Identifying Customers Likely to Churn

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Abstract

As acquiring new customers is costly, it seems logical to keep and satisfy long-time customers rather than to acquire new customers. To reduce churn rates, firms should manage customers proactively to avoid losing churned customers. The study investigated how an Australian DVD rental firm can use customer data to derive indicators of satisfaction, attitude, and commitment to improve the prediction of customer churn in comparison to models calibrated on purchasing behaviour alone. The most significant predictor of churn in these data was a measure of uncertainty and commitment: the number of times a customer changed their subscription plan.

Introduction

In saturated markets, churn rates – the percentage of customers quitting their relationship with a company – can reach 30% per year (Thomas, Blattberg and Fox, 2004; Wei and Chiu, 2002). Due to churn, firms must acquire new customers just to stay even (Kamakura et al., 2003). Yet acquiring new customers is costly (Cao and Gruca, 2005; Lewis, 2006), and not every acquired prospect is profitable. Sometimes acquisition costs can be higher than customer's lifetime revenue, particularly for short-term customers (Novak and Hoffman, 2000).

As a long-term customer is less costly to serve (Ganesh, Arnold and Reinolds, 2000) and might generate more value than other customers (Reichheld, 1996), it seems logical to keep and satisfy longtime customers rather than to acquire prospects (Reichheld, 1996; Reinartz and Kumar, 2003). Furthermore losing a customer could affect customer acquisition, as negative-word-of-mouth can have harmful effects on the firm's future prospects (Allenby, Leone and Jen, 1999; Lopez, Redondo and Olivan, 2006). The reduction of the rate of churn associated with a company's core customers should therefore increase profitability. A key aspect to reducing the churn rate is identifying characteristics related to churn.

Factors related to customer churn rate

In a contractual or subscription setting – formal relationships such as sports club memberships or mobile phone services – customers use the service and pay continuously until they quit (Bolton and Lemon, 1999). The firm knows when the customer quits, such as when they terminate the contract or fail to renew a subscription (Fader, Hardie and Jerath, 2007). In non-contractual relations, the customer rarely notifies the firm when ending the relationship. The firm cannot observe when a customer quits and thus defines customers as active or inactive (Fader, Hardie and Jerath, 2007). But even if firms can identify churned customers, these customers are already lost for the company. Predicting the likelihood of customers to churn helps even firms with contractual or subscription relationships with their customers to intervene proactively (Allenby, Leone and Jen, 1999).

Typically, companies predict propensity to churn from the data they have on hand about their customers: the history of their purchasing behaviour. The length of a customer's relationship, and the recency, frequency, and monetary value of their purchasing can all help to estimate a customer’s propensity to churn (Bolton, Lemon and Verhoef, 2004; Lopez, Redondo and Olivan, 2006). In contractual settings, additional purchases or contractual up- or down-grades suggest changes in customer’s interest. In non-contractual settings, firms focus on customer’s individual purchasing frequency within a certain period as a reflection of interest. Firms can then contact customers and ask for reasons if the frequency decreases significantly (Allenby, Leone and Jen, 1999). The problem with this approach, however, is that purchasing behaviour may not reflect a customer’s propensity to churn (Zeithaml et al., 2006). Customers may form an intention to leave, based on dissatisfaction or a negative attitude to the company, yet continue to purchase as often and as much until they identify the best alternative to switch to.

Satisfaction
In their literature review Gabarino et al. (1999) mentioned two possible forms of satisfaction – overall satisfaction and transaction specific satisfaction. Transaction specific satisfaction relates to an immediate post-purchase evaluation. Overall satisfaction relates to customers’ evaluation of their entire history of transactions, and includes satisfaction with the goods or services that were purchased, and aspects of the firm, such as its physical facilities.

Marketers generally assume that satisfaction increases customer loyalty and relationship length (Dover and Murthi, 2006; Ganesh, Arnold and Reinolds, 2000). However, satisfied customers are not necessarily loyal customers (Oliver, 1999). The relationship between satisfaction and loyalty is complex and non-linear, mostly because there are other influences on relationship length, including price perceptions and commitment (Bolton, Lemon and Verhoef, 2004).

Furthermore, most companies measure satisfaction retrospectively, without considering the context in which it is measured, which results in low reliability and strong bias (Lachane, Beaudoin and Robitaille, 2003). For example, the satisfaction levels of customers who have made a purchase might not be able to explain why other customers left a store dissatisfied without buying anything. Rather than measuring satisfaction after the fact, firms could focus on the antecedents of satisfaction, so that they can proactively manage the satisfaction of customers before they quit (Bolton, 1998). Customer satisfaction is a function of expectations and disconfirmation of customer expectations (Ganesh, Arnold and Reinolds, 2000). These expectations are based on perceptions of the firm, including its performance and the fairness of its pricing (Bolton and Lemon, 1999; Dover and Murthi, 2006).

Commitment
Committed customers will endure occasional dissatisfaction because they are interested in the benefits of a long-term relationship with the firm (Garbarino and Johnson, 1999). For this reason, satisfaction is not as important a predictor of relationship length for committed customers as it is for customers with a short-term perspective, who evaluate each transaction individually (Bolton, Lemon and Verhoef, 2004).

Key antecedents of commitment are shared values, benefits, switching costs and trust (Spake et al., 1999). Communication increases trust, but uncertainty and opportunistic behaviour reduce it (Spake et al., 1999). Uncertainty also has a direct relationship with churn, beyond this indirect relationship via trust (White, Lemon and Hogan, 2007).

Bolton et al. (2004) distinguish two kinds of commitment: affective and calculative. Affective commitment stems from a positive attitude to the firm and therefore an intention to stay committed, which positively influences relationship length (Bolton, Lemon and Verhoef, 2004; Colgate et al., 2007). Calculative commitment stems from rational motives, such as switching costs and perceived price fairness. Changes in these provoke instantaneous churning by customers with calculative commitment, hence the conflicting results in the literature about the relationship between commitment and loyalty, mostly because authors have been ambiguous about which type of commitment they were measuring (Bolton et al. (2004).

Moderators of the Impact of Prices and Switching Costs

Because price fairness and switching costs mainly influence only those customers with calculative commitment, Bolton et al. (2004) found no empirical evidence for a relation between price perception and relationship length. Customer experience is another moderator of the influence of switching costs on loyalty (Reinartz and Kumar, 2000), although experience is a two-edged sword (Dover and Murthi, 2006). The more informed a customer is about the market, the easier for them to switch to a competitor, but the more experienced a customer is with an individual firm, the more benefit they get from the relationship. More experienced customers have a broader knowledge of competitors and therefore might quit more often than inexperienced customers (Dover and Murthi, 2006). Customer knowledge is likely to be generally higher in markets that are more competitive, as firms in these markets target their offers at their competitors' customers (Bolton, Lemon and Verhoef, 2004). On the other hand, buying a product or service for the first time is fraught with uncertainty, whereas with experience, customers can get more value out of a product or service. Johnson et al. (2003) showed that online shoppers traded price sensitivity for the convenience of staying with the site they knew best.

A firm's customers are a highly heterogeneous asset (Bell et al., 2002; Lewis, 2006). Demographics are not enough to predict differences in purchasing behaviour; firms require details of preferences at an individual level (Sivadas, Grewal and Kellaris, 1998; Zorn and Murphy, 2007). However, most firms face the challenge of having only behavioural data easily available for estimating these individual differences, for example, call patterns in the telecommunications industry (Wei and Chiu, 2002). Few studies have investigated the additional benefits of adding cognitive variables, such as satisfaction, and attitudinal variables to models based on behavioural data (Ganesh, Arnold and Reinolds, 2000). This study adds to the literature by exploring whether the more extensive records of behaviour collected by companies with customer websites allow the estimation of individual differences in satisfaction and attitude, which would increase the precision of customer churn models.

Methodology

The research used customer data from an Australian Internet DVD rental company, similar to NetFlix (www.netflix.com) in the USA. Customers subscribe to plans that differ in the number of DVDs a customer can per month. The company accumulates behavioural data such as how often a customer visits the website or up- or downgrades the rental plan. Investigating reasons to churn, the study drew on the behavioural data of 10,156 members and ex-members of the company. As the company offers a free 30 days trial period, deleting customers with a membership length below 31 days left 4,008 ex-members and 2,380 members for the analysis.

Given the right-censored nature of data, a conventional regression has the disadvantage of biased results (Cox, 1972). Therefore a Cox-regression examined how customer purchasing behaviour and potential indices of relationship perceptions related to membership length (survival time).

The number of visits to the company's website (VisitCount), the number of titles reviewed (NoOfTitleReviews), and the time a customer kept a DVD at home (RentalTime) served as proxies for the customer's purchasing behaviour. The more satisfied a customer is, and the more favourable their attitude toward the company, the more effort they are likely to expend in relation to the company, and therefore these rates of behaviour should be higher. But we also included in the model two other, more direct indices of satisfaction and attitude. The first of these was the price of their monthly subscription, which should be higher for more satisfied customers. Monetary value is not a new variable in models of churn, however, and is likely to reflect other influences as well, particularly income. The second index of satisfaction was one that is uniquely available to companies selling, or in this case, renting "taste" goods, which cannot be compared on objective attributes. Instead, customers rely on collaborative filtering techniques (other customers like you bought …), or subjective ratings and reviews, which websites allow fellow customers to contribute. Our expectation was that a negative attitude toward the firm would be reflected in negative ratings of the movies it offered (TitleRating), following an affect transfer process (Kim et al., 1998). For example, Lang et al. (1990) demonstrated that the same individual's ratings of photographs can be reversed from positive to negative by association with a negative event, in their case, an electric shock. Finally, we used the number of times a customer changed their plan (NoOfPlanChanges) as an indicator of uncertainty, which, as mentioned above, has been shown to be a direct influence on customer loyalty, as well as an indirect influence via commitment. We assumed that customers who change their plan several times have less commitment to the firm, or at least, more uncertainty about what their commitment entails.

To compare customers with different membership lengths, the study used values averaged across the membership length (in days) for the six independent variables. In other words, using membership length in days as the denominator calculated daily rates for each independent variable.

Results

Table 1 shows significant results for five out of six of these variables in a Cox-regression predicting the hazard of a customer relationship terminating (χ^2=1010.74, df = 6, p <.001).

Table 1 Coefficients of the Cox-regression analysis

Variable	Beta	Standard Deviation	Wald Test	P	Odds ratio
VisitCount	.170	.034	24.483	<.001	1.185
NoOfTitleReviews	1.851	.378	23.999	<.001	6.364
RentalTime	.000	.000	.420	.517	1.000
PaymentPerMonth	.013	.001	90.379	<.001	1.013
TitleRating	.024	.010	5.881	.015	1.025
NoOfPlanChanges	43.260	1.440	902.004	<.001	6.131E18

Correlations between the independent variables and the dependent variable ranged from .002 (PaymentPerMonth) to −.283 (NoOfPlanChanges), and among the independent variables from .011 (between PaymentPerMonth and VisitCount) to −.119 (between VisitCount and RentalTime). These correlations indicate no lack of discriminant validity between these variables.

Compared to a model that included just the three behavioural variables, the two indicators of satisfaction/attitude significantly increased the explanatory value of the model ($\chi^2(2) = 95.97$, $p < .001$). Adding the final measure of uncertainty/commitment contributed a further significant increase in explanatory value model ($\chi^2(1) = 456.08$, $p < .001$). Only one predictor was insignificant, average DVD rental time, which was one of the three behavioural variables. The uncertainty/commitment variable, the number of plan changes, had the highest odds ratio among the five significant predictors. The number of reviews had the second highest impact on churn propensity, but against expectations, its impact was positive. Similarly, reviews that are more favourable, more visits, and higher payments per month also had unexpectedly positive, and highly significant, influences on tendency to churn.

Conclusion

The study showed that behavioural data indicative of attitude to the firm and satisfaction can increase the prediction of propensity to churn beyond the information provided by the purchase data typically used for this purpose. In line with previous studies, our results support the relationship between uncertainty, and relationship length. We used the number of times a customer changed their subscription plan as an indicator of uncertainty and commitment to the relationship. The more uncertain they were, the more they changed their plan, and the more likely they were to quit the firm. This company could send special offers to customers who change their subscription plans, which signal they are thinking of churning, to focus their efforts on keeping these customers.

We also used average rating given to movie titles as an indicator of attitude toward the firm, but contrary to our predictions, the more favourable these ratings the more likely the customer was to quit. Similarly, the more titles a customer reviewed, the more times they visited the site, and the more money they paid, the more likely they were to quit the relationship. Differences in market knowledge between the customers with the lowest and highest rates of activity may explain these results (Dover and Murthi, 2006; Reinartz and Kumar, 2000). The more enthusiastic the customer was for movie viewing, the more favourable their reviews, the more often they would write reviews, and the more often they would visit the site. However, the more active a customer was, the more knowledgeable they are likely to be about movies and the movie rental market, and therefore the more likely they would be to switch to another competitor, who, for example, might offer more obscure titles.

This study has several limitations. It was an exploratory study testing the potential utility of behavioural indicators of perceptions and attitude, and therefore we used a model of customer survival rather than customer activity. Our model used constant rates of behaviour and purchasing, which hampered their explanatory value in comparison with our uncertainty measure, which documented changes in behaviour, similar to the accelerations and decelerations in activity which make activity models so powerful (Schmittlein and Morrison, 1985). Future research could compare the predictive value of adding attitudinal indicators to a more sophisticated probability model of activity, using different criteria such as mean absolute difference in holdout data. Ideally, a future study would validate these behavioural indicators of attitudes and perceptions against direct measures of these constructs from the same customers. Our data also exhibited results counter to our expectations and perhaps unique to the market we investigated. Future research should test data from markets for other goods and services to test the generalizability of this approach for improving models of customer activity.

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