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Exploring Alternative Predictive Modeling Techniques to Strengthen the Customer Relationship

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ABSTRACT

Maintaining customer loyalty in the financial sector is the key to steady sustainable growth. Being able to predict dissatisfaction as early as possible will ultimately allow a company to interact with the customer in an effort to regain their loyalty. It is no secret that the faster you can satisfy a customer's concerns, the less likely it is that they will seek out your competitor. But what do you do when the customer does not come right out and say they are not satisfied or that they have received a better offer? This paper discusses the benefit of using SAS® software to leverage alternative techniques to linear or multiple regression for the prediction of future attrition and activation. Although more complex and requiring additional time and effort, the use of alternative methods such as Cox model with time dependent variables and Multinomial logistic regression can improve your results significantly.

This presentation is targeted at a management level audience and will focus on the benefits of using alternative modeling methods, not details of the methods themselves.

INTRODUCTION

The Canadian financial marketplace is heavily driven by pricing and rewards. In the case of the credit card industry, this means promotional interest rates, low APR products, variable rate structures and reward cards. Rate and rewards have become the marketers' main tools in acquiring new customers and stimulating usage with existing customers. Unfortunately, rate doesn't appeal to everyone and does not always build loyalty, while rewards and points will build loyalty if you can match the customer needs and desires. If a better offer comes around, your customer will likely quietly move on to your competitor, starting the cycle again when presented with increasingly aggressive offers. Companies today need to take a proactive approach to identifying customers at risk of attrition or lapsing into extended periods of inactivity and act aggressively to delight and retain them. Although some may argue that this is more difficult, it makes financial sense seeing as it costs significantly more to acquire new customers than to retain existing ones. Further exacerbating the issue, we face a finite marketable universe in Canada, truly necessitating judicious management of the customer relationship.

BACKGROUND

Historically, MBNA Canada addressed customer loyalty through the offering of promotional interest rates to the majority of its cardholder base and didn't put much emphasis on proactively identifying customers who weren't engaged by this strategy. This was also demonstrated by the modeling strategy. Though this strategy appeared to be successful, significant money was left on the table either by over investment (i.e. unnecessary marketing expenditure) or by having customers take advantage of an aggressive offer when a more cost effective strategy would have been equally as effective.

Using SAS software, MBNA Canada developed linear or multiple regression models to predict the likelihood of response to a specific product and marketing channel; and in some cases crossed it with a second model predicting an additional factor, such as value. For example, the likelihood to respond to a balance transfer solicitation via telemarketing as well as the predicted transfer amount. The strategy revolved around the development of several individual models for each product offer and channel combination. Although easily implemented it doesn't necessarily allow for the simultaneous comparison of probabilities. If a customer ranks high in each model how do you assign priority? And conversely, if a customer ranks low for all available offers, it doesn't provide the insight necessary to design an offer to proactively stimulate this customer.

MBNA Canada set a goal to develop two models in order to address the above; an attrition model to proactively identify cardholders at risk of attrition and therefore most likely dissatisfied and an activation model, allowing us to predict the reactivation of cardholders who had lapsed into inactivity, through the modeling of past usage behaviour to predict the best reactivation offer.

Extensive research was conducted to determine industry best practices for the selection of the modeling methodology. Most of the literature suggested the use of simple regression methodologies, however, these wouldn't yield the lifts and insight sought.

METHODOLOGY

ATTRITION

Further research led to the decision to leverage the Cox model with time dependent variables in order to identify cardholders who were at risk of attrition. The selection of the Cox model allowed MBNA to estimate the risk of attrition in the same manner as estimating the risk of death in medical studies. The use of time dependent variables was also important, as our hypothesis was based on the fact that the event of attrition would have been preceded by predictable changes in a cardholders account usage. If these signs took place over several months they would not be captured using simple regression techniques.

To avoid the misclassification of a seasonal or occasional user as an attritor, SAS software was used to conduct an exploratory analysis using previous usage history data to establish the appropriate period of inactivity for the definition of attritor.

ACTIVATION

For the activation model, multinomial logistic regression (MLR) was leveraged because of its ability to simultaneously compare multiple target variables. By using MLR, historical transactional data can be used to simultaneously predict multiple usage preferences (cash, retail, travel and services) allowing the development of targeted campaigns, which will "speak" to the customer's preference.

As illustrated in Figure 1 below, MBNA developed a nine level mutually exclusive categorical indicator to be used as the target variable in MLR.

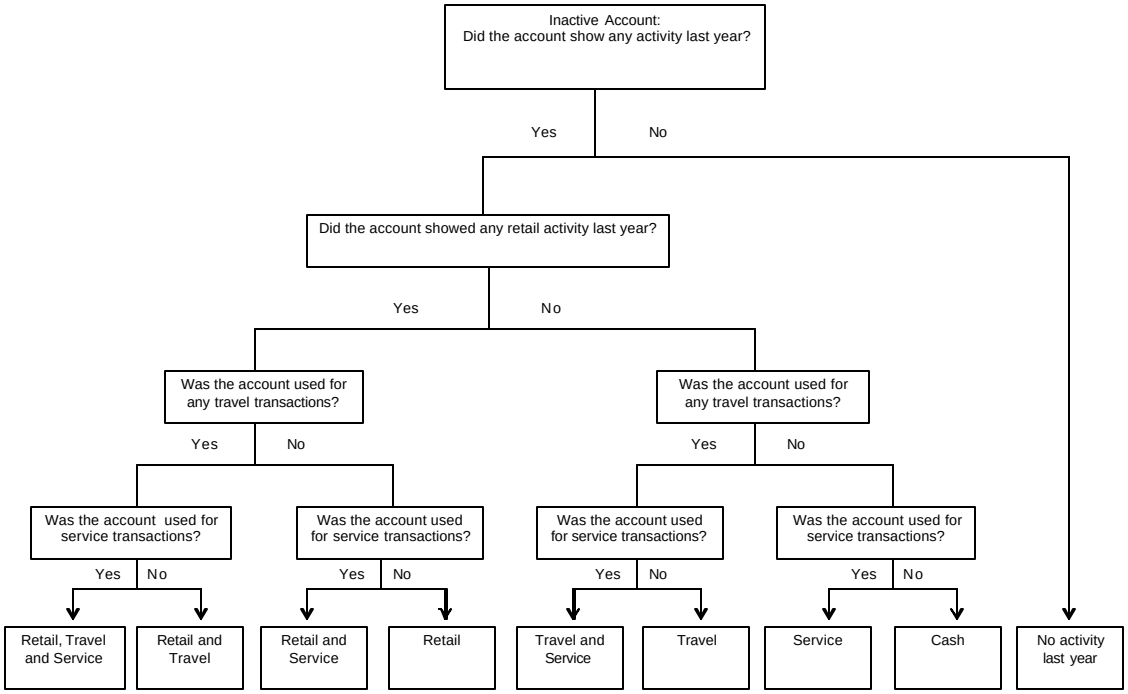

Figure 1. Nine level mutually exclusive categorical indicator

RESULTS

ATTRITION

Using the Cox model with time dependent variables allowed MBNA Canada to identify 71% of all attritors in the best decile. The first decile itself had an attrition rate of 95%, meaning that of every 100 cardholders in decile 1, 95 would attrite. In comparison, an MBNA/Third Party developed model using regression techniques only captured 40% of attritors in the first decile, with an attrition rate of 77%. As shown in Figures 2 and 3 below, the aggregate of deciles 1 and 2 in the MBNA/Third Party model could outperform the first decile of the MBNA developed Cox model, with one concern, the attrition rate within each decile only averages 78%.

Decile	Attrited Accounts			Lift
	% Attrition within Decile	As % to total # of Attrited Accts.	Cum. %	
1	77%	40%	40%	295%
2	79%	41%	81%	105%
3	15%	8%	89%	-73%
4	1%	0%	89%	-99%
5	1%	1%	90%	-99%
6	3%	2%	91%	-97%
7	6%	3%	94%	-96%
8	6%	3%	98%	-96%
9	3%	2%	99%	-98%
10	1%	1%	100%	-99%

Figure 2. MBNA/Third party developed Regression Model

Decile	Attrited Accounts			Lift
	% Attrition within Decile	As % to total # of Attrited Accts.	Cum. %	
1	95%	71%	71%	607%
2	31%	23%	94%	14%
3	6%	5%	98%	-85%
4	2%	1%	100%	-96%
5	1%	0%	100%	-99%
6	0%	0%	100%	-100%
7	0%	0%	100%	-100%
8	0%	0%	100%	-100%
9	0%	0%	100%	-100%
10	0%	0%	100%	-100%

Figure 3. MBNA developed Cox Model with time dependant variables

On occasions where the business case is to identify possible attritors and proactively offer them lower rates, lower fees, increased rewards, etc., in order to proactively retain them, it is important not to dilute your profitability on those who will not attrite. In the case of the MBNA/Third Party regression model, it can be assumed that 1 in 5 accounts in the top decile will not attrite, whereas it is estimated that only 1 in 20 will be falsely identified as an attritor using the Cox model.

MBNA chose a very conservative view of an attritor (7 months of inactivity), 40% of cardholders in decile 1 were active at the time of scoring, and 60% were already progressing through different levels of inactivity. MBNA Canada's opportunity lies with the 40+% of decile 1 who are still active at the time of scoring or in the earliest stages of inactivity. Based on development and validation, 95% of these cardholders will attrite if no action is taken. For example, assuming your cost to acquire a new customer is $250, if you can proactively identify 10,000 cardholders who fall into decile 1 and can retain even a portion of the active accounts, for example 20%, then the use of the model would have saved 800 active customers with a replacement value of over $200,000.

ACTIVATION

The use of multinomial logistic regression (MLR) gave MBNA Canada the opportunity to leverage transactional data to develop several historical usage categories in order to determine the best method of activation. MLR allowed the simultaneous evaluation of each category as well as general activation for each cardholder. The model estimates probabilities for each of the eight target variables:

Retail, Travel and Service
Retail and Travel
Retail and Service
Retail Only
Travel and Service
Travel Only
Service Only
Cash Only

The following probabilities are derived for implementation purposes:

Retail
Travel
Service
General Activation

As shown in figure 4 below, it is now possible to target those cardholders with the highest likelihood to reactivate and also choose an appropriate message. For example, observation 3 has a very high probability of reactivating, with its best opportunity to respond to a retail stimulation offer. The MLR model provides additional insight into possible strategies for marketing a suite of products such as; reward products (travel, merchandise), rebate programs, small business/business for self products and cash advances.

Observation Number after sorting	Probability the account will acivate			
	In general	Retail	Service	Travel
1	0.998	0.909	0.800	0.800
2	0.998	0.942	0.869	0.886
3	0.998	0.882	0.708	0.700
4	0.998	0.913	0.770	0.750
5	0.998	0.910	0.803	0.799
.....	.....	.....	.....	.....
100000	0.329	0.264	0.166	0.150
100001	0.329	0.259	0.187	0.187
100002	0.329	0.278	0.216	0.218
100003	0.329	0.273	0.192	0.183
100004	0.329	0.249	0.147	0.140
100005	0.329	0.145	0.167	0.266

Figure 4. Sample output of Activation model

As is shown through the validation below (Figure 5), using the MLR model, you can localize populations reactivating at rates above 55% in decile 1. For example, if you have the budget to market to 10,000 inactive cardholders in an attempt to reactivate them, you could randomly target and reactivate approximately 900 or you could market to 1,700 in decile 1 and get the same impact. Alternatively, you can use all your marketing dollars and identify 10,000 cardholders in decile 1 and activate approximately 5,500. Remembering that it is less expensive to reactivate than to reacquire, and assuming like above, that it costs $250 to acquire a new customer, reactivating an additional 4,600 cardholders (5,500 – 900) could net future acquisition savings of over $1 million.

	General_active			**Retail_active**			**Service_active**			**Travel_active**		
Decile	**Active %**	**Cum. Active %**	**Cum. Lift**	**Active %**	**Cum. Active %**	**Cum. Lift**	**Active %**	**Cum. Active %**	**Cum. Lift**	**Active %**	**Cum. Active %**	**Cum. Lift**
1	56.9%	56.9%	469.3%	62.3%	62.3%	522.8%	68.0%	68.0%	579.9%	67.6%	67.6%	575.9%
2	11.7%	68.6%	485.9%	9.3%	71.5%	515.5%	8.2%	76.2%	561.9%	8.5%	76.1%	560.9%
3	7.7%	76.3%	463.0%	6.6%	78.2%	481.5%	5.6%	81.8%	517.6%	5.7%	81.8%	518.4%
4	6.0%	82.3%	422.9%	5.3%	83.5%	434.9%	4.6%	86.4%	464.0%	4.7%	86.5%	464.9%
5	4.8%	87.1%	371.0%	4.5%	87.9%	379.4%	3.8%	90.2%	402.1%	3.8%	90.3%	403.1%
6	3.9%	91.0%	309.8%	3.7%	91.6%	316.4%	3.1%	93.3%	333.4%	3.1%	93.4%	334.5%
7	3.2%	94.2%	241.6%	3.0%	94.6%	246.1%	2.5%	95.8%	257.9%	2.4%	95.9%	258.8%
8	2.6%	96.8%	167.6%	2.5%	97.1%	170.7%	2.0%	97.8%	177.7%	1.9%	97.8%	178.0%
9	1.9%	98.6%	86.3%	1.7%	98.8%	88.0%	1.3%	99.1%	91.0%	1.3%	99.1%	90.7%
10	1.4%	100.0%	0.0%	1.2%	100.0%	0.0%	0.9%	100.0%	0.0%	0.9%	100.0%	0.0%
Total	9.1%			6.40%			4.30%			4.30%		

Figure 5. Activation model validation results

MBNA Canada has leveraged this model to identify target markets for reactivation campaigns via retail offers and has experienced 40% lifts over other selection methods.

CONCLUSIONS

After extensive research and the additional time to develop MBNA Canada's attrition and activation models using Cox model with time dependent variables and Multinomial logistic regression respectively, MBNA Canada has achieved its goal to develop models which allow the proactive identification of cardholders at risk of attrition and predict the reactivation of cardholders who had lapsed into inactivity, with better results than simple regression methodologies.

In addition to potentially sizeable expense savings, both the Attrition and Activation models will help MBNA Canada compete in Canada's aggressive and finite credit card market and support its attempts to delight and retain good customers.

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