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Developing recommender systems with the consideration of product profitability for sellers

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Abstract

In electronic commerce web sites, recommender systems are popularly being employed to help customers in selecting suitable products to meet their personal needs. These systems learn about user preferences over time and automatically suggest products that fit the learned model of user preferences. Traditionally, recommendations are provided to customers depending on purchase probability and customers' preferences, without considering the profitability factor for sellers. This study attempts to integrate the profitability factor into the traditional recommender systems. Based on this consideration, we propose two profitability-based recommender systems called *CPPRS* (*Convenience plus Profitability Perspective Recommender System*) and *HPRS* (*Hybrid Perspective Recommender System*). Moreover, comparisons between our proposed systems (considering both purchase probability and profitability) and traditional systems (emphasizing an individual's preference) are made to clarify the advantages and disadvantages of these systems in terms of recommendation accuracy and/or profit from cross-selling. The experimental results show that the proposed HPRS can increase profit from cross-selling without losing recommendation accuracy.

Keywords: Electronic commerce; Recommender systems; Product profitability; Collaborative filtering; Personalization; Cross-selling

1. Introduction

In recent years, recommender system (RS) is rapidly becoming a core tool to accelerate cross-selling and strengthen customer loyalty [37,38] due to the prosperity of electronic commerce. Enterprises have been

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developing new business portals and providing large amount of product information to create more business opportunities and expand their markets [10,22,31]. However, it results in information overload problem which has become the burden of customers when making a purchase decision among a huge variety of products [21,43]. Researchers have developed various techniques to solve this problem. An RS, which can learn about user preferences and automatically suggest products fitting customers' needs, is one of the possible solutions.

Electronic commerce encounters a challenge of how to properly utilize personalization systems based on the users' preferences to attract more customers [20]. RSs have been widely used in many web sites, such as Amazon.com, CDNOW.com, GroupLens, MovieLens, etc. [36]. Most of RSs adopt two types of techniques, the content-based filtering (CBF) and collaborative filtering (CF) approaches [39]. With the CBF approach, one tries to recommend items similar to those a certain user has liked in the past [29,36]. To develop RSs, CF may be the most successful and popular approach [12,25]. For the case of retail transaction dataset, Mild and Reutterer [34] developed an improved CF algorithm for the binary market basket data. In Mild and Reutterer [34], the CF approach is capable to predict multiple item choices at the individual user level.

The CF models can be constructed based on users or items [17]. Recommendations by CF models can be based on the ratings of items and behaviors of users [36]. In the CF approach, one identifies users whose tastes are similar to those of the certain user and recommends items, which they have liked [41]. The CF based RSs have been very successful in both information filtering and electronic commerce domains [35]. Consequently, this study utilizes the CF approach to build RSs, and they are applied to the retailing sector.

In addition, most recommendations are traditionally made merely based on purchasing possibility and customers' preferences. However, it is not enough for an enterprise, because the possibility and preferences should not be the only concerns to enterprises. Profit margin is another crucial factor for sellers. Therefore, we attempt to integrate the profitability factor into traditional systems. The proposed systems are not primarily intended to replace the traditional ones. Considering both the profitability of sellers and the purchase probability of users, this study intends to more properly balance the views between customers and sellers. Therefore, we propose two RSs for retailing called the "*Convenience plus Profitability Perspective Recommender System* (*CPPRS*)" and the "*Hybrid Perspective Recommender System* (*HPRS*)." Two indexes, "product profitability" and "profit from cross-selling", are also used to evaluate the proposed systems. Moreover, comparisons between the proposed systems (considering both purchase probability and profitability) and traditional systems, the *Convenience Perspective Recommender System* (*CPRS*)" and the "*Collaborative Filtering Perspective Recommender System* (*CFRS*) (emphasizing an individual's preference), are made to clarify the advantages and disadvantages of these systems in terms of recommendation accuracy and/or profit from cross-selling. The experimental results show that the proposed HPRS can increase profit from cross-selling without losing recommendation accuracy.

2. Recommender systems

Recently, data mining has increasingly become an important research area in information science and technology (e.g., [32,51–54]). Recommender system (RS) is one of the important techniques in data mining. RS utilizes the opinions of users in a community to help individuals in the same community more efficiently identify content of interest from a potentially overwhelming set of choices [8,39]. RS can enhance the electronic commerce sales in three ways [43] including reinforcing the use of browsers in buyers, intensifying the cross-selling effect and increasing a customer's loyalty. Generally speaking, RS can be defined as a system that helps users find the product items they want by making recommendations based on either the content of the recommended items (with CBF), or ratings of similar customers on the recommended items (with CF) [15,36].

In CBF, both product contents and customer preferences must be analyzed for giving recommendations [6,7]. The CBF approach encounters a difficulty of introducing new items to users [29,36], that is so called the overspecialization problem in Balabanovic and Shoham [3]. Applications of CBF can be found in the related works such as Infofinder [26] and NewsWeeder [28]. The products which can be recommended by CBF are much narrower than that of CF [50]. The CF approach can recommend products with any type of content since the contents of products do not have to be analyzed [2,6,15]. This feature makes the CF model more practical than the CBF model in retailing sector.

Goldberg et al. [14] initially used the term "collaborative filtering" when developing the Tapestry recommender system, which is employed to solve the problem of e-mail overload. The original CF simply refers to a system where people help each other filter their e-mails by recording their reactions to the documents they have read. Additionally, Kohrs and Merialdo [24], Kuo and Chen [27], and Lee et al. [30] developed CF based RSs. Tapestry [14], GroupLens [25], Siteseer [40], Ringo [45], and Phoaks [46] are some RSs using CF. A comprehensive taxonomy of various RSs on the Internet can be found in Montaner et al. [36]. They have also analyzed 37 systems in terms of 8 dimensions to collect the elements of RSs. More recently, Vozalis and Margaritis [48] proposed an improved CF approach integrating Singular Value Decomposition, and Xie et al. [49] developed the distributed CF algorithm with a higher scalability.

The shortcomings of CBF and CF systems were discussed by Montaner et al. [36], and these limitations initiate the hybrid systems. For example, Balabanovic and Shoham [3] and Lawrence et al. [29] developed the hybrid systems by integrating CBF and CF. The association rule algorithm [1] is often applied in market basket analysis in which one analyzes how the items purchased by customers are associated. In some RSs, association rule mining is employed to recommend products [6,41]. This is especially true for collaborative filtering domains. Therefore, association rule algorithm is as well employed to build RSs. Cornelis et al. [11] adopted fuzzy logic to propose a conceptual framework for recommending the one-and-only item which is only one single instance. A special case of the trade exhibition of e-government was used to illustrate this conceptual framework of RS.

In RS, sparsity generally indicates the item-to-user ratio is extremely high (i.e., most users do not rate most items) [33]. The sparsity problem is particularly difficult to deal with in the very beginning of system operation. The cold-start (namely first-rater in [33]) is another difficult issue to introduce new items or make recommendations to new users [44]. As indicated in Schein et al. [44], the problem of new user is symmetric to that of new item if users' profiles can be accessed.

Melville et al. [33] addressed the sparsity and cold-start problems in CF by developing a hybrid system which applies content-based forecasts to transfer a sparse user ratings matrix into a full ratings matrix for recommendations. With the experimentation on movie recommendations, the hybrid system outperforms CF and CBF systems. To address the cold-start problem, Schein et al. [44] also integrated the content and collaborative information to develop a hybrid system which utilizes the expectation maximization learning to approximate a model for a movie dataset. Breese et al. [5] evaluated some RSs with three datasets of MS Web, Neilsen Television and EachMovie. Their results indicated that the availability of votes may influence the favorite of RSs. Kim et al. [23] reported that RS can benefit from combining CF and CBF. They also proposed a hybrid system in which the clustering technique is adopted to obtain users' profiles.

Tso and Schmidt-Thieme [47] developed three RSs in which the first two hybridizes CBF and CF, namely Sequential CBF and CF and Joint Weighting of CF and CBF. The Joint Weighting of CF and CBF method predicts the extent of a user likes the item attributes (content) rather than the class or rating of an item based on attributes. The third is Attribute-Aware Item-Based CF which combines the user ratings and item attributes to calculate the similarities between items. From the experimental results by Tso and Schmidt-Thieme [47], Joint Weighting and Attribute-Aware outperform Sequential CBF and CF. Breese et al. [5] used the concept of inverse user frequency to determine the item weights. The generally voted items have smaller weights than the less voted ones since they are more representative to users' preferences. Bradley and Smyth [4] simultaneously took similarity and diversity into account by the weighting mechanism. Sarwar et al. [42] reported that the item-based CF could outperform the user-based CF by observing their experimental results. For CF, Jin et al. [18] proposed an automatic approach to determine the weights for different items by learning weights from the item ratings given by users. Their approach primarily learns item weights to make similar users closer, while unlike users more isolated. Ghani and Fano [13] developed an RS for apparels which can learn customers' tastes with the semantic attributes of products. These product attributes are collected from retailer websites.

Besides, in practice, profitability may be a primary concern for sellers, but it is not considered in the traditional RSs. Therefore, this study is to discuss the feasibility and benefits when integrating the profitability factor into the traditional CF-based systems. More discussions related to different concerns when building RS are provided in next section.

3. Different perspectives on recommender systems

In this study, we propose two RSs called "*Convenience plus Profitability Perspective Recommender System* (CPPRS)" and "*Hybrid Perspective Recommender System* (HPRS)" based on both purchase probability and product profitability factors. In this section we will compare the proposed systems and the traditional RSs in order to demonstrate the effectiveness of our proposed methods.

3.1. Different perspectives on recommendations

Recommendations can be made from more than one perspective. The existing RSs make recommendations based mainly on purchase probability and assumed items with high purchase probabilities that are likely to satisfy the customers' needs. Therefore, these systems can help sellers to easily define frequently purchased items. In other words, recommendations based on the purchase probability are made from "the convenience perspective of the seller". On the other hand, if a similar customer purchase probability is based on the preferences of the individual customer, then it is from "the buyer's perspective". In addition, "the seller's profit perspective" emphasizes that when an enterprise employs an RS, it should not only satisfy the different needs of customers but also provide a higher profit margin.

In summary, one of the objectives of this paper is to study the effect of RS from different perspectives shown as Table 1. From this table, it's easy to find that the present paper discusses four RSs for retailing and their considerations. These systems are listed as follows:

1. *Convenience Perspective Recommender System* (CPRS) is a convenient approach for sellers to recommend frequently purchased products. It only considers purchase probability.
2. *Collaborative Filtering Perspective Recommender System* (CFRS) recommends products depending only on the purchase probability by similar customers.
3. *Convenience Plus Profitability Perspective Recommender System* (CPPRS) recommends products based on both purchase probability and the product profitability.
4. *Hybrid Perspective Recommender System* (HPRS) makes recommendations by pondering both the purchase probability of similar customers and the product profitability.

3.2. Traditional recommender systems

This section describes the procedures of two traditional RSs, CPRS and CFRS [8,14]. The basic process of the CF approach is shown in Fig. 1. In the beginning, we measure the similarity among customers. Then the CF approach computes purchase probability based on the transaction records of similar customers. Finally, recommendations are made according to this probability. In other words, first, both the CPRS and the CFRS calculate and sort purchase probabilities. Second, N product items with the highest N purchase probabilities are determined and then these items are recommended. The detailed procedures are discussed below.

Table 1
Summary of four recommender systems

RS	Perspectives	Considerations	Degree of personalization
CPRS	Seller's perspective	Purchase probability	Non-personalization
CPPRS	Buyer's perspective Seller's perspective	Purchase probability Product profitability	Non-personalization
CFRS	Buyer's perspective	Purchase probability	Relatively higher degree of personalization
HPRS	Buyer's perspective Seller's perspective	purchase probability product profitability	Relatively lower degree of personalization

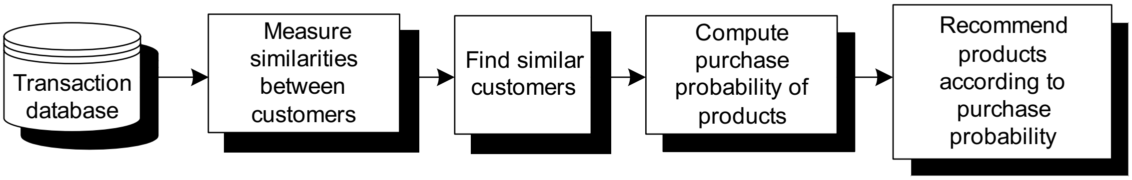

Fig. 1. General procedure of collaborative filtering approach.

3.2.1. Computation of purchase probability and similarity

Before introducing the procedures of RS, we should discuss the computation of purchase probability and similarity. For the binary basket data, the Jaccard coefficient is usually adopted as the similarity measure [19,34]. The Jaccard coefficient is defined in Eq. (1).

$$\omega(t,j) = \frac{n(c_t \cap c_j)}{n(c_t \cup c_j)} = \frac{n(c_t \cap c_j)}{n(c_t) + n(c_j) - n(c_t \cap c_j)} \tag{1}$$

where $\omega(t,j)$ is the similarity between target customer t and customer j, $t \neq j$, $j = 1,2,\ldots,N_c$; $n(c_t \cap c_j)$ is the number of items purchased by both target customer t and customer j; $n(c_t \cup c_j)$ is the number of items purchased by target customer t or customer j; $n(c_t)$ is the number of items purchased by target customer t; $n(c_j)$ is the number of items purchased by customer j.

There are two kinds of purchase probabilities: frequency-based probability and similarity-based probability. The frequency–based purchase probability employed in CPRS and CPPRS is defined as Eq. (2).

$$P_i = \frac{R_i}{NB} \tag{2}$$

where P_i is the purchase probability of product item i, $i = 1,2,\ldots,N_I$; R_i is the purchase frequency of product item i; NB is the total number of market baskets.

The similarity-based purchase probability [5,34] employed in CFRS and HPRS is defined in Eq. (3).

$$P_{t,i} = \kappa \sum_j \omega(t,j) c_{j,i} \tag{3}$$

where $P_{t,i}$ is the probability that target customer t purchases item i; κ is a normalizing factor to ensure the absolute values of weights sum to unity; $\omega(t,j)$ is the similarity between target customer t and customer j; $c_{j,i}$ is the binary choice that customer j purchases item i or not. More detailed information can be found in [5].

$$c_{j,i} = \begin{cases} 1 & \text{if customer } j \text{ purchased item } i; \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

3.2.2. CPRS

The CPRS follows the following procedure, as illustrated in Fig. 2.

Step 1: Compute frequency-based product purchase probabilities (P_i) with respect to Eq. (2).
Step 2: Sort the frequency-based purchase probabilities in descending order.
Step 3: Find the largest N product purchase probabilities.
Step 4: Find N items to recommend with the largest N product purchase probabilities.
Step 5: Return N recommended items.

3.2.3. CFRS

The procedure of the CFRS is shown in Fig. 3. The only difference from the CPRS is the computation of purchase probability. The CPRS utilizes a similarity-based probability instead of a frequency-based probability. The CFRS is made up of the following five steps.

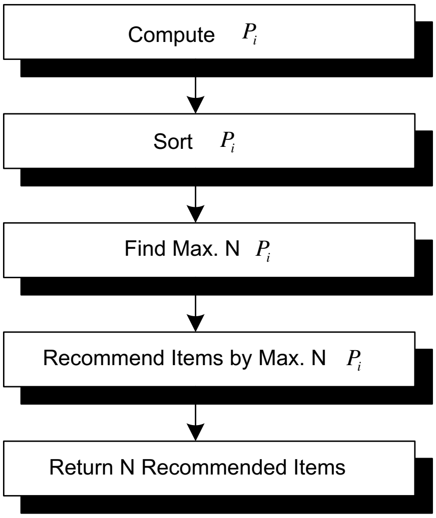

Fig. 2. Procedure of CPRS.

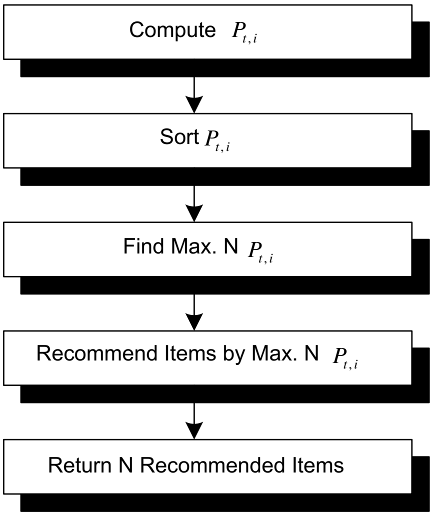

Fig. 3. Procedure of CFRS.

Step 1: Compute similarity-based product purchase probabilities ($P_{t,i}$) with respect to Eq. (3).
Step 2: Sort similarity-based purchase probabilities in descending order.
Step 3: Find N highest similarity-based product purchase probabilities.
Step 4: Find N items to recommend with N largest similarity-based product purchase probabilities.
Step 5: Return N recommended items.

From the previous studies, the hybrid systems of combining CF and CBF may potentially resolve some of the difficulties of sparsity and cold-start. However, many additional data such as product characteristics and customer profiles need be collected and analyzed. In the retail context with a wide array of products, it is very difficult to collect and analyze these data. From the beginning, RS can generate acceptable results if the users' data are well-realized [36]. Users may not intend to spend much time to describe their profiles. Although the users' profiles are important to RS, they are not easy to initialize and maintain. From the survey in [36], the mechanisms of gaining users' data are diverse and vary from manual input to automatic generation.

Introducing new customers and new items can be treated as special cases in this study. In the case of new customers, we can recommend the most frequently bought and/or most profitable items to them. In the case of new items, we can recommend them to the customers having more transactions and/or promote the new items by marketing campaigns.

Incorporating the item attributes (content) can improve the performance of RSs as well as relax some of the problems of sparsity and cold-start. As mentioned above, it is however very difficult to collect and analyze item attributes in the retail context with a wide array of products. Additionally, the preference of customers to the product profitability (computed from the product content of price and cost) differs from that of sellers. This study incorporates the product profitability with respect to the preference of sellers, and takes it as a part of performance measure when making recommendations.

4. Proposed profitability based recommender systems

This section describes the proposed profitability based RSs, CPPRS and HPRS. In addition to the traditional systems, our proposed systems consider the profit margin (product profitability) of the seller in the recommendation. The profitability of product item i can be measured by the profit margin of product item i, and it is defined in Eq. (5).

$$M_i = R_i - C_i \tag{5}$$

where M_i is the profit margin of product item i, $i = 1, 2, \ldots, N_I$; R_i is the unit price of product item i; C_i is the unit cost of product item i. The product of probability and profitability is computed to obtain the average margin. The average margins are then sorted, and the CPPRS and HPRS recommend items that depend on them.

4.1. CPPRS

The CPPRS considers both frequency-based purchase probability and profitability. The steps of the CPPRS are shown in Fig. 4 and are described as follows:

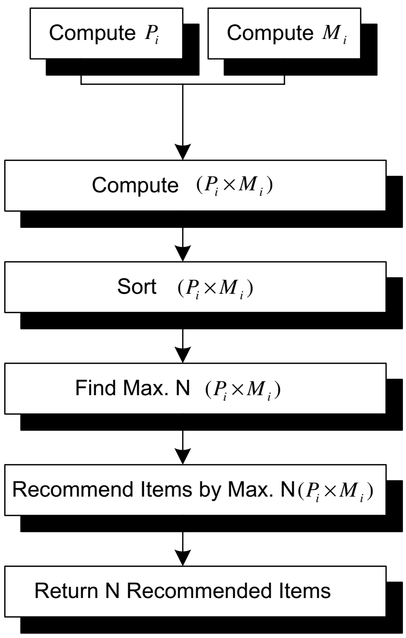

Fig. 4. Procedure of CPPRS.

Step 1: Compute the frequency-based purchase probability (P_i) and the product profitability (M_i) with respect to Eqs. (2) and (5), respectively.
Step 2: Compute the frequency-based average margin with ($P_i \times M_i$).
Step 3: Sort the frequency-based average margins in descending order.
Step 4: Find the N largest frequency-based average margins.
Step 5: Find the recommended N items with the N largest frequency-based average margins.
Step 6: Return the N recommended items.

4.2. HPRS

The HPRS employs the similarity-based purchase probability and profitability. The HPRS procedure is shown in Fig. 5 and is described as follows:

Step 1: Compute the similarity-based purchase probability ($P_{t,i}$) and the product profitability (M_i) with respect to Eqs. (3) and (5), respectively.
Step 2: Compute the similarity-based average margins with ($P_{t,i} \times M_i$).
Step 3: Sort the similarity-based average margins in descending order.
Step 4: Find the N largest similarity-based average margins in descending order.
Step 5: Find the N recommended items with the N largest similarity-based average margins in descending order.
Step 6: Return the N recommended items.

4.3. Comparisons between different perspectives

The comparisons between/among four RSs have been summarized in Table 2. The CPRS and CFRS are existing RSs. The CPPRS and HPRS introduce the profitability factor for sellers. The CPRS and CPPRS are non-personalized because all customers are recommended with the same products. CFRS and HPRS are personalized because (a) for each customer, a set of similar customers (neighbors) is found based on a

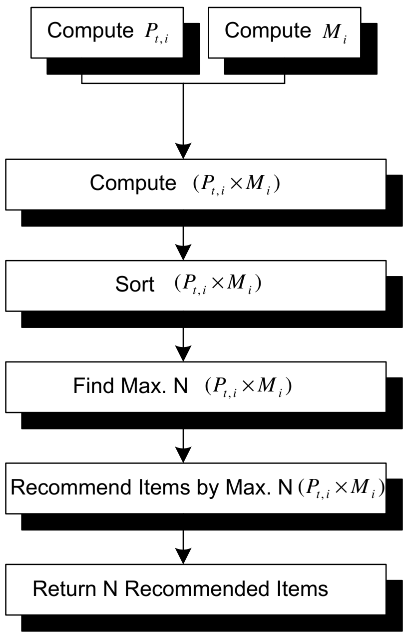

Fig. 5. Procedure of HPRS.

Table 2
Comparisons between/among four recommender systems

	Measures	Reasons of comparison
CPRS vs. CPPRS	Recommendation accuracy	• Comparison between non-personalized recommendations • The effect on recommendation accuracy when product profitability is additionally taken into consideration
CPRS vs. CFRS	Recommendation accuracy	• Comparison between the seller's convenience and the buyer's preference perspective
CFRS vs. HPRS	Recommendation accuracy & profit from cross-selling	• Comparison between personalized recommendations • The effects on recommendation accuracy and profit from cross-selling when product profitability is additionally taken into consideration
CPRS vs. CFRS vs. HPRS	Recommendation accuracy	• Comparison between personalized and non-personalized recommendations • The effect of personalization degree on recommendation accuracy
CPPRS vs. CFRS vs. HPRS	Recommendation accuracy	• Comparison between personalized and non-personalized recommendations • The effect of personalization degree on recommendation accuracy

similarity measure; (b) the neighbors of each customer are different; (c) products recommended to customers are different; and (d) tailored product recommendations are designed.

The CFRS only considers individual customer's preference data (transaction records) regardless of product profitability. In addition to individual customer's preference data (personal information), the HPRS takes product profitability (non-personalized information, and overall product information) into consideration. As a result, the CFRS possesses a higher degree of personalization than the HPRS.

In addition, the parameters related to these four RSs are k and N. Parameter k is the number of customers similar to target one, and parameter N is the number of recommended items based on the customers' market baskets. In the CPRS and CPPRS, N is the only parameter that has to be determined. In the CFRS and HPRS, both parameters k and N have to be determined.

In terms of recommendation accuracy and/or profit from cross-selling, comparisons can be made among systems (CPRS vs. CPPRS, CPRS vs. CFRS, CFRS vs. HPRS, CPRS vs. CFRS vs. HPRS, CPPRS vs. CFRS vs. HPRS). The measures are as well shown in Table 2.

5. Experimentation

5.1. Dataset

The sample database, FoodMart, in Microsoft SQL Server 2000 is used to evaluate these four systems. Because the dataset is obtained from a supermarket, the data sparsity problem is common in this domain. Although, the dataset contains 20,522 market baskets of 5581 customers on 1559 items, the average item included in single market basket is only 4, and the average item purchased by single customer is only 12. The CF approaches cannot recommend products which are less purchased [2,6,15]. The data reduction therefore is necessary to address the data sparsity problem. The data are reduced if items are purchased infrequently, market baskets contain very few items, and customers purchase very few items. The reasons for reducing these three kinds of data are listed as follows:

1. *Item reduction*: In the original dataset, there may be some items appearing seasonally in a short time. Infrequently purchased items are reduced to discard some special events (e.g., promotion campaign and seasonal effect). Besides, infrequently purchased items have little chance to be recommended.
2. *Market basket reduction*: Collaborative filtering is performed with extensive computation. It is necessary to reduce the market baskets containing very few items since there are 1559 items in the original dataset. This reduction can decrease the computation cost when performing recommendations.
3. *Customer reduction*: Before reduction, there are 5581 market baskets. Rejecting customers who purchase very few items can decrease the infrequent customers, and reduce the computation cost of forming customer neighborhood.

The average number of items included in a market basket and the average number of items purchased by a customer are very small (respectively 4 and 12), as well as the market basket size in reduced dataset ranges from 2 to 12, the range of N is therefore reasonably set to 2–12.

The reduced dataset contains 6845 market baskets of 895 customers with 859 product items. To provide more detailed information about the data format used in this study, additional five tables (Tables 3–7) of data samples including the historical transactions in training dataset, transactions in testing dataset, recommended items in testing dataset, product profitability and profit from cross-selling based on one single transaction have been added. These data can be obtained and formatted from FoodMart database.

Table 3
Samples of historical transactions in training dataset

Customer ID	Item set
$C001$	$\{I001, I003, I005, I007, I009\}$
$C002$	$\{I002, I004, I006, I008, I010\}$
$C003$	$\{I001, I002, I003, I004, I005\}$

Table 4
Samples of transactions in testing dataset

Transaction ID	Customer ID	Item set
$T101$	$C001$	$\{I001, I002\}$
$T102$	$C001$	$\{I001, I004\}$
$T103$	$C002$	$\{I002, I003\}$
$T104$	$C003$	$\{I005, I006\}$

Table 5
Samples of recommended items in testing dataset

Transaction ID	Recommended item set
$T101$	$\{I001, I002\}$
$T102$	$\{I002, I004\}$
$T103$	$\{I003, I004\}$
$T104$	$\{I003, I004\}$

Table 6
Samples of product profitability

Item ID	Profitability
$I001$	1.2
$I002$	1.5
$I003$	1.8
$I004$	2.1
$I005$	2.0
$I006$	3.0
$I007$	3.2
$I008$	3.1
$I009$	1.8
$I010$	1.5

Table 7
Samples of profit from cross-selling based on one single transaction

Transaction ID	Recommended and never purchased item set	Profit from cross-selling (PCS_b)
T101	{I002}	1.5
T102	{I004}	2.1
T103	{I003}	1.8
T104	ϕ	0

5.2. Evaluation measures

The measure, F1, which combines Precision and Recall, is usually adopted as the evaluation measure of recommendation accuracy in the related literature [9,41]. Precision, Recall and F1 are mathematically defined in Eqs. (6)–(8), respectively.

$$\text{Precision} = \frac{n(PI \cap RI)}{n(RI)} \tag{6}$$

$$\text{Recall} = \frac{n(PI \cap RI)}{n(PI)} \tag{7}$$

$$\text{F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

where PI represents all items contained in one specific market basket, and RI stands for the items recommended to one specific market basket. Precision is defined as the ratio of the number of correctly recommended items (i.e., the number of items recommended really purchased by customers) to the total number of recommended items. Recall is defined as the ratio of the number of correctly recommended items to the total number of purchased items. F1 is adopted because Precision and Recall are in conflict with each other in nature. Increasing RI leads to an increase in Recall but a decrease in Precision. Precision, Recall and F1 are computed for each individual market basket.

Since in addition the product profitability of sellers is also considered in the proposed RSs, the profit from cross-selling is also used in evaluating the proposed systems. Total profit from cross-selling can be defined as Eq. (9).

$$\text{TPCS} = \sum_b \text{PCS}_b \tag{9}$$

where TPCS is the total profit from cross-selling; PCS_b is the profit from cross-selling based on one single transaction (market basket) b, $b = 1, 2, \ldots, N_b$.

5.3. Experimental results

5.3.1. Comparison between CPRS and CPPRS

In order to study the impact of profitability factor on non-personalized systems, the CPRS and CPPRS are compared in terms of recommendation accuracy. Due to the fact that the market basket size of the testing dataset ranges from 2 to 12, experiments of the CPRS and CPPRS are made with N (the number of recommended items) ranging from 2 to 12. The results of the CPRS and CPPRS are shown in Fig. 6. From this figure it is easy to understand that in most cases the F1 of the CPPRS with different recommended items is significantly lower than that of the CPRS. This indicates that the additional consideration of product profitability in the non-personalized system results in inferior recommendation accuracy.

5.3.2. Comparison between CPRS and CFRS

To only compare the items being recommended by each system from a seller's convenience perspective and only from a buyer's preference perspective, we must evaluate the recommendation accuracies of the CPRS and CFRS. Fig. 6 shows that the recommending of eight items ($N = 8$) in the CPRS result in the best F1 of

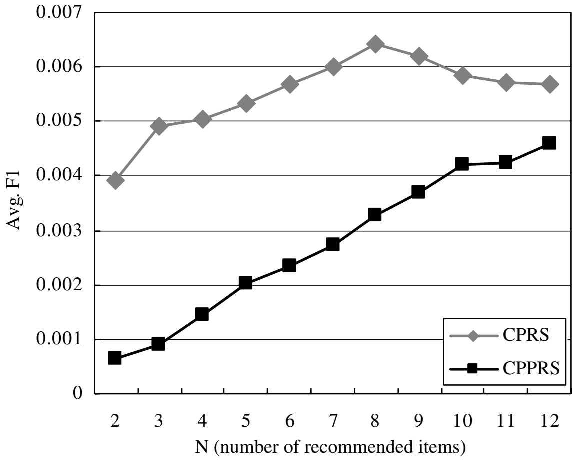

Fig. 6. Experimental results of CPRS and CPPRS on N.

0.00642. Therefore, we fix N to 8 and then compare the CFRS and the CPRS for a set of k (the number of customers similar to the target one). Table 8 summarizes the computational results of the CFRS. From this table, all the recommendation accuracies F1 of the CFRS (from $k = 10$ to 100) are higher than the best result of the CPRS (0.00642). Therefore, the buyers' preference perspective has a positive impact on RSs in terms of recommendation accuracy.

5.3.3. Comparison between CFRS and HPRS

To investigate the impact of additional profitability factor on the personalized systems, CFRS and HPRS are compared in terms of recommendation accuracy (F1) and profit from cross-selling (TPCS). In both the CFRS and HPRS, the parameter settings of k and N are determined by a set of pilot runs. Parameters k and N are then set from 10 to 100 (interval is 10) and from 2 to 12, respectively. For each k, only the combination of (k, N) with the best accuracies of CFRS and HPRS are listed in Tables 9 and 10. Table 9 shows that in most cases the recommendation accuracy of HPRS is higher than that of CFRS. The maximum F1 of HPRS (0.0143) is better than that of CFRS (0.0131).

The total profits from cross-selling (*TPCS*) of CFRS and HPRS are summarized in Table 10. From this table, it is evident that the total profits of the HPRS are significantly larger than that of the CFRS. Even the worst TPCS of HPRS (83.6022) is larger than the best one of CFRS (76.1147). Averagely speaking, the profit from cross-selling of HPRS dramatically increases 432% compared with CFRS. Meanwhile, as Fig. 7 shows, the average F1 of HPRS (0.0125) is slightly better than that of CFRS (0.0099). Therefore, when additionally considering product profitability, the profit from cross-selling can be improved remarkably without decreasing the recommendation accuracy.

Table 8
Experimental results of CFRS (with N fixed to 8)

k	N	F1	Precision	Recall
10	8	0.0067	0.0113	0.0057
20	8	0.0083	0.0145	0.0068
30	8	0.0073	0.0139	0.0054
40	8	0.0067	0.0123	0.0051
50	8	0.0083	0.0150	0.0062
60	8	0.0093	0.0172	0.0071
70	8	**0.0102**	0.0188	0.0077
80	8	0.0085	0.0161	0.0063
90	8	0.0086	0.0161	0.0065
100	8	0.0091	0.0166	0.0068

Table 9
Recommendation accuracies of CFRS and HPRS

CFRS				HPRS			
(k, N)	F1	Precision	Recall	(k, N)	F1	Precision	Recall
(10,11)	0.0010	0.0140	0.0091	(10,4)	0.0139	0.0139	0.0035
(20,12)	0.0099	0.0139	0.0090	(20,11)	0.0119	0.0168	0.0109
(30,11)	0.0086	0.0133	0.0070	(30,12)	0.0128	0.0186	0.0113
(40,12)	0.0089	0.0125	0.0077	(40,12)	0.0098	0.0139	0.0091
(50,12)	0.0101	0.0147	0.0086	(50,12)	0.0116	0.0165	0.0107
(60,12)	0.0112	0.0161	0.0097	(60,11)	**0.0143**	0.0195	0.0138
(70,12)	0.0105	0.0150	0.0091	(70,12)	0.0136	0.0179	0.0134
(80,12)	**0.0131**	0.0182	0.0118	(80,12)	0.0125	0.0168	0.0121
(90,12)	0.0126	0.0175	0.0113	(90,12)	0.0125	0.0168	0.0120
(100,12)	0.0131	0.0179	0.0121	(100,12)	0.0124	0.0165	0.0123

Table 10
Profits from cross-selling of CFRS and HPRS

CFRS		HPRS	
(k, N)	TPCS	(k, N)	*TPCS*
(10,11)	**76.1147**	(10,4)	155.1510
(20,12)	66.1306	(20,11)	153.5530
(30,11)	34.9702	(30,12)	**171.4960**
(40,12)	18.8049	(40,12)	106.2540
(50,12)	21.6847	(50,12)	125.0430
(60,12)	23.6967	(60,11)	116.4090
(70,12)	8.6924	(70,12)	126.6410
(80,12)	13.7868	(80,12)	91.1905
(90,12)	8.6924	(90,12)	95.7923
(100,12)	10.8431	(100,12)	83.6022

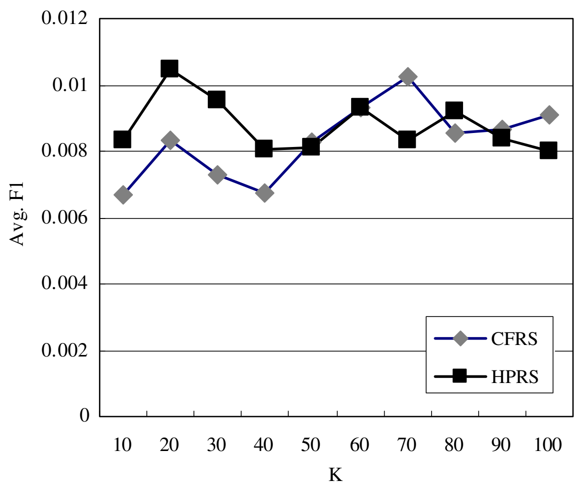

Fig. 7. Recommendation accuracies of CFRS and HPRS (with N fixed to 8).

5.3.4. Comparison among CPRS, CFRS and HPRS

The recommendation accuracies of CPRS, CFRS and HPRS are compared to determine the impact of the degree of personalization on RSs. To compare the CPRS, experiments with the CFRS and the HPRS are run on a set of k with fixed $N = 8$. Fig. 7 illustrates the accuracies of both the CFRS and the HPRS.

The maximum F1 of CPRS, CFRS, and HPRS are 0.0064, 0.0131, and 0.0143, respectively. Compared with CPRS (non-personalized), the recommendation accuracy of CFRS (relatively higher degree of personalization) and HPRS (relatively lower degree of personalization) are significantly higher than that of the CPRS. From Fig. 7, the HPRS outperforms the CFRS in the cases of relatively smaller k in terms of recommendation accuracy.

5.3.5. Comparison among CPPRS, CFRS and HPRS

The recommendation accuracies of CPPRS, CFRS and HPRS are further compared to study the impact of the degree of personalization on RSs. Fig. 6 shows that the CPPRS generates a maximum F1 in the case of $N = 12$. Therefore, CFRS and HPRS are further run on a set of k with fixed $N = 12$. Fig. 8 illustrates the accuracies of the CFRS and HPRS in this experiment.

The maximum F1 in CPPRS, CFRS, and HPRS are 0.0046, 0.0131, and 0.0143, respectively. Compared with the CPPRS (non-personalized), the F1 of CFRS (relatively higher degree of personalization) and HPRS (relatively lower degree of personalization) are significantly higher than that of the CPPRS. At the same time the HPRS outperforms the CFRS in terms of recommendation accuracy. Although personalization can significantly improve recommendation accuracy, we cannot conclude that the higher degree of personalization can produce higher recommendation accuracy. However, the above results do indicate that the HPRS which considers product profitability can be very profitable to sellers.

The approaches are investigated by FoodMart database from supermarket. In such case, thousands of products are offered for sale. It is nearly impossible to find a set of elements that can properly describe the content of all products. The attempt to analyze the content of products is therefore abandoned. The proposed approaches can be adopted in retail industry with a wide array of products, but data reduction may be required if data is sparse.

Parameters k and N, respectively represent the number of customers similar to the target one (customer neighborhood size), and the number of recommended items (top-N items) with respect to customers' market baskets. Herlocker et al. [16] indicated that the customer neighborhood size (k) can influence the performance of CF according to their experimental results, and the best-k-neighbors method is most suited to select users for neighborhood. Sarwar et al. [41] further demonstrated that the optimal neighborhood size is dataset dependent. In [41], the number of items recommended (N) is fixed to 10 in the experimentation.

In CPRS and CPPRS, N is the only parameter that has to be determined; in CFRS and HPRS, both$k$ and N need to be determined by analyzing the metadata of database and by performing some pilot experiments. However, these tasks can be done off-line. In this paper, N is firstly determined by considering the average number of items included in a market basket and the average number of items purchased by a customer. After the determination of N, k is then selected by additional pilot tests.

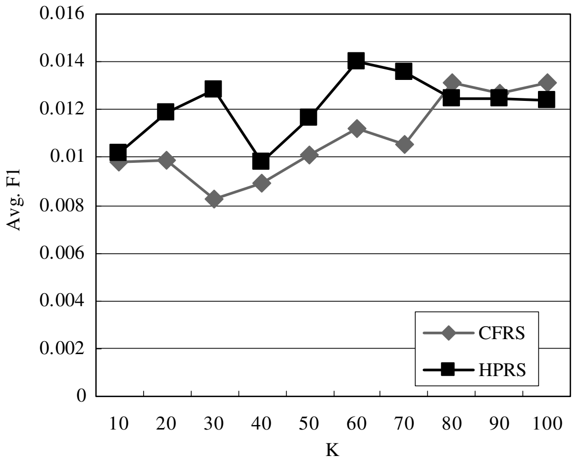

Fig. 8. Recommendation accuracies of CFRS and HPRS (with N fixed to 12).

6. Conclusions

RS is an effective means for solving the information overload problems in the personalized retailing system. Traditional CF algorithms can provide reliable and accurate recommendations by using purchase probability. However, they do not consider the profit margin of sellers. RSs should be designed not only for satisfying the diverse needs of customers, but also for obtaining a better profit margin. In this paper, the additional factor of profitability of sellers has been taken into consideration. Two systems, CPPRS and HPRS, which consider both product profitability and purchase probability were developed in this study. The experimental results show that the proposed HPRS can significantly improve the profit from cross-selling without a reduction in recommendation accuracy.

Furthermore, this paper analyzed four RSs based on different perspectives. Four RSs were compared in terms of recommendation accuracy and/or profit from cross-selling. From the above experimental results, some conclusions can be drawn.

(1) In the non-personalized recommendation, the recommendation accuracy decreases if product profitability is also taken into consideration.
(2) In the case of personalized recommendation, the profit from cross-selling significantly increases if product profitability is also taken into consideration. Moreover, the recommendation accuracy does not drop when product profitability is additionally taken into consideration.

To sum up, RSs that always make recommendations that fit customers' needs can earn their trust and assure the good reputation of the seller. Enterprises should do their best to develop an RS with high recommendation accuracy. In addition to satisfying customers' needs, profitability must be an essential concern to enterprises. Therefore, the profitability for sellers should also be taken into consideration when developing an RS, especially for mass personalization.

There exists no enough evidence to build the relationship between recommendation accuracy (F1) and total profit from cross-selling. From our experimental results, the proposed HPRS however is more favorable than the traditional approaches. The relationship between recommendation accuracy and total profit from cross-selling requires extensive experimentation. Although the results have shown the superiority of the proposed HPRS method, considering the product attributes according to sellers' perspectives is still a tough task. From the survey in [36], there are many existing systems using numerical ratings. The proposed systems based on binary data can be extended to numerical ratings for wider applications. These issues are noteworthy for future works.

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