The Process of the Effective Pricing Strategy Using PRISM

Katsutoshi Yada[1] Kosuke Ohno[1]

[1]Faculty of Commerce, Kansai University

Abstract

The purpose of this paper is to propose a system and process for maximizing store profits to discover the optimal price pattern among various items based on a purchase prediction models. This system, called PRISM, involves the use of data mining techniques to handle a large amount of customer purchase history data. In this paper we have applied PRISM to the customer data of supermarket in Japan and present the utility of PRISM in the real business world.

Keywords: Store Profits, Pricing Strategy, Purchase Data, Data Mining.

1. Introduction

In a deflationary economy, the Japanese retailing industry has been facing a period of extreme price competition for survival. In supermarkets, sales are being carried every day involving various different product categories. The importance of successful execution of such sales is becoming more and more critical. However, in the case of the Japanese food retailing industry, there are almost no food retailing chains that derive prices for the items to be featured in sales by using systematic pre-sale analysis of related prices and accumulated purchase data to create effective pricing strategies. In this paper, we suggest the use of the PRISM system as a support system for generating optimum pricing strategies based on the effective use of high volumes of customer purchase data.

Individual consumers have differing needs and different standards of judgment concerning prices [10]. Therefore, the store marketing staff must have a good understanding of the general purchase behavior of the store's customers and their likely reactions to prices in order to put together effective pricing strategies [9]. When a specific item is sold at a discounted price, this affects the sales of other rival competing products and also affects the sales of related products in other categories. In order to achieve the aim of optimizing store total profit, it is necessary for the marketing staff to understand the complex relationships that exist between various products and between categories and to be able to predict the overall store total profits that will be derived from overall pricing configurations [1]. To the best of our knowledge, there have been no extensive studies of these pricing complexities that have been based on the large amounts of accumulated individual customer purchasing data gathered by means of member-ship club card transactions for obtaining solutions to these pricing questions.

The purpose of this paper is to explain the use of large quantities of such accumulated customer purchasing data for various different pricing situations for building models for predicting the purchases of individual customers and using these models to discover combinations of prices that will make it possible to optimize store total profits. This system and the accompanying analysis process are called "PRISM" (**PRI**cing **S**trategy for **M**aximization of profits). The PRISM system includes data mining techniques for handling large accumulations of customer purchase data. By using these techniques, the probability of purchase of each participant customer in the sample can be predicted. Since these individual predictions involve an immense number of calculations concerning the various combinations of prices for the sale target items and related items in order to generate the optimum pricing patterns, in the case of PRISM, approximating methods are used to calculate the combination of prices that lead to store optimum profit. If PRISM is used, when the store marketing staff attempts to set the discount prices for items to be put on sale, in order to obtain the optimum profit for the store, it becomes possible to ascertain the most suitable prices for rival items and related items in other categories.

2. PRISM

2.1. What is PRISM?

In this paper, we introduce the use of a support system for determining optimum pricing to obtain optimum store total profits called PRISM, a system based on the use of accumulated customer purchase data. In the case of PRISM, it is taken as a given that since every consumer has different standards for judging their acceptance and reactions to the prices for specific items. These behavioral tendencies are extracted for each respondent customer in the sample by determining the probability of whether a given customer will buy a given product at a given prices within the framework of multiple pricing scenarios for many different categories of products based on previous purchase behavior as reflected in the accumulated data for the given customer. The data required for this process is massive in scale so that the PRISM system includes the use of various data mining technology, making it possible to cope with data many gigabytes in size. PRISM calculations do not involve only the items that are to be put on sale, but also includes related items with the objective of determining the optimum pricing combinations to obtain optimum store total sales. Therefore, not only the prices of the items to be put on sale, but also the prices of rival competitive items and related items in other categories and their various combinations are examined. On the question of how to determine the combination of prices that will lead to maximization of total store profit, since the NP complete [3], we are using approximating methods to obtain the pricing patterns that lead to optimum store profits.

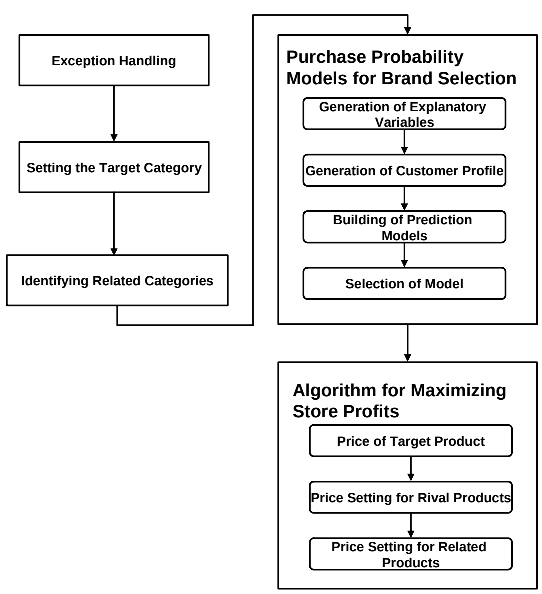

Fig. 1: The PRISM Framework.

2.2. The PRISM Framework

Figure 1 indicates the framework of the PRISM system. The PRISM system consists of five stages as follow. Stage1) Processing of exceptions, 2) Setting up target categories, 3) Discovery of related categories, 4) Construction of purchase probability models, 5) Determining the optimum pricing for maximizing store total profits. Below, there are detailed explanations of these stages and their various respective procedures and algorithms. These explanations provide a general overview of the PRISM system framework.

Processing of exceptions: The objective of the first stage processing of exception is to remove sources of error and noise from the voluminous data. Part of the core of the PRISM system consists of the individual consumer respondent purchase probability models and the degree of accuracy of these models is easily influenced by errors and noise. For example, it is especially important in cases concerning reference price levels for target categories (or specific items), that is, these are prices at which a given consumer will make a purchase if the price goes this level. If the price for a given category or item goes down below a certain level, purchase may suddenly leap. In these types of situation, the PRISM system may not function well. Therefore, we remove the item groups for which these reference prices [5] [6] exist before carrying out the ensuing calculations. By doing this, it is possible to generate more highly accurate purchase probability predictions.

Setting the target categories: The second stage consists of setting the core item categories that are be the target of the pricing strategy being formulated. In the case of the everyday business, if the usual item categories are used, there are frequently cases where this approach leads to difficulties. When picking the items to be included in the respective target item categories, in the case of the PRISM system, the procedure is to use the basic item category for the purpose of generating a target item candidate list. Then, specialists pick the items to analyze from candidate items in the list.

Discovering the related item categories: At the third stage, we use procedures to discover related item categories that have an effect on the pricing of the target sale items. The pricing of certain items does not only affect the sales of rival competing items in the same item category, but also affects are also generated with regard to items in related categories that are likely to be purchased along with the sale target items, causing their sales to rise. In the case of this stage, one of the data mining techniques that are used is “association rule” that is used to extract the item categories that are related to the sales target item category.

The purchase probability models: The objective of the fourth stage is to construct the models that will predict, whether or not, a given target item will be purchased, in various pricing scenarios tested. The pricing data for the items in the related categories that were extracted in stage two and stage three and the customer purchase records are used as explaining variables for the construction of the individual models for calculation of the predicted purchase probabilities for the sale target items for each consumer respondent. As functions that are an integral part of the PRISM system, we use such data mining methods and prediction models as C5.0 and CART, the LOGIT model, etc [2] [4] [7] [8].

Optimum pricing for maximization of store profits: At the final stage, we carry out pricing optimization concerning the target item categories and the related items to attain the maximization of the store total profits. When the prices of certain items are lowered, there are cases where the sales of other items (Rival competing products) are strongly affected. In order to maximize the total profits for a given store that is handling many different items, it is necessary to clarify the complicated relationships that exist between the various items in order to formulate a given pricing strategy. However, since it is impossible to involve all items and pricing combinations to find a given pricing strategy, approximating methods are used in the case of the PRISM system for determining the optimum combination.

3. Experiments

In this section, using Japanese supermarket customer purchase data, PRISM system simulation is used to determine the optimum pricing strategy for obtaining the maximum total profits for a given store and the related pricing patterns are generated. In this case, the data for actually existing stores is used to carry out this simulation to validate the utility of the PRISM system. For this particular case, the data of five different retailing locations belonging to a Japanese supermarket chain for about two years (2003-2004) was used. This involved data for an average 5,000 respondent consumers per store in a month and its size was about 300MB.

3.1. Pricing Simulation

In this paper, the target item was "Chinese cabbage" ("Hakusai") which is sold in 2003in quarters of a cabbage "Q". As a pricing strategy of the store for this item, Hakusai Q, a price of 100 yen per quarter was chosen. PRISM calculations, based on statistical evaluation standards, involved the use of the selected prediction model for this sales target item and competing items in the same category, halves of the same type of cabbage, Hakusai H and a related item, "ponzu," a favorite Japanese citrus-based flavoring condiment used when cooking Hakusai, were extracted from the data. For the related customer purchase tendency data, the amount of money spent on Hakusai in the past was used and was extracted from the total data related to purchases of vegetables.

Using these explaining variables, the purchase prediction models were generated and based on the results of a 10-fold cross verification, the C5.0 algorithm was found to produce the best level of accuracy. Using this these prediction models, the sales were predicted. When the profits from the sales of Hakusai Q, H, and ponzu were calculated, for the case where the prices were set at 100 yen, 198 yen, and 248 yen, respectively, the store profits were maximized.

Figure 2 shows that when Hakusai Q is set at 100 yen and H is set at 198 yen, the ponzu explaining variables change and the total profits for the store can be predicted to undergo a change. From this, the conditions related to the price of the ponzu were varied and calculated for 218 yen, and 248 yen. In these cases, the total sales of the store achieved a maximum, but profits were the greatest at the 248 yen price, as can be seen from the figure. In other words, the pricing patterns related to Hakusai Q at 100 yen and H at 198 yen and ponzu at 248 yen was the pricing pattern that yielded the greatest total profit for the store as calculated using PRISM.

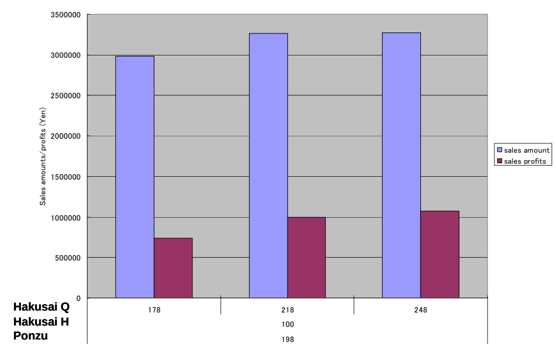

Fig. 2: A simulation involving Hakusai Q, H and Ponzu to obtain the maximum profits for the store.

3.2. Results of an Actual test at Supermarket in Japan

To verify the utility of PRISM, during November 2004, in three Japanese supermarkets, differing pricing patterns including the pattern obtained by using PRISM were tested and the maximum profits obtained for the stores were calculated as part of this verification testing.

Figure 3 shows a part of the tests results involving a pricing pattern of Hakusai Q at 100 yen, H at 198 yen and ponsu at 218 yen. The sales of ponzu at 218 yen reached a maximum for the testing, but in terms of total profits, their profits were the maximum level the when the price was set at 248 yen. From this result, it was also found that focusing only on the target items did not always produce the optimum total profits for the stores. However, it can be said that the relationships of the rival items and the related item prices can be understood and it is possible to obtain an effective overview of these relations and to optimize the profit levels of the stores. Based on the results of these tests, it was possible to conclude that PRISM can generate pricing strategies that can contribute to the maximization of store profits.

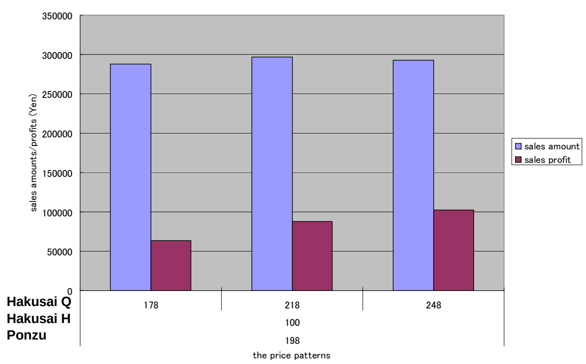

Fig. 3: Results for different pricing patterns used in Japanese supermarket.

4. Conclusion

In this paper, we have introduced a system for the generation of optimum pricing strategies for maximizing store profits, the PRISM system. In this paper, we used Japanese supermarket customer purchasing data to extract optimum pricing patterns and in actual store environments, these pricing strategies were carried out on a test basis resulting in clarifying the utility of PRISM for the purpose of generating pricing patterns that will contribute to maximizing the total profits of the given store.

However, there are, as yet some problem areas that have not been solved yet. The current version of the PRISM system is designed to use the strategic pricing for the target items as the given condition. In the future, it is necessary that these target item prices also be included in the pricing patterns search. In addition, in the case of PRISM, rival store pricing information, etc. cannot as yet be input into the PRISM process. Likewise, the PRISM GUI has not been developed yet. There is a need to add such a system in the future. Moreover, for the case that was used in this paper, the variables involved were relatively limited in number and the sales target items were relatively simple in nature. Henceforth, it will be necessary to use more complicated items to carry out more complicated testing and carry out reiterations of category testing to further the utility offered by the PRISM system.

References

[1] R. C. Blattberg and K. J. Wisniewski. 1989. “Price-induced Pattern of Competition.” *Marketing Science*, Vol.8: 291-309.

[2] L. Breiman, J. H. Friedman, R. A. Olshen and C. J. Stone. 1984. *Classification and regression trees.* Chapman & Hall, New York, NY.

[3] K. Fujisawa, Y. Hamuro, N. Katoh, T. Tokuyama, and K. Yada. 1999. “Approximation of Optimal Two-Dimensional Association Rules for Categorical Attributes Using Semidefinite Programming.” *Proceedings of Second International Conference DS'99*, LNAI 1721, Springer-Verlag: 148-159.

[4] Y. Hamuro, N. Katoh, E. H. Ip, S. L. Cheung and K. Yada. 2003. “Combining Information Fusion with String Pattern Analysis: A New Method for Predicting Future Purchase Behavior.” V. Torra(ed.), *Information Fusion in Data Mining*, *Studies in Fuzziness and Soft Computing*, Vol.123, Springer-Verlag: 161-187.

[5] G. E. Mayhew and R. S. Winer. 1992. “An Empirical Analysis of Internal and External Reference Prices Using Scanner Data.” *Journal of Consumer Research*, Vol.19: 62-70.

[6] T. Mazumdar and P. Papatla. 2000. “An Investigation of Reference Price Segments.” *Journal of Marketing Research*, Vol.37, Issue 2: 246-258.

[7] J. R. Quinlan. 1986. Induction of Decision Trees, *Machine learning*, Vol. 1, Issue 1: 81-106.

[8] J. R. Quinlan. 1993. *C4.5: Programs for Machine Learning*, Morgan Kaufmann Publishers, San Francisco CA.

[9] G. J. Tellis. 1986. “Beyond the Many Faces of Prices: An Integration of Pricing Strategies,” *Journal of Marketing*, Vol.50: 146-160.

[10] J. E. Urbany, P. R. Dickson and R. Kalapurakal. 1996. “Price Search in the Retail Grocery Market.” *Journal of Marketing*, Vol.60: 91-104.

[11] I. H. Witten and E. Frank. 2000. Data Mining: Practical machine learning tools and techniques with JAVA implementations, Morgan Kaufmann Publishers, San Francisco, CA.