, School & Sports, Reference, Literature & Fiction
Children	Baby-3, Ages 4–8, Ages 9–12, All Children's Books
Study Guides	Study Guides-High School, Study Guides-College & University, Study Guides-Graduate & Professional, Study Guides-Careers

$$PP_m = (f_m^{11}, f_m^{12}, f_m^{13}, \ldots, f_m^{93}, f_m^{94}, f_m^{10,1}, \ldots, f_m^{10,4}) \\ = (0, 1, 0, \ldots, 0, 1, 0, \ldots, 0). \tag{3}$$

3.2. Customer profile model

A customer profile is the description of customer interests. In this subsection, we propose a new customer profile model based on product features, and individual and group behavior information. This model consists of the following three steps.

Step 1: To compute an individual's interests, we analyze the customer transaction histories that included clicks, basket insertions, purchases, and interest fields.
Step 2: To compute the interests of a group, we find a group of customers having similar characteristics, and then analyze the transaction histories of the customers contained in that group.
Step 3: Construct customer profiles using the product features, and individual and group interests.

3.2.1. Computation of individual interests

To compute individual interests, we first compute the weighted absolute individual interest of each customer. The weighted absolute individual interest of customer A for the jth feature value in the ith product feature, $WAII_A^{ij}$, is computed by formula (4).

$$WAII_A^{ij} = \alpha_1 \frac{c_A^{ij}}{C_A} + \alpha_2 \frac{b_A^{ij}}{B_A} + \alpha_3 \frac{p_A^{ij}}{P_A} + \alpha_4 \frac{s_A^{ij}}{S_A}. \tag{4}$$

Here, C_A represents the total number of products clicked by customer A, and c_A^{ij} represents the number of products having the jth feature value in the ith product feature clicked by customer A. B_A represents the total number of products inserted into the basket by customer A, and b_A^{ij} represents the number of products having the jth feature value in the ith product feature inserted into the basket by customer A. P_A represents the total number of products purchased by customer A, and p_A^{ij} represents the number of products having the jth feature value in the ith product feature purchased by customer A. S_A represents the total number of feature values selected as interest fields by customer A, and s_A^{ij} is one if the jth feature value in the ith product feature selected as an interest field (otherwise, the value is 0). The parameter α_k represents the weighting value reflecting the relative importance among individual behavior items. Note that $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1$. Fixed or adjusted weighting values can be used.

Next, the weighted relative individual interest of customer A for the jth feature value in the ith product feature, $WRII_A^{ij}$, is computed by formula (5).

$$WRII_A^{ij} = \frac{WAII_A^{ij}}{\frac{1}{|T|}\sum_{t \in T} WAII_t^{ij}}, \tag{5}$$

where T is the set of customers, and $|T|$ is the total number of customers. The value $WRII_A^{ij}$ represents customer A's interest level toward the jth feature value in the ith product feature relevant to other customers.

For example, the values $WAII_A^{12}$ and $WRII_A^{12}$ are calculated as follows. Suppose that the total numbers of clicks, basket insertions, and purchases of customer A are 25, 12, and 8, respectively, and suppose that for the feature value "Foreign Literature" in the product feature "Fiction and Literature", the numbers of clicks, basket insertions, and purchases of customer A are 4, 3, and 2, respectively. Finally, suppose that customer A selects four product feature values as interest fields, and "Fiction and Literature-Foreign Literature" is one of the interest fields. Then, $WAII_A^{12}$ is calculated as $0.2275\left(= 0.25 \times \frac{4}{25} + 0.25 \times \frac{3}{12} + 0.25 \times \frac{2}{8} + 0.25 \times \frac{1}{4}\right)$, if $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 0.25$. If the average of $WAII_t^{ij}$ for all customers is 1.24, $WRII_A^{12} = 0.1834\left(= \frac{0.2275}{1.24}\right)$.

3.2.2. Computation of group interests

To compute the group interest for customer A, we first find the group of customers having characteristics similar to customer A. Note that we call this group "customer group G_A". We find customer group G_A using demographic data such as age, gender, and occupation. Demographic data can be used to identify the types of users that like a certain object (Pazzani, 1999). For example, if customer A is 23 years old, female, and a student, we look for the other customers who have the same age, sex, and occupation as customer A, and then define them as G_A.

Next, the weighted absolute group interest of customer G_A for the jth feature value in the ith product feature, $WAGI_{G_A}^{ij}$, is computed by formula (6).

$$WAGI_{G_A}^{ij} = \alpha_1 \frac{c_{G_A}^{ij}}{C_{G_A}} + \alpha_2 \frac{b_{G_A}^{ij}}{B_{G_A}} + \alpha_3 \frac{p_{G_A}^{ij}}{P_{G_A}} + \alpha_4 \frac{s_{G_A}^{ij}}{S_{G_A}}. \tag{6}$$

Here, C_{G_A} represents the total number of products clicked by customer group G_A, and $c_{G_A}^{ij}$ represents the number of products having the jth feature value in the ith product feature clicked by customer group G_A. B_{G_A} represents the total number of products inserted into the basket by customer group G_A, and $b_{G_A}^{ij}$ represents the number of products having the jth feature value in the ith product feature inserted into the basket by customer group G_A. P_{G_A} represents the total number of products purchased by customer group G_A, and $p_{G_A}^{ij}$ represents the number of products having the jth feature value in the ith product feature purchased by customer group G_A. S_{G_A} represents the total number of feature values selected as interest fields by customer group G_A, and $s_{G_A}^{ij}$ represents the number of jth feature values in the ith product feature selected as interest fields by customer group G_A. The parameter α_k represents the weighting value reflecting the relative importance among group behavior items. Note that $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1$. Fixed or adjusted weighting values can be used.

Finally, the weighted relative group interest of customer group A for the jth feature value in the ith product feature, $WRGI_A^{ij}$, is computed by formula (7).

$$WRGI_A^{ij} = \frac{WAGI_A^{ij}}{\frac{1}{|P|}\sum_{p \in P} WAGI_p^{ij}}, \tag{7}$$

where P is the set of customer groups, and $|P|$ is the total number of customer groups. $WRGI_A^{ij}$ represents the interest level of group G_A toward the jth feature value in the ith product feature relevant to other customer groups.

For example, the values $WAGI_A^{12}$ and $WRGI_A^{12}$ are calculated as follows. Suppose that the total numbers of clicks, basket insertions, and purchases of customer group A are 134, 74, and 25, respectively, and suppose that for the feature value "Foreign Literature" in the product feature "Fiction and Literature", the numbers of clicks, basket insertions, and purchases of customer group A are 28, 20, and 12, respectively. Finally, suppose that the members of group A select 25 product feature values as interest fields, and five persons of the group select "Fiction and Literature-Foreign Literature" as an interest field. Then, $WAGI_A^{12}$ is calculated as $0.289\left(= 0.25 \times \frac{28}{134} + 0.25 \times \frac{20}{74} + 0.25 \times \frac{12}{25} + 0.25 \times \frac{5}{25}\right)$, if $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 0.25$. If the average of $WAGI_P^{ij}$ for all customers is 1.64, $WRGI_A^{12} = 0.451\left(= \frac{0.289}{1.64}\right)$.

3.2.3. Construction of the customer profile

In order to define the profile of customer A, the weighted relative individual and group interest of the customer A, $WRIGI_A^{ij}$, is computed by formula (8).

$$WRIGI_A^{ij} = (\beta_I \times WRII_A^{ij}) + (\beta_G \times WRGI_A^{ij}), \tag{8}$$

where the weighting values β_I and β_G represent the relative importance between $WRII_A^{ij}$ and $WRGI_{G_A}^{ij}$. If $\beta_I = \beta_G = 0.5$, $WRIGI_A^{12}$ is calculated as $0.3172 (= 0.5 \times 0.1834 + 0.5 \times 0.451)$ using the values $WAGI_A^{12} = 0.1834$ and $WRIGI_{G_A}^{12} = 0.451$. Now, the profile of customer A is defined as follows.

$$CP_A = (WRIGI_A^{ij}, \quad i = 1, \ldots, I, j = 1, \ldots, K_i). \tag{9}$$

3.3. Product recommendation using product profile and customer profile

The product recommendation for customer A is performed as follows. First, we compute the similarity between customer A and each product group, using the Euclidean distance defined by formula (10).

$$D_{Am} = \|CP_A - PP_m\| = \sqrt{\sum_{ij}(WRIGI_A^{ij} - f_m^{ij})^2}, m = 1, \ldots, M. \tag{10}$$

Note that a smaller distance denotes a higher similarity. Next, we select product groups with the smallest distance by the predetermined number R_G. Finally, we select special products contained in each selected product group by the predetermined number R_P. The numbers R_G and R_P may be different for each recommendation system.

4. Experiment results

4.1. Experiment setting

To evaluate the performance of the proposed customer profile model, we developed three recommendation systems using three different customer profile models based on: individual purchasing information (CPM-IP), individual behavior information (CPM-IB), and individual and group behavior information (CPM-IGB). These three systems were developed in ASP on IIS 6.0.

The three recommendation systems use identical product profiles, while the systems use different customer profiles. In other words, the systems use different data to build customer profiles. CPM-IP considers only purchase information, while CPM-IB considers four types of individual behavior information: clicks, basket insertions, purchases, and interest fields. CPM-IGB considers four types of individual behavior information (clicks, basket insertions, purchases, and interest fields) and four types of group behavior information (clicks, basket insertions, purchases, and interest fields).

We also developed a book information system that provides book information to customers in order to collect customer behavior and rating data. This system displays brief information for books that are clicked by customers, because it was developed to collect customer behavior and rating data on the Web. We applied the collected data using three recommendation systems and evaluated the performance of each system. The recommendation systems recommended five books in each book group.

A total of 74 people who are familiar with the Internet were asked to rate 40 feature values from 1 to 5 and to purchase ten books using the book information system. We selected customer behavior and rating data from 58 people through refinement of the collected data. We then evaluated the performance of the recommendation systems using the collected data. We assumed that $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 0.25$, $\beta_I = \beta_G = 0.5$, $R_G = 5$, and $R_P = 1$.

4.2. Evaluation metrics

Various metrics have been used to evaluate the performance of recommendation systems. In this paper, we use several metrics, such as classification accuracy, coverage, predictive accuracy, and prediction-rating correlation to evaluate the performance of the proposed customer profile model.

Classification accuracy metrics measure the frequency with which a recommendation system makes correct or incorrect decisions about whether an item is good (Herlocker, Konstan, Terveen, & Riedl, 2004). We use precision, recall, and F1 to measure classification accuracy

(Sarwar, Karypis, Konstan, & Riedl, 2001; Lin, Alvarez, & Ruiz, 2002; Billsus & Pazzani, 1998; Basu, Hirsh, & Cohen, 1998). Precision is defined as the ratio of relevant items selected to the number of items selected, and recall is defined as the ratio of relevant items selected to the total number of relevant items available, shown in formulas (11) and (12), respectively (Herlocker et al., 2004).

$$P = \frac{N_{rs}}{N_s}, \tag{11}$$

$$R = \frac{N_{rs}}{N_r}. \tag{12}$$

Here, N_s is the total number of selected items, N_r is the total number of relevant items, and N_{rs} is the total number of selected items from relevant Items. In this paper, we define N_s, N_r, and N_{rs} as the total number of recommended books, total number of books included in interesting book groups, and total number of recommended books from interesting book groups, respectively. Here, an interesting book group is a book group that has feature value ratings of 4 or 5.

However, increasing the number of recommended items tends to reduce precision and increase recall. An F1-metric can be used to balance the trade-off between precision and recall (Van Rijsbergen, 1979; Liu & Shih, 2005), as shown in formula (13).

$$F_1 = \frac{2 \times P \times R}{P + R}. \tag{13}$$

The coverage of a recommendation system is a measure of the domain of items in the system over which the system can form predictions or make recommendations. Systems with lower coverage may be less valuable to users, since they will be limited in decision making capacity (Herlocker et al., 2004). Coverage is a measure of the percentage of items for which a recommendation system can provide recommendations. A high coverage value indicates that the recommendation system provides assistance in selecting among most of the items. We computed the percentage of recommendation-informed ratings over the total number of ratings as the coverage metric (Sarwar et al., 1998).

Predictive accuracy metrics measure how close the recommendation system's predicted ratings are to the true user ratings (Herlocker et al., 2004). We used MAE to measure predictive accuracy. MAE measures the average absolute deviation between the predicted rating and the user's true rating (Sarwar et al., 1998). MAE is computed by first summing the absolute errors of the corresponding ratings-prediction pairs, and then computing the average. MAE is computed by formula (14).

$$MAE = \frac{1}{|T| \times |C|} + \sum_{t \in T} \sum_{i,j \in C} |r_t^{ij} - p_t^{ij}|, \tag{14}$$

where r_t^{ij} is the rating given to the jth feature value in product feature i by customer t, and p_t^{ij} is the predicted value of customer t on the jth feature value in the ith feature. Finally, C is the set of feature values rated by customer t, and $|C|$ is the total number of elements contained in set C.

Correlation is a statistical measure of agreement between two vectors of data. Three of the most well known correlation measures are Pearson's product-moment correlations, Spearman's ρ, and Kendall's Tau. The Pearson correlation was used by Hill, Stead, Rosenstein, and Furnas (1995) to evaluate the performance of their recommendation system (Herlocker et al., 2004). We use the Pearson correlation coefficient as a measure of correlation between rating and predictions.

4.3. Evaluation results

Table 2 and Fig. 1 show the precision, recall, and $F1$ values used to evaluate classification accuracy of three recommendation systems: RS_IP (recommendation system using CPM_IP), RS_IB (recommendation system using CPM_IB), and RS-IGB (recommendation system using CPM_IGB). A higher value denotes increased accuracy, while a low value denotes less accuracy. RS_IGB shows the best performance among the three systems. This indicates that the proposed customer profile via CPM_IGB can recommend interesting products more correctly than the existing customer profile model. That is, the proposed profile model reflects customer interests better.

Table 3 provides the average coverage during ten purchase periods evaluated by RS_IP, RS_IB, and RS_IGB. The table shows that RS_IGB dramatically improves the average coverage. This indicates that our customer profile model CPM_IGB can recommend more items and has more value to customers than existing customer profile models.

Table 2
Comparison of classification accuracy for RS_IP, RS_IB, and RS_IGB

	RS_IP	RS_IB	RS_IGB
Precision	0.339	0.539	0.640
Recall	0.184	0.286	0.328
F1	0.223	0.352	0.410

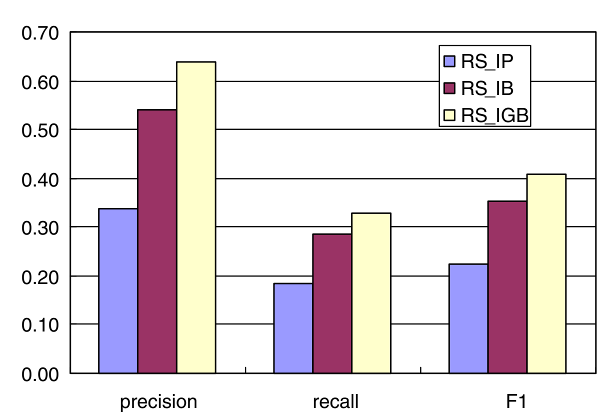

Fig. 1. Comparison of classification accuracy for RS_IP, RS_IB, and RS_IGB.

Table 3
Comparison of coverage for RS_IP, RS_IB, and RS_IGB

	RS_IP	RS_IB	RS_IGB
Coverage (%)	9.207	14.685	28.108

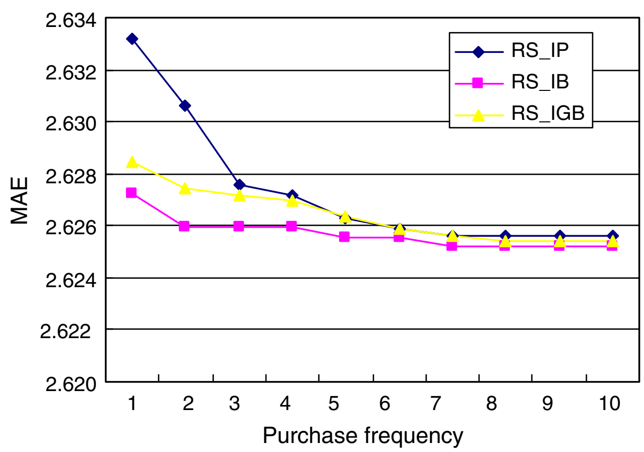

Fig. 2. Comparison of predictive accuracy for RS_IP, RS_IB, and RS_IGB.

Fig. 2 shows MAE value changes with respect to the purchase frequency using the RS_IP, RS_IB, and RS_IGB methods, which are used to evaluate predictive accuracy. The lower the MAE value, the more accurately the recommendation system predicts user ratings. The figure shows that RS-IB receives the lowest MAE value among the three systems, and that RS_IGB obtaines a lower MAE value than RS_IP. However, as the purchase frequency increases, the MAE value of RS_IGB becomes similar to that of RS_IB. Since MAE measures the deviation between a user's true rating and the predicted rating, it is natural for RS_IB to obtain lower MAE values than RS_IGB. Considering this point, we can say that RS_IGB shows good performance with respect to MAE.

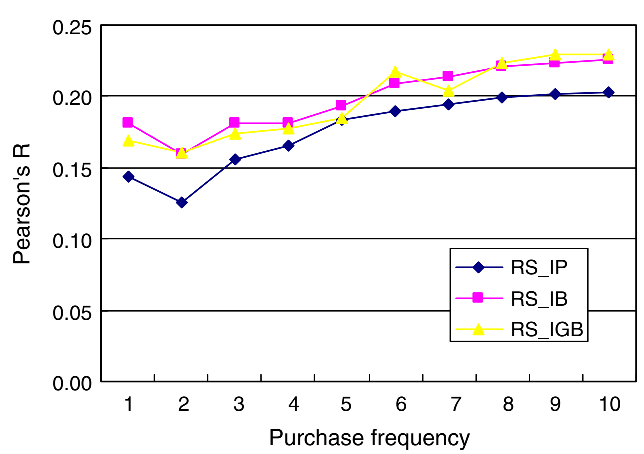

Fig. 3. Comparison of prediction-rating correlation for RS_IP, RS_IB, and RS_IGB.

Fig. 3 shows prediction-rating correlation value changes with respect to the purchase frequency using the RS_IP, RS_IB, and RS_IGB methods. A higher correlation value indicates more accurate recommendations. The figure shows that the correlation values of RS_IB and RS_IGB are higher than those of RS_IP, and the differences in correlation values between RS_IB and RS_IGB may not be practically significant.

5. Conclusions

In this paper, we have proposed a new customer profile model based on individual and group behavior such as clicks, basket insertions, purchases, and interest fields. The proposed model builds customer profiles through three phases. In phase 1, individual interests using individual behavior data are computed. In phase 2, interests using group behavior information are computed. Here, a group is a set of customers having similar demographic data to that of the corresponding customer. In phase 3, customer profiles are constructed using product features, and individual and group interests.

To evaluate the performance of the proposed profile models, we have developed three different recommendation systems RS_IP, RS_IB, and RS_IGB, and used several metrics, such as classification accuracy metrics, coverage, predictive accuracy metrics, and prediction-rating correlation. RS_IP is based on the customer profile model, which uses an individuals' purchase information only. RS_IB is based on the customer profile model, which uses individual behavior information. RS_IGB is based on the proposed customer profile model, which uses individual and group behavior information.

Experimental results show that the RS_IGB method has the best classification accuracy and coverage. In other words, precision, recall, F1, and coverage values are superior in the RS_IGB method. The differences in MAE and correlation values between the RS_IB and RS_IGB methods may not be practically significant. Thus our profile model can recommend interesting products more correctly, and provide many more items than currently available models. This means that the proposed profile model reflects customer interest better, and is more valuable to customers.

Our study contributes to building an improved customer profile model using individual and group behavior data. If the model is applied to content-based filtering and collaborative filtering, the recommendation systems could recommend much more suitable products for customers. The recommendation systems using a more accurate customer profile model can reduce the time and effort required to find information that meets a customer's needs. In so doing, they will improve customer satisfaction and loyalty.

There are some limitations to our study. First, customer groups could not be classified accurately according to their various features, because we used demographic data only in order to classify customer groups. Second, the profile did not reflect individual and group weighting factors, because we assumed that the importance of individual and group behavior data were equal. Therefore, in future work we intend to complement our model using other classification techniques, and propose a procedure to adjust the group and individual behavior significance depending on customer and group behaviors.

References

Ansari, A., Essegaier, S., & Kohli, R. (2000). Internet recommendation systems. *Journal of Marketing Research, 37*(3), 363–375.

Balabanovic, M., & Shoham, Y. (1997). Fab: Content-based, collaborative recommendation. *Communication of the ACM, 40*(3), 66–72.

Basu, C., Hirsh, H., & Cohen, W. (1998). Recommendation as classification: using social and content-based information in recommendation. In *Proceedings of the 1998 workshop on recommender systems* (pp. 11–15). Menlo Park, CA.

Billsus, D., & Pazzani, M. J. (1998). Learning collaborative information filters. In *Proceedings of the 15th international conference on machine learning* (pp. 46–54). Morgan Kaufmann, San Francisco.

Billsus, D., & Pazzani, M. J. (1999). A hybrid user model for news story classification. In *Proceedings of international conference on user modeling* (pp. 99–108). Banff, Canada.

Changchien, S. W., Lee, C.-F., & Hsu, Y.-J. (2004). On-line personalized sales promotion in electronic commerce. *Expert Systems with Applications, 27*(1), 35–52.

Cho, Y. B., Cho, Y. H., & Kim, S. H. (2005). Mining changes in customer buying behavior for collaborative recommendations. *Expert Systems with Application, 28*(2), 359–369.

Cho, Y. H., & Kim, J. K. (2004). Application of Web usage mining and product taxonomy to collaborative recommendations e-commerce. *Expert Systems with Applications, 26*(2), 233–246.

Cunningham, P., Bergmann, R., Schmitt, S., Traphoner, R., Breen, S., & Smyth, B. (2001). WebSell: Intelligent sales assistants for the world wide web. *Kunstliche Intelligenz (KI), 15*(1), 28–32.

Fan, W., Gordon, M. D., & Pathak, P. (2005). Effective profiling of consumer information retrieval needs: A unified framework and empirical comparison. *Decision Support Systems, 40*(2), 213–233.

Herlocker, J. L., Konstan, J. A., Terveen, L. G., & Riedl, J. (2004). Evaluation colaborative filtering recommender systems. *ACM Transactions on Information Systems, 22*(1), 5–53.

Hill, W., Stead, L., Rosenstein, M., & Furnas, G. W. (1995). Recommending and evaluating choices in a virtual community of use. In *Proceedings of ACM CHI'95 conference on human factors in computing systems* (pp. 194–201). ACM, New York.

Huang, Z., Chung, W., & Chen, H. (2004). A Graph Model for E-Commerce Recommender Systems. *Journal of the American society for information science and technology, 55*(3), 259–274.

Krulwich, B., & Burkey, C. (1996). Learning user information interests through extraction of semantically significant phrases. In *Proceedings of the AAAI spring symposium on machine learning in information access* (pp. 100–112). Stanford, CA.

Lang, K. (1995). Newsweeder: Learning to filter net news. In *Proceedings of the twelfth international conference on machine learning* (pp. 331–339). Lake Tahoe, CA.

Lee, C. H., Kim, Y. H., & Rhee, P. K. (2001). Web personalization expert with combining collaborative filtering and association rule mining technique. *Journal of Expert Systems with Application, 21*(3), 131–137.

Lee, W. P., & Yang, T. H. (2003). Personalizing information appliances: A multi-agent framework for TV programme recommendation. *Expert Systems with Applications, 25*(3), 331–341.

Lin, W., Alvarez, S. A., & Ruiz, C. (2002). Efficient adaptive-support association rule mining for recommender systems. *Data Mining and Knowledge Discover, 6*(1), 83–105.

Liu, D. R., & Shih, Y. Y. (2005). Integrating AHP and data mining for product recommendation based on customer lifetime value. *Information and Management, 42*(3), 387–400.

Min, S. H., & Han, I. (2005). Detection of the customer time-variant pattern for improving recommender systems. *Expert Systems with Application, 28*(2), 189–199.

Montaner, M., Lopez, B., & De La Rosa, J. L. (2003). A taxonomy of recommender agents on the Internet. *Artificial Intelligence Review, 19*(4), 285–330.

O'Donova, J., & Smythe, B. (2005). Trust in Recommender Systems. In *Proceedings of IUI'05* (pp. 167–174). San Diego, California.

Pazzani, M. J. (1999). A framework for collaborative, content-based and demographic filtering. *Artificial Intelligence Review, 13*(5–6), 393–408.

Resnick, P., & Varian, H. R. (1997). Recommender systems. *Communications of the ACM, 40*(3), 56–60.

Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2001). Item-based collaborative filtering recommendation algorithm. In *Proceedings of the tenth international world wide web conference* (pp. 285–295). Hong Kong.

Sarwar, B., Konstan, J. A., Borchers, A., Herlocker, J., Miller, B., & Riedl, J. (1998). Using filtering agents to improve prediction quality in the GroupLens research collaborative filtering system. In *Proceedings of CSCW'98* (pp. 345–354). Seattle, WA.

Van Rijsbergen, C. J. (1979). *Information retrieval* (2nd ed.). Butterworth.

Wang, F. H., & Shao, H. M. (2004). Effective personalized recommendation based on time-framed navigation clustering and association mining. *Expert Systems with Application, 27*(3), 365–377.

Wang, Y. F., Chuang, Y. L., Hsu, M. H., & Keh, H. C. (2004). A personalized recommender system for the cosmetic business. *Expert Systems with Applications, 26*(3), 427–434.

Weng, S. S., & Liu, M. J. (2004). Feature-based recommendation for one-to-one marketing. *Expert Systems with Applications, 26*(4), 493–508.

Yen, B. P.-C., & Kong, R. C. W. (2002). Personalization of information access for electronic catalogs on the web. *Electronic Commerce Research and Applications, 1*(1), 20–40.

Zeng, C., Xing, C. X., Zhou, L. Z., & Zheng, X. H. (2004). Similarity measure and instance selection for collaborative filtering. *International Journal of Electronic Commerce, 8*(4), 115–129.