A Conceptual Model of Personalized Pricing Recommender System Based on Customer Online Behavior

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Summary
Recommender systems in the last decade opened new interactive channels between buyers and sellers leading to new concepts involved in the marketing strategies and remarkable positive gains in online sales. Businesses intensively aim to maintain customer loyalty, satisfaction and retention; such strategic long-term values need to be addressed by recommender systems in a more tangible and deeper manner. The reason behind the considerable growth of recommender systems is for tracking and analyzing the buyer behavior on the one to one basis to present items on the web that meet his preference, which is the core concept of personalization. Personalization is always related to the relationship between item and user leaving out the contextual information about this relationship. User's buying decision is not only affected by the presented item, but also influenced by its price and the context in which the item is presented, such as time or place. Recently, new system has been designed based on the concept of utilizing price personalization in the recommendation process. This system is newly coined as personalized pricing recommender system (PPRS). We propose personalized pricing recommender system with a novel approach of calculating consumer online real value to determine dynamically his personalized discount, which can be generically applied on the normal price of any recommend item through its predefined discount rules.

Key words:
Recommender Systems, customer value, online consumer behavior, Price personalization

1. Introduction

A new chapter has opened in online shopping when Kamishima and Akaho proposed at the end of 2011 the first attempt to develop a basic recommender system with price personalization [1]. They coined the system as personalized pricing recommender system (PPRS). PPRS can take an action other than recommendation, namely price personalization which allows the system to adjust the prices for an item based on the customer's willing to buy. The buying willing is addressed and measured through tracking the customer previous purchases to analyze his response to items prices. In order to determine the recommended item price if it will be normal or discounted. We addressed some assumptions given in the work of Kamishima and Akaho to eliminate their existence in our approach. For simplicity, their system operates on assumed conditions that can't be applied to most types of business. It provides the same price for all items which is not the normal matter of business, which is commonly based on presenting various products with various perceived values that are equivalent to various prices. Besides, it has only two pricing values available to be given: a standard and a discounted. Despite that the majority of marketing strategies retailers follow recently imply having one basic price for the product and several different discounted prices offered based on varied recognized situations [2].
Price personalization is the process of tailoring the items prices base on the customer value. In retail e-commerce, customer value has two perspectives. One perspective is based on customer's perception toward seller, which is related to the characteristics of offered products and/or services, web store features, and delivery services [3, 4]. The other perspective is based on seller's perception toward customer, which is related to his profitability and the degree of different contributions provided to the seller's business development [5, 6]. Targeting customer value identifies customer behavior characteristics that can be classified by performing customers segmentation based on the computed value for each customer which produces customer behavior patterns [7].
In this paper we discuss new dimensions or indicators of the online customer behavior while we are proposing personalized pricing recommender system with a novel approach of calculating customer online real value based on exploring new dimensions that can quantitatively measure online behavior characteristics including consumption, cooperation, participation, curiosity, and dedication. Then, based on the generated value we perform customers' segmentation to determine dynamically his personalized discount, which is generically applied on the normal price of any recommend item through its predefined discount rules.

2. Personalization Process

The goal of personalization is to provide users with what they want or need without requiring them to ask for it

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explicitly [8]. This means that a personalization system must somehow predict and expect the customer requirements based on the data collected from either previous or current interactions with the user. Collecting data about customer interaction on the web is based on different kind of web data collection sources [9]: 1.Marketing Data containing the customer relevant data from the web site operational database specially the data gathered directly from the customer. 2. Web Server Data including the server's log files, special error log files, and cookies. 3. Web structure data of the website (topological data) including the relationships between its web pages. Utilization of these web data is one of the dimensions classifying Personalization systems, in addition to the learning paradigm used, the location of the personalization and the process that the interaction takes with the user [10]. The intelligent Techniques for Web Personalization are about retrieving all available information about users of the Web to discover a personal experience which is basically knowledge. And the intelligence of these techniques is at various degrees about the generation of useful, applicable knowledge and the assumption and prediction based on this knowledge and the other relevant domains knowledge at the time of generating the personalized content for the user. Accordingly, the process of personalization can be viewed as an application of data mining and hence requiring support for all the phases of a typical data mining cycle [11] including data collection, pre-processing, pattern discovery and evaluation, in an off-line mode, and finally the deployment of the knowledge in real-time to user on the Web.

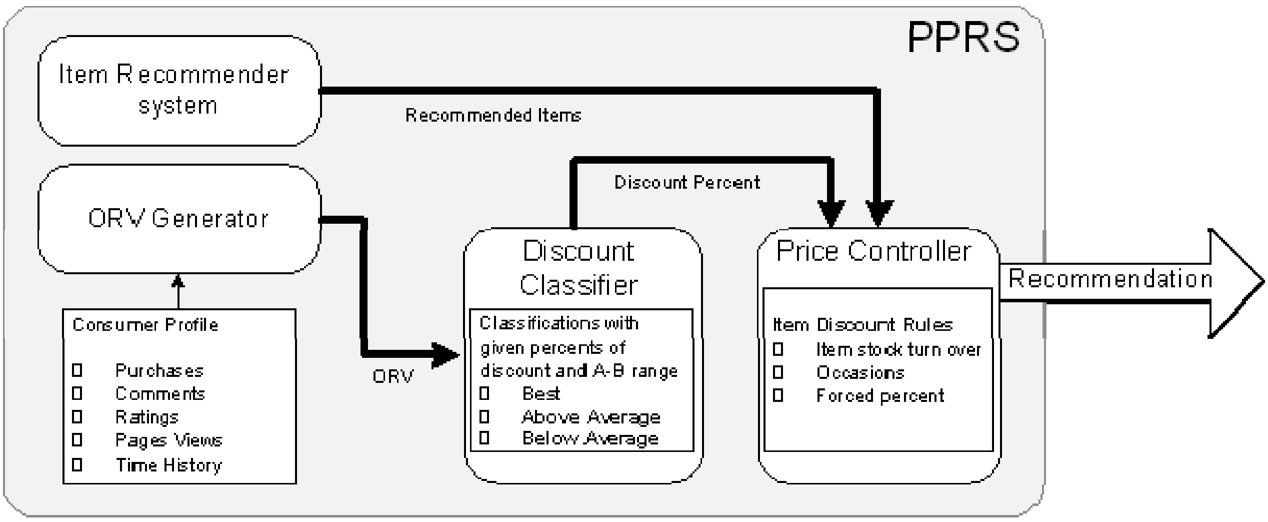

Fig. 1 The proposed price personalized recommender system

3. The Proposed Price Personalized Recommender System

Price personalized recommender system is based on two processes; price personalization and item recommendation. Item recommendation is the process of matching the customer preferences with items features based on different recommendation algorithms which are not in our scope in this study and the price personalization process which is tailoring the price of an item based on customer value. As shown in figure1, the building blocks of the our proposed system regardless the recommender system, the online real value (ORV) generator which computes the customer value based on his purchasing, interactivity and browsing data reflecting new dimensions for online customer behavior. Then, the discount classifier that perform customers segmentation base on the generated ORV for each customer, customers will be divided into three behavioral patterns which are best, average and below average customers. Each customers segment has a certain discount percent assigned to it by the seller. The price controller determine the final price assigned to an item when a recommendation performed to a customer that belongs to one of the mentioned segments, the price controller pricing decision is based on the discounting rules assigned in a predefined way by the seller on each item.

4. Consumer Online Real Value (ORV)

The perceived value from online customer perspective, it is considered as the different positive outcomes that customer can obtain from a seller's web store. In [12], they define the online customer value as the consumer's overall assessment of the net benefits gained from shopping at a store through successfully obtaining quality products and shopping enjoyment. Customer's perceived value toward a retailer is becoming more complex, it's not only derived from high quality or low price [13]. It's a conclusion of trading-off between perceived values of different dimensions including monetary value, convenience value, emotional value, social value and perceived sacrifices [14]. On the other hand, online customer value from the seller point of view is the value of customer's buying behavior that leads to certain revenue in the past and potential revenue in the future [5]. It can be matched with other terms like customer lifetime value, customer equity, and customer profitability. However, it is an effective indicator for identifying the preferred customers and targeting them carefully to increase profitability [5, 6]. Many studies measured the customer value quantitatively, so it can be segmented to discover the different customer behavior patterns. Customer value can be calculated based on customer lifetime value (LTV) which is the present value of all future profits generated from a customer [15]. Basically LTV combines customer Current value that represents historic customer purchase behavior and potential value that denotes the possibility of up-selling and cross-selling in the future. In [6] they proposed mathematical model of customer lifetime value consisted of values of past profit contribution, potential benefit, and defection probability. They used different data mining classification techniques including decision tree, artificial neural network, and logistic regression, to perform customer segmentation based on the values of customer LTV mentioned components. Then, they select the most reliable technique according to the most matched results with the misclassification rate and lift chart. In [5], a new approach is proposed to combine customer targeting and customer segmentation for marketing campaign strategies. They measured customer value by identifying the customer behavior characteristics using recency, frequency, and monetary (RFM) Model and then transformed the output customer data into a binary string as the input format of genetic algorithm to segment customers into several homogenous groups and used the LTV as the fitness values of the genetic algorithm to evaluate the generated customers segments to be matched with the developed campaign strategies and programs.

In the previously mentioned studies that measure online customer values, they focused on the customer behavior only from purchasing perspective concerning the amount of revenue and the number of purchases he does during a certain duration without addressing more important details that give a closer understanding to his behavior like how does he spend that money, how much he is sensitive to prices and what is the consumption volume of his purchases. Additionally, online customer behavior is more than buying; it's about browsing, learning, interacting and sharing. Is that there are a lot of activities customer does on the seller web store which are not addressed in his valuation, despite that they provide direct and/or indirect contribution to the business. For example, customer's navigation on the seller web store increases online traffic and gives him the opportunity to get more profit from having the advantage of using Google AdSense advertising program.

We propose a new mathematical model for calculating online customer value based on his past purchasing, browsing and interactivity data. The customer profile is divided into: 1) historical purchasing data that include the customer's previous orders with the ordered items and their quantities, 2) the historical interactivity data that include customer's commenting and preferential data which are the previous comments and ratings and browsing data, 3) the historical browsing data which are the pages views resulting from previous navigation sessions or visits of the seller web store. Customer valuation is based on five levels or performance indicators that measure his behavior from different dimensions including consumption, curiosity, dedication, cooperation, and participation.

4.1 Consumption Level

It measures the dimension of spending and consumption in online consumer behavior. Consumption level is computed based on a set of indicators derived from the historical purchasing data. It combines spending indicator represented in 1) the average price p of all past ordered items, and consumption indicators including 2) the average number of items per order where is the total number of items per order, and 3) the average item quantity per order

The resulting monetary value reflects a behavioral pattern of customer's spending and consumption. As a matter of fact, each customer has his own values of consumption level indicators derived from his needs, wants, and purchasing power which are accordingly affected by income and lifestyle.

4.2 Dedication Level

This level explores customer online behavior from dimension of involvement degree with the seller and his items, it addresses to what extent the customer's potential online shopping times are dedicated to the seller's web store. It measures the customer total number of past orders r over his time history in months m with seller. Dedication level $F1_i$ for customer i is as follows:

4.3 Cooperation Level

The significance behind cooperation level is focusing on the dimension of giving the opportunity for sellers to learn more about customer feedback and perception toward him, in addition to the business performance and how it can be developed. Customer serious comment on a certain product most probably lies under one or more of the following; positive reviews, negative reviews, suggestions, inquiries and complains. With analyzing these types of comments, seller can have a great knowledge asset for business development through understanding what customer wants. Accordingly, we observe the customer behavior to assess how cooperative the customer is in sharing opinions. Cooperation level $F2_i$ for customer i is measured by counting from his commenting data the total number of comments e he gave in the past over his time history in months m. The equation is as follows:

4.4 Curiosity Level

This level touches the dimension of customer navigation pattern on the seller web store. Basically, web navigation is a set of user's visits to a website, and each visit contains a set of page views. Based on customer browsing data tracked mainly from the log server file, he can browse old web pages that have been opened before and new web pages that are explored for the first time. From the seller perspective, discovering new items regularly on his web store is considerably appreciated, leading to renewable traffic distribution among the presented different items on the web store. And naturally, stable web traffic gives new opportunities for profitable advertising in addition to saving some effort for reaching to customers who already likes to explore the presented items. Hence, tracking the exploration and curiosity side of the customer gives us another perspective of understanding online customer behavior. Curiosity level $F3_i$ is determined for customer i based on the number of unique page views over the customer history in months. For verification, the unique page views must exceed 2 minutes time duration in order to be counted.

4.5 Participation Level

Customer participation in sharing opinion toward different items in a form of scaled rating is very informative for sellers. Each scale rate has a meaning and reflects the customer personal beliefs. Through Customers preferential data, seller can sense market directions toward certain items and consequently can take the right action in the right time. Participation level $F4_i$ for customer i combines the number of ratings over the customer time history in months

4.6 ORV Generator (Calculating Customer Online Real Value)

Customer ORV is the value derived from the weighted impacts of customer online interactivity and involvement on his consumption and spending. The previously mentioned online performance indicators will be classified into monetary and non-monetary indicators. The monetary indicator is the consumption level while the non-monetary indicators are the levels of dedication, cooperation, participation and curiosity. the non-monetary indicators will be combined to calculate the activities rate A_i for customer i through computing their weighted average which varies from indicator to another based on the size of contribution to the development of seller business, and after a set of trial and error iteration we reached to appropriate weights as illustrated in the following equation:

$$A_i = \frac{0.8*F1_i + 0.1*F2_i + 0.05*F3_i + 0.05*F4_i}{4}$$

Accordingly, the online real value ORV_i for customer i is the outcome of applying the activities rate A_i (which is reflecting the customer interactivity and involvement indicators) on the consumption level C_i for customer i (reflecting the spending and consumption indicator) and the equation is as follows:

$$ORV_i = C_i \times A_i$$

5. Discount Classifier

Discount classifier performs customer segmentation based on their online real value (ORV) to provide three customer segments including best customer segment which is assigned form seller with a predefined high discount percent, average customer segment which is assigned with a predefined normal discount percent and the below average customer segment which is excluded from discount. After identifying and valuating all customers' behavior through generating their ORVs, we calculate the average ORV per customer, and extract the AB range which is the range from the average ORV per customer to the best customer who has the maximum ORV. Based on the seller decision and perspective, he divides the AB range into average customer breakpoint and the best customer breakpoint through assigning the percent of each breakpoint. As illustrated in the following equations:

6. Price Controller

Price controller is proposed to apply the discount extracted by the discount classifier from the ORV generator to a specified customer recommended items (given from the recommender system). The extracted discount is applied on the item normal price based on its pricing rules which can be divided into:

- **Forced discount** which means that extracted discount is applied based on a predefined percent that could be 100% of the discount percent or less or 0%.

- **Occasions** based on predefined dates with predefined discount percents for the items, the price controller automatically detect the occasion date and apply the assigned discount.
- **Item stock turn over** which is a measure of the number of times stock is sold or used in a time period such as a year. Price controller can be proposed as a future work that can detect the items stock levels and their turnover rate to make a decision to assign a certain discount on it.

7. Conclusion

Online customer behavior still can be analyzed and explored from new dimensions that give more reliable indicators for predicting his behavior in the future. We addressed most of the activities that a customer can perform in an online web store and we tried to formulate them quantitatively to reach to a meaningful value that reflects the real customer behavior. We believe that personalized pricing recommender system based on the ORV concept can open new trends for maintaining customer retention and loyalty in the online environment.

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