Customer Lifetime Value Modeling with Applications in Python and R

Lessons and experiences from industry and research on how to become a customer-centric organisation

Bart Baesens and Arno De Caigny

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by Bart Baesens and Arno De Caigny

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Cataloging data: customer lifetime value, customer relationship management, data science, analytics, machine learning.

Dedicated to Ann-Sophie Baesens, Victor Baesens, and Hannelore Baesens – Bart

Dedicated to Zosia Daniels – Arno

Contents

Preface

About This Book

Firms and organisations cannot exist without customers. They essentially constitute the key ingredient to make a firm profitable and add shareholder and societal value. Despite recent technological advances in both data storage as well as processing and analysis, many small to large-scale firms are still struggling to quantify customer value, optimise customer relationships, facilitate customer experiences and identify customer journeys.

Due to a nearly continuously expanding product portfolio, with new products and services being developed and marketed on an on-going basis, along a diversity of existing as well as innovative channels, modeling customer lifetime value is a far from simple exercise with many challenges and difficulties arising. More specifically, throughout our dealings with firms, we often found that simple questions such as ”Who is actually your customer?", "Who are your most valuable customers?", "What is the best way to acquire new customers"?, "Why do your customers leave you?", "What product/service should be offered to what customer?", "How can you sell more to your customers?", "How do you measure customer value?", often provoked intense (if not fierce) discussions with answers not always readily available and uniformly agreed upon by business practitioners across different departments. This book tries to answer exactly these questions using data-driven and analytical techniques and insights. More specifically, we try to provide a clear and to-the-point guide of how to define, quantify, model and deploy Customer Lifetime Value (CLV) models from various perspectives by first identifying and defining the key problems and then offering ways to tackle them using carefully selected data combined with state of the art analytics.

What Makes This Book Different?

This book is based on the unique complimentary experience of both authors having worked in (customer) analytics for more than 30 years combined, both in industry and academia. More specifically, both authors have co-authored more than 300 scientific publications and various books on the topics covered in this book and have worked with firms in different industries, including (online) retailers, financial institutions, manufacturing firms, insurance providers, NFP organisations, governments, etc. all over the globe estimating, validating, deploying, governing and monitoring analytical Customer Lifetime Value models.

The authors wrote this book with a very pragmatic focus in mind. In other words, the concepts, methods and techniques covered try to balance out a mix between sound and solid proven theories on the one hand and practical applicability on the other hand. Hence, we deliberately don't focus on overly complex techniques based on heavy mathematical underpinnings with limited to zero added business-value.

The book also comes with a web site *www.clvbook.com* which features various data sets and R/Python code to illustrate the techniques and approaches discussed. This will allow practitioners to efficiently and swiftly try out what they have learned in their own business areas.

Who This Book Is For?

This book is for anyone who is curious to know more about modeling Customer Lifetime Value or intrigued to make his/her organisation fully customer-centric. A first target audience consists of business practitioners across all industries where customers are considered a key asset. Example reader profiles are marketeers, customer/brand/channel/relationship managers, marketing and data scientists. Also consultants may find our book useful to help their clients in their CLV efforts. C-level executives (e.g., Chief Executive Officers, Chief

Marketing Officers, Chief Analytics Officers, Chief Data Officers) as well as tactical and operational levels may benefit from reading this book to be more closely aligned with the data scientists, marketing modelers and analysts directly working on modeling CLV.

Secondly, the book can also used as a handbook by academics teaching courses on the topic, both undergraduate as well as postgraduate. It features various handy add-ons such as multiple choice questions at the end of each chapter, worked out case studies in Python and R, references to background literature and links to ON-LINE courses which can help facilitate the learning experience.

For those who are just starting to find their way around in analytics, we are convinced that this book can be an important guide to help you use it for CLV modeling, but would advice to first briefly refresh your knowledge on descriptive statistics (e.g., mean, standard deviation, confidence intervals, hypothesis testing) so as to maximize your reading experience.

Structure Of The Book

The book starts by providing a basic introduction to CLV modeling where the key concepts are defined and illustrated with some examples. In Chapter 2, we review and refresh various supervised and unsupervised analytical techniques that will be used extensively in later chapters. Chapter 3 discusses the well-known Recency, Frequency and Monetary (RFM) framework as the layman's approach to CLV analysis. The RFM features introduced will be used extensively in later chapters as predictors for various CLV related modeling exercises. Chapter 4 elaborates on customer acquisition by zooming in on look-alike modeling and prospect- and lead conversion modeling. Chapter 5 builds further upon these ideas by reviewing how to set up smart marketing campaigns so as to maximize their response rates and turn leads into customers. Chapter 6 learns how to prevent your customers from churning or leaving your firm. Markov chains are covered in chapter 7 as an interesting tool to see how customers migrate between their different CLV states. Chapter 8 discusses customer journey analysis to better understand how your customers interact with your firm and by means of what channels and/or touchpoints. Chapter 9 elaborates on probabilistic models such as the Pareto/NBD submodel to predict the future number of transactions of a customer and the Gamma/Gamma submodel to estimate the average profit or monetary value per transaction, both essential elements to estimate the CLV. Chapter 10 discusses market segmentation by reviewing both customer heterogeneity and profiling. Recommender systems are extensively reviewed in chapter 11. The book concludes with chapter 12 by covering the deployment, governance and monitoring of CLV models.

We recommend going through the book from start to finish if this is your first reading, and refer back to specific sections later on to get a refresher on specific contents. Since we believe the topic of CLV modeling to be intricate enough already, we have deliberately kept its structure simple and to the point: every chapter is organized in a series of sections with subsections only sparingly being used. We don't overcomplicate the book with lots of (complex) formulas, call-out boxes, etc. We do, however, provide plenty of references which should offer lots of further info and extra reading material to those looking to expand their knowledge.

Additional Learning Material

As already mentioned, the book comes with the following website: *www.CLVbook.com* which features various case studies in Python and R to complement the textual material. Each chapter concludes with a set of multiple choice questions to assist and verify the reader's assimilation of the material. Extensive referencing to background literature is provided to help those readers who are interested in finding out more about a specific topic discussed. The bibliography features more than 150 citations.

Furthermore, as another interesting add-on to the learning experience, we are happy to refer to our following BlueCourses courses (*www.bluecourses.com*):

- Customer Lifetime Value Modeling
- Recommender Systems
- Machine Learning Essentials

- Deep Learning
- Text Analytics

Each of the above courses features several hours of pre-recorded videos, Python/R examples, real-life case studies, multiple choice questions, and various references to background literature. The courses can also be taught on-site if interested (please send us an e-mail in case).

Front Cover

The front cover was shot at Bar Louis *https://www.barlouis.be/* where the idea of the book originated. Bar Louis is a very cozy, trendy bar in the heart of Leuven (Belgium) serving an excellent food and drinks menu run by a passionate and inspiring lady of the house, miss Katelijne Vandenbroeck, whom we are very thankful for this opportunity. Bart is having a Tripel Karmeliet and Arno an Omer, both their favourite (Belgian!) beers. Looking forward to seeing you there!

About The Authors

Professor Bart Baesens is a professor of Big Data & Analytics at KU Leuven (Belgium), and a lecturer at the University of Southampton (United Kingdom). He has done extensive research on big data & analytics, credit risk modeling, fraud detection, and marketing analytics. He co-authored more than 300 scientific papers and ten books. Bart received the OR Society's Goodeve medal for best JORS paper in 2016 and the EURO 2014 and EURO 2017 award for best EJOR paper. His research is summarized at *dataminingapps.com*. He also regularly tutors, advises and provides consulting support to international firms with respect to their analytics and credit risk management strategy. Bart is listed in Stanford University's new Database of Top Scientists in the World. He was also named one of the World's top educators in Data Science by CDO magazine in 2021. He is also co-founder of BlueCourses (*www.bluecourses.com*), an online training platform providing courses on Machine Learning, Fraud Analytics, Credit Risk Modeling, Deep Learning, etc.

Professor Arno De Caigny is professor of business analytics at the triple crown accredited IÉSEG School of Management, Catholic university of Lille and member of the research laboratory LEM (UMR CNRS 9221). Before starting his academic career, he worked as an analytical consultant for Deloitte. His research focuses on improving decision-making in companies through the use of data and quantitative methods. He has vast experience in applying machine learning to solve challenges in the broad marketing domain. He has led numerous projects in various industries, such as financial services, retailing, software, that required customer lifetime value modeling to solve business problems. He has published in internationally renowned and peer-reviewed journals such as European Journal of Operational Research, Decision Support Systems, International Journal of Forecasting and Industrial Marketing Management. He also developed a custom machine learning algorithm that is both comprehensible and accurate, to improve customer retention decision making. This work is one of the top 10 most cited papers in European Journal of Operational Research since 2018.

We hope you enjoy reading through this book as much as we enjoyed writing it. We're always happy to hear feedback and remarks from our readers and can be contacted by email at *Bart.Baesens@kuleuven.be* and *A.De-Caigny@ieseg.fr*.

Chapter 1

Introduction to Customer Lifetime Value

Overview

In this chapter, we set the stage for the remainder of the book. We first relate customer value to firm value and define the customer lifetime value (CLV). We then extensively zoom in on the various revenue and cost components of the CLV. A next section elaborates on customer equity and its relation to CLV. This is followed by reviewing some CLV modeling examples taken from the industry. We discuss various marketing actions that can be undertaken to optimize the CLV. Finally, the chapter concludes by discussing various approaches to model CLV.

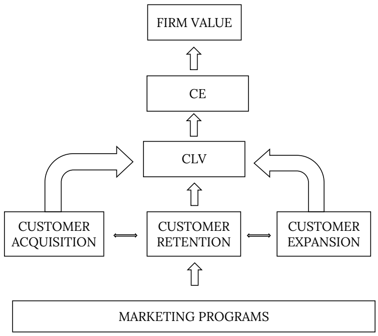

Figure 1.1: Customer value versus firm value.

Setting The Stage

Milton Friedman introduced the age of shareholder primacy, which basically implied that a key reason that companies exist is to maximize shareholder value [1]. This can be done by carefully managing a firm's key assets which are, amongst others, its infrastructure, buildings and equipment, its inventory, its know-how, its employees and its customers. Unfortunately, nowadays, too many companies focus on their physical and financial assets thereby under-prioritizing two of their other key assets: their customers and employees! In this book, we focus on the customers, and how to appropriately value them across their entire lifetime and relationship with the firm.

In their 2006 Journal of Service Research paper, Gupta et al

[1] *https://www.nytimes.com/1970/09/13/archives/a-friedman-doctrine-the-social-responsibility-of-business-is-to.html*

[71] already outlined the relationship between customer value and firm or shareholder value as you can see visualized in Figure 1.1. Marketing programs are typically being setup for customer acquisition, customer retention and customer expansion or deepening of customer relationships. All these directly impact the customer lifetime and as such the customer equity of the firm, which in turn influences firm or shareholder value. Put differently, to maximize firm value firms should invest in their number one asset: their customers!

To further reinforce this statement, the term customer capitalism was put forward by Roger Martin in 2010, then dean of the University of Toronto's Rotman School of Management [113]. The concept primarily boils down to putting your customers first. Too much short term profit and quarterly earnings pressure have a damaging effect on customer relationships and value. Think about cutting back on customer service and experience, minimizing customer call handling times, imposing unjustified and unnecessary customer fees and compromising product quality as examples. This is being further exacerbated by the fact that most modern day accounting standards (e.g., IFRS 9) and reporting rules do not include customer value at all. Luckily, some CEOs are starting to realize and successfully manage the connection between customer and firm value. Popular examples are: Amazon's Jeff Bezos, Costco's Jim Sinegal, and Vanguard's Jack Brennan. As Bezos puts it, customer focus is simply not enough, you have to be customer obsessed.

> "The No 1 Thing that has made us successful by far

> is obsessive compulsive focus on the customer." (Jeff Bezos, CEO Amazon)

Vanguard was an early adopter of the Net Promotor Score (NPS) which essentially captures the response to the question [2]: "How likely are you to recommend a product or service to a friend or colleague?". The question is answered on a scale from 0 to 10 where scores above 9 correspond to promotors with high customer value in terms of generating more sales and positive word-of-mouth whereas scores below 6 represent detractors or customers with low value and at risk of leaving the firm (also called churning). The NPS metric is now used by various firms world-wide to measure and manage customer relationships and value.

Using modern data-driven capabilities, customer health scores nowadays extend traditional NPS scores. NPS scores are still a vital part of customer health, but customer health scores also capture product usage information, elements of cross-functional touch points such as billing or support, and even external review data [78]. Hence, customer health scores promise to serve as a lead indicator to gain a better sense of the customers' engagement. Firms start to sense the importance of their customer base as a source of value and invest in nurturing the relationship with their customers. New roles that focus on the customer, such as customer success managers are popping up. These customer success managers are customer facing, indirect sales roles that have as a primary objective to

[2] *https://netpromoterscore.guru/vanguard-research-com*

engage customers to ensure value outcomes and ongoing successful use of the product [79]. Hence, they fulfill a crucial role in maximizing the long term value of the customer base.

To further illustrate some of our previous points we included three quotes from a recent Harvard Business Review contribution by Rob Markey [111].

> "It would be irresponsible for any leader to ignore customer value as a proven source of profitable growth."

> "Loyalty leaders grow revenues roughly 2.5 times as fast as their industry peers and deliver two to five times the shareholder returns over the next 10 years."

Definition

Customer Lifetime Value (CLV), often also referred to as LifeTime Value (LTV), was defined by Malthouse and Blattberg in 2005 as the present value of the expected benefits less the costs of initialising, maintaining and developing the customer relationship [109]. It can be calculated as:

$$CLV = \sum_{t=1}^{T} \frac{(R_t - C_t)s_t}{(1+d)^t} \tag{1.1}$$

The key elements are:

- the costs at time t: C_t
- the revenue at time t: R_t
- the probability customer is still alive at time t: s_t
- the discount rate (d)
- the time horizon (T)

Month t	**Revenue** R_t	**Cost** C_t	**Survival probability** (s_t)	$(R_t - C_t)s_t/(1+d)^t$
1	150	5	0,94	135,22
2	100	10	0,92	81,50
3	120	5	0,88	98,82
4	100	0	0,84	81,37
5	130	10	0,82	94,57
6	140	5	0,74	95,25
7	80	15	0,7	43,04
8	100	10	0,68	57,43
9	120	10	0,66	67,59
10	90	20	0,6	38,79
11	100	0	0,55	50,40
12	130	10	0,5	54,55
			CLV	**898,53**

Table 1.1: Calculating CLV.

In Table 1.1, you can see an example calculation of the CLV. We calculated the CLV for a 12 month time period taking the weighted average cost of capital or WACC as the discount factor. Note that the yearly WACC was set at 10% which corresponds to a monthly WACC of 1%.

Key Parameters

Let's elaborate on each of the CLV key parameters into some more detail. First the time horizon, T. Theoretically, this should be infinity. Unfortunately, this is practically infeasible since it's simply impossible to predict that far in the future. Based on our business experience, we would suggest to set it to three or five years at maximum.

Next, we have the discount rate d. Theoretically, we don't know this one yet as we would have to wait until T. A difference also needs to be made between the monthly versus yearly discount rate. Remember the relationship $(1 + d) = (1 + m)^{12}$ with d the yearly discount rate and m the monthly discount rate. It is typically chosen according to the company's policy. A first and commonly used option is the Weighted Average Cost of Capital or WACC which is the rate that a company pays to all its security holders (e.g., shareholders and debt) to finance its assets. We have also seen some firms using the inflation as the discount rate. In case the short-term relationship is considered important, a high discount rate is chosen, such as 15% annually. In case a long-term relationship is considered important, a low discount rate is chosen, such as 5% annually. A higher discount rate typically implies a lower CLV since future cash flows are less worth now. Hence, it is recommended to be conservative when setting the discount factor.

The revenues, R_t, and costs, C_t, should incorporate both direct and indirect revenues and costs, if possible. Direct revenues are the revenues of directly interacting with the customer such as a product or service purchase. Examples of indirect revenues are word-of-mouth effects (assuming these are positive) or positive reviews posted by the customer on-line.

Direct costs are the costs to serve a particular customer such as the costs that occur when selling a particular product or service to a customer (e.g., product costs, PayPal costs, delivery costs, etc). Indirect costs are the costs that relate to the various supporting activities as provided by business units such as customer service, IT, etc. Obviously, indirect revenues and costs are a lot harder to quantify that direct costs and revenues that's why we see many firms ignoring those in their CLV calculations. Do note that since R_t and C_t are measured for future timestamps, they need to be estimated themselves and as such can be the result of predictive analytical models.

Finally, we have the survival probability s_t. Remember, this represents the probability the customer is still alive at time t. Also this parameter varies in time depending upon how the customer relationship evolves. It is typically also estimated using survival analysis models [29, 92].

Customer Equity

We already briefly mentioned the term customer equity. First of all, this term has nothing to do with equity in the traditional sense of the word meaning 'ownership'. Essentially, customer equity can be defined as the sum of the customer lifetime values of all customers of the firm,

$$\text{Customer Equity} = \sum_{i=1}^{n} CLV_i, \tag{1.2}$$

with n the number of customers.

When calculating customer equity, one commonly aggregates the CLV across all customers, all products, all channels, etc. Doing this will also allow to spot opportunities such as which customer, product or channel has higher CLV potential which can then be materialized by setting up the right marketing campaigns targeted at the right customer, product or channel.

Customer equity is sometimes also approached from three perspectives: value equity, which represents the customer's evaluation of the value of the product or service (e.g., what do I think about the newest Apple iPhone), brand equity which represents the customer's evaluation of the brand (e.g., how do I perceive Apple as a brand?) and retention equity, which represents the customer's probability to stay with the brand even when it's expensive (e.g., how likely am I to leave from Apple to Samsung?).

Popular examples of firms that have high customer equity are McDonalds, Apple and Facebook. Customers of these firms typically perceive their products to be of high value (value equity), choose the brand for a particular reason (brand equity) and are likely to stay with them and develop a long-lasting sustainable relationship (retention equity).

Customer equity essentially measures how much the firm is worth at a particular point in time as a result of the firm's customer management efforts. As mentioned earlier, it is however directly related to the shareholder value of the firm since a high customer equity value is directly related to a higher profit and hence higher stock prices and/or dividends.

Industry Adoption

By means of CLV modeling, The Royal Bank of Canada (RBC) identified that medical students were high CLV customers[3], evaluated over long periods of time. The bank therefore implemented a program to satisfy their needs early in their careers, as well as during the progression of their careers, with products such as credit cards, help with student loans, and loans to set up new practices. In the first year, RBC's market share in this segment boosted from 2 percent to 18 percent, and average sales were nearly four times higher than those to an average customer. The loyalty of these customers also was very high, which reduces the risk of churn. In summary, this segment represents very high CLV customers, and the firm's targeted acquisition, onboarding, and expansion strategies allowed it to manage those valuable customers as they migrated from being students, to setting up their medical practices, to achieving professional success.

According to research by CounterPoint, a global industry analysis firm headquartered in Asia, an Apple power iPhone user can generate a CLV of about US$2,400 over a period of 30 months by subscribing to its continuously evolving portfolio of

[3]*https://foster.uw.edu/wp-content/uploads/2017/03/MarketingStrategyChapter03-2.4.pptx*

services [4]. In fact, research has indicated that CLV increases about two to three times when a company switches to a subscription model [5]. As an example Amazon prime customers who usually get free shipping and ad-free music streaming (see *https://www.amazon.com/gp/prime*) spend significantly more than non-prime customers. Similar multiples apply with other subscription based providers such as Netflix.

Though CLV should be a key instrument to any marketeer to manage customer relationships, a 2018 report by Criteo[6], an on-line advertising company, examined the state of CLV adoption in UK marketing programs by surveying 100 marketers and 2,023 consumers across the UK. Rather astonishingly, it was found that only over a third (34%) were completely aware of the term and its connotations. Based on our recent dealings with firms, we fear that not much has changed since then.

Marketing Actions To Optimize CLV

Various marketing actions can be undertaken to optimize (i.e., increase or maintain) the CLV. A first example is a customer retention campaign which focuses on keeping possibly dissatisfied customers. As an example, consider a customer contacting

[4] *https://www.counterpointresearch.com/apple-iphone-apple-watch-price-drop-strategic-masterstrok*

[5] *https://www.forbes.com/sites/forbesfinancecouncil/2021/02/22/the-secret-to-long-term-consumer-tech-success-subscription-pricing/?sh=3f9c0f0b5883*

[6] *https://www.criteo.com/wp-content/uploads/2018/03/Criteo-UK-Commerce-Marketing-Forum.pdf*

your service desk to file a complain about your products or service (e.g., expensive roaming tariffs or bad coverage for a Telco provider). This is a customer which is clearly at risk of leaving your firm (also called customer churning, customer defection, customer attrition), hence it may make sense to give him/her a coupon, a free upgrade or some other compensation. Past research has shown that the average customer is actually quite forgiving in the sense that if (s)he feels the dissatisfaction is heard and acted upon by the firm, (s)he will not leave and stay with the firm. We will come back to this more extensively in the chapter on churn prediction.

Another option is further deepening customer relationships by selling additional products or services to your existing customer portfolio using X-selling. The aim here is to change the intended purchase behavior of a customer using patterns learned from data. This can be done in three possible ways: up-selling, cross-selling or down-selling. The idea of up-selling is to sell more of a given product, usually at the time of purchase. An example of this is if you order a lager beer (e.g., Stella Artois) and the waiter recommends an upscale, more expensive beer instead (e.g., a specialty Trappist beer such as Westmalle). Cross-selling aims at selling an additional product or service. For example, the waiter might also recommend some abbey cheese as it pairs well with a Westmalle. Finally, down-selling means selling less of a product or service in order to maintain a sustainable, long-lasting customer relationship. For example, if you had too many beers and order yet another one, the waiter might discourage you from doing so and recommend water instead. From a business perspective, it is important to understand which products are often purchased together, so as to make good recommendations. In fact, building good recommender systems is a research topic on its own with Netflix and Amazon being prominent examples spearheading this technology.

Customer acquisition aims at expanding your customer base by acquiring new customers. This can be done by setting up well-targeted marketing campaigns either off-line or on-line. Popular examples of off-line campaigns are sending out flyers, brochures, order catalogs or billboard advertising. Examples of on-line campaigns are banners (often served by Ad networks such as Google Adsense), e-mails (preferably solicited instead of SPAM), search engine marketing, and social media marketing (on e.g. Facebook, YouTube, Twitter, Instagram, etc).

Simplifying customer experiences is another interesting strategy to contemplate. Far too often, we have witnessed that the customer onboarding processes adopted by many (on-line or off-line) firms nowadays are too complex or red tapey which may create an adverse effect and turn a prospect into a non-interested party. One-click simple buying processes requiring only the strict minimum of information needed to complete the purchase are a highly recommended customer practice. Closely related to this is the payment processes adopted by firms. Far too often, to avoid fraud from happening, these processes involve various steps of authentication with the risk of losing customers during the cumbersome process (requiring sometimes even different hardware devices to confirm your identity). It is however always recommended to properly and accurately offset the complexity of the payment process and the risk of losing customers against the risk of fraud with a simple payment process but less customers lost along the way.

Customer journey analysis is another key marketing tool that could come in handy to optimize your CLV. It basically illustrates the various activities, states or touchpoints and transactions that a customer can be in when buying a mortgage. Customer journey analysis can be used to get a clear and comprehensive picture of the overall process and highlight process deficiencies such as excessive processing times, deadlock situations, circular references, and unwanted customer leakage (due to incorrect web links, for example), among others. We discuss more about customer journey analysis in Chapter 8.

Nowadays customers may provide feedback about your products or services along various social media channels such as Twitter, Facebook, Instagram, etc. Continuously monitoring these streams using social media analytics tools can provide very useful insights into customer (dis)satisfaction which undoubtedly also affect your CLV. Note that this is also often referred to as social listening and can also highly contributed to creating customer intimacy as we discuss below. In fact, one pharmaceutical company we worked with, was doing this to monitor the side effects of the drugs it was selling on social media so as to get a holistic picture on its product usage.

Finally, creating customer intimacy is another option. However, this is at the same time the most challenging strategy to pursue as it highly depends upon a customer's characteristics or behavior. The goal is to be intrusive but in a subtle and well-considered way so as to not create an unwanted disturbing experience to the customer. In fact, some customers (like us for example) don't like to be disturbed at all by their phone companies, utility providers, financial institutions etc. Other ones like to stay continuously updated about new deals and offerings such that they can rest assured they always have the best personalized deal. Distinguishing both groups of customers and serving them according to their needs is a key challenge to pursue customer intimacy. Developing highly personalized relationships with customers is a key building block towards customer intimacy.

Approaches To Model CLV

Various approaches can be adopted to model CLV. A first one is by creating a data set using historically observed CLV values for a representative group of customers as shown in Table 1.2. This data set can then be analysed using classical predictive analytical techniques such as linear regression, regression trees (e.g., CART) and/or (deep learning) neural networks. The performance of these can then be appropriately measured using, e.g., mean squared error (MSE), mean absolute deviation (MAD) or the Pearson correlation (our preferred method!) on an independent hold-out test set hereby assuring no data leakage.

Name	Age	Marital Status	Income	...	CLV
Bart	65	Married	25,000		2,500
Arno	49	Married	40,000		3,800
An	53	Single	60,000		5,000
Laura	50	Married	80,000		6,000
Sophie	44	Married	50,000		4,500
Victor	28	Single	30,000		2,800
...					

Table 1.2: Example data set for CLV modeling.

However, note that perfectly quantifying the CLV is by no means a trivial exercise. No firm in the world will be capable to perfectly quantify all numbers (R_t, C_t, d, T, s_t) provided in the reference formula. Hence, many firms will resort to approximative approaches by for example:

- focusing on very short time horizons, e.g., up to 1 year
- calculating CLV on a product basis, e.g., at the level of an individual checking account
- only considering direct revenues and costs and ignoring indirect costs and benefits which are hard to quantify anyway
- ignoring the discounting factor
- working with average benefit and/or cost values instead of precise values
- defining CLV segments instead of precise CLV values (e.g., Platinum, Gold, Silver, Bronze)
- decomposing CLV in some of its core elements such as customer retention, customer acquisition, and customer journey analysis

All these approximations should not be seen as a showstopper. In fact, in the majority of cases firms can do perfectly well with an ordinal ranking of their customers in terms of CLV instead of a well-calibrated CLV. More specifically, being able to rank your customers from high value to low value can already be very useful for deciding who to target with your marketing campaigns.

Closing Thoughts

In this chapter, we introduced the definition of CLV and discussed its various component. By now it should be clear that accurately quantifying CLV is not an easy exercise. Hence, in the following chapters, we gradually discuss all elements that constitute CLV modeling. We start with a refresher of basic analytical tools that are prerequisite to understand the more advanced chapters. Next, we cover topics that allow to grow the customer base by acquiring new customers, increase the value of the existing customer base through customer development techniques and retain more customers through customer retention modeling. After reading this book, you will be ready to put all this learning into practice.

Application In Python/R

The software example on *www.CLVbook.com* provides a simple illustration of the calculation of CLV. We advise the reader to try it out and then do some sensitivity analysis by playing with the revenues, costs, survival probabilities, discount factor and time horizon and evaluate the impact on the CLV.

Quiz

Question 1

Milton Friedman introduced the age of shareholder primacy, which basically implied that a key reason that companies exist is to

(a) maximize shareholder value.

(b) maximize customer value.

Question 2

To maximize firm value firms should invest in their number one asset:

(a) their infrastructure and equipment.

(b) their customers.

(c) their inventory.

(d) their know-how.

Question 3

Most modern day accounting standards and reporting rules

(a) do include customer value.

(b) do not include customer value.

Question 4

When calculating CLV, many firms set the time horizon T to

(a) 1 year.

(b) 3-5 years.

(c) 10 years.

(d) infinity.

Question 5

In case the short-term relationship is considered important when calculating CLV, it is recommended to set

(a) a low discount factor.

(b) a high discount factor.

Question 6

Which statement is CORRECT?

(a) Customer equity can be defined as the sum of the customer lifetime values.

(b) Customer lifetime value can be defined as the sum of the customer equity.

Question 7

Which actions can be undertaken to increase the CLV?

(a) retaining existing customers.

(b) deepening customer relationships.

(c) acquiring new customers.

(d) simplifying customer experiences.

(e) customer intimacy.

(f) all of the above.

Bibliography

[1] Hossein Abbasimehr, Setak Mostafa, and Javad Soroor. "A framework for identification of high-value customers by including social network based variables for churn prediction using neuro-fuzzy techniques." In: *International Journal of Production Research* 51 (Jan. 2012). DOI: *10.1080/00207543.2012.707342*.

[2] Rakesh Agrawal, Tomasz Imielinski, and Arun Swami. "Mining Association Rules Between Sets of Items in Large Databases, SIGMOD Conference." In: vol. 22. June 1993, pp. 207–. DOI: *10.1145/170036.170072*.

[3] Juliana Alvarez et al. "An Enriched Customer Journey Map: How to Construct and Visualize a Global Portrait of Both Lived and Perceived Users' Experiences?" In: *Designs* 4 (Aug. 2020), p. 29. DOI: *10.3390/designs*4030029.

[4] Eva Ascarza, Raghuram Iyengar, and Martin Schleicher. "The Perils of Proactive Churn Prevention Using Plan Recommendations: Evidence from a Field Experiment."

In: *Journal of Marketing Research* 53.1 (2016), pp. 46–60. DOI: 10.1509/jmr.13.0483.

[5] Adriano Augusto et al. "Automated Discovery of Process Models from Event Logs: Review and Benchmark." In: *IEEE Transactions on Knowledge and Data Engineering* PP (May 2017). DOI: 10.1109/TKDE.2018.2841877.

[6] Aimée Backiel, Bart Baesens, and Gerda Claeskens. "Predicting time-to-chum of prepaid mobile telephone customers using social network analysis." In: *Journal of the Operational Research Society* 67 (Mar. 2016). DOI: 10.1057/jors.2016.8.

[7] Bart Baesens, Daniel Rösch, and Harald Scheule. *Credit Risk Analytics: Measurement Techniques, Applications, and Examples in* SAS. Oct. 2016. ISBN: 978-1119143987. DOI: 10.13140/RG.2.2.14675.17447.

[8] Bart Baesens, Véronique Van Vlasselaer, and Wouter Verbeke. *Fraud Analytics Using Descriptive, Predictive, and Social Network Techniques: A Guide to Data Science for Fraud Detection.* Aug. 2015. ISBN: 9781119133124. DOI: 10.1002/9781119146841.

[9] Bart Baesens et al. "Bayesian neural network for repeat purchase modelling in direct marketing." In: *European Journal of Operational Research* 138 (Apr. 2002), pp. 191–211. DOI: 10.1016/S0377-2217(01)00129-1.

[10] Bart Baesens et al. "Benchmarking state-of-the-art classification algorithms for credit scoring." In: *Journal*

of the Operational Research Society 54 (June 2003). DOI: *10.1057/palgrave.jors.2601545*.

[11] Bart Baesens et al. “Using Neural Network Rule Extraction and Decision Tables for Credit-Risk Evaluation.” In: *Management Science* 49 (Mar. 2003), pp. 312–329. DOI: *10.1287/mnsc.49.3.312.12739*.

[12] P.V.(Sundar) Balakrishnan et al. “Comparative performance of the FSCL neural net and K-means algorithm for market segmentation.” In: *European Journal of Operational Research* 93.2 (1996). Neural Networks and Operations Research/Management Science, pp. 346–357. ISSN: 0377-2217. DOI: *https://doi.org/10.1016/0377-2217(96)00046-X*.

[13] Oren Barkan and Noam Koenigstein. “ITEM2VEC: Neural item embedding for collaborative filtering.” In: Sept. 2016, pp. 1–6. DOI: *10.1109/MLSP.2016.7738886*.

[14] Gaël Bernard and Periklis Andritsos. “A Process Mining Based Model for Customer Journey Mapping.” In: *International Conference on Advanced Information Systems Engineering*. June 2017.

[15] Gaël Bernard and Periklis Andritsos. “Discovering Customer Journeys from Evidence: A Genetic Approach Inspired by Process Mining.” In: May 2019, pp. 36–47. ISBN: 978-3-030-21296-4. DOI: *10.1007/978-3-030-21297-1_4*.

[16] Derrick S. Boone and Michelle Roehm. “Retail segmentation using artificial neural networks.” In: *International*

Journal of Research in Marketing 19.3 (2002). Market Segmentation, pp. 287–301. ISSN: 0167-8116. DOI: *https://doi.org/10.1016/S0167-8116(02)00080-0*.

[17] George Box. "Science and statistics." In: *Journal of the American Statistical Association* 71.356 (1976), pp. 312–329.

[18] Leo Breiman. "Bagging Predictors." In: *Machine Learning* 24 (Aug. 1996), pp. 123–140. DOI: *10.1007/BF00058655*.

[19] Leo Breiman. "Random Forests." In: *Machine Learning* 45 (Jan. 2001), pp. 5–32. DOI: *10.1023/A:1018054314350*.

[20] Seppe vanden Broucke and Bart Baesens. *Practical Web Scraping for Data Science*. Jan. 2018. ISBN: 978-1-4842-3581-2. DOI: *10.1007/978-1-4842-3582-9*.

[21] Seppe vanden Broucke and Jochen Weerdt. "Fodina: A robust and flexible heuristic process discovery technique." In: *Decision Support Systems* 100 (Apr. 2017). DOI: *10.1016/j.dss.2017.04.005*.

[22] Joos C. A. M. Buijs, Rick F. M. Bergmans, and Rachied El Hasnaoui. "Customer journey analysis at a financial services provider using self service and data hub concepts." In: *BPM*. 2019.

[23] Tadeusz Caliński and Harabasz JA. "A Dendrite Method for Cluster Analysis." In: *Communications in Statistics - Theory and Methods* 3 (Jan. 1974), pp. 1–27. DOI: *10.1080/03610927408827101*.

[24] Josep Carmona et al. *Conformance Checking - Relating Processes and Models*. Springer, 2018. ISBN: 978-3-319-99413-0. DOI: *10.1007/978-3-319-99414-7*.

[25] Tianqi Chen and Carlos Guestrin. “XGBoost: A Scalable Tree Boosting System.” In: Aug. 2016, pp. 785–794. DOI: *10.1145/2939672.2939785*.

[26] Zhen-Yu Chen, Peng Shu, and Minghe Sun. “A hierarchical multiple kernel support vector machine for customer churn prediction using longitudinal behavioral data.” In: *European Journal of Operational Research* 223 (Dec. 2012), pp. 461–472. DOI: *10.1016/j.ejor.2012.06.040*.

[27] Paul-Alexandru Chirita, Wolfgang Nejdl, and Cristian Zamfir. “Preventing shilling attacks in online recommender systems.” In: Jan. 2005, pp. 67–74. DOI: *10.1145/1097047.1097061*.

[28] Kristof Coussement et al. “Predicting student dropout in subscription-based online learning environments: The beneficial impact of the logit leaf model.” In: *Decision Support Systems* 135 (2020), p. 113325. ISSN: 0167-9236. DOI: *https://doi.org/10.1016/j.dss.2020.113325*.

[29] D.R. Cox and D. Oakes. *Analysis of Survival Data*. Feb. 2018, pp. 1–201. ISBN: 9781315137438. DOI: *10 . 1201 / 9781315137438*.

[30] Jeroen D’Haen, Dirk Van den Poel, and Dirk Thorleuchter. “Predicting customer profitability during acquisition: Finding the optimal combination of data source and data mining technique.” In: *Expert Systems*

with Applications 40 (May 2013), pp. 2007–2012. DOI: *10.1016/j.eswa.2012.10.023*.

[31] Jeroen D'Haen et al. "Integrating Expert Knowledge and Multilingual Web Crawling Data in a Lead Qualification System." In: *Decision Support Systems* 82 (Jan. 2016). DOI: *10.1016/j.dss.2015.12.002*.

[32] Maurizio Ferrari Dacrema, Paolo Cremonesi, and Dietmar Jannach. "Are We Really Making Much Progress? A Worrying Analysis of Recent Neural Recommendation Approaches." In: *Proceedings of the 13th ACM Conference on Recommender Systems*. RecSys '19. Copenhagen, Denmark: Association for Computing Machinery, 2019, pp. 101–109. ISBN: 9781450362436. DOI: *10.1145/3298689.3347058*.

[33] Koustuv Dasgupta et al. "Social ties and their relevance to churn in mobile telecom networks." In: Jan. 2008, pp. 668–677. DOI: 10.1145/1353343.1353424.

[34] DataReportal. *Digital 2022 April Global Statshot*. URL: *https://datareportal.com/reports/digital-2022-april-global-statshot*. (accessed: 07.07.2022, page:123).

[35] DataReportal. *Digital 2022 April Global Statshot*. URL: *https://datareportal.com/reports/digital-2022-april-global-statshot*. (accessed: 07.07.2022, page:104).

[36] DataReportal. *Digital 2022 Global Overview Report*. URL: *https://datareportal.com/reports/digital-2022-global-overview-report*. (accessed: 07.07.2022, page:87).

[37] Koen De Bock and Dirk Van den Poel. "Predicting Website Audience Demographics for Web Advertising Targeting Using Multi-Website Clickstream Data." In: *Ghent University, Faculty of Economics and Business Administration, Working Papers of Faculty of Economics and Business Administration, Ghent University, Belgium* 98 (Jan. 2009). DOI: *10.3233/FI-2010-216*.

[38] Koen De Bock and Dirk Van den Poel. "Reconciling performance and interpretability in customer churn prediction using ensemble learning based on generalized additive models." In: *Expert Systems with Applications* 39 (June 2012), pp. 6816–6826. DOI: *10.1016/j.eswa.2012.01.014*.

[39] Koen W. De Bock and Arno De Caigny. "Spline-rule ensemble classifiers with structured sparsity regularization for interpretable customer churn modeling." In: *Decision Support Systems* 150 (2021). Interpretable Data Science For Decision Making, p. 113523. ISSN: 0167-9236. DOI: *https://doi.org/10.1016/j.dss.2021.113523*.

[40] Arno De Caigny, Kristof Coussement, and Koen W. De Bock. "A new hybrid classification algorithm for customer churn prediction based on logistic regression and decision trees." In: *European Journal of Operational Research* 269.2 (2018), pp. 760–772. ISSN: 0377-2217. DOI: *https://doi.org/10.1016/j.ejor.2018.02.009*.

[41] Arno De Caigny, Kristof Coussement, and Koen W. De Bock. "Leveraging fine-grained transaction data for cus-

tomer life event predictions." In: *Decision Support Systems* 130 (2020), p. 113232. ISSN: 0167-9236. DOI: *https://doi.org/10.1016/j.dss.2019.113232*.

[42] Arno De Caigny, Kristof Coussement, and Koen W. De Bock. "Leveraging fine-grained transaction data for customer life event predictions." In: *Decision Support Systems* 130 (2020), p. 113232. ISSN: 0167-9236. DOI: *https://doi.org/10.1016/j.dss.2019.113232*.

[43] Arno De Caigny et al. "Incorporating textual information in customer churn prediction models based on a convolutional neural network." In: *International Journal of Forecasting* 36 (Aug. 2019). DOI: *10.1016/j.ijforecast.2019.03.029*.

[44] Arno De Caigny et al. "Uplift modeling and its implications for B2B customer churn prediction: A segmentation-based modeling approach." In: *Industrial Marketing Management* 99 (2021), pp. 28–39. ISSN: 0019-8501. DOI: *https://doi.org/10.1016/j.indmarman.2021.10.001*.

[45] Floris Devriendt, Jeroen Berrevoets, and Wouter Verbeke. "Why you should stop predicting customer churn and start using uplift models." In: *Information Sciences* 548 (2021), pp. 497–515. ISSN: 0020-0255. DOI: *https://doi.org/10.1016/j.ins.2019.12.075*.

[46] Chiara Di Francescomarino et al. "Predictive Process Monitoring Methods: Which One Suits Me Best?" In: (Apr. 2018).

[47] Eustache Diemert et al. "A Large Scale Benchmark for Uplift Modeling." In: *KDD*. London, United Kingdom, 2018. DOI: 10.1145/nnnnnnn.nnnnnnn.

[48] Brendan Andrew Duncan and Charles Peter Elkan. "Probabilistic Modeling of a Sales Funnel to Prioritize Leads." In: *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. KDD '15. Sydney, NSW, Australia: Association for Computing Machinery, 2015, pp. 1751–1758. ISBN: 9781450336642. DOI: 10.1145/2783258.2788578.

[49] J.C. Dunn. "Well-Separated Clusters and Optimal Fuzzy Partitions." In: *Cybernetics and Systems* 4 (Apr. 1974), pp. 95–104. DOI: 10.1080/01969727408546059.

[50] Peter Fader and Bruce Hardie. "A Note on Deriving the Pareto/NBD Model and Related Expressions." In: (Jan. 2005).

[51] Peter Fader, Bruce Hardie, and Ka Lee. ""Counting Your Customers" the Easy Way: An Alternative to the Pareto/NBD Model." In: *Marketing Science* 24 (May 2005), pp. 275–284. DOI: 10.1287/mksc.1040.0098.

[52] Peter Fader, Bruce Hardie, and Ka Lee. "RFM and CLV: Using iso-value curves for customer base analysis." In: *Journal of Marketing Research American Marketing Association* ISSN XLII (Dec. 2005), pp. 415–430. DOI: 10.1509/jmkr.2005.42.4.415.

[53] M.A.T. Figueiredo and A.K. Jain. "Unsupervised learning of finite mixture models." In: *IEEE Transactions on*

Pattern Analysis and Machine Intelligence 24.3 (2002), pp. 381–396. DOI: 10.1109/34.990138.

[54] Martin Fixman et al. “A Bayesian Approach to Income Inference in a Communication Network.” In: Aug. 2016, pp. 579–582. DOI: 10.1109/ASONAM.2016.7752294.

[55] Ronald Edward Frank, William F. Massey, and Yoram Wind. *Market segmentation*. Jan. 1972. ISBN: 978-0135575796.

[56] Yoav Freund and Robert Schapire. “A Short Introduction to Boosting.” In: *Journal of Japanese Society for Artificial Intelligence* 14 (Oct. 1999), pp. 771–780.

[57] Nicholas Frosst and Geoffrey Hinton. “Distilling a neural network into a soft decision tree.” In: *arXiv preprint arXiv:1711.09784* (2017).

[58] Bernard Gaël. “Process Mining-Based Customer Journey Analytics.” PhD thesis. Faculté des Hautes Études Commerciales de l’Université de Lausanne, 2020.

[59] Timnit Gebru et al. “Using deep learning and Google Street View to estimate the demographic makeup of neighborhoods across the United States.” In: *Proceedings of the National Academy of Sciences* 114 (Nov. 2017), p. 201700035. DOI: 10.1073/pnas.1700035114.

[60] Stijn Geuens, Kristof Coussement, and Koen De Bock. “A framework for configuring collaborative filtering-based recommendations derived from purchase data.” In: *European Journal of Operational Research* 265 (July 2017). DOI: 10.1016/j.ejor.2017.07.005.

[61] Barbara Giamanco and Kent Gregoire. “Tweet Me, Friend Me, Make Me Buy.” In: *Harvard business review* 90 (July 2012), pp. 88–+.

[62] Nicolas Glady, Bart Baesens, and Christophe Croux. “A modified Pareto/NBD approach for predicting customer lifetime value.” In: *Katholieke Universiteit Leuven, Open Access publications from Katholieke Universiteit Leuven* 36 (Jan. 2007). DOI: *10.1016/j.eswa.2007.12.049*.

[63] Nicolas Glady, Bart Baesens, and Christophe Croux. “Modeling Churn Using Customer Lifetime Value.” In: *European Journal of Operational Research* 197 (Aug. 2009), pp. 402–411. DOI: *10.1016/j.ejor.2008.06.027*.

[64] Sharad Goel and Daniel Goldstein. “Predicting Individual Behavior with Social Networks.” In: *Marketing Science* 33 (Jan. 2014). DOI: *10.1287/mksc.2013.0817*.

[65] Leo Goodman and William Kruskal. “Measures of Association for Cross Classifications. II: Further Discussion and References.” In: *Journal of The American Statistical Association* 54 (Mar. 1959), pp. 123–163. DOI: *10.1080/01621459.1959.10501503*.

[66] Aditya Grover and Jure Leskovec. “node2vec: Scalable Feature Learning for Networks.” In: vol. 2016. July 2016, pp. 855–864. DOI: *10.1145/2939672.2939754*.

[67] Leo Guelman, Montserrat Guillén, and Ana M. Pérez-Marín. “A decision support framework to implement optimal personalized marketing interventions.” In: *Deci-*

sion Support Systems 72 (2015), pp. 24–32. ISSN: 0167-9236. DOI: *https://doi.org/10.1016/j.dss.2015.01.010*.

[68] Björn Gunnarsson et al. "Deep Learning for Credit Scoring: Do or Don't?" In: *European Journal of Operational Research* 295 (Mar. 2021). DOI: *10.1016/j.ejor.2021.03.006*.

[69] Björn Rafn Gunnarsson et al. "Deep learning for credit scoring: Do or don't?" In: *European Journal of Operational Research* 295.1 (2021), pp. 292–305. ISSN: 0377-2217. DOI: *https://doi.org/10.1016/j.ejor.2021.03.006*.

[70] Christian Günther and Wil Aalst. "Fuzzy Mining – Adaptive Process Simplification Based on Multi-perspective Metrics." In: vol. 4714. Sept. 2007, pp. 328–343. ISBN: 978-3-540-75182-3. DOI: *10.1007/978-3-540-75183-0_24*.

[71] Sunil Gupta et al. "Modeling Customer Lifetime Value." In: *Journal of Service Research* 9 (Nov. 2006), pp. 139–155. DOI: *10.1177/1094670506293810*.

[72] Evert de Haan and Elena Menichelli. "The Incremental Value of Unstructured Data in Predicting Customer Churn." In: *Marketing Science Institute Working Series Paper* 2020 (Aug. 2019).

[73] Ragnhild Halvorsrud, Knut Kvale, and Asbjørn Følstad. "Improving service quality through customer journey analysis." In: *Journal of Service Theory and Practice* 26 (Nov. 2016), pp. 840–867. DOI: *10.1108/JSTP-05-2015-0111*.

[74] Behram Hansotia and Paul Wang. “Analytical Challenges in Customer Acquisition.” In: *Journal of Direct Marketing* 11 (Mar. 1999), pp. 7–19. DOI: 10.1002/(SICI)1522-7138(199721)11:2<7::AID-DIR3>3.0.CO;2-V.

[75] Jon Herlocker et al. “An Algorithmic Framework for Performing Collaborative Filtering.” In: *ACM SIGIR Forum* 51 (Aug. 2017), pp. 227–234. DOI: 10.1145/3130348.3130372.

[76] Geoffrey Hinton, Oriol Vinyals, and Jeffrey Dean. “Distilling the Knowledge in a Neural Network.” In: *NIPS Deep Learning and Representation Learning Workshop*. 2015. URL: *http://arxiv.org/abs/1503.02531*.

[77] R.N. Hiscot. “Chi-square tests for markov chain analysis.” In: *Mathematical Geology* 13 (1981), pp. 69–80.

[78] Bryan Hochstein et al. “An Industry/Academic Perspective on Customer Success Management.” In: *Journal of Service Research* 23.1 (2020), pp. 3–7. DOI: 10.1177/1094670519896422.

[79] Bryan Hochstein et al. “Proactive Value Co-Creation via Structural Ambidexterity: Customer Success Management and the Modularization of Frontline Roles.” In: *Journal of Service Research* 24.4 (2021), pp. 601–621. DOI: 10.1177/1094670521997565.

[80] Arthur E. Hoerl and Robert W. Kennard. “Ridge regression: application to nonorthogonal problems.” In: *Technometrics* 12 (1970), pp. 69–82.

[81] J J Hopfield. “Neural networks and physical systems with emergent collective computational abilities.” In: *Proceedings of the National Academy of Sciences* 79.8 (1982), pp. 2554–2558. DOI: 10.1073/pnas.79.8.2554. eprint: *https://www.pnas.org/doi/pdf/10.1073/pnas.79.8.2554*.

[82] Sebastiaan Höppner et al. “Profit Driven Decision Trees for Churn Prediction.” In: *European Journal of Operational Research* 284 (Dec. 2017). DOI: 10.1016/j.ejor.2018.11.072.

[83] Bingquan Huang, Tahar Kechadi, and Brian Buckley. “Customer churn prediction in telecommunications.” In: *Expert Systems with Applications: An International Journal* 39 (Jan. 2012), pp. 1414–1425. DOI: 10.1016/j.eswa.2011.08.024.

[84] Zan Huang, Hsiu-chin Chen, and Daniel Dajun Zeng. “Applying associative retrieval techniques to alleviate the sparsity problem in collaborative filtering.” In: *ACM Trans. Inf. Syst.* 22 (Jan. 2004), pp. 116–142. DOI: 10.1145/963770.963775.

[85] Cullinan G. J. “Picking them by their Batting Averages’ Recency – Frequency – Monetary Method of Controlling Circulation.” In: *Manual Release* 2103, NY: *Direct Mail/-Marketing Association* (1977).

[86] Dietmar Jannach et al. “Recommender Systems: An Introduction.” In: *Recommender Systems: An Introduction* (Jan. 2010). DOI: 10.1017/CBO9780511763113.

[87] Kathleen Kane, Victor Lo, and Jane Zheng. "Mining for the truly responsive customers and prospects using true-lift modeling: Comparison of new and existing methods." In: *Journal of Marketing Analytics* 2 (Dec. 2014). DOI: *10.1057/jma.2014.18*.

[88] Maurits Kaptein and Edwin van den Heuvel. "Random Variables and Distributions." In: *Statistics for Data Scientists : An Introduction to Probability, Statistics, and Data Analysis*. Cham: Springer International Publishing, 2022, pp. 103–140. ISBN: 978-3-030-10531-0. DOI: *10.1007/978-3-030-10531-0_4*. URL: *https://doi.org/10.1007/978-3-030-10531-0_4*.

[89] Leonard Kaufman and Peter Rousseeuw. *Finding Groups in Data: An Introduction to Cluster Analysis*. Sept. 2009. ISBN: 9780470317488.

[90] M. G. Kendall. "A New Measure of Rank Correlation." In: *Biometrika* 30.1-2 (June 1938), pp. 81–93. ISSN: 0006-3444. DOI: *10.1093/biomet/30.1-2.81*.

[91] Maurice Kendall and Jean D. Gibbons. *Rank Correlation Methods*. 5th ed. A Charles Griffin Title, Sept. 1990.

[92] David G. Kleinbaum and Mitchel Klein. *Survival Analysis: A Self-Learning Text*. Jan. 2005. ISBN: 978-0-387-23918-7. DOI: *10.1007/0-387-29150-4*.

[93] Teuvo Kohonen. "The Basic SOM." In: *Self-Organizing Maps*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2001, pp. 105–176. ISBN: 978-3-642-56927-2. DOI: 10.

1007/978-3-642-56927-2_3. URL: *https://doi.org/10.1007/978-3-642-56927-2_3*.

[94] Teuvo Kohonen. "The self-organizing map." In: *Neurocomputing* 21.1 (1998), pp. 1–6. ISSN: 0925-2312. DOI: *https://doi.org/10.1016/S0925-2312(98)00030-7*.

[95] Michal Kosinski, David Stillwell, and Thore Graepel. "Private traits and attributes are predictable from digital records of human behavior." In: *Proceedings of the National Academy of Sciences of the United States of America* 110 (Mar. 2013). DOI: 10.1073/pnas.1218772110.

[96] A.G. Lafley and Ram Charan. *The Game-Changer: How You Can Drive Revenue and Profit Growth with Innovation*. 2008. ISBN: 978-0307381736.

[97] Yi-ting Lai et al. "Direct Marketing When There Are Voluntary Buyers." In: *Sixth International Conference on Data Mining* (ICDM'06). 2006, pp. 922–927. DOI: 10.1109/ICDM.2006.54.

[98] Sander Leemans, Dirk Fahland, and Wil Aalst. "Discovering Block-Structured Process Models from Event Logs - A Constructive Approach." In: Jan. 2013, pp. 311–329. ISBN: 978-3-642-38696-1. DOI: 10.1007/978-3-642-38697-8_17.

[99] Daniel Lemire and Anna Maclachlan. "Slope One Predictors for Online Rating-Based Collaborative Filtering." In: *Proceedings of the 2005 SIAM International Conference on Data Mining*, SDM 2005 5 (Feb. 2007). DOI: 10.1137/1.9781611972757.43.

[100] Katherine Lemon and Peter Verhoef. "Understanding Customer Experience Throughout the Customer Journey." In: *Journal of Marketing* 80 (June 2016). DOI: *10.1509/jm.15.0420*.

[101] Stefan Lessmann et al. "Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research." In: *European Journal of Operational Research* (doi:10.1016/j.ejor.2015.05.030) (May 2015). DOI: *10.1016/j.ejor.2015.05.030*.

[102] Elen Lima, Christophe Mues, and Bart Baesens. "Domain knowledge integration in data mining using decision tables: Case studies in churn prediction." In: *Journal of the Operational Research Society* 60 (Aug. 2009), pp. 1096–1106. DOI: *10.1057/jors.2008.161*.

[103] Elen Lima, Christophe Mues, and Bart Baesens. "Monitoring and backtesting churn models." In: *Expert Systems with Applications* 38 (Jan. 2011), pp. 975–982. DOI: *10.1016/j.eswa.2010.07.091*.

[104] Greg Linden, B. Smith, and J. York. "Linden G, Smith B and York J: 'Amazon.com recommendations: item-to-item collaborative filtering', Internet Comput. IEEE, , 7." In: *Internet Computing, IEEE* 7 (Feb. 2003), pp. 76–80. DOI: *10.1109/MIC.2003.1167344*.

[105] Jasmien Lismont et al. "Predicting Interpurchase Time in a Retail Environment using Customer-Product Networks: An Empirical Study and Evaluation." In: *Expert*

Systems with Applications 104 (Aug. 2018), pp. 22–32. DOI: *10.1016/j.eswa.2018.03.016*.

[106] Thomas Lix, Paul Berger, and Thomas Magliozzi. "New customer acquisition: Prospecting models and the use of commercially available external data." In: *Journal of Direct Marketing* 9 (Oct. 2006), pp. 8–18. DOI: *10.1002/dir.4000090403*.

[107] Victor Lo. "The True Lift Model - A Novel Data Mining Approach to Response Modeling in Database Marketing." In: *SIGKDD Explorations* 4 (Jan. 2002), pp. 78–86.

[108] Sebastián Maldonado, Julio López, and Carla Vairetti. "Profit-based churn prediction based on Minimax Probability Machines." In: *European Journal of Operational Research* 284.1 (2020), pp. 273–284. ISSN: 0377-2217. DOI: *https://doi.org/10.1016/j.ejor.2019.12.007*.

[109] Edward Malthouse and Robert Blattberg. "Can we predict customer lifetime value?" In: *Journal of Interactive Marketing* 19 (Dec. 2005), pp. 2–16. DOI: *10.1002/dir.20027*.

[110] Paul Mangiameli, Shaw K. Chen, and David West. "A comparison of SOM neural network and hierarchical clustering methods." In: *European Journal of Operational Research* 93.2 (1996). Neural Networks and Operations Research/Management Science, pp. 402–417. ISSN: 0377-2217. DOI: *https://doi.org/10.1016/0377-2217(96)00038-0*.

[111] Rob Markey. "Are You Undervaluing Your Customers?" In: *Harvard Business Review* January-February (2020).

[112] Greg Marshall et al. "Revolution in Sales: The Impact of Social Media and Related Technology on the Selling Environment." In: *The Journal of Personal Selling and Sales Management* 32 (July 2012), pp. 349–363. DOI: 10.2307/23483286.

[113] Roger Martin. "The Age of Customer Capitalism." In: *Harvard Business Review* January-February (2010).

[114] Daniel McCarthy and Elliot Oblander. "Scalable Data Fusion with Selection Correction: An Application to Customer Base Analysis." In: *Marketing Science* 40 (Feb. 2021). DOI: 10.1287/mksc.2020.1259.

[115] Daniel M McCarthy et al. "How to value a company by analyzing its customers." In: *Harvard Business Review* 91 (2020), pp. 51–55.

[116] Matthijs Meire, Michel Ballings, and Dirk Van den Poel. "The added value of social media data in B2B customer acquisition systems: A real-life experiment." In: *Decision Support Systems* 104 (Oct. 2017). DOI: 10.1016/j.dss.2017.09.010.

[117] Nina Michaelidou, Nikoletta Siamagka, and George Christodoulides. "Usage, Barriers and Measurement of Social Media Marketing: An Exploratory Investigation of Small and Medium B2B Brands." In: *Industrial Marketing Management - IND MARKET MANAG* 40 (Oct. 2011). DOI: 10.1016/j.indmarman.2011.09.009.

[118] J Miglautsch. “Thoughts on RFM scoring.” In: *The Journal of Database Marketing* 8 (Aug. 2000), pp. 67–72. DOI: 10.1057/palgrave.jdm.3240019.

[119] Roberto Mora, Ann Clarke, and Per Freytag. “B2B market segmentation: A systematic review and research agenda.” In: *Journal of Business Research* 126 (Jan. 2021), pp. 415–428. DOI: 10.1016/j.jbusres.2020.12.070.

[120] María Óskarsdóttir, Bart Baesens, and Jan Vanthienen. “Profit-Based Model Selection for Customer Retention Using Individual Customer Lifetime Values.” In: *Big Data* 6 (Mar. 2018), pp. 53–65. DOI: 10.1089/big.2018.0015.

[121] María Óskarsdóttir et al. “Social Network Analytics for Churn Prediction in Telco: Model Building, Evaluation and Network Architecture.” In: *Expert Systems with Applications* 85 (May 2017). DOI: 10.1016/j.eswa.2017.05.028.

[122] María Óskarsdóttir et al. “Time series for early churn detection: Using similarity based classification for dynamic networks.” In: *Expert Systems with Applications* 106 (Apr. 2018). DOI: 10.1016/j.eswa.2018.04.003.

[123] Yunus Emre Özköse, Ali Haznedaroğlu, and Levent M. Arslan. “Customer Churn Analysis with Deep Learning Methods on Unstructured Data.” In: *2021 Innovations in Intelligent Systems and Applications Conference (ASYU)*. 2021, pp. 1–5. DOI: 10.1109/ASYU52992.2021.9598974.

[124] Peter Paauwe, Peter Putten, and Michiel Wezel. “DTMC: An actionable e-customer lifetime value model based on

markov chains and decision trees." In: vol. 258. Aug. 2007, pp. 253–262. DOI: *10.1145/1282100.1282147*.

[125] Lawrence Page et al. "The PageRank Citation Ranking: Bringing Order to the Web." In: *Technical Report. Stanford InfoLab* (Nov. 1998).

[126] Savvas Papagiannidis and Eleftherios Alamanos. "Going on a journey: A review of the customer journey literature." In: *Journal of Business Research* 125 (Mar. 2021), pp. 336–353. DOI: *10.1016/j.jbusres.2020.12.028*.

[127] Parag Pendharkar. "Genetic algorithm based neural network approaches for predicting churn in cellular wireless network services." In: *Expert Systems with Applications* 36 (Apr. 2009), pp. 6714–6720. DOI: *10.1016/j.eswa.2008.08.050*.

[128] Ana Perišić, Dubravka Šišak Jung, and Marko Pahor. "Churn in the mobile gaming field: Establishing churn definitions and measuring classification similarities." In: *Expert Systems with Applications* 191 (2022), p. 116277. ISSN: 0957-4174. DOI: *https://doi.org/10.1016/j.eswa.2021.116277*.

[129] Bryan Perozzi, Rami Al-Rfou, and Steven Skiena. "DeepWalk: Online Learning of Social Representations." In: *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (Mar. 2014). DOI: *10.1145/2623330.2623732*.

[130] Phillip Pfeifer and Robert Carraway. "Modeling Customer Relationships Using Markov Chains." In: *Journal*

of Interactive Marketing 14 (Mar. 2000), pp. 43–55. DOI: *10.1002/(SICI)1520-6653(200021)14:23.0.CO;2-H*.

[131] Girish Punj and David W. Stewart. “Cluster Analysis in Marketing Research: Review and Suggestions for Application.” In: *Journal of Marketing Research* 20.2 (1983), pp. 134–148. DOI: *10.1177/002224378302000204*.

[132] Nicholas J. Radcliffe and Patrick D. Surry. “Real-World Uplift Modelling with Significance-Based Uplift Trees.” In: *White Paper TR-2011, Stochastic solutions*. 2012.

[133] Anand Rajaraman, Jure Leskovec, and Jeffrey Ullman. *Mining of Massive Datasets*. Jan. 2014. DOI: *10.1017/CBO9781139058452*.

[134] Papassapa Rauyruen and Kenneth E. Miller. “Relationship quality as a predictor of B2B customer loyalty.” In: *Journal of Business Research* 60.1 (2007), pp. 21–31. ISSN: 0148-2963. DOI: *https://doi.org/10.1016/j.jbusres.2005.11.006*.

[135] Frederick Reichheld. “The One Number you Need to Grow.” In: *Harvard business review* 81 (June 2004), pp. 46–54, 124.

[136] Werner Reinartz and V. Kumar. “The Impact of Customer Relationship Characteristics on Profitable Lifetime Duration.” In: *Journal of Marketing* 67 (Jan. 2003), pp. 77–99. DOI: *10.1509/jmkg.67.1.77.18589*.

[137] Werner Reinartz, Jacquelyn Thomas, and V. Kumar. “Balancing Acquisition and Retention Resources to Maximize Customer Profitability.” In: *Journal of Market-*

ing 69 (Feb. 2005), pp. 63–79. DOI: *10.1509/jmkg.69.1.63.55511*.

[138] Michael Reusens et al. “A note on explicit versus implicit information for job recommendation.” In: *Decision Support Systems* 98 (2017), pp. 26–35. ISSN: 0167-9236. DOI: *https://doi.org/10.1016/j.dss.2017.04.002*.

[139] Francesco Ricci, Lior Rokach, and Bracha Shapira. “Recommender Systems Handbook.” In: vol. 1-35. Oct. 2010, pp. 1–35. DOI: *10.1007/978-0-387-85820-3_1*.

[140] Yossi Richter, Elad Yom-Tov, and Noam Slonim. “Predicting Customer Churn in Mobile Networks through Analysis of Social Groups.” In: Apr. 2010, pp. 732–741. DOI: *10.1137/1.9781611972801.64*.

[141] Hans Risselada, Peter Verhoef, and Tammo Bijmolt. “Staying Power of Churn Prediction Models.” In: *Journal of Interactive Marketing* 24 (Aug. 2010), pp. 198–208. DOI: *10.1016/j.intmar.2010.04.002*.

[142] Michael Rodriguez, Robert Peterson, and Vijaykumar Krishnan. “Social Media’s Influence on Business-To-Business Sales Performance.” In: *The Journal of Personal Selling and Sales Management* 32 (July 2012), pp. 365–378. DOI: *10.2307/23483287*.

[143] Lisa Schetgen, Matthias Bogaert, and Dirk Van den Poel. “Predicting donation behavior: Acquisition modeling in the nonprofit sector using Facebook data.” In: *Decision Support Systems* 141 (Nov. 2020). DOI: *10.1016/j.dss.2020.113446*.

[144] Harald Scheule, Daniel Rösch, and Bart Baesens. *Credit Risk Analytics: The R Companion*. Nov. 2017. ISBN: 978-1977760869.

[145] David Schmittlein, Donald Morrison, and Richard Colombo. "Counting Your Customers: Who-Are They and What Will They Do Next?" In: *Management Science* 33 (Jan. 1987), pp. 1–24. DOI: *10.1287/mnsc.33.1.1*.

[146] D Sculley et al. "Hidden Technical Debt in Machine Learning Systems." In: *NIPS* (Jan. 2015), pp. 2494–2502.

[147] Suvash Sedhain et al. "AutoRec: Autoencoders Meet Collaborative Filtering." In: May 2015, pp. 111–112. DOI: *10.1145/2740908.2742726*.

[148] Savannah Shi and Michael Trusov. "The Path to Click: Are You on It?" In: *Marketing Science* 40 (Oct. 2020). DOI: *10.1287/mksc.2020.1253*.

[149] Wendell Smith. "Product Differentiation and Market Segmentation as Alternative Marketing Strategies." In: *Journal of Marketing* 21 (July 1956), pp. 3–8. DOI: *10.2307/1247695*.

[150] Michał Sołtys, Szymon Jaroszewicz, and Piotr Rzepakowski. "Ensemble Methods for Uplift Modeling." In: *Data Mining and Knowledge Discovery* 29.6 (Nov. 2015), pp. 1531–1559. DOI: *10.1007/s10618-014-0383-9*.

[151] Eugen Stripling et al. "Profit maximizing logistic model for customer churn prediction using genetic algorithms." In: *Swarm and Evolutionary Computation* 40 (Dec. 2017). DOI: *10.1016/j.swevo.2017.10.010*.

[152] Erik Štrumbelj and Igor Kononenko. “Explaining prediction models and individual predictions with feature contributions.” In: *Knowledge and Information Systems* 41 (Dec. 2013), pp. 647–665. DOI: *10.1007/s10115-013-0679-x*.

[153] Panagiotis Symeonidis and Andreas Zioupos. *Matrix and Tensor Factorization Techniques for Recommender Systems*. Jan. 2016. ISBN: 978-3-319-41356-3. DOI: 10.1007/978-3-319-41357-0.

[154] Alessandro Terragni and Marwan Hassani. “Analyzing Customer Journey with Process Mining: From Discovery to Recommendations.” In: Aug. 2018, pp. 224–229. DOI: *10.1109/FiCloud.2018.00040*.

[155] Dirk Thorleuchter, Dirk Van den Poel, and Anita Prinzie. “Analyzing existing customers’ websites to improve the customer acquisition process as well as the profitability prediction in B-to-B marketing.” In: *Expert Syst. Appl.* 39 (Feb. 2012), pp. 2597–2605. DOI: *10.1016/j.eswa.2011.08.115*.

[156] Robert Tibshirani. “Regression shrinkage selection via the LASSO.” In: *Journal of the Royal Statistical Society Series B* 73 (June 2011), pp. 273–282. DOI: 10.2307/41262671.

[157] Kevin Trainor et al. “Social media technology usage and customer relationship performance: A capabilities-based examination of social CRM.” In: *Journal of Business Research* 67 (June 2014), pp. 1201–1208. DOI: 10.1016/j.jbusres.2013.05.002.

[158] Alfred Ultsch. "Emergent self-organising feature maps used for prediction and prevention of churn in mobile phone markets." In: *Journal of Targeting, Measurement and Analysis for Marketing* 10 (Mar. 2002), pp. 314–324. DOI: 10.1057/palgrave.jt.5740056.

[159] Tony Van Gestel et al. "Benchmarking Least Squares Support Vector Machine Classifiers." In: *Machine Learning* 54 (June 2002). DOI: 10.1023/B:MACH.0000008082.80494.e0.

[160] Seppe Vanden Broucke and Bart Baesens. *Managing Model Risk: Lessons and experiences from industry and research on the challenges and dangers of analytical models*. 2021. ISBN: 979-8521686988.

[161] D. Vélez et al. "Churn and Net Promoter Score forecasting for business decision-making through a new stepwise regression methodology." In: *Knowledge-Based Systems* 196 (Mar. 2020), p. 105762. DOI: 10.1016/j.knosys.2020.105762.

[162] Wouter Verbeke, Bart Baesens, and Cristián Bravo. *Profit Driven Business Analytics: A Practitioner's Guide to Transforming Big Data into Added Value*. Jan. 2018.

[163] Wouter Verbeke, David Martens, and Bart Baesens. "Social network analysis for customer churn prediction." In: *Applied Soft Computing* 14 (Jan. 2014), pp. 431–446. DOI: 10.1016/j.asoc.2013.09.017.

[164] Wouter Verbeke et al. "Building comprehensible customer churn prediction models with advanced rule in-

duction techniques." In: *Expert Systems with Applications* 38 (Mar. 2011), pp. 2354–2364. DOI: 10.1016/j.eswa.2010.08.023.

[165] Wouter Verbeke et al. "New insights into churn prediction in the telecommunication sector: A profit driven data mining approach." In: *European Journal of Operational Research* 218 (Apr. 2012), pp. 211–229. DOI: 10.1016/j.ejor.2011.09.031.

[166] Thomas Verbraken, Wouter Verbeke, and Bart Baesens. "A Novel Profit Maximizing Metric for Measuring Classification Performance of Customer Churn Prediction Models." In: *IEEE Transactions on Knowledge and Data Engineering* 25 (Jan. 2012). DOI: 10.1109/TKDE.2012.50.

[167] Thomas Verbraken et al. "Development and application of consumer credit scoring models using profit-based V classification measures." In: *European Journal of Operational Research* 238 (Oct. 2014), pp. 505–513. DOI: 10.1016/j.ejor.2014.04.001.

[168] A. Viterbi. "Error bounds for convolutional codes and an asymptotically optimum decoding algorithm." In: *IEEE Transactions on Information Theory* 13.2 (1967), pp. 260–269. DOI: 10.1109/TIT.1967.1054010.

[169] Nhi Vo et al. "Leveraging unstructured call log data for customer churn prediction." In: *Knowledge-Based Systems* 212 (Jan. 2021), p. 106586. DOI: 10.1016/j.knosys.2020.106586.

[170] Slobodan Vucetic and Zoran Obradovic. "Collaborative Filtering Using a Regression-Based Approach." In: *Knowl. Inf. Syst.* 7 (Feb. 2005), pp. 1–22. DOI: 10.1007/s10115-003-0123-8.

[171] Florian Wangenheim and Tomás Bayón. "The Chain From Customer Satisfaction via Word-of-Mouth Referrals to New Customer Acquisition." In: *Journal of the Academy of Marketing Science* 35 (June 2007), pp. 233–249. DOI: 10.1007/s11747-007-0037-1.

[172] Michel Wedel and Wagner Kamakura. *Market Segmentation: Conceptual and Methodological Foundations*. Vol. 8. Jan. 2000. ISBN: 978-1-4613-7104-5. DOI: 10.1007/978-1-4615-4651-1.

[173] Jochen Weerdt et al. "A multi-dimensional quality assessment of state-of-the-art process discovery algorithms using real-life event logs." In: *Inf. Syst.* 37 (Nov. 2012), pp. 654–676. DOI: 10.1016/j.is.2012.02.004.

[174] Chih-Ping Wei and I-Tang Chiu. "Turning telecommunications call details to churn prediction: A data mining approach." In: *Expert Systems with Applications* 23 (Aug. 2002), pp. 103–112. DOI: 10.1016/S0957-4174(02)00030-1.

[175] Heike Wolters, Christian Schulze, and Karen Gedenk. "Referral Reward Size and New Customer Profitability." In: *Marketing Science* 39 (Nov. 2020), pp. 1166–1180. DOI: 10.1287/mksc.2020.1242.

[176] Ken Wong. "Using Cox regression to model customer time to churn in the wireless telecommunications in-

dustry." In: *Journal of Targeting, Measurement and Analysis for Marketing* 19 (Mar. 2011). DOI: 10.1057/jt.2011.1.

[177] Jiyong Zhang and Pearl Pu. "A recursive prediction algorithm for collaborative filtering recommender systems." In: *RecSys 07: Proceedings of the 2007 ACM conference on Recommender systems*. Jan. 2007, pp. 57–64. DOI: 10.1145/1297231.1297241.

[178] Xiaohang Zhang et al. "Predicting customer churn through interpersonal influence." In: *Knowledge-Based Systems* 28 (Apr. 2012), pp. 97–104. DOI: 10.1016/j.knosys.2011.12.005.

[179] Bing Zhu, Bart Baesens, and Seppe vanden Broucke. "An empirical comparison of techniques for the class imbalance problem in churn prediction." In: *Information Sciences* 408 (Apr. 2017). DOI: 10.1016/j.ins.2017.04.015.

Index