ENHANCED COLLABORATIVE FILTERING: A PRODUCT LIFE CYCLE APPROACH

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ABSTRACT

Recommender systems are ubiquitous not only among e-commerce enterprises but also among various brick-and-mortar firms. Popular collaborative filtering-based recommender systems use only individual customers' preferences discovered in their profiles containing historical purchase (or similar) records. On the other hand, the market trends of products are another factor that can substantially affect the likelihood of products being adopted. Consequently, there are rooms for further improvements in collaborative filtering-based recommendation. In this study, we propose the use of the product life cycle concept based on the Bass model and suggest an approach that integrates the general popularity effect (market trend) and the individual preference effect in order to improve recommendation effectiveness of collaborative filtering. Through experimental validation, we find that our approach of combining the product life cycle concept and collaborative filtering performs better than the approach based on typical user-based collaborative filtering alone. In addition, the experiment results show that the influence of preference and popularity effects may vary based on market characteristics. Consequently, the proposed approach can be used as a marketing tool functioning as a basis for valuable services to customers.

Keywords: Recommender system, Collaborative filtering, Product life cycle, Bass model, Hybrid recommender system

1. Introduction

The rapid and wide spread of information and communications technology including the Internet and smart devices has accelerated people' participation in Web applications, resulting in the considerable growth in the volume of accumulated information. However, it has also created the constant challenges of eliminating noise from signals and differentiating between relevant and irrelevant information. As a means to address it, various recommendation techniques have been proposed to help people find information or items that match their needs [Choi, Lee, & Kim 2017; Jannach et al. 2010; Konstan 2004; Liang, Lai, & Ku 2006; Resnick & Varian 1997]. Among them, collaborative filtering (CF) systems are known to be very successful and widely adopted [Herlocker et al. 2004; Park et al. 2012]. CF techniques employ opinions of target customers and their neighbors to help the target customers effectively identify items (e.g., products or contents) of interest from large, and even overwhelming, sets of choices [Prasad 2003; Resnick & Varian 1997].

However, further improvements over traditional CF recommender systems are necessary to effectively cope with changes in technology. Because CF recommender systems reflect only individual customer profiles in the process of providing a recommendation list, they are limited in capturing market trends [Aimeur & Vézeau 2000]. Often, product or service providers correctly pay more attention to items with significant sales over recent few days and make

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decisions regarding marketing plans based on such recent data. However, traditional recommender systems do not consider these hot items because their sales records may be insignificant in customer profiles.

In order to accommodate this improvement and research need for recommender systems, we propose an approach characterized by the following properties. First, using the product life cycle (PLC) concept found in various theories of market trends, we estimate the *general popularity effect* that is an indication of how popular a product currently is in a given market. The general popularity effect plays a key role in deciding whether to increase or decrease the estimated probability of adoption by customers based on market trends. We use the Bass diffusion model [Bass 1969; Bass, Krishnam, & Jain 1994; Satoh 2001] to compute the general popularity effect. Second, based on popular CF techniques, we estimate the *individual preference effect* that is a measure of how attractive a product is to an individual customer. Finally, we integrate both the general popularity and individual preference effects into one measure for item recommendation. The sensitivity of market trends of products may vary considerably with product types and distribution channels (i.e., on-line vs. physical). Accordingly, our approach allows one to adjust the parameter that determines the relative importance of market trends compared with individual user preferences.

The general popularity effect measures an overall market-level global popularity of a product, regardless individual customers' differences. On the other hand, the individual preference effect reflects a specific customer-level local popularity measure. Though the global popularity influences individuals' exposure to certain products, the individual preference effect is more critically influenced by the popularity locally observed among those who have similar tastes of the individual customer. Our goal is to properly mix both the global and local popularity effects into a single algorithm.

Using various data sets, we validate the proposed PLC-based approach compared with the typical CF. The experiment results over three different data sets indicate that the PLC-based approach achieves higher recommendation accuracy. Therefore, we claim our approach can provide effective marketing tools for marketers. We also expect that our study will provide a basis to expand the area of recommender systems studies to further improve recommendation quality.

2. Literature Review

2.1. Product Life Cycle and Bass Model

A product life cycle (PLC) refers to a model that attempts to exploit the life stages of products. As time passes, the PLC conceptually has four phases: introduction, growth, maturity, and decline. Founded on this concept, the Bass diffusion model [Bass 1969] was developed to explain the market penetration of goods [Peres, Muller, & Mahajan 2010]. Not only does it explains the market growth, but also it attempts to predict when the customers will eventually adopt a product [Bass et al. 1994].

The models related to the Bass model focus not only on this diffusion process but also on the entire sales evolution of products because the graph of likelihood of adoption resembles that of the life stages of products in a market [Hollensen 2010; Steffens 2002]. For example, Dellarocas, Zhang, and Awad [2007] studied the value of online product reviews in forecasting sales based on the Bass model. In order to forecast a new product life cycle curve, Hu et al. [2018] proposed a curve fitting method based on the Bass model. Recent studies extend the diffusion study areas from retail markets to online and virtual markets such as the motion picture [Delre, Broekhuizen, & Bijmolt 2016] and social media [Franses 2015]. Sharp and Miller [2016] studied the diffusion of innovation for emerging technologies.

According to the Bass model, the probability of product adoption is affected by two factors: innovation and imitation. The innovation factor, mostly influenced by mass media communications, indicates that some people adopt a newly introduced product due to its novelty and innovativeness. The imitation factor, mostly influenced by word-of-month communications, indicates that people adopt an existing product because of other people's adoption of the product. In particular, the imitation effect of the Bass model is somewhat related to the collaborative filtering idea in that both consider a potential consumer's purchase behavior being affected by others.

In this study, we will predict the current diffusion position of a product (the PLC score) using the Bass model. The PLC score will be used as an estimation of the product's popularity effect on potential customers' purchasing decision. In other words, the PLC score measures how closely customers in a market follow the market trend. Next, based on the concept from typical user-based CF techniques, we will estimate a purchase likelihood score using customers' transaction histories. Because user-based CF techniques include neighbor transactions when generating recommendation lists, the proposed PLC-based method captures the preference effects of customers, too. In other words, our method uses not only general market trends of a product but also individual customers' purchase likelihood scores that are their probabilities of adopting the product regardless of its market trend. Consequently, we propose a hybrid approach that incorporates market trends in a CF-based recommender system.

2.2. Recommender Systems

Recommendation techniques based on the concept of personalization have received considerable attention in recent years [Adomavicius & Tuzhilin 2005; Garcia-Molina, Koutrika, & Parameswaran 2011; Mulvenna, Anand, & Büchner 2000; Murthi & Sarkar 2003]. Personalization techniques attempt to present only relevant information directly related to users' preferences. According to Garcia-Molina et al. [2011], there are three types of personalization: *information search*, *recommendation*, and *personalized advertisement*. When a user explicitly makes a query based on his/her information need, an information search system (e.g., a search engine) conducts operations in two separate stages: filtering out irrelevant information from a pool of information (a filtering stage) and providing the results ranked in the order based on how well they match the query (a ranking stage). However, recommendation techniques typically do not require an explicit query from users. They provide advice within a domain based on precise models for inferring users' preferences. Personalized advertisement techniques are similar to recommendation techniques but are distinguished because the objects presented to users are commercial advertisements and detailed financial considerations determine their order of priority.

Among these techniques, we focus on recommendation because both users and service providers benefit from them. For users, recommendation techniques can simplify decision-making processes and help them discover goods that were unknown to them. For service providers, they function as a valuable marketing tool. For example, service providers can automatically conduct viral marketing by utilizing recommendation techniques. Service providers can also engage in cross-selling marketing through recommendations. Over the last several decades, various recommendation techniques have been studied to help users find items that match their needs [Hanani, Shapira, & Shoval 2001; Jannach et al. 2010; Konstan 2004; Resnick & Varian 1997]. In particular, many researchers have studied the practical use of recommendation techniques in the real world in the form of recommender systems. The most successful recommender systems are generally known as collaborative filtering (CF) systems that have been developed and improved over the last decade based [Goldberg et al. 1992; Herlocker et al. 2004; Park et al. 2012]. CF techniques employ the purchase records of target users and their neighbors to effectively identify products of interest from large sets of choices [Resnick et al. 1994; Resnick & Varian 1997]. Because CF techniques can help not only online users but also traditional shoppers find relevant information and purchase products in a personalized environment, the application domains of recommender systems have been recently expanded to traditional marketplaces such as department stores, exhibitions, and tourism contexts [Kim, Ryu, & Kim 2012; Moon, Kim, & Ryu 2013].

However, improvements over traditional recommender systems are necessary to address changes in technology. First, traditional CF-based recommender systems use only user profiles in the process of providing recommendation lists, while ignoring market trends that can be often easily obtained [Aimeur & Vézeau 2000; Nguyen & Ricci 2008]. Moreover, they ignore the availability of products varying over time; thus, they may recommend products that are no longer available. In some markets, such as electronics, these limitations tend to create poor recommendations because of rapid changes in product trends. Second, marketers generally make decisions on marketing plans emphasizing recent sales trends of items. Therefore, they want recommender systems to recommend those currently popular items to maximize their sales volume. However, traditional recommender systems do not consider these hot items seriously because their sales may be insignificant when long-term user profiles are analyzed. Finally, although the domains of recommender systems have gradually expanded from online to physical marketplaces, it is difficult to find studies addressing such multiple domains [Berkovsky, Kuflik, & Ricci 2008; Jessenitschnig & Zanker 2009; Walter et al. 2012]. It would be desirable for recommender systems that are tested to be effective regardless of types of marketplace.

3. PLC-based Recommendation

The product life cycle (PLC)-based recommendation system captures two forces influencing potential customers' attention to specific products. The *general popularity effect* is a measure of an overall market-level global popularity measure of a product, regardless individual customers' differences. On the other hand, the *individual preference effect* reflects a specific customer-level local popularity measure. Though the global popularity influences individuals' exposure to certain products, the individual preference effect is more critically influenced by the popularity locally observed among those who have similar tastes of the individual customer. Our goal is to proper mix both the global and local popularity effects into a single algorithm.

Figure 1 summaries the procedure of combining the customer-level local popularity measure and the overall market-level global popularity measure. First, because customers have personal preferences for products regardless of the market trends, we attempt to estimate their preferences based on neighbor purchase records. To this end, we adopt the user-based CF method. The main idea of this method is that neighbors who had similar tastes in the past still have tastes similar with those of the target customer. In other words, to estimate the preference effects of customers, we use the purchase records of k like-minded neighbors and calculate the purchase likelihood scores of products. Second, to estimate the popularity effect of products that are in the purchase records of neighbors, we first estimate the current positions of the products in their life cycles at the time the recommendation is requested. Then, based on the positions of the products in their life cycles, we calculate their product life cycle scores. Finally, as a type of hybrid approach, we combine these scores into the recommendation scores. Because recommendation scores are assumed to be the probabilities of adoption of products, we will recommend *n* products that belong to the top-*n* recommendation scores.

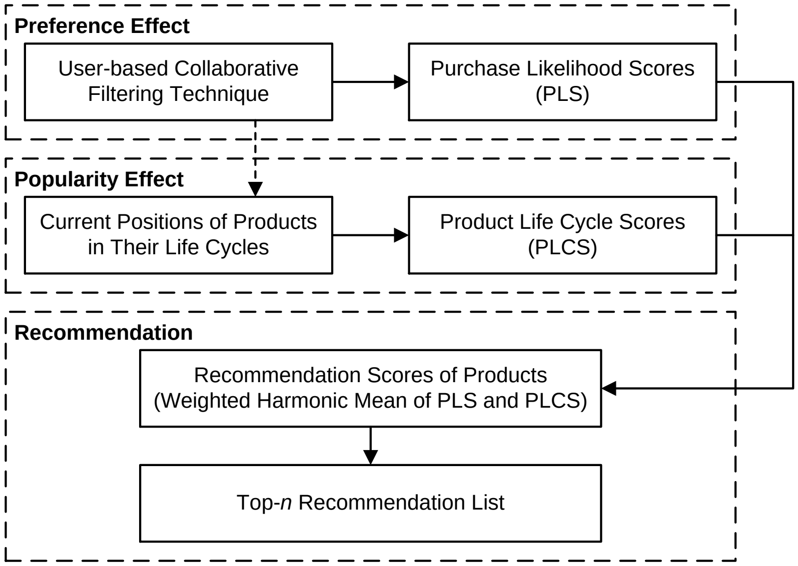


Figure 1. The Overall Procedure

3.1. Estimation of the Individual Preference Effect

To estimate the individual preference effect, we use the typical customer-based collaborative filtering (CF) algorithm. The process of customer-based CF has three steps: profile generation, neighborhood formation, and estimating the purchase likelihood score. For each customer *i*, an interest profile $r_{i,h,t}$ for the product *h* at time *t* is defined as

$$r_{i,h,t} = \begin{cases} 1 & \text{if user } i \text{ purchased product } h \text{ at or before } t, \\ 0 & \text{otherwise.} \end{cases}$$

The essence of CF is to gather information from neighbors whose purchase records are similar to the target customer. To find the best-*k* neighbors for target customer *i*, we calculate the similarity score between *i* and potential neighbor *j* at time *t* using the following correlation index [Herlocker et al. 2004]:

$$\text{sim}(i, j, t) = \frac{\sum_{h \in H} (r_{i,h,y} - \bar{r}_{i,t})(r_{j,h,t} - \bar{r}_{j,t})}{\sqrt{\sum_{h \in H} (r_{i,h,t} - \bar{r}_{i,t})^2 \sum_{h} (r_{j,h,t} - \bar{r}_{j,t})^2}}$$

with

$$\bar{r}_{i,t} = \sum_{h \in H} r_{i,h,t} \Big/ |H| \text{ and } \bar{r}_{j,t} = \sum_{h \in H} r_{j,h,t} \Big/ |H|,$$

where *H* is the set of all products under consideration. The best-*k* neighbors of target customer *i* are those potential neighbors whose similarity scores belong to top *k* among all customers. Finally, we estimate customer *i*'s the purchase likelihood score (PLS) for product *h* as [Adomavicius & Tuzhilin 2005]:

$$\text{PLS}(i, h, t) = \alpha \frac{\sum_{j \in J} (\text{sim}(i, j, t) \cdot r_{j,h,t})}{\sum_{j \in J} \text{sim}(i, j, t)}, \tag{1}$$

where *J* is the set of best-*k* neighbors and *α* is a scale parameter ($0 \le \alpha \le 1$). Using this scale parameter, we control the degree of reflection between the individual preference and general popularity effects. However, since domains have different characteristics such as variations in market trend sensitivity, an appropriate value should be found empirically for each problem domain. We will determine the parameter value for each domain through experimentation.

3.2. Estimation of the General Popularity Effect

To obtain the general popularity effect of a product, we first measure the product's current position in its life cycles. A product's position in its life cycle is estimated by the Bass model [Bass 1969; Bass et al. 1994]. The Bass model for product h is formulated as follows:

$$f_h(t) = \left[p_h + \frac{q_h}{m_h} N_h(t) \right] \left[1 - F_h(t) \right],$$

where m_h is the size of product h's customer base (i.e., the total number of current and potential customers); $N_h(t)$ is the number of customers who have purchased h until time t; p_h is the coefficient of innovation; q_h is the coefficient imitation or *popularity*; $f_h(t)$ is the likelihood (i.e., probability) of adoption of h at time t; and $F_h(t)$ is the cumulative probability of adoption of h at time t.

From this, we obtain the product life cycle score (PLCS) of product h at time t with:

$$\text{PLCS}(h,t) = \begin{cases} (1-\alpha) f_h(t) & \text{if } q_h \geq p_h, \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

where α is a scale parameter ($0 \leq \alpha \leq 1$). Here, we only adopt the general popularity effect when the coefficient of popularity (q_h) is greater than or equal to the coefficient of innovation (p_h). If a product is sold mostly to early adopters who intend to test its innovativeness, it should not be recommended to customers in general. Instead, a product should be recommended to general customers if it is sold to people mainly due to its popularity. It coincides with the underlying assumption of CF-based recommendation [Herlocker et al. 2004] in part: A customer is likely to adopt a product when it is popular among his or her acquaintances.

Without this heuristic, an alternative product life cycle score of product h at time t would be:

$$\text{PLCS}'(h,t) = (1-\alpha) f_h(t). \tag{2′}$$

We further empirically verified that the use of PLCS′ of (2′) in place of PLCS of (2) resulted in substantially worse recommendations in experiments with real world data sets used for this study.

To estimate $f_h(t)$, we must predict three coefficients: p_h, q_h, and m_h. They can be simply estimated with the ordinary least square (OLS) regression method from the following equation [Bass 1969]:

$$\begin{aligned} n_h(t) &= p_h m_h + (q_h - p_h) N_h(t-1) - \frac{q_h}{m_h} \left[N_h(t-1) \right]^2 \\ &= a_1 + a_2 N_h(t-1) - a_3 \left[N_h(t-1) \right]^2, \end{aligned}$$

where $n_h(t)$ is the number of customers who adopt h at time t. That is, $n_h(t) = f_h(t) m_h$ and $N_h(t) = F_h(t) m_h$. Here we have estimated values of the coefficients,

$$\hat{m}_h = \frac{-\hat{a}_2 - \sqrt{\hat{a}_2^2 - 4\hat{a}_1\hat{a}_3}}{2\hat{a}_3}, \quad \hat{p}_h = \frac{\hat{a}_1}{\hat{m}_h}, \text{ and } \hat{q}_h = \hat{p}_h + \hat{a}_2. \tag{3}$$

We call this method of coefficient estimation *the basic OLS method*.

The Bass model's probability function is a continuous function and thus the use of the basic OLS method could result in inaccurate parameters for discrete adoption cases. To address this issue, Satoh [2001] suggested a discrete Bass model:

$$\frac{N_h(t+1) - N_h(t-1)}{2} = p_h m_h + \frac{q_h - p_h}{2} \left[N_h(t+1) + N_h(t-1) \right] - \frac{q_h}{m_h} N_h(t+1) N_h(t-1).$$

For the estimation of the coefficients, the OLS regression is performed on the following:

$$N_h(t+1) - N_h(t-1) = a_1 + a_2 \left[N_h(t+1) + N_h(t-1) \right] - a_3 N_h(t+1) N_h(t-1)$$

and we get

$$\hat{m}_h = \frac{-\hat{a}_2 - \sqrt{\hat{a}_2^2 - \hat{a}_1\hat{a}_3}}{\hat{a}_3},\ \hat{p}_h = \frac{\hat{a}_1}{2\hat{m}_h},\ \text{and}\ \hat{q}_h = \hat{p}_h + \hat{a}_2. \tag{4}$$

We call this method of coefficient estimation *the Satoh method*.

3.3. Top-*n* Recommendation

The last stage of the proposed PLC-based recommendation approach involves generating a recommendation list for the target customer. For recommendation list generation, we first calculate the recommendation score of product h for customer i at time t as the harmonic mean of PLS and PLCS:

$$\mathrm{RS}(i,h,t) = \frac{2}{1/\mathrm{PLS}(i,h,t) + 1/\mathrm{PLCS}(h,t)}.$$

We generate a top-*n* recommendation list of products based on recommendation scores. A higher recommendation score means a higher probability that a customer will purchase the product. Therefore, we sort the products in descending order according to their recommendation scores and return n products with the highest recommendation scores.

4. Empirical Evaluations

4.1. Data Sets and Experiment Design

We used three data sets for the experiments, which are for mobile images and cosmetics products. The data sets include customer identification numbers, purchased items (images or cosmetics), and transaction timestamps. The data sets were collected by a leading mobile service provider in Korea, a cosmetics manufacturing firm running its own retail stores in Korea, and a major online retailer of cosmetics and beauty products in the USA. Because both the mobile and cosmetics product markets are easily affected by content trends, our data sets are appropriate for validation of the proposed approach.

Table 1 includes detailed descriptions of the data sets. Durations of periods of the data sets are a week for the mobile data set, a month for the offline retail cosmetics data set, and two months for the online cosmetics data set. The first period of the offline retail cosmetics data set contains data for the first four months because they are substantially smaller than those of subsequent months. In our study, we adopted a standard evaluation design for *time-based experiments* [Herlocker et al. 2004]. Each data set was divided into a training set containing approximately the first 70% of the entire data set and a test set containing all the remaining 30% data. The training data were used as the basis to configure the proposed method and the benchmark system (a user-based CF). The test data were used to evaluate the performance. To estimate the coefficients, most studies related to the Bass model suggest that there should be at least 10 time periods [Bass et al. 1994; Peres et al. 2010]. Therefore, the training data sets were further divided into 10 time periods for the purpose of coefficient estimation.

Table 1. Data Characteristics

	Mobile Data	*Offline Retail Cosmetics Data*	*Online Cosmetics Data*
Category	on-line	off-line	on-line
Timespan	3 months	14* months	24 months
Dates	June–Aug. 2004	Oct. 2006–Nov. 2007	June 2012–May2014
Duration of a period	1 week	1 month	2 months
No. of periods	13	11*	12
No. of customers	422	236,664	8,162
Avg. purchases per customer	10.5284	10.79681	4.717471
No. of products	160	1,863	3,701
Avg. sales per product	27.7687	1371.56	10.40367
No. of transactions	4,443	2,555,217	38,504

* The first period covers the first four months, while the second to the eleventh periods cover one month each. It is because the first four months include substantially less data than subsequent months.

For the evaluation of performance, well-known precision and recall metrics are available [Herlocker et al. 2004; Sarwar et al. 2000]:

$$\text{recall } (R) = \frac{\text{Number of recommended products among those purchased}}{\text{Number of purchased products}},$$

$$\text{precision } (P) = \frac{\text{Number of purchased products among those recommended}}{\text{Number of recommended products}}.$$

Precision and recall metrics, however, may independently have biases based on the top-*n* set size (for precision) or the test set size (for recall). Therefore, we adopted the popular F-1 metric

$$F\text{-}1 = \frac{2}{1/P + 1/R},$$

which is commonly used in information retrieval and recommender systems research [Herlocker et al. 2004].

4.2. Preliminary Experiments for Parameter Value Selections

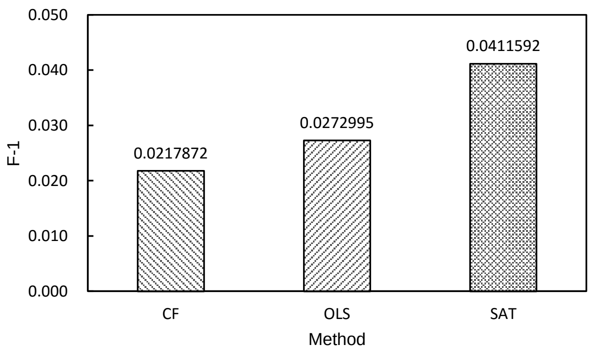
Before performing the experiments to measure accuracy, we determined the ideal values of system parameters using the training data. These parameters include

1. the number of recommended items (i.e., the value of n in the top-n recommendation),
2. the number of nearest neighbors (i.e., the value of k in the best-k neighbors of CF), and
3. the scale parameter (α).

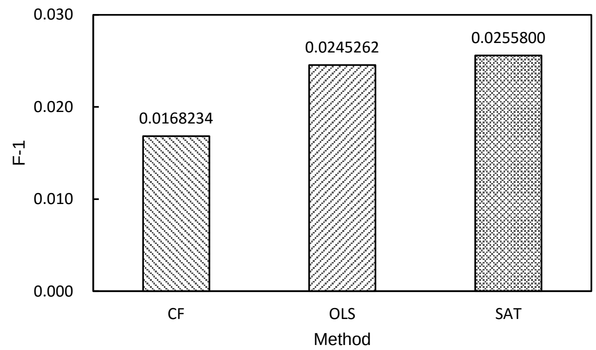
To select the n value, we randomly chose 20 pairs of k and α values. Then, we performed preliminary experiments using the training data sets. We found that $n = 10$ for the first two data sets and $n = 5$ for the third data set were acceptable values. Then, with these n values, we performed further preliminary experiments with the training data sets to choose k and α. For the neighborhood size k, we had to consider the total customer bases of the three data sets (i.e., 422, 236664, and 8162, respectively) so that the k value for the first data set had to be smaller than those for the second and the third data sets. For α, we considered values of 0.1 to 0.9 with the increment of 0.1. The preliminary experiments (with $n = 10$ for the first two data sets and $n = 5$ for the third data set) were done for various combinations of k and α. After the preliminary experiments, we selected $k = 14$, 300, and 80, respectively, and $\alpha = 0.3$, 0.9, and 0.2, respectively, for the first mobile data, the second retail cosmetics data, and the third online cosmetics data sets. When the CF and the proposed method did not agree on parameter values giving the best accuracy, we checked parameter values giving the next best accuracy until the parameters of the CF and the proposed methods agree.

4.3. Experiment Results

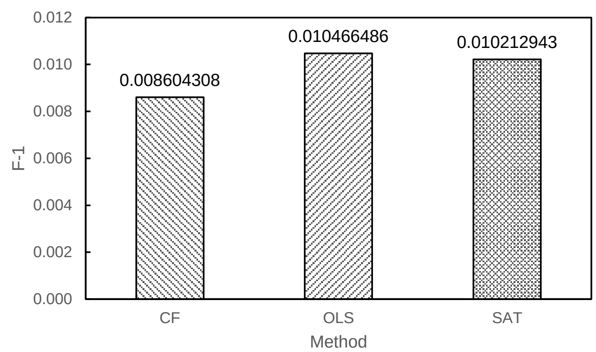
After obtaining the parameter values for experiments, using the training data, we built the benchmark CF system and two systems based on the proposed algorithm, one with the basic OLS method of Equation (3) and the other with Satoh method of Equation (4). The recommendation performance was measured by comparing the recommendations suggested by the systems and the actual purchase data in the testing data. The overall performance results are in Figure 2, where CF indicates the result of the benchmark CF system, OLS indicates the result of the proposed approach with the basic OLS method of PLC coefficient estimation, and SAT indicates the result of the proposed approach with the Satoh's discrete method of coefficient estimation.



(a) Mobile Data



(b) Retail Cosmetics Data



(c) Online Cosmetics Data

Figure 2. Comparison of Overall Accuracy

Table 2. ANOVA Result

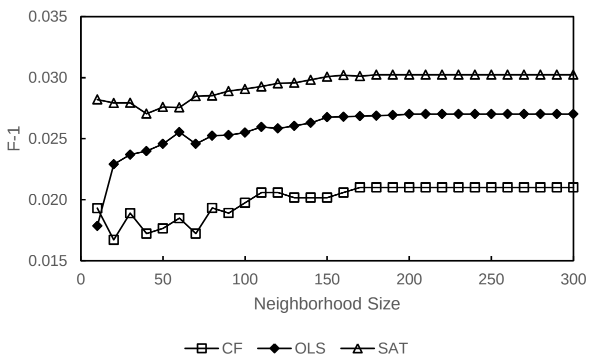
	Method 1 (i)	*Method 2 (j)*	*Mean Difference (i – j)*	*Std Err*	*Sig.*
Mobile Data	CF	OLS	–.00555	.00017	.000
	CF	SAT	–.01718	.00027	.000
	OLS	SAT	–.01163	.00030	.000
Retail Cosmetics Data	CF	OLS	–.00699	.00025	.000
	CF	SAT	–.00800	.00026	.000
	OLS	SAT	–.00101	.00031	.003
Online Cosmetics Data	CF	OLS	–.00181	.00004	.000
	CF	SAT	–.00157	.00005	.000
	OLS	SAT	.00024	.00005	.000

As shown in Figure 2, the proposed approach exhibited higher accuracy than the CF system. Between the PLC coefficient estimation methods of the proposed approach, the Satoh method showed higher accuracy for the mobile data and the retail cosmetics data sets, whereas the OLS method showed marginally higher accuracy for the online cosmetics data set. However, the differences between the OLS and the SAT methods for the retail cosmetics data and the online cosmetics data sets were negligible, though the SAT method resulted in much better performance for the mobile data set. Thus, we conclude that the proposed approach with the SAT method should be the finally chosen algorithm. In addition, a one-way analysis of variance (ANOVA) was conducted to examine the difference among the three methods. The result showed that F-1 scores of the three models were significantly different (Mobile data: $F = 13.17$, $p < 0.01$; Retail Cosmetics data: $F = 508.757$, $p < 0.01$; Online Cosmetics data: $F = 851.444$, $p < 0.01$). The detailed result is shown in Table 2.

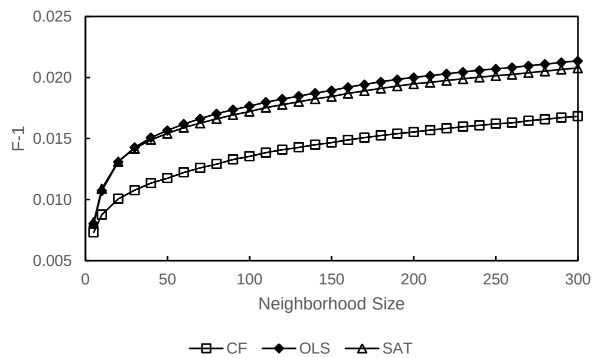
4.4. Sensitivity of Experiment Parameters

The selected parameters for the previously presented experiment results may not be the best because they were chosen from the training data sets only. In order to see their overall effects, we performed additional experiments with the training and testing data sets.

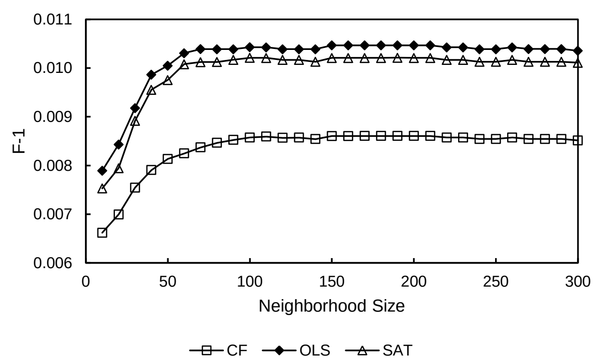
First, to see the effect of neighborhood sizes, we conducted experiments with varying neighborhood sizes from 1 to 300 with the increment of 9 or 10. For the customer-based CF technique, the neighborhood size is known to influence performance measured as the required computation time and the recommendation accuracy [Herlocker et al. 2004; Konstan 2004; Sarwar et al. 2000]. For the PLC-based approach that includes a CF step, the neighborhood size also played a key role in modulating the individual preference effects for the target customers. The experiment result is shown in Figure 3. As shown in the Figure, the proposed approach exhibited better performance at almost every neighborhood size setting, regardless of the estimation methods used. In general, once a recommender system achieved a high accuracy with a certain neighborhood size, increasing the size did not improve the accuracy. However, in experiments with the cosmetics data set, the accuracy values consistently increased up to the neighborhood size of 300 because the retail cosmetics data set included a large number of customers (i.e., 236,664). Our additional experiments showed that beyond the neighborhood size of 400, there was no improvement with more neighbors. Finally, from this sensitivity result, we found that with the mobile data set, the ideal neighbor set size for CF was 5, that for OLS was 164, and that for SAT was 176. With the online data set, the ideal neighborhood size for CF was 180, that for OLS was 150, and that for SAT was 190 though there were relatively small improvements beyond the size of 80 for all methods.



(a) Mobile Data



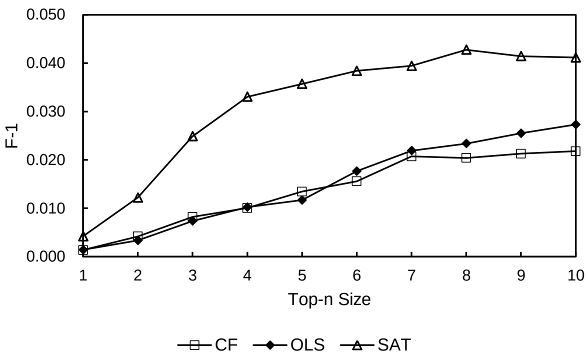
(b) Retail Cosmetics Data



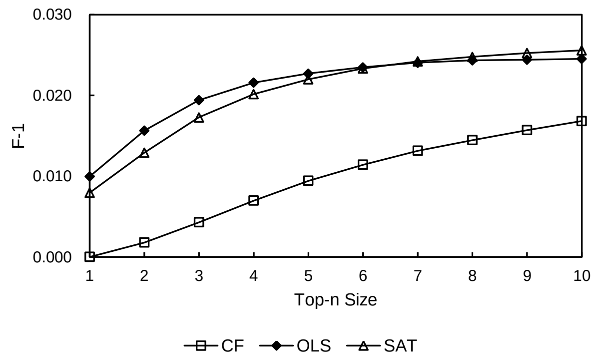
(c) Online Cosmetics Data

Figure 3. Sensitivity of the Neighborhood Size

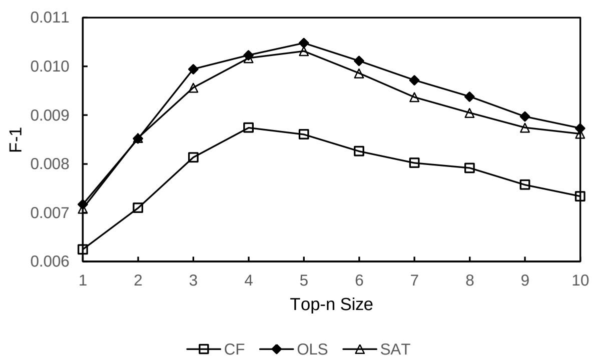
To find the ideal recommendation size, we performed experiments with varying sizes from 1 to 10, as shown in Figure 4. In the mobile data set, the benchmark CF system shows only slightly higher accuracy than the basic OLS method until the top-*n* value reaches 5. However, the accuracy of the SAT method increases rapidly until the top-*n* value reaches 5. The accuracies of the proposed approach in the retail cosmetics data also increase rapidly until the top-*n* value reaches 5. Here, however, the basic OLS method shows the highest accuracy until the top-*n* value reaches 6. For both the mobile data and the retail cosmetics data sets, 10 appears to be an acceptable top-*n* size. For the online cosmetics data set, all methods showed the best accuracies when the top-*n* value is 5.



(a) Mobile Data



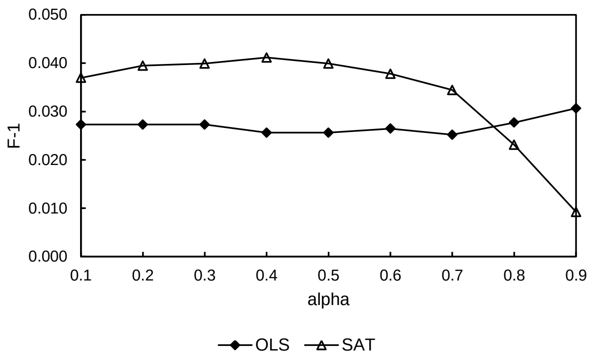
(b) Retail Cosmetics Data



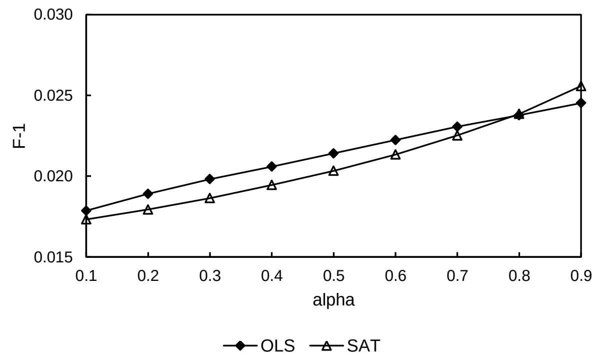
(c) Online Cosmetics Data

Figure 4. Sensitivity of the Recommendation Size

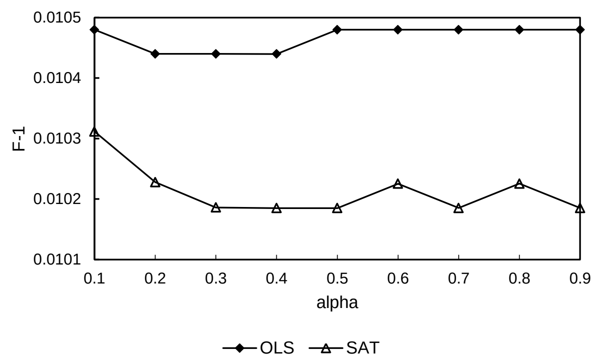
The scale parameter (α) of Equations (1) and (2) in our approach plays a key role in determining how PLS and PLCS affect RS. Thus, we examined the sensitivity of the parameter setting, as shown in Figure 5. A higher value of the scale parameter means that the influence of the PLS on the RS is stronger. In other words, when the ideal value of the scale parameter is high, the individual preference effect is considered significant in making recommendations. For the mobile data set, the highest performance was achieved when the alpha parameter was 0.3–0.5 (0.3 for OLS and 0.4 for SAT), while for the retail cosmetics data set, the highest performance was achieved when the scale parameter was 0.9. For the online cosmetics data set, the highest performance was achieved when the scale parameter is 0.1. Thus, we noticed that the scale parameter (determining whether the general popularity effect or the individual preference effect would be more influential) did not depend on product types. However, perhaps it depends on the sales channels. Both the mobile data and online cosmetics data sets were obtained from virtual stores, but the retail cosmetic sets were from brick-and-mortar stores.



(a) Mobile Data



(b) Retail Cosmetics Data



(c) Online Cosmetics Data

Figure 5. Sensitivity of the Scale Parameter (α)

5. Conclusion

5.1. Summary

In this paper, we propose a hybrid recommendation approach based on the product life cycle (PLC) concept using the Bass model [Bass 1969; Bass et al. 1994]. While the PLC concepts based the Bass model is widely accepted in marketing literature, it has not been used for recommender systems despite conceptual similarities between product diffusion and recommendation. Though the PLC model and the recommendation as a form of personalization [Im 2007; Mulvenna et al. 2000; Murthi & Sarkar 2003] differ in that the former addresses the general market penetration of a product while the latter works on the estimation of an individual target customer's product adoption likelihood, their conceptual similarities allow us to combine them in recommendation. That is, the main contribution of our study is the introduction of the PLC concept for improvement in collaborative filtering (CF)-based recommendation. In order to improve the overall quality of recommendation, we propose an approach that integrates both general popularity effects (market trends) and individual preference effects (customer preferences). In our study, we suggest that recommendation be based on not only estimation of individual customers' preferences obtained through the CF algorithm but also market trends utilizing the Bass model.

Through experiments on three data sets of two distinct products (i.e., mobile images and cosmetics) utilizing two different sales channels (i.e., online and offline retail stores), we find that the proposed PLC-based recommendation approach performs better than traditional customer-based CF systems. In addition, we show the proper settings for recommendations in online sales and offline sales environments. The experiment results show that the influence of preference and popularity effects can vary based on the characteristics of distribution channels. Therefore, we claim that our approach can provide efficient marketing tools for marketers and an opportunity to expand the domains of recommender systems. In addition, our approach combines recommender systems and marketing theories. Using well-known theories supported by pioneering researchers, and we suggest an approach based on interdisciplinary convergence research. Moreover, we find that global effects such as market trends are also important in predicting individual preferences. Therefore, this study provides implications for researchers and managers. First, in recommender studies, most researchers have concentrated on finding some factors that influence individual preferences. In particular, thanks to the development of machine learning techniques such as deep learning, many researchers have focused on more accurate item/user modeling. However, our experimental results show that additional factors related to the market are also important in inferring personal preferences. Moreover, through the experiment for the scale parameter, our study found that the proper value depends on the sales channels, not on product types. Therefore, to improve the performance of a recommender system, this study suggests that further researches should consider modeling for specific target market domains. Second, our method contains the process that estimates the current position of the life cycle for each product. Managers may use this to determine product lines that they intend to focus on. In addition, using the scale parameter values, they may identify proper marketing efforts for the distribution channels. For example, our results show that customers of the online cosmetic market are affected by individual preferences but customers of the offline cosmetic market are affected by general popularity. In sum, our method may provide some insights in formulating marketing strategies.

5.2. Observations and Discussions

From the performance experiment results, we notice that the use of PLC increases recommendation accuracy for all three data sets. The results not only show that individual products' positions at their life cycles affect their attractiveness to potential customers, but also indicate that the use of both PLC and CF indices in the proposed algorithm improves the recommendation quality. The neighborhood size is an influential factor and determining a proper size is practically important. If the neighborhood size is same as the whole customer base, the CF recommendation becomes a best-seller list recommendation, which does not personalize recommendations and thus performs worse than both customer-based and item-to-item CF methods [Linden, Smith, & York, 2003]. On the other hand, if the neighborhood size is very small, the individual preference effect provided by CF becomes negligible. The sensitivity experiments show proper sizes for the three data sets. Depending on product types, optimal neighborhood sizes experimentally determined are different. Even if products are the same (i.e., cosmetics and beauty products of the second and the third data sets), proper neighborhood sizes differ for different sale channels.

In the sensitivity experiments for the scale parameter, we see a possibility of difference in recommendations between online and physical store environments. The general popularity effect is more important than the individual preference effect in the online store. That is, customers in online sales environments are more easily affected by market trends. However, in the physical stores, customer preferences are influenced more by their neighbors' purchase records, though the general popularity effect plays some roles in recommendation.

5.3. Limitations and On-Going Studies

However, our approach has some limitations. First, we considered only two products (i.e., cosmetics and mobile image products) over online and offline sales environments. In our study with limited data sets, we did not see any difference between types of products, but some difference between sales channels. Experiments with additional data sets covering more product types over online and offline environments will give more solid insights on the relative importance between the general popularity effect (obtained from products' product life cycle positions) and the individual preference effect (estimated by collaborative filtering). We will extend our study to include various types of data sources

Second, researchers have recently considered non-accuracy metrics such as diversity, serendipity [Kotkov, Wang, & Veijalainen 2016], and implicit feedback [Choi et al. 2016; Hu, Koren, & Volinsky 2008] because they can capture other effects (i.e., longer-term profitability) of recommender systems. At the moment, we did not test how the addition of PLC into CF would affect non-accuracy metrics, in particular, the diversity measure. The general popularity effect of PLC is a form of global index (like a best-seller index) and thus would decrease recommendation diversity. On the other hand, the PLC score of Equation (2) quickly decreases as a product's market gets saturated. That is, the general popularity effect of PLC quickly adapts to the market status and tends to limit repeated recommendation of the same product. In sum, until experimentally verified, we cannot tell the effect of PLC on the diversity measure. Therefore, in future work, we plan to test our approach in various domains with both accuracy and non-accuracy metrics.

Third, the proposed method directly adds the general popularity effect and the individual preference effect as their harmonic mean. There can be various other possibilities to combine these two effects. One of them is to sequentially apply them. The purchase likelihood score of CF in Equation (1) finds top-m products first. Among them, the PLC score of Equation (2) is used to select top-n (where $n \leq m$). This algorithm can be computationally more efficient than the algorithm proposed in this paper. However, it can miss some popular products in the recommendation list. Alternatively, the opposite sequence can be used to determine top-n. This algorithm can be useful for customers who have not purchased products for a while. Such infrequent customers' neighbors tend to contain rather outdated products in their profiles; thus, a recommendation list from them may not be useful at all. The use of the PLC score first will generate currently popular m products, from which the purchase likelihood score generates top-n products. There are many other possibilities to design recommendation algorithms. We will evaluate several potential algorithms and propose perhaps not just single algorithm but rather a group of algorithms that can be used for various types of products and customers.

Finally, in our study, we adopted the simple Bass model for PLC estimation. However, there are many different PLC models built on characteristics of products (Rink & Swan, 1979). The proposed algorithm may work better if more appropriate PLC models are adopted. We plan to test the proposed hybrid method with other PLC models and report the results in the subsequent research paper.

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