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Churn management optimization with controllable marketing variables and associated management costs

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ABSTRACT

In this paper, we propose a churn management model based on a partial least square (PLS) optimization method that explicitly considers the management costs of controllable marketing variables for a successful churn management program. A PLS prediction model is first calibrated to estimate the churn probabilities of customers. Then this PLS prediction model is transformed into a control model after relative management costs of controllable marketing variables are estimated through a triangulation method. Finally, a PLS optimization model with marketing objectives and constraints are specified and solved via a sequential quadratic programming method. In our experiments, we observe that while the training and test data sets are dramatically different in terms of churner distributions (50% vs. 1.8%), four controllable variables in three marketing strategies significantly changed through optimization process while other variables only marginally changed. We also observe that the most significant variable in a PLS prediction model does not necessarily change most significantly in our PLS optimization model due to the highest management cost associated, implying differences between a prediction and an optimization model. Finally, two marketing models designed for targeting the subsets of customers based on churn probability or management costs are presented and discussed.

1. Introduction

The propensity of customers to terminate their relationships with service providers has forced many companies in competitive markets to shift their strategic focus from customer acquisition to customer retention (Chen & Hitt, 2002; Venkatesan & Kumar, 2004). This is mainly because companies can increase the average net present value of a customer by up to 95% by boosting the customer retention rates by 5%. In particular, with exceptionally high annual churn rates (20–40%), the mobile telecommunications service providers eager to launch successful churn management programs to maximize their revenues (Kim, Park, & Jeong, 2004; Eshghi, Haughton, & Topi, 2007; Glady, Baesens, & Croux, 2009). For this purpose, many data mining and statistical models have been presented to accurately identify prospects or possible churners in the automotive, insurance, and telecommunication industry. Such models include PLS regressions (Lee, Kim, Lee, Cho, & Im, 2011), decision trees (Kim, 2006; Xiea, Lia, Ngaib, & Yingc, 2009), ANNs (Buckinx & Poel, 2005; Mozer, Wolniewicz, Grimes, Johnson, & Kaushansky, 2000), support vector machines (Coussement & Van den Poel, 2008), genetic algorithms (Au, Chan, & Yao, 2003; Kim, Street, Russell, & Menczer, 2005), or dynamic programming models (Gönül & Shi, 1998). A recent discussion about advantages and disadvantages of various models for churn management can be found in (Hadden, Tiwary, Roy, & Ruta, 2007; Neslin, Gupta, Kamakura, Lu, & Mason, 2006).

While such prediction models are very important for successful churn management, most prediction models are limited in the sense that they do not consider implementations costs associated with churn management programs (Bult & Wansbeek, 1995; Kumar & Shah, 2004). Note that, according to these predictive models, marketing managers may identify likely churners based on the estimated churn probability, and chooses top *x*% of customers as target customers to offer retention marketing promotions (Lee et al., 2011). However, most retention marketing promotions bear different cost structures and hence should be administered with care. For example, one of the most common retention programs among telecommunication service providers is to provide customers who renew their contract periods a financial incentive that allows them to purchase a new mobile device at a deeply discounted price. Another popular retention program is to simply provide a better customer call center service in regards to billing and call quality peacefully through educated and experienced receptionists to resolve many questions and complaints and enhance customer

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satisfaction and loyalty (Fornell & Wernerfelt, 1987; Gustafsson, Johnson, & Roos, 2005; Mittal & Kamakura, 2001; Reinartz, Thomas, & Kumar, 2005). Note that while two retention programs may or may not be equally effective, providing a new mobile device at a deeply discounted price may cost more than providing a better call center service.

In this paper, we propose a churn management model based on partial least square (PLS) optimization that explicitly considers management costs of controllable marketing variables. The PLS method in this paper will be used not only as a prediction model to predict churners but also as a control model combined with optimization method to maximize the effects of churn management strategies at minimum cost. Ideally, limited resources for retention promotions should be allocated to most likely churners who generate most revenues while minimizing the management costs of such retention promotions. The detailed objectives of this research are: (1) to categorize and validate controllable and uncontrollable marketing variables; (2) to determine the management costs of each controllable marketing variable by applying a triangulation analogy method; and (3) to develop and solve a PLS optimization model that minimizes the total cost of implementing three retention marketing strategies while satisfying the objective of retention marketing strategies.

The remainder of this paper is organized as follows. Section 2 provides a brief review of PLS model for prediction and control purposes and a triangulation method for management cost estimation. In Section 3, the overall research framework is introduced, and data sets are explained. In the following Section 4, a PLS-based optimization model is presented in a mathematical form after controllable marketing variables are identified and their management costs are assigned. Section 5 first presents experimental results from a PLS optimization model designed for entire customers. Then two marketing models designed for targeting the subsets of customers based on churn probability or management costs are presented and discussed. Finally, Section 6 provides the conclusion of the paper and suggests several direction of further research.

2. Partial least square and triangulation analogy

2.1. Partial least square (PLS) method

The PLS method is a multivariate projection approach that can consider both multiple responses and multiple predictors variables. In particular, it has been known to be robust with data sets that contain measurement errors and collinearity (Geldadi & Kowalski, 1986; Malthouse, Tamhane, & Mah, 1997). Naturally, one of the most popular applications of PLS models is to transform original large-scale data into lower dimensional data to deal with highly correlated data between independent and dependent variables (Lakshminaraynan et al., 1997). In this process, several PLS factors are extracted to explain most of the variation in both independent and dependent variables (Chong, Albin, & Jun, 2007). When a nonlinear relationship is implicitly assumed among dependent and independent variables, nonlinear PLS models can be estimated to construct nonlinear functional relationships using either neural networks or Gaussian kernel (Qin and McAvoy, 1992; Malthouse et al., 1997; Rosipal & Trejo, 2002; Shawe-Taylor & Cristianini, 2004).

The PLS method can be valuable as an alternative to well known data mining models to predict response variables or as a path model to understand structural relationships among records. In a recent study (Laitinen, 2008), PLS is utilized in building a predictive system with some success to assess failure probability in small- and medium-sized Finnish firms using financial and non-financial variables and reorganization plan information. In several other studies (Qin and McAvoy, 1992; Kim, Jung, Lee, & Kim, 2012; Lee et al., 2011; Wiener, Obando, & O'Neill, 2010), PLS prediction models not only showed superior or comparable performance against other data mining algorithms, but also showed the usefulness of identifying key input variables for biology and marketing applications. However, we have not seen papers that apply a PLS model both as a prediction model and as an optimization model for churn marketing management. Note that a PLS optimization model can be combined with a PLS prediction model as well as any one of data mining prediction algorithms. Since several comparative studies (Kim et al., 2012; Lee et al., 2011; and references therein) investigated the performance of PLS prediction models against different prediction models, we limit our interests to the specification and application of a PLS optimization model assuming that a (PLS) prediction model is readily available.

In this study, a linear PLS method (Lee et al., 2011) is first used as a prediction model to predict churners based on demographic, psychographic, and historical service usage information. Note that in prediction tasks, the number of latent variables is an important factor that affects the predictive accuracy. Typically, the number of latent variables is chosen by a cross validation considering the proportion of variations explained by each latent variable. At the same time, the variable importance in projection (VIP) has been proposed and used as a measure of importance of each variable contributing the response of interest. The VIP of jth variable is calculated as the sum of weights on the latent variable from jth variable divided by the total weights. Fundamentally, our final PLS prediction model includes only a set of predictors with high VIP scores to improve the comprehensibility and reduce computational complexity of a prediction model.

The PLS method is also used as an optimization model for churn management in our study. For churn management optimization, the PLS optimization model is first specified after marketing managers identify controllable and uncontrollable marketing variables among the chosen input variables with high VIP scores from the PLS prediction model. Then managers subjectively assign to controllable marketing variables management costs that are required to change one unit value of the chosen controllable marketing variable. Once the overall marketing objective (e.g., reducing churn probabilities of all the customers on average by 20% while minimizing the management costs of marketing variables) and constraints are specified, the PLS optimization model can be solved with an iterative optimization algorithm procedure such as sequential quadratic programming technique.

2.2. Triangulation method for estimating management costs

The main objective of this study is to reduce churn probabilities of all the customers on average by 20% while minimizing the management costs of controllable marketing variables. Therefore, to find realistic and meaningful solutions from the PLS optimization model for churn management, it is necessary to assign the management costs to identified controllable variables. While it is ideal to use the actual implementation costs of controllable variables in the PLS optimization model, it is extremely difficult to estimate the actual costs of marketing variables due to the lacks of historical data and/or the inseparability of associated indirect and direct costs. Therefore, it is necessary to use a new method to estimate the management costs of controllable marketing variables and a triangulation method that has been popularly adopted in agile software engineering and development community (Cohn, 2006) can be regarded as an attractive and feasible alternative. Note that one of the most important and difficult tasks of the project managers in software development projects is to accurately estimate the size and duration of projects, which in turn determines the scheduling and budgets.