Models for Customer Valuation

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This is a commented list of literature related to various aspects of customer valuation, which I found useful for my own understanding of concepts like customer-centricity, customer lifetime value (CLV), and stochastic models for predicting future customer activity.

1 General and managerial aspects of customer lifetime value

[1] Blattberg, Robert C., Byung-Do Kim, Scott A. Neslin. 2008. *Database Marketing: Analyzing and Managing Customers*. International Series in Quantitative Marketing, New York, NY : Springer. Chapters 5-7.

[2] Fader, P. 2013. *Customer Centricity: Focus on the Right Customers for Strategic Advantage*. Wharton Executive Essentials, Philadelphia.

[3] Gupta, S., D. Hanssens, B. Hardie, W. Kahn, V. Kumar, N. Lin, N. Ravishanker, S. Sriram. 2006. Modeling Customer Lifetime Value. *Journal of Service Research* **9**(2) 139.

[4] Jain, D., S.S. Singh. 2002. Customer Lifetime Value Research in Marketing: A Review and Future Directions. *Journal of Interactive Marketing* **16**(2) 34–46.

[5] Kumar, V. 2008. *Customer Lifetime Value: The Path to Profitability*. Foundations and trends in marketing, Now Publishers.

[6] Kumar, V., W. Reinartz. 2012. *Customer Relationship Management: Concept, Strategy, and Tools*. Springer Texts in Business and Economics, Springer. Chapters 5-6.

[7] Malthouse, Edward C. 2001. Assessing the performance of direct marketing scoring models. *Journal of Interactive Marketing* **15**(1) 49 – 62.

[8] Malthouse, Edward C., Robert C. Blattberg. 2005. Can we predict customer lifetime value? *Journal of Interactive Marketing* **19**(1) 2 – 16.

[9] Reinartz, W.J., V. Kumar. 2000. On the profitability of long-life customers in a noncontractual setting: An empirical investigation and implications for marketing. *Journal of Marketing* **64**(4) 17–35.

[10] Shah, D., R. Rust, A. Parasuraman, R. Staelin, G.S. Day. 2006. The Path to Customer Centricity. *Journal of Service Research* **9**(2) 113–124.

[11] Winer, Russell S. 2001. A framework for customer relationship management. *California Management Review* **43**(4) 89–105.

2 Overviews of stochastic models of buyer behavior

Here are some useful review articles featuring a specific class of probabilistic models of buyer behavior. For a given customer cohort acquired at time t_0, these models propose that (i) while active, each customer makes purchases according to the specific assumptions of a repeat-buying process and (ii) remains active for a ”lifetime duration", which follows the assumption of a dropout process (thus, ”buy-till-you-die" or BTYD). For each of these two process components, BTYD models allow for heterogeneity across customers, which is modeled using (typically independent) mixture distributions. For model estimation, BTYD require only condensed information of the complete customer purchase, which is compressed into a set of individual-level sufficient summary statistics (x, t_x, T): (1) the number of past transactions x (frequency), (2) the timing of the most recent transaction t_x (recency), and (3) the total observation time T since the customer was acquired.

[12] Fader, Peter S., Bruce G. S. Hardie, Subrata Sen. 2014. Stochastic models of buyer behavior. *The History of Marketing Science*, chap. 7. World Scientific Publishing Co. Pte. Ltd., 165–205.

[13] Fader, Peter S., Bruce G.S. Hardie. 2015. Simple probability models for computing CLV and CE. *Handbook of Research on Customer Equity in Marketing*. Edward Elgar Publishing, Inc., Cheltenham, UK.

[14] Fader, P.S., B.G.S. Hardie. 2009. Probability models for customer-base analysis. *Journal of Interactive Marketing* **23**(1) 61–69.

3 A selection of BTYD models

The most widely recognized benchmark BTYD model is the Pareto/NBD [22]. It assumes a Poisson purchase process and an exponentially distributed lifetime for the dropout process. The related parameters vary across customers following independent gamma distributions. The gamma-exponential mixture results in a Pareto distribution and the gamma-Poisson mixture leads to a negative binomial distribution (NBD), thus the model is referred to as Pareto/NBD.

Extensions of the Pareto/NBD model mostly modify the dropout process. For example, the Betageometric/NBD model (BG/NBD) adjusts the dropout story by restricting defection to repurchase incidents [18]. The MBG/NBD [15] and the CBG/NBD [20] modify this variant by allowing for an additional dropout opportunity immediately after the initial purchase. Other extensions include the periodic death opportunities (PDO) model, which decouples the discrete dropout opportunities from the purchase process [21]. The gamma-Gompertz/NBD model allows for a non-constant hazard rate in the dropout process [16]. The beta-geometric/beta-Bernoulli (BG/BB) model is a discrete-time analog of the Pareto/NBD [19].

[15] Batislam, E.P., M. Denizel, A. Filiztekin. 2007. Empirical validation and comparison of models for customer base analysis. *International Journal of Research in Marketing* **24**(3) 201–209.

[16] Bemmaor, Albert C, Nicolas Glady. 2012. Modeling purchasing behavior with sudden "death": A flexible customer lifetime model. *Management Science* **58**(5) 1012–1021.

[17] Dziurzynski, Lukasz, Edward Wadsworth, Daniel McCarthy. 2014. *BTYD: Implementing Buy 'Til You Die Models*. URL `http://CRAN.R-project.org/package=BTYD`. R package version 2.4.

[18] Fader, P.S., B.G.S. Hardie, K.L. Lee. 2005. Counting your customers the easy way: An alternative to the Pareto/NBD model. *Marketing Science* **24** 275–284.

[19] Fader, P.S., B.G.S. Hardie, J. Shang. 2010. Customer-base analysis in a discrete-time noncontractual setting. *Marketing Science* **29**(6) 1086–1108.

[20] Hoppe, D., U. Wagner. 2007. Customer base analysis: The case for a central variant of the Betageometric/NBD model. *Marketing - Journal of Research and Management* **3**(2) 75–90.

[21] Jerath, K., P.S. Fader, B.G.S. Hardie. 2011. New perspectives on customer "death" using a generalization of the Pareto/NBD model. *Marketing Science* **30**(5) 866–880.

[22] Schmittlein, D.C., D.G. Morrison, R. Colombo. 1987. Counting your customers: who are they and what will they do next? *Management Science* **33**(1) 1–24.

4 Extending BTYD models towards a CLV model

BTYD models typically focus on making individual-level predictions of the expected number of future transactions, which can easily be discounted to yield a net present value towards a fully faceted CLV model, which a sub-model for the purchase amount per transaction [25]. Extending BTYD models toward a fully faceted CLV model requires a sub-model for the purchase amount per transaction, for example by assuming a standard normal [26], a log-normal [23], or a gamma-gamma [24] sub-model for purchase amounts.

[23] Borle, Sharad, Siddharth S. Singh, Dipak C. Jain. 2008. Customer lifetime value measurement. *Management Science* **54**(1) 100–112,VI.

[24] Colombo, R., W. Jiang. 1999. A stochastic RFM model. *Journal of Interactive Marketing* **13**(3) 2–12.

[25] Fader, P.S., B.G.S. Hardie, K.L. Lee. 2005. RFM and CLV: Using iso-value curves for customer base analysis. *Journal of Marketing Research* **42**(4) 415–430.

[26] Schmittlein, D.C., R.A. Peterson. 1994. Customer base analysis: An industrial purchase process application. *Marketing Science* **13**(1) 41–67.

5 Further extensions and recent developments

Recent contributions to the literature on BTYD models include (but are not limited to) the following topics: (1) Incorporating time-invariant and/or time-variant covariates [27, 35]. (2) Bayesian estimation of the Pareto/NBD model parameters and variations [30, 27, 28]. (3) Allowing for more flexibility of the underlying interpurchase timing model [36, 29, 34]. (4) Incorporating non-stationary repurchase behavior in a broader class of hidden Markov models [33, 32]. (5) Studying the impact of ”clumpiness” and regularity in the timing process on the predictions of future activities [37, 31].

[27] Abe, Makoto. 2009. Counting your customers one by one: A hierarchical Bayes extension to the Pareto/NBD model. *Marketing Science* **28**(3) 541–553.

[28] Conoor, Sandeep S. 2010. Customer-base analysis in noncontractual settings. Ph.D. thesis, Northwestern University.

[29] Fader, P.S., B.G.S. Hardie, H. Chun-Yao. 2004. A dynamic changepoint model for new product sales forecasting. *Marketing Science* **23**(1) 50–65.

[30] Ma, S.-H., J.-L. Liu. 2007. The MCMC approach for solving the Pareto/NBD model and possible extensions. *Proc. Third Internat. Conf. Natural Computation (ICNC 2007)*, vol. 2. IEEE, 505–512.

[31] Platzer, Michael, Thomas Reutterer. 2015. Incorporating regularity in stochastic repeat-buying models. Working Paper at the Department of Marketing, WU Vienna.

[32] Schwartz, E.M., E.T. Bradlow, P.S. Fader. 2014. Model selection using database characteristics: Developing a classification tree for longitudinal incidence data. *Marketing Science* **33**(2) 188–205.

[33] Schweidel, D.A., E.T. Bradlow, P.S. Fader. 2011. Portfolio dynamics for customers of a multiservice provider. *Management Science* **57**(3) 471–486.

[34] Schweidel, D.A., P.S. Fader. 2009. Dynamic changepoints revisited: An evolving process model of new product sales. *International Journal of Research in Marketing* **26**(2) 119–124.

[35] Schweidel, D.A., G. Knox. 2013. Incorporating direct marketing activity into latent attrition models. *Marketing Science* **32**(3) 471–487.

[36] Wu, C., H.-L. Chen. 2000. A consumer purchasing model with learning and departure behaviour. *Journal of the Operational Research Society* **51**(5) 583–591.

[37] Zhang, Y., E.T. Bradlow, D.S. Small. 2015. Predicting customer value using clumpiness: From RFM to RFMC. *Marketing Science* **34**(2) 195–208.