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Social Networks
UNIVERSITY RESEARCH PRIORITY PROGRAM

Estimating Individual Customer Lifetime Values with R: The CLVTools Package

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1. Background

In general, customer lifetime value (CLV) describes the long-term economic value of customers and gives managers an idea of how customers evolved over time.

With **individual CLV** firms may...

- Identify future most valuable customer.
- Minimize Spending for unprofitable customer.
- Optimize and benchmark customer development.

Using **aggregated CLV** firms may...

- Evaluate relational marketing actions.
- Improve financial valuation of a firm (due diligence).

Non-contractual setting are most challenging

In contrast to contractual settings, where customer "announce" when they leave the company, in non-contractual settings customer churn is not observed.

Two different non-contractual settings have to be distinguished:

- **Discrete non-contractual:** Churning customers are not observed. Purchase occasions are limited to specific discrete events. Examples are movie theater, donations.
- **Continuous non-contractual:** Churning customers are not observed. The customer can freely choose when to purchase. Examples: Retailing, hotel industry.

Discrete Non-contractual

Continuous Non-contractual

2. Research Question

How to enable researchers and practitioners to estimate customer lifetime value in non-contractual settings?

Research Objective

Provide a universal **R** framework for probabilistic customer attrition model that is extendable and easy to use. The framework should feature the following model variations:

- time-invariant contextual factors
- time-varying contextual factors
- Correlation between purchase and attrition process

3. Latent Customer Attrition Models

Among the various approaches to assess CLV, probabilistic customer attrition models stand out due to their ability to **simultaneously forecast a customer's actual lifetime and future transactions** (Gupta and Zeithaml 2006). This is especially valuable in non-contractual settings, where customer attrition is not observed. Probabilistic customer attrition models build up not only on a strong tradition in marketing (Fader and Hardie 2009), but they **perform well in out of sample settings to predict CLV** in manifold business environments (Romero, van der Lans, and Wierenga 2013). Their real-world applicability has been shown for many non-contractual businesses e.g. medical supply firms, insurances (Schmittlein and Peterson 1994), high-tech B2B manufacturers (W. J. Reinartz and Kumar 2003) and retailers (Abe 2009; Fader, Hardie, and Lee 2005a; Platzer and Reutterer 2016).

Probabilistic modeling approaches in marketing use **stochastic processes to model observed customer behavior**. The modeler assumes that customers' behavior varies across the population according to a probability distribution:

- By using a negative binomial distribution (NBD) to model customers' purchase behavior, Ehrenberg (1959) was the first to start the long tradition of probabilistic models in marketing.
- In his model the "random" mean transaction rate of customers is characterized by a Poisson distribution. Variation of the mean transaction rate across customers, customer heterogeneity, is modeled by a Gamma distribution.
- The combination of both distributions results in a negative binomial distribution.
- The first probabilistic models focused on customers' purchase behavior only, but ignored customer attrition completely. With the Pareto/NBD model, (Schmittlein et al. 1987) are the first to propose a model that is capable of modeling customers' lifetime and transaction behavior simultaneously, which is today still seen as the "gold standard" of probabilistic customer attrition models.

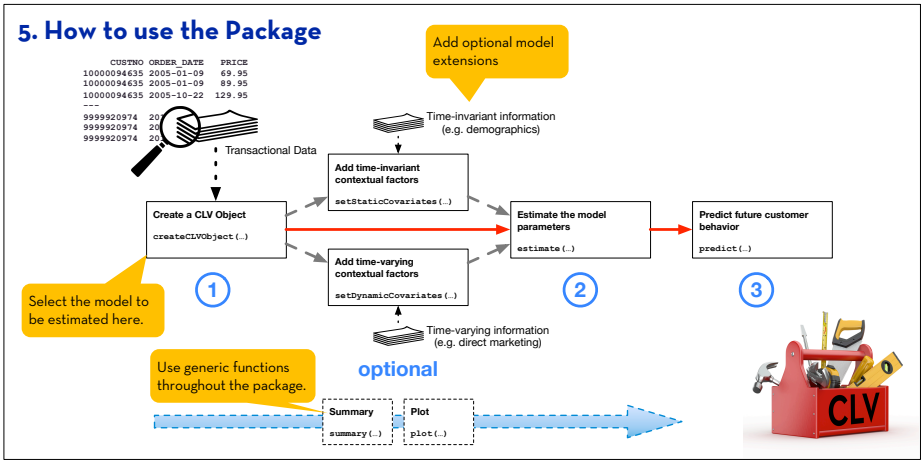
4. Many Model Variations Exist

To cope with the different settings and different customer characteristics **many different variations of probabilistic customer attrition models have been developed**. While the basic concept remains the similar, different underlying distributions are used to capture customer behavior. In addition, extensions to cope with contextual factors or relax model assumptions where added. For many models, an implementation exist, however a generalized framework unifying the power of the many variations is missing.

The proposed coding framework provides options for the following model variations:

- time-invariant contextual factors (Fader and Hardie 2007)
- time-varying contextual factors (Bachmann and Meierer 2019)
- Correlation between purchase and attrition process (Park and Fader 2004)

5. How to use the Package



6. Result

The `CLVTools` package is a **toolbox for various probabilistic customer attrition models**. It provides a framework which is easy to use but at the same time also easy to extend with further model and model features.

- Class-based (S4) framework that is easy to extend as...
  - the package provides base classes for all models and
  - model specific inherited class(es).
- Easy to use by implementing...
  - base methods for the generic functions (summary, plot, estimate, predict ...).
  - intuitive error handling and validity checks.
- Handler for the optimizer is provided (allows for restrictions & extensions).

	btyd	Btydplus	CLVTools
Usage of S4 classes and generic methods	no	no	yes
Option for time-invariant cont. factors	no	yes	yes
Option for time-varying cont. factors	no	no	yes
Optional Model Extensions	no	no	yes
Process correlation	no	no	yes
Regularization	no	no	yes
Equality constraints	no	no	yes
Available on CRAN	yes	yes	soon

7. Conclusion

With `CLVTools` we aim at providing a **comprehensive framework for probabilistic latent customer attrition models** that is easy to use for practitioners as well as researchers by providing a standard workflow independent of the model type. The package is based on a flexible class-based framework that is **easily extendable** in order to accommodate the large variety of probabilistic latent customer attrition models available. Additionally the package is **the first to provide advanced extensions for probabilistic customer attrition models such as option for time-varying contextual factors, correlation between the underlying processes, regularization and equality constraints**. The package is designed to handle large datasets and to take advantage of a multicore infrastructure.

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The Role of Time-Varying Contextual Factors in Latent Attrition Models for Customer Base Analysis

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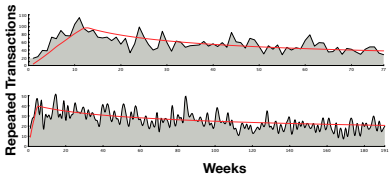
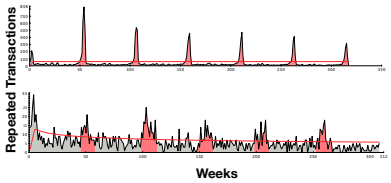
1. Background

Nowadays, **modeling customer purchases and attrition in non-contractual businesses is a straight-forward task**, but this simplicity comes at a price. Having access to recency and frequency data of customers' past transactions allows marketers to apply the Pareto/NBD model (Schmittlein, Morrison, and Colombo 1987). However, predictions are said to represent an educated guess rather than a precise value (Fader 2012; Malthouse 2009; Wübben and Wangenheim 2008).

- In general, prediction of transactions in non-contractual business settings works well.



- But purchasing patterns in some industries lead to less accurate predictions of the Pareto/NBD model:



2. Research Question

Efforts to improve the original Pareto/NBD model are manifold. However, **there exists no generalization that allows modeling time-varying contextual factors in a continuous non-contractual setting.**

Study	Setting	Time-invariant factors		Time-variant factors		Endogeneity Control	Maximum Likelihood	Gamma Heterogeneity	DERT/ DECT
	continuous	attrition	purchase	attrition	purchase				
Schmittlein, Morrison & Colombo (1987)	x						x	x	
Gupta (1991)	x				x		x	x	
Fader & Hardie (2007)	x	x	x				x	x	
Abe (2009)	x	x	x					x	
Singh, Borle & Jain (2009)	x	x	x						
Neslin & Rhoads (2009)	x	x	x						
van Oest &Knox (2012)	x						x	x	
Schweidel & Knox (2013)		x	x	x	x	x	x		
Knox & van Oest (2014)	x					x	x	x	
Braun & Schweidel & Stein (2015)	x	x		x			x	x	x
Platzer & Reutterer (2016)	x							x	
Gopalakrishnan, Bradlow & Fader (2017)	x	x	x	x	x				
Dew & Ansari (2018)				x	x				
McCarthy & Fader (2018)	x		x		x				
Xia, Chatterje & May (2019)	x		x	x					
This paper	x	x	x	x	x	x	x	x	x

3. Model & Contribution

In this paper, **we propose a latent attrition model that allows time-varying contextual factors to be modeled in continuous non-contractual settings**. Distinct to previous literature, we combine all following characteristics within the proposed approach:

(1) continuous nature of both, the purchase or attrition process

(2) possibility to include multiple time-varying and -invariant contextual factors which can separately influence both processes, only one or none,

(3) gamma heterogeneity for both processes,

(4) reduction to the standard Pareto-NBD model when estimated without any contextual factors,

(5) closed-form maximum-likelihood solution,

(6) derivation of managerial relevant expressions.

Relying on two simulation studies and the empirical analysis of three retailing datasets we assess the performance of the proposed approach and benchmark it against state-of-the-art Pareto- and Non-Pareto-type models. The results provide evidence about the inferential and predictive ability of our approach. In detail, we find:

(a) An **increased predictive accuracy** when including contextual factors,

(b) differences in the **increase of predictive accuracy depending on the scope of the modeled contextual factors**, i.e. individual level contextual factors increase predictive accuracy more than aggregated-level contextual factors,

(c) reliable **identification of the impact of exogenous factors** on both processes,

(d) reliable **identification of the impact of endogenous factors** on both processes when relying on (latent) IV approaches,

(e) a **key role of controlling for endogeneity to derive reliable parameter estimates**, but neglectable importance for predictive accuracy.

Managerial applications of a latent attrition model with such characteristics and performance are widespread: Combined with a Gamma/Gamma model (Colombo and Jiang 1999; Fader, Hardie, and Lee 2005), it enables academics and managers improves the identification of best future customers more accurately. In addition, the possibility to control for endogenous contextual factors allows to rigorously identify and quantify drivers of two important pillars of customer lifetime value (CLV), i.e. customers' purchases and attrition process.

4. Data: Three Retailing Datasets

- Multichannel retailer & Sporting goods retailer with **individual level** time-varying contextual factors
- Electronic retailer with **aggregate level** time-varying contextual factors

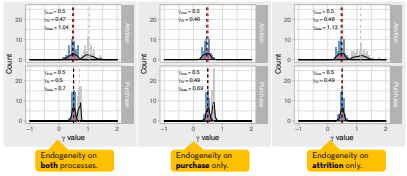
	Multichannel	Electronic	Sporting
Sample size (#cust.)	1'402	1'522	1'071
Time frame	7.7 years	6 years	6 years
Number of purchases	5'012	18'968	1'155
Zero repeaters	850	265	629
Estimation period	1 year	2 years	2 years
Cohort length	3 months	3 months	3 months
Time-varying cont. factors	D. Marketing Seasonal Pat.	Seasonal Pat.	D. Marketing (D. Marketing)[2] Seasonal Pat.
Time-invariant cont. factors	Acq. Channel	Gender Income	-

5. How to Handle Endogenous Contextual Factors?

Most of the contextual factors are non-random.
→ i.e. direct marketing decision are mostly based on a customer's purchase history.
We **propose the following methods to control for endogeneity**:

- 2-step IV approach for linear parameters for the endogenous variable
- Control function approach for non-linear parameters for the endogenous variable (Petrin and Train 2010)
- Copula correction method for discrete and binary endogenous variables or if IV is not available (Park and Gupta 2012)

The proposed model is able to recover endogenous contextual factors (here for the example of the 2-step IV approach):



6. Results

The presented results are from the multichannel retailer. Performance of the other two datasets is comparable.

We can quantify the determinants of customers' purchase and attrition process:

		Standard Pareto/NBD		Expended Pareto/NBD		
	LL-Value	-2'056		-2'020		
	BIC	4'083		3'967		
Pareto/NBD Parameters	r	1.134	*	1.610	*	Unobserved heterogeneity in transaction level is explained by contextual factors
	alpha	107.944	**	183.349	**	
	s	0.181	***	0.652	***	Unobserved heterogeneity in customer attrition is explained by contextual factors
	beta	0.373		10.374		
Contextual Factors	$gamma_{purc,k,1}$	-		0.441	***	Direct marketing on purchase level
	$gamma_{purc,k,2}$	-		0.729	***	Seasonality on purchase level
	$gamma_{purc,k,3}$	-		0.088		Channel on purchase level
	$gamma_{tlk,1}$	-		-4.428		Direct marketing on churn
	$gamma_{tlk,2}$	-		-4.404		Seasonality on churn
	$gamma_{tlk,3}$	-		1.330	***	Channel on churn

These parameters can be interpreted as the rate elasticity of the contextual factors.

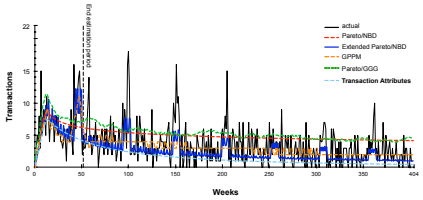
Better predictive performance on an individual level:

Prediction		Extended Pareto/NBD	Standard Pareto/NBD	Transaction Attribute	Pareto/GGG	GPPM
1 year	Individual MAE	0.263	0.306	0.326	0.301	0.346
	Aggregated MAE	2.229	2.840	2.864	3.130	1.668
2 years	Individual MAE	0.422	0.514	0.510	0.497	0.598
	Aggregated MAE	2.180	2.725	2.878	2.854	3.593
3 years	Individual MAE	0.538	0.681	0.638	0.650	0.820
	Aggregated MAE	2.013	2.635	2.655	2.692	3.936
4 years	Individual MAE	0.651	0.851	0.760	0.800	1.062
	Aggregated MAE	1.945	2.447	2.586	2.452	4.255
5 years	Individual MAE	0.757	1.025	0.871	0.950	1.347
	Aggregated MAE	1.895	2.389	2.509	2.316	4.255
6 years	Individual MAE	0.845	1.172	0.952	1.079	1.678
	Aggregated MAE	1.837	2.381	2.440	2.286	4.255
6.7 years	Individual MAE	0.904	1.277	1.022	1.171	1.951
	Aggregated MAE	1.779	2.364	2.357	2.238	4.255

Better identification the top customers:

		Extended Pareto/NBD	Standard Pareto/NBD	Transaction Attribute	Pareto/ GGG	GPPM
Best 10% Customers	High, correctly classified (%)	38.79	36.64	38.64	36.21	36.21
	Low, correctly classified (%)	87.86	87.44	87.44	87.35	87.35
	Overall correctly classified (%)	79.74	79.03	79.03	78.89	78.89
	Low but classified high (%)	12.13	12.56	12.56	12.65	12.65
	High but classified low(%)	61.21	63.36	63.36	63.79	63.79
	Overall incorrectly classified (%)	20.26	20.97	20.97	21.11	21.11
Best 20% Customers	High, correctly classified (%)	61.17	40.86	46.73	42.21	42.21
	Low, correctly classified (%)	82.06	71.53	74.66	73.20	73.31
	Overall correctly classified (%)	75.46	61.84	65.83	63.41	63.48
	Low but classified high (%)	17.94	28.47	25.33	26.80	26.69
	High but classified low(%)	38.83	59.14	53.27	57.79	57.79
	Overall incorrectly classified (%)	24.54	38.16	34.17	36.59	36.52

Better predictive performance on an aggregate level:



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