Churn Management Optimization via Partial Least Square (PLS) Model with Controllable Marketing Instruments and Associated Management Costs

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ABSTRACT

In this paper, we use a partial least square (PLS) optimization method as a prediction model to estimate the churn probabilities of customers and as a control model after configuring optimization objective and constraints with relative management costs of controllable variables. In our experiment, 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 played a key role in optimization process. We also observe that the most significant variable for prediction does not necessarily play an important role in optimization model because of the highest management cost. In addition, we show that marketing managers even further maximize financial outcomes of marketing campaigns by selecting customers based on churn probability or management cost.

Keywords

Churn management, PLS prediction model, PLS optimization model, Triangulation, Sequential quadratic programming

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 and Hitt, 2002; Venkatesan and 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. 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 (Lee et al., 2011; Xiea et al., 2009; Buckinx and Poel, 2005; Au et al., 2003).

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 and Wansbeek, 1995; Kumar and Shah, 2004). 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 enhance customer satisfaction and loyalty (Mittal and Kamakura, 2001; Reinartz et al., 2005; Gustafsson et al., 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 model that is used both as a prediction model to predict churners and as a control model to maximize the effects of churn management strategies at the minimized cost. Ideally, limited resources for retention promotions will 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.

The remainder of this paper is organized as follows. Section 2 provides a brief review of PLS for prediction and control model and a triangulation method for management cost estimation. The overall research framework and data sets are introduced in Section 3, and a PLS-based optimization model is presented in Section 4. Section 5 presents experimental results and Section 6 provides the conclusion of the paper.

PARTIAL LEAST SQUARE AND TRIANGULATION ANALOGY

Partial Least Square (PLS) Method

The PLS method is a multivariate projection approach that can model both multiple responses and multiple predictors variables, even when multicollinearity among predictors are suspected. In particular, it has been known to be robust with data sets that contain measurement errors and collinearity, and one of the most popular applications of PLS models is to reduce the original large-scale data to lower dimensional data to deal with highly (both linearly and nonlinearly) correlated data between independent variables and dependent variables (Geldadi and Kowalski, 1986; Lakshminaraynan et al., 1997). In this study, the PLS method 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 chosen by a cross validation considering the proportion of variations explained by each latent variable and the variable importance in projection (VIP) is used to measure the importance of each variable. Fundamentally, our final PLS prediction model includes only a set of predictors with high VIP scores to improve the comprehensibility and reduce computational complexity (Refer to Lee et al., (2011) for mathematical description of PLS model).

The PLS method is also used as an optimization model for churn management in our study. For churn management optimization, the PLS control mathematical model is specified after marketing managers identify controllable and uncontrollable marketing variables and 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) is specified, the PLS control mathematical model can be solved with an iterative optimization algorithm procedure such as sequential quadratic programming technique. Note that our model can be easily configured to other optimization problems with different objectives (e.g., x% decrease in churn probability) and actual association costs that may result in economic profits.

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, it is ideal to use the actual implementation costs of controllable variables in the PLS optimization model. However, it is extremely difficult to estimate the actual costs of marketing variables due to the lack of historical data and/or the inseparability of associated indirect and direct costs. Therefore, we decide to use the concept of relative management cost that marketing managers subjectively estimate based on the “relative difficulty” of controlling a specific instrument compared with other instruments. This triangulation method has been used to accurately estimate the size and cost of software development (Cohn, 2006).

We adopt a part of Fibonacci sequence (1, 2, 3, 5, and 8) as possible estimates of management costs. To apply this method, a marketing manager selects one of the “easiest” variables to control among all the marketing variables and assign the lowest value of “1”. Then, for each remaining controllable variables, its management cost is determined by comparing its managerial difficulty against that of the easiest variable (i.e., one with the cost estimate of “1”) or an assortment of those that have already been estimated. Then, the closest value from the Fibonacci sequence is chosen as the final estimate. This method reflects the fact that humans are better at estimating relative size than absolute size (Lederer, 1998; Vicinanza et al., 1991), and the greater risks associated with estimates for difficult instruments because of nonlinear property of Fibonacci sequence. In addition, it can not only reflect unique preferences and experiences of a specific marketing manager but also consider preferences of multiple marketing managers by averaging individual cost estimates through thorough discussion to obtain better results (Hoest and Wohlin 1998; Johnson et al., 2000).

RESEARCH FRAMEWORK AND DATA SET

Research Framework

Our research framework is illustrated in Figure 1. As the first step, it is necessary to preprocess raw data into a readily available format for further analysis. In this study, two different techniques—eliminating records with missing values and variable selection—are used separately or together for preprocessing raw data. Once preprocessed data sets are obtained, a PLS prediction model is developed to estimate the churn probability for each customer. Note that our PLS prediction model is built with a set of chosen input variables with high VIP values only and corresponding the number of latent variables (i.e., score variables) to reduce computational complexity and improve the managerial understanding of outcomes.

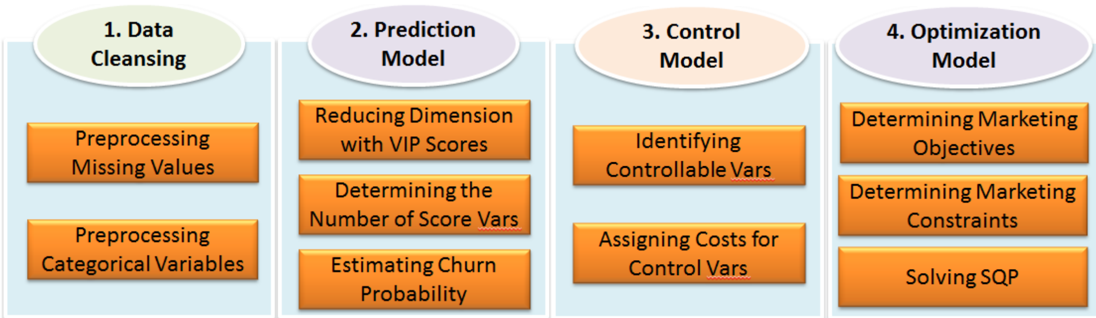

Figure 1 Research framework

At the third step, a PLS control model is conceptually developed by first categorizing variables in the PLS prediction model into controllable and uncontrollable variables and assign management costs for each controllable variable. Note that input variables that are useful for building a highly accurate prediction model may not be ideal because they are not controllable or are associated with high management costs. Then, it is converted into an optimization model by specifying the marketing objective in a mathematical expression and limiting the number of changes and ranges of controllable instruments with additional constraints if necessary. Finally, the designed optimization problem is solved using successive quadratic programming (SQP) (Biegler, 1995).

Data Set

The data sets used in this study are provided by the Teradata Center for CRM at Duke University, and the original data set for calibration has 171 predictor variables of 100,000 observations with a churn indicator variable. While the actually observed churning rate is approximately 1.8%, churners were oversampled to create a 50–50 split between churners and nonchurners in the provided calibration data set. As a preprocessing step for our analysis, the original data sets are preprocessed as follows. First, most categorical variables are excluded because of high missing rate or being encoded into multiple binary variables which makes low predictive power. We include only 11 categorical variables which are either indicator variables or countable variables such as number of handsets and number of subscribers. Second, continuous variables with more than 20% of missing values are eliminated. We take 123 predictors including 11 categorical variables and 112 continuous variables in data preprocessing step. Finally, records with missing values in the data set with 123 predictors are removed from further analysis. After preprocessing steps, the training set contains 67,181 observations with 32,862 churners (48.92%), while the test set contains 34,986 observations with 619 churners (1.8%), respectively.

DESIGN OF CONTROL AND OPTIMIZATION MODEL

Identification of controllable variables

To identify controllable variables out of 46 variables in the PLS prediction model, we assume that all the controllable variables can be adopted for one of three possible marketing strategies: device management strategy (DMS), revenue management strategy (RMS), and complaints management strategy (CMS). The main purpose of DMS is to manipulate controllable variables that are directly or indirectly related to mobile devices. A plausible example of DMS is to provide new mobile devices at deeply discounted prices for the customers whose service contracts will expire soon on the condition that they will renew their service contracts for two more years. In contrast, the main purpose of RMS is to effectively control revenue related variables after carefully reviewing fee structures of various services and customers' services usage patterns. For example, one of possible RMS is to solicit users who frequently overuse their voice and data plan beyond their allowance for premium services at marginal increases of service fees. Finally, the main objective of CMS is to provide highly responsive services to the customers who have complained technical difficulties and billing discrepancies so that they are satisfied and hence decide to stay with the current service plan for the remaining contract period. In the end, a total of 18 controllable variables for DMS (5 variables), RMS (10 variables), and CMS (3 variables) are identified, and they are listed in Table 1. We subjectively determine the relevance of each controllable variable to a specific marketing strategy after considering the objectives of each strategy and natures of variables.

Assignment of management costs to controllable variables

The next step is to assign management costs to controllable variables using a Fibonacci sequence (1, 2, 3, 5, and 8). We first note that the implementing DMS based on device related controllable variables is relatively difficult without the mutual agreements between the service provider and customers. Therefore, we decide to assign high values (>= 5) as management costs to these controllable variables. In particular, we assign the highest management cost (i.e., the value of 8) to "Total number of months in service" variable because of its dependency on service quality and customer satisfaction in addition to device factors. In contrast, we assign the lowest value (i.e., the value of 1) to all CMS variables because the service provider can easily change them (e.g., for "Account spending limit" variable, the service provider can simply set on or off the spending limit of the chosen customer account). Finally, we assign from low to high values to the RMS variables. Specifically, we assign the value of 1 to all range variables of (overage) revenues because of their simple statistic natures, and the value of 3 to most mean or average of revenue variables. However, we assign the value of 5 to "Mean monthly revenue (charge amount)" because of its dependency on service fee structures associated with customers' credit history and competitors' fee strategy. While this process is necessarily based on subjective judgments of researchers or marketing managers on the relative difficulty of manipulating controllable variables (i.e., management costs), our research framework can easily accommodate different management cost structures without changing the structure.

Optimization Model and Solution Procedure

Assuming that a marketing manager wants to reduce churn probabilities of all the customers on average by 20% by manipulating p controllable variables while minimizing management costs of controlling them, we formulate our PLS optimization model as follows:

$$\min_x \sum_{j=1}^{p} c_j * (x_j - x_j^{opti.})^2 \quad (1)$$

$$\text{s.t. } (0.8) * \sum_{i=1}^{p} b_j * x_j - \sum_{j=1}^{p} b_j * x_j^{opti.} \geq 0 \quad (2)$$

$$x_i \geq 0 \text{ for all } i \text{ , } x_{aslflg}, x_{refurb} \leq 1 \quad (3)$$

where x_j and $x_j^{opti.}$ represents the current and the desired value of a controllable variable j. Therefore, the objective function in Equation (1) represents the penalty on the deviations of the x_j from the $x_j^{opti.}$ weighted by c_j, the management cost of a controllable variable j. The constraint equations (2) and (3) simply specify the 20% reduction of churn probability associated with PLS regression coefficient b_j and feasible ranges of variables with the upper bounds of two indicator variables, "Accounting spending limit" and "Handset: refurbished or new", respectively. This non-linear optimization is then solved using sequential quadratic programming (SQP) (Gill et al., 1984) which transform the original problem into an easier sub-problem that can be easily solved and then used as a basis of iterative procedure. The SQP is well known for its efficiency, accuracy, and percentage of successful solutions over a large number of problems (Schittowski, 1985).

EXPERIMENTAL RESULTS

Optimization Model Designed for Entire Customers

The outputs of the optimization model in terms of the mean values of controllable variables for all the customers before and after optimization from both training and test data sets are presented in Table 1. Note that, in Table 1, Mean^{bo} represents the mean values of controllable marketing variables before optimization while Mean^{ao} represents the mean values of optimized controllable marketing variables to reduce churn probabilities of all the customers on average by 20% while minimizing management costs of controlling these variables. Remember that the total cost of reducing churn probabilities by 20% is not expressed as the monetary value but as the difficulty of controlling efforts of each variable. The final prediction model also includes the impact direction of each variable ('+' implying a positive impact and '-' implying a negative impact) on the churning decision of service users. For example, the "Number of days (age) of current equipment" variable is associated with the highest VIP score (2.995) and positively affects the churning decision (i.e., a service user who has kept her current mobile equipment longer is more likely to churn). It is also noted that the variable, "Handset-refurbished or new", is considered the second most important variable (VIP score = 1.9089) although it negatively affects the churning decision of service users.

We immediately note from Table 1 that the changes in the mean values of all the variables during the optimization were consistent with our expectation: the mean values of marketing variables that positively (negatively) impact on churn decision decreases (increases) to reduce churn probabilities. One interesting finding is that while the training and test data sets are dramatically different in terms of churner distributions (50% vs. 1.8%), the same seven variables in bold fonts were statistically significantly changed ($p < 0.001$) while other variables were not changed at all or only marginally changed. In particular, four variables such as two DMS variables ("Number of handsets issued" and "Number of models issued"), "Range of total monthly recurring charge" from RMS, and "Account spending limit" from CMS showed higher than 40% of changes during the optimization. This indicates that these four controllable variables from three marketing strategies should be considered simultaneously for optimization to maximize the synergistic effects of multiple marketing strategies.

Table 1. Mean values of controllable variables before and after optimization

Marketing Strategies	Variables	VIP Score	Churn Impact	Cost	Train data			Test Data		
					Mean^bo 1)	Mean^ao 2)	Change (%)	Mean^bo	Mean^ao	Change (%)
DMS	Number of days (age) of current equipment	2.995	+	5	415.51	415.31	-0.048	388.33	388.16	-0.044
	Handset: refurbished or new	1.9089	-	5	0.85538	0.9374	**9.589** [3]	0.86477	0.92674	**7.166**
	Total number of months in service	1.3268	-	8	19.915	21.482	**7.868**	19.805	21.096	**6.519**
	Number of handsets issued	1.3	+	5	1.794	0.87908	**-50.999**	1.8426	0.92185	**-49.970**
	Number of models issued	1.1964	-	5	1.5514	3.7318	**140.544**	1.5895	3.3868	**113.073**
RMS	Range of revenue of voice overage	1.5562	+	1	28.067	27.873	-0.691	26.414	26.263	-0.572
	Range of revenue of data overage	1.5556	+	1	28.511	28.303	-0.730	26.887	26.724	-0.606
	Mean revenue of voice overage	1.4597	+	3	12.134	12.067	-0.552	11.365	11.313	-0.458
	Mean overage revenue	1.4586	+	3	12.365	12.286	-0.639	11.616	11.554	-0.534
	Range of revenue (charge amount)	1.3976	+	1	39.983	39.392	-1.478	38.565	38.077	-1.265
	Mean total monthly recurring charge	1.3051	-	2	44.825	47.035	**4.930**	46.636	48.457	**3.905**
	Mean monthly revenue (charge amount)	1.2278	+	5	56.201	56.14	-0.109	56.892	56.842	-0.088
	Average monthly revenue over the previous three months	1.1572	-	3	56.528	56.988	0.814	57.448	57.827	0.660
	Average monthly revenue over the life of the customer	1.1497	+	3	54.823	53.921	-1.645	55.483	54.739	-1.341
	Range of total monthly recurring charge	1.0299	-	1	6.6881	10.863	**62.423**	7.3618	10.803	**46.744**
CMS	Account spending limit	1.4448	-	1	0.096858	0.94427	**874.901**	0.11522	0.9819	**752.196**
	Billing adjusted total number of calls over the life of the customer	1.1091	-	1	2792.4	2792.4	0.000	2856.6	2856.6	0.000
	Billing adjusted total minutes of use over the life of the customer	1.0375	-	1	7303.4	7303.4	0.000	7557.4	7557.4	0.000

1) Mean^bo: mean values of controllable variables before optimization
2) Mean^ao: mean values of controllable variables after optimization
3) Changes (%) in bolds were statistically significant at $\alpha = 0.01$

Another interesting finding we made is that the most important two variables for prediction in terms of VIP scores do not necessarily change most significantly during the optimization process. For example, the change of "Number of days (age) of current equipment" variable with the highest VIP score was not statistically significant. While the change of "Handset: refurbished or new" variable with the second highest VIP score (7.166% on test set) was statistically significant, but the magnitude of its change was minimal compared to changes in afore-mentioned four variables. These finding imply that each marketing variable plays different role in prediction and optimization models, and this warrants further investigations.

Optimization Model Designed for Subsets of Customers

We note that not all customers have the same churn probability and management cost to reduce their churn probability can be significantly different. For example, from test data, we found that the total minimized cost to reduce churn probabilities of all customers by 20% was found to be 1,329,440.73 (units of management costs, or difficulty of controlling efforts), ranging from 0 to 511.57 among customers. Therefore, it is still valuable if we can reduce the cost by narrowing down the scope of marketing campaigns (i.e., considering a subset of customers). For example, it is possible that marketing managers may target only top *x*% of customers with high churn probabilities or minimal management costs, and use two evaluation metrics, hit rate and cumulative percentage of management cost, to measure the success of marketing campaign. In this paper, the hit rate is defined as the number of correctly identified churners out of churner candidates. When only *x*% of customers predicted most likely to churn are considered, it is called a hit rate at a target point *x*%. For example, if the model is required to select 1000 customers who are most likely to churn from 10,000 observations, and 100 of them turn out to be one of 500 actual churners, then a hit rate at target point 10% (1000/10,000=10%) is 20% (100/500=20%). At the same time, the cumulative percentage of management cost is also computed at a target point *x*% by dividing the sum of management costs of all customers up to a target point *x*% by the total minimized management costs (1,329,440.73) of all the customers. The lift curve and the cost curve show the trend of hit rates and the cumulative percentage of management costs over all possible target points.

The Figure 2 shows that it is still possible to maximize the outcome of marketing campaign by targeting only top *x*% of customers who are most likely to churn. The lift curve shows that the hit rates are higher across all target points than those of a random selection scenario (shown along the diagonal line). Note that this is an additional benefit of PLS control and optimization model that reduce churn probabilities of all customers to a certain level. However, it is also observed that management cost curve is located above the diagonal line, indicating that selecting and targeting top *x*% of customers who are most likely to churn cost more (or be more difficult to manage) than the case of targeting randomly chosen customers. This is possible when marketing managers need to control more controllable variables or controllable variables associated with higher management costs to reduce the churn probability for customers who are most likely to churn. Therefore, the final decision of selecting the best target point should consider both differences in management cost and hit rates of two models. For example, if the service provider believes that extra revenue generated from the proposed model by more accurately predicting churners (i.e., measured by the difference between a lift curve and a diagonal line) is greater than extra management cost of the proposed model (i.e., measured by the difference between a management cost curve and a diagonal line), it is suggested that marketing managers select customers for marketing programs based on churn probability at a suggested target point.

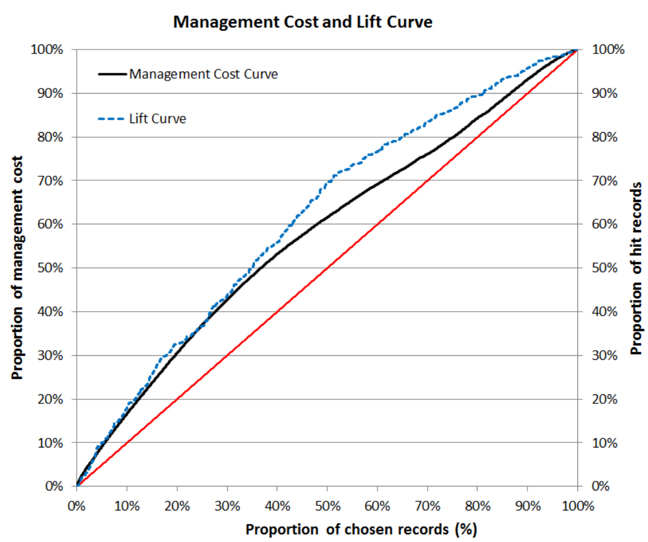

Figure 2. Customer selection based on churn probability

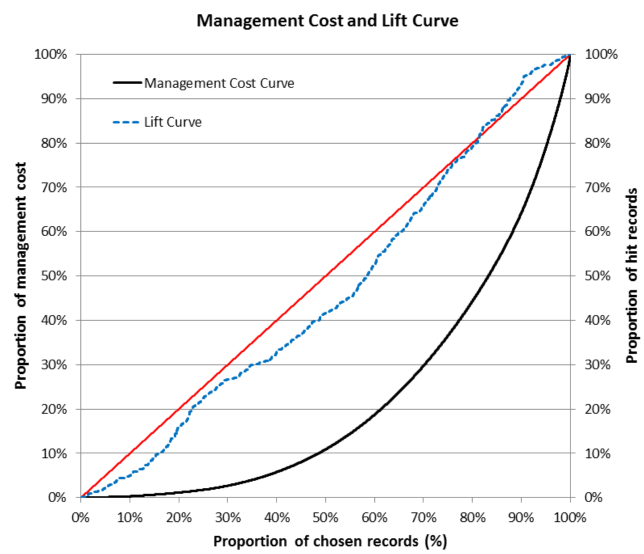

Figure 3. Customer selection based on management cost

The Figure 3 show management cost and lift curves when marketing managers select top *x*% of customers who are associated with the lowest management costs. We expect that the management cost of such a scenario will result in a cost curve under the diagonal line. In particular, the cost curve is assumed to take a shape of J in which the cumulative management cost of top *x*% of customers is very low, but it is increasing at an exponential rate once more customers with higher management costs are selected for churn management campaign. The management cost and lift curve in Figure 3 confirms our expectation, showing a J shape of management cost and a lift curve that is consistently located under the diagonal line. For example, the cumulative management cost of top 50% of customers with the lowest management costs explain only 10% of the total management cost of all customers in the test data. In particular, the cumulative management costs of the proposed model over target points at 10%, 20%, and 30% of records are less than 3% of the total management cost of all customers. Our simple calculation shows that, up to target point 50%, the random model will cost between four times (at target point 50%) and ten times (at target point 10%) more than the proposed model that intelligently selects candidate customers based on associated management costs.

In comparison, the lift curve of the proposed model is located under the diagonal line across the entire proportion of chosen customers except 80% or higher. This implies that randomly predicting churners is more accurate than selecting customers based on management costs for the churner prediction task. For example, the proportion of hit records when top 50% of customers with the lowest management costs are targeted for churn management program is about only 40% of entire hit records (=619 records). While this is discouraging, this outcome is possible because our model does not consider the probability of churning at all in this scenario. In addition, we claim that the proposed model is still superior to a random model because it costs significantly less management costs than a random model while the difference of two models in terms of hit records is only marginally significant. Note also that the proposed model already reduces the churn probability of all customers by 20% during an optimization process.

6. CONCLUSION AND FUTURE RESEARCH

In this paper, we present a churn optimization model based on the PLS prediction and control model that help marketing managers accomplish their marketing objectives not only by reducing the churn probability of all customers via optimization routine but also by reducing the management costs via customer selection. In addition, the proposed model is very customizable and generalizable by allowing managers to incorporate different marketing strategies and associated marketing variables in each marketing strategy.

One of limitations of the proposed model is that management costs associated with marketing variables do not directly bear financial values. Therefore, a follow-up study may estimate the impact of input variables when they are associated with absolute financial values on the outcomes of the proposed model. In particular, it will be interesting to estimate the financial values from reduced churn probability of all the customers in the optimization process. At the same time, additional financial profits from customers selected based on churn probability or management cost can also be estimated. By doing so, marketing managers can not only determine an optimal objective goal in the optimization process but also maximize the financial profits for target marketing.

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