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journal or publication title	2006 IEEE International Conference on Systems, Man and Cybernetics
page range	2121-2126
year	2006-10
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URL	http://hdl.handle.net/10112/6934

2006 IEEE International Conference on
Systems, Man, and Cybernetics
October 8-11, 2006, Taipei, Taiwan

The Practice of an Optimal Pricing Strategy for Maximizing Store Profits Using PRISM

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Abstract— **The purpose of this paper is to introduce a process for implementing optimal pricing that uses PRISM to maximize store profits. PRISM is a system and process that uses data mining technology to process large volumes of data, then develops a probability model for customer purchases, and which then uses a heuristic approach to identify the pricing pattern that will maximize store profits. For this paper, we used customer purchase data from Japanese supermarkets to identify the optimal pricing pattern for curry roux, which would maximize store profits.**

I. Introduction

IN recent years, most businesses have been confronted with fierce price competition. Price is the one marketing parameter that has the most significant effect on a business's profits, and the importance of this is getting greater and greater. In Japan, at supermarkets every day, some kind of discount is being offered on merchandise in most categories. The purpose of these kinds of sales is to either increase sales of one's own products, or to increase one's market share. But in most cases, pricing is not determined scientifically; rather it is determined based on past experience or by instinct. For a scientific approach, background data is essential, and so it is conceivable that the massive volume of customer purchase data that is accumulated at supermarkets could serve as an important source for pricing scientifically.

In conventional pricing research, one would be hard pressed to argue that these kinds of huge volumes of purchase data have been used effectively. There are two reasons for this. First is the complexity of consumer purchasing behavior, and second is the fact that the size of the data is just too large. Since individual consumers each have different needs, their reactions to prices are also different [8], [9]. Consequently, we need to build a product selection model which reflects the different needs of customers. However, there has not been enough study on how to actually build such a model. Then there is the fact that consumer purchasing behavior is influenced by such a wide range of marketing parameters [1]. In particular, the prices of competing products and related products significantly affect the selection criteria of consumers. However, since the number of products that retailers handle is so enormous, it has been extremely difficult to comprehend the complex relationships between products.

This work was partially supported by the grant-in-aid for scientific research on priority area "Active Mining" and RCSS in research fund "Academic Frontier" Project for Private Universities from the Japanese Ministry of Education, Culture, Sports, Science and Technology.

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It is believed that customer purchase data will provide us with important information for shedding light on the wide range of effects that these marketing parameters have. However, because the customer purchase data is so immense, sophisticated information processing skills are needed to process it. One of these sophisticated information processing techniques is data mining. Data mining is the process and system for extracting useful patterns from large volumes of data. In previous studies, however, there have never been any frameworks put forward which attempt to use data mining techniques to design pricing strategies, thereby designing effective marketing strategies. The purpose of this paper is to recommend PRISM, a process that utilizes data mining techniques to identify pricing patterns that maximize store profits from vast amounts of customer purchase history data. By using our proposed PRISM, one can identify the optimal pricing pattern, not just for the merchandise on sale, but for competing products and related products too. We are proposing an information system which understands the relationships between products and categories, and which supports effective marketing strategies, based on purchase probability models for individual customers.

II. What Is PRISM?

A. PRISM

In this paper, we recommend PRISM. PRISM supports the implementation of optimal pricing strategies for maximizing store profits, by utilizing the vast amounts of customer purchase history data. There is an assumption that, since individual consumers each have different standards of value, their reactions to prices will also be different. Based on this assumption, PRISM extracts individual tendencies from customer purchase data, and then predicts whether individual customers will make purchases under various product pricing structures. The purpose of PRISM is to maximize store profits earned from all related merchandise, not just from target products. Accordingly, the focus is not just on prices and profits obtainable from target products, but also on prices and profits from rival merchandise and from related products in other categories.

In marketing research, up until now, studies on pricing strategies have indicated the importance of various price factors that regulate decisions on purchasing certain products. Various factors have been verified which impact considerably

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on purchase decisions, including reference prices, previous purchasing experience, brand loyalty [2], [4], [6], product properties, customer properties, store communication, quality, and the frequency of sales promotions [5]. Furthermore, verification for such target products as coffee, yoghurt and eggs, has not just been by questionnaire, but also by using a portion of the customer purchase data held by retailers [3], [7], [10]. These studies have generated many explanatory variables from the panel data (customer properties data) and the associated sales data, and they have attempted to build customer purchase probability models for specific products.

However, these existing studies contain a number of problems. First, the studies have only dealt with sales data sampled from subsets of customers, and so the data has not been sufficient enough to cover a scope appropriate for store management. Second, since the purpose of existing studies has been to identify and verify the important parameters that impact on consumers' selections of brands, there has not been sufficient verification specifically targeted at price. Third, since the focus has been on purchase probability models for brand selection, no attention has been paid to the groups of products outside the target category. As a consequence, most studies have lacked the perspective of maximizing a store's overall revenue and profit.

PRISM is built based on MUSASHI [12]. Since it involves flexible preprocessing techniques and data mining algorithms, it makes it possible to handle the large volumes of data for an entire store. Also, since PRISM uses approximate solutions and avoids combinatorial explosions, it is able to extract pricing patterns which are optimal from the perspective of store management. Finally, PRISM encompasses products from related categories in its analysis, rather than being limited to just the category to which the target product belongs. As a result, it is possible to extract a pricing pattern that is designed to maximize sales across a range which is broader than traditionally possible. PRISM's basic algorithm has the potential to be applied across a broad range of applications, and it would seem that it has a practical usefulness.

B. The PRISM Framework

Figure 1 shows the PRISM framework [13]. PRISM is comprised of the following five stages: 1) Exception handling, 2) Setting the target category, 3) Identifying related categories, 4) Building the purchase probability model, and 5) Optimal pricing for maximizing store profits. The following section gives a detailed description of the approaches and algorithms contained within each of the five stages, and provides an overview of the PRISM framework.

1) Exception Handling: The purpose of the first stage exception handling is to eliminate the errors and noise data contained in the large volume of data. The accuracy of the purchase probability model, which is a core part of PRISM, is easily influenced by errors and noise data. The data is cleaned in order to build a highly accurate model.

2) Setting the Target Category: During the second stage, the target category is set to the category which contains the product that is subject to the pricing strategy. "Target category" refers to the collection of similarly useful products which are in direct competition with the target product at the time a customer makes a product selection. When defining the target category, PRISM uses basic product classifications and other information to output a list of product lines which are candidates for analysis. An expert then selects the products from this list.

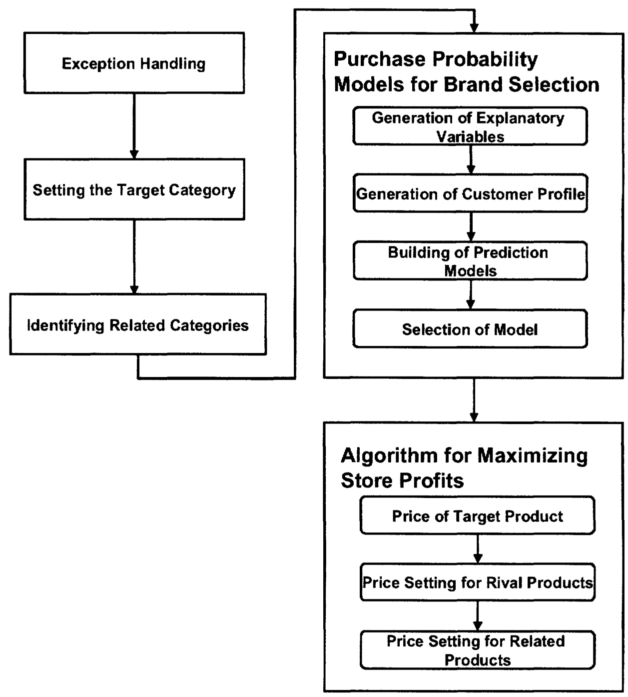

Fig. 1. The PRISM framework.

3) Identifying Related Categories: During the third stage, we identify related categories which indirectly affect (or are affected by) the pricing of the target product. The pricing of certain products, not only impacts directly on the sales of rival products in the target category, but also influences the sales of products from other related categories, which tend to be purchased in conjunction with the target product. In this paper, we call these product lines, "related categories". During this stage, lift values [11] are used to extract the target product's related categories.

4) The Purchase Probability Model: The purpose of the fourth stage is to build a purchase probability model that predicts whether the target product will be purchased under various pricing structures. By setting the explanatory variables to the customer's past purchase history, and to the price information for products belonging to the target category and related categories (which were extracted in the second and third stages), a predictive model is built that can calculate the probability for each individual customer purchasing the target product. In PRISM, we use a binary logit model [3] as the predictive model.

5) Optimal Pricing for Maximizing Store Profits: During the final stage, we carry out optimal pricing on the target product category and on related products in order to maximize store profits. By reducing the price of certain products, sales of other products (rival products) may be significantly affected. In order to maximize the overall profits of stores handling numerous products, we must clarify the complex relationships between those products, before we map out a pricing strategy. However, since it is not possible to devise a pricing strategy that takes into account the combination of all prices for all products, with PRISM, we seek proximately better combinations of prices.

III. EXPERIMENTS

In this case, we investigated in detail the process for identifying the optimal pricing pattern for maximizing store profits, by utilizing the customer purchase data from Japanese supermarkets. During this process, not only did we discover the optimal pattern, which was the original purpose, but we discovered the difference in price sensibility between brands. PRISM, the pricing tool that we developed, possesses great applicability, and shows a potential for generating broad knowledge. In the case that we deal with in this paper, we have used customer purchase data from 3 supermarket stores in the Tokyo region, from the period April - July, 2005. The average number of visiting customers at each of the stores is 5,000 per month, and the size of the data is approximately 300MB per store per month.

A. The Curry Roux Market

In this paper, curry roux has been taken up as the target product for designing pricing strategies. Curry is one of the Japanese people's most popular dishes. Curry roux, one of the ingredients, is sold at all kinds of retailers, including supermarkets and convenience stores. Nowadays, curry comes in a variety of forms, including retort-pouch, cup and microwave meals, and it occupies an important position in the foodstuffs market. Figure 2 shows the trend of monthly sales of curry roux at the subject stores. The vertical axis shows the sales figures for each month. Basically, sales are stable throughout the whole year. The most common unit price is between 200 and 300 yen. Three major manufacturers occupy a substantial share of the market. In this case, we focus on the products of these three manufacturers.

Next, we will look at the characteristics of the customers who purchase curry roux. Curry is cooked by combining curry roux with other ingredients. Consequently, customers who purchase curry roux also tend to purchase many other products at the same time. For example, when customers purchase curry roux, they also purchase 4 - 5 more products than those customers who purchase stew. Also, in terms of amounts spent at each store visit, curry roux customers purchase several hundred yen more than those customers who purchase stew or other product lines.

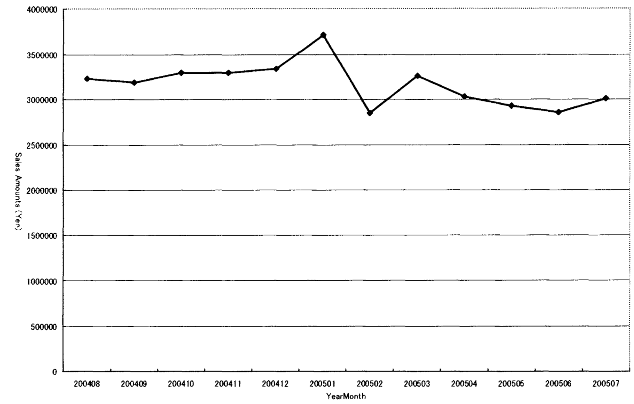

Fig. 2. The trend of monthly sales for curry roux.

B. Target Category and Related Categories

The target product category in this case is the curry roux category. As a result of eliminating the extreme data, such as for sales and errors, we selected four products as products (brands) to be included in the target category. Next, we set the related categories. Potential related categories are first extracted using PRISM, based on their lift values (meaning their association with curry roux), and then an analyst selects the appropriate items from the potential categories. Table 1 shows the lift values for each category against curry roux. Since the subject stores are located in the Kanto region, a strong connection can be seen between curry roux and pork. A strong connection to other ingredients necessary for curry has also been found, including potatoes and onions. As a result of a detailed investigation of each category, pork, beef, potatoes and stew were set as the related categories for this analysis.

Table 1. Lift value against curry roux.

Category	Lift value
Diced pork	12.651
Diced beef	9.103
Potatoes	5.78
Onions	4.433
Seafood mix	4.295
Stew	4.251
Carrots	4.216

C. Building the Purchase Probability Model

Using data from the above target category and related categories, a purchase probability model is built in which each consumer selects certain products.

1) Generation of Explanatory Variables: First, using the sales data from the subject stores, explanatory variables related to external reference prices are generated. A price master is created, arranged by store and date, for all products included in the curry roux target category and in the potatoes and other related categories. Errors were eliminated, and the price master was generated for a total of 14 products which have statistically significant relationships with curry: 4 curry brands, 4 potato products, 1 port product, 2 beef products, and 3 stew products.

Table 2. List of explanatory variables selected by the Brand A purchase probability model.

Variable	B	Standard error	Significance probability
Brand A unit price	-0.042	0.001	0.000
Brand B unit price	0.008	0.001	0.000
Brand C unit price	0.007	0.003	0.023
Brand D unit price	0.038	0.004	0.000
Stew E unit price	-0.067	0.009	0.000
Stew F unit price	0.012	0.002	0.000
Stew G unit price	0.017	0.003	0.000
Potato unit price (bag)	0.005	0.001	0.000
Potato unit price (loose)	-0.026	0.003	0.000
Beef unit price	-0.005	0.001	0.000
Storewide amounts decile	0.159	0.025	0.000
Store visit count decile	-0.126	0.016	0.000
Prepared foods decile	0.067	0.014	0.000
Vegetables decile	-0.084	0.028	0.002
Curry purchase count decile	-0.055	0.019	0.003
Stew amounts decile	-0.026	0.010	0.009
Nil curry loyalty	0.952	0.097	0.000
Brand A curry loyalty	1.923	0.096	0.000
Previously purchased brand: A	3.400	0.061	0.000
Previously purchased brand: B	1.078	0.072	0.000
Previously purchased brand: C	1.666	0.087	0.000
Previously purchased brand: D	0.941	0.119	0.000
Previously purchased brand: Other brand	0.922	0.074	0.000
Previously purchased brand: Nil	2.447	0.071	0.000
Constant	6.315	2.332	0.007

2) Generation of Customer Profiles: Next, we generate explanatory variables related to internal reference prices—in other words, variables related to the customer characteristics based on actual past purchases. These variables include explanatory variables based on decile analysis, and explanatory variables based on brand loyalty. Decile analysis is an analysis tool for customer management, which classifies all customers into ten (or five) customer groups with equal customer numbers, based on a ranking of customers by purchase amounts. In PRISM, ten variables are generated, including deciles for storewide amounts and deciles for related categories.

In making purchase decisions, it is said that loyalty for a product (brand) has a significant influence. PRISM supposes two types of indicators of loyalty: curry loyalty and previously purchased brand. The former defines a customer of having brand loyalty if there is a single product that accounts for at least 51% of previously purchased curry roux products. The existence of loyalty for each brand is provided for as explanatory variables. If none of the brands account for at least 51%, then a "nil-loyalty" explanatory variable is added. The latter adds, as an explanatory variable, the brand which the customer has most recently purchased. 22 variables for curry loyalty and previously purchased brands were generated for each customer, and used in building the model.

3) Construction of the Prediction Model: In building a highly accurate predictive model, we used the stepwise method to select a small number of effective explanatory variables. Table 2 is a list of the explanatory variables which were selected by the purchase probability model for Brand A (which has the greatest share of the curry roux market) using a binary logit model. The coefficient for the unit price of Brand A is negative (-0.042). This indicates that the probability of purchasing Brand A will rise as the unit price decreases. In contrast, the unit prices for the rival brands (Brand B, C, and D) have positive coefficients. This means that the probability of purchasing Brand A will rise as the unit price of any of these rival products decreases. Furthermore, there is a trend in customer profiles, that the greater a customer's brand loyalty to Brand A, the higher the probability of purchasing it. In this way, by examining the purchase probability model we can now understand consumer behavior in a way that was only understood instinctively before. This sequence was repeated for all products in the target category and all products in related categories. From the results, we focused on a pricing pattern for curry roux and potatoes which we observed to have a statistically significant influence.

4) The Optimal Pricing Strategy: Finally, using the purchase predictive model, we run a pricing simulation for maximizing store profits. Figure 3 shows the simulated results of the total gains from sales of all curry roux in a pricing pattern with four curry roux products. The results show that the maximum storewide profit achieved when Product A is 158 yen, is when Product B is 178 yen, Product C is 168 yen, and Product D is 228 yen. This pricing pattern is different to the pricing pattern which maximizes total sales. Consequently, we need to decide whether to focus on nominal sales or profits, depending on the store's marketing strategy.

During the process of designing this pricing strategy, we were able to acquire much knowledge. For example, when building the purchase probability model, we discovered that purchases of Product A (which has the greatest share of the curry roux market) is virtually unaffected by the prices of other rival brands, and that purchases of the other curry roux products (B, C and D) are most affected by the price of Product A. Also, Product A was significantly affected by related products, including the price of potatoes or stew. It became evident that, when determining the prices of curry roux products, in order to maximize store profits, we need to pay particular attention to the price of related products during sales of the top product, and to the price of Product A when selling the other products at a discount. This kind of knowledge was regarded by the staff at the stores as a

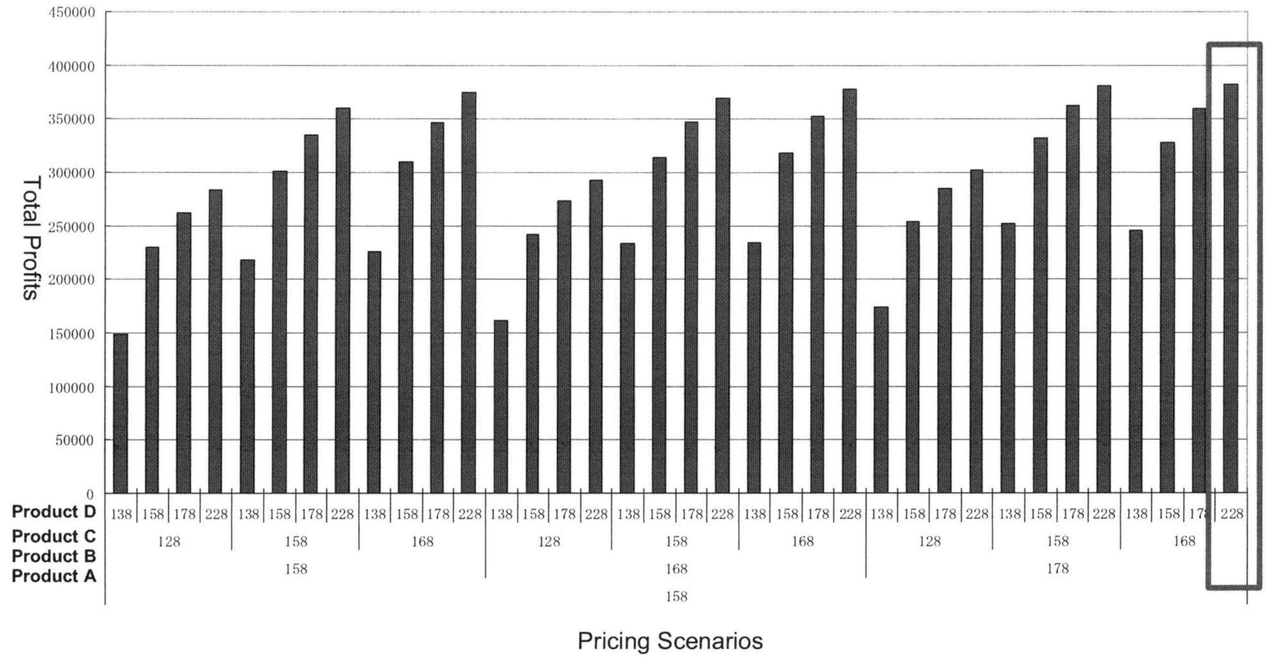

Fig. 3. Simulated total profits for curry roux pricing patterns.

particularly important insight.

IV. Conclusion

In this paper, we have introduced PRISM—a system for designing optimal pricing strategies that maximize store profits. During the study, by using customer purchase data from supermarkets in Japan to extract an optimal pricing pattern, and by actually running a simulation of that pricing pattern, we have shown that the pricing pattern generated by PRISM does contribute to maximizing store sales and profits.

However, we are challenged by many problems that we need to resolve. One is the fact that in PRISM, the prices for rival products and products in related categories, which become candidate prices when searching for pricing patterns, are limited to only those prices which the store has actually used in the past. Consequently, it cannot be denied that optimal prices are contained within those prices that have never been used before. Also, the current version of PRISM cannot incorporate the concept of price ranges; and it does not build models that reflect a sense of products being reasonably priced, which is felt by real consumers. In order to resolve these problems, it is necessary to develop new algorithms to avert combinatorial explosions. A possible solution might be to incorporate region rules into PRISM, which are handled under association rules.

Furthermore, when related categories are extracted in PRISM, lift values are used which are based on the target product. However, by being restricted to just these lift values, there is a chance that atypical relationships that influence profit may be overlooked. Similarly with the selection of rival products, when the related categories are selected, it will be necessary to allow for the selection of more effective product lines by introducing specialized knowledge. Also, PRISM does not have a mechanism that allows for the input of price information from rival stores. Consequently, it appears as though that it will be necessary to incorporate into the model, the probabilities that customers will visit certain stores. In addition, store and customer information - including POP, shelving arrangements, the existence of aisle-end displays, education level of each customer, age of purchaser and so on - has not been reflected in PRISM. It is clear that store and customer information does have a significant effect on customer purchases, and so it will be necessary to integrate this information into PRISM in the future. Finally, we will need to repeat the experiments on more complex products and categories, and we will need to clearly demonstrate the differences of the usefulness of PRISM between products and between categories.

Acknowledgment

The authors would like to thank the anonymous reviewers for their insightful comments and suggestions on this paper.

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