Price Bundling for Personalized Recommendation

Li-Hua Li¹, Rong-Wang Hsu², *Shao-Shin Hung³, and Pei-Jung Tsai⁴

¹,²,⁴Institute of Informatics, Chaoyang University of Technology Taiwan, R.O.C
²Department of Computer Science and Information Engineering, WuFeng Institute of Technology, Chiayi, Taiwan, R.O.C

¹lhli@cyut.edu.tw; ²ronger@mail.wfc.edu.tw; ³²⁴hss@cs.ccu.edu.tw; ⁴carol_sunny1215@hotmail.com

Abstract: Bundled pricing, the selling of two or more products or services for a single price, is becoming increasingly common in the service industry. From the consumer's perspective, the bundling of services can offer monetary savings. The pricing bundling literature has focused on many of the aspects of bundling that are associated with providing monetary savings to the consumer. There are, however, many issues with price bundling that have not been addressed. If personalized recommendation is implemented concurrently through bundling or tie-in sales strategies, businesses are likely to increase sales opportunities for their products. In other words, the businesses design the product composition and they rarely take into account customer requirement and preferences. Therefore, we propose the periodical product bundling - recommendation system (PPB-RS), thereby analyze customer's periodical needs, preferences, and product purchasing periodicity, while taking the product periodicity and preference as reference for product composition of bundling or tie-in sales strategy. The empirical experiment from the study proves the superior performance of PPB-RS.

Keywords: Price Bundling, Personalization, Recommendation System, Tie-in Sales Strategy, Service

1. Introduction

Bundled pricing, the selling of two or more products or services for a single price, is becoming increasingly common in the service industry. Within the services industry, bundling has become a commonplace strategy. Hotels, resorts, air and cruise lines, for example, offer packages that combine transportation, lodging, meals and attraction admissions. From the firm's perspective, the use of bundling as a marketing strategy for services makes perfect economic sense, considering that they are perishable; underutilized services are opportunities that are lost forever. From the consumer's perspective, the bundling of services can offer monetary savings. Many researches have focused on many of the aspects of bundling that are associated with providing monetary savings to the consumer. For example, bundling is particularly popular in the service sector. Examples are vacation packages (airline ticket, hotel accommodation plus rent-a-car), insurance packages, or menus in restaurants (hors d'oeuvre, entree, dessert). In the fast food industry, "value meals" are heavily sold at special discounts. The key here is to use the strength of one product to attract customers to other items of the company. There are, however, many issues with price bundling that have not been addressed. For the consumer, there are several potential non-price related costs associated with bundling. For example, from personal experience we have noted that a common complaint of cruise passengers is that, although the base price is set low, passengers are "nickelized" and "dimed" for services once aboard. Even if consumers are not displeased with the overall monetary cost, they might be displeased with the incompleteness of the bundle. On the other side, with prosperity in the development of internet, the number of the global internet-surfing population has an unceasingly climbing tendency, which has also brought effects from digital transaction patterns and E-commerce industries. Personalized product and services based on personal demand for individual customers become popular.

To increase sales, bundling or tie-in sales strategies are frequently applied on the sales of various products. Such type of sales means selling two or more products or services combined bundling or tie-in sales to the market [3,4]. This is
a so-called marketing strategy which has been extensively applied on product promotion, with the objective of raising the sales volume of a product, and to enhance the overall sales performance to increase business profits. This strategy can lower production costs, increase product exposure, sales opportunities and to enhance customer royalty, as well as expanding market share. Therefore, bundling or tie-in sales have become a general marketing tool for businesses.

However, due to massive amount of data or numerous varieties of products, customers also face problems [5,6,7] overload, which results in customers spending more time to read about product information and to search out the products they really need. Therefore how to reduce the product searching time for customers and to effectively present the truly required products for customers, have literally become the foremost important issues for the businesses nowadays. Accordingly, a recommendation system has been created in response to solving problems of information overload.

Recommendation system is a personalized service means [6,7,8,9] base on information filtering (IF). The main objective here is to analyze customer purchasing behavior and appeals through customers’ personal historic data. The recommendation system in accordance with customers past historic transaction records or through historic transaction records of other customers with similar preferences, is used to successfully predict and to infer product with preferences for customers, and appropriately provide possible potential demand information of customers, hence not only to induce customer’s purchasing desire but also to increase opportunities of product cross-sell.

In order to increase business profit and to raise opportunities for product sales, in the past there have been scholars who have proposed a bundling or tie-in sales recommendation system to raise sales volume. Recommendation system not only possesses analytical and predictive functions, but also can filter out suitable product to accomplish personalized sale according to customer’s historical transaction records. Therefore, this system is applicable for recommending online bundling or tie-in sales to customers. Although bundling or tie-in sales strategies have multiple advantages in product exposure, effects in enhancing customer royalty and market share expansion, the combination method of product composition differs from the traditional single product sales had resulted in the sole consideration of product bundling to reduce stock in the implementation process, while the lack of consideration of consumers (customers) personal demand or preferences has made the product composition not completely fulfilling customer demand and preferences, and usually will disappoint customers in purchasing and fail to stimulate purchasing rate. Even though product exposure increases, customer demand has not been completely been fulfilled. Nonetheless some studies [4] have pointed out that to improve flaws in customer demand through bundling or tie-in sales recommendation system, this however does not proactively recommend personalized product oriented toward customer personal demand, which will ultimately reduce the recommendation efficacy and quality. Therefore, how to choose an appropriate personalized product under existing bundling or tie-in sales strategy has become more important. In view of this, the study will emphasize on improvement on above-mentioned issues and to propose an analytical method on consumer product purchasing with periodical product bundling sales or tie-in sales strategy, thereby enhance recommendation efficacy on personalized product through this concept.

To acquire customer consuming habits more precisely, the study applies RFM (Recency, Frequency, Monetary)[13,26] Analytical Method to analyze customer user profile for personal preference and consuming habit, then assess the acquired customer repeating demand, product preference level and purchasing periodicity after analysis, followed by the result of this assessment to achieve automatic sales combining proactive periodical recommendation through content-oriented recommendation and personalization method which combines mixed bundling or tie-in sales strategy, in order to provide customers with a periodical recommendation mechanism.
2. Related work
Due to the participants in this study mainly involve on periodical consumer product for bundling or tie-in sales, the objective of the study is to achieve recommendation for personalized product, thereby this chapter will review with an emphasis on the relevant techniques and theories adopted by this study.

2.1 Bundling or Tie-in Sales
From the practical perspective of marketing, promotional strategy is one marketing activity used by businesses to stimulate customer needs, providing inducing factors which are beneficial to customer purchasing in short-term period, while stimulation of customer purchasing desire has been on the strategies commonly applied to product promotion [34, 7-13, 15, 16]. Simply put, it is the bundling or tie-in sales strategy. In real life, promotional activities can be easily recognized in that bundling or tie-in sales Strategy is part of the product promotion techniques, for example, a red-labeled product when bundles with a green-label product aims for raising product sales volume, therefore increase the overall sales performance and business profits.

2.2 Recommendation System
Recommendation system refers to an information-filtering service technique [17-20] according to customer’s preferences or appeals, which assists customers in solving problems with information overload, and in delivering out useful information to recommend to the customers. on the other hand [18], considers the general information-filtering system could also be addressed in a more general term of recommendation system. Recommendation system is an approach to shift out information and to provide a personalized service through applying techniques in statistics, information filtering information capture and knowledge discovery, thereby provide personalized recommendation [17,33] on a real-time interactive approach for products or services.

However, how to effectively implement recommendation mechanism in an intensively competitive environment of E-commerce in order to increase market share and to enhance competitiveness, has become relatively more important. Scholar as [19,20] has suggested the application of recommendation on E-commerce will bring more effects for businesses. Due to this study places emphasis on the study of regular purchasing products (known as the consumer products), analysis on the relationship between customer purchasing behavior and product purchasing periodicity is used to discover customer’s periodical purchasing behaviors and to reinforce the importance for customer demand. The study adopts a content-oriented recommendation, in expectation to comply with the objectives of recommendation for personalized preferences or required commodities, consequently to stimulate customer repurchasing.

2.3 Personalization
Traditional marketing strategy is nothing more than regarding customer group as a single selling target and to provide promotional services to customers within this group. Personalized demand is a starting point for recommendation system [22, 23], which is analyzed through the customers’ historical transaction records and appeals in the past, then be given with appropriate recommendation. In recent years, scholars (N. Weißenberg et al., 2004) have proposed on using user profile to collaborate in personalization. Due to the advantages of descriptive self-portraits, interests, preferences and basic information in user profile, user profile is often referred to the information representing personal characteristics. Therefore a detailed user profile is commonly used to build and to support the one-to-one marketing strategy to accomplish personalized recommendation.

Customer lifetime value (CLV) refers to the life cycle of customer royalty, which is beneficial in developing personalized marketing strategy for target customers. In order to favor drafting personalized marketing strategy for customers, some scholars [24-29] proposed RFM on the analytical method, to evaluate customer lifetime values, consequently allowing businesses to obtain information on customer royalty and contribution and thereby find an efficient customer by applying appropriate marketing strategies to raise customer repurchasing opportunities and their royalty. In addition, RFM
analytical method can also be used as a responsive pattern to market segmentation [26,27,28]

2.4 Assessment on Recommendation Efficacy

Assessment on the efficacy of the recommendation system generally adopts precision and recall as the assessment indicator [31,32] of recommendation quality. However, it is usually difficult to obtain an equilibrium position between precision and recall, for example, an increase in system recommendation items (meaning the number in the denominator is larger) will result in a lower precision and higher recall, therefore the F1(Fallout) indicator [23] combines precision and recall to improve the paradox between the two, in order to achieve a more precise evaluation through the indicator evaluation. The study uses the above-mentioned three assessment indicators for assessing the recommendation efficacy. The philosophy of the recommendation lies on whether the objective of a successful recommendation could be genuinely achieved at each assessment. Therefore the quantitative issue is not included in the recommendation product.

3. Our Algorithm

First, our system is mainly consisted of two major sections (See Figure 1 and Figure 2), with the first section analyzing on personal historical transaction records and calculating customers’ preferences and periodical needs on various products, then obtain the recommendation period and level of appeal for the products. The second section recommends products based on customer requirement or degree of preference, in order to achieve objectives in recommending personalized product. The following subsections will explain the role of each module plays.

3.1 Personalized Bundling Module (PBM) and Personalized Recommendation

The study adopts mixed bundling strategy to select appropriate bundled products for customers, timely provide customers with personalized recommendation to increase customer repurchasing rate and to raise their loyalty. According to the Top-n concept brought up by scholar Sarwar et al. [23], select Top-n preference product, \( PD_a^i \), from the degree of preference \( P_i \) for \( i \) category from customer \( a \), collect the first products, then recommend the periodical time \( RPR[d_{\text{max}} + T(i)_{\text{now}}; d_{\text{min}} + T(i)_{\text{now}}] \) for periodical product as the starting point for recommendation.
Offer early recommending periodical product or Top-n preference product to customers before the next periodicity takes place. Table 1 illustrates the cross-sell and mixed bundling strategy for the two products, thereby finding out a bundling strategy applicable to the customers and timely recommending suitable products. The relevant bundling algorithm processing and the flowchart are demonstrated in Figure 3.

Table 1 Mixed bundling strategy

<table>
<thead>
<tr>
<th>Product</th>
<th>Periodical Product</th>
<th>Top-n Preference Product</th>
</tr>
</thead>
</table>

Step1: Preprocessing – read and define user profile CPa for customer a. Read the content of the profile CPa of customer a, and define CPa as struct with m number of previously purchased product information.

Step2: Descent Sort – use quick sort to sort the $P_i$ values in sequence Arrange the degree of preference values $P_i$ for each i category by customer a in sequential order. Use quick sort to arrange the $P_i$ values in the order from large to small. The $P_i$ values after sorting will put the higher $P_i$ value preference product to the first location, while periodical product is sorted after the preference product. Therefore it will be easy to find out the Top-n preference product for customer a.

Step3: Accumulate the count number of periodical product and preference product separately: The degree of preference values $P_i$ for i category from customer a is listed separately as periodical product or preference product. The count number of periodical product or preference product is accumulated respectively. Therefore the two Struct for preference and periodical, as well as the variables in each column are also defined respectively:

1. product category: $i$;
2. max recommendation days: $PRP_{i,d_{max}}$;
3. min recommendation days: $PRP_{i,d_{min}}$.

(4) transaction time: $T(i)_{now}$ for i category for the product purchased.

The preference values $P_i$ of each category of products purchased by customer will then be accumulated in the count number of periodical product or preference product, in order to effectively analyze the level of customer’s demanding for each product.

Step4: Bundling strategy to generate personalized recommendation table. Analyze the demanding strength customer a held for periodical product and preference product by accumulating the count number of the periodical product and preference product respectively. Save the number counts of the periodical product and preference product into the variables of zero_count and count, analyze the overall ratio of the count number from the number of products purchased by customer with the variable information in the zero_count and count. Analyze the count number accounting for the overall ration of m items of products for customer with variables in zero_count and count, and using these three conditions, zero_count $\geq m/2$, zero_count $< m/2$, and zero_count $= 0$ respectively, to assess the level of demanding for the periodical products and preference products from the customers in order to find the suitable product bundling strategy for the customer.
Finally according to the personalized strategy select a suitable product combination to produce a personalization recommendation record table for feedbacks to the customers at the best recommendation.

4. Experiment Results and Analysis

In this paper, we assume that the parameters for the periodical product bundling recommendation system were constrained in such circumstances. Accordingly, the aims of the experiment include the following objectives. First, our system can calculate the periodical purchasing and degree of preference for each product, then find out the periodical recommendation time and preference demand for products; Second our algorithm could produce a personalized product recommendation table; Third, the system recommends personalized bundling product; Finally, we analyze the product category with the concept of mixed bundling strategy and prove that the recommendation framework is successful in assessing the recommendation efficacy.

4.1 Experiment Data Source

The study employs the Foodmart2000 database for food & supermarket sale provided by Microsoft SQL2000 as a simulation of a trading database for internet marketplace, which is then used to verify the periodical recommendation efficacy for the PPB-RS, with an introduction of transaction record database, customer database, time database, product database and product category table as the empirical evidences for analyzing and verifying the study methodology. The product category table is mainly categorized into food, drink and other non-consumable products, with 1,560 products available. According to the product attributes, which are classified in 100 classes, 34 categories and 14 types, only the 34 categories are used by the study to analyze and recommend product categories. The scope of analysis for this experiment is selected from the one year and half timeframe from the marketplace transaction records from 1997/1/1 to 1998/6/30, with a total of 1,594 customers and 100,406 transaction records. The transaction records during the half year timeframe (1998/7/1 to 1998/12/31) have been used to assess the verification results of the recommendation efficacy for the methodology in this study.

4.2. Analysis on Periodical Purchasing Module (PPHM)

Taking an example on customer CID 2398, the history transaction records have listed the \( R \)-value for each \( i \) category purchased by the customer, in the proceeding Table 3. In this table, some products have been purchased only once and therefore could not present the transaction time frame \( T_{Fi} \) and the transaction time frame collection \( T_{Fi} \) respectively. The transaction time frame collection \( T_{Fi} \) of other \( i \) category is described as the follow.

The periodical purchase of the all categories purchased by customer CID 2398 has been calculated and analyzed on Table 4.

Table 3 Results of \( R \)-value obtained from transaction time (Days) frame.

<table>
<thead>
<tr>
<th>Category No.</th>
<th>Last Transaction Time ( F_{(0)} ) (Indicated by Time Code)</th>
<th>Current Transaction Time ( F_{(0)} ) (Indicated by Time Code)</th>
<th>Transaction Time Frame ( T_{Fi} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>789</td>
<td>464</td>
<td>( T_{Fi} = 126 )</td>
</tr>
<tr>
<td>14</td>
<td>484, 491</td>
<td>620</td>
<td>( T_{Fi} = 129 )</td>
</tr>
<tr>
<td></td>
<td>711, 769</td>
<td>711</td>
<td>( T_{Fi} = 91 )</td>
</tr>
<tr>
<td>30</td>
<td>792, 852</td>
<td>852</td>
<td>( T_{Fi} = 59 )</td>
</tr>
<tr>
<td>31</td>
<td>789, 851</td>
<td>858</td>
<td>( T_{Fi} = 66 )</td>
</tr>
<tr>
<td>34</td>
<td>464, 491</td>
<td>620</td>
<td>( T_{Fi} = 129 )</td>
</tr>
</tbody>
</table>

The result of the analysis of each \( i \) Category is shown in Table 5. Hypothesize the periodical frequency threshold \( \theta = 4 \), the purchasing count number \( CPC_i \) for category 34 and other categories fall below \( \theta = 4 \) therefore the purchasing periodicity of that product, bias \( B_i \), periodical standard deviation \( \sigma \) and the recommendation period range \( RPR \) \([d_{min}, d_{max}]\) could not be obtained (represented by the sign “-”). In the
future, when customer 2398 purchase a product, the system will re-analyze and calculate customer’s purchasing periodicity and the degree of preference \( P_i \), and store the updated analysis result in the user profile \( CP^{2398} \).

### 4.3. Analysis on Personal Preference Module (PPRM)

We set \( n=3 \), which is the top 3 preference products selected from the \( PD_i \) collection. Table 6 lists the purchasing count number \( CPC_i \) for \( i \) category, the total purchased quantity \( SP_i \) and the degree of preference \( P_i \) within the one year and half timeframe from 1997/1/1 to 1998/6/30 for customer CID2398. From the table, we have observed category 14 and category 31 are the personal periodical products for customer CID2398, while the preference products fall in the Top-3 products in category 34, 10 and 11.

Table 4 Periodical purchasing analysis of each category

<table>
<thead>
<tr>
<th>Category No.</th>
<th>Transaction Time Frame ( TP_i )</th>
<th>Purchasing QTY ( m^i )</th>
<th>Periodical Time for Category ( PT )</th>
<th>Min Purchasing Periodicity ( PT_{min} )</th>
<th>Average Purchasing Periodicity ( PT )</th>
</tr>
</thead>
<tbody>
<tr>
<td>14</td>
<td>( TP_{14}=126 )</td>
<td>2</td>
<td>63</td>
<td>0.5</td>
<td>17.17</td>
</tr>
<tr>
<td></td>
<td>( TP_{14}=27 )</td>
<td>3</td>
<td>9</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( TP_{14}=19 )</td>
<td>8</td>
<td>16.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( TP_{14}=91 )</td>
<td>3</td>
<td>30.3</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( TP_{14}=78 )</td>
<td>4</td>
<td>19.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( TP_{14}=3 )</td>
<td>3</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( TP_{14}=59 )</td>
<td>4</td>
<td>14.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( TP_{14}=1 )</td>
<td>2</td>
<td>0.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( TP_{14}=6 )</td>
<td>2</td>
<td>3</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( TP_{14}=29 )</td>
<td>2</td>
<td>14.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>31</td>
<td>( TP_{31}=12 )</td>
<td>7</td>
<td>11.1</td>
<td>0.3</td>
<td>8.8</td>
</tr>
<tr>
<td></td>
<td>( TP_{31}=3 )</td>
<td>9</td>
<td>0.3</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( TP_{31}=59 )</td>
<td>5</td>
<td>11.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( TP_{31}=16 )</td>
<td>1</td>
<td>12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>34</td>
<td>( TP_{34}=27 )</td>
<td>2</td>
<td>13.5</td>
<td>13.5</td>
<td>39</td>
</tr>
<tr>
<td></td>
<td>( TP_{34}=129 )</td>
<td>2</td>
<td>64.5</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5 Analysis of periodical recommendation range for each category

<table>
<thead>
<tr>
<th>Category No.</th>
<th>Other ( \sigma )</th>
<th>( PT_{min} )</th>
<th>( PT )</th>
<th>( B )</th>
<th>( \sigma )</th>
<th>( RPR ) ( \delta_{min}, \delta_{max} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>14</td>
<td>0.5</td>
<td>17.17</td>
<td>16.67</td>
<td>12.56</td>
<td>0.5,13</td>
<td>0.5,13</td>
</tr>
<tr>
<td>31</td>
<td>0.3</td>
<td>8.8</td>
<td>8.5</td>
<td>5.6</td>
<td>0.3,59</td>
<td>0.3,59</td>
</tr>
<tr>
<td>34</td>
<td>13.5</td>
<td>39</td>
<td>39</td>
<td>39</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In addition, the study also includes timely recommendation method as a control group for comparison with the study, while applying precision, recall and SSR respectively to assess the recommendation efficacy from the experiment results of the periodical recommendation method and timely recommendation method. As illustrated from the following Figure 4, it is clearly that among all assessment indicators, the periodical recommendation system has a better recommendation effects than timely recommendation.

Fig.4. A comparison between periodical and timely recommendation efficacy

Table 6 Experiment data from successfully sale rate

<table>
<thead>
<tr>
<th>Item</th>
<th>SSR</th>
<th>Participants</th>
<th>Total Participants</th>
<th>Overall Average Successfully Sale Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Successfully Sale Rate (SSR)</td>
<td>0%–59%</td>
<td>27</td>
<td>60%–69%</td>
<td>44</td>
</tr>
</tbody>
</table>

Nonetheless, in order to assess whether if the recommended items or product from the recommendation system will comply with the recommendation objectives, the study has applied the concept of coverage rate to propose on assessing the recommendation efficacy of the overall successful experiment with SSR. Table 6 demonstrates an assessment result from recommendation efficacy for the SSR proposed by the study. Figure 5 clearly shows the recommendation efficacy of the periodical recommendation system is more effective than the timely recommendation. Among the total of 1,594...
participants for the experiment, 1,333 participants were recommended with 100% SSR thereby resulting in a 96% SSR of the overall recommendation efficacy.

Fig. 5 A comparison chart between periodical and timely successfully sale rate

5. Conclusion and future work

In this paper, a framework which is a combination of mixed bundling strategy, content-oriented recommendation techniques and personalized concept of recommendation system was proposed. The data framework was extended the traditional recommendation system, taking into account the lack of pricing bundling strategy for discover more interesting bundles. We have compared the performance of periodical and timely recommendation efficacy. The results show that for traditional commercial dataset, our framework works more efficiently than ever.

References
[14] W. B. Dodds, B. M. Kent, and G. Dhruv, Effects of Price, Brand, and Store


