PATTERNS OF CUSTOMER EXIT IN A CONTRACT-BASED SUBSCRIPTION SERVICE

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ABSTRACT

Customer exit is one of the most extreme forms of complaining behavior, as pointed out by Hirschman (1970). It may be precipitated or accompanied by some negative affect toward the company supplying the service, although it may also be caused by a more distanced calculation of price and value. The timing of the customer's intended exit is extremely important, and has been studied heavily. That timing is complicated for a service which has been initiated by a contract with a definite lifespan, and attention centers on the importance of the contract expiration date and the customer's post- (and sometimes pre-) expiration behavior. The supplier is typically very interested in such exit patterns, their relationship to available internal information, and their consequences for such customer retention tactics. In this paper, we outline a method for viewing the exit propensity of cellular telephone customers, most of whom initiate service through the signing of a contract for a specified term. The production of these estimated propensities follow classical statistical survival analysis, and are augmented by the output of a neural net model for customer lifetime data. These propensities for exit then take the form of a statistical hazard function, whose components estimate the conditional probability of a customer's departure in the *t*th month of his/her service. These hazard functions will be categorized and related to internal company database information. This determines a way of segmenting customers, and creating indicators of that segmentation. Finally, we suggest a way to use this information to understand the customer's situation and to develop retention tactics. This concept is an extension of the classical use of lifetime value (LTV) as developed for the mail order industry, in that it affords a way of quantifying the value of allocating marketing strategies to customers with different valuations.

INTRODUCTION

Customer exit is one of the most extreme forms of complaining behavior, as pointed out by Hirschman (1970). It may be precipitated or accompanied by some negative affect toward the company supplying the service, although it may also be caused by a more distanced calculation of price and value. The emotional antecedents of the customer's intended exit is extremely important, and has been studied heavily (e.g. Singh and Wilkes, 1991). Somewhat less attention has been paid to the timing and duration of the exit (although see Huefner and Hunt, 1994). This timing is complicated for a service that has been initiated by a contract with a definite lifespan, and attention centers on the importance of the contract expiration date and the customer's post- (and sometimes pre-) expiration behavior. The supplier is typically very interested in such exit patterns, their relationship to available internal information, and their consequences for such customer retention tactics.

Note how the interaction of a contract, and the timing of exit place this sort of exit near the classic Hirschman notion of exit, and Huefner and Hunt's extension. In their 1994 paper, the latter authors outline the notion of such post-exit behaviors as retaliation and grudge holding. In the marketing situation we discuss, contract expiration marks the time at which exit becomes generally possible, and interest centers on actual exit behavior before and after this point. Rather than duration *after* (avoidance) as developed by Huefner and Hunt, we discuss durations *until* exit after exit becomes possible. As we will see, for some contract expiration has nothing to do with exit, for others it is the cue to leave as quickly as possible, while for still others it is a brief time of search for a better deal. Thus, this discussion takes place in a way parallel to that of Huefner/Hunt, with contract expiration being the pivotal event rather than exit itself.

In this paper, we outline a method for viewing the exit propensity of cellular telephone customers, most of whom initiate service through the signing of a contract for a specified term. These propensities will be categorized and related to internal company database information. Finally, we suggest a way to use this information to understand the customer's situation and to develop retention tactics. This concept is an extension of the classical use of lifetime value (LTV) as developed for the mail order industry (e.g. Aaker, Kumar and Day, 1998; Schell, 1990), in that it affords a way of quantifying the value of allocating marketing strategies to customers with different valuations.

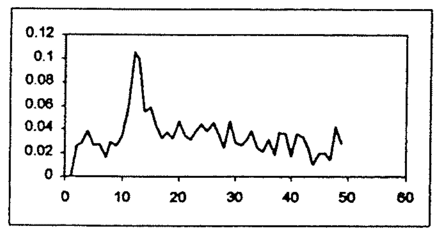
HAZARD FUNCTIONS AND THEIR PREDICTION FROM COMPANY DATA

In the United States, residential customers generally obtain cellular telephone service by signing a contract for a fixed period, frequently 12 months. At the end of that time, the customer can leave the company's service without penalty, or renew their contract, or choose to remain without the need to sign a further contract. From the supplier's viewpoint, a given customer has a birth date (the contract initiation date), an age, and a time of "death," i.e. the time of terminating service (either to take up service with another provider, or to leave the cellular market altogether.) At each age, a customer has a probability of death, generally depending on his age as well as many other factors. The set of these probabilities for all possible ages is called a hazard curve, of which Figure 1 is an example.

Customer age is plotted on the horizontal axis, while the death probabilities are plotted on the vertical axis. Like most hazard curves, this one displays information that can be very useful for relationship marketing. The expiration of the one-year contract signed at service initiation is clearly shown by the "spike" in the hazard rate around 12 months. For this customer, it is also interesting that the hazard rate is relatively low both before and after the time of expiration. As we will see below, this is not always the case.

There are several accepted ways of estimating hazard curves. Hazard for entire populations can be estimated through the celebrated Kaplan-Meier technique (Kaplan and Meier, 1958), and the effects of covariates can be incorporated in a proportional hazards model (Cox and Oakes, 1984). For purposes of this paper, though, we use a neural net technique described in Drew et al., 1999. A related technique can be found in Street (1998). Discussion of the technical details of the neural net model are beyond the scope of this paper; what is important for our purposes is its production of a hazard function for each customer in a market. The resulting hazard curves are unique to each individual in the sample under consideration, but they tend to fall into one of four main types or segments, within which the individual hazards are quite closely multiples of each other. The implications of these segments are significant for understanding customer exit from this service.

Figure 1
A Typical Hazard



PATTERNS OF HAZARDS

Through the statistical clustering of the individual hazard functions discerned by the neural net, four basic patterns of hazards were discovered. Within each of the four basic patterns, hazard functions of individual customers were multiples of the reference hazard (that is, each individual's complete hazard over all months is just a multiple of a single reference hazard). Within each segment, of hazard pattern, the multiple is a complicated function of the customer data from the company database. Thus, a proportional hazards model (Cox and Oakes, 1984) holds within each segment. These multiples are a way of arraying the hazards within each segments, and Figure 2 shows the segment hazards with regularly spaced functions displayed. (Within each segment, the multiples of the hazard functions were sorted from lowest to highest, and the hazards corresponding to the 10th, 25th, 50th,

Figure 2
Hazard Function Segments from NN Models

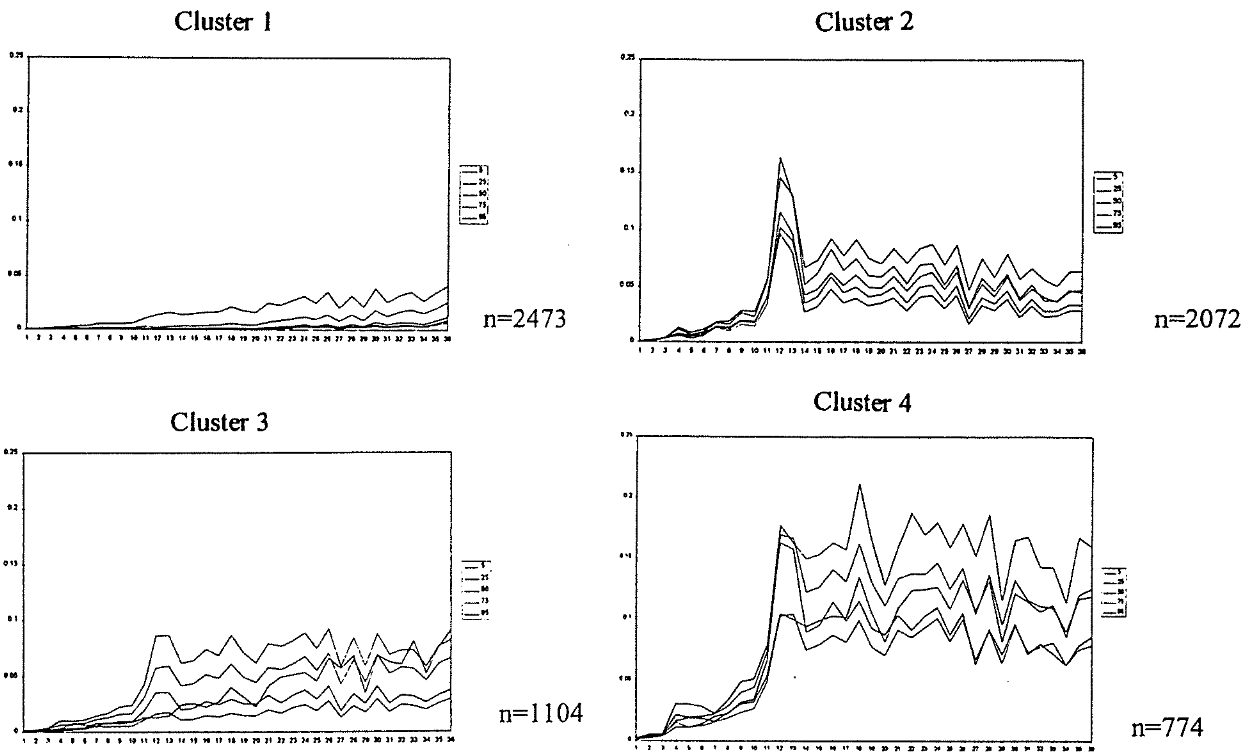


Table 1

Cluster-Segment	Contract-Related Exit Timing	Implications for Retention Effort
1 (n=2473)	No effect of contract expiration	No pre-expiration contact required. Contact may trigger churn.
2 (n=2072)	Small increase in churn propensity at expiration Post-expiration churn remains elevated	Moderate pre-expiration effort needed. New contract or continued contacts needed.
3 (n=1104)	Large spike in churn at expiration; Low churn thereafter	Concentrate effort on pre-expiration; Contract renewal may not be required
4 (n=774)	Large increase in churn at expiration; Post-expiration churn high and increasing	High intensity effort pre-expiration; Continued competitive offers to designated customers

75th, and 90th percentile are shown.)

These four hazard clusters constitute a useful customer segmentation in terms of their interaction with cellular service and its contracts. This segmentation has important interpretations of a customer's state of mind in using cellular service, and important intuitive implications for the company's retention efforts for these different segments. These are summarized in Table 1.

It is interesting to contrast clusters 1 and 4, in the light of buying strategies. Cluster 1 evidently represents customers who have high (psychological) barriers to switching cellular suppliers, while cluster 4 seems to be composed of those who switch as frequently as contracts allow. These spectrum ends are reminiscent of the "lost-for good" and "always a share" models developed by Jackson (1985).

HAZARD PATTERNS AND COMPANY DATA

These patterns have an important meaning for company marketing and retention efforts. Insofar as these patterns are discerned by a neural net, whose mechanisms are effectively unknowable, and because the clusters are based on mere geometric shapes of the resultant hazard curves, company needs require their relating to internal data and customer histories. Although a classical tool such as discriminant analysis could be used for this task, the likely nonlinear covariate effects indicates use of decision tree methods (Hand and Henley, 1997). In these methods, the entire dataset, with its initial distribution of the four cluster types, is repeatedly split based on values of explanatory variables. In an ideal analysis, the splitting results in subsets of data which consist solely of one cluster. In our data, the explanatory variables included:

Detailed Billing	A special, extra-cost feature; often associated with business customers
Total Charges	Total charges on a customer's monthly bill; includes access charge, air time, roaming charges, etc.
Peak_MOU	Number of monthly minutes of use (MOU) billed at defined peak hours
Channel	Sales channel (e.g. GTE distributor, auto dealer) through which the service was initially purchased
Total Calls	Total number of calls in a month

The CHAID results, i.e. the splitting rules which define paths to the most discriminatory subsets, lead to the summaries of the covariate effects indicated in Table 2.

Intuitively, it seems that Cluster 1 is composed of such customers as the "safety and security" set, who possess their cellular telephone as an emergency and convenience device. Cluster 3 comprises users who have a moderate flat-rate access charge accommodating all their calling needs. Cluster 4, in contrast, comprises customers with rate plans whose flat rates do not fit their high calling volumes. These may well be customers who would be better served by a different rate plan; their high post-contract churn probabilities indicate that such improved plans are often obtained through alternative suppliers. It may be that Cluster 2, a scaled-down version of Cluster 4, may also comprise customers with inappropriate contracts.

With these data, it is not easy to characterize rate plans that do or do not accommodate a customer's needs, as this concept is ultimately an affect not well revealed by objective company data. A simple calculation such as dollar cost per minute of telephone use is not appropriate because this ratio tends toward infinity when usage becomes small. A somewhat more general treatment is to model an "average" cost per use function as a simple least-squares regression of monthly cost on monthly minutes-of-use. Residuals from the resulting regression line are a measure of how relatively high or low is a customer's total bill compared with his/her usage minutes. The higher the residual, the higher the customer's relative cost, and the less appropriate the rate plan under which the calling was done. One might anticipate then, that cluster 3 would have lower values for this residual than clusters 2 or 4.

Table 3 below shows selected summary statistics for this variable over the four clusters.

Observe that cluster 3 has the lowest values for residual means, the 75th and the 90th percentiles, although the medians are about equal. Cluster 3 customers have better rate plans in that their above-median usage-adjusted costs tend to be substantially smaller than for the more churn-prone clusters 2 and 4.

Table 2

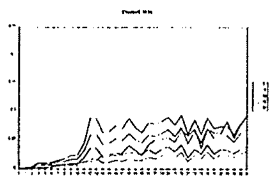
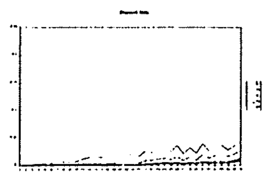
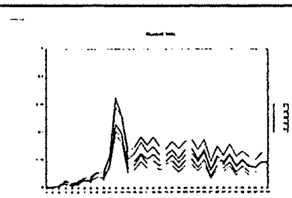
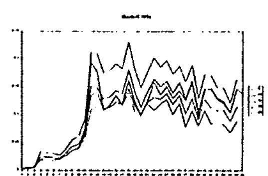
Cluster No.	Shape	Distinguishing Features
2		No influence of available covariates: A reference shape
1		Detailed Bill; Few calls/month
3		Two distinct types: • Zero Charge for MOU, Many Calls/Month • No Detailed Bill, Low Total Charge
4		High total charge

Table 3

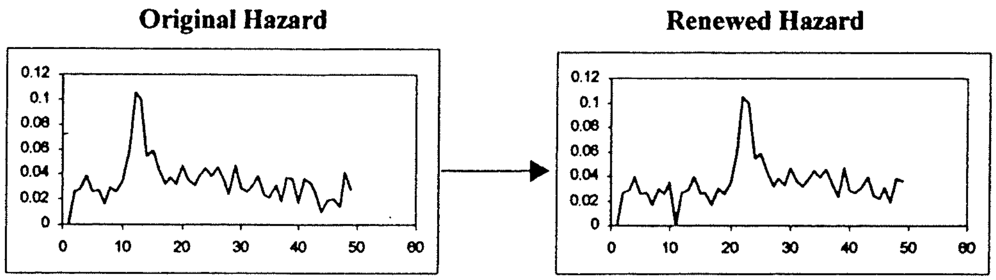
Cluster	Median	75th Percentile	90th Percentile
1	-5.49	7.14	25.94
2	-6.15	7.98	36.26
3	-6.98	4.09	16.81
4	-6.71	12.60	47.98

USING THE HAZARD PATTERNS FOR RETENTION STRATEGIES AND TACTICS

Contract expiration at (usually) 12 months is a crucial event for both the cellular company and its customer. An organized cellular provider should construct a retention strategy, contacting and offering significant retention inducements (e.g. a new phone or better rate plan) to one portion of its customers, while offering lessor--or no--inducements to other portions, and ignoring (i.e. not contacting) yet other portions. Each of these three strategies can be put in the same economic form: by combining contact costs and inducement costs into an aggregated concession cost, the issue becomes the size of the concession to offer to each customer.

Through our neural net model, each customer has a unique hazard function, and the cluster analysis above indicates the form and desired outcome of that customer's retention approach (e.g. ignore Cluster 1 customers). Analysis of each customer's hazard function, combined with knowledge of his/her expected revenue leads to an individual estimate of revenue gain to guide the retention effort.

Figure 3
The Effect of Contract Renewal



One way to quantify this gain is the following. A given retention effort has as its goal the modification of the customer's hazard function. For instance, the supplier may attempt to renew the customer's contract. In this case it is reasonable to expect that his/her new hazard function has its original form up to the time of renewal, after which the modified hazard function is a translation of the original so it begins its cycle at that time. At the time of renewal, the conversion of the customer's hazard function into, say, the form on the right leads to an increase in his/her estimated remaining lifetime, which can be calculated from the components of the old and new hazard function. For the Cluster 3 customer renewing at, say, 10 months, the original and modified hazard functions look like Figure 3.

As revenues (i.e. total charges from the company's viewpoint) are quite constant over time, and costs are effectively constant, the increased estimated lifetime is multiplied by the monthly revenue for each hazard function. The difference is the incremental gain from that customer's retention. The resulting calculation determines a reference value to guide the size of the concession one might extend to the customer. For example, a $100 cellular phone may be readily conceded to a customer whose contract renewal would increase his LTV by $400; the same phone, however, might perhaps only be sold at cost to someone with an incremental LTV of $85.

DISCUSSION

These hazard functions are useful in themselves, as the preceding paragraphs have shown. They are also connected to the notion of lifetime value (LTV) which has been useful in the mail-order industry. In that context, the LTV measure was an advance over customer segmentation by revenue, in that it provided a way of mediating the difference between a high-revenue, low purchase frequency customer and a low revenue, high frequency customer. Indeed, to a financial expert, the notion of LTV is a meaningful one. It is a way of valuating a customer as an asset, much like a raw material or a depreciated piece of capital equipment. It does, however, have less meaning for business operations since there is no intrinsic relation between a high LTV customer and his/her reaction to such marketing efforts as service improvement or retention strategies. That is, LTV is meaningful only when one presumes that a customer's behavior is unaffected by his or her relationship with that company. This is not always the case. With the production of an individual customer hazard function, the company can begin to base operational and marketing decisions on their effect on customer hazard, increase in remaining lifetime, and revenue increase. Some possible effects can be postulated based on an assumed company drive toward contract renewal (or its lack of effort), as we have attempted above. More sophisticated effects from more complex or actual efforts would, of course, require careful experimental design and analysis. In that case, the methodology by which we produced the hazard functions shown here provides a tool for quantifying those efforts.

CONCLUSION

The timing of customer exit can be displayed through the use of hazard probabilities developed by a neural net trained on observed exit times. The patterns have a fairly simple structure, and can be used to segment customers to determine their relationship to the contract governing their first 12 month's cellular service usage. The exit timings revealed by each hazard segment gives insight into how the customer reacts to his/her contract, and their forms suggest some strategies for marketing. In particular, each segment suggests a unique and optimal strategy for the retention contact, and each customer's hazard function allows the calculation of a reasonable retention effort.

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