Helping Online Customers Decide through Web Personalization

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The Web-based personalization system proposed here uses both collaborative filtering and Web usage mining to give online shoppers the personalized recommendations they need to purchase products more intelligently.

As business-to-consumer electronic markets mature on the Web, competition in the online retail marketplace heats up, driving down profit margins for existing competitors and new entrants alike. To survive in this environment, much less gain a competitive advantage, a successful online retailer must provide a bundle of attractive, personalized services that satisfy its customers' needs. Increasingly, e-commerce sites are turning to rigorous personalization studies to help solve this problem.

Web-based personalization consists of activities, such as providing customized information, that tailor the user's Web experience—browsing a Web site or purchasing a product, for example—to that user's particular needs. Thus, personalization systems aim to identify customers online, understand and predict their buying patterns, identify what they want or need without requiring them to ask for it explicitly, and deliver appropriate offers in personalized formats directly to them.[1,2]

This article describes a personalized recommender system designed to provide online customers with information to help them decide which products to purchase. Recommendation is often part of a site's personalization because it helps the site adapt to each customer. The system combines two of the newest and most popular approaches to generating recommendations: collaborative filtering and Web usage mining. As this article will show, integrating collaborative filtering with Web-usage-mining techniques lets the system produce better recommendations more intelligently than earlier approaches that used only such data-mining techniques as clustering, association or sequencing mining, or profiling.[2,3]

Personalization techniques

The science behind personalization has undergone tremendous changes, and several Web-based personalization systems have been proposed in recent years. Although personalization can be accomplished in numerous ways, most Web personalization techniques so far fall into three major categories: *decision rule-based filtering*, *content-based filtering*, and *collaborative filtering*.[4,5]

Decision rule-based filtering surveys users to obtain user demographics or static profiles, then lets Web sites manually specify rules based on them. It delivers the appropriate content to a particular user based on the rules. However, it isn't particularly useful because it depends on users knowing in advance the content that interests them.

Content-based filtering relies on items being similar to what a user has liked previously.

Collaborative filtering, also called social or group filtering, is the most successful personalization technology to date. In use with many of the most successful recommender systems on the Web,[6] it typically uses explicit user ratings of products or preferences to sort user profile information into peer groups. It then tells users what products they might want to buy by combining their personal preferences with those of like-minded individuals.

However, collaborative filtering has limited use for a new product that no one has seen or rated, and content-based filtering to obtain user profiles might miss novel or surprising information. Additionally, traditional Web personalization techniques, including collaborative or content-based filtering, have other problems, such as reliance on subject user ratings and static profiles or the inability to capture richer semantic relationships among Web objects.

To overcome these shortcomings, the new Web per-

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sonalization tool, *nonintrusive personalization*, attempts to increasingly incorporate Web usage mining techniques. Web usage mining uses data mining algorithms to automatically discover and extract patterns from Web usage data and predict user behavior while users interact with the Web.[7,8] Although Web usage mining has exposed limitations—sparsity in usage data or regular changes in site content, for example—personalization based on Web usage mining has several advantages over traditional techniques.[9] For example, it can dynamically develop user profiles from user patterns while reducing the need to explicitly obtain subjective user ratings or registration-based personal preferences, which are prone to biases. So, the personalization system's performance does not degrade over time.

Web usage mining in this article extracts the customers' current browsing patterns, derives purchase deliberation to psychographically cluster customers (buying-attitude-based segmentation), and obtains implicit user ratings for recommended products from Web usage data. Collaborative filtering needs customer communities or peer groups to compute the set of recommendations. This article provides two methods to find them: *buying-attitude-based segmentation* from the customer's browsing history and *buying-behavior-based segmentation* from the customer's purchase history.

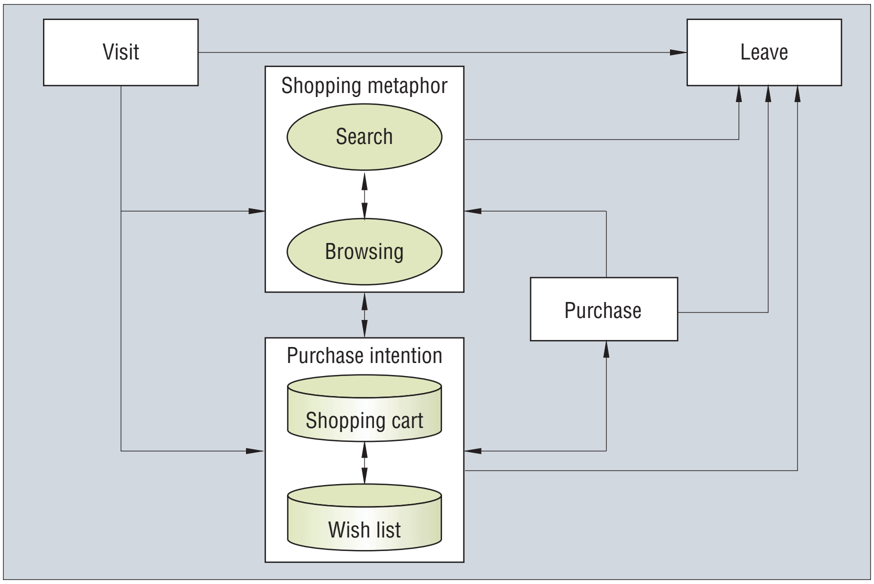

Figure 1. Overview of the Web user life cycle on an e-commerce Web site.

The recommender system

I developed and tested the recommender system for a Korean e-commerce site as part of its online automobile parts and supplies shopping mall. To evaluate its effectiveness, I adopted implicit user ratings from usage data to observe each type of recommendation and compare its performance without annoying users.

Web user life cycle

For a high-involvement purchase, such as a car, customers often go through a rigorous buying process. Using previous buyer behavior literature on online shopping Web sites,[10] Figure 1 summarizes the shopping stages and their interactions in high-customer-involvement purchases. It will guide the design of the recommendation functions necessary for effective customer support. The five stages of goal-driven buyer behavior—called the Web user life cycle—are

1. Recognition of the need to visit the Web site
2. Product information search using shopping metaphors, such as searching or browsing (surfing)
3. Alternative products evaluation and purchase desire
4. Purchase action
5. Site exit and postpurchase evaluation

A good Web site must help buyers through all these stages, which necessitates providing consistent and well-designed recommendations at all buying stages.

System overview

The overall process of collaborative and usage-based Web recommendation has two components: offline and online. The offline component and its functionality comprise

- *A data transformation agent.* This agent prepares for data mining and Web usage mining resulting in customer purchasing and browsing history files.
- *Web mining and data mining agents.* These agents derive customer clusters based on two types of segmentation bases—such as a psychographic variable (purchase deliberation) and behavioral variables (purchase recency, frequency, and monetary values)—and the renewal of customer browsing or purchasing patterns.
- *A recommendation generation agent.* This agent discovers the four types of association rules—mild, moderate (Types A and B), and strong—on the basis of derived customer clusters.

One of the offline component's special features is providing users with recommendations through such methods as email after they've left the site.

Once the system accomplishes mining tasks, the architecture's online component uses frequent item sets and other items (the best-selling products, the newest products, and so on) to give users dynamic recommendations based on their purchasing and browsing histories.

The online component comprises an *interface agent*, a *matching agent*, and the *HTTP server*. The interface agent provides an interface between the HTTP server and its users for customer interaction. The Web server helps identify a user and tracks the active user session as the interface agent makes HTTP requests. The server does this in several ways, such as rewriting a URL or temporarily caching the Web server access logs.

The matching agent looks up the recommendation list database to extract a set of recommended products for the target user for each Web user life cycle stage. It then sends the recommendation set to the client browser through the interface agent. The matching agent also uses a customer's current navigational activity to reflect his or her current interests before deriving the recommendations from the database. Figure 2 depicts an overall architecture showing the system's essential components.

Product taxonomy

Structuring and standardizing product descriptions is significant in e-commerce

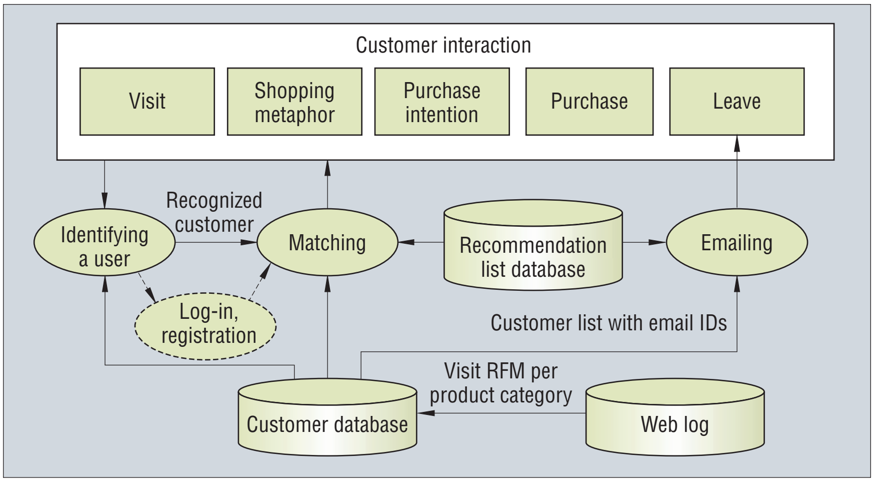

Figure 2. Overall architecture of collaborative and usage-based Web recommender system.

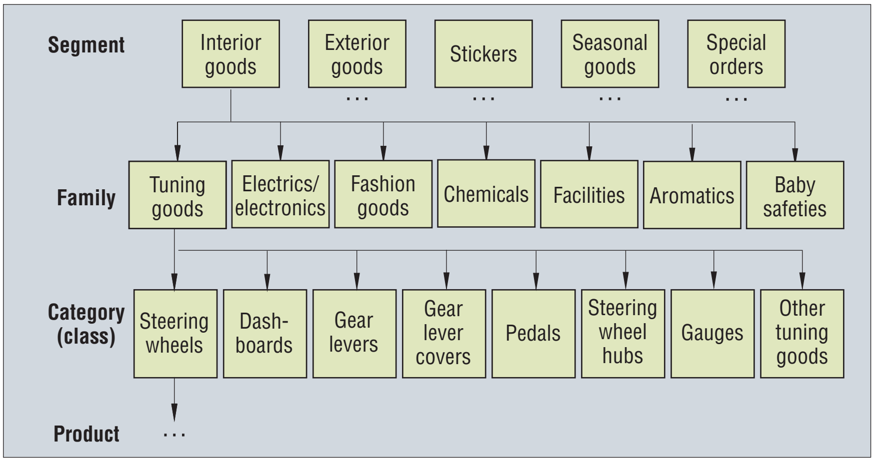

Figure 3. Sample product taxonomy of the online store.

because it ensures that buyers and sellers can electronically communicate about product information. However, in business-to-consumer e-commerce, which deals with more generic products, each shopping mall in a specific domain might describe its products using a different product hierarchy. Although this article's example is specific to an automotive parts shopping mall, the taxonomy is typical of the multilevel hierarchy representing various retail product catalogs.[3,10]

The online store's products have a four-level classification: segment, family, category (class), and product. About 1,500 products are divided into five segments, 21 families, and 174 categories. Figure 3 illustrates the hierarchical classification schema and an example of interior goods. This product taxonomy characterizes the online retailer's preferences; other retailers could use different hierarchies to represent their product catalogs.

Collaborative filtering and customer segmentation

To generate recommendations for a target customer with collaborative filtering, I use the following steps:

1. The recommender system assigns customers to peer groups based on their purchasing histories or their page-to-page browsing behavior prior to making purchases.
2. When an established customer returns to the site, the system can base a recommendation on what members of his or her peer group have purchased.

Customer segmentation breaks customers into peer groups with common needs. Behaviors among the groups, however, differ significantly.[5] Although four general bases for customer segmentation exist—demographic, geographic, psychographic, and behavioral—and have many segmentation variables, this study uses only behavioral segmentation and psychographic segmentation (see Figure 4); they provide more knowledge on each customer's actual spending preferences and more accurate behavior predictions than demographic- and geographic-based segmentations, which are generally useful.[3,11] When using all types of segmentation bases does not show much difference in effectiveness compared to one using only the psychographic and behavioral bases, then the latter is enough to segment customers from the cost-versus-effect perspective.

Buying-behavior-based segmentation

BBBS focuses on behavioral variables, including product usage. Segmentation by product usage uses a method called *purchase RFM* (recency, frequency, and monetary value) *analysis* to segment customers on the basis of how long since they made purchases, how frequently they make purchases, and how much money they spend.

Given numerous purchase transactions, segmentation identifies a few customer stereotypes that represent dominant characteristics (features) present in the customer's purchase behavior. Some common algorithms used to perform clustering include the self-organizing map (SOM), which uses a neural clustering method to divide the online retailer's customers into numerous groups with similar purchase RFM values.

The SOM uses competitive learning (that is, a winner-take-all algorithm). When an input pattern is imposed on the neural network, the algorithm selects the output node with the smallest Euclidean distance between the presented input pattern vector and its weight vector. Only this winning neuron generates an output signal from the output layer; all other neurons in the layer have a zero output signal. Because learning involves weight vector adjustment, only the neurons in the winning neuron's neighborhood can learn with this particular input pattern. They do this by adjusting their weights closer to the input vector. The neighborhood's size initially includes all units in the output layer. However, as learning proceeds, it progressively shrinks to a predefined limit, and fewer neurons adjust their weights closer to the input vector. Lateral inhibition of weight vectors that are distant from a particular input pattern might also occur.

The SOM does unsupervised clustering;

that is, given training patterns that contain inputs only, the SOM assigns output units that represent clusters to inputs. Once trained, a SOM forms a topological map using the output layer. Mapping input customer RFM patterns to the output customer segments reflects the inputs' existing similarities. The self-organizing algorithm not only assigns cluster centers to units, but also tends to group similar centers close together, and thus implies the clusters' relationship and the network's topological behavior.

Table 1 summarizes the nine segments, which are derived from a three-by-three SOM; it shows the fraction of total customers assigned to each cluster and the most significant characteristics—average recency, frequency, and monetary values—that make the clusters unique. The raw input data for this analysis are 3,000 customers from 1 May to 1 November 2001.

Each row represents a cluster, with the largest cluster containing 21.3 percent (639 out of 3,000) of the customers and the smallest 4.7 percent (141 out of 3,000). A cluster's average recency (or frequency or monetary value) is defined as the ratio of the total recency (or frequency or monetary value) of customers in a cluster to the cluster's entire customer population. We can consider as loyal segments clusters three, six, and seven, (18.8 percent), which contain recent, frequent, and high-spending shoppers based on minor recency figures and above-average frequency and monetary values.

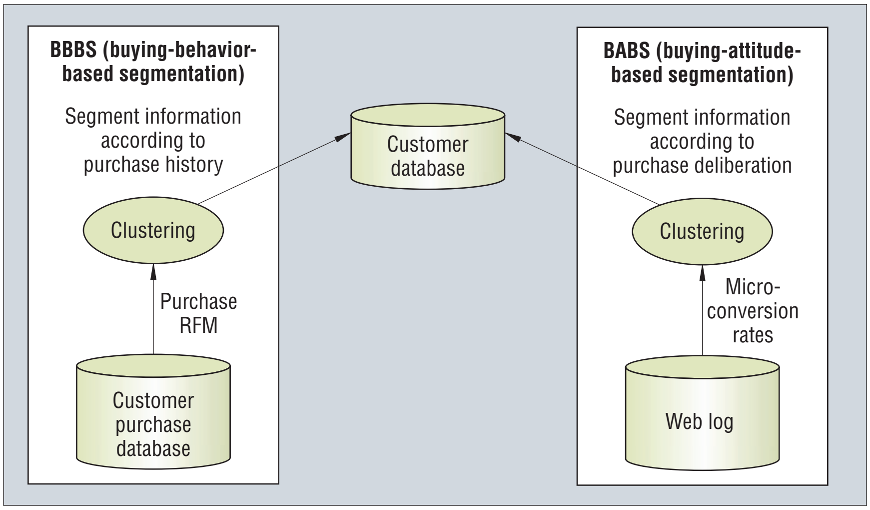

Figure 4. Two types of customer segmentation: buying-behavior-based segmentation versus buying-attitude-based segmentation.

Table 1. Summary of customer cluster characteristics: Buying-behavior-based segmentation.

	Characteristic vectors (centroid)			
Cluster	Fraction of customers (%)	Average recency	Average frequency	Average monetary value
1	11.2	162.4	1.3	482.9
2	21.3	436.2	1.2	465.6
3	4.7	88.5	7.0	3,352.3
4	8.0	295.2	2.5	1,520.8
5	8.1	167.3	1.7	1,351.7
6	7.7	83.8	3.6	1,617.5
7	6.4	122.5	3.8	2,730.8
8	20.6	68.9	1.4	544.0
9	12.0	278.6	1.5	573.6
Total average		214.3	2.1	1,022.2

Buying-attitude-based segmentation

BABS focuses on customers' psychographic variables, including purchase deliberation. An online customer's purchase deliberation is the elapsed time between a customer's first considering buying and the actual purchase.

Online retailing lets us understand each customer's purchasing attitude and browsing behavior prior to the purchase. Microconversion rates for an e-commerce Web site can express purchase deliberation because we can view the Web site as a collection of advertisements for the store's individual products. The microconversion rate extends the traditional conversion rate (the percentage of visitors who purchase from the store[3,5]). As typical customers move from visit to purchase on the Web user life cycle, the click rates for each pair of adjacent stages represent the degree of purchase deliberation. To consider the degree of purchase deliberation, the following four microconversion rates might be necessary:

- *List-to-detail rate*: the number of products on a product list viewed in detail
- *Detail-to-cart rate*: the number of items viewed in detail that are placed into a shopping cart or wish list
- *List-to-cart rate*: the number of items on a product list directly placed into a shopping cart or wish list
- *Cart-to-purchase rate*: the number of items in the shopping cart or wish list that are purchased

Following Ravi Kalakota and Andrew Whinston's classification scheme,[12] this study classifies customers as either impulsive, patient, or analytical from the purchase deliberation perspective. The recommender system uses Web logs recording the customer's clicks to derive microconversion rates and identify the customer's degree of purchase deliberation (although a customer might show such behavior prior to purchasing a product as idleness or failure). Other explanations about purchase deliberation include the following:

- Impulsive buyers purchase products quickly with little analysis.
- Patient buyers purchase products after making a certain number of comparisons.
- Analytical buyers do substantial research before deciding to purchase products or services.

This study considers only three microconversion rates—list-to-detail, detail-to-cart, and list-to-cart—to represent customers' purchase deliberation. Table 2 presents the microconversion rates according to three different types of purchase deliberation. Impulsive buyers have low list-to-detail, high detail-to-cart, and high list-to-cart rates because they scarcely compare products or

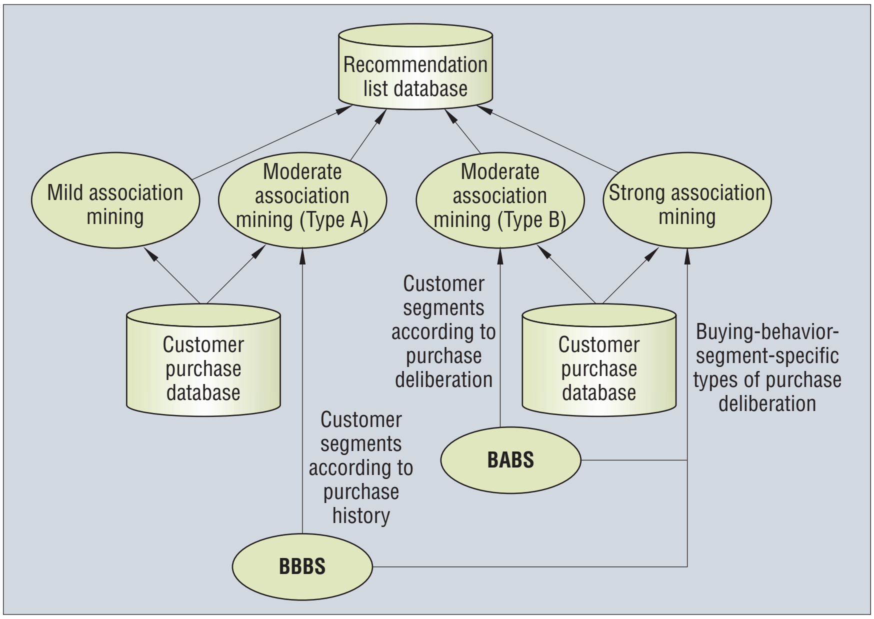

Figure 5. Four types of association mining: mild, moderate (Types A and B), and strong.

Table 2. The relationship between purchase deliberation types and microconversion rates.

	Microconversion rate		
Purchase deliberation	**List-to-detail**	**Detail-to-cart**	**List-to-cart**
Impulsive buyers	Low	High	High
Patient buyers	Middle	Middle	Middle
Analytical buyers	High	Low	Low

Table 3. Summary of customer cluster characteristics: Buying-attitude-based segmentation.

		Characteristic vectors (centroid)		
Cluster	**Fraction of customers (%)**	**Average list-to-detail rate (%)**	**Average detail-to-cart rate (%)**	**Average list-to-cart rate (%)**
1	24.7	36.06	20.88	9.58
2	3.4	16.24	2.63	10.62
3	4.4	21.42	7.12	21.16
4	17.3	21.44	14.28	13.98
5	6.1	33.38	9.39	6.75
6	14.6	26.87	11.89	4.18
7	29.5	10.96	26.72	8.72
Total average		23.77	14.41	9.57

tend to quickly buy products they view only once in detail.

Patient buyers' list-to-detail, detail-to-cart, and list-to-cart rates are usually mid-sized values because they are middle-roaders. Analytical buyers' list-to-detail, detail-to-cart, and list-to-cart rates are high, low, and low, respectively. They make more extensive comparisons between products than patient buyers.

Table 3 presents the results of a three-by-three SOM that formed seven clusters using BABS (purchase deliberation). The raw input data for this analysis are also 3,000 customers, as used previously in the BBBS.

Tables 2 and 3 together show that, although heuristic, cluster one probably represents patient buyers (24.7 percent) based on the mid-sized values in the detail-to-cart and list-to-cart rates. Clusters 2, 3, 4, and 7 have impulsive buyers (54.6 percent), and clusters 5 and 6 contain analytical buyers (20.7 percent).

The recommender system will use this information on customer segments later to perform association mining and product matching.

Association mining

After assigning customers to peer groups based on BBBS or BABS, the recommender system uses association mining to make recommendation lists for segmented customers based on what their peer group members have been buying. Association mining is necessary to guide customers to things they don't know they need.

Given a customer purchase database, where each sequence is a transaction list ordered by transaction time and each transaction comprises a set of items (for example, products or product categories), association mining finds all product affinities with a predefined minimum support; I define the support as the fraction of total transactions that support those associations.[4]

In this study, the system derives four types of association rules (as previously mentioned) from the customer purchase database at both the product and product category levels: mild, moderate (Types A and B), and strong (see Figure 5). Mild association mining computes the product associations of all customers in the database. So, the transactions used to calculate support and confidence (the fraction of transactions containing consequent items to transactions containing antecedent items) encompass all customers' transactions in the database.

Moderate association mining produces lists of the associative products for each customer segment being identified. Then, the system uses this segment-specific list as input to generate recommendations for a target customer in that particular segment. List generation per each segment is based on the collaborative-filtering assumption that customers in the same segment have common preferences. Type A moderate associations are extracted from BBBS and Type B from BABS. In this case, the system reduces the total transactions used to calculate support and confidence to the specific customer segments' transactions. Strong association mining extracts product affinities of customers who share similar purchasing attitudes (that is, purchase deliberation) in purchasing-behavior-based segments.

Association mining occurs offline, and the system keeps the product affinities information (that is, association rules) in the recommendation list database, so work needed during the online customer interaction is minimal.

Contents of the recommendation list database

No matter the type of associations, association mining discovers the following rules:

- *Associative products at the product level: product => product rules*, which are sorted in descending order of criteria, such as confidence. The recommender system only computes simple associations containing a single item in both the rule's antecedent and consequent because of clarity of understanding and computational complexity.
- *Associative products at the product category level: category => product rules*. One way to derive these rules is to classify product categories of the product => product association rules' antecedents, replace products in antecedents with their categories, and compute the arithmetic means of confidence. Category => product rules extend the range of the target customer's interest to the category level, which groups those products sharing a common use or function.
- *Associative categories at the product level: product => category rules*. Deriving the product => category rules is similar to calculating the category => product rules, except it uses the product => product rules' consequents instead of antecedents to classify product categories. The best products belonging to the consequent (product category)—such as the best-selling products, the products with the highest conversion rate, and the newest products—help cross-sell an incremental product to the target customer and form part of the recommendation list database.
- *Associative categories at the product category level: category => category rules*. Replace products in the product => product rules' antecedents and consequents with their categories and compute the arithmetic means of confidence. One reason for deriving such rules is to highlight the most popular items in the consequent for the target customer, especially when he or she visits the site.

Figure 6 shows a subset of strong association rules computed at the product and category levels for both loyal and impulsive customers. The raw input data for this analysis are 8,000 product-level transactions for 3,000 customers. Although complex patterns are possible, the system computes only simple association rules containing a single item.

I can choose a threshold on the support measure to limit the rules after experimenting with different values on this parameter and inspecting the results. Although heuristic, this choice produces a reasonable number of

Product	Product	Support (%)	Confidence (%)
Chrome-plated bumper molding: 12 mm wide, 5m, 60 cm long	Chrome-plated bumper molding: 8 mm wide, 5 m long	2.1	55.2
Gear lever cover: Motor speed side knob set	Gear lever cover: Autocom gear lever bonnet	3.2	52.1
Chrome-plated bumper molding: 12 mm wide, 5m, 60 cm long	Chrome-plated bumper molding: 10 mm wide, 5 m long	1.7	44.8
Sticker: My name is - E	Sticker: My name is - L	2.2	44.7
Ahngaro side lamp (chrome)	Solar white bulb (3 types)	4.1	40.5
Chrome-plated bumper molding: 10 mm wide, 5 m long	Chrome-plated bumper molding: 8 mm wide, 5 m long	2.9	39.3
Gear lever: Racing shift ball (aluminum + natural leather)	Gear lever cover: Autocom gear lever bonnet	1.6	38.7
Pedal: Carex side pad	Pedal: Carex racing sports pad	2.7	37.5
Sticker: My name is - A	Sticker: My name is - I	1.9	36.6

(a)

Product category	Product category	Support (%)	Confidence (%)
Gear lever cover	Gear lever cover	3.2	52.1
Chrome-plated bumper molding	Chrome-plated bumper molding	2.4	43.9
Rear light/ brake light	Headlight	4.1	40.0
Small sticker	Small sticker	2.3	39.1
Gear lever	Gear lever cover	1.6	38.7
Pedal	Pedal	2.7	37.5

(b)

Product	Product category	Support (%)	Confidence (%)
Gear lever cover: Motor speed side knob set	Gear lever cover	3.2	52.1
Chrome-plated bumper molding: 12 mm wide, 5m, 60 cm long	Chrome-plated bumper molding	1.9	50.0
Sticker: My name is - Y	Small sticker	3.0	44.7
Ahngaro side lamp (chrome)	Headlight	4.1	40.5
Solar white bulb (3 types)	Rear light/ brake light	4.1	39.5
Chrome-plated bumper molding: 10 mm wide, 5 m long	Chrome-plated bumper molding	2.9	39.3
Gear lever: Racing shift ball (aluminum + natural leather)	Gear lever cover	1.6	38.7
Pedal: Carex side pad	Pedal	2.7	37.5
Chrome-plated bumper molding: 8 mm wide, 5 m long	Chrome-plated bumper molding	2.9	36.7

(c)

Product category	Product	Support (%)	Confidence (%)
Gear lever cover	Gear lever cover: Autocom gear Lever bonnet	3.2	52.1
Chrome-plated bumper molding	Chrome-plated bumper molding: 8 mm wide, 5 m long	2.5	47.2
Small sticker	Sticker: My name is - O	2.3	45.3
Chrome-plated bumper molding	Chrome-plated bumper molding: 10 mm wide, 5 m long	2.3	40.8
Rear light/ brake light	Solar white bulb (3 types)	4.1	40.5
Headlight	Ahngaro side lamp (chrome)	4.1	39.5
Gear lever	Gear lever cover: Autocom gear lever bonnet	1.6	38.7
Pedal	Pedal: Carex racing sports pad	2.7	37.5
Small sticker	Sticker: My name is - K	2.4	37.4

(d)

Figure 6. Sample of strong association rules computed at product or category levels: (a) product => product rules; (b) category => category rules; (c) product => category rules; and (d) category => product rules.

Figure 7. Sample screen shots: (a) visiting the online store and (b) viewing a specific product. (Some Korean words were translated into English for readers' understanding.)

strong association rules (when setting the threshold to 1 percent, around 130 rules are produced). The first association rule's textual format in Figure 6b is "52.1 percent of customers in the loyal and impulsive customer segment who buy a gear lever cover also buy another gear lever cover." The fifth rule says when a loyal and impulsive customer buys a gear lever, the customer also buys a gear lever cover in 38.7 percent of the cases.

Making recommendations according to the Web user life cycle

Because Web users are getting more impatient with slow recommendation downloads, online stores should design their home pages to follow high-priority accessibility. Accordingly, for a user visiting the store, the recommender system quickly discovers and highlights the most important recommendations.

After recognizing a Web user, the recommender obtains the user's browsing history since his or her last visit from the customer database, which can be expressed with visit RFM per product category. Visit recency describes how long it has been since a customer visited a product category. As a category's visit recency increases, the potential for future purchases from that category decreases. Visit frequency is how many times a customer visits a category. Visit monetary value calculates the number of visited product pages per category.

The recommender takes the user directly to the product list page of the most recent product category the user is interested in and, therefore, has the smallest (zero, in most cases) visit recency and the largest visit frequency and visit monetary values. If two or more categories have equal visit RFM, the recommender randomly selects one category. The recommender matches the user to the recommendation list database to draw a set of recommendations and displays them on the user's browser. The recommendations include the following:

- The category's best products
- The most associative category's best products
- The associative products with the category

Figure 7 shows sample screen shots of how the system recommends a product to the target customer. The customer belongs to the loyal and impulsive segment, and his or her visit RFM values focus on the gear levers category since the last visit. When the customer visits the site, the recommender opens a product list page from the gear levers category (see Figure 7a).

Viewing a specific product or placing an item into a shopping cart

In pursuit of their own goals, Web users often use searching and browsing to find product information. When a user follows a page link to a product detail page or places an item into a shopping cart (or on a wish list), the recommender refers to the recommendation list database for the user and shows the user the recommendation set that appears relevant to his or her current action as follows:

- The associative products at product level from product => product rules
- The associative products at category level from category => product rules
- The associative categories at product level from product => category rules and their best products
- The associative categories at category level from category => category rules and their best products

Association rules remain static and unchanged until the next association mining. However, customers' interests and needs continuously change. The recommender system must capture this change. To do so, the customer database also contains each customer's browsing behavior since his or her last purchase, which can be expressed with visit RFM values per product category. These visit RFM values differ from those previously used to serve a customer visiting the Web site. The former records a customer's browsing history per category since his or her last purchase and the latter records a customer's browsing history per category since his or her last visit. Therefore, the former's values are zero whenever the customer makes a purchase, and the latter has new values whenever the customer visits the store.

For example, when a customer visits the online store and looks at four products in the steering wheel category, followed by two products in the pedals category and two more in the steering wheel category, the customer's visit RFM values for the steering wheel category since his or her last purchase are 0, 2, and 6; visit RFM values for the pedals are 0, 1, and 2. For other categories in the store, visit frequency and visit monetary values remain the same, but visit recency increases by one. The product categories that a user has wanted since his or her last purchase probably have smaller (0, in some cases) visit recency value and larger visit frequency and visit monetary values than others.

From the previous purchase to the new purchase, if visit RFM values are evenly distributed across product categories, the recommender system displays the associative products (or product categories) stored in the recommendation list database in order of support and confidence. However, if a customer's browsing behavior is narrowly distributed around specific categories, the recommender places them on top of display listings.

Figure 7b explains how the system makes a recommendation to the target customer when he or she views "gear lever: racing shift ball" in detail. If the target customer belongs to the loyal and impulsive customer segment and strong associations are used (see Figure 6) the system determines the recommendations as follows:

- The most associative product at product level—gear lever cover: Autocom gear lever bonnet
- The most associative product at category level—gear lever cover: Autocom gear lever bonnet
- The most associative category at product level—Gear lever covers
- The most associative category at category level—Gear lever covers

Making a purchase or leaving

While a customer is making a purchase and checking out, the recommender gives him or her a customized offer for additional products. It looks up the recommendation list database to find the purchase's most associative products and the best products of the most associative category and displays them on the customer's browser to induce additional purchases before he or she leaves. If the customer permits, the recommender notifies him or her of matched recommendations through email.

When a user leaves the site without purchasing any products, the recommender makes a recommendation based on the user's history of purchases (purchase RFM values) and historical browsing behavior (visit RFM values) through a method such as email.

Evaluating and renewing recommendation lists

The most time-consuming tasks for Web personalization are data preparation and mining, which are accomplished when the customers are offline. The system stores the recommendation sets derived from mining tasks in the recommendation list database so that the online component can provide real-time recommendations. Therefore, from the Web usability perspective, the recommender system's online response time can satisfy the users' speed requirements (although much depends on the network's speed and the server and client computers' computing capabilities.

To evaluate the recommender system's predictive effectiveness and guarantee a reliable experiment, the online shopping site runs multiple Web servers, which operate together and deal with actual customers doing real shopping. Among the multiple Web servers, the users connect to one virtual server that represents the actual ones. The virtual server automatically does the load balancing and determines which server the user's request gets redirected to. The users access the same content regardless of which server they connect to. The Web servers described previously are divided into two groups; the treatment group has the recommender and the control group does not. Under such circumstances, the virtual server's redirection might not be random. However, because the amount of access to these two groups should eventually be same, there is no concern about random sampling. Users will access the shopping site without recognizing the experiment's existence, which guarantees that the same customers get the same services during the study.

Although an online shopping mall must reveal the product recommendation's logic, and a customer can select specific types of association mining in the real application, this article compares the performance of four types of association mining based on microconversion rates. By obtaining implicit microconversion rates from usage data as the result of user Web interactions, no explicit and subjective user ratings are collected or retained, letting the experiment track the performance without annoying the user.

Figure 8 illustrates 25 observations and a performance comparison of the four types of association mining versus "without recommendation" for the steering wheel category.

To understand the gradual change of microconversion rates, the system collects information on them (how many products on a product list are placed into a shopping cart or a wish list) from the Web servers' usage data, and I can make several interesting observations:

- *Intercategory variation.* The microconversion rate distributions over time differ among product categories in the store. Figure 8 shows the microconversion rate distribution for steering wheels. These results mean that each product category has its own specific characteristics—for example, one category's recommendations are more welcome than others.
- *Within-category similarity.* The microconversion rates' distributions without recommendations and with recommendations show similar fluctuation patterns over time within a category. Additionally, the time series graphs in Figure 8 indicate moderately large positive correlations—0.6, 0.8, and 0.67—between mild associations and Type A moderate associations, between Type B moderate associations and strong associations, and between strong associations and mild associations. These result from the characteristics of customers who are interested in that category at the time observed.

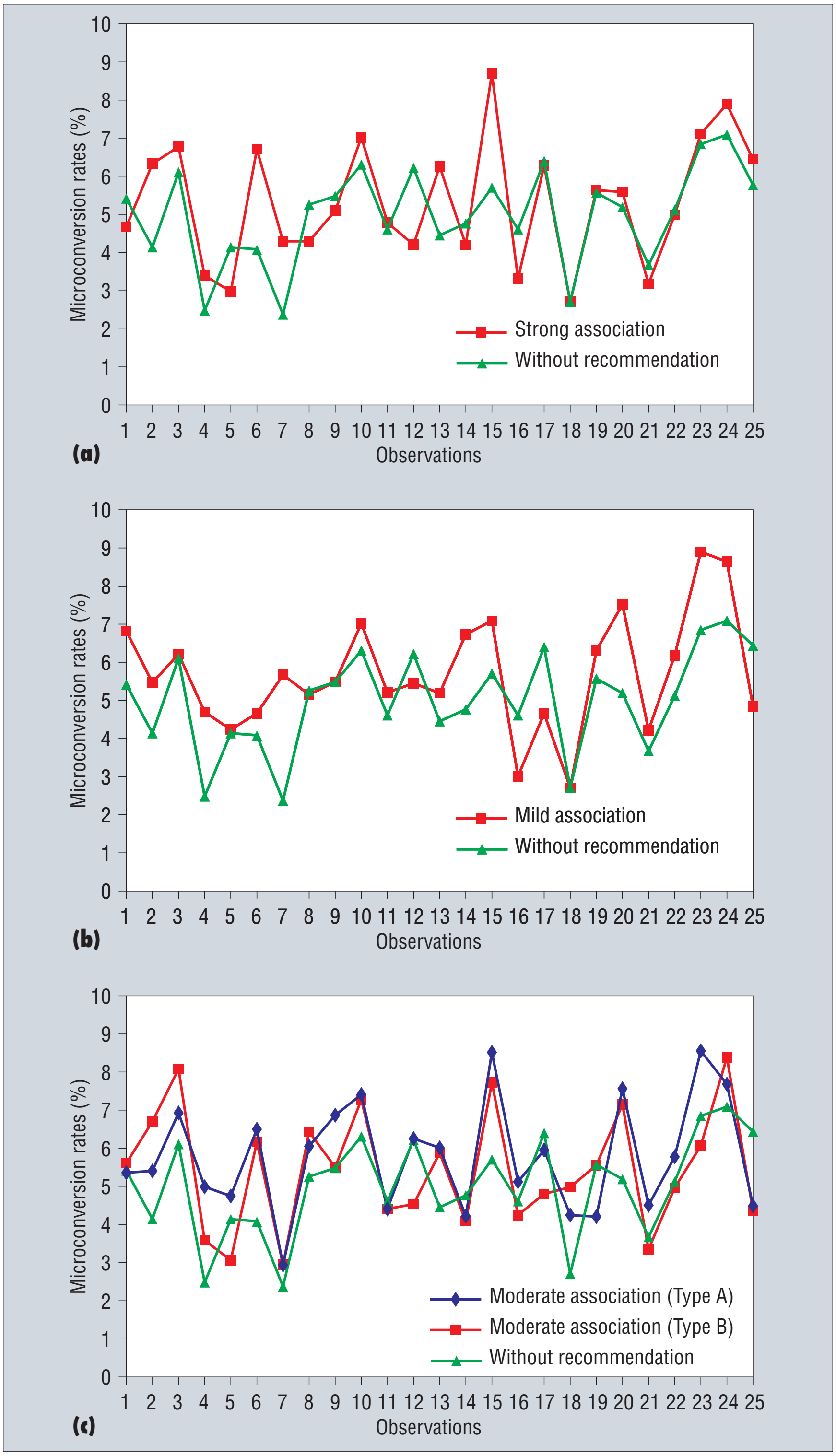

Figure 8. Performance evaluation of the recommender system. The green lines indicate the distribution of the microconversion rates without recommendations.

- *Stability of recommendations.* Recommendations with mild associations have more stable microconversion rates than those with strong associations because the former's standard error of estimate (SEE)—a good indication of the regression analysis's usefulness—is 1.49, lower than the latter's (1.62). That is, recommendations with mild associations attract customers more uniformly to purchase from the category than those with strong associations. This results from the fact that mild associations are derived from generic customers' purchase behavior, and strong associations from very specific customers who share common purchase and browsing behavior. Further proof is that the SEE of recommendations with Type A moderate associations reaches 1.5, the SEE of recommendations with Type B moderate associations reaches 1.58, and they are smaller than the SEE of recommendations with strong associations.
- *Without recommendations versus with recommendations.* The microconversion rates for recommendations with mild associations are better than those obtained without the recommendations. The mean score for the recommendations with mild associations is 5.70, while the mean score without recommendations is 5.01. The Student's t-test demonstrates a significant difference at the 0.05 level between the two means. The differences between the two means, 0.77 for Type A moderate associations, 0.46 for Type B moderate associations, and 0.27 for strong associations, also show significant differences at the 0.05 level. These results suggest that the recommendation using association mining is a useful one-to-one personalization tool that appeals to the target customer compared with no recommendations taken.

Using a control chart such as that in Figure 8, I can continuously monitor the recommender system's performance. The ratio of *violated product categories* to total product categories the online store offers is computed at a specific observation time. Violated categories are categories whose microconversion rates obtained without recommendations exceed those with recommendations. Whenever the violation ratio exceeds a set threshold for the four types of associations, the recommender starts deriving new associations for those violated types, and it is time to create new recommendation lists for the customers.

Web usage is a strong criterion for depicting and understanding Web customers' interests. All of the Web customers' activities in the shopping mall (such as searching, browsing, and purchasing) are directly stored in Web logs. Web usage mining analyzes those Web logs and identifies

Web customers' interests and preferences. This research discovered the following users' interests by mining Web usage:

- The recommender system can capture users' short-term interests through Web directory and search services after they've visited the shopping site.
- It can identify users' medium-term interests through visit RFM values, which represent their browsing behavior history (per product category) since their last purchases.
- It can also derive users' long-term interests from product affinities for peer groups through collaborative filtering utilizing purchase RFM measures and purchase deliberation degrees.

Collaborative filtering, the most successful personalization technology to date, often matches the current user's profile against other users' similar records. However, traditional customer-profiling methods require the users to explicitly and subjectively describe themselves to obtain ratings or preferences. These profiles eventually become obsolete. So, the profiles must be obtained dynamically from user patterns. This is why Web personalization uses Web usage mining. Consequently, the system's prediction performance and accuracy for providing better recommendations do not degrade over time as the profiles age, and the customer's privacy is protected from intrusive profiling, which requires explicit customer input.

The recommender system described here offers several advantages over other solutions:

- The recommender system considers the degree of customers' purchase deliberation when differentiating between them psychographically, formulating customer profiling. Not much attention has been paid to purchase deliberation, which might dictate online shopping's success or failure. I used the microconversion rates calculated from Web usage to quantitatively represent the degree of purchase deliberation and, later, derive peer groups.
- It derives four types of association rules among products or product categories through BBBS or BABS. Prior research has usually extracted only one type of association.
- The recommender's architecture lets it make a recommendation to customers at any time, at any stage in the Web user life cycle. Almost all Web shopping malls just display the recommendations on the homepage when a customer connects to the Web site, but this recommender takes the customer directly to the list page of the product category the customer is most recently interested in and displays the best products, such as the best-selling products, the products with the highest conversion rates, and the newest products in that category along with the associative products and categories (adaptive Web site). The recommender also uses a customer's current navigational activity to reflect his or her current interest before extracting recommendations from the list database.
- When evaluating its performance, renewing association rules, and making a recommendation to a customer, the recommender needs no explicit user input; it is unobtrusive.

Future research can extend the work this article presents several ways. First, this study used several variables: microconversion rates for representing purchase deliberation and for the recommender system's performance test, purchase RFM values for behavioral segments clustering, and visit RFM values for deriving customers' Web navigational patterns. Although they performed well, we can extend almost all these variables to include richer information. We should also give attention to alternative features with better predictive performance than previous ones. If we could significantly improve predictive accuracy using such alternatives, it would provide the basis for future research in this kind of analysis.

Second, researchers must perform more empirical studies that cover different types of online service providers (for example, game malls). Such work will help identify the generic architecture and common components (for example, profiling and matching) reusable in Web personalization.

Acknowledgments

The Kyungpook National University Research Fund, 2002, supported this research.

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