Optimization of Store Performance Using Personalized Pricing

Cem Baydar, Ph.D Director, Peppers & Rogers Group

Currently, most of the grocery stores provide special discounts to their customers under different loyalty card programs. However, since each individual's shopping behavior is not taken into consideration, these discounts do not help optimize the store performance. We believe that a more determined approach such as individual pricing could enable retailers to optimize their store performance by giving special discounts to each customer. Our approach requires each customer is modeled as an agent and his/her shopping behavior is obtained from transaction data. Then, the overall shopping behavior is simulated and the store performance is optimized using Monte-Carlo simulations and evolutionary computation. The results showed that individual pricing outperforms the traditional product-centered approach significantly.

Introduction

As the competition in retail industry increases, retailers are becoming much more obligated to optimize their store performance. Currently, most of the grocery chains in the U.S offer loyalty programs. However, these loyalty programs mostly apply blanket couponing technique by offering the same discounts to their subscribers. However, humans are different and each individual has his/her own preference of products and price levels. Therefore modeling each customer separately and providing him/her individual coupons could improve the store performance. This type of offering is known as one-to-one marketing in the literature. Our proposed approach assumes that by using a sufficiently rich transaction data, it is possible to capture each regular customer's shopping behavior.

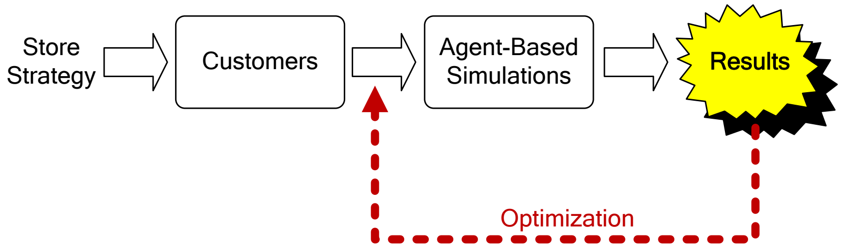

Fig. 1: Outline of the Proposed Approach

Then, individual models (agents) can be generated using this behavioral information and an agent-based system can be developed to simulate overall shopping behavior. The inputs for this agent-based simulation system can be provided by a store manager based on a strategy defined by the relative importance of three factors: profits, sales volume and customer loyalty. Finally, the system can use agent-based simulations in combination with evolutionary computation to identify the set of discounts for each customer. Figure 1 shows the overall approach. We have developed a system and tested the proposed approach against different blanket couponing pricing strategies. The results showed that individual pricing outperforms blanket couponing approach significantly. We believe that retailers can optimize their store performance by applying individual pricing.

Our Approach

One-to-one marketing is a customer relationship management paradigm which aims building customer loyalty by trying to sell as many as products as possible to one customer at a time [2, 3]. Unlike the traditional clustering approach, one-to-one marketing aims to treat each customer as an individual rather than a part of a segment. Grocery retail has always been an interest for the application of one-to-one marketing. In retail industry, most supermarkets use customer loyalty cards and several companies have also started to analyze the premise of one-to-one marketing in addition. The main advantage is that in grocery business almost every customer is a repeated buyer and grocery goods are consumed at a constant rate. Therefore, there is sufficient amount of data to model each regular customer's shopping behavior. Our approach uses an agent-based [1] modeling and simulation approach which is different from the more focused store optimization research approaches found in the literature. In agent-based computational modeling, only equations governing the micro social structure are included (i.e., shopping behavior of each individual). Then, the overall macroscopic structure of the system grows from the bottom-up. Typically for grocery store optimization, revenues, costs and sales volume are taken into account as complex mathematical equations. However in agent-based approach, these values are determined by summing up each customer's shopping activity such as his/her shopping frequency and spending. The implementation steps of our approach are as follows:

1. Model each customer's shopping behavior from transaction data.
2. Create customer models as agents using these models.
3. Perform agent-based simulations and optimize the store performance for a given store strategy.

Problem Statement and Formulation

A grocery store manager has to decide on the store strategy based on the relative importance of three goals: profits, sales volume and customer satisfaction. These goals are contradictory (i.e., a store manager could maximize customer satisfaction by reducing all prices to zero). Therefore, what determines the overall store performance is the difference between each objective. We can visualize the task of setting a store strategy as adjusting the three levers as shown in Figure 2.

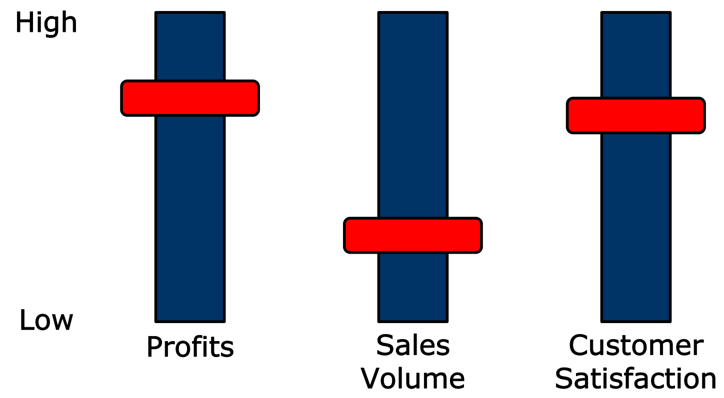

Fig. 2: Three goals to determine store strategy.

The optimization strategy can be defined in mathematical terms as:

$$\text{Maximize} f(x,y,z) = w_1x + w_2y + w_3z \quad (1)$$

where, x is the profit, y is the sales volume, z is the customer satisfaction, while w_1, w_2 and w_3 are the appropriate weights determined by the store manager. Since we are using agent-based models, there is no way of exploring x, y and z dimensions directly. Therefore, they are not the decision variables. The decision variables of this problem are the set of discounted products and discount values for these products. Both of these variables are different for each customer since we are giving individual discounts. Therefore, two questions are being addressed to maximize the objective function:

1. What is the optimal set of products for each customer?
2. What should be the discount values on these products?

Problem Modeling

There are two types of models that we consider for this problem: *store model* and *customer model*.

Store Model. The store model consists of several parameters such as:

- The number of products
- Quantity stored from each product
- Sales price of each product
- Product replenishment frequency
- Replenishment threshold
- Replenishment size
- Daily stock keeping cost of each product (inventory cost)

Customer Model. Each customer is modeled with several shopping properties such as:

- Shopping frequency
- Price sensitivity for each product
- Buying probability for each product
- Consumption rate for each product

Price sensitivity is defined for each product since a customer may have different shopping behavior towards each product. A person's buying probability can be influenced by giving a discount. This change is formulated as:

$$\Delta BP = (1 - \Omega(kd)) \tag{2}$$

where, ΔBP is the change in buying probability, d is the discount rate, k is the price sensitivity, and $\Omega(\cdot)$ is a probabilistic normal distribution function with mean kd and standard deviation $(1/3)kd$. The following formula is used to calculate the updated buying probability:

$$BP(A) = BP'(A)\Delta BP(A) \tag{3}$$

where, $BP(A)$ is the new buying probability of product A after price change, $BP'(A)$ is the buying probability before price change, $\Delta BP(A)$ is the change in buying probability due to the discount offer. In addition to these properties, there are two behavioral rules:

1. As the customer buys a product continuously, he/she starts building loyalty towards that product (i.e., buying probability increases)
2. If the customer finds the prices high for him/her or can not find a product from his/her shopping list, he/she gets frustrated and his/her probability of arrival decreases.

Understanding associations between products is very important when giving individual discounts. For one customer, Pepsi and Coke may be substitutes but for another who likes both products they may be independent. If a discount is given on one of the substitute or complement products, the other product's buying probability will also change. Two types of association are possible between products: *complements* and *substitutes*.

One way of understanding whether two products are dependent is using a statistical dependency test. If two products are independent, then the probability of their co-occurrence is the same as the product of the probabilities of the individual events. For example if Coke and Pepsi occurred separately in 25% of all baskets, then the expected co-occurrence of these two products is 6.25%. Any significant deviance (positive and negative) from this expected value may indicate product dependency.

It is imperative that when giving individual discounts the targeted products should be chosen carefully in order to obtain better store performance. Ineffective discounts may decrease both the customer satisfaction level and profitability. If there are two substitute products A and B, the buying probability of the dependent product B changes according to the given discount on product A using the following formula:

$$\Delta BP(B) = \frac{BP(B)}{BP(A) + BP(B)} - DeltaBP(A) \tag{4}$$

As it can be seen from the equation above, if the change in buying probability of product A is positive, the change in the substitute product is negative. The change is proportional to the relative importance of the buying probabilities between product A and B. For complement products, the change is directly proportional with product A so the negative sign should be removed.

Finally, each customer has a satisfaction function. In order to measure this, we calculate the sum of the buying probabilities of the products which are expected to be purchased by the customer when he/she comes into the store. Then, we calculate the sum of buying probabilities of the products, which were bought in the simulation after discounts. The satisfaction function is defined as the ratio of these two summations as given in the following equation:

$$SF = \frac{\sum BP_a}{\sum BP_e} \tag{5}$$

where, BP_a is the simulated buying probabilities after discounts and BP_e is the expected buying probabilities. As discussed earlier, if a person can not find an item from his/her shopping list or finds the prices high, he/she skips buying that product. Therefore, his/her satisfaction function decreases proportionally depending on the buying probability of that item (i.e., favorite items have much impact on the satisfaction function). This also affects his/her shopping arrival probability.

Optimization

The overall optimization stage is composed of 3 steps:

1. Performing sensitivity analysis on the product space of each customer to select the most suitable products from substitute pairs;
2. Applying the developed optimization algorithm;
3. Ranking of the products to identify the product set for a specified number of discount coupons.

Since discounts should be given on only one product from each substitute group, the first step is reducing the search space by selecting these suitable products. In this step, we pick products one-by-one from each substitute pair and perform sensitivity analysis by applying 1% discount to that product. Then, we simulate the shopping behavior and compare the store performance in profits, sales volume and customer satisfaction between all substitute products. Based on these comparisons, the product which has the most effect on store performance is chosen from each product group. By following this procedure for each customer, we reduce the number of product space for the optimization phase.

In the second step, we apply the optimization algorithm to the set of products selected and obtain the optimal discounts to maximize the store performance. In order to solve this optimization problem, we have developed a hybrid parallel simulated annealing algorithm which uses the survival of the fittest method based on evolutionary computation concepts. At first, the search space is divided into n equal parts and a population of m starting points is selected from each part. Then, using simulated annealing each member starts exploring its neighborhood in a parallel fashion. After each evaluation, better members are replicated while worse members are eliminated from the population based on their fitness value, which is the value of objective function, or in other words, the store strategy.

It should be also noted that we evaluate the objective function $f(S)$, k times using Monte-Carlo simulation since the shopping behavior is probabilistic. This evaluation makes the problem computationally extensive. By eliminating worse members in the population, we also reduce unnecessary computations in a non-promising region and explore a more promising region with multiple members in parallel. Detailed information about this algorithm can be found in our previous work [3].

Case Study

In order to compare the two approaches, we have built a sample database of 200 customers with 100 products from a real grocery store and investigated the performance difference against same allowance on promotion spending. As a promotion strategy, for the following 15 days, we would like to spend $ 1,150 on the discounts and we want to maximize the customer satisfaction.

One possible approach is using a traditional approach such as giving 10% discount on top-10 favorite products. Another approach is by following the individual discounting strategy, giving 10 coupons to each individual at the store entrance with different discount levels on different products. For the optimization process we have selected our objective function as:

$$\text{Maximize} f(x,y,z) = 0.25x + 0.75z \tag{6}$$

where, x represents the profits and z the customer satisfaction. Both approaches were simulated in the developed environment. It was observed that individual pricing outperforms the traditional approach significantly by increasing the customer satisfaction by 8.75%. Figure 3 shows the results.

This and other case studies conducted [4] showed that personalized pricing outperforms the traditional product-centric approach significantly by increasing customer satisfaction and profits. We believe that personalized pricing will again outperform the traditional approach since it optimizes the store performance by looking at each customer's shopping behavior.

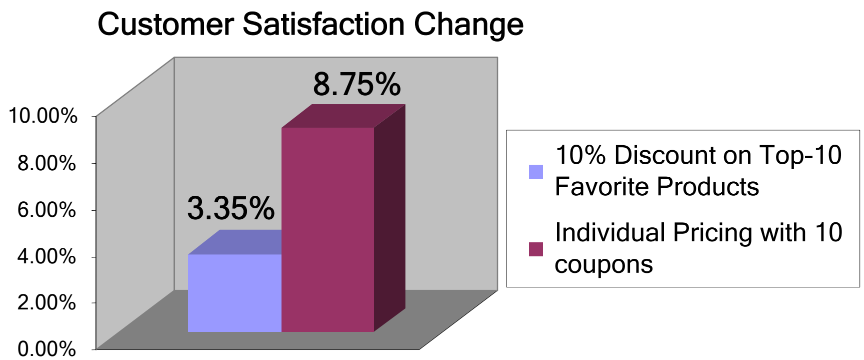

Fig. 3: Results of the case study.

Discussions and Conclusion

For retail sectors with tighter profit margins and where customer loyalty is highly dependent on the prices offered, it is essential to optimize the resources spent on increasing the customer satisfaction. Grocery retail is one of these sectors. Currently, most of the grocery stores provide a type of loyalty program which provides same discounts to subscribed customers. However this product-centered approach is efficient up to some level since customers are being divided into several segments and treated as a part of the segment rather than an individual

Our discussed approach is based on agent-based modeling and simulation, which models each customer's shopping behavior to simulate the store performance. We have developed a system to simulate the shopping behavior and optimize the store performance. We have conducted several case studies using this environment and compared the performance of two approaches. The results showed that individual pricing outperforms the traditional product-centered approach significantly. Several implementations have been conducted with industry partners and encouraging results were achieved. We believe that the discussed approach will impact the grocery retail significantly by increasing the customer satisfaction, sales volume and profits.

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About the author

Cem Baydar is currently working as a Director at Peppers & Rogers Group, a leading strategy and management consulting firm. In this capacity, he worked with many senior executives and helped them craft their marketing and sales strategy to make their corporations more profitable using customer-centric strategies. Prior to joining Peppers & Rogers Group, Cem worked as the Director of Analytical Solutions at comScore Inc., the leading on-line market research and consulting company in the US. Prior to comScore, he worked at Accenture's Innovation Group as Manager for 5 years. Dr. Baydar received his Ph.D from The University of Michigan, Ann Arbor in 2001. With two patents, many published articles and a book; he has a proven track record in innovation, business strategy development, and incubation and evaluation of emerging technologies, including the application of Genetic Algorithms to complex real-world problems.

Company homepage: www.peppersandrogers.com
Email: cem.baydar@gmail.com