Journal of Business Research 67 (2014) 983–989

Contents lists available at ScienceDirect

Journal of Business Research

The role of lifetime activity cues in customer base analysis

Daniel Hoppe *, Udo Wagner **

University of Vienna, Austria

ARTICLE INFO

Article history:
Received 16 November 2010
Received in revised form 11 September 2011
Accepted 19 December 2011
Available online 5 September 2013

Keywords:
Customer lifetime value
Purchase behavior
Stochastic models of consumer behavior
Pareto/NBD

ABSTRACT

This paper develops the notion of lifetime activity cues in customer base analysis. The authors first discuss the impact of lifetime indicators, such as customers' conceptual response to marketing activities, and then demonstrate how such lifetime cues can be embedded into the Pareto/NBD model. The authors theoretically analyze the implication of this additional behavioral indication on the model's predictions. In an illustrative example, they aim to establish an intuitive understanding of the effects of such information. Evidence from the cellular phone industry supports the relevance of this concept: The empirical study finds a substantial improvement in predictive accuracy in two independent holdout samples. The study concludes with a discussion of the managerial relevance of the proposed approach and opportunities for further research.

© 2013 Elsevier Inc. All rights reserved.

1. Introduction

Consider the following scenario: Every few weeks, Mr. Gallardo-Cortez, an experienced online shopper, receives promotional e-mails from different online firms he signed up with in the past. One e-mail from a leading international Internet bookstore informs him of some soon-to-be-released titles, with a prompt to "click here to learn more," and so he does. Another e-mail originates from one of the major online auctioning houses. After some disappointing experiences with online auctions in general, he is not interested and moves the message to the wastebasket unread.

From a marketer's perspective, these two typical examples of online marketing activities have very different results. The online auction house cannot draw any clear conclusions from the lack of response. For example, the customer might have overlooked the message, his spam filter might have intercepted the message, or, finally, he might have seen the message but was not interested in the particular content. In contrast, the Internet bookstore considers the customer's response highly relevant from a marketing perspective and can link this reply directly to customer base analysis.

When customers click on personalized links in e-mails, participate in online surveys and sweepstakes, or log in to their accounts, regardless of the information channel, marketers receive the same clear message: He or she is still a viable customer. The customer might not buy on that particular occasion but, in principle, is still interested in the products and services the company offers. How does this activity relate to marketing models for customer base analysis? Common analytical approaches to the dominating business model of direct marketing and Internet retailing—that is, *non-contractual* customer relationships—consider information on customer activity status solely in the form of purchase incidents (e.g., Fader, Hardie, & Lee, 2005). Moreover, this approach is in line with RFM rules in use by practitioners who evaluate the status of their customers by concentrating on the time since their last purchase (recency), the number of purchases observed so far (frequency), and the cumulative sales volume achieved so far (monetary value). Such rules imply a trade-off between the chances of a customer having defected at some point after his or her last purchase and the chances of a customer simply not having bought during the time span between the last transaction and the end of the observation horizon.

The most prominent model to implement such a trade-off is Schmittlein, Morrison, and Colombo's (1987; hereinafter, SMC) integrated stochastic *purchase incidence/lifetime duration* model. With this model, SMC concentrate on customers' purchase intensities and dropout rates. The observed number of purchases within a certain period provides a clear indication for the first aspect. However, usually no apparent information for dropout rates is present because, typically, clients leave businesses without giving explicit notice. To overcome this problem, SMC postulate rather simple assumptions about the individual lifetime processes, which enable them to infer whether a customer is likely to still be active. However, extant literature (e.g., Hoppe & Wagner, 2010; Schmittlein & Peterson, 1994) shows that the estimation of the lifetime duration process is usually much less precise than the estimation of the purchase incidence process. This result is intuitively reasonable when considering that more information is available on the latter process.

To the best of the authors' knowledge, no previous study has considered lifetime activity cues such as the one given in the previous example

* Correspondence to: D. Hoppe, Department of Marketing, University of Vienna, Oskar-Morgenstern-Platz 1, A-1090 Vienna, Austria. Tel./fax: +41 44388 8666, +41 44388 8686.
** Correspondence to: U. Wagner, Department of Marketing, University of Vienna, Oskar-Morgenstern-Platz 1, A-1090 Vienna, Austria. Tel./fax: +43 1 4277 38012, +43 1 4277 38014.
E-mail addresses: Hoppe.Daniel@bcg.comt (D. Hoppe), udo.wagner@univie.ac.at (U. Wagner).

0148-2963/$ – see front matter © 2013 Elsevier Inc. All rights reserved.
http://dx.doi.org/10.1016/j.jbusres.2013.08.004

(i.e., looking at soon-to-be-released titles) within the context of stochastic models of consumer behavior. This gap might be a shortcoming because if a customer indicates his or her activity status at some point in time *after* the last observed purchase, he or she must have been active at least up to that moment. Given the limited information about lifetime duration that SMC use (i.e., a distributional assumption with an estimation of the parameters of this distribution at the aggregate level), the incorporation of such information provides promise for improvements.

Therefore, the purpose of this paper is to extend SMC's Pareto/NBD model to account for lifetime activity cues (Section 2). To establish an intuitive understanding of potential effects of incorporating such information, Section 3 provides an illustrative example. Measures for conditional expected purchase and dropout rate are compared from three different perspectives: a pure NBD model, a pure Pareto model, and the extended Pareto/NBD model. Section 4 applies the proposed model to the cellular phone market and concentrates on the probability and classification of customers to still be active as the most important measures of the Pareto/NBD model. The study finds a substantial improvement of predictive accuracy and confirms the improvement with two independent holdout samples. Section 5 summarizes the findings and identifies areas for further research.

2. Model formulation

As mentioned previously, the Pareto/NBD model is one of the most prominent models for customer base analysis because the model helps managerial decision making with respect to the following issues:

- Which clients most likely represent active customers?
- Which clients are candidates for churn prevention measures?
- How many customers does the firm currently have?
- How has the customer base grown over the past years?
- What level of transactions should the firm expect in the future from those existing clients?

When discussing the proposed extension of the Pareto/NBD model, the paper focuses on the first issue, but the other issues benefit from this extension as well.

2.1. Incorporation of activity cues at the individual level

Appealing features of the Pareto/NBD model are the reasonable behavioral assumptions, the parsimonious parameterization, the limited requirements on per-customer data, and the broad empirical support (for an overview of the latter, see Hoppe & Wagner, 2010). The model arises from the following five assumptions (SMC justify these assumptions in detail):

Assumption 1. Customers' individual purchase incidents follow a Poisson process $X(t)$ with rate λ. Therefore, the probability to purchase x times within an interval of length t is

$$P(X(t) = x|\lambda) = \frac{(\lambda \cdot t)^x e^{-\lambda \cdot t}}{x!}. \tag{1}$$

Assumption 2. Each individual customer's lifetime τ follows an exponential distribution with rate μ. Therefore, the density function $f(\tau\,|\mu)$ is

$$f(\tau|\mu) = \mu \cdot e^{-\mu \cdot \tau}. \tag{2}$$

Assumption 3. The individual-level purchase rates λ are gamma distributed across customers with the shape parameter r and scale parameter α, with density function $f_\Gamma(\lambda\,|r,\alpha)$.

Assumption 4. The individual-level dropout rates μ are gamma distributed across customers with the shape parameter s and scale parameter β, with density function $f_\Gamma(\mu\,|s,\beta)$.

Assumption 5. Purchase process and lifetime process are independent of each other.

The assumption of constant individual-level purchase rates λ and dropout rates μ implies stationary conditions. The mixture of Poisson-distributed purchases with gamma heterogeneity yields the well-known NBD model. Compounding an exponential lifetime distribution with gamma heterogeneity results in a Pareto distribution of the second kind, and the combination of both processes constitutes the Pareto/NBD model. To apply this model, requirements are only minimal for customer-specific information: the number of purchases made so far x, the time of the last purchase t_x, and the time of reference T, that is, the time span in which the observation of the customer's buying behavior took place.

In non-contractual customer relationships, the lifetime τ of an individual customer is a latent trait and inference from the observed purchase incidents is necessary (see Fig. 1). Within the time frame from t_0 to t_x, purchases are recorded, and therefore the lifetime for this particular customer equals at least t_x. The Pareto/NBD model does not use any other information and infers whether the customer is still active at time T or has already quit the firm. Therefore, SMC introduced the notion of $P(Alive|Information)$ for this key measure. In other words, the Pareto/NBD model weights the odds of observing either

a) a lifetime of $\tau > T$ (e.g., τ_1 in Fig. 1) and an interpurchase time of at least T–t_x (because t_x is the time of the last purchase) or
b) a lifetime $\tau \leq T$ (e.g., τ_2 in Fig. 1) and an interpurchase time of at least τ–t_x.

Although prior research has found that extensions with covariates are useful for the NBD model (Abe, 2009; Gupta, 1991; Jen, Chou, & Allenby, 2003), the Pareto/NBD model does not account for any further information. However, an appealing feature of the Pareto/NBD model is allowing for the consideration of additional information on customer activity status when weighting probabilities. Let t_A denote the time of a customer's last observed *activity* (apart from *purchase incidents*). As Fig. 1 shows, a customer with a purchase history of (x, t_x, t_A, and T) has the following properties (if no activity cue on this customer after his or her last purchase has taken place, then $t_A = t_x$ and, consequently, no extension of the Pareto/NBD occurs):

(i) He or she purchased x times by time t_x, and therefore (see Assumption 1)

$$P_1 := P(X(t_x) = x\,|\lambda) = \frac{(\lambda \cdot t_x)^x e^{-\lambda \cdot t_x}}{x!} \tag{3}$$

(ii) He or she did not purchase between t_x and t_A, and therefore (see Assumption 1)

$$P_2 := P(X(t_A - t_x) = 0\,|\lambda) = e^{-\lambda \cdot (t_A - t_x)}. \tag{4}$$

(iii) He or she did not purchase after t_A and either (see Fig. 1)
- stopped doing business with the company between t_A and T, which results in (see Assumptions 1, 2, and 5; note that τ is unknown in this case)

$$P_3 := P(X(\tau - t_A) = 0,\ \ t_A \leq \tau \leq T\,|\lambda, \mu) = \int_{t_A}^{T} \left(e^{-\lambda \cdot (\tau - t_A)} \cdot \mu \cdot e^{-\mu \cdot \tau}\right) d\tau \tag{5}$$

- is still an active customer after time T, which results in (see

Download English Version:

https://daneshyari.com/en/article/1017846

Download Persian Version:

https://daneshyari.com/article/1017846

Daneshyari.com