Customer Lifetime Value

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This technical note introduces what is CVL and its benefits and limitations

clv | customer analytics | r

The problem

- **Problem**: we don't understand our customer. We don't know if a specific customer is relevant for our organization.
- As we discussed in session 1, we can use value as a proxy.
- **Goals**:
- We want to know how much value a customer is generating for the organization.
- We want to understand how the generated value is going to evolve.
- We want to segment customers based on value.
- **Why?** To perform specific actions for different customer groups

How we solve the problem

- We need to measure the value a customer generates for a company.
- We have many ways to measure value: CLV (Customer Lifetime Value), RFM (Recency-Frequency-Monetary Value), ARPU (Average Revenue Per User), ARPA (Average Revenue Per Account), ARMU (Average Margin Per User), ARMA (Average Margin per Account),...
- Some approaches just consider the past (RFM, ARPU, ARPA, ARMU, ARMA)
- Others consider the complete lifetime of a customer. Therefore it is required to predict the future behaviour.

In this session, we will focus on CLV.

What is CLV

Customer Lifetime Value can be understood as:

> A prediction of all the value a business will derive from their entire relationship with a customer.

We need a more formal definition:

> The net present value of the profits linked to a specific customer once the customer has been acquired, after subtracting incremental costs associated with marketing, selling, production and servicing over the customer's lifetime. (Blattberg et al. 2008)

There are several challenges when measuring the CLV: (1) Contractual or non-contractual settings, (2) do we have the required customer data? (3) how to estimate future customer interactions, (4) allocate costs per customer,...

Main Concepts in CLV

In order to measure CLV we need:

- **Cash flow**: the net present value of the income generated by the customer throughout their relationship with the organization
- **Lifecycle**: the duration of the relationship with the organization
- **Maintenance costs**: associated costs to ensure that the flow of revenue per customer is achieved
- **Risk costs**: risk associated with a client
- **Acquisition costs**: costs and effort required to acquire a new customer.
- **Retention costs**: costs and effort required to retain a new customer.
- **Discount rate**: expresses the amount of interest paid/earned as a percentage of the balance at the end of the (annual) period.

Additionally,

- **Recommendation value**: impact of the recommendations of a customer in its sphere of influence on company revenue
- **Segmentation improvements**: additional customer segmention information that can be applied before or after measuring the CLV

How to measure the value

The calculation of CLV can be based on:

- ARPU/ARPA (can be considered as an approximation to historic CLV)
- AMPU/AMPA (can be considered as an approximation to historic Historic CLV)
- RFM (can be considered as an approximation to historic CLV, only applicable to predict the next period)
- Historic CLV (based on CLV Formula(s))
- Predictive CLV, based on several probability/Econometrics/Persistence Models/Machine Learning/Growth and dissemination models such as:
- Moving Averages
- Regressions
- Bayesian Inference
- Pareto/NBD (Negative Binomial Distribution)

Depending if our customers are in a contractual setting or not, we use different approaches:

- **Contractual**:
- Naive - Basic Structural Model of CLV (Jain and Singh 2002; Berger and Nasr 1998)
- Recency, Frequency, Monetary (RFM) Summaries (e.g., Donkers, Verhoef, and de Jong 2007)
- Markov Chains
- Hazard Rate Models (Borle, Singh, and Jain 2008)

- Survival Regression (Rupert, 1997)
- Supervised Machine Learning using Random Forest
- **Non-contractual**:
- Management Heuristics (based on manager experience and a practical approach)
- Distribution based approaches:
- Pareto/NBD (Schmittlein, Morrison, and Colombo 1987)
- Beta-Geometric/NBD or BG/NBD (Fader, Hardie, and Lee 2005 b)
- Markov Chain Models (Pfeifer and Carraway 2000; Rust, Lemon, and Zeithaml 2004)
- Markov Chain Monte Carlo (MCMC) Data Augmentation Based Estimation Framework (Singh, Borle, and Jain 2008)

Contractual tends to be easier to deal with as there is certainty of the clients current status (Alive vs. Dead).

CLV General formula

Based on the previous definition, the formula is:

$$CLV = \sum_{t=1}^{\infty} \frac{E[\hat{V}_t]}{(1+\delta)^{t-1}}$$

Where $\hat{V}$ represents the customer's net profit to the firm and δ represents the discount rate at each time period. This formula requires:

- The probability of a client leaving in a given period
- The discount multiplier of capital for the given period
- Expected Revenue per client
- Cost of relationship maintenance

For the historic CLV (only considering the past), then $E[\hat{V}_t]$ can be substited by $(p_t - c_t)r_t$ where

- p_t is the price paid by the customer in time t,
- c_t is the direct costs for customer service in time t,
- r_t is the probability that the client returns to buy or is alive in time t,
- and we consider T (time horizon to estimate historic CLV) instead of ∞

A simplification

Let's consider that p y c are constant values and r is a decresing function in time (r^t), then the formula becomes:

$$CLV = \sum_{t=1}^{\infty} \frac{(p-c)r^t}{(1+\delta)^{t-1}} = (p-c)\sum_{t=1}^{\infty} \frac{r^t}{(1+\delta)^{t-1}} = \frac{(1+\delta)(p-c)r}{1+\delta-r}$$

For one time only, we are including the proof of this result. **Proof**. Let's consider:

$$S_N = \sum_{n=1}^{N} \frac{r^t}{(1+\delta)^{t-1}} = (1+\delta)\sum_{n=1}^{N}\left(\frac{r}{(1+\delta)}\right)^t$$

That means

$$S_N = (1+\delta)\left[\frac{r}{(1+\delta)} + \ldots + \left(\frac{r}{(1+\delta)}\right)^N\right]$$

Now we consider:

$$\left(\frac{r}{(1+\delta)}\right) * S_N = (1+\delta)\left[\left(\frac{r}{(1+\delta)}\right)^2 + \ldots + \left(\frac{r}{(1+\delta)}\right)^{N+1}\right]$$

Combining both of them:

$$S_N - \left(\frac{r}{(1+\delta)}\right) S_N = (1+\delta)\left[\frac{r}{(1+\delta)} - \left(\frac{r}{(1+\delta)}\right)^{N+1}\right]$$

Then,

$$S_N = (1+\delta)\left[\frac{\frac{r}{(1+\delta)} - \left(\frac{r}{(1+\delta)}\right)^{N+1}}{1-\left(\frac{r}{(1+\delta)}\right)}\right]$$

And applying limits and simplyfing the fraction, we obtain the desired outcome.

$$CLV = (p-c)\lim_{N=1}^{\infty} S_N = (p-c)(1+\delta)\frac{r}{1+\delta-r}$$

CLV limitations

- It can not be used if we don't have costs.
- There are many ways to allocate costs.
- We need to estimate the future behaviour of the customer and there are many different forecasting techniques.
- Therefore, it is important to remember that:

  Our ability to predict the future is limited by the fact that to some extent is contained in the past.

- What mathematically means we are under some continuity conditions (or the hyphotesis are true)

Steps to apply CLV

- **[BU]** Discuss whether CLV fits as a metric in our business
- **[DP]** Identification and understanding of sources and meta-data
- **[DP]** Extract, transform, clean and load data
- **[M]** Choose CLV method
- **[M/E]** Analyze results and adjust parameters
- **[D]** Present and explain the results

Benefits

CLV aims to model the net revenue fo all customers based on their past behaviour. Successfully answering this question provides:

- Ability to create business objectives
- Better understanding of customers
- Having a common numerical analysis criteria
- Ability to have an alert system
- Improved management of the sales force
- Adjusting the marketing expenditure
- Targeting marketing expenditure to avoid a client leaving
- Targeting former clients to restart profitable relationships

Use Cases

- Create market strategies based on CLV
- Customer segmentation based on CLV
- Forecasting and customer evolution per segment
- Create different communication, services and loyalty programs based on CLV
- Awake "non-active" customers
- Estimated the value of a company (startup, in the context of acquisition). The value generated by all our customers is called **Customer Equity** and is used to evaluate companies (with no significant income yet).
- Create a segmentation based on CLV as in figure 1.

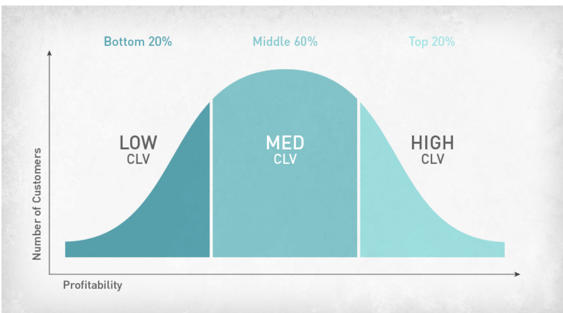

Fig. 1. Using CLV to segment your customers

ARPU as CLV aproximation

ARPU (Average Revenue per User) can be used to calculate historical CLV. The process that we follow is:

- calculate the average revenue per customer per month, add them up
- and then multiply by 12 or 24 to get a one- or two-year CLV.

Let's suppose we have just to customers, and their transactions in several days as in table (1).

Customer Name	Purchase Date	Amount
Josep	January 1, 2015	$150
Josep	May 15, 2015	$50
Josep	June 15, 2015	$100
Laura	May 1, 2015	$45
Laura	June 15, 2015	$75
Laura	June 30, 2015	$100

Table 1. RFM-based Customer Segmentation

Then:
Josep's ARPU is

$$(150 + 50 + 100)/6 = 50$$

Laura's ARPU is

$$(45 + 75 + 100)/2 = 110$$

.

Adding these two numbers gives you an average monthly revenue per customer of $160/2 = 80$. To find a 12-month or 24-month CLV, multiply that number by 12 or 24.

The benefit of an ARPU approach is that it is simple to calculate, but it does not take into account changes in your customers' behaviors.

Note: ARPA is when we consider **accounts** instead of user. AMPU is when we consider average margin instead of average revenue. AMPA is when we consider average margin and accounts instead of average revenue and users.

How does ARPU relate to CLV?

$$CLV = \sum_{t=1}^{\infty} \frac{(ARPU_t - CCPU_t) r_t}{(1 + WACC)^{t-1}} - AC$$

References

- Modeling Customer Lifetime Value
- CLTV, Harvard
- The 16 business benefits of Customer Lifetime Value
- Dominique Hanssens's Research
- BTYD package
- BTYDplus package
- foretell: Projecting Customer Retention Based on Fader and Hardie Probability Models
- Kinshuk Jerath, Peter S. Fader, Bruce G.S. Hardie, Customer-base analysis using repeated cross-sectional summary (RCSS) data, European Journal of Operational Research, Volume 249, Issue 1, 16 February 2016, Pages 340-350, ISSN 0377-2217, http://dx.doi.org/10.1016/j.ejor.2015.09.002.
- Can the negative binomial distribution predict industrial purchases? John W Wilkinson , Giang Trinh , Richard Lee , Neil Brown. Journal of Business & Industrial Marketing 2016 31:4 -Rajkumar Venkatesan, V. Kumar (2004) A Customer Lifetime Value Framework for Customer Selection and Resource Allocation Strategy. Journal of Marketing: October 2004, Vol. 68, No. 4, pp. 106-125
- R package for exploratory data analysis
- Measuring Customer Lifetime Value: Models and Analysis
- Probability Models for Customer-Base Analysis
- SMCRM: Data Sets for Statistical Methods in Customer Relationship Management by Kumar and Petersen (2012)
- An Introduction to Predictive Customer Lifetime Value Modeling